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Site Index Model for Southern Subtropical Masson Pine Forests Using Stand Dominant Height

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Abstract: Stand dominant height has a close relationship with stand productivity and is not much affected by stand density and thinning within a reasonable density range, making it an excellent indicator for estimating stand site quality. Topographic factors (altitude, aspect, slope, etc.) have a significant influence on the growth process of stand level, and the combination of different site factors increases the randomness of the evaluation of forest productivity. In this paper, with one-way ANOVA, it was determined that the effects of density and management mode on the Masson pine stand dominant height were not significant. The data on the Masson pine stand dominant height in the southern subtropics in Guangxi, China, were analyzed, and the GADA model was established using the nonlinear least squares method, the Bayesian approach, and the one-level nonlinear mixed-effects model with the topographic factor as the random effect, respectively. The results indicated that the nonlinear mixed-effects model had the best fitting performance and the highest prediction accuracy for stand site quality (a 0.27% improvement in R^2 compared to the least squares method and a 1.30% improvement in R^2 compared to the Bayesian approach), while the model obtained by the Bayesian approach had more elasticity and biological significance. In summary, when the data distribution is uniform and comprehensive, introducing terrain factors into the establishment of site index models can provide a more scientific basis for estimating the productivity of southern subtropical Masson pine stands under different site conditions. When the data distribution is uneven, applying the Bayesian approach can make the site index model more biologically meaningful. The stand site quality model can predict the potential production capacity of forests, which is an important basis and can support forest management and harvest prediction. The results of this study provide a theoretical and practical basis for the establishment of a reasonable site index model for the Masson pine stand.

Keywords: GADA; site index model; mixed-effect model; dominant height; terrain factor; Bayesian approach

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1. Introduction

The site quality is related to the ability of forest land to support tree growth [1], referring to the production potential of established forests or other vegetation types on a certain site [2]. In forest management, how to measure the site quality of a forest stand has an important impact on predicting the productive capacity of timber volume and biomass of the stand and determining the optimal management program [3,4]. Due to stochastic factors such as ecology and climate, the growth of tree height (including dominant and average tree height) is a stochastic process and is influenced by site quality. For many tree species, volume production potential is positively correlated with tree height growth and is not significantly affected by stand density and thinning, so estimating site quality based on stand dominant height is one of the most commonly used and effective methods [2,5,6]. However, although the direct assessment method of evaluating site quality based on stand dominant height implies the influence of environmental factors on the growth of tree height, it does not explain the specific dominant factors. Therefore, the establishment of the site index model should fully consider the site factors [7–9].

For all equations reflecting the relationship between tree height and age, the differential forms can always be obtained using the difference method. Bailey et al. (1974) first proposed the Algebraic Difference Approach (ADA) to establish a differential model by specifying a shape-related parameter in the growth equation as a free parameter and built a polymorphic site index model for New Zealand Pinus radiata D. Don plantations [10]. However, many studies have shown that the shapes of tree height growth curves of dominant trees under different site conditions are not isomorphic, i.e., the tree height growth rates, curve shapes, and asymptotic maxima (potential tree heights) of dominant trees under different site conditions are different [11,12]. A reasonable site index model should satisfy the properties of multiple horizontal asymptotes (different tree height maxima) and polymorphism (different inflection points) at the same time, whereas the differential site index model derived using the ADA method can only satisfy the properties of multiple horizontal asymptotes or polymorphism due to the setting of only one free parameter in the ADA method [13–15]. Cieszewski et al. extended the ADA method and put forward the generalized algebraic difference approach (GADA) [16]. The GADA method has received much attention for its ability to construct clusters of polymorphic site index curves with variable-level asymptotic poles [16–19].

The selection of appropriate estimation techniques is crucial for the accurate estimation of site quality. The nonlinear least squares method is a classical statistical method widely used in parameter estimation. Compared with the classical method, the Bayesian approach has the unique advantage of treating the parameters to be estimated as random variables. Sun et al. established a spatial stand index model for forest ecosystems in the Ozarks of Missouri by utilizing the research results of Berger, J.O. et al. as a reference [20,21]. In addition, nonlinear mixed-effects modeling has received more and more attention in forestry in recent years. Fang et al. established an improved Richard growth model with nonlinear mixed effects to simulate the dominant height growth of slash pine (*Pinus elliottii* Engelm.) under different afforestation treatments [22]. Calegario et al. used a two-factor nonlinear mixed-effects model with a sample plot and clone to model the dominant height growth of Eucalyptus plantation forests in Brazil [23]. Zhu et al. built a mixed-effects model with random effects of site type groups by taking terrain and soil factors and their combinations as random effects, improving the accuracy of estimating forest productivity at the regional level [12]. To summarize, the nonlinear mixed-effects model is particularly suitable for data with multi-layer structures or complex relationships, which can help researchers more accurately understand and predict the behavior of the data.

