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Comparison between artificial neural networks and some mathematical models in leaf area estimation of Red Chief apple variety

Red Chief elma çeşidinde yapay sinir ağları ve bazı matematiksel modeller kullanılarak yaprak alan tahminlerinin karşılaştırılması

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ABSTRACT

Leaf area index is an important variable in ecological and physiological studies. This study was aimed to determine the most suitable model explaining the leaf area estimation and weekly growth of leaf parameters in Red Chief apple variety. In the first part of the study, the leaf area was modeled through two different models (Model-1 and Model-2) developed based on ANN and power function (LA= Ax^B). In the second part, the weekly growth of each of the leaf width, length and area parameters were analyzed according to the Gompertz and Logistics function. The results of analysis revealed that leaf area estimations performed by ANN (Training: R^2= 0.98, RMSE= 0.922, MAD= 0.614, MAPE= 4.22; Testing: R^2= 0.94, RMSE= 3.346 MAD= 1.889 MAPE= 4.88) were more successful than Model-1 and Model-2. In addition, Gompertz has come to the fore as the model that best describes the weekly growth in all leaf parameters (Width: R^2= 0.98, RMSE= 0.154, MAD= 0.134, MAPE= 3.65, Length: R^2= 0.98, RMSE= 0.180, MAD= 0.145, MAPE= 2.26 and Leaf area: R^2= 0.99, RMSE= 0.73, MAD= 0.654, MAPE= 4.60).

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ÖZ

Yaprak alan indeksi ekolojik ve fizyolojik çalışmalarda önemli bir değişkendir. Çalışmada, Red Chief elma çeşidinde yaprak alan tahmini ve yaprak parametrelerinin haftalık büyümesini açıklayan en uygun modelin belirlenmesi amaçlanmıştır. Bu amaçla çalışmanın ilk kısmında ANN ve power fonksiyonuna (LA= Ax^B) dayalı geliştirilen iki farklı model (Model-1 ve Model-2) aracılığıyla yaprak alanı modellenmekte, ikinci kısmında yaprak en, boy ve alan parametrelerinin her birinin haftalık büyümeleri Gompertz ve Lojistik fonksiyona göre analiz edilmektedir. Analiz sonuçlarına göre yaprak alan tahmininde ANN'nin (Eğitim: R^2= 0.98, RMSE= 0.922, MAD= 0.614, MAPE= 4.22; Test: R^2= 0.94, RMSE= 3.346, MAD= 1.889, MAPE= 4.88) Model-1 ve Model-2'den daha başarılı tahminlerde bulunduğu gözlemlenmiştir. Bunun yanında yaprak parametrelerinin tamamında haftalık büyümeyi en iyi açıklayan modelin Gompertz olduğu (En: R^2= 0.98, RMSE= 0.154, MAD= 0.134, MAPE= 3.65, Boy: R^2= 0.98, RMSE= 0.180, MAD= 0.145, MAPE= 2.26 ve Yaprak alanı: R^2= 0.99, RMSE= 0.73, MAD= 0.654, MAPE= 4.60) görülmüştür.

1. Introduction

In terrestrial ecosystems, leaf area index (LAI) is directly related to plant growth, photosynthesis rate, evapotranspiration and yield (Pandey and Singh 2011). Leaf area estimation is valuable for studies such as; plant nutrition, plant competition, plant-soil-water relations, plant protection measures, respiration, light reflection and heat transfer in plants (Mohsenin 1986). Therefore, rapid, handy, economical and precise estimation of leaf area is very important for botanists. Measuring the surface area of a large number of leaves can be both time-consuming and require intensive labor.

Several methods have been developed to facilitate the leaf area measurement (Rouphael et al. 2010). Leaf area measurement methods can be categorized as: destructive and non-destructive methods (De Swart et al. 2004). Destructive methods require excision of the leaf from the plant and include drawing, blueprinting, photographing, image analysis and measuring by a conventional planimeter or an electronic leaf area meter. The destructive methods are time-consuming and require expensive equipment. Therefore, a simple, quick and reliable non-destructive method is needed to estimate the leaf area (Keramatlou et al. 2015). The leaf area is not directly measured in non-destructive methods. Instead, mathematical models are developed to correctly estimate the leaf area, using easily measured leaf parameters such as leaf length, leaf width and leaf stalk length (Schwarz and Kläring 2001). Regression analysis has been commonly used to determine the relationship between leaf area, leaf length and leaf width and/or leaf length x width (Palmer 1987; Sérgio et al. 2004; Sala et al. 2015). However, the use of artificial intelligence based estimation methods such as artificial neural network (ANN), which does not require strict assumptions on the data, can provide successful results in leaf area estimation (Shabani et al. 2017). The ANN becomes a common method in modeling complex input-output dependencies (Maren et al. 1990). Several authors indicated that the ANN gives reliable results in comparison with conventional methods (Moosavi and Sepaskhah 2012; Yuan et al. 2017).

