Terrestrial laser scanning to estimate plot-level forest canopy fuel properties

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\textbf{A B S T R A C T}

This paper evaluates the potential of a terrestrial laser scanner (TLS) to characterize forest canopy fuel characteristics at plot level. Several canopy properties, namely canopy height, canopy cover, canopy base height and fuel strata gap were estimated. Different approaches were tested to avoid the effect of canopy shadowing on canopy height estimation caused by deployment of the TLS below the canopy. Estimation of canopy height using a grid approach provided a coefficient of determination of $R^2 = 0.81$ and an RMSE of 2.47 m. A similar RMSE was obtained using the 99th percentile of the height distribution of the highest points, representing the 1% of the data, although the coefficient of determination was lower ($R^2 = 0.70$). Canopy cover (CC) was estimated as a function of the occupied cells of a grid superimposed upon the TLS point clouds. It was found that CC estimates were dependent on the cell size selected, with 3 cm being the optimum resolution for this study. The effect of the zenith view angle on CC estimates was also analyzed. A simple method was developed to estimate canopy base height from the vegetation vertical profiles derived from an occupied/non-occupied voxels approach. Canopy base height was estimated with an RMSE of 3.09 m and an $R^2 = 0.86$. Terrestrial laser scanning also provides a unique opportunity to estimate the fuel strata gap (FSG), which has not been previously derived from remotely sensed data. The FSG was also derived from the vegetation vertical profile with an RMSE of 1.53 m and an $R^2 = 0.87$.

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\section{1. Introduction}

An accurate, spatially explicit, description of fuels is critical to prevent fire ignition and propagation, to model fire behaviour and to reduce fire effects since, amongst the fire fundamentals triangle vertices, fuels are the only component that humans can modify, through thinning or prescribed fires, to reduce fire hazard (Koutsias and Keris, 2003; Salas and Chuvieco, 1994). In order to assess crown fire hazard as well as to design appropriate silvicultural treatments and prioritize treatment areas to reduce crown fire potential (Keane et al., 2005), an accurate description of canopy fuel characteristics is necessary.

Several canopy characteristics have been found to be related either directly or indirectly to the occurrence and behaviour of crown fires, and form the input for a number of fire behaviour and effects models such as NEXUS (Scott, 1999), FARSITE (Finney, 1998) and FLAMMAP (Stratton, 2006). Canopy height (CH) is an important canopy property since it indirectly influences crown fire occurrence through its effect on wind speed reduction and fuel moisture content (Reinhardt et al., 2006) as well as lofting of embers from a flaming tree (Albini, 1979a). Several definitions of canopy height can be found in the literature. Scott and Reinhardt (2005) defined it as the average height of the tallest five trees in the plot; Reinhardt et al. (2006) proposed to compute it as the highest point at which the CBD exceeds a given threshold, and Reeves et al. (2009) defined CH as the basal area-weighted mean height of the dominant and co-dominant trees within each 30-m grid cell used in the LANDFIRE project. Canopy cover (CC) represents the proportion of the forest floor that is covered by the vertical projection of the tree crowns. This variable characterizes the horizontal continuity of canopy fuels, affecting the potential development and propagation of crown fires, and it is used together with CH in fire modelling to estimate the wind reduction factor and fine fuel moisture content (Albini and Baughman, 1979b; Rothermel et al., 1986). Canopy base height (CBH) is an important parameter in modelling the transition of surface to crown fires since it determines the distance between the canopy and the ground. Several definitions of CBH can be found in the literature. Finney (1998) defined CBH as the vertical distance from the ground to the base of live crowns, whereas Ottmar et al. (1998) defined it as the height of the lowest continuous live or dead
branch material of the tree canopy. Within the context of assessing the risk of crown fires, CBH has been defined as the lowest height above the ground at which there is sufficient canopy fuel to allow vertical propagation of fire through the canopy (Scott and Reinhardt, 2001). This minimum amount of fuel, which is represented by the minimum canopy bulk density (CBD) value required to propagate the fire to the crown, has been established somewhat arbitrarily using a wide range of values, for example, 0.011 kg/m$^3$ (Keane et al., 2006), 0.04 kg/m$^3$ (Mitsopoulos and Dimitrakopoulos, 2007) and 0.037 kg/m$^3$ (Sando and Wick, 1972). Despite the fact that this latter definition can be considered appropriate for fire risk assessment, it cannot be directly determined in the field.

