



1     **Improvement in accuracy of aboveground biomass estimation in**  
2     ***Eucalyptus nitens* plantations: effect of bole sampling intensity and**  
3                                   **explanatory variables**

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11     **Abstract:**

12             Two sets of aboveground biomass equations were fitted for stem only and stem plus  
13 crown predictive variables in *Eucalyptus nitens* plantations in Northern Spain. A sample of 40  
14 trees was chosen after a complete study of variation in tree height and diameter in the region.  
15 The trees were felled and the biomass was divided into the following components: wood,  
16 bark, thick branches, thin branches, twigs, leaves and dead branches along the stem. Bole  
17 biomass was estimated by systematic subsampling of one 5 cm-thick disk every 0.5 m. Such  
18 intensive subsampling enabled determination of the effect of subsampling intensity on  
19 accuracy and bias of wood estimation, considering two ratio-type estimators: stem weight to  
20 dry matter, **determined by the complete weighing (CW) method (i.e. of the fresh weight of the**  
21 **entire stem) and volume to dry matter, determined by the partial weighing (PW) method.** The  
22 changes in moisture content and basic density along the stem explained the serious risk of **dry**  
23 **mass or weight** overestimation when a systematic subsample is considered. The average basic  
24 density was usually found at a relative height of 30-35% along the stem. The default choice of

1 the bottom disk or log as the first section resulted in overestimations for the *CW* method and  
2 underestimations for the *PW* one. The biomass equations were fitted by seemingly unrelated  
3 regression, with corrections for heteroscedasticity carried out by weighted fitting. Diameter at  
4 breast height was the best explanatory variable, and the inclusion of height did not improve  
5 the accuracy, except for wood. The inclusion of crown variables improved the predictive  
6 ability for crown fractions, **increasing** the accuracy for estimating thick branches (by 10.8%),  
7 twigs (by 19.1%) and leaves (by 17.3%). **The biomass of each fraction decreased in the**  
8 **following order:** wood>bark>thick branches>dead branches along the stem>leaves>thin  
9 branches>twigs. The changes in these percentages with diameter class and the predictive  
10 ability of the fitted equations were also studied.

11 *Keywords:* *Eucalyptus nitens*, biomass, ratio type estimators, wood basic density, wood  
12 moisture; crown variables

13

## 14 **1. Introduction**

15 Destructive sampling and subsequent regression analysis is the most common method  
16 used to estimate tree biomass (Parresol, 1999). Biomass estimation at tree level is a necessary  
17 first stage in estimating stand biomass, and the main sources of error in this process are: i)  
18 selection of trees for sampling; ii) measurement of independent and dependent variables in  
19 sampling trees; iii) choice of a suitable form of the allometric relationship and values for any  
20 adjustable parameters in the equation; iv) field measurement of the independent variables in  
21 the objective population, and v) application of allometric equations to objective populations  
22 for individual **tree** biomass estimation and summation to obtain stand estimates (Cunia, 1987,  
23 Ketterings et al., 2001). Each of these steps has an associated error that must be minimized;  
24 the errors involved in step ii are the least well studied (Satoo and Madgwick, 1982, Cunia,  
25 1987, Parresol, 1999, Ketterings et al., 2001).

1           The errors in the assessment of sample tree dependent variables are strongly influenced  
2 by the **procedure** (Cunia, 1987): i) subsampling selection, ii) fresh and dry weight estimation,  
3 and iii) subsampling intensity. With small trees, fresh and dry weighing of the entire tree is  
4 not time consuming nor expensive and is therefore **recommended** (Parresol, 2001). However,  
5 direct measurement becomes more expensive as tree size increases, and subsampling becomes  
6 inevitable (Satoo and Madgwick, 1982, Parresol, 1999). Fresh weight can be measured  
7 directly or estimated by several methods. One of the most commonly used methods of  
8 determining the fresh weight of trees and estimating the dry weight is to use ratio-type  
9 estimators (Briggs et al., 1987), in which the relationships between dry/fresh weight or dry  
10 weight/fresh volume are assessed in a sample and applied to the rest of the tree for dry weight  
11 estimation. The main advantage of these methods is the simplicity of application and  
12 determination, although it is well known that ratio estimators are biased (Cunia, 1979,  
13 Valentine et al., 1984).

14           **Some methods provide unbiased, efficient estimations, such as randomized-branch**  
15 **sampling (RBS) and importance sampling (IS) methods, which use auxiliary information to**  
16 **select elements in the sample to reduce the variance of the estimator (Valentine et al., 1984,**  
17 **Parresol, 1999). RBS is a type of multi-stage probability sampling, which is used to select a**  
18 **path so that resultant segments of the path comprise a probability sampling of the entire tree.**  
19 **IS is a continuous analog involving sampling discrete units with probability proportional to**  
20 **size (Gregoire et al., 1995). These methods are of interest for estimating fractions such as**  
21 **branches or foliage, although in practice they are time-consuming and difficult to apply.**

22           To apply ratio type estimators, stems can be weighed and disks removed to determine  
23 moisture content **(by the complete fresh weighing, CW method)** or volume can be estimated  
24 and short sample logs weighed to obtain volume to mass conversion factors **(by the partial**  
25 **weighing, PW method)**. Subsampling across the bole can be done by random stratified

1 sampling, as carried out by Briggs et al. (1987), although most researchers use a fixed number  
2 of sections across the stem, with the position chosen systematically (i.e. (Saint-André et al.,  
3 2005)), randomly, or with a probability proportional to a given dimension. This was the case  
4 for Kleinn and Pelz, (1987), who chose disks with a probability of selection proportional to  
5 estimated volume. On the other hand, the *PW* method is preferred for large trees in sites with  
6 difficult access, as fresh weighing of the whole stem is quite laborious and time consuming  
7 (Snowdon et al., 2000). In the *CW* method, the distribution of moisture along the stem is the  
8 main source of error for dry weight estimation, whereas in the *PW* method, it is the variation  
9 in basic density along the bole height that affects that error. In both cases, sampling intensity  
10 and distribution should guarantee a suitable description of the variability in moisture content  
11 and specific density.

12 Diameter at breast height ( $d$ ) and total height ( $h$ ) are the most common dependent  
13 variables used in biomass regression, because of their ease of measurement and predictive  
14 capacity (Parresol, 1999, Snowdon et al., 2000). However, because of the current increasing  
15 interest in obtaining accurate predictions of crown fractions for bioenergy, nutrient stability  
16 and silvicultural or ecological studies, there is a corresponding increasing interest in crown  
17 biomass modelling. Some authors have observed that the use of crown variables as  
18 explanatory variables improves the accuracy of biomass equations (Satoo and Madgwick,  
19 1982, António et al., 2007). In biomass studies in which high precision is required for crown  
20 fractions, and destructive sampling cannot be applied, highly accurate models are required.

21 The objectives of the present study were: i) to obtain biomass estimation tools for a fast  
22 growing species, *Eucalyptus nitens*, in northwestern Spain, considering the most complete set  
23 of aboveground components; ii) to evaluate the bias and accuracy of wood biomass estimation  
24 for different intensities of systematic subsampling across the stem and two ratio-type  
25 estimators (dry/fresh weight and dry mass/fresh volume), iii) to evaluate the increased

1 accuracy derived from the inclusion of crown variables in the estimation of individual tree  
2 biomass components, and iv) to evaluate the ability of the proposed equations to estimate the  
3 proportion of each biomass component over total aboveground biomass, for a range of  
4 diameter classes.

## 5 **2. Materials and methods**

### 6 *2.1. Study site and trees sampled*

7 This study was carried out in northwestern Spain, in an inland area located at elevations  
8 of 500 to 1000m, with average precipitation of 900-1200 mm and average annual temperature  
9 of 12-13°C (Martínez Cortizas and Pérez Alberti, 1999). Although frost occurrence limits  
10 planting of the most common *Eucalyptus* species in Spain (*Eucalyptus globulus* Labill.),  
11 *Eucalyptus nitens* (Deane & Maiden) Maiden was successfully introduced in the mid 1990s,  
12 providing yields of 15-50 m<sup>3</sup> ha<sup>-1</sup> yr<sup>-1</sup> (Pérez-Cruzado, 2009).

13 As the aim of the present study was to construct biomass models that are as  
14 representative as possible, sampling consisted of two phases: 1) study of the variability of the  
15 most commonly used independent variables in biomass equations at tree level (*d* and *h*, see  
16 below) across the distribution area, and 2) destructive sampling of trees covering the observed  
17 range (Parresol, 1999). For this purpose, 76 plots were established (see location in Fig. 1),  
18 covering the observed range of ages and site qualities, with a minimum plot size of 314 m<sup>2</sup>,  
19 which is generally suitable for biomass estimation procedures in plantations (Satoo and  
20 Madgwick, 1982).

