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CROP PRODUCTION

Area estimation of soybean leaves of different shapes with artificial neural networks

Ludimila Geiciane de Sá[1], Carlos Juliano Brant Albuquerque[1], Nermy Ribeiro Valadares[1], Orlando Gonçalves Brito[2], Amara Nunes Mota[1], Ana Clara Gonçalves Fernandes[1] and Alcinei Místico de Azevedo[1*]

[1]Instituto de Ciências Agrárias, Universidade Federal de Minas Gerais, Av. Universitária, 1000, 39404-547, Bairro Universitário, Montes Claros, Minas Gerais, Brazil. [2]Universidade Federal de Lavras, Lavras, Minas Gerais, Brazil. *Author for correspondence. E-mail: alcineimistico@hotmail.com

ABSTRACT. Leaf area is one of the most commonly used physiological parameters in plant growth analysis because it facilitates the interpretation of factors associated with yield. The different leaf formats related to soybean genotypes can influence the quality of the model fit for the estimation of leaf area. Direct leaf area measurement is difficult and inaccurate, requires expensive equipment, and is labor intensive. This study developed methodologies to estimate soybean leaf area using neural networks and considering different leaf shapes. A field experiment was carried out from February to July 2017. Data were collected from thirty-six cultivars separated into three groups according to the leaf shape. Multilayer perceptrons were developed using 300 leaves per group, of which 70% were used for training and 30% for validation. The most important morphological measures were also tested with Garson's method. The artificial neural networks were efficient in estimating the soybean leaf area, with coefficients of determination close to 0.90. The left leaflet width and right leaflet length are sufficient to estimate the leaf area. Network 4, trained with leaves from all groups, was the most general and suitable for the prediction of soybean leaf area.

Keywords: *Glycine max*; multilayer perceptrons; computational intelligence.

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Introduction

Measuring leaf area is fundamental for studying the photosynthetic efficiency of plants, determining biotic and abiotic damage to crops, analyzing growth, and estimating crop yield (Hosseini, McNairn, Merzouki, & Pacheco, 2015). The length and width of the leaf blade have been used to estimate the leaf area in fruit trees (Teobaldelli et al., 2019), vegetable crops (Padrón et al., 2016; Toebe et al., 2019), and ornamental crops (Fascella, Maggiore, Zizzo, Colla, & Rouphael, 2009; Giuffrida et al., 2011), among others.

For soybean crops, the primary method to estimate leaf area is with mathematical models, using the linear dimensions of the leaf (Bakhshandeh, Kamkar, & Tsialtas, 2011; Richter et al., 2014). However, soybean leaves have different shapes and sizes, which can affect the leaf area estimation. Moreover, the presence of three leaflets can also hinder this evaluation.

Leaf area can be measured using destructive or non-destructive means, and several methods have been developed to facilitate this measurement. However, such methods, including the use of leaf discs, millimeter graph paper, desktop or portable scanners, conventional planimeter, or photography, require the excision of a part of the plant. Thus, the same leaf cannot be successively measured (Fallovo et al., 2008). Some of these methods are destructive, require the use of high-cost equipment, and are time consuming and labor intensive. In other words, the development of a low-cost, fast, reliable, and non-destructive method is a challenge for leaf area measurement.

Mathematical regression models with linear and non-linear approaches (Silva, Lima, Bendini, Nomura, & Moraes, 2008) are frequently used to estimate the leaf area based on the length and width of the leaf blade (Shabani et al., 2017). Recently, the artificial neural network (ANN) technique has been considered as a fundamental alternative to estimating and predicting several traits (Guimarães, Donato, Azevedo, Aspiazú, & Silva Junior, 2018). Additionally, different studies have shown that ANNs often provide better results than traditional methods (Moosavi & Sepaskhah, 2012).

Artificial neural networks can be used for several purposes in agricultural science, such as the prediction of crop production (Guimarães et al., 2018), fruit weight (Soares, Pasqual, Lacerda, & Silva, 2013; Rad, Koohkan, Fanaei, & Rad, 2015), or evapotranspiration (Pandorf et al., 2016), and soil parameter estimation (Oliveira, Sari, Castro, & Pedrollo, 2017). The use of ANNs is a non-parametric technique that is tolerant to data loss and does not require detailed information on the system to be modeled (Silva et al., 2014). Notably, however, we did not find reports of studies that used RNAs to estimate the soybean leaf area in the literature, nor articles that considered different leaf shapes.

