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Mobile terrestrial laser scanner applications in Precision Fruticulture/Horticulture and tools to extract information from canopy point clouds

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Abstract

LiDAR sensors are widely used in many areas and, in recent years, that includes agricultural tasks. In this work, a self-developed mobile terrestrial laser scanner based on a 2D light detection and ranging (LiDAR) sensor was used to scan an intensive olive orchard, and different algorithms were developed to estimate canopy volume. Canopy volume estimations derived from LiDAR sensor readings were compared to conventional estimations used in fruticulture/horticulture research and the results prove that they are equivalent with coefficients of correlation ranging from r=0.56 to r=0.82 depending on the algorithms used. Additionally, tools related to analysis of point cloud data from the LiDAR-based system are proposed to extract further geometrical and structural information from tree row crop canopies to be offered to farmers and technical advisors as digital raster maps. Having high spatial resolution information on canopy geometry (i.e. height, width and volume) and on canopy structure (i.e. light penetrability, leafiness and porosity) may result in better orchard management decisions. Easily obtainable, reliable information on canopy geometry and structure may favour the development of decision support systems either for irrigation, fertilization or canopy management, as well as for variable rate application of agricultural inputs in the framework of precision fruticulture/horticulture.

Keywords: LiDAR, canopy modelling, crop mapping, olive orchard, mobile terrestrial laser scanner, Precision Fruticulture.

Introduction

Knowledge of the geometry (i.e. size, volume, shape) and structure (i.e. leaf area index, leaf density, wood structure and volume) characteristics of tree plantations is gaining importance in advanced fruit growing/fruticulture, especially when implementing precision agriculture techniques. This is due to the strong relationship between these characteristics and the use of water, nutrients and light by plants (Lee and Ehsani 2009) and their productivity and quality (Arnó et al. 2013; Rufat et al. 2014). Moreover, the main activities involved in tree crop management, such as: i) irrigation, ii) fertilization, iii) crop protection and iv) canopy management, could be carried out in a more selective and accurate manner if these canopy properties are taken into account (Rosell and Sanz 2012). Thus, knowledge of tree row crop characteristics should improve farm management, making it more efficient and sustainable. Because of the high complexity of tree crops, the measurement of canopy characteristics is usually done manually, and therefore, has been limited to a few simple parameters for commercial purposes (i.e. height and width). However, more complex parameters have been restricted to research because of difficulty in estimation and/or the costly procedures required (i.e. LAI and canopy permeability). Additionally, manual measurements are usually inaccurate and time consuming. Hence, it is not commercially feasible to perform measurement series of orchards for management purposes. For that, it is necessary to have robust and affordable electronic sensors and data processing systems to use in commercial fruit crop management.

The most used instrumental techniques to characterize tree canopies include digital photography, photogrammetry, stereoscopy and LiDAR (light detection and ranging) as described in Rosell and Sanz (2012) and in Li et al. (2014). The first three share the use of digital cameras, which benefit from belonging to a segment of consumer products and are economically accessible. LiDAR systems are based on a laser source that emits light pulses which impact the object of interest. By measuring the time elapsed between the light pulse emission and the return of the backscattered light (time-of-flight) or by phase shift, the device determines the distance to the object. In recent years, several studies have used mobile terrestrial laser scanners (MTLS) based on 2D LiDAR sensors to characterise tree crops in agricultural environments (Sanz-Cortiella et al. 2011; Walklate et al. 2002). Subsequently, these systems were used to obtain relevant data from the canopy such as volume and shape (Auat Cheein et al. 2015; Miranda-Fuentes et al. 2015; Rosell et al. 2009a), LAI (Arnó et al. 2013; Rosell et al. 2009b) and woody structures (Méndez et al. 2014; Wang et al. 2014). In this context, Rosell et al. (2009a and 2009b) showed the existence of strong correlations between 3D models generated by an MTLS and manually-obtained canopy volume, leaf area and LAI measurements. Other research has also demonstrated the capacity of LiDAR systems to determine the geometry and structure of tree crops and the potential advantages of using this information in relevant agricultural tasks, such as precise pesticide and fertilizer applications and irrigation (Gil et al. 2014; Gongal et al. 2015). Canopy volume and LAI have been computed on a real-time basis by estimating the cross-sectional areas of the tree rows and sliced canopy volumes to subsequently correlate them with manual LAI measurements (Escolà et al. 2007; Pallejà et al. 2010). Canopy foliar density has been estimated for citrus with a canopy boundary-smoothing algorithm (Wei and Salyani 2005) and for comparing occupied and free canopy volumes (Chen et al. 2013). Moorthy et al. (2011) used a stationary terrestrial laser scanner to obtain olive tree canopy structure and foliage parameters. However, the use of stationary laser scanners is not pragmatic when large areas are to be scanned. One of the main limitations of LiDAR-based systems is their inability to measure inside the crowns, due to the interaction between the laser beam and the outermost vegetative elements. The recent introduction of terrestrial multi-return laser scanners may improve the performance of current sensors in tree crop characterization. Other authors have used time-of-flight cameras and structured light sensors, which enable the acquisition of depth images and 3D point clouds of plants, for several agricultural purposes (Chéné et al. 2012; Nock et al. 2013; Rosell-Polo et al. 2015). However, these sensors are still not ready to be used in a feasible way in commercial orchards since they need to be either further developed, stationary, or to take multiple shots of the scene from different angles to obtain useful data.

More recently, unmanned aerial vehicles (UAV) have been used in olive orchards to derive 3D point clouds from digital images using photo-reconstruction methods. Good results were achieved for isolated trees (Díaz-Varela et al. 2015; Torres-Sánchez et al. 2015; Zarco-Tejada et al. 2014) and in hedgerows (Díaz-Varela et al. 2015; Torres-Sánchez et al. 2015). The monitored parameters were canopy height, canopy projected area and canopy volume.

In view of this background, the objective of the present work was to characterize the canopy of an intensive olive orchard in hedgerows from data generated by a self-developed MTLS. Canopy volume estimates derived from LiDAR readings were compared to conventional estimates used in fruticulture

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research under the hypothesis that MTLS can produce equivalent estimates but in a more automated, repeatable and objective way. Apart from the development of the algorithms required for data processing, the effects of some factors on the canopy volume estimations are discussed. Part of the results was presented at the 10th European Conference on Precision Agriculture (Escolà et al. 2015). Additionally, some extra tools related to point cloud analysis are proposed to extract further geometrical and structural information from tree row crop canopies. Such tools may be used by researchers in their trials, but also by farmers and technical advisors to take better management decisions in the framework of precision fruticulture/horticulture.

Materials and methods

Experimental olive orchard

The measurements were carried out on an irrigated, super-intensive commercial 10-year-old olive orchard (*Olea Europaea* cv. Arbequina) that produces high-quality oil. The orchard was located in Torres de Segre, Catalonia, Spain (X = 296850 m, Y = 4599700 m, UTM 31N/ETRS89). Planting and training systems were designed so that the harvesting was completely mechanized, with machines similar to grape harvesters (Figure 2). The orchard had an area of 2.5 ha and consisted of 16 NE–SW oriented rows 4.5 m apart, with a tree spacing of 2.2 m (approx. 1010 trees ha^{-1}). However, the area of the sub-plot characterized with the MTLS was 1 ha, with row lengths ranging from 125 to 190 m. The maximum tree height and width were approximately 3.75 m and 2 m, respectively.