In the literature it is often the case that the terms crown and canopy are used indistinctly to describe canopy fuel characteristics; however, it should be remarked that the term crown refers to individual tree characteristics whereas the term canopy makes reference to stand characteristics.

Estimation of canopy fuel properties has relied mainly on field measurements using direct or indirect methods. Direct methods require destructive sampling of trees to determine biomass by component (live or dead fuels) and size class (Küçük et al., 2008; Mitsopoulos and Dimitrakopoulos, 2007; Reinhardt et al., 2006; Scott and Reinhardt, 2005) allowing for the generation of allometric equations to derive these properties from inventory data. Direct methods are generally difficult to implement in an operational way and so non-destructive indirect methods, based on optical data or measurements readily available to forest managers (Reinhardt et al., 2006), have been developed.

In the last decade airborne LiDAR systems both, discrete return and full waveform have been proved useful to estimate canopy fuel properties. For example, Andersen et al. (2005) established an empirical model relating LiDAR metrics to field-based canopy height, which was defined as the highest height at which the canopy fuel density was greater than 0.011 kg/m$^3$. Skowronski et al. (2007) also found that mean canopy height could be accurately approximated using the 80th percentile of all LiDAR returns. A voxel-based approach was proposed by Popescu and Zhao (2008) to estimate the CBH of individual trees, by fitting a fourth degree polynomial to the vertical profile of individual trees and finding the first inflection point after the maximum of that polynomial. Riaño et al. (2003, 2004) defined the CBH as the height at which the 1st percentage of canopy hits occurred. Similarly, Holmgren and Persson (2004) computed CBH as the height of the highest 0.5 m height interval containing less than 1% of the total number of non-ground laser returns within a crown area. CBD has been effectively estimated from LiDAR data by deriving regression models (Andersen et al., 2005; Hall et al., 2005) and by relating foliage biomass to canopy volume (Riaño et al., 2003, 2004). CC can be derived from LiDAR data as the proportion of canopy returns to all returns, or by the ratio of the intensity of canopy returns to the intensity of all returns within a plot (Garcia et al., 2010; Morsdorf et al., 2006). More recently, the capability of ground-based or terrestrial LiDAR systems (TLS) to estimate vegetation properties such as diameter at breast height (DBH), tree height, or timber volume, has been shown (Henning and Radtke, 2006; Hopkinson et al., 2004; Watt and Donoghue, 2005). Parameters such as leaf area index (LAI) (Hosoi and Omasa, 2006; Lovell et al., 2003) and gap fraction (Danson et al., 2007) have also been successfully estimated using TLS systems. Loudermilk et al. (2009) investigated the capability of TLS to characterize surface fuels at individual plant and plot scales. They found that fuel volume estimated using point-intercept fuel sampling was significantly larger than the volume derived from TLS data at an individual scale but not at a plot scale. They also found that surface fuel height distribution could be measured more reliably using TLS data than point-intercept measurements. Given the capacity of TLS to provide very high-density three-dimensional point data, they represent an opportunity to obtain information on vegetation structure that is difficult to gather from either destructive or any other field-based measurement.

The main objective of this work was to evaluate the potential of TLS data to characterize forest canopy fuel properties at plot level. Specifically, canopy height and canopy cover were estimated. In addition, an automatic procedure was developed to derive the canopy base height from a voxel-based vegetation vertical profile (VVP). Finally, the fuel strata gap (FSG), which represents the distance between the surface and the canopy fuel strata, was also estimated.

