

Measurement and Assessment Methods of Forest Aboveground Biomass: A Literature Review and the Challenges Ahead

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1. Introduction

The measurement and assessment of aboveground tree biomass (bole, branches, and foliage), or M , plays a key role in the management of forest resources. Estimates are required for evaluating: a) the stocks and fluxes of several biogeochemical elements and b) the amount of primary energy obtainable from forests as an alternative to fossil fuels. Moreover, biomass is a fundamental state variable in several ecological and eco-physiological models (Brown, 1997; Chavé et al., 2005; Návar, 2009a,b; Richardson et al., 2002). The development and use of allometric equations is the standard methodology for the estimation of tree, plot, and regional aboveground biomass (Brown, 1997). Dry weight measurements conducted on harvested trees, fresh and dry weights of biomass components and recording independent tree variables are required to construct allometric equations at the species, stands or tree community levels. Alternate M assessment methods include the multiplication of bole volume by its wood specific gravity; with branch and foliage biomass integrated using other approaches. Standing bole volume, V , can be also multiplied by biomass expansion factors, BEF, at the tree level or stand scale to compute M . Allometric biomass equations can be classified according to the parameter estimation method as empirical, semi-empirical and process, theoretical models. Using three meta-analysis datasets, empirical equations are reported in log-linear (82.6%), non-linear (12.0%), seemingly un-related (3.9%), linear (0.7%), and non-linear seemingly un-related (0.6%) regression. Diameter at breast height, D , and at the bole base, Db , canopy height, H , canopy area, CA , and wood specific gravity, ρ_w , are common exogenous variables that individually or in combination explain M with deviations larger than 16% of the mean measured tree aboveground biomass value (Chavé et al., 2005). A fully theoretical, physically parameterized model is available (West et al., 1997), although preliminary evaluations demonstrate that it requires further refinement before can be recommended as a non-destructive M assessment methodology. More flexible, restrictive models that make use of only a small number of harvested trees and fit available allometric equations result in good M approximations (Zianis & Mencuccini, 2004). Semi-empirical non-destructive models based on shape-dimensional analysis and assuming a constant exponent value are being tested for simple and complex forests with compatible preliminary M assessments (Návar, 2010a,b). This wealth of information on biomass allometry necessitates be properly describing, organizing, and classifying in order to better

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understand weakness and robustness of available methods to compute tree and eventually plot and regional aboveground biomass. For places deprived of tree allometry, a combination of a wide range of allometric equations developed off site appears to improve tree M evaluations according to the Central Limit Theorem.

Biomass stocks and their spatial distribution remain poorly evaluated at the plot scale regardless of the wealth of information on tree biomass allometry (Chavé et al., 2003; Houghton et al., 2001, 20015; Návar et al., 2010). The conventional methodology that expands tree M to sample inventory stands is: a) a grid of sampling plots and b) allometric equations fit tree data recorded in the forest inventory, since there is scarce information on allometric equations that straightforward calculate plot or stand M. New approaches that employ timber volume are named BEF and at the present they require calibration to appraise local plot M (Brown, 2002). Uncertainties of more than two orders of magnitude are identified when calculating plot M by applying different off site allometric models to forest inventory datasets and main sources of variation are: a) the error due to tree measurements, b) ground sampling uncertainty, and above all, c) the error due to the choice of an allometric model relating M to other tree dimensions (Chavé et al., 2003; Návar et al., 2010).

Tree or plot M interpolates at larger spatial scales, AGB, by a variety of field measurements, environmental gradients and remote sensing techniques (Houghton, 2005a,b). A diversity of remote sensing techniques, spatial resolutions, tree and forest attributes, and interpolation methodologies make AGB assessment highly variable, with uncertainties as large as three orders of magnitude. Main sources of variation are attributable to: a) the precision of estimated tree or stand M, b) the interpolation method applied, c) the lack of a good correlation between ground and remote sensing data, d) the correct location of ground data, e) the representativeness of plots across the landscape, f) temporal variations in the satellite image, g) the correct area of each forest class, and h) others. Combining remote field data collection techniques (LIDAR) with locally-derived tree allometry and the semi-empirical shape-dimensional non-destructive model of tree M assessment would eventually improve AGB at the spatial scale of interest.

Given this brief literature review, the reliable M estimation of trees, plots, stands or tree communities remains a key challenge for the successful implementation of sustainable forest management plans. This paper deals with the description of available tree allometry, how they contrast to provide tree, plot and regional M assessments and what are the future challenges ahead. Preliminarily observations point towards the combination of available conventional allometric models with restrictive, semi-empirical and theoretical non-destructive methods of tree or plot M evaluation while universally-applied functions emerge. In addition, the interpolation of improved tree or plot M appraisals to regional scales with a combination of field techniques, environmental gradient approaches and remote sensing methods must eventually improve AGB assessments at regional and national spatial scales.

Key words: Measuring and assessing aboveground biomass, empirical, semi-empirical, theoretic models, tree, stand and regional scales.

2. Aboveground tree biomass allometry

2.1 Introduction

Aboveground tree and forest biomass is the living and dead matter in standing trees and shrubs and can be classified in foliage, branches, and boles. Bark, hardwood and softwood

are timber biomass components. The evaluation of conventional goods and environmental services furnished by forests entails the assessments of tree, stand and regional M. The stocks and fluxes of several biogeochemicals are calculated with the evaluation of M (Brown, 1997; Houghton, 2005). So is the amount of primary energy obtainable from forests as an alternative to fossil fuels (Richardson et al., 2002). In addition, standing aboveground biomass is a fundamental state variable in several ecological and eco-physiological models (Zianis & Mencuccini, 2004).

The development and application of allometric equations is the standard methodology for aboveground tree biomass estimation (Brown et al., 1989; Chavé et al., 2001; 2003; Návar, 2009a). A simple classification of allometric equations based on methods of parameter estimation is: empirical, semi-empirical and theoretical models. Meta-analysis studies report examples of empirical functions (Ter Mikaelian & Korzukhin, 1997; Jenkins et al., 2003; Zianis & Mencuccini, 2004; Zianis et al., 2005; Návar, 2009b). Non-destructive models such as the empirical reductionist (Zianis & Mencuccini, 2004); the semi-empirical shape-dimensional analysis (Návar, 2010a), the constant *B*-slope approach (Návar, 2010b) and process, theoretical methods (West et al., 1999) are also available in the scientific literature.

Empirical allometric equations are statistically parameterized with measured, weighted and recorded field and laboratory tree biomass data. The conventional allometric biomass model ($\ln(M) = \ln(a) + B\ln(D) \pm e_i$); where *M* and *D* are log transformed and the *a* and *B* the scalar coefficients estimated by least square techniques in linear regression, is the most commonly fitted and reported equation. Other parameter-fitting techniques and mathematical forms of biomass equations are classified as: non-linear, seemingly un-related linear, linear and non-linear seemingly un-related regression, power and exponential functions. Tree diameter recorded at breast height, basal diameter, canopy cover, canopy height and wood specific gravity commonly explain individually or in conjunction tree M with deviations larger than 16% of the mean measured tree M.

