Gaziosmanpaşa Üniversitesi Ziraat Fakültesi Dergisi
Journal of Agricultural Faculty of Gaziosmanpasa University
https://dergipark.org.tr/tr/pub/gopzfd

Araştırma Makalesi/*Research Article*

JAFAG
ISSN: 1300-2910
E-ISSN: 2147-8848
(2024) 41(3) 178-185
doi:10.55507/gopzfd.1537132

Developing Leaf Area Prediction Model for Curly Lettuce Grown Under Salinity Stress and Applied with Foliar Salicylic Acid

Mehmet Sait KİREMİT[1*]

[1]Ondokuz Mayıs University, Faculty of Agriculture, Department of Agricultural Structures and Irrigation, Samsun
***Corresponding author's email:** mehmet.kiremit@omu.edu.tr

Alındığı tarih (Received): 22.08.2024 Kabul tarihi (Accepted): 04.11.2024

Abstract: Accurate and non-destructive methods for measuring leaf area are crucial for understanding the growth and physiological variations of plants under stress conditions. This investigation aimed to develop and assess the effectiveness of various regression models for predicting the leaf area of curly lettuce cultivated under different irrigation water salinities (IWS: 0.30, 4.15, 8.0 dS m^{-1}) and salicylic acid doses (SA: 0, 1, 2 mM). The coefficient of determination (R^2) values for the models ranged from 0.505 to 0.968, with Root Mean Square Error (RMSE) values between 4.59 and 17.79 cm² and Mean Absolute Error (MAE) values of 3.44 to 13.05 cm². Using only leaf length (LL) and leaf width (LW) can effectively estimate the leaf area of curly lettuce plants (Model 3, R^2: 0.962, RMSE: 7.58 cm², MAE: 5.34 cm²). Incorporating IWS and SA into prediction models enhanced their accuracy and reliability. The best model for estimating the leaf area of curly lettuce was found from Model 13, which integrated all four parameters—SA, IWS, LL, and LW—achieving the highest R^2 (0.968) and the lowest RMSE (4.59 cm²) and MAE (3.44 cm²). Finally, using leaf area prediction models that consider stress conditions can enhance crop management by allowing accurate monitoring of plant health and growth in agriculture.

Keywords: Lactuca sativa, leaf dimensions, non-destructive methods, precision agriculture, regression models.

Tuzluluk Stresi Koşullarında Yetiştirilen ve Yapraktan Salisilik Asit Uygulanan Kıvırcık Marul İçin Yaprak Alanı Tahmin Modelinin Geliştirilmesi

Öz: Stres koşulları altında bitkilerin büyümesini ve fizyolojik değişimlerini anlamak için yaprak alanının doğru ve bitkiye zarar vermeyen yöntemlerle ölçülmesi büyük önem taşımaktadır. Bu çalışmada farklı sulama suyu tuzlulukları (IWS: 0.30, 4.15, 8.0 dS m^{-1}) ve salisilik asit dozları (SA: 0, 1, 2 mM) altında yetiştirilen kıvırcık marulun yaprak alanını tahmin etmek için çeşitli regresyon modellerinin geliştirilmesi ve etkinliğinin değerlendirilmesi amaçlanmıştır. Modeller için R^2 değerleri 0.505 ile 0.968 arasında, RMSE değerleri 4.59 ile 17.79 cm² ve MAE değerleri 3.44 ile 13.05 cm² arasında bulunmuştur. Sadece yaprak uzunluğu (LL) ve yaprak genişliği (LW) kullanılarak kıvırcık marul bitkilerinin yaprak alanı etkili bir şekilde tahmin edilebileceği anlaşılmıştır (Model 3, R^2: 0.962, RMSE: 7.58 cm², MAE: 5.34 cm²). IWS ve SA' nın tahmin modellerine dahil edilmesi elde edilen regresyon eşitliklerinin doğruluk ve güvenilirliklerini artırmıştır. Kıvırcık marulun yaprak alanını tahmin etmek için en iyi model, en yüksek R^2 (0.968) ve en düşük RMSE (4.59 cm²) ve MAE (3.44 cm²) değerlerinin elde edildiği dört parametreyi (SA, IWS, LL ve LW) entegre eden Model 13 olduğu belirlenmiştir. Sonuç olarak, stres koşullarını dikkate alan yaprak alanı tahmin modellerinin kullanılması, tarımda bitki sağlığı ve büyümesinin doğru bir şekilde izlenmesine olanak sağlayarak ürün yönetimini iyileştirebilir.

Anahtar Kelimeler: Lactuca sativa, yaprak boyutları, tahribatsız yöntemler, hassas tarım, regresyon modelleri.

1. Introduction

Leaf area (LA) plays a crucial role in studies related to plant growth and physiology, aiding researchers in comprehending the intricate relationships between plants and their surroundings (Rahimikhoob et al., 2023). It offers valuable information on processes such as photosynthesis functions, stomatal behavior, and the distribution of nutrients within leaves (Huang et al., 2022). The size of the leaf is directly connected to a plant's capacity to absorb solar energy, produce energy, and facilitate essential photosynthetic processes crucial for its growth. (Tanaka et al., 2022; Ribeiro et al., 2024). Furthermore, analyzing LA can reveal how plants adapt to various environmental stressors, including water-salt stress, light, and diagnosing nutrient deficiencies (Soheili et al., 2023; Kiremit et al., 2024).