2. Methods

2.1. Study area

The study was carried out in Delamere Forest (53.22597 N; 2.6429 W), which is managed by the U.K. Forestry Commission and is located around 40 km south-west of Manchester, within the county of Cheshire, covering 972 ha (Fig. 1). The study area is mainly composed of homogeneous stands of Scots pine and larch, as well as mixed stands of oak and birch. Eight circular plots with a radius of 10 m were selected and located in several deciduous and coniferous stands within the study site, representing different species and development stages. The deciduous stands, plots D1, D2 and D3 were composed of birch (Betula spp.), oak (Quercus spp.) and Sweet chestnut (Castanea sativa) and were more than 100 years old. The plot density as expressed by basal area ranged between 23.3 and 44.2 m$^2$ ha$^{-1}$. The coniferous stands, plots C1 and C2 were composed of Scots pine (Pinus sylvestris) and Corsican pine (Pinus nigra var. maritima) aged 65 years, with a plot density of 36.9 and 40.6 m$^2$ ha$^{-1}$, respectively; plot C3 was composed of Corsican pine (Pinus nigra var. maritima) and Weymouth pine (Pinus strobus) aged 40 years, with a density of 39.1 m$^2$ ha$^{-1}$; and finally plots L1 and L2 were composed of younger Japanese larch (Larix kaempferi) aged 30 years and a plot density of 25.1 and 44.8 m$^2$ ha$^{-1}$, respectively.

![Fig. 1. Location of the study area.](image)
2.2. Field data

Field measurements were carried out in July 2009 and August 2009. For all trees in the target plot the diameter at breast height (DBH), crown diameter, height and crown base height were measured using a fiberglass tape and a Suunto PM5 clinometer. The crown base height was determined as the height of the lowest continuous live branches of the tree canopy. The crown diameter was defined as the average value of two perpendicular measurements taken from the edges of the projected canopy. From these field measurements the vertical canopy profile, which represents the vertical distribution of the crown volume within the plot, was generated following Drake et al. (2002). Thus, each crown was assumed to have a cylindrical shape and its size was determined by the crown length (defined as the distance from the tree top to the base of the crown) and the crown diameter. Subsequently, the resulting crown volumes were segmented into vertical sections of 30 cm. This bin size was considered adequate to represent the vertical distribution of vegetation at plot level. Finally, the cross-sectional area of the intersected crowns within 30 cm vertical bins was summed up, resulting in the canopy vertical profile.

In order to characterize the understory vegetation, four perpendicular (N, S, E, W) transects were performed from the centre of the plot, and the height and diameter of each individual in contact with the tape was measured (Schreuder et al., 2004). Afterwards, the same procedure used to derive the canopy profile was applied to the understory vegetation, also approximating each individual as a cylinder. Finally, from the distribution of understory vegetation and the canopy profiles the VVP was derived for each plot. Fig. 2 shows an example of the VVPs generated for two characteristics plots of the study area.

2.3. Ground-based LiDAR data acquisition

TLS data were acquired in April 2009 at the eight target plots. The plot location was surveyed using a Magellan ProMark3 GPS with differential correction based on data from the permanent Ordnance Survey active GPS network. The TLS system used was a Riegl LMS-Z390i, which operates at a wavelength of 1550 nm, and can quickly and accurately acquire 3D images up to a range of about 400 m. The laser beam is 10 mm in diameter as it leaves the device and has a beam divergence of 0.3 mrad, which equates to a beam 13 mm wide at 10 m range. Following the methodology proposed by Danson et al. (2007) the scanner was mounted on a tripod at 1.4 m above the ground looking at the zenith, that is with an inclination angle of 90°. First returns were recorded within a scan angle of approximately 80° and a frame scan angle of 180°, with an angular resolution of 0.1 degrees. In an attempt to cover the whole of the plot, the scanner was rotated by 90° and a second orthogonal scan was performed. For 6 out of 8 plots, and immediately after the scans were performed, spatially coincident hemispherical photographs were collected using a Nikon D70s digital camera with a calibrated hemispherical lens.

