Estimation of stand variables in *Pinus radiata* D. Don plantations using different LiDAR pulse densities

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Summary

This study aimed to verify the validity of linear, power function and exponential models to estimate stand variables in Galician Atlantic forests of *Pinus radiata* D. Don using Light Detection and Ranging (LiDAR). These forests differ in structure and species composition from boreal forests, in which this methodology is fully developed. The models tested use LiDAR-derived canopy height and intensity distribution metrics as explanatory variables to predict the following stand attributes: mean height, dominant height, stand basal area, stand volume, stand crown biomass, stand stem biomass and stand aboveground biomass. Exponential models performed best in most cases, with goodness-of-fit statistics similar to those reported in the international literature for boreal forests. The coefficient of determination ranged from 0.44 (for stand crown biomass) to 0.87 (for dominant height), and the root mean square error/mean·100 ranged from 8.2 per cent (for dominant height) to 31.6 per cent (for stand stem biomass). Model precision did not essentially vary after reducing 94 per cent of the original point cloud, i.e. when laser pulse density was reduced from 8 pulses m⁻² to only 0.5 pulses m⁻².

Introduction

Accurate and timely information on current growing stock is essential for forest management. Conventional forest inventory methods often employ detailed measurements at a small set of sampling plots distributed randomly or systematically over the forest area which are then used to estimate average values of the required stand variables and their standard errors. The quality of the estimates over the forest area are thereby limited by the cost of establishing sufficient sample plots to capture the existing variability (Lovell et al., 2005). This type of inventory is extremely labour intensive and expensive (Hall et al., 2005) and does not practically allow for acquiring full inventory coverage of large areas on the ground.

One of the main advantages of remote sensing techniques is their capacity to obtain spatially explicit data over large areas in a timely and economic fashion (Hall et al., 2005). Airborne laser scanning, also referred to as Light Detection and Ranging (LiDAR), is an active remote sensing technique which has been widely used in topographic mapping (Kraus et al., 2006; Kobler et al., 2007). LiDAR sensors are designed to provide three-dimensional data, thus allowing direct measurement of the canopy structure (Reitberger et al., 2008; Wagner et al., 2008). In vegetated areas, most laser pulses are reflected back to the sensor from the leaves and branches of the vegetation canopy. However, a certain fraction of pulses reaches the ground surface through small gaps in the vegetation canopy (Hollaus et al., 2007).

Accordingly, it is possible to generate a Digital Terrain Model (DTM) by filtering LiDAR data (for algorithm comparison, see Sithole and Vosselman, 2004) and interpolating the points classified as ground and a Digital Surface Model (DSM) by interpolating the first return
points (Hyppä et al., 2004) or the points classified as high vegetation (Gonçalves-Seco et al., 2011). A Digital Canopy Model (DCM) can be calculated by subtracting the DTM from the DSM (Hyppä et al., 2004). The DCM is used to estimate most forest stand attributes, such as mean heights, basal area, volume and aboveground biomass (Dubayah and Drake, 2000; Lee and Lucas, 2007). Alternatively, when working with the LiDAR point cloud, Z coordinates can also be processed into normalized heights, i.e. the difference between the points classified as high vegetation and the DTM (Riaño et al., 2003; Korhonen et al., 2008; Gonçalves-Seco et al., 2011).

Research on LiDAR for forest inventory applications has focused on small-footprint scanners, using mainly two different approaches: 'single-tree' and 'stand-level'. Individual tree detection and delineation from spatially dense LiDAR data is more expensive than the stand-level inventory approach. The latter establishes empirical relationships between variables commonly used in forest planning such as mean height (Næsset, 1997a, 2002, 2004; Magnussen et al., 1999; Næsset and Bjørknes, 2001; Holmgren et al., 2003; Hall et al., 2005; Stephens et al., 2007; Treitz et al., 2010); mean diameter (Næsset, 2002, 2004); quadratic mean diameter (Treitz et al., 2010); stand basal area (Means et al., 2000; Næsset, 2002, 2004; Hall et al., 2005; Stephens et al., 2007; Treitz et al., 2010); timber volume (Næsset, 1997b, 2002, 2004; Means et al., 2000; Holmgren et al., 2003; Hollaus et al., 2007; Rombouts et al., 2008; Treitz et al., 2010); dominant height (Næsset, 2002, 2004; Lovell et al., 2005; Stephens et al., 2007; Rombouts et al., 2008; Treitz et al., 2010); stem number (Næsset, 2002, 2004; Hall et al., 2005; Treitz et al., 2010); total aboveground biomass (Hall et al., 2005; Treitz et al., 2010); foliage biomass, canopy base height and canopy bulk density (Hall et al., 2005); tree age and total carbon (Stephens et al., 2007) or canopy metrics (Musk and Osborn, 2007). Other authors have used the height distribution for different purposes: Riaño et al. (2003) estimated canopy cover and height to model fire risk; Holmgren and Persson (2004) used both the height distribution of laser returns and the intensity of the returned pulses to classify forest species.

Laser pulse density is one of the factors that most affects the height accuracy of the laser-derived DTM. If the ground elevation or the uppermost portion of the forest canopy is not well detected, the normalized heights of the trees and the DCM obtained are underestimated (Lefsky et al., 2002; Hyppä et al., 2008). Despite this, the estimation of the forest stand variables may not be affected. In this sense, the results obtained from small-footprint LiDAR sensors indicate that laser pulse density does not greatly affect the prediction of some variables such as mean and dominant height, quadratic mean diameter, stand basal area, stand volume or stand aboveground biomass (Maltamo et al., 2006; Gobakken and Næsset, 2007; Stephens et al., 2007; Treitz et al., 2010) when the point cloud was reduced between 94.4 and 95.3 per cent. Magnusson (2006) observed a significant increase in the root mean square error (RMSE) for mean height and stand volume estimates when the laser pulse density was drastically dropped from 2.5 to 0.004 pulses m⁻² (reduction of 99.8 per cent). According to Gobakken and Næsset (2007), this fact must be verified in different forest stands and regions.

