

Research Article

Biomass Modelling of *Androstachys johnsonii* Prain: A Comparison of Three Methods to Enforce Additivity

Tarquinio Mateus Magalhães^{1,2} and Thomas Seifert²

¹Departamento de Engenharia Florestal, Universidade Eduardo Mondlane, Campus Universitário, Edifício No. 1, 257 Maputo, Mozambique

²Department of Forest and Wood Science, University of Stellenbosch, Stellenbosch 7602, South Africa

Correspondence should be addressed to Tarquinio Mateus Magalhães; tarqmag@yahoo.com.br

Received 26 January 2015; Revised 23 March 2015; Accepted 5 April 2015

Academic Editor: Piermaria Corona

Copyright © 2015 T. M. Magalhães and T. Seifert. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Three methods of enforcing additivity of tree component biomass estimates into total tree biomass estimates for *Androstachys johnsonii* Prain were studied and compared, namely, the conventional (CON) method (a method that consists of using the same independent variables for all tree component models, and for total tree model, and the same weights to enforce additivity), seemingly unrelated regression (SUR) with parameter restriction, and nonlinear seemingly unrelated regression (NSUR) with parameter restriction. The CON method was found to be statistically superior to any other method of enforcing additivity, yielding excellent fit statistics and unbiased biomass estimates. The NSUR method ranked second best but was found to be biased. The SUR method was found to be the worst; it exhibited large bias and had a poor fit for the biomass. Therefore, we recommend that only the CON and NSUR methods should be used for further estimates, provided that their limitations are considered, that is, exclusion of contemporaneous correlations for the CON method and consideration of the significant bias of the NSUR method.

1. Introduction

In the early 1960s, *Androstachys johnsonii* Prain (*A. johnsonii*) had already been reported to be almost completely restricted to Mozambique [1], presumably due to overexploitation. Five decades later, there is still a lack of studies on this species in any branch of forest science, particularly tree allometry, supporting that this species may indeed be restricted to Mozambique. Moreover, in Mozambique, biomass models have rarely been reported for any tree species, and no such models have been described for *A. johnsonii*. Isolated studies in Mozambique have focused on Miombo woodlands and some forest plantations and are often part of research theses or forestry projects; therefore, the results are not always made public. Generally, such studies have only considered the aboveground biomass and have not included a breakdown of further tree components.

A. johnsonii woodlands (Mecrusse) are very important. Besides being restricted to Mozambique [1], Mecrusse has important socioeconomic value to local communities, which

use stakes of *A. johnsonii* in the construction of homes, shelters, and furniture and sell them for income generation. At the global scale, Mecrusse is reported to be a tipping point in regional ecological and socioeconomic development [2], hence the importance of modelling and estimating its biomass.

The estimation of aboveground biomass is important to predict the amount of carbon that is sequestered [3–5], to assess nutrient cycling and fluxes and energy wood potentials [4, 6], and to provide estimates for the different tree components [5]. These types of estimates are important for several reasons as follows: (i) stem wood biomass is an important quantity because this component is the only one used in the forest industry, and the carbon therefore remains stored for a long time and is not released into the atmosphere; (ii) in many species, branches and foliage are left in the forest and decompose, releasing CO₂ and nutrients; (iii) in some species, especially broadleaf species, the branches are collected by members of local communities for use as firewood, which will result in release of CO₂;

TABLE 1: Summary statistics for the independent and dependent variables.

Variable	Minimum	Q0.25	Median	Average	Q0.75	Maximum	SD	CV (%)
DBH (cm)	5.00	11.00	17.50	17.59	24.00	32.00	7.51	42.72
Total tree height, H (m)	5.69	11.21	12.77	12.32	13.90	16.00	2.14	17.35
Crown height, CH (m)	0.70	3.74	5.16	5.05	6.15	9.92	2.01	39.86
Live crown length, LCL (m)	1.10	5.50	7.05	7.27	8.90	13.50	2.47	34.05
Belowground biomass (kg)	2.55	11.66	36.04	47.73	73.49	162.10	41.21	86.33
Stem wood biomass (kg)	4.95	30.51	103.18	124.07	197.62	357.35	99.50	80.20
Stem bark biomass (kg)	0.68	3.52	11.17	14.20	22.60	55.80	12.37	87.14
Crown biomass (kg)	3.04	13.68	37.36	58.39	80.44	216.69	59.08	101.17
Total tree biomass (kg)	12.48	59.90	204.39	244.39	368.23	752.57	204.33	83.61

Q0.25 = first quartile; Q0.75 = third quartile; SD = standard deviation; CV = coefficient of variation.

(iv) the stump and root system are left in the forest, allowing the stump to either sprout (regrow), continuing the sequestration process, or decompose along with the roots, releasing CO₂ and nutrients; and (v) in some tree species, belowground biomass can account for more than one-third of the total biomass [7]. Hence, it is critical to estimate the biomass of all tree components as well as the total tree biomass in order to assess the global carbon balance.

However, the biomass estimates of the considered tree components often do not sum to the estimate of the total tree biomass, and a desired and logical feature of the tree component regression equations is that the predictions of the components sum to the prediction for the total tree. This feature is called additivity. Various authors, such as Goicoa et al. [5], Kozak [8], Cunia [9], Cunia and Briggs [10, 11], Jacobs and Cunia [12], Parresol [4, 13], and Carvalho and Parresol [14], have proposed and/or discussed various methods to ensure the property of additivity.

The objective of this study was to fit independent linear and nonlinear tree component and total tree biomass models and compare three methods of enforcing the property of additivity (the conventional (CON) method, seemingly unrelated regression (SUR) with parameter restriction, and nonlinear seemingly unrelated regression (NSUR) with parameter restriction) for *A. johnsonii* tree species.

The CON method consists of using the same independent variables for all tree component models, and for total tree model, and the same weights to enforce additivity [4]. The SUR and NSUR methods consist in first fitting and selecting the best linear and nonlinear models, respectively, for each tree component. The total tree model is a function of the independent variables used in each component model. Then, all models, including the total, are fitted again simultaneously using joint-generalized least squares under the restriction of the coefficients of regression which ensures the additivity property [4].

2. Materials and Methods

2.1. Study Area. Mecrusse is a forest type where the main species, many times the only one, in the upper canopy is *A. johnsonii* [15].

In Mozambique, Mecrusse woodlands are mainly found in Inhambane and Gaza provinces and in Massangena, Chicualacuala, Mabalane, Chigubo, Guijá, Mabote, Funchalouro, Panda, Mandlakazi, and Chibuto districts. The eastern-most Mecrusse patches, covering the last five districts, were defined as the study area. The study area had an extension of 4,502,828 ha [16], of which 226,013 ha (5%) was covered by Mecrusse woodlands.

The climate is dry and tropical throughout the study area, except in the west part of the Panda district and the southwest part of the Mandlakazi district, where the climate is humid and tropical [16–21]. The climate has two seasons: the warm or rainy season from October to March and the cool or dry season from March to September [17–21].

The mean annual temperature is generally greater than 24°C, and the mean annual precipitation varies from 400 to 950 mm [16–21]. According to FAO classification [22], the soils in the study area are mainly Ferralic Arenosols covering more than 70% of the study area [16]. Arenosols, Umbric Fluvisols, and Stagnic soils are also predominant in the northern-most part of the study area [16].

The study area is characterized by a shortage of water resources as well as precipitation; thus, of the five districts that made up the study area, only the districts of Chibuto and Mandlakazi have water resources [16–21], either from precipitation or from lakes and rivers.

2.2. Data Acquisition. A total of 93 trees (2 to 6 per plot) selected across all size classes (Table 1) were destructively sampled within 23 circular plots randomly located in the study area. Diameter at breast height (DBH), total tree height (H), crown height (CH), and live crown length (LCL) were measured on the felled trees. Trees were divided into the following tree components: (1) root system, (2) stem wood, (3) stem bark, and (4) crown. Tree components were sampled and the dry weights were estimated as follows.

2.2.1. Root System. The stump height was predefined as being 20 cm for all trees and considered as part of the taproot, as recommended by Parresol [13] and because in larger *A. johnsonii* trees this stump height (20 cm) is affected by

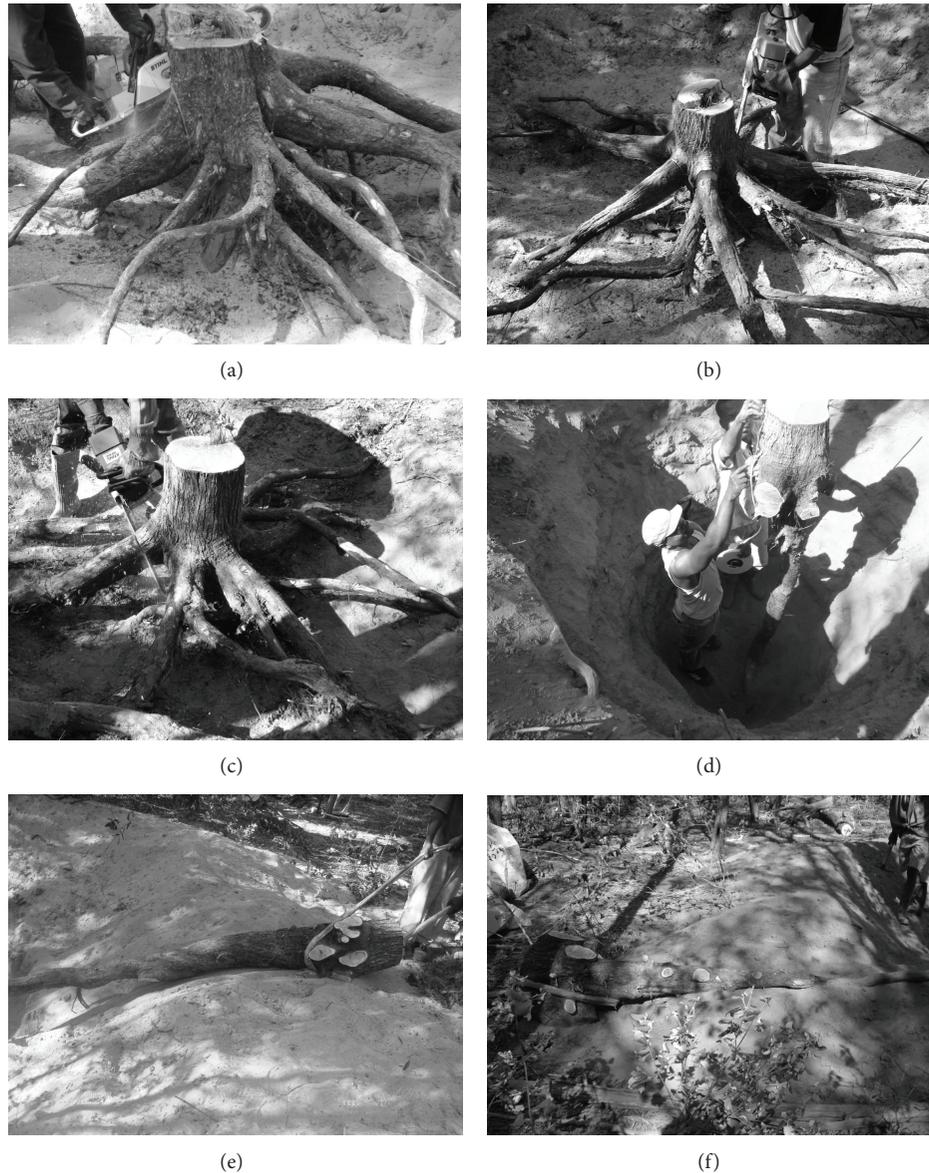


FIGURE 1: Separation of lateral roots from the root collar/taproot (a, b, and c) and removal of the taproot including the root collar and the stump (d, e, and f).

the root buttress; therefore, the root collar was also considered part of the taproot. The root system was divided into 3 subcomponents: fine lateral roots, coarse lateral roots, and taproot. Lateral roots with diameters at insertion point on the taproot < 5 cm were considered as fine roots and those with diameters ≥ 5 cm were considered as coarse roots.