21 A sample size of 40 trees was chosen because of the low variability in site conditions  
22 and densities of plantations, most of which were established with the MacAlister provenance.  
23 The sampled trees were chosen in two steps, two trees per diameter and height class were first  
24 selected, and 16 additional trees were then chosen, considering the relative importance of each  
25 diameter class in the population. The aim of this procedure was to cover the full range of tree

1 size, which is shown for height and diameter in Fig. 2. Trees were felled in 12 plots, in which  
2 the values of the quadratic mean diameter and  $d$  of the trees sampled was similar; undamaged,  
3 healthy trees that represented the dominant and codominant strata, were chosen. The average  
4 standard deviation and range of representative stand and single tree variables, for both the  
5 population and the sample are shown in Table 1. The variability in crown variables was  
6 similar to that observed in stem variables, unlike in other studies (Satoo and Madgwick,  
7 1982).

8 The following variables were measured in the sample trees while still standing: diameter  
9 at breast height ( $d$ , cm) and stump diameter at 0.15 m ( $d_{st}$ , cm), both measured in two  
10 perpendicular directions to the nearest mm; total height ( $h$ , m) and live crown base height,  
11 defined as the height of the first live branch insertion in the stem ( $h_{cb}$ , m), both measured to  
12 the nearest dm; crown diameter ( $d_c$ , m) measured in two perpendicular directions following  
13 the cardinal points to the nearest cm. Living crown length ( $h_c$ , m) was estimated as difference  
14 between total height ( $h$ ) and live crown basis height ( $h_{cb}$ , m). Crown volume ( $v_c$ ) was  
15 calculated from  $h_c$  and  $d_c$  by assimilating the crown shape to an ellipsoid (1). Descriptive  
16 statistics for these variables are shown in Table 2.

$$v_c = \frac{4}{3} \pi \left( \frac{d_c}{2} \right)^2 \left( \frac{h_c}{2} \right) \quad (1)$$

17

## 18 2.2. Ratio type estimators and subsampling

19 The felled trees were cut into 0.5 m logs to a small-end diameter of 7 cm. The logs were  
20 weighed fresh and a systematic subsample of one 5 cm-disk in the bottom part of each log  
21 was taken, also considering a further disk at the top of the stem. Sample disks were weighed  
22 fresh and transported to the laboratory in plastic bags. The over and under-bark diameters of

1 the disks were measured in two directions and the bark and wood were then separated and  
2 weighed.

3 For each disk, the dry wood **weight** was measured after oven drying at 105°C to constant  
4 weight and the ratio of the dry/fresh weight of the wood was determined. Only one composite  
5 sample per tree was considered for the bark. Fresh bark of all disks was weighed jointly, and  
6 dried to determine dry bark weight, thus enabling the ratio of dry/fresh weight of bark to be  
7 obtained for each tree.

8 The dry weight of wood and of bark in each log was calculated from the average ratios  
9 calculated for the delimiting disks. The total wood ( $W_w$ , to a small-end diameter over bark of  
10 **7cm**) and bark ( $W_b$ , evaluated till the threshold diameter considered for wood) dry biomass in  
11 each tree was calculated as sum of the biomass of each log.

12 Four biomass fractions were considered for the crown: thick branches ( $W_{Tb}$ , diameters  
13 over bark 2-7cm), which also include the tops of the boles, thin branches ( $W_{tb}$ , diameters over  
14 bark 0.5-2cm), twigs ( $W_t$ , diameter less than 0.5 cm) and leaves ( $W_l$ ). Dead branches in the  
15 stem ( $W_{db}$ ) is also an important fraction in *Eucalyptus nitens*. Crown **biomass was** first  
16 fractioned in the field into three groups:  $W_{Tb}$ ,  $W_{db}$  and the sum of  $W_{tb}$ ,  $W_t$  and  $W_l$ , and then  
17 weighed fresh, with a balance, to the nearest 10g. A subsample of 10-15% of fresh weight of  
18 each fraction was taken to represent the top, medium and bottom part of the crown. These  
19 subsamples were weighed in the field, with scales, to the nearest 0.01g.

20 The composite subsample of  $W_{tb}$ ,  $W_t$  and  $W_l$ , was fractioned and weighed in the  
21 laboratory and the proportion of each fraction was determined to enable estimation of the  
22 fresh weight of each crown fraction. The dry weight of each fraction was then estimated from  
23 the dry/fresh weight ratios.

24 *2.3. Methodologies for bole mass estimation*

1 The information obtained enabled comparison of two methods of estimating bole mass  
2 or weight at a range of sampling intensities. The *CW* method consisted of determining the  
3 complete stem weight and estimating dry weight from disks. Disk subsampling intensity was  
4 modified considering a series of inter-disk distances which were multiples of 0.5. For each  
5 inter-disk distance tested, there were several solutions, depending on the height of the first  
6 section considered. For the logs between two disks, the dry weight estimation was calculated  
7 from the average dry weight wood ratio of each disk, and for basal and terminal logs the disks  
8 immediately above or below the log were considered.

9 For the *PW* method, it was considered that only one part of the stem was weighed, and  
10 for the rest of the tree the volume was calculated from diameter under bark measured every  
11 0.5 m along the stem and by use of the Smalian formula. The length of the weighed and cubed  
12 log was made to range between 0.5m and the total stem height (up to a small-end diameter of  
13 7cm), considering a variable position of the log along the stem. The fresh weight of the log  
14 was transformed to dry weight by considering the moisture content derived from the whole set  
15 of disks taken each 0.5 m. Volume to dry weight ratios were then used to estimate the total  
16 dry mass of the stem by multiplying by the calculated volumes.

17 Both methods and sampling intensities were compared with the results obtained by the  
18 *CW* method and disk equidistance of 0.5 m, considering the relative difference in the biomass  
19 estimation for each tree (2).

$$RD = \frac{(\hat{W} - W)}{W} \cdot 100 \quad (2)$$

20 where  $\hat{W}$  is the predicted bole mass value with each sampling methodology and intensity.

21 The combinations of inter-disk distances, weighed log lengths and starting point along  
22 the bole provided a relative difference value, and these were plotted against subsampling  
23 intensity for different diameter classes. The 95% confidence intervals were obtained

1 considering a normal distribution for different classes of sampling intensity. The default  
 2 consideration of the bottom disk (*CW* method) or the bottom log (*PW* method) was considered  
 3 separately for comparison.

#### 4 2.4. Models and fit

5 Models for predicting biomass of tree components are usually based on the allometric  
 6 relationship (3) between tree biomass and tree variables. This was then used as the basic form  
 7 of the models to be fitted (Zianis and Mencuccini, 2004).

$$W_i = b_1 \cdot x_1^{b_2} \cdot \dots \cdot x_n^{b_{n+1}} \quad (3)$$

8 where  $W_i$  is the dry mass biomass of the fraction  $i$  and  $x_n$  are the independent variables.

9 The model fitting was carried out in two steps. First, each biomass fraction was fitted  
 10 individually considering each independent variable and their combinations, by use of the  
 11 minimum generalized squares in the MODEL procedure of SAS/STAT® (SAS Institute Inc,  
 12 2004). As initial parameters in the iteration process, a previous linear fit was carried out for  
 13 all combinations of variables, with the linearized allometric model (Parresol, 2001), by use of  
 14 the REG procedure of SAS/STAT®. In selecting the best model for each family of equations,  
 15 the following statistics were calculated for each equation: bias (*MRES*, 4), root mean square  
 16 error (*RMSE*, 5) and adjusted determination coefficient ( $R^2_{Adj}$ , 6).

$$MRES = \frac{\sum_{i=1}^N (W_i - \hat{W}_i)}{N} \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (W_i - \hat{W}_i)^2}{N - p}} \quad (5)$$

$$R^2_{Adj} = \left( \frac{\sum_{i=1}^N (W_i - \hat{W}_i)^2}{\sum_{i=1}^N (W_i - \bar{W}_i)^2} \right) \cdot \left( \frac{N-1}{N-p} \right) \quad (6)$$

1 where  $N$  is the number of data used in the fitting,  $p$  is the number of parameters to be  
 2 estimated,  $\bar{W}_i$  is the average value of the dependent variable.

3 In the second step, each family of equations was fitted simultaneously by the seemingly  
 4 unrelated regressions method (SUR) to guarantee the additivity of the system (Parresol,  
 5 2001). This method is based on the fit of an apparently non related equation system formed by  
 6 the regression functions of the **biomass fractions considered** and the total biomass. The SUR  
 7 method iteratively forces the sum of the components to equal the equation for total biomass,  
 8 ensuring that the global solution is the best possible, although the solution for each  $k$  fraction  
 9 is not necessarily the best. The independent variables in the system of equations for biomass  
 10 components has to be the same as in the total biomass equation (Parresol, 2001), and in fact  
 11 this equation was expressed as the sum of each component equation to ensure the additivity of  
 12 the system (Álvarez-González et al., 2007). The MODEL procedure of SAS was applied to  
 13 obtain the SUR estimates, considering the parameters obtained in the individual fitting as  
 14 initializers.

