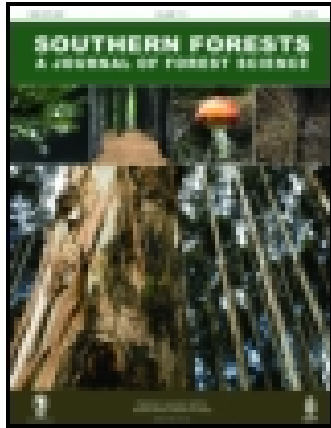


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Biomass equations for selected drought-tolerant eucalypts in South Africa

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In the water-scarce environment of South Africa, drought-tolerant eucalypt species have the potential to contribute to the timber and biomass resource. Biomass functions are a necessary prerequisite to predict yield and carbon sequestration. In this study preliminary biomass models for *Eucalyptus cladocalyx*, *E. gomphocephala* and *E. grandis* × *E. camaldulensis* from the dry West Coast of South Africa were developed. The study was based on 33 trees, which were destructively sampled for biomass components (branchwood, stems, bark and foliage). Simultaneous regression equations based on seemingly unrelated regression were fitted to estimate biomass while ensuring additivity. Models were of the classical allometric form, $\ln(Y) = a + x_1 \ln(\text{dbh}) + x_2 \ln(h)$, of which the best models explained between 70% and 98% of the variation of the predicted biomass quantities. A general model for the pooled data of all species showed a good fit as well as robust model behaviour. The average biomass proportions of the stemwood, bark, branches and foliage were 60%, 6%, 29% and 5%, respectively.

Keywords: additivity, allometry, biomass, *Eucalyptus*, modelling, seemingly unrelated regression

Introduction

South Africa is a water-scarce country with mean annual rainfall of 450 mm (van Wyk et al. 2001; Louw and Smith 2012). Magumba (1998) pointed out that about 21% of the country, especially in the Western Cape region, receives less than 400 mm of rainfall per year and precipitation is received mainly in winter when temperatures are low, resulting in minimal vegetative growth during that period. As a result of water scarcity and the generally dry conditions of South Africa, most of the more suitable land has been allocated to agricultural crop production while forest plantations were established on marginal sites, which have often relatively poor soil and water for growth (Poynton 1979; van Wyk et al. 2001).

A lack of suitable land to support plantations and woodlot establishment led to an exploration for drought-tolerant species (van Wyk et al. 2001) that could supplement the traditionally established species used in woodlots on existing and emerging farms. Different eucalypt species were planted in experimental plots under the Dry Land Industrial and Rural Afforestation Project (DIRAP), with the following objectives: (1) identification and selection of appropriate tree species and provenances, (2) multiplication of selective material by vegetative propagation, (3) determination of the most appropriate methods of plantation establishment and management on marginal sites, and (4) developing an efficient and less intensive management system for various community forestry objectives (Magumba 1998). This trial showed that *Eucalyptus gomphocephala*, *E. cladocalyx* and the hybrid *E. grandis* × *E. camaldulensis*

were superior in drought tolerance and growth rate in the selected environment. Since then, several studies have determined different aspects of tree growth of these species (Magumba 1998; van Wyk et al. 2001; Botman 2010). For example, Botman (2010) conducted a study on the production of woodlots for bioenergy, which revealed that *E. grandis* × *E. camaldulensis* and *E. grandis* × *E. urophylla* were very useful for biomass production.

Forest biomass assessment has become an important issue in the world mainly due to three reasons: (1) climate change and carbon sequestration, (2) determination of ecosystems dynamics, especially growth and yield, and (3) renewable energy as an alternative for fossil fuels (Bettinger and Boston 2009; Dovey 2009; Baishya and Barik 2011; Goicoa et al. 2011; Kitenge 2011; Seifert et al. 2014). Samalca (2007) defined biomass as 'organic material both above and below ground; living and non-living...'. In the following, the focus will be put on phytomass – biomass attached to plants. Below-ground phytomass consists of roots, whereas above-ground biomass includes all living and dead biomass above ground. Kunneke et al. (2014) have summarised ways of biomass resource assessment using terrestrial and airborne methods. Most methods involve ground truthing based on models that have been derived by destructive sampling. Field measurement approaches are the most common method employed in biomass assessment because of their simplicity and the robust data obtained (Chiyenda and Kozak 1984; Samalca 2007; van Laar and Akça 2007; Kunneke et al. 2014).

Biomass models derived from destructive sampling are typically based on regressor variables, such as diameter at breast height (dbh) and tree height (h), to predict complex variables, such as total tree dry weight or biomass compositions (Grundy 1995; van Laar and Akça 2007; Mutakela 2009; FAO 2012; Seifert and Seifert 2014).

The simplest forms of biomass models are transformed linear models, which are fitted by least squares regression for parameter estimation. However, non-linear functions are increasingly common as well (Cunia 1986; Smith 1993; FAO 2012). However, for the benefits of using the linear regression framework, models are often linearised by transforming dependent and independent variables; nevertheless, this generates a biased biomass quantity estimation that needs to be corrected (Verwust 1991; Samalca 2007; Seifert and Seifert 2014).

Despite the existence of different biomass models for eucalypt species, specific models for predicting biomass for the selected drought-tolerant species in South Africa are lacking (Ackerman et al. 2013). No models have so far been established for *E. cladocalyx* or *E. gomphocephala*. Existing biomass equations for *E. grandis* × *E. camaldulensis* (Dye et al. 2004) have been established with data originating from sites that receive much higher average precipitation (1 100–1 300 mm) in a different rainfall regime (summer rainfall areas). It is not clear whether the allometric relations between dbh, h and biomass will remain constant for trees grown in a substantially drier environment.