First, the root system was partially excavated to the first node, using hoes, shovels, and picks, to expose the primary lateral roots (Figures 1(a)–1(c)). The primary lateral roots were numbered and separated from the taproot with a chainsaw (Figures 1(b) and 1(c)) and removed from the soil, one by one. This procedure was repeated in the subsequent nodes until all primary roots were removed from the taproot and the soil. Finally, the taproot was excavated and removed (Figures 1(d)–1(f)). The complete removal of the root system

was relatively easy because 90% of the lateral roots of *A. johnsonii* are located in the first node, which is located close to ground level (Figures 1(a)–1(d)); the lateral roots grow horizontally to the ground level, and do not grow downwards; and because the taproots had, at most, only 4 nodes and at least 1 node (at ground level).

Fresh weight was obtained for the taproot, each coarse lateral root and for all fine lateral roots. A sample was taken from each subcomponent, fresh weighed, marked, packed in a bag, and taken to the laboratory for oven drying. For the taproot, the samples were two discs, one taken immediately below the ground level and another from the middle of the taproot. For the coarse lateral roots, two discs were also taken, one from the insertion point on the taproot and another from the middle of it. For fine roots the sample was 5 to 10% of

the fresh weight of all fine lateral roots. Oven drying of all samples was done at 105°C to constant weight (i.e., to, approximately, 0% moisture content), hereafter, referred to as dry weight.

2.2.2. Stem Wood and Stem Bark. Felled trees were scaled up to a 2.5 cm top diameter. The stem was defined as the length of the trunk from the stump to the height that corresponded to 2.5 cm diameter. The remainder (from the height corresponding to 2.5 cm diameter to the tip of the tree) was considered a fine branch. The stem was divided into sections, the first with 1.1 m length, the second with 1.7 m, and the remaining with 3 m, except the last, whose length depended on the length of the stem. Discs were removed on the bottom and top of the first section and on the top of the remaining sections; that is, discs were removed at heights of 0.2 m (stump height), 1.3 m (breast height), and 3 m, and the successive discs were removed at intervals of 3 m to the top of the stem, and their fresh weights were measured using a digital scale.

Diameters over and under bark were taken from the discs in the North-South direction (previously marked on the standing tree) with the help of a ruler. The volumes over and under the bark of the stem were obtained by summing up the volumes of each section calculated using Smalian's formula [27, 28]. Bark volume was obtained from the difference between volume over bark and volume under bark.

The discs were dipped in drums filled with water for its saturation (3 to 4 months) and subsequent determination of the saturated volume and basic density. The saturated volume of the discs was obtained based on the water displacement method [29] using Archimedes' principle. This procedure was done twice: before and after debarking; hence, we obtained saturated volume under and over the bark.

Wood discs and respective barks were oven dried at 105°C to constant weight. Basic density was obtained by dividing the oven dry weight of the discs (with and without bark) by the relevant saturated wood volume [27, 30]. Therefore, two distinct basic densities were calculated: (1) basic density of the discs with bark and (2) basic density of the discs without bark.

We estimated the basic density at point of geometric centroid of each section using the regression function of density over height [31]. This density value was taken as representative of each section [31].

2.2.3. Crown. The crown was divided into two subcomponents: branches and foliage. Primary branches, originating from the stem, were classified in two categories: primary branches with diameters at the insertion point on the stem ≥ 2.5 cm were classified as large branches, and those with diameters < 2.5 cm were classified as fine branches.

Large branches were sampled similarly to coarse roots, and fine branches and foliage were sampled similarly to fine roots. All the leaves from each tree were collected and fresh weighed together and a sample was taken for oven drying. The subcomponents branches and foliage were not treated as separated components because in the preliminary analysis the weight of the foliage did not show significant variation with DBH, H , CH , and LCL , exhibiting, therefore, poor fits.

2.2.4. Tree Component Dry Weights. Dry weights of coarse and fine roots, large and fine branches, and foliage were obtained from the "fresh weight/oven dry weight" ratio of the respective samples by multiplying it by the relevant subcomponent total fresh weight. Dry weights of the root system and crown were obtained by summing up the relevant subcomponents' dry weights.

Dry weights of each stem section (with and without bark) were obtained by multiplying respective densities by relevant stem section volumes. Stem (wood + bark) and stem wood dry weights were obtained by summing up each section's dry weight with and without bark, respectively. The dry weight of the stem bark was obtained from the difference between the dry weights of stem and stem wood. Finally, the total tree biomass was obtained by adding the component dry weights.

2.3. Data Analysis. Several linear and nonlinear regression model forms were tested for each tree component and for the total tree using weighted least squares (WLS). The weight functions were obtained by iteratively finding the optimal weight that homogenises the residuals and improves other fit statistics. Independent tree component models were fitted with the statistical software package R [32] and the functions `lm` and `nls` for linear models and nonlinear models (the latter of which using the Gauss-Newton algorithm). The best linear and nonlinear biomass equations selected are given in (1) and (2), respectively. Among the tested weight functions ($1/D$, $1/D^2$, $1/DH$, $1/DLCL$, $1/D^2H$, and $1/D^2LCL$), the best weight function was found to be $1/D^2H$, for all tree component equations (linear or nonlinear). Although, the selected weight function might not be the best one among all possible weights, it is the best approximation found. Consider

$$\begin{aligned}\hat{Y}_{\text{Roots}} &= b_0 + b_1 D^2 H, \\ \hat{Y}_{\text{Stem-wood}} &= b_0 + b_1 D^2 H, \\ \hat{Y}_{\text{Stem-bark}} &= b_0 + b_1 D^2 H,\end{aligned}\quad (1)$$

$$\begin{aligned}\hat{Y}_{\text{Crown}} &= b_0 + b_1 D^2 LCL^{0.25}, \\ \hat{Y}_{\text{Total-tree}} &= b_0 + b_1 D^2 H, \\ \hat{Y}_{\text{Roots}} &= b_0 (D^2 H)^{b_2}, \\ \hat{Y}_{\text{Stem-wood}} &= b_0 D^{b_1} H^{b_2}, \\ \hat{Y}_{\text{Stem-bark}} &= b_0 D^{b_1} H^{b_2}, \\ \hat{Y}_{\text{Crown}} &= b_0 D^{b_1} LCL^{b_2}, \\ \hat{Y}_{\text{Total-tree}} &= b_0 (D^2 H)^{b_2}.\end{aligned}\quad (2)$$

The CON method used the same independent variables for all tree component models and the total tree model and used the same weight functions [4], achieving additivity automatically [5]. For this method, the most frequent best linear model form in (1) among tree components was used for all other components and for total tree biomass. The most frequent

TABLE 2: Coefficients of regression of SUR using the system of the best linear models.

Tree component	Weight function	b_0 (\pm SE)	b_1 (\pm SE)	b_2 (\pm SE)
Roots	$1/D^2H$	0.1404 (\pm 0.5950)	0.0046 (\pm 0.0002)*	
Stem wood	$1/D^2H$	0.1025 (\pm 0.4193)	0.0070 (\pm 0.0001)*	
Stem bark	$1/D^2H$	0.1076 (\pm 0.3150)	0.0001 (\pm 0.0001)	
Crown	$1/D^2H$	-1.8559 (\pm 1.5017)	0.1124 (\pm 0.0044)*	
Total tree	$1/D^2H$	-1.5053 (\pm 1.8765)	0.0117 (\pm 0.0002)*	0.1124 (\pm 0.0044)*

“*” = significant at $\alpha \geq 5\%$; “ ” = not significant at any probability level.

TABLE 3: Fit statistics of SUR using the system of the best linear models.

Tree component	Weight function	Adj. R^2 (%)	$S_{y,x}$ (kg)	CV (%)	MRSE (kg)	MR (kg)	$\hat{\sigma}_{ii}$	$\hat{\sigma}_{SUR}^2$
Roots	$1/D^2H$	56.00	34.9040	73.1758	0.2750	0.3227*	0.1503	
Stem wood	$1/D^2H$	22.17	116.6327	94.0069	0.5181	1.1685*	1.7454	
Stem bark	$1/D^2H$	-29.22	18.1996	128.1809	0.8488	0.1751*	0.0432	1.0028
Crown	$1/D^2H$	81.50	28.5040	48.8144	1.4814	-0.1298*	0.1087	
Total tree	$1/D^2H$	63.19	249.5561	102.1272	0.2332	1.5366*	14.4049	

“*” = significant at $\alpha \geq 5\%$; “ ” = not significant at any probability level.

model form in (1) is $\hat{Y} = b_0 + b_1 D^2 H$; therefore, the structural system of equations for the CON method is given in

$$\begin{aligned}
 \hat{Y}_{\text{Roots}} &= b_{10} + b_{11} D^2 H, \\
 \hat{Y}_{\text{Stem-wood}} &= b_{20} + b_{21} D^2 H, \\
 \hat{Y}_{\text{Stem-bark}} &= b_{30} + b_{31} D^2 H, \\
 \hat{Y}_{\text{Crown}} &= b_{40} + b_{41} D^2 H, \\
 \hat{Y}_{\text{Total-tree}} &= \hat{Y}_{\text{Roots}} + \hat{Y}_{\text{Stem-wood}} + \hat{Y}_{\text{Stem-bark}} + \hat{Y}_{\text{Crown}} \\
 &= (b_{10} + b_{20} + b_{30} + b_{40}) \\
 &\quad + (b_{11} + b_{21} + b_{31} + b_{41}) D^2 H \\
 &= b_{50} + b_{51} D^2 H.
 \end{aligned} \tag{3}$$

The SUR method consisted of first fitting and selecting the best linear models for each tree component. The total tree model was a function (sum) of the independent variables used in each tree component model. Then, all models, including the total, were fitted again simultaneously using joint-generalized least squares (also known as SUR) under the restriction of the coefficients of regression, which ensured additivity.

