

RESEARCH ARTICLE

Linear Mixed-Effects Models to Describe Individual Tree Crown Width for China-Fir in Fujian Province, Southeast China

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Abstract

A multiple linear model was developed for individual tree crown width of *Cunninghamia lanceolata* (Lamb.) Hook in Fujian province, southeast China. Data were obtained from 55 sample plots of pure China-fir plantation stands. An Ordinary Linear Least Squares (OLS) regression was used to establish the crown width model. To adjust for correlations between observations from the same sample plots, we developed one level linear mixed-effects (LME) models based on the multiple linear model, which take into account the random effects of plots. The best random effects combinations for the LME models were determined by the Akaike's information criterion, the Bayesian information criterion and the -2logarithm likelihood. Heteroscedasticity was reduced by three residual variance functions: the power function, the exponential function and the constant plus power function. The spatial correlation was modeled by three correlation structures: the first-order autoregressive structure [AR(1)], a combination of first-order autoregressive and moving average structures [ARMA(1,1)], and the compound symmetry structure (CS). Then, the LME model was compared to the multiple linear model using the absolute mean residual (AMR), the root mean square error (RMSE), and the adjusted coefficient of determination ($adj-R^2$). For individual tree crown width models, the one level LME model showed the best performance. An independent dataset was used to test the performance of the models and to demonstrate the advantage of calibrating LME models.

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Introduction

China-fir (*Cunninghamia lanceolata* (Lamb.) Hook) is the most commonly grown afforestation species in southeast China because of its fast growth and good wood qualities. It is widely used for buildings, furniture, bridge construction and many other purposes. According to the National Continuous Forest Inventory, approximately 11.26 million hectares and 734.09 million cubic meters of China-fir were distributed over 10 provinces in China in 2010.

Growth and yield models are commonly used for forest management planning because they can simulate stand development and production under various management alternatives [1; 2]. As an important tree variable, the crown width (CW) of individual trees is a fundamental component of forest growth and yield prediction frameworks [3; 4], and it is also crucial for assessing the competitive level, tree vigor, microclimate, biological diversity, mechanical stability, fire susceptibility and behavior under wind stress, amongst other features [5]. The tree crown displays the leaves to capture radiant energy for photosynthesis and is strongly correlated with tree growth [6]. Therefore, measurements of the tree crown are often made to aid the understanding and quantification tree growth [7]. However, it is excessively costly and time consuming to measure the crown width of trees [8; 9]. As a result, it is necessary to establish accurate crown width models for forest managers to predict crown width precisely based on the crown data from adequate numbers of sample trees within different sample plots.

Regression analysis, such as the Ordinary Linear least Squares (*OLS*) regression, is the most commonly used statistical method in forest modeling [10]. Most crown width models are simple linear or nonlinear functions of diameter at breast height (DBH), estimated using linear or nonlinear regression [8; 9]. The fitting data for crown width models are usually collected by measurements of trees within different plots, also known as cross-sectional data [11; 12]. The hierarchical nature of the data results in spatial correlation among measurements made in the same sampling unit (i.e., plot) [13]. However, the hierarchical structure is often ignored and independence of observations is assumed [8–10; 14; 15]. Furthermore, the data are autocorrelated and cannot be considered independent samples of the basic plot population [13]. The *OLS* regression assumption of independent residuals is therefore violated, biasing the estimates of the standard error of the parameter estimates [16].

Linear mixed-effects (*LME*) models that include both fixed-effects and random-effects provide an efficient means of analyzing some kinds of cross-sectional data [17; 18]. The fixed-effects parameters are associated with an entire population or with certain repeatable levels of experimental factors, and the random-effects parameters are related to individual experimental units drawn at random from a population. These parameters account for spatial correlation by defining the covariance structure of the model's random component and by using this structure during parameter estimation. Because of their advantages, *LME* models provide an efficient statistical method for explicitly modeling hierarchical stochastic structure and are increasingly applied to forest growth and yield modeling [19–23]. Use of *LME* models allows the models to be calibrated by predicting random components from plot-level covariates when a new subject is available and is not used in the fitting of the model by using the empirical best linear unbiased predictors (EBLUPs) [22; 24–26].

The main purpose of this research was to develop an individual tree crown width model for *C. lanceolata* in Fujian province, southeast China, on the basis of data derived from 55 sample plots. A one-level (plots effects) linear mixed modeling approach was applied to the hierarchical structure of the data. This diminished the level of variance among the sampling units. Our preliminary analysis showed that the *LME* model effectively removed the heteroscedasticity and spatial correlation in the data and therefore could be an important tool for the sustainable management of China-fir within the study area. The predictive ability of the developed model and the applicability of the *LME* model were demonstrated using separate validation data.