A long-term study was conducted in the orchard to test the response of trees to different irrigation and fertilization strategies. The trial was conducted during the years 2012 and 2013, and consisted of combining and replicating five irrigation treatments with three nitrogen (N) doses and two potassium (K) doses, in 56 randomly distributed blocks. Each block consisted of six trees, but only some of the four central trees were monitored. Tree growth was monitored in the control trees by observing the following: 1) average per tree visual canopy volume estimation of two central trees (VCV IRTA); 2) per tree lateral canopy area derived from image analysis of one central tree (FL); 3) per tree combined canopy volume (VCM IRTA) computed by multiplying FL values by a representative tape-measured canopy width. For this purpose, a single-lens reflex digital camera (Nikon D5100, Nikon, Japan; with Tamron SP AF 10-24 mm F/3,5-4,5 Di II LD ASL IF, Tamron, Japan) and specific software (Photoshop CS6, Adobe Systems, USA; ImageJ, NIH, USA) were used, following the methodology proposed in Lordan et al. (2015). The blocks were monitored at three different development stages: 1) springtime, at the beginning of the season, just after pruning; 2) summertime, at the beginning of pit hardening; 3) wintertime, at the end of the season after harvesting.

Mobile terrestrial laser scanner

The MTLS developed to characterize tree canopies integrated a 2D LiDAR sensor and a GNSS1200+ (Leica Geosystems AG, Heerbrugg, Switzerland) RTK-GNSS system (a real-time kinematics global navigation satellite system receiving GPS and Glonass constellation signals). Both were connected to a rugged laptop suitable for work in field conditions. The acquisition system used a self-developed LabVIEW (National Instruments, Austin, USA) program which merges and stores the receiver co-ordinates and LiDAR data. The sensor used was a UTM30-LX-EW time-of-flight LiDAR (HOKUYO, Osaka, Japan) which has a range of 30 m. The sensor performs 40 scans per second (40 Hz). To simplify, it was considered that each scan provided measurements contained in a vertical plane perpendicular to the travel direction, approximately perpendicular to the tree rows. It has multi-return capabilities and provides up to three distance measurements corresponding to partial impacts on different objects for the same emitted laser pulse. After processing each received return signal, the sensor determines the distance at which the object impacted by the incident light pulse is located. The scanning window was set to 270º with an angular resolution of 0.25º. The measurements were given

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in polar co-ordinates, i.e. angle and distance of each measurement, taking the centre of the LiDAR sensor as the origin of the co-ordinates. The output was a set of 1081 first return signals per scan and a number of second and third return signals per scan, whenever they existed. The sensor was attached to a mast below the RTK-GNSS rover receiver antenna, so that the absolute co-ordinates of the sensor were recorded continuously. The 90º blind sector was pointing upwards so that 540 laser beams were aimed at the right-hand side of the sensor, 540 were aimed at the left-hand side, and the central beam was perpendicular to the ground. Some of the beams impacted the ground, others impacted several adjacent rows, and some did not impact anything (Figure 1).

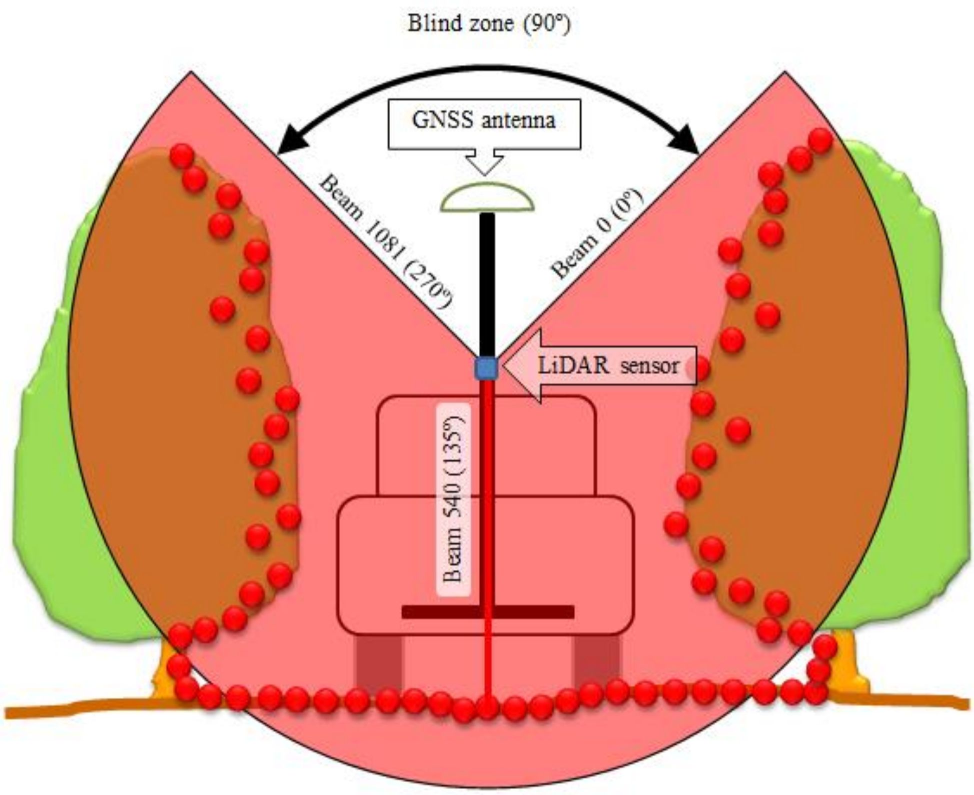

Fig. 1 Diagram of the mobile terrestrial laser scanner and its components

<u>Experimental Orchard scanning</u>

During orchard scanning, the system was mounted on an all-terrain vehicle in order to move it along the hedgerow alleyways of the orchard, at a height of 2 m above the ground, as shown in Figure 2. That height was experimentally set in a way to properly detect the top and bottom branches of the hedgerow. The travel speed was approx. 4 km h^{-1}, leading to a distance between two consecutive scans of approximately 27 mm. Each single scan consisted of impacts of the laser beam on several adjacent rows on both sides and on the ground. The crop was scanned with the MTLS at three different dates during the 2013/2014 season, as close as possible to the conventional monitoring of the crop. The first scan was performed after pruning (19/4/2013), the second in summer (15/7/2013), and the third at the end of the season (10/3/2014).

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Fig. 2 View of an alleyway of the orchard (left). MTLS attached to the vehicle (right)

Tools for geometric canopy characterization

The points were transferred and stored in relative polar co-ordinates with the origin at the centre of the sensor. The data were then post-processed. The first step in data processing was to transfer the receiver antenna absolute ETRS89 UTM co-ordinates to the LiDAR sensor. As the position of the sensor was the origin of the polar measurements, each of the measured points was georeferenced in absolute rectangular co-ordinates with an accuracy of approximately ±0.05 m (from specifications: approximately ±0.03 m from sensor accuracy and approximately ±0.02 m from the RTK-GNSS receiver). For each scanned alleyway, a point cloud consisting of approximately between 6 and 7.5 million points from the adjacent tree rows and from the ground was obtained. Finally, merging the point clouds from the 17 alleyways, a 3D point cloud of the whole orchard was obtained. Point cloud data management was done with self-developed algorithms while point cloud visualization and some specific computation were performed with CloudCompare (CloudCompare [GPL software] v2.6.1 2015). Subsequently, the 3D point cloud was classified into canopy and ground points. Points located at a height less than 0.3 m above the ground were discarded. The remaining points were classified into different files, one for each tree row. The row point clouds were created according to four different methods (M_i):

- M1: each row containing first return points obtained from two adjacent alleyways.
- M2: each row containing first return points obtained from four adjacent alleyways.
- M3: each row containing first and second return points obtained from two adjacent alleyways.
- M4: each row containing first and second return points from four adjacent alleyways.

Third return data were not considered reliable and were discarded.