The best linear model forms were found to be $\hat{Y} = b_0 + b_1 D^2 H$ for belowground, stem wood, and stem bark biomasses and $\hat{Y} = b_0 + b_1 D^2 \text{LCL}^{0.25}$ for the crown biomass. Summing up the best model forms from each tree component, the model form obtained for the total tree biomass was $\hat{Y} = b_0 + b_1 D^2 H + b_2 D^2 \text{LCL}^{0.25}$.

However, the system of equations obtained by combining the best linear model forms per component under parameter restriction will not yield effective and precise estimates because, according to SAS Institute Inc. [33], for SUR to be effective, the models must use different regressors.

This requirement is not verified, as three of the four components have identical regressors. Indeed, according to Srivastava and Giles [34], applying SUR to system of the best equations given above is of no benefit when the component equations have identical explanatory variables. Moreover, as stated by Greene [35] and Bhattacharya [36], a system of linear SUR equations with identical regressors yields ineffective estimates of coefficient vectors when compared to equation-by-equation ordinary least squares (OLS).

To eliminate the ineffectiveness caused by identical regressors, SUR was applied using second best regression equations for belowground and stem wood biomasses such that the different tree component equations could have different regressors. The resulting system of equations of biomass additivity is given in (4). However, the results of SUR using the best independent model forms are given in Tables 2 and 3, for demonstration proposes of the ineffectiveness caused by identical regressors. Consider

$$\begin{aligned}
 \hat{Y}_{\text{Roots}} &= b_{10} + b_{11} D^2 + b_{12} H, \\
 \hat{Y}_{\text{Stem-wood}} &= b_{20} + b_{21} D^2, \\
 \hat{Y}_{\text{Stem-bark}} &= b_{30} + b_{31} D^2 H, \\
 \hat{Y}_{\text{Crown}} &= b_{40} + b_{41} D^2 \text{LCL}^{0.25}, \\
 \hat{Y}_{\text{Total}} &= (b_{10} + b_{20} + b_{30} + b_{40}) + (b_{11} + b_{21}) D^2 \\
 &\quad + b_{31} D^2 H + b_{41} D^2 \text{LCL}^{0.25} + b_{12} H \\
 &= b_{50} + b_{51} D^2 + b_{52} D^2 H + b_{53} D^2 \text{LCL}^{0.25} + b_{54} H.
 \end{aligned} \tag{4}$$

Note from the equations in (4) that the intercepts of all tree component biomass models are forced (constrained, restricted) to sum to the intercept of the total tree biomass model, the coefficients of regression for the regressor D^2 in the root system and stem wood biomass models are

TABLE 4: Standard error of the expected and predicted values for different methods.

Statistic	Absolute form	Relative form
Standard error of the expected value for CON	$S(E(y_0)) = S_{y,x} \sqrt{\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{SS_x}}$	$S(E(y_0)) \% = \frac{S(E(y_0))}{\hat{y}_i} \times 100$
Standard error of the predicted value for CON	$S(y_{0i} - \hat{y}) = S_{y,x} \sqrt{1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{SS_x}}$	$S(y_{0i} - \hat{y}) \% = \frac{S(y_{0i} - \hat{y})}{\hat{y}_i} \times 100$
Standard error of the expected value for SUR	$S(E(y_0)) = \sqrt{S_{\hat{y}_i}^2} = \sqrt{f_i(b)' \hat{\Sigma}_b f_i(b)}$	$S(E(y_0)) \% = \frac{S(E(y_0))}{\hat{y}_i} \times 100$
Standard error of the predicted value for SUR	$S(y_{0i} - \hat{y}) = \sqrt{S_{\hat{y}_i}^2 + \hat{\sigma}_{SUR}^2 \hat{\sigma}_{ii} \psi_i(\theta_i)}$	$S(y_{0i} - \hat{y}) \% = \frac{S(y_{0i} - \hat{y})}{\hat{y}_i} \times 100$
Standard error of the expected value for NSUR	$S(E(y_0)) = \sqrt{S_{\hat{y}_i}^2} = \sqrt{f_i(b)' \hat{\Sigma}_b f_i(b)}$	$S(E(y_0)) \% = \frac{S(E(y_0))}{\hat{y}_i} \times 100$
Standard error of the predicted value for NSUR	$S(y_{0i} - \hat{y}) = \sqrt{S_{\hat{y}_i}^2 + \hat{\sigma}_{NSUR}^2 \hat{\sigma}_{ii} \psi_i(\theta_i)}$	$S(y_{0i} - \hat{y}) \% = \frac{S(y_{0i} - \hat{y})}{\hat{y}_i} \times 100$

Sources: Parresol [13], Lambert et al. [23], Parresol and Thomas [24], Snedecor and Cochran [25], and Yanai et al. [26].

SS_x = sum of squares of the independent variable; $S_{y,x}$ = standard deviation of the residuals; x_0 = particular value of x for which the expected value y is estimated, $E(y_0)$; $S_{\hat{y}_i}^2$ = estimated variance for the i th system equation on the observation \hat{y}_i ; $f_i(b)'$ = a row vector for the i th equation from the partial derivatives matrix $F(b)$, it is $f_i(b)$ transposed; $\hat{\Sigma}_b$ = estimated covariance matrix of the parameter estimates; $f_i(b)$ = a column vector for the i th equation from the partial derivatives matrix $F(b)$; $\hat{\sigma}_{SUR}^2$ = SUR system variance; $\hat{\sigma}_{NSUR}^2$ = NSUR system variance; $\hat{\sigma}_{ii}$ = the (i, i) element of the covariance matrix of the residuals $\hat{\Sigma}$ (error covariance matrix); it is the covariance error of the i th system equation; and $\psi_i(\theta_i)$ = estimated weight.

constrained to sum to the coefficient of regression for D^2 in the total tree biomass model, and the coefficients for the regressors H , D^2H , and D^2LCL ^{0.25} in the root system, stem bark, and crown biomass models, respectively, are constrained to be equal to the coefficients of the same regressors in the total tree biomass model, thereby achieving additivity.

The NSUR method had the same characteristics and was performed using the same procedures as the SUR method except that the system of equations was composed of nonlinear models. For reference, please see Brandeis et al. [3], Parresol [13], Carvalho and Parresol [14], and Carvalho [37]. The system of equations (including the total tree biomass) obtained by combining the best nonlinear model forms per component under parameter restriction is given by

$$\begin{aligned}
\hat{Y}_{\text{Roots}} &= b_{10} (D^2H)^{b_{11}}, \\
\hat{Y}_{\text{Stem-wood}} &= b_{20} D^{b_{21}} H^{b_{22}}, \\
\hat{Y}_{\text{Stem-bark}} &= b_{30} D^{b_{31}} H^{b_{32}}, \\
\hat{Y}_{\text{Crown}} &= b_{41} D^{b_{42}} LCL^{b_{43}}, \\
\hat{Y}_{\text{Total}} &= b_{10} (D^2H)^{b_{11}} + b_{20} D^{b_{21}} H^{b_{22}} \\
&\quad + b_{30} D^{b_{31}} H^{b_{32}} + b_{41} D^{b_{42}} LCL^{b_{43}}.
\end{aligned} \tag{5}$$

Note that the coefficients of regression of each regressor in each tree component model are forced (constrained, restricted) to be equal to coefficients of the equivalent regressor in total tree model, allowing additivity.

The systems of equations in (4) and (5) were fitted using PROC SYSLIN and PROC MODEL in SAS software

[33], respectively, using the ITSUR option. Restrictions (constraints) were imposed on the regression coefficients by using SRESTRICT and RESTRICT statements in PROC SYSLIN and PROC MODEL procedures, respectively. The start values of the parameters in PROC MODEL were obtained by fitting the logarithmized models of each component in Microsoft Excel.

2.4. Model Evaluations and Comparison. The best tree component and total tree biomass equation were selected by running various possible regressions on combinations of the independent variables (DBH, H , and LCL) and evaluating them using the following goodness of fit statistics: adjusted coefficient of determination ($Adj.R^2$), standard deviation of the residuals ($S_{y,x}$) and CV of the residuals, mean relative standard error (MRSE), mean residual (MR), and graphical analysis of the residuals. The computation and interpretation of these fit statistics were previously described by Goicoa et al. [5], Gadow and Hui [38], Meyer [39], Magalhães [40], and Ruiz-Peinado et al. [41]. The best models are those with highest $Adj.R^2$, smallest $S_{y,x}$, and CV of the residuals, MRSE, and MR and with the residual plots showing no heteroscedasticity, no dependencies or systematic discrepancies.

In addition to the goodness of fit statistics described above, the methods of enforcing additivity were compared using percent standard error of the expected value and percent standard error of the predicted value, as computed in Table 4. The smaller the percent standard error of the expected and percent standard error of the predicted values is, the better the model is in predicting the biomass.

SUR and NSUR methods were used instead of, for example, simply summing the best component biomass models (i.e., Harmonization procedure [42]), because in the latter case the total biomass is not modelled and therefore its fit

TABLE 5: Regression coefficients and goodness of fit statistics for the best linear and nonlinear models in (3) and (4), respectively.

