

Informe Final (Final Report)

VALIDACIÓN DE LA TÉCNICA LIDAR TERRESTRE MÓVIL Y SOFTWARE ASOCIADO PARA LA ESTIMACIÓN DE BIOMASA SECA AÉREA EN PIES INDIVIDUALES DE Paulownia (Paulownia elongata x fortunei cv)

VALIDATION OF MOBILE TERRESTRIAL LASER SCANNER (MTLS) TECHNIQUE AND ASSOCIATED SOFTWARE FOR ABOVE AND BELOWGROUND DRY BIOMASS ESTIMATION IN INDIVIDUAL TREES OF Paulownia (Paulownia elongata x fortunei cv.)

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1) HYPOTHESIS

To date, the software used to process point clouds can only directly assess volumes and other directly measurable variables in both stems and branches.

If the existence of a significant and high correlation between dendrometric variables is confirmed, that is, the existence of significant allometric relationships, mainly between aerial biomass and stem and/or branch volumes, then it is to be expected that stem and/or branch volume parameters obtained from point clouds generated by the Lidar technique and processed with certain software, are also significantly related to the aerial biomass to be estimated.

Therefore, in this work we will obtain the dendrometric parameters of a sample of paulownia trees using destructive techniques and defining the fundamental allometric relationships between biomass parameters and other variables (e.g., diameter at breast height -DBH-, stem volume -Vs-, branch volume -Vb- and total volume -Vsb, stem plus branches-). Subsequently, the these usual dendrometric parameters are extracted from point clouds and statistical models are proposed between biomass (obtained by destructive analysis) and the parameters extracted from point clouds captured with the LIDAR technique and processed using two different software, "Lis PRO 3D Pipes" and "AID-FOREST".

Therefore, the main hypothesis to be validated is that the software used to extract the dendrometric information of the trees based on point clouds is sufficiently precise and accurate to be able to estimate the desired tree biomass parameters.



2) GOALS

The objectives of the present work are as follows:

- 1. To quantify the dendrometric parameters of each of the 19 trees under study.
- 2. To quantify the above-ground and below-ground dry biomass of all compartments of the 19 trees of *Paulownia elongata x fortunei*.
 - Quantify the dry biomass of the whole stem.
 - To quantify the total dry biomass of branches.
 - To quantify the total dry biomass of roots.
 - Transform biomass data (kg) to CO₂ data (kg) stored in the trees.
- 3. To determine the fundamental allometric relationships between aboveground (and belowground) dry biomass, and the rest of the dendrometric variables.
- 4. To establish a statistical model to estimate above-ground (and below-ground) biomass based on variables obtained from point clouds generated using the mobile terrestrial Lidar technique and associated software, which provides different parameters such as stem and branch volume (in addition to DBH and total height of the tree).



3) METHODS

Field methods

A total of 19 Paulownia trees will be selected from the existing dimensional classes, i.e. from 2-7 years old plantations in Ondara (Alicante) municipal area. Diameters at breast height (DBH) ranged between 8 to 40 cm.

Each tree was cut at 0.2-0.3 m aboveground. Once each tree was felled, it was divided into logs of 1 m in length and the diameter with bark, bark thickness and length of the log were measured in the field.

In addition, all the logs were weighed using a scale (maximum weight 60 kg, precision, 20 g). A sample was taken from each log for subsequent laboratory analysis.

Similarly, all branches were cut and weighed fresh (using the previous scale) and their insertion diameters were measured. A sample of 5-7 branches per tree were selected from within the range of branch sizes, i.e., small, medium and large branches. Their base diameters of the principal axis, total branch length, fresh weight, number of secondary branches per principal axe, diameter at the mid-length and length of each secondary branch were measured too. In addition, a small sample of branches were submitted to the laboratory to obtain their moisture content.

With an excavator, all the coarse and fine roots (as far as could be seen) were removed and weighed fresh (using a scale of 1000 kg and precision of 0.5 kg). A sample was selected and submitted to the laboratory for moisture analysis.

For more details see López-Serrano et al., 2005.

Laboratory methods

The moisture content of the wood was evaluated in the laboratory and its specific density (gr dry biomass/volume) was obtained. For this purpose, the drying of the samples was carried out in an oven according to the standard UNE-EN 13183-1, Moisture content of a piece of sawn timber. Part 1: Determination by oven-drying method.



In addition, for the determination of the carbon content (and other elemental components of wood, i.e. nitrogen, hydrogen), a LECO TruSpec elemental analyser was used. This equipment combusts a sample quantity of between 100 mg and 400 mg in a highly oxidising atmosphere, depending on the density of the sample and the expected composition. The combustion gases are directed to different cells in which the percentage of each element is counted individually. The carbon and hydrogen content are determined by infrared absorption and the nitrogen content by thermal conductivity.