This study was carried out to determine the estimation of leaf area by ANN and some mathematical models (Gompertz and Logistics) using the width and length measurement values of leaf samples, and the weekly growth rate of Red Chief apple variety.

2. Materials and Methods

The leaves of Red Chief apple cultivar which were grafted on MM 106 semi-dwarf apple rootstock were used as plant material in the study. Leaf samples were taken in the vegetation period and transferred to the laboratory in ice packs. The length and width measurements were carried out from the longest and widest parts of the leaves (Montero et al. 2000; Demirsoy and Demirsoy 2003; Serdar and Demirsoy 2006; Celik et al. 2011). The leaf area was calculated using Placom Intelligent Planimeter with 3 replications.

The data for leaves of the Red Chief apple cultivar were analyzed in two different axes. The estimation of leaf area by ANN and some mathematical models was the first axis, and the second one is the determination of the most suitable model that explains the leaf width, length and area growth. The ANN and power function (LA= Ax^B) were used to estimate the leaf area, and Gompertz and Logistics function were used to model the weekly growth of the leaves.

2.1. Artificial Neural Network (ANN)

The ANN method was developed inspiring from the working and learning ability of the brain (Öztemel 2016), and was based on the operating principle of a biological nerve cell which has 3 layers; input, hidden and output layers (Dawson and Wilby 1998). The number of neurons in the input and output layers may differ depending on the number of variables (dependent and independent variables) defining the inputs and outputs of the problem being investigated, while the trial and error method is common in determining the number of neurons to be included in the interlayer (Yavuz and Deveci 2012; Özşahin and Singer 2019a). Different learning types can be preferred in the ANN to learn the relationship between the outputs corresponding to the inputs. The learning types in ANN are defined as supervised, unsupervised, mixed and reinforced (Akıllı and Atıl 2014). In the training process of the network, minimizing the difference between the actual values and the results produced by the network is aimed; thus, the updates of link weights iteratively continues until reaching the error level determined in this process (Takma et al. 2012). The model performance is evaluated with the test dataset when the learning process is completed (Özşahin and Singer 2019b).

In this context, the general representation of the process steps followed in the ANN approach for the leaf area estimation using the leaf width and length measurement values was schematically presented in Figure 1.

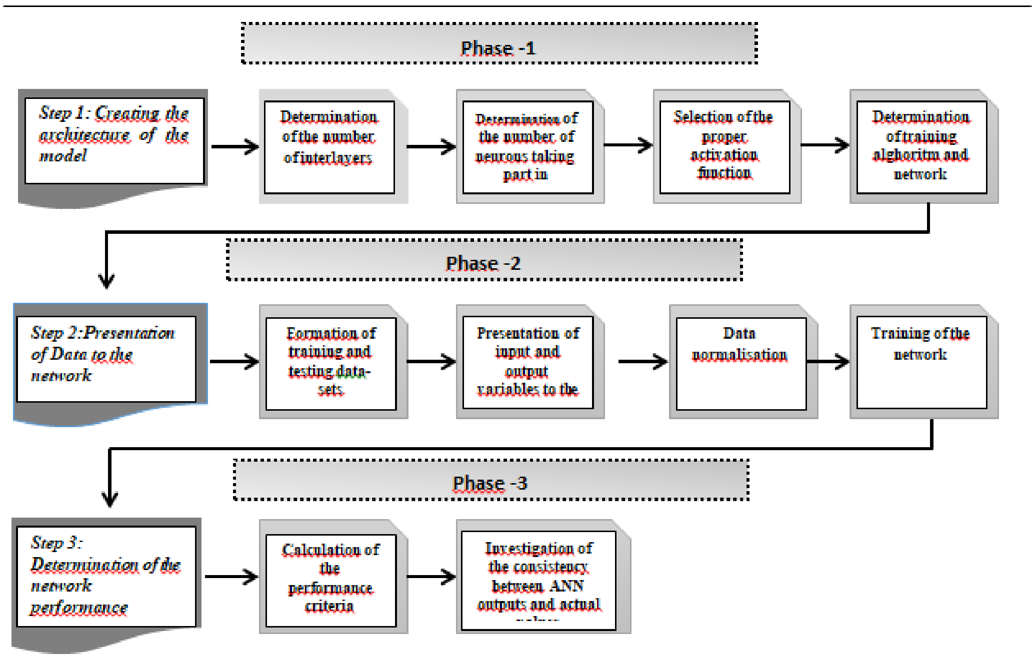

Figure 1. Flowchart in estimation of leaf area in the ANN model.

