Estimation of stand density using aerial LiDAR information: Integrating the area-based-approach and individual-tree-detection methods in plantations of *Pinus radiata.*

Estimación de la densidad de rodal a partir de información LiDAR aérea integrando el método de masa y árbol individual en plantaciones de *Pinus radiata*.

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SUMMARY

A mixed approach was applied using aerial LiDAR information to estimate the stand density in a *Pinus radiata* plantation. The methods used individual tree detection (ITD) information to improve stand density estimates from the approach-based area (ABA) method. Method 1, which corresponds to the traditional ABA estimation in a linear mode, obtained a RMSE = 23.6 % and a AIC = 840.9, where the LiDAR metrics used were in the 95 % percentile and the ratio between first returns over 1.3 m (COV). Method 2, which corresponds to an Individual Tree Detection (ITD) algorithm configured with a search window of 3 meters and a height defined by the 50th percentile, resulted in a RMSE = 49%. The mixed method 3 used the number of trees detected in method 2 as an additional metric in the ABA method, generating RMSE = 20.9 % and a AIC = 822.1. Method 4 was defined as mixed with error, which incorporated the number of trees estimated using the ITD method as another predictor variable, generating a RMSE = 21.3 % and a AIC = 835.2. The method with the best performance was 3, reducing 2.7 percentage points with respect to the RMSE of method 1 (traditional ABA). The integration of the ABA and ITD methods improved estimations of stand density, and also achieved better representation of the spatial variability of the number of trees at complete stand level.

Keywords: forest inventories, remote sensing, ABA method, ITD method.

RESUMEN

Se aplicó un enfoque mixto utilizando información LiDAR aérea para estimar la densidad del rodal en una plantación de *Pinus radiata*. El método utiliza la información de la identificación de árbol individual (ITD) para mejorar las estimaciones de la densidad de rodal del método de estimación a nivel de masa (ABA). En el método 1 que corresponde a la estimación tradicional ABA en un modelo lineal obtuvo un RMSE = 23,6 % y un AIC = 840,9; donde las métricas LiDAR usadas fueron el percentil 95 % y razón entre primeros retornos sobre 1,3 metros (COV). El método 2, el cual corresponde a un algoritmo de identificación de árboles ITD configurado en una ventana de búsqueda de 3 metros y una altura definida por el percentil 50 %, generó una RMSE = 49 %. El método 3 mixto utilizó el número de árboles identificados en el método 2 como una métrica adicional en el método ABA, generando RMSE = 20,9 % y un AIC = 822,1. El método 4 definido como mixto que incorpora el número de árboles estimados por el método ITD como otra variable predictora, generó RMSE = 21,3 % y AIC = 835,2. El método con mejor performance fue el 3, reduciendo 2,7 puntos porcentuales con respecto a la RMSE del método 1 (ABA tradicional). La integración del método ABA e ITD mejoró las estimaciones de la densidad de rodal, además logró representar mejor la variabilidad espacial del número de árboles a nivel de rodal completo.

Palabras clave: inventarios forestales, sensoramiento remoto, método ABA, método ITD.

INTRODUCTION

Forest inventory is the main tool for evaluation of forest resources, and its results are used to support forest management (Zhang *et al.* 2016). To generate reliable estimators of stand condition variables (*e.g.* volume, basal area, dominant height, stand density), in forest inventories, it is important to achieve greater precision in field measurement. Traditionally, this information is recorded from field sampling plots assigned to a statistical design. Depending on the intensity of sampling and the accessibility of the terrain, this process involves human labor, increasing information processing time and operational costs (Goodbody *et al.* 2017). To support the implementation of inventories and as an alternative evaluation, recently new techniques based on remote sensing, such as LiDAR (Light Detection

and Ranging), have been developed that have improved the evaluation of forests.

The first uses of LiDAR technology in forest inventories were implemented by the area based approach (ABA) method. This consists of obtaining a cloud of points by flying over the study area, and obtaining metrics including values and statistics representing the height distribution of the LiDAR returns of the forest. The relationship between forest dasometric variables and metrics is described using models, which allow estimations to be made over the entire area of interest. The advantages of this method are numerous, among them the fact that it allows the estimation of physical parameters of the forest over large areas. Additionally, it is possible to make estimates in areas that are difficult to access, which reduces operating costs in relation to the traditional forest inventory. White *et al.* (2013) indicated that one of the main advantages of LiDAR inventories in contrast to traditional inventories is that they allow the identification of forest variability, generating estimates over the entire area in a raster output format, where each pixel of the raster contains an estimate of the variable of interest.