15 Lack of homogeneity in error variance, or heteroscedasticity, is commonly observed in  
 16 biomass equations (Parresol, 1993, Parresol, 2001). As with the standard errors of the  
 17 parameter estimates, heteroscedasticity was detected by representing the studentized residuals  
 18 against the real values, and the White (1980) and Breusch and Pagan (1979) tests were  
 19 applied. Heteroscedasticity was corrected by weighted fitting (Schaeigel, 1982, Clutter et al.,  
 20 1983, Cunia, 1987, Parresol, 1999, Parresol, 2001), by use of the inverse of the variance of  
 21 the residuals ( $\sigma_i^2$ ) assigned at each observation as a weighting factor, and use of the potential  
 22 expression (7) (Neter et al., 1989).

$$\sigma_i^2 = x_i^k \quad (7)$$

1 The value of the  $k$  exponent can be calculated by the optimization method proposed by  
 2 Harvey (1976), which consists of using the model errors fitted without weights ( $\hat{e}_i$ ) as  
 3 dependent variable in the potential variance error model (Álvarez-González et al., 2007), the  
 4 linearized form of which is shown in expression (8).

$$\ln(\hat{e}_i^2) = a + k \cdot \ln(x_i) \quad (8)$$

5 For each fraction, the value of the  $k$  exponent was determined for the independent  
 6 variables or the combination of these that provided the best fit. In those cases in which the  
 7 statistics did not detect heteroscedasticity, the weighted fit was carried out anyway. The  
 8 values of the  $k$  exponents were added to the fitting program in SAS/STAT® (SAS Institute  
 9 Inc, 2004). After fitting, the models were again subjected to heteroscedasticity tests to verify  
 10 their correctness.

### 11 **3. Results**

#### 12 *3.1. Estimation of bole biomass through systematic subsampling*

13 The relative difference ( $RD$ ) obtained by the  $CW$  method was plotted against systematic  
 14 subsampling intensity (disks  $m^{-1}$  of stem), for three dimensional classes: DC1 ( $d < 14$ cm), DC2  
 15 ( $14 < d < 24$ cm) and DC3 ( $d > 24$ cm) (Fig. 3). The figure shows overestimates for all the data,  
 16 with a clear trend for the relative error to decrease as sampling intensity increased. **Small trees**  
 17 **are clearly biased towards overestimation ( $d < 14$  cm), but the tendency for overestimation**  
 18 **decreases greatly with increasing tree size.** A threshold of 5% relative error would mean a  
 19 minimum subsampling intensity of 0.95 disks  $m^{-1}$  (DC1), 0.8 disks  $m^{-1}$  (DC2) or 0.75 disks  $m^{-1}$   
 20 (DC3). These values were respectively 0.7, 0.4 and 0.3 disks  $m^{-1}$ , for a relative error  
 21 threshold set at 10%. It is important to note that the default consideration of the stem bottom  
 22 as the position of the first disk would mean a systematic tendency to overestimation.

1           The *RD* values obtained for the *PW* method were plotted against the subsampling  
2 intensity, expressed as the percentage of stem height that was weighed (Fig. 4). Only the  
3 higher diameter classes were considered in this case, as there is no reason to avoid obtaining  
4 the complete fresh weight of small trees. In this case there was again a clear tendency for the  
5 weights to be overestimated, which was even clearer for the highest diameter class. This  
6 procedure ensured a maximum relative error of 5%, only when 90% of the stem was weighed  
7 for both dimensional classes considered. This percentage was 55% when the threshold of  
8 relative error was set at 10%. In this case, consideration of the bottom log as the one that  
9 should be weighed systematically led to underestimation.

10           The differences in the two methods arise from the observed trends in moisture content  
11 and basic density along the stem. The moisture content (wet basis) in relation to the relative  
12 height along the stem indicates an increasing trend that is more marked at the bottom 20%,  
13 where around 40% of bole dry matter occurs (Fig. 5). The increasing trend of basic density ( $\rho$ ,  
14  $\text{kg m}^{-3}$ ) along the stem, which can easily explain the underestimations derived from the  
15 default use of the bottom log in the *PW* method, is shown in Fig. 6.

16           Such increasing trends, which have been described for different species of eucalypts,  
17 with some exceptions, such as for *Eucalyptus regnans*, indicate the possibility of studying the  
18 relative height at which the average basic density can be found. This value was plotted for the  
19 sampled trees with non-zero amounts of wood (Fig. 7). The relative height tended to decrease  
20 with increasing breast height diameter. These results are of great interest for defining the  
21 height along the stem that should be sampled to obtain a good estimate of basic density.

22           For the *PW* method, it should be considered that the errors would be cumulative if  
23 transformation of fresh weight of the log to dry weight is carried out after obtaining  
24 information derived from disks with equidistance greater than 0.5 m. Moreover, the volumes

1 were calculated considering 0.5 m logs, which could provide volume estimates close to those  
2 obtained from water displacement of fresh samples (Brown et al., 1995).

### 3 3.2. *Fitting of biomass equations*

4 The first step in developing single tree biomass equations for aboveground biomass  
5 components was to fit the allometric model considering one explanatory variable. The best  
6 predictive results were obtained with  $d$  for all the components, although  $d_{st}$  showed good  
7 predictive values for  $W_{db}$ ,  $W_{Tb}$  and  $W_{tb}$ . There was a clear relationship between all biomass  
8 components and  $d$  (Fig. 8). The combined use of  $d$  and  $h$  as explanatory variables increased  
9 the accuracy of predictions only in the case of the wood component.

10 The information derived from these fittings was used to consider the best combination  
11 of independent variables to add to the allometric model, fitting two sets of equations: stem  
12 equations, based exclusively on  $d$  and  $h$ , and crown equations, in which crown variables were  
13 also considered. The models used and the statistics of the simultaneous fitting are shown in  
14 Table 3. The crown variables with the best predictive ability were crown length and crown  
15 diameter. The observed versus predicted values for both set of equations are shown in Figs. 9  
16 and 10. The weighted adjustment ensured homoscedasticity for all the models fitted.

17 Prediction of the parameters for the simultaneous fit are shown in Table 4. All the  
18 exponential parameters were significant, whereas some of the multiplicative parameters were  
19 not. This was considered acceptable, as the exponential parameters represent the relative  
20 growth of one part of the tree in proportion to another (Broad, 1998), and provide information  
21 about the distribution of primary net production among different fractions (António et al.,  
22 2007), whereas the multiplicative parameters have not a clear biological meaning.

23 The explanation of  $W_{tot}$  was high for stem variables as a unique estimator, and the  
24 combination of  $d$  and  $h$  provides the best results for this fraction. All crown variables, except  
25  $h_{cb}$ , work well individually as predictors for this fraction but the model is less accurate than

1 for stem variables. The inclusion of  $h_c$  or  $v_c$  as a predictor with  $h$  slightly improved the  
2 accuracy, but the parameter that affects the crown volume was not significant.

3 The worst fit was obtained with  $W_{db}$ , as already reported by other authors who have  
4 studied this fraction in *Eucalyptus* (Saint-André et al., 2005). Fitting of this fraction with  
5 crown variables provided a slight increase in accuracy and reduced bias, which is reasonable  
6 because almost all dead branches were collected along the stem and  $h_{cb}$  is a direct  
7 measurement of this length. This suggests that changes in dry weight of this fraction may be  
8 more closely related to density than to tree variables.

9  $W_b$  was more closely related to stem than to crown variables, and no additional  
10 improvements in estimations were obtained by addition of other variables. No crown  
11 variables were necessary for a good fit of  $W_w$ .

12 The inclusion of  $d_c$  as a crown variable provided a 10.8% increase in accuracy  
13 (measured as *RMSE*, Eq. 5) and reduced bias (Eq. 4) by 41.4% for the  $W_{Tb}$  explanation (data  
14 not shown). The overall results from use of only stem variables were good, and the adjusted  
15 coefficient of determination reached as high as 89.7%. In the case of thin branches, the  
16 simultaneous fitting with crown variables provided poorer fits.

17 The explanation of  $W_{tb}$  was high with  $d$  as the only estimator, the inclusion of  $h$  did not  
18 improve the accuracy and the estimation of its respective parameter was not significant. All  
19 crown variables were individually poorer estimators than  $d$ , but inclusion of  $d_c$  or  $v_c$  provided  
20 a slight improvement in accuracy, although respective parameters were not significant.