Considering the abovementioned context, this study developed strategies to efficiently estimate soybean leaf area using artificial neural networks that efficiently analyze leaves of different shapes.

Material and methods

The experiment was carried out from February to July 2017 at the Institute of Agricultural Sciences (IAS) of the Federal University of Minas Gerais, regional campus of Montes Claros, Minas Gerais State, Brazil (16º51'00'' S; 44º55'00'' W; 630 m altitude). The soil is predominantly classified as Cambisol. According to Köppen's classification, the climate in that region is of the Aw type (i.e., tropical wet and dry), with dry winters and rainy summers.

Thirty-six commercial soybean cultivars (Table 1) were grouped according to their leaf shape and planted in a simple lattice experimental design (6 × 6), with two replications, and about 40 plants per plot. The leaves were of three distinct shapes, namely lanceolate, triangular, and elliptic (Figure 1).

Table 1. Soil, cultivars, corporation, and leaf shape groups; Montes Claros, Minas Gerais State, Brazil, 2018.

Group	Cultivar	Corporation
1	CD 2728 IPRO	Coodetec
1	NS 7209 IPRO	Nidera
1	RK 6813 RR	GDM
1	RK 7814 IPRO	Monsoy
2	97R21	DuPont Pioneer
2	97R73	DuPont Pioneer
2	98Y12	DuPont Pioneer
2	99R03	DuPont Pioneer
2	99R09	DuPont Pioneer
2	BMX Desafio	BRASMAX
2	BMX Potencia RR	BRASMAX
2	CD 2730 IPRO	Coodetec
2	CD 2737 RR	Coodetec
2	CD 2750 IPRO	Coodetec
2	CD 2817 IPRO	Coodetec
2	DM 6563RSF IPRO	DONMARIO
2	DS 5916 IPRO	DowAgroSciences
2	M 5947 IPRO	Monsoy
2	M 6210 IPRO	Monsoy
2	M 8210 IPRO	Monsoy
2	NS 6906 IPRO	Nidera
2	NS 6909 IPRO	Nidera
3	98Y30	DuPont Pioneer
3	AS 3610 IPRO	AGROESTE
3	AS 3730 IPRO	AGROESTE
3	BMX Ponta IPRO	BRASMAX
3	CD 2720 IPRO	Coodetec
3	M 6410 IPRO	Monsoy
3	M 7110 IPRO	Monsoy
3	NA 5909 RG	Nidera
3	NS 5959 IPRO	Nidera
3	NS 7000 IPRO	Nidera
3	NS 7300 IPRO	Nidera
3	NS 7338 IPRO	Nidera
3	TMG 7062 IPRO	TMG

Leaves were randomly collected at different positions on each plant to obtain different leaf sizes and, hence, to enable the generalization of the model to be adjusted. Multilayer perceptron (MLP) networks were used to predict the leaf area, with the aid of the RSNNS package in R software. In the MLP training process, the length and width data of each leaflet were used as input variables, and the recorded leaf area was used as the desired output. The estimation of the leaf area was performed with a scanner (HP Photosmart C4480, Hewlett-Packard, Palo Alto, CA, USA) and the Image-Pro Plus software (v. 4.5).

Figure 1. Examples of the three leaf shapes of soybean cultivars-lanceolate (A), triangular (B), and elliptic (C) used in this study.

Three hundred leaves from each shape group were used, totaling 900 leaves. From this selection, 70% of the leaves were assigned for training, and 30% for validation.