The Third National Forest Inventory indicates that Pinus radiata D. Don stands occupy a total surface area of ~90 000 ha in Galicia, north-west Spain (Xunta de Galicia, 2001), with a current rate of planting of ~6000 ha year⁻¹ (Álvarez Álvarez, 2004). The wide distribution and the high growth rate of the species have also made it very important to the forest industry in northern Spain, with an annual harvest volume of 505 000 m³ in the period 1992–2001 (MAPA, 2003). P. radiata is also one of the most commonly used species in reforestation programmes, particularly those involving communal forests and abandoned agricultural land (Castedo-Dorado et al., 2007), which usually belong to private landowners with small land ownerships. In this situation, it is practically impossible to obtain full inventory coverage of large areas on the ground using field inventory with systematic sampling techniques, which are mainly applied in the region for planning purposes.

This study aims to test the applicability of linear, power function and exponential models to predict mean height, dominant height, stand basal area, stand volume, stand crown biomass, stand stem biomass and stand aboveground biomass in P. radiata plantations in Galicia using height and intensity data from a discrete-return LiDAR system, given the importance of this species in the forestry industry of the region and the potential of the method for reducing data acquisition costs. In addition, the effects of a reduction in LiDAR sampling densities on the model precision are examined considering data availability because the Spanish National Geographic Institute will soon release low-density LiDAR data (0.5 pulses m⁻²) for the whole of Spain.

Materials and methods

Study area

The study area was located in Galicia, north-west Spain and covered ~36 km² of P. radiata forests. A study site was defined as a 4.130 × 8.787 km rectangle according to the following UTM coordinates for the site boundaries: (586315; 4783000) and (595102; 4787130) (Blue rectangle in the Figure 1). The forests in this area are representative of the Atlantic P. radiata stands in Galicia, characterized by low-intensity silvicultural treatments and by the presence of tall shrub.

LiDAR data

The LiDAR data was acquired in September 2007 using an Optech ALTM 3025 system, operated at 1064 nm, with a laser repetition rate of 25 kHz, a scan frequency of 200 Hz, a maximum scan angle of ±17⁰ and a flying height of 1300 m above sea level. The amount of overlap was 60 per cent and as such a theoretical laser pulse density of 8 pulses m⁻² was obtained.
Fieldwork
A total of 54 square plots of 225 m² were located and measured in the *P. radiata* plantations of the study area between August and December 2007, which were subjectively selected to represent the existing range of ages, stand densities and sites (Red dots in Figure 1 represent the centre of the field plots). Topographical surveys were carried out using total stations and a Global Positioning System to determine the location of the four corners and the position of every tree within the plots.

For all the trees in each sample plot, two measurements of diameter at breast height (1.3 m above ground level) at right angles were made using callipers to the nearest millimetre, and the arithmetic mean of the two measurements was calculated. A Vertex III hypsometer was used to measure the total tree height in all the trees.

The outside bark volume of each tree was estimated using the equation for *P. radiata* in Galicia developed by Diéguez-Aranda et al. (2009):

$$v = 4.851 \times 10^{-5} \cdot d^{4.83} \cdot h^{1.04},$$

while the dry weight of the biomass fractions of each tree were estimated from the following equations reported in Diéguez-Aranda et al. (2009):

$$w_w + w_{w7} = 0.01230 \cdot d^{4.694} \cdot h^{4.133}$$

$$w_h = 0.003600 \cdot d^{2.616}$$

$$w_{b2-7} = 1.938 + 0.001065 \cdot d^2 \cdot h$$

$$w_{b0.5-2} = 0.03630 \cdot d^{2.609} \cdot h^{-0.9417}$$

$$w_{b0.5} = 0.007800 \cdot d^{0.864}$$

where $v$ is outside bark stem volume (cubic metre), $w_w$ is stem wood biomass (kilogram), $w_{w7}$ is wood and bark biomass on branches with 7 cm minimum top diameter (kilogram), $w_h$ is bark biomass on stem (kilogram), $w_{b2-7}$ is wood and bark biomass on branches with 7 cm maximum butt diameter and 2 cm minimum top diameter (kilogram), $w_{b0.5-2}$ is wood and bark biomass on branches with 2 cm maximum butt diameter and 0.5 cm minimum top diameter (kilogram), $w_{b0.5}$ is wood and bark biomass on branches with 0.5 cm maximum butt diameter (kilogram), $w_l$ is needles biomass (kilogram), $d$ is diameter at breast height outside bark (1.3 m above the ground level, centimetre) and $h$ is total tree height (metre).