21 The use of crown diameter in the prediction of  $W_l$  increased the accuracy by 19.1%,  
22 although the bias was higher for the crown equation system. The crown height also improved  
23 the accuracy of estimation of  $W_l$  by 17.3%. Crown variables by themselves explained more  
24 than 59% of the variability in  $W_l$ . Estimation of these two components and  $W_{Tb}$  was greatly  
25 improved by use of crown variables.

### 3.3. Proportions of each biomass component

The statistics for the **dry weight biomass** fractions considered in the present study are shown in Table 1. Wood is particularly important in the total biomass, representing about 70% of total dry **weight** for the average tree size, which emphasizes the importance of its accurate estimation. The next fractions in importance are bark (10%) and thick branches, dry branches, leaves, thin branches and twigs. The relative proportions of each component, plotted against diameter, including a set of 8 small trees which were not used for fitting, are shown in Fig. 11. The proportion of some of these components in trees of different diameter class have been used as parameters in physiological growth models, and accurate estimation by use of the models proposed in this paper is desirable.

The proportion of each component related to total aboveground biomass is becoming critical in a scenario of increasing harvesting of biomass components that were previously left in place in forest soils. The proportion of wood, commonly referred to as the harvest index, increased with diameter (Fig. 11), although the trend was not continuous because of the need to consider a threshold diameter. Consequently, the component of thick branches may account for a large share of total aboveground biomass for trees with a diameter still too small to have a significant wood fraction. The bark fraction was defined as the bark fraction in the stem, and the bark of sections less than 7 cm in diameter was included in thick or thin branches, which explains the low percentages shown for diameters less than 12 cm. As a result, the equations presented here would provide reasonable estimates of biomass component percentages for diameters larger than 12 cm. For smaller diameters, exclusive use of the equation predicting total biomass is recommended.

## 4. Discussion

#### 1           4.1. Stem biomass estimation

2           The results of this study show that the error may be important, and will depend on the  
3 intensity of subsampling, when ratio-type estimators are used to estimate dry weight. The  
4 error also depends on the method used (complete fresh weight or partial fresh weight) and on  
5 the average tree size. Other authors have observed that ratio-type estimators provide biased  
6 estimates (Cunia, 1979, Valentine et al., 1984, Briggs et al., 1987). These overestimates are as  
7 large as the decreases in both subsampling intensity and average tree size. Overestimation is  
8 clearly a more serious error than underestimation (Satoo and Madgwick, 1982) because it  
9 does not err on the side of safety i.e. for carbon accounting procedures.

10          Wood moisture content and basic density change along the stem (Satoo and Madgwick,  
11 1982) (Figs. 5 and 6), and affect the estimation of dry biomass by the *CW* and *PW* methods  
12 respectively. Minimum moisture content and basic density occur in the basal part of the stem,  
13 which is obviously where most of the accumulated weight and volume occur. This effect must  
14 therefore be taken into account with a sufficient and well distributed number of subsamples  
15 along the stem. One way of addressing this problem, when taper functions are available, is the  
16 density integral approach (Parresol and Thomas, 1989). The weighed average is an alternative  
17 method that gives more importance to those observations in the lower part of the stem, and  
18 therefore more closely related to volume.

19          Chave et al. (2001) reported that the biomass values of the smallest trees strongly affect  
20 the values of the model parameters in the allometric relation. This effect is even stronger  
21 when a weighted adjustment methodology is used, because the smallest trees, which are less  
22 variable, are more important than the largest trees because of heteroscedasticity correction. It  
23 is therefore advisable to obtain the complete dry weight of the stem of small trees.

24          The degree of accuracy required depends on the objective of the estimation, although  
25 equilibrium between sampling intensity and the level of precision must be ensured (Brown et

1 al., 1995). If ratio-type estimators are chosen for stem dry biomass estimation, a relatively  
2 intensive subsampling scheme should be implemented, as others authors indicated for both  
3 ratio-type and density-integral methods (Parresol, 1999). Comparing the methods considered  
4 here, the *CW* method produced better results for the largest dimensional class than the *PW*  
5 method (Figs. 3 and 4). This is because, for a given length of cubed and weighed part, the  
6 proportion over total stem (as an indicator of sampling intensity) differs depending on tree  
7 size, and therefore becomes less important as tree size increases. This must be taken into  
8 account because the *PW* method is usually used for large trees in which complete weighing is  
9 time-consuming.

10 The results clearly show the trends in relative errors derived from a default  
11 consideration of the bottom disk or the bottom log as the first section to measure. It is  
12 advisable, if systematic sampling is to be used, to establish the subsampling intensity before  
13 randomizing the position along the stem of the first disk or log to be measured. In the case of  
14 the *PW* method it is not recommended to take only one sample log per tree, although this was  
15 the approach used in this study. The subsampling intensity should be split along the stem, and  
16 a good representation of the bole area where average basic density is likely to be found is  
17 advisable. Most published papers do not provide information about the proportion of weighed  
18 and cubed logs or their distribution along the stem, although the most reasonable distribution  
19 would be systematic or random, with the subsampling intensity chosen on the basis of  
20 statistical criteria.

21

#### 22 *4.2. Biomass equations from stem and crown variables*

23 Although it is known that  $d$ ,  $h$  and  $W$  are closely related (Satoo and Madgwick, 1982),  $h$   
24 is not always included in biomass equations together with  $d$  because both are correlated and  
25 inclusion of  $h$  adds only negligible accuracy (Jokela et al., 1986, Ter-Mikaelian and

1 Korzukhin, 1997, Johansson, 1999, Verwijst and Telenius, 1999, Snowdon et al., 2000,  
2 Brown, 2002, Porté et al., 2002, Jenkins et al., 2003). In this study, inclusion of  $h$  together  
3 with  $d$  only resulted in improved accuracy in the case of wood, although other authors have  
4 reported significant improvement for several fractions (Loomis et al., 1966, Pearson et al.,  
5 1984, Bartelink, 1996, Reed and Tomé, 1998, Monserud and Marshall, 1999). In their study  
6 on *Eucalyptus globulus*, António et al. (2007) observed improvements in the sum of residual  
7 squares of 72%, 8%, 12% and 10% for wood, bark, leaves and branches respectively, after  
8 inclusion of  $h$  together with  $d$ . It is possible that in the present study the tree sample was not  
9 representative of the entire variability in height for a given diameter.

10 Some studies included  $h$  and  $d$  in biomass models, together with density, age and site  
11 index (Ter-Mikaelian and Parker, 2000, António et al., 2007), and these models are therefore  
12 suitable for comparing different sites (Ketterings et al., 2001). Other studies included age as  
13 an independent variable in biomass equations (Porté et al., 2002, Saint-André et al., 2005),  
14 thus producing dynamic models with which biomass increments can be estimated by  
15 derivative analysis. Although individually  $d_{st}$  worked well as a predictor, it is seldom  
16 measured in forest inventories. On the other hand, it is sometimes useful to estimate **dry**  
17 **biomass** when trees are already cut down and only stump dimensions are available.

18 It has been observed that some crown variables work well as predictors of crown  
19 fractions (Clark, 1982, Satoo and Madgwick, 1982, Carvalho and Parresol, 2003). In the  
20 present study, inclusion of crown variables improved the *RMSE* by 1.8%, 10.8%, 19.1% and  
21 17.3% for respectively dead branches, thick branches, twigs and leaves, in the individual fit.  
22 These improvements are smaller than those obtained by António et al. (2007) for *Eucalyptus*  
23 *globulus* in Portugal, probably because of the lower genetic variability in the plantations  
24 considered in that study. The best improvement was for leaves, which implies better  
25 estimations of a fraction that is very difficult to predict and is very important as regards

1 nutrition and ecology. Overall, the results indicate a low accuracy of estimation of the bark  
2 fraction in the present study, in comparison with reports for other species of *Eucalyptus*.  
3 Wood, bark and thin branches depend on the same variables in both systems of equations, and  
4 the results obtained by simultaneous fitting were generally only slightly less accurate. For  
5 leaves, the reduction in  $R^2_{Adj}$  derived from simultaneous fitting was 6.3%.

6 The ability of the fitted biomass equations to evaluate the proportion of each  
7 aboveground biomass component for a range of diameters has seldom been studied. The  
8 proportions are often considered as parameters for ecophysiological models, particularly for  
9 small diameters (Sands and Landsberg, 2002). The present results show that, if a threshold  
10 diameter is considered for defining a wood component, minimum breast height diameter must  
11 be considered to define the range of use of the biomass components equations, if sound  
12 estimation of these percentages is sought.

