

Estimating potential tree height in *Pinus radiata* plantations using airborne laser scanning data

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Abstract

Representing the spatial distribution of trees and competition interactions in growth models improves growth prediction and provides insights into spatially explicit forecasts for precise silvicultural interventions. However, this information is rarely taken into account over large areas because obtaining the spatial distribution of individual trees and estimating their competition is both expensive and time consuming. Airborne laser scanning enables rapid estimation of tree height and other attributes over large areas. In this study, we implemented an individual tree detection approach to first extract tree attributes of *Pinus radiata* D. Don plantations, and second to use this spatially explicit information on tree location and competition to forecast potential tree height, defined as a maximum projected tree height at rotation age. To do so, using a chronosequence of tree heights, we developed a tree height growth model using a Chapman–Richards function, utilizing the effect of intertree competition and stand-level top height (TH) on the tree height growth. The results showed that using chronosequence of heights, competition, and TH resulted in accurate predictions of potential tree height (root mean square error = 2.9 m; mean absolute percentage error = 0.154%). We concluded that individual tree height growth is significantly influenced by competition, with increased competition values associated with reductions in potential height growth by 22.2% at 30 years.

Key words: forest plantations, competition index, Chapman-Richards, chronosequence, airborne laser scanning

Résumé

La représentation de la distribution spatiale des arbres et des interactions de compétition dans les modèles de croissance améliore la prédiction de la croissance et permet d'obtenir des prévisions spatialement explicites pour des interventions sylvicoles précises. Cependant, ces informations sont rarement prises en compte sur de grandes surfaces car l'obtention de la distribution spatiale des arbres individuels et l'estimation de leur concurrence sont à la fois coûteuses et longues. Le balayage laser aéroporté (ALS) permet d'estimer rapidement la hauteur des arbres et d'autres attributs sur de grandes superficies. Dans cette étude, nous mettons en œuvre une approche de détection des arbres individuels pour extraire d'abord les attributs des arbres des plantations de Pinus radiata D. Don. Les plantations de don, et deuxièmement d'utiliser ces informations spatialement explicites sur l'emplacement des arbres et la concurrence pour prévoir la hauteur potentielle des arbres, définie comme une hauteur maximale projetée des arbres à l'âge de la rotation. Pour ce faire, en utilisant une chronoséquence de la hauteur des arbres, nous avons développé un modèle de croissance de la hauteur des arbres en utilisant une fonction de Chapman-Richards, en utilisant l'effet de la compétition inter-arbres et de la hauteur du sommet (HS) au niveau du peuplement sur la croissance de la hauteur des arbres. Les résultats montrent que l'utilisation de la chronoséquence des hauteurs, de la compétition et de la hauteur de la cime permet de prédire avec précision la hauteur potentielle des arbres (RMSE = 2,9 m et MAPE = 0,154 %). Nous concluons que la croissance en hauteur des arbres individuels est significativement influencée par la compétition, avec des valeurs de compétition accrues associées à des réductions de la croissance en hauteur potentielle de 22,2 % à 30 ans. [Traduit par la Rédaction

Mots-clés : plantations forestières, indice de compétition, Chapman-Richards, chronoséquence, balayage laser aéroporté

1. Introduction

Reliable growth and yield forecasting is critical for guiding forest management decision making (García 1994), allowing for both long-term timber resource planning (Coops 2015; Tompalski et al. 2021) and informing a variety of silvicultural regimes (García 1990). Improved growth estimations in intensively managed plantation environments provide insights into the most appropriate thinning and pruning intensities to enhance productivity (García 1990), improve cost-efficient approaches for fertilizer applications (From et al. 2015), and assist with financial decision making (Picard et al. 2012).

Forest growth models are designed to describe individual trees and (or) forest stand dynamics, as well as to project tree or stand attributes into the future (Cao 2014; Tompalski et al. 2021). The type, number of attributes, and level of abstraction of these models vary with stand-level models typically requiring less detailed information than single tree models (Yue et al. 2008; Pretzsch 2009). The site index (SI) concept, expressed as the height of dominant and co-dominant trees at a reference age, is a commonly used estimator of potential stand productivity (Fontes et al. 2003; Skovsgaard and Vanclay 2008). It has been demonstrated that for dominant and co-dominant trees, height is a stable predictor of site productivity over time for most species (Burkhart and Tomé 2012). Nevertheless, SI is a height-based metric that ignores other stand dynamics, such as tree position, stem density, and competition, all of which have been shown to be important determinants in explaining tree and forest stand growth patterns (Briseño-Reyes et al. 2020). By definition, SI is designed to describe productivity for larger spatial units because it is based on the forest stand-level top height (TH). For instance, tree competition, which mostly impacts intermediate and suppressed trees, is not explicitly reflected in SI. As a result, it is less useful for accurately describing productivity at a finer spatial scale or characterizing forest yield fluctuations caused by changes in micro-environmental conditions (Bontemps and Bouriaud 2014). Therefore, using SI as a single representation of forest productivity is challenging, particularly in short rotation stands, necessitating the development and testing of additional tree height models.

Individual tree growth models, which represent the highest level of abstraction and resolution in forest yield prediction, provide detailed information on changes in tree dimensions over time (Burkhart and Tomé 2012). Individual tree height modelling is an alternate method to SI for predicting growth that can provide insights into spatially explicit forecasts for precise silvicultural interventions (Schröder et al. 2007). The spatial distribution of trees, which, for example, influences competitive interactions among trees, with subsequent implications for tree growth (Perry et al. 2008), has been identified as a critical piece of information for improving thinning management decisions (Wikström et al. 2011; Vauhkonen and Pukkala 2016). Furthermore, estimating potential individual tree height, defined as the maximum individual tree height at a specific time (most commonly the end of the rotation), provides information for silviculture decisions and harvesting schemes, as well as indicating the potential economic value per tree (Vauhkonen and Pukkala 2016).

Several studies have incorporated inter-specific spatial and horizontal distributions of tree locations into individual tree growth models by incorporating functions based on crown overlap (Dale and Shugart 1985), tree height (Versace et al. 2019), diameter (Hegyi 1974), and the size of and the distance to competitors. The majority of this research has found that competition in growth models improves the accuracy of predicting tree growth (Biging and Dobbertin 1995; Sandoval and Cancino 2008). For example, Pukkala and Kolström (1987) found strong relationships ($R^2 = 0.4-0.7$) between competition indices and diameter growth, while **De Luis et al.** (1998) found that competition explains 79%–84% of the variability in tree volume growth in the stand. Alternatively, Vauhkonen and Pukkala (2016) were able to optimize tree selection under economic objectives based on potential tree height in a simulated stand utilizing varying levels of tree competition. Nonetheless, field measurements of individual tree attributes, such as tree location, stem height, and competition, are limited due to the difficulty of identifying both the top of the tree and its entire crown in dense forest stands, as well as the time and cost of doing so over large areas (West 2015).

