Canopy characterization of sweet chestnut coppice in the north of Spain from lidar data

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Abstract
The Leaf Area Index (LAI) is a key parameter that helps to understand the connection between canopy structure and ecosystem functions. In this study, the main aims were to examine the impact of forest management on canopy structure using LiDAR data to characterize the canopy vertical profile, as well as to develop LAI models and an LAI mapping tool for sweet chestnut (Castanea Sativa Mill.) coppice. Twenty-one circular plots (r = 10 m) were established, each of which was submitted to one of the following forest management treatments: Control, with no intervention (3300–3700 stems ha⁻¹); Treatment 1, one thinning to leave a living stock density of 900–600 stems ha⁻¹; or Treatment 2, a more intensive thinning, leaving 400 stems ha⁻¹. A LAI field measurement was made in all plots and the study area was recorded by LiDAR. With the LiDAR, two types of metrics were calculated: standard elevation metrics and canopy metrics. The results showed the different canopy layers of the study area, highlighting how the resprout layer influences the canopy structure of sweet chestnut coppice. By combining the LiDAR data and the LAI field estimates, various linear and nonlinear models were developed and tested, the linear model being found to have the best performance ($R^2 = 0.79$) for the study area. With the selected linear model and other LiDAR data of interest such as the 95th percentile, an automatic mapping tool was designed. This tool allows spatially information to be generated that can be used to implement management strategies.

Keywords Canopy vertical profile · Castanea sativa Mill. · Mapping tool · LAI$_e$ model · Canopy layers · Resprout layer

Introduction
Forests are highly complex systems influenced by numerous external and internal factors, making the development of sustainable forest management strategies, though crucial, somewhat challenging (Ceccherini et al. 2020).

Forest management operations impact on the complete forest ecosystem. For example, thinnings not only result in increased diameter growth, altering internal wood properties and enhancing the production of quality wood, but also provoke changes in canopy structure. Canopy structure refers to the organization, both horizontal and vertical, of the above-ground elements of vegetation including position, type, connectivity and quantity, as well as organization changes over time (Bréda 2008; Parker 1995). As such, it is closely related to ecosystem functions, playing an important role in the relationships between structural complexity, biodiversity, stand productivity, carbon balance and ecosystem services.

Estimates of canopy structure can be derived through the active remote sensing technology LiDAR (Light Detection and Ranging), which is able to directly characterize vertical forest structure (Lim et al. 2003; Lovell et al. 2003; Coops et al. 2007). LiDAR is an active sensor that uses light in the form of a pulsed laser to measure the distance (as a function of time) between the light being emitted from the sensor and that being reflected back off the target, thereby generating a 3D structure of the targeted element. As such, in a forest, the laser pulses from the LiDAR are not only reflected back from the canopy, but also from the ground and other vegetation elements in those places where the laser pulse travels through the gaps that exists in the canopy. This ability of LiDAR allows information to be retrieved about the underlying terrain, enabling better characterization of the different canopy layers (Lesfky et al. 2002; Mkaouar et al. 2018;...
Nelson et al. 1998). For these reasons, LiDAR technology has been investigated in depth in terms of its value in the acquisition of data related to forest biomass, wood volume, stem density, canopy height, canopy cover and forest inventory parameters and structural characteristics, among other applications (e.g. Bergen et al. 2009; Coops et al. 2007; Leeuwen and Nieuwenhuis 2010; Magnussen et al. 2018; Popescu et al. 2002).

There is an important parameter that helps to understand the connection between canopy structure and ecosystem functions (Bréda 2008), the Leaf Area Index (LAI). LAI, first described by Chen and Black (1992), “quantifies the total one-sided green leaf area per unit of ground surface as a dimensionless quantity”. In fact, LAI is used as a proxy of plant growth (Mkaouar et al. 2018) and is considered a standard quantitative tool to quantify canopy through the assessment of foliage levels and leaf surface area (Bréda 2008). As a result, LAI field measurement methods have been investigated in depth, where optical methods are those most commonly implemented in field measurements, such as the Canopy Light Analyzer LAI-2000/2200/2200C or hemispherical cameras (Jonckheere et al. 2004; Weiss et al. 2004). However, these methods are costly and time-consuming, hence there is need to develop another technique to evaluate LAI. In recent decades, therefore, considerable effort has been dedicated to estimating LAI from LiDAR data in vegetation environments with a variety of species and in different regions (e.g. Heiskanen et al., 2015; Jensen et al. 2008; Korhonen et al., 2011; Lovell et al. 2003; Pearse et al. 2017; Qu et al., 2020; Richardson et al., 2009; Solberg et al. 2006, 2009, 2010; Zhang et al. 2017; Zhao and Popescu 2009). Some of these studies estimated LAI from the canopy gap fraction using the Beer-Lambert law and based on LiDAR data and validated the models using LAI field estimates obtained with the optical instruments (Richardson et al. 2009; Solberg et al. 2009; Zhao and Popescu 2009).

