Models for biomass prediction of *Cunninghamia lanceolata* tree and stands in Southeastern China

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Abstract

Large uncertainties still remain when using existing biomass equations to estimate total tree and forest stand scale. In this paper, we develop individual-tree biomass models for Chinese fir (*Cunninghamia lanceolata* （*Lamb.*）*Hook.*) stands in Fujian Province, southeast of China. For this, we used 74 previously established models that are most commonly used to estimate tree biomass, and selected the best fit models and modified it. The results showed the published model with ln(B) (biomass), ln(D) (diameter at breast height), $(\ln(H))^2$, (total height) $(\ln(H))^3$ and ln(WD) (wood density) to be the best fitting model for estimating the tree biomass of Chinese fir. Furthermore, we observed that variables D, H (height), WD significantly correlated with the total tree biomass estimation model, as a result of it portraying the natural logarithm structure to be the best tree biomass structure. Finally, when a multi-step improvement on tree biomass model was performed, the analytic model with TV (tree volume), WD and BECF (biomass wood density conversion factor), achieved the highest accuracy simulation. Therefore, when combined with TV, WD and BECF to tree biomass volume coefficient bi for Chinese fir, the optimal model is the forest stand biomass (SB) estimation model, model with variables of stand volume (SV) and coefficient bi.

Key words: *Cunninghamia lanceolata*, stand, generic models, total tree biomass.

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1Introduction

Forest managers are constantly facing new problems and challenges including climate change, mitigation and adaptation. To meet a variety of ecological demands created by social valuations (Taeroe et al. 2015). In the future, different business deal in forestry, scientific measurements of the value of forest ecological services need to have high precision and forest biomass prediction model is indisputable(Hounzandji et al. 2015, Zeng 2015). In addition to climate change, the development of a regional biomass energy industry, carbon distribution and artificial forests the energy management problems still exist, so the high accuracy of forest stand biomass models is important(Temesgen et al. 2015, Qiu et al. 2015).

The current biomass equations mainly use the following methods, biomass factor method, the outlier growth equation method and the volume source biomass method (R.Ostadhashemi et al 2014). At present many forest biomass estimation models mainly use diameter at breast height (D) to estimate biomass (Jenkins 2003). This method lacks specificity for different tree species and site features and the accuracy of the area measurement is always poor, resulting in high precision on only a small scale (Hailemariam et al 2015).

In different allometric equation methods, Jenkins et al. (2003) have incorporated data from published studies into new biomass estimation equations. In order to adapt to different research purposes, many researchers have performed many trials and modified different models in recent years (Ostadhashemi et al. 2014). In previous researches, Li et al. (2010) and Dimitris et al. (2005) summarized the biomass models with diameter at breast height (D), tree height (H), D^2H and DH as the independent variables. They used a combination of the commonly used power function model, exponential model and the polynomial model to simulate a part of or the whole plant wood biomass. Similarly, Liu et al. (2015) established a relevant analysis of the biomass of the shrub using a new biomass model. Almeida et al. (2014) included the D2 related to the analysis of biomass

With the progress of biomass research and utilization, José established the site index (SI) and forest biomass variable model of stand basal area(José 2015). The study showed that as the objective changed the reliability of the D indicator does not meet the needs of practical forestry estimates (Zheng et al. 2015). Wood density (WD) and stand basal area (G) have become more and more popular. For example, Gurdak et al. (2014) and Sabina et al. (2011) used a combination of D and H and WD, respectively, to establish a logarithmic and an exponential biomass model in combination with these indicators. Timothy et al. (2004) used a fusion variable and established a logarithmic model to estimate the biomass of the Amazon forest. To study the structural relationships between form factor, wood density, and biomass in African savanna woodlands, Matthew et al. (2014) established a variable containing the D, H, WD and G logarithmic combined biomass model

Several studies (Timothy et al. 2004, Matthew et al. 2014, Zou et al. 2015), assert that, within the small area, an increase in the stem biomass, increases the independent variable and the goodness of fit of the model. This results in large-scale forest biomass estimations that consider the use of binary and tertiary biomass models. This is necessary in order to obtain a higher accuracy of the estimates (Zou et al., 2015). Therefore, in view of the different purposes and the actual demand, an increase in the independent variable parameter of the biomass model is meaningful (Zuo et al. 2015). In many cases, however, when the model was used to assess the biomass, the evaluation accuracy of large-scale or small-scale areas was not high, or there was uncertainty or restrictions (Jenkins 2003). For instance, the definition of a forest stand is uncertain at large and small scales. So the selection of either scale leads to uncertainty when selecting a model (Malhi et al., 2006). In order to solve this problem, Zuo et al. (2014) used different biomass estimation parameters to analyze the biomass estimation model of fir forests.Gomez - Garcia et al. (2014) used using D and H as the independent variables to determine 8 parameters in a forest stand biomass model.