### 13 **5. Conclusions**

14 Two systems of equations were fitted for aboveground biomass components of  
15 *Eucalyptus nitens*. The inclusion of crown variables as predictive variables provided poorer  
16 results for total biomass, wood and thin branches, but improved the accuracy of estimation for  
17 twigs, leaves, thick branches and dead branches.

18 Stem subsampling affects estimation of the wood fraction. If a systematic subsample of  
19 disks or logs is taken, the variation in moisture content or basic density along the stem should  
20 be considered. Less intensive sampling usually leads to overestimation of biomass with both  
21 methods (complete fresh weighing or partial fresh weighing). The minimum subsampling  
22 intensity for an assumed  $\pm 5\%$  *RD* in wood dry biomass estimation depends on the tree  
23 diameter class, with a range of 0.75 to 0.95 disks  $m^{-1}$  in the *CW* method. Use of the *PW*  
24 method would require very intense subsampling to reduce the relative error, independently of

1 tree size. The average basic density usually occurs at a relative height of 30-35% along the  
2 stem. It is not always advisable to choose the first section of study at the bottom of the stem.

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24  
25

1 **TABLES**

2  
3 **Table 1. Statistics for stand and single tree variables in the population (76 plots, 3864 trees)**  
4 **and the sample plots (12 plots, 40 trees).**

		Stand variables			Individual tree variables	
		<i>SI</i> (m)	<i>N</i> (stems ha <sup>-1</sup> )	Age (yr)	<i>d</i> (cm)	<i>h</i> (m)
All plots	Average (Std. dev.)	15.3 (4.4)	1089 (280)	9.5 (4.2)	18.5 (7.5)	20.2 (6.4)
	Range	8.8 - 20.8	446 - 1560	2 - 18	1.0 - 59.6	2.2 - 48.3
Sample plots	Average (Std. dev.)	15.7 (2.7)	1101 (223)	10.2 (2.8)	19.5 (7.7)	19.3 (5.5)
	Range	9.8 - 18.9	446 - 1401	2 - 13	1.1 - 47.0	2.4 - 35.1

5 **Where *SI* is the site index (m at reference age of 6 years); *N* is stand density (stems ha<sup>-1</sup>), *d* is**  
6 **diameter at breast height (cm), and *h* is the total height (m).**

7  
8 **Table 2. Descriptive statistics of sampled trees.**

Variable	Average	Maximum	Minimum	St. Dev.
Independent variables				
<i>d</i> (cm)	20.84	41.55	3.95	10.04
<i>d<sub>st</sub></i> (cm)	25.63	52.40	6.60	12.13
<i>h</i> (m)	19.94	30.80	4.40	7.27
<i>h<sub>cb</sub></i> (m)	12.55	20.60	2.80	4.68
<i>h<sub>c</sub></i> (m)	7.39	19.80	1.20	4.21
<i>d<sub>c</sub></i> (cm)	3.50	8.55	1.25	1.66
<i>v<sub>c</sub></i> (m <sup>3</sup> )	81.78	566.5	1.00	129.3
Dependent variables (kg tree <sup>-1</sup> )				
<i>W<sub>l</sub></i>	10.73	48.85	0.28	12.94
<i>W<sub>t</sub></i>	4.15	23.33	0.18	5.10
<i>W<sub>tb</sub></i>	4.40	18.46	0.04	4.53
<i>W<sub>Tb</sub></i>	13.57	75.65	1.29	18.71
<i>W<sub>w</sub></i>	168.43	599.5	0	176.9
<i>W<sub>b</sub></i>	24.59	111.3	0	28.33
<i>W<sub>db</sub></i>	11.29	68.28	0.03	13.64
<i>W<sub>tot</sub></i>	237.2	838.2	2.54	248.1

9 **Definitions of independent and dependent variables are given in sections 2.1 and 2.2,**  
10 **respectively. *W<sub>tot</sub>* refers to total aboveground biomass.**

11  
12 **Table 3. Models selected for simultaneous fitting of each equation system.**

Fraction	Stem equation system				Crown equation system			
	Model	RMSE	MRES	R <sup>2</sup> Adj	Model	RMSE	MRES	R <sup>2</sup> Adj
<i>W<sub>tot</sub></i>	$W_{tot} = \sum W_i$	37.9	2.86	0.98	$W_{tot} = \sum W_i$	39.9	1.36	0.97
<i>W<sub>db</sub></i>	$b_{1,1} \cdot d^{b_{1,2}}$	10.6	0.32	0.40	$b_{2,1} \cdot d^{b_{2,2}} \cdot h_{cb}^{b_{2,3}}$	10.4	-0.04	0.42
<i>W<sub>b</sub></i>	$b_{1,3} \cdot d^{b_{1,4}}$	15.3	0.72	0.71	$b_{2,4} \cdot d^{b_{2,5}}$	15.3	0.30	0.71
<i>W<sub>w</sub></i>	$b_{1,5} \cdot d^{b_{1,6}} \cdot h^{b_{1,7}}$	17.9	0.32	0.99	$b_{2,6} \cdot d^{b_{2,7}} \cdot h^{b_{2,8}}$	18.2	-0.16	0.99
<i>W<sub>Tb</sub></i>	$b_{1,8} \cdot d^{b_{1,9}}$	6.0	1.05	0.90	$b_{2,9} \cdot d^{b_{2,10}} \cdot d_c^{b_{2,11}}$	5.4	0.62	0.92
<i>W<sub>tb</sub></i>	$b_{1,10} \cdot d^{b_{1,11}}$	2.2	0.13	0.76	$b_{2,12} \cdot d^{b_{2,13}}$	2.4	0.24	0.71
<i>W<sub>t</sub></i>	$b_{1,12} \cdot d^{b_{1,13}}$	2.1	0.07	0.83	$b_{2,14} \cdot d^{b_{2,15}} \cdot d_c^{b_{2,16}}$	1.7	0.26	0.89
<i>W<sub>l</sub></i>	$b_{1,14} \cdot d^{b_{1,15}}$	5.6	0.25	0.81	$b_{2,17} \cdot d^{b_{2,18}} \cdot h_c^{b_{2,19}}$	4.6	0.15	0.87

1 Definitions of the different fractions are given in section 2.2.  $W_{tot}$  refers to total aboveground  
 2 biomass.

3  
 4  
 5 **Table 4.** Parameters for simultaneous fitting of equations.

Parameter	Estimate	Appr.SE	Pr >  t	Parameter	Estimate	Appr.SE	Pr >  t
$b_{1,1}$	0.145	0.05	0.0063	$b_{2,1}$	0.0079	0.0077	0.3137
$b_{1,2}$	1.403	0.12	<.0001	$b_{2,2}$	1.279	0.313	0.0003
$b_{1,3}$	0.013	0.0083	0.1177	$b_{2,3}$	1.254	0.411	0.0044
$b_{1,4}$	2.361	0.1892	<.0001	$b_{2,4}$	0.0318	0.016	0.0545
$b_{1,5}$	0.0094	0.0024	0.0004	$b_{2,5}$	2.1079	0.156	<.0001
$b_{1,6}$	2.0329	0.082	<.0001	$b_{2,6}$	0.0149	0.0034	0.0001
$b_{1,7}$	1.0562	0.1335	<.0001	$b_{2,7}$	2.0515	0.081	<.0001
$b_{1,8}$	0.000059	0.000064	0.3586	$b_{2,8}$	0.8946	0.128	<.0001
$b_{1,9}$	3.7599	0.2983	<.0001	$b_{2,9}$	0.00082	0.0010	0.4124
$b_{1,10}$	0.0128	0.005	0.0153	$b_{2,10}$	2.6444	0.4403	<.0001
$b_{1,11}$	1.8579	0.131	<.0001	$b_{2,11}$	0.7627	0.265	0.0069
$b_{1,12}$	0.00092	0.00049	0.07	$b_{2,12}$	0.030047	0.0098	0.0042
$b_{1,13}$	2.6322	0.159	<.0001	$b_{2,13}$	1.590388	0.1168	<.0001
$b_{1,14}$	0.0053	0.0034	0.1281	$b_{2,14}$	0.006228	0.0028	0.0329
$b_{1,15}$	2.3931	0.197	<.0001	$b_{2,15}$	1.949093	0.1932	<.0001
				$b_{2,16}$	0.218899	0.01909	0.0259
				$b_{2,17}$	0.016847	0.0102	0.109
				$b_{2,18}$	1.515742	0.2651	<.0001
				$b_{2,19}$	0.774688	0.1934	0.0003

6  
 7  
 8  
 9  
 10 **FIGURE CAPTIONS**

11  
 12 **Fig. 1.** Location of the measured plots (dots) and the distribution of *Eucalyptus nitens* in  
 13 north-western Spain (shaded area).

14  
 15 **Fig. 2.** Height-diameter distribution of *Eucalyptus nitens* in an initial inventory in north-  
 16 western Spain.

