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IMPROVING INDIVIDUAL CROWN BIOMASS ESTIMATION BY INCORPORATING COMPETITION FACTORS USING MIXED EFFECT MODELS FOR *PINUS KESIYA*

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Due to the high uncertainty of tree crown biomass modeling, it is crucial to estimate individual tree crown biomass by incorporating competition factors using mixed effect models. The crown biomass of 128 sampling trees was investigated at three typical sites of the natural *Pinus kesiya* forest in Pu'er city of Yunnan province, China. Considering the random effects of the site index and incorporating competition factors, the branch and needle biomass models were constructed using the nonlinear mixed effect model. The results showed that: (1) the mixed effects models, including the fixed effect of competition factors, had a better fitting performance than the ordinary mixed model for branch biomass, however, mixed effects models without the fixed effect of competition factors had the best-fit performance for the needle biomass; (2) mixed effect models incorporating competition factors had better prediction ability because of the highest precision. The increase in accuracy varied from 49.87 to 70.27% for branch biomass and from 66.19 to 66.57% for needle biomass. Mixed-effects models, considering site effect and competition factors, may provide a flexible and powerful tool for individual crown biomass estimation.

Keywords: Crown biomass, mixed-effect model, site quality, competition factors, *Pinus kesiya*

INTRODUCTION

Forest biomass is one of the most basic quantitative characteristics of the forest ecosystem, reflecting the complex relationship between forest matter circulation and energy flow, and an essential element of studying the carbon sequestration ability of the ecosystem and the function of the carbon sink (Chave et al. 2003, West 2009). Forest carbon storage is closely related to its capacity for carbon sequestration, which in turn depends on forest biomass and carbon fraction (Fu et al. 2017a, Courard-Hauri et al. 2016). Generally, the carbon contents of different species are similar. Thus estimating forest biomass has become the most critical issue for estimating forest carbon storage (Zou et al 2015). Furthermore, tree biomass estimates are the basis for forest carbon inventories and estimation, which help to clarify the roles of forests and improve sustainable forest management (Henry et al. 2015, Temesgen et al. 2015). Therefore, accurate forest biomass estimation can provide foundation data for forest carbon inventories and promote further understanding of the carbon cycle of the ecosystems (Fu et al. 2014).

Biomass equations play an essential role in forest carbon estimation in the future (Temesgen et al. 2015). Therefore, research on biomass measurements and estimates will increase in the coming years to meet the needs of carbon storage estimation, and provide a valuable tool to understand the carbon cycle of terrestrial ecosystems (Ou et a1. 2016). Although destructive measurement could gain more accurate biomass data, it is challenging, time-consuming and laborious. Thus, biomass is often assessed using two indirect approaches, i.e., the biomass factor method or biomass models (Somogyi et al. 2007). Many studies have summarised many biomass models based on previous studies, and more than 2600 biomass models have been established worldwide, involving more than 100 tree species (Ter-Mikaelian & Korzukhin 1997, Jenkins et al. 2003). In these models, the most common variables used to estimate biomass are both diameter at breast height (DBH) and tree height (H). Few models have considered the environmental factors into the models. Moreover, biomass models have the worse fitting and prediction performance, especially for the components, except for wood or stem. Thus, it is vital to construct a better estimation by incorporating environmental factors into the models.

Estimation of tree crown biomass is the focus and difficulty of biomass research. On one hand, in terms of the significance of crown biomass estimation, the crown is the main part of the trees for photosynthesis and respiration. Its structure and distribution in stands not only directly determine the individual form, productivity and vitality of trees, but also affect the distribution pattern of populations (Wang et al. 1990, Kramer 1966). At the same time, crown biomass is an essential component of forest biomass and carbon. Crown biomass and its distribution partly affect the productivity of forest ecosystems, which are also vital evaluation indicators of leaves' photosynthetic efficiency (Li 2004). Therefore, it is of great significance to further study crown biomass.