The procedure used is derived from the experimental standard UNE-CEN/TS 15104 EX Solid biofuels. Determination of total carbon, hydrogen and nitrogen content. Instrumental methods".

Lidar measurements

All trees were scanned using a ZEB-HORIZON (GeoSLAM ltd., Nottingham, UK) as the MTLS device.

The postprocessing point cloud to obtain dendrometric parameters was carried out using two different software: AID-FOREST (López-Serrano et al. 2022) and the Lis PRO 3D Pipes (reference). Figure 1 shows the configuration parameters used for AID-FOREST processing.

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| Number | of matches | 8 | | | | |
| Percenta | ge of intersection | 0.7 | | | | |
| Offset de | tection adjust | -0.05 | | | | |
| X Resolut | tion for detection | 0.01 | | | | |
| Y Resolut | tion for detection | 0.01 | | | | |
| Z Resolu | tion for detection | 0.2 | | | | |
| Resolutio | on of terrain models | 0.2 | | | | |
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Figure 1. Configuration parameters for point cloud data processing using AID-FOREST software.

Data processing

To obtain total fresh biomass of the stem, all log weights were added together. Similarly, the total stem volume resulted of add all log volumes. Finally, total fresh weight of the roots and the branches were measured in situ.

To obtain dry biomass of the stem, we obtained the moisture (%, in humidity basis) of each slice of logs. Then, a model for log moisture was defined in base to the DBH and the height of the slice. This model was applied to each tree and log and the dry biomass of the log for each tree was obtained.



To obtain the dry biomass of the branches, we obtained the moisture of the selected samples, and the dry biomass of the branches was calculated.

Finally, to obtain the total volume of the branches, a ratio estimator sampling was carried. This methodology needs to know the population parameter of the fresh biomass of the branches (that was measured in field) and a variable measured in the population (this was the insertion diameters of all the branches in the stem). Thus, using all the sampled branches, a model for volume and biomass per branch was defined. After, we applied this model to each tree in base to the branch insertion diameters. Thus, the estimated total branch biomass was compared with the total branch biomass measured in field and a ratio estimator was defined. The total branch volume was obtained similarly. Finally, the ratio estimator for branch biomass was applied to the total volume to correct the bias that the methodology based on branch diameter insertion could introduce.

Statistical analysis

Allometric relationships between components of the tree, or some biomass or CO2 storage versus dendrometric variables estimated from Lidar point clouds using different software were defined using a single or multiple regression analysis. All models were simplified (if necessary) using the forward stepwise regression method, based on the general linear test statistic (F-test, Neter et al., 1996). The best model was chosen by selecting the highest R2, lowest SEE, lack of colineality of the predicting variables (low variance inflation factor), and based on an analysis of the residuals which examined both the graphs of residuals and the Durbin-Watson statistic. In all cases, the model chosen was one that explained the behaviour of the variable of interest with a clear physical basis.

Multiple regression analysis, using indicator (or dummy variables), were used to detect if there were significant differences between the intercepts and slopes of the models defined for each date type of trees (that originated from the first plantation -saplings- or that they are resprouts, -chirpials-), using the general linear test statistic (F-test; Neter et al., 1996) to test some hypotheses about regression coefficients.



Correction for bias was applied in all log-transformed allometric equations (Mod. # 42, 44, 46, 47, 49, 51 and 52, see conclusions), adding the correction factor k (k = $s^2/2$, where s^2 is the residual variance of the model) to the models when are in log transformed way, or $e^{(s^2/2)}$ when are in exponential way, according to Sprugel (1983) and Parresol (1999).



4) RESULTS

• Destructive essay results

Stem wood moisture did not depend on tree size. However, figure 1 shows the variability of wood moisture as a function of the aboveground height of the log. The wood moisture is maximum at ground level, and it decreases with increasing height along the stem. Nevertheless, for tall trees, from two thirds in height there is an increase in wood moisture but without reaching the levels occurring at the base of the stem.

Regarding branch moisture content, figure 2 shows that it decreases as DBH increases. On the contrary, root moisture did not depend on tree size.

Thus, we defined different statistical models to obtain an estimate of moisture for the different compartments in order to calculate dry biomass per compartment. Table 1 shows these statistical models.

Regarding to the carbon content of the Paulownia wood (for roots, stem and branches) the result showed an average of 50.8% (±0.8 standard error) de carbon content in a dry basis, i.e., per a kg of dry biomass, there are 0.508 kg of C. However, to take into account the sampling error, from now on we will use the value of 50% to convert dry biomass to carbon content (IPCC, 1996; Brown, S. 1997).