Semi-empirical non-destructive methods of tree M computations that focus on independent and easy ways to calculate the conventional allometric scalar coefficients had been recently proposed. They require both physical and statistical parameters. The fractal methodology coupled with shape-dimensional relations was preliminary explored with good degree of precision for temperate trees of northwestern Mexico (Návar, 2010a) and for Mexican tropical forests (Návar et al., 2010). This procedure assumes that bole volume and top height allometric relations suffice to calculate the *a* and *B* scalar coefficients. When contrasted with the conventional allometric model, this method results in compatible tree M assessments. A reduced semi-empirical, non-destructive model that assumes the *B*-scalar exponent is a constant value and the *a*-scalar intercept is a function of the standard wood specific gravity value is also under close mathematical advancement with good preliminary precision for North American temperate trees (Návar, 2010b).

The classic theoretical allometric model, WBE, was developed with the use of fractal techniques (West et al., 1999). Two variables, a *C*-scalar coefficient and the entire tree specific gravity, ρ , suffice to calculate tree M; since it assumes the *B*-scalar exponent is a fixed value of 8/3. The WBE equation is physically parameterized but, at the present, it needs further refinement before can be recommended as non-destructive method of M assessment. Discussions regarding its application are ongoing and they center on the right value of the *B*-slope scalar coefficient that it has been shown to be smaller than 2.67 (Zianis & Mencuccini, 2004; Pilli et al., 2006; Návar, 2009a,b; 2010b).

Other approaches involve the bole volume estimation and then multiplied by the standard wood specific gravity value (Mohren & Klein Goldewijkt, 1990). A dimensionless biomass expansion factor, BEF, escalates bole volume to total tree M (Brown, 1997). Gracia et al. (2004); Lehtonen (2005); Návar-Cháidez (2009); Silva-Arredondo and Návar-Cháidez, (2009) reported independent BEF at the tree level or plot scales, which are developed by employing biomass of the entire tree in conjunction with bole volume allometry.

Tree M assessments are variable regardless of the wealth of information on biomass allometry. For harvested trees, deviations have been reduced to close to 16% with the use of D, H and ρ_w , (Chavé et al., 2005). However, the expansion of these equations to trees with other dimensions or outside the forest area where the equation was developed deserves more attention.

2.2 The need for tree allometry

A great number of allometric equations have been reported for North American and European tree species and forests (Ter Mikaelian & Korzukhin, 1997; Jenkins et al., 2003; Zianis & Mencuccini, 2004; Zianis et al., 2005; Fehrmann & Klein, 2006; Chojnaky, 2009; Návar, 2009a). Tree allometry for complex tropical (Brown, 1997; Chavé et al., 2001; 2003; 2005) and semi-arid, sub-tropical tree species (Návar et al., 2002a; 2004; Návar, 2009b) and forest plots (Martínez-Yrizar et al., 1992; Návar et al., 2002b) are less represented. At regional scales, current allometric data for complex, diverse tropical forests are almost entirely based on Southeast Asian (Brown, 1997; Ketterings et al., 2001) and South American measurements (Overmann et al., 1994; Araujo et al., 1999; Chavé et al., 2001; 2005; Chambers et al., 2001; Brandeis et al., 2006; Feldpausch et al., 2006). Brown (1997) and Chave et al. (2005) reported a set of allometric equations for tropical world forests; however, several sites were not well typified in this data set. For example, with the exception of the report published by Cairns et al. (2000), most Mexican tropical forests remains with limited information on tree and stand M development, analysis and comparisons.

2.3 Development of tree allometry

The development of conventional biomass allometry compels that trees are harvested. Measurements of diameter at breast height and at the bole base are carried out on each standing tree. Top height is better measured once the tree is felled down. Tree dissection into the main biomass components: stem or bole, foliage, and branches are performed on felled trees. Boles are logged into smaller sizes to facilitate weighting. Foliage, branches, and dissected logs are fresh weighted separately per tree. The total fresh weight of each component for each tree is obtained in the field using scales. Samples of each component of each tree are fresh weighted and oven-dried in the laboratory (to constant weight at 70°C). Sample fresh and dry weights must be precisely recorded, since dry to fresh weight ratios for each sample of each component multiplied by the total fresh weight of each biomass component calculate total dry biomass per each tree component. Deviations of this methodology have been proposed where only small portions of each biomass component are weighted and the remaining is calculated by dimensional analysis.

2.4 Fitting allometric equations

A data matrix of exogenous, independent variables (D, Db, H, CA, pw, etc.) and dependent variables (dry foliage, branch, bole, and/or total aboveground biomass) for n, number of

harvested trees are available for fitting tree biomass equations. That is, allometry relates one measurement of an organism to another. Easily measured variables such as diameter and top height relates to volume, biomass, etc, which are more difficult to make.

A wide range of empirical allometric models are available in the scientific literature to fit collected biomass data using the independent variables described above. They can be classified as simple log-linear, simple linear, simple non-linear, multiple linear and non-linear, seemingly un-related linear and non-linear regression equations. Power or exponential functions also projects tree M, although they are scarcely reported in the scientific literature. Allometric equations quite often fit each individual biomass component (i.e., see for example the biomass equations compiled by Ter Mikaelian & Korzukhin, 1997; and Návar, 2009b). However, Cunnia and Briggs (1964) showed that when summing the equations for boles, branches, and foliage, results would often deviate from the recorded total aboveground biomass. Therefore, Cunnia & Briggs (1984; 1985) and Parresol (1999; 2001) developed advanced regression techniques and computer programs for estimating coefficient values for endogenous variables that simultaneously calculate individual equation parameters and restrict scalar coefficients to add total tree M. Biomass datasets are also a vital source of information to fit theoretical, semi-empirical non-destructive and restrictive methods of tree M assessment but sometimes other independent variables must be collected.

Biomass datasets should be split into: a) fitting and b) validating models. However, biomass studies are expensive and quite often data is not sufficient to calculate scalar coefficients with small variance that are consistent with population mean parameters. These issues addressed further below must be the center of future allometric studies.

The Log-linear equation. The most commonly reported mathematical model for biomass allometry takes the form of the Log linear-transformed function:

$$\ln(M) = \ln(a) + B\ln(D) \pm e_i \quad (1)$$

Equation [1] and [2] are similar but not mathematically equivalent:

$$\begin{aligned} \ln(M) &= \ln(a) + B\ln(D) \pm e_i \\ M &= \exp(\ln(a) + B\ln(D)) \pm e_i \\ M &= aD^B \pm e_i \end{aligned} \quad (2)$$

Where \ln = the logarithmic transformation function; e_i = error.