On the other hand, tree biomass is affected by tree size, geographic region, stand origin, crown density and site quality (Fu et al. 2014, Ma et al. 2018). Especially, site quality and competition are two of the most critical factors for tree growth. Competition can affect forest community structure by interacting with biotic and abiotic factors (Sahney et al. 2010). Competition index is important to explain the change in stand structure and is a helpful tool for predicting the development of individual trees (Pukkala & Kolström 1987, Biging & Dobbertin 1995). Many studies have reported that competition significantly affects tree crown characteristics (Hasenauer & Monserud 1996, Gill et al. 2000, Paulo et al. 2002, Fu et al. 2017b). With the increase in stand density, individual trees could be restricted in their crown growth, and even die (Bragg 2001). Crowns grow narrower with stronger competition, thus, crown biomass can be affected by competition (Deleuze et al. 1996). In addition, the site quality of forestland can reflect its capacity to grow trees, and the site index is one of the most commonly used indexes for evaluating site quality (Carmean 1975). Timilsina et al. (2013) found that site index negatively correlated with DBH growth. Wirth et al. (2002) found that site quality effected the distribution pattern of aboveground net primary production for Siberian Scots pine. The biomass model is the most common method to estimate tree crown biomass, leading to more extensive variability in crown biomass measurement and estimation, due to the difficultly of accurate measurement compared with wood or stem of the tree. Thus, considering the effect of competition factors on crown biomass, it is immensely significant to construct high-precision crown biomass models. The forest growth and harvest model is a set of equations describing the law of forest or stand growth. The mixed effect model has been developed rapidly and is widely used in medicine, agriculture, economy, forestry and other fields (Littell et al. 1996). The mixed effects model could reflect not only the average change trend of the overall data but also the individual difference by variance and covariance structures because of inclusion of both fixed and random effects (Yang & Huang 2018). It has advantages over other models in dealing with irregular and unbalanced data and analysing the data's correlation. It also shows flexibility in analysing repeated measurements and longitudinal data and satisfying assumptions (Li 2009).

Meanwhile, the method performs better in fitting and estimating than the ordinary fixed effect model (Zhang & Borders 2004, Fehrmann et al. 2008, Pearce et al. 2010, Fu et al. 2012, 2014). At present, the mixed effect model is widely used in forestry research. However, the research mainly focused on the fundamental tree measurement factors, such as individual tree and stand's tree height variable, diameter and sectional area, volume and accumulation, etc. (Fehrmann et al. 2008, Pearce et al. 2010, Fu et al. 2012, 2014). Moreover, only a few studies have focused on crown biomass. Thus, it is of great significance to construct a high-precision biomass model for estimating and mastering the changing law of biomass of tree crowns.

MATERIALS AND METHODS

Subject investigated

Simao pine (*Pinus kesiya*), a geographic variation of *P. kesiya* in China, is distributed mainly over Southern and Western Yunnan province, and also Laos, Northern and Central Vietnam (Xue & Jiang 1988, Wang et al. 2019). It is the representative species of the southwest mountains of the subtropical zone in China. It is also one of the main afforestation species in Yunnan. Simao pine forest has significant economic, ecological and carbon sink values (Wu & Dang 1992, Wen et al. 2010, Yue & Yang 2011). Simao pine is a particular forest type in Yunnan natural forests. The distribution area and volume account for 11% of the woodland area in Yunnan (Xue & Jiang 1988). Moreover, the mature natural forest has higher stability.

Study sites

Three typical sites in the main distribution area of Simao pine forests were selected (Figure 1). All sites belong to Pu`er city, Yunnan province of Sothern-Western China, and are located at N 22° 02′ to N 24° 50′, E 99° 09′ to E 102° 19′. The altitudes are from 317 m to 3370 m, and the Tropic of Cancer traverses the middle. Due to the influence of the subtropical monsoon climate, there is no frost in most areas, with mild winter and summer, thus, holding the excellent reputation of 'the pearl of the green sea' and 'natural oxygen bar'. The means of annual temperature range from 15 to 20.3 °C, and the yearly gross precipitations range from 1100 mm to 2780 mm (Ou et al. 2015).