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Chinese fir (*Cunninghamia lanceolata* （*Lamb.*）*Hook.*) is one of the most popular plantation timber species in China due to its good timber quality, fast growth, straight stem and high resistance of bending (Guan et al. 2015, Zhao et al. 2009). To evaluate stand biomass for Chinese fir forests at large scale, the model must be extended to the entire stand or planted region for accurate biomass estimation (Pasalodos-Tato et al. 2015). Because the selection of an established forest biomass model may not suit the Chinese fir stand the use of a more reasonable stand variable also needs to be researched (Gomez-Garcia et al. 2015). In few studies for Chinese fir stand biomass it was found that the models based on a large sample of forest biomass had a relatively high accuracy and being able to be applied in large area, whereas the regional models with small sample were limited to small area (Li et al. 2010).

This paper aims at: (1) base on the published biomass models, accurately fitting the total tree biomass (TB) for *Cunninghamia lanceolata* （*Lamb.*）*Hook.* (2)Selected and modified the best tree biomass (TB) model published before for the tree biomass (TB) of *Cunninghamia lanceolata* （*Lamb.*）*Hook* .(3) Base on the best (modified) tree biomass model, calculate the tree biomass (TB) volume coefficient (bi) for *Cunninghamia lanceolata* （*Lamb.*）*Hook.* (4) Model for biomass prediction of *Cunninghamia lanceolata* （*Lamb.*）*Hook.* stands (SB) by tree biomass volume coefficient (bi) and stand volume (SV).

2Materials and methods

2.1Materials

The study area is in Jiangle state-own forest farm located between 117°05′-117°40′E and 26°26′-27° 04′ N, Fujian province, China. The main species of the forest farm are *Cunninghamia lanceolata* （*Lamb.*）*Hook.*, *Pinus massoniana Lamb*, *Phyllostachys heterocycla (Carr.) Mitford cv. Pubescens*. The region is characterized by ferromagnesian (red) soils and has mean annual precipitation of approximately 1699 mm, a mean annual frost-free season of 287 days, and a mean annual temperature of 18.7 ℃. We sampled four regions, which were divided into 35 plots of *Cunninghamia lanceolata* trees and are represented by I, II, III and IV, respectively **(Fig 1).** Established between 2010 and 2014, the plots vary in size from 400 to 600 m^2.

In the plots, we measured the diameters at breast height (DBHs) over the bark (at 1.3 m above ground) of fresh trees (height > 1.3 m) and the total tree height of 35 trees that were felled for stem analysis. Before felling each tree, we measured two attributes: diameter at breast height (1.3 m above ground) and total tree height (H). After felling, we measured the diameter at intervals of 1 meter above the breast height depending on the total tree height by diameter tape. These diameters were measured along the largest axis and smallest axis. Base diameters of all sections were measured at intervals of 1 meter. (1)The fresh masses of stem wood, stem bark, branch, and foliage were measured, and subsamples were selected and weighed in the field. (2)Fresh mass of stem bark was equal to fresh mass of stem or trunk multiplied by bark percent from subsamples. (3) The whole roots were excavated out, and fresh weights of stump (below ground level), coarse roots (more than 10 mm), middle roots(2–10 mm) and small roots (0-2 mm) were measured, respectively, and subsamples were selected (Zeng, 2015).Taking of subsamples for determination of fresh to dry weight ratios (65 ℃). Based on the ratio of dry biomass to fresh biomass, the biomass of stem, bark, foliage and root was calculated and then summed to obtain the total biomass of each tree (TB). Table 1 summarizes the characteristics of the selected trees (Xu et al. 2014).

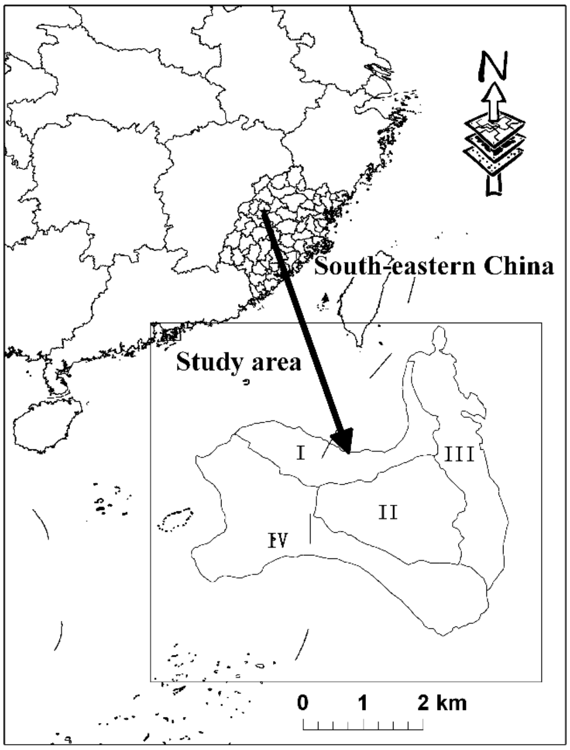

Figure 1: Four sites in Fujian province, Southeast China, where 35 trees were sampled.