In the LiDAR inventory, the metrics obtained from the point cloud are related to stand condition variables measured in field plots. In the modeling phase, linear, non-linear and non-parametric structure models have been evaluated, reporting different results. Most studies highlight the accuracy of indicators obtained when modeling the mean or dominant stand height, agreeing that it is the easiest variable to predict. González-Ferreiro *et al.* (2012) indicated that the dominant height of a stand has a high correlation only using LiDAR metrics of the height distribution, *e.g.* with the 95th percentile of the point cloud. Treitz *et al.* (2012) modeled stand height, and reported $R^2 = 0.95$ in the estimation of height in LiDAR inventories conducted in Canadian forests. For other stand variables, good results have also been reported. Silva *et al.* (2017) developed basal area models for *Pinus taeda* L. in southern Brazil, obtaining a coefficient of determination (R^2) of 0.93 and a root mean square error (RMSE) of 7.74 %. Sheridan *et al.* (2015) generated models of biomass and total volume in eastern Oregon in the United States, reporting R^2 of 0.87 and 0.88, respectively.

Generally, using the ABA method for modeling of height, basal area and volume, good indicators of quality of fit have been reported, though problems arise when trying to predict stand density. Here, most of the research reports R^2 values lower than 0.50 and high estimation error evaluated according to RMSE. Treitz *et al.* (2012) generated estimation models for stand density using aerial LiDAR data with a resolution of 3.2 points m^{-2} and obtained an R^2 of 0.23. More promising results were reported by Sánchez *et al.* (2018), who obtained an R^2 of 0.52 working with LiDAR data of only 0.5 points m^{-2} in a very fragmented study area with low stand density. Silva *et al.* (2016), studying *Pinus taeda* stands with aerial LiDAR of resolution 4 points m^{-2}, mentioned the difficulty of estimating stand density using the ABA method. In that study, an R^2 of 0.38 was obtained

using a linear model, values much lower than the precision obtained in the estimation of mean height of R^2 of 0.94.

An alternative method to describe stand density using LiDAR technology is the individual tree detection (ITD) method. This consists of the identification of each individual in the population, using information on the shape and dimensions of the crown to identify and locate each tree (Hyyppa 1999). The success of this method depends upon the quality of the LiDAR point cloud and the algorithm implemented for tree identification (Wallace *et al.* 2014). In the literature, several procedures to work with the ITD method are described, and these studies have reported accurate estimates for the height, volume, basal area and stand density. Sačkov *et al.* (2016) argue that this method is the best alternative for estimating variables in stands with high complexity in terms of the number of trees and number of species. Gaete (2012) used an ITD method to correctly identify more than 90 % of trees with a relative error of 4 % with respect to the traditional inventory of the study in plantations of Pinus radiata in Chile and specified the advantages of using LiDAR inventories, such as greater spatial coverage and speed of data collection. However, the success of this method depends on the number of points (point m^{-2}) and high computational costs. Alternatively, some studies have integrated both the ABA and ITD methods to generate estimators of stand variables. Goldbergs *et al.* (2018) integrated both methods to estimate biomass in the Australian savanna at different spatial scales. Lindberg *et al.* (2010) applied ABA with the nearest neighbor method (kNN) to predict a target distribution matrix at the plot level, and then adjusted the height and DBH parameters of the trees obtained using ITD. However, Vastaranta *et al.* (2012) used ITD results to substitute field data for calibrating the ABA method for volume estimation of a boreal forest in Finland with RMSE results of 24.8 % and 25.9 % with the traditional ABA method and ITD-calibrated ABA, respectively. Kankare *et al.* (2013) found similar results when comparing both models in the estimation of volume and biomass, obtaining better RMSE results in the ABA method calibrated with ITD.

Studies incorporating both methods have focused on the variables of easier estimation from the ABA method, and the strategy for estimating stand density has moved toward the individual tree approach. Thus, the main objective of this work is to generate a method to improve stand density estimates using aerial LiDAR by integrating the ABA and ITD methods. A mixed method approach was proposed which uses the ITD method individualization results as an additional predictor in ABA method models to estimate the number of trees in *Pinus radiata* D. Don stands.

METHODS

Study area and LiDAR data capture. The study was conducted on a 99.2 ha site with 16-year-old plantations of *P. radiata*, owned by Forestal Arauco. The property is in Curanilahue, in the Biobío Region, in Chile, characterized

by the Cordillera de la Costa, with annual rainfall of 1,874 mm and an average temperature of 13 °C. There were 78 randomly distributed plots of 500 m², with the plot center determined by the Trimble R1 GPS model 99133 of sub-meter precision. LiDAR data capture was performed with a Trimble Harrier 68i model sensor with 400 kHz power and 200 Hz triggering rate, mounted on a Cessna model C-172 aircraft, at a flight altitude of 800 m above ground level, generating an average point density of 12 points m⁻².

LiDAR information processing. The processing began with cleaning the point clouds, filtering probable out-of-range returns according to the height parameters of the forest in the study area. Soil classification was performed using the *laz* information with the *lasground* command, obtaining the digital terrain model (DTM) with a resolution of 25 cm. Then, the points not classified as soil were used to generate the digital surface model (DSM) with a resolution of 25 cm. The normalization of the *laz* cloud made it possible to generate the canopy height model (CHM). After the CHM generation, the metrics of the entire study area were determined at a pixel resolution of 22.36 m (500 m²), which were obtained from a height of 1.3 m to avoid the effect of competing vegetation on the value of the metrics. In this phase, the processing of the *laz* information was performed using LAStools software (Rapidlasso 2018). Each metric generated a *tiff* raster of the entire study area. The metrics obtained are described in table 1.

