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Araştırma Makalesi

Tarım Deneylerinin Modellenmesinde ANOVA ve ANFIS Yaklaşımlarının Kullanılması

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Öz

Uyarlamalı Ağ Tabanlı Bulanık Çıkarım Sistemi (ANFİS), teknoloji, üretim, sağlık, sosyal ve eğitim gibi pek çok branşta, ilgilenilen konuyu etkileyen faktörleri ve faktör düzeylerini, oluşturduğu çok sayıda kurala bağlı olarak ve çok küçük bir deneysel hata ile analiz edebilmekte ve modelleyebilmektedir. Tarım alanında da özellikle tarımsal alan seçimi ve teknolojik ürün geliştirme gibi problemlerin çözümü için uygulanmaktadır. Ürün yetiştirilmesi gibi belirli bir zaman aralığındaki durum tespit çalışmalarında ise genellikle klasik istatistik yöntemlere başvurulmaktadır. Bu yöntemlerin başında da deney tasarımı yöntemleri veya başka bir deyişle varyans analizi (ANOVA) yöntemleri gelmektedir. ANOVA ile modellenen deneyler ile ilgilenilen konuyu etkileyen faktörler ve bu faktörlerin düzeyleri, kullanılan yönteme ait tek bir kurala göre analiz edilir. ANOVA'nın tek kuralına karşılık ANFİS'in çok sayıda kuralı ile oluşturduğu modelin Hata Kareler Ortalamasının Karekökü (RMSE) çok daha küçük olduğundan daha güçlü sonuçlar vermektedir. Tarımsal ürünlerin zamana bağlı olarak ANFİS ile modellenmesi, bu alanda veri madenciliği çalışmalarını destekleyebilecektir. Bu çalışmada tarım alanında gerçekleştirilen bir durum tespit çalışması hem ANOVA hem de ANFİS ile modellenmiş ve benzer bulgular elde edilmiştir. Bununla birlikte çoğunlukla ANFİS'e ait RMSE değerleri ANOVA'dan küçük bulunmuştur. Ayrıca ANFİS çıktıları ile gerçek ölçümler arasındaki ilişkiler incelenmiştir.

Anahtar kelimeler: Tarımsal deneylerin modellenmesi, ANFİS, ANOVA.

Using ANOVA and ANFİS Approaches in Modelling Agricultural Experiments

Abstract

Adaptive Neuro-Fuzzy Inference System (ANFIS) can analyze the factors and factor levels affecting the subject of interest in many branches such as technology, production, health, social and education, depending on the many rules it creates and with a very small experimental error (RMSE). and modelling. It is also applied in the field of agriculture, especially for the solution of problems such as agricultural field selection or technological product development. On the other hand, classical statistical methods are generally used in due diligence studies in a certain time period, such as product cultivation. Experimental design methods or in other words analysis of variance (ANOVA) methods come first among these methods. With the experiments modeled by ANOVA, the factors affecting the subject of interest and the levels of these factors are analyzed according to a single rule of the method used. Since the Root Mean Square Error (RMSE) of the model formed by the multiple rules of ANFIS versus the single rule of ANOVA is much smaller, it gives stronger results. Modeling agricultural products with ANFIS depending on time will support data mining studies in this field. In this study, first both ANOVA and ANFIS methods were briefly explained, and then the data of a due diligence study carried out in agriculture were modeled by both methods and similar findings were obtained. However, mostly the standard deviation (RMSE) values of ANFIS were found to be smaller than ANOVA. In addition, the relationships between ANFIS outputs and real measurements were examined.

Key words: Modeling of agricultural experiments, ANFIS, ANOVA.

Introduction

Analysis of variance (ANOVA) has been a widely used method in statistics for many years. In order for ANOVA to be applied, certain assumptions must be carried out. In agricultural experiments, ANOVA is frequently used because these assumptions, which are explained in detail, can be met in general, have high statistical power, and give original results.

Adaptive Neuro-Fuzzy Inference System (ANFIS) is based on the idea of combining the advantages of artificial neural networks such as learning ability and fuzzy logic's ease of making decisions like humans and providing expert knowledge (Erginel and Şentürk, 2015). Thus, while the learning and computational power of artificial neural networks can be given to fuzzy logic inference systems, the ability of fuzzy logic inference systems to make decisions and provide expert knowledge like humans is gained in artificial neural networks.

Despite the widespread use of ANOVA in agriculture, the ANFIS method has come to the fore as an alternative in recent years because, while applying ANFIS, a large number of rules are created and a model is obtained as much as the number of rules created. In contrast to the single ANOVA model created for the data obtained from an experiment, since the number of models tried in ANFIS is much higher, the standard deviation, that is, the experimental error value (RMSE), of ANFIS is obtained with a lower value. This shows that ANFIS is a more powerful statistical method than ANOVA. In agricultural studies (although the number of studies is limited), ANFIS has been found to be a recommended statistical approach due to its small RMSE value. International studies of the last ten years support the usability of ANFIS in this field and its superiority over other approaches. For example, Naderloo et al. (2012) used ANFIS to estimate the grain yield of irrigated wheat fields in Abyek town of Ghazvin province, Iran. As a result, they revealed that the grain yield could be predicted with good accuracy by the method. Sabanci et al. (2017a; 2017b; 2020) used ANFIS to classify wheat grains and determined bread or durum wheat with image processing techniques. Khoshnevisan et al. (2014) again used ANFIS to estimate wheat grain yield based on energy inputs. At the same time, they applied the artificial neural networks (ANNs) method within the scope of the study and compared them with ANFIS.

As a result,they determined that ANFIS was more effective than ANN. Kaveh et al. (2018) also revealed that ANFIS gave better results than ANN in determining the drying properties of potatoes, garlic and melons. Danmardeh et al. (2017), also investigated chemical properties of soil in intercropping using ANN and ANFIS models and, found that ANFIS had more accurate forecasts than ANN. On the other hand, Shastry et al. (2015), determined which factor was effective in high wheat yield with the ANFIS method and multiple linear regression models, taking into account biomass, extractable soil water (ESW), radiation and rain in estimating wheat yield. Thus, they revealed that ANFIS gave better results than multiple linear regression models due to its smaller RMSE value. Similar to sugarcane yield classification of Jayashree et al. (2016), Development of an Intelligent Irrigation Decision Support System (SIDSS) for managing irrigation in agriculture of Navarro-Hellín et al. (2016), Sirabahenda et al. (2017) used the ANFIS method to estimate suspended sediment concentrations in catchments affected by agriculture and Đokić and Jović (2017) have analyzed the impact of industry and agriculture on gross national product (GDP), industry or agriculture. Houshyar et al. (2017) combined ANFIS and Geographical Information System (GIS) to assess the sustainability of winter wheat in Iran and concluded that this combination was a capable tool for estimating sustainability indices. Mohaddes and Fahimifard (2018), compared ANFIS with ARIMA, which is the most common econometric linear estimation method, in estimating the econometric sizes of agricultural product exports (1, 2 and 4 years), and as a result, they determined that ANFIS was a more effective method. Srilakshmi et al. (2018) stated that model estimation methods such as ANFIS provided a broad examination of technologies. Using the Soil and Water Assessment Tool (SWAT) model and the ANFIS-based model to estimate suspended sediment concentrations (SSC) and sediment loads in the Mill River watershed (PEI, Canada), Sirabahenda et al. (2020) emphasized that the ANFIS model predicted the measured SSC more accurately than the SWAT model, and as a result, an ANFIS-based model could be used to simulate the impact of land use changes on sediment distribution in a river. Del Cerro et al. (2021) also applied experimental methods and ANFIS to select the estimation of evapotranspiration (ETo) estimation model that best fits the semi-arid region in South India. In conclusion, they stated that the results of ANFIS models were promising and can be used as prediction methods.

Many studies have been carried out on different agricultural topics or products with ANFIS, and in some, different agricultural indices, statistical or fuzzy methods have been compared with ANFIS. However, no study comparing ANOVA, which is one of the most frequently used methods in this field, and ANFIS has been found. With this study, it has been shown that the ANFIS method can also be applied in time-dependent agricultural situation assessments.

In section of material and method, the experiment carried out in the agricultural field and the ANOVA and ANFIS methods that will be used in modeling the data obtained from this experiment have been explained. Then applications have been carried out and the results have been presented. In addition, the relationship between ANFIS outputs and application data has been examined. And last, discussion and conclusions have been given.

Material and Method

In the comparison of ANFIS and ANOVA methods, the data has been obtained within the scope of the project numbered TAGEM/HAYSÜT/137, dated March 1, 2012-30 March 2015 and named "Carcass and Meat Quality Characteristics of Gray Breed Cattle Produced in Organic System" (Hanoğlu Oral et al., 2017) . The methods to be used in modeling the data of this study have been explained.

Analysis of Variance (ANOVA)

Experiments can be defined as special processes organized in order to obtain meaningful data, and ANOVA can be defined as the study of organizing the factor or factor groups that play a role in the formation of the event or phenomena of interest, estimating their effects and measuring the reliability of the predictions (Şentürk, 2010). In ANOVA, the independent variable is called the factor, and the values of the independent variable are called factor levels.

In order for ANOVA to be applied, certain assumptions must be carried out. These are counted as the measurement of the dependent variable with the least interval scale, the compliance of the populations with the normal distribution, the homogeneity of the variances, and the repetition of the sampling in accordance with the rules.

ANOVA is based on three basic principles: repetition, randomization and blocking. The repeat phase is when the experiment is performed multiple times under the same conditions. Randomization refers to the order in which each operation or trial of the experiment is to be performed randomly, and statistical methods require that the observations (or errors) be independently distributed random variables. Blocking is a design technique used to reveal the precision of the comparison between the factors of interest in the experiment (Montgomery, 2001).

ANOVA is to divide and analyze the sum of the squares of the deviations of the data obtained as a result of the experiment from the general mean, according to the factors causing the said deviations (Nsiak, 2017).

In the one-way ANOVA model, also known as the means model, there is a single factor and various levels or trials of this factor. The aim here is to examine the effects of trials on the dependent variable. The deviation of each observation value from the general mean is due to two reasons. The first is that the mean of the group to which the observation value belongs is different from the general mean, and the second is that each term shows a deviation from its own group mean, since there is a difference between the observations in the same group (Şentürk, 2010).

Some studies may not be concerned with only one factor. The nature of the event itself may also have the effect of a second factor on the observation units obtained. Thus, the model in which the effects of various levels of two factors on a dependent variable are examined is called the two-way ANOVA model. The effect that may arise as a result of transactions between different levels of factors is called the interaction effect (Şentürk, 2010). When the effects of more than one factor on a dependent variable are examined, the interaction effect should also be examined.