Thus, the aim of this study was to develop biomass equations to estimate above-ground biomass for the selected drought-tolerant eucalypt genotypes *E. gomphocephala*, *E. cladocalyx*, and *E. grandis* × *E. camaldulensis* grown in a dry winter-rainfall environment. In order to develop reliable equations, particular attention has been paid to the fact that the biomass models should satisfy the additivity property, which means that individual models for biomass components deliver the same result, when all summed as the regression model for the total biomass.

Materials and methods

Study sites

Samples were taken from three sites (Pampoenvlei farm, Chemfos and Coetzenburg) located on the western Atlantic coastline of South Africa in the Western Cape province. Pampoenvlei is located at 33°29' S and 18°23' E, Chemfos at 32°57' S and 18°26' E, while Coetzenburg is situated in the Stellenbosch area at 33°57' S and 18°52' E (Botman 2010; du Toit et al. 2012).

The study sites experience a Mediterranean-type climate with winter rainfall and dry hot summer months. Botman (2010) indicated that Pampoenvlei and Chemfos are classified as semi-arid areas with winter rainfall of less than 400 mm, received between April and August (Table 1). Temperature ranges between 7 °C to more than 35 °C with an aridity index of between 0.20 and 0.50 (du Toit et al. 2012). Coetzenburg is classified as a dry subhumid area because it receives slightly higher rainfall than the other two sites.

The potential natural vegetation covering the study sites is Fynbos (Magumba 1998). Fynbos is dominated

by sclerophyllous scrubs growing up to 3 m in height. Magumba (1998) identified two types of Fynbos: (1) Coastal Fynbos and (2) Coastal Renosterveld. The major plant families represented in these two vegetation types are Proteaceae and Restionaceae, which are influenced by the soil types in their proportional contributions.

The terrain at Pampoenvlei farm and Chemfos is almost flat with a slope of less than 3%, whereas Coetzenburg is located on a slope at Stellenbosch mountain (Botman 2010). Soils at these sites have been classified according to the South African Soil Classification System (SASCS) as Lamotte, Constantia, Fernwood and Kroonstad, which all support normal rooting systems (Magumba 1998; van Wyk et al. 2001). During winter, water tables can be found between 2 and 3 m from the soil surface (Botman 2010).

Methods

Biomass modelling was done as a two-stage upscaling procedure (Seifert and Seifert 2014); in Step 1, the biomass of the components was upscaled from samples to individual tree level, and Step 2 provided models for upscaling from tree to stand level with the help of easily measurable ancillary variables such as dbh and h . The study concentrated on the model development. The upscaling procedure itself, which can be done based on all trees or stand averages (see e.g. Kunneke et al. 2014), was not part of this study.

Field sampling

In order to obtain a representative distribution of tree sizes in the sampling process, trees were sampled from three diameter classes – small, medium and large trees – according to the diameter spectrum prevalent in the experimental plots. The small trees had diameters less than 21 cm, medium class tree diameters were between 21 and 30 cm, whereas the large trees had diameters above 30 cm. A total of 28 trees were sampled from the Pampoenvlei farm and Chemfos. In addition, five small trees with diameters less than 12 cm were sampled from Coetzenburg in order to improve the dbh and h relationship (Kunneke et al. 2014).

Prior to felling, different measurements were taken for each sampled tree, such as dbh, h and crown height. After felling, discs were cut at 0.3 m, 1.3 m, 25% and 60% height, and at 5 cm stem diameter over bark. In order to reconstruct the stem volume more precisely, stem

Table 1: Climatic characteristics of the study sites

Climatic information	Chemfos	Coetzenburg	Pampoenvlei
Mean annual rainfall (mm)	400	735	592
Mean annual temperature (°C)	17.5	17.3	18
Mean maximum of warmest month (°C)	28	28	29
Mean maximum of coldest month (°C)	8	8	8
Mean annual minimum temperature (°C)	11	12	12
Altitude (m asl)	220	250	70
Coordinates	32°57' S, 18°26' E	33°57' S, 18°52' E	33°29' S, 18°23' E

diameters were additionally measured at every metre up to 5 cm stem diameter over bark. The sampling followed routines established by Innventia for comparison of growth and properties of trees of different species and growth conditions (Lundqvist et al. 2013), and the upscaling process was done according to the methodology proposed by Seifert and Seifert (2014).

Reconstruction of crown biomass

Given that not all branches could be measured in the field, a regression-supported sampling and upscaling was employed. Sample branches were collected following a range of different sizes along the stem. A minimum of five branches per tree were sampled for biomass upscaling. These branches were also sampled for leaf and branch biomass (wood and bark combined). Furthermore, the diameters of all the branches were recorded as well as their location on the stem; dead branches were measured separately. The samples were further prepared for drying in the laboratory where the leaves were stripped from the branches. The samples were dried at 60 °C to constant weight. The resulting dry foliage and branch biomass data formed the basis for the regression models that were used to predict total branch biomass of a tree based on all branch diameters.

Stem biomass reconstruction

The biomass of stemwood and bark was determined for each stem section individually by multiplying section volume with the respective basic density of the stem section. The stem volume was reconstructed using Smalian's formula as suggested in Ackerman et al. (2013). Based on piecewise volume determination of the stem measurements, the sample discs were used to derive wood density and bark thickness. Stem diameter under and over bark were measured for all the sample discs in four directions in order to calculate the bark and xylem volume.