Table 2 shows both the dendrometric parameters and biomass variables for the 19 trees analysed and table 3 shows the magnitude of CO₂ stored at tree level for each compartment.

However, table 4 shows that some small trees have very high percentage of root biomass regarding to the total aboveground biomass. Revised field data, we check that these trees were resprouts of previous paulownia trees that were cut. That should be take into account to define allometries for root biomass or CO2 estimations.

Lis PRO 3D results

Similarly, table 5 shows the main dendrometric parameters obtained from point clouds using Lis PRO 3D software.

<u>AID-FOREST results</u>



Finally, table 6 shows the main dendrometric parameters obtained from point clouds using AID-FOREST software.

<u>Allometric relationships</u>

Working only with dendrometric variables from destructive essays, we obtained the different relationships between these variables (allometries). Table 7 shows a summary of the main relationships that demonstrate the significative and high correlation between biomass (or CO2) variables with volume or DBH.

When DBH is used as predictive variable, models are not linear, but they need some transformation to get the best fit (square root or natural log).

However, when biomass is regressed to volume of stem or total (branches + stem) we can use the linear relationships, because between biomass and volume did exist a quasi-functional relationship (the specific wood density).

Since there are significant allometric relationships using variables measured via destructive essays, then it is reasonable to expect that if variables obtained from LIDAR point clouds is able to estimate some volume variables, then there will are also significant models for estimating biomass from volume variables obtained from LIDAR point clouds.

In general, DBH and Vs predictive variables had a significant relationship with all biomass compartments. It is true than Vs, as predictive variable, improved both the determination coefficient and residual deviation in front of DBH (see table 7).

<u>Ability of AID-FOREST and Lis PRO 3D Pipes software to estimate</u> <u>dendrometric variables.</u>

Dendrometric variables such as DBH, total height (Ht) and total stem volume (Vt) were compared in from of DBH, Ht and Vt estimated by both AID-FOREST and Lis PRO 3D Pipes software. Table 8 shows the comparative results for DBH variable, showing a significant bias on the DBH estimation using Lis PRO software (underestimation of 1.78 cm regarding to real DBH). Similarly, table 9 shows a significant overestimation of Vt when Lis PRO was used (-0.097 m³). And finally,

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table 10 shows a significant underestimation of the total height when Lis PRO was used (+1.78 m). In contrast, AID-FOREST software produced no significant bias in either DBH, Ht or Vt (Tables 8 to 10).

Figures 4 to 6 show the significant and accurate relationships between diameters, total height and volume obtained for both point cloud software, being slightly better when AID-FOREST was used.

Models for CO₂ estimation as a function of Lidar estimates.

Simple regression models were defined for CO_2 storage for the whole tree and for their compartments. Table 11 shows the significant relationships between CO_2 storage per tree and the different concepts of volume measured from the point cloud using the Lis PRO software. Similarly, table 12 shows similar models where the predictive variable was stem volume obtained via AID-FOREST software.

The results permit us conclude that both Lis PRO and AID-FOREST software estimate accurately the total CO₂ stored by paulownia trees and per compartments (tables 11 and 12). Moreover, the presented models are not and artificial relationships but based on parameter highly correlated in a single way, i.e., near a proportionality (and ratio estimator).

When the Lis PRO software was used, it was surprising that the most significant predictor variable was branch volume (Table 11, models 20, 23, 26, 29 and 32). However, this result is reasonable, given that branches support the entire photosynthetic apparatus of the tree and, therefore, a proportionality between total CO₂ or biomass and branches is expected. Nevertheless, for branch CO₂ and stem CO₂, the most correlated variables should be Vb-PRO and Vs-PRO, respectively, because they are the predictive variables that have the same nature as the parameter they are intended to estimate. Because paulownia trees could be subjected to pruning in a different way depending on sites or stands, the relationship with Vb-PRO could not be stable and it would change with the type of pruning carried out.

Regarding AID-FOREST software, the lonely predictive variable used is the stem volume (Vsz, see table 12) for all the interest variables, because AID-FOREST is not able to measure the branch volume of the tree. However, AID-FOREST gives similar estimations than Lis PRO



software when this predictor variable is used (Vs-PRO, tables 11 and 12).

In general, either software gives a good estimate of the biomass and CO_2 parameters. Table 13 shows the comparative absolute and relative residual deviation for both software estimations using different predictive volume variables. Note that mean residual is always 0 for all CO_2 variables estimated, i.e., the total stored CO_2 estimation of a set of trees shall have a random error equal to 0.

Finally, table 14 shows the best regression models that predict both aboveground and belowground CO2 storage of the paulownia trees, as a function of stem volume or DBH estimated from AID-FOREST. Similarly, table 15 shows the best regression models using stem volume or stem+branch volume or DBH estimated from LIS-PRO software.