Three-way ANOVA model is used when three factors and different levels of these factors are concerned, and similarly when n factors and different levels of these factors are concerned. Experiments created in this way are called multi-factor experimental design [29]. Using the data obtained as a result of the experiment, it is possible to define ANOVA as a function of the factors considered and their interactions (Nsiak, 2017; Muluk et al., 1994). The test of whether there is a statistically significant difference between the factors of interest and factor levels is calculated with the F distribution.

In this study, the multi-factor ANOVA model has been applied.

Table 1 shows a two-way ANOVA table. Similarly, three-way, etc. multi-factor ANOVA tables can be obtained. The F statistic calculated in the table is therefore decided by comparing it with the theoretical F statistic value.

Let $Y_{i..}, Y_{.j.}$: average of observations below the ith level of factor A and factor B, respectively, $Y_{...}$: general average of all observations, $y_{ij.}$: interaction at the jth level of factor B and ith level of factor A, n:total number of observations, a: number of levels of factor A, b: number of levels of factor B and n: number of observations in each group represent. Then formed as follows in Table 1 for the two-way ANOVA model.

Table 1. Table of two-way ANOVA (Nsikak, 2017)

Source of variation	Degrees of freedom (df)	Sum of squares (ss)	F
Factor A $(\delta)_i$	$a-1$	$\frac{\sum_{i=1}^{a} Y_{i..}^2}{bn} - \frac{Y_{...}^2}{abn}$	$\frac{\left(\frac{ss_\delta}{a-1}\right)}{ms_E}$
Factor B $(\theta)_j$	$b-1$	$\frac{\sum_{j=1}^{b} Y_{.j.}^2}{an} - \frac{Y_{...}^2}{abn}$	$\frac{\left(\frac{ss_\theta}{b-1}\right)}{ms_E}$
Interaction $(\delta\theta)_{ij}$	$(a-1)(b-1)$	$\frac{\sum_{i=1}^{a}\sum_{j=1}^{b} Y_{ij.}^2}{n} - \frac{\sum_{i=1}^{a} Y_{i..}^2}{bn} - \frac{\sum_{j=1}^{b} Y_{.j.}^2}{an} + \frac{Y_{...}^2}{rts}$	$\frac{\left(\frac{ss_{\delta\theta}}{(a-1)(b-1)}\right)}{ms_E}$
Error (e_{ij})	$ab(n-1)$	$ss_Y - ss_\delta - ss_\theta - ss_{\delta\theta}$	
Total	$abn-1$	$\sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{n} Y_{ijk}^2 - \frac{Y_{...}^2}{abn}$	

Adaptive Network Based Fuzzy Inference System (ANFIS)

ANFIS is to use artificial neural networks to adjust and find the structure and variables of the system (Erginel and Şentürk, 2015; Jung and Sun, 1995). There are two important adjustments in network-based inference systems: structural adjustment and variable adjustment. Structural adjustment includes the number of variables to be calculated, the number of rules, the definition of each input-output variable as fuzzy sets, and the construction of the rules, while variable adjustment includes calculating the centers, slopes, widths and weights of the fuzzy logic rules of membership functions (Erginel and Şentürk, 2015).

ANFIS was introduced by Jang in 1993. Jang's ANFIS model uses the Sugeno fuzzy logic inference system to implement the ability to make decisions like humans and provide expert knowledge, and the Backpropagation Learning Algorithm to apply the learning ability of artificial neural networks (Jang, 1993). An ANFIS architecture with two inputs such as x_1 and x_2,one output such as *y* and four rules is as shown in Figure 1:

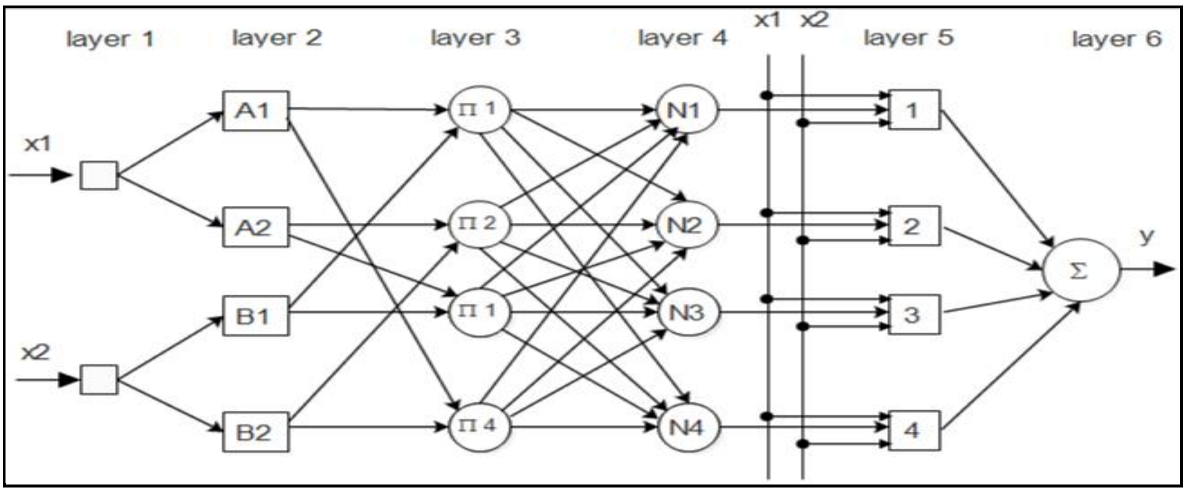

Figure 1. ANFIS architecture (Ghanei et al., 2017)

The gradient functions of each layer and the operation of the layers are as follows, respectively. (Jang and Sun, 1997; Jang, 1993; Ghanei et al., 2017; Kim and Park, 2002; Yılmaz et al., 2004):

Layer 1: It is the input layer. Each gradient in this layer is the input gradients through which the input signals are transferred to other layers.

Layer 2: It is the blur layer. Each gradient in this layer represents fuzzy sets such as A_j and B_j $(j = 1,2)$. It uses the Generalized Bell membership function while separating the input values into fuzzy sets. Here, the output of each gradient is the membership degrees that depend on the input values and the membership function used. The membership degrees obtained from the 2nd layer are $\mu_{A_j}(x)$ and $\mu_{B_j}(y)$.

Layer 3: It is the rule layer. Each gradient in this layer expresses the rules and numbers created according to the Sugeno fuzzy logic inference system. The output of each rule gradient, μ_i, represents the product of the membership degrees from the 2nd layer. The output of each gradient here also shows the firing strength of a rule. μ_i values are obtained as follows,

$$y_i^3 = \Pi i = \mu_{A_j}(x) \times \mu_{B_i}(y) \quad (j = 1,2)(i = 1,n).$$

Here y_i^3 represents the output values of the 3rd layer and n represents the number of gradients in this layer.

Layer 4: It is the normalization layer. Each gradient in this layer accepts all gradients from the rule layer as input values and the normalized firing level of each rule is calculated in this layer. Normalized firing level, i for i gradient. It is expressed as the ratio of the firing level of the rule to the firing level of all the rules. If the normalized firing level $\bar{\mu}_i$ of the ith gradient is calculated as follows,

$$y_i^4 = Ni = \frac{\mu_i}{\sum_{i=1}^{n} \mu_i} = \bar{\mu}_i \quad (i = 1,n).$$

Layer 5: It is the defuzzification layer. Each gradient in this layer is associated with the input values x_1 and x_2 and the output values of each gradient of the normalization layer. The weighted result values of a given rule are calculated at each gradient in the defuzzification layer. The output value of the ith gradient in the 5th layer is as follows,

$$y_i^5 = \bar{\mu}_i[p_i x_1 + q_i x_2 + r_i] \quad (i = 1,n).$$

The variables (p_i, q_i, r_i) here are the set of result parameters of the ith rule.

Layer 6: It is the total layer. There is only one gradient in this layer and is tagged with $\sum$. Here, the output values of each gradient in the 4th layer are summed and the real value of the ANFIS system is obtained as a result. The output value y of the system is obtained as follows,

$$y = \sum_{i=1}^{n} \bar{\mu}_i\,[p_i x_1 + q_i x_2 + r_i].$$

As seen in the operation of the ANFIS architecture, it is important to know the input (x_1, x_2) and the result variable (p_i, q_i, r_i) values. ANFIS's learning algorithm optimizes both input and outcome variables. While the learning process is taking place, ANFIS uses the hybrid learning algorithm. The hybrid learning algorithm consists of using the least squares method and the back propagation learning algorithm together (Kahraman and Onar, 2015).

The hybrid learning algorithm consists of two parts: feed forward and feedback. In feedforward, the values of the result parameters are calculated by the least squares method by taking the input parameters constant, while in the feedback, the input parameters are calculated by the back propagation learning algorithm by taking the result parameters constant. It is possible to summarize how feed forward and feedback processes occur with Table 2 (Jang and Sun, 1997; Jang, 1993).

Table 2. Hybrid Learning Algorithm (Jang, 1993)

Hybrid Learning Algorithm	Feedforward	Feedback
Input Parameters	Constant	Backpropagation Learning
Output Parameters	Least Squares Method	Constant

Here, the feed-forward and feedback cycle continues until the entire system error is less than a specified error value or does not change much. The error value to be calculated, on the other hand, is equal to the square root value of the mean squared error, in a sense, the standard deviation value of the system. The formula for the RMSE value is as follows,

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(T_i - y_i)^2}{N}}.$$

In the formula, T_i is the real values, y_i is the values obtained from ANFIS, and N is the sample size (Jang and Sun, 1997; Jang, 1993; Kim and Park, 2002).

The Back Propagation Learning Algorithm: This is used to calculate the input parameters in the feedback part of the hybrid learning algorithm of ANFIS. This method, also called the standard back propagation algorithm, reduces the sum of squares of the error with the back propagation method. The "gradient" decrease method is used to reduce the error at each step (Erginel and Şentürk, 2015). The learning algorithm consists of three stages: feed forward, calculation and back propagation of the error, and updating the weights. In the back propagation learning algorithm, the error value obtained from the output of the network is reflected backwards to the input layer, and the necessary weight variables are adjusted. The aim here is to bring the error criterion to zero for all input values at the end of the learning process (Erginel and Şentürk, 2015; Jang, 1993).

Results

In this section, the data of the study titled "Carcass and Meat Quality Characteristics of Gray Breed Cattle Producted in Organic System (Hanoğlu Oral et al., 2017)" is modeled with ANOVA and ANFIS, respectively, and presented above. Then, the real study data and ANFIS outputs are compared.

