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Automated computation of leaf area index from fruit trees using improved image processing algorithms applied to canopy cover digital photograpies

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ABSTRACT

Leaf area index (LAI) is a critical parameter in plant physiology for models related to growth, photosynthetic activity and evapotranspiration. It is also important for farm management purposes, since it can be used to assess the vigor of trees within a season with implications in water and fertilizer management. Among the diverse methodologies to estimate LAI, those based on cover photography are of great interest, since they are non-destructive, easy to implement, cost effective and have been demonstrated to be accurate for a range of tree species. However, these methods could have an important source of error in the LAI estimation due to the inclusion within the analysis of non-leaf material, such as trunks, shoots and fruits depending on the complexity of canopy architectures. This paper proposes a modified cover photography method based on specific image segmentation algorithms to exclude contributions from non-leaf materials in the analysis. Results from the implementation of this new image analysis method for cherry tree canopies showed a significant improvement in the estimation of LAI compared to ground truth data using allometric methods and previously available cover photography methods. The proposed methodological improvement is very simple to implement, with numerical relevance in species with complex 3D canopies where the woody elements greatly influence the total leaf area.

1. Introduction

Leaf area index (LAI) is a dimensionless parameter that relates the total area of leaves in the canopy (one sided) with a specific area of soil (Jonckheere et al., 2004). This index is of high importance in plant physiology and plant modeling to up-scale other physiological parameters that are usually measured at the leaf scale. Therefore, an accurate LAI estimation will allow more precise values of physiological information at the whole-plant or whole-tree level. This index is also useful to quantify the level of plant vigor, canopy architecture and water demands at the whole-plant or tree level.

Direct or indirect methods can be used to quantify and estimate LAI (Bréda, 2003). The direct, or allometric, methods consider a partial or complete defoliation of the canopy to assess total leaf area of the plants or trees, which can be associated to a specific area of soil. The latter method offers an accurate measure of real leaf area (LA) and can be used to calibrate other indirect methods. The destructive nature of the direct methods does not allow resampling the same trees; therefore it is impossible to assess growing patterns within a season and between seasons. An alternative to destructive methods are the indirect methods based on mathematical algorithms that describe the transmission of light through the canopy to estimate total LA which is based on Beer's Law (Bréda, 2003; Jonckheere et al., 2004; Vose et al., 1995; Weiss et al., 2004). These methods require estimates of the canopy light extinction coefficient (k) and corrections of leaf overlaps by assuming that foliage is randomly distributed in the canopy (Garrigues et al., 2008; Vose et al., 1995). However, instrumentation based on the latter principle could be cost prohibitive and requires high level of know-how to acquire and analyze the data. Examples of this instrumentation are Ceptometers (AccuPAR LP-80, Decagon Devices Inc., Pullman, WA, USA) and LI-Cor 2000 and 2200 (Licor

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Inc., Lincoln, Nebraska. USA). Furthermore, errors associated to this type of instrumentation are on the order of 10–40% underestimations (Bréda, 2003) compared to observed data, which could be associated to the scattering of blue light (Macfarlane et al., 2007). Due to the latter, it is recommended to use these instruments in cloudy conditions or close to dawn or dusk, which involves a practical complication for these methods (LI-Cor 2000-2200 Manual. Licor Inc., Lincoln, Nebraska. USA).

Other indirect methods are based on digital photography, such as digital hemispherical photography (DHP) or fish-eye and cover photography, which estimates LAI by analyzing the size of gaps within canopies and associating these with the level of light transmission through them (Duveiller and Defourny, 2010; Macfarlane et al., 2007; Martens et al., 1993). The fish-eye photographic method requires specific hardware (fish-eye lens) and makes use of non-automated image analysis software (Fuentes et al., 2008). Furthermore, results from fish-eye photography are similar to those found with cover photography for forests (Macfarlane et al., 2007), which does not require any extra hardware besides a common digital camera with medium pixel resolution (5 Megapixels) (Pekin and Macfarlane, 2009). Pekin and Macfarlane (2009) indicated the advantages of this method in comparison to the fish-eye method, arguing that digital images can be routinely obtained during normal working hours because sky luminance is more even, facilitating pixel classification. Additionally, common digital images are rectangular shaped providing higher resolution than DHP methods. Common digital images are less sensitive to photographic exposure providing more accurate measurements of the gap fraction at the zenith. Recently, Fuentes et al. (2008) developed an semi-automated method to analyze cover photography, in order to estimate LAI and other canopy architecture parameters. This method has been based on the cover photography method developed by Macfarlane et al. (2007) adding the automation by batch analyzing images to identify the big gaps within canopies. The application of this semi-automated method proposed resulted in good estimations of LAI for Australian forests compared to indirect methods and satellite methods (Fuentes et al., 2008), for apple trees compared to allometry and using a variable light extinction coefficient (Poblete-Echeverria et al., 2015) and for grapevines compared to allometry, high resolution satellite information and indirect methods (Fuentes et al., 2014).