In the ANN model studied, the leaf width and length measurement values have been presented as input data under appropriate network topology in Step 1, while leaf area measurements have been presented to the network as 2 inputs and 1 outputs (Figure 1). The number of intermediate layers and the number of neurons in this layer were determined by trial and error method as 1:6 as a single layer with 6 neurons. In Step 2, the data set is divided into two parts as training and testing. All the data were subjected to normalization process in the range of [-1 1]. The use of hyperbolic tangent in the intermediate layer and the linear transfer function in the output layer were preferred. Finally, Scaled Conjugate Gradient (SCG) back-propagation algorithms was used for the network training. In Step 3, the performance of the model was evaluated by some statistical criteria stated in equations 1-4 (Akkol et al. 2017).

The ANN model used in estimation of leaf area was examined in comparison with two different mathematical models based on power equation as Model-1 and Model-2. The equations for the Model-1 and Model-2 were given in Table 1.

Table 1. Equations for the leaf area estimation models used in the study.

Models	Nonlinear function	Linear form
Model- 1	$Y_{LA}=A(W)^B$	$\ln(Y_{LA}) = \ln(A)+B\ln(W)$
Model- 2	$Y_{LA}=A(L)^B$	$\ln(Y_{LA}) = \ln(A) + B\ln(L)$

A and B refer to model coefficients.

2.2. *Analysis of leaf parameters with nonlinear models*

Temporal (weekly) growths of the width, length and area parameters of a leaf were modeled as the secondary goal of the study. Data were analyzed with two different growth functions, Gompertz and Logistics. Equational expressions regarding the models used were shown in Table 2 (Kıymaz et al. 2018a; Kıymaz et al. 2018b).

Some goodness of fit criteria used in comparing the model performances were given in equations 1-4, respectively (Akkol et al. 2017). The evaluations revealed that RMSE, MAPE and MAD values of the model were low and R^2 value was high.

Table 2. Models and related equations.

Models	Model expression
Gompertz	$Y_t=b_0\exp(-b_1\exp(-b_2t))$
Logistic	$Y_t=b_0(1+b_1\exp(-b_2t))^{-1}$

b_0: asymptotic value, b_1: growth values of apple leaves in the vegetation period, b_2: growth rate, t: time (week).

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{Y}_i-\bar{Y})^2}{\sum_{i=1}^{n}(Y_i-\bar{Y})^2} \qquad (1)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{Y}_i-\bar{Y})^2}{n}} \qquad (2)$$

$$\mathrm{MAD} = \frac{\sum_{i=1}^{n}|Y_i-\hat{Y}_i|}{n} \qquad (3)$$

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n}\left|\frac{Y_i-\hat{Y}_i}{Y_i}\right|}{n}\times 100 \qquad (4)$$

In equations, n is the number of sample data (number of leaves taken for measurement), Y_i is the measured values, $\hat{Y}_i$ is the prediction value, i is the estimation value and $\bar{Y}_i$ is the mean value. MATLAB R2013.a and Microsoft Office Excel software were used in ANN modeling.

3. Results

Descriptive statistics on width, length and leaf area were given in Table 3. The mean values of leaf length, width and area were 4.37 cm, 7.40 cm and 23.90 cm^2, respectively.

Table 3. Descriptive statistics of width, length and area of leaf samples.

Data sets	Measurement	Min	Max	Mean	SEM	N
Inputs	L	1.50	8.20	4.37	0.12	125
	W	2.00	12.00	7.40	0.18	125
Output	LA	2.75	65.25	23.90	1.09	125

L: Leaf length (cm), W: Leaf width (cm), LA: Leaf area (cm^2), SEM: Standard Error of Mean.

The findings of the study were given in two parts. In the first part, the results of regression analysis based on ANN and Power equation, and the most appropriate model selection explaining the weekly growth of leaf parameters (width, length and area) is given in the second part.