Masson pine (*Pinus massoniana* Lamb.) is a native pioneer tree species widely distributed in the region south of the Yangtze River Basin in China. It is characterized by fast growth and productivity, tolerance to barrenness, and adaptability, with high economic value. It is often used as a plantation species for afforestation in southern China [24]. Terrain factors (altitude, slope, aspect, etc.) have a significant impact on the growth process at the stand level [25]. Meantime, the combination of different terrain factors increases the randomness of forest productivity evaluation [11,12]. In addition, different management models may have an impact on the growth process of the forest stand [26]. The aims of this study are to establish a site index model for southern subtropical Masson pine forests and analyze the impact of terrain factors on stand growth processes. The research process of this study is as follows: (1) Conduct variance analysis on different densities of Masson pine forests to explore the impact of stand density on the dominant height of Masson pine forests; (2) Conduct variance analysis on different management models of Masson pine forests to explore the impact of management modes on the dominant height of Masson pine forests; (3) Group the data based on the results of variance analysis, using the generalized difference algebra method to derive a site index model with stand dominant height, and estimating model parameters by the nonlinear least squares method, the Bayesian approach, and nonlinear mixed-effects models to evaluate the site quality of Masson pine forest; (4) Select random effects based on terrain factors and analyze the impact of terrain factors on the growth of Masson pine stands. The results of this study provide a theoretical and practical basis for establishing a reasonable site model of the Masson pine forest in the southern subtropics.

2. Materials and Method

2.1. Study Sites and Data

The study area is located in the Tropical Forestry Experimental Center of the Chinese Academy of Forestry, Chongzuo City, Guangxi Province, China, with a southern subtropical semi-humid-humid climate (Figure 1). The area has sufficient light, with annual sunshine hours of 1218–1620 h; abundant rainfall, obvious changes in the wet and dry seasons, with an average annual rainfall of 1200–1500 mm and an annual evaporation of 1261–1388 mm; the average annual temperature is 20.5–21.7 °C, with a maximum temperature of 40.3 °C and a minimum temperature of −1.5 °C, and a ≥10 °C active cumulative temperature of 6000–7000 °C; the soil is dominated by latosol and red soil, followed by purplish soil, and then yellow soil and a small amount of limestone soil; the zonal soil is latosol soil (including purple soil), with an area of about 10,000 hm^3, accounting for 52% of the operating area [27].

The understory species in the study area are mainly *Magnolia sumatrana* var. glauca (Blume) Figlar and Noot., *Castanopsis hystrix* Hook. f. and Thomson ex A. DC., *Litsea cubeba* (Lour.) Pers., *Quercus griffithii* Hook. f. and Thomson ex Miq., *Erythrophleum fordii* Oliv., *Michelia gioii* (A. Chev.) Sima and H. Yu, *Schima argentea* E. Pritz. ex Diels.

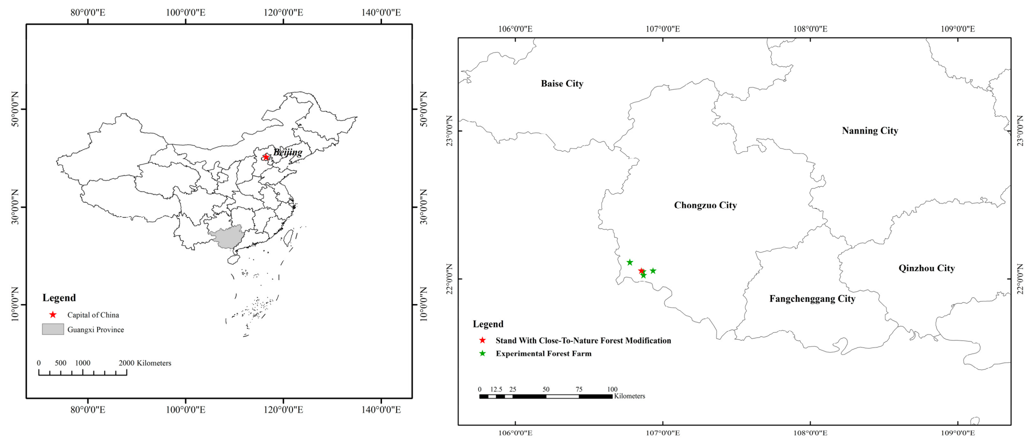

Figure 1. Research regions in Guangxi Province, China.

