Modeling Compatible Single-Tree Aboveground Biomass Equations of Masson Pine (*Pinus massoniana*) in South China

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Abstract: In the background of facing up to the global climate change, it is becoming the inevitable demand to add forest biomass estimation in national forest resource monitoring. The biomass equations to be developed for forest biomass estimation should be compatible with volume equations. Based on the tree volume and aboveground biomass data of Masson pine (*Pinus Massoniana* Lamb.) in south China, the one, two and three-variable aboveground biomass equations and biomass conversion functions compatible with tree volume equations were constructed using the error-in-variable simultaneous equations in this paper. The results showed: (i) the prediction precision of aboveground biomass estimates from one variable equation was more than 95%; (ii) the regressions of aboveground biomass equations improved slightly when tree height and crown width were used together with diameter on breast height, although the contributions to regressions were statistically significant; (iii) for biomass conversion function on one variable, the conversion factor was decreased with growing diameter, but for conversion function on two variables, the factor was increased with growing diameter while decreased with growing tree height.

Key words: aboveground biomass; error-in-variable simultaneous equations; mean prediction error; compatibility; *Pinus Massoniana*

1 Introduction

Since forest ecosystems play irreplaceable roles in regulating global carbon balance and mitigating global climate change, the forest biomass monitoring is becoming more important all over the world. For implementing the monitoring and assessment of national forest biomass, it is becoming the inevitable demand to develop generalized single-tree biomass models suitable for large scale forest biomass estimation. The stem biomass, which is equal to stem volume multiplying wood density, contributes about 70% of total aboveground biomass of individual tree. Thus, aboveground biomass is highly related to tree volume. The national monitoring for forest volume deriving from tree volume equations have been conducted for several decades, but the national monitoring for forest biomass deriving from tree biomass equations have been implemented for recent years, and even have not been taken in many countries including China (Tomppo *et al*, 2010). Considering the high relationship between biomass and volume, the biomass equations should be compatible with volume equations when forest biomass was added to national forest resources monitoring.

According to the foreign literatures available, the compatibility or additivity between total biomass and biomass components was studied by several researchers (Parresol, 1999, 2001; Bi *et al*, 2004), but study reports about compatibility between biomass and volume equations was not found yet. Hansen (2002) compared and analyzed the consistency and accuracy of volume and biomass estimates in the Forest Inventory and Analysis (FIA) program of the USDA Forest Service, and concluded that various data sources for modeling and different model forms resulted in the inconsistency of the estimates of trees in different locations for the same species with the same size, but the compatibility between biomass and volume equations was not discussed. The domestic studies about compatibility were almost confined to those between total biomass and biomass components (Zhang *et al*, 1999; Xu & Liu, 2001; Xing & Wang, 2007; Cheng *et al*, 2007, 2008). Only a few studies involved the compatibility with volume while considering the additivity between total biomass and biomass component equations (Xu, 1999b; Luo *et al*, 1999; Zeng *et al*, 1999a; Tang *et al*, 2000). However, tree volume was simply regarded as an explainable variable, just like diameter and height, of the biomass equation, and compatible volume equation was not established simultaneously. Thus, the following problems are still existing: (i) volume which was estimated from diameter and height, not measured directly in field survey, is an error-in-variable, not an error-free-variable, so it is improper that volume was regarded as an explainable variable without error in the biomass equation; (ii) a bias will be produced when applying the biomass equation to estimate forest biomass, because the volume was estimated from other volume equation, not from a compatible one; (iii) the parameter estimates may be unstable, because of the self-correlation among diameter, height and volume.

Aiming at solving these problems, the error-in-variable simultaneous equations (Tang *et al*, 2001; Tang & Wang, 2002; Tang & Li, 2002; Tang *et al*, 2008) will be used in this study. Based on the tree volume and aboveground biomass data of Masson pine (*Pinus Massoniana* Lamb.) in south China, one, two and three-variable aboveground biomass equations and biomass conversion functions compatible with tree volume equations will be constructed at first; then the series of aboveground biomass equations will be compared with each other, and the properties of biomass conversion functions with increasing diameter and height will be analyzed.