The downside of the photographic methods is that they incorporate non-leaf material within images, such as trunks (in the case of trees), branches and fruits (in the case of fruit trees), wires and structures from training systems (in the case of grapevines). For this reason, Bréda (2003) proposed that results from the image analysis of cover photography should be called Plant Area Index (PAI) rather than LAI. In the case of forests with closed canopies, Macfarlane et al. (2007) and Fuentes et al. (2008) found that the inclusion of trunks and branches are not significant for the accuracy of estimated LAI. However, this effect could be relevant for horticultural crops and perennial fruit trees, especially in early stages of growth within a season. The effect has been demonstrated for grapevines 'Merlot', which presented an overestimation of LAI of around 3% on average using the cover photography method compared to allometry from bud-burst until veraison. In the later stage, the canopy was big enough to cover branches and cordons, reducing significantly the estimation error (Fuentes et al., 2014). This error is seemingly non-significant for grapevines, which can be associated to the training system used (Vertical Shoot Positioning) and the architecture of canopies, which are highly managed (clumping index close to 1). However, for fruit trees with open canopies, such as apple, pear or cherry trees, the object segmentation method to isolate leaves from branches and stems has been not evaluated previously.

In the case of apple trees in Chile, the cover photography and analysis method proposed by Fuentes et al. (2014) obtained an error of 44.6% in the LAI estimation when using a common light extinction coefficient compared to allometric LAI. The LAI estimation improved, with an error of 17.5%, by using a k obtained from a model based on canopy cover for the same images. A further improvement on the estimation was achieved by measuring incident and below canopy photosynthetic active radiation (PAR) to obtain a proxy of k with an error of only 8.5% in comparison to allometric LAI (Poblete-Echeverria et al., 2015). The latter work makes evident that significant errors can be introduced in the estimation of LAI due to the complexity of fruit tree canopies and the sensitivity of the LAI algorithms to k. Reducing this error by incorporating further light interception measurements complicates measurements in field conditions.

Object segmentation is one of the most discussed problems in digital image processing. There are segmentation methods based on the application of simple operators such as the gradient (Gonzalez and Woods, 2008), iterative algorithms for automatically estimating thresholds (Otsu, 1979), and highly sophisticated methods such as Active Contours based on Variational Calculus (Chan and Vese, 2001). To address the trade-off between the precision level and economic and computational costs of the method implementation Occam's razor is applicable, according to which under the same conditions, the simpler explanation is usually preferable. Following the Law of Parsimony, to estimate the leaf area index, a 2-level thresholding method is proposed. This method addresses the segmentation problem with low complexity techniques, allowing the use of conventional devices to capture and process images.

Based on the original cover photography code developed by Fuentes et al. (2008), this paper aims to automate filtration of non-leaf material from digital images using specific segmentation algorithms based on the combination of RGB and CIE Lab color model (CIE, 1976). The proposed method also allows the revision of pre-obtained images to improve the estimation of LAI and other canopy architecture parameters.

2. Theoretical background of color models

A color model is a three-dimensional space (if the model has 3 channels), and the colors are points or vectors within that space. Color models provide a way to represent colors and such representation must be unique, *i.e.* a color must be associated to a single vector. In literature, three types of color models are described (Gonzalez and Woods, 2008). The first type corresponds to color representations depending on hardware requirements. Among these models are the RGB (for computer screens) and CMYK (for mixing inks in printers). The second type represents the color by its cognitive parameters, i.e. parameters that come from the way the brain interprets visual information. A representative example is the HSV model that considers the hue (H), saturation (S), and an indication of light intensity (V). These two types of color models are not designed for digital image processing because they are not perceptually correct, i.e. two different colors are not necessarily far from each other in the vector space. The Commission Internationale d'Eclairage (International Commission on Illumination, www.cie.co.at) has developed color models that are perceptually correct such as CIE Lab (CIE, 1976). These models allow to compare colors using Euclidean Distance. For this reason, the latter model is extensively used in industrial applications, particularly in various image processing problems that come from agriculture.

This research corresponds to a case of color object segmentation, *i.e.* the segmentation of leaves from the rest of the tree image. The use of the CIE Lab model allows to naturally address the needs of the problem. CIE Lab nonlinear expressions from the standard CIE XYZ can be found in traditional image processing literature (Gonzalez and Woods, 2008) as follows:

$$L^* = 116 \cdot f\left(\frac{Y}{Y_n}\right) - 16 \tag{1}$$

$$a^* = 500 \cdot \left[f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right] \tag{2}$$

$$b^* = 200 \cdot \left[f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right] \tag{3}$$

$$f(t) = \begin{cases} t^{\frac{1}{3}} & \text{for} \quad t > \left(\frac{6}{29}\right)^3 \\ \frac{1}{3} \cdot \left(\frac{29}{6}\right)^2 \cdot t + \frac{4}{29} & \text{otherwise} \end{cases} \tag{4}$$

where X, Y and Z correspond to the coordinates in the CIE Lab XYZ model; X_n, Y_n and Z_n are the tristimulus values for a reference white point; L, a^* and b^* are the channels in the CIE color model.