Data investigation and measuring

The 128 sample pines in 45 plots located in three sites were selected, cut and investigated. The information of the plots, including latitude, longitude, degree of slope and aspect of slope were recorded, and the tally of each plot was investigated. The average height of dominant trees (H_t) and the average age of stands (A) were calculated to obtain the site index (SI). The sample tree information, including diameter at breast height (DBH), tree height (H), crown length (CL) and crown width (CW) were recorded. Besides, the neighboring trees within 5 meters of the sample trees were measured, and the tree species, their DBH and H, and the distance from the sample trees were recorded. The biomass of the branches and needles was measured one by one. According to Meng (2006), the fresh weight of the branches and needles are measured in three parts according to crown length. Then, the samples were taken to determine the rate of water content according to the different parts. The samples were then taken to a laboratory and put in an oven to dry at 105 °C. Finally, the branch and needle biomass, and the basic statistics of the sampling trees were calculated, as listed in Table 1.

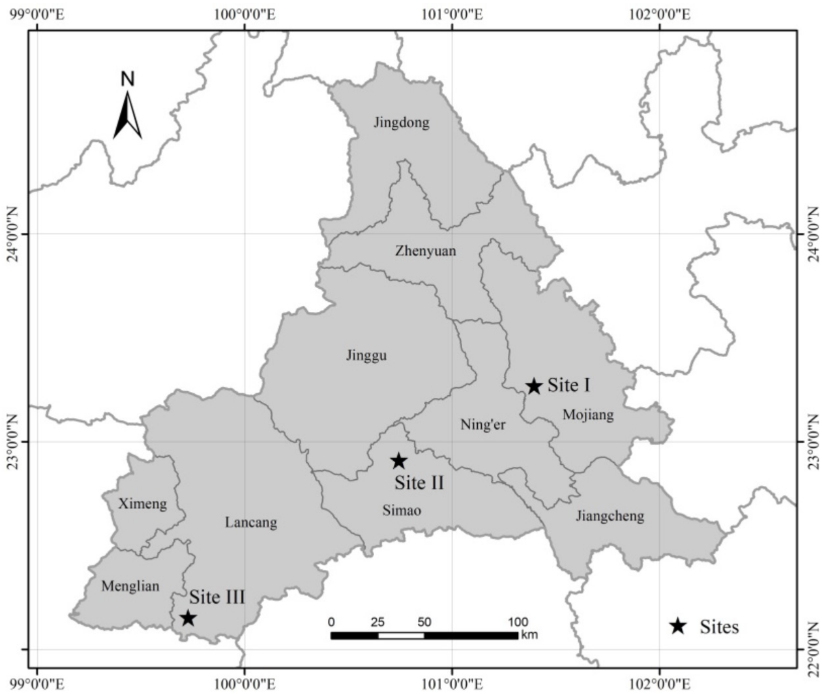

Figure 1 Map of the study sites

Table 1 Basic characteristics of the sampling trees

Variables	Min.	Max.	Mean
Age/a	8.00	82.00	39.46
Diameter at breast height/cm	4.40	58.30	27.20
Tree height/m	6.10	37.00	19.00
Crown length/m	2.30	20.50	9.09
Crown width/m	2.00	19.72	8.34

Data calculation

The site index of each plot was calculated using Equation (1) according to Wang (2003). The competition index of Hegyi was selected to reflect the competition of the sampling trees using Equation (2) (Hegyi 1974).

$$SI = H_t \times \exp\left(\frac{15.46}{A} - \frac{15.46}{20}\right) \quad (1)$$

$$CI_i = \sum_{j=1}^{n}\left(\frac{D_j / D_i}{DIST_{ij}}\right) \quad (2)$$

where SI is the site H_t index, is the average stand height of the dominant trees, and A is the average age of the stand. In this study, the basal age is 20 years, CI_i is the competition index, $DIST_{ij}$ is the distance between tree i to tree j. D_i is the DBH of sample tree, is the DBH of the competition tree j around the sample tree i.

