Integrating area-based and individual tree detection approaches for estimating tree volume in plantation inventory using aerial image and airborne laser scanning data

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Remote sensing has been increasingly used to assist forest inventory. Airborne Laser Scanning (ALS) systems can accurately estimate tree height in forests, and are being combined with more traditional optical images that provide further details about the horizontal structure of forests. To predict forest attributes two main techniques are applied to process ALS data: the Area Based Approach (ABA), and the Individual Tree Detection (ITD). The first part of this study was focused on the effectiveness of integrating ALS data and aerial imagery to estimate the wood volume in *Eucalyptus urograndis* plantations using the ABA approach. To this aim, we analyzed three different approaches: (1) using only ALS points cloud metrics (RMSE = 6.84%); (2) using only the variables derived from aerial images (RMSE = 8.45%); and (3) the integration of both 1 and 2 (RMSE = 5.23%), which underestimated the true volume by 2.98%. To estimate individual tree volumes we first detected individual trees and corrected the density estimate for detecting mean difference, with an error of 0.37 trees per hectare and RMSE of 12.68%. Next, we downscaled the total volume prediction to single tree level. Our approach showed a better result of the overall volume in comparison with the traditional forest inventory. There is a remarkable advantage in using the Individual Tree Detection approach, as it allows for a spatial representation of the number of trees sampled, as well as their volume per unit area - an important metric in the management of forest resources.

Keywords: Forest Inventory, Airborne Laser Scanning, Treetop Detection, *Eucalyptus* Plantation, Area-based Approach, LiDAR

Introduction

Intensively managed forest plantations have an important role, both nationally and internationally, due to their ability to efficiently produce large quantities of biomass. This biomass can be utilized in forms suitable for bioenergy or, after processing into cellulose-derivatives, in materials such as paper. The myriad uses of fibers derived from intensively managed plantation forests can aid in the reduction of anthropogenic pressures on natural forests, while simultaneously generating millions of jobs (Payn et al. 2015).

In Brazil, 4.4 million jobs are generated directly and indirectly by forest plantations, and the total reforested area exceeds 7.6 million hectares (IBA 2014). Of this area, 72% is composed of *Eucalyptus* spp., a key genus in Brazilian forest plantations. The reasons for the success of *Eucalyptus* spp. plantations in Brazil include *Eucalyptus*’ rapid growth, genetic improvement, and its tolerance of a wide range of climatic conditions (Silva et al. 2014).

In order to manage the growth and yield of these plantations, annual forest inventories are required. In general, the traditional approaches to conducting plantation inventories follow the precepts of sampling theory, which is based on ground measurements collected from simple random sampling plots. The forest attributes of interest are then inferred for an entire stand based on observations collected at each sample plot (Paris & Bruzone 2015). However, considering the difficulties in field surveys such as sampling error, bias, and the intensive use of time and labor, remote sensing represents an important additional tool for monitoring large areas accurately and efficiently.

Both active and passive remote sensors have been presented as feasible alternatives for estimating forest variables. High spatial resolution optical data is useful at providing spectral information on species and condition (Wang et al. 2004, Monnet et al. 2010), while active remote sensing technologies, such as Airborne Laser Scanning (ALS), can provide highly accurate forest height data (Wulder et al. 2000). When predicting forest inventory attributes using ALS data or aerial images, two main approaches can be applied: the Area-based Approach (ABA – Nasset 2002, White et al. 2013) and the Individual Tree Detection...
For Bogs andorge characteristics. However, algorithms nor-
approach is less suitable (when tree-level information such as stem
racy compared to traditional inventory shown to have similar or improved ac-
diameter, or average height have been
stand attribute variables from ALS data, stand attributes over large areas (Brei-
tions of ITD detection, involving the aggre-
gation of the tree numbers in a grid cell, according to ABA. By aggregating trees
into grid cells it is possible to know how
many trees were detected or not in each
cell, so long as detection rates are com-
pared with ground truth data and the most
appropriate methodology to correct devia-
tions is used. This approach, also used in
this study, can lead to a reduction in the
number of systematic errors, and to an in-
creased accuracy in the estimation of the
number of trees per hectare, a variable
extremely important to forest managers
(Simões 2008, Breidenbach & Astrup
2014).