Subsequently, metrics were obtained for each of the 78 measured plots. This process was performed by intersecting the plot surface over the normalized LiDAR point cloud. The metrics obtained here were the same as for the entire study area, and in this phase the metrics were obtained using the FUSION/LDV software (Mcgaughey 2020).

Modeling the ABA method. In this first phase, models for stand density estimation were generated following the ABA workflow. The models proposed here have the general expression of linear models (equation 1).

Table 1. Canopy height metrics obtained with LiDAR.

Métricas de altura del dosel obtenidas con LiDAR.

Metrics	Description
H_{MAX}	Maximum height
H_{MIN}	Minimum height
H_{AVG}	Average height
STD	Standard deviation
COV	Percentage of first returns relative to all returns over 1.3 m (Canopy Cover)
$P_{50}, ..., P_{99}$	Percentile value of the height distribution between 50 to 99 %.

$$y_{ABA\_i} = \beta_0 + \sum_{j=1}^{K} \beta_j x_{ij} + \epsilon_i \qquad [1]$$

Where y_{ABA} is the estimated stand density in the *i*-th plot measured in the field, β_0 and β_j are the linear parameters of the model, x_{ji} is the *j*-th metric selected from a total of *K*-metrics in the *i*-th plot measured in the field, and ε_i is the model error. In this model the metrics were incorporated into the multiple linear models. The model with a combination of the different metrics was selected according to the root mean square error (RMSE) (equation 2) and the Akaike index (AIC) (equation 3).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \qquad [2]$$

$$AIC = n\ln\left(\frac{SSE}{n}\right) + 2p \qquad [3]$$

Where y_i are the observed values, $\hat{y}_i$ are the estimated values, n is the number of observations, *p* is the number of parameters in the model, and *SSE* is the sum of the squares error. Once the best model for stand density prediction was selected, estimates for the stand were generated using the ABA method.

ITD method. This method consisted of estimating stand density from the individual tree crown identification algorithm implemented in the LidR package in the R software described by Roussel *et al.* (2018). This algorithm is based on the measurement of the height of the trees with a CHM, where it delimits and identifies each tree according to crown size. The algorithm requires tree canopy search start height (*h*) and search window (*w*) parameters. For this purpose, the values of *h* were sensitized between the percentiles *P50*, *P60*, *P70*, *P80* and *P90*, and for *w* between 2, 2.5, 3 and 3.5 m. This sensitization made it possible to identify the combination of h and *w* that minimizes the difference between the number of trees measured in each plot and the trees identified by the algorithm. The best configuration was selected according to RMSE. Once the combination of h and w was selected, an output with the trees identified was obtained, and the whole stand's density was estimated using the ITD method, generating an output raster in a grid with the same resolution as the results of the ABA method. In this way, the format of the ITD method output was configured as y_{itd} so that it can be used as an input to the mixed method (figure 1).

Mixed method. The mixed method proposed in this research used the number of trees identified in the ITD method as an additional metric to the model selected in the ABA method. Linear (equation 4) and non-linear (equations 5 and 6) models were used.
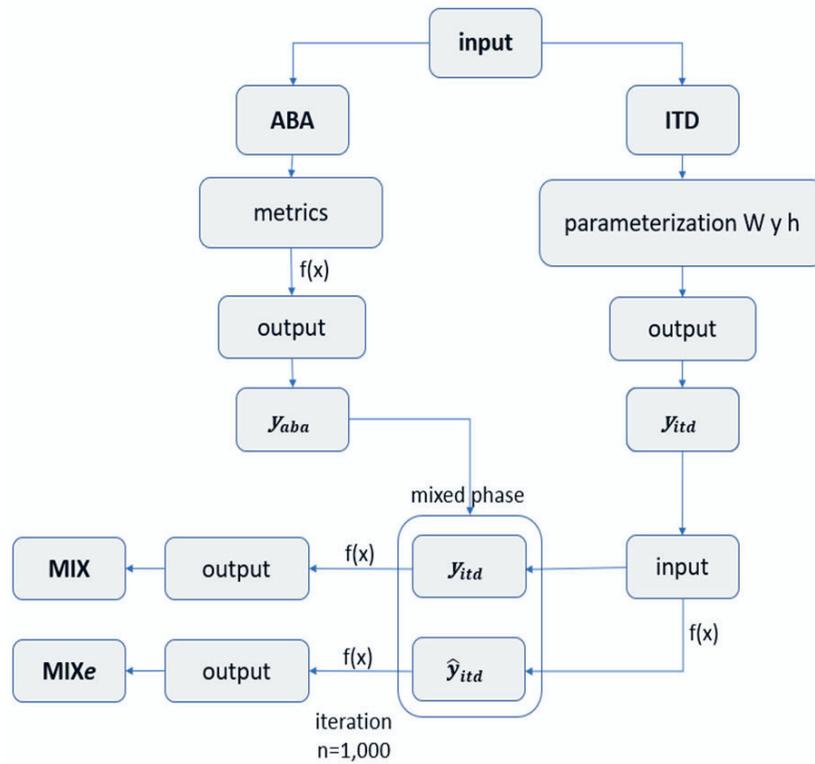
Figure 1. Scheme of the calculation workflow of the methods evaluated for estimating stand density.