The data of this study were obtained from 92 Masson pine forest plots (80 conventional management plots and 12 close-to-natural transformed plots). From four experimental forest farms, Fubo (22°03′04.4964″ N, 106°51′56.2248″ E), Baiyun (22°06′48.8196″ N, 106°46′36.2820″ E), Shaoping (22°03′24.9264″ N, 106°56′02.4468″ E), and Qingshan (22°01′34.8744″ N, 106°52′08.6232″ E), 80 plots of Masson pine pure forest under conventional management (rotation period management) were selected. The sample plot, generated from 1 km equidistant sampling, is arranged in groups of three sample circles with a radius of 6.51 m and a total area of 400 m^2 (Figure 2a). The sample plot was established in 2011 (establishment of background data including altitude, slope, and aspect) and remeasured in 2013, 2015, 2017, and 2019. Each tree with a diameter at breast height greater than 5 cm was surveyed (tree height, diameter at breast height, and tree grade), and shrub and grass surveys were conducted.

In the Fubo experimental forest farm, some Masson pine pure forests of the same age were subjected to close-to-natural transformation [28], with a total area of 24 ha. The afforestation time was 1993, and the planting density was 2500 trees/ha. After afforestation, continuous management and tending had been carried out for 3 years. In 2000, release cutting was carried out with a designed thinning intensity of 25%. The first thinning was carried out in 2004, with a thinning intensity of 35%. After tending, the forest density was 1220 trees/ha. In 2007 (when the forest age was 14 years), a close-to-natural transformation was designed and implemented, and the forest development stage was in a competitive growth stage. A total of 12 close-to-natural transformed forest sample plots were set up in 2007, with reserved densities divided into three levels (225–300 trees/ha, 450–600 trees/ha, 600–750 trees/ha), each with four replicates. Measurement of diameter at breast height (DBH) and height of all trees with DBH greater than 5 cm in the sample plot began in 2008 until every two years of remeasuring in 2018. The sample plot is a circular shape with a radius of 11.29 m, with a total area of 400 m^2 (Figure 2b) [26].

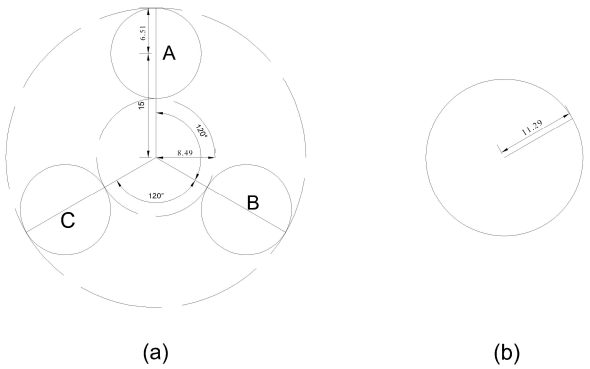

Figure 2. Sample plot design plan ((**a**) represents conventional management forest sample plot design and A, B and C are three small sample circles with a radius of 6.51 m; (**b**) represents close-to-natural transformed forest sample plot design).

In the conventional management (rotation period management) Masson pine pure forest sample plot, respectively, select one dominant tree from each of the three sample plots A, B, and C to calculate the average dominant tree height of the sample plot; in the close-to-natural transformed Masson pine forest sample plot, selected three dominant trees in the sample circle to obtain the average dominant tree height [2]. A total of 70% of the obtained data is randomly selected as the training set, and the remaining 30% as the validation set (Table 1).

Table 1. The information about dominant height, age, terrain, and stand density on Masson pine forests.