Table 1: Mean diameter at breast height (1.3) (D), total height (H), age, BECF (BCEF = BEF * WD, BEF is biomass expansion factor), volume(V), wood density (WD), total tree biomass (TB) for sampled biomass trees.

	D(cm)	H(m)	Age	BECF	V (m^3)	WD	B (kg)
Mean	17.0	15.8	24.4	391.8	0.2655	304.2	107.8
SD	7.3	6.7	9.5	81.4	0.31	59.7	101.3
Minimum	5.1	4.1	6	236.3	0.0060	117.0	4.6
Maximum	38.4	31.8	38	613.8	1.7091	427.1	482.4

2.2Model fitting and evaluation

74 biomass models were selected (Dimitris et al. 2005; Dimitris et al., 2004; Dimitris et al., 2011). The nls (non-linear least squares regression) function was used to fit the equations with R project. Different starting values were used for the parameters to ensure that a global minimum was achieved.

The best function was selected on the basis of four statistical criteria: mean absolute bias (MAB), root mean square error (RMSE), average relative error (ARE) and the adjusted coefficient of determination (R^2) (Zhang 2011). The formulae of these statistics are as follows:

$$MAB = \frac{\sum_{i=1}^{n}\left|(B_i - \hat{B}_i)\right|}{n} \qquad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(B_i - \hat{B}_i)^2}{n-1}} \qquad (2)$$

$$ARE = \sum(\left|(B_i - \hat{B})/B_i\right|)/n*100\,\% \qquad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(B_i - \hat{B}_i)^2}{\sum_{i=1}^{n}(B_i - \overline{B})^2} \qquad (4)$$

Where B_i and $\hat{B}_i$ are the biomass measurements and predictions, respectively; $\overline{B}$ is the average of measurements; n is the data size.

2.3Variable computed

(1)V (volume): Based on taper model, formula (5) was used to calculate the volume of trees (Mei et al. 2015).

$$V = \frac{\Pi}{40000}\int_0^H D^2\left(\frac{(H-h)}{(H-1.3)}\right)^{(3.482321-2.153699*h^{0.007})} dh \qquad (5)$$

where H is the total height, D is the diameter at breast height, h is the height above ground level. Add all the tree volume together as the stand volume, tree-level and stand-level biomass prediction expanded by the stand volume.

(2)BEF (biomass expansion factor): BEF= Aboveground biomass / Trunk biomass (Luo 2014).

(3)WD (wood density): WD=Aboveground biomass/ Stem dry weight (kg*m-3).

(4)BECF (biomass wood density conversion factor): BCEF = BEF * WD (Enes et al., 2014).

(5)Accuracy (%) = (predict value/ measure value)*100%.

3Results

3.1Total tree biomass model

The best method to calculate total tree biomass (include both aboveground and belowground) can be seen from the fitting results (Table 2). Based on the models accuracy evaluation variable analysis, the MAB in model No.1 is the lowest among the candidate models (Fig 2). From the perspective of total statistics, the average relative error (ARE) is of great importance. When comparing the ARE, the ARE of model No.1 is 7.037, model No.2 is 12.623, and model No.3 is 15.931, so the simulation effect of model No.1 is the best.

Table 2. 74 Commonly used biomass models that have been previously published.