Oven-dry weight (at 60 °C) of the stem and bark samples was measured separately. Basic densities for the discs were determined using x-ray-based computer tomography (CT-scanning) following a method proposed by du Plessis et al. (2013). An industrial General Electric L240 micro-CT scanner was used for this purpose at the Department of Forest and Wood Science, Stellenbosch University.

CT-scanning images were then reconstructed in three dimensions. The resulting x-ray attenuation (imaged as grey values) related to absolute material density. Density calibration curves were then constructed based on 13 wood samples of known density (du Plessis et al. 2013) to translate the CT-scanner grey values to density values.

Statistical analysis: fitting biomass models

Biomass models were fitted for the total biomass and the biomass components of trees based on a pooled data set of all species and for each species separately. Data analysis focused mainly on biomass model formulation that ensured additivity. Parresol (2001) and Goicoa et al. (2011) defined additivity as a condition in which the predictions from the biomass component regression sum up to the predictions from the total tree biomass model. The general systems of equation were presented as illustrated in Equations 1 and 2.

$$\text{Linear model: } y_i = a_i + bx_i + e_i \quad (1)$$

$$\text{Log-transformed model: } \ln(y_i) = a_i + b\ln(x_i) + e_i \quad (2)$$

where y_i represent the biomass, a_i and b_i the estimated parameters, x_i represents the independent variables (e.g. dbh, h and crown height), and e_i is the residual error.

An adequate statistical procedure for fitting these systems of equation is simultaneous multivariate regression. Seemingly unrelated regression (SUR) is one form of simultaneous equation fitting that has been proven effective in modelling cross-equation correlation (Srivastava and Gile 1987; Parresol 1999; Cadavez and Henningsen 2011). SUR was performed with the statistical software R using the Systemfit package (R Core Team 2013; Henningsen and Hamann 2013).

All models were tested for basic regression assumptions, such as normality, homogeneity of variance and independence of the data. Normality was tested on the residuals of the regression using the Shapiro–Wilk test, whereas homoscedasticity was evaluated visually on the plots of predicted values against residuals (Ackerman et al. 2013).

The following goodness-of-fit statistics were used for model comparison as suggested in Parresol (1999); (1) degree of determination, also known as fit index (R^2), (2) root mean square error (RMSE) and Akaike's information criterion (AIC). Generally, these models were logarithm-transformed models that need to be back-transformed. However, logarithm-transformation models yield biased biomass quantities in the process of back-transformation (Cunia 1986; Hellman and Fowler 1999; Samalca 2007). In order to correct the bias during back-transformation the error term must be squared and divided by 2 (Equation 3), as pointed out by Seifert and Seifert (2014), based on the work of Sprugel (1983).

$$\exp(\text{biomass}) = \exp(b_0 + b_1(\text{dbh}) + e^2/2) \quad (3)$$

where \exp is the exponential, b_0 and b_1 are estimated parameters, and e is the error (standard deviation) associated with the model.

Results

Tree biomass descriptive statistics

The mean dbh for 33 sampled trees was 25.23 cm and mean height was 15.3 m. *Eucalyptus cladocalyx* had a mean dbh of 29.36 cm, whereas that of *E. gomphocephala* was 20.78 cm and *E. grandis* × *E. camaldulensis* was 27.23 cm (Table 2).

Table 2: Description of sample trees for the biomass study with minimum, mean, maximum values and standard deviation

Species	Variable	Min.	Mean	Max.	SD
<i>E. cladocalyx</i>	dbh (cm)	21.5	29.36	37.1	4.4
	h (m)	13	15.31	18.5	1.7
<i>E. gomphocephala</i>	dbh (cm)	7.2	20.78	32.6	8.1
	h (m)	7.8	12.76	19.4	3.2
<i>E. grandis</i> × <i>E. camaldulensis</i>	dbh (cm)	16.1	27.23	36.5	6.8
	h (m)	12.3	15.41	17.7	1.2

Upscaling of biomass

Table 3 shows the selected branchwood and foliage biomass models, which were developed to upscale branch biomass from branch basal area (ba) and branch diameter (d). These models were used in the upscaling of biomass from the sampled branches to the tree level. In each case, several models were established and the best biomass models were selected to predict biomass for the branches and foliage. Degrees of determination between 0.60 and 0.70 were achieved. Branchwood biomass models fitted the data generally better than foliage biomass models as indicated by the higher R^2 values (Table 4). The best-fitting models were selected based on the AIC with consideration of significance of the full model and all of its estimated parameters.

The distribution of mean biomass for all the components after upscaling to tree level showed that on average stem biomass contributed 62% (CI 95% \pm 2.37) of the pooled biomass, which was the largest percentage as expected (Figure 1). Branches had a percentage of 26% (CI 95% \pm 1.34) and bark contributed 7% (CI 95% \pm 0.56). Foliage had the lowest contribution towards the total biomass with less than 5% (CI 95% \pm 0.34).

Fitted biomass model

In the second modelling step that provided models for

upscaling from the tree to the stand, there was a strong relationship between biomass for each component and the independent variables. The strength of the relationships was confirmed by the Pearson's moment correlation coefficient (r), of which values were in the range of 0.70 to 0.90. Stem biomass had the best relationship with dbh, whereas the relationship between foliage and dbh was not as good as that for other components (Figure 2).