To ensure the best efficiency in network training, both input and output data were standardized to the interval between 0 and 1, using the following equation:

$$V_n = [1 + (V_{obs} - V_{max})]/(V_{max} - V_{min}),$$

where: V_n is the normalized value, V_{obs} is the observed value, V_{max} is the maximum value of the sample, and V_{min} is the minimum value of the sample. The maximum and minimum values found for each variable are shown in Table 2. As for standardization, the *normalizeData* function from the RSNNS package was used (Bergmeir & Benítez, 2012). The maximum number of training times was arbitrarily set to 500. One hundred trainings were performed for the network architecture, with six neurons in the intermediate layer (Figure 2). The logistical activation function was used in the intermediate layer. To output layer the linear layer was considered.

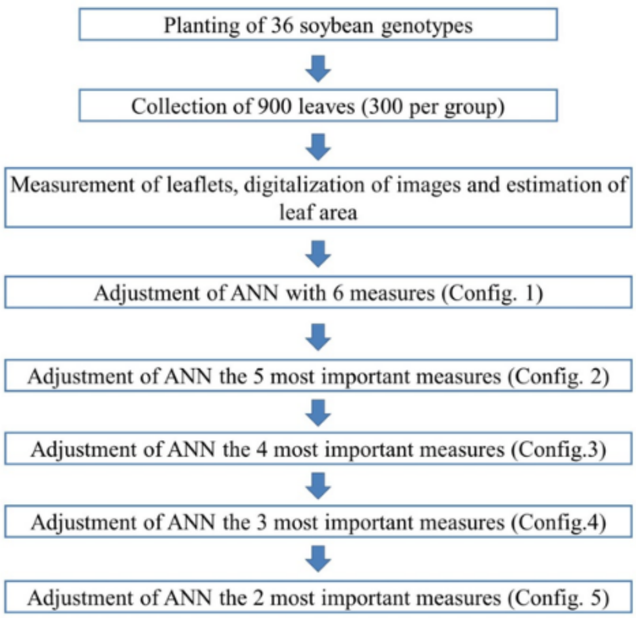

Figure 2. Multilayer perceptron neural network architecture used in the leaf area estimation, based on the length and width of three leaflets.

The mean square error (MSEmean) and the coefficient of determination (R^2mean) were also obtained for the adjusted networks, by considering different network architectures. The relative importance of the measures in each evaluation was estimated with the method of Garson (1991), using the Garson function from the NeuralNetTools package.

After choosing the best network architecture for each group, 100 new trainings were performed with each of the four networks for the four groups (the fourth group was composed of all three predefined groups). Then, new coefficients of determination were obtained.

The dispersion of the estimated leaf area was represented as a function of the actual leaf area in the validation sample to enable the visualization of the efficiency of the networks. In addition, coefficients of determination were considered as indicative of the quality of the model, by assessing its goodness of fit. The functions *expand.grid* and *predict* from the RSNNS package were used to generate the data necessary to plot the leaf area response surface graphs as a function of the leaflet length and width. The values predicted by the ANNs are normalized and, hence, had to be denormalized to obtain data at the desired scale (i.e., cm^2). Thus, the RSNNS package function *denormalizeData* was used, which considers the expression:

$$V_{dn} = V_{max} + (V_n - 1) * (V_{max} - V_{min}),$$

where: V_{dn} is the denormalized value, V_n is the normalized value, V_{min} is the minimum value of the sample, and V_{max} is the maximum value of the sample. Finally, response surface graphs were generated from the data predicted by the network using SigmaPlot software v.11.

Results and discussion

The coefficient of variation values of the leaflets, according to their position in the leaf (i.e., central, left, and right leaflets), did not vary much between the groups (Table 2). Since the leaves were randomly chosen, a significant variation in leaf area was observed in the first, second, and third groups, with coefficients of variation of 39.38%, 41.70%, and 40.02%, respectively. Notably, the efficiency and the generalization in the prediction of the leaf area with ANNs depend on the variation of the leaf shape and size in the sample used for training (Fallovo et al., 2008; Wang & Zhang, 2012).

Table 2. Descriptive analysis of the length, width, and leaf area of the three leaflets in each soybean group.