Variable	Training Set (70%)				Validation Set (30%)			
	Min.	**Max.**	**Mean**	**Std.**	**Min.**	**Max.**	**Mean**	**Std.**
Age/year	3.00	40.00	20.31	6.75	4.00	36.00	19.73	6.94
Dominant height/m	4.43	25.80	16.51	3.83	4.95	26.60	16.18	4.37
Altitude/m	169.00	800.00	378.70	121.52	179.00	800.00	405.90	150.72
Slope/°	0.00	42.00	23.52	9.63	0.00	42.00	25.89	8.86
Stand Density/trees/ha	125.00	1775.00	733.25	380.41	75.00	1625.00	765.66	362.30

Based on forest survey and planning, as well as previous research, site factors are divided, and the random forest method is used to analyze the relative importance of site factors to the stand dominant height [11,12]. When constructing the mixed-effect site index model of the Masson pine forest, the site factors with more importance were discretized, and random effects were selected as variables. The discretization criteria referred to the corresponding classifications in China's forestry survey and forest planning (Table 2) [11,29].

Table 2. Terrain and soil factors applied to random forest and their classes.

Site Factors	Class					
Altitude	4 classes by 200 m (0–800 m)					
Slope	≤15°		15° < slope ≤ 30°		>30°	
Aspect	Sunny slope	Semi-sunny slope		Shady and semi-shady slope		None slope
Slope position	Ridge	Upper slope	Middle slope	Lower slope	Valley	Flat
Soil type	Red earth	Brick-red earth	Purple earth	Yellow earth	Lateritic red soil	

2.2. One-Way ANOVA

In this study, two one-way ANOVA were conducted on the dominant height of Masson pine stands with three densities (225–300 trees/ha, 450–600 trees/ha, and 600–750 trees/ha) and two management modes (conventional management and close-to-natural transformation), respectively. The content of one-way ANOVA is as follows:

The one-way ANOVA of the growth of the dominant height of Masson pine stands with different retention densities was performed on 12 twenty-five-year (25a) sample plots of close-to-natural transformed Masson pine forests.

We selected four 25-year-old (25a) Masson pine sample plots with the same initial planting density and terrain (altitude, slope, and aspect) as the close-to-natural transformed forest from 80 conventional management plots of Masson pine and conducted a one-way ANOVA of the dominant height of Masson pine stands under different management modes with the 25-year-old close-to-natural transformed forest plots.

Based on the results of two one-way ANOVA analyses, the data were grouped to establish a site index model for the southern subtropical Masson pine forest.

2.3. Generalized Algebraic Difference Equations

Based on previous research, four basic equations (Gompertz, Hossfeld IV, Korf, and Richards) were selected, and a simple functional relationship between a variable related to site quality and the original model parameters was established to derive the relevant GADA equation (Table 3) [16–19,30].

Table 3. Base models and difference equations considered to develop the age-dependent growth equations.

Base Equation	Free Parameters	Solution for χ	GADA Dynamic Equation	No.
Gompertz: $DH = ae^{-ce^{-bt}}$	$a = e^{\chi}$ $c = c_2\chi$	$\chi = \frac{\ln DH_1}{1 - c_2 e^{-bt_1}}$	$DH_2 = e^{\chi} e^{-(c_2\chi)e^{-bt_2}}$	E1
	$a = e^{\chi}$ $c = c_2\chi^{-1}$	$\chi = \frac{\ln DH_1 + \sqrt{(\ln DH_1)^2 + 4c_2 e^{-bt_1}}}{2}$	$DH_2 = e^{\chi} e^{-(c_2\chi^{-1})e^{-bt_2}}$	E2
Hossfeld IV: $DH = a\left(1 + ct^{-b}\right)^{-1}$	$a = a_1 + \chi$ $c = c_1 + c_2\chi$	$\chi = \frac{DH_1 + DH_1 c_1 {t_1}^{-b} - a_1}{1 - DH_1 c_2 {t_1}^{-b}}$	$DH_2 = (a_1 + \chi)\left[1 + \left(c_1 + c_2\chi\right){t_2}^{-b}\right]^{-1}$	E3
Korf: $DH = ae^{-bt^{-c}}$	$a = e^{\chi}$ $b = b_1 + b_2\chi$	$\chi = \frac{\ln DH_1 + b_1 {t_1}^{-c}}{1 - b_2 {t_1}^{-c}}$	$DH_2 = e^{\chi} e^{-(b_1 + b_2\chi){t_2}^{-c}}$	E4
	$a = e^{a1\chi}$ $b = \chi$	$\chi = \frac{\ln DH_1}{a_1 - {t_1}^{-c}}$	$DH_2 = e^{a_1\chi} e^{-\chi {t_2}^{-c}}$	E5
Richards: $DH = a\left(1 - e^{-bt}\right)^{c}$	$a = e^{\chi}$ $c = c_1 + c_2\chi$	$\chi = \frac{\ln DH_1 - c_1 \ln\left(1 - e^{-bt_1}\right)}{1 + c_2 \ln\left(1 - e^{-bt_1}\right)}$	$DH_2 = e^{\chi}\left(1 - e^{-bt_2}\right)^{c_1 + c_2\chi}$	E6
	$a = e^{\chi}$ $c = c_2\chi^{-1}$	$\chi = \frac{\ln DH_1 + \sqrt{(\ln DH_1)^2 - 4c_2 \ln\left(1 - e^{-bt_1}\right)}}{2}$	$DH_2 = e^{\chi}\left(1 - e^{-bt_2}\right)^{c_2\chi^{-1}}$	E7

