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LEAF AREA PREDICITION IN RICE (*ORYZA SATIVA* L.) CULTIVARS USING MULTIPLE REGRESSION ANALYSIS

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Summary: Leaf area is one of the most important parameter for plant growth. Reliable equations were offered to predict leaf area in *Oryza sativa* L. cultivars. All equations produced for leaf area were derived as affected by leaf length and leaf width. As a result of ANOVA and multi-regression analysis, it was found that there was close relationship between actual and predicted growth parameters. The leaf area prediction models in the present study are LA= (a) + (b x L) + (c x W) where LA is leaf area, L is leaf length, W is maximum leaf width and a, b, c are co-efficiencies. R^2 values were changed between 0.75 – 0.97 and standard errors were found to be significant at the $p<0.001$ significance level.

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Abbreviations: LA – leaf area; L – leaf length; W – maximum leaf width; R^2 – regression coefficiency; y_i – dependent variable; x_i – independent; ß – p-dimensional parameter.

INTRODUCTION

Leaf area has been measured in experiments concerning some physiological phenomenon such as light, photosynthesis, respiration, plant water consumption and transpiration In addition, leaf number and area of a plant have an important role in some cultural practices such as training, pruning, irrigation, fertilization, etc (Odabas et al., 2009a; Cirak et al., 2008; Cirak et al., 2005a; Cirak et al., 2005b; Odabas et al., 2005). Leaf area estimation is an important biometrical observation for evaluating plant growth in field and pot experiments (Kumar and Sharma, 2010). Leaf area plays an important role in photosynthesis, light interception, water and nutrient use, crop growth and development (Caliskan et al., 2010a; Caliskan et al., 2010b; Caliskan et al., 2009). Non-destructive methods for the estimation of leaf area may be useful to determine the relationship between leaf area and plant growth rate. Simple regression models related to leaf area and crop growth rate were applied to estimate

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crop yields. Since leaf development has a strong relationship with crop growth, knowing the change in leaf area may be useful for estimating crop growth (Celik and Odabas 2009).

The leaf area estimation models that aim to predict leaf area non-destructively can provide researchers with many advantages in the agricultural experiments (Odabas et al. 2009b). Moreover, these kinds of models enable researchers to carry out leaf area measurements on the same plants over the course of the study (Gamiely et al., 1991; NeSmith, 1991; NeSmith, 1992; Williams and Martinson, 2003). Leaf area can be determined by using expensive instruments and/or predictive models. Recently, new instruments, tools and machines such as hand scanners and laser optic apparatuses have been developed for leaf area and fruit measurements. These are very expensive and complex devices for both basic and simple studies. Furthermore, non-destructive estimation of leaf area saves time as compared with geometric measurements (Erper et al., 2011). Leaf area can be also measured quickly, accurately, and nondestructively using a portable scanning planimeter (Rouphael et al. 2010; Odabas et al. 2010). For this reason, several leaf area prediction models have been proposed for certain plant species in previous studies (Odabas et al., 2009c; Odabas et al., 2008; Odabas et al., 2005).

There have not been published reports concerning leaf area prediction models in rice cultivar. Due to the lack of such information, we aimed to develop reliable equations that allow non-destructive estimation of leaf area through linear measurements on this plant.

MATERIALS AND METHODS

Plant material and culture conditions

A total of 18 rice cultivars namely KA-189, Halilbey, Osmancik, KA-305, Ribe, Ergene, 7721, Kizilirmak, Baldo, Maretti, Negıs, Karadeniz, Rocca, Demir, Surek-85, Kral, Ece and Trakya were used as plant material. Seeds were sown in May 2009 according to a randomized complete block design with 3 replications. Plot size was 20 m^2 and every plot consisted of 500 plants m^{-2}. Fertilizer equivalent to 150 kg ha^{-1} of NH_4SO_4 was applied according to cultivars.