Materials and Methods

Data

The pure China-fir stands are located in Jiangle County (117°05'–117°40'E, 26°26'–27°04'N), Fujian Province, southeast China. The soil type is red soil, the average annual precipitation is

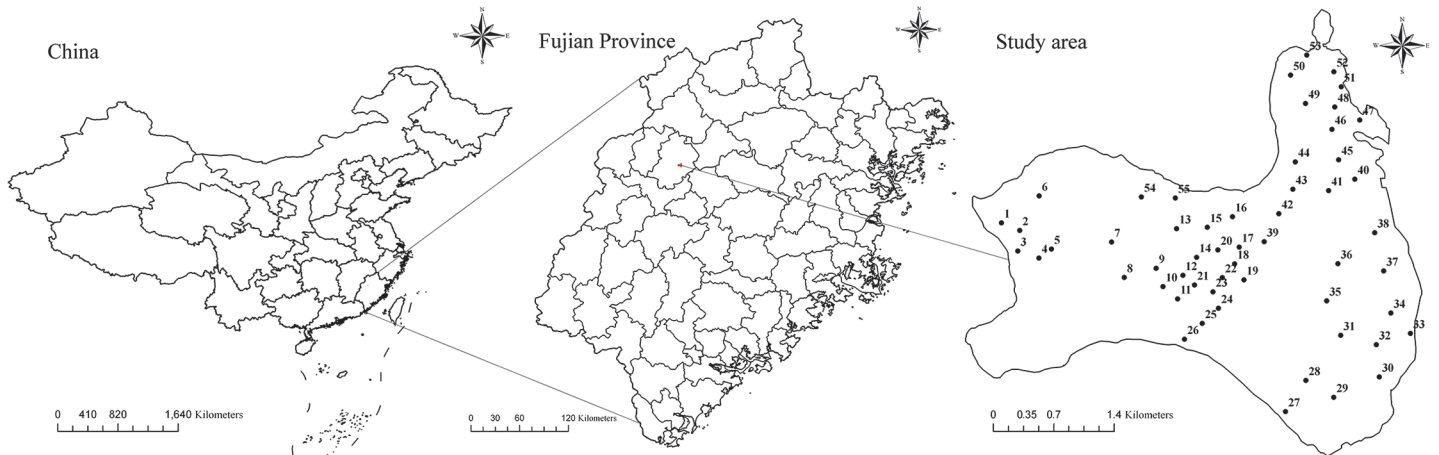


Fig 1. Fifty-five sample plots of pure China-fir plantation stands.

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approximately 1699 mm, the annual mean frost-free season is 287 days, and the annual mean temperature is 18.7°C.

Data from four thousand one hundred ninety-nine trees were obtained from 55 single-species plots of plantation-grown China-fir on the Jiangle state-owned forest farm in Fujian Province, southeast China (Fig 1). The Jiangle state-owned forest farm issued permission for each location, and the field studies did not involve endangered or protected species. The sample plots were square and varied in size from 400 to 600 m². All standing live trees (height > 1.3 m) on the plots were measured for DBH (outside bark), tree height, height to crown base (height above ground to crown base) and crown width. Three to five dominant trees on each plot were chosen to calculate plot dominant height and diameter. Crown width was taken as the arithmetic mean of two crown widths, obtained from measurements of four crown radii in four directions (from the east, west, south and north to the center of tree, respectively) representing two perpendicular azimuths [8]. The crown width data were randomly divided into two groups; 75% of the points were used for model fitting, and 25% were used for model validation, which can be claimed as independent. The fitting and validation data consisted of 2587 trees from 39 plots and 1613 trees from 16 plots, respectively. Summary statistics for both the fitting and validation data are shown in Table 1. The crown data are graphically depicted in Fig 2.

Methods

The covariate selection. DBH is an important tree characteristic and the variable that has the greatest correlation with crown width [27]. In addition to DBH, CW is explained by other tree and stand attributes, [9; 28] such as a reduction in growth from increases in stand density, SD (tree ha⁻¹) and basal area, BA (m²·ha⁻¹) [22; 29]. In addition, CW is also influenced by tree size variables, such as sample tree height (H) and height to crown base (HCB), and stand variables, such as stand age (A), plot dominant height, DH (m), plot dominant diameter at breast height, DD (cm), plot quadratic mean diameter, QMD (cm) [28; 30; 31], plot mean height, MH (m), and site index, SI (m at 20 yr).

Crown width multiple linear model. Independent variables were identified and a backward stepwise linear regression routine that started with all candidate variables, tested the deletion of each variable using a chosen model comparison criterion, deleted the variable (if any) whose removal improved the model the most, and repeated this process until no further improvement was possible, was applied to reduce the number of chosen variables to avoid

Table 1. Summary statistics for increments datasets.

