BRIEF COMMUNICATION

Leaf area prediction for corn (*Zea mays* L.) cultivars with multiregression analysis

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Abstract

Leaf area is one of the most important parameter for plant growth. Reliable equations were offered to predict leaf area for *Zea mays* L. cultivars. All equations produced for leaf area were derived as affected by leaf length and leaf width. As a result of *ANOVA* and multiregression analysis, it was found that there was a close relationship between actual and predicted growth parameters. The produced leaf-area prediction model in the present study is LA = a + b L + c W + d LZ where LA is leaf area, L is leaf length, W is maximum leaf width, LZ is leaf zone and a, b, c, d are coefficients. R^2 values were between 0.88–0.97 and standard errors were found to be significant at the p<0.001 significance level.

Additional key words: leaf area; multiregression analysis; *Zea mays* L.

Leaf area is routinely measured in experiments of interesting crops where some physiological phenomenon such as light, photosynthesis, respiration, water consumption and transpiration are being studied (Gottschalk 1994, Kerstiens and Hawes 1994, Picchioni and Weinbaum 1995, Centritto *et al.* 2000, Cirak *et al.* 2008). Leaf-area estimation is an important biometrical observation for evaluating plant growth in field and pot experiments (Kumar and Sharma 2010). In addition, leaf number and area of a plant are important in terms of cultural practices such as training, pruning, irrigation, fertilization, *etc*. The leaf-area estimation models that aim to predict leaf area nondestructively can provide researchers with many advantages in the agricultural experiments. 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, 1992, Williams and Martinson 2003). Leaf area can be determined by using expensive instruments and/or prediction 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, nondestructive estimation of leaf area saves time as compared with geometric measurements. Leaf area can be also measured quickly, accurately, and nondestructively using a portable scanning planimeter (Rouphael *et al.* 2010). For this reason, several leaf-area prediction models have been produced for certain plant species in the previous studies (Odabas *et al.* 2005). Reports concerning leaf-area prediction model for *Zea mays* L. have not been published yet. Due to the lack of such information, we aimed to develop reliable equations that allow for the nondestructive estimation of leaf area through linear measurements on this plant.

Ten dent corn cultivars were sown in May 2009 according to a randomized complete block design with 3 replications. Plot size was 22.4 m^2 and every plot consisted of 4 ear-to-row progenies 70 cm apart and 8 m long. Fertilizer equivalent to 60-120-150 kg ha^{-1} of N-P_2O_5-K_2O, was applied according to cultivars. A total of 10 *Zea mays* L. cultivars, namely Helen, Semal, P32W86, OSSK602, DK6610, P6137, Simon, Tieber, Bolson, and ADA523 were used as the plant material. The cultivars which were used in the research are between FAO 600 – FAO 700 maturity groups.

Leaf samples (50 leaves for each cultivars) were

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

collected. Thus, total of 500 leaves were processed at the same day as they were collected in the following manner. At first, they 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,* Japan) was used to measure actual leaf area of the copy. Selection of leaf dimensions for 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 factors, maximum leaf width (W) and length (L) were selected to correlate with leaf area. W was measured from tip to tip at the widest part of the lamina and L 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 L and W.

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

Given a data set $\{y_i, x_{i1}, \cdots, x_{ip}\}_{i=1}^{n}$ 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 form

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

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 vector form as $y = x\,\beta + \varepsilon$ where

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, x = \begin{pmatrix} x_1' \\ x_2' \\ \vdots \\ x_n' \end{pmatrix} = \begin{pmatrix} x_{11} \cdots x_{1p} \\ x_{21} \cdots x_{2p} \\ \vdots \;\ddots\; \vdots \\ x_{n1} \cdots x_{np} \end{pmatrix}, \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

Some remarks on terminology and general use: y_i is called the regressand, endogenous variable, response variable, measured variable, or 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. Alternatively, there may be an operational reason to model one of the variables in terms of the others, in which case there needs be no presumption of causality. x_i values are called regressors, exogenous variables, explanatory variables, covariates, input variables, predictor variables, or 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. Sometimes one of the regressors can be a nonlinear function of another regressor or of the data, as in polynomial regression. 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 LA was conducted with various subsets of the independent variables, namely L, W, and LZ. LZ is leaf area according to on the corncob or under the corncob. Statistical significance of the results was tested by one-way analysis of variance (*ANOVA*). The best estimating equations for the leaf area (LA) of the plants tested were determined with the R-program. Multiple regression analysis was carried out until the least sum of square was obtained (Cirak *et al.* 2005). 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 the leaf area in maize. It was found that most of the variations in leaf area values were explained by the selected parameters, which are L, W, and LZ (Table 1).

The variation in the parameters was between 88% for Semal, 97% for Simon and Bolson. Means ± standard deviations, minimum and maximum values for the actual and estimated leaf area of the cultivars. The produced leaf area prediction models in the present study are shown in Table 1.

Although correlations among L and W with LA have been widely used (Elsner and Jubb 1988), some studies also include petiole length and leaf mass (Montero *et al.*

Table 1. Fitted coefficients (*b, c, d*) and constant (*a*) values of the model used to estimate the plant leaf area (LA = a + b L + c W + d LZ) [LA in cm²] of single leaves from length (L), width (W) and leaf zone (LZ) measurements. Coefficient of determination (R^2), mean square errors (MSE), $n = 50$.