Airborne LiDAR technology, also known as airborne laser scanning (ALS), accurately measures the distance between a sensor and a target providing highly accurate and detailed three-dimensional point clouds representing objects in space (Habib et al. 2005). ALS facilitates the estimation of accurate "wall-to-wall" forest attributes rapidly and efficiently over broad areas (Akay et al. 2009), making it an important data source for inventorying and modelling growth in forest plantations (Maltamo et al. 2014). Numerous studies have demonstrated the utility of ALS in supporting forest inventories, including estimation of attributes such as height, stems number, basal area, and volume (van Leeuwen and Nieuwenhuis 2010; Maltamo et al. 2014; Görgens et al. 2015).

The two main approaches for estimating forest attributes from ALS are the area-based approach (ABA), which estimates forest characteristics across a regular grid (e.g., $20 \text{ m} \times 20 \text{ m}$), and individual tree detection (ITD). ITD approaches typically necessitate a higher point cloud density (>10 points/m²) than ABA approaches, are more complex, and are influenced by stand structure and higher computational demands (Treitz et al. 2012). Recent advancements in the density of ALS point clouds have facilitated the development of ITD algorithms, which provide direct estimation of tree attributes by detecting and measuring individual tree crown area and tree height (Spriggs et al. 2017). Hence, ITD approaches could offer an improved understanding of tree dynamics that is directly applicable to forest management (Jeronimo et al. 2018). ITD techniques are also more likely to be useful for tree identification in even-aged plantations where stands are composed of regular-sized trees, single species, and simple development patterns, with previous research in pine plantations using ITD explaining between 63% and 93% of the variation in individual tree volume (Bortolot and Wynne 2005; Popescu 2007; Huang et al. 2009; Naveed et al. 2019; Corte et al. 2020).

In addition, studies have used ITD approaches to define competition parameters using individual tree height and distance to the neighbour tree for biomass prediction, with accuracy (R^2) ranging from 90% to 95% and greater than 0.66, respectively (Lin et al. 2016; Versace et al. 2019). Other studies, such as Pont et al. (2021), have significantly reduced the prediction residual for tree height and wood stiffness when data on tree competition derived from ALS were included. Recent chronosequence studies using remote sensing and ALS data have estimated both tree and stand growth attributes, demonstrating the ability to predict growth with a single

Fig. 1. Map showing in olive green the spatial distribution of *P. radiata* plantations (Forestal Arauco), with black bold borders the ALS survey location and in red the field inventory data. Additionally, the upper right image shows the delineation of the study areas of the Americas. [Colour online]



ALS point cloud when multiple remeasurements of ALS features over time are unavailable (Tompalski et al. 2015b). However, studies linking individual tree competition information with chronosequences of ALS-derived tree height have received less attention, yet have the capacity to inform plantation productivity and management up to the end of stand rotation.

In this paper, we developed a method for generating potential tree height models in *Pinus radiata* D. Don even-aged plantations in central-south Chile. To accomplish this, using a single survey of ALS data, we

 undertook an ITD-based approach to extract tree locations and determine its accuracy;

- assessed the effect of tree competition and TH (a stand-level variable) on the upper asymptote of tree height growth model separately, and in combination; and
- incorporated those metrics into a height chronosequence for individual tree height prediction, built using individual tree height from the ITD at different ages covering the entire plantation rotation.

2. Data

2.1. Study site

The study area is located within *P. radiata* plantations in central-south Chile, from Región del Maule (latitude 35°14′S) to Región de los Ros (latitude 40°6′S), on private land owned



by Forestal Arauco (Fig. 1). This region is distinguished by its heterogeneous topography, which includes the coastal Andes ranges, the central valley, and the Andes foothills. The study area is divided into three sections. The northern area (6989 ha) has a warm temperate climate, on metamorphic and granitic soils (Casanova et al. 2013). The annual precipitation totals about 900 mm, with the majority falling in winter. The central area, which covers 27 281 ha, is located on marine sediment-derived soils along the coast and metamorphicderived soils in the valley. The climate is rainy temperate (1200 mm per year), with dry periods in summer and wetter periods throughout the remainder of the year. The southern area (1640 ha) has a temperate rainy climate (over 1500 mm annually) and is situated on highly productive volcanic ash soil deposits (Olmedo et al. 2020).

2.2. ALS data

The ALS data were acquired over 35 000 ha (Fig. 1) and covered all three areas and stand ages from 0 to 24 years (rotation age). The data were collected once between February and November 2020 using an Optech Galaxy Prime scanning system at an altitude of 3000 m above ground on a Tecnam P2006 plane (Table 1). Up to 5 returns were recorded per pulse. Within the area of interest, the pulse density (i.e., first return point density) was 20.8 pulses/m², while the overall point density was 29.2 points/m².

2.3. Field inventories

To verify the ITD approach, a total of 167 field inventory plots were established and measured once, using a random placement design, over the three regions, between 2018 and 2019 (Fig. 1). The field plots were 20 m \times 20 m in size with plot corners and center located using a Trimble R1 GNSS Receiver, with an estimated horizontal error of 0.60 m. Total tree count, diameter at breast height (DBH), and tree height were measured for all trees within the plot using a tree caliper and Haga altimeter, respectively. Tree location was not recorded.

2.4. Site index data

An external stand-level SI map was available for the study area. The existing map was developed using 64 190 observations of 20-year-old *P. radiata* stands (SI age) with environmental variables (topography, vegetation index, soil properties, and climate) used as predictors. The map was available at a 90 m × 90 m level of detail (Gavilán-Acuña et al. 2021) and was used to perform a stratification of the ALS data. The data were stratified into five productivity classes for *P. radiata* (<26, 26– 28, 28–30, 30–32, and >32 m) to cover the entire variability of site and tree height conditions.

3. Methods

3.1. ALS data pre-processing

The raw ALS data were processed using a standard set of routines, which included tiling, ground classification,

Table 1. Airborne laser scanning (ALS) data acquisitionparameters.

Acquisition parameter	Value
Sensor	Optech Galaxy Prime
Utilized plane	Tecnam P2006
Flying height	3000 m AGL
Average flying speed (knots)	115
Pulse repetition frequency (kHz)	700
Scan angle	26 °
Returns recorded	Up to 5
Overlap	60%
Average point density	29.2 points/m ²
Average pulse density	20.8 pulses/m ²

noise removal, and height normalization. The LAStools software package (version 211206) was used for processing (Isenburg 2021). The lasground algorithm was used to classify the ground (default parameters). To convert point elevations to heights above ground, the lasheight algorithm was used.

3.2. Overview of the approach to model tree height growth

Our overall objective was to create an individual tree height growth model using a chronosequence of ALS-based height and estimates of stand competition to forecast potential tree height. Chronosequences were developed by combining tree height estimates from stands of varying ages for which this information was available at the stand level based on the planting date. We assumed that tree height growth and potential tree height are a function of four variables: tree height, tree position, tree competition (three tree-level metrics), and TH (stand-level variable). The presented approach consisted of three key processing steps (Fig. 2). First, an ITD approach was parametrized and validated using field inventory data. Second, ALS plots were chosen using a stratification based on SI (5 classes) and rotation age (17 classes), and the validated ITD approach was used to detect trees and extract their attributes. Third, tree competition was computed. Finally, we generated an individual tree height model using a Chapman-Richards (CR) model form, using 80% of the data, with accuracy assessed with the remaining 20%. We compared the effect of TH and tree competition on the upper asymptote of the height growth curve in the CR equation using the Akaike information criterion (AIC), mean absolute percentage error (MAPE), Bayesian information criterion (BIC), and root mean square error (RMSE), which are expressed as follows:

(1) AIC = $2K - 2\ln\left(\widehat{L}\right)$

(2) MAPE =
$$\frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - \widehat{y}|}{y_i}$$

 $BIC = Kln(n) - 2ln(\overline{L})$

Fig. 2. A flowchart showing the steps for the individual tree growth model. [Colour online]



(4) RMSE =
$$\sqrt{\frac{\sum_{i=1}^{n} (\widehat{y} - y_i)^2}{n}}$$

where \hat{y} is the predicted height value, y_i is the observed height value, n is the number of trees, K is the number of parameters estimated by the model, and \hat{L} is the maximized value of the likelihood function of the model.