ANOVA Results of the Study of "Carcass and Meat Quality Characteristics of Gray Breed Cattles Produced in Organic System"

Multi-factor ANOVA results have been summarized in the tables below (Hanoğlu Oral et al., 2017). There are comparison results of ANOVA of CP (Crude Protein), ASH (Ash), Cfat (Crude fat), Cfiber (Crude fiber), NDF (Notr Detergante Fiber), ADF (Acid Detergante Fiber) and ADL (Acid Detergante Lignin) chemical analysis data from 7 different shrubs (1: *Phillyrea latifolia* (PL), 2: *Juniperus oxycedrus* (JO), 3: *Paliurus spina-christi* (PSC), 4: *Spartium junceum* (SJ), 5: *Anagyris foetida* (AF), 6: *Quercus infectoria* (QI) and 7: *Quercus coccifera* (QC)) obtained in 3 replicates each 12 terms (months) for 2 years (1: 2013, 2: 2014) in Table 3. In Table 4, the ANOVA results regarding the comparison of the hay yields of the mentioned shrubs based on the FHY (Fresh High Yield), DHY (Dry High Yield) and DMR (Dry Matter Ratio) data obtained in 3 repetitions for 2 years (1: 2013, 2: 2014) and 2 terms (1: May, 2: November) have been given. Table 5 summarizes the ANOVA results of CP, ASH, Cfat, Cfiber, NDF, ADF and ADL chemical analysis data obtained from two ungrazed (1) and grazed (2) rangelands with 3 replicates each 12 terms for 2 years (1: 2013, 2: 2014). In In Table 6, ANOVA results have been given in which FHY, DHY and DMR for hay yield values are compared from the ungrazed rangeland in 3 repetitions each 12 terms for 2 years (1: 2013, 2: 2014).

Table 3. ANOVA results of the variation of the chemical components of the shrubs with respect to species and time

	P values						
Source	CP	ASH	Cfat	Cfiber	NDF	ADF	ADL
Term	0,000**	0,000**	0,000**	0,000**	0,000**	0,000**	0,000**
Year	0,309	0,575	0,795	0,310	0,251	0,108	0,214
Shrub	0,000**	0,000**	0,000**	0,000**	0,000**	0,000**	0,000**
Term*Year	0,357	0,290	0,999	0,992	0,324	0,128	0,473
Term*Shrub	0,000**	0,000**	0,000**	0,000**	0,000**	0,000**	0,000**
Year*Shrub	0,417	0,434	0,977	0,878	0,998	0,941	0,333
Error	**0,330**	**0,164**	**0,091**	**0,43**	**0,6**	**0,67**	**14,9**

* Significant at α=0,05 significance level, ** Significant at α=0,01 significance level

When the chemical analysis data is compared according to shrubs, terms and years in Table 3, it is clear that all data shows a statistically significant difference according to the effects of shrub, term and syrup*term effects.

It is clear that all data changes according to the shrub and term effects in Table 4. FHY differs according to shrub, term and shrub*term, DHY differ according to shrub and term, and DMR differs according to shrub, term, shrub*term and year*term effects, significantly.

Table 4. ANOVA results of variation of the shrub hay yields with respect to species and time

	P values		
Source	FHY	DHY	DMR
Term	0,000**	0,000**	0,000**
Year	0,119	0,146	0,594
Shrub	0,000**	0,004**	0,000**
Term*Year	0,980	0,925	0,096
Term*Shrub	0,008**	0,388	0,000**
Year*Shrub	0,321	0,529	0,010**
Error	**36,346**	**6,711**	**20,25**

* Significant at α=0,05 significance level, ** Significant at α=0,01 significance level

Table 5. ANOVA results of the variation of the chemical components of hay in the rangelands (ungrazed or grazed) with respect to time

	P values						
Source	CP	ASH	Cfat	Cfiber	NDF	ADF	ADL
Term	0,000**	0,000**	0,000**	0,000**	0,000**	0,000**	0,000**
Rangeland	0,069	0,575	0,622	0,093	0,159	0,000**	0,191
Year	0,000**	0,265	0,262	0,000**	0,272	0,308	0,259
Term*Rangeland	0,024*	0,000**	0,001**	0,001**	0,204	0,015*	0,000**
Term*Year	0,009**	0,229	0,029*	0,102	0,027*	0,857	0,448
Rangeland*Year	0,013*	0,600**	0,743	0,197	0,227	0,047*	0,769
Error	**0,5134**	**0,7393**	**0,38424**	**3,424**	**11,25**	**1,467**	**0,8156**

* Significant at α=0,05 significance level, ** Significant at α=0,01 significance level

According to Table 5, it can be said that all data varies according to the term effect. CP and Cfiber differ according to year, ADF differ according to rangeland, data which other of NDF differs according to term*rangeland, CP, Cfat and NDF differ according to term*year and CP, ASH and ADF differ according to rangeland*year effects, significantly.

Shown that all data (FHY, DHY and DMR) differs significantly according to year, term and year*term effects in Table 6.

Table 6. ANOVA results of variation of the hay yields in rangeland (ungrazed) with respect to time

	P values		
Source	**FHY**	**DHY**	**DMR**
Year	0,037*	0,000**	0,001**
Term	0,000**	0,000**	0,000**
Year*Term	0,000**	0,000**	0,000**
Error	**5462**	**984,7**	**36,10**

* Significant at α=0,05 significance level, ** Significant at α=0,01 significance level

ANOVA Results of the Study of "Carcass and Meat Quality Characteristics of Gray Breed Cattles Produced in Organic System"

Firstly, the change of chemical analysis measurements obtained from 7 different shrups under the effects of year and term were investigated. The shrubs were coded as *PL*=1*, JO*=2*, PSC*=3*, SJ*=4*, AF*=5*, QI*=6 and *QC*=7 in this review. Chemical analysis variables of CP, ASH, Cfat, Cfiber, NDF, ADF and ADL were observed with 3 replications for 7 different shrubs, 12 terms (months) and 2 years (as 2013=1 and 2014=2), and 504 data obtained from each chemical analysis variables were randomly assigned. It was reserved for training (378) and testing (126). ANFIS was performed with the *7 12 2* model for each chemical analysis using the Generalized Bell membership function in Matlab 2021b. Each model was created according to 168 rules after 100 trainings. The training and test errors (RMSE) obtained from the ANFIS models for these data are given in Table 7.

Table 7. RMSEs obtained from *7 12 2* ANFIS models applied to chemical analysis data of shrubs using Generalized Bell Membership Function and created according to 168 rules after 100 trainings

	Training	Test
CP	0,453610	2,48820
ASH	0,319950	0,89507
Cfat	0,223618	0,62053
Cfiber	0,505320	2,03040
NDF	0,601600	5,89780
ADF	0,712074	7,32890
ADL	**3,638230**	**3,39880**

RMSE values in bold are smaller than obtained by ANOVA.

The distributions of the ANFIS outputs in Table 7 are shown in Figure 2 (blue and red dots represent real data and ANFIS outputs, respectively).

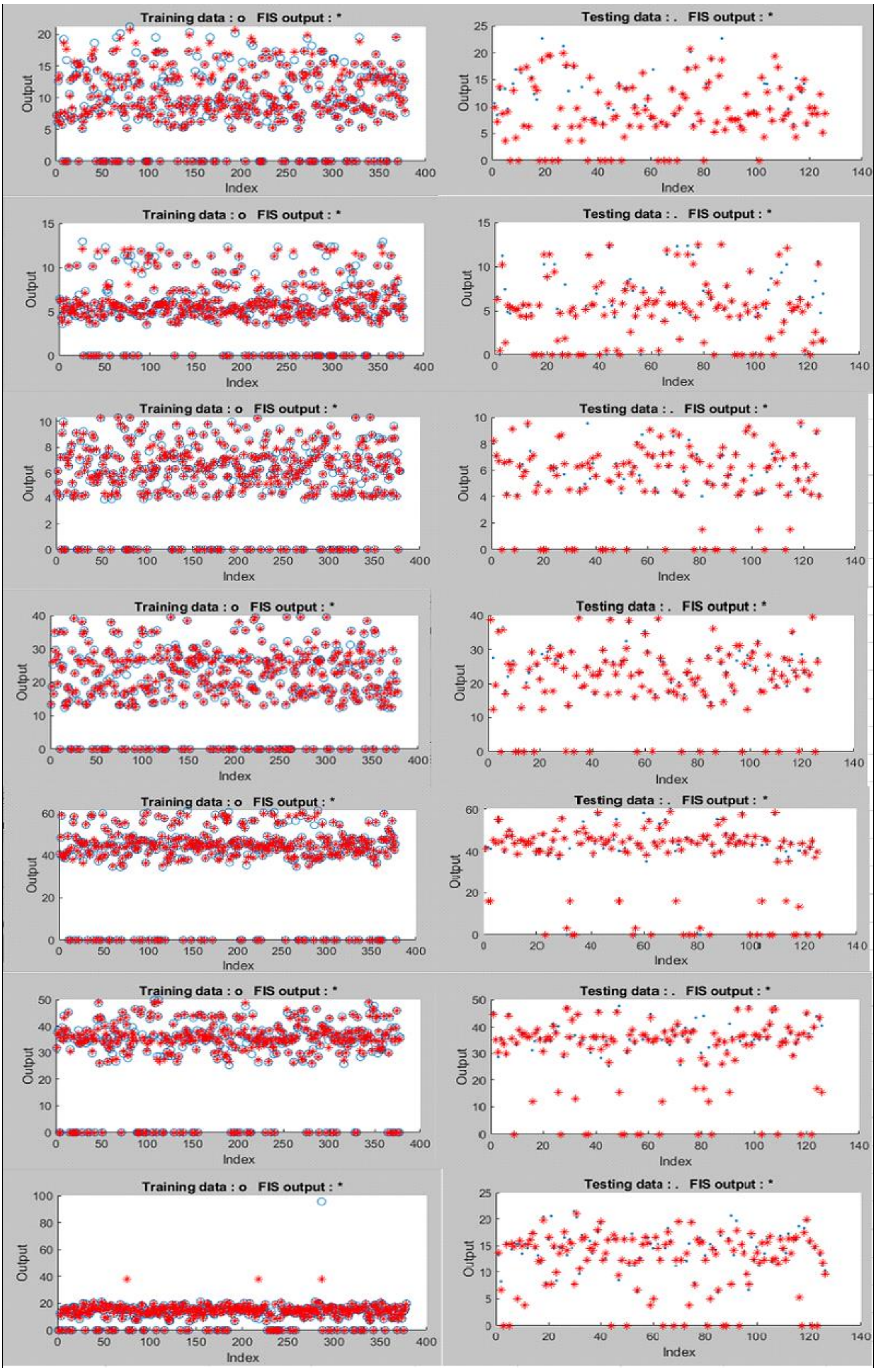

Figure 2. ANFIS outputs of CP, ASH, Cfat, Cfiber, NDF, ADF and ADL chemical analysis, respectively.