Variables	Fitting data				Validation data			
	Mean	Min	Max	sd	Mean	Min	Max	sd
CW (m)	2.53	0.4	7.4	0.95	2.42	0.3	8.2	0.93
DBH (cm)	14.44	2.0	44.4	6.75	13.54	1.5	44.2	5.84
H (m)	13.36	1.2	36.5	5.56	12.11	1.3	30.8	5.35
HCB (m)	7.68	0.1	21.5	4.08	6.98	0.3	19.8	4.52
DH (m)	18.01	6.9	30.3	4.93	15.78	6.5	26.2	5.78
DD (cm)	21.43	8.0	38.6	5.13	20.43	10.1	36.0	6.88
A (yr)	22.63	7.0	49.0	9.43	18.10	5.0	40.0	8.73
SI (m at 20 years)	17.13	12.0	24.0	3.69	16.89	12.0	22.0	2.86
SD (trees ha ⁻¹)	2311	617	4500	1044.85	2862	467	4400	907.91
QMD (cm)	15.03	4.8	25.2	4.64	13.80	9.9	26.9	3.50
MH (m)	14.01	4.2	21.3	4.00	12.06	5.0	21.4	4.25
BA (m ² ·ha ⁻¹).	29.54	3.4	68.0	16.11	42.4	16.9	99.82	20.11

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overfitting. Variance inflation factors (VIF<10), which provide an index that measures how much the variance of an estimated regression coefficient is increased because of collinearity, were also computed to reduce the number of chosen variables to avoid multicollinearity, which could result in numerically unstable estimates of the regression coefficients. Stepwise regression fits an observed dependent dataset using a linear combination of independent variables. The statistical methods were implemented in R, which is a free software environment for statistical computing and graphics [32]. The dependent variable is determined from a linear equation combining the values of the independent dataset with coefficients established by the regression. The statistical results were assessed in terms of the absolute mean residual (AMR), root mean square error (RMSE), and the adjusted coefficient of determination (adj-R²), which accounts for the number of predictors. The calculation formulas of these statistics are listed as follows:

$$AMR = \sum_{i=1}^M \sum_{j=1}^{n_i} \frac{|y_{ij} - \hat{y}_{ij}|}{n_i} \quad 1$$

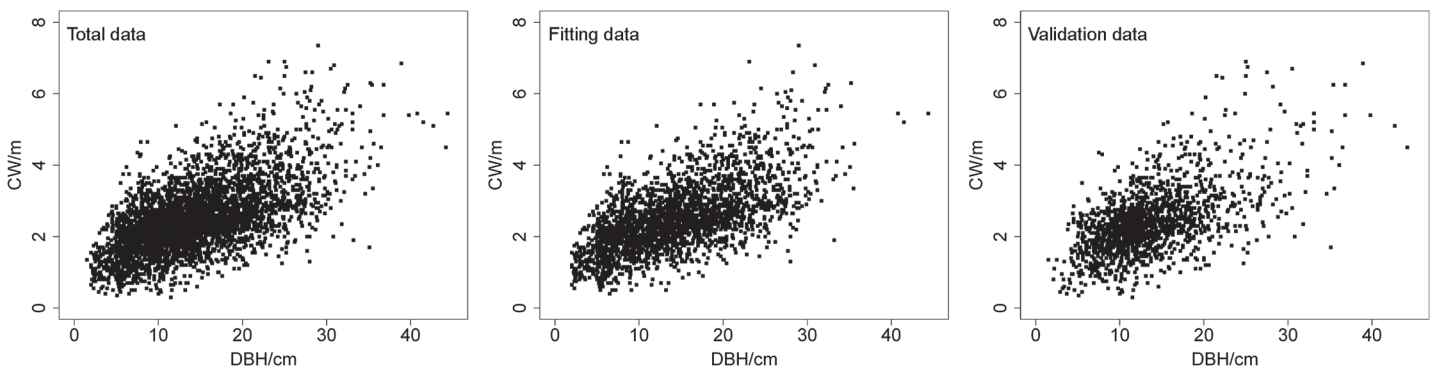


Fig 2. Plots of crown width against DBH for China-fir.

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$$RMSE = \sqrt{\sum_{i=1}^M \sum_{j=1}^{n_i} \frac{(y_{ij} - \hat{y}_{ij})^2}{n_i - r}} \tag{2}$$

$$adj-R^2 = 1 - (n_{ij} - 1) \frac{\sum_{i=1}^M \sum_{j=1}^{n_i} \frac{(y_{ij} - \hat{y}_{ij})^2}{n_i - r}}{\sum_{i=1}^M \sum_{j=1}^{n_i} (y_{ij} - \bar{y})^2} \tag{3}$$

where M is the number of plots, n_i is the number of observations in plot i , r is the number of parameters in the model, y_{ij} is the crown width of the j th tree taken from the i th plot, \hat{y}_{ij} is the crown width prediction, and \bar{y} is the average of observations. The accuracy of the models was tested against the fitting data and against independent validation data from the same plot [23].