3.3. Optimal ITD parameter determination

We used an ITD algorithm developed by Li et al. (2012), implemented in the lidR package in R (Roussel et al. 2021) to detect and segment individual tree crowns. The algorithm consists of two stages - after tree tops are located based on local maxima filtering, the surrounding points are then allocated to their associated tree clusters by selecting a spacing threshold (search radius) (Li et al. 2012). Several parameters of the algorithm can be adjusted by the user and affect the resulting set of detected trees. The search radius around tree tops is based on a minimum spacing criterion given a tree height, which by default is 2 m for trees taller than 15 and 1.5 m for trees shorter than 15 m, with a minimum height of 2 m. These parameters were tuned to find the best search radius values by running iteratively over all 167 field plots and modifying the parameter values between 0.2 and 2.8 m for trees less than 15 m tall and 0.7-3.3 m for trees taller than 15 m tall. The optimum set of ITD parameters was chosen based on the coefficient of determination (R²) and RMSE calculated using the number of detected trees and the reference number of trees measured in the field. The results of the ITD algorithm were a spatial layer of individual tree location, estimated crown size, and shape (Li et al. 2012), which were derived from the convex of all points assigned to that tree.

3.4. Data stratification

For this study, we performed a space-for-time substitution (Pickett 1989) that resulted in a chronosequence of individual tree height constructed with trees of different ages and growing at different sites. We built the chronosequence using the previously available SI layer as a stratifier to select ALS plots to extract individual tree height. According to Næsset (2002), stratification based on site productivity is a good tool for efficiently representing distinct forest stand conditions because it allows for coverage of the entire variability of tree height over the plantation. We extracted three ALS plots for each age ranging from 7 (tree heights exceeding 2 m, which is the criterion used in the ITD algorithm) to 24 years (harvesting time) for a total of 343 ALS plots of 20 m by 20 m.

3.5. Individual tree and stand metrics

Individual metrics, such as ZTOP (tree height, calculated as the highest return within the returns classified as part of ITD), tree location, crown area, and crown radius (using the convex hull), were determined in the selected forest stands using the calibrated ITD algorithm. The ZTOP attribute was used to develop the chronosequence of tree heights. TH was calculated as the average height of the 100 tallest trees per ha rather than the largest DBH (Pretzsch et al. 2015). As our ALS plots are 0.04 ha, this definition results in defining TH by the four tallest trees per plot. According to Gatziolis (2007), there is no significant difference in TH values when using DBH versus tree height, which is used and considered for SI estimates (Tompalski et al. 2015*a*).

3.6. Competition index

Tree competition can be defined as an interaction between neighbouring individuals in a shared environment with limited resource supply that results in a reduction in growth, survival, and reproduction (Begon et al. 1986). This can be expressed mathematically as a competition index (CI). There are numerous CIs described in the literature, which can be classified into two types: (*i*) distanceindependent indices that use only non-spatial information about aggregate tree size and (*ii*) distance-dependent indices that require spatially explicit tree coordinate locations (Radtke et al. 2003; Contreras et al. 2011), providing more reliable predictions for single tree growth (Biging and Dobbertin 1995).

For this study, two distance-dependent CIs were considered: (*i*) CI_H proposed by Hegyi (1974), which is calculated using the individual spatial coordinates per tree and the distance to its neighbours modified by Braathe (1980) to account for tree height instead of DBH and (*ii*) CI based on inverse distance weighting (IDW) — CI_{IDW} (Pont et al. 2021), which was used to quantify the distance to its neighbours only. The CIs are calculated as follows:

(5)
$$CI_{\rm H} = \sum_{ij=1}^{n} \frac{H_i/H_j}{D_{ij}+1}$$

(6)
$$CI_{IDW} = \frac{\sum_{j=1}^{n} H_j \times \frac{1}{D_{ij}^2}}{\sum_{j=1}^{n} \frac{1}{D_{ij}^2}}$$

where H_j is the height of the neighbour tree *j*, H_i is the height of subject tree *i*, and D_{ij} is the distance between the subject tree *i* and neighbour tree *j*. The interaction between neighbouring individual information per tree was collected in a fixed radius per ALS plot, based on 3.5 times the average tree crown radius (obtained during ITD metric extraction), as recommended by Contreras et al. (2011) and Lorimer (1983). To quantify CI for edge trees, a buffer of 10 m was established around the selected ALS plots, from which individual metrics were also measured, allowing information from neighbouring trees around edge trees to be collected.

3.7. Tree height growth model

Based on Von Bertalanffy's growth theory (Von Bertalanffy 1957), we fitted a CR function that expresses tree increment as a combination of anabolic processes (αY^{β}) that cause tree growth and catabolic processes (γY) that limit or diminish growth. This method has previously been used to estimate basal area growth (Pienaar and Turnbull 1973), DBH growth (Zhao-gang and Feng-ri 2003), dominant height growth (López-Sánchez et al. 2015), and, most recently, the effect of thinning management intensities on dominant height growth estimation (Zapata-Cuartas et al. 2021). The CR approach's base form is represented by

(7)
$$\frac{\mathrm{d}Y}{\mathrm{d}t} = \alpha Y^{\beta} - \gamma Y$$

where $\frac{dy}{dt}$ denotes changes in growth rate. When using chronosequence data, the height growth rate of an individual tree is not available; therefore, the CR model form described above must be transformed, using Bernoulli's integration equation (Salas-Eljatib 2020), which allows us to obtain the parameters α , β , and γ . This equation form is represented as follows:

(8)
$$Y = \Theta \times (1 - e^{-\Phi \times t})^{1/(1-\beta)} + \varepsilon$$

where Y is the variable to be predicted, Θ is the asymptote value of the response Y, Φ is related to the proportion of Y, β is a shape parameter of the height growth curve (or an allometric constant), and *t* is age (Clutter et al. 1983; Lei and Zhang 2004). Note that the relations between eqs. 7 and 8 are $\Theta = (\alpha/\gamma)^{[1/(1-\beta)]}$ and $\Phi = \gamma(1-\beta)$.

We assume that both TH and CI are related to the curve's upper asymptote, allowing us to compute the potential tree height or maximum individual tree height at the end of the rotation based on the current state of the tree individuals and knowledge of the variability of growth observed in different geographical areas from the tree height chronosequence. To represent this, we have included these variables in the Θ asymptote value:

(9)
$$\Theta = \Theta_1 \times (TH^{\Theta_2}) \times (CI^{\Theta_3})$$

where Θ_1 , Θ_2 , and Θ_3 are parameters, TH is the top height of the stand, and CI is the competition index (CI_H or CI_{IDW}).