Table 4 shows the final models for each species and a system of pooled models, which included the data from all the three species. In each set of equations, the total biomass model was the best-fitting model as it had the highest R^2 value and the lowest RMSE value. For example, the pooled model had an R^2 value of 0.96, the *E. gomphocephala* total biomass model had an R^2 value of 0.98, that for *E. cladocalyx* had an R^2 value of 0.96 and that for *E. grandis* \times *E. camaldulensis* had an R^2 value of 0.98. Foliage biomass models had the least goodness of fit based on R^2 and RMSE values.

Model goodness of fit

Model goodness of fit and suitability was tested using R^2 , RMSE, significance of the parameters, and by visual assessment of the plot of the residual vs predicted values. The model formulated in this study had high R^2 values

Table 3: Crown upscaling models from sample branch to tree level. B_{bm} = Branch wood biomass, F_{bm} = foliage biomass, ba = branch basal area

Species	Component	Model	R^2
Pooled	Foliage	$F_{bm} = 147.34 + 233874(ba)$	0.70
	Branches	$\ln(B_{bm}) = 2.05 + 10.53\ln(d)$	0.71
<i>E. cladocalyx</i>	Foliage	$F_{bm} = 254.59 + 260150.49(ba)$	0.77
	Branches	$\ln(B_{bm}) = 1.95 + 2.14\ln(d)$	0.81
<i>E. gomphocephala</i>	Foliage	$\ln(F_{bm}) = 1.59 + 1.55\ln(d)$	0.71
	Branches	$\ln(B_{bm}) = 1.92 + 2.02\ln(d)$	0.78
<i>E. grandis</i> \times <i>E. camaldulensis</i>	Foliage	$F_{bm} = 76.28 + 224039.4\ln(d)$	0.62
	Branches	$\ln(B_{bm}) = 2.03 + 2.1\ln(d)$	0.61

Table 4: Final biomass equations according to components and species with bias correction factors (BCF). BK = bark biomass, F = foliage biomass, B = branch wood biomass, S = stem biomass, T = total above-ground tree biomass (all in kg); h = tree height (m); dbh = stem diameter at breast height (cm); RMSE = root mean squared error

Species	Component	Model	R^2	RMSE	BCF
Pooled	Bark	$\ln(Bk) = -3.49 + 0.73\ln(dbh)$	0.92	0.094	0.019
	Foliage	$\ln(F) = -2.36 + 1.58\ln(dbh)$	0.64	0.484	0.019
	Branches	$\ln(B) = -3.62 + 1.47\ln(dbh) - 2.07\ln(h)$	0.88	0.412	0.019
	Stem	$\ln(S) = -5.59 + 2.16\ln(dbh) + 1.48\ln(h)$	0.98	0.155	0.019
	Total	$\ln(T) = -5.59 + 2.16\ln(dbh) + 1.45\ln(h)$	0.96	0.094	0.019
<i>E. cladocalyx</i>	Bark	$\ln(Bk) = 2.81 + 0.23\ln(dbh) - 0.59\ln(h)$	0.77	0.886	0.018
	Foliage	$\ln(F) = -8.58 + 3.45\ln(dbh)$	0.5	0.326	0.018
	Branches	$\ln(B) = -14.62 + 2.07\ln(dbh)$	0.75	0.447	0.018
	Stem	$\ln(S) = -4.73 + 1.802\ln(dbh) + 1.57\ln(h)$	0.95	0.085	0.018
	Total	$\ln(T) = -4.014 + 2.33\ln(dbh) + 0.82\ln(h)$	0.96	0.094	0.018
<i>E. gomphocephala</i>	Bark	$\ln(Bk) = -1.21 + 1.99\ln(dbh)$	0.78	0.27	0.021
	Foliage	$\ln(F) = -0.68 + 1.44\ln(dbh)$	0.78	0.26	0.021
	Branches	$\ln(B) = -4.40 + 5.85\ln(dbh)$	0.6	0.27	0.021
	Stem	$\ln(S) = -4.40 + 5.85\ln(dbh)$	0.85	0.34	0.021
	Total	$\ln(T) = -1.156 + 1.89\ln(dbh) + 0.75\ln(h)$	0.98	0.07	0.021
<i>E. grandis</i> \times <i>E. camaldulensis</i>	Bark	$\ln(Bk) = -3.41 + 0.72\ln(dbh)$	0.93	0.12	0.131
	Foliage	$\ln(F) = -0.68 + 1.44\ln(dbh)$	0.79	0.33	0.131
	Branches	$\ln(B) = -8.94 + 1.45\ln(dbh)$	0.95	0.2	0.131
	Stem	$\ln(S) = -3.86 + 1.73\ln(dbh) + 1.33\ln(h)$	0.97	0.097	0.131
	Total	$\ln(T) = -3.49 + 2.22\ln(dbh) + 0.79\ln(h)$	0.98	0.038	0.131

ranging from 0.70 to 0.98. The goodness of fit was also confirmed by the small RMSE values (Table 4, Figure 4).

The overall models and all of the estimated parameters were significant with smaller p -values ($p < 0.05$). Normality and homoscedasticity assessments indicated no deviation from normality (Shapiro–Wilk test, $p > 0.05$) and no heteroscedasticity pattern was detected in the residual plots as shown in Figure 3 and Figure 4, respectively.

Discussion

Model interpretation

The most common independent variables used in biomass modelling are dbh, d^2h (squared dbh times height) and crown dimensions (Parresol 1999). In addition to these variables, h was also used to improve the model fit.