Canopy height information extraction

Some of the laser beams impacted the ground. The average Z co-ordinate of those points was calculated to minimize the effect of plants, although the alleyways had little ground vegetation. The average value was set as the reference ground co-ordinate for each scan. The height above ground of all points classified as part of the canopy was calculated by subtracting the ground Z reference co-ordinate from their actual Z co-ordinate on a per scan basis. Subsequently, the points of each row created according to the four different methods were classified into sections (also called slices) of 0.1 m length along the rows, according to the distance of each point to the beginning of its row. The result of this operation was a set of vertical prisms 0.1 m wide (slices) containing subsets of the point cloud of each row. For each 0.1 m slice, the maximum height was computed and stored together with the X and Y co-ordinates of the prism centroid. Descriptive statistics were applied to extract information about the canopy height (Figure 3).

Extraction of canopy width information

For each vertical slice along the rows, points were subsequently grouped every 0.1 m in the vertical plane, confining them to new horizontal rectangular prisms of 0.1 × 0.1 × prism_width m along the canopy rows all over the orchard. The actual prism width was computed as the distance between the two most distant points in the cross-section plane of the row. Each slice contained several canopy width estimations at 0.1 m vertical intervals. For each 0.1 m row section, the average width of all contained widths was computed and stored together with the X and Y co-ordinates of the section centroid. Additionally, all widths contained in each slice were also stored together with the X and Y co-ordinates of the horizontal prism centroid. Descriptive statistics were applied to extract information about the canopy width (Figure 3).

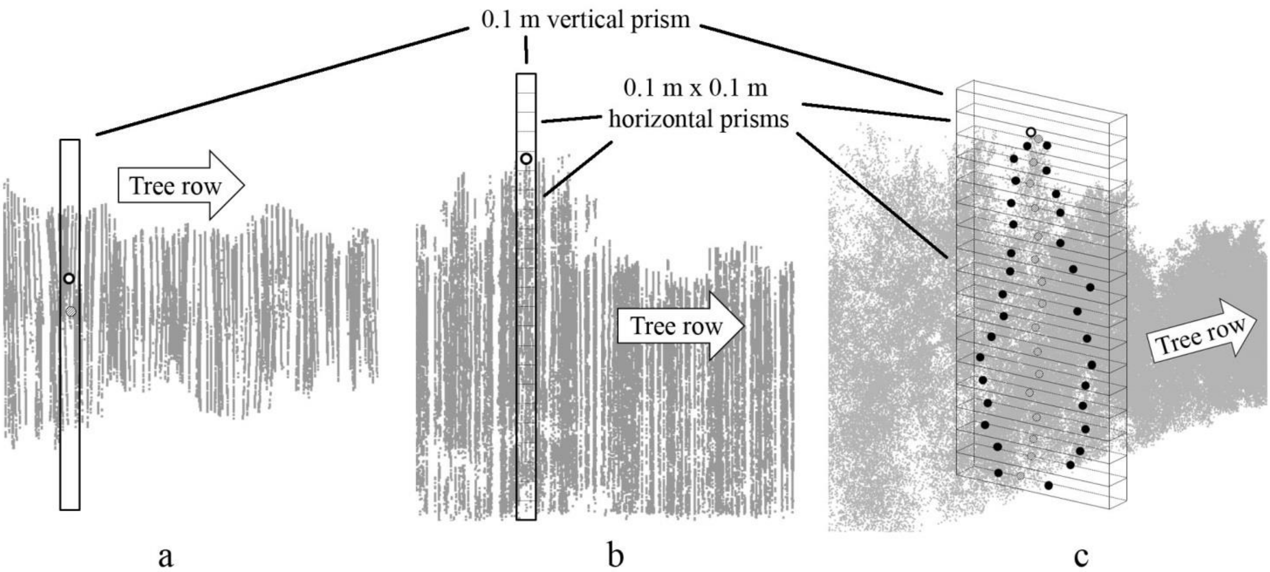

Fig. 3 Diagram with different views a point cloud representing a tree row section. (a) Top view of the row showing one of the 0.1 m vertical prisms (b) Side view of the row showing one of the 0.1 m vertical prism and its 0.1 x 0.1 m horizontal prisms. (c) Perspective view of the row with one vertical prism containing several horizontal prisms. White circles represent the maximum height point within the vertical prims, grey circles represent the prims centroids and solid points represent the two more outer points in each horizontal prism.

Canopy volume information extraction

The horizontal prism volumes were computed as 0.1 × 0.1 × prism_width, expressed in m^3. The volume of each 0.1 m vertical slice was computed as the sum of the volumes of the prisms contained. Each volume slice was assigned to the X and Y centroid co-ordinates. The canopy volume was computed for all row point clouds created according to the four different methods at the three different scanning dates. Once the canopy height, width and volume were computed on a per 0.1 m basis, data could be grouped to obtain values on a per 1 m basis or on a per tree basis (that is, considering 2.2 m sections of the row). Descriptive statistics were applied to extract information about the canopy volume, and raster maps were created to represent the spatial distributions of the canopy volume.

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Effect of the method on the creation of row point clouds
The canopy volumes at full development stage computed according to the four different methods were compared. The data were analysed with JMP® 12 Pro (SAS Institute Inc., Cary, USA), comparing the canopy volume means for each method with the Tukey-Kramer HSD test.

Comparison of MTLS and conventional canopy volume estimation methodologies
The canopy volume slices calculated every 0.1 m along the rows (using the four different methods) were assigned to each of the 56 trial blocks using ArcGIS for Desktop 10.3 (ESRI, Redlands, USA). Specifically, two volumes were calculated in a way similar to that of monitoring tree growth:

- VCV LiDAR M_i: corresponds to the volume of a section of 2.2 m computed as the average of two central trees (a section of 4.4 m) of each study block for methods 1 to 4.
- VCM LiDAR M_i: corresponds to the volume of a single central tree (a section of 2.2 m) of each study block for methods 1 to 4.

Canopy volumes of the blocks estimated visually (VCV IRTA), by image analysis (VCM IRTA), and by laser scanning (VCV LiDAR M_i and VCM LiDAR M_i) were compared using the matrix of correlation coefficients and comparing the volume means with the Tukey-Kramer HSD test.

Effect of wind on the canopy volume estimation
In addition to the three scans to compare the LiDAR-derived results with the conventional methods to estimate canopy volume, the orchard was scanned in wintertime during a windy day to assess the effect of wind on the canopy volume estimation. The windy day had an average of 4.03 km h^{-1} wind speed during the scanning period (from 11 h to 13 h), while the calm day had an average of 1.46 km h^{-1} wind speed during the same scanning period. Canopy volumes computed every 0.1 m for all rows were analysed with JMP® 12 Pro, comparing the canopy volume means with the Tukey-Kramer HSD test.

<u>Map generation</u>
One of the best ways to present and analyse the results of the distribution of variables within the orchard is using digital maps. In this work, the variographic analysis and mapping of volumes were performed using the extension Geostatistical Analyst of ArcGIS for Desktop 10.3. The interpolation was performed with ordinary Kriging or Gaussian process regression according to the semi-variogram models fitted in each case. The model selection criterion was the minimization of the root mean square errors. Canopy height, width and volume raster maps were created for each date to represent the spatial and temporal variability. Furthermore, difference raster maps were generated in order to analyse the growth of the vegetation in terms of canopy volume between dates.

<u>Tools for canopy structure characterization</u>
Canopy structure has to do with the distribution of leaves to optimize sunlight capture. Two different tools to monitor canopy structure, relating the laser beam impacts on the canopy and canopy density are presented. The results are connected to concepts such as canopy permeability, porosity or even penetrability.