Finally, crown biomass ($w_{cr}$), stem biomass ($w_{st}$) and aboveground biomass ($w_{abg}$) were calculated from the sum of the fractions of biomass included:

$$w_{cr} = w_{b2-7} + w_{b0.5-2} + w_{b0.5} + w_l$$

$$w_{st} = w_w + w_{w7} + w_h$$

$$w_{abg} = w_{cr} + w_{st}$$

The field measurements (heights and diameters) and the estimated volumes and dry weight of the biomass fractions were used to estimate the following stand variables of each plot in a per hectare basis: mean height ($H_m$), dominant height ($H_d$), stand basal area ($G$), stand volume ($V$), stand crown biomass ($W_{cr}$), stand stem biomass ($W_{st}$) and stand aboveground biomass ($W_{abg}$). Such estimates were used to develop models to derive these stand variables from LiDAR data. Table 1 represents the average, minimum, maximum and standard deviation of the forestry

![Figure 1. Inventory plots.](https://academic.oup.com/forestry/article-abstract/85/2/281/526525)
Table 1: Forestry stand parameters of the sample plots (n = 54)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Average</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tree number (stems ha(^{-1}))</td>
<td>755</td>
<td>311</td>
<td>1556</td>
<td>290</td>
</tr>
<tr>
<td>d</td>
<td>23.5</td>
<td>9.9</td>
<td>40.9</td>
<td>6.0</td>
</tr>
<tr>
<td>(H_m)</td>
<td>16.8</td>
<td>7.3</td>
<td>26.6</td>
<td>3.9</td>
</tr>
<tr>
<td>(H_d)</td>
<td>22.9</td>
<td>10.9</td>
<td>34.3</td>
<td>5.0</td>
</tr>
<tr>
<td>G</td>
<td>35.7</td>
<td>10.7</td>
<td>86.1</td>
<td>13.7</td>
</tr>
<tr>
<td>V</td>
<td>308</td>
<td>43</td>
<td>865</td>
<td>165</td>
</tr>
<tr>
<td>(W_{cr})</td>
<td>29.9</td>
<td>10.4</td>
<td>72.3</td>
<td>11.6</td>
</tr>
<tr>
<td>(W_{st})</td>
<td>121.3</td>
<td>16.0</td>
<td>347.8</td>
<td>66.8</td>
</tr>
<tr>
<td>(W_{abg})</td>
<td>151.2</td>
<td>26.4</td>
<td>420.2</td>
<td>78.0</td>
</tr>
</tbody>
</table>

\(d\) = diameter at breast height outside bark (1.3 m above ground, cm), \(H_m\) = mean height (m), \(H_d\) = dominant height (m), \(G\) = stand basal area (m\(^2\) ha\(^{-1}\)), \(V\) = stand volume over bark (m\(^3\) ha\(^{-1}\)), \(W_{cr}\) = stand crown biomass (t ha\(^{-1}\)), \(W_{st}\) = stand stem biomass (t ha\(^{-1}\)), \(W_{abg}\) = stand aboveground biomass (t ha\(^{-1}\)).

Examination of the original point cloud showed that many cells had more than 16 returns m\(^{-2}\). Therefore, to obtain a regular distribution of LiDAR returns and to investigate the effect of the LiDAR point cloud density on the estimation of stand variables, two datasets were generated: one with a final density of 1 return m\(^{-2}\) and another one with 16 returns m\(^{-2}\) (equivalent to 0.5 and 8 pulses m\(^{-2}\)).

**Extraction of LiDAR variables**

For the two reduced datasets (0.5 and 8 pulses m\(^{-2}\)), the FUSION software (McGaughhey, 2009) was used to perform filtering, interpolation and DTM/DCM generation operations as well as to compute the following variables related to the metrics of heights and return intensity distributions within the limits of the 54 field plots: mean, maximum and minimum values, mode, standard deviation, variance, interquartile distance, coefficients of skewness and kurtosis, average absolute deviation and percentiles. In addition, the percentage of returns above a specific height threshold was estimated.

The following steps were carried out with several processing programmes implemented in the FUSION LiDAR Toolkit (McGaughhey, 2009). Firstly, ground returns were extracted from the LiDAR point cloud using the GroundFilter tool, which implements a filtering algorithm adapted from Kraus and Pfeifer (1998) based on linear prediction (Kraus and Mikhail, 1972). Secondly, these returns were used to generate a DTM grid using the GridSurfaceCreate tool, which computes the elevation of each grid cell using the average elevation of all points within the cell; if no point is in the cell, it is filled by interpolation using the neighbouring cells. Thirdly, the normalized LiDAR point cloud was obtained by subtraction of the ellipsoidal height of the DTM from the Z coordinate of each LiDAR return using the ClipData tool; this tool was used also to exclude returns below a normalized height of 2 m, which were considered as not belonging to tree crowns (e.g. hits on shrub, rocks, and logs). Fourthly, the normalized LiDAR point cloud was clipped with the limits of each field plot – which were stored as polygons in Esri shapefiles – using the PolyClipData tool; an independent file was created per plot. Fifthly, the metrics of heights and return intensity distributions of these 54 clipped and normalized point clouds were computed using the CloudMetrics tool.

**Regression models**

Linear, (multiplicative) power function and exponential models were used to establish empirical relationships between field measurements and LiDAR variables. Their respective general expressions are as follows:

\begin{equation}
Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \epsilon
\end{equation}

\begin{equation}
Y = \beta_0 X_1^{\beta_1} X_2^{\beta_2} \ldots X_n^{\beta_n} + \epsilon
\end{equation}

\begin{equation}
Y = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n) + \epsilon
\end{equation}
where \( Y \) are field values of \( H_\text{m} \) (metre), \( H_d \) (metre), \( G \) (square metre per hectare), \( V \) (cubic metre per hectare), \( W_{sd} \) (kilogram per hectare), \( W_{st} \) (kilogram per hectare) and \( W_{shk} \) (kilogram per hectare), and \( X_1, X_2, \ldots, X_n \) may be variables related to the metrics of heights and return intensity distributions or measurements related to canopy closure, all of them computed from the datasets with resolutions of 8 and 0.5 pulses m\(^{-2}\). The variables related to height distribution can be: \( b_{\text{mean}}, b_{\text{max}}, b_{\text{median}}, b_{\text{mode}}, \) \( b_{\text{SD}}, b_{\text{skew}}, b_{\text{kurt}}, b_{\text{IID}}, b_{\text{AAD}}, b_{95}, b_{10}, b_{25}, \ldots, b_{95}, b_{25} \) or \( b_{75} \), which are the minimum, maximum, mean, median, mode, standard deviation, coefficients of skewness and kurtosis, interquartile distance, average absolute deviation, percentiles and first and third quartiles values of the height distribution of laser returns for each plot (metre), respectively. The variables related to return intensity distribution are based on the same statistics as the variables related to height distribution, but in this case, they are denoted with the letter \( i \) instead of \( b \). The variables related to the canopy closure can be: \( r_{2,5} \), which is the number of returns above 2 m height for each plot or \( c_2 \), which is the ratio of the number of laser hits above 2 m height to the number of first returns for each plot, expressed as a percentage. The additive error term \( \varepsilon \) is assumed to be normally, independently and identically distributed with zero mean.

