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A modeling study with an artificial neural network: developing estimation models for the tomato plant leaf area

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Abstract: The leaf area measurement is an important parameter in understanding the growth and physiology of a plant. Therefore, this study aimed to develop the best leaf area estimation model for tomato plants grown in plastic greenhouse conditions. The artificial neural network (ANN) and regression analysis techniques were used in the formation of a leaf area estimation model by using the leaf width and leaf length measurements determined by the linear measurement method. The plant material for the study consisted of 420 leaf samples of the Typhoon F1 tomato type grown in plastic greenhouse conditions. In the comparison of the created models according to both methods, the criteria of selecting low values for the root mean square error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE), and high value for the determination coefficient (R^2) were taken into account, and the best estimation models were determined. In the comparison made according to these criteria, it was concluded that the error values of the ANN model [R^2 = 0.96, RMSE = 3.30, MAE = 1.94, and MAPE = 0.05] were lower than those of the regression model [R^2 = 0.92, RMSE = 4.71, MAE = 3.31, and MAPE = 0.08], and that the ANN method provided a better fit to the actual values; therefore, the ANN model can be used as an alternative method in estimating the leaf area.

Key words: Artificial neural network, leaf length, leaf width, leaf area, regression, tomatoes

1. Introduction

The tomato (*Solanum lycopersicum* L.) has an important place in the economy of Turkey (Mamay and Yanık, 2012). It is known that the share of tomato production is about 44% of the total annual vegetable production in this country, and 73% of the tomatoes are grown in open fields while the remaining 27% are grown in greenhouses (TUIK, 2013). Determining the best management practices to increase yield and fruit quality has been the focus of research. Leaf area is an indicator of crop growth and productivity, and its measurement in agricultural studies is an important parameter in understanding photosynthesis, light interception, the use of water and nutrients, plant growth, and yield potential (Aase, 1978; Smart, 1985; Williams, 1987; Centritto et al., 2000; Campostrini and Yamanishi, 2001). The leaf area measurements required for obtaining this information are divided into two types: direct and indirect methods (Celik and Uzun, 2002; Cristofori et al., 2007; Demirsoy, 2009). Of these methods, indirect measuring methods are low-cost methods that can be calculated using simple mathematical equations and take less time than the direct measurement methods (Gamiely et al., 1991; Demirsoy and Demirsoy, 2003; Demirsoy et al., 2004; Serdar and Demirsoy, 2006). Researchers working in the agricultural field need fast, cost efficient, reliable, and nondestructive methods (Peksen, 2007; Demirsoy, 2009). Therefore, the indirect methods that reveal the mathematical relationship between the leaf area and one or more leaf dimensions (length and width) are more advantageous than the direct methods (Robins and Pharr, 1987; Elsner and Jubb, 1988; Kersteins and Hawes, 1994). Trying to establish regression equations between the leaf area and linear leaf measurements is one of the most frequently used nondestructive and indirect methods. It estimates the leaf area from mathematical equations involving linear measurements of leaves. A mathematical model (that usually has high accuracy) can be obtained by correlating the leaf length, leaf width, and petiole length, or some combination of these variables, with the actual leaf area of a sample of leaves using regression analysis (Gamiely et al., 1991; Demirsoy and Demirsoy, 2003; Demirsoy et al., 2004; Blanco and Folegatti, 2005; Serdar

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and Demirsoy, 2006; Peksen, 2007; Fallovo et al., 2008; Kumar, 2009; Demirsoy and Lang, 2010). Today, there are many mathematical models for identifying the leaf areas of horticulture plants by making use of linear measurements of leaf width, length, and some combination of these variables. It is extremely important, however, that such a model be reliable and accurate. Therefore, any new or improved model should be validated. There are many studies on the validation process for different plants such as tomato (Dumas, 1990; Astegiano et al., 2001; Schwarz and Kläring, 2001; Blanco and Folegatti, 2003; Beyhan et al., 2008), cucumber (Robbins and Pharr, 1987; Uzun and Çelik, 1999; Blanco and Folegatti, 2005; Cho et al., 2007), pepper (Uzun and Çelik, 1999), eggplant (Uzun and Çelik, 1999; Rivera et al., 2007), watermelon (Rajendran and Thamburaj, 1987), avocado (Uzun and Çelik, 1999), red current (Uzun and Çelik, 1999), kiwifruit (Uzun and Çelik, 1999), grapes (Elsner and Jub, 1988; Uzun and Çelik, 1999), cherry (Demirsoy and Demirsoy, 2003; Demirsoy and Lang, 2010), and peach (Demirsoy et al., 2004).

