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Research Article

A Comparison of Artificial Neural Networks and Some Nonlinear Models of Leaf Area Estimation of Sugar Beet at Different Nitrogen Levels

Sultan KIYMAZ[1*], Ufuk KARADAVUT[2], Ahmet ERTEK[3]

[1]Ahi Evran University, Agriculture Faculty-Department of Biosystems Engineering, Kırşehir/Turkey
[2]Ahi Evran University, Agriculture Faculty-Department of Animal Science, Biometry and Genetic Unit, Kırşehir/Turkey
[3]Suleyman Demirel University, Agriculture Faculty-Department of Irrigation and Drainage, Isparta/Turkey

*Corresponding author e-mail: skiymaz@ahievran.edu.tr

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Abstract

Leaf area is related to many physiological and agronomic studies including growth, photosynthesis, transpiration, and energy balance. The study aimed to determine the leaf area estimation of sugar beet (*Beta vulgaris* L.) at different nitrogen levels under field conditions. The study was conducted out in split plots in randomized complete blocks with three replications in 2012-2013, and measurements were taken from leaf parameters, such as length (L) and width (W), petiole length, and the total number of leaf per a sugar beet. The artificial neural networks and such non-linear methods as the Logistic, Richards, and Gompertz were compared to estimate the leaf area measurements. As a result, all models have shown the highest identification success in the level of third fertilization. While the ANN model in the first three fertilizer doses showed a higher definition of success compared to other models, the Richards model in the fourth fertilizer dose has been more successful. An increase in the nitrogen level has accelerated the plant growth. While the ANN model remained insufficient for very rapid growth identification, the Richards model is defined in more successful rapid growth.

Key words: Comparison, non-linear models, neural network model, sugar beet.

Yapay Sinir Ağları ve Bazı Doğrusal Olmayan Modellerin Farklı Azot Seviyelerindeki Şeker Pancarı Yaprak Alan Tahmininin Karşılaştırılması

Özet

Yaprak alanı, birçok büyüme, fotosentez, terleme ve enerji dengesini içeren agronomik ve fizyolojik çalışmalarla ilgilidir. Çalışma, tarla koşullarında farklı azot seviyelerindeki şeker pancarının (*Beta vulgaris* L.) yaprak alanı tahmininin belirlenmesini amaçlamıştır. Çalışma, tesadüf bloklarında bölünmüş parseller deneme deseninde 3 tekerrürlü olarak 2012-2013 yıllarında yürütülmüştür. Ölçümler yaprak boyu, yaprak eni, yaprak sapı uzunluğu ve bitki başına toplam yaprak sayısı gibi yaprak parametrelerinden alınmıştır. Yapay sinir ağları ve Lojistik, Richards ve Gompertz gibi doğrusal olmayan yöntemler yaprak alanı ölçümlerini tahmin etmek için karşılaştırıldı. Sonuç olarak, tüm modeller üçüncü gübreleme düzeyinde en yüksek tanımlama başarısını göstermiştir. İlk üç gübre dozunda yapay sinir ağları (YSA) modelinde diğer modellere göre daha yüksek bir başarı düzeyi gösterilirken, dördüncü gübre dozunda Richards modeli daha başarılı olmuştur. Azot seviyesinin artması ile bitkinin büyümesi hızlanmaktadır. YSA modeli hızlı büyüme tanımlamasında yetersiz kalırken, Richards modeli daha hızlı büyümede daha başarılı olarak tanımlanmıştır.

Anahtar kelimeler: Karşılaştırma, doğrusal olmayan modeller, sinir ağları modeli, şekerpancarı.

Introduction

Leaf area (LA) is important for plant physiology and morphology. Therefore, it should be monitored and measured at all stages of growth (Blanco and Folegatti, 2005). In addition, quality and yield of plants are directly affected by the total leaf area, which determinate photosynthesis and transpiration efficiency Asner et al. (2003), Serdar and Demirsoy (2006), Peksen, (2007) Achten et al. (2010), Bakhshandeh et al. (2011). Leaf area (LA) is the most studied leaf parameters (leaf area, length, width). Leaf morphology in different environmental conditions and plant growth is influenced by factors such as growth, nutrition, water availability, and temperature. Determination of LA under field circumstances is related to time, labor limitations, expensive investment and developed equipment. Therefore, leaf dimensions (such as length and width) were proposed to accomplish some limitations. Leaf area models have been developed for many field crops such as cotton, maize, sunflower, sugar beet and wheat (Tsialtas and Maslaris 2008).