**Model fitting and selection**

Linear models were fitted using ordinary least squares applying the REG procedure of SAS/STAT® (SAS Institute Inc., 2004), while power function and exponential models were fitted using nonlinear regression with the Gauss–Newton method implemented in the NLIN procedure of the same statistical package. In a previous step, the last two models were linearized taking natural logarithms from both sides of equations 12 and 13, in order to select the best subset of independent variables to be included on each and to obtain initial estimates of the parameters using the linear regression technique (Myers, 1990, p. 444).

Once the complete linear form of the models was specified, an examination took place to determine whether all terms of the models should be retained in the final regression equations. This process involved fitting a number of subset models and comparing the relative performance of these models (Clutter et al., 1983, p. 318). Although there are different approaches for selecting the subset models to be fitted by linear regression (Draper and Smith, 1998; chapter 15), the Mallows’ \( C_p \) selection method of the REG procedure – which performs all possible subset regressions and lists the models in ascending order of \( C_p \) – was used. Multicollinearity among the explanatory variables was checked with the condition index; in agreement with Belsley (1991), regressions with a condition index above 30 were discarded. Finally, only models in which all the parameter estimates were significant at 5 per cent level were considered.

Comparison of the estimates for the different models (linear, power function and exponential) was based on numerical and graphical analyses of the residuals. Three statistics were calculated: the coefficient of determination \( R^2 \), the RMSE and the Bayesian Information Criterion (BIC) proposed by Schwarz (1978). Although BIC was used as the final criterion for model selection (Penña, 2002, p. 570), it does not give an intuitive idea of model precision. \( R^2 \) (also referred to as pseudo-\( R^2 \) when applied in nonlinear regression) shows the proportion of the total variance of the dependent variable that is explained by the model. Although there are several shortcomings associated with the use of \( R^2 \) in nonlinear regression, the general usefulness of some global measure of model adequacy would seem to override some of those limitations (Ryan, 1997, p. 424). The RMSE gives an idea of the precision of the estimates in the same units as the dependent variable.

If we are interested in comparing candidate models in terms of their predictive capabilities, it must be taken into account that ordinary residuals are measures of quality of fit and not measures of quality of future prediction (Myers, 1990, p. 168) and therefore the model must be validated. For validation, only a newly collected dataset can be used (Kozak and Kozak, 2003). A variety of validation methods have been proposed because of the scarcity of such data (e.g. splitting the dataset or cross-validation, double cross-validation), but they seldom provide any additional information compared with the respective statistics obtained directly from models built from entire datasets (Kozak and Kozak, 2003). Moreover, according to Myers (1990, p. 170) and Hirsch (1991), the final estimation of the model parameters should come from the entire dataset because the estimates obtained with this approach are more precise than those obtained from the model fitted from only one portion of the data. We therefore decided to defer model validation until a new dataset is available for assessing the quality of the predictions.

**Effects of density reduction**

Using a similar procedure to that proposed by Treitz et al. (2010) but considering only laser pulse density as the factor of interest, absolute prediction errors from the best linear, power function and exponential models developed for each variable were calculated by plot:

\[
e_{ij} = |Y_i - \hat{Y}_i|
\]

where \( e_{ij} \) is the absolute prediction error of the \( ij \)th plot (from 1 to 54) associated with the \( j \)th LiDAR pulse density (0.5 and 8 pulses m\(^{-2}\)), \( Y_i \) is the stand variable obtained from field measurements for the \( ij \)th plot, and \( \hat{Y}_i \) is the corresponding predicted value for the \( ij \)th plot and the \( j \)th LiDAR pulse density.

For each model type and variable, the nonparametric Kruskal–Wallis one-way analysis of variance by ranks (Kruskal, 1952; Kruskal and Wallis, 1952) was used for comparing the absolute prediction errors distributions by LiDAR pulse density factor. If the computed value of the test suggests rejecting the null hypothesis, there is a high likelihood that the two samples represent populations with different median values (Sheskin, 2004; pp. 757–761).
Results

Tables 2 and 3 summarize the parameter estimates and goodness-of-fit statistics of the best model fit by stand variable (\(H_m, H_d, G, V, W_{cr}, W_{st}, W_{abg}\)) and reduced dataset (0.5 and 8 pulses m\(^{-2}\)) (Supplementary data which also includes the information by model type – linear, power function and exponential – is available).

Mean height and dominant height modelling

For \(H_m\), the linear model performed better, followed by the exponential and the power function models, according to BIC (Supplementary Table 1). The linear model explained 75.9 per cent of the variability for the 8 pulses m\(^{-2}\) dataset and 78.6 per cent for the 0.5 pulses m\(^{-2}\) dataset (Tables 2 and 3). Few differences were found in terms of \(R^2\) for the 8 pulses m\(^{-2}\) dataset, with 1.0 per cent difference between the linear (the best) and the power function (the worst) models; for the models fitted to the 0.5 pulses m\(^{-2}\) dataset, the difference was 2.4 per cent.