Since there is a clear relationship between canopy structure and LAI (Bréda 2008), in 1999, Lefsky et al. adapted the use of LiDAR data to obtain the Canopy Vertical Profile (CVP), that is, the vertical distribution of the elements of the canopy from the ground to the maximum height. They also studied CVP according to different stand ages, from very young to old growth. This methodology was also employed in 2003 by Lovell et al. to obtain certain structural parameters such as cover, height and foliage profile. In 2007, Coops et al. used this same methodology to obtain CVPs and also used a probability function to summarize and retrieve the CVP. Nowadays, these studies constitute the basis for the characterization of the differentiation of the canopy layer throughout CVP. In recent years, LiDAR data have been employed not only to ascertain LAI associated with trees, but also that relating to understory components (Hamraz et al. 2017; Melo et al. 2019; Mkaouar et al. 2018; Zhang et al. 2017). This is particularly interesting with respect to those species that resprout from a stump following felling as the regrowth generates an important additional layer in the understorey.

One such species is the sweet chestnut (Castanea Sativa Mill.), which is extensive across the northwest of Spain and is of great importance as it produces quality wood in relatively short rotations, mainly in coppiced form (Menéndez-Mígueléz et al. 2014). This reality has provoked a growing interest from forest managers, forest owners and other stakeholders for new sustainable forest management tools for use with sweet chestnut. However, most traditional coppice stands have been abandoned or their rotation time has been increased considerably due to the socioeconomic changes that occurred in the past in rural areas (Conedera et al. 2004; Menéndez-Mígueléz et al. 2013). Traditionally, silvicultural treatments such as thinning are not employed in the management of sweet chestnut coppice stands, meaning that the full potential of the species, which requires management in order to achieve quality timber, has not been exploited (Mannetti et al. 2020). In this respect, in order to manage sweet chestnut for ‘quality’ wood production, further studies that consider and emphasize these aspects are needed, some of which are currently in progress (Prada et al. 2020).

In this context, the main aim of this study was to use LiDAR data to examine the impact of forest management on sweet chestnut coppice canopy structure through (1) the characterization of the vertical canopy structure from the ground to maximum height, (2) the development of LAI models from LiDAR data (3) the generation of a tool to estimate LAI and other variables for forest management planning at a large scale.

### Material and methods

#### Study area

The research site is located in Redes Natural Park which occupies the eastern central area of the Principality of Asturias in the north of Spain (Fig. 1). The annual rainfall ranges from 987 to 1351 mm, with an average annual temperature in the area of 10–11 °C. The study site has a northern orientation with high slope (45–57%) and is between 600 and 700 m above sea level. This study was conducted as a pilot forest management trial made up of three different treatments in sweet chestnut coppice stands: (1) Control, where there were no management operations (3300–3700 stems ha⁻¹), (2) Treatment 1, which consisted of one thinning that left a stock density of between 600 and 900 stems ha⁻¹ and (3) Treatment 2, which involved a more intensive thinning that resulted in a stock density of around 400 stems ha⁻¹. Thinning treatments were carried out at the end of 2015.
in winter when the sweet chestnut loses its leaves. In the Control and Treatment 1 plots, Oak (*Quercus Petrea*) is also present.

**Field data: forest inventory and LAI measurements**

Forest inventory data (Table 1) were collected from previously established permanent plots in the area by CETEMAS (Forest and Wood Technology Centre), and with this information, certain stand variables were calculated to characterize the study area. These plots were inventoried twice: first in winter 2015 (installation year) and then in summer 2019 (Fig. 2).

LAI field measurements were collected in July 2019, using an LAI-2200C plant canopy analyzer, from 21 circular plots (*r* = 10 m). The location of the plots was based on a grid system whereby where each plot centre was separated from those around it by 30 m. The locations of the plot centres were recorded using a GPS TrimbleExplorer XH™ (Trimble, Sunnyvale, CA, USA) with submetric accuracy and the total number of LAI plots per trial depended on the total surface area covered by each treatment.