2 Materials

The data of 150 sample trees used in this study were the aboveground biomass and tree volume measurements of Masson pine in south China, which came from destructive sampling in 2009. The sample trees were located in Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Hunan, Guangdong, and Guizhou provinces and Guangxi autonomous region (about 20^{o}-35^{o} N, 102^{o}-123^{o} E). The number of sample trees was approximately distributed by the proportion to stocking volume of Masson pine forests in the nine provinces or autonomous region. The sample trees were distributed evenly in ten diameter classes of 2, 4, 6, 8, 12, 16, 20, 26, 32cm, and more than 38cm. In addition, the trees in each diameter class were distributed by 3～5 height classes as evenly as possible. Thus, the samples were representative in the large-scale region. Diameter at breast height and crown width of sample trees were measured in the field. After the tree was felled, the total length (tree height) and length of live crown were also measured. The trunk was divided into 11 sections on the points of 0, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 tree height, and the base diameters of all sections were measured from which the tree volume was computed using Smalian's formula. In addition, the fresh weights of stem wood, stem bark, branches, and foliage were measured respectively, and subsamples were selected and weighed in the field. After taken to the laboratory, each subsample was oven dried at 85℃ until a constant weight was reached. According to the ratio of dry weight to fresh weight, each compartment biomass could be computed and the aboveground biomass of the tree was obtained by summation. The general situation of the data is listed in Table 1.

Table 1 The general situation of data used in this study

Statistics	Diameter/cm	Height/m	Crown width/m	Crown length/m	Tree volume/dm^3	Aboveground biomass/kg
Mean	16.6	12.0	4.47	6.24	301.59	169.100
Min	1.5	2.0	0.60	1.30	1.22	0.317
Max	47.2	27.6	12.00	17.52	1825.45	1039.144
S.D.	12.1	7.2	2.55	3.56	175.36	233.739

3 Methods

3.1 Modeling compatible equations

3.1.1 error-in-variable model

For commonly used regression model, it is assumed that observed values of independent variables exclude errors, and observed values of dependent variables include errors. The errors may result from various sources, such as sampling error and observing error, which are called measurement errors in general. When observed values of both independent and dependent variables include measurement errors, the ordinary least squares (OLS) method is no longer adequate, and two-stage error-in-variable modeling method is necessary for fitting the regression model (Tang *et al*, 2001; Tang & Wang, 2002; Tang & Li, 2002). Li *et al* (2004) established compatible growth table and volume table using error-in-variable modeling method; Li & Tang (2006) studied the estimation procedure of the whole stand model with measurement error, and concluded that the simultaneous nonlinear error-in-variable equations method was better than the OLS method.

Multivariate nonlinear error-in-variable simultaneous equations (also called nonlinear error-in-variable model) has the following vector form (Tang *et al*, 2008):

$$\begin{cases} f(y_i, x_i, c)=0 \\ Y_i=y_i+e_i,\ i=1,2,\ldots,n \\ \mathrm{E}(e_i)=0,\ \mathrm{cov}(e_i)=\sigma^2\boldsymbol{\Psi} \end{cases} \quad (1)$$

where x_i are observed values of q-dimensional error-free-variable, Y_i are observed values of p-dimensional error-in-variable, f is m-dimensional vector function, and y_i is the unknown true value of Y_i. The covariance matrix of error e_i denotes as $\boldsymbol{\Phi}=\sigma^2\boldsymbol{\Psi}$, where $\boldsymbol{\Psi}$ is the structure matrix of error e_i, and σ^2 is error of the estimate.