Cultivar	Fitted coefficients with MSE and constant a [cm²]	b [cm]	c [cm]	d	R^2
Helen	–935.11 ± 63.24	8.63 ± 0.37	71.41 ± 8.85	107.21 ± 27.56	0.93
Semal	–738.43 ± 67.48	6.83 ± 0.34	40.32 ± 7.77	175.00 ± 28.85	0.88
P32W86	53.76 ± 109.48	7.74 ± 0.30	49.35 ± 7.96	–345.80 ± 30.64	0.96
OSSK602	–517.83 ± 52.35	6.58 ± 0.26	47.46 ± 6.62	22.51 ± 17.71	0.94
DK6610	–434.92 ± 53.45	4.21 ± 0.34	87.23 ± 5.64	–68.87 ± 23.04	0.91
P6137	–304.97 ± 112.00	11.23 ± 0.44	0.52 ± 1.50	152.18 ± 38.78	0.90
Simon	–367.69 ± 71.36	9.54 ± 0.22	38.93 ± 6.95	–71.49 ± 14.87	0.97
Tieter	–834.56 ± 73.72	8.52 ± 0.36	59.41 ± 8.87	109.03 ± 37.89	0.91
Bolson	–504.63 ± 61.50	8.48 ± 0.25	42.94 ± 7.75	0.32 ± 19.82	0.97
ADA523	–1,486.90 ± 114.86	10.37 ± 0.32	119.74 ± 11.71	39.64 ± 24.42	0.96

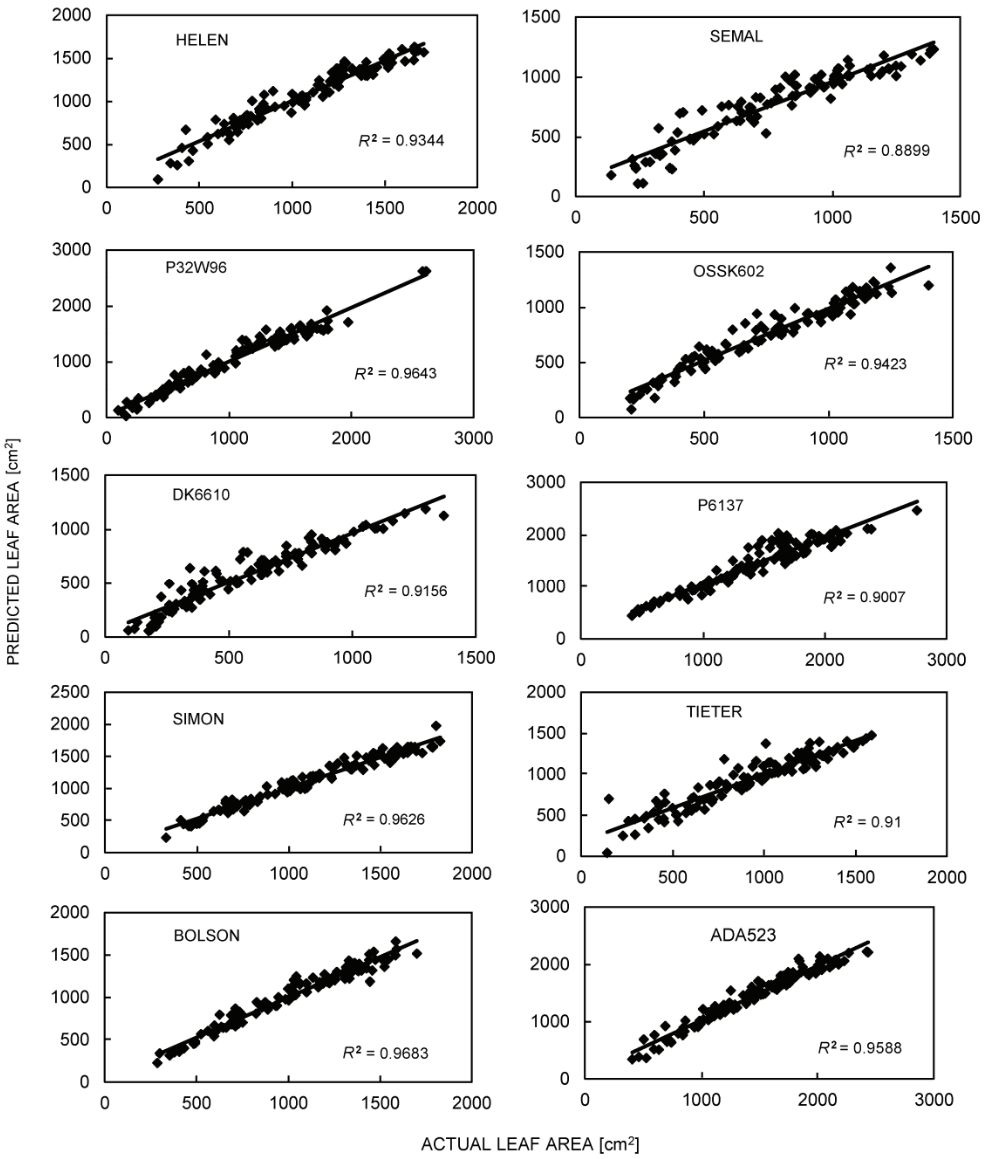

Fig. 1. Relationship between actual and predicted leaf area in *Zea mays* L. cultivars.

2000). L and W have been generally chosen for their simplicity and accuracy since these measurements are nondestructive. A very close relationship between actual and predicted LA for corn was found in this study (Fig. 1).

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

The simple models for predicting LA were developed for corn, an important plant species in Turkey and all over the world. Mathematical model shown in Table 1 would be useful tools for prediction of LA for many plants without using expensive devices. Since the maximum W and L are dimensions that can be easily measured in the field, use of these equations would enable researchers to make nondestructive measurements or repeated measurements on the same leaves. Such equations would also allow researchers to estimate LA in relation to factors like crop load, drought stress, and insect damage.

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