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Predicting the Leaf Area of Grapevines (*Vitis vinifera* L. cv Cabernet Sauvignon and Shiraz)

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Abstract: The planimetric leaf area of grapevines leaf blades (LA) is required as input data in many grapevine growth models and quantitative studies of the soil plant atmosphere continuum. A subset of 300 scanned grapevine leaves was used to identify and compare allometric statistical models for the prediction of the leaf area of grapevines (cultivars Cabernet Sauvignon and Shiraz). The Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and Δ (RMSE – MAE) were used as discriminatory critera. Six families of models drawn from the literature were computed as well as a stepwise regression using up to six possible predictor variables. Each family was fitted to each cultivar for three vineyard sites. In addition, generic models were computed by aggregating the data across sites and cultivars. The "Queensland" (stepwise regressions) family performed best, closely followed by the "Elsner2" and "Montero". The MAE of some generic models was sometimes smaller than that of their components, due to the influence of sites and/or cultivars. Site and cultivar specific stepwise regressions are proposed as being generally the most accurate methodology for the estimation of leaf surface area. Simple models were generally less accurate than models integrating several predictor variables.

Key words: leaf surface area; grapevines; statistical models; allometric relationships

Introduction

Leaf area (LA, the planimetric surface area of grapevine blades) is an important component of crop models focusing on yield, competition with weeds, and energy and water exchanges in the soil plant atmosphere continuum (Yin et al. 2003). Furthermore, as technologies such as infrared thermography (Moller et al. 2007) refine our knowledge of when to apply limited and expensive irrigation water, an estimation of the components of the total canopy surface area is required to match volumetric irrigation to canopy characteristics.

In grapevine growth models, LA and the leaf area index (LAI, the ratio of total vine LA to the soil surface area) is commonly derived as a function of ambient temperature (such as Growing Degree Days) using generic equations, ignoring the possible impact of sites and cultivars (Gutierrez et al. 1985; Bindi et al. 1997). Indirect methods of assessing canopy characteristics, principally LAI, have also been successfully tested in vineyards, but require destructive calibration in all cases (Ollat et al. 1998). These methods are useful for monitoring the development of LAI but are not part of the present research. Non destructive allometric relationships between leaf dimensions and/or the length of the four veins of grapevine leaves (such as L1 to L4, Galet, 1998) and LA have been reported. Such models have one or two predictor variables, using data collected over one growing season and are reported to have achieved coefficients of determination (R^2) generally greater than 0.93 for the evaluation of the area of primary leaves. Figure 1 illustrates the predictor variables found in the literature, and used in this study.

These statistical models are of the form

$$LA = a + bX_1 + cX_2 \qquad \text{(Equation 1)}$$

Where LA is the response variable (Leaf Area)

a is the intercept of the regression

b and c are the parameters of the regression

X_1 and X_2 are the independent variables of the regression

Carbonneau (1976) proposed a model based on the summation of L2 and L2g (referred to as ΣL2 in the original work) in order to account for the known asymmetry of grapevine leaves (n= 450 leaves, 9 cultivars sampled). Sepulveda and Kliewer (1983) used the product LxWp (L= leaf length and Wp the petiolar width, such that L and Wp are perpendicular) as indicator variable on cultivars Chardonnay and Chenin Blanc (n= 200 leaves). Smith and Kliewer (1984) used the product LxW (the distance between the extremity of L2 and the symmetrical vein, L2g) as indicator variable (n= 153 leaves, cultivar was Thompson Seedless, data collected over two seasons). LxW was also proposed by Galet (1998), Gutierrez and Lavin (2000) (n= 625, cultivar Chardonnay), Montero et al. (2000) (n= 1739, cultivar Cencibel, data collected over two seasons) and Jemaa et al. (2004) (n= 50 leaves in each of five cultivars - Sultanine, Superior Seedless, Razegui, Turky and Sakasly). Elsner and Jubb (1988) proposed two models, one using L1xW as predictor variable and the other a multiple regression using W^2 as X_1 and $L1^2$ as X_2 (n= 500 leaves, cultivar Concord). Gutierrez and Lavin (2000) also used L1xW as the predictor variable for the estimation of LA arising from secondary (lateral) shoots. Finally, Schultz (1992) created an empirical model for grapevines using L^2 as X_1 and L as X_2 (n= 116 leaves, cultivar White Riesling). This model was calibrated in Germany and validated in California (Schultz, 1992).