3.1. *Analysis of results obtained by ANN and mathematical models*

In ANN, where width and length measurement values of leaves were considered as input to the network and leaf area as output, 60% of the data (n= 75) was allocated to test the network, and the remaining 40% (n= 50) was used as test data to evaluate the performance of the network used. These datasets were also analyzed for two different models based on power equation, and R^2, MAD, RMSE and MAPE values obtained were given in Table 4.

The ANN, considering the R^2 value, MAD, RMSE and MAPE criteria, yielded better results than Models 1 and 2 which were developed using only the width and length parameters (Table 4).

Table 4. The results of regression analysis based on ANN and Power equation.

Performance Criteria	Model -1		Model -2		ANN	
	Training	Testing	Training	Testing	Training	Testing
R^2	0.912	0.833	0.88	0.696	0.982	0.940
MAD	1.941	3.061	2.146	4.113	0.614	1.889
RMSE	2.535	3.695	2.746	5.025	0.922	3.346
MAPE	12.69	9.004	14.78	12.19	4.221	4.877

Training and test models
Model-1: Training $Y_{LA}= 1.53W^{1.8049}$; Testing: $Y_{LA}= 2.952\ W^{1.443}$
Model-2: Training $Y_{LA}= 0.4653L^{1.8964}$; Testing: $Y_{LA}= 0.7061\ L^{1.765}$

3.2. Findings on weekly growth of leaf width, length and area parameters

The most suitable model explaining the growth of leaf width, length and area were determined in the second part of the study by using mean weekly measurements. Two different models, Gompertz and Logistics, were used for this purpose. The parameter values of the aforementioned models were given in Table 5.

The values of some goodness of fit criteria calculated for the models were given in Table 6. The best model (width, length, area) which had the highest R^2 and the lowest RMSE, MAD and MAPE values for all three parameters was Gompertz model (Table 6). The fit graphs between weekly measurement values and measurement values for leaf width, length and area were shown in Figure 2, respectively.

The R^2 values in the Gompertz model for all the leaf width, height and area parameters approached 1.0 more than those in the Logistics model and explained the real measurement values at a high rate (Figure 2).

4. Discussion and Conclusions

The leaf area is an important parameter for physiological and agronomic studies. Therefore, reliable data on leaf area is crucial in determining the physiological characteristics of apple, which is one of the most produced and consumed fruits in Turkey and rest of the world. Several mathematical estimation models have been developed for various plants, using leaf length and width parameters obtained using non-destructive methods. Various combinations of leaf width and length parameters were used in estimation of leaf area for different plants, and regression analysis was frequently preferred to investigate the relationship between the parameters (Williams III and Martinson 2003; De Swart et al. 2004; Sérgio et al. 2004; Cho et al. 2007; Peksen 2007; Rivera et al. 2007; Kumar 2009). In addition, studies employing the ANN method and regression analysis together (Vazquez-Cruz et al. 2013; Küçükönder et al. 2016; Yuan et al. 2017), showed that ANN method provided better results and could be an alternative to regression analysis. Ozturk et al. (2019) stated that ANN models were more accurate in terms of both the training and testing phases compared to the multiple linear regression models.

Kıymaz et al. (2018a) who carried out a study using nonlinear methods such as artificial neural networks, Logistic, Richards and Gompertz models in estimating the leaf area of sugar beet, reported that all models exhibited high identification success. In another study carried out to estimate bean leaf area using Gompertz, Weibull, Logistics and Monomolecular models, Kıymaz et al. (2018b) reported that the Gomperzt model was the most successful model, followed by the monomolecular model.

The results of this study revealed that ANN provides more successful estimations than Model-1 and Model-2, which are based on only leaf width and length parameters. In addition, Gompertz model has given the best estimation result for the weekly leaf growth. In this context, mathematical methods such as ANN and Gompertz, which have been used to estimate the leaf area of different plants, can be considered successful and effective estimation tool to estimate the measurement values of the Red Chief apple cultivar.

The results concluded that the use of mathematical modeling tools will contribute to the researchers as an alternative method to reduce labor, economic cost and save time by accurately determining the leaf area and weekly leaf growth values.

Table 5. The values of model parameters.

Measurements	Model	b_0	b_1	b_2
Width	Gompertz	6.623	1.252	0.222
	Logistic	6.301	2.105	0.312
Length	Gompertz	9.883	1.134	0.295
	Logistic	9.628	1.809	0.387
Leaf Area	Gompertz	49.630	2.373	0.223
	Logistic	43.195	6.392	0.389

Table 6. Comparison of performances for nonlinear mathematical models.