Measurements

Leaf samples (50 leaves for each cultivar) were collected. Thus, a total of 900 leaves were processed on the same day as they were collected. At first, leaves were placed on the photocopier desktop by holding flat and secure and copied on A3 sheet (at 1:1 ratio). Then, Placom Digital Planimeter (Sokkisha Planimeter Inc., Model KP-90) was used to measure actual leaf area of the copy. Selection of leaf dimensions per measurement was governed by variation in leaf characteristics (e.g., size, shape, and symmetry) and practical constraints (e.g., ease and accuracy of measurements under field conditions). Considering these factory maximum leaf width (W) and length (L) were selected to correlate with leaf area (cm^2). Leaf width (cm) was measured from tip to tip at the widest part of the lamina and leaf length (cm) was measured from lamina tip to the point of petiole intersection along the midrib. The leaf positions were selected with regard to points that could be easily identified and used to facilitate the measurement of leaf length and width.

Model construction

The general purpose of multiple regression is to learn more about the relationship between several independent or predicted variables and a dependent or criterion variable. Given a data set

$$\{y_i, x_{i1}, \ldots, x_{ip}\}_{i=1}^{n}$$

of n statistical units, a linear regression model assumes that the relationship between the dependent variable y_i and the p-vector of regressor's x_i is linear. This relationship is modelled through a so-called "disturbance term" ε_i – an unobserved random variable that adds noise to the linear relationship between the dependent variable and regressors. Thus the model takes the form:

$$y_i = \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i = x'_i\beta + \varepsilon_i,$$
$$i = 1, \ldots, n,$$

Where $'$ denotes the transpose, so that $x_i'\beta$ is the inner product between vectors x_i and β. Often these n equations are stacked together and written in a vector form as $y = X\beta + \varepsilon$, where:

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, x = \begin{pmatrix} x'_1 \\ x'_2 \\ \vdots \\ x'_n \end{pmatrix} = \begin{pmatrix} x_1 & \cdots x_{1p} \\ x_2 & \cdots x_{2p} \\ \vdots & \ddots \vdots \\ x_{n1} & \cdots x_p \end{pmatrix}, \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

Some remarks on terminology and general use: y_i is called the dependent variable. The decision as to which variable in a data set is modelled as the dependent variable and which are modelled as the independent variables may be based on a presumption that the value of one of the variables is caused by or directly influenced by the other variables. x_i values are called independent variables. Usually a constant is included as one of the regressors. The corresponding element of β is called the intercept. Many statistical inference procedures for linear models require an intercept to be present, so it is often included even if theoretical considerations suggest that its value should be zero. The model remains linear as long as it is linear in the parameter vector β. The regressors x_i may be viewed either as random variables, which we simply observe, or they can be considered as predetermined fixed values, which we can choose. Both interpretations may be appropriate in different cases, and they generally lead to the same estimation procedures; however, different approaches to asymptotic analysis are used in these two situations. β is a p-dimensional parameter vector. Its elements are also called effects or regression coefficients. Statistical estimation and inference in linear regression focuses on β. ε_i is called the error term, disturbance term, or noise. This variable captures all other factors, which influence the dependent variable y_i other than the regressors x_i. The relationship between the error term and the regressors, for example whether they are correlated, is a crucial step in formulating a linear regression model, as it will determine the method to use for estimation (Erper et al., 2011). Multiple regression analysis of the data was performed for each plant separately. A search for the best model for predicting leaf area (LA) was conducted with various subsets of the independent variables, namely, leaf length (L) and leaf width (W). Statistical significance of the results was tested by one-way analysis of variance (ANOVA). The best estimating equations for LA of the plants tested were determined with the R-program. R-program is a language and environment for statistical computing and graphics. R-program provides a wide variety of statistical (linear and nonlinear modeling, classical statistical tests, time-series analysis, classification, clustering, etc.) and graphical techniques, and is highly extensible. R-program provides an open source route to participation in that activity. Multiple regression analysis was carried out until the least sum of square was obtained (Cirak et al., 2005).