Leaf area can be measured using destructive or non-destructive, direct or indirect methods (Patrício & Rieder, 2018). Destructive methods, which require removing leaves for measurement, can impact plant health and quality even though they yield accurate data (Pandey & Singh, 2011). Non-destructive methods, such as laser scanning and digital imaging, allow for precise LA assessment without damaging the plant throughout its life cycle (Ribeiro et al., 2024; Tunca et al., 2024). Indirect methods, which estimate LA based on dimensions like length and width, are cost-effective and simplify the measurement process. The key difference between direct and indirect methods is that direct methods measure LA outright, while indirect methods rely on observable parameters (Ribeiro et al., 2022).

Regression models for predicting LA offer a practical, non-invasive measurement approach (Cemek et al., 2020; Ribeiro et al., 2022). These models relate measurable parameters (like leaf length and width) to actual LA, reducing the need for invasive techniques and minimizing harm to plants (Pandey & Singh, 2011; Ribeiro et al., 2024). Nevertheless, the performance of these models was significantly affected by plant variety, stress conditions, and data handling (Amorim et al., 2024). Therefore, it is essential to carefully choose and rigorously validate models to guarantee that the forecasts regarding LA are not only trustworthy but also meaningful. This rigorous process is vital for achieving accurate results that can be trusted, as the quality of the models used directly impacts the validity of the predictions made regarding LA. With this perspective, many previous researchers have developed various empirical models to predict LA for different plants, including green pepper (Cemek et al., 2011), bell pepper (Cemek et al., 2020), basil cultivars (Ribeiro et al., 2022), chokeberry (Akyüz & Cemek, 2024), lettuce (Rahimikhoob et al., 2023), sweet potato (Ribeiro et al., 2024).

Lettuce (*Lactuca sativa* L.) is a worldwide famous leafy vegetable, particularly significant in Türkiye for its nutritional benefits and economic contribution to agriculture. (Şalk et al., 2008). Rich in vitamins, minerals, and antioxidants, lettuce is widely consumed fresh and in salads (Şalk et al., 2008). Its cultivation thrives in Türkiye's favorable climate, making it a key component of the country's horticultural sector. Therefore, measuring LA is essential for assessing plant health and growth. Thus, determining the best method for calculating LA is crucial, given lettuce's agricultural and economic relevance.

As far as we know, there is a deficiency of studies evaluating and comparing different methods for forecasting LA in lettuce cultivated under different stress conditions. Therefore, the present work aims to evaluate the effectiveness of different regression models for estimating the LA of curly lettuce through non-destructive techniques and compares predictive models using statistical criteria. Finally, for researchers and agronomists, using prediction models for LA can improve decision-making in agriculture, such as optimizing irrigation and other management practices to improve crop yields.

2. Material and Method

2.1. Experimental site

The pot trial was conducted at the Faculty of Agriculture, Ondokuz Mayıs University, Samsun, Türkiye, from 5 February to 11 May 2020. A plastic sheet was used to cover the top of the research area to protect the experiment against rainfall. During the entire growing season, a data logger recorded daily temperature and relative humidity. The relative humidity ranged from 28.1% to 100%, while the temperature varied between 0.2°C and 29.2°C. The experimental soil used was classified as loam, consisting of 31.0% silt, 23.4% clay, and 45.6% sand. The experimental soil contained 0.78 mg of nitrogen, 69.5 mg of phosphorus, and 148.4 mg of potassium per kg. Additionally, the soil had a saturated electrical conductivity of 0.22 dS m^{-1} and a pH value of 6.81.

Seeds of curly lettuce (Lactuca sativa L., cv. Couster) from Intfa Seed Company were utilized in this research. They were sown in trays and grown in a greenhouse until ready for transplantation. Healthy and uniform lettuce seedlings were chosen and transferred to 4.83 dm^3 circular plastic pots, measuring 22 cm in height, with top and bottom diameters of 18.4 cm and 15 cm, respectively. Each pot was planted with a single seedling. Before planting, the soil was naturally air-dried and sifted through a 4 mm mesh sieve. Each pot was then filled with 4.5 kg of air-dried soil. Base fertilizers consisting of phosphate and potassium were added at rates of 0.58 g and 0.88 g per pot, respectively. Nitrogen fertilizer was applied at 0.35 g per pot, with half added during seedling transplantation and the other half after one month. Diammonium phosphate, potassium sulfate, and urea chemical fertilizers were utilized to provide phosphate, potassium, and nitrogen fertilization, respectively. The fertilization procedure for growing lettuce adhered to the recommendations outlined by (Şalk et al., 2008)