The scalar coefficients a and B of equations [1] and [2] are calculated by least square techniques in linear regression. Before conducting this statistical test; M and D data is log transformed. The transformation improves parameter estimation by reducing variability and heteroscedasticity. This technique frequently named the intrinsic linear regression entails a weighting parameter to further reduce heterogeneous variance since the logarithmic transformation compresses the data in both axes. When the biomass units are re-transformed back to the original units, the largest data values are often underestimated. Beskersville (1965) recommended to multiply equation [1] by a correction factor, CF, that is calculated as $CF = \exp(MSE/2)$, where: MSE = mean square error of the regression analysis of variance. Equation [1] is the standard, classical allometric biomass model reported in compiled equations by Ter Mikaelian & Korzukhin (1997); Jenkins et al. (2003); Zianis & Mencuccini (2004); and Návar (2009b). The standard error, S_y , of equation [1] is in logarithmic M units and consequently it is not equivalent to: $S_y = \sqrt{MSE}$ where MSE = mean

square error. Therefore, equation [1] has to be fitted to the original tree data to evaluate M and with measured and estimated M, Sy can be calculated in conventional M dimensions.

The Linear equation. Linear equations frequently reported in allometric studies take the following form:

$$M = a + BX \pm e_i \therefore M = BX \pm e_i \quad (3)$$

Where X = D²H (m³), BA (m²), Canopy Cover (%).

Least square techniques in linear regression conventionally estimates the scalar coefficients, *a* and *B*. Basal area, the combined variable, D²H, or canopy cover are the explanatory, exogenous variables of equation [3]. The allometric function that entails basal area was originally calculated by measuring M in plots and it has the advantage that can be escalated down to the individual tree level. Examples of this equation are found in Martínez-Yrizar et al. (1992). When using D²H as independent variable, examples are reported in Padron and Navarro (2004) and in Návar-Cháidez et al. (2004a). Flombaum and Sala (2007) found canopy cover (%) predicted better shrub M for Argentinean semi-arid shrublands. The standard error, Sy, of equation [3] is evaluated in conventional M units.

The Non Linear equation. The non-linear equation takes the form of the end portion of model [2], although the error is multiplicative:

$$M = aD^B \cdot e_i \quad (4)$$

Equation [4] is similar but mathematically not equivalent to equation [2], since scalar coefficients are estimated using one of the several non-linear parameter-fitting techniques available such as Newton, Gauss-Newton, Marquardt, etc. That is, scalar coefficient values differ if estimated in linear or non-linear regression techniques. Návar (2009a) reported several examples for temperate tree species of northwestern Mexico. Non-linear models report the analysis of variance in conventional M units and therefore Sy can be straightforwardly computed.

The multiple linear or non linear equations. The multiple linear or intrinsically linear equations take the form:

$$M = a + BX_1 + CX_2 + DX_3 + \dots + ZX_n \pm e_i \quad (5)$$

Or

$$M = (\exp^{(a+BX_1+CX_2+DX_3+\dots+ZX_n)}) \pm e_i \quad (6)$$

Or a combination of both. Where: X₁, X₂, X₃,..., X_n = D, D², D²H, ρ_w, ρ_wD²H

Least square techniques in linear or intrinsically linear multiple regression calculates scalar coefficients *a*, *B*, *C*, *D*, *Z*. Brown (1997) and Chavé et al. (2005) reported classical examples for world dry, moist and rain tropical forests that use D, H, and ρ_w as exogenous variables. Multiple linear models supply the standard error of M as the root mean square. Intrinsically linear multiple regression models require a similar procedure to that described in model [1] to calculate Sy in standard M units.

Seemingly un-related linear regression. Seemingly un-related regression is the recommended statistical technique to develop tree allometry for endogenous variables, since biomass components are related each other; i.e., leaf biomass relates to branch biomass, these associates to bole biomass, and all these components make total aboveground biomass

(Cuninia & Briggs, 1984; 1985; Parresol, 1999; 2001). Therefore, a simple example of a set of biomass component equations that are linearly related takes the following forms:

$$\begin{aligned}
 M &= M_l + M_{br} + M_{bo} \pm e_i \\
 M_l &= a_l + B_l(D^2H) \pm e_i \\
 M_{br} &= a_{br} + B_{br}(D^2H) \pm e_i \\
 M_{bo} &= a_{bo} + B_{bo}(D^2H) \pm e_i \\
 M &= a_l + B_l(D^2H) + a_{br} + B_{br}(D^2H) + a_{bo} + B_{bo}(D^2H) \pm e_i = \\
 M &= (a_l + a_{br} + a_{bo}) + (B_l + B_{br} + B_{bo})(D^2H) \pm e_i \\
 M &= a + B(D^2H) \pm e_i
 \end{aligned} \tag{7}$$

Where: l = leaf or foliage, br = branch, bo = bole or stem. All six scalar coefficients, a_l , a_{br} , a_{bo} , B_l , B_{br} , and B_{bo} are independently and simultaneously estimated by least square techniques in linear regression with the constraint that $M = M_l + M_{br} + M_{bo}$. That is, the sum of each component equals the total tree M.

Parresol (1999) developed and reported this regression technique in computer programs using examples for *P. eliottii* trees. N  var et al. (2004a) fitted this technique for young pine trees of Durango, Mexico and N  var et al. (2004b) did it for semi-arid, sub-tropical shrub species of northeastern Mexico.

Seemingly un-related non-linear regression. For un-related non-linear regression, a set of equations written in a simple format are:

$$\begin{aligned}
 M &= (M_l + M_{br} + M_{bo}) \cdot e_i \\
 M_l &= a_l D^{B_l} \cdot e_i \\
 M_{br} &= a_{br} D^{B_{br}} \cdot e_i \\
 M_{bo} &= a_{bo} D^{B_{bo}} \cdot e_i \\
 M &= (a_l D^{B_l} + a_{br} D^{B_{br}} + a_{bo} D^{B_{bo}}) \cdot e_i
 \end{aligned} \tag{8}$$

Where: M_l = foliage biomass, M_{br} = branch biomass; M_{bo} = bole biomass; and a and B are statistical parameters that are independently and simultaneously estimated by least square techniques in non-linear regression and restricted to provide total aboveground biomass.

Parresol (2001) reported the mathematical development and computer programs for this technique and empirical examples can be found in N  var (2009b).

2.5 Examples of empirical equations fitted to an independent dataset

Empirical allometric equations should be cautiously fitted since they may significantly deviate from tree M records. For example, N  var (2009b) reported applications of these empirical equations to a biomass dataset taken for complex semi-arid, sub-tropical shrub species of northeastern Mexico (Figure 1).