3. Materials and methods

3.1. Location and plant material

This study was carried out in a commercial cherry orchard (*Prunus avium*) of eight hectares (ha) in size, located in Teno, Curicó Province, Maule Region, Chile (34.83° LS; 71.06° LW; 296 m. a. s. l.). All data was obtained in March 2013 with the aim to minimize interference with the production period. For this purpose, 20 trees were selected based on similar canopy architecture, production potential, trunk diameter, height and vigor. Of these trees, 10 corresponded to the cultivar 'Bing', which were planted in 2005. These trees were grafted on CAB 6p rootstocks in an area of 2 ha. Their planting density was 2 m between trees and 3.5 m between rows with a total of 1,429 trees ha^{-1}. The other 10 trees corresponded to the cultivar 'Sweetheart' grafted on Maxma 14 rootstock. They were planted in 2006, in a 3.5 ha area with a plantation density of 2 m between trees and 4.5 m between rows (1111 trees ha^{-1}). Both cultivars are irrigated with drip irrigation with drippers separated every 1 m and with a 3.6 L h^{-1} flow of water. None of the sampled trees were submitted to water stress throughout the season. The agronomical management for these trees was standard according to current practices by the grower.

3.2. Image data acquisition

For each tree selected, cover images were obtained with a conventional digital camera (DC-CAM 3200Z, Creative Labs, Singapore) (f 5.7–16.3 mm; lens aperture range F 2.6–4.9; 3.2 megapixels of resolution). This camera was mounted looking upward at 0.5 m height using a tripod. The alignment of the camera to obtain images at 0° zenith angle was achieved with the aid of a bubble level in the tripod. Each tree was divided in four quadrants. In each of these quadrants, the tripod and camera was located at 0.5 m distance from the trunk as shown in Fig. 1. A total of 4 images were obtained per tree, resulting in a total of 40 images per cultivar (80 images in total). The camera alignment and position, number of images per tree and digital image treatment followed previous work (Fuentes et al., 2008; Macfarlane et al., 2007). All digital images were saved to Joint Photographic Expert Group (JPEG) format (2048 × 1536 pixels). All images were acquired at least two hours before or after the sun passed through the zenith to avoid inclusion of direct light in the pictures (Poblete-Echeverria et al., 2015).

Fig. 1. Example of upward-looking images per quadrant obtained in the field. Tripod and digital camera positions were standardized at 0.5 m distance from the tree trunk and 0.5 m height from the ground respectively.

The image acquisition was performed with a very simple camera, in order to provide a low cost solution possible to implement in field conditions. The camera used provides images encapsulated in JPEG format, but the color model is RGB (all conventional digital cameras provide images in RGB model). The resolution of the camera optical sensor is sufficient to address the problem considering that the distance between the camera and the base of the tree is about 0.5 m. Additionally, the losses caused by the compression algorithms are negligible and have no effect on the accuracy needs of the study (Pekin and Macfarlane, 2009). It is noted that the experiments can be performed with any conventional camera, including cell phone cameras widely used nowadays (Fuentes et al., 2012).

3.3. Allometric measurements of total leaf area per tree

Within the same week of measurements, all the trees selected were completely defoliated after images were acquired (10 trees for 'Bing' and 10 trees for 'Sweetheart'). All the leaves per tree collected were weighted in the field using a portable scale (SP-300 weight meter, Urania, Swisstron, USA). From each of the samples, a sub-sample of approximately 0.4 kg was collected and weighted again using a higher precision scale (Precisa 2200c weight meter, Swiss Quality, USA). The sub-samples were stored in individual paper bags, and properly labeled, transported inside a cooler with ice packs to avoid leaf dehydration for leaf area measurements.

For each of the sub-samples, digital images of leaves were obtained in controlled conditions. For this purpose, each of the leaves per subsample was positioned on a white wooden surface of 1.2 × 1.2 m dimension as shown in Fig. 2(a). The same digital camera used for LAI estimations was mounted on a platform at a set height of 2 m.

The analysis procedure for leaf images considered the conversion of the color images (Red, Blue and Green) to grey scale (Hue, Saturation, Value) images (RGB to HSV). The V channel was chosen as a representation of the grey scale as can be seen in Fig. 2(b). The V channel image was then converted automatically to a binary image (Fig. 2(c)) that allows counting total pixels corresponding to leaves (with value = 1) compared to the background (with value = 0). This method allowed obtaining the total leaf area per subsample, when calibrated to a known surface area as scale, to be associated to the respective sub-sample weights. Finally, by using a simple linear regression, the total LAI per tree can be obtained by comparing the leaf area and weight per sub-sample with the weight of the total leaves per tree.