No	Model	a	b	c	d	e	MAB	RMSE	R^2
1	$\ln(B)\sim a+b*\ln(D)+c*(\ln(H))^2+d*(\ln(H))^3+e*\ln(WD)$	-5.744	2.480	-0.217	-0.278	0.60	7.675	13.656	0.982
2	$B\sim \exp(a)*(D+1^b*H^c*\exp(d*D)*\exp(e*H)$	-6.104	5.162	-1.340	-0.138	0.10	8.017	11.750	0.987
3	$B\sim \exp(a)*(D+1)^b*H^c*\exp(d*D)$	-6.250	3.389	0.704	-0.064		8.601	12.602	0.985
4	$B\sim a+b*D+c* D^2+d*H+e*D*H$	-2.878	4.827	-0.124	-7.493	0.60	9.892	13.796	0.981
5	$\ln(B)\sim a+b*\ln(D^2*H)+c*\ln(WD)$	-4.720	0.831	0.370			10.007	18.936	0.967
6	$\ln(B)\sim a+b*\ln(D)+c*\ln(WD)$	-5.702	2.546	0.504			10.025	19.425	0.965
7	$\ln(B)\sim a+b*\ln(D)+c*\ln(H)+d*\ln(WD)$	-5.723	2.567	-0.020	0.507		10.095	19.895	0.965
8	$B\sim a+b*D+c* D^2+d*(D^3/H)$	-9.452	-0.808	0.572	-0.171		10.961	14.627	0.979
9	$B\sim a+b*D^2+c*D +d*D*H$	-10.924	-0.696	0.198	0.200		11.029	14.847	0.979
10	$B\sim a+ D^2*b+D*H*c$	-16.477	0.195	0.183			11.130	14.894	0.978
11	$\ln(B)\sim a+(D/(D+10))*b$	-2.411	10.864				11.440	15.666	0.976
12	$\ln(B)\sim a+b*(D/(D+7)+c*H+d*\ln(H))$	-2.785	10.899	0.005	-0.046		11.558	21.683	0.954
13	$\ln(B)\sim a+(D/(D+11))*b+c*\ln(H)$	-2.121	10.451	0.071			11.628	16.219	0.974
14	$B\sim \exp(a+b*\ln(D^2*H))$	-1.823	0.748				11.809	16.116	0.975

15	$B \sim a*(D^2*H)^b$	0.162	0.748				11.809	16.116	0.975
16	$B \sim a*D^b*H^c$	0.171	1.574	0.650			11.943	15.834	0.976
17	ln(B)~a+b*(D/(D+11))	-2.111	10.757				11.970	16.732	0.973
18	$B \sim exp(a)*(D+1)^b*H^c$	-2.050	1.617	0.674			12.316	16.148	0.975
19	$B \sim exp(a+b*ln(D^2*H*G))$	-1.543	0.436				12.455	16.285	0.975
20	$B \sim a+b*H+c*D^2$	-24.870	1.493	0.319			12.669	16.118	0.975
21	ln(B)~a+b*D/(D+13)+c*H+d*ln(H)	-1.582	10.205	0.005	0.040		12.796	21.425	0.955
22	$B \sim a+b*D^2$	-11.692	0.349				12.853	16.582	0.973
23	$B \sim a+b*D^2*H+c*D^2$	-13.130	0.001	0.363			12.940	16.810	0.973
24	$B \sim a+b*D+c*D^2*H$	-48.700	6.542	0.006			12.968	16.736	0.974
25	B~a+b*D^c	-20.336	0.559	1.869			13.007	16.442	0.974
26	ln(B)~a+(D/(D+14))*b+c*ln(H)	-1.499	10.211	0.106			13.028	21.937	0.953
27	ln(B)~a+(D/(D+ 13))*b	-1.643	10.667				13.037	20.706	0.958
28	$B \sim a+b*D+c*D^2$	-23.013	1.314	0.317			13.118	16.628	0.974
29	ln(B)~a+(D/(D+14))*b	-1.456	10.666				13.578	23.191	0.948
30	ln(B)~a+b*D/(D+18)+c*H+d*ln(H)	-1.338	10.419	-0.020	0.360		13.790	23.329	0.947
31	$B \sim a*D^b$	0.245	2.090				14.713	18.004	0.969
32	B~exp(a+b*ln(D)	-1.407	2.090				14.713	18.004	0.969
33	$ln(B) \sim a+b*ln(D)+c*ln(H*D^2)$	-2.821	2.117	0.143			14.812	29.533	0.915
34	ln(B)~a+(D/(D+5))*b	-5.560	13.001				14.864	24.769	0.940
35	$ln(B) \sim a+b*ln(D)+c*H+d*ln(H*D^2)$	-2.794	2.139	0.001	0.130		14.879	30.159	0.911
36	ln(B)~a+b*ln(D)+c*H	-2.676	2.441	0.008			15.654	34.441	0.884
37	ln(B)~a+b*ln(D)	-2.843	2.550				15.682	32.304	0.901
38	ln(B)~a+b*ln(pi*D)	-5.762	2.550				15.682	31.826	0.901
39	ln(B)~a+b*(D/(D+30)+c*H+d*ln(H))	-1.261	11.587	-0.005	0.074		15.714	28.420	0.921
40	ln(B)~a+(D/(D+18))*b	-0.901	10.841				15.877	34.020	0.887
41	$B \sim a*(WD*D^2*H)/1000$	0.054					15.900	35.951	0.878
42	$B \sim a+b*H+c*D^2*H$	-24.710	4.595	0.008			15.983	20.399	0.961