For \(H_d\) and the 8 pulses m\(^{-2}\) dataset, the exponential model provided the best results in terms of BIC (\(R^2 = 86.5\) per cent, see Table 3), followed by the linear and the power function models (Supplementary Table 2). Conversely, for the 0.5 pulses m\(^{-2}\) dataset, the linear model revealed a better fit in terms of BIC (\(R^2 = 84.6\) per cent, see Table 2), as compared with the exponential and the power function models (Supplementary Table 2). Small differences were found between the models, with a maximum increment of \(R^2\) of 1.8 per cent for the models fitted for the 8 pulses m\(^{-2}\) dataset and a maximum increment of \(R^2\) of 0.3 per cent for the models fitted for the 0.5 pulses m\(^{-2}\) dataset.

In general, height percentiles proved to be reliable statistics for predicting \(H_m\) and \(H_d\), while intensity statistics also added valuable information; the variables related to canopy cover did not contribute any information (Supplementary Tables 1 and 2). Strong correlations between \(H_d\) and the 95th height percentile (\(h_{95}\)) were observed because it was included as regressor in all the models.

Stand basal area modelling

For both reduced datasets (0.5 and 8 pulses m\(^{-2}\)), exponential models performed best for \(G\) estimation, followed by linear and power function models, according to BIC (Supplementary Table 3). The exponential model fitted for the 8 pulses m\(^{-2}\) dataset explained 69.2 per cent of the variability, whereas the model fitted for 0.5 pulses m\(^{-2}\) dataset showed an \(R^2 = 67.8\) per cent (Tables 2 and 3). The differences in terms of fit between models were large, with a maximum increment of \(R^2\) of 19.8 per cent for the models fitted for the 0.5 pulses m\(^{-2}\) dataset and 14.3 per cent for the models fitted for the 8 pulses m\(^{-2}\) dataset.

| Stand variable | Model | Independent variable | Parameter estimate | SE \(^*\) | \(t\)-value | \(P > |t|\) | \(R^2\) | RMSE (m) | BIC |
|----------------|-------|----------------------|-------------------|--------|-----------|--------|--------|---------|----|
| \(H_m\)        | Linear| \(b_0\) parameter    | 7.542             | 1.644  | 4.59      | <0.0001| 0.786  | 1.810  | 72.06 |
|                |       | \(h_{median}\)       | 0.8622            | 0.0632 | 13.65     | <0.0001|        |        |       |
|                |       | \(b_d\)              | -0.02487          | 0.0112 | -2.22     | 0.0312 |        |        |       |
| \(H_d\)        | Linear| \(b_0\) parameter    | 4.171             | 1.140  | 3.66      | 0.0006 | 0.846  | 1.988  | 82.19 |
|                |       | \(b_{95}\)            | 0.9494            | 0.0561 | 16.91     | <0.0001|        |        |       |
| \(G\)          | Exponential| \(b_0\) parameter | 1.976             | 0.2254 | 8.77      | <0.0001| 0.678  | 8.066  | 245.4 |
|                |       | \(b_{SD}\)           | 0.1155            | 0.0222 | 5.20      | <0.0001|        |        |       |
|                |       | \(b_{skw}\)          | -0.2452           | 0.0726 | -3.38     | 0.0014 |        |        |       |
|                |       | \(b_{h5}\)           | 0.04559           | 0.0123 | 3.71      | 0.0005 |        |        |       |
| \(V\)          | Power | \(b_0\) parameter    | 2.126             | 1.167  | 1.82      | 0.0742 | 0.691  | 92.53  | 497.0 |
|                | Function| \(h_{median}\)      | 1.839             | 0.192  | 9.58      | <0.0001|        |        |       |
| \(W_{cr}\)     | Exponential| \(b_0\) parameter | 8.629             | 0.226  | 38.16     | <0.0001| 0.687  | 6765   | 972.5 |
|                |       | \(b_{SD}\)           | 0.1264            | 0.0221 | 5.72      | <0.0001|        |        |       |
|                |       | \(b_{skw}\)          | -0.2388           | 0.0730 | -3.27     | 0.0020 |        |        |       |
|                |       | \(b_{h5}\)           | 0.04684           | 0.01230| 3.81      | 0.0004 |        |        |       |
|                |       | \(r_2\)              | 0.005473          | 0.001690| 3.24      | 0.0022 |        |        |       |
| \(W_{st}\)     | Exponential| \(b_0\) parameter | 9.802             | 0.214  | 45.91     | <0.0001| 0.732  | 35205  | 1143  |
|                |       | \(b_{skw}\)          | -0.3423           | 0.0905 | -3.78     | 0.0004 |        |        |       |
|                |       | \(b_{h5}\)           | 0.09000           | 0.0102 | 8.82      | <0.0001|        |        |       |
| \(W_{abg}\)    | Exponential| \(b_0\) parameter | 10.13             | 0.1896 | 53.41     | <0.0001| 0.746  | 40469  | 1162  |
|                |       | \(b_{SD}\)           | 0.2408            | 0.0261 | 9.23      | <0.0001|        |        |       |
|                |       | \(b_{skw}\)          | -0.3773           | 0.0844 | -4.47     | <0.0001|        |        |       |
|                |       | \(b_{h5}\)           | 0.0776            | 0.0133 | 5.83      | <0.0001|        |        |       |

* For the power function and exponential models, the SEs are approximate values.
Independent variables related to metrics of heights and return intensity distributions and measurements related to canopy closure proved to be reliable statistics for predicting $G$ (Supplementary Table 4).