17  
 18 **Fig. 3.** Relative difference for three dimensional classes: DC1 ( $d < 14\text{cm}$ ;  $n = 6922$ ), DC2  
 19 ( $14 < d < 24\text{cm}$ ;  $n = 17075$ ) and DC3 ( $d > 24\text{cm}$ ;  $n = 18360$ ), plotted against sampling intensity  
 20 (disks per stem meter) for the CW method. Continuous black line: average value for all data;  
 21 dotted black lines: 95% confidence intervals for all data; continuous grey line: average value  
 22 for alternatives that include bottom log.  $n$  is the number of simulated alternatives for each  
 23 dimensional class.

24  
 25 **Fig. 4.** Relative difference for two dimensional classes: DC2 ( $14 < d < 24\text{cm}$ ;  $n = 7712$ ) and  
 26 DC3 ( $d > 24\text{cm}$ ;  $n = 12001$ ), plotted against sampling intensity (fraction of stem height  
 27 weighed) for the PW method. Continuous black line: average value for all data; dotted black  
 28 lines: 95% confidence intervals for all data; continuous grey line: average value for  
 29 alternatives that include bottom log.  $n$  is the number of simulated alternatives for each  
 30 dimensional class.

1 **Fig. 5.** Changes in moisture content (%) and accumulated stem dry weight (%) plotted against  
2 relative height along the stem (until 7 cm of diameter over bark). Continuous line: average  
3 value; dotted lines: 95% confidence intervals.  
4

5 **Fig. 6.** Changes in basic density ( $\rho$ ,  $\text{kg m}^{-3}$ ) and accumulated stem fresh volume (%) plotted  
6 against relative stem height (until 7 cm of diameter over bark). Continuous line: average  
7 value; dotted lines: 95% confidence intervals.  
8

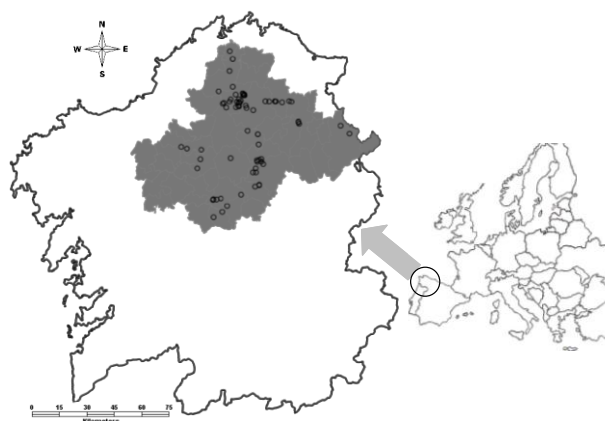
9 **Fig. 7.** Changes in relative stem height (%) where composite average basic density ( $\rho$ ) is  
10 found in relation to breast height diameter of sampled trees. Continuous line: average value;  
11 dotted lines: 95% confidence intervals.  
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13 **Fig. 8.** Relationship between dry weight of each biomass fraction ( $\text{kg tree}^{-1}$ ) and diameter at  
14 breast height ( $d$ , cm). Open circles represent trees used in the regression analysis ( $n = 40$ ), full  
15 circles represent additional felled trees for the partitioning study ( $n = 8$ ).  
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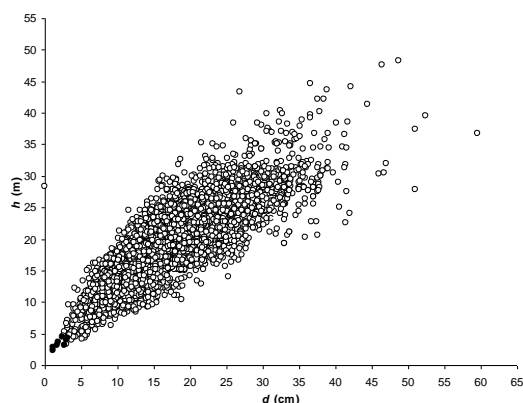
17 **Fig. 9.** Relationship between observed-predicted dry weight values for each biomass  
18 component ( $\text{kg tree}^{-1}$ ) in the *Stem* system of equations.  
19

20 **Fig. 10.** Relationship between observed-predicted dry weight values for each biomass  
21 component ( $\text{kg tree}^{-1}$ ) in the *Crown* system of equations.  
22

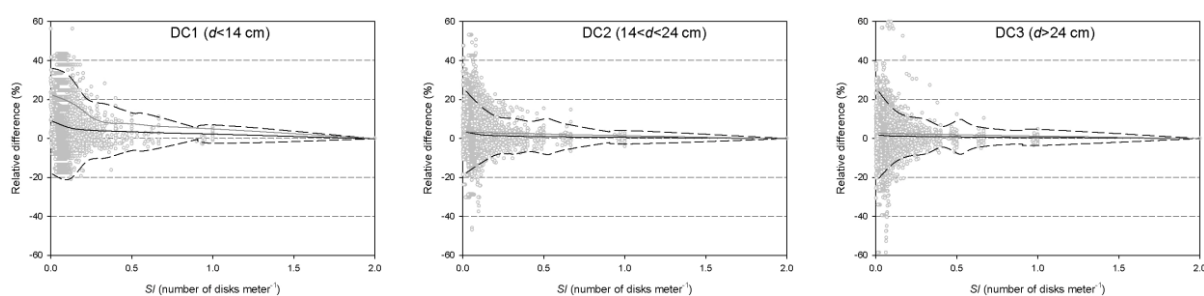
23 **Fig. 11.** Proportion of each biomass fraction over total aboveground biomass. Open figures:  
24 trees used in developing biomass equations; filled figures: additional small trees; lines:  
25 prediction of biomass equations.  
26



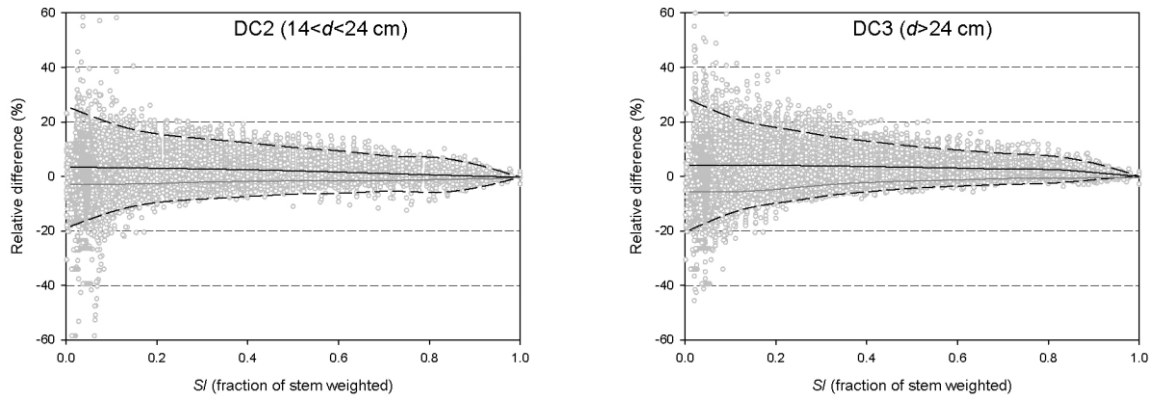
1 Fig. 1. Location of the measured plots (dots) and the distribution of *Eucalyptus nitens* in  
 2 north-western Spain (shaded area).  
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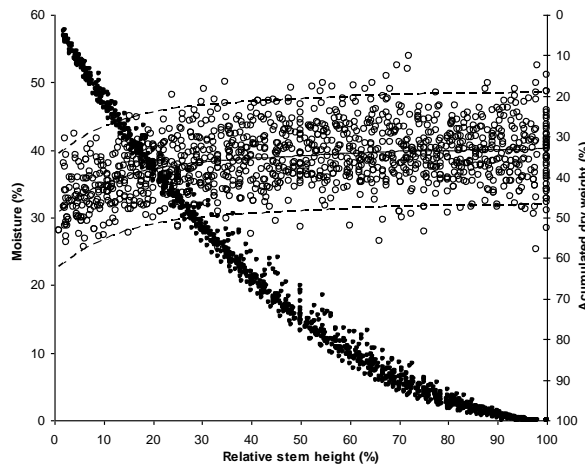
6 Fig. 2. Height-diameter distribution of *Eucalyptus nitens* in an initial inventory in north-  
 7 western Spain.  
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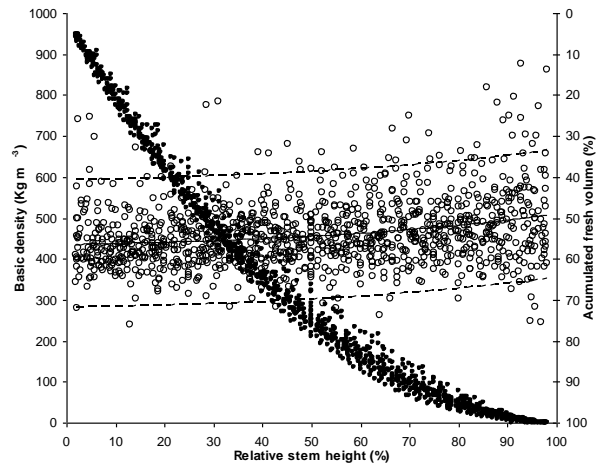
11 Fig. 3. Relative difference for three dimensional classes: DC1 ( $d < 14$  cm;  $n = 6922$ ), DC2  
 12 ( $14 < d < 24$  cm;  $n = 17075$ ) and DC3 ( $d > 24$  cm;  $n = 18360$ ), plotted against sampling intensity  
 13 (disks per stem meter) for the CW method. Continuous black line: average value for all data;  
 14 dotted black lines: 95% confidence intervals for all data; continuous grey line: average value  
 15 for alternatives that include bottom log.  $n$  is the number of simulated alternatives for each  
 16 dimensional class.  
 17  
 18