Groups	Parameters	LL1	LW1	LL2	LW2	LL3	LW3	Leaf area
1	Maximum (mm)	147.000	105.000	203.000	94.000	132.000	81.000	210.877
	Mean (mm)	91.781	49.140	78.050	46.543	76.852	46.194	87.392
	Minimum (mm)	30.000	26.000	37.000	19.000	30.000	21.000	26.435
	Standard deviation (mm)	17.352	11.855	17.617	11.673	16.223	11.330	34.420
	CV (%)	18.906	24.125	22.572	25.081	21.110	24.527	39.386
2	Maximum (mm)	155.000	96.000	142.000	102.000	142.000	100.000	286.225
	Mean (mm)	95.170	60.210	83.057	57.969	83.098	57.884	112.639
	Minimum (mm)	51.000	27.000	36.000	26.000	40.000	24.000	29.6503
	Standard deviation (mm)	20.076	12.659	20.067	14.129	19.864	13.959	46.973
	CV (%)	21.095	21.025	24.161	24.373	23.905	24.115	41.702
3	Maximum (mm)	140.000	93.000	124.000	85.000	132.000	110.000	216.887
	Mean (mm)	89.209	50.707	75.378	47.852	74.546	47.384	88.750
	Minimum (mm)	52.000	21.000	36.000	24.000	32.000	20.000	30.969
	Standard deviation (mm)	18.443	10.915	17.737	11.840	18.086	12.453	35.522
	CV (%)	20.674	21.525	23.530	24.744	24.262	26.282	40.024

LL1: central leaflet length; LW1: central leaflet width; LL2: left leaflet length; LW2: left leaflet width; LL3: right leaflet length; LW3: right leaflet width.

In this study, the length and width data of each leaflet blade in each group were used as input layer information (i.e., explanatory variables), and the leaf area data were used as the output layer (i.e., dependent variable). Knowing which explanatory variable is the most important in the ANN prediction process is crucial because it reduces the number of measures to be taken from the plant.

This study used Garson's method (1991) to estimate the relative importance of the descriptors. In each network configuration, the least important variable was excluded until it reached the network configuration 5, with the two most important variables for the leaf area estimation. The most important traits were as follows: the left leaflet length and right leaflet width in group 1; the central leaflet length and left leaflet width in group 2; the right leaflet length and left leaflet width in group 3; and the right leaflet length and left leaflet width in group 4 (Table 3).

The study of the contribution of traits to neural networks is fundamental when evaluating several variables, facilitating the exclusion of less important traits and reducing labor and computational effort (Paliwal & Kumar, 2011). Except for the first leaf, the soybean leaves are trifoliate, which triplicates the time and effort required to measure one leaf compared with that necessary for single-leaf crops. However, the present results indicate that two measures are sufficient to obtain a good area estimate of three leaflets with ANNs (Bakhshandeh et al., 2011; Richter et al., 2014).

Table 3. Means of the coefficient of determination (R^2 mean) and mean square error (MSE) for the adjusted networks, considering the different network architectures and relative importance of the variables in each evaluation (estimated with Garson's method).

Groups	Config.	Relative importance						R^2 mean	EQM mean
		LL1	LW1	LL2	LW2	LL3	LW3		
1	1	0.149±0.006	0.126±0.007	0.235±0.011	0.133±0.007	0.177±0.008	0.179±0.007	0.923	0.003
	2	0.170±0.009	-	0.250±0.014	0.173±0.007	0.197±0.008	0.21±0.0085	0.920	0.003
	3	-	-	0.328±0.017	0.185±0.008	0.269±0.013	0.218±0.010	0.916	0.003
	4	-	-	0.432±0.017	-	0.262±0.013	0.306±0.011	0.915	0.003
	5	-	-	0.582±0.019	-	-	0.418±0.019	0.885	0.004
2	1	0.158±0.007	0.15±0.007	0.162±0.007	0.190±0.007	0.152±0.008	0.187±0.007	0.938	0.002
	2	0.173±0.008	-	0.174±0.008	0.241±0.008	0.172±0.008	0.240±0.008	0.937	0.002
	3	0.226±0.010	-	0.219±0.011	0.250±0.011	-	0.306±0.010	0.939	0.002
	4	0.328±0.011	-	-	0.361±0.012	-	0.311±0.012	0.940	0.002
	5	0.397±0.014	-	-	0.603±0.014	-	-	0.929	0.003
3	1	0.150±0.007	0.164±0.007	0.119±0.006	0.236±0.009	0.188±0.009	0.143±0.008	0.858	0.006
	2	0.168±0.008	0.192±0.008	-	0.268±0.010	0.218±0.009	0.154±0.008	0.859	0.006
	3	0.186±0.008	0.237±0.010	-	0.307±0.010	0.271±0.010	-	0.859	0.006
	4	-	0.246±0.012	-	0.330±0.010	0.424±0.011	-	0.864	0.005
	5	-	-	-	0.509±0.013	0.491±0.013	-	0.861	0.006
4 (1, 2 e 3)	1	0.168±0.008	0.141±0.007	0.153±0.007	0.191±0.008	0.182±0.009	0.164±0.009	0.922	0.002
	2	0.184±0.009	-	0.167±0.009	0.245±0.010	0.207±0.011	0.198±0.010	0.921	0.002
	3	0.242±0.012	-	-	0.32±0.0130	0.22±0.011	0.219±0.011	0.923	0.002
	4	0.261±0.015	-	-	0.426±0.015	0.314±0.012	-	0.920	0.002
	5	-	-	-	0.522±0.016	0.478±0.016	-	0.919	0.002