Model fitting

The study selected DBH, H, CL and CW of the sampling trees to construct various models, respectively, and used determination coefficient (R^2) and root mean square error (RMSE) to select the optimal models as the general model (GM) (Table 2). Furthermore, The site effect was determined as a random effect, and the mixed-effects models without the fixed effect of competition factors (MEM) were constructed according to Pinheiro and Bates (2000). Mixed parameters, variance structures (including power and exponential function), and covariance structures (including Gaussian, spherical and exponential function) were selected using S-Plus software. Finally, based on MEM, the mixed-effects models with fixed effect of competition factors (MEMC) were built by incorporating the competition factors of the individual trees, which were regarded as fixed effects and were added to estimating parameters of MEM.

Model evaluation and validation

For the fitting indices, including log likelihood (logLik), Akaike information criterion (AIC) and Bayesian information criterion (BIC) were selected to evaluate their performance, and the formulas are listed in Equation (3)–(5).

$$\text{logLik} = \ln L(\hat{\theta}_L, x) \quad (3)$$

$$AIC = -2 \ln L(\hat{\theta}_L, x) + 2q \quad (4)$$

$$BIC = -2 \ln L(\hat{\theta}_L, x) + q \times \lg n \quad (5)$$

where $\hat{\theta}_L$ is the maximum likelihood estimation of $\hat{\theta}$ for the likelihood function of model $L(\hat{\theta}_L, x)$, x is a random sample, q is the number of the unknown parameter, and n is the number of the sample.

For the model validation, the study selected four indices, such as, sum relative error (RS), mean relative error (EE), mean relative absolute error (RMA) and predict precision (P), to reflect the prediction performance of the models (Ou et al. 2014). The formulas are listed in Equation (6)–(9).

$$RS = \frac{\sum (y_i - \hat{y}_i)}{\sum \hat{y}_i} \times 100\% \quad (6)$$

$$EE = \frac{1}{N}\sum\left(\frac{y_i - \hat{y}_i}{\hat{y}_i}\right) \times 100\% \quad (7)$$

Table 2 Fitting results of parameters of the basic branch and needle biomass models

Model	a	b	c	d	R^2	RMSE
$W_{br} = a \times DBH^b \times H^c$	0.001	4.347	1.514	-	0.814	1772.128
$W_{bl} = a \times DBH^b \times H^c \times (CW^c\,CL)^d$	0.555	1.993	2.053	0.273	0.432	28.792

$$\text{RMA} = \frac{1}{N}\sum\left|\frac{y_i - \hat{y}_i}{\hat{y}_i}\right| \times 100\% \quad (8)$$

$$P = \left[1 - \frac{t_\alpha\sqrt{\sum(y_i - \hat{y}_i)^2}}{\hat{y}_i\sqrt{N(N-T)}}\right] \times 100\% \quad (9)$$

where y_i is the observed value, $\hat{y}_i$ is the predicted value, $\hat{y}_i$ is the mean of the predicted value, t_a is the t value at a confidence level with a = 0.05, N is the number of the sample, T is the parameter numbers of models.

RESULTS

Basic mixed-effects model (MEM)

Fitting results of different parameters combined by **s**electing mixed parameters are listed in Table 3. According to the principle, the smaller the AIC and BIC, the bigger the logLik, which is better. The optimal fitting results emerged when parameter c was regarded as the mixed parameter of the branch biomass model (AIC = 942.9418, BIC = 955.5507, logLik = -466.4709). When parameter d is the mixed parameter, the needle biomass model had the best fitting performance (AIC = 578.1188, BIC = 593.2496, logLik = -283.0594).

The fitting results of covariance structure showed that none can improve the precision of models whether it is spherical, Gaussian or exponential function (Table 4), and covariance structure was not added to both branch and needle biomass models. While considering variance structures, the models had a better fitting with lower AIC and BIC. The optimal fitting results emerged when the power function was regarded as the variance structure for the branch and needle biomass model (Table 4).