The various prediction models for leaf area by using linear and non-linear models for many agricultural crops have been developed and investigated by researchers. The artificial neural networks have been recently used as one of the most important ways to estimate leaf area in field crops. According to the statistical technique, the Artificial Neural Networks (ANNs) have a greater capacity to analyze data, particularly when the properties are complex, and all the data do not follow a similar distribution pattern (Atkinson and Tatnall 1997; Moghaddam et al. 2010).

Nitrogen (N) is a nutrient critical to the growth and yield of agricultural crops. Although some studies have been carried out on sugar beets, leaf area estimation models for the sugar beets grown at different nitrogen levels are little investigated (Květ and Marshall 1971; Tsialtas and Maslaris 2005; 2007; 2008; Lemaire et al. 2008; Albayrak and Yüksel 2009; Cemek et al. 2011). The objective of this study was to estimate the leaf area of the sugar beet (*Beta vulgaris* L.) at different nitrogen levels under field conditions using artificial neural networks and non-linear methods.

Materials and Methods

Study area

This experiment was carried out in Çukurçayır, Kırşehir for two growing seasons (2012 and 2013). The study area is located in Çukurçayır in the center of the Kırşehir province in Turkey, with a latitude from 36°42´ to 39°16´ N and longitude from 31°14´ to 34°26´ E and 1017 m altitude.

According to the long-term (1970-2012) average annual temperature, humidity, precipitation, wind speed and sunshine duration are as follows; 11.4°C, 55%, 384.4 mm, 2.7 m s^{-1}, and 7.2 h, respectively. The average annual temperature is 11.3°C and total annual rainfall is 383.4 mm during the crop growth period from April to October (Kırşehir Regional Meteorology Station, 2013).

The soil texture is silty-clay-loam (SCL). The pH was 7.52–7.61 between depths of 0.3 and 0.9 m. The average value of organic matter, available phosphorus, and available potassium range from 1.10 to 1.99%; 52 to 168 kg ha^{-1}; 333 to 1056 kg ha^{-1}, respectively, at a 0.3-0.9 m soil depth (Kiymaz and Ertek, 2015).

Experimental design, sowing and fertilization

The Isella sugar beet variety was used as the experimental material. The seeds were sown at 1.5–2 cm depths using a five-row mechanic beet seeder. The experiment design was a split plot in randomized complete blocks with three replications and the size of each plot was 2.25 m in length x 9 m in width (20.25 m^2). Seed sowing was performed on April 1, 2012 and 2013 according to the sowing program of Kırşehir Sugar Factory (Kiymaz and Ertek, 2015).

Four nitrogen fertilizer levels are as follows N_1:30 kg ha^{-1}; N_2: 40 kg ha^{-1}; N_3: 50 kg ha^{-1} and N_4: 60 kg ha^{-1}). Fertilizer applications were made according to the soil analysis results. The same amounts of fertilizers were applied to all of the experimental plots. A compound fertilizer of 12–30–12% N, P_2O_5, K_2O and nitrogen were applied at a rate of 50 kg ha^{-1} and 160 kg ha^{-1} prior to planting on April 14, 2012 and on April 2, 2013; the remaining amount of nitrogen was applied to all experimental plots in the form of ammonium sulfate (21% N) in two parts on June 28 and July 25 in both irrigation seasons (Kiymaz and Ertek, 2015).

Measurements

Irrigation was applied at seven-day intervals. Measurements started after three days following the first irrigation, and then measurements were taken after three days following each irrigation at 10-days intervals and continued until final irrigation. All leaf measurements were taken twelve times (June 24, July 2, 8, 22, and 29; August 5, 12, 19, and 26; September 2, 9, and 16).

Three plants randomly were selected per plot. All of the nine plants were measured from three replication plants on the same leaves in the middle of each plot. The leaf area and petiole length were measured using a planimeter (Placom KP-90N) and a tape measure, respectively. The measurements of leaf parameters were leaf length

(L), leaf width (W), petiole length, and the total number of leaf per a sugar beet. The number of leaves in each plot was counted by hand. All the leaf parameters are expressed in cm, except for the total leaf number per sugar beet.