LL1: central leaflet length; LW1: central leaflet width; LL2: left leaflet length; LW2: left leaflet width; LL3: right leaflet length; LW3: right leaflet width. Values followed by the ± symbol refer to the deviations for the obtainment of the confidence intervals (t-test, 5% significance level).

The values of the coefficients of determination were high (i.e., R^2 between 0.85 and 0.94), which indicates that the estimation of soybean leaf area by the multilayer perceptron neural network method was efficient for all the soybean cultivars. As for the MSE, it expresses the magnitude of the error for the adjusted networks: the closer it is to zero, the better the network.

Shabani, Ghaffary, Sepaskhahc, and Kamgar-Haghighi (2017) concluded that ANNs are efficient in estimating the leaf area of different plant species, whereas other methods require a specific equation for each type of plant. This means that even if new soybean cultivars are released every year (Richter et al., 2014), adjusting new networks will not be necessary. Notably, similar results were reported by Bakhshandeh et al. (2011). Therefore, a network including leaves of the different groups (1, 2, and 3) was also adjusted, resulting in a good quality of fit.

For the best visualization of the efficiency of leaf area prediction with our ANN, the values found for each group (a, b, and c) and the data of the validation samples (d) are displayed in Figure 3. The prediction efficiency of ANNs depends on the variation of the leaf shape (i.e., length and width) and the genetic materials used for training (Fallovo et al., 2008; Wang & Zhang, 2012). Thus, the use of a large number of soybean cultivars in this study resulted in a generalist model that is accurate for leaf area prediction regardless of leaf shape and size. The determination coefficients of groups 1, 2, and 3 were 0.9374, 0.9737, and 0.9395, respectively. All groups simultaneously had a coefficient of determination of 0.959. This result reveals that over 95% of the leaf area information was explained by the leaf area estimated by the multilayer perceptron networks. Bakhshandeh et al. (2011) and Richter et al. (2014) also found R^2 values with linear regressions that were higher than 0.95. Interestingly, ANNs are also efficient in estimating the leaf area of other species, such as pepper (R^2 = 98%) (Ahmadian-Moghadam, 2012), corn (R^2 = 98%) (Odabas, Ergun, & Oner, 2013), and cabbage (R^2 = 96%) (Azevedo et al., 2017).

The coefficients of determination of the four neural networks used in the leaf area prediction, according to each group, are presented in Table 4. Network 4 was efficient for all groups, and its coefficient of determination was similar to those of the other networks. This result indicates that network 4 was the most generalist one.