3.1.2 Compatible models

According to the ministerial standard LY208-77 of China, the standard form of two-variable tree volume equation is as follows (Ministry of Agriculture and Forestry of China, 1978):

$$V=a_0D^{a1}H^{a2} \quad (2)$$

where V is tree volume (m^3), D is diameter at breast height 1.3m (cm), H is tree height (m), and a_0, a_1, a_2 are parameters. The nonlinear tree biomass equation is commonly formed as (Parresol, 1999, 2001):

$$M=b_0x_1^{b1}x_2^{b2}\ldots x_i^{bi} \quad (3)$$

where M is aboveground biomass of a single tree, x_i are tree size variables such as D and H, and b_i are model parameters. If only two variables are considered for biomass equation, then model (3) has the same form:

$$M=b_0D^{b1}H^{b2} \quad (4)$$

as model (2). Considering the high relationship between biomass and volume, and according to the study results (Xu, 1999a; Zeng *et al*, 1999a; Luo *et al*, 1999; Tang *et al*, 2000), the regression model on two variables between biomass and volume can be expressed as follows:

$$M=f(D,H)\cdot V=c_0D^{c1}H^{c2}\cdot V \quad (5)$$

where $f(D,H)$ is the conversion function from volume to biomass (also called conversion factor), and c_i are model parameters. Obviously, from models (2), (4) and (5), the following relations can be obtained:

$$c_0=b_0/a_0, \quad c_1=b_1-a_1, \quad c_2=b_2-a_2 \quad (6)$$

It is well known that if models (2), (4) and (5) were estimated independently, the parameter estimates would not meet the needs of expression (6). Therefore, in order to insure the compatibility between aboveground biomass M and tree volume V, a system of nonlinear error-in-variable simultaneous equations based on models (2) and (5) was formed where D and H were regarded as error-free-variables, and V and M as error-in-variables. The parameters of the system were estimated using the two-stage error-in-variable modeling method so that the volume and biomass equations based on the same data sets were compatible with each other, and a compatible conversion function from tree volume to aboveground biomass was also obtained. Acting as for comparison, the regression models on one variable D and three variables D, H and Cw (crown width) were fitted too, which are simply called one-variable model and three-variable model respectively. In addition, to make the conversion values from volume to biomass be harmonious, set the units of biomass M and volume V to be kg and dm^3 ($1/1000m^3$) respectively.

3.1.3 Processing of heteroscedasticity

Biomass and volume data exhibit heteroscedasticity (Luo *et al*, 1992; Zeng, 1996, 1998; Zeng *et al*, 1999b; Zhang *et al*, 1999; Xu, 1999b; Parresol, 1999, 2001), that is, the error variances are not constant over all observations. If models (2) and (5) are fitted to such data, then some countermeasures to eliminate the influences of heteroscedasticity are necessary. The commonly used methods are logarithmic regression and weighted regression (Zeng & Tang, 2011). Here the latter was used for nonlinear models (2) and (5), and the weight function of each model was determined from the regression equation fitted independently by OLS. The fitting results of weighted regression, using the general weight function ($W=1/f(x)^2$) presented by Zeng (1998) and the weight function based on residual errors of the model estimated by OLS independently, were compared with each other which showed that two weights worked well and the latter function was slightly better. Then, the weight functions on one or two variables derived from residual errors of models fitted by OLS were also compared, and the result showed the performance were almost the same. Therefore, the weight functions used in this paper were one variable regression equations, $e^2=g(D)^2$, deriving from residual errors of volume and biomass models fitted by OLS independently, and when using ForStat2.1 (Tang *et al*, 2008) to estimate the parameters by the two-stage error-in-variable modeling method, two sides of the models (2) or (5) were multiplied by the weight factor $G = 1/g(D)$.

3.2 Evaluation and Test of Models

3.2.1 Evaluation of models

Three statistics were used for model evaluation, which are R^2 (determination coefficient), *SEE* (standard error of estimate), and *MPE* (mean prediction error). The R^2, *SEE* and *MPE* are calculated by the following expressions (Parresol, 1999; Zeng *et al*, 1999b):

$$R^2 = 1 - \sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2 \qquad (7)$$

$$SEE = \sqrt{\sum (y_i - \hat{y}_i)^2 / (n-p)} \qquad (8)$$

$$MPE = t_\alpha \cdot (SEE / \bar{y}) \cdot \sqrt{n} \times 100 \qquad (9)$$

where y_i and $\hat{y}_i$ are observed and estimated values of *i*-th sample tree respectively, $\bar{y}$ is sample mean of observed values, n is the number of sample trees, p is the number of parameters, and t_α is the *t*-value for confidence level α with the freedom of n-p (for α=0.05, $t_\alpha \approx 1.98$).