Tree component	Weight function	b_0 (\pm SE)	b_1 (\pm SE)	b_2 (\pm SE)	Adj. R^2 (%)	$S_{y,x}$ (kg)	CV (%)	MRSE (kg)	MR (kg)
Linear models									
Roots	$1/D^2H$	0.2522 (\pm 0.6334)	0.0097 (\pm 0.0002) [*]		94.94	9.59	20.10	0.1520	$-2.05E - 14$
Stem wood	$1/D^2H$	0.6616 (\pm 1.1451)	0.0251 (\pm 0.0004) [*]		97.49	19.66	15.84	0.0255	$-7.96E - 16$
Stem bark	$1/D^2H$	0.1895 (\pm 0.3503)	0.0028 (\pm 0.0001) [*]		84.24	4.97	34.97	0.3397	$-1.96E - 16$
Crown	$1/D^2H$	-1.9106 (\pm 1.5216)	0.0984 (\pm 0.0044) [*]		84.24	27.06	46.34	1.0292	$-2.43E - 01$
Total tree	$1/D^2H$	1.4066 (\pm 2.1984)	0.0494 (\pm 0.0008) [*]		97.61	34.92	14.29	0.0247	$-1.24E - 15$
Nonlinear models									
Roots	$1/D^2H$	0.0091 (\pm 0.0024) [*]	1.0074 (\pm 0.0841) [*]		94.94	10.40	21.79	0.1480	$1.90E - 05$
Stem wood	$1/D^2H$	0.0197 (\pm 0.0063) [*]	1.8210 (\pm 0.0567) [*]	1.3081 (\pm 0.1559) [*]	97.71	18.83	15.18	0.0272	$-3.40E - 04$
Stem bark	$1/D^2H$	0.0022 (\pm 0.0019)	1.7451 (\pm 0.1564) [*]	1.4084 (\pm 0.4355)	84.84	5.70	40.11	0.3770	$-2.04E - 03$
Crown	$1/D^2H$	0.0350 (\pm 0.0137) [*]	2.1318 (\pm 0.1385) [*]	0.5290 (\pm 0.1482) [*]	84.42	26.89	46.05	0.5396	$-2.59E - 01$
Total tree	$1/D^2H$	0.0533 (\pm 0.0093) [*]	0.9920 (\pm 0.0196) [*]		97.60	38.68	15.83	0.1192	$1.10E - 05$

SE = standard error; “*” = significant at $\alpha \geq 5\%$; “ ” = not significant at any probability level.

statistics are unknown and because the sum of tree component models with the best fits does not guarantee good fit in the total model and might produce biased estimates for whole tree biomass [6] and, further, because SUR and NSUR, unlike the CON method, take into account the contemporaneous correlation among residuals of the component equations [4, 13, 14, 24].

Nevertheless, the standard deviation and CV of the residuals for the harmonization approach (HAR) were compared with those obtained for SUR and NSUR approaches. Since, in HAR procedure, the total tree biomass is obtained simply by summing the best component models, the standard deviation of the residuals can be computed using the variance of a sum (6) [4, 13]. Consider

$$S_{y,x(\text{Total})} = \sqrt{\sum_{i=1}^c S_{y,x(i)}^2 + 2 \sum \sum S_{ij}}, \quad (6)$$

where $S_{y,x(\text{Total})}$ and $S_{y,x(i)}$ are the standard deviation of the residuals of the total tree biomass model and of the i th tree component biomass model and S_{ij} is the covariance of i th and j th tree component biomass models.

The CV of the residuals is, therefore, computed as

$$CV_{(\text{Total})} = \frac{S_{y,x(\text{Total})}}{\bar{Y}_{\text{total}}} \times 100, \quad (7)$$

where \bar{Y}_{total} is the average total tree biomass (per tree).

3. Results

3.1. Independent Tree Component and Total Tree Models. The fit statistics and the coefficient of regression for the best tree component and total tree models are given in Table 5 for linear and nonlinear models.

All linear and nonlinear regression equations yielded satisfactory fit statistics. The linear models presented an adjusted R^2 varying from 84.24% for stem bark and crown biomass

regressions to 97.61% for total tree biomass regression; the precision, as measured by the coefficient of variation (CV) of the residuals, varied from 14.29% for total tree biomass regression to 46.34% for crown biomass regression. On the other hand, the adjusted R^2 for nonlinear models varied from 84.42% for crown biomass regression to 97.60% for total tree biomass regression, and the CV of the residuals varied from 15.18% to 46.05%. For either linear or nonlinear models, the biases, as measured by the mean residual (MR), were found to be statistically not significant using Student’s t -test, and relatively poor fit statistics were found for stem bark and crown biomass regressions.

3.2. Forcing Additivity. In the models in (1), the most frequent best linear model form is $\hat{Y} = b_0 + b_1 D^2H$, which was found to be the best for the root system, stem wood, stem bark, and total tree biomasses. This model form was also ranked as the second model form for crown biomass. Therefore, to enforce additivity using the CON approach, this model form was generalized for all tree components and for total tree biomasses, as can be seen from (3). Tables 6 and 7 illustrate the regression coefficients and the goodness of fit statistics, respectively, for the CON method presented in (3), the SUR method in (4), and the NSUR method in (5).

3.2.1. The CON Method. The results of the CON method were the same as for equation-by-equation WLS in Table 5, except that the model for crown biomass was replaced in order to have the same regressors as the remaining tree components. Better performances were found for total tree, belowground, and stem wood biomass regressions.

The graphs of the residuals against predicted values for the CON method are presented in Figure 2 and did not show any particular trend or heteroscedasticity. The cluster of points was contained in a horizontal band, showing no particular trend, with the residuals almost evenly distributed under and over the axis of abscissas, meaning that there were not obvious model defects.

TABLE 6: Coefficients of regression for CON, SUR, and NSUR methods.

Tree component	Weight function	b_0 (\pm SE)	b_1 (\pm SE)	b_2 (\pm SE)	b_3 (\pm SE)	b_4 (\pm SE)
CON method						
Roots	$1/D^2H$	0.2522 (\pm 0.6334)	0.0097 (\pm 0.0002)*			
Stem wood	$1/D^2H$	0.6616 (\pm 1.1451)	0.0251 (\pm 0.0004)*			
Stem bark	$1/D^2H$	0.1895 (\pm 0.3503)	0.0028 (\pm 0.0001)*			
Crown	$1/D^2H$	0.3033 (\pm 1.5640)	0.0118 (\pm 0.0006)*			
Total tree	$1/D^2H$	1.4066 (\pm 2.1984)	0.0494 (\pm 0.0008)*			
SUR method						
Roots	$1/D^2H$	1.6513 (\pm 2.3498)	0.1016 (\pm 0.0040)*	-0.4056 (\pm 0.2584)		
Stem wood	$1/D^2H$	-3.8911 (\pm 0.9553)*	0.2106 (\pm 0.0047)*			
Stem bark	$1/D^2H$	0.1285 (\pm 0.3260)	0.0014 (\pm 0.0001)*			
Crown	$1/D^2H$	-1.9730 (\pm 1.5045)	0.1114 (\pm 0.0044)*			
Total tree	$1/D^2H$	-4.0843 (\pm 3.1723)	0.3122 (\pm 0.0068)*	0.0014 (\pm 0.0001)*	0.1114 (\pm 0.0044)*	-0.4056 (\pm 0.2584)
NSUR method						
Roots	$1/D^2H$	0.0075 (\pm 0.0022)*	1.0137 (\pm 0.0326)*			
Stem wood	$1/D^2H$	0.0131 (\pm 0.0040)*	1.7962 (\pm 0.0549)*	1.4113 (\pm 0.1470)*		
Stem bark	$1/D^2H$	0.0001 (\pm 0.0011)	1.6545 (\pm 0.1942)*	1.7332 (\pm 0.5460)*		
Crown	$1/D^2H$	0.0407 (\pm 0.0159)*	2.2302 (\pm 0.1343)*	0.3146 (\pm 0.1214)*		
Total tree	$1/D^2H$					

SE = standard error; “*” = significant at $\alpha \geq 5\%$; “ ” = not significant at any probability level.

TABLE 7: Fit statistics for CON, SUR, and NSUR methods.

Tree component	Weight function	Adj. R^2 (%)	$S_{y,x}$ (kg)	CV (%)	MRSE (kg)	MR (kg)	$\hat{\sigma}_{ii}$	$\hat{\sigma}_{SUR}^2$	$\hat{\sigma}_{NSUR}^2$
CON method									
Roots	$1/D^2H$	94.94	9.59	20.10	0.1520	-2.05E - 14	—		
Stem wood	$1/D^2H$	97.49	19.66	15.84	0.0255	-7.96E - 16	—		
Stem bark	$1/D^2H$	84.24	4.97	34.97	0.3397	-1.96E - 16	—	—	—
Crown	$1/D^2H$	82.16	25.11	43.01	1.5596	1.71E - 15	—		
Total tree	$1/D^2H$	97.61	34.92	14.29	0.0247	-1.24E - 15	—		
SUR method									
Roots	$1/D^2H$	82.44	22.06	46.24	0.1378	0.1769*	0.0581		
Stem wood	$1/D^2H$	72.47	60.59	48.83	0.1732	0.6599*	0.5943		
Stem bark	$1/D^2H$	52.84	10.56	74.38	0.2403	0.0930*	0.0157	0.9906	—
Crown	$1/D^2H$	81.96	27.22	46.62	1.4330	-0.1188*	0.1053		
Total tree	$1/D^2H$	86.88	96.67	39.56	0.0791	0.8109*	9.1562		
NSUR method									
Roots	$1/D^2H$	92.76	12.84	26.92	0.1168	0.0805*	0.0244		
Stem wood	$1/D^2H$	92.27	35.66	28.74	0.0440	0.3116*	0.1718		
Stem bark	$1/D^2H$	78.12	6.85	48.25	0.2084	0.0423*	0.0072	—	4.7801
Crown	$1/D^2H$	85.27	26.41	45.23	0.8348	-0.0049	0.0859		
Total tree	$1/D^2H$	67.76	53.32	21.82	0.0321	0.4296*	6.7590		

“*” = significant at $\alpha \geq 5\%$; “ ” = not significant at any probability level.

3.2.2. *SUR Method.* As can be verified from Table 7, the adjusted R^2 varied from 52.84% for stem bark to 86.88% for total tree biomass regression, and the CVs of the residuals varied from 39.56% for total tree biomass regression to

74.38% for stem bark. All tree components and total tree models were found to be biased, and all of these models underestimated the biomass, except for the crown biomass, which was overestimated, as was observed from the mean