Models

In the study, the artificial neural networks and such non-linear models as the Logistic, Richards, and Gompertz models were compared for the leaf area estimation in the sugar beets. Levenberg-Marquarth algorithm is used as a learning algorithm in artificial neural networks model. It is preferred because it is fast and stable. Learning vector quantization (LVQ) is used as learning vector in the study. While modeling artificial neural networks, the data are divided into two groups. The first group is for model learning and the second group is for model testing. As the neuron input parameter of the model, a total of 250 measurement values were used five times from five plants per measurement. Only the first and last values of the plant sizes were used for the input values. The reason for this is that it is possible to make probability estimates in future measurements. The process was completed with 16 iterations in the study. It makes it harder to learn output with fewer than 16 iterations. Generally, the values used in the training of the artificial neural network model are called target values. Plant height measurements were taken as target values in our study.

The non-linear models were given by Eqs (1), (2), and (3) as the following equations (Draper and Smith, 1998; Karadavut, 2009).

Non-linear models as the following equations:

Logistics growth model is given by Eqs

$$Y = a/(1-be^{-ct}) \quad (1)$$

Richards growth model is given by Eqs

$$Y = a(1 \pm be^{-ct})^{d} \quad (2)$$

Gompertz growth model is given by Eq

$$Y = ae^{-be^{-ct}} \quad (3)$$

Where a refers to an asymptote value, b refers to size of values of the leaf in the period in which they start to grow, c is the net growth ratio, d is the inflexion point, e is natural logritmical based. The comparisons of models were made with the coefficient of determination (R^2), Mean Squared Error (MSE), Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE) and Bias (BIAS).

Statistical analyses

For the identification of nonlinear models Statistica 6.0 software was used, but for the neural network model MATLAB program is used for analysis (Douglas and Donald, 1998; Karadavut, 2009).

Results and Discussion

Non-linear regression models were analyzed and the obtained results were compared with the neural network model (Table 1). In addition, determination coefficients (R^2), MSE, MAD, MAPE, and BIAS values are given in Table 1. Considering the models in Table 1, the highest coefficient of determination with R^2= 94.78 in the level nitrogen of N_3 were obtained, the lowest coefficient of determination was obtained as R^2= 91.20 in the level nitrogen of N_4.

In the nitrogen level of N_3, the ANN model showed R^2 = 97.1 as a prediction success. This was followed by the Richards model with R^2= 96.7. On the whole, in the first three nitrogen levels the ANN model has been involved in the first place, while the Richards model was in the second place. The Logistic and Gompertz models received values close to each other. Only, in the nitrogen level of N_3, the Gompertz model was included before the Logistic model. Considering the value of the MSE, the MSE in the nitrogen level of N_1 and N_3 were obtained as almost the same value, while MSE in the nitrogen level of N_4 with 3.47 reached fairly a high level. Considering the value of MAD, the lowest value (2.37) obtained in the nitrogen level of N_3. This followed the nitrogen level of N_1 with 2.57, while the nitrogen level of N_4 reached the highest level. As a result of these, the values of coefficient of determination and MSE showed descriptions of success as the highest degree in the first three nitrogen doses, while the descriptions of success reduced in the nitrogen level of N_4. Models were forced to explain the rapid growth of the plants. This situation shows a little difficulty in the growth of plants and a rapid growth of crops with increasing doses of fertilizer. Accordingly, the Richards model showed more successful identification with high R^2 and low MSE. In general, Richards model reveals better adapt to the changes. However, ANN model more successfully describes rapid change and sudden movements of growth.

Considering the value of MAPE, the highest MAPE was obtained in the nitrogen level of N_1 with 2.82, this was followed by the nitrogen level of N_4 with 3.26. The highest percentage MAPE was nitrogen level of N_4 (5.19%).

Considering the value of BIAS, the lowest value was determined in the nitrogen level of N_3 with 0.20, this was followed by the nitrogen level of N_1 with 0.26. The maximum BIAS value was determined in the nitrogen level of N_4 with 0.51; this was followed by the nitrogen level of N_1 with 0.26.

When the values of MSE, MAD, MAPE, and BIAS is evaluated in general, the ANN model and the Richards models revealed close values, however, the values obtained from the ANN model were slightly under the Richards model for the first three nitrogen levels. The Richards model was placed ahead of the ANN model in the nitrogen level of N_4. In the ANN model the first three nitrogen doses showed that descriptions of success were higher than the other models. Especially, variations of leaf area in these nitrogen doses may be due to more stability.

Increasing nitrogen levels accelerated growth and the ANN model based on this acceleration describes the rapid growth. The Richards model is suggested in defining the leaf area grown in a short time. The Logistic and the Gompertz models show that all nitrogen levels and the comparison criteria were fairly under the values compared to the ANN and Richards models, accordingly, these models did not show success estimation in the leaf area issue.