Laser beam penetrability and light extinction
In general, sunlight plays a key role in regulating photosynthesis, leaf development and the distribution of fruit production zones within the canopy. Therefore, researchers and agronomists are very interested in having tools to understand how light interacts with the canopy. An analysis of a light beam penetrating a crop canopy can be approximated by a Poisson model as described in Equation 1 (Walklate 1989):

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$$P(x) = exp(-ax) \qquad (1)$$

where *P(x)* is the probability of light beam penetration, x is the distance along the light beam towards the interior of the canopy, and a is usually considered to be the foliar density responsible for the extinction of the light beam through the canopy.

A specific method was developed to test the exponential laser beam extinction as it passes through the canopy of the olive tree. Given a row section defined from one tree trunk to the next tree trunk (2.2 m length), vertical prisms 0.1 m wide and parallel to the row axis were defined across the canopy. The method consisted of counting the number of impacts contained in each prism to analyse the laser beam penetration into the canopy. For this purpose, only the sensor readings from a single side of the row were considered. Cropping the point cloud and classifying and counting the points were performed with the program CloudCompare 2.6.1. The Poisson law can be checked by fitting the data to an exponential model (Equation 2),

$$N = A \cdot exp(Kd) \qquad (2)$$

where N is the number of impacts of the point cloud, d is the horizontal distance measured into the canopy, K is the extinction coefficient, and A is the second model parameter. The fit of the model was performed using JMP® 12 Pro. The agricultural interest of such models is to assess how sunlight penetrates the canopy according to the extinction coefficient obtained.

Laser beam interception and canopy leafiness and porosity

The laser beams aimed at both sides turned into intercept points on the ground of the present alleyway, on close adjacent canopies, on the ground of adjacent alleyways and on far adjacent canopies (for beams going through the close adjacent canopies) and non-returning beams. The designed algorithm consisted of classifying the points and computing two ratios: 1) the leafiness ratio (LR), as the ratio between the intercepted beams (b_i) on the right and left close adjacent canopies and the potentially intercepted beams (b_p) for each side of the scan, and 2) the porosity ratio (PR) as the complementary value to 1. The ratios were computed on a single scan basis and range from 0 to 1. The potentially intercepted beams were computed for each scan and side of the sensor, considering the number of laser beams emitted at a 0.25° angular resolution (a) between the lowest intercepted beam (b_{pl}) and the highest intercepted beam (b_{ph}) as expressed in Equation 3.

$$LR = \frac{b_i}{b_p} = \frac{b_i}{\frac{(b_{ph} - b_{pl})}{a}} = 1 - PR \qquad (3)$$

The result of the algorithm was a value for each ratio for each side of the sensor assigned to a point located 0.5 m away from the row axis in the intersection between the scanning plane and the ground. Finally, raster maps were constructed to represent the spatial distribution of the canopy leafiness and porosity ratios.

Results and discussion

3D orchard point cloud

The 3D georeferenced point cloud of the olive orchard obtained in March 2014 is shown in Figure 4. There were a total of 16 rows. The number of points in the rows ranged from 4 to 6 million points, depending on the row length. The global point clouds obtained at the three different dates had more than 80 million first return points and more than 8 million second return points each (including canopy

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and ground impacts). That is an average point density of about 8,800 points m^{-2}. That is from 22 to 2,200 times denser than the values reported by Díaz-Varela et al. (2015) and Zarco-Tejada et al. (2014), and from 2 to 25 times denser than values reported by (Torres-Sánchez et al. 2015) from their UAVs.

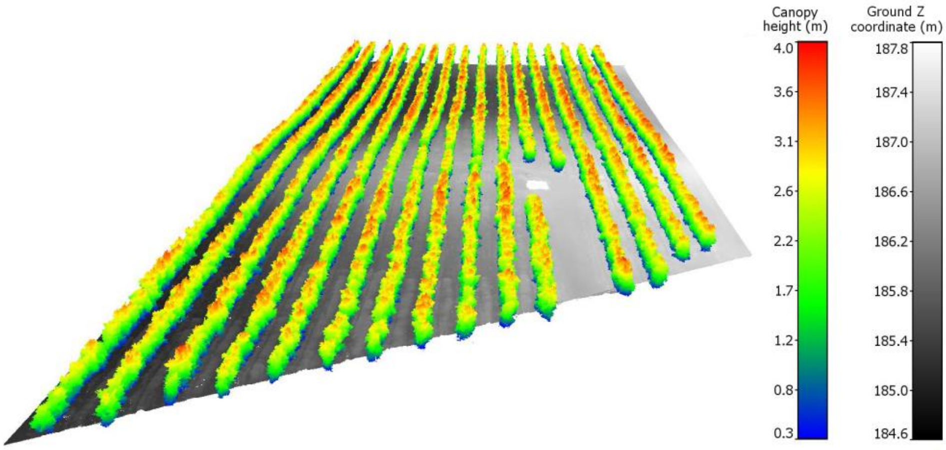

Fig. 4 Three-dimensional georeferenced point cloud of 1 ha olive orchard scanned in March 2014. Colours in tree rows represent tree height. Ground points are represented in grey scale according to their Z co-ordinate

<u>Canopy geometric information</u>

Results related to the canopy geometric information extraction are focused on the full development stage (10 March 2014) with point clouds created according to Method 1. Results for different stages and methods may be different, but the proposed tools and interpretation of the results may be equivalent.

Canopy height

The complete point cloud of sixteen scanned rows was classified into approximately 25,750 slices 0.1 m wide, each with its own maximum point height. Figure 5a shows a histogram and box plot of the height population. Table 1 shows statistical parameters describing the population. As the orchard is machine harvested, the farmer controls the height of the canopy to fit the harvester. This is why the height population distribution is concentrated around 3.16 m, and the coefficient of variation is not very high (12.91%). Canopy height information is very important for farmers, since in some countries, dosages of pesticides are based on this parameter. Height information provided in this way is much more accurate and representative than heights obtained using current farm and research methods.

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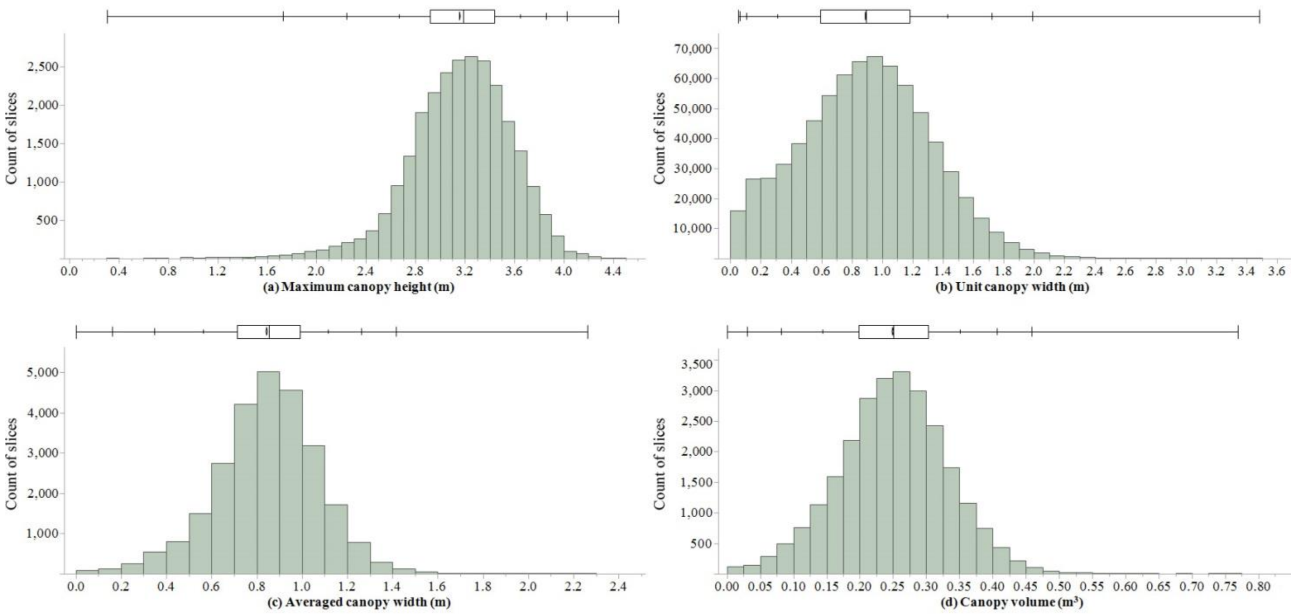