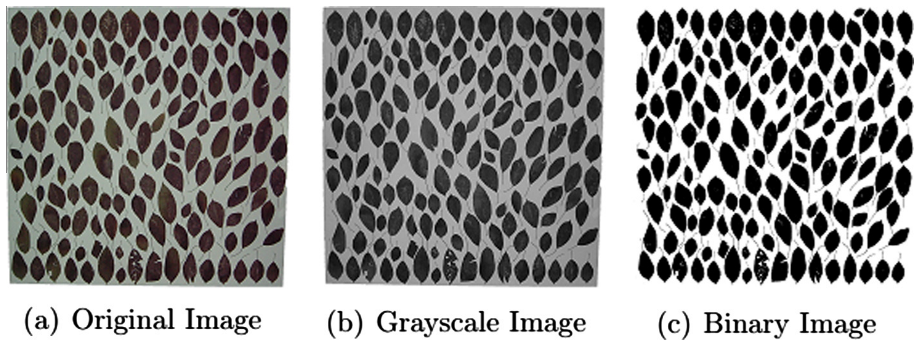

Fig. 2. Image processing example for sub-sampled leaves per tree to obtain a linear model between total leaf area and weight. This model was used to up-scale to the weight of leaves for the whole-tree to obtain total leaf area per tree.

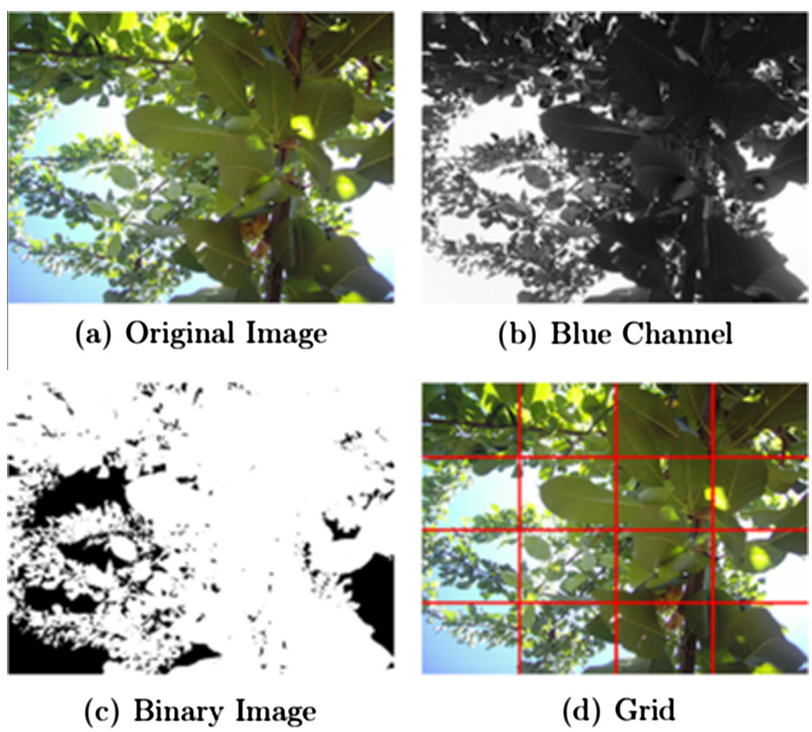

Fig. 3. Example of the proposed segmentation procedure to estimate leaf area index of fruit trees using the original method proposed by Fuentes et al. (2008). (a) Original Red Blue and Green (RGB) image. (b) Blue channel filtered; (c) binary image obtained from blue channel; (d) sub-division of image to analyze gap size and apply LAI algorithms. The latter sub-division is set by the user (Fuentes et al., 2008).

4. Estimation of LAI using digital images

The estimation of LAI using cover digital images was based on the method proposed by Fuentes et al. (2008). The steps to analyze the images and to obtain the relevant parameters were: (i) image capture per quadrant as shown in Fig. 3(a); (ii) the image was transformed to a binary image through a selection of an appropriate threshold using the blue channel (B) from the RGB image (Fig. 3(b)). This channel was used since it allows a proper discrimination of leaf material from sky and clouds (Fuentes et al., 2008). Results from the segmentation of the images using the latter method is shown in Fig. 3(c); (iii) the binary image is sub-divided in a $n \times n$ matrix as shown in Fig. 3(d), where n is a parameter defined by the user.

The total pixels from gaps in the image is defined as g_T and the total pixels corresponding to gaps present in one of the $n \times n$ regions is defined as g_L. Based on g_T and g_L the cover and crown cover fractions are calculated using the following algorithms:

$$f_c = 1 - \frac{g_L}{p_T} \quad (5)$$

$$f_f = 1 - \frac{g_T}{p_T} \quad (6)$$

where p_T correspond to the total pixels in the images (2048×1536 pixels).