The artificial intelligence technology provides alternative methods that are increasingly used and produce rather successful results in estimation studies as compared with conventional methods. The artificial neural network (ANN) method is one of them. ANN studies have shown that this method, when used in the agricultural field, produces highly successful results and can serve as an alternative to conventional methods. Vazquez-Cruz et al. (2012) developed an ANN model to determine the response of tomato leaf area to different climate conditions such as CO_2 concentration, PAR, and temperature, along with different salicylic acid treatments. The results showed that the ANN model was a useful tool in understanding the complex relationships between greenhouse conditions and leaf area development. Vazquez-Cruz et al. (2013) established a correlation between carotenoid content, measured by HPLC, the color parameters of the tomato surface, and the leaf area of tomato plants during tomato ripening by means of regression models and ANNs to estimate lycopene and β-carotene contents. They compared the performances of the regression models and the ANN models. The results showed that the ANN approach could be used for practical purposes in order to estimate carotenoid variations in tomato fruit in response to environmental conditions in order to satisfy the production of high quality tomato fruits. Elizondo et al. (1994) used ANN in order to estimate soybean germination and physiological maturity dates, and obtained real-like results with minimum prediction error. Tamari et al. (1996) comparatively examined the adaptability of linear regression and ANN models to estimate soil hydraulic conductivity in Mexico, and stated that ANN produced more successful results. Parmar et al. (1997) evaluated peanut harvest contamination with alpha toxins by using ANN with a network structure consisting of 8 hidden layers in which a total of 4 different input data, including soil temperature, drought time, product age, and collected heat units, were used.

In recent years, in Turkey and around the world, ANN applications have been used in many areas of agriculture because they are both practical and economical. Since the network in this method performs learning through examples, the determination of examples, introducing them to the network, and programming the network can be sufficient to solve a problem. In addition, finding samples, creating network architecture, training, and putting them into use in real time is possible within a very short time period in the ANN, making it very efficient (Akkaya, 2007).

The ANN is composed of biological nerve cells (artificial neurons) the development of which was inspired by the working principles of the human brain. In neural networks, it is possible to resolve any kind of problem that is too difficult and complex to be solved with classical methods. The general structure of an ANN consists of 3 different layers: an input layer, a hidden layer (interlayer), and an output layer. The input layer consists of neurons that enable the transfer of information received from the outside world to the hidden layer and only provide transmission to the next layer without any action on the input data (Canakci and Hosoz, 2006). The hidden layer is the part in which the data from the input layer is sent to the output layer after processing, and it can consist of a single layer or of multiple layers in some cases. The output layer is the part in which outputs consistent with the input data are produced by processing the data from the hidden layer (Canakci and Hosoz, 2006).

The purpose of the present study was to create the best predictive model for leaf area estimation and to express it through ANN and regression analysis by making use of the measurement values of leaf width and length parameters of a tomato plant grown in a plastic greenhouse.

2. Materials and methods

2.1. Materials

The study was conducted in a detached bow-roofed plastic greenhouse in Kahramanmaraş Province with 150 m^2 floor space. The greenhouse was cooled with natural ventilation through top openings to avoid the adverse effects of temperature on plant growth, and with a fan-pad system in times when the natural ventilation was inadequate. The greenhouse soil had a clayey structure. The Typhoon F_1 breed beef tomato was used as plant material in the greenhouse. A total of 10 rows for planting were made in the greenhouse. Three-leaf seedlings were brought in trays. We utilized row spacing of 40 cm, a top row of 40 cm, and double row planting. We left a service road of 100 cm every two rows. A total of 420 seedlings were planted in the greenhouse and plant density was 2.8 plant/m^2. The study was carried out between 22 March 2012 and 12 July 2012.