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43	$B\sim a+b*D^{2}*H+c*H^{2}$	1.586	0.007	0.197			15.996	20.989	0.958
44	$B\sim a+b*D+c*(D^{2}*H)^{2}$	-85.590	10.830	0.000			16.618	21.062	0.958
45	$B\sim a+b*H^{2}+c*H^{3}$	0.373	0.155	0.010			20.297	27.868	0.924
46	$B\sim a*H^{b}$	0.061	2.595				20.318	28.225	0.925
47	$B\sim a+b*D+c*H^{2}$	-81.275	7.637	0.200			20.367	26.335	0.934
48	B=aV+b	312.470	24.740				20.502	26.497	0.934
49	$B\sim a+b*D^{2}*H$	27.464	0.011				20.986	27.187	0.930
50	B~a+b*D	-118.191	13.264				22.249	29.696	0.917
51	B~a+b*D+c*H	-115.504	15.366	-2.428			22.285	29.212	0.919
52	$B\sim a*H*D^{2}$	0.013					23.777	34.283	0.886
53	$B\sim a+b*H+c*(D^{2}*H)^{2}$	-64.280	9.985	0.000			25.411	30.737	0.911
54	$B\sim a+b*(1/D^{2}*H)*D^{2}*H$	-23.380	0.445				25.779	31.257	0.905
55	$\ln(B)\sim a+b*\ln(D)^{2}$	0.405	0.484				26.178	81.410	0.355
56	B~a*exp(H*b)	14.665	0.112				26.306	32.099	0.900
57	B~a*exp(b*D)	23.845	0.081				28.721	32.615	0.899
58	$B\sim a*BA^{b}*SI^{c}$	1.067	0.604	1.206			30.605	61.748	0.640
59	ln(B)~ln(a)+b*H	4.070	0.172				34.697	90.892	0.219
60	B~a+b*H	-105.634	13.467				36.505	47.096	0.790
61	B~a+b*ln(D)	-387.080	180.950				37.662	53.784	0.727
62	$B\sim a*\ln(H*D^{2})+b$	58.273	-365.449				38.751	55.563	0.699
63	$B\sim a+b*\ln(D^{2}*H)$	-365.451	58.274				38.751	56.399	0.699
64	B~a+b*ln(H)	-295.080	151.940				45.808	64.782	0.603
65	ln(B)~ln(a)+b*D								
66	$\ln(B)\sim \ln(a)+b*D^{2}*H$								
67	$B\sim(WD/a)*\exp(b*\ln(D)+c*(\ln(D))^{2}+d*(\ln(D)^{3})+e)$					Misconvergence			
68	B~(WD/a)*exp(b*ln(D)+c)								

69	$B \sim exp(a+b*ln(D)+c*(ln(D))^2+d*ln(H)+e*ln(G))$
70	$B \sim a*H^b*(D+1)^{(c+d*ln(D))}$
71	$B \sim a*D^2+(D^2-b)*c$
72	$ln(B) \sim a+b*ln(D)+c*ln(D^2)+d*ln(H)$
73	$B \sim exp(a+b*ln(D))+exp(c+d*ln(D))$
74	$B \sim a+(b*(1/D^2)+c*(1/D^2))*D^2$

Where a, b, c, d, e, f is the model parameters; RMSE, MAD and R^2 is model evaluation index; V is stem volume (m^3); B is the whole tree biomass (kg); D is the diameter at breast height (cm); H is the tree total height (m); G is a basal area (m^2); BCEF is biomass wood density conversion factor, that is, the ratio of aboveground biomass over buck volume ($kg*m^{-3}$); BEF is biomass expansion factor, that is, the ratio of aboveground biomass over trunk biomass, dimensionless; BCEF = BEF * WD (Enes, Fonseca, 2014); WD is wood density, the dry weight per unit volume of wood ($kg*m^{-3}$); Ln is the natural logarithm (Zuo et al. 2014).