**Stand volume modelling**

In $V$ estimation, the exponential model showed superior performance in terms of BIC for the 8 pulses m$^{-2}$ dataset ($R^2 = 79.4$ per cent, see Table 3), followed by the power function and linear models (Supplementary Table 4). For the 0.5 pulses m$^{-2}$ dataset, a power function model performed better according to BIC ($R^2 = 69.1$ per cent, see Table 2). In this case, the power function was closely followed by the exponential ($R^2 = 74.3$ per cent) and linear ($R^2 = 70.6$ per cent) models (Supplementary Table 4). An increment of $R^2$ of 7.0 per cent was obtained between the best (exponential) and worst (linear) type of model sorted by BIC for the 8 pulses m$^{-2}$ dataset. In the case of the 0.5 pulses m$^{-2}$ dataset, the best model (a two parameter power function) in terms of BIC provided the lowest $R^2$ value, which may be explained by the fact that the BIC penalizes the number of parameters in a model (the linear and exponential models have four parameters).

Independent variables related to the metrics of heights and return intensity distributions and measurements related to canopy closure proved to be reliable statistics for predicting $V$ (Supplementary Table 4).

**Stand crown biomass modelling**

In $W_{cr}$ modelling, the exponential model performed best, as shown by the BIC, with $R^2$ values of 68.8 and 68.7 per cent for the 8 and 0.5 pulses m$^{-2}$ datasets, respectively (Tables 2 and 3). The exponential model was followed by linear and power function models in both cases (Supplementary Table 5). As in the case of $G$ and $V$ modelling, the differences between models were greater than the differences observed for $H_m$ and $H_d$. The difference in terms of $R^2$ between the best and worst models was 20.4 and 24.4 per cent for the 0.5 and 8 pulses m$^{-2}$ datasets, respectively. Independent variables related to the metrics of heights and return intensity distributions and measurements related to canopy closure proved to be reliable statistics for predicting $W_{cr}$ (Supplementary Table 5).

**Stand stem biomass modelling**

In $W_{st}$ modelling, exponential models produced the best results for the 8 and 0.5 pulses m$^{-2}$ datasets, accord-
ing to BIC, with values of $R^2$ of 82.7 and 73.2 per cent, respectively (Tables 2 and 3). The exponential model was followed by power function and linear models (sorted by increasing values of BIC) for the 0.5 pulses m$^{-2}$ dataset, while power function and linear models showed the same values of BIC for the 8 pulses m$^{-2}$ dataset (Supplementary Table 6). Big differences between models were found for the 8 pulses m$^{-2}$ dataset, with a maximum increment of $R^2$ of 15.0 per cent; conversely, a little increment of $R^2$ of 2.5 per cent between the best and the worst model sorted by BIC was obtained for the 0.5 pulses m$^{-2}$ dataset. Independent variables related to the metrics of heights and return intensity distributions and measurements related to canopy closure proved to be reliable statistics for predicting $W_{abg}$ (Supplementary Table 6).

**Stand aboveground biomass modelling**

As for $H_m$, $H_d$ and $W_{abg}$ estimates are encouraging, insofar as some models reached $R^2$ values of up to 80 per cent. Exponential models explained 80.4 and 74.6 per cent of the variability for the 8 and 0.5 pulses m$^{-2}$ datasets, respectively (Tables 2 and 3). They provided the best results in terms of BIC, followed by the linear and power function models for the 8 pulses m$^{-2}$ dataset; the power function performed better than the linear model (according to BIC) for the 0.5 pulses m$^{-2}$ dataset (Supplementary Table 7). Similarly as for $G$, $V$ and $W_{cr}$, significant differences were found between the models. The largest differences amounted to an increment of $R^2$ of 15.9 per cent for the models fitted using the 8 pulses m$^{-2}$ dataset and to an increment of $R^2$ of 8.2 per cent for the models fitted using the 0.5 pulses m$^{-2}$ dataset. Independent variables related to the metrics of heights and return intensity distributions and measurements related to canopy closure proved to be reliable statistics for predicting $W_{abg}$ (Supplementary Table 7).

**Effects of density reduction**

In order to choose the appropriate test for comparing the absolute prediction errors of each dataset, a previous diagnosis of $e_g$ distributions (see equation 14) was performed to determine whether parametric statistical assumptions were satisfied. The Shapiro–Wilks test for normality (Shapiro and Wilk, 1965, 1968 – which is described in Conover, 1980, 1999) was used to determine if residuals were normally distributed. In addition, deeper analyses were carried out using a Quantile–Quantile plot. The results of the Shapiro–Wilks test and visual inspection of residuals showed non-normal distributions for all the studied $e_g$ distributions. Therefore, the nonparametric Kruskal–Wallis one-way analysis of variance by ranks (Kruskal, 1952; Kruskal and Wallis, 1952), which does not assume normal population, was used for comparisons.

For all the pairwise comparisons performed, the computed chi-square approximation of the Kruskal–Wallis test statistic $(H)$ was below the tabled critical 0.05 chi-square value ($\chi^2 = 3.84$) for 2–1 degrees of freedom. Therefore, the alternative hypothesis – not equality of medians – was not supported at the 0.05 level in all cases ($H < \chi^2_m$, $a = 0.05$ and $P > 0.05$; see Supplementary Table 8). Results suggest that the reduction of the LiDAR point cloud has no effect on model fit. Actually, models adjusted for $H_m$ (linear, power function and exponential), $V$ (power function), $W_{cr}$ (linear and power function), $W_{abg}$ (power function) and $W_{abg}$ (power function) performed even better at lower densities, as shown by BIC values (Supplementary Tables 1–7).

In general, the selected models were slightly different for the two datasets (Supplementary Tables 1–7), except in $H_d$ modelling, where strong correlations between $H_d$ and the 95th height percentile ($b_{95}$) were observed for both reduced datasets and the power function for $V$ modelling, where $b_{median}$ was selected as independent variable in both.