A chronosequence of tree height does not provide individual tree height growth shape information when TH and CI are included because the measured trees do not share the same geographic spatial information or competition interactions. As a result, both Φ and β were set as constants to ensure that the model estimates fall within the expected range of height increment values.

The effect of variance on tree height prediction was modelled using the heteroskedastic trend between height and explanatory variable relationship, which increases with higher height values (Sandoval et al. 2021). This is critical for producing unbiased parameters for the CR equation and avoiding heteroskedastic effects in our prediction residual, which is calculated using the following equation:

(10)
$$\sigma = \sigma_1 \times Y^{\sigma^2}$$

where σ_1 and σ_2 are parameters and Y is the predicted tree height.

Using the abovementioned model formulation 9, we used TH and CI separately and in combination and developed the models using 80% of the ALS plots. All of these combinations were tested for tree height predictions and compared with the remaining 20% of the data for validation using AIC, BIC, MAPE, and RMSE.

3.8. Parameter estimation

Each of the models for tree height prediction was adjusted using the maximum likelihood method to predict goodnessof-fit and predictive capacity. For this, the iterative maximum likelihood method was used, as well as a Nelder–Mead algorithm (Nelder and Mead 1965) to minimize a negative log-likelihood function. The calculations were carried out in Python using the minimize method from the SciPy library (SciPy Community 2013). To examine the significance of each model parameter using 80% of the data for model calibration, a bootstrap with 150 iterations was used to obtain the 95% confidence interval.

Fig. 3. Relationship between the number of stems/ha from the field data and the best tuned ITD algorithm. The diagonal red line has slope 1 and origin zero. [Colour online]



Table 2. Summary information for selected ALS plots using 80% of the data for model calibration.

Stratification class	No. of trees	No. of ALS plots	Height (m)	Top height (m)
<26	1214	43	11.2 (2–31.7)	13.5 (6.5–28.3)
26–28	1165	52	16.1 (2.9–32.5)	18.3 (7.4–31.8)
28-30	1227	52	17.0 (2.1–35.9)	19.4 (8.7–35.5)
30–32	1480	63	18.1 (2–37.7)	20.2 (9.3-36.5)
>32	1718	65	20.3 (2.1-41.1)	23.3 (9.8–40.3)
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Note: The values shown are the mean, followed by the range in parentheses.

4. Results

4.1. Individual tree detection

The most appropriate parameters for the Li algorithm (Li et al. 2012) for ITD in the *P. radiata* plantation were search radii of 1.39 m (for trees shorter than 15 m) and 1.9 m (for trees taller than 15 m) based on the highest detection accuracy. The R^2 for the agreement between the number of detected and field-measured trees across all sites was 0.75, with an RMSE of 105 trees/ha, and is shown in Fig. 3.

This prediction is more accurate for field plots with a tree density of 375–750 individuals/ha, with an average residual of 60 trees/ha (68% of total field data), than in denser field plots. The accuracy of prediction is lowered in field plots with more than 750 stems/ha, which are underestimated by an average residual of 120 trees/ha.

A total of 8169 trees were detected across the five SI stratification classes. The average height was 19.2 m, with a range of 6.4–40.3 m. Of the located trees, 275 ALS plots resulting in 6804 trees were used for calibration (as summarized in Table 2) and used to generate the chronosequence (Fig. 4), with the remaining 68 ALS plots and 1365 trees remaining for validation.

4.2. Model fitting

Figure 4 shows the generic form of the individual tree height model fit to the chronosequence of ALS-derived tree height using eq. 8. When validated against the validation set, the model fit had an AIC of 57.1, a MAPE of 0.21, a BIC of 84.04, an RMSE of 3.69 m (Table 4), and a standard deviation that ranges from 1.7 m at 7 years to 7.4 m at 24 years (Fig. 4).

Table 3 shows parameter estimates for the model with various TH and CI values and their combinations. According to the bootstrap standard error with the estimated confidence interval, all of the parameters are significant. This is demonstrated by the fact that when using iterations to obtain 95% confidence intervals for the parameter's estimation, none of them contain zeros, indicating that the asymptote model cannot be used to derive a simple model because none of the parameters are eliminated.

Table 4 displays the model accuracies in the validation data set between observed and predicted tree height, as well as the model evaluation. The combination of the CI_H and

Fig. 4. Fitted Chapman–Richards model in a chronosequence of tree height. The middle red line represents the mean predicted value, while the top and bottom dashed red lines show the standard deviation. [Colour online]



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the TH in CR has the highest precision (RMSE = 2.9 m and MAPE = -0.15%) and a better-fit model for tree height prediction (AIC = -265 and BIC = -238). A comparison of CIs reveals that CI_H has a stronger representation of height growth than CI_{IDW}, with a significant reduction in the model prediction (AIC = -68.2, BIC= -46.7, MAPE = 0.168%, and RMSE = 3.11 m vs. AIC = -63.3, BIC= -41.8, MAPE = 0.172%, and RMSE = 3.34 m). The predicted vs. observed height of the trees using the best model (that included both TH and CI_H) in the validation set shows bias >4 m for 70% of the height observations (Fig. 5A).

4.3. Potential tree height and competition index

Figure 6 depicts the effect of CI and TH as independent factors on the potential tree height capacity, which is represented by the upper asymptote of the height growth curve. As increased site productivity improves potential tree height values, TH is positively related to height growth. Competition, on the other hand, has the opposite effect, as shown by CI_{H} (optimal CI representation for tree height estimate), with high CI values lowering potential tree height.

Figure 7A shows the height growth curves over time for the highest precision model, which incorporates both TH and CI, with varying CI values. Due to increased competition, potential tree height differences can be reduced by 22.2% at 30 years across a range of CI values (8 m of difference for a CI_H of value 1 to a CI_H of 6). Figure 7B depicts how a range of CI values affects both current annual increment (CAI) and mean annual increment (MAI), resulting in a 1 year difference in the age at which the average production per year is maximized (represented as the intersection point between CAI and MAI) between CI_H of 1 and CI_H of 6. The spatial representation of the mean CI_H value for a forest stand is shown in Fig. 8.

5. Discussion

In this paper, we used ALS-derived individual tree heights and plantation age to develop tree height models and assess the influence of tree competition and stand-level TH on individual tree height growth trajectory. When multiple height measurements of individual trees are unavailable, the benefit of using a single ALS-derived tree inventory and deriving a tree height chronosequence for estimating potential tree height is demonstrated. Similar to Tompalski et al. (2015b), who used a chronosequence of stand height properties to define site productivity, the methodology in this paper allowed us to define individual tree height while avoiding the need for future data acquisitions. Simultaneously, it provides forest managers with information to improve silviculture management by focusing on trees that will be taller per stand at the end of the rotation based on their potential tree height.