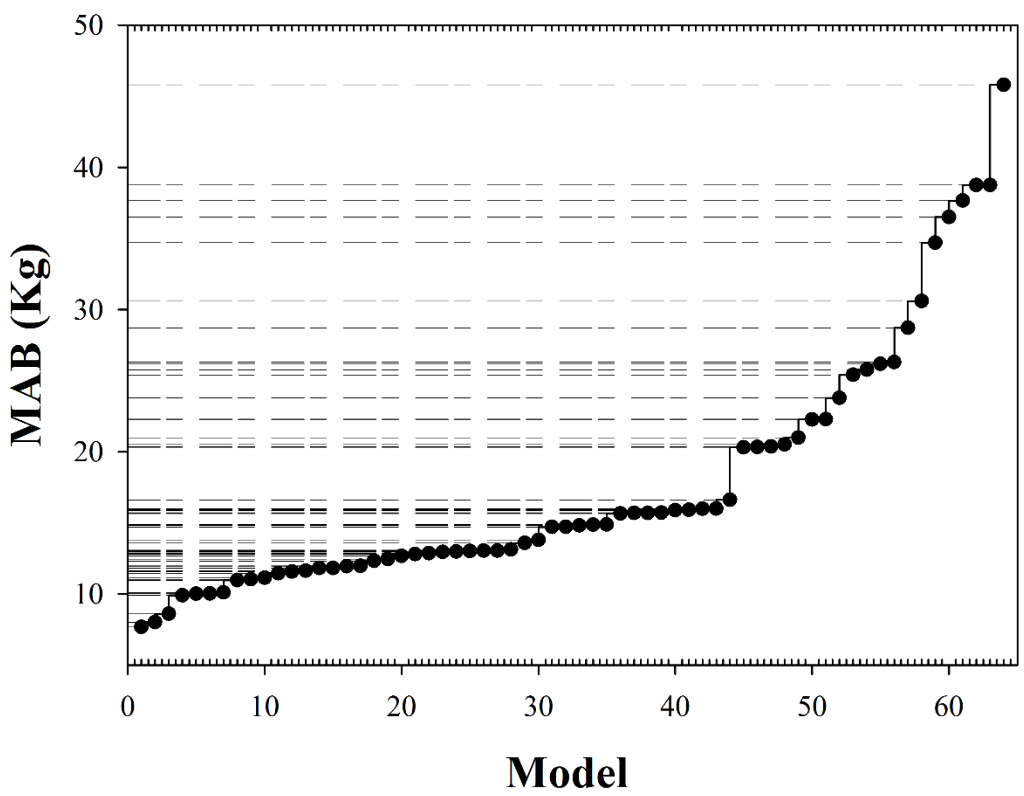


Figure 2: The MAB of 64 convergence biomass models in table 2.

3.2Stand biomass model

(1) Based on the above analysis, the model can be used for the natural logarithms of the mathematical model structure.

(2)The parameters of the model can consider the 3 indices of D, H and WD(Gomez-Garica Esteban et al. 2014, Gurdak et al. 2013).

(3) The size of the trees can be described by the forest measurements D and H, and the D and H are comprehensive statistics for the volume (TV) (André et al. 2015).

(4)According to the (1), (2), and (3) analyses, the improved expression can be written as:

$$\ln (TB) = a + b*\ln(TV)+c*\ln(WD) \quad (75)$$

After an analysis of the fit: a = 3.5743, b = 0.8887, c = 0.4106, MAB = 9.051, RMSE = 16.424, R^2 = 0.975.

A comprehensive comparison of model 5 (with 3 variables) and model 75, under the conditions of the 3 variables model, the evaluation indicates of RMSE and R^2 are similar but the mean absolute bias of model 75 is smaller than model 5 at 0.956. Compared to other model, model 75 has easy measure stand variable and can better explain the biomass, which has an obvious relationship between tree volume and wood density. At this step, the accuracy is less than model 1, model 75 not the best biomass model. So we need keep on modifying model 75.

(5) In analysis (4), model 75 used an expression of V performed very well, as in the Fang's study (Fang 2001), which signifies that a certain type of biomass is closely associated with timber volume ratio (BEF) (Taeroe et al. 2015). The equation BCEF=BEF*WD is combined with model No.75 in accumulation variable BECF (Zuo et al. 2014), thus introducing BECF parameters. That is, model 75 can be further written as:

$$\ln(TB) = a + b*\ln(TV) + c*\ln(WD) + d*\ln(BECF) \quad (76)$$

which is defined as model 76.

After fitting model 76, a = 0.3766, b = 0.9685, c = 0.9365, d = 0.1538, MAB = 4.8483, RMSE = 9.3294, R^2 = 0.992.

(6) The comparative analysis of model 1 and model 76 showed that, after inserting the biomass conversion factor BECF, the MAB dropped to 4.8483, less than model No.1 by 2.8267, the RMSE decreased to 7.09, less than model 1 by 6.566 and R^2 increased by 0.017. Model including the variable of BECF, increasing the accuracy significantly.