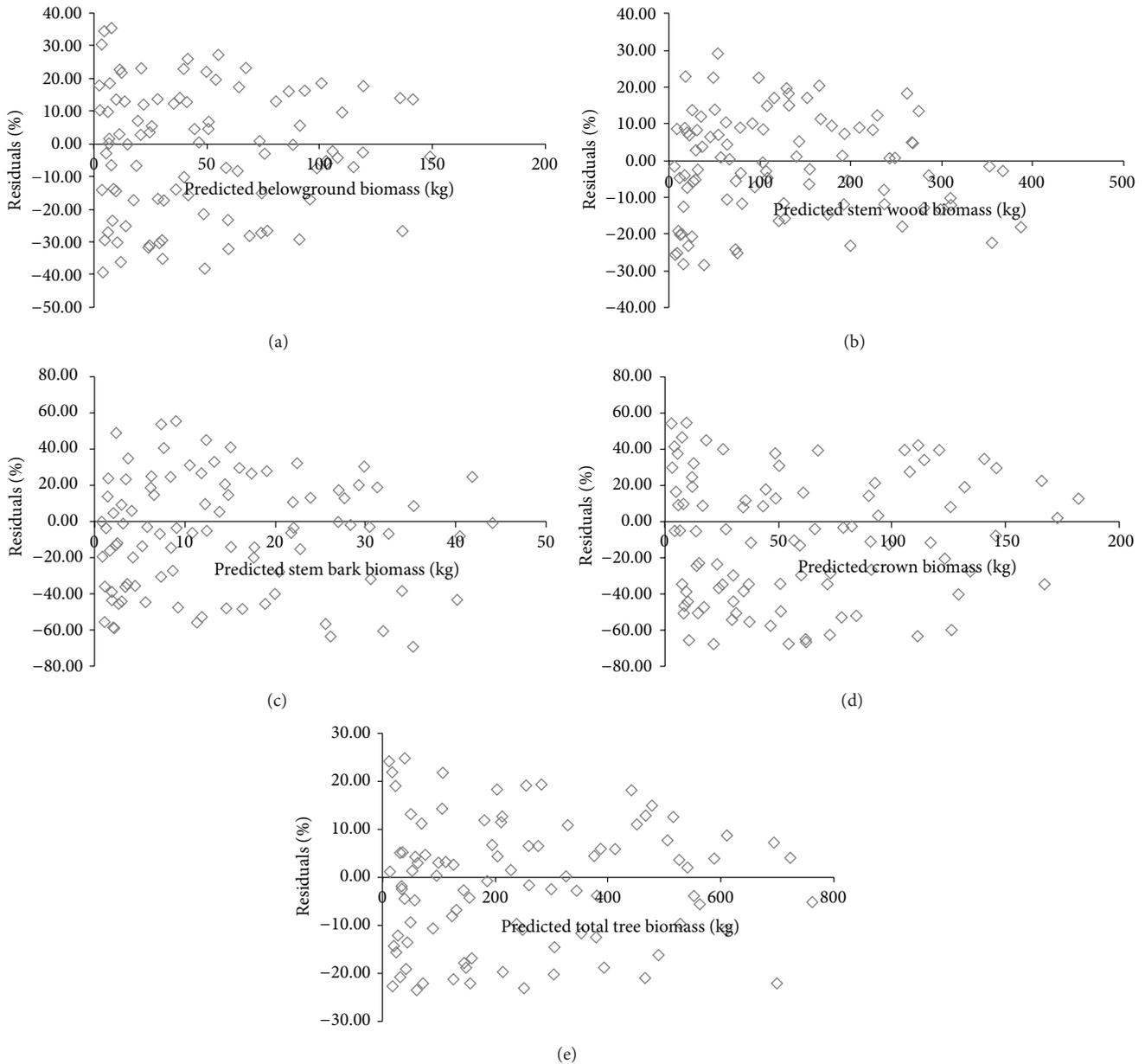


FIGURE 2: Residuals against predicted biomass for the CON method: (a) belowground, (b) stem wood, (c) stem bark, (d) crown, and (e) total tree biomass.

residual (MR). Using Student's *t*-test, these biases (MRs) were found to be statistically significant (statistically different from zero).

The biases, model defects (under and/or overestimation, heteroscedasticity), and patterns that indicated systematic discrepancies are illustrated by the graph of the residuals in Figure 3. Analyses of the residuals for SUR did not reveal heteroscedasticity but showed that the residuals were mostly agglomerated over the axis of abscissas, meaning that the designed models predicted biomass values smaller than the observed ones, underestimating the biomass (producing positive residuals). This happened to all tree components, except for the crown biomass.

3.2.3. NSUR Method. Component models (Tables 6 and 7) showed an adjusted R^2 varying from 78.12% for stem bark to 92.76% for roots. The lowest adjusted R^2 was found for the total tree model (67.76%). The CVs of the residuals varied from 21.82% for total tree to 48.25% for the stem bark model. All tree components (except the crown) and the total tree models were biased, underestimating the biomass significantly, as shown by the observation that the MRs were significantly different from zero.

Overall, the distribution of the residuals (Figure 4) was satisfactory. Minor defects were found for crown and total tree models.

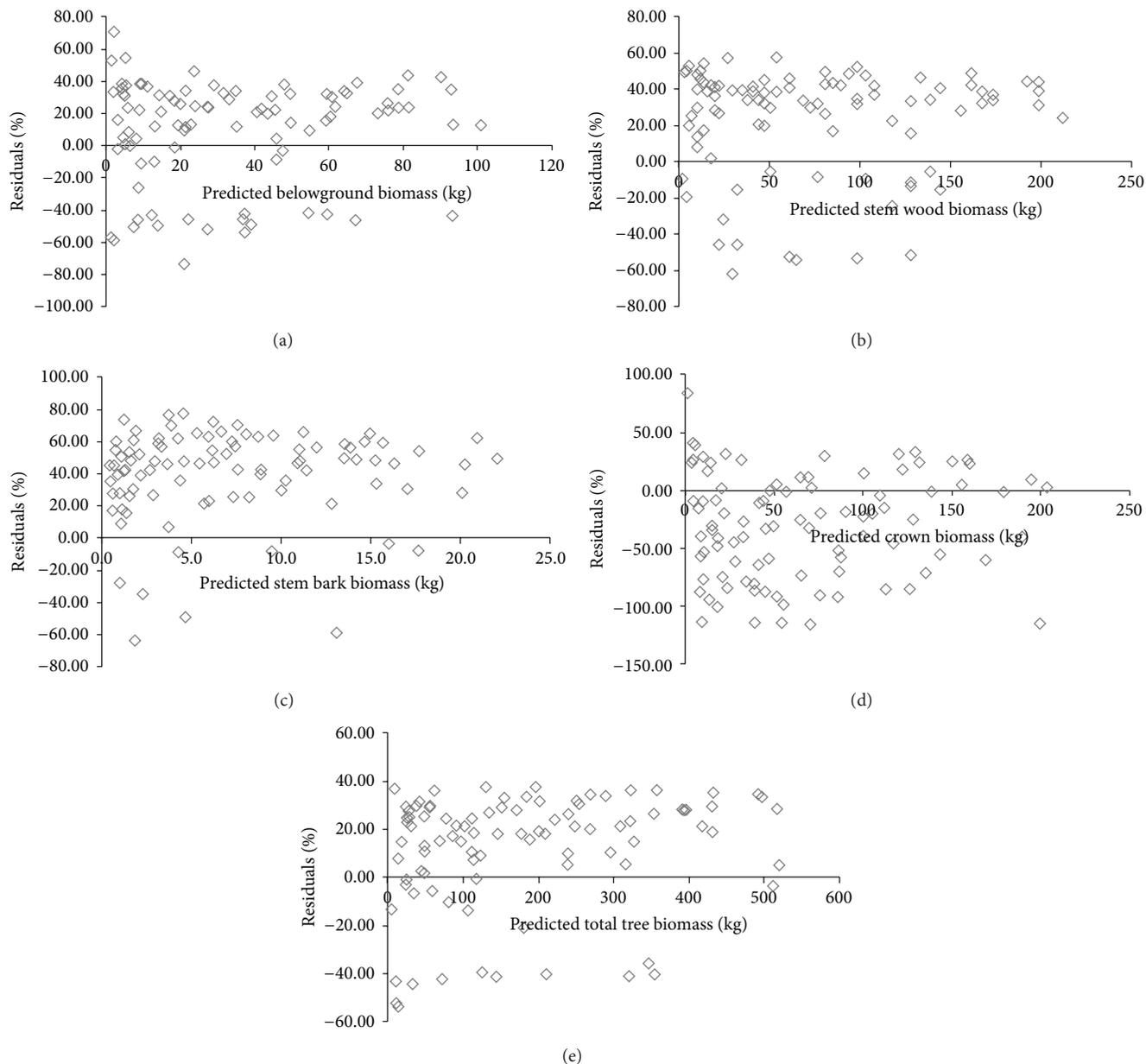


FIGURE 3: Residuals against the predicted biomass for the SUR method: (a) belowground, (b) stem wood, (c) stem bark, (d) crown, and (e) total tree biomass.

Comparing the different methods based on the relative standard errors of the expected and predicted values for total tree biomass, computed from 11 randomly selected trees from different diameter classes (Table 8), we found that the conventional method had the smallest average standard errors of the expected and predicted total tree biomass values (2.02% and 2.20%, resp.), followed by the NSUR method (3.52% and 3.68%, resp.), and lastly the SUR method (7.72% and 7.75%, resp.). These data indicated that the CON method yielded narrower confidence and prediction intervals than the NSUR and SUR methods.

4. Discussion

4.1. Independent Tree Component and Total Tree Models. Linear and nonlinear models were fitted for tree component and total tree biomass estimation. The difference between the performance of the selected linear and nonlinear tree component models is negligible. However, Salis et al. [43], Ter-Mikaelian and Korzukhin [44], and Schroeder et al. [45] found nonlinear models to perform better than the linear ones.

The crown models for both linear and nonlinear models were found to be less accurate and precise than the other tree