The presented method relied on ALS-derived individual tree heights. We did our best to accurately detect individual trees; however, due to limitations in field measured reference data (no stem map), the ITD algorithm validation was based only on the total number of detected trees. Nevertheless, when calibrating the ITD algorithm, we visually assessed the results to minimize omission and commission errors. In a single-layer pine plantation with majority of trees being

Model	Asymptote model	Parameter	Estimate	Boot SE	Lower limit	Upper limit
Generic form (<mark>eq</mark> . 4)	$\Theta \times (1 - e^{-\Phi \times (age)})^{1/(1 - \beta)}$	α	1.155	0.025	1.115	1.196
		β	0.593	0.018	0.563	0.623
		γ	0.259	0.025	0.217	0.301
		$\sigma 1$	0.289	0.005	0.282	0.297
		$\sigma 2$	-0.981	0.08	- 1.112	-0.85
CI _{IDW}	$\Theta = \Theta 1 \times (\mathrm{CI}_\mathrm{IDW}^{\Theta 2})$	Θ1	22.633	0.503	21.837	23.49
		$\Theta 2$	0.176	0.007	0.164	0.188
		$\sigma 1$	0.52	0.006	0.51	0.53
		$\sigma 2$	-0.742	0.088	- 0.886	- 0.598
TH	$\Theta = \Theta 1 \times (\mathrm{TH}^{\Theta 2})$	Θ1	22.804	0.571	21.866	23.743
		$\Theta 2$	0.165	0.008	0.152	0.178
		$\sigma 1$	0.53	0.007	0.518	0.542
		$\sigma 2$	-0.718	0.10	-0.882	-0.554
CI _H	$\Theta = \Theta 1 {\times} (CI_{H}^{\Theta 2})$	Θ1	44.856	0.578	43.906	45.806
		$\Theta 2$	-0.188	0.013	-0.21	-0.167
		$\sigma 1$	0.536	0.007	0.525	0.547
		$\sigma 2$	-0.805	0.097	- 0.966	-0.645
TH + CI _{IDW}	$\Theta = \Theta 1 \times (TH^{\Theta 2}) \times (CI^{\Theta 3}_{IDW})$	Θ1	37.091	1.113	35.260	38.922
		$\Theta 2$	- 0.936	0.047	-1.013	-0.858
		Θ3	0.988	0.042	0.919	1.056
		$\sigma 1$	0.486	0.007	0.474	0.498
		$\sigma 2$	-0.503	0.093	-0.657	-0.35
TH + CI _H	$\Theta = \Theta 1 \times (TH^{\Theta 2}) \times (CI_{H}^{\Theta 3})$	Θ1	30.914	1.351	28.692	33.136
		$\Theta 2$	0.102	0.011	0.085	0.12
		Θ3	-0.118	0.016	-0.144	-0.092
		$\sigma 1$	0.526	0.006	0.516	0.536
		$\sigma 2$	-0.74	0.101	-0.905	-0.574

Table 3. Parameter estimates for eq. 4 (generic form), for which $\Theta = (\alpha/\gamma)^{[1/(1 - \beta)]}$, and eq. 5, using various combinations of competition index (CI_H and CI_{IDW}) and TH on the upper asymptote parameter.

Note: σ 1 and σ 2 are model variance parameters. Boot SE = standard error of the bootstrap estimate; lower and upper limit bound for a 95% confidence interval.

Table 4. Model validation using the Chapman–Richards methodology for three growth predictions between the observed and predicted H using 20% of the data for validation, with different statistical estimators displaying the Akaike information criterion (AIC), Bayesian information criterion (BIC), root mean square error (RMSE), and mean absolute percentage error (MAPE).

	Fit/error statistics					
Model	AIC	BIC	RMSE	MAPE		
Generic form	57.1	84	3.69	0.211		
TH	28.1	49.5	3.23	0.175		
CI _{IDW}	-63.3	-41.8	3.34	0.172		
$TH + CI_{IDW}$	-35.7	-8.8	3.28	0.171		
CI _H	-68.2	-46.7	3.11	0.168		
$TH + CI_H$	-265.1	-238.2	2.9	0.154		

similar in size and in equal spacing, the lack of stem map is not as important as in case of natural stands. As a result, the ITD approach closely matches the measured total number of trees from field inventories. Nonetheless, there was a bias in the number of stems predicted in higher density field plots (above 750 trees per hectare), which may be attributed to edge effects that occur when tree tops near the plot's edge are missing in the ALS data and vice versa. Similar findings for ITD were made in a high-density point cloud using a Unmanned Aerial Vehicle (UAV) (Balsi et al. 2018), as well as ALS (Packalen et al. 2015).

Our results show that the potential tree height is influenced by both stand variables (TH) and tree variables (CI and individual height). When included in the model, they produced the most accurate prediction (RMSE = 2.9 m, MAPE = 0.154%). Other studies have found similar results for predicting tree survival and diameter growth (Cao 2014), as well as developing new models for predicting forest growth (Yue et al. 2008). The second-best model (CI_H) was developed by including competition, clearly demonstrating the effect of the surrounding trees and implying a close relation-

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Fig. 5. Relationship between (A) observed height and predicted tree height and (B) residual for predicted tree height. [Colour online]



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ship between individual tree height growth and competition (RMSE = 3.11 m, MAPE = 0.168%), which has been well established in previous height prediction research (Versace et al. 2019; Briseño-Reyes et al. 2020). When tested as an individual parameter, TH ranks fourth in terms of tree height prediction (RMSE = 3.23 m, MAPE = 0.175%), outperformed by CI_H , which could be explained by the fact that this variable represents productivity for forest stand, rather than individual tree. Although the statistical results for the different combinations of variables for individual height prediction shown in Table 4 may appear similar, small gains in accuracy may still contribute to improved forest management interventions in intensively managed plantations and result in significant economic benefit.

In this study, both CIs were able to account for tree competition, which has a negative impact on the potential tree height. The CI_{IDW} (accounts for location of surrounding trees only) was slightly less accurate in tree height growth estimations (RMSE = 3.34 m, MAPE = 0.172%) than the CI_H (includes location and heights of surrounding trees), indicating that in an even-aged plantation, even a low level of height heterogeneity plays an important role in the development of individual height growth, most likely related to light availability. Several studies in plantation forests have found similar results in terms of the importance of CI in growth, particularly when CIs that take tree dimensions into account are used (De Luis et al. 1998; Sandoval and Cancino 2008; Lin et al. 2016). The ability of ALS to easily extract height metrics and the spatial coordinates of tree individuals, as found in previous studies (Lin et al. 2016; Versace et al. 2019; Pont et al. 2021), enables an important benefit to account for tree competition in individual tree height growth predictions.

One of the most significant advantages of the proposed methodology is its ability to quantify the effect of CI and re-

Fig. 6. (A) Top height and (B) individual tree competition index (CI_H) relationship with the upper asymptote of the growth curve (potential tree height).



lating those values to potential tree height. Individual treebased analysis, as noted by Uhl et al. (2015), is essential for understanding the complex spatial interactions driving height growth variation within the stand, allowing a potential strategy to achieve maximum individual tree height values at a

Fig. 7. Tree growth under different competition values (CI_H) in (A) height and (B) mean annual growth and current annual growth. [Colour online]



desirable time based on an optimum plantation density, although additional analysis regarding economic return and optimum stand density is required. Similarly to a previous research on the distance-dependent model and forest growth (Fransson et al. 2019), direct selection of trees for thinning prescriptions based on spacing and competition may provide an important tool for efficiently selecting trees for thinning prescriptions. This could directly improve forest yield by using potential tree height as a criterion to identify the most commercially valuable trees per stand.