RESULTS AND DISCUSSION

Leaf area is associated with many agronomic and physiological processes including growth, photosynthesis, transpiration, photon interception, and energy balance (Rouphael et al., 2007). Multiple regression analysis was used for determination of the best fitting equation for estimation of leaf area in rice. It was found that most of the variations in leaf area values were explained by the selected parameters, which are leaf length (cm) and leaf width (cm) (Table 1). The variation in the parameters was between 75 % for Halilbey and 97 % for Baldo. The produced leaf area prediction models in the present study are shown in Table 1.

According to the regression analysis, which was about the estimation of leaf areas of cultivars, the R^2 values observed varied from 0.75 to 0.97. Determination of the importance level of mathematical equations was obtained by using coefficients and corresponding independent x variable (leaf area) and dependent y variables (leaf length and maximum leaf width).

Mathematical model was developed by multiple regression analysis for estimation of leaf area as follows: LA= (a) + (b x L) + (c x W) where LA is leaf area, L is leaf length, W is maximum leaf width and a, b, c are co-efficiencies.

The relation between the leaf area corresponding to the real values and the approximate leaf area obtained from a mathematical equation is shown in Fig. 1. The coefficients, their standard errors and R^2 values of the new produced equations predicting leaf area in rice (*Oryza sativa* L.) cultivars are shown in Table 1.

Although the correlation of leaf length and width with leaf area has been widely used (Elsner and Jubb, 1988), some studies also include petiole length and leaf weight (Montero et al., 2000). Length and width have been generally chosen for their simplicity and accuracy since these measurements are non-destructive. In the present study, a very close relationship between actual and predicted leaf area in rice was found (Fig. 1).

Our results were similar to other studies mentioned above that used linear measurements of leaves from different plants for estimating leaf area. Coefficients of determination were generally high for the best-fit models in the current and previous studies. However, the differences among the rice cultivars observed in the present study were not surprising due to differences in size and shape of leaves of the genotypes.

Simple models for predicting leaf area were developed for rice, an important plant species in Turkey and all over the world. Mathematical models shown in Table 1 would be useful tools for prediction of leaf area in many other plants without using expensive devices. Since the maximum leaf width and length are dimensions that can be easily measured in the field, the use of these equations would enable

Table 1. The coefficients, their standard errors and R^2 values of the new produced equations predicting leaf area in rice (*Oryza sativa* L.) cultivars.

Cultivars	Coefficient ± SE	Length (L) ± SE	Max. Width ± SE	R^2
KA-189	-5.97 ± 5.22	0.90 ± 0.08***	0.69 ± 0.58	0.82
HALILBEY	3.11 ± 5.70	0.99 ± 0.12***	-0.16 ± 0.91	0.75
OSMANCIK	-31.71 ± 7. 50***	1.16 ± 0.06***	13.71 ± 2.79***	0.93
KA-305	-2.29 ± 6.54	1.26 ± 0.12***	1.01 ± 0.87	0.80
RIBE	-6.12 ± 5.41	1.05 ± 0.09***	2.45 ± 0.87**	0.85
ERGENE	-10.34 ± 11.60	1.23 ± 0.12	2.24 ± 2.70	0.82
7721	1.35 ± 3.66	0.99 ± 0.08***	0.27 ± 0.78	0.85
KIZILIRMAK	-11.88 ± 6.77	1.28 ± 0.11***	2.35 ± 0.76**	0.85
BALDO	-16.21 ± 4.08**	1.49 ± 0.06***	1.40 ± 0.73	0.97
MARETTI	-10.53 ± 9.02	1.36 ± 0.12***	3.42 ± 1.58*	0.85
NEGIS	-3.13 ± 7.13	1.29 ± 0.10***	1.27 ± 0.92	0.88
KARADENIZ	-9.41 ± 6.36	1.52 ± 0.08***	1.20 ± 0.70	0.93
ROCCA	-14.77 ± 9.99	1.65 ± 0.10***	0.99 ± 2.01	0.91
DEMIR	-11.73 ± 4.83**	1.52 ± 0.08***	0.87 ± 0.76	0.93
SUREK-85	2.16 ± 9.60	1.56 ± 0.10***	-1.19 ± 1.17	0.91
KRAL	-8.39 ± 6.98	1.60 ± 0.11***	0.06 ± 0.99	0.89
ECE	-2.27 ± 7.65	1.27 ± 0.11***	-0.42 ± 1.65***	0.85
TRAKYA	-10.97 ± 6.47	1.24 ± 0.10***	2.43 ± 1.42	0.85