Fig. 5 Histograms and box plots at full development stage (March 2014) of (a) maximum canopy height on a 0.1 m slice basis, (b) unit canopy width on a 0.1 × 0.1 m prism basis, (c) averaged canopy width on a 0.1-m slice basis, and (d) canopy volume on a 0.1 m slice basis

Table 1 Descriptive statistics of maximum canopy height, canopy width and canopy volume populations on a 0.1 m slice basis and unit canopy width on a 0.1 × 0.1 m prism basis at full development stage (March 2014)

Descriptive statistics	Maximum canopy height (m)	Unit canopy width (m)	Averaged canopy width (m)	Canopy volume (m^3)
Mean	3.160	0.890	0.845	0.249
Standard Deviation	0.408	0.420	0.225	0.081
Mean upper CI 95%	3.165	0.891	0.848	0.250
Mean lower CI 95%	3.155	0.889	0.842	0.248
Coefficient of variation	12.91%	47.12%	26.58%	32.64%
Minimum	0.308	0.050	0.000	0.000
Maximum	4.440	3.482	2.261	0.769
Median	3.187	0.895	0.855	0.251
Mode	3.200	0.855	0.784	0.257

Canopy width

The preliminary result of the algorithm designed to estimate canopy widths was a set of unit widths of crosswise 0.1 × 0.1 m prisms within the vertical canopy slices and along the rows. Figure 5b shows the histogram and box plot of the unit canopy width population and Table 1 shows the statistical parameters. The coefficient of variation shows that unit canopy widths are much more variable than canopy height, as they are not as controlled by the farmer as canopy height and consist of many more observations.

When analysing the values by 0.1 m heights, a representative canopy cross section of the orchard can be sketched (Fig. 6). From 0.4 to 2.8 m, the mean, median and mode values are similar but mode values differ at lower and upper heights. This happens because, at those heights, the canopy is not as uniform as it is at medium heights. The canopy shape is also an important parameter when setting up

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the air outlets of orchard sprayers, and could be of interest when planning and assessing the result of pruning operations.

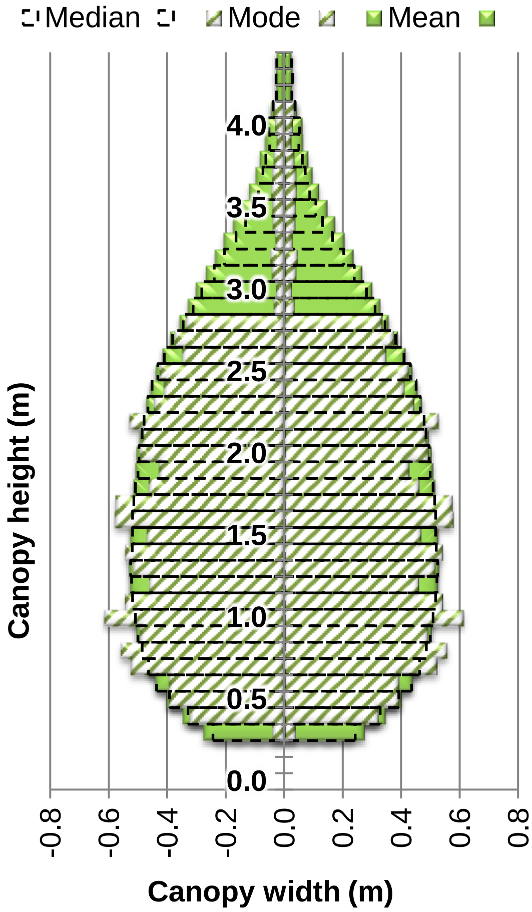

Fig. 6 Representative canopy cross section of the orchard at full development stage (March 2014) expressed with mean, median, and mode canopy width values

Averaging the unit widths of vertical canopy slices provides the average canopy width and standard deviation on a 0.1 m basis along the rows. Figure 5c shows the histogram and box plot of the average canopy width population, and Table 1 shows its statistical parameters. Although averaged, the canopy width still presents a higher coefficient of variation than canopy height at the full development stage. It is important to keep in mind that tree rows are not perfectly regular hedgerows and the trunk areas have wider cross sections.

Canopy volume

Finally, once the canopy height and width were obtained, the canopy volume on a per slice basis was computed. Canopy volume is directly related to the health and vigour of plants, and hence is an indirect way to estimate them. Figure 5d shows the histogram and box plot of the average canopy volume population, and Table 1 shows its statistical parameters.

Raster maps

Besides knowing the canopy parameter distributions and their descriptive statistics, it is very important to know the continuous spatial distribution of structural parameters within the orchards. In agriculture, the best way for farmers and technical advisors to see this is by means of digital maps. Figure 7 shows the spatial distribution of canopy height, width and volume at full development stage, grouping the data on a 1 m basis (i.e. 10 slices). Spatial variability in this orchard changed due to intentionally introduced differences in management of irrigation and fertilization based on research

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trials. However, in commercial farms, the variability may be induced by soil heterogeneity, pests and diseases or even by management operations, among other factors. Once provided with such information, farmers and technical advisors should look into the orchard to understand what is happening and decide on the most suitable management operations.

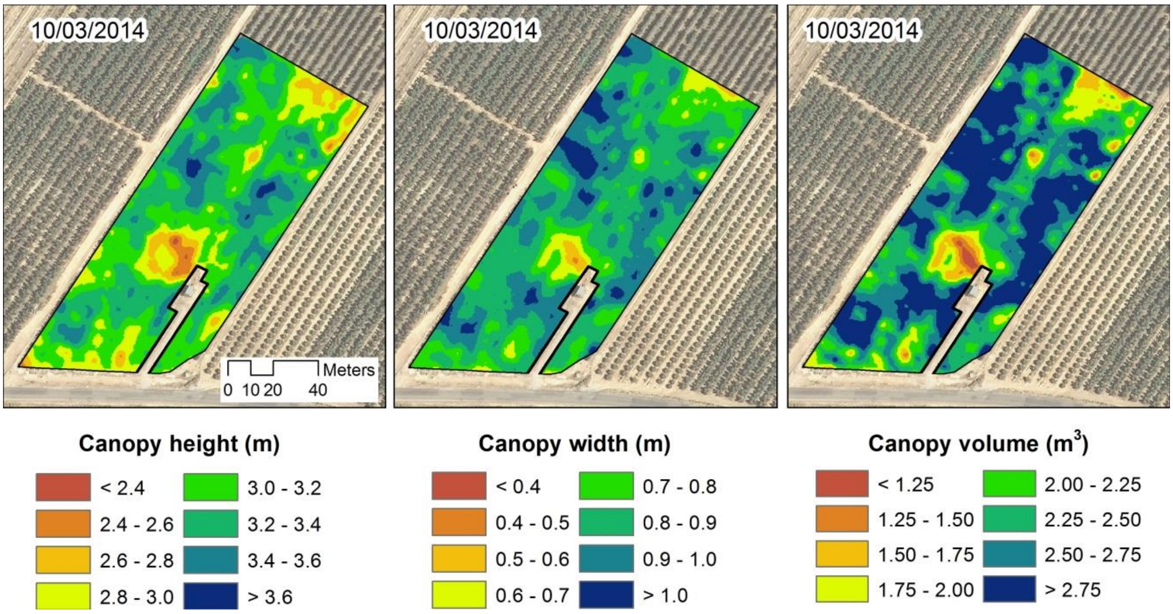

Fig. 7 Raster maps representing the spatial distribution of canopy height (left), canopy width (centre), and canopy volume (right) on a 1-m basis at full development stage