2.4. Ground-based LiDAR data assessment

Prior to the derivation of the variables of interest an exploratory analysis of the data was performed to better understand the data collected and to assess the potential of TLS data to derive important parameters that characterize canopy fuels at a plot level (Fig. 3).

Fig. 3 shows how the upper parts of the canopies presents a lower concentration of returns, although for plots D1, D2 and D3, which presented a canopy cover of less than 50%, the number of returns reaching the upper part of the canopy is higher; that is the effect of the occlusion caused by the lower canopy elements was smaller. The base of the canopies is easily identified for plots C1, C2 and C3 and so, the canopy base height (CBH) may be determined. Nevertheless, for the rest of the plots the continuity observed between the canopy and the understory vegetation, hampers the identification of the base of the canopy. Moreover, for plots C1 and C2 two fuel layers can be clearly distinguished and the fuel strata gap can be identified without difficulty. On the other hand, plots L1 and L2 showed a high concentration of returns in the centre and lower parts hampering the identification of canopy characteristic.

2.5. Canopy height

Canopy height was computed from field data as the average height of those trees with a DBH ≥ 10 cm, since it was considered to provide a better representation of the canopy height within a plot than averaging the height of just a few trees.

In order to estimate the canopy height from the TLS data, the point cloud was segmented into ground and non-ground returns. From the ground returns, a digital elevation model (DEM) was constructed using a spline interpolation. The height above the ground of the non-ground returns was computed in relation to the DEM. With these data, three different approaches were used to estimate the canopy height. First, the mean, the median, and the 95th and 99th percentiles were derived from the distribution of the canopy returns within the plot as is commonly done using ALS data. Canopy returns were considered as those with a height greater than the canopy base height obtained for each plot (described in Section 2.7). The 99th percentile was used instead of the maximum height to avoid possible outliers. The second approach estimated the canopy based on those points above the 99th percentile of the height distribution. Despite keeping only the 1% of the points, still a large amount of returns (more than 4000) remained for each plot given the high density of TLS data. Subsequently, the mean, the median

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**Fig. 2.** Vegetation vertical profiles for two characteristics plots. **Left:** plot C1 (Scots pine and Corsican pine); **right:** plot D1 (Birch, Oak and Sweet chestnut).
and the 95th and 99th percentiles were derived from these highest points. For the third approach, a canopy height model (CHM) with a cell size of 50 cm was created for each plot by selecting the highest point within each cell. Next the average and median height and the 95th and 99th percentiles were calculated from the CHM. The latter two approaches were expected to be less sensitive than the first method to the high concentration of returns in the lower parts of the canopy due to the data acquisition configuration, which could bias the estimation of the canopy height from TLS data. Moreover, the second and third methods are also independent of the accuracy in the determination of the CBH.

2.6. Canopy cover

Canopy cover has been successfully estimated from airborne LiDAR as the proportion of the canopy returns over all laser hits (Morsdorf et al., 2006; Riaño et al., 2004). Using a terrestrial LiDAR system, Danson et al. (2007) developed a model to estimate gap fraction, which compares the number of returns recorded by the system with the number of pulses that would be recorded if each pulse emitted by the system had a return.

The approach used in this study to estimate canopy cover used a grid of occupied/non-occupied cells. Consequently, TLS returns with a height over 1.4 m, which was the height of the TLS and the camera during data acquisition in the field, were arranged in an x-y grid and those cells occupied by at least one point were assigned a value of 1, whereas those cells that were not occupied and therefore represented a gap, were given a value of 0. From this binary image CC was calculated using the following expression

\[ CC = \frac{\sum \text{Occupied cells}}{\sum \text{Plot cells}} \]

where \( \sum \text{Occupied cells} \) represent the number of cells within the plot including at least one point and \( \sum \text{Plot cells} \) represent the number of cells contained in the plot.