The LAI-2200C is a portable instrument, in this case consisting of a control unit and an optical sensor, that directly provides an LAI value that may include vegetation which is not leaves and is thus referred to as Effective LAI (henceforth here, *LAI*<sub>e</sub>) (Chen and Black 1992). This device has been widely used in *LAI*<sub>e</sub> studies, and several extensive review papers have established it as an appropriate tool for *LAI*<sub>e</sub> field measurements (e.g. Bréda 2008; Fang et al. 2019; Goude et al. 2019; Jensen et al. 2008; Jonckheere et al. 2004; Korhonen et al. 2011; Morsdorf et al. 2006; Pearse et al. 2017; Solberg et al. 2009; Thimonier et al. 2010). The LAI-2200C incorporates five concentric rings with central zenith angles of 7, 23, 38, 53 and 68 degrees in a “fish-eye” optical sensor, measuring in the blue band (320–490 nm). The measurements of *LAI*<sub>e</sub> were made below the canopy and also in a clearing, the latter to simulate the light falling directly on the crown. These two measurements were required in order to calculate the ratio between the two transmittances

| Table 1 | Summary of forest inventory data from the permanent plots of CETEMAS |
|---------|---------------------------------------------------------------------|
|         | Control BT/AT2015 | AT2019 | Treatment 1 BT2015 | AT2015 | AT2019 | Treatment 2 BT2015 | AT2015 | AT2019 |
| *t* (years) | 13 | 16 | 13 | 13 | 16 | 16 | 16 | 19 |
| *N* (trees ha<sup>-1</sup>) | 3338 | 3169 | 3756 | 622 | 545 | 3664 | 439 | 439 |
| *G* (m<sup>2</sup> ha<sup>-1</sup>) | 13.93 | 15.48 | 21.10 | 4.77 | 5.41 | 29.85 | 5.84 | 7.04 |
| *D*m (cm) | 7.49 | 7.98 | 8.31 | 10.54 | 11.85 | 9.85 | 12.79 | 14.09 |
| *H*m (m) | 9.27 | 10.23 | – | 12.44 | 13.32 | – | 12.91 | 11.41 |
| *V* (m<sup>3</sup> ha<sup>-1</sup>) | 52.54 | 66.52 | – | 19.82 | 26.58 | – | 36.87 | 45.41 |
| *Area* (ha) | 1.01 | 2.76 | 1.31 |
(above and below the canopy). This ratio was recalculated into $LAI_e$ as described in the instrument manual (LI-COR Inc. 2015). All measurements were performed under uniform overcast skies to reduce the effect of scattered light in the canopy, and the sensor was equipped with a 90° view restrictor in accordance with the manufacturer’s instructions.

In the forest, $LAI_e$ field measurements were conducted using the plot layout employed in similar previous studies (Solberg et al. 2006, 2009) within the circular plots mentioned above. In each plot, one measurement was taken at the plot centre, and another four—one at each cardinal point—were made at 3 m from the centre. Due to the differences in the canopy cover, to guarantee a low standard error of $LAI_e$, supplementary measurements ($n = 17$) were collected at random within the plot.

**LiDAR data**

LiDAR data were collected in leaf-on conditions in summer 2019, at the same time as the $LAI_e$ field data were measured, using a Velodyne VLP-16 LiDAR scanner mounted on an unmanned aerial vehicle (drone). The laser wavelength of the device was 905 nm with a field of range of ± 15° Vertical FOV / 360° Horizontal FOV. The sensor recorded a maximum of 2 returns per pulse, and a minimum density of 25 points m$^{-2}$ was achieved over the area. LiDAR data were recorded for all the stands in the study area, which included all the $LAI_e$ plots.

A number of steps were followed in order to obtain the LiDAR metrics needed to model $LAI_e$ for sweet chestnut coppice (Fig. 3).