Grundy (1994) indicated in the study of biomass in Miombo woodlands that dbh and d^2h alone gave high R^2 values of up to 0.90. Further addition of h to the model as a predictor variable resulted in a small improvement of R^2 to 0.96. The same was obvious in the present study, in which the basic independent variables was dbh, whereas h was also used to compliment dbh. However, in most cases, h was observed not to be significant, most likely because of the small sample size (33 trees) and the too small spread of heights within the sampled tree population.

The models formulated in this study explained between 70% and 98% of the variation on biomass, which is comparable to similar studies (e.g. Magalhães and Seifert 2015). The total biomass model had the best fit in most cases followed by the stem biomass model, whereas foliage models showed the least goodness of fit. This is a general observation in biomass modelling because foliage biomass is influenced by many climatic parameters and is known to change over the year (Magumba 1998). In separate studies conducted by Seifert and Müller-Starck (2008), Saint-André et al. (2004) and Zohar and Karschon (1984), similar models were obtained with R^2 values of up to 0.96; however, foliage models had consistently the lowest degrees of determination with R^2 values of about 0.50.

The goodness of fit was confirmed by attaining regression assumptions. Normality was tested on the residual and heteroscedasticity was assessed by plotting the predicted values against the residuals. The plots (Figure 4) did not show any clear noticeable pattern, therefore confirming the uniformity of variance (homoscedasticity). Nevertheless, Samalca (2007) stated that it is common in biomass data to have an increased variance with an increase in tree dimensions. Thus, logarithmic transformation was employed

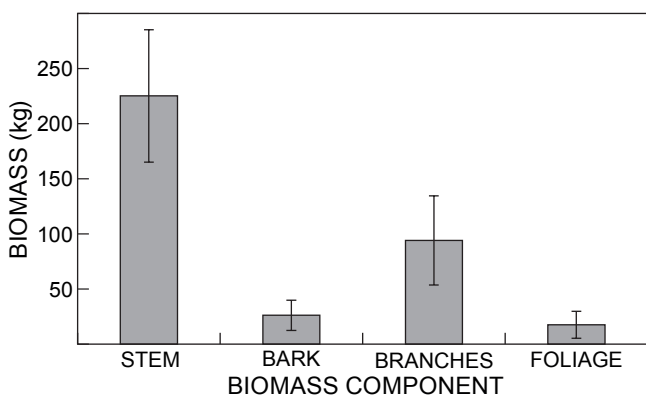


Figure 1: Mean biomass composition according to the biomass components. Error bars represent the SD

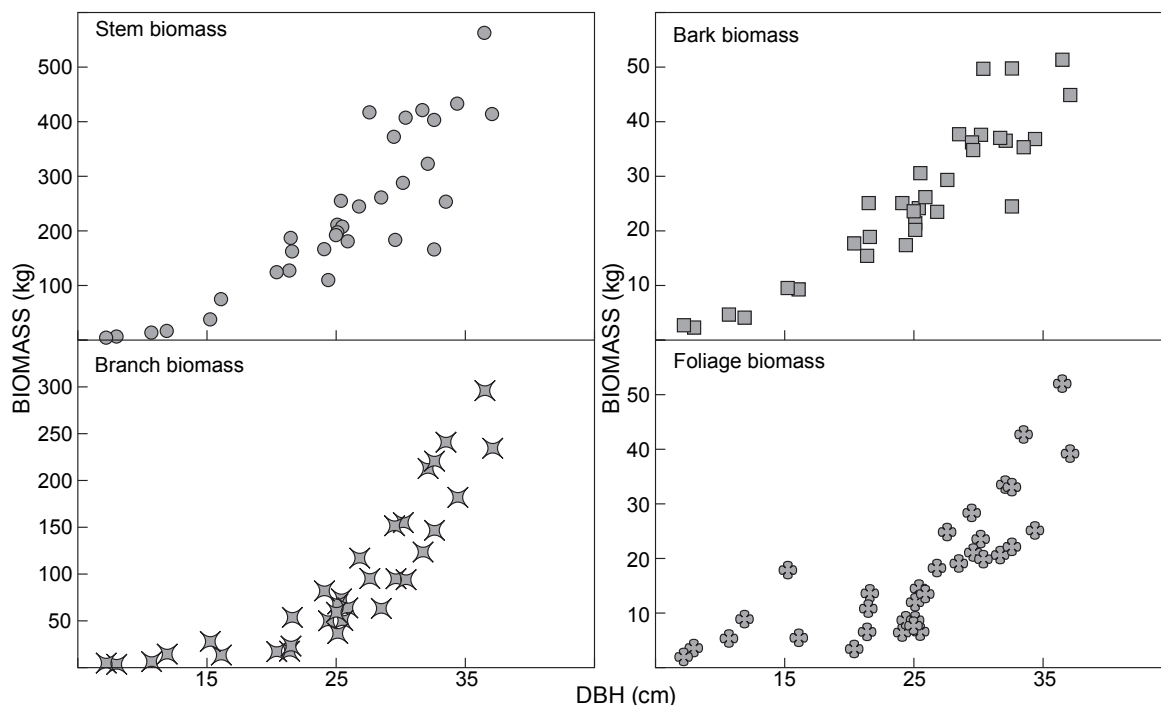


Figure 2: Biomass and diameter at breast height (DBH) relationship for the pooled biomass components