Because a cell was considered to be completely occupied although only one return was contained within it, the effect of the pixel resolution in the estimation of canopy cover was assessed using several cell sizes: from 50 cm to 10 cm at 10 cm intervals, and from 5 cm to 1 cm at 1 cm intervals.

Since the canopy cover represents the vertical projection of the crowns of the trees, several authors have pointed out the suitability of limiting the computation of fraction cover to a subset of zenith angles instead of the whole dataset when using optical indirect methods (Keane et al., 2005; Scott and Reinhardt, 2005). Thus, after identifying the optimal cell size, CC was estimated for different zenith angles from 5° to 60° at 5° intervals to find the most appropriate zenith angle to be used.

CC estimates derived from LiDAR data were compared with CC derived from hemispherical photographs processed with CAN-EYE and acquired for six out of eight plots.

2.7. Canopy base height

Canopy base height was automatically identified from plot-level vegetation vertical profiles. In order to generate the VVP, the laser returns were assigned to 0.3 m × 0.3 m × 0.3 m voxels, and a binary approach was used by considering occupied/non-occupied voxels (Hopkinson et al., 2004; Hosoi and Onasai, 2006). Fig. 4 shows a representation of occupied voxels within plot C1.

Subsequently, it was possible to compute the frequency of returns as well as the CC at each height interval. Fuel strata were identified by considering a minimum CC necessary to propagate a fire to the crown and the CBH was considered as the minimum height of the highest fuel stratum.

The algorithm developed can be summarized as:

i. Generation of the VVP at 0.3 m height intervals.
ii. Smoothing of the VVP by applying a moving average. Two filter sizes were tested, namely a 3 height interval moving average and a 5 height interval moving average.
iii. Application of a CC threshold: a minimum CC threshold was applied as equivalent to the minimum amount of fuel required to propagate fire vertically through the canopy. Thus, those height intervals having a fraction cover < 5% were set to 0. This threshold
was somewhat arbitrary in the same way that the minimum CBD values that are commonly applied to define the CBH; therefore a second CC threshold of 10% was also tested.

iv. Identification of fuel strata: the height at which each vegetation layer occurred (CC ≥ 5%) established the limits of the fuel strata present in the plot.

v. Selection of CBH: CBH was considered as the lower limit of the upper fuel stratum found.

Fig. 5 shows an example of the application of the algorithm to plot C1. This plot was selected to be representative since the canopy characteristics were easily identified. The first image (top left) shows the VVP derived using height bins of 30 cm. The top right image shows the VVP after smoothing using a 0.9 m moving average. The bottom left image represents the CC threshold applied to differentiate different fuel strata (dashed line) as well as their vertical limits (horizontal lines). Finally, the bottom right image shows the final fuel strata identified.

Similarly, a field-based CBH was calculated from the VVP derived from field measurements, and was used as the CBH reference value for comparison with the CBH estimated using TLS data.

2.8. Fuel strata gap

The fuel strata gap was defined by Cruz et al. (2004) as the distance between the top of the surface fuel stratum and the bottom of the canopy stratum. This variable can better describe the crown fire potential since it represents the distance between the fuel strata,
whereas the CBH represents the distance between the canopy fuel stratum and the ground. The FSG variable has not been previously derived from remotely sensed data and use of TLS data represents a unique opportunity to estimate it.

From the VVP, and using the algorithm developed to estimate the CBH, it was also possible to determine the existence of different fuel layers and the distance between them. Thus, the FSG was considered as the gap between the CBH and the upper limit of the fuel stratum below the CBH. This approach provided estimation at a plot level of the FSG that was compared to the FSG derived from field measurements.

3. Results

3.1. Canopy height

Table 1 shows the result of CH estimated from field measurements and from terrestrial LiDAR. It also shows the root mean square error (RMSE) and coefficients of determination ($R^2$).