1 **Fig. 4.** Relative difference for two dimensional classes: DC2 ( $14 < d < 24$  cm;  $n = 7712$ ) and  
 2 DC3 ( $d > 24$  cm;  $n = 12001$ ), plotted against sampling intensity (fraction of stem height  
 3 weighed) for the *PW* method. Continuous black line: average value for all data; dotted black  
 4 lines: 95% confidence intervals for all data; continuous grey line: average value for  
 5 alternatives that include bottom log.  $n$  is the number of simulated alternatives for each  
 6 dimensional class.  
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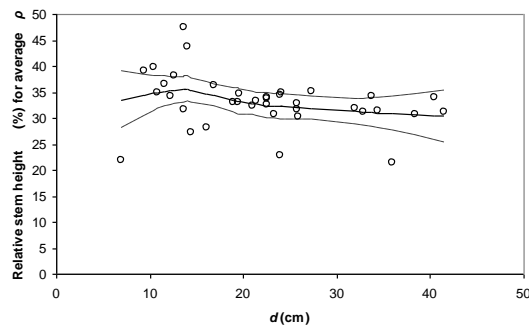


8 **Fig. 5.** Changes in moisture content (%) and accumulated stem dry weight (%) plotted against  
 9 relative height along the stem (until 7 cm of diameter over bark). Continuous line: average  
 10 value; dotted lines: 95% confidence intervals.  
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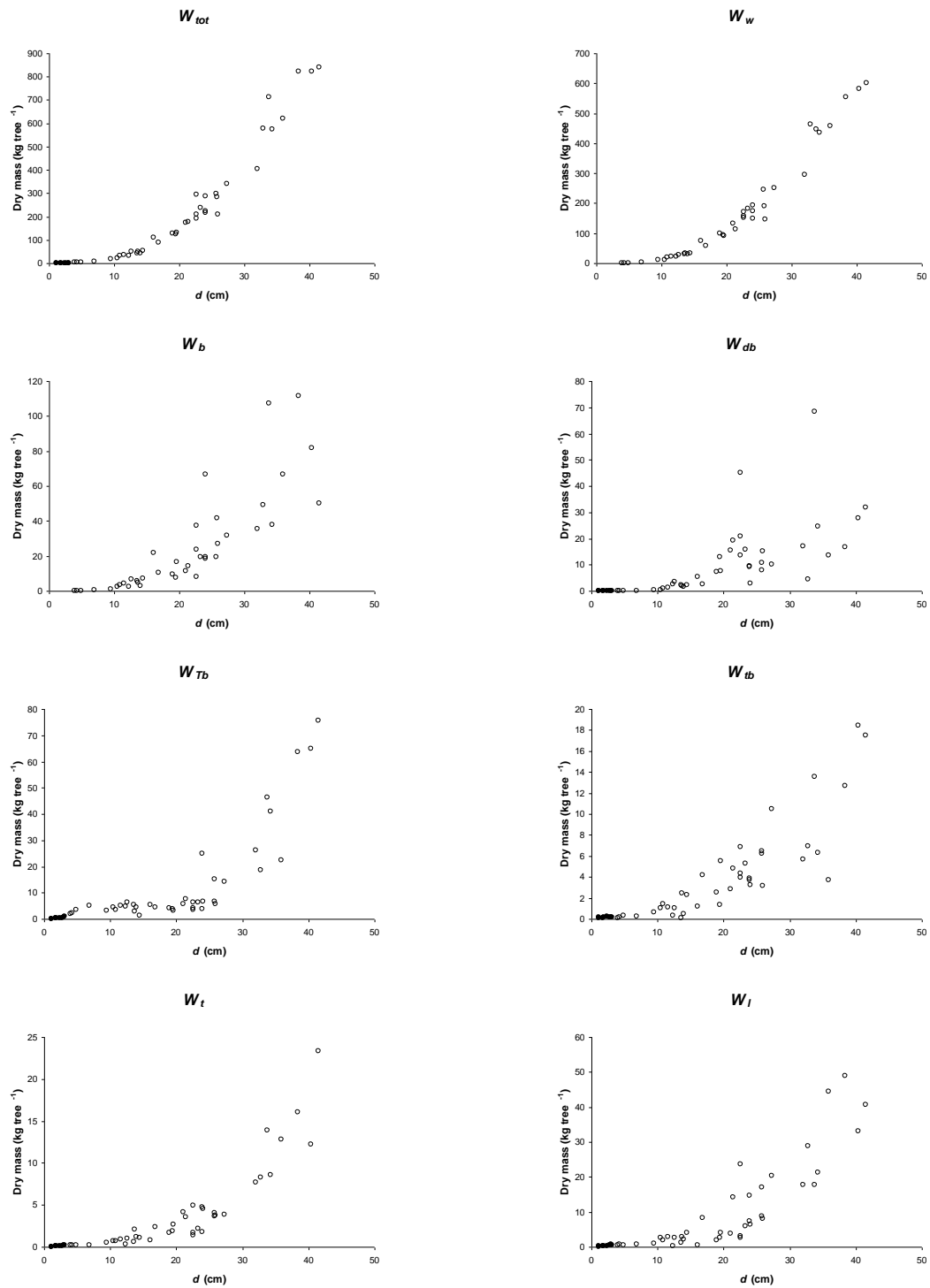
1 **Fig. 6.** Changes in basic density ( $\rho$ ,  $\text{kg m}^{-3}$ ) and accumulated stem fresh volume (%) plotted  
 2 against relative stem height (until 7 cm of diameter over bark). Continuous line: average  
 3 value; dotted lines: 95% confidence intervals.