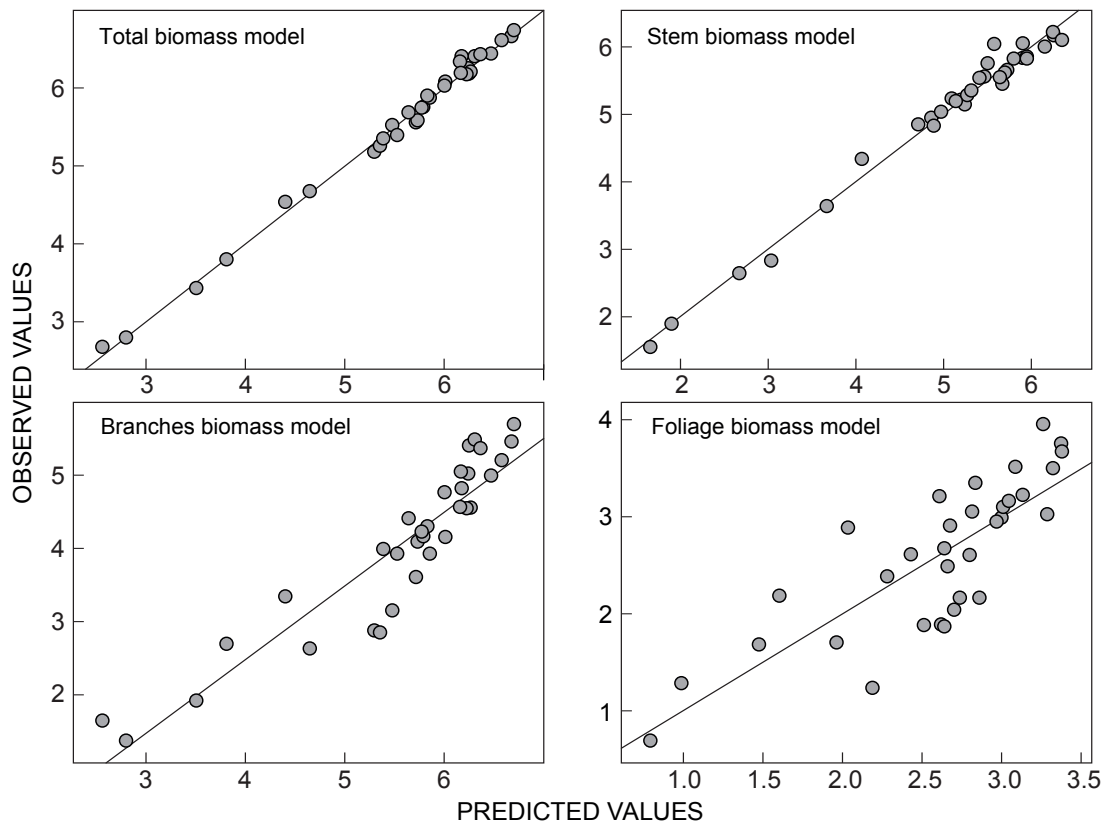


Figure 3: Predicted vs observed values for the pooled biomass models

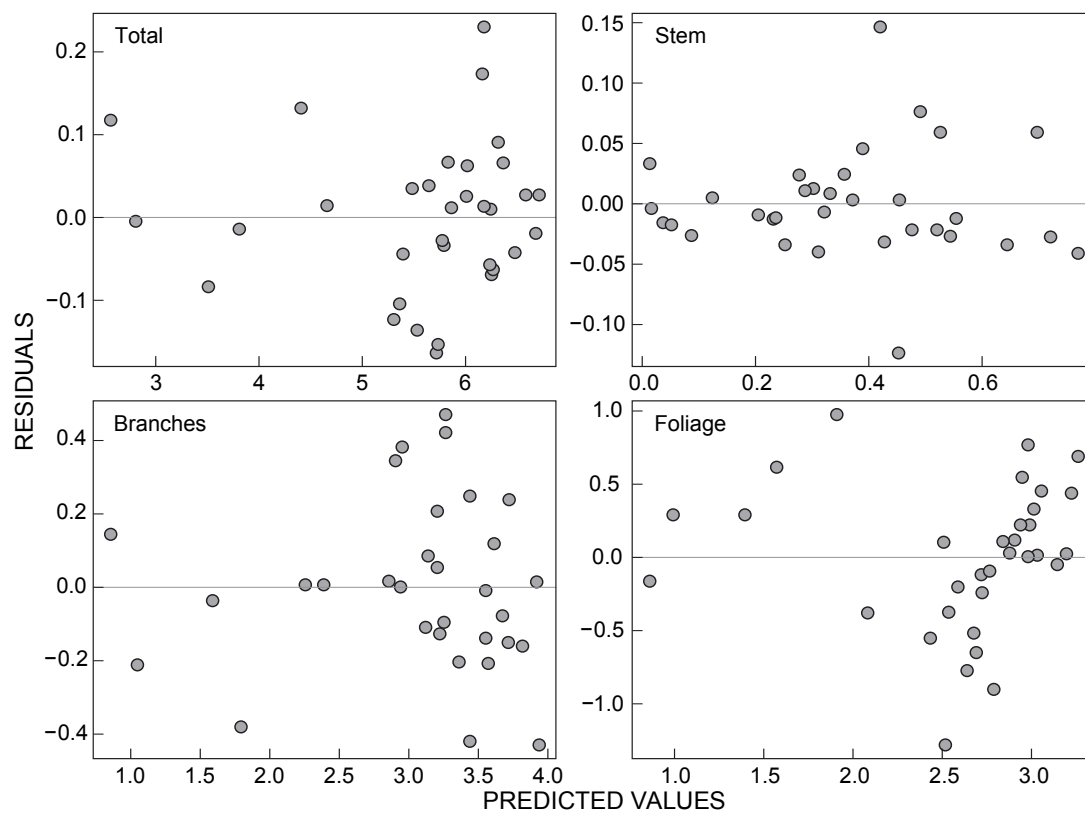


Figure 4: Predicted vs residuals plots for the biomass models

for achieving uniformity of variance in the model as suggested by Sprugel (1983) and Smith (1993).