Esquema del flujo de trabajo de cálculo de los métodos evaluados para la estimación de la densidad del rodal.

$$y_{MIX_i} = \beta_0 + \beta_1 ITD_i + \sum_{j=2}^{K} \beta_j x_{ij} + \epsilon_i \qquad [4]$$

$$y_{MIX_i} = \beta_1 ITD_i^{\beta 2} \prod_{j=3}^{K} x_{ij}^{\beta j} + \epsilon_i \qquad [5]$$

$$y_{MIX_i} = \beta_0 + \beta_1 ITD_i^{\beta 2} \prod_{j=3}^{K} x_{ij}^{\beta j} + \epsilon_i \qquad [6]$$

Where y_{MIX} is the estimated density of the stand in the i-th plot measured in the field using the mixed method, β_0 and β_j are the parameters of the models, x_{ji} is the j-th metric selected in the i-th measured plot, ITD is the number of trees identified by the individualization algorithm and ε_i is the model error. Model selection in this method was carried out according to the RMSE and AIC.

Mixed method with error. In this method, the estimation of the ITD method generated by a non-linear model was incorporated ($\hat{y}_{itd}$) as an additional metric to the model selected in the ABA method. Here, the value incorporated corresponds to the estimated value of the stand density, where the residual variance of the model is known ($\hat{y}_{itd}$).

Therefore, this method was called a mixed model with the incorporation of error in the predictor variables (MIXe). The mixed method with error in the predictor variables (MIXe) incorporated the number of trees estimated from equation 7 $\hat{y}_{itd}$. This estimation replaced the variable ITD from the MIX model in equations 4, 5 and 6. Here the residual variance of $\hat{y}_{itd}$ is known, and this was incorporated into the MIXe model through Monte Carlo simulations in 1,000 iterations, assuming. $\varepsilon_i \sim N(0, \sigma^2_{\hat{y}_{ITD}})$ The workflow schematic is detailed in figure 1.

$$\hat{y}_{itd_i} = \beta_1 ITD_i^{\beta 2} + \epsilon_i \qquad [7]$$

Analysis at the field level. The number of trees for the total stand area was estimated for the four methods evaluated (ABA, ITD, MIX and MIXe). These estimates were compared with the number of trees estimated from the traditional inventory determined from a sample of 78 plots. For the ABA, MIX and MIXe methods, the mean estimators and their variance were calculated using the bootstrapping-pairs approach described by Sandoval y Bustamante (2020).

RESULTS

ABA method. Model three generated the lowest RMSE values (table 2). The models with the best performance were a combination of both height percentile and COV metrics. The model that showed the best result used the *P95* and *COV* metrics, obtaining values of RMSE = 215.2 trees ha^{-1} (23.6 %), AIC = 840.9 and R^2 = 0.42. In the three selected models, parameters b_0 and b_1 were not significant, indicating that the height percentile metrics do not contribute significantly to the estimation of stand density in the presence of the *COV* metric. The similarity in the residual values of the models and the large difference in parameter values shows the difficulty of estimating stand density. However, this method generated a weak relationship between estimated and observed values, which only allows generation of average estimates of stand density, without representing the variability of stand density (figure 2).

ITD method. Sensitization of the parameters search start height (*h*) and search window (*w*) of tree canopy generated better results using the height percentile *h = P50* and *w* = 3 m. This search configuration to identify the tree crown was obtained by analyzing the relationship between the number of trees measured in the 78 plots and those identified by the algorithm implemented in the LidR package in R software. This configuration generated a difference between the trees measured and identified in the RMSE plots of 279.9 trees ha^{-1} (49 %). A higher RMSE value was obtained in this method relative to the RMSE values obtained in the ABA method. Additionally, the ITD method underestimated stand density values (figure 2),

Table 2. **Parameters and indicators of ABA models.**

Parámetros e indicadores de modelos ABA.