All statistical techniques previously described converge into a single equation for more compact biomass datasets as it was shown for young pine trees of northwestern Mexico by N  var (2009b). Note that all equations mimic well the non-linear nature of this M-Db relationship even though multiple linear and seemingly un-related linear equations are fitted to this data.

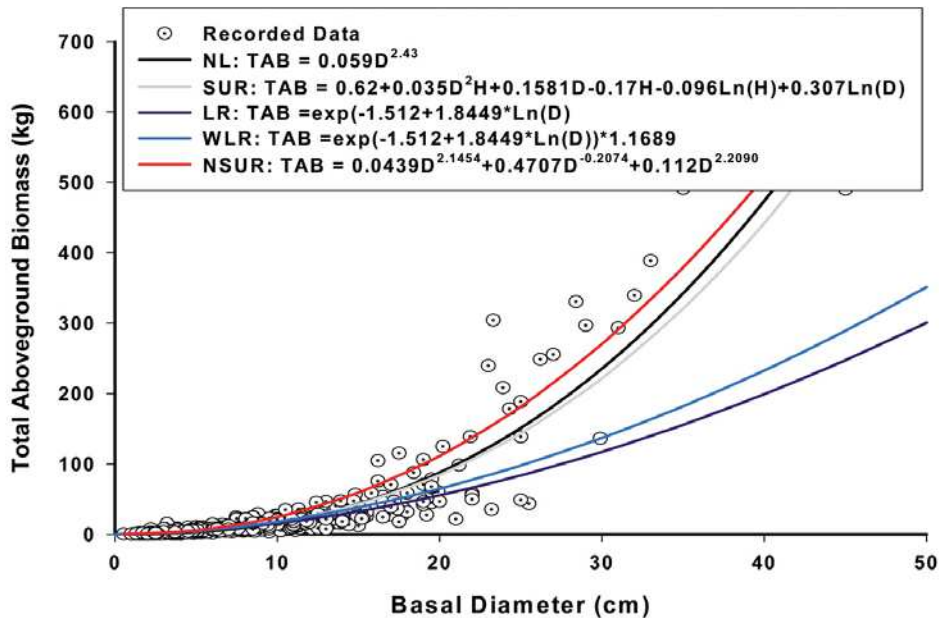


Fig. 1. Five empirical allometric equations fitted to aboveground biomass for 913 shrubs and small trees harvested in northeastern Mexico (NL = Non linear regression, SUR = Seemingly un-related non-linear regression, LR = Linear regression, WLR = weighted linear regression, NSUR = non-linear seemingly un-related regression).

2.6 Other allometric models reported in the scientific literature

Other empirical allometric equations reported in the scientific literature were compiled for European tree species by Zianis et al. (2005) but they fall within these major power and exponential classifications: $M=a+bD^c$; $M=a+b[D/(D+cf)]+dX_1+\dots+nX_n$; $M=a \cdot (D+1)^{[b+c \log(D)]} \cdot Hd$; $M=a \cdot (1-\exp(-b \cdot D))^c$.

Where: cf is a standard coefficient; a, b, c are statistical coefficients to be estimated; X_1, \dots, X_n are the independent variables described by D, D^2, DH, DH^2 , etc.

Multicollinearity problems arise when several related exogenous variables explain M making the model unstable in the correct coefficient values.

2.7 Examples of the application of empirical tree allometry to biomass data sets

The application of several available allometric equations to independent biomass datasets often results in M assessments with large deviations. Figure 2 shows examples for tropical dry and rain forests as well as for the IAN 710 *Hevea brasiliensis* hybrid trees. Tree allometry is frequently developed with sample data that does not meet the probabilistic sampling requirements. Therefore, local tree allometry improves tree M predictions in contrast to biomass equations developed for tree species with a wide spatial distribution range (Návar-Cháidez, 2010). As a consequence fitting off-site allometric equations often show large tree M uncertainties, which are addressed in the following section of this chapter. Deviations have also been explained by changes in wood specific gravity values and shifts in bole tapering and slenderness. Local, specific tree M allometry has been recommended by Návar-

Cháidez (2010) but further contrasting studies are required in order to understand variations between on-site and off-site equations.

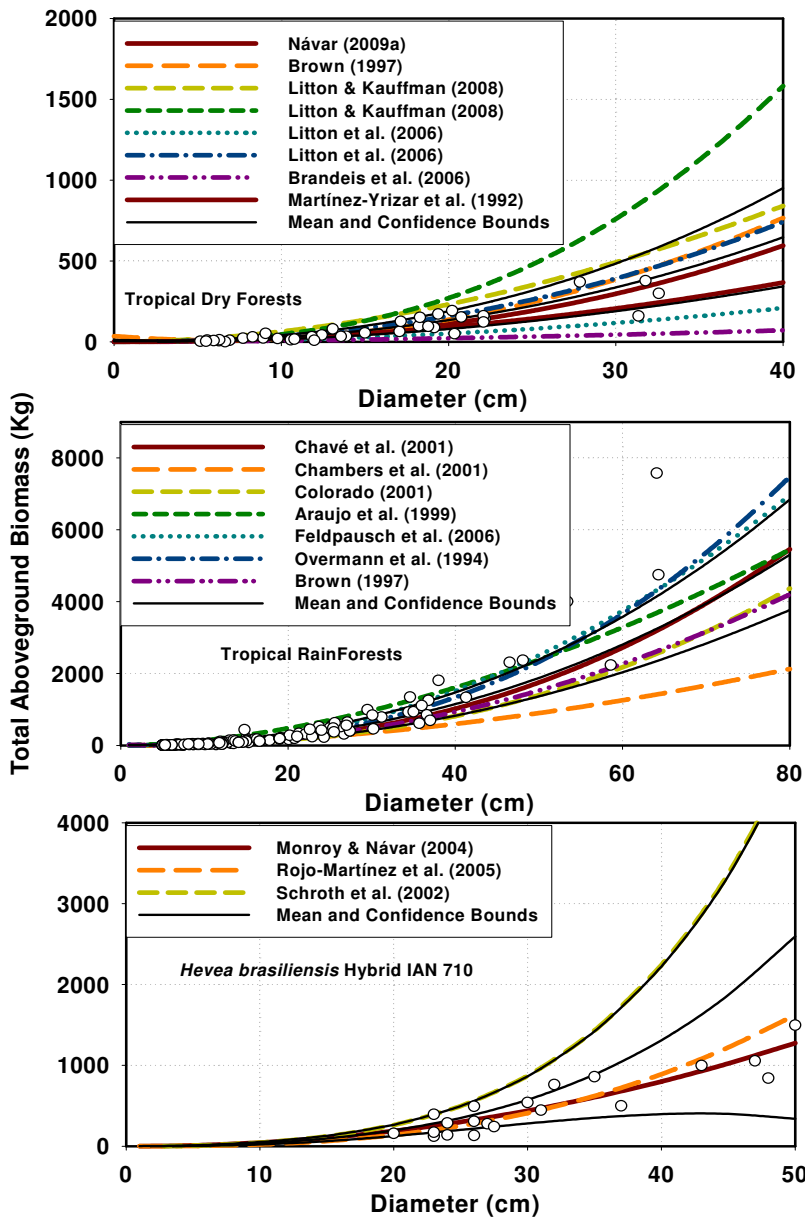


Fig. 2. Aboveground biomass estimates for tropical dry and rain forests as well as for the IAN 710 *Hevea brasiliensis* Muell. hybrid trees of Mexico (Data Sources: Návar, 2009a; Brown, 1997 and Monroy & Návar, 2005).