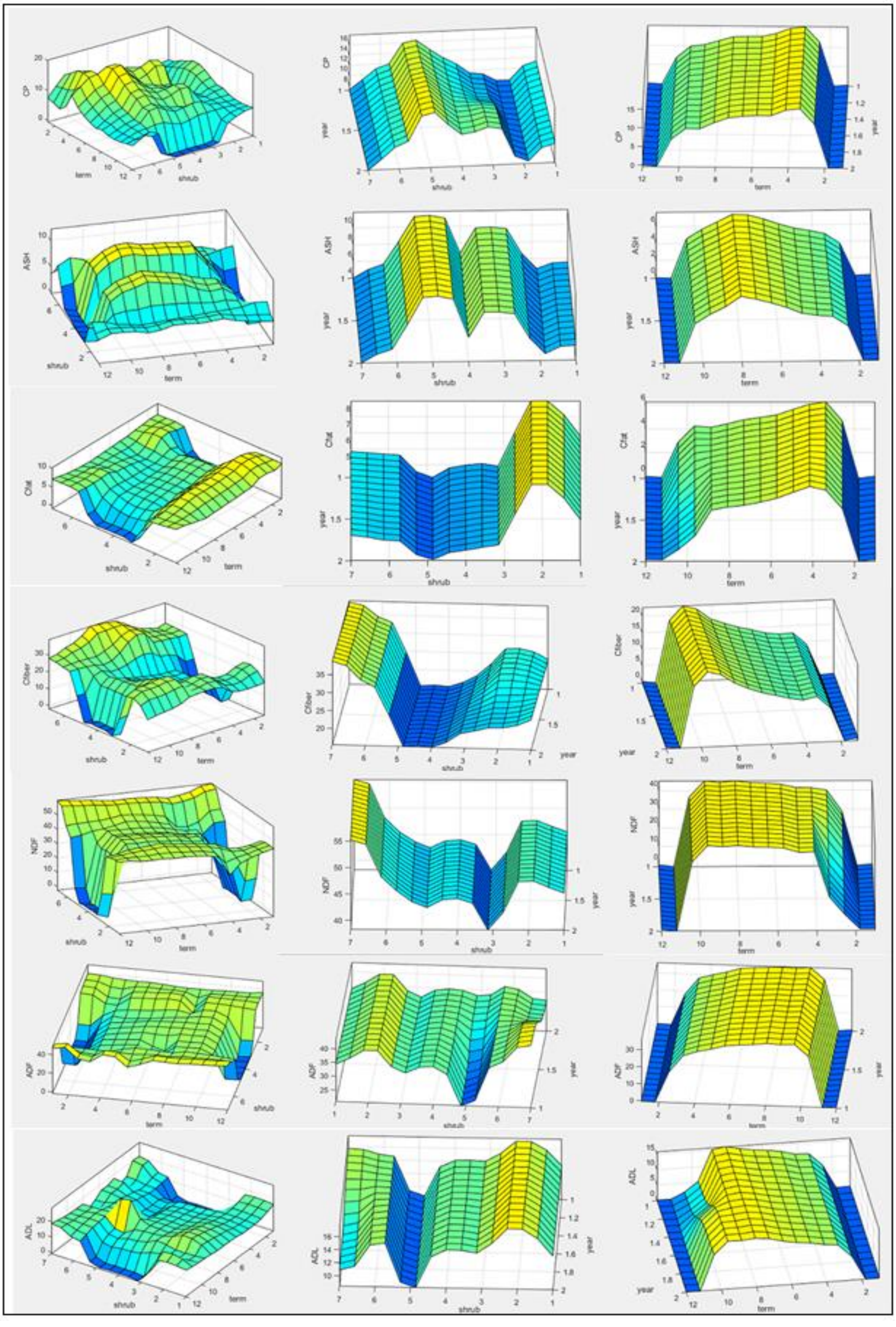

Figure 3. Changes of ANFIS outputs of CP, ASH, Cfat, Cfiber, NDF, ADF and ADL chemical analysis according to shrub, term and year effects.

It is seen that ANFIS outputs are close to the real data. The surface graphics obtained as a result of the created ANFIS models are presented in Figure3.

PSC, SJ and *QI* in March, *PL* and *QC* in April, *AF* in May and *JO* in August reached the highest CPs. *JO* had the least CP, while *AF* had the most.

JO in January, *QC* in March, *PL* in April, *PSC, SJ* and *AF* in August and *QI* in November reached the highest ASHs. The shrubs with the lowest and highest ASH are *QC* and *AF*, respectively.

All shrubs reached the highest Cfat values in March. The lowest and highest Cfat values are observed from *QC* and *AF*, respectively.

PL and *QI* in June, *QC* in August, *JO* and *PSC* in September, *SJ* and *AF* in October reached the highest Cfiber values. The lowest and highest Cfiber values are observed from *SJ* and *QC*, respectively.

JO, SJ, AF and *QI* in August, *PSC* in October, *PL* in November and *QC* in December reached the highest NDFs. The lowest and highest NDF are observed from PSC and QC, respectively.

PL and *QC* in February, *JO* in August, *QI* in September and *PSC, SJ* and *AF* in October reached the highest ADFs. The lowest and highest ADF are observed from *PSC* and *QC*, respectively.

QC in February, *SJ* and *AF* in August, *QI* in September, *JO* and *PSC* in October and *PL* in December reached the highest ADL values. The lowest and highest ADL measurement are from QC.

Similar CP, ASH, Cfat, Cfiber, NDF, ADF and ADL data was measured at the same terms in both years. It is understood that all chemical data obtained from shrub species differs according to shrubs and terms, but not according to years. No chemical data could be obtained from November to February in *PSC, SJ* and *AF*.

However, it is seen that the second and third surfaces are flat, and the first surfaces are not flat (bumpy). In other words, while the change of one of the variables on the first surfaces affects the other, the changes of the variables on the second and third surfaces do not affect each other. For this reason, it is possible to say that CP, ASH, Cfat, Cfiber, NDF, ADF and ADL values changed depending on the shrub and term main effect factors, as well as the interaction of the shrub*term and besides, they were not affected by the year factor. These results are consistent with the final report of the study mentioned.

Secondly, the change of yield values obtained from 7 different shrups under the effects of year and term was investigated. In this review, shrubs were coded as in the previous analysis. The yield variables of FHY, DHY and DMR were obtained with 3 repetitions for 7 different shrubs, 2 terms (as May=1 and November=2) and 2 years (as 2013=1 and 2014=2), and each yield data was randomly assigned as 84 data for training (63) and test (21). ANFIS was performed with the *7 2 2* model for each yield variables using the Generalized Bell membership function in Matlab 2021b. Each model was created according to 28 rules after 100 trainings. The training and test errors (RMSE) obtained in the ANFIS models created from the yield data of the Shrubs have been given in Table 8.

Table 8. RMSEs from the *7 2 2* ANFIS models applied to the yield data of the shrubs using the Generalized Bell Membership Function and created according to 28 rules after 100 trainings

	Training	Test
FHY	**5,21378**	**5,0337**
DHY	**1,92791**	**3,0189**
DMR	**3,65487**	**16,6374**

RMSE values in bold are smaller than obtained by ANOVA.

The distributions of the ANFIS outputs in Table 8 are shown in Figure 4 (blue and red dots represent real data and ANFIS outputs, respectively).

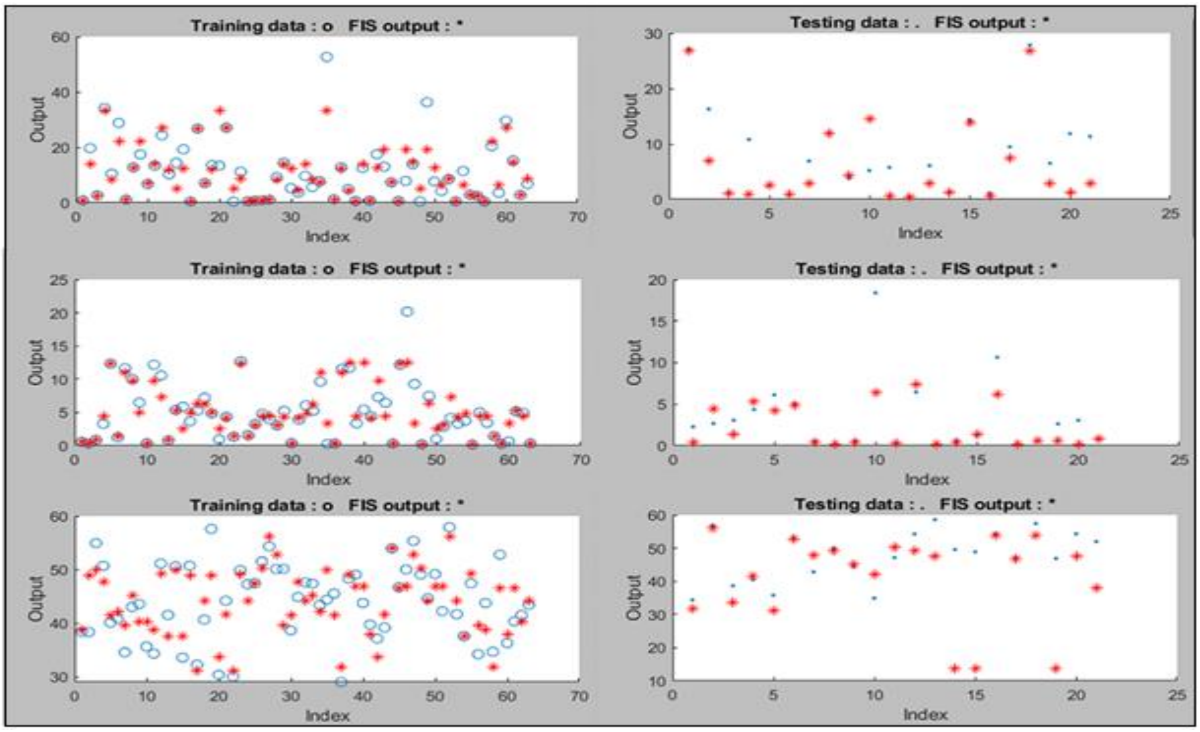

Figure 4. ANFIS outputs of FHY, DHY and DMR shrub yields, respectively

It is seen that ANFIS outputs are close to the real data. The surface graphics obtained as a result of the created ANFIS models are presented in Figure 5.