2.2. Experimental design

The research was laid out following a randomized complete block design involving two factors: three doses of salicylic acid (SA) (SA_0: 0, SA_1: 1, and SA_2: 2 mM) and three levels of water salinity (S_1: 0.30, S_2: 4.15, and S_3: 8.0 dS m^{-1}), leading to a total of 9 treatments (3×3) with three replicates for each treatment (totaling 27 pots). Before transplanting, each pot's field capacity was determined by saturating the soil with tap water and covering the tops with a plastic sheet to prevent evaporation. After 48 hours, when drainage ceased, each pot was weighed, and this weight was recorded as the field capacity (Ünlükara et al., 2008; Kiremit and Arslan, 2018). Soil water depletion was monitored by weighing each pot throughout the growth cycles, and irrigation was applied when 30% of the available soil water was used by evapotranspiration during the growing season. Saline water treatments were applied 10 days post-transplanting, along with 15% leaching water during each irrigation to prevent excessive salt buildup in the pots. Two saline irrigation waters (4.15 and 8.0 dS m^{-1}) were prepared by mixing NaCl and $CaCl_2$ in a 1:1 ratio with tap water (0.30 dS m^{-1}). Prior to saline water applications, all pots received equal irrigation using 0.30 dS m^{-1} to ensure seedling adaptability to pot conditions. Foliar solutions of 0, 1, and 2 mM SA were prepared with 0.01% Tween 20 and deionized water, and foliar applications were made using a manual hand sprayer. The 0 mM SA treatment served as a control, consisting only of deionized water. Foliar applications began 12 days post-transplantation and continued every two weeks until harvest.

2.3. Leaf area analysis

The lettuce plants were harvested 76 days after being transplanted from each pot. Subsequently, all lettuce leaves were detached from the stem. The leaf area, width, and length measurements for each treatment were evaluated through image analysis. All lettuce leaves from each plant were photographed and analyzed using Adobe Photoshop CS6 imaging software. The positions of leaf length and leaf width for calculating leaf area are illustrated in Figure 1.

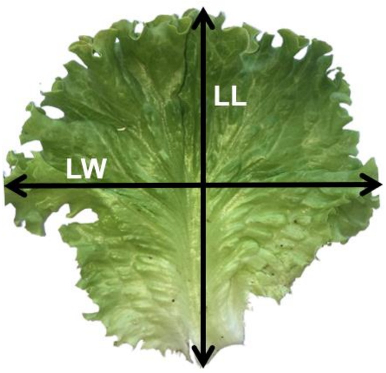

Figure 1. Position for measuring the width (LW) and length (LL) of lettuce leaves.
***Şekil 1**. Marul yapraklarının genişliği (LW) ve uzunluğunu (LL) ölçme konumları.*

2.4. Multi-linear regression analysis

Multiple linear regression analysis was applied to forecast LA using several variables, including leaf length, leaf width, salicylic acid, and irrigation water salinity. Thirteen different models were created with different input parameters to identify the best model for predicting the LA of curly lettuce plants. The model input parameters can be found in Table 1.

Table 1. The input parameters for models.
***Çizelge 1.** Modeller için girdi parametreleri*

Model No	Model input
M1	LL
M2	LW
M3	LL, LW
M4	SA, IWS
M5	SA, LL
M6	SA, LW
M7	SA, LL, LW
M8	IWS, LL
M9	IWS, LW
M10	IWS, LL, LW
M11	SA, IWS, LW
M12	SA, IWS, LL
M13	SA, IWS, LL, LW

#LL: Leaf length; LW: leaf width; SA: Salicylic acid; IWS: Irrigation water salinity.

The regression models were developed using the stepwise regression method principle (Fahrmeir et al., 2022) and analyzed using IBM SPSS 25.0 statistical software. Model variables were considered significant if their significance level was $P \leq 0.05$. Variables with a significance level greater than $P > 0.05$ were not included in the model equation. All variables in the regression models obtained had a significance level of $P \leq 0.05$. The regression model's general equation is as follows:

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} \beta_{ij} X_i X_j + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \varepsilon \qquad (1)$$

Where Y depicts the estimated leaf area; X_i and X_j stand for independent variables (LL: leaf length; LW: Leaf width; IWS: Irrigation water salinity, SA: Salicylic acid), and β, β_i, and β_{ii} represent the intercept, linear coefficients, and quadratic coefficients respectively. B_{ij} denotes the interaction coefficients between variables; k is the number of variables examined; and ε represents the error term.

2.6. Statistical evaluation of the developed models

The developed models' accuracy was assessed using three common metrics: the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE), as defined in Equations 2-4 by

Willmott and Matsuura (2005). These metrics provide a comprehensive evaluation of the models' effectiveness.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(M_i - P_i\right)^2}{\sum_{i=1}^{n}(M_i - P_{avg})^2} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(M_i - P_i\right)^2}{n}} \quad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|M_i - P_i\right| \quad (4)$$

Where, M_i: measured values of LA; P_i: predicted values of LA; P_{avg}: average of the measured value of LA; n: number of observations; i: th observations of the variables measured and predicted.

3. Results and Discussion

3.1. Description of the sampled data

The average values of leaf parameters (LL, LW, and LA) for the different treatments are depicted in Table 2. The collected data showed that leaf length varied between 7.2 and 10.0 cm for SA_0, 7.9 and 12.5 cm for SA_1, and 8.5-12.5 cm for SA_2 (Table 2). Leaf width ranged from 6.8-12.1 cm for SA_0, 7.3 and 11.8 cm for SA_1, and 7.3-9.6 cm for SA_2 (Table 2). Moreover, the actual LA of curly lettuce plants varied from 31.9 to 75.6 cm^2 (SA_0), 37.5 and 92.0 cm^2 (SA_1), and 40.2 and 72.6 cm^2 (SA_2) (Table 2). The leaf width and length of the lettuce decreased linearly as salinity stress increased. The smallest values for these characteristics were noted at 8.0 dS m^{-1} under all foliar application conditions. However, lettuce plants treated with 1 and 2 mM SA via foliar application exhibited greater leaf length values compared to those treated with 0 mM SA (Table 2).