As stated in the literature, collecting multiple ALS data for an entire area of interest is not always possible due to limited resources or restrictions associated with covering remote or large areas (Luther et al. 2019). As a result, the primary advantage of using a chronosequence to predict tree height growth is that it enables a low-cost method of forecasting maximum tree height by the end of the rotation using a single ALS data set. As a result of using a chronosequence to estimate potential tree height, an anamorphic height growth outcome model based on the integration of TH and CI in the asymptote parameter is produced, which is comparable to previous forest stand SI prediction research (Fontes et al. 2003; Burkhart and Tomé 2012). This refers to a single height growth shape for all prediction attributes that is scaled up and down, with different asymptotes for different conditions. **Fig. 8.** Spatial representation for the CI_H mean value per stand, followed by the range in brackets, for (A) CI = 1 (0.8–2.1); (B) CI = 2.1 (1.4–3.5); and (C) CI = 3.2 (2.4–5.1). [Colour online]



Chronosequence studies, on the other hand, make the assumption that all ALS plots and measured trees differ only in age and that all trees have the same abiotic, biotic component histories, and geographical position (Williamson and Likens 1990), which is unlikely in most cases. This presents a challenge and a disadvantage for the CR growth equation used in this way, limiting a more flexible dynamic approach due to a lack of individual height growth rates or current annual height growth data, and resulting in an inability to predict the height growth constant parameter from the CR equation. As a result, using this formulation to depict the competition factor changing over time is not feasible because it requires both Φ and β to be estimated in the CR equation regarding the effect of TH and CI. When using a single ALS data set, however, a chronosequence of tree height accurately predicts the asymptote value of the height growth curve per tree, which can be used to forecast future thinning plans and indirectly deduce growth survival patterns (Zhao et al. 2010).

The value of using height chronosequences to forecast potential tree height from a single ALS data set was demonstrated in this study. This method is likely to be applicable to other species and regions where a relatively simplistic forest pattern allows for accurate ITD. It is critical to examine two ALS measurements to estimate height growth pattern over time to develop polymorphic models with variable asymptotes and height growth trajectories, as well as including the model variance to develop probabilistic outcomes regarding potential tree height. Although competition was spatially registered successfully using a single ALS from tree-based analysis, a true forest height growth situation comprises dynamic CI values along the age rotation, which was kept constant for this study. More advancements from multiple ALS measurements may also improve the CI dynamics on forest height growth over time.

6. Conclusion

In conjunction with the stand TH attribute, CI reduces the prediction error and improves tree height growth prediction, providing additional insights into forest productivity for thinning management decisions. ALS is a useful tool for quantifying CI in large areas for forest management and stand productivity estimations, strengthening the SI concept, and allowing spatial explicit forecasting within the forest stand. Our findings support the use of a chronosequence to predict individual tree height growth in a time-cost efficient manner, particularly to predict potential tree height as an indicator of the most commercially valuable tree within the forest stand.

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Data availability

The datasets generated and (or) analyzed during the current study are available from the corresponding author upon reasonable request.

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Author contributions

Conceptualization, GGA and NCC; data curation, GGA; investigation, GGA; formal analysis, GGA and PMQ; methodology, PT, PMQ, and GGA; validation, NCC and PT; visualization, NCC and PT; writing—original draft, GGA; writing—review and editing, NCC and PT; supervision, NCC.

Competing interests

The authors declare that there are no competing interests.

References

- Akay, A.E., Oğuz, H., Karas, I.R., and Aruga, K. 2009. Using LiDAR technology in forestry activities. Environ. Monit. Assess. 151(1–4): 117–125. doi:10.1007/s10661-008-0254-1. PMID: 18365761.
- Balsi, M., Esposito, S., Fallavollita, P., and Nardinocchi, C. 2018. Singletree detection in high-density LiDAR data from UAV-based survey. Eur. J. Remote Sens. 51(1): 679–692. doi:10.1080/22797254.2018.1474722.
- Begon, M., Harper, J.L., and Townsend, C.R. 1986. Ecology: individuals, populations and communities. Blackwell Scientific Publications, Oxford.
- Biging, G.S., and Dobbertin, M. 1995. Evaluation of competition indices in individual-tree growth models. For. Sci. 41: 360–377.
- Bontemps, J.D., and Bouriaud, O. 2014. Predictive approaches to forest site productivity: recent trends, challenges and future perspectives. Forestry, 87(1): 109–128. doi:10.1093/forestry/cpt034.
- Bortolot, Z.J., and Wynne, R.H. 2005. Estimating forest biomass using small footprint LiDAR data: an individual tree-based approach that incorporates training data. ISPRS J. Photogramm. Remote Sens. **59**(6): 342–360. doi:10.1016/j.isprsjprs.2005.07.001.
- Braathe, P. 1980. Height increment of young single trees in relation to height and distance of neighboring trees. Mitt. Forstl. VersAnst. 130: 43–48.
- Briseño-Reyes, J., Corral-Rivas, J.J., Solis-Moreno, R., Padilla-Martínez, J.R., Vega-Nieva, D.J., López-Serrano, P.M., et al. 2020. Individual tree diameter and height growth models for 30 tree species in mixed-species and uneven-aged forests of Mexico. Forests, 11(4): 1–16. doi:10.3390/ F11040429.
- Burkhart, H.E., and Tomé, M. 2012. Modeling forest trees and stands. Springer, Dordrecht. doi:10.1007/978-90-481-3170-9.
- Cao, Q.V. 2014. Linking individual-tree and whole-stand models for forest growth and yield prediction. For. Ecosyst. 1(1): 1–8. doi:10.1186/ s40663-014-0018-z.
- Casanova, M., Salazar, O., Seguel, O., and Luzio, W. 2013. The soils of Chile. Springer, Dordrecht. p. 191. doi:10.1007/978-94-007-5949-7.
- Clutter, J.L., Fortson, J.C., Pienaar, L.V., Brister, G.H., and Bailey, R. L. 1983. Timber management: A quantitative approach. John Wiley & Sons, Inc.
- Contreras, M.A., Affleck, D., and Chung, W. 2011. Evaluating tree competition indices as predictors of basal area increment in western Montana forests. For. Ecol. Manage. 262(11): 1939–1949. doi:10.1016/ j.foreco.2011.08.031.
- Coops, N.C. 2015. Characterizing forest growth and productivity using remotely sensed data. Curr. For. Reports 1(3): 195–205. doi:10.1007/ s40725-015-0020-x.
- Corte, A.P.D., Rex, F.E., de Almeida, D.R.A., Sanquetta, C.R., Silva, C.A. Moura, M.M., et al. 2020. Measuring individual tree diameter and height using GatorEye High-Density UAV-Lidar in an integrated crop-livestock-forest system. Remote Sens. 12(5): 863. doi: 10.3390/ rs12050863.
- Dale, V.H., and Shugart, H.H. 1985. A comparison of tree growth models. Ecol. Modell. **29**: 145–169. doi:10.1016/0304-3800(85)90051-1.
- De Luis, M., Raventós, J., Cortina, J., Moro, M.J., and Bellot, J. 1998. Assessing components of a competition index to predict growth in an

even-aged Pinus nigra stand. New For. **15**(3): 223–242. doi:10.1023/A: 1006507017646.