LME model method. Available data were from measurements of trees located in sample plots. Because of this nested structure, there is high correlation among observations taken from the same plot. To alleviate this issue, a linear mixed-effects model approach has been proposed by other authors [10; 33]. For a single level of grouping, a general expression for a LME model can be defined as [17; 20; 34]:

$$\begin{aligned} CW_{ij} &= X_{ij}\beta + Z_{ij}b_{ij} + \epsilon_{ij}, \quad i = 1, \dots, M, \quad j = 1, \dots, n_i \\ b_{ij} &\sim N(0, D), \quad \epsilon_{ij} \sim N(0, R_{ij}) \end{aligned} \tag{4}$$

where CW_{ij} is the crown width of the j th tree taken from the i th plot, β is the p -dimensional vector of fixed effects (where p is the number of fixed-effects parameters in the model), b_{ij} is the q -dimensional vector of random effects associated with plot i that is assumed to follow a normal distribution with mean zero and a variance-covariance matrix D (where q is the number of random-effects parameters in the model), X_{ij} (of size $n_i \times p$) and Z_i (of size $n_i \times q$) are known fixed-effects and random-effects regressor matrices, and ϵ_{ij} is the n_i -dimensional within-group error vector with a spherical Gaussian distribution [35], which is assumed to be normally distributed with zero expectation and a positive-definite variance-covariance structure R_{ij} , generally is a $n_i \times 1$ vector for the residual items $[e_{i1}, e_{i2}, e_{i3}, \dots, e_{ij}, \dots, e_{in_i}]^T$ [36]. Both the random-effects b_{ij} and the within-group errors ϵ_{ij} are assumed to be independent for different groups and to be independent of each other for the same group.

Ascertainment of mixed parameters. To fit the mixed-effects models, the key question is which parameters in the model should be considered as random effects and which ones could be treated as purely fixed effects. Generally, an alternative model-building approach is to start with a model with random effects for all parameters and then examine the fitted object to decide which, if any, of the random effects can be eliminated from the model [18]. Therefore, different combinations of model parameters were tested to ascertain their importance with respect to crown width, and the best model was selected by Akaike’s information criterion (AIC) [37], Bayesian information criterion (BIC) [38] and -2 logarithm likelihood (-2 LL) [31]. The less criteria a model has, the better it performs. An appropriate variance function structure for LME models were determined by a likelihood ratio test (LRT) [18; 39]. All LME models presented in this paper were fitted using the LME function in the R statistical software environment.

Determining the structure of R. This special matrix structure R (which is allowed to depend on both random and fixed effects, as well as on a set of common but unknown parameters) can include both correlation effects and weighting factors to account for within-group

heteroscedasticity and spatial correlation [35; 36; 40]. A general expression for the matrix is given by [40; 41]:

$$\mathbf{R} = \sigma^2 \mathbf{G}^{0.5} \mathbf{I} \mathbf{G}^{0.5} \tag{5}$$

where (in this case) for tree j in plot i , with n_i increment, \mathbf{R} is the $n_i \times n_i$ intraindividual variance-covariance matrix which defines within-group variability, \mathbf{G} is a $n_i \times n_i$ diagonal matrix of the within-group error variance structure (heteroscedasticity), \mathbf{I} is a $n_i \times n_i$ matrix showing the within-group autocorrelation structure of error, and σ^2 is a scaling factor for the error dispersion [10]. To remove variance heterogeneity, we used the power function, exponential function and constant plus power function as the variance functions to fit crown width models [18].

$$V(\epsilon_{ij}) = \sigma^2 \text{DBH}_{ij}^{2\delta} \tag{6}$$

$$V(\epsilon_{ij}) = \sigma^2 \exp(2\delta \text{DBH}_{ij}) \tag{7}$$

$$V(\epsilon_{ij}) = \sigma^2 (\delta_1 + \text{DBH}_{ij}^{\delta_2})^2 \tag{8}$$

Correlation structures were used to address the within-tree spatial correlations observed in the data [42; 43]. A method was selected from among three commonly used approaches: the first-order autoregressive structure [AR(1)], a combination of first-order autoregressive and moving average structures [ARMA(1,1)], and the compound symmetry structure (CS) [18].

$$\mathbf{AR}(1) = \sigma^2 \begin{bmatrix} 1 & \rho & \rho^2 \\ \rho & 1 & \rho \\ \rho^2 & \rho & 1 \end{bmatrix} \tag{9}$$

$$\mathbf{ARMA}(1, 1) = \sigma^2 \begin{bmatrix} 1 & \gamma & \gamma\rho \\ \gamma & 1 & \gamma \\ \gamma\rho & \gamma & 1 \end{bmatrix} \tag{10}$$

$$\mathbf{CS} = \begin{bmatrix} \sigma^2 + \sigma_1 & \sigma_1 & \sigma_1 \\ \sigma_1 & \sigma^2 + \sigma_1 & \sigma_1 \\ \sigma_1 & \sigma_1 & \sigma^2 + \sigma_1 \end{bmatrix} \tag{11}$$

where ρ is the autoregressive parameter, γ is a moving average component, and σ_1 is the residual covariance [44; 45].

Parameter estimation. The parameters in the equations were estimated by maximum likelihood (ML) using the Lindstrom and Bates (LB) algorithm implemented in the R *LME* function [17; 18]. The LB algorithm and *LME* function are detailed in several articles; see, for example, [17; 18].