Note: DH_i is the average height of the dominant trees in the stands in ${t_i}^{th}$ year (i = 1 or 2).

2.4. Bayesian Approach

The strength of the Bayesian approach lies in its ability to integrate domain knowledge, introduce prior information, and provide more comprehensive uncertainty modeling, thereby demonstrating excellent performance in various scenarios. The Bayesian approach allows the prior information of parameters to be directly incorporated into the estimation process. This feature is particularly beneficial when data are scarce or noisy, as it can reduce the risk of overfitting and improve the robustness of the model [31].

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)}$$

where both the sample and the parameters are random variables. p denotes the probability distribution or density equation, $p(\theta)$ is the prior distribution of the parameter θ, and $p(y)$ is the marginal density function of y, which means $p(y) = \int p(y|\theta)p(\theta)d\theta$. The value of the distribution $p(y)$ does not depend on θ.

The model with the best least squares fit was used as the base model, and the Bayesian approach was performed using the parameter estimates obtained from the least square method as a priori information. Bayesian estimation was implemented using the stan function in R4.3.0 with 500,000 total iterations, 100,000 burn-in periods, and a maximum tree depth of 15 [32].

2.5. Nonlinear Mixed-Effects Models

The nonlinear mixed-effects site index model was developed for Masson pine forests with altitude, slope, aspect, and their combinations as random effects, respectively [12].

The model was expressed as follows:

$$\begin{cases} DH_{ij} = f\left(\varphi_{ijk}, t_{ij}, t_{ik}, DH_{ik}\right) + \varepsilon_{ijk} \\ \varphi_{ijk} = A_{ijk}\beta + B_{ijk}u_n \\ u_n \sim N(0, \Psi) \\ \varepsilon_{ijk} \sim N\left(0, \sigma^2\right) \\ i = 1, \ldots M, j = 2, \ldots P, j > k > 0, k \in Z, n \in Z^+ \end{cases}$$

where DH_{ij} represents the dominant height of the i^{th} plot at j^{th} measure; DH_{ik} represents the dominant height of the i^{th} plot at k^{th} measure. $f(\cdot)$ is a generalized difference algebraic equation for each sample plot about the average height of the dominant tree with the variable t_{ij}, t_{ik}, DH_{ik}, and the formal parameter vector is φ_{ijk}. A_{ijk} and B_{ijk} are design matrices of the parameter vectors of the fixed effects β and random effects u_n, respectively. Ψ and σ^2 are the variance of the normal distribution of the random effects variable u_n and random error ε_{ijk}, which are assumed to be mutually independent random variables. M is the number of sample plots, P is the total amount of effective data observed on the i^{th} plot, and n is the number of classifications of random effect variable u.

2.6. Model Evaluation

Four statistical evaluation metrics are applied to determine the performance of the model, including the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and Akaike's information criterion (AIC). The higher R^2 and the lower RMSE, MAE, and AIC, the better the model performance [12].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(DH_i - \widehat{DH}_i\right)^2}{\sum_{i=1}^{n}\left(DH_i - \overline{DH}_i\right)^2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(DH_i - \widehat{DH}_i\right)^2}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|DH_i - \widehat{DH}_i\right|}{n}$$

$$AIC = 2k - 2\ln(L)$$

where DH_i is the i^{th} observed value, $\overline{DH_i}$ is the mean value, $\widehat{DH_i}$ is the i^{th} estimated value, and n is the number of samples. k is the number of parameters (degrees of freedom) in the model, and $\ln(L)$ is the logarithm of the maximum likelihood estimate of the model.