The LiDAR point cloud was classified as either background or not background with FUSION software V4.00 (McGaughey 2020), after which the point cloud was normalized against the ground surface height. The LiDAR standard elevation metrics were also computed with FUSION taking different fixed radii starting with the 10 m radius established for the $LAI_e$ plots in the field and...
increasing the radius by 2 m each time up to a limit of 30 m, following the methodology described by Pearse et al. (2017). This was done because the LiDAR and the LAI-2200c do not sample the same canopy volume; LiDAR uses a vertical cylinder and the LAI-2220c an inverted cone. Moreover, since sweet chestnut resprouts from the stump and this generates another canopy layer in addition to the principal one, and because the volume of the cone depends on the height of the canopy, the LiDAR metrics were computed for different heights (2, 3, 4, 5 m) up to the maximum height of each tree. The optimum choice of the height threshold is crucial in this type of study in order to reliably identify ground hits as those that are below the height threshold and those above it as corresponding to the canopy (Zhao and Popescu 2009). Following the testing of the various radii and height measurements, those most representative of the field measurements were selected to form the basis of the LiDAR standard elevation metrics.

Among the LiDAR standard elevation metrics extracted with FUSION, the KDE (kernel density estimation) metrics were considered essential to differentiate the layers within the canopy because it calculates the number of peak heights (minimum and maximum values and the range between them) using a Gaussian kernel to construct a probability density function for the peaks in each plot. In addition, the Profile Area, a new metric of FUSION V.4.00, was used, which corresponds to the area under the height percentile profile or curve (Hu et al. 2019). Both metrics are considered important in describing canopy vertical structure, so they were computed from ground to maximum height.

Another set of LiDAR metrics based on the canopy structure (LiDAR canopy metrics) were also calculated from ground to treetop following the methodology developed by Lefsky et al. (1999) and amended by Coops et al. (2007). Using the LiDAR point cloud data, for each circular plot, the canopy was divided vertically from the ground to the maximum height into 1 m intervals, resulting in a series of small cylinders, which were then classified into one of four canopy classes. First, each cylinder was classified as empty or filled depending on the absence or presence of LiDAR points. After that, the empty cylinders were divided into “Open gap” if they were situated above the canopy and “Closed gap” if they were below it. In the case of the filled cylinders, they were classified as “Euphotic” if they were located in the uppermost 65% of all filled cylinders and “Oligophotic” if below it (Fig. 4).

Using these same point cloud cylinders (Fig. 4), the Weibull density function was used to describe the Canopy Height Distributions (CHD) in the CVP. Weibull function is commonly applied to characterize foliage distribution for various species due to its flexibility in representing various distribution shapes (Coops et al. 2007; Lovell et al. 2003; Melo et al. 2019; Zhang et al. 2017). The two Weibull coefficients, i.e. scale ($\alpha_1$) and shape ($\beta_1$), were fitted as explained in previous studies using LiDAR data (Coops et al., 2007; Lovell et al., 2003). Scale provides the position and the distribution of the movement in vertical scaling (the shape of the distribution density curve), while shape explains the capacity to increase or decrease the breadth of the distribution.

![Fig. 4 LiDAR metrics based on the canopy structure](image-url)
Density-based LiDAR metrics were also calculated as the proportion of points above the percentiles (1st, 5th, 10th, 20th, 25th, 30th, 40th, 50th, 60th, 70th, 80th, 90th, 95th, and 99th) as was proposed by Zhang et al. (2017). A summary of the LiDAR metrics with their corresponding descriptions is shown in Table 2.

### LiDAR metrics selection and LAIₑ models

After extraction of the LiDAR metrics and using the selected radius and height threshold, the LiDAR data must be related to LAIₑ. Adding the LiDAR standard elevation metrics to those related to CVP computed from the LiDAR point cloud generates a large dataset of variables that can be used for model development. To simply the number of variables prior to model development, the metrics (Table 1) with low correlations with LAIₑ (r < 0.6) or highly correlated with other variables were excluded, and thus, only the remaining metrics were used in the regression analysis (Pearse et al. 2017; Zhao and Popescu 2009).

Stepwise linear and nonlinear allometric modelling were chosen in contrast to nonparametric statistical learning approaches, because with small samples, it is usually wise to use simple methods (Pearse et al. 2017). However, the choice of the model for predicting LAIₑ from LiDAR data must be determined by the modeller, and in most cases, it is dependent on the number of in situ LAIₑ observations available (Zhao and Popescu, 2009).

As final model selection criteria, the coefficient of determination ($R^2$) and the root mean square error ($RMSE$) were used. $R^2$ indicates the proportion of variation explained by the model, while $RMSE$, which uses the same units as the dependent variable, gives an idea of the mean error when using the model.