According to Packalén et al. (2011), the
advantage of using ITD approaches is that
the correct detection of individual trees
could reduce the number of plots needed for
an accurate and unbiased inventory.
Breidenbach & Astrup (2014) also note
that the ITD approach is inherently more
intuitive than ABA because the response
variables are related to each tree (the
smallest unit in a management system),
providing coordinates that can be tied to
individual tree growth, as well as explicit
links to tree growth and yield models.
In the case of ALS data, ITD approaches re-
quire high density point clouds, which can
be impractical because of the cost of data
collection (Mehtätalo et al. 2014).

The merging of ALS and optical remote
sensing data can assist in the accurate esti-
mation of forest attributes, with algo-
rithms based on height or brightness (Hu-
Seemann 2003, Wang et al. 2004, Roberts
et al. 2005, Monnet et al. 2010, Packalén et
ALS and Landsat image data to improve
accuracy of timber volume estimation as
compared with estimates based on ALS
and images variables alone. This compar-
sion is also employed in the present study,
though we used high spatial resolution im-
age. For instance, the ABA and ITD ap-
proaches can be combined to estimate
wood biomass or volume in forest planta-
tions (Næsset 2002, Brandtberg et al.
2003).

In this study, we use ABA and ITD to esti-
mate stand volume in Eucalyptus spp. plan-
tations using ALS and high spatial resolu-
tion multispectral image data. To this goal,
we first modeled the stand volume using
standard ABA approaches, using different
combinations of ALS-based and image-
based metrics as independent model vari-
ables. Second, we used an ITD-based ap-
proach to estimate tree count, applying a
rection method to improve single tree
detection, which is integrated with the
stand volume predicted using ABA. Finally,
we merge the two approaches (ITD and
ABA), that yields volume predictions at the
single tree level. We conclude by discussing
the possibilities of using ABA for individual
tree volume predictions.

Materials and methods

Study area
The study was performed in a forest plan-
tation owned by FIBRIA S.A. company,
located in São Luiz do Paraitinga in São
Paulo State, Brazil (23° 33’ S, 45° 34’ W and
23° 30’ S, 45° 31’ W – Fig. 1). The dominant
species in the study area is Eucalyptus uro-
grandis, which is a hybrid between Eucalypt-
us urophylla and Eucalyptus grandis (Fe-
reira 1979). According to Köppen & Geiger
(1954), the climate is humid subtropical
(Cwa) characterized by cold winters and
rainy summers, with average annual pre-
cipitation of 1210 mm and a mean monthly
temperature of 20.2 °C (CEPAGRI 2014).
The topography of the study area is complex,
with elevations varying from 974 to 1266 m
a.s.l. and the average slope is 24.3 degrees.

The forest stands in the study area were
planted in December 2006 and harvested
between April and May 2013, following a
standard 6.5 year rotation period. All har-

Fig. 1 - The study area near São Luiz do Paraitinga (São Paulo, Brazil), including the 6.5
year-old Eucalyptus urograndis forest plantation analyzed in this investigation.
vested wood was taken to a mill. The trees were planted in rows with fixed tree spacing (2 × 3 m), resulting in a density of 1667 stems per hectare.

**Field measurements**

Reference data were based on field measurements collected at 48 circular plots (r = 11.28 m, area of 400 m²) between April and May of 2013 prior to harvesting. In each plot, all diameter at breast height (DBH) were recorded, and the height of 10 trees were measured. Heights for all remaining trees in the plot were then estimated by applying the Curtis (1967) hypsometric model, adjusted based on the 10 measured trees in each plot. Tree volume was estimated with locally-developed volume models based on the model proposed by Schoepfer (1966 – Tab. 1). The geographical location of the plots were obtained using high-precision GPS receivers (ProXRT® Trimble Inc., Sunnyvale, CA, USA) at the center of each plot.

After harvesting, all wood arriving at the mill was weighed. The wood density was obtained according to Archimedes’ principle and, therefore, the total volume of wood at the mill could be defined by weight-to-volume (W-V) relationships obtained in the density measurement process. A complete description can be found in Batista (2014).

**Remote sensing data**

ALS data were acquired by a RIEGL LMS-Q680® system (Riegl Gmbh, Horn, Austria) simultaneously on 15 January 2012 with aerial photographs under free-cloud conditions. The average ALS point density was 5 pulses per m². An orthophoto was generated from aerial images with a pixel size of 0.15 cm. The 4 spectral bands were blue (429-514 nm), green (514-600 nm), red (600-676 nm) and near-infrared (695-831 nm).