Hunt and Hodson (1999) showed that low resolution scanning (75 dots per inch (dpi)) combined with image processing was as accurate and required less calibration than traditional planimetry methods for analysis of area of leaves of varying complexity.

The objectives of this work were to assess the level of accuracy achieved by statistical leaf area models of increasing generic nature, using allometric predictors, for 2 cultivars and at 3 sites.

Materials and Methods

Three vineyards located in the Granite Belt wine region, extending from 25 km North to 25 km South of Stanthorpe, Queensland, Australia (25.6653°S, 151.9333°E) were used for data collection during the 2002-03 season. The region is elevated at 871 m above sea level. Soils are duplex, with a sandy A-horizon of varying depth overlying a heavier clay B-horizon. The vines were trained to a Vertical Shoot Positioned system (VSP) and rows oriented North-South. The season was unusually dry, with rainfall in the lowest 20% of seasons (www.bom.gov.au/climate/averages/). As a result of dry conditions, site 1 had more surface water storage available for irrigation purposes than sites 2 and 3. Similar, site 2 had more available water than site 3. The vines were drip irrigated as per vineyard managers' perception of irrigation requirement and available water. The combination of high evaporative demand and depleted soil water is likely to have resulted in adaptive responses by the grapevines, including a reduction in LA with increasing water stress (Campbell and Norman, 1998). The data collected in this study are therefore representative of a range of environmental constrains on leaf area development.

Fifty leaves from Cabernet Sauvignon (CS) Shiraz (Sh) from each site were collected. These data were a subset of a much larger dataset. In the large dataset, entire shoots were collected and defoliated at the sites used in this study in eight occasions during the 2002-03 growing season (Guisard, 2004). Leaves within the large dataset were given a unique identifier and a random number generation was created in Microsoft Excel. No secondary leaves were used. Leaves used in this study ranged from leaves located at position 6 from apex (leaf 1 being the most recently opened leaf) to basal leaves. No selection was made as a function of leaf exposure to the sun. Nine measurements were taken for each leaf using and digital image analysis software ImageTool 3 (University of Texas, USA) in combination with electronic scanning using commercial flat bed scanner Canon "Lide 30". L1, L2, L3, L4, (as per Galet, 1998) and L, W, Wp and L2g (Figure 1) as well as LA were measured using the "object analysis" facility of ImageTool 3. Statistical analysis of the data was carried out using SPLUS 2000 Professional Release 2 (MathSoft Inc.). Linear regressions were of the form:

$$\hat{y}_i = a + bX_1 + cX_2 + \ldots + jX_n \qquad \text{(Equation 2)}$$

Where $\hat{y}_i$ is the fitted Leaf Area

a is the intercept of the regression (for regressions with one independent variable) b … j are model parameters

X_1 to X_n are independent predictor variables

Seven model families were retained in this work (Table 1). Six were identical to the literature previously cited. As no literature sources used transformation of data, raw data was used for the computation of these models. A seventh ("Queensland") family was computed using a stepwise regression of the log transformed data captured in this study. Log transformation of the data was necessary due to the departure from normality of the residuals (data not shown) (Neter et al. 1996). This study did not assess the requirement for the transformation of previously published models and makes no assumption about its necessity; rather, it applies the methodologies proposed by others as found in the literature.

Input variables used for the "Queensland" family included L1 to L4, L and W. Each model family was fitted to nine linear regressions (Table 1), including Cabernet Sauvignon and Shiraz regressions at sites 1, 2 and 3 (termed "CS1", "CS2", "CS3", "Sh1", "Sh2" and "Sh3" respectively). In addition, a site independent model was termed "all" for each cultivar (termed "CSall" and "Shall"). Finally, a generic model for all cultivars and sites was termed "All".

All models were evaluated across families for their ability to predict Leaf Area (LA) using coefficients of determination (R^2), the Mean Absolute Error (MAE, Equation 3) (Mayer and Buttler, 1993) and the Root Mean Square Error (RMSE, Equation 4).

$$MAE = \frac{\sum |y_i - \hat{y}_i|}{n} \qquad \text{(Equation 3)}$$

Where: yi is the measured Leaf Area

ŷ is the fitted Leaf Area

n is the sample size

$$RMSE = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n-k}} \qquad \text{(Equation 4)}$$

Where: *k* is the number of parameters fitted by the regression, including the intercept

By definition, RMSE and MAE follow similar trends but RMSE is always greater than MAE. In addition, RMSE is more influenced by large residuals than MAE. The estimator Δ (RMSE