The measured leaves were randomly selected from the greenhouse at different dates. Selected leaf samples were measured with a ruler, according to previously published methods (Schwarz and Kläring, 2001; Kumar, 2009; Vazquez-Cruz et al., 2012), and the actual leaf area was measured with a planimeter (Demirsoy and Demirsoy 2003; Demirsoy et al., 2004; Peksen, 2007; Beyhan et al., 2008). A total of 420 leaves were analyzed in the present study. At first, the maximum length (L) from the petiole to the central leaflet and the maximum width of each leaf (W) (perpendicular to the maximum length) were measured with a hand ruler (Figure 1). Second, each leaf was placed on an A3 sheet and then a Placom Digital Planimeter (Intelligent Planimeter, Model KP-21C) was used to measure the actual leaf area. The leaf width (cm) and length (cm) of the leaf samples were also measured in order to be used for model construction. All values were recorded to the nearest 0.1 cm.

2.2. Methods

Two different methodological approaches were utilized. In the first one, a mathematical model was developed using a power equation for estimating the leaf area with leaf width and leaf length parameters. The analysis was conducted with various combinations of the independent variables such as length (L), width (W), length square (L^2), width square (W^2), length × width (W × L), length square × width ($L^2 \times W$), length × width square ($L \times W^2$) and length square × width square ($L^2 \times W^2$). The power equation ($Y = aX^b$) was used when creating models for each of these independent variables, and this equation was transformed into [$\ln(Y) = \ln(a) + b\ln(x)$] form; its correlation with the dependent variable (LA) was determined by regression analysis. The regression model coefficient, R^2, and F and MSE values (the error variance criteria) were found for each of these independent variables. In the selection of the best estimation model among the created models, the minimum MSE and the maximum R^2 criteria were used. The validity of the model was determined by the level of compliance between the actual and the predicted values. A prediction model was developed using the ANN method as the second approach in the study. In the ANN modeling, the network structure was designed including 1 input layer, 1 hidden layer, and 1 output layer. The input layer was created with two neurons, which contained the leaf width (LW) and leaf length (LL) parameters, and the output layer was created with one neuron for the purpose of estimating the leaf area (LA) (Figure 2). The parameters of the designed network are given in Table 1.

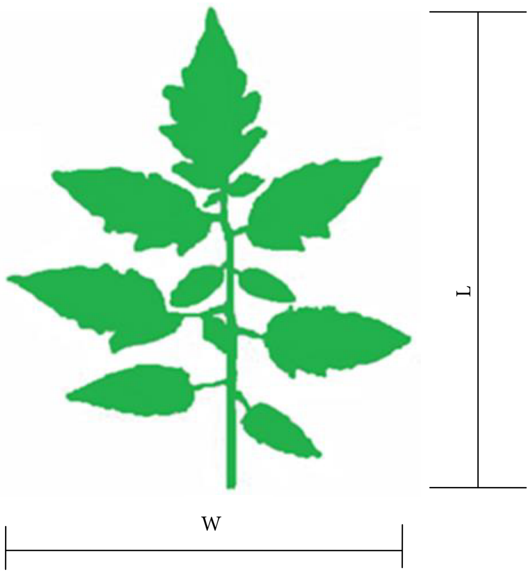


Figure 1. Tomato leaf showing positions of length (L) and width (W) measurements.

The data for the network model used were reorganized; 70% were used to train the network and the remaining 30% were used as test data to test the validity of the ANN model. In modeling, a multilayer feed-forward neural network was used. The analysis data were normalized in the range of 0.0–1.0, and then the formula indicated below (in Eq. (1)) was used in the conversion of these values to their original values.

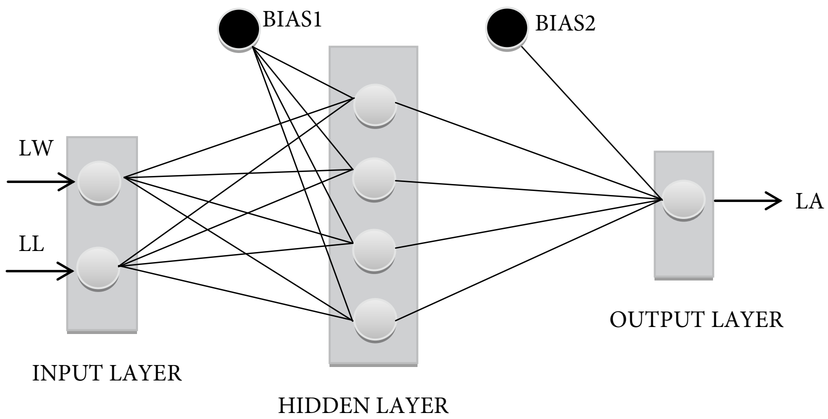
$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