The developed models contain from one to four explanatory variables. In most cases, they belong to the three types of measurements carried out using LiDAR data: variables related to the metrics of heights and return intensity distributions and measurements related to canopy closure (Supplementary Tables 1–7).

**Discussion**

We used an approach based on statistical canopy height and intensity distribution for deriving forest information from laser scanner data. Regressors are assessed from laser-derived surface models and canopy height point clouds and then are directly used for forest attribute estimation (Hyppä et al., 2008). Therefore, the model fit will be influenced by the precision of the generated DCM or the point cloud processed into canopy heights.

It was already noticed in the 1980s that the use of small-footprint laser systems leads to an underestimation of tree height (Hyppä et al., 2008), which is a logical consequence of the operation of the scanner (Gaveau and Hill, 2003; Gonçalves-Seco et al., 2011). To detect the uppermost portion of a forest canopy, we will expect to require a sufficient density of laser pulse footprints that allows for tree top sampling and a sufficient amount of reflecting material in each laser pulse footprint that allows for the generation of a detectable return signal (Hyppä et al., 2008).

Furthermore, errors in DTM will lead to errors in DCM. In addition to the errors caused by the sensor and the methods and algorithms used; the quality of a laser-derived DTM is affected by data characteristics, such as point density, first/last pulse, flight height or scan angle and the errors caused by the characteristics of complexity of the target, among which type of terrain, flatness of terrain, density of the canopy or amount and height of understory (Hyppä et al., 2008). Even so, relatively good canopy height information can be collected with various parameter configurations. Among the above factors, pulse density can be considered the most influential (Hyppä et al., 2008).

The study of cost-effective methods for accurately assessing forest variables involves the evaluation of point
clouds of various pulse densities. To this end, real data of the same area collected at a given time with various LiDAR flight configurations (particularly different flight heights and scan angles) would be desirable. The lack of such information may be overcome by artificially reducing the LiDAR dataset. Although this approach does not fully mimic the real reduction that would be obtained with different flights, it allows for the study of the most important factor in canopy height modelling. Also, bearing in mind that results are strongly site-dependent and that derived relationships could be influenced by the structural complexity of the site (Goodwin et al., 2006), further studies should be carried out in the future using real data along diverse environments and with different flight parameters in order to assess the possibilities of low-density laser data, acquired with the highest possible flight height and incidence angle over large areas.

In this sense, our results demonstrate that management-relevant forest stand variables can be modelled with reasonable precision in Atlantic P. radiata plantations using medium- and low-density laser data and that they are similar to those reported in the international literature.

Mean height modelling results ($R^2 = 0.75–0.82$, RMSE = 1.71–1.96 m) are slightly lower than the results reported for boreal forests. Gobakken and Næsset (2007) obtained an $R^2 = 0.87$ for a laser pulse density of 1.2 pulses m$^{-2}$ and an $R^2 = 0.93$ for 0.9 pulses m$^{-2}$ in Norway spruce (Picea abies (L.) Karst.) and Scots pine (Pinus sylvestris L.) forests of south-eastern Norway. Treitz et al. (2010) obtained $R^2$ values of 0.95, 0.94 and 0.94 for models fitted to LiDAR datasets of 3.2, 1.6 and 0.5 returns m$^{-2}$, respectively, in black spruce (Picea mariana (Mill) B.S.P) forests of Canada. The models developed in our study proved very stable after reduction of LiDAR pulse density (see Supplementary Table 8). This result is in agreement with Treitz et al. (2010), who despite having found significant differences ($P \leq 0.10$) with their highest level of decimation (0.5 returns m$^{-2}$), claimed that this case appeared rare in the context of the overall dataset of their study and could be due to random chance alone.

Dominant height showed a strong correlation with the 95th height distribution percentile ($h_{95}$). Actually, $h_{95}$ explained up to 84.9 per cent (RMSE = 1.98 m) of the variability of $H_d$ when it was included as a regressor in the linear model. The predictive performance for $H_d$ improved when the 10th percentile of the intensity distribution ($i_{10}$) was included in the exponential model ($R^2 = 0.87$, RMSE = 1.88 m). These results are considerably lower than those reported for New Zealand P. radiata forests by Stephens et al. (2007), who obtained $R^2 = 0.96$ and RMSE = 1.82 m for a laser pulse density of 9 pulses m$^{-2}$. Treitz et al. (2010) also achieved better results, with $R^2$ values of 0.92, 0.93 and 0.90 for models fitted to LiDAR reduced datasets of 3.2, 1.6 and 0.5 returns m$^{-2}$, respectively, in black spruce (P. mariana (Mill) B.S.P) forests of Canada. The models developed in our study proved very stable after reduction of the LiDAR pulse density (see Supplementary Table 8), which confirms the suggestions of Stephens et al. (2007), who observed that the RMSE for dominant height decreased by less than 1 per cent for densities of up to 0.1 pulses m$^{-2}$ and reported significant losses of model precision below that density; the same conclusion was reached by Treitz et al. (2010), who did not find evidence that a reduction of LiDAR density affected model precision. The analysis of dominant height revealed that the information provided by the 95th percentile for canopy height distribution ($h_{95}$) was virtually unchanged after having reduced the laser pulse density, which corroborates the results reported by Gobakken and Næsset (2007), who suggested that intermediate and upper height percentiles were more stable metrics than the maximum values of canopy height distribution ($h_{max}$ in this case).