Ranking	Model	R^2	RMSE (trees ha^{-1})	RMSE (%)	AIC
1st	Y_{ABA} = 449.1880^{ns} - 15.0690^{ns} *P95* + 10.4360* *COV*	0.42	215.2	23.6	840.9
2nd	Y_{ABA} = -59.6070^{ns} + 5.1050^{ns} *P80* + 10.5250* *COV*	0.41	216.5	23.7	841.9
3rd	Y_{ABA} = 31.5037^{ns} + 0.0485^{ns} *P90* + 10.8111* *COV*	0.41	216.6	23.7	842.0

ns: denotes the non-significance of the parameter; *: denotes significance of the parameter ($P < 0.05$).
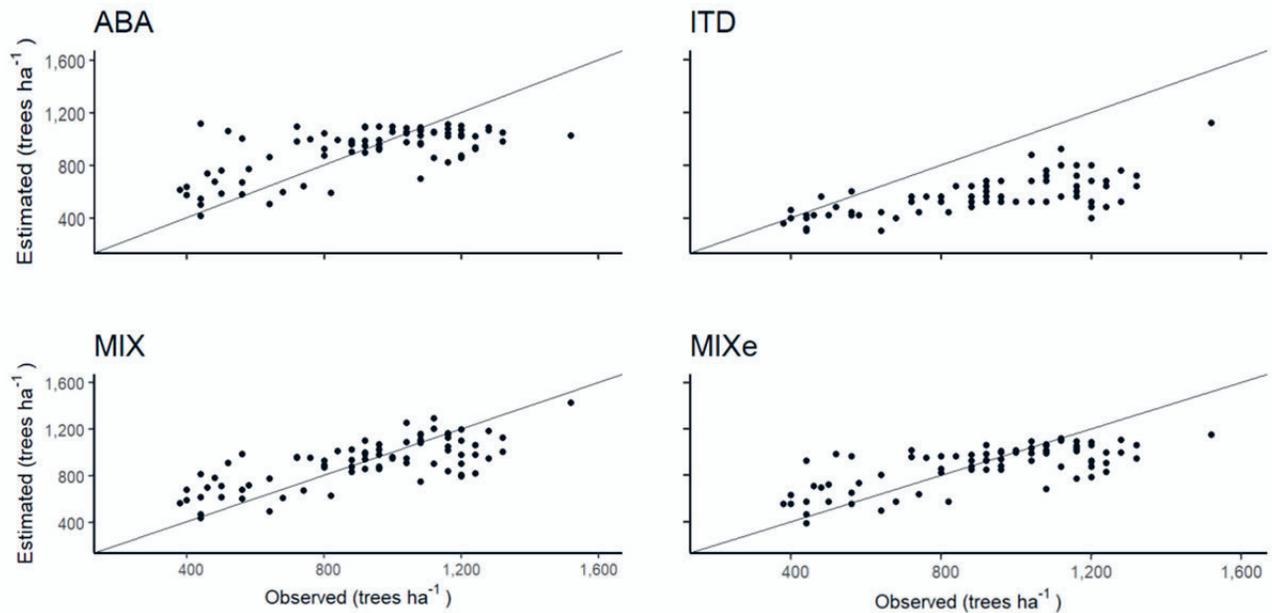
Figure 2. Relationship between measured and estimated stand density with the best ABA, ITD, MIX and MIXe models evaluated in the sample plots.

Relación entre la densidad del rodal medida y estimada con los mejores modelos ABA, ITD, MIX y MIXe evaluados en las parcelas de muestreo.

identifying only 61 % (560 trees ha^{-1}) of the trees measured in the traditional inventory.

Mixed method. The number of trees identified by the ITD method was incorporated as an additional metric in ABA models with the previously selected *P95* and *COV* metrics (table 3). The best model for y_{MIX} presented an RMSE = 190.7 trees ha^{-1} (20.9 %), AIC = 822.1, and an R^2 = 0.53. This method reduced the RMSE by 2.7 percentage points with respect to the ABA method (23.6 %). In these models, the parameters associated with the *COV* and ITD metrics were significant, but the parameter associated with the *P95* metric was not. The RMSE of the best models were similar, so here the selection was made according to the AIC criterion. The estimation of the selected model for the MIX method generated a closer relationship between the values of the estimated and observed stand density values since a higher value of R^2 and a lower value of RMSE were obtained, showing that this method allows a better representation of the variability in relation to the estimates generated for the ABA and ITD methods (figure 2).

Mixed method with error. The model selected in the MIX method incorporated the partial stand density estimate made by the ITD model by adding its residual variance. The $\hat{y}_{itd}$ model used to estimate partial stand density generated a value of RMSE = 200.9 trees ha^{-1}. Thus, new parameters of the MIX model were obtained, generating a MIXe model that reached RMSE = 207.5 trees ha^{-1} (21.3 %) and an AIC = 835.2 (table 4). In the MIX method, the *COV* and $\hat{y}_{itd}$ metrics generated significant parameters.

With this method, the relationship between observed and estimated stand density decreases with the incorporation of the error variable approach compared to the MIX method (figure 2).

Evaluation at the field level. Estimates for the entire stand were generated with each of the four methods evaluated in a raster layer at the 500 m^2 resolution pixel (figure 3). The MIX method generated the greatest variability in the spatial representation of stand density at the stand level, with estimates of up to 1,500 trees ha^{-1}. However, the traditional ABA method generated more homogeneous stand density estimates, centered only around the average. This method could not capture the spatial variability of stand density (table 5). The ITD method generated estimates that did not exceed 900 trees ha^{-1}, showing an underestimation of the stand density estimate compared to the estimates of the other methods. The pixel estimation by the methods generated a right skewed distribution, except for the stand density estimation in the ITD method, which showed a more normal distribution.