In the equation, X_{norm} refers to the normalized value, X refers to the original value of the variable, and X_{max} and X_{min} refer to the original maximum and minimum values of the variables, respectively (Vazquez-Cruz et al., 2012). In the training of the network, the input value coming to the network (Net) was calculated by the following formula:

$$Net = \sum_{i=1}^{n} x_i w_i + \theta_i \tag{2}$$

In the equation, θ_i is the threshold (bias), x_i refers to the ith input values, and w_i refers to the weight value corresponding to the ith value (Öztemel, 2003). When calculating this output value corresponding to the net input value, a sigmoidal activation function was used in Eq. (3) (Öztemel, 2003):

$$F(Net) = \frac{1}{1 + e^{(-Net)}} \tag{3}$$



*LW: leaf width (cm), LL: leaf length (cm), LA: leaf area (cm^2).

Figure 2. The architectural structure of ANN designed to estimate the leaf area.

Table 1. Summary of ANN parameters.

Parameter	Value
The number of neuron in input layer	2
The number of hidden layers	1
The number of neuron in hidden layer	4
The number of output layer	1
The learning algorithm	Levenberg–Marquart algorithm (LM)
The learning rate	0.2
The momentum coefficient	0.8
The learning cycle	1000
Activation function	Sigmoidal

The weight values (W_i) in Eq. (2) were randomly assigned initially to form the output values (leaf area) corresponding to the input values (leaf width and leaf length) presented to the network, and then were updated by the system. An error graph was generated following each iteration; we used those graphs to observe whether learning took place. In addition, the error value was taken as 1.10^{-5}, the maximum number of iterations was taken as 1000, and 50 epoch were done to end the algorithm in each run. The differences between the input and output values (error) were calculated according to the following equation:

$$E = \frac{1}{2}\sum_{k=1}^{m}(y_k - t_k)^2 \qquad (4)$$

In the equation, y_k refers to the output value, which is created by the neural network, and t_k refers to the actual output value (Fauset, 1994). The network training process was terminated when the specified error value was achieved. The obtained output values and the observed values were compared in order to determine their compliance level. Several reports in the literature have indicated that the ANN output values can be expressed in closed form depending on the input values, the connection weight values between neurons, the threshold (bias) values, and the normalization values (Guzelbey et al., 2006; Pala and Caglar, 2007; Shahin et al., 2008; Caglar et al, 2009; Tadesse et al., 2012). In the present study, the sigmoid activation function was used. For this reason, the formulas for the sigmoid activation function were utilized, as reported in Tadesse et al. (2012). In this context, a closed form equation for leaf area estimation can be developed and restated via the following 2 equations:

$$O_1 = \frac{1}{1 + e^{-\left(bias_0 + \sum_{k=1}^{r} \frac{w_{k,1}^{h0}}{1 + e^{-H_k}}\right)}} \quad (5)$$

$$H_k = \sum_{j=1}^{q} w_{j,k}^{ih} \times l_j + bias_k \quad (6)$$

where q and r are the number of input parameters and the number of hidden neurons, respectively; $bias_k$ and $bias_0$ are the bias (threshold) of the *kth* hidden neuron (h_k) and the bias (threshold) of the output neuron, respectively; wj_k^h and w_1^{ho} are the weight of the link between l_j and h_k and the weight of the link between h_k and O_1, respectively (Tadesse et al., 2012). In order to compare the ANN and the regression model, the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the coefficient of determination (R^2) values were used. According to these criteria, the model that gives a higher value of R^2 and lower values of RMSE, MAE, and MAPE was determined as the optimal model. The equations for these criteria and the terms in the equations are given below:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{Y} - Y_i)^2}{n}}$$

$$\text{MAE} = \frac{\sum_{i=1}^{n} | Y_i - \hat{Y}_i |}{n}$$

$$\text{MAPE} = \frac{\sum_{i=1}^{n} \left| \frac{(Y_i - \hat{Y}_i)}{y_i} \right|}{n} \times 100, y_i \neq 0$$

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

where n is the total number of samples, Y_i is the observed value, and $\hat{Y}_i$ is the predicted value (Öztürk, 2012; Takma et al., 2012). In the ANN modeling, the "Neural Network Toolbox" menu in the R2009a version of the MATLAB software was used. SPSS 15.0 and Excel 7.0 were used in the other computational processes done with regression analysis.