Table 2. Some statistical values of lettuce grown under different water salinity and foliar applied salicylic acid.
***Çizelge 2**. Farklı tuzlu su ve yapraktan salisilik asit uygulanan koşullarda yetiştirilen marul bitkisinin bazı istatistiksel değerleri.*

Treatments	Leaf length (LL, cm)			Leaf width (LW, cm)			Leaf length (LA, cm^2)		
	Mean ± SD	Min	Max	Mean ± SD	Min	Max	Mean ± SD	Min	Max
$SA_0 \times S_1$	10.0 ± 2.5	5.6	16.0	12.1 ± 1.7	8.9	16.1	75.6 ± 31.1	38.5	159.9
$SA_0 \times S_2$	8.1 ± 1.9	5.2	12.9	10.8 ± 1.3	6.0	13.3	52.5 ± 15.1	24.6	91.2
$SA_0 \times S_3$	7.2 ± 0.7	5.5	8.4	6.8 ± 1.0	5.0	8.5	31.9 ± 6.8	16.0	44.8
$SA_1 \times S_1$	12.5 ± 1.5	9.8	15.4	11.8 ± 1.7	8.6	15.2	92.0 ± 22.2	56.8	139.5
$SA_1 \times S_2$	10.5 ± 1.2	8.9	13.8	8.7 ± 1.8	5.4	13.3	56.6 ± 15.5	36.6	111.0
$SA_1 \times S_3$	7.9 ± 0.7	6.1	9.7	7.3 ± 0.9	5.3	8.9	37.5 ± 5.2	25.2	49.3
$SA_2 \times S_1$	12.5 ± 1.3	9.8	15.0	9.6 ± 1.9	6.4	13.1	72.6 ± 19.9	45.7	110.9
$SA_2 \times S_2$	9.3 ± 1.1	7.2	11.5	7.7 ± 1.8	3.9	10.7	45.8 ± 12.6	18.9	67.6
$SA_2 \times S_3$	8.5 ± 1.0	6.4	10.8	7.3 ± 1.8	3.4	10.2	40.2 ± 12.6	17.1	59.5

#SA_0, SA_1, and SA_2 denote 0, 1, and 2 mM SA doses, respectively. S_1, S_2, and S_3 indicate 0.30, 4.15, and 8.0 dS m^{-1} saline waters, respectively.

Table 3. Developed regression equations for the prediction of lettuce leaf area by using various input parameters.
***Çizelge 3.** Farklı girdi parametreleri kullanılarak marul yaprağı alanının tahmini için geliştirilen regresyon denklemleri.*

Model No	Regression equation
M1	$LA = -34.23 + 9.40 \times LL$
M2	$LA = -23.50 + 8.69 \times LW$
M3	$LA = 10.36 + 0.85 \times LW - 1.68 \times LL + 0.66 \times LW \times LL - 0.12 \times LW^2 + 0.01 \times LW \times LL^2$
M4	$LA = 87.74 - 10.11 \times IWS - 2.8 \times SA^2 + 0.44 \times IWS^2 + 0.49 \times SA^2 \times IWS$
M5	$LA = 20.33 + 9.59 \times SA - 2.47 \times LL - 1.84 \times SA \times LL + 0.7 \times LL^2$
M6	$LA = 64.64 - 13.61 \times SA – 12.54 \times LW + 5.74 \times SA \times LW - 5.7 \times SA^2 + 1.08 \times LW^2 - 0.21 \times SA \times LW^2$
M7	$LA = -11.92 + 4.68 \times LW + 0.3 \times LL + 0.81 \times SA \times LL + 0.19 \times LW \times LL - 0.18 \times LW^2 - 0.08 \times SA \times LL^2 + 0.02 \times LW \times LL^2$
M8	$LA = 80.7 - 2.59 \times IWS - 10.78 \times LL + 0.89 \times LL^2 + 0.01 \times IWS \times LL^2$
M9	$LA = 31.64 - 2.96 \times IWS - 0.69 \times LW + 0.23 \times IWS^2 + 0.45 \times LW^2 - 0.01 \times IWS \times LW^2$
M10	$LA = 27.54 - 1.04 \times IWS - 1.3 \times LW - 2.72 \times LL + 0.85 \times LW \times LL - 0.02 \times IWS^2 - 0.09 \times LW^2 + 0.01 \times IWS^2 \times LW$
M11	$LA = 27.1 + 20.55 \times SA + 2.23 \times IWS - 6.14 \times LW - 4.03 \times SA \times IWS + 3.48 \times SA \times LW - 10.59 \times SA^2 + 0.83 \times LW^2 + 0.44 \times SA^2 \times IWS - 0.2 \times SA \times LW^2 - 0.03 \times IWS \times LW^2 + 0.06 \times SA^2 \times IWS^2 + 0.02 \times SA \times IWS \times LW^2$
M12	$LA = 60.98 + 13.52 \times SA - 2.54 \times IWS - 7.36 \times LL - 3.07 \times SA \times IWS - 2.36 \times SA \times LL - 0.3 \times SA^2 + 0.86 \times LL^2 + 0.27 \times SA \times IWS \times LL + 0.19 \times SA \times IWS^2 + 0.01 \times SA^2 \times LL^2$
M13	$LA = 4.37 - 0.09 \times IWS + 1.93 \times LW - 2.51 \times LL + 1.03 \times SA \times LW + 0.01 \times SA \times LL + 0.29 \times LW \times LL + 0.05 \times IWS^2 + 0.35 \times LL^2 - 0.01 \times IWS \times LW \times LL - 0.09 \times SA \times LL^2$