2.8 Randomness of scalar coefficients with sample size

Empirical allometric equations pose scalar coefficients that are statistically calculated. For example, the conventional model [1] has the a -intercept and the B -slope scalar values. The scalar coefficients vary with the species, diameter structure, structural tree diversity, the parameter-fitting techniques, sample size, etc. Indeed, scalar parameters show large variations in meta-analysis studies even though they are calculated with the same regression technique. For example, the B -scalar exponent has a mean (standard deviation) value of 2.37 (0.27), 2.38 (0.23), and 2.40 (0.22) reported by Zianis & Mencuccini (2004), Návar (2009b), and Fehrmann & Klein (2006), respectively. Návar-Cháidez (2010), in a biomass simulation study with 600 trees, found that the a and B scalar values randomly oscillate with sample sizes of less than 60 trees pointing out at the need for harvesting sufficient trees to calculate parameter values that are consistent with population means and that have the least variance (Figure 3). Tree M calculations with this set of scalar parameters produce deviations as large as 30%.

2.9 Alternate tree allometry models

2.9.1 Reduced number of harvested trees to develop M assessment models

Zianis and Mencuccini (2004) proposed the small tree sampling scheme to simplify allometric analysis irrespective of tree species and forest site. The methodology harvests only two small trees that quite often are $D < 25$ cm. With recorded D and M , available allometric equations for similar tree species and for similar data ranges found in the forest inventory are fitted. Those equations that predict tree M as close as to the measured values are selected and an average of scalar coefficients a and B values are estimated to come up with an individual allometric model. This approach was tested with a good balance between acceptable biomass predictions and low data requirements (Návar-Cháidez, 2010). Contrasting results are reported in Figure 6.

2.9.2 The empirical non-destructive model of M assessment

Zianis and Mencuccini (2004) developed the reductionist model [9] by fitting empirical relationships between the B -scalar exponent and the slope of the power relationship between H - D , B^* . The resulting equation was $B = 1.9262 + 0.6972B^*$; $r^2=0.42$. In a similar fashion, the scalar intercept was projected with the calculated B -scalar exponent taking advantage of the good relationship between these coefficients; $a = 7.0281B^{-4.7558}$; $r^2=0.70$. These two equations empirically describe the conventional model [1] scalar coefficients, as follows:

$$M = aD^B \quad (9)$$

$$\left[(7.0281 * B^{-4.7558}) D^{(1.9262+0.6972B^*)} \right]$$

Where: B^* is the scalar exponent of the H - D power relationship; B = is the scalar exponent derived from the empirical equation that relates B vs. B^* .

2.9.3 The theoretical model of tree M assessment

The West et al. (1999) theoretical model, WBE, was developed using the fractal geometry analysis that applies to natural occurring networks that carry sustaining fluids in organisms, in which each small part of the network is a self-similar replicate of the whole. Hence the fractal model offers much proportionality relating components of structure and function. The WBE framework describes aboveground biomass with the following equation:

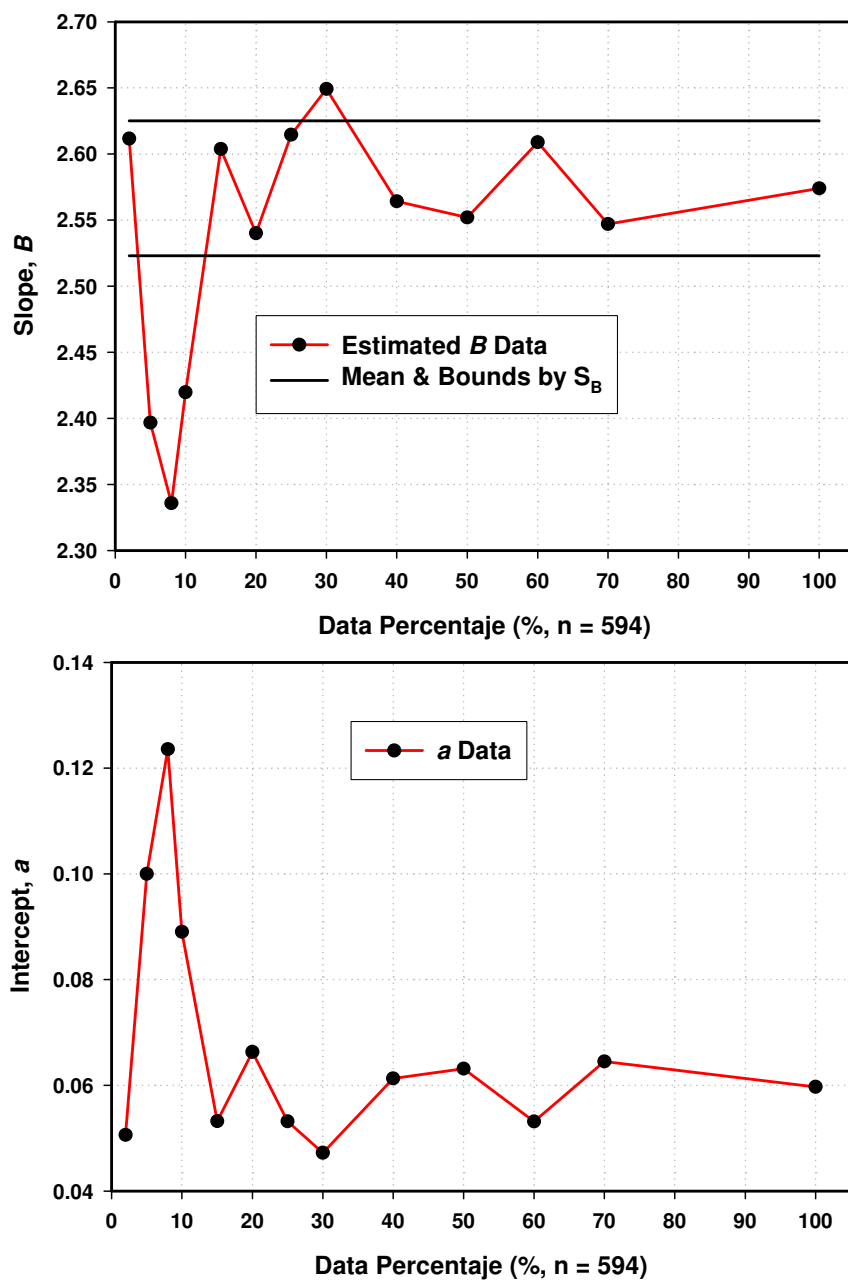


Fig. 3. Randomness of the scalar coefficients a and B as function of the percentage of data sampled for fitting the conventional allometric model.

$$M = (C\rho)D^B$$

$$M = (C\rho)D^{8/3} \quad (10)$$

The scalar exponent, B , is fixed to $8/3$ (2.67); ρ is the wood specific gravity that is referred as the total tree specific gravity (an average of the specific gravity for wood, bark, branches and leaves); and C is a proportionality constant. Note that $B = 2.67$.