Graph diagnosis about the current annual increment (CAI) and the mean annual increment (MAI) of stand dominant height is used to evaluate models based on statistical indicator selection.

$$CAI = \frac{df(t)}{dt}$$

$$MAI = \frac{f(t)}{t}$$

where $f(t)$ is a GADA dynamic model that determines the initial stand dominant height and time, t is stand age.

All models were implemented in R 4.3.0, with the Bayesian approach applied to the STAN package and nonlinear mixed-effects models fitted in the NLME package (Appendix A).

3. Results

3.1. One-Way ANOVA of Different Densities and Management Modes on the Dominant Height of Forest Stands

The effect of different densities on the Masson pine stands' dominant height is not significant (Table 4), and the dominant height data of Masson pine stands with different densities can be mixed together to establish a model.

Table 4. Analysis of variance for dominant height of Masson pine close-to-natural transformed stands (25a) under different retention densities.

	Df	Sum Sq	Mean Sq	F Value	Pr (>*F*)
Density	2	7.265	3.633	3.496	0.075
Residuals	9	9.351	1.039		

The effect of different management modes on the Masson pine stands dominant height is not significant (Table 5), and the dominant height data of Masson pine stands with different management modes can be mixed together to establish a model.

Table 5. Analysis of variance for dominant height of Masson pine stands (25a) under different management modes.

	Df	Sum Sq	Mean Sq	F Value	Pr (>*F*)
Management mode	1	1.995	1.995	0.770	0.395
Residuals	14	36.284	2.592		

3.2. Basic GADA Model Selection

Seven GADA models (E1–E7) were fitted using data from 92 sample plots of Masson pine forests, and the optimal model M4 was selected based on the evaluation indicators obtained, which had the highest R^2 (R^2 = 0.9341) and the lowest root mean square error (RMSE) and absolute mean square error (MAE) (RMSE = 1.0435, MAE = 0.8521) (Table 6).

Table 6. Information on parameter estimation based on nonlinear least squares method and model evaluation.

No.	Parameters	Estimate	Std. Error	*p*-Value	R^2	RMSE	MAE	AIC
M1	b	0.068639	0.007925	<0.001	0.9134	1.1963	0.9369	627.83
	c2	0.621136	0.030307	<0.001				
M2	b	0.067648	0.007848	<0.001	0.9225	1.1320	0.8967	602.47
	c2	7.280496	0.399721	<0.001				
M3	a1	22.281017	0.824898	<0.001	0.9317	1.0625	0.8915	550.01
	b	1.274450	0.110856	<0.001				
	c1	−0.001802	0.000218	<0.001				
	c2	5.184688	2.183751	0.019				
M4	b1	−9.911901	3.712181	0.008	0.9341	1.0435	0.8521	563.14
	b2	2.911217	1.121908	0.010				
	c	0.271303	0.099897	0.007				
M5	a1	1.045529	0.012011	<0.001	0.9192	1.1554	0.9167	604.51
	c	0.100515	0.069586	0.150				
M6	b	0.031715	0.010543	0.003	0.8896	1.3511	1.0693	661.8762
	c1	−0.797494	0.122048	<0.001				
	c2	0.484051	0.072742	<0.001				
M7	b	0.014400	0.011646	0.218	0.9260	1.1061	0.8753	586.15
	c2	3.290686	0.189392	<0.001				

3.3. Site Index Model with Different Random Effects

The relative importance based on an increase in node purity is shown in Figure 3. Altitude was the most important site factor influencing stand dominant height, followed by slope and aspect. The slope position and soil type had less influence than the first three variables (Figure 3 left). The ranking results of the importance of the site factors were the same as those without the age variable (t1 and t0) and initial dominant height (h0) (Figure 3 right).

For the optimal site index model of Masson pine forests (M4), the nonlinear mixed-effect site index models (M4.1–M4.7) were established using altitude, slope, aspect, and their combinations as random effects. All nonlinear mixed-effect models have improved accuracy. Among them, where aspect is used as a random effect, the model accuracy is the highest (R^2 = 0.9366, RMSE = 1.0242, MAE = 0.8381, AIC = 568.23) (Table 7).