LA: Leaf area, LL: leaf length; LW: Leaf width; IWS: Irrigation water salinity, SA: Salicylic acid.

The maximum leaf width was observed in the $SA_0 \times S_1$ treatment. In particular, applying 1 and 2 mM SA to the leaves improved the leaf length of lettuce plants under S_1 conditions in comparison to 0 mM SA. In terms of LA values, the $SA_1 \times S_1$ treatment showed a higher LA value than the other treatments. As shown in Table 2, the foliar application of SA had a positive impact on the LA of lettuce plants under salt-stress conditions. Exogenous salicylic acid significantly reduced lipid damage and maintained membrane integrity, thereby preventing oxidative damage from salt stress (Peng et al., 2021). Additionally, Nigam et al. (2022) concluded that foliar spray of SA enhanced spinach LA by increasing photosynthesis and improving water and nutrient uptake. Ghassemi-Golezani and Farhadi (2022) reported that endogenous salicylic acid reduced the translocation of toxic ions (Na^+ and Cl^-) to the shoots, enhanced the uptake of essential cations, and improved the LA of pennyroyal plants under salinity stress. Our results align with Kusvuran and Yilmaz (2023) and Yavuz et al. (2023), who reported that exogenous SA increased the LA of lettuce plants under saline conditions.

Table 4. Statistical evaluation of the developed models.
Çizelge 4. *Regresyon modellerinin istatistiksel değerlendirmesi*

Model No	R^2	RMSE (cm^2)	MAE (cm^2)
M1	0.728	13.18	9.70
M2	0.719	13.40	10.29
M3	0.962	7.58	5.34
M4	0.505	17.79	13.05
M5	0.837	10.22	8.10
M6	0.853	9.71	7.07
M7	0.965	5.58	4.09
M8	0.794	11.47	8.90
M9	0.787	11.70	8.23
M10	0.966	4.95	3.72
M11	0.844	10.94	8.36
M12	0.866	9.29	7.25
M13	0.968	4.59	3.44