With these parameters the crown porosity (ϕ) per image can be calculated as

$$\phi = \frac{f_f}{f_c} \quad (7)$$

From these equations and assuming a known light extinction coefficient (k), the measured LAI (LAI_A) can be calculated as follows:

$$\mathrm{LAI}_A = -f_c \frac{\ln \phi}{k} \quad (8)$$

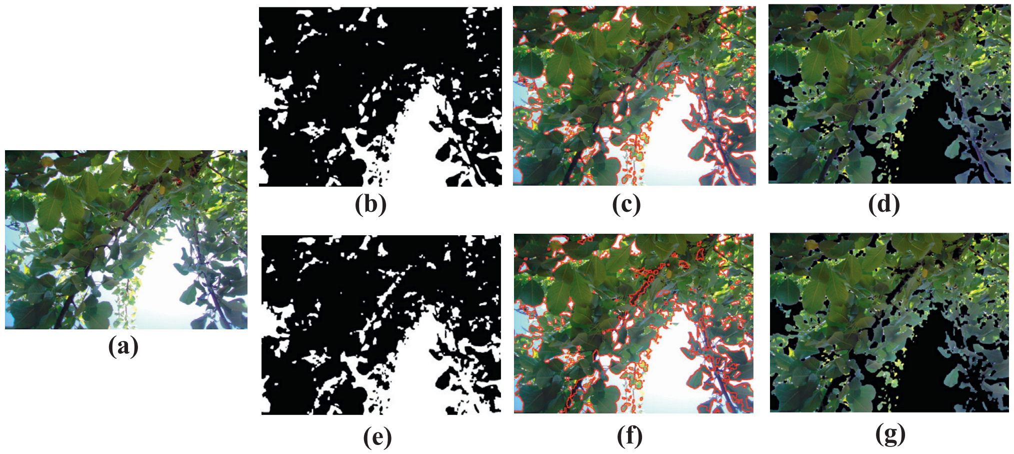

Fig. 4. Proposed improvement of leaf area index estimation for fruit trees using a two-level automated segmentation to isolate non-leaf material from the analysis where: (a) is the original image; (b), (c) and (d) are the resulting images for the first segmentation level and (e), (f) and (g) are the resulting images for the second segmentation level.

The clumping index $\Omega(0)$ can be also calculated using the following expression:

$$\Omega(0) = \frac{(1-\phi)\cdot\ln(1-f_f)}{\ln(\phi)\cdot f_f} \tag{9}$$

Based on Eq. (9), an effective LAI (LAI_e) can be calculated by the following expression:

$$\mathrm{LAI}_e = \mathrm{LAI}_A \cdot \Omega(0) \tag{10}$$

According to Fuentes et al. (2008), from each sub-division, a big gap is considered if 75% of pixel counts corresponds to sky. Furthermore a $k = 0.5$ was used for Eucalyptus trees (Fuentes et al., 2008; Macfarlane et al., 2007). For grapevines, a k between 0.65 and 0.75 was used according to the phenological stage of the crop (Fuentes et al., 2014). In this study, a suitable big gap criteria and k was assessed for cherry trees by a combinatory analysis of 36 cycles to obtain the best values resulting in a best fit of the LAI estimated with the LAI measured by allometry. The range for the big gap threshold considered for this analysis was between 0.65 and 0.7. The values of k were between 0.2 and 0.75 with a 0.05 step giving 12 values of k for each big gap threshold.

5. Proposed improvement of LAI estimation

The method proposed by Fuentes et al. (2008) has been applied to forest trees, grapevines (Fuentes et al., 2014) and apple trees (Poblete-Echeverria et al., 2015) and it has been made available as a smartphone and tablet PC application (Fuentes et al., 2012). However, the method incorporates non-leaf material in the analysis, which can compromise accuracy in the estimation of LAI from fruit trees, especially if specific k values are not available. Automatic segmentation of non-leaf pixels such as sky, stems, branches and fruits reduce the input parameters of the original algorithm, which at the present time must be entered manually. This automatic segmentation substantially simplifies the operating conditions of the algorithm, considering that it is no longer necessary to manually enter the size of the grid to divide the image, the big gaps threshold and the sky threshold.

The first level is the automatic segmentation of the B channel from the RGB model by applying the well-known Otsu algorithm (Otsu, 1979). The second level of segmentation corresponds to the automatic detection of pixels belonging to trunks, branches, fruits or any other non-leaf material. For this purpose, the original RGB image is transformed to a CIE Lab color code, which allows the separation of wood from leaves using the following rule:

$$Iw_{i,j} = \begin{cases} 1 & \text{if} \quad A_{i,j} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

where I_w corresponds to the binary image that contains the segmentation of pixels that are non-leaf material, A_{ij} corresponds to a pixel from the "a" channel from the CIE Lab color model.