As can be seen from this table, the metrics derived from the height distribution of the plot canopy returns underestimated the canopy height. Height estimations using this method are biased by the large amount of returns from the lower parts of the canopy, causing a large underestimation. The 99th percentile yielded a coefficient of determination ($R^2 = 0.47$, $p$-value $> 0.01$) and the lowest error with an RMSE of 5.66 m, representing 18% of the highest mean height measured in the field. As for the second approach used, TLS estimates of the canopy heights were closer to the field measurements. Again the 99th percentile of the highest points provided the lowest error with RMSE of 2.94 m (9.5% of the highest field measurement). The second and third approaches showed similar results in terms of RMSE but the 99th derived from the CHM yielded higher coefficient of determination ($R^2 = 0.81$, $p$-value $< 0.01$) and the RMSE increases again and the finest resolution gives the largest error (RMSE = 44.68%).

The effect of the resolution is also represented in Fig. 7, which represents the projection of the LiDAR returns on the XY plane (left), the result of the grid approach at a coarse 30 cm resolution (centre).
and at a higher 5 cm resolution (right) for plot D1. It is clear that the image at a resolution of 5 cm more closely resembles the image generated from the horizontal projection of the canopy returns. It also shows a similar distribution of canopy gaps whereas for the coarser resolution image almost all pixels are occupied and consequently, only the larger gaps can be identified.

As for the effect of the zenith angle on CC estimations using a pixel resolution of 3 cm, the RMSE ranged between 15.81% for the largest zenith angle of 60° and 24.22% for the smallest zenith angle of 5° (Table 3). Small differences of around 2% were found for zenith angles between 10° and 50°. Compared to hemispherical photograph estimates, it can be seen that TLS overestimated CC for all zenith angles in plots D1 and D3, and in almost all zenith angles for plot C3. For plots C1 and L1 an underestimation of the CC was observed for almost all zenith angles considered, whereas plot L2 presented a clear underestimation, with values higher than 40%.

3.3. Canopy base height

Table 4 presents the results of the canopy base height obtained applying the segmentation of the vertical canopy profile using a filter width of 3 height intervals, which provided the optimum results. Differences with field measurements ranged between 0.9 m and 14.7 m and the RMSE was 5.95 m. If plot L2, which gave the highest error, was not considered the RMSE decreased significantly to 3.09 m, and the coefficient of determination between estimated and observed CBH increased from $R^2 = 0.41$ to $R^2 = 0.86$ ($p$-value < 0.001).

3.4. Fuel strata gap

Table 5 presents the FSG estimated for each plot using LiDAR data and that derived using field measurements. As with the CBH, plot L2 presented the largest error. When this plot was excluded from the analysis, the RMSE was reduced from 5.29 m to 1.53 m, and the coefficient of determination increased from $R^2 = 0.09$ to $R^2 = 0.87$ ($p$-value < 0.01).

### Table 3

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<th>Zenith angle limit</th>
<th>Plot C1</th>
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### Table 4

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### Table 5

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RMSE = 5.95
RMSE* = 3.09

* Without considering plot 6.

### Table 3

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<th>Plot D3</th>
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4. Discussion

4.1. Canopy height

The underestimation of canopy height found for the first approach, which used the metrics derived from the canopy returns, can be explained by the bottom-up configuration employed in this study. As a consequence of the occlusion caused by lower parts of the canopy the upper canopy is under-sampled. ‘Soft’ targets such as vegetation canopies may produce multiple signals, and by recording only first returns the information that could be gathered from higher parts of the canopy is missed. The use of the height distribution of the points above the 99th percentile or metrics derived from the CHM greatly reduced the effect of canopy shadowing. This could be explained by the very high density of points, which increases the probability of the laser beam reaching the highest parts of the canopies. In addition, the use of a grid approach allows for a more detailed description of the canopy surface reducing the bias in height estimation that could arise from the presence of an exceptionally tall tree, which would bias the height estimation upwards. Lovell et al. (2003) pointed out the importance of ensuring that the returns used in calculating the mean height correspond to different trees in order to avoid this bias. The accuracy of the CHM method (RMSE = 2.47 m) is somewhat higher than that obtained by Maas et al. (2008) using TLS data, who at a plot level reported an RMSE that ranged between 3.2 m and 4 m. Slightly more accurate results were obtained by Hopkinson et al. (2004) who found an underestimation of 1.5 m. The higher accuracy in the latter study is explained by a different scan configuration for data acquisition, with multiple scans taken from several locations outside the plot.