(7) Through the above analysis, we can conclude that model 76 is the optimal tree biomass model for Chinese fir, namely:

$$\ln(TB) = 0.3766 + 0.9685*\ln(TV) + 0.9365*\ln(WD) + 0.1538*\ln(BECF) \quad (77)$$

The wood density and conversion coefficient, in combination with a different volume size, can estimate the biomass of a species. From the definition of a forest stand, which can be determined for a tree species, the WD and BECF are consistent (Timothy et al. 2004). Therefore, the unit stand biomss model (bi) can be:

$$bi = \exp(0.3766 + 0.9685*\ln(TV) + 0.9365*\ln(WD) + 0.1538*\ln(BECF)) \quad (78)$$

This paper defined bi as the stand biomass coefficient (Sabina et al. 2011). The stand biomass model can be written as:

$$SB = bi * SV/TV \quad (79)$$

where SV is the stand volume (m^3), SB is stand biomass (kg), TV is the sample tree volume (m^3).

n is defined as n = SV/TV, which can be used to obtain:

$$SB = bi * n \quad (80)$$

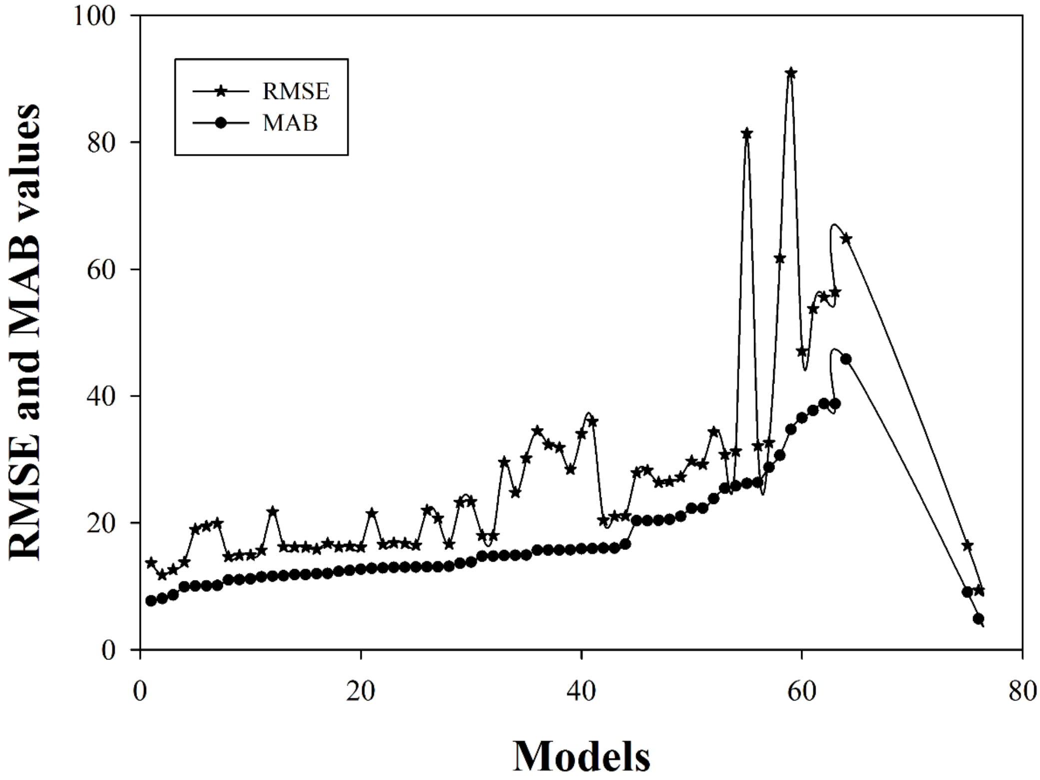
In this new model, the parameter is less than model No.1, making it highly significant in forestry and biology, like a universal biomass model.

4Discussion

In this paper, we used previous research to reconstruct a stand biomass estimation model for Chinese fir. Compared with the best previous biomass model the precision of our model is higher and the absolute bias in the mean is nearly 3 times lower for Chinese fir (Fig 3).