Also, as validation is important in terms of evaluating the predictive performance of any models developed, the leave-one-out cross-validation was used. It considers the difference between the observed value and the predicted value whereby one piece of data in turn is omitted from the analysis to fit the model and the model is fitted to the remaining $n-1$ data. The cross-validation of each model was based on the analysis of $RMSE$, $R^2$ and PRESS statistics. PRESS (prediction sum of squares) is a model validation method used to assess a model's predictive ability and to compare regression models.

### Table 2 Description of LiDAR metrics for modelling LAIₑ

| LiDAR metrics                        | Description                                                                                     |
|--------------------------------------|-------------------------------------------------------------------------------------------------|
| **LiDAR standard elevation metrics** |                                                                                                |
| All returns                          | All returns from ground to maximum height of the LiDAR point cloud                              |
| All returns above height threshold   | All returns from height threshold to maximum height of the LiDAR point cloud                    |
| Proportion return above height threshold | All returns from height threshold to maximum height of the LiDAR point cloud, expressed as a percentage |
| First returns above height threshold | Only first returns from height threshold to maximum height of the LiDAR point cloud            |
| Proportion of first returns above height threshold | Only first returns from height threshold to maximum height of the LiDAR point cloud, expressed as a percentage |
| Canopy relief ratio                  | Canopy cover generated by FUSION                                                               |
| Skewness and Kurtosis of heights     | The skewness and kurtosis of the heights of first returns with respect to the total            |
| Percentile Heights                   | The percentiles of the canopy height distributions (1st, 5th, 10th, 20th, 25th, 30th, 40th, 50th, 60th, 70th, 80th, 90th, 95th, and 99th) |
| Mean, maximum and minimum height     | Mean, maximum and minimum height above ground of all points                                    |
| KDE (kernal density estimator)       | Number of peak heights with minimum and maximum values                                          |
| Profile area                         | Area under the height percentile profile or curve                                              |
| **LiDAR canopy metrics**             |                                                                                                |
| Return proportion                    | Proportion of returns in each 1 m of height of the cylinders from the ground to the maximum height |
| Mean return proportion               | Mean of the proportion of returns considering different ranges of interval, for example from the height threshold to the maximum height |
| Density-based metrics                | The proportion of points above the percentile heights compared to total number of points        |
| Open and Closed gap zones            | Proportion of empty cylinders located above and below the canopy, respectively                   |
| Euphotic and Oligophotic zones       | Respectively, the proportion of cylinders located within the uppermost percentiles (above 65%) of all filled cylinders and those below the same point in the canopy vertical profile |
| $\alpha$ and $\beta$ parameter of Weibull distribution | The scale parameter, $\alpha$, and shape parameter, $\beta$, of the Weibull density distribution fitted to CHD |
LiDAR-LAI<sub>e</sub> Map tool

The selected model was used to develop a tool to generate an automatic map of leaf area index at stand level. The processing of LiDAR data at stand level was programmed in a script, including the generation of a Digital Terrain Model (DTM) and CHM models with a pixel size of 10 m. Moreover, the calculation of all LiDAR metrics mentioned above and the selected LAI<sub>e</sub> model were incorporated into the tool (Fig. 5). The process starts with the selection of the appropriate LiDAR data and the creation in the area of interest (AOI) followed by the calculation of LiDAR metrics and ends with the generation of different raster maps: mean height (H<sub>m</sub>), using the 95th Percentile Height; coverage (FCC), using the percentage of first returns and LAI<sub>e</sub> raster applying the adjusted model.

Results

The LAI<sub>e</sub> field estimates ranged from 1.62 to 2.54 in the LAI<sub>e</sub> plots established in the study area. The LiDAR standard elevation metrics (Table 3) were extracted considering the same sampling radius of 10 m as used in the LAI<sub>e</sub> plots and a height threshold of 5 m because these were the measurements that provided the best agreement with the LAI<sub>e</sub> field measurements.

Referring to the LiDAR canopy metrics (Fig. 6), the representation of the proportion of LiDAR points in each cylinder reveals three different canopy layers. They were also identified through the different peak heights which are also seen in the KDE LiDAR metrics (Table 3). The first canopy layer corresponds to the sweet chestnut sprouts and ranges from 1 to 5 m, though this varied greatly between plots. For example, in plot 1, there is almost no resprouting but in plot 21, almost 30% of the return points correspond to this layer. The second canopy layer ranges from 10 to 17 m and corresponds to the sweet chestnut layer. This layer was identified because it concurs with the inventory field data (Table 2).