Comparisons between measurements and predictions by the WBE and other empirical equations were carried out for several biomass data sets. In general, empirical models approximated better recorded tree M values than the WBE one (Zianis and Mencuccini, 2004). Pilli et al. (2006) suggested that M could be estimated by using universal B parameters that change with the forest age. Návar (2009b) found evidence that B is a function of diameter at breast height and Návar (2010b) successfully tested the hypothesis that B is a function of the place where diameter is measured.

2.9.4 Semi-empirical non-destructive models of tree M assessment

a) The shape-dimensional relationships derived from fractal geometry. Návar (2010a) proposed according to the classical physics equation, that mass is a function of volume \times specific gravity. Analogous, the aboveground biomass components are linearly and positively related to stem volume, V , and the entire bole wood specific gravity, ρ ; $M = (V \times \rho)$. A simple dimensional analysis shows that the volume of a tree bole is $V = (a_v D^2 H)$; where $a_v = 0.7854$ if the bole volume is a perfect cylinder. For temperate tree species of northwestern Mexico, mean a_v values of 0.55 have been calculated demonstrating that tree boles or pieces of stems have a non-standard shape that is only approximated by ideal objects. Therefore, the description of natural items falls beyond the principles provided by Euclidean geometry. Mandelbrot (1983) introduced the neologism of fractal geometry to facilitate the understanding of the form and shape of such objects. A positive number between two and three is a better estimation of the tree's crown dimension, and it is assumed that the overall shape of a tree (stem and crown) may possess a similar fractal dimension. In mathematical terms:

$$V = f(a_v D^d H^h) \quad (11)$$

Where: a_v is a positive number that describes the taper and d and h are positive numbers with $2 \leq d+h \leq 3$.

Since $2 \leq d+h \leq 3$, tree shapes can be described as hybrid objects of surface and volume because they are neither three-dimensional solids, nor two-dimensional photosynthetic surfaces and indentations and gaps are the main characteristics of their structure (Zeide, 1998).

The scaling of H with respect to D has been examined in terms of stress and elastic similarity models following biomechanical principles. When stress-similarity for self-loading dictates the mechanical design of a tree, H is predicted to scale as the $1/2$ power of D (McMahon, 1973) and a final steady state H is attained in old trees that reflects an evolutionary balance between the costs and benefits of stature (King, 1990). Empirical data found that H scales to the 0.535 power of D for a wide range of plant sizes, supporting this hypothesis (Niklas, 1994). However, for local biomass studies, the B^* coefficient diverges from the $1/2$ power and it is a function of several variables. Hence, if $H = f(a_h D^{B^*})$ with $0 < B^* \leq 1 \approx 1/2$, then Eq. (2) becomes

$$V = f(a_v D^d H^h) = (a_v a_h) D^{d+hB^*} \quad (12)$$

Furthermore, if tree biomass is assumed to be proportional to V (with the tree specific gravity as the proportionality constant), then $M = f(a_v a_h D^{d+hB^*} \times \rho)$ and in conjunction with Eq. (1), the B -scalar exponent, $B_{theoric}$, is:

$$B_{theoric} = d + hB^* \quad (13)$$

And the a -scalar intercept, $a_{theoric}$, is:

$$a_{theoric} = (a_v^* a_h) \quad (14)$$

Finally, a fully theoretical model that requires the following relationships $V = f(D, H)$ and $H = f(D)$, in addition to the wood specific gravity of the entire aboveground biomass is;

$$M = \rho(a_v a_h) D^{d+hB^*} \quad (15)$$

Model [15] was described as the shape-dimensional analysis approach (Návar, 2010a). In the absence of total aboveground tree ρ and a_h data, the intercept coefficient can be preliminarily derived taking advantage of the good relationship between the scalar coefficients, as follows;

$$a_{theoric} = (a_v^* a_h) \rho = f(B_{theoric} = d + hB^*) \quad (16)$$

With this empirical relationship, a final non-destructive semi-empirical model of aboveground biomass assessment is;

$$\begin{aligned} M &= a_{theoric} = (a_v^* a_h) \rho = \\ &f(B_{theoric} = d + hB^*) \\ M &= a_{theoric} D^{B_{theoric}} \end{aligned} \quad (17)$$

Meta-analysis studies noted that the scalar coefficients a and B are negatively related to one another in a power fashion because high values of both a and B would result in large values of M for large diameters that possibly approach the safety limits imposed by mechanical self loading (Zianis & Mencuccini, 2004; Pilli et al., 2006; and Návar, 2009a; 2009b). This mathematical artifact offers the basic tool for simplifying the allometric analysis of forest biomass in this approach.

In the meantime tree ρ and a_h data is collected, model [17] is a preliminary non-destructive semi-empirical method for assessing M for trees of any size. The procedure can be applied as long as volume allometry is available in addition to the relationship between a - B that has to be developed preferentially on-site. The methodology is flexible and provides compatible tree M evaluations since large estimated B values would have small a figures and vice versa. Site-specific allometry can be derived with this model that may improve tree M estimates in contrast to conventional biomass equations developed off-site. Three major disadvantages of this non-destructive approach are: a) the inherent colinearity problems of estimating a with B , b) the log-relationships between $V = f(D, H)$ and $D = f(H)$ are required in order to estimate B , and c) an empirical equation that relates a to B should be developed on site or alternatively use preliminary reported functions by Zianis & Mencuccini (2004) and by Návar (2009a; 2010a). All these three equations estimate compatible a -intercept values with

an estimated B slope coefficient. Examples of the application of this semi-empirical model are reported in Figure 6.

b) Reducing the dimensionality of the conventional allometric equation by assuming a constant B slope coefficient value. The development of a model that is consistent with the WBE (model [10]) and the conventional log-transformed, most popular equation (model [1]) was proposed by Návar (2010b). Models [1] and [10] have the following common properties: $a = C\rho$; $B_{WBE} \neq B$; $B_{WBE} = 2.67$ and B is a variable that it is a function of several tree and forest attributes, including sample size; they both feed on diameter at breast height as the only independent variable. The main WBE model assumption is that the B_{WBE} -scalar slope coefficient is a constant value. This assumption has spurred recent research on semi-empirical allometric models. Hence, Ketterings et al. (2003) and Chavé et al. (2005) reduced the dimensionality of model [1] by proposing a constant B -slope coefficient, as well. Tree geometry analysis and assuming that D scales to $2.0H$; where H is the slope value of the $H = f(D)$ relationship; i.e., $D^{2.0H}$ are some methods justified for finding this constant. In this report, I hypothesized, according to the Central Limit Theorem, that compilations and Meta analysis studies on biomass equations should shed light onto the population mean B -scalar slope coefficient value.