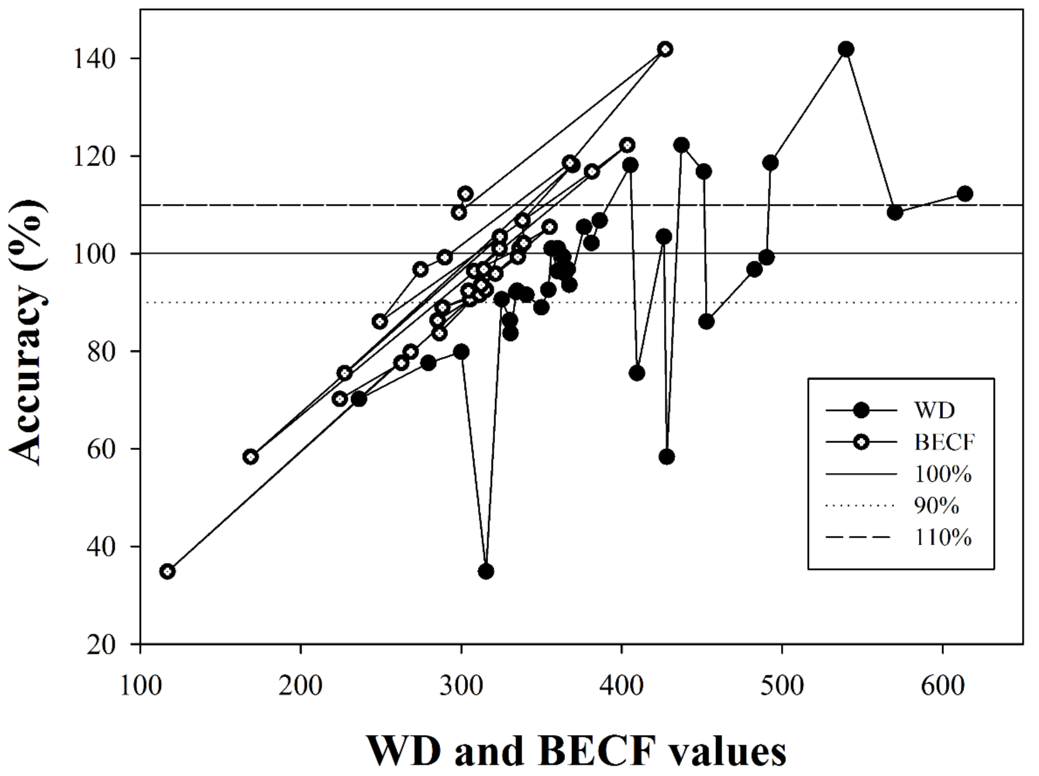
The buck volume, wood density, and biomass wood density conversion coefficient BECF indices are included in the new model. The variable D and H are included in the stock volume estimation variable V, so the model explains the key elements that influence the biomass. At the same time the forest tree total biomass model contains the aboveground and belowground biomass. With the total tree biomass as the dependent variable, the model estimates all biomass components of a tree, which gives the model the advantage of compatibility, it is better than estimate the biomass model using one parts of one tree (Menéndez-Miguélez et al. 2013). In case of Chinese fir biomass estimation model to estimate forest biomass directly the model needs the biomass of all the tree organs or the total diameter at breast height, tree height and basal area. However, this type of estimation not only is incompatible but also has too much variance in the estimations. Based on the single tree volume calculate the tree biomass and stand biomass is a good way.

Over the 35 types of trees, the precision is stable, and the highest accuracy is found in the BECF from 300 to 350, WD from 350 to 400, the accuracy up to 90% (Fig 4). The BECF smaller than 363.49, the estimate value is small the measure value, or it will bigger than measure value (Crecente-Campo 2010). The parameters are easy to obtain, so this method is highly feasible.



251

252 Figure 3: MAB and RMSE values of different biomass estimation models.



253

254 Figure 4: Changes of model accuracy with parameters WD and BECF.

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In a different analysis strategy for a different age structure coefficient of Chinese fir plantations that provides the stand biomass bi, this series of parameters can be used to estimate forest stand biomass for different sized stands. The dynamic stand volume can be combined with the site index and age estimates of growth, and the calculation formula for the stand volume (SV) forecast can be used to perfect the forest biomass estimation model using easy stand measurement variables (Návar, 2015).

Compared to the model Fang published in the journal of Science in which they applied a biomass conversion factor (BEF) for large-scale biomass estimation (Fang, 2001), but in this paper we used the biomass wood density and conversion factor BCEF (BCEF=BEF*WD) to estimate the stand biomass. Because our model also considered density of the wood as variable, our model has the same biological meaning. Using this better estimation variable, the new model established in this paper for small-scale stands can also have a high prediction precision, better scale adaptability, and the ability to use the tree volume of forest management data to calculate the bi of different species.

In this paper, we propose a new forest biomass model: B = bi * n, where bi is the first proposed variable for different tree species. As a new variable parameter, the relationship between bi and stand indicators still needs further in-depth study (Litton et al, 2008).

5Conclusions

Depending on the degree of accuracy pursued, the buck volume (TV), diameter at breast height (D), tree total height (H), biomass wood density conversion factor (BCEF), wood density (WD), and the natural logarithm ln combined together produce the best tree biomass model ln(TB)= a + b*ln(TV) + c*ln(WD) + d*ln(BECF).

We provided the first available models for stand biomass. For different species, it is necessary to calculate the stand biomass coefficient bi first, and then the stand biomass can be estimated easily using the formula SB=bi*n. The model has high precision, and the parameter is less than in model No.1, which makes the model highly significant for

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forestry and tree biology. Higher efficiency of the models, for bi, the BECF from 300 to 350, WD from 350 to 400 trees has high precision in stand biomass estimation, the parameters are easy to obtain, and it is highly feasibly. The model is very useful in evaluating the ecological benefit of forest planning, and can be useful for carbon stock age and sequestration assessments in those fast-growing plantations.

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