3. Results

The descriptive statistics of leaf width, leaf length, and leaf area measurements in the data set used in the analyses in order to develop the leaf area estimation model are given in Table 2.

The R^2, F, and MSE values of the estimation model created with regression analysis are shown in Table 3. From Table 3 a strong correlation between leaf area and all used parameters ($P < 0.01$) was observed. The R^2 values of the models were between 81% and 92%, and the MSE values were between 0.012 and 0.032. The R^2 value of Model 5, which was created by using the L × W parameter, was the highest, and its MSE value was the lowest among the created estimation models; therefore, it was chosen as the best estimation model (Table 3).

Accordingly, the best selected leaf area estimation model was developed as $\ln(LA) = 1.038 + 0.89 \ln(L \times W)$. By observing the compliance of the predicted values and the actual values, it was decided whether the model was valid or not. It was found that there is a 92% correlation between the predicted values and the actual values (Figure 3).

In the present study, the ANN model approach was used as the second method. A network structure shown in Figure 2 was designed for the modeling of ANN. The data set was divided into two parts: training data and test data. By random selection 30% of the data were used as test data. Out of a total of 420 data items, 294 were trained in the network and the accuracy of the trained network model was tested with 126 data items. The results according to the ANN model are given in Table 4. According to the results in Table 4, R^2 values were between 94% and 97% in the model training and testing phase, and MAPE values (one of the model performance criteria) were between 4% and 8%. Because these values were less than 10%, the estimation model was determined to have a high degree of accuracy (Lewis, 1982). The consistency between the estimated values and the actual values of the leaf area found during the ANN training and testing phases is

Table 2. Descriptive statistics values of the data used in the study.

Parameters	Max	Min	Mean and standard deviation
LW (cm)	11	2.8	5.22 ± 1.31
LL (cm)	19.40	5.60	5.60 ± 2.56
LA (cm^2)	105.49	13.27	38.91 ± 16.96

*LW: Leaf width (cm); LL: Leaf length (cm); LA: Leaf area (cm^2).

Table 3. The equations of the leaf area estimation model computed by regression.

Model no.	Independent variable	Equation of model tested	Linear equation	R^2	F-value	Pr > F	MSE
1.	Length (L)	$\ln(LA) = \ln(a) + b\ln(L)$	$Ln(LA) = 0.753 + 1.640 \ln(X)$ (0.055)** (0.031)**	0.87	2814.413	< 0.0001	0.022
2.	Width (W)	$\ln(LA) = \ln(a) + b\ln(W)$	$Ln(LA) = 2.678 + 1.595 \ln(X)$ (0.164)** (0.037)**	0.81	1827.458	< 0.0001	0.032
3.	Square of length (L^2)	$\ln(LA) = \ln(a) + b\ln(L^2)$	$Ln(LA) = 0.753 + 0.821 \ln(X)$ (0.055)** (0.015)**	0.87	2814.413	< 0.0001	0.022
4.	Square of width (W^2)	$\ln(LA) = \ln(a) + b\ln(W^2)$	$Ln(LA) = 2.678 + 0.797 \ln(X)$ (0.164)** (0.019)**	0.81	1827.458	< 0.0001	0.032
5.	Leaf length × leaf width (L × W)	$\ln(LA) = \ln(a) + b\ln(L \times W)$	$Ln(LA) = 1.038 + 0.89 \ln(X)$ (0.051)** (0.012)**	0.92	2678.215	< 0.0001	0.012
6.	Leaf length square × leaf width ($L^2 \times W$)	$\ln(LA) = \ln(a) + b\ln(L^2 \times W)$	$Ln(LA) = 0.857 + 0.589 \ln(X)$ (0.044)** (0.008)**	0.91	5252.764	< 0.0001	0.013
7.	Leaf length × leaf width square ($L \times W^2$)	$\ln(LA) = \ln(a) + b\ln(L \times W^2)$	$Ln(LA) = 1.356 + 0.584 \ln(X)$ (0.07)** (0.0309)**	0.90	4028.675	< 0.0001	0.016
8.	Leaf length square × leaf width square ($L^2 \times W^2$)	$\ln(LA) = \ln(a) + b\ln(L^2 \times W^2)$	$Ln(LA) = 1.038 + 0.445 \ln(X)$ (0.051)** (0.006)**	0.91	5253.838	< 0.0001	0.013

All variables in the models above were significant at $P < 0.01$.