A key question in fitting the *LME* models is to estimate the random effects parameters. In this study, they can be calculated with the information from measured trees, such as the measurements of CW and DBH, by the Empirical Best Linear Unbiased Predictors (EBLUPs) [34].

$$\hat{b}_{ijk} \approx \hat{\mathbf{D}} \hat{\mathbf{Z}}^T (\hat{\mathbf{R}} + \hat{\mathbf{Z}} \hat{\mathbf{D}} \hat{\mathbf{Z}}^T)^{-1} \hat{\epsilon}_{ijk} \tag{12}$$

where $\hat{\mathbf{D}}$ is the estimated variance-covariance matrix for the random-effects \hat{b}_{ijk} , $\hat{\mathbf{R}}$ is the

estimated variance-covariance matrix for the error term, and $\hat{\mathbf{Z}}$ is the estimated partial derivatives matrix with respect to random effects parameters.

Results

Selection of the basic crown width model

The following formula is the composition of individual tree size variables and stand variables for predicting crown width using OLS:

$$CW_{ij} = \beta_0 + \beta_1 DBH_{ij} + \beta_2 H_{ij} + \beta_3 HCB_{ij} + \beta_4 DH_i + \beta_5 DD_i + \beta_6 A_i + \beta_7 SI_i + \beta_8 SD_i + \beta_9 QMD_i + \beta_{10} MH_i + \beta_{11} BA_i + \epsilon_{ij} \quad 13$$

where $\beta_0 - \beta_{11}$ are the formal parameters.

To avoid overfitting and multicollinearity between independent variables, the backward stepwise linear regression routine and the variance inflation factor were used to reduce the number of chosen variables. In addition, we took into account the biologically reasonable and the factors that exhibited significance (Pr value < 0.05) between independent variables. The variable selection process involves a series of steps beginning with the stepwise regression method together with VIF control to identify those variables that may be useful in the model. DH, A and MH were removed from Eq 13 because their VIF > 10 (VIF_{DH} = 27.48, VIF_A = 13.61, VIF_{MH} = 17.72). As a result, the final diameter growth model for fir plantations can be expressed as:

$$CW_{ij} = \beta_0 + \beta_1 DBH_{ij} + \beta_2 H_{ij} + \beta_3 HCB_{ij} + \beta_4 DD_i + \beta_5 SI_i + \beta_6 SD_i + \beta_7 QMD_i + \beta_8 BA_i + \epsilon_{ij} \quad 14$$

The statistics used for the selection of the basic model are shown with equations in Table 2.

Construction of LME models

There would be ninety different combinations of no more than four random-effects parameters for Eq 14 while simultaneously considering plots effects. The LME models with more than four random-effects parameters could not reach convergence.

LRT, AIC, BIC and -2 LL statistics were compared between the LME models with the best different combinations of random-effects parameters and are shown in Table 3. The model of Eq 14, incorporating plots effects on $\beta_0, \beta_1, \beta_2$ and β_3 (Eq 14.4), yielded the smallest AIC, BIC and -2 LL and had significant differences when compared to the other LME models (Eqs 14.1–14.3)

Table 2. Comparison of fitting statistics and estimated variance components of the models with different alternatives of covariates inclusion, residual variance function and variance components estimation method.

Model	Intercept	DBH	H	HCB	DD	SI	SD	QMD	BA
Eq 14	1.3450	0.1235	-0.0212	-0.0275	0.0236	-0.0077	2.31×10 ⁻⁵	-0.0127	-0.0105
(standard error)	(0.0904 ^{***})	(0.0032 ^{***})	(0.0050 ^{***})	(0.0045 ^{***})	(0.0035 ^{***})	(0.0037 [*])	(4.4×10 ⁻⁵ [*])	(0.0054 ^{**})	(0.0009 ^{***})
Eq 14.4	1.1812	0.1103	0.0073	-0.0238	0.0152	-0.0115	9.07×10 ⁻⁵	-0.0182	-0.0060
(standard error)	(0.5102)	(0.0066 ^{**})	(0.0080 [*])	(0.0079)	(0.0193)	(0.0197)	(7.68×10 ⁻⁵ ^{**})	(0.0265)	(0.0048)
Eq 14.4.8	0.6693	0.1090	0.0085	-0.0217	0.0231	-0.0134	0.0002	-6.93×10 ⁻³	-0.0075
(standard error)	(0.4490 [*])	(0.0061 ^{***})	(0.0060 [*])	(0.0062 ^{**})	(0.0154 [*])	(0.0163 [*])	(0.0001 ^{**})	(0.0217 [*])	(0.0038 ^{**})

^{**} means Pr value < 0.05

^{***} means Pr value < 0.01

^{****} means Pr values < 0.001.