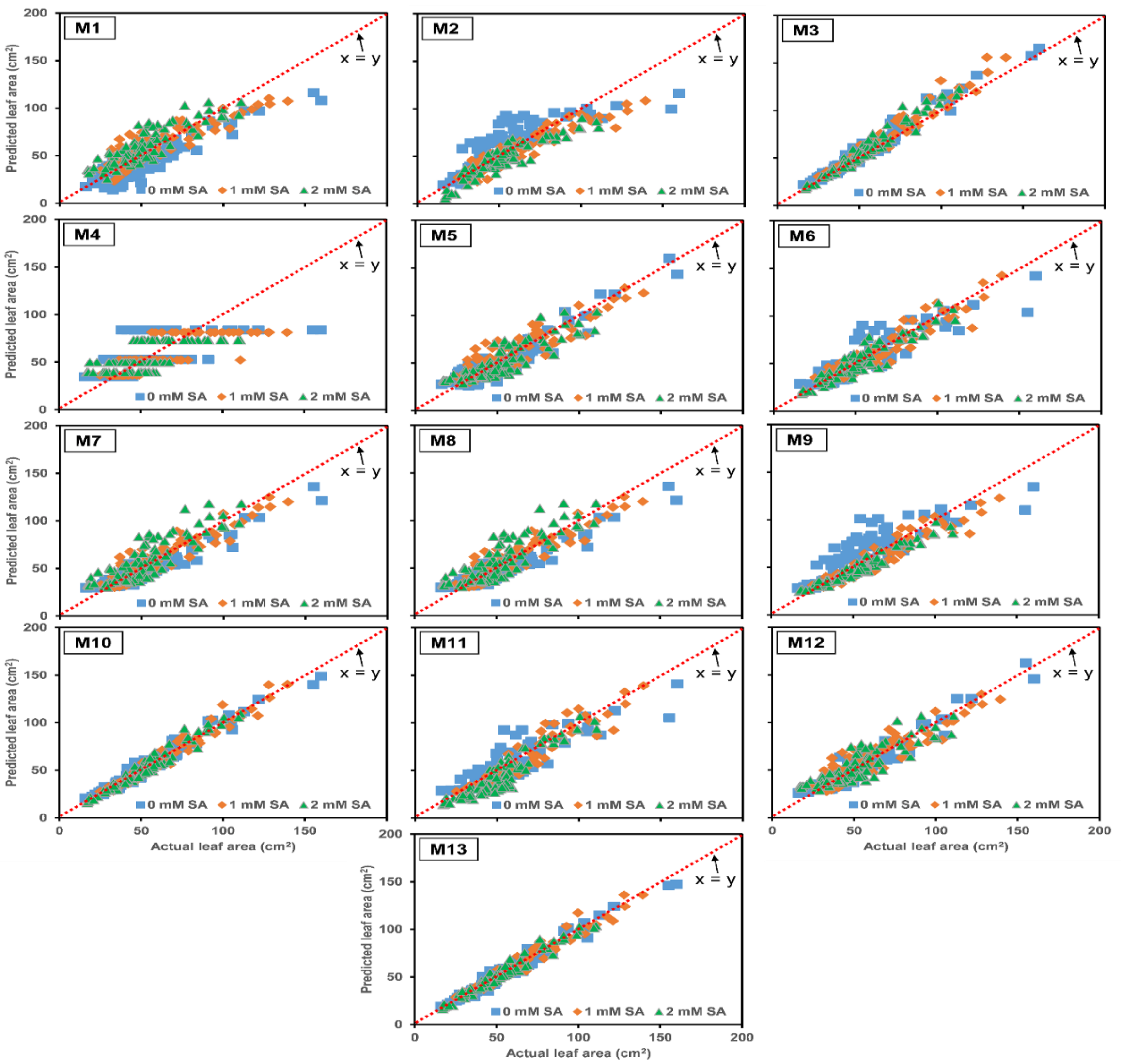

Figure 2. Relation between actual leaf area and predicted leaf area with different regression models.
Şekil 2. *Gerçek yaprak alanı ile tahmin edilen yaprak alanı arasındaki ilişki.*

3.2. Comparison of developed regression models

In the present investigation, 13 models were developed to forecast the LA of curly lettuce under varying salinity stress and SA doses. The regression equations are detailed in Table 3, with determination coefficients (R^2) ranging from 0.505 to 0.968 (Table 4). The RMSE values varied between 4.59 and 17.79 cm^2, while the MAE ranged from 3.44 to 13.05 cm^2. The scatter plots for the actual LA and predicted LA for each model are depicted in Fig. 2. Notably, Models 1 and 2, which used only one leaf dimension (LL or LW), explained 72% of the total variation in LA (Table 4). However, combining both dimensions in Model 3 significantly enhanced estimation accuracy, achieving a high R^2 of 0.962 and low RMSE (7.58 cm^2) and MAE (5.34 cm^2). Model 4 showed the poorest accuracy in predicting the LA, with the highest RMSE (17.79 cm^2) and MAE (13.05 cm^2). This suggests that creating a regression equation using SA and IWS inputs is not appropriate for accurately predicting the LA of curly lettuce. When IWS or SA parameters were included either individually or together in LL and LW models, the predictability of the regression models significantly increased. This suggests that incorporating IWS or SA in LA regression models is crucial for achieving highly accurate models. When comparing Model 7 and Model 10, they both exhibit high R^2 values (0.965 and 0.966) that are very close. However, Model 7 has RMSE and MAE values of 5.58 and 4.09 cm^2, respectively, while Model 10 has values of 4.95 and 3.72 cm^2, respectively. These results suggest that incorporating IWS along with LL and LW parameters significantly enhanced the accuracy of the model's predictive capability. However, in Model 11 and Model 12, incorporating SA and IWS with only LL or LW parameters significantly reduced the predictive capability of the models, suggesting that the use of LL and LW parameters enhanced the accuracy of the developed models. Among all the models, Model 13 exhibited the highest accuracy in predicting the LA of curly lettuce, with R^2, RMSE, and MAE values of 0.968, 4.59 cm^2, and 3.44 cm^2, respectively. By including IWS, SA, LL, and LW parameters in the development of prediction models, the accuracy of the regression equation was improved. Therefore, incorporating stress conditions into LL and LW prediction models will lead to more accurate predictions of the LA for curly lettuce cultivation. This additional information provides a more detailed insight into the predictive capabilities of the models when stress conditions are considered. Considering all of these factors, the use of Model 13 resulted in the highest accuracy in estimating LA, improving prediction accuracy by reducing RMSE by 7.84% and 21.57% compared to models M10 and M7, respectively.

Leaf area is a vital variable in studies of plant growth and development, affecting light absorption, photosynthesis, and the efficiency of water loss. It directly influences how plants respond to fertilizers and irrigation methods (Soheili et al., 2023). For instance, in lettuce, a larger LA enhances light capture and photosynthesis, improving growth, yield, and nutritional quality. Understanding LA is essential for optimizing productivity and maintaining the quality of lettuce crops. Numerous studies have focused on estimating LA by measuring leaf dimensions, typically using the combination of LL and LW as parameters in LA models. For instance, Peksen (2007) proposed LA = 0.919 + 6.82×LL×LW equation for faba pean leaf estimation. Cemek et al. (2011) utilized leaf measurements (LL and LW) to create regression models for estimating the LA of green pepper. They suggested that incorporating these measurements significantly enhanced the predictive accuracy of the models. Kandiannan et al. (2009) introduced a model to estimate the LA of ginger as LA = 0.0146 + 0.6621*LW, with an R^2 value of 0.997. This model is considered a dependable method for non-destructively estimating the LA of ginger plants. Ribeiro et al. (2020) proposed the equation LA = 0.6740*LW, which effectively estimates the LA of E. pauferrense using a linear model without intercept.