- Fontes, L., Tomé, M., Coelho, M.B., Wright, H., Luis, J.S., and Savill, P. 2003. Modelling dominant height growth of Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) in Portugal. **76**(5): 509–523.
- Fransson, P., Nilsson, U., Lindroos, O., Franklin, O., and Brännström, Å. 2019. Model-based investigation on the effects of spatial evenness, and size selection in thinning of *Picea abies* stands. Scand. J. For. Res. 34(3): 189–199. doi:10.1080/02827581.2019.1577914.
- From, F., Strengbom, J., and Nordin, A. 2015. Residual long-term effects of forest fertilization on tree growth and nitrogen turnover in boreal forest. Forests, 6(4): 1145–1156. doi:10.3390/f6041145.
- García, O. 1990. Growth of thinned and pruned stands. *In* New approaches to spacing and thinning in plantation forestry. Ministry of Forestry, FRI. p. 1–10.
- García, O. 1994. The state-space approach in growth modelling. Can. J. For. Res. 24: 10. doi:10.1139/x94-244.
- Gatziolis, D. 2007. Lidar-derived site index in the U.S. Pacific Northwest: challenges and opportunities. ISPRS Work. Laser Scanning 2007 Silvi-Laser 2007, Espoo, Sept. 12-14,2007, Finl. LIDAR-DERIVED (January): 136–143.
- Gavilán-acuña, G., Olmedo, G.F., Mena-quijada, P., Guevara, M., Barríaknopf, B., and Watt, M.S. 2021. Reducing the uncertainty of radiata pine site index maps using an spatial ensemble of machine learning models. Forests, **12**: 77.
- Görgens, E.B., Packalen, P., da Silva, A.G.P., Alvares, C.A., Campoe, O.C., Stape, J.L., and Rodriguez, L.C.E. 2015. Stand volume models based on stable metrics as from multiple ALS acquisitions in eucalyptus plantations. Ann. For. Sci. 72(4): 489–498. doi:10.1007/s13595-015-0457-x.
- Habib, A., Ghanma, M., Morgan, M., and Al-Ruzouq, R. 2005. Photogrammetric and Lidar data registration using linear features. Photogramm. Eng. Remote Sensing, 71(6): 699–707. doi:10.14358/PERS. 71.6.699.
- Hegyi, F. 1974. A simulation model for managing jack-pine stands. In Growth models for tree and stand simulation. Edited by J. Fries. Royal College of Forestry, Stockholm, Sweden.p. 74–90.
- Huang, S., Hager, S.A., Halligan, K.Q., Fairweather, I.S., Swanson, A.K., and Crabtree, R.L. 2009. A comparison of individual tree and forest plot height derived from Lidar and InSAR. Photogramm. Eng. Remote Sensing, 75(2): 159–167. doi:10.14358/PERS.75.2.159.
- Isenburg, M. 2021. LAStools. Version 211206, Academic. [WWW Document]. https://rapidlasso.com/ [accessed 18 April 2021].
- Jeronimo, S.M.A., Kane, V.R., Churchill, D.J., McGaughey, R.J., and Franklin, J.F. 2018. Applying LiDAR individual tree detection to management of structurally diverse forest landscapes. J. For. 116(4): 336– 346. doi:10.1093/jofore/fvy023.
- Lei, Y.C., and Zhang, S.Y. 2004. Features and partial derivatives of Bertalanffy-Richards growth model in forestry. Nonlinear Anal. Model. Control, 9(1): 65–73. doi:10.15388/na.2004.9.1.15171.
- Li, W., Guo, Q., Jakubowski, M.K., and Kelly, M. 2012. A new method for segmenting individual trees from the Lidar point cloud. Photogramm. Eng. Remote Sensing, 78(1): 75–84. doi:10.14358/PERS.78. 1.75.
- Lin, C., Thomson, G., and Popescu, S.C. 2016. An IPCC-compliant technique for forest carbon stock assessment using airborne Lidar-derived tree metrics and competition index. Remote Sens. 8(6): 528. doi:10. 3390/rs8060528.
- López-Sánchez, C.A., Álvarez-González, J.G., Diéguez-Aranda, U., and Rodríguez-Soalleiro, R. 2015. Modelling dominant height growth in plantations of *Pseudotsuga menziesii* (Mirb.) Franco in Spain. South. For. 77(4): 315–319. doi:10.2989/20702620.2015.1077417.
- Lorimer, C.G. 1983. Tests of age-independent competition indices for individual trees in natural hardwood stands. For. Ecol. Manage. 6(4): 343–360. doi:10.1016/0378-1127(83)90042-7.
- Luther, J.E., Fournier, R.A., van Lier, O.R., and Bujold, M. 2019. Extending ALS-based mapping of forest attributes with medium resolution satellite and environmental data. Remote Sens. 11(9): 1092. doi:10. 3390/rs11091092.
- Maltamo, M., Næsset, E., and Vauhkonen, J. 2014. Forestry applications of airborne laser scanning. Concepts and case studies. Springer, Dordrecht.
- Næsset, E. 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field

data. Remote Sens. Environ. **80**(1): 88–99. doi:10.1016/S0034-4257(01) 00290-5.