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(Pr<0.0001).

$$CW_{ij} = (\beta_0 + u_{0i}) + \beta_1 DBH_{ij} + \beta_2 H_{ij} + \beta_3 HCB_{ij} + \beta_4 DD_i + \beta_5 SI_i + \beta_6 SD_i + \beta_7 QMD_i + \beta_8 BA_i + \epsilon_{ij} \tag{14.1}$$

$$CW_{ij} = (\beta_0 + u_{0i}) + (\beta_1 + u_{1i})DBH_{ij} + \beta_2 H_{ij} + \beta_3 HCB_{ij} + \beta_4 DD_i + \beta_5 SI_i + \beta_6 SD_i + \beta_7 QMD_i + \beta_8 BA_i + \epsilon_{ij} \tag{14.2}$$

$$CW_{ij} = (\beta_0 + u_{0i}) + (\beta_1 + u_{1i})DBH_{ij} + (\beta_2 + u_{2i})H_{ij} + \beta_3 HCB_{ij} + \beta_4 DD_i + \beta_5 SI_i + \beta_6 SD_i + \beta_7 QMD_i + \beta_8 BA_i + \epsilon_{ij} \tag{14.3}$$

$$CW_{ij} = (\beta_0 + u_{0i}) + (\beta_1 + u_{1i})DBH_{ij} + (\beta_2 + u_{2i})H_{ij} + (\beta_3 + u_{3i})HCB_{ij} + \beta_4 DD_i + \beta_5 SI_i + \beta_6 SD_i + \beta_7 QMD_i + \beta_8 BA_i + \epsilon_{ij} \tag{14.4}$$

where $\beta_0 - \beta_8$ are the fixed effects parameters and u_{0i} , u_{1i} , u_{2i} and u_{3i} are the random-effects parameters generated by plots effects on β_0 , β_1 , β_2 and β_3 , respectively.

LME model with heteroscedasticity and spatial correlation

We used the power function, the exponential function or the constant plus power function as the variance functions and AR, ARMA(1,1) or CS as the correlation structure to update [Eq 14.4](#) to reduce heteroscedasticity and spatial correlation. The LME models with variance functions and correlation structures are shown in [Table 4](#). In this study, Equation 14.4.1 is the same as [Eq 14](#). The best models were chosen with the smallest AIC, BIC and -2 LL. Thus, the

Table 3. Performance criteria of LME models for combinations of random effects.

Equation	Mixed parameters	Number of parameters	AIC	BIC	-2 LL	LRT	Pr values
14.1	β_0	10	7910.90	7980.64	7888.90	—	—
14.2	β_0, β_1	11	7820.25	7902.68	7794.25	94.64	<0.0001
14.3	$\beta_0, \beta_1, \beta_2$	12	7751.38	7852.83	7719.38	76.26	<0.0001
14.4	$\beta_0, \beta_1, \beta_2, \beta_3$	13	7723.20	7850.01	7683.20	34.80	<0.0001

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Table 4. Comparisons of intercept effect mixed model performance for fir plantations diameter increment data with different within-tree correlation structures and different variance functions.

Equation	Variance function	Correlation structure	Number of parameters	AIC	BIC	-2LL	LRT	Pr values
14.4.1	Homogeneous	Independent	13	7723.20	7850.01	7683.20	—	—
14.4.2	Power	Independent	14	7458.74	7591.89	7416.74	266.46 ^a	<0.001
14.4.3	Exponent	Independent	14	7422.96	7556.11	7380.96	302.24 ^a	<0.001
—	—	—	—	—	—	—	436.97 ^b	<0.001
14.4.4	Const plus power	Independent	15	7444.24	7573.73	7400.24	322.95 ^a	<0.001
14.4.5	Homogeneous	AR(1)	14	7473.63	7606.78	7431.63	251.56 ^a	<0.001
—	—	—	—	—	—	—	368.08 ^b	<0.001
14.4.6	Homogeneous	ARMA(1,1)	14	7356.06	7495.55	7312.06	371.13 ^a	<0.001
14.4.7	Homogeneous	CS	14	7725.20	7858.35	7683.20	3.31×10 ⁻⁶ ^a	0.9985
14.4.8	Exponent	ARMA(1,1)	16	6989.99	7135.82	6943.99	739.21 ^a	<0.001

^a Likelihood ratio is calculated with respect to Equation 14.4.1

^b Likelihood ratio is calculated with respect to Eq 14.4.8

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final models of plots effects are:

Equation 14.4 + Equation 6 14.4.2

Equation 14.4 + Equation 7 14.4.3

Equation 14.4 + Equation 8 14.4.4

Equation 14.4 + Equation 9 14.4.5

Equation 14.4 + Equation 10 14.4.6

Equation 14.4 + Equation 11 14.4.7

Equation 14.4 + Equation 6 + Equation 10 14.4.8

Parameter estimates

The LME CW model with plots effects is then defined by the following expression:

$$\begin{aligned}
 CW_{ij} = & (0.8247 + u_{0i}) + (0.1093 + u_{1i})DBH_{ij} + (0.0095 + u_{2i})H_{ij} + (-0.0219 + u_{3i})HCB_{ij} \\
 & + 0.0181DD_i - 0.0105SI_i + 0.0004SD_i - 0.0121QMD_i - 0.0064BA_i + \epsilon_{ij}
 \end{aligned}$$