Finally, the third canopy layer, ranging from 17 to 20 m, is the oak which appears in some of the plots. In plots from 15 to 21 and plot number 6, the absence of a peak in the 20 m height reveals absence of oak but the rest of the plots each have a peak, of varying magnitude, at around 20 m, meaning the presence of oak. For example, plot 3 has a similar presence of both sweet chestnut and oak as the two peaks have a similar proportion of returns, but plot 1 has more sweet chestnut and plot 13 has more oak.

The spatial distribution of the four canopy classes for sweet chestnut coppice (Fig. 7) shows that for plots 1 to 14, except for plot 6, the maximum height reached by the trees is more than 20 m, in contrast to the remaining plots where the maximum height is below 20 m. In general, there were more filled cylinders in Oligophotic zones than

### Table 3 Summary of LiDAR Standard Elevation metrics used to develop the LAI<sub>e</sub> models

| LiDAR Standard Elevation metrics | Mean   | Max    | Min    | Sd     |
|----------------------------------|--------|--------|--------|--------|
| Proportion of first returns above 5 m | 76.78  | 98.95  | 50.95  | 13.91  |
| Canopy relief ratio              | 0.53   | 0.69   | 0.39   | 0.09   |
| 5th Percentile                   | 8.01   | 9.58   | 5.83   | 1.20   |
| 10th Percentile                  | 9.21   | 10.82  | 6.87   | 1.16   |
| 50th Percentile                  | 13.41  | 20.15  | 10.20  | 2.40   |
| 80th Percentile                  | 16.63  | 22.30  | 11.49  | 3.44   |
| 90th Percentile                  | 17.99  | 23.09  | 12.00  | 3.89   |
| 95th Percentile                  | 18.91  | 23.93  | 12.33  | 4.07   |
| Mean height                      | 13.54  | 18.12  | 9.91   | 2.16   |
| SD Height                        | 3.41   | 5.43   | 1.70   | 1.22   |
| Skewness                         | −0.18  | 1.05   | −1.65  | 0.81   |
| Kurtosis                         | 3.25   | 6.26   | 1.65   | 1.39   |
| Maximum height                   | 21.46  | 26.14  | 13.83  | 4.34   |
| Minimum height                   | 5.01   | 5.06   | 5.01   | 0.01   |
| KDE (number of peaks)            | 2.38   | 5.00   | 1.00   | 1.02   |
| KDE maximum                      | 17.47  | 24.03  | 10.00  | 4.74   |
| KDE minimum                      | 10.20  | 18.65  | 5.23   | 3.37   |
| Profile area                     | 53.41  | 68.93  | 39.28  | 8.23   |
in Euphotic zones with percentages ranging, respectively, from 15 to 40% and 9% to 21%. In the case of empty cylinders, the proportion that were Closed gap was smaller (18%–34%) than those that were Open gap (15%–56%).

The Weibull function fitted to the $LAI_e$ plots shows there to be different tendencies in the plots with or without oak (Fig. 8). In plots with oak, a greater proportion of LiDAR points is accumulated in the sweet chestnut and oak layers, so the peak of the function tends to be in that part of each plot figure, but in the case of the plots with absence of oak, the resprouting layer in most cases accumulate more LiDAR points in that zone, so the peak of the weibull function tends to be in that part of the figure.

The best linear and nonlinear models for estimating $LAI_e$ were selected (Eq. 1 and 2, respectively) on the basis of goodness-of-fit statistics. In both equations, all parameters were significant at the 5% level.

\begin{equation}
LAI_e = 3.710 \cdot D05 - 5.322 \cdot D80
\end{equation}

\begin{equation}
LAI_e = 98.130 \cdot \text{mean}_5_{\text{maximum height}}^{1.315} \cdot D80^{-0.199}
\end{equation}

where $LAI_e$ is the effective leaf area index, $D05$ and $D80$ are the density-based metrics above the 5th and 80th quartiles, respectively, and mean$5_{\text{maximum height}}$ is the mean return proportion from the height threshold (5 m) and the maximum height.

The values of the statistics used to compare the models (Table 4) indicate that both models performed reasonably...
in terms of fitting and cross-validation and also with respect to the relationship plotted between the observed values of $LAI_e$ and the values predicted by the models (Fig. 9).