Initially we separated ALS ground returns from the vegetation returns, to generate a 15 cm resolution DTM and DSM, which is the minimum size resolution based on point density (McCullagh 1988). The DTM was used to normalize the point cloud, followed by the generation of the most usual metrics (such as tree height, canopy cover, topography, image bands and ratios) from each type of remote sensing data by describing the properties of the point clouds and spectral properties of the images. For the generation of these metrics, only first returns of the ALS point cloud were used and the reflectance value of each pixel in the aerial image was aggregated into a 5 × 5 m grid cell. These metrics were then used in subsequent statistical modeling as explanatory variables. In total, 39 metrics were generated (Tab. 2).

**Modeling approach to estimate total wood volume**

The first step was the estimation of wood volume using the ABA. Three different methods were applied, depending on the input data source. In the first approach, only variables derived from ALS data were used, in the second approach only variables derived from the imagery were used, and in the final one we combined both sets of variables.

One of the most important considerations when working with a large number of predictor variables in a multiple linear regression is variable selection. To that end, we applied the Best Subset Selection (BSS), which matches an appropriate model to each model size (James et al. 2014, Lumley 2014, R Developing Core Team 2007). To select a model among those suggested by BSS, we applied a k-fold cross-validation (k=5). The application of a cross-validation, similar to the leave-one-out method, allows for a better understanding of model behavior, especially when using a database that was not utilized for model adjustment (James et al. 2014). After applying the cross-validation we chose the model according to the RMSE. In this study, we used a confidence interval with a p-value equal to 0.05 generated from 1000 simulations. The total volume of the forest stands was obtained by the mean ABA estimation multiplied by the total area.

**Variable selection and model adjustment**

The k-fold estimate of RMSE is computed by averaging the values obtained by eqn. 1:

\[ CV_k^2 = \frac{1}{k} \sum_{j=1}^{k} \text{MSE}_j \]

where \( CV_k^2 \) is the k-fold cross validation and \( \text{MSE} \) is the mean square error. The linear model assumptions were verified according to (Peña & Slate 2006), where the assumptions were verified for each of the chosen models with statistical tests and

**Table 1 - Descriptive statistics of the reference plots (n=48) for the basal area (C), diameter at breast height (DBH), total height (HT), dominant height (\( H_{\text{dom}} \)) and cellulose volume without bark (V).**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>G (m² ha⁻¹)</td>
<td>27.08</td>
<td>39.16</td>
<td>33.96</td>
<td>2.75</td>
</tr>
<tr>
<td>DBH (cm)</td>
<td>13.80</td>
<td>17.34</td>
<td>16.00</td>
<td>0.65</td>
</tr>
<tr>
<td>HT (m)</td>
<td>20.82</td>
<td>27.93</td>
<td>24.89</td>
<td>1.70</td>
</tr>
<tr>
<td>( H_{\text{dom}} ) (m)</td>
<td>25.20</td>
<td>33.27</td>
<td>29.79</td>
<td>2.06</td>
</tr>
<tr>
<td>V (m² ha⁻¹)</td>
<td>223.19</td>
<td>391.99</td>
<td>331.16</td>
<td>37.27</td>
</tr>
</tbody>
</table>

**Table 2 - List of the variables selected for model inclusion in each of the three approaches adopted in this study.**

<table>
<thead>
<tr>
<th>Data</th>
<th>Category</th>
<th>ALS metrics</th>
<th>Acronym</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALS</td>
<td>Height</td>
<td>Minimum height</td>
<td>( h_{\text{min}} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum height</td>
<td>( h_{\text{max}} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mean height</td>
<td>( h_{\text{mean}} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Variance of height</td>
<td>( h_{\text{var}} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Standard deviation of height</td>
<td>( h_{\text{sd}} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Coefficient of variation of height</td>
<td>( h_{\text{cv}} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mode of height</td>
<td>( h_{\text{mode}} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Kurtosis of height</td>
<td>( h_{\text{ku}} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Height percentiles: 1st, 5th, 10th, 20th, 25th, 30th, 40th, 50th, 60th, 70th, 75th, 80th, 90th, 95th, 99th</td>
<td>( h_{1}, h_{5}, h_{10}, h_{20}, h_{25}, h_{30}, h_{40}, h_{50}, h_{60}, h_{70}, h_{75}, h_{80}, h_{90}, h_{95}, h_{99} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Number of first returns above mean</td>
<td>( C_{\text{mean}} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Number of returns above 2 m</td>
<td>( C_{\text{mean}} )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Percentage of canopy</td>
<td>( C_{\text{s}} )</td>
</tr>
<tr>
<td>Topography</td>
<td>Slope (°)</td>
<td>Mean altitude</td>
<td>( A_{\text{mean}} )</td>
</tr>
<tr>
<td>Aerial Image</td>
<td>Spectral Properties</td>
<td>Band 1 - blue</td>
<td>B1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Band 2 - green</td>
<td>B2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Band 3 - red</td>
<td>B3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Band 4 - near infrared</td>
<td>B4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Normalized Difference Vegetation Index</td>
<td>NDVI</td>
</tr>
</tbody>
</table>