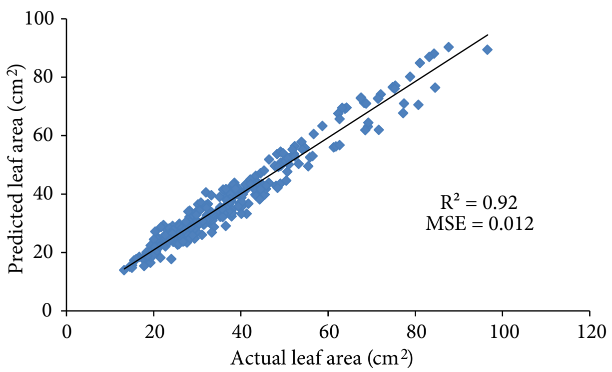


Figure 3. The compliance of the estimation results of the regression analysis with the actual values.

Table 4. The results of the ANN model.

	Training data (n = 294)	Testing data (n = 126)	Overall data (n = 420)
RMSE	2.34	4.84	3.30
MAPE	0.04	0.08	0.05
MAE	1.47	3.03	1.94
R^2	0.97	0.94	0.96

shown in Figures 4 and 5. The estimated values computed via the ANN model and the actual values were highly consistent. The R^2 value was 97 in the training phase, and 94 in the testing phase (Figures 4 and 5). For the leaf area estimation, the compliance graph between the predicted values of the models created according to both methods and the actual values are given in Figure 6. Accordingly, the R^2 value found with the ANN model was higher than that found with the regression model, while the error criteria values of the ANN model were lower (Figure 6).

The parameter values used to express the leaf area prediction with ANN in closed form and their equational expressions were indicated previously (Eqs. (5) and (6)). The values to be used in the formulas indicated in Eqs. (5) and (6) are given in Tables 5 and 6, respectively. Eqs. (7)–(10) were created by using Table 5, and were expressed in closed form by putting in Eq. (11). Because the result in Eq. (11) was not normalized, it should be converted into its original value by using Eq. (1).

$$N_1 = -1.315X_1 - 2.461X_2 + 0.105, \quad (7)$$

$$N_2 = -2.883X_1 - 3.833X_2 - 0.088, \quad (8)$$

$$N_3 = -1.578X_1 - 1.801X_2 - 0.651, \quad (9)$$

$$N_4 = -1.094X_1 - 1.020X_2 - 0.010, \quad (10)$$

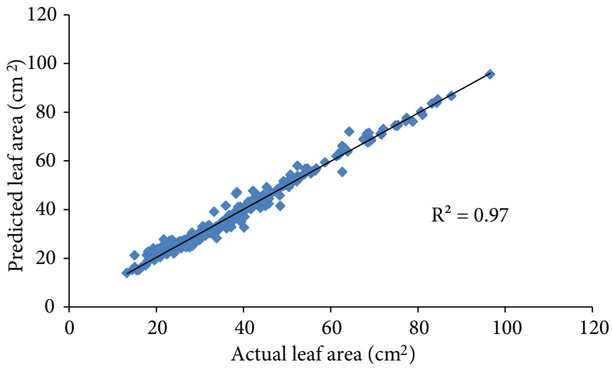


Figure 4. ANN training results.

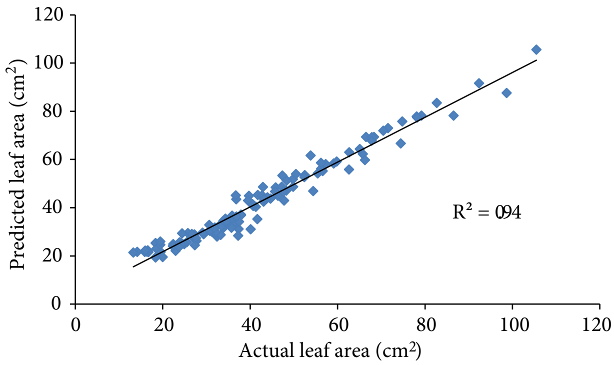


Figure 5. ANN testing results.