– MAE) was hence computed to assess the presence and impact of such residuals on the fitted models. Finally, the impact of aggregating datasets on increasingly generic models of leaf area estimation was evaluated by computing the Mean Average Percent Error (MA%E Equation 5) (Schaeffer, 1980; Mayer and Buttler, 1993), and dissociating an aggregated dataset into its site and cultivars components.

$$MA\%E = \frac{100}{n}\sum\left(\frac{|y_i - \hat{y}_i|}{y_i}\right) \qquad \text{(Equation 5)}$$

A qualitative assessment of statistical linear models using MA%E below 10% is usually deemed acceptable for use in physiological and ecological studies (Schaeffer, 1980; Mayer and Buttler, 1993) and is used in this study.

Results and Discussion

Although 72 linear regressions were fitted, the 18 regressions for the “Schultz” (second worst performing) and “Sepulveda” families (worst performing) yielded the poorest results and will therefore not be considered further. All retained models are presented in Table 2.

The number of predictor variables retained when using the stepwise methodology to create the “Queensland” family of models ranged between 2 and 5. LogW was identified as a predictor variable in the every “Queensland” models. This result is in agreement with the choice of predictor variables in the “Elsner1”, “Elsner2”, “Montero” and Sepulveda” models. Similar, Log L was selected in all but one stepwise regression (“CS2”), in agreement with the “Montero”, “Schultz” and “Sepulveda” models. These results demonstrate the importance of LogW and LogL as predictor variables.

The temporal stability of the models arising from the stepwise regressions should be validated over several seasons. Furthermore, the intercepts and parameters of all the models are likely to vary on a seasonal basis.

R^2 ranged from 0.79 to 0.99, with a large number of models showing $R^2 \geq 0.96$. Although these results indicate that changes in predictor variables adequately explain changes in LA (model fitting), they do not describe the variability of the regression, hence R^2 is not a sensitive indicator for model selection. MAE ranged between 2.40 and 15.55 cm^2. The most accurate models on the basis of the values of MAE were “Queensland” for “CS1” (identical value as “Montero”), “CS3”, “Sh1”, “Sh3”, “Shall” and “All”, Elsner2” for “CS2” and “Montero” for “CS1”, “Sh2” and “CSall”.

RMSE ranged between 3.72 and 21.66 cm^2. These extreme values did not correspond with the fitted models identified as extremes when using MAE, demonstrating RMSE’s sensibility to extreme residuals. The most accurate models on the basis of the values of RMSE were “Queensland” for “CS1”, “Sh1”, “Sh3”, “Shall” and “All”, Elsner2” for “CS2” and “CSall” and “Montero” for “CS3” and “Sh2”.

The absolute value of Δ for the most accurate models ranged between 0.85 and 6.11 cm^2. In 7 of the 9 best regressions, the lowest Δ did not originate from a combination of the lowest MAE and lowest RMSE. The use of MAE and RMSE alone does not clearly explain the behavior of the extreme residuals. By contrast, in the case of “Queensland” for “Shall” and “All”, the lowest observed Δ, together with the lowest observed MAE and RMSE confirms that these models have generally low residuals and few extreme residuals.

In five cases (these being “CS1”, ”CS2”, “Sh1”, “Sh2” and “Sh3”), the lowest MAE was associated with the lowest RMSE but not the lowest Δ. For these models, Δ ranged between 1.30 and 2.84 cm^2, demonstrating that theses “less than optimum” Δ values may require subset analysis if high accuracy is necessary when estimating LA. In general terms however, when low MAE was associated with low RMSE, the impact of extreme residuals was likely to be low when the size of the sample increased, as would be the case with complete field canopies analyses. This study therefore recommends that most accurate models be determined using simultaneous lowest MAE, RMSE and Δ. When this is not possible, a combination of the lowest MAE and RMSE is proposed as the most appropriate indicator. Finally, lowest MAE alone can be used when lowest MAE and RMSE combinations are not available as it not influenced as strongly as RMSE by extreme residuals. The “Best” models in this study were therefore “Queensland” for “CS1”, “CS3”, “Sh1”, “Sh3”, “Shall” and “All”, “Elsner2” for “CS2” and “Montero” for “Sh2” and “CSall”. Cultivar specific “CS1”, “Sh1” and “Sh2” models had lower MAE than generic models “CSall” and “Shall”. By contrast, generic “CSall” and “Shall” models had lower MAE than cultivar specific “CS2”, “CS3” and “Sh3” models. This unexpected result is explained by the fact that best models were chosen across families of models, hence a family specific generic model may perform well overall, but poorly over one of its components. This is evident in that the most generic model (“All”) had lower MAE than the best Shiraz generic model (“Shall”) or site specific model “Sh3”.