As mentioned above, using leaf length and width parameters effectively predicts LA across different plants. Our findings show that incorporating stress-related variables, such as IWS and SA, enhances the model's ability to account for variations in LA due to these stressors. This results in more accurate predictions, as the model is better suited to address the complexities of real-world scenarios where stress conditions are prevalent. Consequently, the model closely aligns with the actual observed LA in plants under diverse environmental conditions. For instance, integrating water deficit rates and irrigation water salinity parameters with LL and LW models enhanced predictability for bell pepper (Cemek et al., 2020) and chokeberry (Akyüz and Cemek, 2024) compared to using LL and LW alone. Kiremit (2024) suggested that melatonin doses and soil salinity parameters can effectively predict the LA of sweet corn seedlings. Finally, it can be confidently recommended that Model 13 is highly suitable for providing efficient and precise predictions regarding the area of curly lettuce leaves. This model effectively eliminates the necessity for expensive and potentially cumbersome methods, making it a practical choice for those seeking to enhance their prediction accuracy without incurring high costs.

4. Conclusion

The study presents a model for estimating LA in curly lettuce based on leaf width and length, enabling non-invasive and straightforward predictions without requiring specialized staff or costly equipment. In this context, Model 3 can accurately predict LA using only leaf width and length as inputs. Moreover, Model 13 is suitable for predicting LA in curly lettuce under varying irrigation water salinity and salicylic acid levels. By incorporating these factors into the prediction models, the accuracy and reliability of the models are improved, making them valuable tools for understanding and managing plant growth in different conditions. The regression equations developed can help researchers in future studies on the growth, physiology, and propagation of curly lettuce, providing a precise and non-destructive method.

References

Akyüz, A., & Cemek, B. (2024). Development of leaf area model in chokeberry plant grown in different ırrigation water quality. *Anadolu Journal of Agricultural Sciences*, 39(1), 207–219. https://doi.org/10.7161/OMUANAJAS.1419318

Amorim, P. E. C., Pereira, D. de F., Freire, R. I. da S., de Oliveira, A. M. F., Mendonça, V., & Ribeiro, J. E. da S. (2024). A non-destructive method for leaflet area prediction of Spondias tuberosa Arruda: an approach to regression models. *Bragantia*, 83, e20230269. https://doi.org/10.1590/1678-4499.20230269

Cemek, B., Unlukara, A., & Kurunc, A. (2011). Non-destructive leaf-area estimation and validation for green pepper (*Capsicum annuum* L.) grown under different stress conditions. *Photosynthetica*, 49(1), 98–106. https://doi.org/10.1007/S11099-011-0010-6/METRICS

Cemek, B., Ünlükara, A., Kurunç, A., & Küçüktopcu, E. (2020). Leaf area modeling of bell pepper (*Capsicum annuum* L.) grown under different stress conditions by soft computing approaches. *Computers and Electronics in Agriculture*, 174, 105514. https://doi.org/10.1016/J.COMPAG.2020.105514

Fahrmeir, L., Kneib, T., Lang, S., & Marx, B. D. (2022). *Regression: Models, Methods and Applications: Second Edition,* Springer Berlin Heidelberg, 1–746. https://doi.org/10.1007/978-3-662-63882-8/COVER

Ghassemi-Golezani, K., & Farhadi, N. (2022). The efficacy of salicylic acid levels on photosynthetic activity, growth, and essential oil content and composition of pennyroyal plants under salt stress. *Journal of Plant Growth Regulation*, 41(5), 1953–1965. https://doi.org/10.1007/s00344-021-10515-y

Huang, G., Shu, Y., Peng, S., & Li, Y. (2022). Leaf photosynthesis is positively correlated with xylem and phloem areas in leaf veins in rice (*Oryza sativa*) plants. *Annals of Botany*, 129(5), 619–631. https://doi.org/10.1093/AOB/MCAC020

Kandiannan, K., Parthasarathy, U., Krishnamurthy, K. S., Thankamani, C. K., & Srinivasan, V. (2009). Modeling individual leaf area of ginger (*Zingiber officinale Roscoe*) using leaf length and width. *Scientia Horticulturae*, 120(4), 532–537. https://doi.org/10.1016/J.SCIENTA.2008.11.037

Kiremit, M. S. (2024). Effect of melatonin on increasing leaf development of sweet corn seedlings under salt stress conditions. *International Congress of Sustainable Agriculture,* (pp. 310–316), 01-03 March 2024, Iğdır, Türkiye .