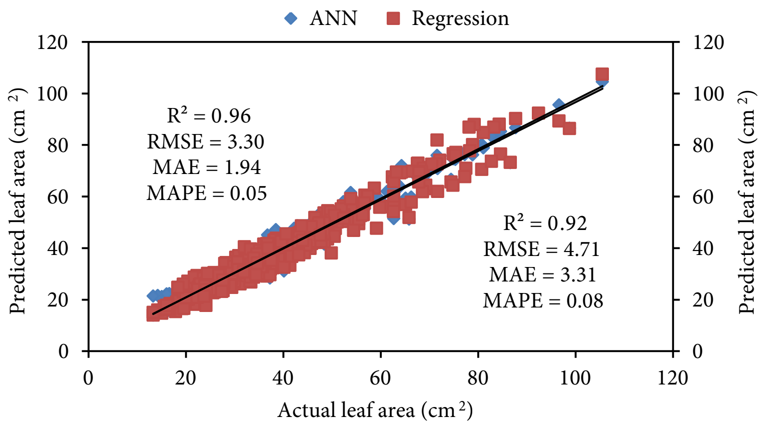


Figure 6. Comparison of the predicted leaf area using ANN and regression models.

Table 5. The weight values between the input layer and the hidden layer.

	The number of neurons in the hidden layer (i)			
Weights	1	2	3	4
W_{1i}	−1.315	−2.883	−1.578	−1.094
W_{2i}	−2.461	−3.833	−1.801	−1.020
Bias1	0.105	−0.088	−0.651	−0.010

Table 6. The weight values between the hidden layer and the output layer.

Weights	The number of neurons in the hidden layer (i)				Bias2
	1	2	3	4	
W_i	−1.043	0.818	−2.776	−1.504	1.798

The output LA_v may be found as follows:

$$LA_v = \left(\frac{1}{1 + e^{\left(\left(\frac{-1.043}{1+e^{-N1}} + \frac{0.818}{1+e^{-N2}} - \frac{2.776}{1+e^{-N3}} - \frac{1.504}{1+e^{-N4}} + 1.798\right)\right)}} \right) \quad (11)$$

4. Discussion and conclusion

The present study aimed to develop the best leaf area prediction model for the tomato plant. For this purpose, the models expressed as power equations involving various combinations of leaf width and length parameters (independent variables) were transformed into a linear form and leaf area estimation models were developed by regression analysis (Table 3). As a result of regression analysis, the best prediction model was determined as ln(LA) = 1.038 + 0.89 ln(L × W) (with the lowest MSE and the highest R^2). When model validation was performed, a correlation of 92% was found between the predicted values and the actual values (Figure 3). In addition, a strong correlation between the leaf area and all parameters used was also found ($P < 0.01$).

This high correlation showed that the parameters of leaf width and length were effective in the leaf area estimation, and thus estimation could be done with these parameters. Other studies on the development of leaf area prediction models also reported similar results (Demirsoy and Demirsoy, 2003; Serdar and Demirsoy, 2006; Cho et al., 2007; Cristofori et al., 2007; Peksen, 2007; Kumar, 2009; Celik et al., 2011).

In the present study, as a second approach, the ANN method was used in order to develop an estimation model. The leaf width and length values were introduced to the network as input, and the leaf area values were introduced as output in the ANN structure (Figure 2). The network training process was terminated when the specified error value was achieved, and the compliance between the resulting output values and the actual values was investigated. The validity of the model was tested with test data. It was found that there is a 97% correlation in the training phase, and a 94% correlation in the test phase between the area values estimated using ANN and the actual values (Figures 4 and 5). Test results showed that the network has a good generalization capacity (Smith, 1986). As a result of the model comparison of the two methods, it was determined that the error values of ANN were minimum (RMSE, MAE, MAPE) and its R^2 was higher. The ANN method was more successful in estimating the actual values according to regression analysis (Figure 6). Similar results were reported in many ANN studies in the field of agriculture (Liu et al., 2010; Vazquez-Cruz et al., 2012; Khoshnevisan et al., 2014; Guine, 2015; Were et al., 2015).

Consequently, the best leaf area prediction model was developed by using two different techniques in the present study. The compliance of the ANN estimation results with the actual values was high. This shows that it is possible to measure the leaf area with no damage by using the ANN prediction model in a short time without the need for expensive devices. In addition, the ANN output values were expressed in a sigmoid function form in this study. When considering the lack of studies on the development of ANN formulas in such a closed form in the agricultural field in recent years, this study can provide a new perspective for future research.

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