The linear model was slightly better than the nonlinear, having a better $R^2$ and lower RMSE and PRESS, and it was therefore the one finally selected for the $LAI_e$ calculations. In the selection of variables, both BIC (Bayesian information criterion) and AIC (Akaike Information Criteria) were considered to resolve problems of overfitting. Table 5 shows the results of the ANOVA procedure for the linear model, demonstrating that the p value for the F test statistic is below 0.001. This provides strong evidence against the null hypothesis (parameters = 0), so both variables including in the regression model significantly predict the $LAI_e$, the contribution of D05 being the greater of the two.

Figure 10 shows the outputs for a sweet chestnut forest stand of the map tool developed in this study which uses LiDAR data as input for. The results are consistent with field data, which produced values of $LAI_e$ of between 1.11 and 2.83.
Discussion

Characterizing the vertical profile of forest crowns is critical to support forest management activities and maintaining or improving carbon balance and ecosystem services. As such, this study, using LiDAR technology, created a canopy vertical profile for sweet chestnut coppice in northern Spain, along with a map tool for characterizing forest stands. In addition, different forest management strategies, in this case thinning at two different intensities, were considered.

The \( \text{LAI}_e \) field results presented here are a reference for this species in the study area in that they consider different forest management activities (thinning intensities). The values for \( \text{LAI}_e \) found in this work are similar to those found in studies based on deciduous forests of other species, although none of them consider management activities (Cutini et al. 1998; Le Dantec et al. 2000). The results presented here are, however, in line with a previous study of forest management in the study area in terms of \( \text{LAI}_e \) values (Prada et al. 2020).

The plot radius and height threshold used to extract LiDAR data in this study were, respectively, 10 m and 5 m. The selection of the optimal radius and height in the extraction of LiDAR metrics for estimating \( \text{LAI}_e \) has been investigated in depth as they are key factors and also impact directly on forest characterization. Morsdorf et al. (2006) found that 15 m was the optimal radius. However, Riaño et al. (2004) found that the estimation of \( \text{LAI}_e \) from LiDAR data was best when data were selected using a radius similar to the height of the canopy, which is in accordance with the results of Solberg et al. (2009) where LiDAR data were taken from a plot with a radius of 0.75 times the tree height. With respect to the height threshold, it is important to take into account that the sweet chestnut considered here sprouts from stump. In previous studies, this was not taken into account, so although there are some reviews of optimum height threshold (e.g. Pearse et al., 2017), in this case, the height threshold was set as 5 m because it was more or less the height limit of the resprout layer, as well as being the limit established for the start of the canopy of adult trees (Fig. 6). To obtain predictions with lower errors, it would be necessary to adapt these height thresholds to the type of forest stand involved and thus further studies would be necessary.

Previous research has demonstrated the adaptability and appropriacy of LiDAR data in differentiating the different canopy layers throughout the vertical profile of the forest (Lesfksy et al. 1999; Lovell et al. 2003), which is essential for the effective planning of silviculture actions (Melo et al. 2019; Mkaouar et al. 2018). In this study, canopy layer differentiation provided valuable information on the proportion of each layer that would otherwise have been very difficult to obtain. For example, the greater maximum heights (Fig. 6) in some plots were able to be linked to the presence of oak trees, and the KDE data enabled the differentiation of a canopy layer for oak between 18 and 24 m, for sweet chestnut from 10 to 13 m height and around 5 m for sweet chestnut resprouting. Clearly, being able to identify such canopy characteristics from LiDAR data requires far less investment, both time and money, than having to collect field data. Another important fact is the ability of the LiDAR data to identify the resprout layer in sweet chestnut coppice, as can clearly be seen in Fig. 6. It represents from 0 to 5 m, more or less, indicating the suitability of the limit threshold of 5 m that was chosen as it enables the adult canopy to be distinguished.

Additionally, thinning treatment can be seen to have a direct effect on the resprout layer. In plots 15–21 where there was more intensive thinning (Treatment 2), the proportion of LiDAR points related to the resprout layer accounted for a larger proportion of the LiDAR returns, indicating the

Fig. 10 Outputs from the map tool developed in this study: a coverage b 95th percentile, representing the height of the sweet chestnut forest stand c \( \text{LAI}_e \) values obtained using the \( \text{LAI}_e \) model developed in this study
The presence of foliage, than in plots such as plot 1 (a control plot), where the resprout layer is scarcely discernable. This is a direct consequence of the thinning treatment, which produces an opening in the canopy layer so the light reaches the resprout layer and the resprouts grow more vigorous. Previous research in the study area with sweet chestnut coppice (Prada et al. 2020) using satellite imagery time-series data detected that the year after a thinning its effect is clearly seen but four years later, similar to the time interval in this study, the canopy recovers to pretreatment coverage levels. The resprout layer obviously contributes to this, and the present study provides useful information on how the canopy layers are distributed within forest stands: although satellite images four years after thinning do not distinguish the effects of the thinning treatment, in this work, we clearly see how cover in this layer increases as the intensity of the treatment increases.