Table 3 Mixed parameters selection of the branch and needle biomass models

Components	No.	Mixed parameters	AIC	BIC	logLik
Branch	1	a	956.1888	968.7978	-473.0944
	2	b	944.4905	957.0994	-467.2452
	3	c	942.9418	955.5507	-466.4709
	4	a, b	946.4905	961.6213	-467.2453
	5	a, c	944.9417	960.0724	-466.4708
	6	b, c	944.9417	960.0725	-466.4709
	7	a, b, c	946.9418	964.5944	-466.4709
	8	—	954.1888	964.2760	-473.0944
Needle	1	a	578.1255	593.2562	-283.0627
	2	b	578.1189	593.2496	-283.0595
	3	c	578.1255	593.2562	-283.0627
	4	d	578.1188	593.2496	-283.0594
	5	a, b	580.1189	597.7714	-283.0595
	6	a, c	580.1255	597.7780	-283.0627
	7	a, d	580.1188	597.7714	-283.0594
	8	b, c	580.1189	597.7714	-283.0595
	9	b, d	580.1188	597.7714	-283.0594
	10	c, d	580.1188	597.7714	-283.0594
	11	a, b, c	582.1189	602.2932	-283.0595
	12	a, b, d	582.1188	602.2931	-283.0594
	13	a, c, d	582.1189	602.2932	-283.0594
	14	b, c, d	582.1189	602.2932	-283.0594
	15	a, b, c, d	584.1189	606.8149	-283.0594
	16	—	586.1255	608.7344	-288.0627

logLik = log likelihood

Table 4 Comparison of mixed-effects models with random effects from site index for the branch and needle biomass

Models				Branch			Needle		
No.	Random effects SI	R-Matrix							
		Variance structure	covariance structure	AIC	BIC	logLik	AIC	BIC	logLik
1	No	No	No	954.1888	964.2760	-473.0944	586.1255	608.7344	-288.0627
2	Yes	No	No	942.9418	955.5507	-466.4709	578.1188	593.2496	-283.0594
3	Yes	Power	No	818.2164	833.3471	-403.1082	438.5645	456.2170	-212.2822
4	Yes	Exponential	No	830.3617	845.4924	-409.1808	445.3331	462.9856	-215.6665
5	Yes	No	Gaussian	944.9424	960.0731	-466.4713	580.1193	597.7718	-283.0597
6	Yes	No	Spherical	944.9429	960.0736	-466.4714	580.1201	597.7726	-283.0601
7	Yes	No	Exponential	944.9423	960.0730	-466.4711	580.1191	597.7716	-283.0596
8	Yes	Power	Exponential	820.2004	835.3161	-403.1002	440.5565	458.20633	-212.2782

AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = log likelihood, SI = site index

Mixed-effects model incorporating competition factors (MEMC)

The study took competition factors of an individual tree as fixed effects and added them into estimating parameters of MEM. Different combinations with competition factors were fitted into the models, and both optimal models for branch and needle were selected and listed in Equations (10) and (11):

$$W_{br} = a \times DBH^{b} \times H^{c+uc+c1\times Cl} \quad (10)$$

$$W_{bl} = a \times DBH^{b+b1\times Cl} \times H^{c+uc+c1\times Cl} \times (CW^{2}CL)^{d+uc} \quad (11)$$

where W_{br} is individual branch biomass, W_{bl} is individual needle biomass, DBH is tree diameter at breast height, H is tree height, CW is crown width, CL is crown length and CI is competition index of the individual tree.

Moreover, the branch biomass mixed-effects model with fixed effect of competition factors had a lower value of AIC but had a more significant value of BIC and logLik than MEM, however, the difference was negligible. While, for the needle biomass, the mixed-effects model with fixed effect of competition factors had a significant improvement in model fitting, and it differed significantly from MEM with an excellent fitting result (AIC = 441.4767, BIC = 464.1728, logLik = -211.7383). Furthermore, considering the variance and covariance structures, the appropriate optimal results of the branch biomass model was the model with variance structure of power function and covariance structure of spherical function (AIC = 815.4262, BIC = 835.6005, logLik = -399.7131). The optimal fitting results of the needle biomass model occured when only the power function was considered as variance structure (AIC = 441.4727, BIC = 464.1688, logLik = -211.7363) (Table 5).