Although the number of plots sampled was small, the correlations between TLS-derived and field-based canopy heights were statistically significant except for the first approach (p-value > 0.05) and so, these results provide useful insights into the potential of the TLS to estimate canopy height.

4.2. Canopy cover

It was found that the errors in canopy cover estimates diminished as the resolution of the sampling grid increased up to 3 cm and for higher resolutions the errors increased again. This can be explained by the angular resolution used, 0.1°, which at a range of 10 m means that the distance between two points would be 1.75 cm. Therefore, pixels of 1 cm would be smaller than the distance between points causing underestimation of the canopy cover because CC is computed as the proportion of occupied pixels. Although this effect could be partly compensated by the broadening of the footprint with the distance, this increase is smaller than the increase in separation between returns at the same distance. For coarser resolutions the overestimation found is a consequence of the rasterization process applied (Van der Zande et al., 2006), since a pixel is considered as completely occupied even though only one return may have occurred in that cell.

As for the effect of the zenith angle, the largest errors were found for the smallest zenith angle (up to 5°). When such a small angles are considered, differences between CC estimated from hemispherical photographs and from TLS can be caused by misregistration between them or if one of the systems is not well levelled. These errors are partly compensated when applying larger zenith angle thresholds.

Another factor that may explain the differences between hemispherical photographs and TLS estimates of CC is the shadowing caused by lower canopy material that affects not only to the canopy height estimation but also to the derivation of CC since the upper canopy is partly missed and therefore, the amount of material in the higher parts of the canopy is underestimated. Occlusion also affects the outer parts of the plots due to the shadowing caused by trees closer to the instrument. Moreover, although TLS scans were carried out under calm wind conditions, even a slight wind could cause substantial movement of the canopy elements, especially the foliage, and would affect the results of both, the hemispherical photographs and the TLS since they were not collected simultaneously.

The results are also affected by the fact that the hemispherical photographs and the TLS might sample different areas depending on the stand density. More specifically, considering a zenith angle of 55° and a distance of 20 m, any tree with a height of at least 14 m would be within the field of view of the hemispherical photographs if they are not occluded by trees closer to the point of view. Taking into account that the mean height of the plots was higher than 15 m this means that the hemispherical photographs could include trees further than the boundaries of the plot, whereas the TLS data were clipped to 10 m.

There also some factors related to the hemispherical photographs that could explain the differences found, such as photographs taken under sub-optimal sky conditions, which could cause an underestimation of the canopy cover (Zhang et al., 2005), or the use of automatic exposure settings and manual image thresholding (Danson et al., 2007; Solberg et al., 2009). These variables affecting hemispherical photographs will introduce some differences with CC estimated from TLS data.

4.3. Canopy base height

Canopy base height was systematically underestimated. This underestimation could be explained because in the field the canopy base height was measured at the point where the lowest living branch inserted into the tree so the inclination of branches was not taken into account, which would reduce the canopy base height. Inclination of branches is captured with TLS data since returns may correspond to different parts of the branches. The generation of the VVP also affects the estimation of the CBH. Thus, when generating the VVP from field data the canopy data was collected from the lowest continuous living branches and so, dead branches were not included. Nevertheless, the TLS data used to generate the VVP was based on range measurements only and thus, it was not possible to distinguish dead from living branches, which in some cases resulted in a continuous layer. The use of intensity data along with range data could help in distinguishing dead from living canopy material. Smoothing of the VVP, which is dependent on the width of the filter applied also affected the results. Likewise, the CC threshold applied greatly affected the result. The threshold applied was based on the critical CBD values used by Mitsopoulos and Dimitrakopoulos (2007) and Scott and Reinhardt (2005), where the threshold used represented approximately 5% of the CBD of the stand with the highest CBD. Although there was no direct relationship between CC and CBD, the same proportion was applied to the CC since the critical CBD values commonly used are defined arbitrarily. Application of a more restrictive threshold of CC ≥ 10% provided worse CBH estimations (results not shown).