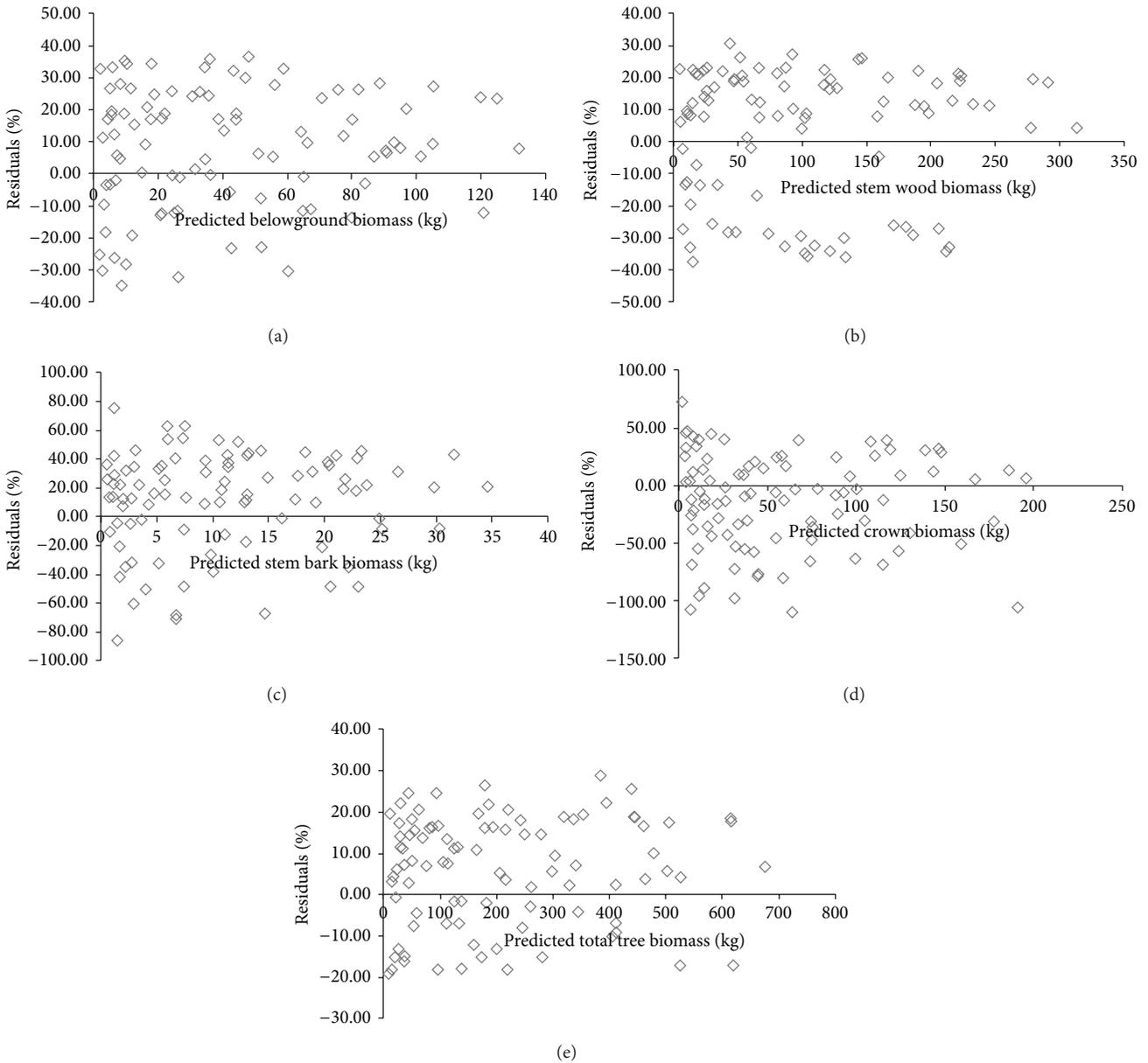


FIGURE 4: Residuals against predicted biomass for the NSUR method: (a) belowground, (b) stem wood, (c) stem bark, (d) crown, and (e) total tree biomass.

component models, as evaluated by its adjusted R^2 and CVs of the residuals, suggesting more variability. According to Pardé [46], as cited by Carvalho and Parresol [14], this is because of the variability of the internal crown structure, number of branches, and variation in wood density along the branches.

4.2. Additivity. Based on all of the results and analyses, the CON method was significantly superior to the SUR and NSUR methods and showed the best fit statistics for every tree component and total tree biomass models, including the largest adjusted R^2 , smallest CV of the residuals, and no significant model bias or defects. However, although the CON method was found to be statistically superior, it should be noted that it holds only under the assumption

of independence among components [4], implying that the residuals are interrelated, therefore not taking into account contemporaneous correlations.

Among the methods that consider contemporaneous correlations (i.e., SUR and NSUR), NSUR appeared superior to SUR. For all tree components, NSUR was superior to SUR, with the higher adjusted R^2 , smaller CV of the residuals, and less bias. However, the total tree model of the SUR method presented a higher adjusted R^2 when compared to the total tree model of the NSUR method. Figure 5 shows that the SUR method described the data quite poorly, whereas the CON and NSUR methods described the data satisfactorily, even for the total tree model, for which the SUR method had the higher adjusted R^2 value than the NSUR method.

TABLE 8: Relative standard errors (%) of the expected and predicted total tree biomass values for 11 randomly selected trees.

<i>D</i>	<i>H</i>	CH	LCL	CON		SUR		NSUR	
				$S(E(y_0))\%$	$S(y_{0i} - \hat{y})\%$	$S(E(y_0))\%$	$S(y_{0i} - \hat{y})\%$	$S(E(y_0))\%$	$S(y_{0i} - \hat{y})\%$
5.00	7.60	6.50	1.10	9.8935	10.7478	57.0913	57.3862	7.7570	9.4475
8.00	9.16	2.12	7.04	2.4664	2.8828	7.7433	7.7598	5.7686	5.8364
10.00	9.59	1.55	8.04	0.9218	1.3087	4.1622	4.1682	4.9674	4.9854
12.50	13.40	5.80	7.60	0.4477	0.6223	2.8034	2.8049	3.3916	3.3943
15.00	13.12	2.23	10.89	0.7874	0.8454	2.0203	2.0209	3.1360	3.1370
17.50	13.95	8.07	5.88	1.0461	1.0676	1.8206	1.8209	2.4721	2.4726
20.00	13.85	4.60	9.25	1.1791	1.1906	1.7894	1.7895	2.1321	2.1324
22.50	13.04	6.00	7.04	1.2514	1.2590	1.7775	1.7775	2.0573	2.0575
25.00	14.53	4.50	10.03	1.3547	1.3584	1.8523	1.8523	2.0828	2.0828
27.50	13.46	2.89	10.57	1.3843	1.3873	1.9000	1.9000	2.2690	2.2690
30.50	15.05	2.16	12.89	1.4515	1.4529	1.9571	1.9571	2.6660	2.6660
Average				2.0167	2.1930	7.7198	7.7489	3.5182	3.6801

$S(E(y_0))\%$ = relative standard error of the expected value; $S(y_{0i} - \hat{y})\%$ = relative standard error of the predicted value.

TABLE 9: *t*-test for the restriction imposed for weighted SUR.

Restriction	DF	Parameter estimate	Standard error	<i>t</i> value	Pr > <i>t</i>
$b_{50} = b_{10} + b_{20} + b_{30} + b_{40}$	-1	0.6255	0.1204	5.2	<0.0001
$b_{51} = b_{11} + b_{21}$	-1	2230.6100	355.5158	6.27	<0.0001
$b_{52} = b_{31}$	-1	390.4832	43.5058	8.98	<0.0001
$b_{53} = b_{42}$	-1	227.0888	24.8863	9.13	<0.0001
$b_{54} = b_{12}$	-1	4.7892	1.4875	3.22	0.0010

Note: the restrictions are as stated in (4).

The predicted regression lines in Figure 5 were obtained from 11 randomly selected trees from different diameter classes (2 trees per diameter class, except the last where only 1 tree was selected due to fewer representative trees); therefore the lines are function of changing all variables (refer to Table 8), hence exhibiting waves, since other variables (*H*, CH, and LCL) did not necessarily increase as DBH increased.

As shown in Figure 5, the regression lines for the CON and NSUR methods followed the same trend, and the CON method described the data slightly better than the NSUR method. Additionally, for all components, the SUR regression line was the poorest fit, especially for belowground, stem wood, stem bark, and total tree biomasses.

As shown in Table 7, the variance of the NSUR system was almost five times larger than that of the SUR system; however, the covariance errors for all tree components were almost two times smaller for the NSUR method; this last observation may explain the better fit of the NSUR method as all of the components in the NSUR method had larger R^2 values and smaller CVs of the residuals than those in the SUR method.

Several authors, including Parresol [4, 13], Carvalho and Parresol [14], Goicoa et al. [5], Carvalho [37], and Návarecháidez et al. [42], have compared different methods of enforcing additivity. All of these authors have concluded that either SUR or NSUR achieves more efficient estimates and should be the choice for additivity. However, Parresol [4] suggests that the constraint of additivity (restriction of the parameters) may compromise the efficiency of the results,

a conclusion supported by SAS Institute Inc. [33], which states that restrictions should be consistent and not redundant; that is, the data must be consistent with the restriction. In fact, the lower efficiency and precision of the SUR and NSUR estimates when compared to the CON method are associated with the imposed restriction as *t*-test results based on all the restrictions imposed on SUR and NSUR were highly significant, indicating that the data were not consistent with the restriction and that the models did not fit as well with the restriction imposed. For greater details, please see Tables 9 and 10, which are SAS outputs that test the significance of the restrictions imposed for weighted SUR and weighted NSUR, respectively.

Carvalho [37] compared methods of enforcing additivity and found that the bias (MR) for stem wood was slightly larger when the models were fitted simultaneously using SUR than when tree components were fitted separately using ordinary least squares (OLS), even though other fit statistics had improved with SUR. Similar findings were observed by Goicoa et al. [5], who found that the SUR method was highly biased as it exhibited large MR and mean relative standard error (MRSE) values.

Parresol [4, 13], Carvalho and Parresol [14], and Carvalho [37] found that multivariate procedures (SUR and/or NSUR) produce more reliable estimates than when equations are estimated independently (e.g., the CON method or independent tree component models). However, Repola [47] found no significant improvements in parameter estimates using

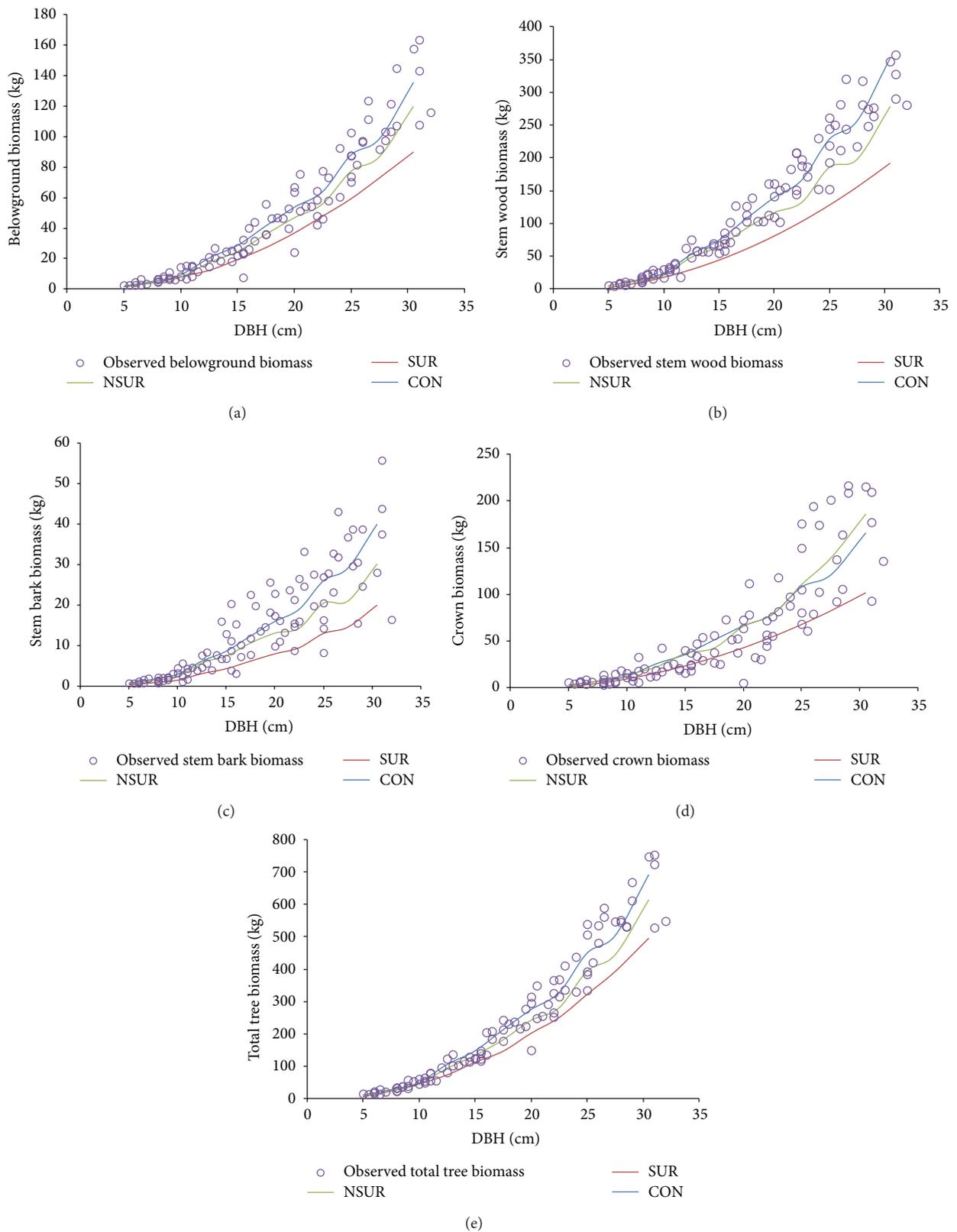


FIGURE 5: Observed biomass versus DBH values and regression lines obtained from the different methods of achieving additivity for (a) belowground, (b) stem wood, (c) stem bark, (d) crown, and (e) total tree biomass.

