Assessing the potential of adaptive individual tree detection to improve accuracy of area-based stand density modelling in ALS-assisted forest inventory

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1. Introduction

Airborne Laser Scanning data enables the accurate three-dimensional characterization of vertical forest structure, and have proven to be an information-rich asset for forest managers, enabling the generation of highly detailed digital elevation models and the estimation of a range of forest inventory attributes with high accuracy (Coops et al., 2021; White et al., 2016). The most common LiDAR-derived forest attributes in the bibliography are height, volume, above ground biomass, canopy cover and basal area. Despite being a variable of great importance for forest management, tree density is not a variable frequently estimated from ALS data using area-based approaches. Several studies (Goerndt et al., 2011, 2010; Hall et al., 2005; Næsset and Bjerknes, 2001) have shown that estimation of tree density using area-level LiDAR metrics was difficult because of the lack of correlation between density and canopy height characteristics.

ALS data have also been successfully used to identify individual trees across forest stands, thanks to easily accessible and applicable algorithms. The local maxima CHM-based methods are the most frequently found in literature to identify the treetops, due to its simplicity and ease of use compared to other methods based on full point cloud analysis (Latella et al., 2021; Wu et al., 2016; Zhao et al., 2014). The CHM-based approaches have proven to be quite effective in very regular vegetation pattern, especially when only one layer of the tree canopy is present, and in coniferous stands. Nevertheless, this approach may provide lower-accuracy results when applied under more complex structures (Ene et al., 2012; Richardson and Moskal, 2011). The accuracy of the CHM-based methods used to identify individual trees is known to be highly influenced by the parameter setting. It has been described the extreme sensitivity to the size of the cell window that is used to inspect the CHM and detect the height maxima. The window size, indeed, represents the main and most critical parameter to achieve satisfactory accuracy. A large window smooths the variations of canopy height and drastically reduces the detected peaks, whereas a small one can dramatically increase the number of peaks. Although it is known that the optimum value of this parameter depends on stand characteristics such as the species composition, its height, degree of irregularity, or degree of competition, the literature does not provide robust criteria for the window size setting and, therefore, the CHM-methods require site-specific measurements and calibration (Latella et al., 2021; Popescu and Wynne, 2004).

In this paper we analyze the potential for using individual tree detection (ITD) to improve the accuracy of tree density estimation in ALS area-based forest inventories. To do that, we use a CHM-based algorithm for tree detection based on a local maximum filter, with adaptive parametrization of the window size based on stand structural attributes. The experiment uses inventory data from even-aged *Pinus radiata* plantation forests, and compares the result of stand density estimation when: (1) modelled using only point cloud-derived metrics, (2) modelled using point cloud-derived metrics together with the number of trees detected by ITD, (3) calculated from basal area (G) and quadratic mean diameter (Dg), both modelled with point cloud-derived metrics, and (4) calculated directly through ITD.

2. Data and Methods

2.1 Field data

Field data was acquired from the Spanish National Forest Inventory (northern Atlantic region). We used 82 plots measured from November 2017 to March 2018 in the provinces of Gipuzkoa and Bizkaia, dominated by *Pinus radiata* (more than 90% of basal area of this species). Only plots where trees were accurately geolocated (manually checked with the help of orthophotos and LiDAR-derived CHM) were

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included in this sample. Each NFI plot is made up of 4 subplots with a radius of 5, 10, 15 and 25 meters. In these four subplots, the trees were measured with DBH greater than 7.5, 12.5, 22.5 and 42.5 cm respectively. Consequently, within the 10-meter subplot, all trees with diameter greater than 12.5 were measured. We used this subplot for subsequent analysis.

2.2 ALS data

ALS data were acquired by Hazi foundation within the LIFE Healthy Forest project (LIFE14 ENV/ES/000179), cofounded by the Basque government, between March and October 2017, using a LEICA ALS70-HP system with a mean density of 2.2 pulse/m^2 and RMSEZ < 0.15 meter. Pre-processed data is available in 500×500 m tiles, with points already classified as ground, low and high vegetation, buildings, outliers and unknown. All point cloud data analyses in this work have been performed with the functions of the lidR package for R (Roussel et al., 2020).

2.3 Data analysis

We first run tree detection on the area covered by the field plots using the algorithm *lmf*, implemented in the *find_trees* function of the lidR package for R. We did it iteratively with the parameter window size (*ws*) taking values from 2 to 8 each 0.2 m. The *hmin* parameter was set to 6 meter to be coherent with the minimum diameter of 12.5 cm measured in the 10-meter IFN plots, and the *shape* parameter was set as "circular", since the natural crown of *Pinus radiata* tends to this shape. For each value of *ws* and in each plot, we compared the result of tree detection with the trees measured in the field. We assessed the quality of the results by calculating the ratio *trees detected (CHM) / trees measured (field)*, named as "*ratio_det_ifn*".

We then selected as the optimal *ws* value for each plot that with the lower error in that ratio, computing the error as: *abs(1 - ratio_det_ifn)*. Once we had the optimal *ws* value for each plot, we analysed its relationship with the ALS point-cloud metrics at the plot level, and fitted an Extreme Gradient Boosting (XGB) model using the xgboost package for R (Chen and Guestrin, 2016), to predict the optimal *ws* parameter depending on them.

On the other hand, we fitted predictive models for stem density, basal area and the quadratic mean diameter as usual in area-based approach, using ALS point-cloud derived metrics as predictors. To process ALS metrics, the point cloud was clipped to the corresponding NFI 10-meter subplot. Models were fitted using XGB as well.

Finally, we used the predicted value for the optimal *ws* parameter to run ITD within each plot, and modelled again stand density adding the resulting number of trees detected by ITD as an additional variable to point-cloud derived metrics. In order to compare all possible ways to estimate stem density within this workflow, we also compute the stem density from predicted basal area (G) and quadratic mean diameter (Dg).

3. Results and discussion

Our results showed that the optimal value for the *ws* parameter has a significant relationship with certain ALS point-cloud derived metrics. Concretely, the best model to predict *ws* used standard deviation, entropy and interquartile range of height distribution, together with the mean height, as predictors, and reported a relative RMSE of 26.837%. Overall, predicted values of *ws* varied depending on mean tree size and tree size inequality, as reflected by the point-cloud metrics selected in the best model.

When we used the predicted *ws* parameter to detect the number of trees within the plots, and related the resulting number of trees with the stand density measured in the NFI field plots, we found that the number of detected trees using this methodology is not a good standalone predictor for stand density (RMSE: 39.757%). However, its performance improves when used in combination with a selection of ALS point-cloud derived metrics, concretely, the 95th percentile of height returns, and the Canopy Relief Ratio (i.e., a quantitative descriptor of the relative shape of the canopy from altimetry observation). This combination of variables allowed us to reach 19.061% relative RMSE in the estimation of stand density, compared to 24.376% obtained when using the best combination of ALS point-cloud derived metrics alone. The alternative of calculating the density from the predicted G and Dg reported 23.947% relative RMSE.

The result of this study shows the potential of this workflow for improving the accuracy in stand density estimation based on ALS point-cloud metrics, but is just a promising first step that deserves further development with the use of variable radius search windows, as well as the use of alternative tree detection methods.

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