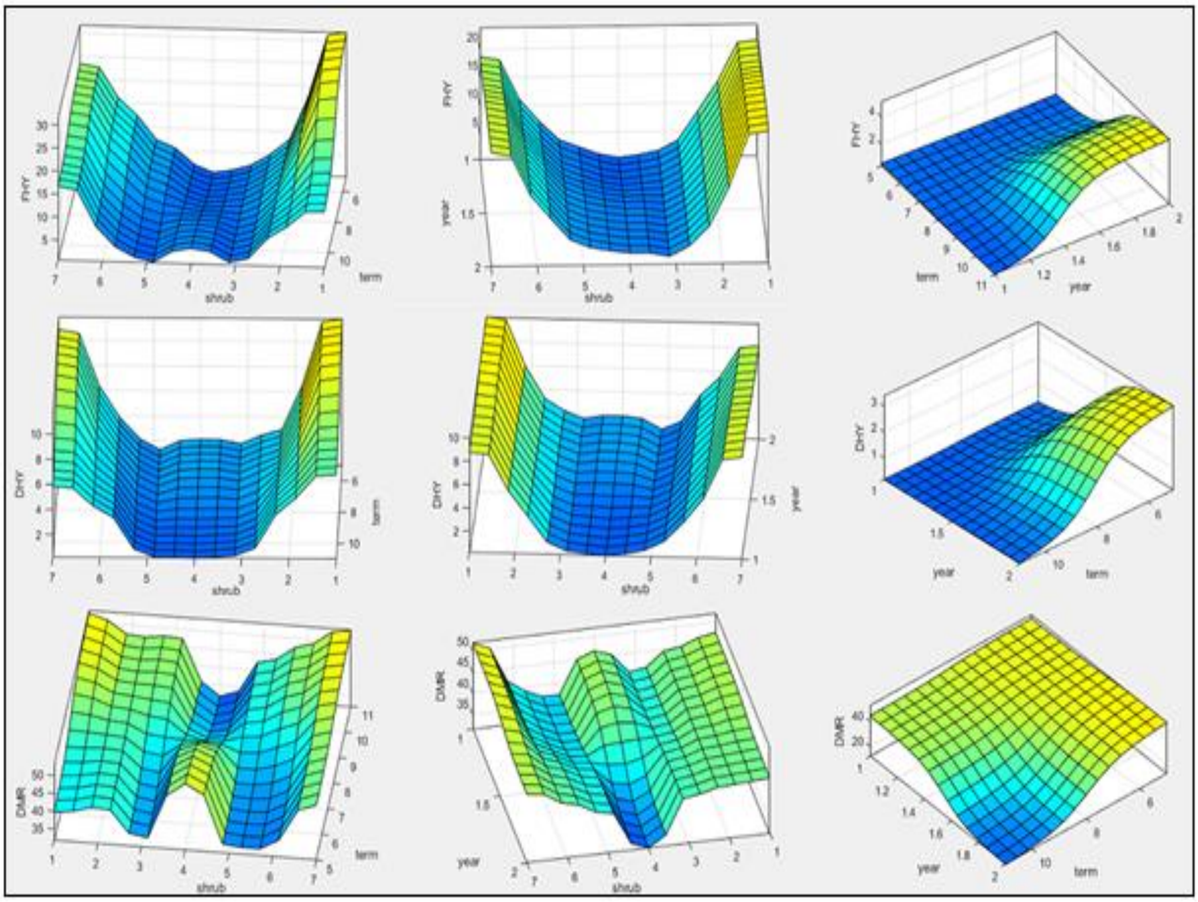

Figure 5. Changes of ANFIS outputs of FHY, DHY and DMR shrub yields according to shrub, term and year effects.

The lowest and highest FHY were obtained from *AF* and *QC*, respectively. The lowest and highest DHY values were obtained from *AF* and *PL*, respectively. And, the lowest and highest DMR values obtained from *PL*. All the shrub yield variables were clearly different between shrub and term factors. The data obtained from the first year was lower than the second year, but these differences were not statistically significant. Contrary to DMR, FHY and DHY data was considerably higher in May than November in both years.

According to the ANOVA results (Hanoğlu Oral et al., 2017), although the year*term interaction effect was significant (p=0.01<0.05), the curves did not intersect. And, although the shrub*year interaction effect was not statistically significant (p=0.096>0.05), when the graph was examined, it is seen that the curves intersect each other, that is, there is an interaction between them. Other results are same with the final report of the study mentioned.

Thirdly, the changes in chemical variables of hay obtained from 2 different rangelands according to time (year and term) were investigated. In this study, the rangeland species were coded as grazed=1 and ungrazed=2. CP, ASH, Cfat, Cfiber, NDF, ADF and ADL hay chemical variables were obtained in 2 different rangeland, 12 terms (months) and 3 repetitions for 2 years (as 2013=1 and 2014=2). Each variable was randomly assigned 150 data for training (113) and test (37). ANFIS was performed with the *2 12 2* model for each variable using the Generalized Bell membership function in Matlab 2021b. Each model was created according to 48 rules after 100 trainings. The training and test errors (RMSE) obtained in the ANFIS models created from the data are given in Table 9.

Table 9. RMSEs obtained from the *2 12 2* ANFIS models applied to the hay chemical variables of Rangelands using the Generalized Bell membership function and created according to the 48 rules after 100 trainings

	Training	Test
CP	0,566649	1,99190
ASH	**0,603821**	2,34150
Cfat	0,411984	0,81194
Cfiber	**1,555230**	3,85070
NDF	**2,539600**	16,5605
ADF	**0,899797**	8,48240
ADL	**0,731058**	4,99350

RMSE values in bold are smaller than obtained by ANOVA.

The distributions of the ANFIS outputs in Table 9 are shown in Figure 6 (blue and red dots represent real data and ANFIS outputs, respectively).

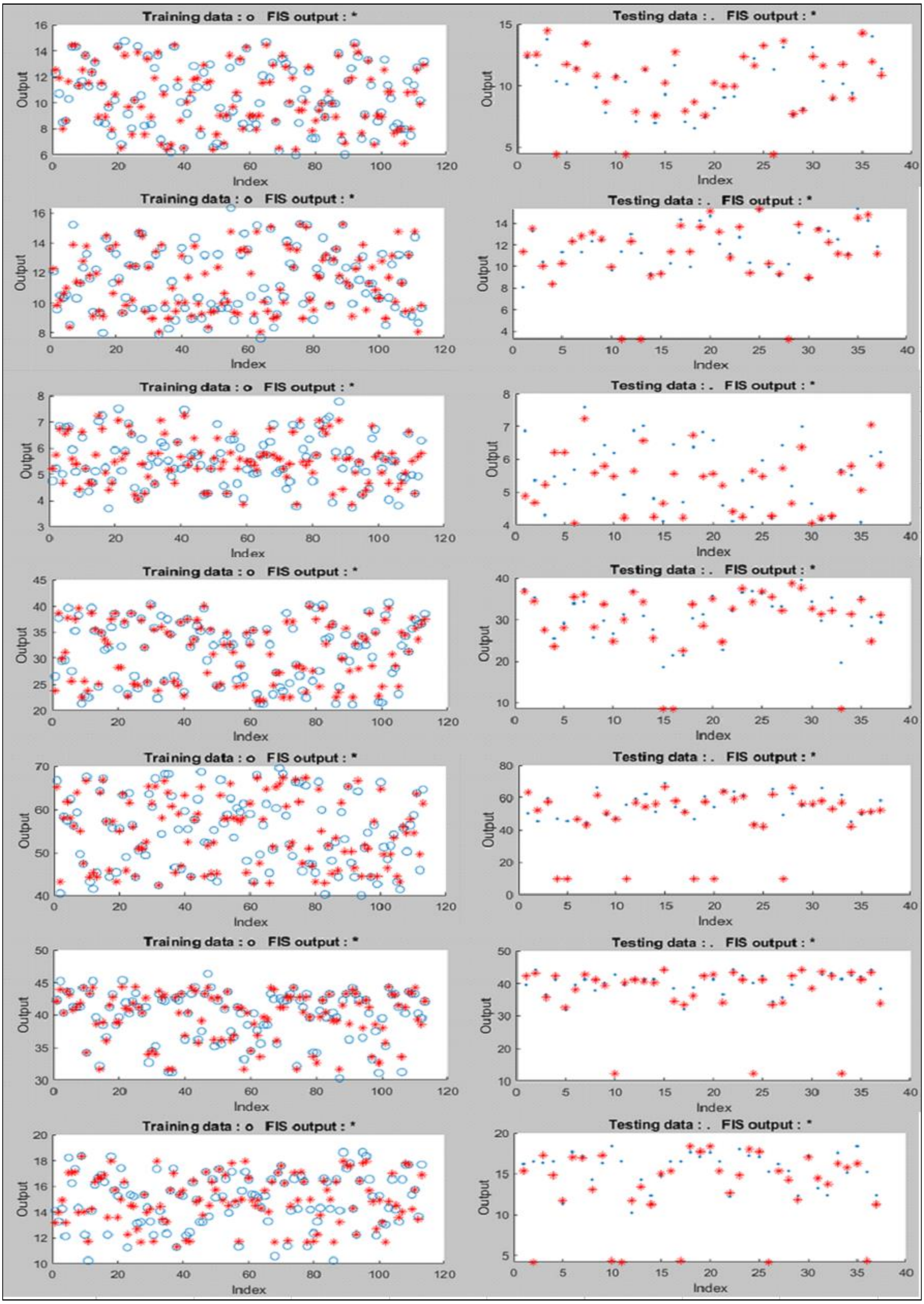

Figure 6. ANFIS outputs of CP, ASH, Cfat, Cfiber, NDF, ADF and ADL hay chemical analysis, respectively.

It is seen that ANFIS outputs are close to the real data. The surface graphics obtained as a result of the created ANFIS models are presented in Figure 7.