TABLE 10: *t*-test for the restriction imposed for weighted NSUR.

Restriction	Parameter estimate	Standard error	<i>t</i> value	Pr > <i>t</i>
Res1	-3162.70	356.20	-8.88	<0.0001
Res2	-210.46	23.76	-8.86	<0.0001
Res3	-4392.79	489.80	-8.97	<0.0001
Res4	-178.30	19.99	-8.92	<0.0001
Res5	-150.95	16.78	-9.00	<0.0001
Res6	-6811.46	732.60	-9.30	<0.0001
Res7	-20.27	2.19	-9.25	<0.0001
Res8	-17.20	1.85	-9.31	<0.0001
Res9	-877.64	94.86	-9.25	<0.0001
Res10	-111.99	12.20	-9.18	<0.0001
Res11	-84.74	8.80	-9.63	<0.0001

Note: res1 to res11 are the restrictions imposed to each of the 11 regression coefficients in the total tree model, as stated in (5).

SUR when compared to the case where the models are fitted independently.

Due to the large bias found using the SUR method, this method cannot be used for biomass estimation of any tree component. However, because the bias is far smaller than that of the SUR method, the NSUR method can be used for biomass estimation as long as the bias is considered. Moreover, while the NSUR method is not superior to the CON method in terms of bias, it does have the advantage of considering contemporaneous correlation, which the CON method does not.

The CV of the residuals for total tree biomass model obtained using the HAR procedure for the linear and nonlinear models was 72.4 and 69%, respectively, 83 and 216% larger than the CV for total tree model obtained using the SUR and NSUR procedures, respectively. This shows that, in this case, the model for total biomass obtained using SUR or NSUR procedure provides more precise results than what would be obtained by summing up the individual component models to the total (HAR procedure).

4.3. Extrapolation. The models fitted in this research (separately or simultaneously) are based on a dataset of 93 trees with diameters varying from 5 to 32 cm. *A. johnsonii* trees can reach diameters at breast height (DBHs) larger than 35 cm. In a forest inventory of *A. johnsonii* tree with a minimum DBH of 10 cm, Magalhães and Soto [48] (unpublished data) found only 13 trees per ha with DBHs larger than or equal to 30 cm, corresponding to only 5% of trees per ha. In this study, using 23 plots randomly distributed in the study area and a minimum DBH of 5 cm, we found only 19 trees per ha with diameters larger than or equal to 32.5 cm, corresponding to 1.54% of the total number of trees per ha. This implied that no serious bias would be added when extrapolating the models (independent tree component or NSUR models) outside the diameter range used to fit the models since very few trees were found outside the diameter range.

The models can also be safely applicable and valid over the whole range of areas where *A. johnsonii* occurs and outside the study area. This is true because the study area covered the entire range of soil and climate variations where *A. johnsonii* occurs (despite the apparent lack of large variations). For example, besides the Chibuto, Mandlakazi, Panda, Funhalouro, and Mabote districts that comprised the study area, Mecrusse (*A. johnsonii* stands) is also found in Mabalane, Massangena, and Chicualacuala districts. However, in these latter districts, the soils were nearly identical to those of the study area, composed mainly of Ferralic Arenosols [16, 22]. Similarities were also found with regard to climate and hydrology, especially with regard to rain shortage [17–21].

4.4. Effect of the Measurement Procedures on the Estimates. In this study, wood density was obtained by dividing oven dry weight (at 105°C) of the discs (with and without bark) by the relevant saturated wood volume [27, 30] (air not included). It is noteworthy to mention that different definitions of the weight and volume of the discs would potentially influence the estimates of density and therefore biomass. For example, Husch et al. [28] define density as the ratio of oven dry weight and green volume (air included). Compared to the definition adopted by us, such a definition would potentially lead to large values of wood density and consequently wood biomass, as saturated volume is the maximum volume [49] and is expected to be larger than green volume.

Moura et al. [49] found no significant differences between those densities, as according to these authors, the densities must be quite the same because volume is not expected to vary above the fibre saturation point (FSP). FSP of a wood is here defined as the maximum possible amount of water that the composite polymers of the cell wall can hold at a particular temperature and pressure [50], excluding, therefore, free and adsorbed water. Differences in wood density and biomass estimates could also be found if the discs were dried to different moisture content (e.g., 12%) or if a different drying temperature was used (e.g., 65°C).

Stem was defined as the length from the top of the stump to the height corresponding to 2.5 cm diameter. Differences among stem definitions (e.g., different stump height or different minimum top diameter, stump considered as part of the stem) would affect the biomass estimates, especially stem and root biomasses. Different estimates of root biomass could also be found if the root system was partially removed, as performed by many authors (e.g., [41, 51–54]), if the depths of excavation were predefined [41, 51, 55], if fine roots were excluded [56, 57], and if root sampling procedures were applied, for example, where only a number of roots from each root system are fully excavated, and then the information from the excavated roots is used to estimate biomass for the roots not excavated [58–60].

5. Conclusions

This study showed that CON method was found to be unbiased and to fit the tree component and total tree biomass well; however, the CON method had the disadvantage of not

considering contemporaneous correlations. Among methods that consider contemporaneous correlations, NSUR was far superior to SUR and fit the biomass reasonably well; however, both methods were significantly biased. The CON method can be used safely as long as its limitation is considered. The NSUR method can also be used as long as the bias is accepted and taken into account. Moreover, we recommend that the SUR method should not be used due to its bias and poor description of biomass data. Since the data sets used to build the models (both independent and simultaneous) represented many variations (all diameters, soils, and climatic ranges), the selected models can be used for extrapolation.

Appendix

See Figure 1 and Tables 2 and 3.

The Table 3 shows the results of SUR using the system of the best linear model forms. However, as 3 of the 5 equations in the system use the same independent variables, the SUR is not effective: it has lower adjusted R^2 , sometimes negative, larger CV of the residuals, larger system variance ($\hat{\sigma}_{SUR}^2$) and larger component covariance errors ($\hat{\sigma}_{ii}$) when compared to the results in Tables 6 and 7. The most jeopardized equations are those sharing the same independent variables.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

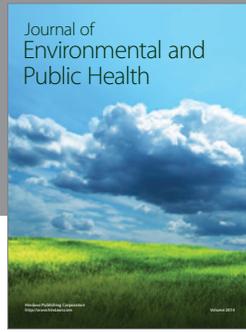
This study was funded by the Swedish International Development Cooperation Agency (SIDA). Thanks are extended to Professor Almeida Siteo for his advices during the preparation of the field work and to the field and laboratory team involved in felling, excavation, and fresh- and dry-weighting of trees and tree samples: Albino Américo Mabjaia, Salomão dos Anjos Baptista, Amélia Saraiva Monguela, João Paulino, Alzido Macamo, Jaime, Bule, Adolfo Zunguze, Viriato Chiconele, Murrombe, Paulo Goba, Dinísio Júlio, Gerente Guarinare, Sá Nogueira Lisboa, Francisco Ussivane, Nkassa Amade, Cândida Zita, and José Alfredo Amanze. The authors would also like to thank the members of local communities, community leaders, and Madeiraarte Forest Concession for the unconditional help. Acknowledges are also due to two anonymous reviewers whose insightful comments and suggestions have improved considerably this paper.