The values observed, and the estimated models are shown in Figure 1a, 1b, 1c and 1d. While the models in the first fertilizer level are close together to the movement growth in the first five measurements, significant changes have begun to be shown after the sixth measurements (Figure 1a). However, it was observed that significant deviations have occurred in the growth curve in the fourth and fifth measurement periods (Figure 1b). The values estimated with actual values in the nitrogen level of N_3 showed a trend quite close to each other (Figure 1c). However, growth has not been steady; it showed regular deviations. The estimated values of growth in the nitrogen level of N_4 are acted in a certain harmony and sharp deviations have not been observed (Figure 1d).

Table 1. Comparison criteria of neural network model and the non-linear regression models in estimating leaf growth of sugar beet in different nitrogen levels.

Nitrogen levels	Models	Comparison criteria				
		R^2	MSE	MAD	MAPE	BIAS
N_1	Richards	92.7	1.714	2.311	1.084	0.176
	Logistic	90.4	2.044	2.844	4.641	0.357
	Gompertz	90.3	2.013	2.756	4.586	0.348
	ANN	93.1	1.697	2.118	0.972	0.144
Means		91,6	1.867	2.507	2.821	0.256
N_2	Richards	94.3	1.321	1.988	1.613	0.219
	Logistic	90.6	3.455	3.612	7.389	0.655
	Gompertz	90.5	3.512	3.643	7.393	0.619
	ANN	95.6	1.152	1.913	1.506	0.196
Means		92.7	2.360	2.789	4.475	0.422
N_3	Richards	96.7	1.070	1.706	1.322	0.112
	Logistic	92.3	2.816	3.171	5.442	0.308
	Gompertz	93.0	2.705	3.004	5.061	0.299
	ANN	97.1	0.925	1.618	1.202	0.096
Means		94.7	1.879	2.375	3.257	0.204
N_4	Richards	95.3	1.416	2.140	1.503	0.186
	Logistic	89.6	4.611	5.069	8.160	0.781
	Gompertz	87.4	5.817	5.217	9.014	0.851
	ANN	92.5	2.018	2.611	2.072	0.211
Means		91.2	3.466	3.759	5.187	0.507

Conclusions

The artificial neural networks and such non-linear methods as the Logistic, Richards, and Gompertz were compared to estimate the leaf area measurements. As a result, all models have shown the highest identification success in the third fertilization level. While the ANN model in the first three fertilizer doses showed a higher definition of success compared to other models, the Richards model in the fourth fertilizer dose has been more successful. The increasing nitrogen level has accelerated plant growth. While the ANN model remained insufficient for very rapid growth identification, the Richards model was more successful in defining rapid growth.