Whenever canopy volume maps are available for different dates, there is the opportunity to create growth maps. Growth maps were computed by subtracting canopy volume values from maps at two different dates. Figure 8 shows the spatial distribution of canopy volume at two different dates on a 1-m basis and the canopy growth between them, highlighting spatial variability in growth rates. Although this is an artificially generated variability, the same procedure could be used in commercial orchards to monitor canopy growth and detect areas with low growth rates. Negative growth rates in Figure 8 may have two causes. 1) Low growth rates together with inaccuracies of the system may produces close-to-zero negative volume growth, and 2) mechanized harvesting before March 2014 might have somehow altered the canopy (broken branches and canopy compression).

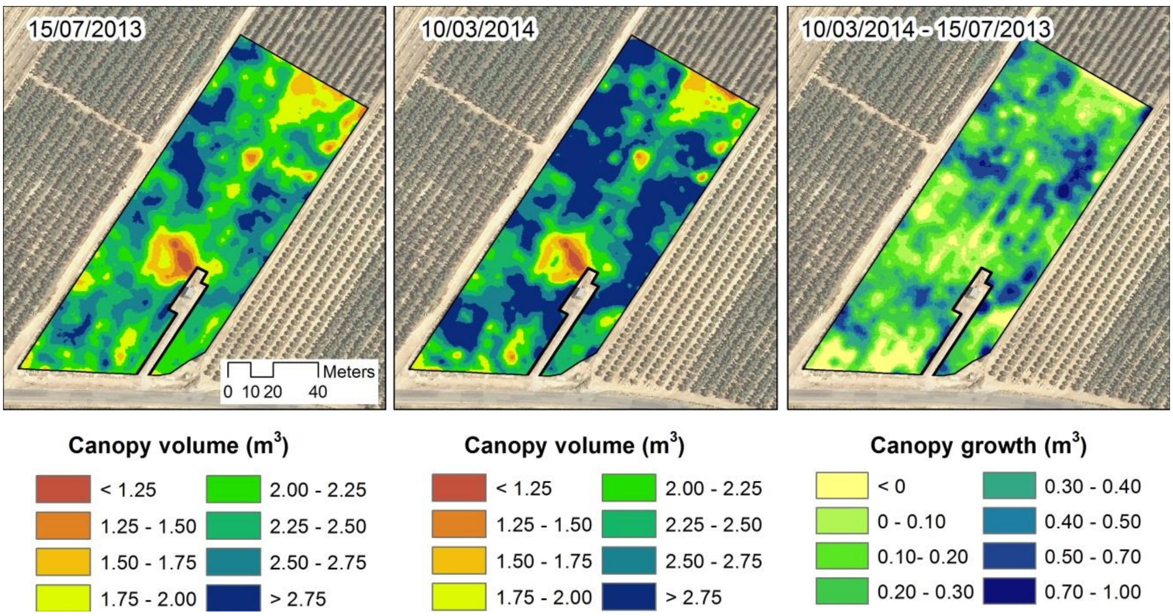

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Fig. 8 Canopy volume raster maps for two dates on a 1-m basis and their difference, representing autumn canopy growth (right)

Effect of the method to create the row point clouds

The different methods used to create the tree row point clouds from sensor data to compute canopy volume produced significantly different results, as seen in Table 2. Sensor readings obtained from two adjacent alleyways (i.e. Method 1 and Method 3) resulted in significantly lower canopy volumes than using data from four adjacent alleyways (i.e. Method 2 and Method 4). This may be explained by the different point of view of the sensor when scanning at 2.1 m from the row axis or when scanning the same row from 6.3 m. Additionally, although the manufacturer does not provide information on the beam cross section, it is to be expected to increase with distance, decreasing the ability of the system to detect gaps within the canopy. Another point is that distance to the target reduces vertical sampling resolution since the LiDAR sensor emits the beams in a radial way. That could also introduce differences in the canopy volume estimations. Moreover, using only the first return beams to compute the canopy volume (i.e. Method 1 and Method 2) produced significantly lower canopy volume values than when the second return beams were also used (i.e. Method 3 and Method 4). However, differences were smaller between Method 1 and Method 3, resulting in equivalent results for March 2014, when the canopy was bigger.

Table 2 Canopy volume mean comparison on a 0.1-m basis according to row point cloud creation method

Row point cloud creation method	April 2013 Mean canopy volume (m^3)	July 2013 Mean canopy volume (m^3)	March 2014 Mean canopy volume (m^3)
M1	0.194a	0.229a	0.250a
M2	0.218c	0.236c	0.257b
M3	0.197b	0.232b	0.252a
M4	0.248d	0.246d	0.273c

Mean values with different letters in columns are significantly different (Tukey-Kramer HSD, α = 0.05)

Comparison between MTLS and conventional canopy volume estimation methodologies

When comparing all the canopy volumes (all dates and blocks), a strong correlation (r=0.906) was found between the visual and semi-manual canopy volume estimations (VCV IRTA and VCM IRTA, respectively). Strong correlations (Table 2) were also found between them and their equivalent MTLS estimates (VCV LiDAR and VCM LiDAR), according to the four different methods used to create the row point clouds (Table 3). The correlations were estimated by restricted maximum likelihood (REML) method and all correlation coefficients have p-values <0.0001. In comparing the canopy volume mean values (Table 4), it is seen that the visual estimation of canopy volumes (VCV IRTA) produced larger values than other methods. Additionally, the use of image analysis together with a manual estimation of canopy width to estimate canopy volumes (VCM IRTA) was equivalent to most of the estimation methods except for visual estimations (VCV IRTA) and for Method 4 applied to one tree (VCM L M4). The inclusion of second return measurements in close adjacent rows (Method 3) results in the canopy volume means being closer to the reference value (VCM IRTA). From the results shown in Table 2 and Table 4, it may be recommended to only use first return data from close adjacent alleyways (Method 1) when creating the row point clouds owing to its simplicity. Although canopy volumes estimated from Method 1 and Method 3 can be considered equivalent (Table 4), in stages with low vegetation considering the second return data from close adjacent alleyways may be of interest since Method 1 and Method 3 produce slightly different results (Table 2).

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Table 3 Matrix of correlation coefficients between canopy volumes for all blocks and dates on a per tree basis.

	VCM IRTA	VCM L M1	VCM L M2	VCM L M3	VCM L M4	VCV IRTA	VCV L M1	VCV L M2	VCV L M3	VCV L M4
VCM IRTA[1]	1.000									
VCM L M1[2]	0.797	1.000								
VCM L M2[2]	0.710	0.976	1.000							
VCM L M3[2]	0.796	0.999	0.978	1.000						
VCM L M4[2]	0.558	0.882	0.953	0.889	1.000					
VCV IRTA[3]	0.906	0.822	0.771	0.824	0.659	1.000				
VCV L M1[4]	0.802	0.955	0.923	0.954	0.820	0.825	1.000			
VCV L M2[4]	0.720	0.935	0.943	0.936	0.886	0.776	0.979	1.000		
VCV L M3[4]	0.800	0.953	0.923	0.953	0.826	0.826	0.999	0.982	1.000	
VCV L M4[4]	0.568	0.839	0.896	0.845	0.935	0.669	0.876	0.947	0.885	1.000

[1] VCM IRTA: canopy volume estimated by image analysis and a manual canopy width for one tree of the block
[2] VCM L M_i: canopy volume obtained with the MTLS according to the different methods for one tree of the block
[3] VCV IRTA: canopy volume estimated visually as an average of two trees of the block
[4] VCV L M_i: canopy volume obtained with the MTLS according to the different methods for two trees of the block
The correlations were estimated by restricted maximum likelihood method and all have p-values <0.0001.