Model evaluation

All mixed-effect models were better than a basic model in fit indices (Table 6), and MEMC was the optimal branch biomass model. However, MEM was the optimal for needle biomass. Mixed effect models had a better prediction performance than the basic model for branch biomass because of the lower error indices and higher prediction precision. The BM had lower values of error indices for needle biomass, and the differences among the three models were minor. The MEMC had the highest estimation precision for both branch and needle biomass, and the values were 70.27 and 66.57%, respectively (Table 6). The model parameters and the fitting indices of the basic and mixed effect models for both branch and needle biomass are listed in Table 7.

DISCUSSION

Many studies showed that the mixed-effects modeling approach could obtain a more accurate estimation than traditional approaches, even though only one random effect was considered (Zhang & Borders 2004, Wirth et al. 2004,

Table 5 Comparison of mixed-effects models incorporating competition factor as fixed effect for the branch and needle biomass

Models					Branch			Needle		
No.	Random effects SI	Competition factors	R-Matrix							
			Variance structure	Covariance structure	AIC	BIC	logLik	AIC	BIC	logLik
1	Yes	No	No	No	942.9418	955.5507	66.4709	578.1188	593.2496	283.0594
2	Yes	Yes	No	No	942.8683	955.9991	466.4342	441.4767	464.1728	211.7383
3	Yes	Yes	Power	No	No convergence			441.4727	464.1688	211.7363
4	Yes	Yes	Exponential	No	824.4370	842.0895	405.2185	454.2895	476.9856	218.1447
5	Yes	Yes	No	Gaussian	946.8687	964.5212	66.4343	443.4442	468.6621	211.7221
6	Yes	Yes	No	Spherical	946.8690	964.5215	466.4345	443.4441	468.6619	211.7220
7	Yes	Yes	No	Exponential	946.8688	964.5213	466.4344	443.4444	468.6622	211.7222
8	Yes	Yes	Power	Spherical	815.4262	835.6005	399.7131	443.3073	468.5252	211.6537

AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = log likelihood, SI = site index

Table 6 Model evaluation results for the branch and needle biomass

Indices		Branch			Needle		
		Basic model	Mixed effect model with SI effect	Mixed effect model with SI effect and competition factors	Basic model	Mixed effect model with SI effect	Mixed effect model with SI effect and competition factors
Fitting	AIC	954.1888	818.2164	815.4262	576.1255	438.5645	441.4727
	BIC	964.2760	833.3471	835.6005	588.7344	456.2170	464.1688
	logLik	-473.0944	-403.1082	-399.7131	-283.0627	-212.2822	-211.7363
Validation	RS	46.50	3.08	5.39	10.22	9.13	11.04
	EE	30.45	4.81	4.95	13.61	17.37	23.26
	RMA	64.10	31.00	28.89	53.35	54.08	56.90
	P	49.87	69.27	70.27	66.19	65.73	66.57

AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = log likelihood, SI = site index

Fehrmann et al. 2008). The previous findings were consistent with the results of this study. In this study, it was found that the site quality had been considered as a random effect and incorporated into the model, and the mixed effect models had a better fitting performance than basic models for both branch and needle biomass. It indicated that site quality affects the crown biomass. The findings were similar to the study by Ou et al. (2016) who reported that model fitting can be improved by incorporating random effects with a region or site quality, or both, for the aboveground biomass of the natural Simao pine forest.

Moreover, forest biomass estimation variations can be observed significantly due to different ecological zones and sites, and site quality affects tree growth and distribution that influences aboveground biomass (Alves et al. 2010,). For example, the total biomass of *Nothofagus antarctica* decreased as site quality declined, and the aboveground components (stems and leaves) allocated more biomass in the best sites. Zou et al. (2015) pointed out that modeling crown biomass was significantly different in four pine species growing in different regions in China, and the different site quality may be the cause of it. Thus, site quality greatly determines live tree biomass (de Castilho et al. 2006).