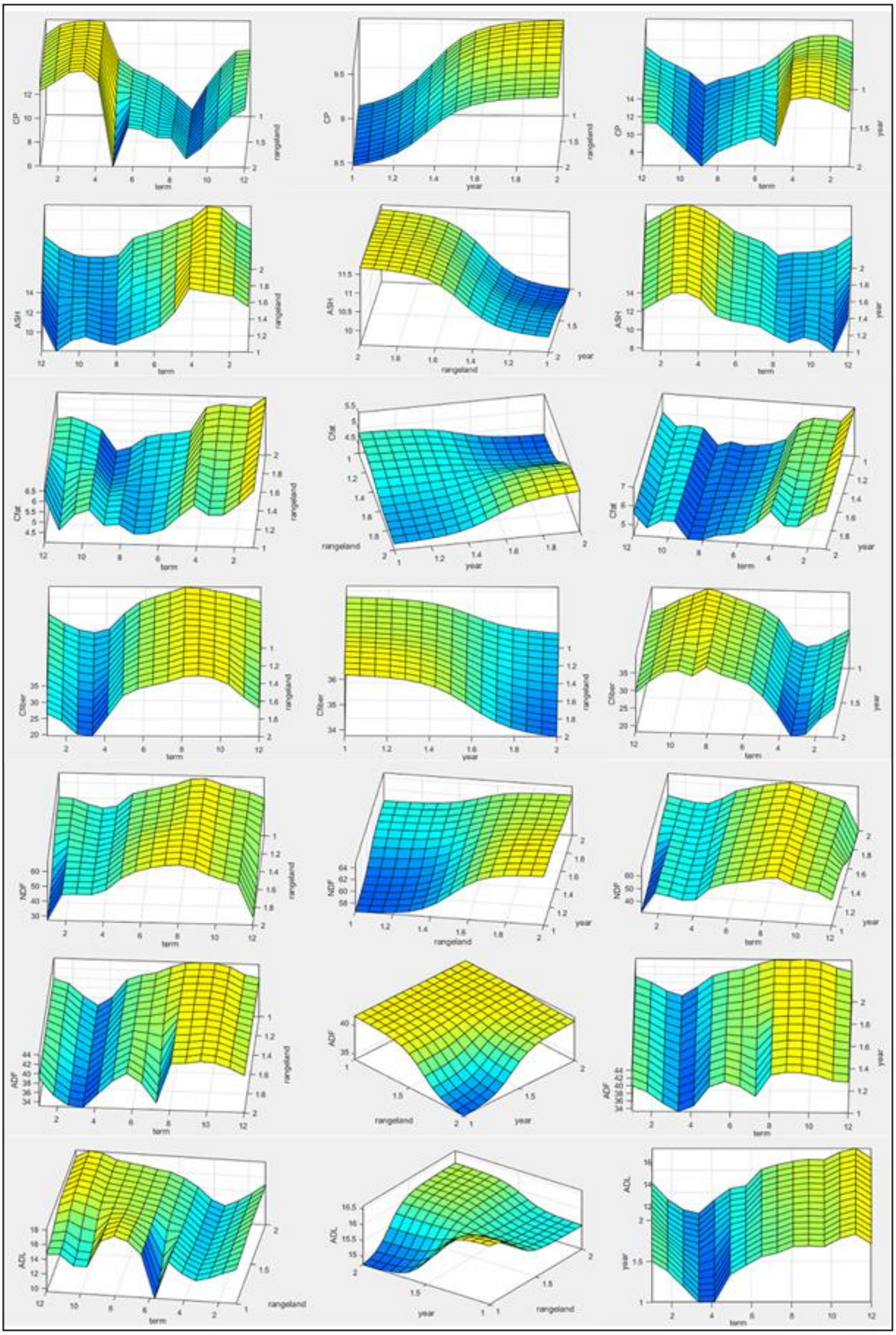

Figure 7. Changes of ANFIS outputs of hay chemical analysis according to rangeland, term and year effects.

Rangeland factor had no significant effect on hay chemical variables. However, all of the chemical variables varied according to term effect. CP measurements of the second year were higher than the first year, while Cfiber measurements of the first year were higher than the second. Variables other than CP and Cfiber were not affected by the year factor.

The lowest and highest CP measurements were obtained in the grazed rangeland in September and in the ungrazed rangeland in March, respectively. The lowest and highest ASH measurements were obtained in grazed rangeland in August and March, respectively. The lowest and highest Cfat measurements were obtained in September in the ungrazed rangeland and in January in the grazed rangeland, respectively. The lowest and highest Cfiber measurements were obtained in March in the ungrazed rangeland and in August in the grazed rangeland, respectively. The lowest and highest NDF measurements were obtained in March in the ungrazed rangeland and in September in the grazed rangeland, respectively. The lowest and highest ADF measurements were obtained in March in the ungrazed rangeland and in August in the grazed rangeland, respectively. The lowest and highest ADL measurements were obtained in the ungrazed pasture in March and December, respectively.

However, for all variables except NDF, the first surfaces showing the interaction of rangeland and term factors were bumpy. That is, for all hay chemical variables except NDF, measurements in ungrazed or grazed rangelands were affected by the term factor. It is possible to say that the third surfaces of the CP, Cfat and NDF variables were affected the interaction of term and year factors. Similarly, the second surfaces in the graphs for the CP, ASH and ADF variables were affected interaction of rangeland and year factors. The fact that the other surfaces were flat, showed that there was no interaction between the factors. These results are also same with the final report of the study mentioned.

Fourth and lastly, the change of hay yield variables obtained from the ungrazed rangeland under the effect of time (year and term) was investigated. In this review, FHY, DHY and DMR hay yield variables were obtained with 3 repetitions for 2 years (2013: 1 and 2014: 2) and 12 terms (months), and 150 data were randomly assigned for training (113) and test (37). In Matlab 2021b, ANFIS was performed with the *2 12* model for each hay yield variable using the Generalized Bell membership function. Each model was created according to 24 rules after 100 trainings. The training and test errors (RMSE) obtained from the ANFIS models have been given in Table 10.

Table 10. RMSEs obtained from the *2 12* ANFIS models applied to the hay yield variables of the ungrazed rangeland using the Generalized Bell Membership Function and created according to the 24 rules after 100 trainings

	Training	Test
FHY	**69,79800**	**73,9108**
DHY	**29,02120**	**30,8661**
DMR	**5,68776**	**5,8916**

RMSE values in bold are smaller than obtained by ANOVA.

It is seen that ANFIS outputs are close to the real data. The surface graphics obtained as a result of the created ANFIS models are presented in Figure 8.

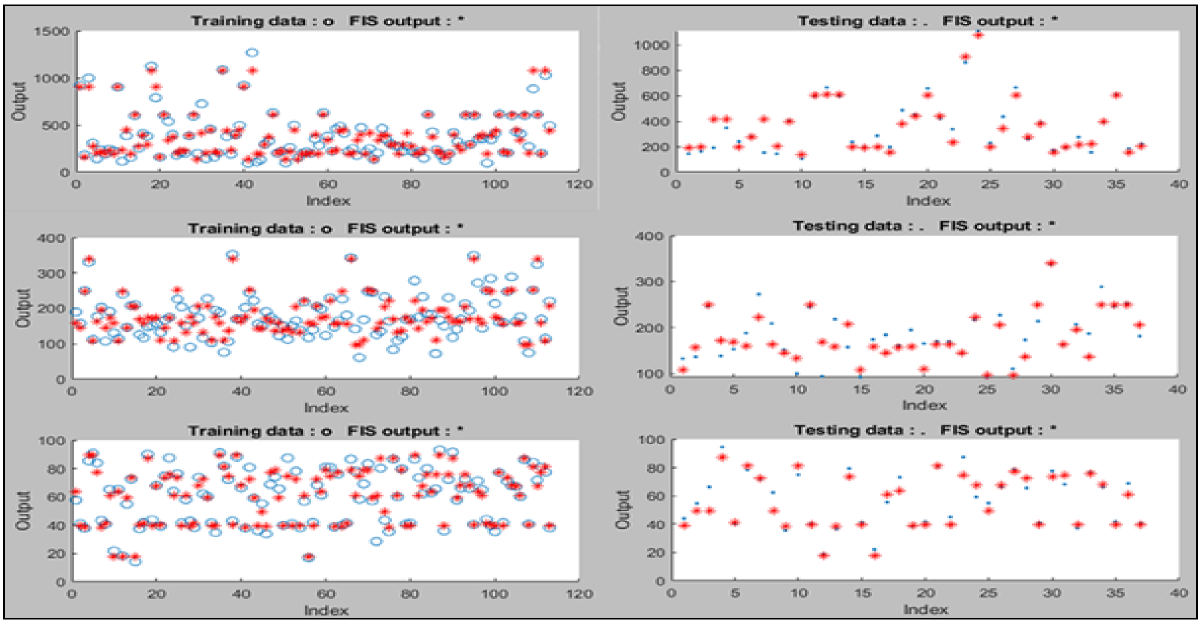

Figure 8. ANFIS outputs of FHY, DHY and DMR hay yields, respectively.

It is seen that ANFIS outputs are close to the real data. The surface graphics obtained as a result of the created ANFIS models are presented in Figure 9.

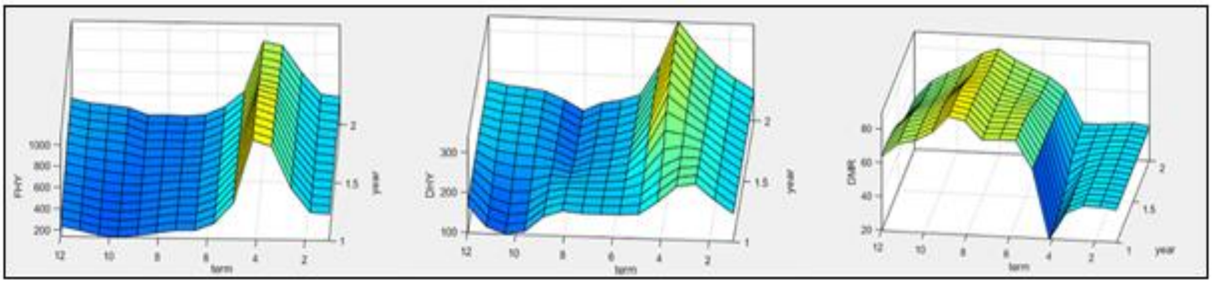

Figure 9. Changes of ANFIS outputs of hay yields of ungrazed rangeland according to time.

According to the first surface, FHY values of 2014 were higher than 2013 in April, and on the contrary, lower than May, October, November and December. However, FHY values obtained in each January, February, March, June, July, August and September terms were similar for both years.

According to the second surface, DHY measurements of 2014 in June, July and August were higher than in 2013, on the contrary, they were lower in April, May, October, November and December. However, DHY values obtained in each January, February, March and September terms were similar for both years.

According to the third surface, DMR measurements of 2014 were higher than 2013 in May, June, August, September, October, November and December, but on the contrary, they were lower in April. However, the DMR values obtained in each January, February, March and July terms were similar for both years.

All of the surfaces in Figure 9 showed fluctuations in both year and term variables. This means that all variables (FHY, DHY and DMR) varied statistically significantly according to both years and terms. The change of one of the factors affected the other. These results also coincide with the final report of the study mentioned.

Comparison of Real Data and ANFIS Outputs

All ANFIS outputs have been compared with the real data in the same order. For this purpose, scatter charts were created for the real data and ANFIS outputs of each model in MS Office Excel software and linear trends were drawn. The coefficient of determination (R2) for each trend has been given. The closer the R2 value is to 1, the closer the ANFIS outputs are to the real data (Piepho, 2019).

Firstly, the chemical measurements obtained from the shrub species depending on the term and year factors and the ANFIS outputs, the distributions of which are shown in Figure 2, have been compared. The results are presented in Figure 10.