3.2.2 Test of models

Three methods were applied to test the models, which are hypothesis test of mean values for paired data, consistency test of regression models, and significance test of difference between models.

(1) Hypothesis test of mean values

Assuming that the difference between the mean values estimated from two biomass models was zero, that is, let us set H_0: $\mu_1 - \mu_2 = 0$, and take the difference of paired estimates $d = x_1 - x_2$ as a new variable. Then, the statistical index of *t*-value can be calculated as follows (Gao, 2001):

$$t = \frac{\bar{d}}{S_{\bar{d}}} = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\dfrac{\sum (d - \bar{d})^2}{n(n-1)}}} = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\dfrac{\sum d^2 - n\bar{d}^2}{n(n-1)}}} \qquad (10)$$

From the comparison between the *t*-value above and the critical t_a value with degree of freedom n-1, we can determine whether the difference was significant or not between the two biomass models. If *t*-value is larger than t_a, then reject the hypothesis H_0; otherwise, accept it.

(2) Consistency test of regression models

Supposing that the estimates from two biomass models were y and x respectively. If the parameters (a, b) in linear regression equation $y=a+bx$ were not significantly different from (0, 1), then we can conclude that the estimates of two biomass models are very consistent. The statistical index is calculated as follows (Tang *et al*, 2008):

$$F_A = \frac{\frac{1}{2}(a\sum y_i + b\sum x_i y_i - 2\sum x_i y_i + \sum x_i^2)}{\frac{1}{n-2}(\sum y_i^2 - a\sum y_i - b\sum x_i y_i)} \qquad (11)$$

which obey the F-distribution with degrees of freedom $f_1=2$ and $f_2=n-2$. If $F_A>F_{0.05}$, then the two models are significantly different; if $F_A \leqslant F_{0.05}$, then the estimates of two models are almost same.

(3) Significance test of difference between models

The difference between biomass models can be examined by F-test. An F-statistic can be computed and compared with the critical F-value to determine if the estimates are significantly different between the two biomass models (Meng *et al*, 2008):

$$F_B = \frac{(SSE_1 - SSE_2)/(df_1 - df_2)}{SSE_2 / df_2} \qquad (12)$$

where SSE_1 and df_1 are the sum of square error and degree of freedom of model 1 respectively; and SSE_2 and df_2 are the sum of square error and degree of freedom of model 2 respectively.

4 Results

4.1 Compatible biomass equations

Using the tree volume and aboveground biomass data of 150 sample trees for Masson pine in south China, nonlinear error-in-variable simultaneous equations based on one, two and three variables were fitted through ForStat2.1, and applying the parameter estimates to compute the statistics from expressions (7)～(9). The parameter estimates and statistical indices of one, two and three-variable aboveground biomass equations and conversion functions compatible with tree volume are listed in Table 2 and Table 3.

Table 2 Parameter estimates of compatible tree volume and aboveground biomass equations

Models	Parameter estimates										
	Volume equations			Biomass equations				Conversion functions			
	a_0	a_1	a_2	b_0	b_1	b_2	b_3	c_0	c_1	c_2	c_3
One-variable	0.14575	2.46775	/	0.10991	2.37379	/	/	0.75411	-0.09376	/	/
Two-variable	0.085755	1.89740	0.83854	0.078596	2.12525	0.40965	/	0.91652	0.22785	-0.42889	/
Three-variable	0.085419	1.89691	0.84055	0.078495	2.05384	0.43271	0.09221	0.91894	0.15693	-0.40784	0.09221

Note: The weight factors were derived from residual errors of volume and biomass models fitted by OLS independently, which are $1/D^{1.97}$ and $1/D^{2.12}$ respectively for one and two-variable volume equations, and $1/D^{2.28}$, $1/D^{2.12}$ and $1/D^{2.05}$ for one, two and three-variable aboveground biomass equations. It is the same in Table 3.