Application of the model

The models were formulated based on three eucalypt genotypes (*E. cladocalyx*, *E. gomphocephala* and *E. grandis* × *E. camaldulensis*), which have been proven to be drought tolerant on the dry West Coast of South Africa. Hence, application of these models should be confined to these genotypes in conjunction with consideration of the climatic conditions of the sampled sites. This suggests that the models might also be used to predict biomass for genotypes in regions with similar climatic conditions other than the study site. However, this must be done with caution because the number of sampled trees was fairly small. The most robust estimation could be expected from the pooled model (at the cost of losing specificity).

In addition, the models were established on a sample with limited diameter range (7–37 cm), hence extrapolation (predictions outside the range) must not be done otherwise erroneous biomass quantities may be attained, as pointed out by van Zyl (2005). However, as already mentioned before, the models remain preliminary and must be validated against further data.

Conclusions

In this study, sets of equations were developed for the prediction of total and component above-ground biomass of three selected drought-tolerant eucalypts. Five models were formulated for each genotype, which included four models for the biomass components (stem, bark, branches and leaves) and one model predicting total biomass. In addition, another set of five models was parameterised for the pooled data, which included the samples from all the three genotypes.

The tested predictor variables were dbh, d^2h and h . In most cases, dbh was used as the major predictor variable whereas h was included, where significant, to improve the model fit. However, given the limited number of sampled trees ($n = 33$) from only a few even-aged stands in the sample, h was not significant in a number of models. This explains why these models must be considered as preliminary and hence the need to include more trees in future research. The models explained high percentages of variation, which were shown by the R^2 values. The normality and homoscedasticity assumptions were tested and satisfied statistically by the model, while additivity was achieved by using SUR.

This study is the first to establish above-ground biomass models for *E. gomphocephala* and *E. cladocalyx* and the first to fit models for *E. grandis* × *E. camaldulensis* trees growing in very dry winter rainfall conditions. With the necessary caution the models might be used as a baseline for above-ground biomass resource assessment despite the limited sample size in this study.

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References

- Ackerman P, Ham C, Dovey S, du Toit B, de Wet J, Kunneke A, Seifert T, Meincken M, von Doderer C. 2013. The use of forest residues for bioenergy in southern Africa. ICFR Bulletin 03/2013. Pietermaritzburg: Forest Engineering Southern Africa and Institute for Commercial Forestry Research.
- Baishya R, Barik SK. 2011. Estimation of tree biomass, carbon pool and net primary production of an old-growth *Pinus kesiya* Royle ex. Gordon forest in north-eastern India. *Annals of Forest Science* 68: 727–736.
- Bettinger P, Boston K. 2009. *Forest management and planning*. Amsterdam: Elsevier; Boston, MA: Academic Press.
- Botman I. 2010. Production of eucalypt woodlots for bio-energy in the Winelands region of the Western Cape. MSc thesis, Stellenbosch University, South Africa.
- Cadavez VA, Henningsen A. 2011. The use of seemingly unrelated regression (SUR) to predict the carcass composition of lambs. FOI Working Paper 2011/12. Copenhagen: Institute of Food and Resource Economics, University of Copenhagen.
- Chiyenda SS, Kozak A. 1984. Additivity of component biomass regression equations when the underlying model is linear. *Canadian Journal of Forest Research* 14: 441–446.
- Cunia T. 1986. Construction of tree biomass tables by linear regression technique. In: Wharton EN, Cunia T (eds), *Estimating tree biomass regressions and their error*. General Technical Report NE 117. Broomall, PA: US Department of Agriculture, Forest Service, Northeastern Forest Experiment Station. pp 27–37.
- Dovey SB. 2009. Estimating biomass and macronutrient content of some commercially important plantation species in South Africa. *Southern Forests* 71: 245–251.
- du Plessis A, Meincken M, Seifert T. 2013. Quantitative determination of density and mass of polymeric materials using microfocus computed tomography. *Journal of Non-destructive Evaluation* 32: 413–417.
- du Toit B, Botman I, Kunneke A. 2012. Tree-based strategies to mitigate climate change whilst providing bio-energy, employment and ecosystem services in the Winelands region, Western Cape, South Africa. Paper presented at the IUFRO Forest Ecology Symposium: Sustaining Forests and Humans in Changing Landscapes, 5–12 November 2012, Concepción, Chile.
- Dye PJ, Jacobs S, Drew D. 2004. Verification of 3-PG growth and water-use predictions in twelve *Eucalyptus* plantation stands in Zululand, South Africa. *Forest Ecology and Management* 193: 197–218.
- FAO (Food and Agriculture Organization of the United Nations). 2012. *Manual for building tree volume and biomass allometric equations from field measurement to prediction*. Rome: FAO.
- Goicoa T, Militino T, Ugarte H. 2011. Modelling aboveground tree biomass while achieving the additivity property. *Environmental and Ecological Statistics* 18: 367–384.
- Grundy M. 1995. Wood biomass estimation in dry miombo woodland in Zimbabwe. *Forest Ecology and Management* 72: 109–117.
- Henningsen A, Hamann JD. 2013. Systemfit: estimating systems of simultaneous equations. New York: Wiley. Available at <http://cran.rproject.org/web/packages/systemfit/index.html>.
- Hellman JJ, Fowler GW. 1999. Bias, precision, and accuracy of four measures of species richness. *Ecological Applications* 9: 824–834.