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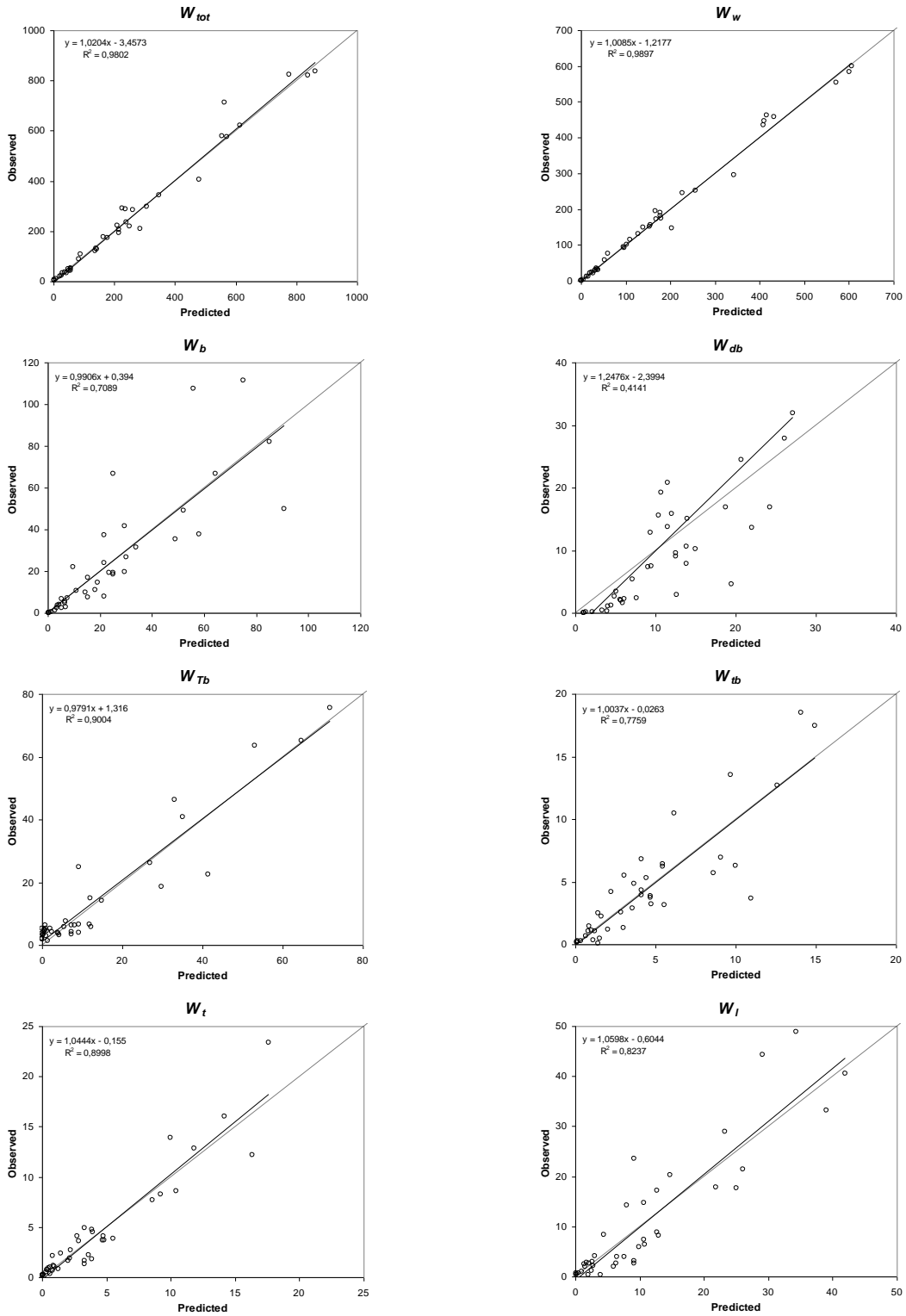


6 **Fig. 7.** Changes in relative stem height (%) where composite average basic density ( $\rho$ ) is  
 7 found in relation to breast height diameter of sampled trees. Continuous line: average value;  
 8 dotted lines: 95% confidence intervals.

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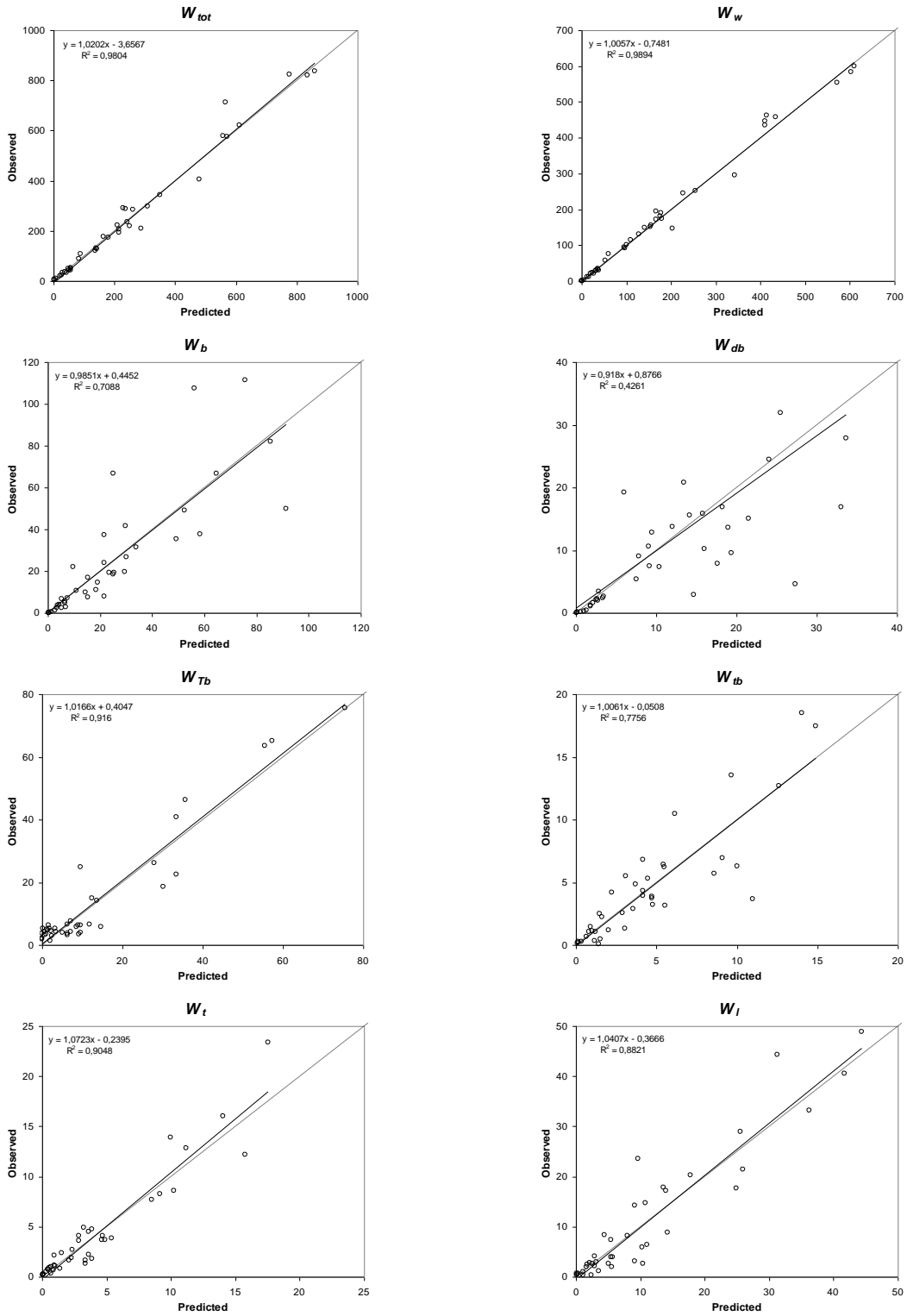


1 **Fig. 8.** Relationship between dry weight of each biomass fraction (kg tree<sup>-1</sup>) and diameter at  
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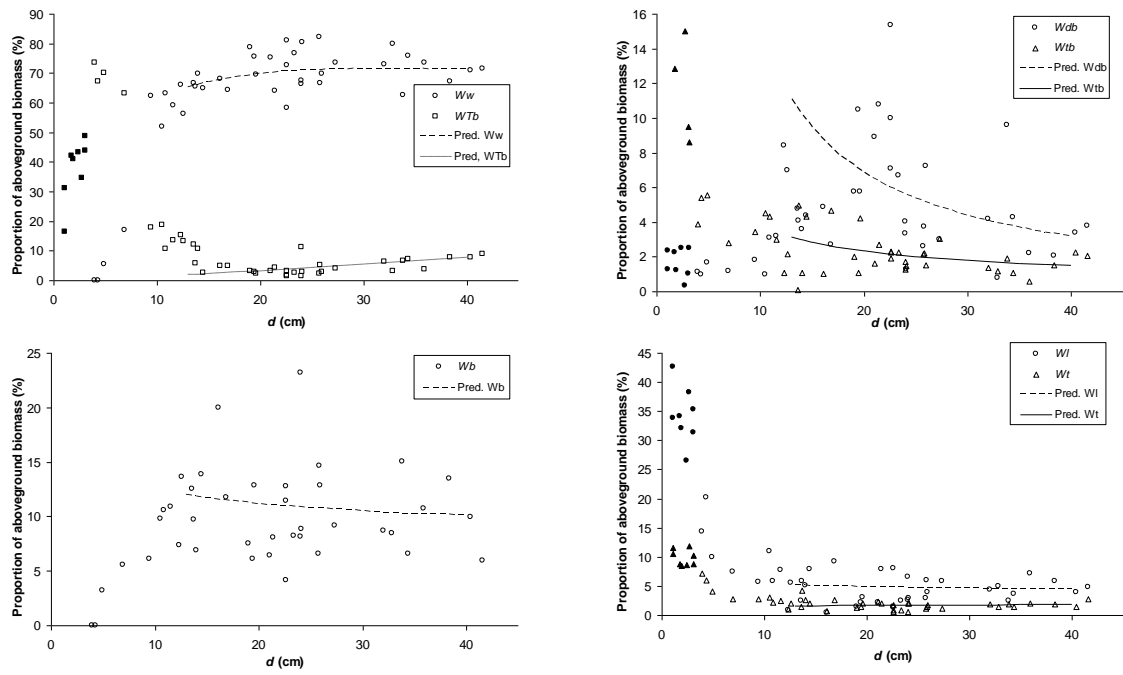


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