The coefficient of determination found in this study (R² = 0.86) was higher than that obtained by other researchers using airborne systems (Andersen et al., 2005; Holmgren and Persson, 2004; Popescu and Zhao, 2008) as would be expected given the more favourable point of view of TLS to measure the CBH. Although Holmgren and Persson (2004) and Popescu and Zhao (2008) reported lower RMSE values, it is worth noting that these values referred to those trees correctly detected by LiDAR, rather than all trees within the plot. The higher RMSE found in this study is also consequence of two plots with a high density of dead or isolated branches in the lower canopy that were not distinguished by the LiDAR data, so that the estimated CBH was 0.
4.4. Fuel strata gap

Compared to field measurements, TLS underestimated FSG, however, in terms of modelling the risk of transition from surface to crown fire, underestimation of FSG might be less problematic than overestimation of this variable. As this variable is computed from the CBH previously derived as well as the height of the surface fuel stratum, its accuracy is highly dependent on the accuracy with which the different strata are established.

The presence of dead branches could affect the estimates of FSG and, although they were not considered during the field work in some cases they can represent ladder fuels, which were defined by Ottmar et al. (1998) as “the height of the lowest live or dead branch material that could carry fire into the crown” reducing the distance between the surface and the canopy fuel strata.

5. Conclusions

This study represents the first attempt to assess the potential of a terrestrial LiDAR system to derive important canopy fuel characteristics at a plot level. Since the output results from fire behaviour and effects models are dependent on the quality of the input canopy characteristics, development of accurate, spatially explicit methods is needed. TLS data allow for a more precise description of the distribution of canopy material, which could help in modelling canopy fuels to improve the results of crown fire behaviour models.

Canopy height derived from the terrestrial system is generally underestimated, mainly due to the shadow caused by lower branches. This effect can be particularly important due to the acquisition setting used. Nevertheless, the use of metrics derived from the height distribution of the highest points, or metrics derived from the CHM partly reduced this effect.

Canopy cover was estimated using a binary approach of occupied/non-occupied pixels. Nevertheless, this approach is very dependent on the cell size used, with the optimum size being related to the angular scan resolution used (0.1°). It was also found that the zenith angle used influenced the results, especially for smaller zenith angles. The effect of the zenith angle remained quite constant between 10° and 50°.

A simple method was derived to estimate CBH from the vegetation vertical profiles derived from an occupied/uncorrelated voxels approach. This method permitted not only estimation of the CBH but also to identify the different fuel strata present in the plot and consequently to estimate the FSG. This variable has not been previously estimated from remotely sensed data and, although less commonly used in fire behaviour models than CBH, it can better describe the potential transition from a surface to a crown fire due to the fact that it represents the distance between the canopy and the surface fuel strata.

Given the capacity of TLS systems to provide a dense three-dimensional point clouds, they are suitable to represent the distribution of the fuels, both horizontally and vertically.

Although the number of plots used in this study was small, the range of canopy types and the adoption of a common measurement approach provide a clear indication of the potential of TLS systems to characterize canopy fuels. TLS data have also the potential to be used as a means to validate ALS measurements, although more research is needed in this area, particularly because the different perspective of the data acquisition will cause bias in the sampling of the vegetation, downwards and upwards respectively. Also, the effect on the estimation of canopy fuel characteristics of different TLS data acquisition designs, such a lateral sideview observations, or observations of plots from multiple viewpoints, to reduce the occlusion effect, requires more investigation.

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References