According to the information from the 78 sample plots evaluated in the traditional inventory, the mean stand density is 913 trees ha^{-1} with a sampling error of 6.9 % (table 5). All the methods evaluated generated estimates of a lower number of trees per unit area. In the ABA method, the estimate of the average stand density at the plot level was 874 and for the MIX method it was 828 trees ha^{-1}, both being lower than the average estimated in the traditional inventory. Although the mixed method generated a lower stand density estimate, a correct comparison between the

Table 3. Parameters and indicators of mixed models.

Parámetros e indicadores de modelos mixtos.

Ranking	Model	R^2	RMSE (trees ha^{-1})	RMSE (%)	AIC
1st	y_{MIX} = 2.8592^{ns} ITD$^{0.5616*}$ COV $^{0.5001*}$	0.53	190.7	20.9	822.1
2nd	y_{MIX} = 340.7499^{ns} + 0.894*ITD - 14.3895^{ns} P95 + 5.2288*COV	0.55	190.7	20.9	823.0
3rd	y_{MIX} = -1513.5134^{ns} + 296.6964^{ns} (ITD $^{0.2263*}$ COV $^{0.1525*}$)	0.55	191.1	21.0	823.3

ns: denotes the non-significance of the parameter; *: denotes significance of the parameter ($P < 0.05$).

Table 4. Models used for the estimation of stand density in the MIXe method.

Modelos utilizados para la estimación de la densidad del rodal en el método MIXe.

Method	Model	R^2	RMSE (trees ha^{-1})	RMSE (%)	AIC
ITD Estimation	$\hat{y}_{itd}$ = 3.4272^{ns} (ITD $^{0.09684*}$)	0.46	200.9	21.2	833.9
MIXe	y_{MIXe} = 6.1562^{ns} (($\hat{y}_{itd}$ ± σ)$^{0.8056*}$ COV $^{0.2238*}$)	0.62	207.5	21.3	835.2

ns: denotes the non-significance of the parameter; *: denotes significance of the parameter ($P < 0.05$).

methods must be made according to the confidence intervals. The methods that generated estimations by intervals through bootstrapping-pairs presented an uncertainty value of representation close to 3 %, a lower value compared to the sampling error of the traditional forest inventory method (6.9 %).

DISCUSSION

The estimation of stand density obtained using the best model of the ABA method generated values of RMSE = 23.6 % and an R^2 = 0.42. Generally, these results are in agreement with the RMSE and R^2 values reported in other
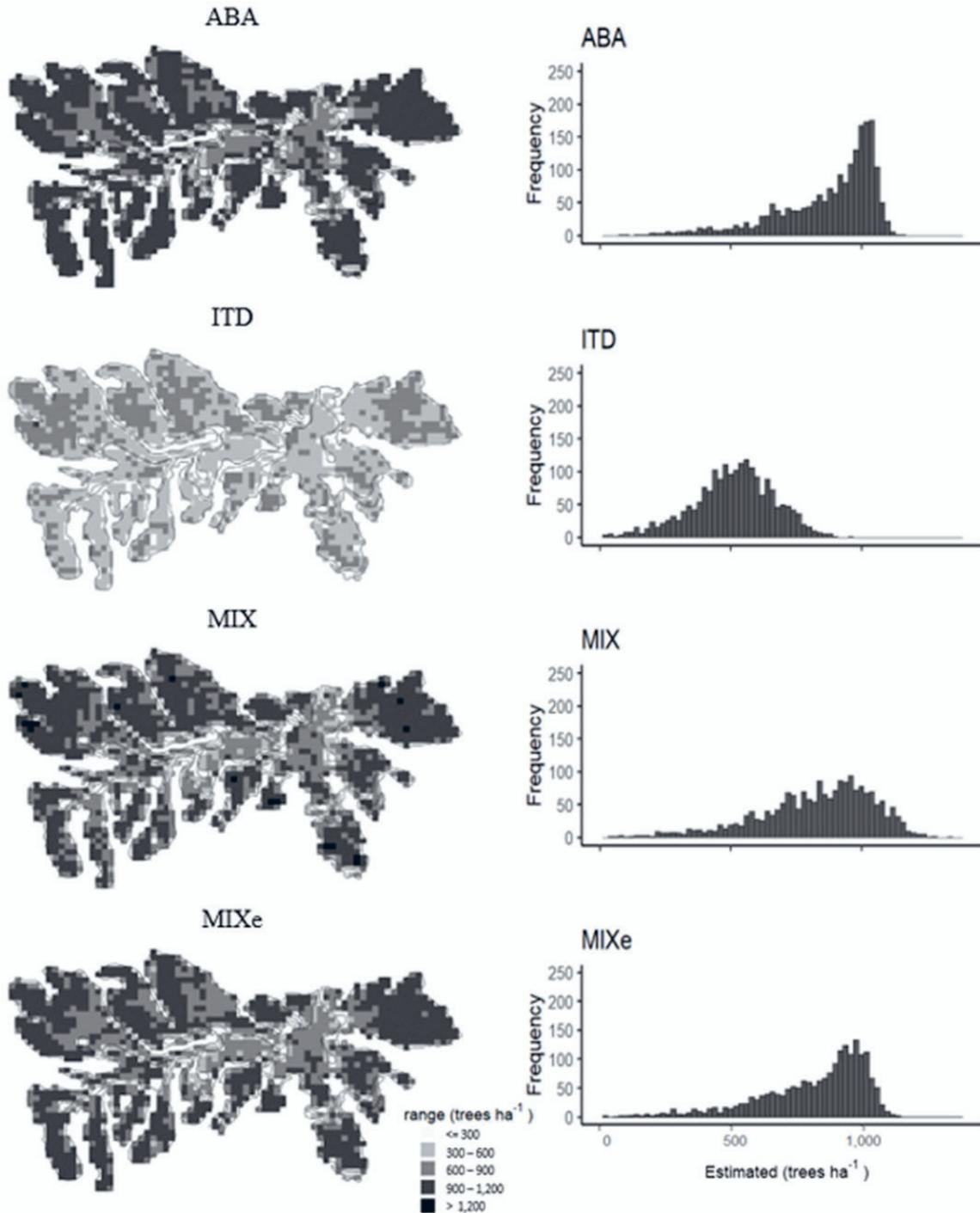
Figure 3. Spatial distribution of stand density estimates for each of the methods.