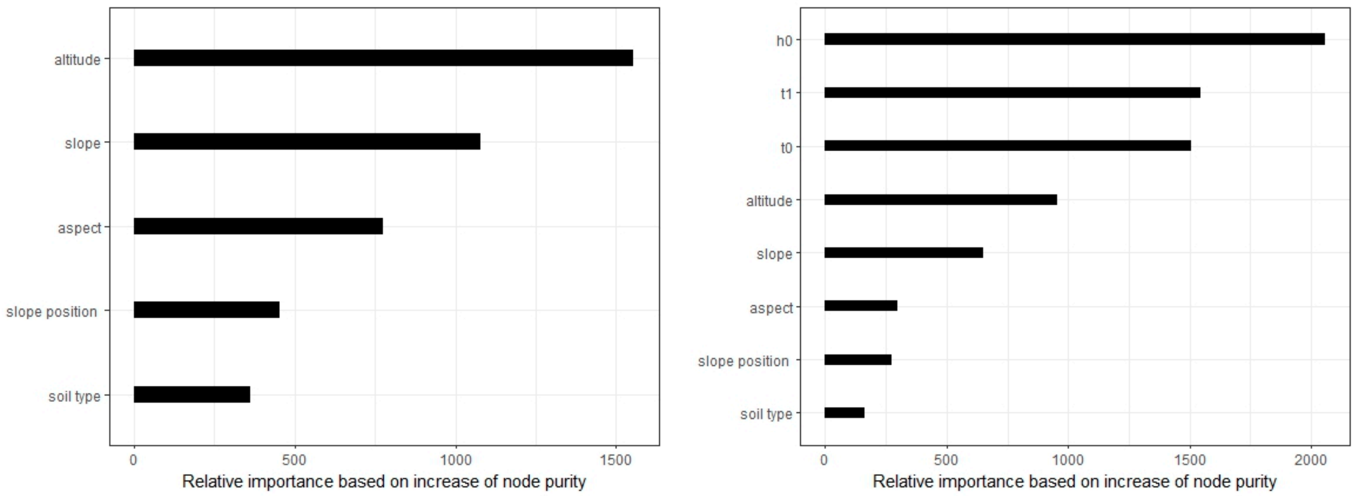

Figure 3. Analysis of the relative importance of site factors and inherent variables on the stand dominant height.

Table 7. Information on nonlinear mixed-effects model.

Random Effects	Random Effects Construct Variables	Levels	$b1$	Std. Error	$b2$	Std. Error	c	Std. Error	R^2	RMSE	MAE	AIC	No.
Altitude	$b1$	4	−8.465137	3.157405	2.476417	0.955311	0.228937	0.099898	0.9347	1.0387	0.8447	564.88	M4.1
Slope	$b1 + b2$	3	−9.749985	2.824700	2.890913	0.840261	0.273461	0.074471	0.9352	1.0351	0.8499	569.06	M4.2
Aspect	$b2 + c$	4	−8.636531	3.177930	2.562699	0.973702	0.242117	0.100209	0.9366	1.0242	0.8381	568.23	M4.3
Altitude × Slope	$b1 + b2$	11	−9.910294	3.711532	2.910942	1.121779	0.271305	0.099903	0.9341	1.0435	0.8520	569.14	M4.4
Altitude × Aspect	$b1$	11	−7.186774	2.646211	2.127407	0.802359	0.193630	0.098107	0.9356	1.0315	0.8390	565.06	M4.5
Slope × Aspect	c	10	−9.468011	3.565104	2.782777	1.076361	0.260356	0.100196	0.9346	1.0401	0.8490	565.15	M4.6
Altitude × Slope × Aspect	$b2$	23	−8.978159	3.380999	2.635419	1.019855	0.246411	0.100142	0.9348	1.0386	0.8479	565.20	M4.7

3.4. Comparison of Three Methods

The nonlinear mixed-effects model is superior to the nonlinear least square method, especially M4.3 (R^2 improved by 0.27%), while the Bayesian approach accuracy slightly decreased compared to the least squares method (R^2 decreased by 1.30%) (Table 8).