Table 3 Fit statistics of compatible tree volume and aboveground biomass equations

Models	R^2		*SEE*		*MPE*(%)	
	Volume	Biomass	Volume	Biomass	Volume	Biomass
One-variable	0.9543	0.9559	89.80	49.25	4.81	4.71
Two-variable	0.9844	0.9654	52.59	43.79	2.82	4.19
Three-variable	0.9845	0.9670	52.53	43.88	2.82	4.10

Note: R^2=Determination coefficient, *SEE*=Standard error of estimate, *MPE*=Mean prediction error.

4.2 Test results for comparison between models

Appling the afore-mentioned compatible one, two and three-variable aboveground biomass equations to calculate the statistics of t, F_A and F_B from expressions (10)～(12), and compare them with the critical values for a=0.05 to determine if the differences are statistically significant (see Table 4).

Table 4 Statistics of comparison among compatible aboveground biomass equations

Statistics	Comparison between		
	One and two-variable models	One and three-variable models	Two and three-variable models
t	2.27*	2.33*	0.81
F_A	8.39*	9.07*	1.06
F_B	40.18*	24.62*	7.32*

Note: "*"means significant difference.

5 Discussions

The results in Table 3 show that for one variable models, the R^2 and *MPE* values of tree volume and aboveground biomass equations are not very different, and the R^2 values are both more than 0.95 while the *MPE* values are both less than 5%; for two-variable models, the statistical indices of volume equations improve obviously where *SEE*-value decreases about 41% and *MPE*-value decreases about 2 percentages, while the statistical indices of aboveground biomass equations improve slightly where *SEE*-value decreases about 11% and *MPE*-value decreases only 0.5 percentages. We know that the trunk of a tree can be described approximately as a cone, and the volume is almost a function of diameter and height. However, the aboveground biomass is composed of two major components, stem and crown, which have complementary effect in biomass estimates, that is, for a tree with the same diameter, when stem biomass increases with height, crown biomass decreases, or vice versa. Thus, the aboveground biomass mainly depends upon the size of diameter, which is consistent with the conclusion presented by West *et al* (1997, 1999). In addition, according to the results of another study for compatible equations system of aboveground biomass and components, when biomass models were expanded from one variable to two and three variables, the regression of stem biomass equation improved significantly, but the regressions of aboveground biomass and other components equations improved slightly (Zeng & Tang, 2010). This research achievement confirmed that the analysis above was reasonable.

The results in Table 4 show that both two-variable and three-variable biomass models are significantly different from one-variable biomass model, which means tree height and crown width are effective for improving the prediction precisions of aboveground biomass models. For the comparison between two-variable and three-variable models, statistics of t and F_A show no significant difference, but F_B does show significant difference which means the contribution of crown width to aboveground biomass estimation is statistically significant. The first two statistics are mainly taking the predicted estimates into consideration while the last statistic is mainly considering whether or not the sum of square errors decreases significantly with inclusion of another explainable variable. In summary, the prediction precision of one-variable biomass model is more than 95% which could be applied to estimate forest biomass in large scale region; the prediction precision of two-variable biomass model is only 0.5 percentages higher than that of one-variable model, but the difference is statistically significant; and the prediction of three-variable biomass model is almost the same as that of two-variable model.