Many studies have shown that aboveground competition strongly affects trees' productivity and reproductive capacity (Nötzold et al. 1997, Pattison et al. 1998, Delucia et al. 1998). On the other hand, plants preferentially allocate biomass to organ harvesting, the most limiting resource according to the 'optimal partitioning' and 'popular biomass allocation' theories (Thornley 1972). The biomass allocation would prefer tree

Table7 Fitting parameters of branch and needle biomass models

Parameters	Branch biomass models of individual tree			Needle biomass models of individual tree		
	Basic model	Mixed effect model with site quality effect	Mixed effect model with site quality effect and competition factors	Basic model	Mixed effect model with site quality effect	Mixed effect model with Site quality effect and competition factors
a	0.0010	0.0842	0.0747	0.5550	0.1720	0.1122
b	4.3470	3.3107	3.2338	1.9930	1.3604	1.4546
b1	-1.5140	-1.5294	—	—	—	0.0044
c	—	—	-1.4239	-2.0530	-1.2612	-1.3153
c1	—	—	0.0006	—	—	-0.0034
d	—	—	—	0.273	0.4199	0.4445
AIC	954.1888	818.2164	815.4262	586.1255	438.5645	441.4727
BIC	964.276	833.3471	835.6005	608.7344	456.217	464.1688
logLik	-473.0944	-403.1082	399.7131	-288.0627	-212.2822	-211.7363
D matrix	—	D = 0.0223	D = 0.0268	—	D = 0.0376	D = 0.0385
Heteroscedastic function value (power function)	—	0.7880	0.9137	—	1.0913	1.0925
Covariance function value	—	—	Range = 1.4962	—	—	—
Residual error	—	1.1018	0.6787	—	0.4679	0.4651

AIC = Akaike information criterion, BIC = Bayesian information criterion, logLik = log likelihood

crowns with little light and tree roots with limited nutrients or water. It indicates that competition may have a meaningful impact on the biomass allocation of trees. Thus, competition would be the critical factor in improving tree crown biomass estimation.

This shows that the mixed-effect model has better fitting performance and adaptability than the traditional model in tree crown biomass estimation. The mixed-effect model can provide a better prediction performance by incorporating random effects (Calama & Montero 2004, Yang & Huang 2011). Fu et al. (2014) also found that the mixed effect model has better adaptation than ordinary least squares models, and fits by considering environment differences. Moreover, a few mixed-effect models incorporated environmental factors (e.g., topographical and climatic factors) to obtain a better fitting (Ou et al. 2016, Fu et al. 2017b). The models incorporating the fixed effect of the competition factor have better prediction ability with higher precision. Especially, for the branch biomass, the prediction accuracy of the mixed models is more than 38.9% higher than that of the basic model. Ou et al. (2014) built the individual branch and needle biomass models of the natural *Pinus kesiya* forests using ordinary least square and geographically weighted regression. The mean relative absolute error of the mixed effect models in this study were lower than the models in the study by Ou et al. (2014). Therefore, it indicates that environmental factors can be used to improve biomass estimation for individual tree crowns. Furthermore, the results were consistent with other studies on tree height, DBH, volume, the dominant height of the stand, stand volume and forest biomass using the mixed effect model (Mehtätalo 2004, Fehrmann et al. 2008, Pearce et al. 2010, Fu et al. 2012, Fu et al. 2014, Ou et al. 2016).

CONCLUSIONS

To obtain accurate models for the individual tree crown biomass, the branch and needle biomass of 128 sampling trees were investigated in natural *Pinus kesiya*. The mixed effect model technology was applied by considering the random effects of the site index and incorporating competition factors. The fitting performance of the crown biomass can be improved by using mixed effect models with random effect of site quality and fixed effect of competition based on basic models. While the prediction precision could be significantly increased for branch biomass, the differences were not apparent for needle biomass. Therefore, the mixed effect models incorporating site effect and competition factors could provide a more accurate estimation for the individual crown biomass.

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