Where

$$u_i = \begin{bmatrix} u_{0i} \\ u_{1i} \\ u_{2i} \\ u_{3i} \end{bmatrix} \sim N \left\{ \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, D = \begin{pmatrix} 0.5323 & 0.0916 & -0.5342 & -0.7542 \\ 0.0916 & 0.0360 & -0.5718 & -0.3328 \\ -0.5342 & -0.5718 & 0.0262 & 0.3987 \\ -0.7542 & -0.3328 & 0.3987 & 0.0323 \end{pmatrix} \right\}$$

$$\varepsilon_{ij} \sim N(0, R_{ij} = 0.3592G_i^{0.5}I_iG_i^{0.5})$$

$$V(\varepsilon_{ij}) = \exp(0.4366DBH_{ij})$$

$$ARMA(1, 1) = \begin{bmatrix} 1 & 0.9610 & -0.7731 \\ 0.9610 & 1 & 0.9610 \\ -0.7731 & 0.9610 & 1 \end{bmatrix}$$

Model prediction

The predictive ability of Eq 14 was evaluated using prediction procedures and Eq 1–3 on both fitting and validation data. The performance of the LME models, with and without modeling the error structure, was evaluated using cross-validation procedures for both fitting and validation data; the random effects were predicted with the EBLUPs (Eq 12), using the measurement data.

Table 5 lists the three prediction statistics of Eq 14, Eq 15 and Eq 15 without random effects for both fitting and validation data. Compared with Eq 14, Eq 15 had a higher adj-R², 0.7226 compared to 0.4733, and lower RMSE, 0.4854 compared to 0.6688, and AMR, 0.3688 compared 0.4954, for the validation data. In Fig 3, the residuals of Eq 14 and 15 are plotted against the fitted values. The fitted values of these equations are plotted against the observed values in Fig 4. Based on the above analysis, we can conclude that Eq 15, incorporating the random effects plots, was better than Eq 14. The LME model provides a model for predicting the expected values of crown width for individual trees of China-fir in the single-species plantations of the study area.

Discussion

In this study, a backward stepwise linear regression was used to establish a multiple linear individual tree crown width model for China-fir. The relative importance of explanatory variables used to predict the crown width were assessed. Generally, DBH is the tree size variable most related to crown width [27]. In addition to DBH, the tree size variables (such as H and HCB in this study) and stand variables (such as DH in this study) are also obvious factors affecting the crown width [20; 22; 46; 47]. Both stand and tree development are linked to the DH because it

Table 5. Evaluation indices of each model.

Model	Effects	Fitting data			Validation data		
		AMR	RMSE	adj-R ²	AMR	RMSE	adj-R ²
Eq 14		0.5306	0.6914	0.4694	0.4954	0.6688	0.4733
Eq 15	Mixed effects	0.4027	0.5070	0.7147	0.3688	0.4854	0.7226

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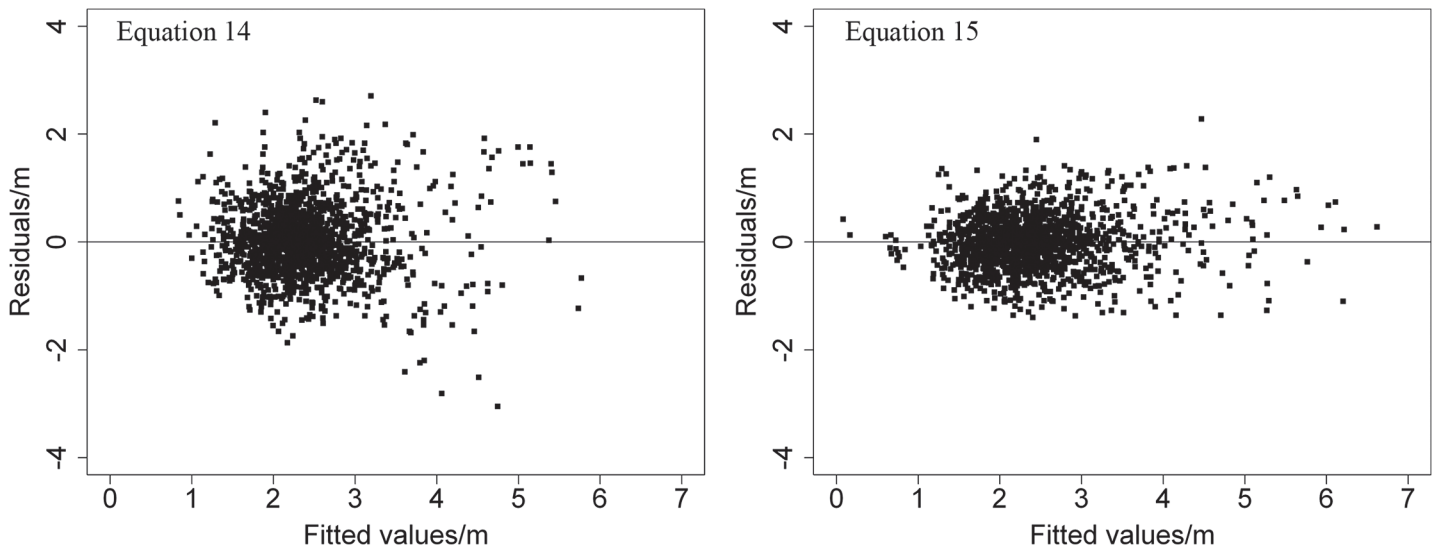


Fig 3. Distribution of residuals for two equations fitting crown width of China-fir trees.