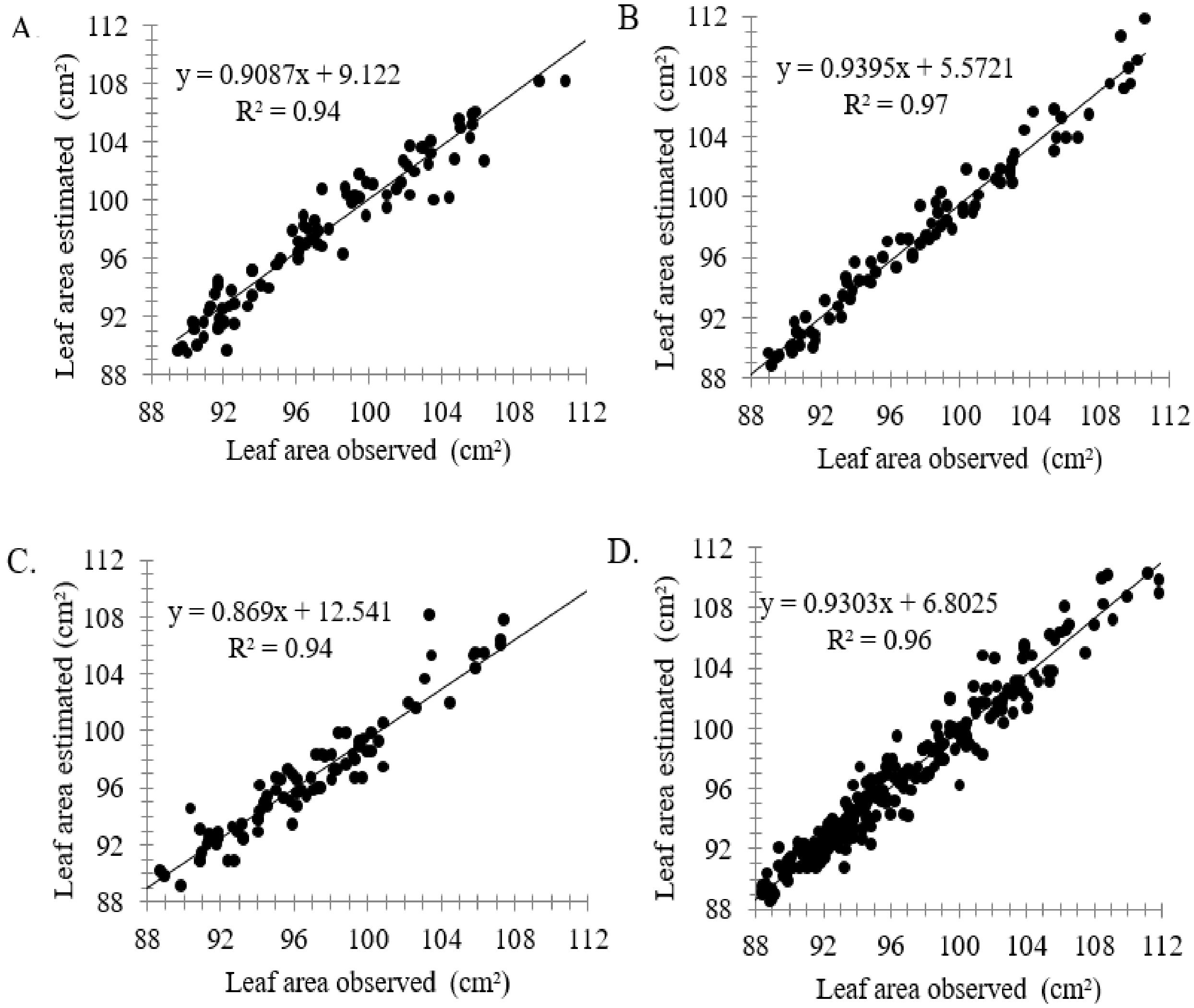

Figure 3. Dispersion of the leaf area estimated by the multilayer perceptron artificial neural networks, according to the leaf area observed in the validation sample of leaves from group 1 (A), group 2 (B), group 3 (C), and for all groups (D).

Table 4. Coefficients of determination obtained with the neural networks selected in the leaf area prediction of plants from groups 1, 2, and 3, and from the sum of these three groups (4).