Table 4 Canopy volume mean comparison for all blocks and dates on a per tree (2.2 m section) basis, expressed in m^3

VCV IRTA	VCM L M4	VCV L M4	VCM L M2	VCV L M2	VCM IRTA	VCM L M3	VCV L M3	VCM L M1	VCV L M1
6.88a	5.89b	5.85b,c	5.42b,c,d	5.40b,c,d	5.33c,d	5.23d	5.21d	5.18d	5.17d

Values with different letters are significantly different (Tukey-Kramer HSD, α = 0.05)

Effect of wind on the canopy volume estimation

Canopy volume slices were computed from point clouds created from MTLS data obtained on a windy and a calm day occurring soon after, using the four methods. Overall means were compared according to the *wind condition* factor (i.e. windy and calm), and significant differences were found, around 0.001 m^3. When comparing all means according to the *wind condition* and the *method* factors, no significant difference was found between windy and calm conditions for each method (Table 5). However, when individual means from each method were compared, only M3 presented significant differences between windy and calm canopy volumes, around 0.002 m^3. This indicates that a 4 km h^{-1} wind does not introduce much inaccuracy when estimating canopy volume with MTLS, although in the field, leaves and branches were clearly swinging. That is very useful information in deciding whether to continue scanning or postpone operations when a light breeze starts blowing once scanning has already begun.

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Table 5 Canopy volume mean comparison in calm and windy (approx. 4 km h^{-1}) conditions on a 0.1-m basis according to the row point cloud creation method

Factors	Mean canopy volume (m^3)	Standard Deviation (m^3)	Minimum (m^3)	Maximum (m^3)	Coefficient of variation (%)	Median (m^3)
M1 windy	0.254a	0.076	0.000	0.571	30.05	0.254
M1 calm	0.253a	0.079	0.000	0.581	31.16	0.253
M2 windy	0.261c	0.077	0.000	0.575	29.53	0.260
M2 calm	0.260c	0.079	0.000	0.581	30.45	0.260
M3 windy	0.257b	0.077	0.000	0.727	30.04	0.256
M3 calm	0.254a,b	0.079	0.000	0.583	31.07	0.254
M4 windy	0.276d	0.078	0.000	0.749	28.43	0.275
M4 calm	0.276d	0.080	0.000	0.589	29.13	0.275

Mean values with different letters in columns are significantly different (Tukey-Kramer HSD, α = 0.05)

Tools for structural canopy characterization

Laser beam penetrability and light extinction

Figure 9a shows the distribution of the number of impacts as the laser beam penetrates the canopy from one side of the row. Initially, the number of impacts increased as the beams penetrated the canopy, reached a peak and then decreased rapidly towards the inside of the canopy. At first sight, the Poisson law does not conform to this type of distribution. However, it was possible to adjust the data to the Gaussian model described in Equation 4:

$$N = A \cdot exp\left[-\left(0.5 \cdot \left(\frac{d-B}{C}\right)^2\right)\right] \qquad (4)$$

where N is the number of impacts, d is the horizontal distance into the canopy, A is the height of the curve's peak, B is the position of the peak centre, and C (standard deviation) determines the width of the 'bell'. In this case, the model fit was very satisfactory (R^2 = 0.973; $RMSE$ = 183), and allowed for a possible interpretation of the behaviour of sunlight in this crop. In the first section, the sunlight could easily penetrate the canopy up to a distance of approximately 0.8 m (B = 0.785 m). Beyond this point into the canopy, light would have greater difficulty penetrating, which would explain why the flower and fruit production zones were concentrated within this 0.8–1.0 m layer of the outer part of the canopy. Figure 9b shows how the information supplied by the laser sensor (MTLS) can be interpreted in terms of lighting conditions for the canopy. Moreover, the Poisson law was still valid when only impacts belonging to the interior of the canopy were considered in Equation 2 (Fig. 9b) in accordance with previous research (Arnó et al. 2013; Walklate 1989). The goodness of fit (R^2 = 0.988; $RMSE$ = 115) was better than with the Gaussian model, and light extinction was corroborated by a negative coefficient (K = -0.041). Comparison of the extinction coefficients can be used to evaluate the effect of different pruning systems or different irrigation schemes on canopy structure and, consequently, on the lighting conditions. In short, agronomists will have new information that may be useful for improving farm management. This algorithm is not intended to be run on a real-time basis. This allows the user to focus on representative hedgerow sections of variable lengths rather than single scans as in Chen et al. (2013) and Wei and Salyani (2005).

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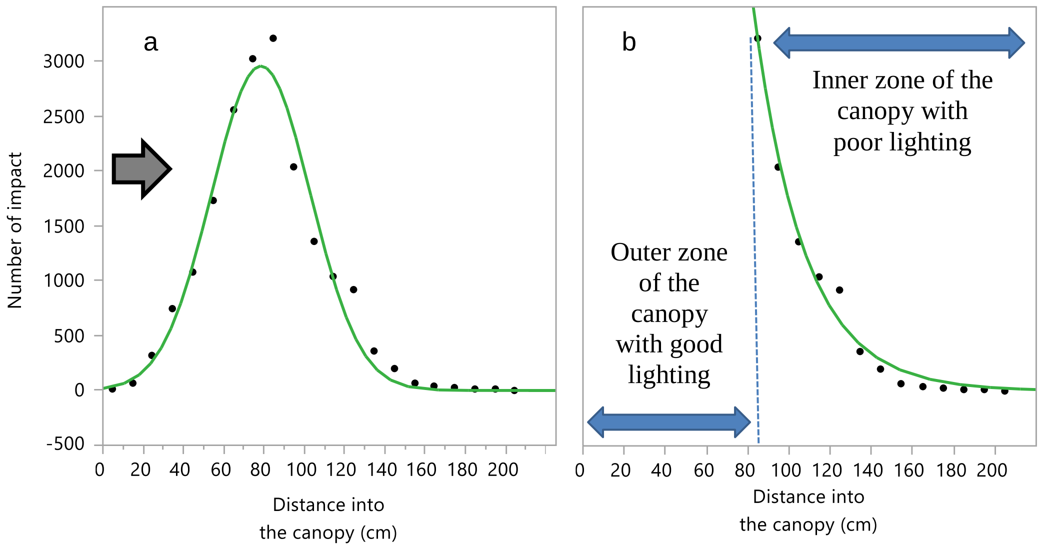

Fig. 9 (a) Gaussian distribution model of impacts as the laser beams penetrate the canopy from the scanning alleyway to the canopy interior (arrow), and (b) exponential modelling of the impacts inside the canopy

Laser beam interception and canopy leafiness and porosity

Laser beam interception depends not only on the canopy structure but also on the laser beam angle of incidence on the canopy. Such angle of incidence depends on the scanning side of the row and the sensor height (i.e. distance to the ground), since the MTLS mounts a radial LiDAR. The former is the reason why Figure 10 (left) shows differences in canopy row sides. Figure 10 (right) shows the spatial distribution of leafiness in the orchard at the full development stage (March 2014). Canopy leafiness information complements the information provided by the canopy volume map, since it provides information about what is inside the computed volumes. This is very relevant, since the canopy volumes are mainly filled with leaves, which are responsible for energy transformation in trees. Additionally, canopy leafiness is the opposite of canopy porosity, which is related to light penetration, canopy aeration to avoid fungal diseases and retention of sprayed foliar-absorbed plant protection products. Obtaining information on the canopy structure may lead to better farm management decisions. This algorithm may be run on a real-time basis, since it does not require much processing power or time, and is based on a per scan computation. Nevertheless, it takes into account more information than Wei and Salyani (2005), as they smoothed the canopy profile of each scan but discounted the beams going through the hedgerow.