Návar (2010b) summarized several Meta analysis studies on aboveground biomass. Table 1 shows statistical results of these studies compiled from the work conducted by Jenkins et al. (2003); Zianis and Mencuccini (2004); Pilli et al. (2006); Fehrmann and Kleinn (2006); Návar (2009a,b) where there is increasing evidence that the population mean B -value is around 2.38. This coefficient differs from the WBE scaling exponent. The Návar (2010b) equation,

		Scalar coefficients								
		a			a -re-calculated			B		
	N	\bar{x}	σ	CI	\bar{x}	σ	CI	\bar{x}	σ	CI
Jenkins et al. (2003)	10(2456)	0.11	0.03	0.02	0.12	0.03	0.02	2.40	0.07	0.05
Ter Mikaelian and Korzukhin (1997)	41	0.15	0.08	0.03	0.11	0.04	0.01	2.33	0.17	0.05
Fehrmann and Klein (2006)	28	0.17	0.16	0.06	0.12	0.02	0.01	2.40	0.25	0.09
Návar (2009b)	78	0.16	0.15	0.03	0.14	0.09	0.02	2.38	0.23	0.05
Návar (2010a)	34	0.10	0.11	0.04	0.12	0.05	0.02	2.42	0.25	0.08
Zianis and Mencuccini (2004)	277	0.15	0.13	0.01	0.12	0.04	0.01	2.37	0.28	0.03
μ		0.14	0.11	0.03	0.12	0.05	0.01	2.38	0.21	0.06

N = number of biomass equations; \bar{x} = average coefficient value; σ = Standard deviation; CI = confidence interval values ($\alpha = 0.05$; D.F = $n-1$); μ = population mean. Jenkins et al. (2003) compiled 2456 grouped in 10 biomass equations for temperate North American clusters of tree species. Ter Mikaelian and Korzukhin (1997) reported equations for 67 North American tree species but I employed only 41 equations that describe total aboveground biomass. Návar (2009b) reported a Meta-analysis for 229 allometric equations for Latin American tree species but only 78 fitted the conventional model for aboveground biomass. Návar (2010) reported B -scalar exponent values for 34 biomass equations calculated from shape-dimensional analysis. Zianis and Mencuccini (2004) reported equations for 279 worldwide species. It is recognized that several studies report the equations that were compiled by Jenkins et al. (2003).

Table 1. Scalar coefficients of the allometric conventional model and re-calculated a -scalar intercept values assuming that $B = 2.38$ for six meta-analysis studies.

consistent with the work conducted by Burrows (2000) and Fehrmann and Kleinn (2006), shows that the scaling exponent of the WBE model is correct as long as $D_{0.10}$ m is reported in the allometric model. Enquist et al. (1998) and West et al. (1999) defined that the WBE approach was derived on the assumption that the relationship between diameter and tree height, H , scales with the assumed exponent value of $2/3$. This coefficient has been found to be close to $1/2$ as it was discussed above.

The assumption of a constant B -scaling exponent value necessitates the re-calculation of the a -scalar intercept value for available allometric equations. A graphical example for this approach is shown in Figure 4 for 41 total aboveground biomass equations reported by Ter Mikaelian & Korzukhin (1997).

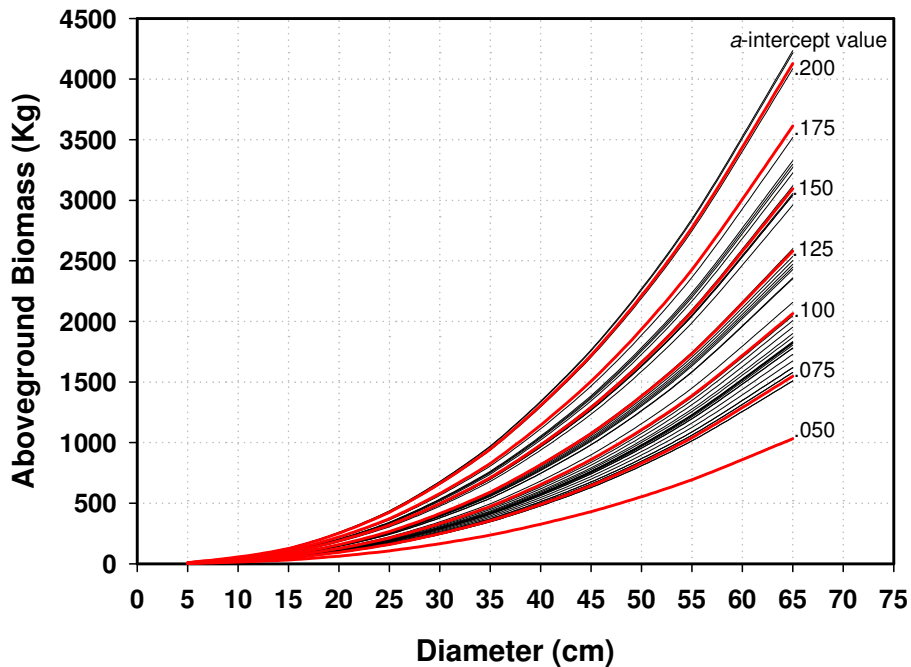


Fig. 4. Total aboveground biomass equations for 41 North American tree species reported by Ter Mikaelian and Korzukhin (1997) overlapped with allometric equations that assume a constant B -slope value of 2.38 and re-calculating the a -intercept scalar coefficients. Note the suitability of the reduced semi-empirical, non-destructive model of tree M assessment.