Network used	Group Samples			
	1	2	3	4
Network 1	0.937	0.921	0.860	0.912
Network 2	0.913	0.973	0.852	0.916
Network 3	0.871	0.916	0.939	0.908
Network 4	0.911	0.935	0.862	0.959

To maximize the applicability of the present study, Figure 4 shows the leaf area predicted by ANNs, based on the different values of leaf blade length and width for each group and all leaf shapes. That is, this figure enables the prediction of soybean leaf area from the leaflet width and length.

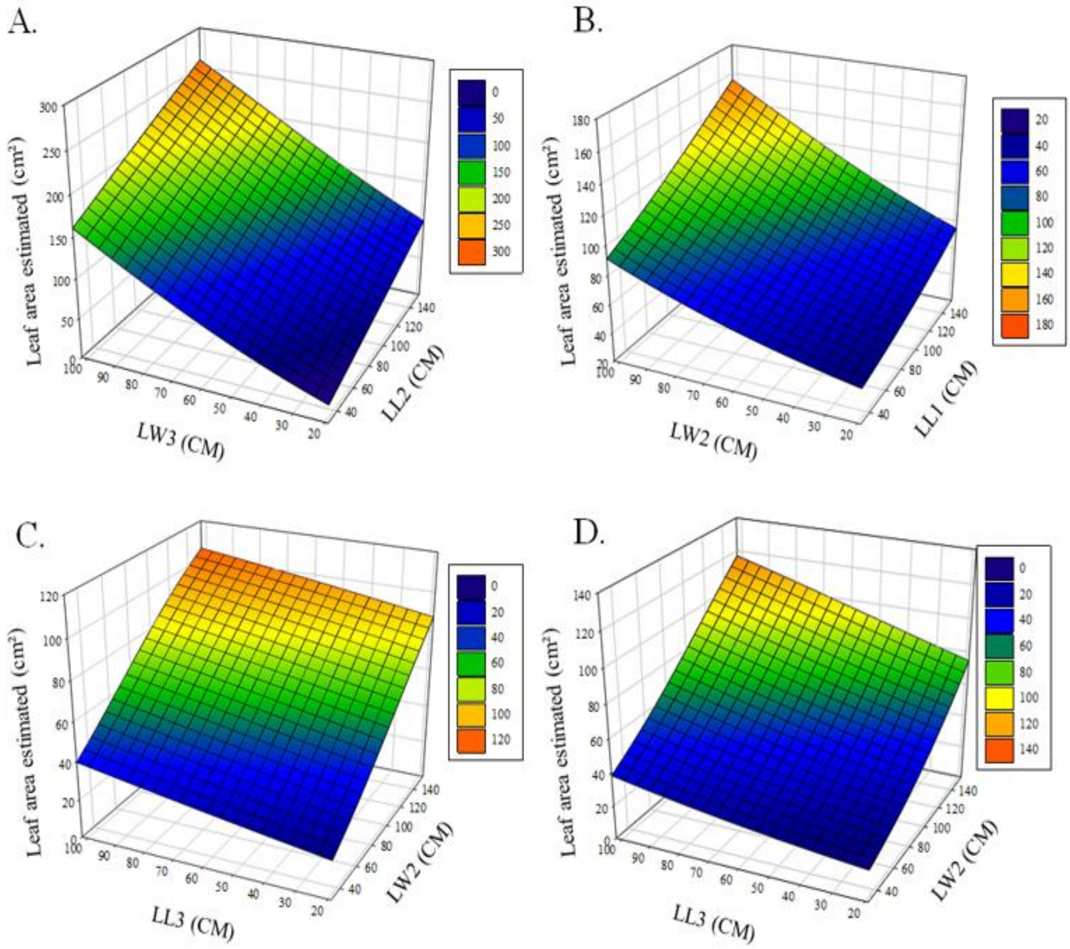

Figure 4. Response surface of predicted leaf area (cm^2) in function of the width and length values of leaves from group 1 (a), group 2 (b), group 3 (c), and for all the groups (d).

Conclusion

Multilayer perceptron artificial neural networks are efficient in predicting the leaf area in soybean cultivars. Measuring the left leaflet width and right leaflet length is sufficient to estimate the soybean leaf area. Network trained with leaflets of all groups, is more generalist and, consequently, more suitable for the prediction of soybean leaf area.

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