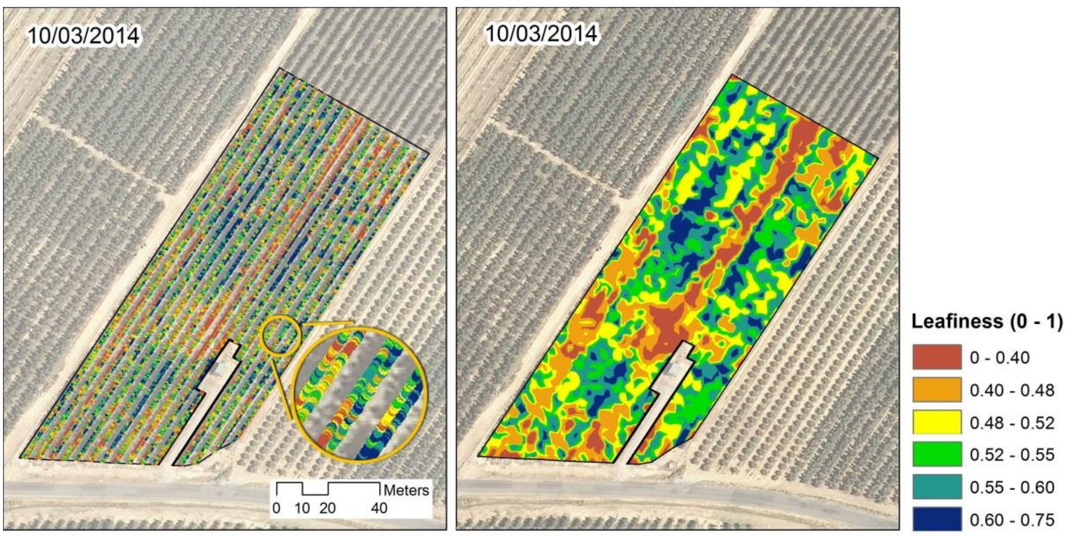

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Fig. 10 Canopy leafiness ratio values (left) and leafiness raster map (right) at full development stage

Accuracy of the system, implementation and other considerations

As the tools presented in this work are based on point cloud analysis, the only error source to be considered from the ones highlighted in Pallejà et al. (2010) is the LiDAR sensor orientation. Errors related to the sensor position and trajectory are overcome when using an RTK-GNSS receiver to locate the sensor. The results presented in this work are from data of a preliminary version of the MTLS. That version did not include any inertial measurement unit or stabilizer for the LiDAR sensor. Hence, sensor data may be affected by uneven ground. However, canopy volume estimations derived from MTLS data were consistent with those estimated on a semi-manual basis by horticultural researchers. The question is: Are the reference volumes accurate enough to be considered as ground-truth to be compared with much higher resolution measurements such as the MTLS data? The answer could be another question: How can canopy volume in the field be measured with high resolution and high accuracy? Nevertheless, the objective of this work was to compare the estimations obtained using conventional methods to assess canopy volume in research trials with LiDAR-based estimations.

The MTLS is being improved, and further trials are being done to improve the overall accuracy of the system. However, the data process and tools developed in this work would run regardless of the data source, although the results would be more accurate with more accurate georeferenced point clouds.

From a commercial implementation point of view, the developed MTLS is being designed with consideration for use on its own, attached to a tractor while the farmer performs other orchard operations such as mowing or spraying. Once driven around the whole orchard, the farmer could take it to the office, download the stored raw data, and run the associated process software to obtain the descriptive statistics and raster maps. Farmer associations and/or co-operatives could own such a system and use it in turn so that no single farmer has to bear all the cost. The cost of the MTLS components has been decreasing recently, and the capabilities are being enhanced, so it is not irrational to consider ownership of an MTLS on a per farm basis. However, a balance has to be found between highly accurate but very expensive systems and affordable ones with lower specifications. Further trials are planned in order to determine the accuracy and resolution requirements for agricultural uses of MTLS.

MTLS and the associated data processing are a potential solution to help farmers make better management decisions. The possibility of easily obtaining reliable information on the canopy geometry and structure may favour the development of decision support systems either for irrigation, fertilization, or canopy management, as well as for variable rate application of agricultural inputs in the framework of precision fruticulture/horticulture.

Other alternatives to create point clouds, such as mounting consumer-grade RGB cameras or accurate LiDAR systems on UAVs are also of interest. Many questions arise when comparing them to MTLS, apart from the obvious ones related to work capacity. (1) Point densities in MTLS clouds may be greater than those obtained from UAVs (Díaz-Varela et al. 2015; Torres-Sánchez et al. 2015; Zarco-Tejada et al. 2014). However, it is unclear which densities would be optimal. Some approaches and recommendations have been published for forestry applications, but to the best of the authors' knowledge, none have been proposed for agriculture. Point cloud densities may be even higher for stationary terrestrial laser scanners, and point clouds may be fused with RGB information as described in Moorthy et al. (2011) but this type of instrument are much more expensive than the MTLS developed. (2) Penetration into the canopy seems to be shallower in digital surface models derived from photo-reconstruction, while many laser beams may go through the canopy when using MTLS. Canopy penetration is a key point for extracting information on canopy porosity. (3) What is the best point of view to characterize the canopy? Sideways in a radial manner such as in MTLS or from a nadir view as in UAVs? A comparison of MTLS and UAV-derived agricultural canopy characterizations would be of interest, since technological progress leads to automated operation and data processing, but users will still have to choose the appropriate working parameters to extract accurate and reliable canopy information.

Conclusions

The MTLS and tools developed in this study have proved to be a good solution to rapidly and objectively obtain geometric and structural parameters from tree row crop canopies and their spatial distribution within the orchards. MTLS-derived high spatial resolution information about the canopy height, width and volume for the whole orchard is much more accurate than trying to find representative values estimated using a tape or more sophisticated methods, such as those currently being used by farmers and researchers.

Most canopy volume results derived from the self-developed mobile terrestrial laser scanner measurements were equivalent to the semi-manual estimations (by image analysis and manual canopy width measurement) performed in fruticulture/horticulture research trials. That makes MTLS a good alternative to current research methods for canopy volume estimations.

The method used to create the tree row point clouds affects the computed canopy parameters in a minor degree. Owing to its simplicity, it may be recommended to only use first return data from close adjacent alleyways (Method 1) to create the row point clouds. Regarding the wind, although it is not recommended to scan orchards in windy conditions, breezes up to 4 km h^{-1} do not alter canopy volume estimations significantly, and would allow completion of scanning operations.

Besides canopy volume, the proposed tools to estimate geometrical (i.e. canopy height, width and growth) and structural parameters (i.e. canopy light penetrability and canopy leafiness and porosity) provide interesting high resolution information for monitoring the canopy. Such information cannot be feasibly gathered manually with sufficient spatial and temporal resolution in commercial farms. Additionally, digital raster maps are also a good tool to present and analyse the spatial variability of the extracted parameters. Further work needs to be done in order to validate these tools.

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