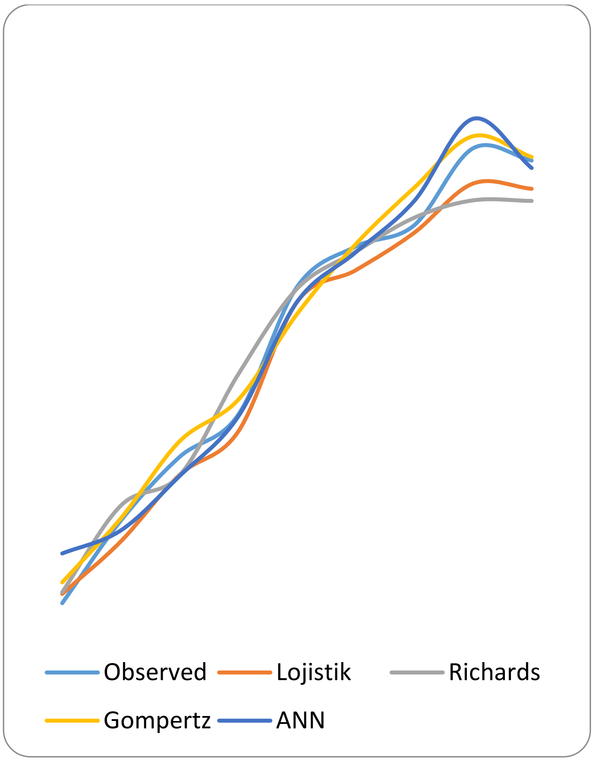

Figure 1a

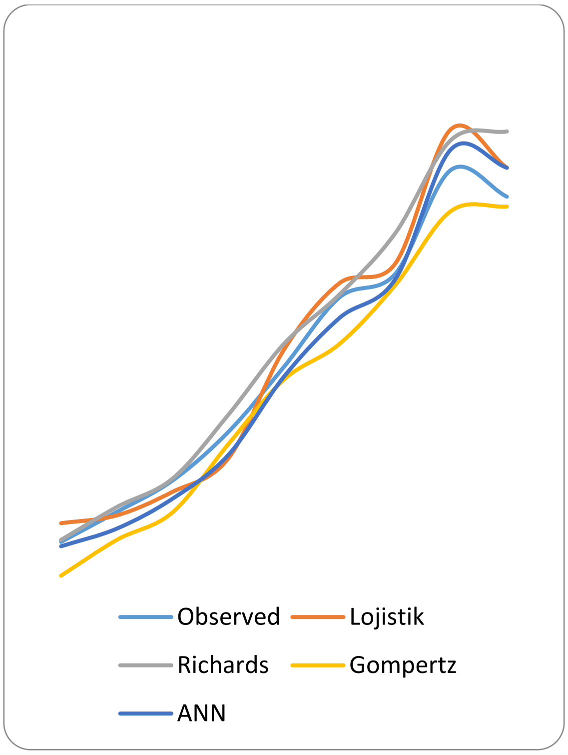

Figure 1b

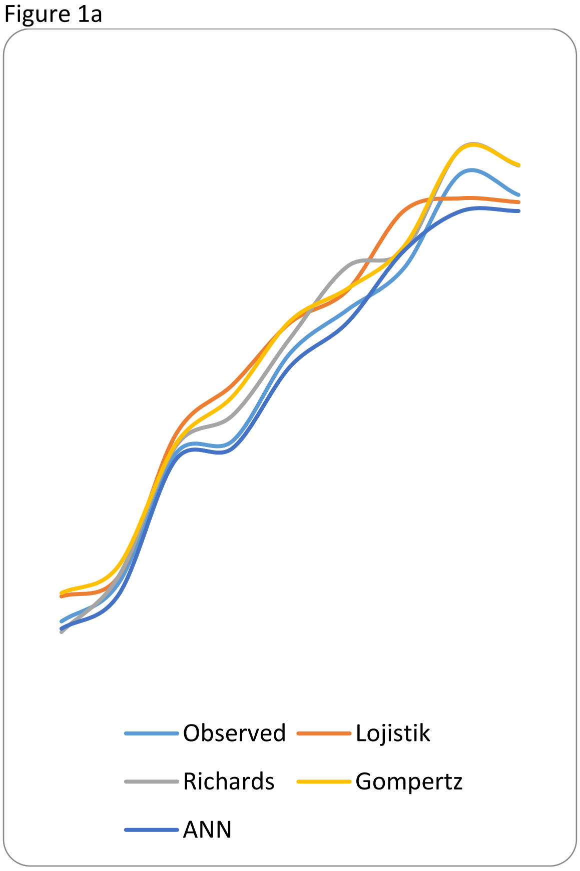

Figure 1c

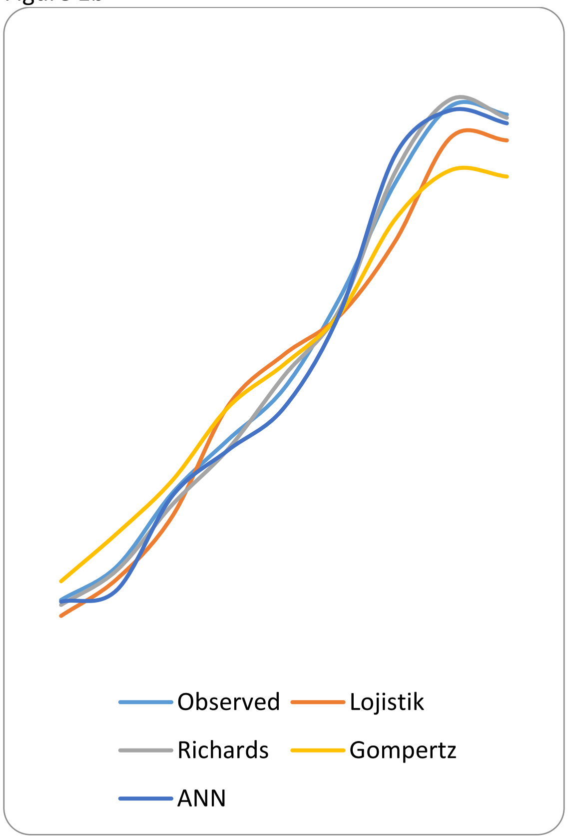

Figure 1d

Figure 1. The values observed and estimated models.

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