- Naveed, F., Hu, B., Wang, J., and Hall, G.B. 2019. Individual tree crown delineation using multispectral LiDAR data. Sensors (Switzerland), 19(24): 1–21. doi:10.3390/s19245421.
- Nelder, J.A., and Mead, R. 1965. A simplex method for function minimization. Comput. J. 7(4): 308–313. doi:10.1093/comjnl/7.4.308.
- Olmedo, G.F., Guevara, M., Gilabert, H., Montes, C.R., Arellano, E.C., Barría-Knopf, B., et al. 2020. Baseline of carbon stocks in Pinus radiata and Eucalyptus spp. plantations of Chile. Forests, **11**(10): 1–28. doi:10.3390/f11101063.
- Packalen, P., Strunk, J.L., Pitkänen, J.A., Temesgen, H., and Maltamo, M. 2015. Edge-Tree correction for predicting forest inventory attributes using area-based approach with airborne laser scanning. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 8(3): 1274–1280. doi:10.1109/ JSTARS.2015.2402693.
- Perry, G.L.W., Enright, N.J., Miller, B.P., and Lamont, B.B. 2008. Spatial patterns in species-rich sclerophyll shrublands of southwestern Australia. J. Veg. Sci. 19(5): 705–716. doi:10.3170/2008-8-18441.
- Picard, N., Saint-André, L., and Henry, M. 2012. Manual for building tree volume and biomass allometric equations: from field measurement to prediction. Food and Agricultural Organization of the United Nations, Rome, and Centre de Coopération Internationale en Recherche Agronomique pour le Développement.
- Pickett, S.T.A. 1989. Space-for-time substitution as an alternative to longterm studies. *In* Long-term studies in ecology. *Edited by* G.E. Likens. Springer, New York. doi:10.1007/978-1-4615-7358-6_5.
- Pienaar, L.V., and Turnbull, K. 1973. The Chapman–Richards generalization of Von Bertalanffy's growth model for basal area growth and yield in even-aged stands. For. Sci. 19: 22. doi:10.1093/forestscience/ 19.1.2.
- Pont, D., Dungey, H.S., Suontama, M., and Stovold, G.T. 2021. Spatial models with inter-tree competition from airborne laser scanning improve estimates of genetic variance. Front. Plant Sci. 11(January): 1–9. doi:10.3389/fpls.2020.596315.
- Popescu, S.C. 2007. Estimating biomass of individual pine trees using airborne LiDAR. Biomass Bioenergy, **31**(9): 646–655. doi:10.1016/j. biombioe.2007.06.022.
- Pretzsch, H. 2009. Forest dynamics, growth and yield. Springer, Berlin/Heidelberg.
- Pretzsch, H., del Río, M., Ammer, C., Avdagic, A., Barbeito, I. Bielak, K., et al. 2015. Growth and yield of mixed versus pure stands of Scots pine (*Pinus sylvestris* L.) and European beech (*Fagus sylvatica* L.) analysed along a productivity gradient through Europe. Eur. J. For. Res. 134(5): 927–947. doi:10.1007/s10342-015-0900-4.
- Pukkala, T., and Kolström, T. 1987. Competition indices and the prediction of radial growth in Scots pine. Silva Fenn. 21(1): 55–67. doi:10. 14214/sf.a15463.
- Radtke, P.J., Westfall, J.A., and Burkhart, H.E. 2003. Conditioning a distance-dependent competition index to indicate the onset of intertree competition. For. Ecol. Manage. 175(1–3): 17–30. doi:10.1016/ S0378-1127(02)00118-4.
- Roussel, J.R., Auty, D., Boissieu, F.D., Meador, A.S., Bourdon, J., and Goodbody, T.R. 2021. Package 'lidR'.Available from https://github.com/Jea n-Romain/lidR [accessed 23 May 2021].
- Salas-Eljatib, C. 2020. Height growth–rate at a given height: a mathematical perspective for forest productivity. Ecol. Modell. **431**(July): 109198. doi:10.1016/j.ecolmodel.2020.109198.
- Sandoval, S., and Cancino, J. 2008. Modeling the edge effect in even-aged Monterrey pine (*Pinus radiata* D. Don) stands incorporating a competition index. For. Ecol. Manage. 256(1–2): 78–87. doi:10.1016/j.foreco. 2008.03.053.
- Sandoval, S.M., C.R, Olmedo, G.F., Acuña. E., and Mena-Quijada, P. 2021. Modelling above-ground biomass of *Pinus radiata* trees with explicit multivariate uncertainty. Forestry: **95**: 380–390.

- Schröder, J., Röhle, H., Gerold, D., and Münder, K. 2007. Modeling individual-tree growth in stands under forest conversion in East Germany. Eur. J. For. Res. **126**(3): 459–472. doi:10.1007/ s10342-006-0167-x.
- SciPy Community. 2013. SciPy Reference Guide 0.7.
- Skovsgaard, J.P., and Vanclay, J.K. 2008. Forest site productivity: a review of the evolution of dendrometric concepts for even-aged stands. Forestry, 81(1): 13–31. doi:10.1093/forestry/cpm041.
- Spriggs, R.A., Coomes, D.A., Jones, T.A., Caspersen, J.P., and Vanderwel, M.C. 2017. An alternative approach to using LiDAR remote sensing data to predict stem diameter distributions across a temperate forest landscape. Remote Sens. 9(9): 944. doi:10.3390/rs9090944.
- Tompalski, P., Coops, N.C., White, J.C., and Wulder, M.A. 2015a. Augmenting site index estimation with airborne laser scanning data. For. Sci. 61(5): 861–873. doi:10.5849/forsci.14-175.
- Tompalski, P., Coops, N.C., White, J.C., Wulder, M.A., and Pickell, P.D. 2015b. Estimating forest site productivity using airborne laser scanning data and Landsat time series. Can. J. Remote Sens. 41(3): 232– 245. doi:10.1080/07038992.2015.1068686.
- Tompalski, P., Coops, N.C., White, J.C., Goodbody, T.R.H., Hennigar, C.R. Wulder, M.A., et al. 2021. Publisher correction: estimating changes in forest attributes and enhancing growth projections: a review of existing approaches and future directions using airborne 3D point cloud data. Curr. For. Rep. **7**(1): 25–30. doi:10.1007/ s40725-021-00139-6.
- Treitz, P., Lim, K., Woods, M., Pitt, D., Nesbitt, D., and Etheridge, D., 2012. LiDAR sampling density for forest resource inventories in Ontario, Canada. Remote Sens. 4(4): 830–848. doi:10.3390/rs4040830.
- Uhl, E., Biber, P., Ulbricht, M., Heym, M., Horváth, T. Lakatos, F., et al. 2015. Analysing the effect of stand density and site conditions on structure and growth of oak species using Nelder trials along an environmental gradient: experimental design, evaluation methods, and results. For. Ecosyst. 2(1): 17. doi:10.1186/s40663-015-0041-8.
- van Leeuwen, M., and Nieuwenhuis, M. 2010. Retrieval of forest structural parameters using LiDAR remote sensing. Eur. J. For. Res. 129(4): 749–770. doi:10.1007/s10342-010-0381-4.
- Vauhkonen, J., and Pukkala, T. 2016. Selecting the trees to be harvested based on the relative value growth of the remaining trees. Eur. J. For. Res. 135(3): 581–592. doi:10.1007/s10342-016-0956-9.
- Versace, S., Gianelle, D., Frizzera, L., Tognetti, R., Garfi, V., and Dalponte, M. 2019. Prediction of competition indices in a Norway spruce and silver fir-dominated forest using Lidar data. Remote Sens. 11(23): 1– 19. doi:10.3390/rs11232734.
- Von Bertalanffy, L. 1957. Quantitative laws in metabolism and growth. Q. Rev. Biol. 32(3): 217–231. doi:10.1086/401873.
- West, P.W. 2015. Tree and forest measurement. Springer, Cham. doi:10. 1007/978-3-319-14708-6.
- Wikström, P., Edenius, L., Elfving, B., Eriksson, L.O., Lämås, T., Sonesson, J., et al. 2011. The Heureka forestry decision support system: an overview. Math. Comput. For. Nat. Sci. 3(2): 87–95.
- Williamson, M., and Likens, G.E. 1990. Long-term studies in ecology. Approaches and alternatives. J. Anim. Ecol. 59: 381. doi:10.2307/5183.
- Yue, C., Kohnle, U., and Hein, S. 2008. Combining tree- and stand-level models : a new approach to growth. For. Sci. **54**: 553–566.
- Zapata-Cuartas, M., Bullock, B.P., Montes, C.R., and Kane, M.B. 2021. A dynamic stand growth model system for loblolly pine responding to mid-rotation treatments. Forests, 12(5): 556. doi:10.3390/ f12050556.
- Zhao-gang, L., and Feng-ri, L. 2003. The generalized Chapman–Richards function and applications to tree and stand growth. J. For. Res. 14(1): 19–26. doi:10.1007/bf02856757.
- Zhao, D., Kane, M., and Borders, B.E. 2010. Development and applications of the relative spacing model for loblolly pine plantations. For. Ecol. Manage. 259(10): 1922–1929. doi:10.1016/j.foreco.2010.02. 003.