R^2: regression coefficients, SE: standard error, L: leaf length, W: maximum leaf width, equations. *, **, ***: significant at the level of $p < 0.05$, 0.01 and 0.001, respectively.

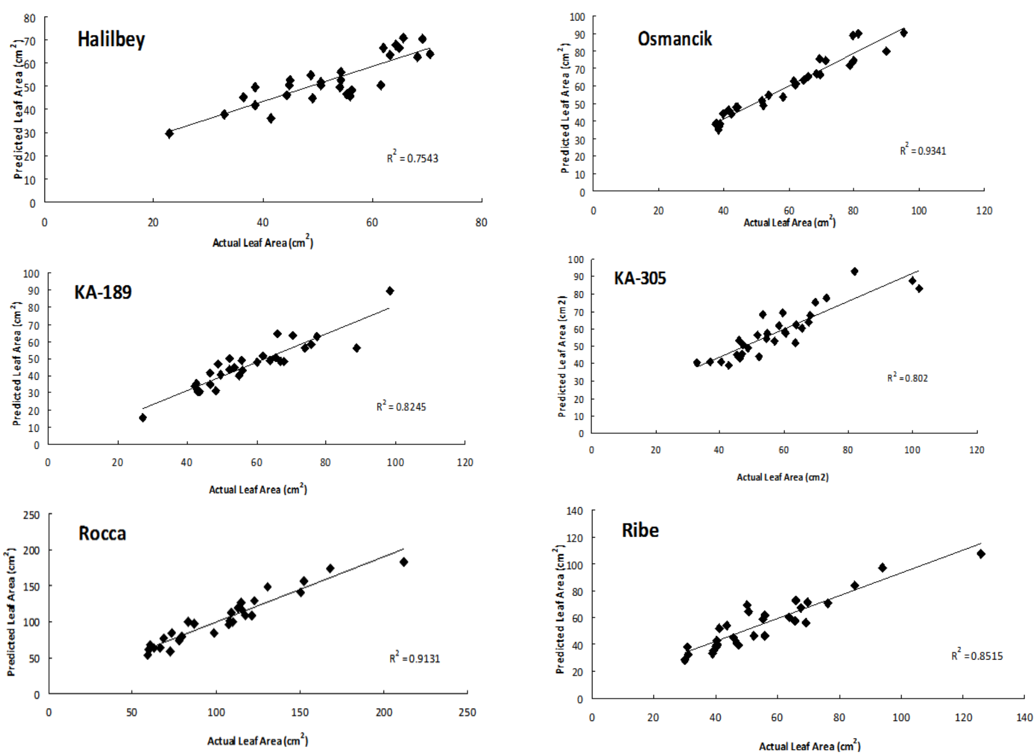

Figure 1-1. Relationship between actual and predicted leaf area in *Oryza sativa* L. cultivars.