By implementing the two-level segmentation method proposed, it is possible to automatically count the number of pixels corresponding to non-leaf material (nwood) to be eliminated from the LAI estimation by the following expression:

$$\mathrm{nwood} = \sum_{i}^{n}\sum_{j}^{m} Iw_{i,j} - \sum_{i}^{n}\sum_{j}^{m} Ig_{i,j} \tag{12}$$

where Ig corresponds to a binary image of $n \times m$ resulting from the first level of segmentation. From the resulting values of Eqs. (12), (5) and (6) can be modified to eliminate pixels corresponding to non-leaf material through the following expressions:

$$f_c = 1 - \frac{g_L}{p_T - \mathrm{nwood}} \tag{13}$$

$$f_f = 1 - \frac{g_T}{p_T - \mathrm{nwood}} \tag{14}$$

Fig. 4 depicts the results of the proposed two-level segmentation method. Fig. 4a shows the original image. The first level of segmentation is shown in Fig. 4(d). Fig. 4(b) is the binary image of the sky segmentation, Fig. 4(c) highlights in [2]red the contours around the sky gaps and Fig. 4(d) shows the segmented pixels of the original image. From the previous images it can be seen that sky pixels were correctly segmented resulting in images containing pixels from leaves and from non-leaf materials. The second level of segmentation is presented in Fig. 4(e), (f) and (g). Fig. 4(e) corresponds to the binary image. In Fig. 4(f) the non-leaf material from the canopy is highlighted by a red contour, and finally Fig. 4(g) presents resulting leaf pixels of the proposed segmentation method.

It is important to note that two-level thresholding simplifies the addressed segmentation problem. In general, the segmentation by levels or hierarchical segmentation divides the overall problem into simpler segmentation sub-problems, and designs a solution that is implementable in field conditions. While it is true that the blue region exists in the CIE Lab model, the dividing line is not linear. Fig. 5a shows the CIE Lab color model with $L = 25\%$, Fig. 5b shows the CIE Lab model with $L = 75\%$, and Fig. 5c shows the curve

[2] For interpretation of color in Fig. 4, the reader is referred to the web version of this article.

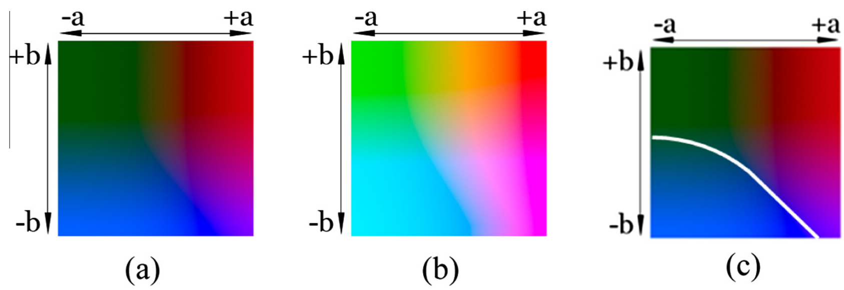

Fig. 5. CIE Lab model considering the luminance parameter: (a) $L = 25\%$; (b) $L = 75\%$ and (c) blue separation curve (highlighted in white color). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Comparison between averaged values (Mean) and standard deviations (SD) of leaf area index (LAI) estimated using the original (LAI_{eo}) and improved method (LAI_{ei}) against the allometric method (LAI_A) for the Sweetheart cultivar. CV is the coefficient of variation.

Tree	LAI_A	Mean[a] LAI_{eo}	Mean[a] LAI_{ei}	SD[a] LAI_{eo}	SD[a] LAI_{ei}	% error LAI_{eo}	% error LAI_{ei}
1	2.89	3.50	2.98	1.57	1.33	21.05	3.15
2	2.74	4.33	3.97	1.93	1.77	57.89	44.70
3	2.34	3.90	2.93	1.74	1.31	66.99	25.60
4	2.41	3.25	3.04	1.45	1.36	35.04	26.15
5	2.38	3.91	3.52	1.74	1.74	64.21	47.86
6	2.59	4.54	4.09	2.03	1.83	75.72	58.24
7	2.25	3.98	3.82	1.78	1.70	76.73	69.49
8	2.66	5.29	4.77	2.36	2.13	98.91	79.47
9	2.74	4.48	3.58	2.00	1.60	63.29	30.51
10	2.38	4.21	3.95	1.88	1.76	76.83	66.11
Mean	2.54	4.14	3.66	1.85	1.65	63.67	45.13
SD	0.21	0.58	0.58				
CV (%)	8.46	13.90	15.83				

[a] Denotes that the averages of LAI were computed using all combinations of big gaps (0.65–0.7) and light extinction coefficient (0.2–0.75).

separating the blue region from the other colors with $L = 25\%$. From the above figures it is noted firstly that the boundaries between colors are diffuse and difficult to identify even for a human expert, and secondly, that depending on the level of luminance (L) the separation curve changes its shape.