Kiremit, M. S., Akınoğlu, G., Mitrovica, B., & Rakıcıoğlu, S. (2024). Enhancing drought-salinity stress tolerance in lettuce: Synergistic effects of salicylic acid and melatonin. *South African Journal of Botany*, 172, 212–226. https://doi.org/10.1016/J.SAJB.2024.07.021

Kiremit, M. S., & Arslan, H. (2018). Response of leek (*Allium porrum* L.) to different irrigation water levels under rain shelter. *Communications in Soil Science and Plant Analysis*, 49(1), 99–108. https://doi.org/10.1080/00103624.2017.1421652

Kusvuran, S., & Yilmaz, U. D. (2023). Ameliorative role of salicylic acid in the growth, nutrient content, and antioxidative responses of salt-stressed lettuce. *Acta Scientiarum Polonorum Hortorum Cultus*, 22(1), 75–85. https://doi.org/10.24326/ASPHC.2023.4603

Nigam, B., Dubey, R. S., & Rathore, D. (2022). Protective role of exogenously supplied salicylic acid and PGPB (*Stenotrophomonas* sp.) on spinach and soybean cultivars grown under salt stress. *Scientia Horticulturae*, 293, 110654. https://doi.org/10.1016/J.SCIENTA.2021.110654

Pandey, S. K., & Singh, H. (2011). A simple, cost-effective method for leaf area estimation. *Journal of Botany*, 2011(1), 658240. https://doi.org/10.1155/2011/658240

Patrício, D. I., & Rieder, R. (2018). Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Computers and Electronics in Agriculture*, 153, 69–81. https://doi.org/10.1016/J.COMPAG.2018.08.001

Peksen, E. (2007). Non-destructive leaf area estimation model for faba bean (*Vicia faba* L.). *Scientia Horticulturae*, 113(4), 322–328. https://doi.org/10.1016/J.SCIENTA.2007.04.003

Peng, Y., Yang, J., Li, X., & Zhang, Y. (2021). Salicylic acid: biosynthesis and signaling. *Annual review of plant biology,* 72(1), 761-791. https://doi.org/10.1146/ANNUREV-ARPLANT-081320-092855

Rahimikhoob, H., Delshad, M., & Habibi, R. (2023). Leaf area estimation in lettuce: Comparison of artificial intelligence-based methods with image analysis technique. *Measurement*, 222, 113636. https://doi.org/10.1016/J.MEASUREMENT.2023.113636

Ribeiro, J. E. da S., Nóbrega, J. S., Coêlho, E. D. S., Dias, T. J., & Melo, M. F. (2022). Estimating leaf area of basil cultivars through linear dimensions of leaves. *Revista Ceres*, 69(2), 139–147. https://doi.org/10.1590/0034-737X202269020003

Ribeiro, J. E. da S., Coêlho, E. dos S., Figueiredo, F. R. A., Melo, M. F., Ribeiro, J. E. da S., Coêlho, E. dos S., Figueiredo, F. R. A., & Melo, M. F. (2020). Non-destructive method for estimating leaf area of Erythroxylum pauferrense (*Erythroxylaceae*) from linear dimensions of leaf blades. *Acta Botánica Mexicana*, 2020(127). https://doi.org/10.21829/ABM127.2020.1717

Ribeiro, J. E. da S., Silva, A. G. C. da, Lima, J. V. L., Oliveira, P. H. de A., Coêlho, E. dos S., Silveira, L. M. da, & Barros Júnior, A. P. (2024). Leaf area prediction of sweet potato cultivars: An approach to a non-destructive and accurate method. *South African Journal of Botany*, 172, 42–51. https://doi.org/10.1016/J.SAJB.2024.07.006

Şalk, A., Arın, L., Deveci, M., & Polat, S. (2008). *Special vegetables*. University of Namık Kemal, Faculty of Agriculture, Department of Horticulturae.

Soheili, F., Heydari, M., Woodward, S., & Naji, H. R. (2023). Adaptive mechanism in Quercus brantii Lindl. leaves under climatic differentiation: morphological and anatomical traits. *Scientific Reports* 13(1), 1–12. https://doi.org/10.1038/s41598-023-30762-1

Tanaka, M., Keira, M., Yoon, D. K., Mae, T., Ishida, H., Makino, A., & Ishiyama, K. (2022). Photosynthetic enhancement, lifespan extension, and leaf area enlargement in flag leaves increased the yield of transgenic rice plants overproducing rubisco under sufficient N fertilization. *Rice*, 15(1), 1–15. https://doi.org/10.1186/S12284-022-00557-5/FIGURES/7

Tunca, E., Köksal, E. S., Öztürk, E., Akay, H., & Taner, S. Ç. (2024). Accurate leaf area index estimation in sorghum using high-resolution UAV data and machine learning models. *Physics and Chemistry of the Earth, Parts A/B/C*, 133, 103537. https://doi.org/10.1016/J.PCE.2023.103537

Ünlükara, A., Cemek, B., Karaman, S., & Erşahin, S. (2008). Response of lettuce (*Lactuca sativa var.* Crispa) to salinity of irrigation water. *New Zealand Journal of Crop and Horticultural Science*, 36(4), 265–273. https://doi.org/10.1080/01140670809510243

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research*, 30(1), 79–82. https://doi.org/10.3354/CR030079

Yavuz, D., RASHID, B. A. R., & Seymen, M. (2023). The influence of NaCl salinity on evapotranspiration, yield traits, antioxidant status, and mineral composition of lettuce grown under deficit irrigation. *Scientia Horticulturae*, 310, 111776. https://doi.org/10.1016/J.SCIENTA.2022.111776