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graphical analysis (Peña & Slate 2014, R Developing Core Team 2007). The approach was then chosen based on the lowest RMSE and the linear model assumptions analysis, generating a predicted wood volume map for the entire study area. This prediction was validated with stand inventory data and information about tree volume received by the mills, after harvesting.

**Individual tree volume**

**Individual Tree Detection based on aerial images**

For the second step we used high resolution multispectral images for detecting individual tree-tops, applying the local maximum filtering method, where the central location of the crown is assigned the highest spectral value (Wang et al. 2004, Kumar 2012). We applied fixed and varying sizes of moving window, based on the methodology proposed by Kumar (2012) and Pereira (2014). The window sizes varied from 0×3 m, 0×5 m, 0×7 m to 0×9 m (Kumar 2012, Pereira 2014). The individual tree detection procedure was performed for each of the 4 spectral bands, and the first principal component (first PCA) of the bands (Wang et al. 2004). According to Wang et al. (2004), the PCA effectively aggregates a large quantity of information and shows good results for ITD.

To generate the final ITD product, all five intermediate outputs were used. First, the layer with the highest number of detected trees, with their locations visually corrected, was taken as the basis for ITD. From this layer, we removed all the tree-tops in a 0.7 m buffer around each tree to avoid multiple peaks from single tree. Tree-tops detected in the second layer, outside this buffer were added creating a new layer of additional ITD points. This layer was then taken as the new basis for ITD. This procedure was repeated until all layers had contributed to the generation of a single ITD layer.

**Merging the ITD approach with ABA**

Based on the final ITD layer, stem counts were aggregated into 5×5 m grid cells, according to ABA. Following this, the number of trees in each grid cell was identified by local maxima derived from the ITD approach, resulting in a graphical representation of the number of trees per hectare for the entire study area.

**Detection and correction of the mean difference (MD) in total area**

The mean difference (MD) detection of the ITD approach was done by comparing the number of detected trees and the number of observed trees in the inventory plots. The difference between the two was considered the response variable, while the ALS and image variables were considered the predictor variables, leading to the modeling of the ITD mean difference, and its prediction for the entire study area. In our case this MD was modeled with 3 variables, maximum height, slope, and ITD detection, as explanatory variables. These variables were selected by applying the Best Subset Selection method and cross-validation, as described earlier. The MD detection model was applied to the entire study area, representing the MD per hectare, to correct the initial estimates of tree count per pixel.

**Estimating individual tree volume**

In order to generate the volume per tree in each 5×5 m cell, the previously-estimated stand volume for the entire study area (m³ ha⁻¹), obtained by the integration of ALS data and high-resolution imagery, was divided by the number of trees per hectare detected by the ITD approach.

**Results**

**Modeling approach to estimate total wood volume**

The best fitting models obtained by cross-validation contained 4 parameters, including the intercept, for all the three approaches tested (Tab. 3). In the first approach (using ALS data variables only), the chosen model was based on height percentiles (h₁₀, h₅₀, h₉₀) and elevation (Aₑₑₑ). In the second approach, where only image predictors were used, the selected variables were B₃, NDVI, B₁/B₃ and B₁/B₄. In the third approach, where both remote sensing data sources were used as predictors, two ALS-based and two image-based variables were selected (hₑₑₑ, Aₑₑₑ, B₄, B₂/B₃). The RMSE for each approach was 6.84%, 8.45% and 5.23%, respectively. Among the three analyzed approaches, we chose the model that combined ALS data and airborne imaging sensors.
Tree volume estimation using aerial image and ALS data

and image information, according to the corresponding adjusted R² value (Tab. 3).

Fig. 2 displays the relationship between the observed and predicted values of stand volume obtained for each approach. Although the homoscedasticity of residuals was not rejected, their distribution was asymmetric in the first and second approach, suggesting non-normality, while in approach 3 the distribution of residuals showed to match a normal distribution. Therefore, the third approach was selected for wall-to-wall stand volume prediction and subsequent comparisons with the inventory and mill-based volumes as reference values.