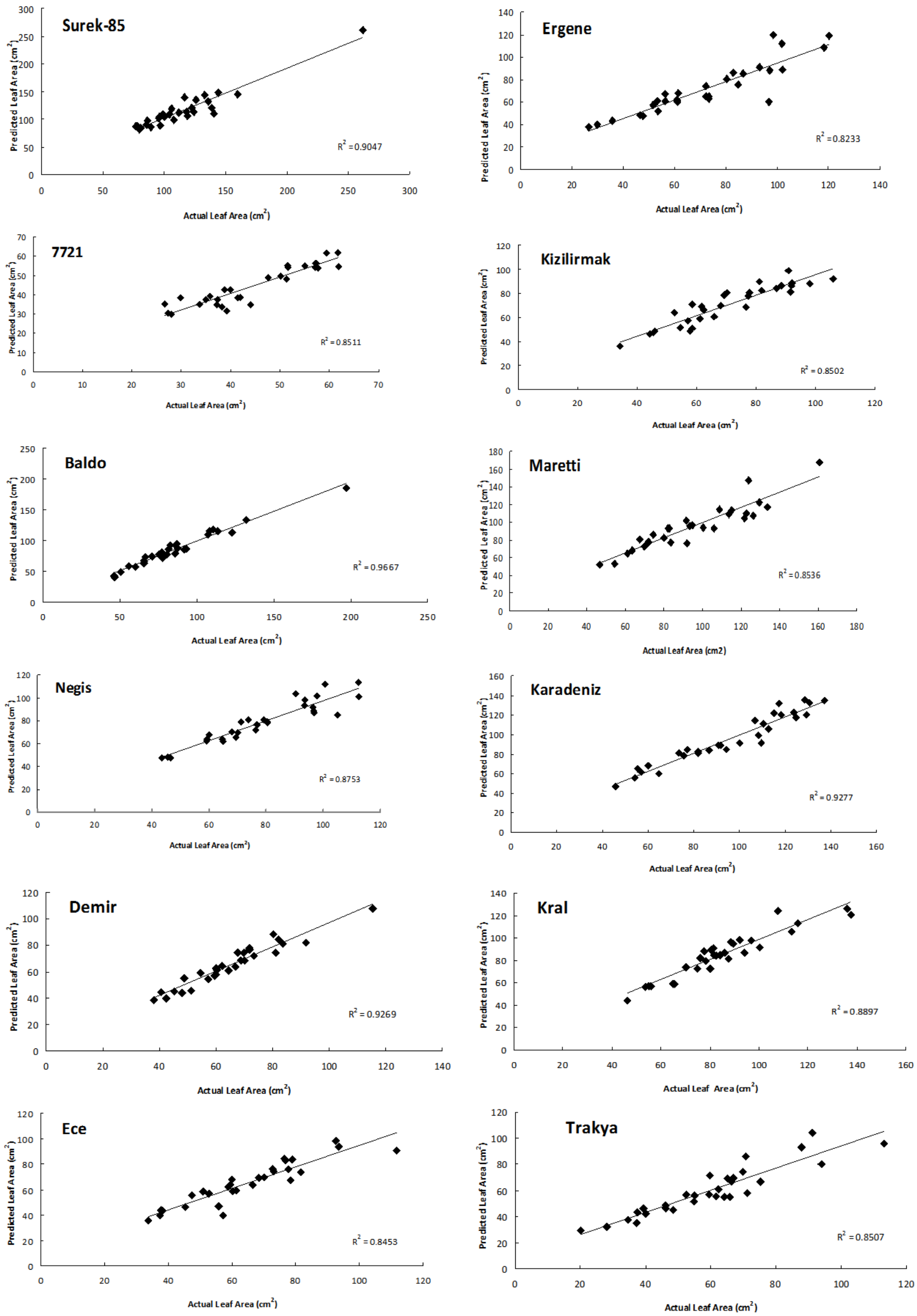

Figure 1-2. Relationship between actual and predicted leaf area in *Oryza sativa* L. cultivars.

researchers to make non-destructive measurements or repeated measurements on the same leaves. Such equations would also allow researchers to estimate leaf area in relation to factors like crop load, drought stress and insect damage.

CONCLUSION

In this study, we developed leaf area prediction models for eighteen rice cultivars. These mathematical models can be very useful tools for prediction of leaf area without using expensive devices during the course of the experiment. Besides, they are time-consuming and can be used safely by researchers.

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