Distribución espacial de las estimaciones de densidad del rodal para cada uno de los métodos.

Table 5. Comparison between estimations of the stand density realized by traditional inventories and four methods evaluated.

Comparación entre estimaciones de la densidad del rodal realizadas por inventarios tradicionales y cuatro métodos evaluados.

Method	Mean (trees ha⁻¹)	Standard deviation	Estimation uncertainty (%)	Estimation intervals
Traditional	913	279.90	6.90*	[850 - 976]
ABA	874	26.27	3.01	[847 - 901]
ITD	510	-	-	
MIX	828	26.40	3.19	[801 - 855]
MIXe	827	25.45	3.08	[801 - 853]

*: Sampling error calculated in a simple random sampling design based on the 78 plots measured.

investigations, which mention that the ABA method does not generate accurate stand density estimates. Treitz *et al.* (2012) generated estimation models for stand density in boreal forest, using a LiDAR information cloud of 3.2 points m⁻², and obtained an $R^2 = 0.23$ product of species variability and higher density in the study area. Silva *et al.* (2016) obtained an $R^2 = 0.38$ in the estimation of stand density with a linear model in *Pinus taeda* stands with aerial LiDAR of resolution 4 points m⁻². Sánchez *et al.* (2018) obtained an $R^2 = 0.52$ working with LiDAR data of only 0.5 points m⁻² in a very fragmented study area with low stand density. Generally, the literature highlights the difficulty of estimating stand density with the ABA method, where the models predict only average values of the total study area, being of little use when they must represent spatial variability (Silva *et al.* 2016). Other authors have also found greater difficulty in estimating stand density in deciduous and heterogeneous forests because, having leafy crowns and height variability, the stand density would be underestimated by not being able to identify the smallest trees. This effect is even stronger in dense forests, where it is difficult to delimit the crowns (Spriggs *et al.* 2015).

The estimation of stand density using the individualization algorithm (ITD method) generated the highest RMSE values as compared to the other three methods evaluated in this study. The algorithm only detected 61 % of the individuals present in the 78 plots using LiDAR information of 12 points m⁻², strongly underestimating the observed stand density. Sačkov *et al.* (2016) working with a LiDAR information cloud of 30 points m⁻², reached values close to 70 % in the detection of dominant trees, mentioning that the ITD method is the best alternative for estimating variables in stands with high complexity in terms of the number of trees and number of species. Pearse *et al.* (2019) implemented an identification method based on the voxel concept and evaluated it at different densities of the LiDAR cloud, concluding that the estimation of stand density is the variable that most depends on the scanning density (points m⁻²). They mentioned that the worst results of their estimates were with a density of 1 point m⁻², as the estimation of stand density was improved with a cloud

of 70 point m⁻². Wallace *et al.* (2014) mention that the algorithm implemented for tree identification is improved significantly by increasing the density of the LiDAR point cloud from 5 to 50 points m⁻². Thus, LiDAR information with higher scanning density would improve the accuracy of tree identification using the ITD method, though this would increase the computational requirement and its cost.

In the ITD method implemented in the LidR package of the R software, the optimal search window (*w*) was 3 x 3 for individual tree identification. Within the LidR package, the Watershed algorithm is implemented, based on a method for determining watersheds using a submergence algorithm, which consists of simulating the flooding of the inverted CHM layer, where the deepest points within the "watershed" are identified as the tree canopy. Algorithm parameters such as search window, CHM resolution and stand spacing, decrease the detection rate in homogeneous forest. Therefore, the parameter *w* must be adapted to the type of forest and the characteristics of the LiDAR cloud. As for the search height (*h*), the 50th percentile was used for calibrating the identification of individuals. Generally, other studies have used the total height for the search of individuals within the stand, but these suggest using values above 4 m as search height when heterogeneous forests with understory presence are found. They also mentioned that using between 50 and 70 % of the quantiles of the height metrics to observe the average and upper structure of a forest improves accuracy of the estimation of stand density (Wu *et al.* 2019). These studies mention avoiding the use of full height (or low percentiles) to avoid problems with understory presence in heterogeneous forests.