Stand basal area estimates derived from exponential models ($R^2 = 0.69$, RMSE = 7.88 m$^2$ ha$^{-1}$ for 8 pulses m$^{-2}$; $R^2 = 0.68$, RMSE = 8.07 m$^2$ ha$^{-1}$ for 0.5 pulses m$^{-2}$) were slightly higher than the values obtained for P. radiata by Stephens et al. (2007) using power function models ($R^2 = 0.66$, RMSE = 8.02 m$^2$ ha$^{-1}$) but slightly lower than some estimates for boreal areas carried out by Næsset (2002) or for Canadian broadleaf forests conducted by Lim et al. (2003), with values of $R^2 = 0.86$ for both studies. Treitz et al. (2010) achieved $R^2$ values of 0.92, 0.91 and 0.94 for models fitted to LiDAR reduced datasets of 3.2, 1.6 and 0.5 returns m$^{-2}$, respectively, in a black spruce (P. mariana (Mill) B.S.P) forest of Canada. The models developed in our study were very stable after thinning LiDAR pulse density (see Supplementary Table 8), which is in agreement with Stephens et al. (2007), who found that the RMSE for basal area decreased by less than 1 per cent for densities up to 0.1 pulses m$^{-2}$. The same conclusion was reached by Treitz et al. (2010), who did not find evidence, at 10 per cent significance level, that a reduction of LiDAR density affected model precision for stand basal area.

The results of stand volume modelling ($R^2 = 0.68–0.79$, RMSE = 76.9–94.1 m$^3$ ha$^{-1}$) are close to those reported by Hollaus et al. (2007) for Austrian alpine forests ($R^2 = 0.84$, RMSE = 96.8 m$^3$ ha$^{-1}$) but significantly lower than those reported by Næsset (2004) for boreal forests ($R^2 = 0.83–0.97$, RMSE = 32.9–67.8 m$^3$ ha$^{-1}$) and Treitz et al. (2010) for black spruce (P. mariana (Mill) B.S.P) forests in Canada ($R^2$ values of 0.95, 0.93 and 0.94 for models fitted to LiDAR reduced datasets of 3.2, 1.6 and 0.5 returns m$^{-2}$, respectively). In our study, $V$ models proved very stable after reduction of LiDAR pulse density (see Supplementary Table 8), in agreement with various studies that demonstrated that large laser pulse density reductions hardly affected the fit of the models for volume estimation (Gobakken and Næsset, 2007; Hollaus et al., 2007; Treitz et al., 2010). Furthermore, power function models – widely used in the international literature for volume estimation – have demonstrated a great stability because results have been even better at low densities (Supplementary Table 4). The modelling results for $W_{cr}$ ($R^2 = 0.44–0.69$, RMSE = 6.75–8.75 t ha$^{-1}$), $W_c$ ($R^2 = 0.68–0.83$, RMSE = 28.9–38.3 t ha$^{-1}$) and $W_{abc}$ ($R^2 = 0.65–0.80$, RMSE = 35.9–46.9 t ha$^{-1}$) suggest that LiDAR is a valuable tool for estimating biomass fractions in Atlantic P. radiata plantations, insofar as the values obtained are similar to the values of
G and V. In the case of $W_{\text{spt}}$ the $R^2$ value obtained from exponential models was similar to those reported by Hall et al. (2005), who obtained an $R^2 = 0.74$ for Pinus ponderosa Doug. ex Laws forests in US using a laser pulse density of 1.23 pulses m$^{-2}$ but considerably lower than those achieved by Treitz et al. (2010), with values of $R^2$ of 0.93, 0.91 and 0.93 for models fitted to LiDAR reduced datasets of 3.2, 1.6 and 0.5 returns m$^{-2}$, respectively, in black spruce (P. mariana (Mill) B.S.P) forests of Canada. As in the rest of the variables, models were very stable after thinning LiDAR pulse density (see Supplementary Table 8), which is in agreement with Treitz et al. (2010), who did not find evidence, at 10 per cent significance level, that a reduction of LiDAR density affected model precision for stand aboveground biomass.

In general, exponential models performed better for all the variables, using both 8 and 0.5 pulses m$^{-2}$ datasets, except for $H_m$ for which linear models were better in terms of BIC for both reduced datasets and for $V$, for which the power function model performed better (in terms of BIC) for the 0.5 pulses m$^{-2}$ dataset. A difference above 5 per cent in terms of $R^2$ was obtained between the ‘best’ and ‘worst’ model for each variable (except for $H_m$, $H_d$ and $W_{st}$ using the 0.5 pulses m$^{-2}$ dataset), which confirms the importance of model selection. The difference between power function models and exponential models is subtle and becomes gradually evident only as data accumulates. When only small differences between models are observed, any of the models can be used. This is particularly true if the goal is to interpolate values between known data points, insofar as difficulties arise only when we attempt to extrapolate far beyond a dataset. Because power models slowly diverge from similar-looking exponential models, what works as a model in the short-term may miss long-term trends.

Conclusions

Exponential and power function regression models were equally valid, but exponential models performed better in estimating most of the variables. Yet, exponential models must be tested in different forest types, regions and data ranges in order to verify the applicability of the models.

Our results suggest that, for forest stand variable estimation, laser pulse density can be reduced to low densities (up to 0.5 pulses m$^{-2}$) without significant loss of information, at least for the following key stand variables: mean and dominant height, stand basal area, stand volume and stand biomass fractions. Yet, because of the usual density variation across areas observed in the LiDAR data provided by the companies responsible for the flights, data should be acquired at slightly higher densities.

In the light of the results of this study, the low-density LiDAR data (0.5 pulses m$^{-2}$) that will soon be released by the Spanish National Geographic Institute will be an excellent source of information for forest management, especially for reducing forest inventories costs.

Supplementary data

Supplementary data are available at Forestry Online.

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Conflict of interest statement

None declared.

References


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