Given the averaging nature of MAE, the MA%E of each of the generic models ("CSall", "Shall" and "All") are influenced by the arithmetic average of their components (Table 3). For the best cultivar specific generic models (“CSall” and “Shall”), site 2 contributed more to the MA%E than sites 1 or 3 for Cabernet Sauvignon and least for Shiraz. Similar, for the best site and cultivar independent generic model (“All”), Shiraz contributed more to the MA%E than Cabernet Sauvignon.

In general terms, all models performed well below the MA%E qualitative threshold of 10%. Some small differences were observed between models, ranging within approximately 1%. Although seemingly small, these differences may have a significant impact on quantitative ecophysiological studies, particularly when using point scale measures of plant functions (such as assimilation or transpiration rates) and using LA as a multiplier for ecosystem studies.

Conclusions

The aims of this work were to evaluate the accuracy of seven statistical models for the evaluation of leaf surface area using scanned electronic data. The accuracy of the models was found to be best represented when using a combination of the lowest MAE, RMSE and Δ. Generic models were shown to perform well, and sometimes better than site specific models. However, it was demonstrated that this result was due to the arithmetic averaging nature of the components of a generic model. Stepwise regressions using L, W, and L1 to L4 as indicator variables were found to have lower MAE and RMSE in most cases. The most important variables were L and W, but L1 to L4 measures improved the estimation of LA in all but one case. This study concludes that the most accurate method to estimate leaf area is to use a stepwise regression methodology on a cultivar, site and seasonal basis. When accuracy is less critical, generic models can be used and are likely to achieve acceptable results (MA%E < 10%).

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Table 1 Predictor variables used by the various families of predictive models. All but "Queensland" models are presented as described in the literature (see text for all references). "Queensland" models are stepwise statistical linear regressions and are presented in decreasing order of predictor variable importance, as displayed in the stepwise regression output. CS = Cabernet Sauvignon, Sh = Shiraz, X_1 to X_5 are predictor variables of the linear regressions.

Model family	Cultivar	Site	Response	X_1	X_2	X_3	X_4	X_5
Carbonneau			LA	(L2+L2g)				
Elsner 1			LA	L1W				
Elsner 2			LA	W^2	$L1^2$			
Montero			LA	LW				
Schultz			LA	L^2	L			
Sepulveda			LA	LWp				
Queensland	CS	1	LogLA	LogW	LogL			
	CS	2	LogLA	LogW	LogL2	LogL4	LogL	
	CS	3	LogLA	LogW	LogL	LogL3	LogL1	
	Sh	1	LogLA	LogW	LogL	LogL3		
	Sh	2	LogLA	LogW	LogL	LogL2	LogL4	
	Sh	3	LogLA	LogW	LogL	LogL2	LogL3	
	CS	all	LogLA	LogW	LogL	LogL3		
	Sh	all	LogLA	LogW	LogL	LogL3	LogL2	LogL4
	Generic	all	LogLA	LogW	LogL	LogL3	LogL2	LogL4

Table 2 Summary of the linear regressions for 5 families of linear regression models fitted to 2 cultivars (CS, Cabernet Sauvignon; Sh, Shiraz) and 3 sites (1 to 3). n = number of replicates used in the regression. k = number of parameters (letters "a" to "f") fitted to the regressions used in the computation of RMSE (See Equation 4). Shaded cells indicate the best performing model for each site/cultivar combination and for each performance indicators. MAE and RMSE expressed in cm^2. See text for full definition of MAE (Mean Absolute Error), MA%E (Mean Absolute Percent Error), RMSE (Root of the Mean Squared Error) and Δ (RMSE – MAE).