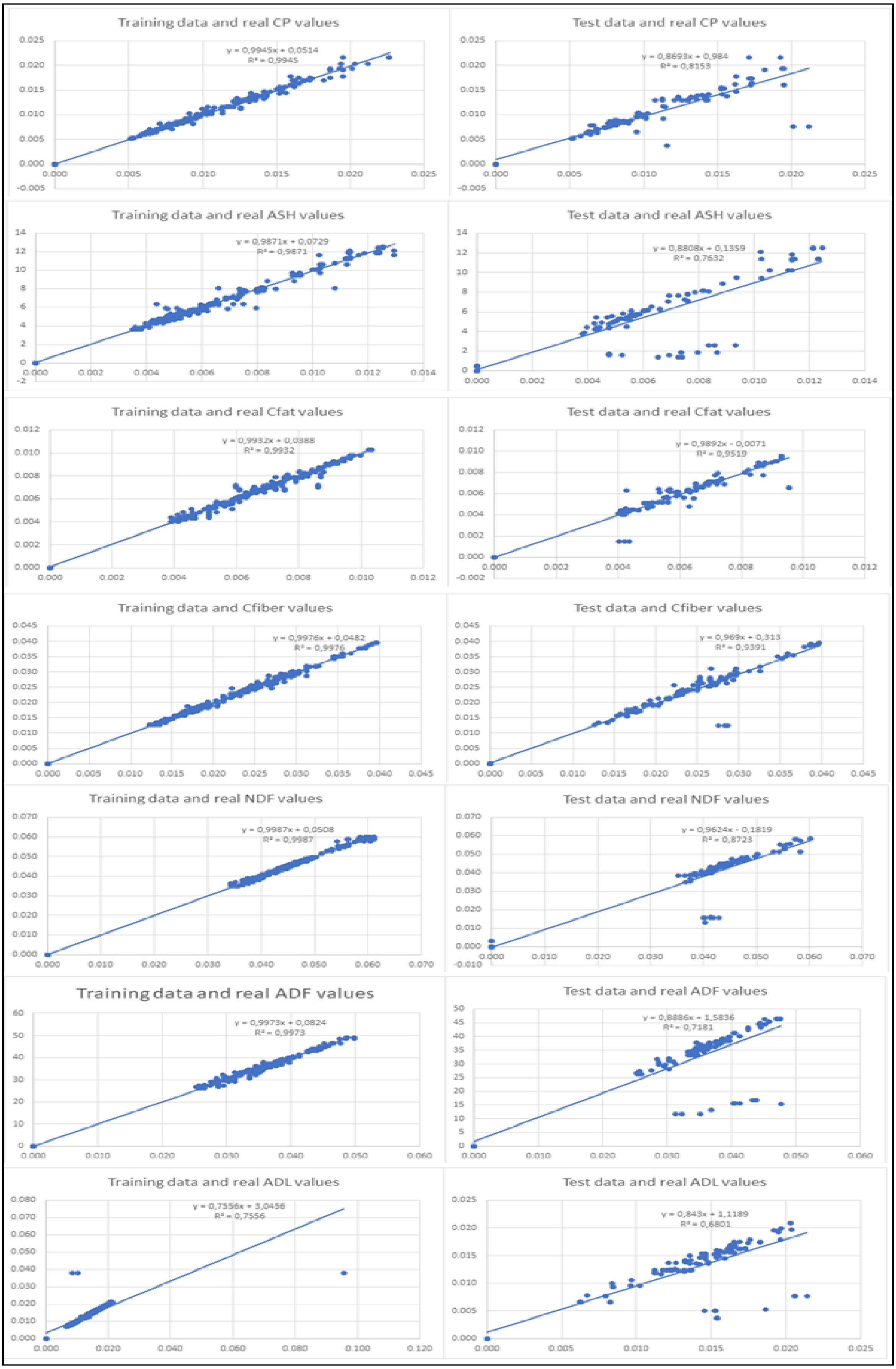

Figure 10. Comparison of real shrub chemical measurements with ANFIS outputs.

It is seen that ANFIS outputs have been close to real shrub chemical measurements. R^2 values were high especially for the training data (R^2 values obtained when the real and training data were compared as 0,9945; 0,9871; 0,9932; 0,9976; 0,9987; 0,9973; 0,7556, respectively for CP; ASH; Cfat; Cfiber; NDF; ADF; ADL).

Secondly, the yield values obtained from the shrub species depending on the term and year factors and the distributions of ANFIS outputs are shown in Figure 4, were compared. The results were presented in Figures 11.

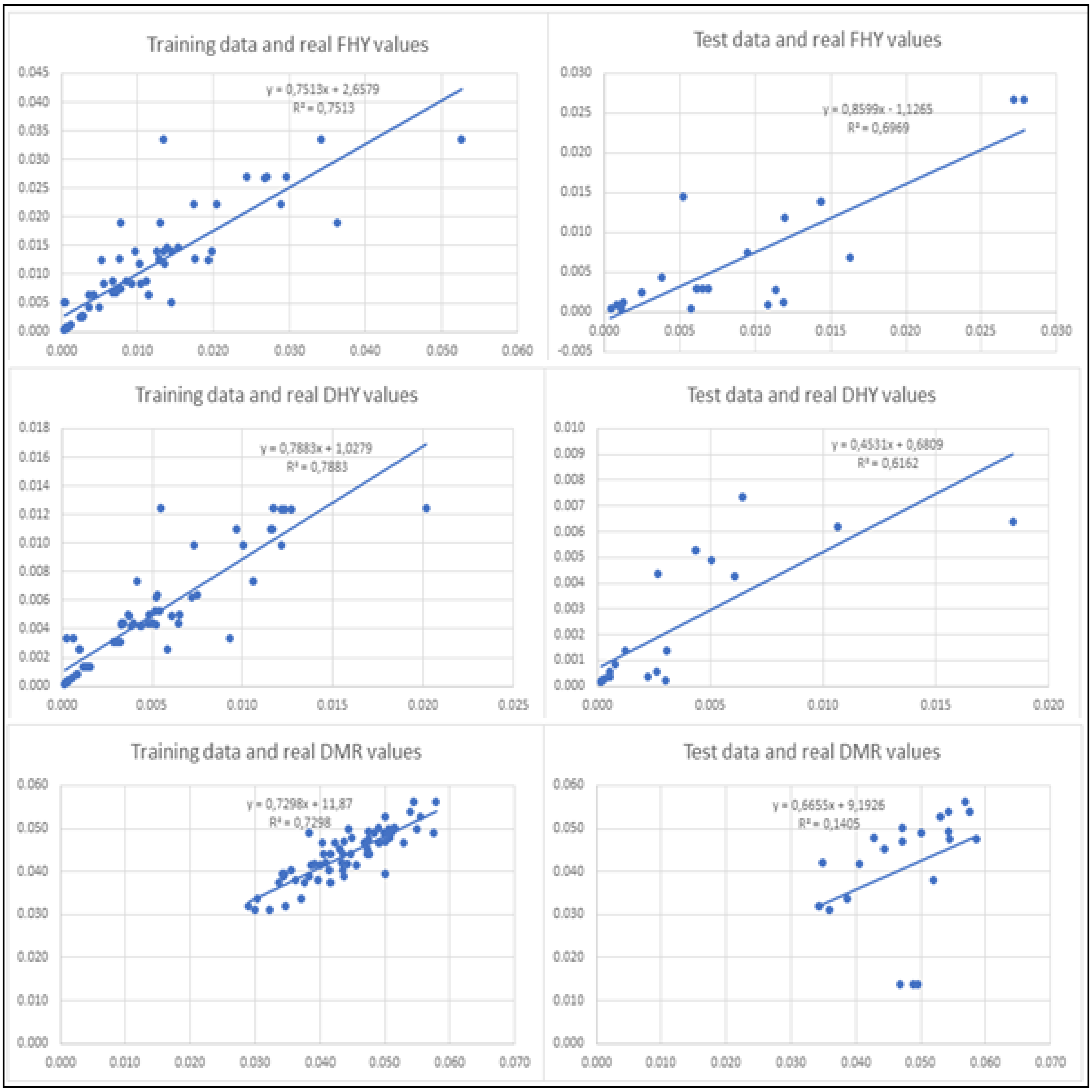

Figure 11. Comparison of real shrub yields and ANFIS outputs.

It is seen that ANFIS outputs were close to real shrub hay yields. R^2 values were high especially for the training data (R^2 values obtained when the real and training data were compared as 0,7513; 0,7883; 0,7298 respectively for FHY; DHY; DMR).

Thirdly, hay chemical measurements obtained from rangeland species depending on the term and year factors and the ANFIS outputs, the distributions of which were shown in Figure 6, were compared. The results were presented in Figure 12.