References

- [1] G. A. Cardoso, *Madeiras de Moçambique: Androstachys johnsonii*, Serviços de Agricultura e Serviços de Veterinária, Maputo, Mozambique, 1963.
- [2] P. Leadley, H. M. Pereira, R. Alkemade et al., "Biodiversity scenarios: projections of 21st century change in biodiversity and associated ecosystem services," Technical Series 50, Secretariat of the Convention on Biological Diversity, Montreal, Canada, 2010.
- [3] T. Brandeis, D. Matthew, L. Royer, and B. Parresol, "Allometric equations for predicting Puerto Rican dry forest biomass and volume," in *Proceedings of the 18th Annual Forest Inventory and Analysis Symposium*, pp. 197–202, 2006.
- [4] B. R. Parresol, "Assessing tree and stand biomass: a review with examples and critical comparisons," *Forest Science*, vol. 45, no. 4, pp. 573–593, 1999.
- [5] T. Goicoa, A. F. Militino, and M. D. Ugarte, "Modelling above-ground tree biomass while achieving the additivity property," *Environmental and Ecological Statistics*, vol. 18, no. 2, pp. 367–384, 2011.
- [6] K. Repola, *Modelling tree biomasses in Finland [Ph.D. thesis]*, University of Helsinki, Helsinki, Finland, 2013.
- [7] C. M. Litton, M. G. Ryan, D. B. Tinker, and D. H. Knight, "Belowground and aboveground biomass in young postfire lodgepole pine forests of contrasting tree density," *Canadian Journal of Forest Research*, vol. 33, no. 2, pp. 351–363, 2003.
- [8] A. Kozak, "Methods for ensuring additivity of biomass components by regression analysis," *The Forestry Chronicle*, vol. 46, no. 5, pp. 402–405, 1970.
- [9] T. Cunia, "On tree biomass tables and regression: some statistical comments," in *Proceedings of the Forest Resource Inventory Workshop*, W. E. Frawer, Ed., pp. 629–642, Colorado State University, Fort Collins, Colo, USA, July 1979.
- [10] T. Cunia and R. D. Briggs, "Forcing additivity of biomass tables: some empirical results," *Canadian Journal of Forest Research*, vol. 14, no. 3, pp. 376–385, 1984.
- [11] T. Cunia and R. D. Briggs, "Forcing additivity of biomass tables: use of the generalized least squares method," *Canadian Journal of Forest Research*, vol. 15, no. 1, pp. 23–28, 1985.
- [12] M. W. Jacobs and T. Cunia, "Use of dummy variables to harmonize tree biomass tables," *Canadian Journal of Forest Research*, vol. 10, no. 4, pp. 483–490, 1980.
- [13] B. R. Parresol, "Additivity of nonlinear biomass equations," *Canadian Journal of Forest Research*, vol. 31, no. 5, pp. 865–878, 2001.
- [14] J. P. Carvalho and B. R. Parresol, "Additivity in tree biomass components of Pyrenean oak (*Quercus pyrenaica* Willd.)," *Forest Ecology and Management*, vol. 179, no. 1–3, pp. 269–276, 2003.
- [15] J. Mantilla and R. Timane, *Orientação para manejo de mcrusse*, SymfoDesign, Maputo, Mozambique, 2005.
- [16] DINAGECA, *Mapa Digital de Uso e Cobertura de Terra*, CENACARTA, Maputo, Mozambique, 1990.
- [17] MAE, *Perfil do Distrito de Chibuto, Província de Gaza*, MAE, Maputo, Mozambique, 2005.
- [18] MAE, *Perfil do Distrito de Mandhlakaze, Província de Gaza*, MAE, Maputo, Mozambique, 2005.
- [19] MAE, *Perfil do Distrito de Panda, Província de Inhambane*, MAE, Maputo, Mozambique, 2005.
- [20] MAE, *Perfil do Distrito de Funhalouro, Província de Inhambane*, MAE, Maputo, Mozambique, 2005.
- [21] MAE, *Perfil do distrito de Mabote, provincia de Inhambane*, MAE, Maputo, Moçambique, 2005.
- [22] FAO, *FAO Map of World Soil Resources*, FAO, Rome, Italy, 2003.
- [23] M.-C. Lambert, C.-H. Ung, and F. Raulier, "Canadian national tree aboveground biomass equations," *Canadian Journal of Forest Research*, vol. 35, no. 8, pp. 1996–2018, 2005.

- [24] B. R. Parresol and C. E. Thomas, "Econometric modeling of sweetgum stem biomass using the IML and SYSLIN procedures," in *Proceedings of the 16th Annual SAS User's Group International Conference*, pp. 694–699, SAS Institute, Cary, NC, USA, 1991.
- [25] G. W. Snedecor and W. G. Cochran, *Statistical Methods*, Iowa State University Press, Ames, Iowa, USA, 8th edition, 1989.
- [26] R. D. Yanai, J. J. Battles, A. D. Richardson, C. A. Blodgett, D. M. Wood, and E. B. Rastetter, "Estimating uncertainty in ecosystem budget calculations," *Ecosystems*, vol. 13, no. 2, pp. 239–248, 2010.
- [27] I. A. Gier, *Forest Mensuration (Fundamentals)*, International Institute for Aerospace Survey and Earth Sciences (ITC), Enschede, The Netherlands, 1992.
- [28] B. Husch, T. W. Beers, and J. A. Kershaw Jr., *Forest Mensuration*, John Wiley & Sons, New York, NY, USA, 4th edition, 2003.
- [29] M. A. M. Brasil, R. A. A. Veiga, and J. L. Timoni, "Erros na determinação da densidade básica da madeira," *CERNE*, vol. 1, no. 1, pp. 55–57, 1994.
- [30] J. Bunster, *Commercial Timbers of Mozambique, Technological Catalogue*, Traforest, Maputo, Mozambique, 2006.
- [31] T. Seifert and S. Seifert, "Modelling and simulation of tree biomass," in *Bioenergy from Wood: Sustainable Production in the Tropics*, T. Seifert, Ed., vol. 26 of *Managing Forest Ecosystems*, pp. 43–65, Springer, Amsterdam, The Netherlands, 2014.
- [32] R Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, 2013.
- [33] SAS Institute, *SAS/ETS User's Guide, Version 8*, SAS Institute, Cary, NC, USA, 1999.
- [34] V. K. Srivastava and D. E. A. Giles, *Seemingly Unrelated Regression Equations Models: Estimation and Inference*, Marcel Dekker, Inc., New York, NY, USA, 1987.
- [35] W. H. Greene, *Econometric Analysis*, Macmillan, New York, NY, USA, 2nd edition, 1989.
- [36] D. Bhattacharya, "Seemingly unrelated regressions with identical regressors: a note," *Economics Letters*, vol. 85, no. 2, pp. 247–255, 2004.
- [37] J. P. Carvalho, "Uso da propriedade da aditividade de componentes de biomassa individual de *Quercus pyrenaica* Willd. com recurso a um sistema de equações não linear," *Silva Lusitana*, vol. 11, pp. 141–152, 2003.
- [38] K. V. Gadov and G. Y. Hui, *Modelling Forest Development*, Kluwer Academic Publishers, Dordrecht, The Netherlands, 1999.
- [39] H. A. Meyer, *A Correction for a Systematic Errors Occurring in the Application of the Logarithmic Volume Equation*, Forestry School Research, State College, Pa, USA, 1941.
- [40] T. M. Magalhães, *Calibration of commercial volume and form factor tables for *Androstachys johnsonii* for Madeiraarte concession in Changanine-Memo villages [M.S. thesis]*, University of Copenhagen, Copenhagen, Denmark, 2008.
- [41] R. Ruiz-Peinado, M. del Rio, and G. Montero, "New models for estimating the carbon sink capacity of Spanish softwood species," *Forest Systems*, vol. 20, no. 1, pp. 176–188, 2011.
- [42] J. J. Nívar-Cháidez, N. G. Barrientos, J. J. G. Luna, V. Dale, and B. Parresol, "Additive biomass equations for pine species of forest plantations of Durango, Mexico," *Madera y Bosques*, vol. 10, no. 2, pp. 17–28, 2004.
- [43] S. M. Salis, M. A. Assis, P. P. Mattos, and A. C. S. Pião, "Estimating the aboveground biomass and wood volume of savanna woodlands in Brazil's Pantanal wetlands based on allometric correlations," *Forest Ecology and Management*, vol. 228, no. 1–3, pp. 61–68, 2006.
- [44] M. T. Ter-Mikaelian and M. D. Korzukhin, "Biomass equations for sixty-five North American tree species," *Forest Ecology and Management*, vol. 97, no. 1, pp. 1–24, 1997.
- [45] P. Schroeder, S. Brown, J. Mo, R. Birdsey, and C. Cieszewski, "Biomass estimation for temperate broadleaf forests of the United States using inventory data," *Forest Science*, vol. 43, no. 3, pp. 424–434, 1997.
- [46] J. D. Pardé, "Forest biomass," *Forest Abstracts*, vol. 41, pp. 343–362, 1980.
- [47] J. Repola, "Biomass equations for birch in Finland," *Silva Fennica*, vol. 42, no. 4, pp. 605–624, 2008.
- [48] T. M. Magalhães and S. J. Soto, *Relatório de Inventário Florestal da Concessão Florestal de Madeiraarte: Bases para a elaboração do plano de manejo de conservação dos recursos naturais*, Departamento de Engenharia Florestal (DEF), Universidade Eduardo Mondlane (UEM), Maputo, Mozambique, 2005.
- [49] S. Moura, D. Abella, and O. Anjos, "Evaluation of wood basic density as an indirect measurement of the volume of wood raw material," in *Proceedings of the Wood Science and Engineering in the Third Millennium (ICWSE '07)*, pp. 72–78, Braşov, Romania, June 2007.
- [50] L. A. Simpson and A. F. M. Barton, "Determination of the fibre saturation point in whole wood using differential scanning calorimetry," *Wood Science and Technology*, vol. 25, no. 4, pp. 301–308, 1991.
- [51] C. R. Sanquetta, A. P. D. Corte, and F. Da Silva, "Biomass expansion factor and root-to-shoot ratio for *Pinus* in Brazil," *Carbon Balance and Management*, vol. 6, article 6, pp. 1–8, 2011.
- [52] P. E. Levy, S. E. Hale, and B. C. Nicoll, "Biomass expansion factors and root: shoot ratios for coniferous tree species in Great Britain," *Forestry*, vol. 77, no. 5, pp. 421–430, 2004.
- [53] N. Soethe, J. Lehmann, and C. Engels, "Root tapering between branching points should be included in fractal root system analysis," *Ecological Modelling*, vol. 207, no. 2–4, pp. 363–366, 2007.
- [54] T. Kallikokoski, P. Nygren, and R. Sievänen, "Coarse root architecture of three boreal tree species growing in mixed stands," *Silva Fennica*, vol. 42, no. 2, pp. 189–210, 2008.
- [55] K. I. Paul, S. H. Roxburgh, J. R. England et al., "Root biomass of carbon plantings in agricultural landscapes of southern Australia: development and testing of allometrics," *Forest Ecology and Management*, vol. 318, pp. 216–227, 2014.
- [56] C. M. Ryan, M. Williams, and J. Grace, "Above- and below-ground carbon stocks in a miombo woodland landscape of mozambique," *Biotropica*, vol. 43, no. 4, pp. 423–432, 2011.
- [57] A. Bolte, T. Rahmann, M. Kuhr, P. Pogoda, D. Murach, and K. V. Gadov, "Relationships between tree dimension and coarse root biomass in mixed stands of European beech (*Fagus sylvatica* L.) and Norway spruce (*Picea abies* [L.] Karst.)," *Plant and Soil*, vol. 264, no. 1–2, pp. 1–11, 2004.
- [58] W. A. Mugasha, T. Eid, O. M. Bollandsås et al., "Allometric models for prediction of above- and belowground biomass of trees in the miombo woodlands of Tanzania," *Forest Ecology and Management*, vol. 310, pp. 87–101, 2013.

- [59] S. Kuyah, J. Dietz, C. Muthuri et al., "Allometric equations for estimating biomass in agricultural landscapes: II. Belowground biomass," *Agriculture, Ecosystems and Environment*, vol. 158, pp. 225–234, 2012.
- [60] K. Niiyama, T. Kajimoto, Y. Matsuura et al., "Estimation of root biomass based on excavation of individual root systems in a primary dipterocarp forest in Pasoh Forest Reserve, Peninsular Malaysia," *Journal of Tropical Ecology*, vol. 26, no. 3, pp. 271–284, 2010.



Hindawi

Submit your manuscripts at
<http://www.hindawi.com>