The MIX method obtained the best results according to R^2, RMSE and AIC, decreasing RMSE by 11.4 % with respect to the traditional ABA method. The studies that integrate the ABA and ITD methods have focused on the estimation of biomass and stand volume, reporting different results. Lindberg *et al.* (2010) using a k-Nearest Neighbors (kNN) model to estimate stand variables in the ABA method, compared the results with the ITD method and a third method where they calibrated the ABA method with ITD. In this study, LiDAR information of 10 points m⁻² was

used, obtaining a decrease in RMSE from 52 % to 37 % in the estimation of stand density when calibrating the ABA method with ITD.

Vastaranta *et al.* (2012) carried out a comparison of two methods for calibrating the ABA method, using the results of the ITD method and the results of a traditional inventory for the volume estimation of a boreal forest in Finland using a LiDAR cloud of 10 points m^{-2}. In that study, RMSE values of 24.8 % and 25.9 % were obtained with the traditional ABA method and ABA calibrated with ITD, respectively. The ABA-ITD method underestimated the volume by up to 9 % compared with the traditional ABA method, due to the fact that the calibration variables are estimated with ITD, increasing the error by not using field data. Xu *et al.* (2014) calibrated the tree diameter distributions in the ABA method with the estimation of the ITD method, working with a LiDAR cloud of 12 points m^{-2} to estimate the volume and log selection, obtaining higher accuracy mainly in the pulpwood stock and decreasing the RMSE by 7.73 % in the best case when integrating both methods. Recently, Goldbergs *et al.* (2018) integrated both methods to estimate biomass in the Australian savanna at different spatial scales, obtaining values higher than 70 % in the detection of dominant and co-dominant trees.

When comparing the traditional ABA method with ABA-ITD, Kankare *et al.* (2013) found similar results when comparing both methods for estimating volume and biomass, working with a LiDAR cloud of 10 points m^{-2}. Most of the aforementioned studies that have integrated the ABA and ITD methods worked with a LiDAR cloud of between 10 and 12 points m^{-2}, in which better results have been obtained in the estimation of stand density with the integration of the ABA and ITD methods, as compared to working with the methods separately. Goldbergs *et al.* (2018), in agreement with other studies, point out the need to use LiDAR information at densities greater than 10 points m^{-2} to improve the accuracy of the estimated variables.

The estimation of stand density improves when integrating the ABA method with ITD, decreasing the residuals of the models used, and allowing for better representation of the spatial variability of stand density at the plot level. The stand density estimates using the four methods evaluated underestimated the mean stand density compared with the traditional inventory method. The largest difference was observed in the ITD method, similar to the work of Lindberg *et al.* (2010), who attributes this difference to the low point density of the LiDAR information cloud. Xu *et al.* (2014) related this tendency to underestimation due to the greater number of trees within the stand. In the case of the estimation with the ABA method, this is affected by the heterogeneity of the stand structure, due to the different silvicultural management when performing the stand analysis. Despite the underestimation, the values obtained in the ABA method are within the range of the traditional inventory estimation due to the sampling error. Although the methods generate a difference with respect to

the mean value of the traditional inventory, it is important to mention that the comparison of the methods should not be made in relation to the average, but should consider the estimation by the interval, the predictive capacity evaluated in the measured plots and the capacity to represent the spatial variability of the stand density.

CONCLUSIONS

The method that integrates ABA and ITD (MIX method) generated the best estimate of stand density in the modeling phase as compared to the four methods evaluated, reporting values of R^2 = 0.42, RMSE of 23.6 % and AIC = 840.9. In the ABA method, the best estimation of stand density was with a linear model that used the metrics *P95* and *COV*, generating an RMSE of 23.6 %. In the ITD method, the use of a search window *w* = 3 and a height *h* = *P50* generated the best results of tree identification using the LidR package implemented in the R software. However, the ITD method only identified 61 % of the trees measured in the sampling plots, underestimating the stand density in a higher proportion compared to the other methods. The integration of the ABA and ITD methods improved the precision of stand density estimation, presenting greater spatial variability at both plot and stand level, compared with the ABA and MIXe methods, which represented the lowest variability in the estimation of stand density. Thus, the mixed method proposed in this study improved the estimation of stand density and its spatial representativeness in relation to the traditional ABA method using the same LiDAR information base of 12 points m^{-2}, without involving higher costs in the acquisition of higher resolution LiDAR clouds.

AUTHOR CONTRIBUTION

ML: formal analysis, interpretation of results, and writing. SS: conceptualization of the work, information management, supervision, and review.

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