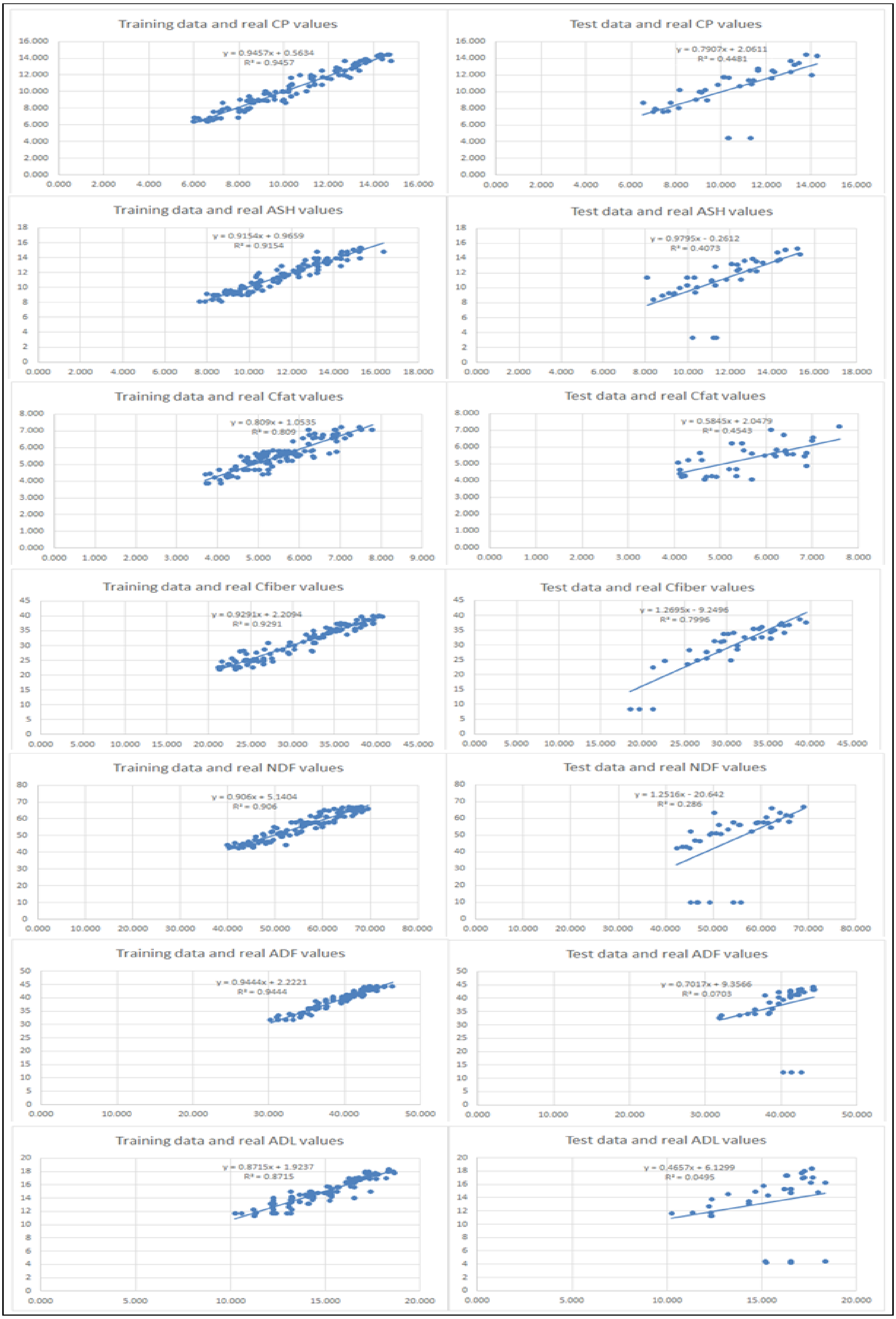

Figure 12. Comparison of real hay chemical measurements of rangeland species and ANFIS outputs.

It is clear that ANFIS outputs were close to real hay chemical measurements of rangelands. R^2 values were high especially for the training data (R^2 values obtained when the real and training data were compared as 0,9945; 0,9457; 0,9154; 0,809; 0,9291; 0,906; 0,9444; 0,8715, respectively for CP; ASH; Cfat; Cfiber; NDF; ADF; ADL).

Fourth and lastly, the hay yields obtained from the ungrazed rangeland depending on the year and term factors and the distributions of ANFIS outputs, which were shown in Figure 8, were compared. The results were presented in Figure 13, respectively.

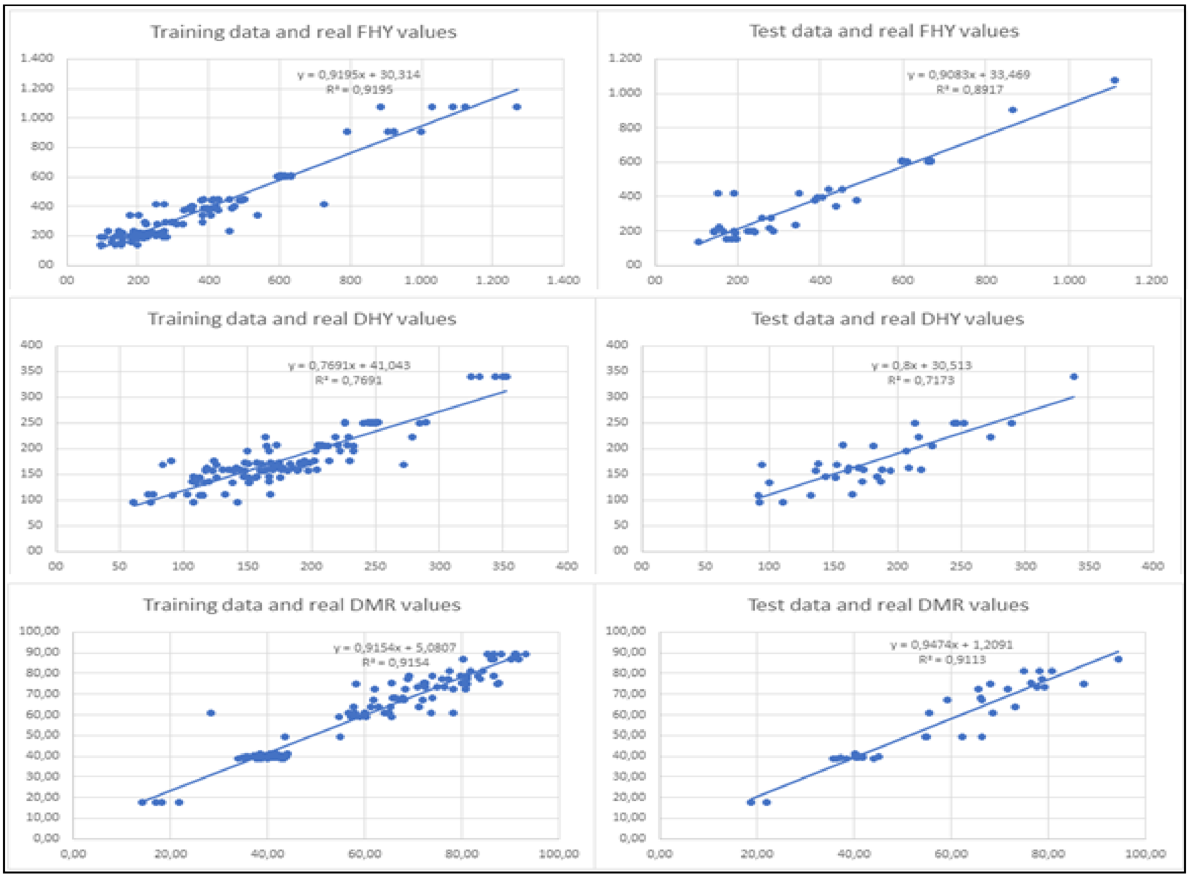

Figure 13. Comparison of real ungrazed rangeland hay yields and ANFIS outputs.

It is seen that ANFIS outputs were close to real ungrazed rangeland hay yields. R^2 values were high especially for the training data (R^2 values obtained when the real and training data were compared as 0,9195; 0,7691; 0,9154 respectively for FHY; DHY; DMR).

Discussion

In this study, the relationship between the results obtained with ANOVA and ANFIS models has been investigated. When the results in Chapter 3 were examined, it was seen that the data obtained with ANOVA could also be modeled with ANFIS and similar results could be obtained with a smaller experimental error.

When the results were examined, it was understood that all ANFIS outputs were close to the real data. However, this inference was made only based on the coefficient of determination (R^2). In order to say that the ANFIS method is a suitable method for this study, it should be compared with the RMSE amounts obtained in the ANOVA results, taking into account a metric criterion such as RMSE together with R^2 (Saplioglu and Ramazan, 2020).

Firstly, RMSEs of chemical measurements obtained from shrub species depending on term and year factors were investigated. When the values written in bold in Table 3 were compared with the values in Table 7, the RMSE for ADL obtained with ANFIS was smaller than that obtained with ANOVA. ANOVA had smaller RMSEs than ANFIS for CP, ASH, Cfat, Cfiber, NDF and ADF. However, these values were very close to each other. The reason why ANOVA gave a smaller RMSE than ANFIS was that sampling could not be performed from three bush types in November, December, January and February, and the measurement values for these factor levels were entered as 0 (zero) in the analysis.

Secondly, RMSEs of shrub yields depending on term and year factors were examined. When the values written in bold in Table 4 were compared with the values in Table 8, it was seen that the RMSE values obtained with ANFIS for all three yield parameters (FHY, DHY and DMR) were considerably smaller than ANOVA. However, looking at Table 3, although the year*term interaction was found to be significant ($p=0.01<0.05$) according to the ANOVA results of the DMR measurements, it would be better to say that the third surface of Figure 5 was flat, that is correct to say, there was no interaction between the year and term factors. On the contrary, although the shrub*year interaction was not found statistically significant as a result of ANOVA ($p=0.096>0.05$), when the first surface in Figure 5 was examined, it was seen that the surface was not flat (bumpy), that is, there was an interaction between them. Because the year*term interaction was found to be significant, the curves of the year and term factors did not intersect. Again, although the shrub*year interaction was not statistically significant, the curves of shrub and year factors intersected. Therefore, it seems appropriate to use ANFIS results.

Thirdly, the RMSEs of hay chemical measurements obtained from two rangelands depending on the term and year factors were examined. When the values written in bold in Table 5 are compared with the values in the Table 9, it was clear that the RMSEs obtained with ANFIS for herb chemical parameters other than CP and Cfat were smaller than those obtained with ANOVA. The RMSE values obtained with ANOVA for CP and Cfat were very close to those obtained with ANFIS.

Fourth and lastly, the RMSEs of the hay yield measurements obtained from the ungrazed rangeland depending on the year and term factors were examined. When the values written in bold in Table 6 were compared with the values in Table 10, it was seen that the RMSE values obtained with ANFIS for all three yield variables (FHY, DHY and DMR) were considerably smaller than ANOVA.

While applying ANFIS, rules are created and a model is obtained as much as the number of rules created. In contrast to the ANOVA model on which the experiment planning is based, the RMSE of ANFIS is obtained with a lower value since the number of models tested in ANFIS is much higher (Mosavi et. al, 2021). This is a positive indicator for ANFIS and shows that it can benefit from fuzzy logic approach as a powerful alternative method to ANOVA (Şentürk, 2010). In this study, it was seen that the results obtained as a result of the models created for both methods overlap. However, RMSEs of ANFIS were mostly smaller than of ANOVA. This shows that ANFIS is a more powerful method than ANOVA.

When the figures of ANFIS outputs are examined, it is clear that some outputs overlap with real data and some are gathered around real data. The reason why not all outputs overlap with real data is that real data is obtained experimentally. In other words, the real data will change from year to year due to the variation arising from physically occurring and uncontrollable factors (annual and/or seasonal precipitation, temperature, etc.). As the number of years of the experiment (therefore, the number of observations) increases, the overlap between the ANFIS outputs and the real data will increase (Şentürk, 2010). In a similar way, when an experimental data of maybe 20, 30 or 50 years is evaluated, ANFIS outputs and real data will all overlap and it can be concluded that ANFIS results are more reliable than ANOVA.

In this study, ANFIS and ANOVA have been compared for Type-I fuzzy numbers and similar results have been obtained. It has been argued that ANFIS models are statistically powerful and may be superior to ANOVA in the long run. In future studies, the performance of ANFIS in modeling a similar experimental data can be examined in interval type 2 or hesitant fuzzy numbers.

Conflict of Interest Statement: The authors of the article declare that there is no conflict of interest between them.

Researchers' Contribution Rate Statement Summary: The authors declare that they have contributed equally to the article.

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