The canopy volume distributions in Fig. 7 shed some light on the vertical structure of sweet chestnut forest. Again, the importance of the resprout layer is demonstrated by the closed gap zone which reaches up to 5 m. Above this point, if canopy volume distribution is related to height (Figs. 6 and 7), it can be seen that in the plots with the presence of oak (1–5 and 7–14), the Oligophotic zone occupies a greater volume due to the increased presence of sweet chestnut than in the euphotic zone where oak predominates. However, this pattern changes when there is no oak, and the Oligophotic and Ephotic zones tend to have similar volumes. This is the first element of the characterization of the canopy volume distribution in sweet chestnut forest. Other authors have focused on species such as coniferous forest, broad-leaved forest, mixed forest, hemlock and eucalyptus (Lesky et al. 1999; Lovell et al. 2003; Zhang et al. 2017) and found different canopy volume distributions depending on the site and species.

The selected $LAI_e$ models use different LiDAR metrics in their formulation than other studies, but result in similar $R^2$ values (Coops et al. 2007; Jensen et al. 2008; Solberg et al. 2009; Zhang et al. 2017). Rather than using regression analysis in modelling the $LAI_e$, other authors have employed physically-based models, but the resulting $R^2$ values are also similar to those found in this study (Heiskanen et al. 2015; Korhonen et al. 2011). Other studies such as Pearse et al. (2017) have explored nonparametric techniques since they have used more plots than in this study. However, the importance of this work relies on the fact that it is the first attempt to relate $LAI_e$ with different thinning intensities in sweet chestnut coppice and data related to this type of management intervention are difficult to obtain because it is not often carried out. Consequently, in the future, the model can be improved by adding more field information in order to strengthen the $LAI_e$ models for sweet chestnut coppice in the north of Spain.

Finally, the mapping tool developed in this paper allows spatial information to be generated that is of value in implementing management strategies that improve productivity, ecosystem functions, forest management planning and fuel management. While this tool could be further improved with new models and the inclusion of new variables based on LiDAR metrics, the results provided here indicate that the statistics derived from the LiDAR data, and the models developed based on them, are suitable for calculating CVP and have great potential for its analysis (Lovell et al. 2003). Apart from that, the usefulness of the tool is that it is easily upgradable, and improved models or models of other species can be incorporated. In addition, LAI is a variable that is not included in field inventories due to in situ evaluation being complicated, so a model like that presented in this study is useful in spite of the specific conditions in which it has been developed.

**Conclusions**

In this study, the methodology used and developed is of great interest because the characterization of the canopy vertical profile is of enormous benefit in terms of improving forest management planning, ecosystem functioning, structural biodiversity and ecosystem services. The assessment included the descriptive capacity of a set of LiDAR metrics related to standard elevation and canopy structure with respect to different thinning treatments.

The LiDAR metrics generated from the point cloud help to understand how the different canopy layers are distributed throughout the canopy of sweet chestnut coppice forest stands. The resprout layer was demonstrated to have a high impact on forest vertical structure. On the basis of the height threshold corresponding to average resprouting height, the LiDAR point cloud data could be used to distinguish resprouting from adult trees in the CVP, as well as to indicate the presence of other species (i.e. oak) in some parts of the study area. This is a good example of the valuable information that can be obtained from LiDAR data. Also, a full characterization of the canopy was made from the ground to maximum height which provides not only data on the differentiation of the layers already mentioned but also a completed description of the distribution of the different canopy zones.

The results of the $LAI_e$ models demonstrated its reliability in the study area (Cross-validation: $R^2$ (0.79) and $RMSE$ (0.20)). Using these models, the generation of $LAI_e$ maps for all the study area was possible, but the tool was designed in a way that other LiDAR variables of interest can also be mapped. As a consequence, this information will help forest managers in decision-making planning, allowing them to consider not only productive options, but also
the biodiversity and structural parameters of sweet chestnut forest stands.

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Declarations

Conflicts of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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