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is a measurable stand characteristic that indicates site quality in terms of the stand growth and yield capacity [20]. The variables H and HCB showed a significant effect on the crown width because they are closely related to tree size and have an important role in crown fire initiation and spread [47; 48]. Therefore, we selected the diameter at breast height, tree height, height to crown base, plot dominant height, plot dominant diameter at breast height, stand age, site index, stand density, plot quadratic mean diameter, plot mean height and basal area as the independent variables to establish an individual tree crown width model. However, variance inflation factors were used to avoid potential overfitting and multicollinearity.

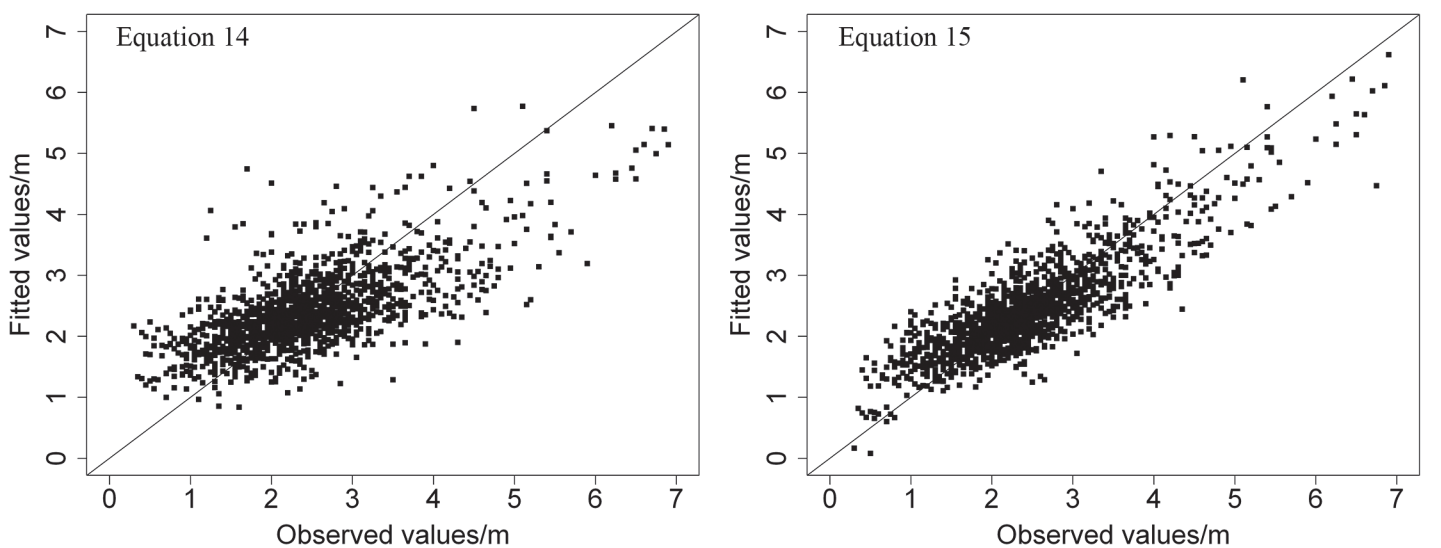


Fig 4. Fitted values of two equations for crown width of China-fir trees against observed values.

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Conclusions

Eleven variables were selected in this study to describe crown width (Eq 13) of China-fir in pure plantation stands in Fujian province, southeast China. Then, the backward stepwise linear regression routine and the variance inflation factor were used to reduce the number of chosen variables (Eq 14). The one-level (plot) LME model using the variance function structure and correlation structure approach were used to estimate the relationship of the chosen variables with crown width for individual trees. The results showed that the one-level LME models with mixed effects, considering variance function structure and correlation structure (Eq 15), provided better model fitting and more precise estimations than the LME models without mixed effects (Eq 14) (Table 5 and Figs 3 and 4). Therefore, we recommend using a linear mixed effects modeling approach to build an individual tree crown width model.

Author Contributions

Conceived and designed the experiments: XH SYJ. Performed the experiments: XH SYJ WXJ WJ FY. Analyzed the data: XH WJ FY. Contributed reagents/materials/analysis tools: XH SYJ WXJ WJ FY. Wrote the paper: XH.

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