Family	Cultivar	Site	n	k	a	b	c	d	e	f	R^2	MAE	RMSE	Δ
Carbonneau	CS	1	50	2	-45.20	9.08					0.93	5.23	6.66	1.44
		2	50	2	-81.87	11.82					0.95	5.68	7.92	2.24
		3	50	2	-114.54	14.35					0.92	8.28	10.49	2.21
	Sh	1	50	2	-70.81	11.19					0.94	5.70	7.50	1.81
		2	50	2	-126.61	14.76					0.94	8.68	11.52	2.84
		3	50	2	-132.44	15.74					0.91	15.55	21.66	6.11
	CS	all	150	2	-80.16	12.05					0.94	8.61	10.82	2.21
	Sh		150	2	-128.06	15.26					0.95	12.31	16.81	4.50
	All		300	2	-110.28	14.18					0.94	11.68	15.45	3.77
Elsner 1	CS	1	50	2	4.28	0.86					0.96	3.31	4.94	1.63
		2	50	2	-0.06	0.92					0.98	3.95	5.17	1.22
		3	50	2	3.55	0.92					0.96	5.91	7.60	1.69
	Sh	1	50	2	3.80	0.85					0.95	5.33	7.02	1.69
		2	50	2	-0.63	0.91					0.98	4.70	6.69	1.99
		3	50	2	8.51	0.88					0.96	11.97	14.59	2.62
	CS	all	150	2	0.15	0.93					0.98	4.61	6.25	1.64
	Sh		150	2	1.32	0.90					0.98	7.36	10.08	2.73
	All		300	2	1.97	0.90					0.98	6.10	8.47	2.37
Elsner 2	CS	1	50	3	2.40	0.51	0.26				0.98	2.81	3.86	1.05
		2	50	3	0.41	0.47	0.37				0.98	3.25	4.63	1.37
		3	50	3	0.49	0.55	0.26				0.98	3.52	5.03	1.51
	Sh	1	50	3	3.22	0.54	0.16				0.98	3.03	4.32	1.29
		2	50	3	-3.12	0.54	0.27				0.99	3.73	5.26	1.52
		3	50	3	3.09	0.47	0.35				0.97	8.97	11.86	2.89
	CS	all	150	3	-0.05	0.53	0.29				0.99	3.25	4.53	1.28
	Sh		150	3	-1.25	0.49	0.34				0.99	5.39	7.97	2.58
	All		300	3	0.64	0.50	0.32				0.99	4.55	6.68	2.13
Montero	CS	1	50	2	1.84	0.64					0.98	2.40	3.74	1.35
		2	50	2	-0.38	0.66					0.97	3.70	5.97	2.27
		3	50	2	2.48	0.65					0.99	3.40	4.25	0.85
	Sh	1	50	2	3.58	0.63					0.98	3.44	4.78	1.34
		2	50	2	2.04	0.64					0.99	3.26	4.98	1.72
		3	50	2	8.61	0.64					0.97	9.23	12.70	3.47
	CS	all	150	2	0.76	0.65					0.99	3.15	4.74	1.59
	Sh		150	2	1.49	0.65					0.99	5.37	8.45	3.08
	All		300	2	1.30	0.65					0.99	4.26	6.84	2.58
Queensland	CS	1	50	3	-0.11	1.07	0.86				0.98	2.40	3.72	1.33
		2	50	5	-0.23	1.31	0.50	-0.30	0.51		0.99	3.37	4.86	1.50
		3	50	5	-0.12	1.05	1.06	0.15	-0.31		0.99	3.36	4.43	1.07
	Sh	1	50	4	-0.12	1.40	0.44	0.15			0.99	2.97	4.27	1.30
		2	50	4	-0.12	1.14	0.58	0.22	0.10		0.99	3.75	5.38	1.63
		3	50	5	-0.66	1.05	0.44	0.34	0.19		0.99	6.91	9.75	2.84
	CS	all	150	4	-0.13	1.18	0.72	0.09			0.99	3.53	5.01	1.47
	Sh		150	6	-0.11	1.21	0.46	0.13	0.18	0.06	0.99	4.35	6.65	2.30
	All		300	6	-0.11	1.15	0.61	0.08	0.12	0.05	0.99	3.87	5.79	1.92

Table 3 Decomposition of the Mean Absolute Percent Error (MA%E, %) of the generic models of leaf area estimation for the "Elsner2", "Montero" and "Queensland" families of models into their cultivar (CS, Cabernet Sauvignon, Sh, Shiraz) and site components (sites 1, 2 and 3). Shaded cells indicate best performing model for each fitted model (defined here as having the lowest MA%E).