If we hypothesized that the best models are those where the predictive variables are the directly measured in field using classical methods (Eq. 16 -table 6- for aboveground CO₂ predicted from stem volume or eq. 41 in table 14 from DBH as predictive variable), then the best predictive models that come closest to these for aboveground CO₂ are the Eq. 43 (when using AIDFOREST software) or Eq. 54 when LIS-PRO software is used.

For belowground CO_2 storage, the best model using field predictor variables were Eq. 45 and Eq. 46 -Table 14- for DBH and Vs, respectively). Consequently, Eq- 47 (using Vsz, AIDFOREST measured) approximates to Eq. 46. However, using LIS-PRO, the proposed model (Eq. 56) is less accurate.

Because there are 5 trees that come from resprouts, the belowground CO_2 storage estimation improves if we define two different models for each kind of tree. Thus Eq. 48 and 49 improve significantly the Root CO_2 estimations. Similarly occurs in Eq. 57 and 58 when DBH-PRO is used. However, models with only 5 trees are not enough and they should be take with caution.

For the before, the final proposed models for the whole CO_2 storage by the trees are shown in Eq. 50 (table 14) and Eq. 59 (table 15), respectively for DBHz and DBH-PRO.



- All models regarding to biomass or CO₂ estimation using as predictive variables those obtained from LIDAR point clouds and the two-software essayed, were highly significative.
- Predictive variables based on LIDAR points clouds were as efficient as those measured directly by classical techniques (e.g. DBH measured with callipers or Vs).
- Due to the relative high residual deviation (SEE, table 12, mainly for belowground biomass and belowground CO₂ storage) the models cannot estimate accurately CO₂ storage for individual trees.
- However, if the aim is to obtain the storage for a set of trees, the greater the number of individuals, the greater the precision and accuracy, tending to a 0 error.
- In addition, the models will be very accurate when applied sequentially to the same trees to obtain increases in biomass or CO₂ storage. In this case, the CO₂ increment along a period will have a very low estimation error as a consequence of the high correlation between the biomass or CO₂ variables measured at two different times at the same tree, according to Taylor (1997):

Be "*y*" the increment of the CO₂ stored by a tree at two different dates $(x_1 \text{ and } x_2)$, $y = x_2 - x_1$, being \mathcal{E}_{x2} and \mathcal{E}_{x1} the unknow errors of the x_1 and x_2 variables and $r_{x_1x_2}$ the correlation coefficient. Then, the \mathcal{E}_y , error of the difference, will be (according to Taylor, 1997):

$$\mathcal{E}_{y} = \sqrt{\sum_{j=1}^{2} \left(\frac{\partial y}{\partial x_{j}} \mathcal{E}x_{j}\right)^{2} + 2r_{x_{1}x_{2}}\left(\frac{\partial y}{\partial x_{1}} \mathcal{E}x_{1}\right)\left(\frac{\partial y}{\partial x_{2}} \mathcal{E}x_{2}\right)}$$

Applying to our case, and simplifying



$$\mathcal{E}_y = \sqrt{(\mathcal{E}x_1)^2 + (\mathcal{E}x_2)^2 - 2r_{x_1x_2}\mathcal{E}x_1\mathcal{E}x_2}$$
 Eq. 60

Such the Eq. 60 shows, the high coefficient of correlation (r) between both x_i variables (near 1, because come from the same tree) makes the CO₂ increment error minimum.

- The high variability for belowground CO₂ storage is a consequence of the existence of two types of trees in the sample: trees that never were cut and resprout from previous cut trees. This causes, being a resprouting species, the accumulation of biomass in the root against the new tissue generated both in the stem and in the branches and, consequently, a hight variability of root biomass for similar stem size.
- The measurement of stem volume and branch volume as predictive variables did not improve the CO₂ storage estimation in from of the DBH. Consequently, we proposed this variable (estimated via AIDFORES or LIS-PRO software) as the most efficient predictive one and, in addition, is easy to obtain via LIDAR point clouds and the associate software.
- This study does not guarantee that the DBH was the most efficient predictive variable, since only trees of one site quality were selected. In the case of different seasonal conditions (trees of paulownia in different site qualities), perhaps Vz will be much more explanatory than DBH, but this is a hypothesis that would have to be corroborated.
- To consider the existence of individuals with different root ages as a consequence of successive cutting and resprouting periods, a new experimental design would be needed to include trees in different stadiums.
- As final model to be used, in base to field data, for the estimation of the total CO₂ (kg tree⁻¹) stored by a set of trees (brinzal trees, i.e., trees that were never previously cut; this excludes the resprouted trees), we propose the following model based on DBHz (cm, measured via AIDFOREST software):TOTco2 = 26.62 * e^(0.105*DBHz)



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