5.1. Statistical analysis

The assessment of measured and estimated values of LAI considered the comparison of each individual value of measured LAI (LAI_A) against the LAI estimation from digital images (1) using the original method proposed by Fuentes et al. (2008) (LAI_{eo}) and (2) digital LAI estimated with the improved method of segmentation proposed in this paper (LAI_{ei}). The comparisons considered the averages (Mean), the standard deviation (SD) and the coefficient of variation (CV). All aforementioned digital estimations of LAI were produced considering a combinatory analysis of the big gap threshold (from 0.65 to 0.7 in steps of 0.05, only for the original method), and the k value ranged between 0.2 and 0.75 (with a cumulative increment of 0.05 in an iterative process), for both original and improved methods. From this combinatory analysis, the resulting best estimations of LAI_{eo} and LAI_{ei} were obtained by minimizing the Root Mean Square Error (RMSE) (Mayer and Butler, 1993). The statistical analysis of measured and estimated values (LAI_{eo} and LAI_{ei}) was performed considering the linear regression method including the determination coefficient (R^2), percentage of error (%) (Gowda et al., 2008), the RMSE and the index of agreement (d) (Willmott, 1981).

6. Results and discussions

Results are first shown separately per cultivar and then combining all the data from both cultivars for a global comparison. Results of LAI estimations in the 20 evaluated trees are presented in Tables 1 and 2 for 'Bing' and 'Sweetheart', respectively. They summarize the averaged and standard deviations of LAI, considering all combinations of k and big gaps thresholds indicated previously in Section 3.

6.1. 'Sweetheart' trees

In Table 1 it can be seen that the LAI_{ei} averaged for all the trees are closer to the LAI_A values compared to LAI_{eo} obtained by the original method. Furthermore, the standard deviation (SD) of estimated LAI_{ei} is lower than the SD of LAI_{eo}. The highest individual values for percent of error were 99% and 79% for LAI_{eo} and LAI_{ei}, respectively. Individual comparisons of estimations of leaf area index were effectively improved by the segmentation method proposed. Averaged% error were higher by nearly 19% for the estimations computed with the original method.

6.2. 'Bing' trees

The results for the 10 trees assessed for the cultivar Bing are presented in Table 2, where similar results to the cultivar Sweetheart can be seen: the averaged LAI_{ei} values are closer than LAI_{eo} to LAI_A. Also, the SD for LAI_{ei} is lower compared to the SD of LAI_{eo}. In comparison to estimations for 'Sweetheart', 'Bing' showed a more modest performance than aforementioned. In this regard, an average percent of error of 121% was observed for values of LAI_{eo}, presenting the highest individual value for percent of error for the tree N°7 (190%). After the application of the improved model, the estimations showed slight improvement, reaching values of percent of error under 93%. Averaged% error for the estimations of LAI using the segmentation method were 59% lower than those obtained using the original method.

Table 2
Comparison between averaged values (Mean) and standard deviations (SD) of leaf area index (LAI) estimated using the original (LAI_{eo}) and improved method (LAI_{ei}) against the allometric method (LAI_A) for the Bing cultivar. CV is the coefficient of variation.

Tree	LAI_A	Mean[a] LAI_{eo}	Mean[a] LAI_{ei}	SD[a] LAI_{eo}	SD[a] LAI_{ei}	% error LAI_{eo}	% error LAI_{ei}
1	2.71	4.74	3.97	2.12	1.77	74.81	46.40
2	2.76	5.06	3.60	2.26	1.62	83.06	30.11
3	3.06	4.52	3.85	2.02	1.73	47.79	26.09
4	2.76	5.61	4.31	2.51	1.93	103.15	55.88
5	2.46	6.68	4.42	2.98	1.97	171.43	79.64
6	2.42	5.05	4.04	2.26	1.80	108.64	67.14
7	2.19	6.35	4.22	2.83	1.89	190.00	92.74
8	2.64	6.29	4.42	2.81	1.97	138.36	67.66
9	2.48	5.84	4.18	2.61	1.87	135.33	68.45
10	2.43	6.32	4.60	2.82	2.06	159.88	89.34
Mean	2.59	5.64	4.16	2.52	1.86	121.25	62.35
SD	0.24	0.77	0.30				
CV (%)	9.42	13.56	7.26				

[a] The averages of LAI were computed using all combinations of big gaps (0.65–0.7) and light extinction coefficient (0.2–0.75).