Measurements	Models	Performance Criteria			
		R^2	RMSE	MAD	MAPE
Width	Gompertz	0.98	0.154	0.134	3.656
	Logistic	0.97	0.165	0.143	4.011
Length	Gompertz	0.98	0.180	0.145	2.263
	Logistic	0.98	0.197	0.160	2.524
Leaf Area	Gompertz	0.99	0.73	0.654	4.602
	Logistic	0.99	0.87	0.712	5.776

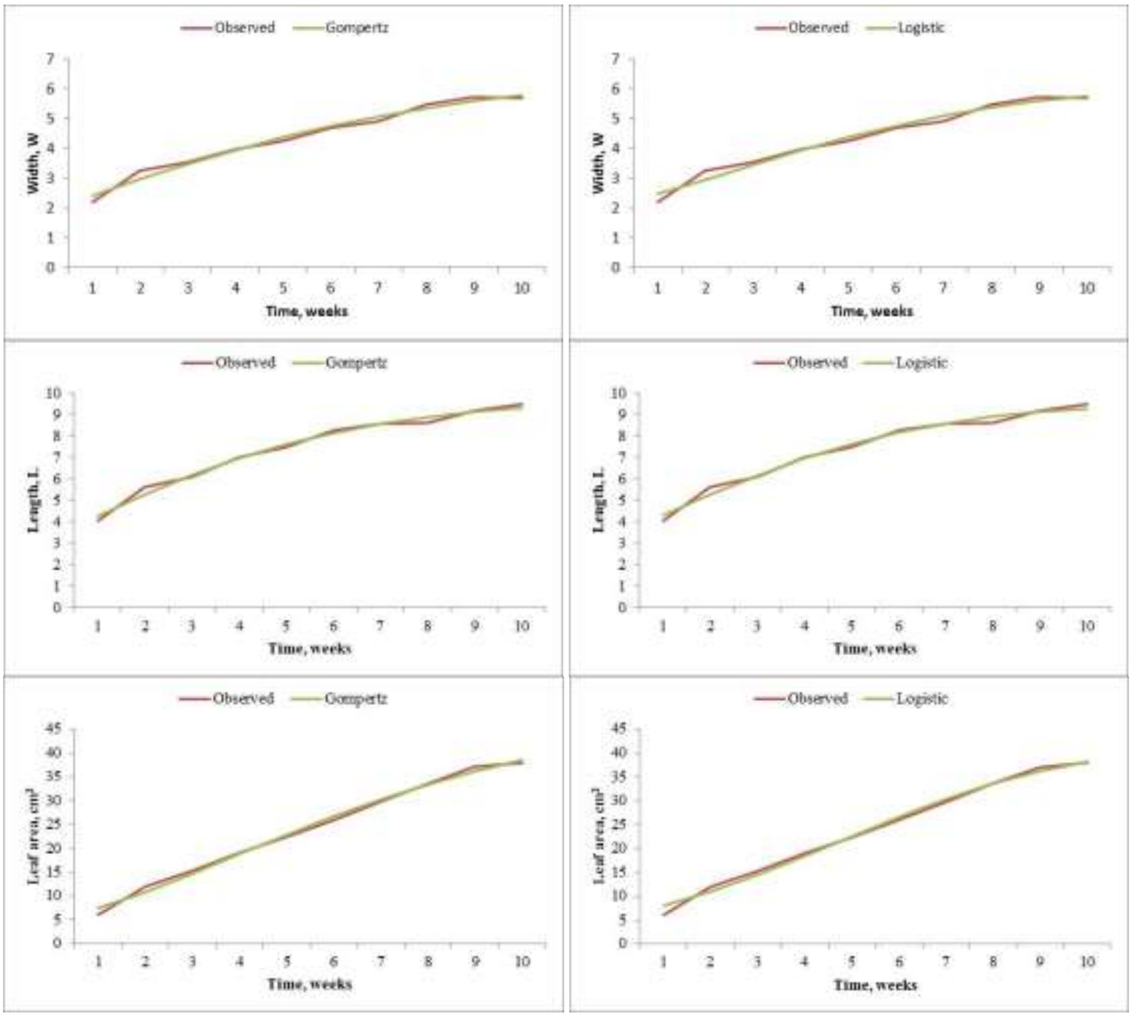

Figure 2. The values of measured and estimated by models.

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