- Kitenge EM. 2011. Harvesting of invasive woody vegetation (*Eucalyptus lehmanii*, *Leptospermum laevigatum*, *Acacia cyclops*), as energy feedstock in the Cape Agulhas Plain of South Africa. MSc thesis, Stellenbosch University, South Africa.
- Kunneke A, van Aardt J, Roberts W, Seifert T. 2014. Localisation of biomass. In: Seifert T (ed.), *Bioenergy from wood: sustainable production in the tropics. Managing Forest Ecosystems* vol. 26. Dordrecht: Springer. pp 11–41.
- Louw JH, Smith WC. 2012. Forest site classification. In: Bredenkamp BV, Upfold S (eds), *South African forestry handbook* (5th edn). Pretoria: South African Institute of Forestry. pp 27–41.
- Lundqvist S-O, Grahn T, Olsson L. 2013. Properties of materials from birch – variations and relationships. Part 1: Growth, wood density and biomass. Innventia Report no. 390. Stockholm: Innventia AB.
- Magalhães TM, Seifert T. 2015. Biomass modelling of *Androstachys johnsonii* Prain: a comparison of three methods to enforce additivity. *International Journal of Forestry Research* 2015: Article ID 878402, 17pp.
- Magumba DA. 1998. An eco-physiological study in relation to water use for tree growth of *Eucalyptus camaldulensis* and *E. globulus* on the dry west coast of South Africa. MSc thesis, Stellenbosch University, South Africa.
- Mutakela PS. 2009. Biomass prediction models for *Colophospermum mopane* (mopane) in Botswana. MSc thesis, Stellenbosch University, South Africa.
- Parresol BR. 1999. Assessing tree and stand biomass: a review with examples and critical comparisons. *Canadian Journal of Forest Science* 13: 573–593.
- Parresol BR. 2001. Additivity of nonlinear biomass equations. *Canadian Journal of Forest Resources* 31: 865–878.
- Poynton RJ. 1979. *Tree planting in southern Africa, vol. 2: The eucalypts*. Pretoria: Department of Forestry.
- R Core Team. 2013. R: a language and environment for statistical computing. Vienna: R Foundation for Statistical Computing. Available at <http://www.R-project.org/>.
- Saint-André L, M'Bou AT, Mabilia A, Mouvondy W, Jourdan C, Rouspard O, Deleporte P, Hamel O, Nouvellon Y. 2004. Age-related equations for above- and below-ground biomass of a *Eucalyptus* hybrid in Congo. *Forest Ecology and Management* 205: 199–214.
- Samalca IK. 2007. Estimation of forest biomass and its error: a case in Kalimantan, Indonesia. MSc thesis, International Institute for Geo-Information Science and Earth Observation, Enschede, The Netherlands.
- Seifert T, Müller-Starck G. 2008. Impacts of fructification on biomass production and correlated genetic effects in Norway spruce (*Picea abies* L. [Karst.]). *European Journal of Forest Research* 128: 155–169.
- Seifert T, Ackerman P, Chirwa P, von Doderer C, du Toit B, Görgens J, Ham C, Kunneke A, Meincken M. 2014. Bioenergy from wood in the tropics. In: Seifert T (ed.), *Bioenergy from wood: sustainable production in the tropics. Managing Forest Ecosystems* vol. 26. Dordrecht: Springer. pp 1–10.
- Seifert T, Seifert S. 2014. Modelling and simulation of tree biomass. In: Seifert T (ed.), *Bioenergy from wood: sustainable production in the tropics. Managing Forest Ecosystems* vol. 26. Dordrecht: Springer. pp 42–65.
- Smith RJ. 1993. Logarithmic transformation bias in allometry. *American Journal of Physical Anthropology* 90: 215–228.
- Sprugel DG. 1983. Correcting for bias in log-transformed allometric equations. *Journal of Ecology* 64: 209–210.
- Srivastava VK, Giles DE. 1987. *Seemingly unrelated regression equations models: estimation and inference*. New York: Marcel Decker.
- van Laar A, Akça A. 2007. *Forest mensuration. Managing Forest Ecosystems* vol. 13. Dordrecht: Springer.
- van Wyk G, van Laar A, Theron JM. 2001. Yield potential of selected *Eucalyptus* genetic stock on the sandy soils of the South African Cape West Coast. *Southern African Forestry Journal* 191: 9–19.
- van Zyl L. 2005. Stem form, height and volume models for Teak in Tanzania. MSc thesis, Stellenbosch University, South Africa.
- Verwust T. 1991. Logarithmic transformations in biomass estimation procedures violation of the linearity assumption in regression analysis. *Biomass and Bioenergy* 1: 175–180.
- Zohar Y, Karschon R. 1984. Above-ground biomass of *Eucalyptus camaldulensis* in Israel. *Southern African Forestry Journal* 128: 26–29.