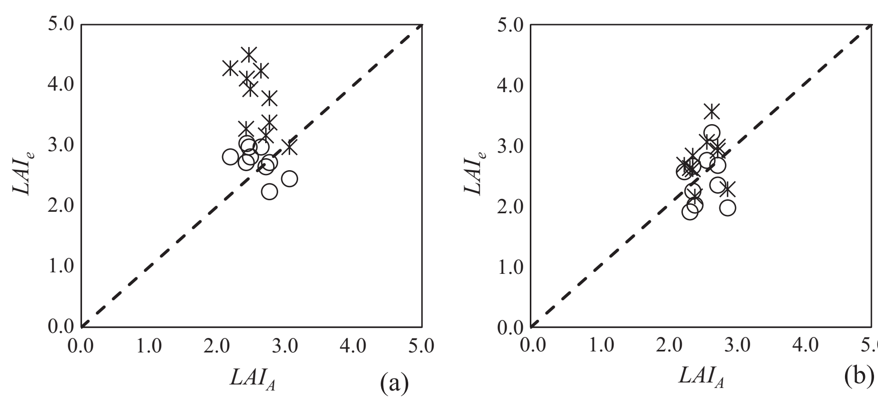

Fig. 6. Global results for the estimation of leaf area index (LAI) for the best results considering thresholds of big gaps and light extinction coefficient for the (a) bing and (b) sweetheart cultivars (asterisks = original LAI_{eo} method; empty circles = improved LAI_{ei} method incorporating the segmentation prodecure). Subscripts A and e denotes measured, and estimated values, respectively.

6.3. Results using the combined analysis

As indicated in Section 3, the absence of field measurements of big gaps and light extinction coefficient (input parameters of the model) required the evaluation of algorithm performance by combining values for these parameters in several incremental steps. The closest agreement between LAI_A against LAI_{ei} and LAI_{eo} considering the best combinations of k (=0.7) and big gaps (=0.6) thresholds are depicted in Fig. 6. In 'Bing', Fig. 6(a) depicts that the cloud of points for the original model (asterisks) overestimated the values of leaf area index showing values ranged between 2.9 and 4.5. In contrast, the improvement in LAI estimations added by the automated segmentation method (instead of the hand selection of big gap threshold) provided better results than the original method, concentrating the points around the 1:1 line, with values of LAI from 2.24 to 3.03 (empty circles). 'Sweetheart' Fig. 6(b) presents a better behavior of both original and improved LAI computing method, where the estimated values show similar trends, making it difficult to distinguish the effect of the improvement. Notwithstanding, in general it can be clearly seen that the estimations of LAI_{ei} (empty circles) are closer to the 1:1 line compared to those from the LAI_{eo} (asterisks) for the two cultivars.

The statistical analysis presented in Table 3 suggests that despite the improvement applied by the automated segmentation procedure, the effect was only perceptible for the estimations of LAI for the trees of the 'Bing'. Indeed, in both evaluated cultivars the coefficients of determination were high (>0.85), showing in 'Bing' a RMSE = 0.45, which is lower than the observed prior to the application of the segmentation method (RMSE = 1.35). For 'Sweetheart' the improvement was not important obtaining similar values of RMSE: 0.43 and 0.46 for LAI_{eo} and LAI_{ei}, respectively. The index of agreement was low for 'Bing' where values close to 0.1 were observed for both methods, suggesting a low agreement between observed and estimated values of leaf area index. In contrast, the index of agreement for 'Sweetheart' was higher than 'Bing' trees obtaining similar values near 0.4 for both LAI estimation methods. Differences indicated in the estimations of leaf area index between 'Bing' and 'Sweetheart' reaffirm that the woody elements of plants offers a low influence in the estimations of this parameter when a digital photography is utilized. These results are in agreement with previous work (Kucharik et al., 1997) that suggest that the cleaning of pixels contained in a digital image eliminating woody elements such as trunks, stem and branches could have a little influence in the estimations of LAI, in comparison to the high dependence of this method on

Table 3
Statistical analysis of leaf area index computed using the original model (LAI_{eo}) and improved model (LAI_{ei}).

	'Bing'			'Sweetheart'		
	R^2	RMSE	d	R^2	RMSE	d
LAI_{eo}	0.85	1.35	0.13	0.87	0.46	0.41
LAI_{ei}	0.86	0.45	0.10	0.86	0.43	0.44

R^2 is the coefficient of determination; RMSE is the root mean square error and d is the index of agreement.

the light extinction coefficient of Beer's Law, which was considered as a fixed value in this study.

According to the results, this study has shown that the use of a two-level automated segmentation process for cover photography of fruit tree canopies improved the processing of digital images for LAI estimation. This study also demonstrated that the LAI algorithm is highly sensitive to the selection of an appropriate *k* value. This issue has been addressed in Poblete-Echeverria et al. (2015) and in the development of a computer application to estimate LAI (Fuentes et al., 2012). In the future, this application is expected to employ a customized sensor that measures Photosynthetically Active Radiation (PAR), which can be incorporated to the LAI calculation. The use of this sensor plus the methodology proposed in this paper is expected to result in potential estimations of LAI for fruit trees with less than 8% error (Poblete-Echeverria et al., 2015).

7. Conclusions

A modified method to analyze cover photography from cherry trees to obtain LAI has been presented. The reference method was proposed by Fuentes et al. (2008), which is a semi-automated batch process of conventional digital images from the tree canopy. The proposed improvement consisted in the automation of the image segmentation process based on a two-level thresholding stage, which eliminates the need to enter configuration parameters manually. The results presented herein suggest that this method is an affordable and easy alternative to implement in field conditions, allowing a future implementation on portable and conventional devices such as smartphones and tablets.

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