Finally, the properties of biomass conversion factor ($CF=M/V$) with increasing diameter and height were analyzed. The change trends of biomass conversion factor for Masson pine in south China with diameter and height are showed in Figure 2 and Figure 3. If to be considered independently, then the conversion factor decreases with increasing diameter or height, and the relationship to height is more close (if power functions were fitted to $CF-D$ and $CF-H$ data sets, then the determination coefficients were 0.0985 and 0.2491 respectively); and if to be considered dependently, then the effect of relationship between D and H could not be ignorable. From the results in Table 2, the parameter c_1 in conversion function on one variable is negative which is consistent with the trend in Figure 2; and the two parameters in conversion function on two variables are offset in some extent where c_1 is positive and c_2 is negative. It is because when tree volumes are the same, the crown biomass of a thin and tall tree such as those in dense forest is less than that of a thick and short tree such as those in sparse forest or isolated trees, then the conversion factor is smaller; and when tree heights are the same, the crown biomass of a large tree is more than that of a small tree, then the conversion factor is larger.

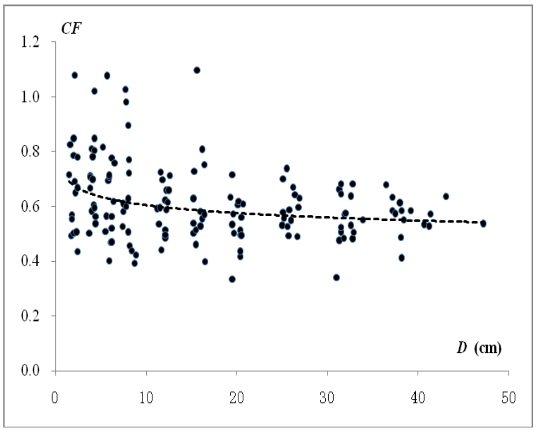

Figure 2 Conversion factor changes with diameter

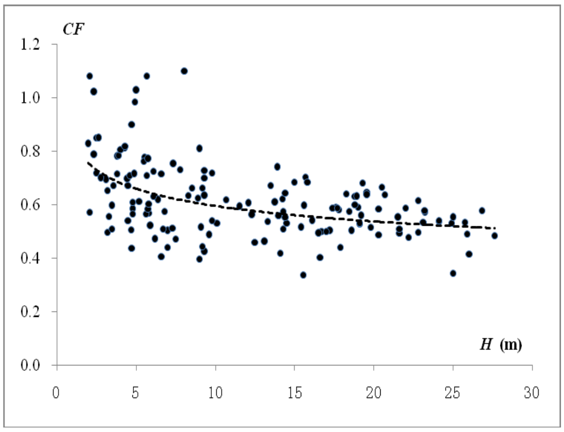

Figure 3 Conversion factor changes with height

6 Conclusions

In this paper, based on the tree volume and aboveground biomass data of Masson pine in south China, the one, two and three-variable aboveground biomass equations and conversion functions compatible with tree volume were established using the error-in-variable simultaneous equations. The tree volume and aboveground biomass equations were fitted simultaneously as a whole, consequently, the equations were highly harmonious and the parameter estimates were relatively stable. The aboveground biomass and tree volume equations can be used independently for estimation of forest biomass and forest volume. If previous volume equations are still applied in forest resource monitoring, then the conversion functions should be used to convert tree volume to aboveground biomass, as a consequence of which, the estimates of forest biomass and forest volume will be coordinated. From this study, it is concluded as follows:

(1) The incongruity between volume and biomass estimates could be effectively resolved using the error-in-variable simultaneous equations. Tree volume and aboveground biomass equations and the conversion function could be established simultaneously so that the three models are compatible with each other.

(2) The comparison results of one, two and three-variable models showed that when tree height and crown width were used as other explainable variables together with diameter, the regression of volume equation improved obviously while the regression of aboveground biomass equations improved slightly.

(3) For one-variable biomass conversion function, conversion factor decreases with growing diameter; and for two-variable biomass conversion function, conversion factor increases with growing diameter but decreases with growing tree height.

(4) From the one-variable compatible equations established in this paper for Masson pine, the prediction precisions of tree volume and aboveground biomass estimates are more than 95%; and from the two-variable compatible equations, the precision of tree volume estimate is more than 97%, but the precision of aboveground biomass estimate is only 0.5 percentages higher than that of one-variable equation.

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