Across the whole study area, the mean estimated volume per hectare based on the ABA method was 319.9 m³, totaling 44,466.1 m³. When this result was compared with the volume measured at the mill (considered the true volume by the company), we found a difference of 2.98%, while when comparing the forest inventory data with the mill volume, it overestimated by 3.29%. In addition, it was observed that the combination of both ALS and imagery data could provide more information regarding the occurrence of drought and canopy gaps in the forest.

Semi-ITD approach to estimate wood volume per tree

Overall, using the ABA method 151,048 trees were detected in the study area, with an average of 994 trees ha⁻¹, while the average number of trees per hectare estimated by the forest inventory was 1708 trees ha⁻¹. Therefore, approximately 42% of the trees were not detected using the above approach, reinforcing the need to correct the remotely sensed tree count by modeling the tree count mean difference (MD).

After identifying the predictive mean difference model, we performed a linear adjustment using the least squares method. The model selected used three variables: maximum height (hmax); the slope (S) estimated from ALS data; and the number of trees detected in the aerial images found using the semi-ITD approach (Tab. 3), which had an RMSE of 12.66%.

The average number of trees per hectare detected by the conversion of ITD into ABA (semi-ITD) for the study area after mean difference (MD) correction was 1707.7, while the inventory data provided a figure of 1708.3 trees per hectare. Therefore, the mean volume per tree estimated from study data was 0.188 m³, while the mean volume of an individual tree derived from forest inventory was 0.195 m³. Fig. 3 shows the wall-to-wall tree volume maps generated in this work.

Discussion

Accurate stand attribute estimates are critical for effective forest plantation management, partly due to their markedly shorter rotation ages and faster growth rates relative to natural forests (Packalén et al. 2011). Moreover, for proper management of forest plantations, information on individual trees is of high value (Simões 2008). Remote sensing has proven to be an excellent data source for supporting sustainable forest management (Wulder et al. 2000). However, obtaining accurate estimates of forest attributes is often still elusive (Saarela et al. 2015). Our results indicate that the combination of different remote sensing data sources to estimate stand volume can lead to improved accuracy of predictions (RMSE = 5.23%).

In this research, we used two approaches to estimate stand volume in Eucalyptus spp. plantations using ALS as well as high spatial resolution multispectral image data. We first modeled the stand volume using ABA with different combinations of ALS- and image-derived metrics as input data, in three different models. Despite ABA slightly underestimated stand volume (2.98%) compared to the reference volume (total wood volume measured at the mill) the results were close to those obtained by the forest inventory. However this approach could be enhanced by predicting the number of trees using the ITD approach, this introducing a correction method to improve tree count predictions. We then integrated that information with stand volume previously predicted using the ABA method, allowing for the calculation of mean individual tree volume.

The model applied in the volumetric prediction used two variables derived from aerial imagery, the near infrared band (B4) and the green/red (B2/B3) ratio, and two ALS-derived variables of height (hmax) and cover (Amax). Using the ratio between the green and red bands is analogous to using the near infrared and red bands ratio. The

Fig. 3 - Maps of ABA-derived predictions for stand volume (top left), corrected number of trees (top right) and mean tree volume (bottom).

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For Biotics and Forests and Frory 301 station, based primarily on slope, allowed us to make corrected estimates of tree volume to one year, as is the case in this study. Despite improvements over ALS data, we showed a higher correlation with the standard deviation (i.e., heterogeneity) of a plot, which made tree detection from the images more difficult. In general, the correction procedure applied to our tree counting process performed well, showing good agreement with the ALS-derived counts and leading to individual tree volumes with negligible mean difference and low RMSE (12.66%). Our corrected estimates of tree count were greater than uncorrected values identified from the image-based detection by 713.7 trees per hectare, very close to extant estimates based on the forest inventory. The final estimates of individual tree volume after mean difference correction were 0.188 m$^3$ per tree, 3.5% less than the inventory estimate (Simões 2008, Packalén et al. 2011).

We demonstrated that a traditional ITD approach can be modified by using ABA, in spite of losing the exact location of each tree, but enabling to obtain the desired tree density information (Breidenbach & Astrup 2014).

**Conclusions**

Accurate information about wood volume at both the stand and individual tree levels is required to support the effective management of forest plantations. In this study we enhanced the traditional area-based approach using individual tree detection. The integration of geometrical and spectral information provided by ALS and aerial imagery, respectively, allows for the reliable predictions of volume at both spatial scales. Moreover, remote sensing data integration results in lower mean difference and RMSE. Our approach allowed for the estimation of individual tree volume with negligible bias.

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