The re-calculation of the a -intercept is not straightforward. That is, the mathematical solution for the a -scaling intercept is not unique. For a reported biomass equation, it is a function of D , as it is described in the following example:

$$M = a_{kn} D^{b_{kn}} \therefore M = a_{ukn} D^{2.38}$$

$$a_{ukn} = \frac{a_{kn} D^{b_{kn}}}{D^{2.38}} = a_{kn} D^{(b_{kn}-2.38)} \quad (18)$$

Using the example for the *Alnus rugosa*, Ter Mikaelian and Korzukhin (1997) reported the following equation: $\ln(M) = 0.2612 + 2.2087\ln(D)$. Then, by assuming that the B -scalar exponent value is 2.38 instead of 2.2087, the new a_{unk} -intercept figure is mathematically solved as follows:

$$\begin{aligned} a_{\text{unk}} &= \frac{0.2612D^{2.2087}}{D^{2.38}} = \\ &= 0.2612D^{(2.2087-2.38)} \\ \text{if } D &= 10 \text{ cm}; a_{\text{unk}} = 0.1760 \\ \text{if } D &= 70 \text{ cm}; a_{\text{unk}} = 0.1261 \end{aligned} \quad (19)$$

Using simulated M-D data, the statistical a_{unk} -intercept value would be 0.1229. Therefore, the mathematical method of finding the value of a_{unk} is skewed. In the absence of a statistical program, it is recommended to estimate the a -scaling intercept by mathematically solving equation [19] with the largest D value recorded in the biomass study or in the forest inventory. The re-calculation of the a -scalar intercept can also be derived with the assumption that $B = 2.67$ or any other B -constant coefficient and produce similar goodness of fit. For 41 allometric aboveground equations reported by Ter Mikaelian and Korzukhin (1994), the mean (confidence interval) a -scalar intercept value is 0.1458 (0.026). Re-calculated values with the assumption that $B = 2.38$ and that $B = 2.67$ result in mean values of 0.1174 (0.012) and 0.042 (0.0045), respectively. The recalculated a -value with the assumption that $B = 2.38$ outcome consistent and unbiased a -intercept figures, statistically similar to those of the original equations (Table 1). The assumption that $B = 2.67$ deviates notoriously the intercept coefficient values by 3.5 orders of magnitude. That is, the WBE model has to be re-defined in either the B -scalar exponent to 2.38 or the C coefficient to a higher value.

A set of biomass equations would have a constant B -scalar exponent, a set of re-calculated a_{unk} figures and standard ρ_w values, a data source sufficient to construct the reduced semi-empirical, non-destructive method of M assessment. This methodology assumes: a) that the bole wood specific gravity, ρ_w , is similar to the entire tree specific gravity, ρ , value; and b) that a_{unk} and ρ_w are linearly related with a 0 intercept, and a slope coefficient that describes the C proportionality constant of the WBE model. Návar (2010b) derived the following relationship: $M = (0.2457(\pm 0.0152))\rho_w D^{2.38}$ for 39 biomass equations for temperate North American tree species. That is, the equation within brackets computes the a -scalar intercept with only ρ_w values. This mathematical function is called the Návar (2010b) reduced equation and it is expected to vary between forests and between forest stands. Therefore, this relationship must be locally developed when information is available. Brown (1997) and Chavé et al. (2005) for worldwide tropical species and Miles and Smith (2009) for North American tree species reported comprehensive lists of ρ_w values. If for one moment, it is again assumed that $\rho_w = \rho$, and that $B = 2.38$, then the C coefficient of the Návar (2010) model would have confidence bounds of 0.2304 and 0.2609 for North American temperate tree species, respectively. The application of this model to 10 clusters of species reported by Jenkins et al., (2003) is reported in Figure 5. The Návar (2010b) reduced model deviates notoriously for the woodland tree species showing that it is specific in nature.

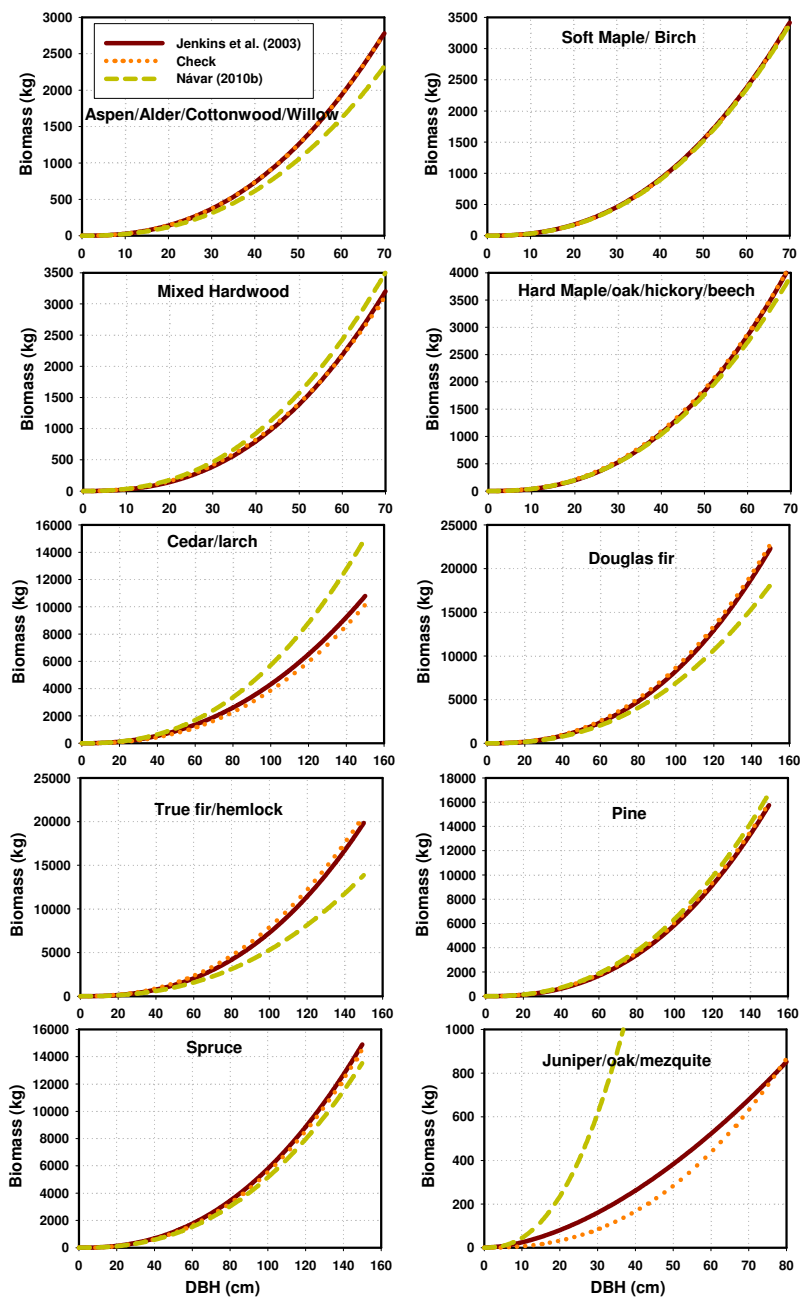


Fig. 5. Contrasts between the reduced semi-empirical, non-destructive model of Návar (2010b) and empirical equations for 10 clusters of tree species reported by Jenkins et al., (2003) for North American tree species.

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