			"Elsner2"		"Montero"		"Queensland"	
Fitted model	Cultivar	Site	Component	Average	Component	Average	Component	Average
CSall	CS	1	5.10	3.91	3.92	3.58	5.14	4.08
		2	3.84		4.11		3.70	
		3	2.79		2.72		3.39	
Shall	Sh	1	3.80	4.02	4.08	3.91	3.59	3.33
		2	3.07		2.80		2.64	
		3	5.18		4.87		3.75	
All	CS	1	4.68	4.25	4.00	3.74	3.47	3.50
		2	3.79		2.67		2.70	
		3	4.84		4.95		3.83	
	Sh	1	4.89		3.97		4.14	
		2	3.79		4.16		3.77	
		3	3.40		2.71		2.87	

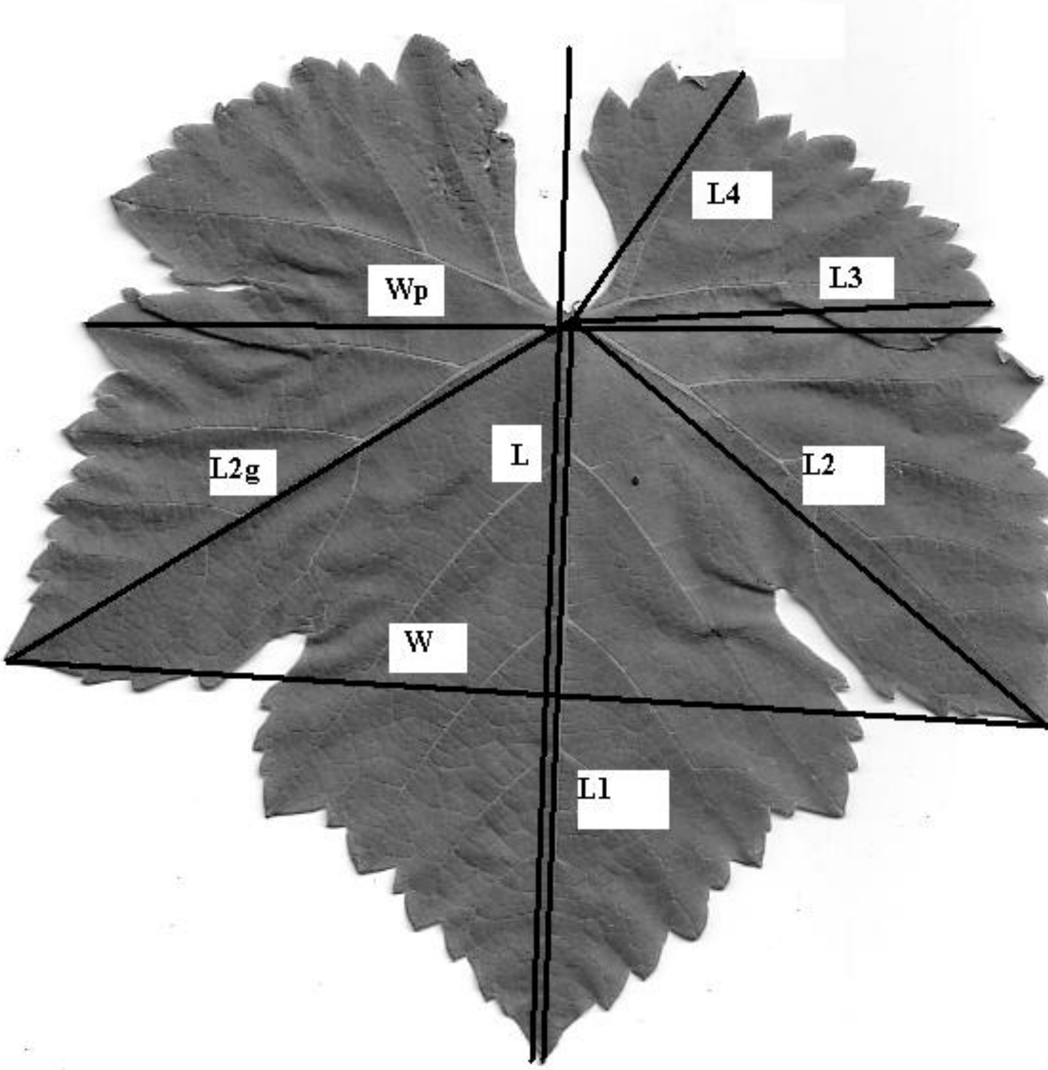

Figure 1 Predictor variables measured on grapevine leaves for the creation of allometric statistical models of leaf area (LA) on Cabernet Sauvignon and Shiraz cultivars. All the predictor variables were drawn from the literature. For full description of the various lengths, see text.