Table 8. Information on comparison of three parameter estimation methods.

Method	Parameters	Estimate	Std. Error	p-Value	R^2	RMSE	MAE	AIC
Nonlinear Least Squares (M4)	$b1$	−9.911901	3.712181	0.008	0.9341	1.0435	0.8521	563.14
	$b2$	2.911217	1.121908	0.010				
	c	0.271303	0.099897	0.007				
Bayesian Approach (M4.8)	$b1$	9.407929	0.007374	-	0.9220	1.1357	0.8975	-
	$b2$	−0.738057	0.001373	-				
	c	0.268599	0.000014	-				
Nonlinear Mixed-Effects Model (M4.3)	$b1$	−8.636531	3.177930	0.007	0.9366	1.0242	0.8381	568.23
	$b2$	2.562699	0.973702	0.009				
	c	0.242117	0.100209	0.017				

In addition, in terms of residual plots, the nonlinear mixed-effects model (M4.3) performs better than the basic model and the Bayesian approach model (M4 and M4.8) (Figure 4).

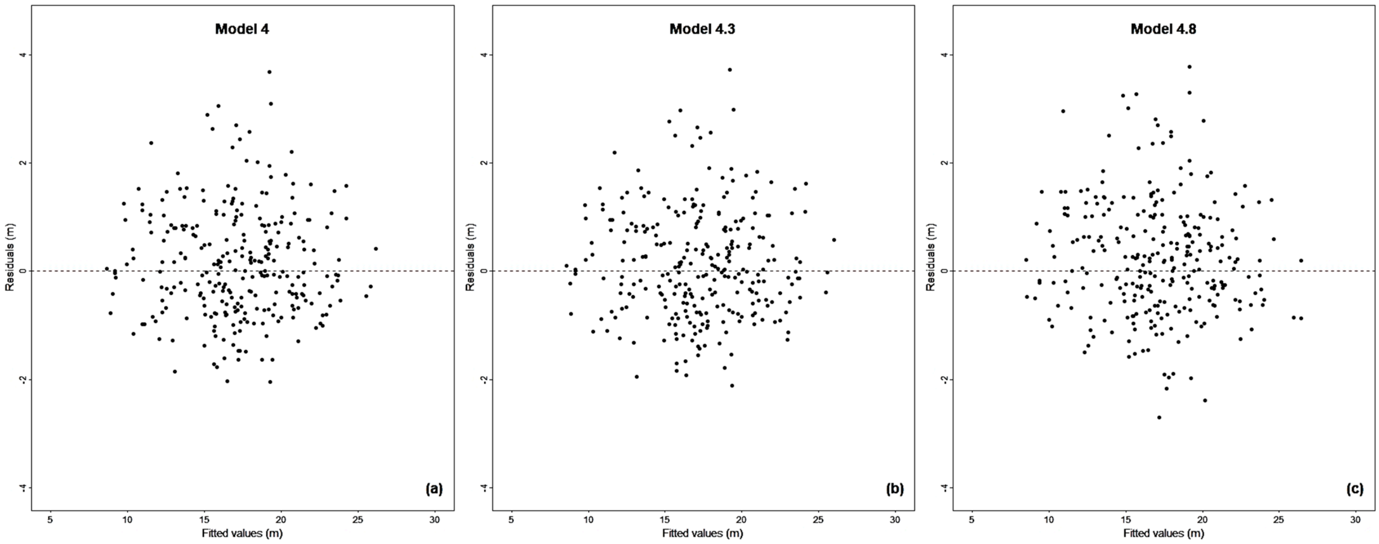

Figure 4. The residual diagram of the excellent site index models ((**a**) represents M4; (**b**) represents M4.3; (**c**) represents M4.8).

Based on the sample points and practical application, plot the cluster of site index curves for models M4, M4.3, and M4.8 with a reference age (t0) of 20 years, a site index class interval of 2 m, and a site index range of 13 to 21 m; The models all have suitable fitting performance and can also simultaneously conform to the properties of multiple horizontal asymptotes and polymorphism (Figure 5).

Graph diagnosis about the current annual increment (CAI) and the mean annual increment (MAI) is used to evaluate M4, M4.3, and M4.8. According to the polymorphic site index curves of Masson pine for different site classes, the relationship between the current annual increment and mean annual increment of Masson pine stand dominant height is plotted (Figure 6).

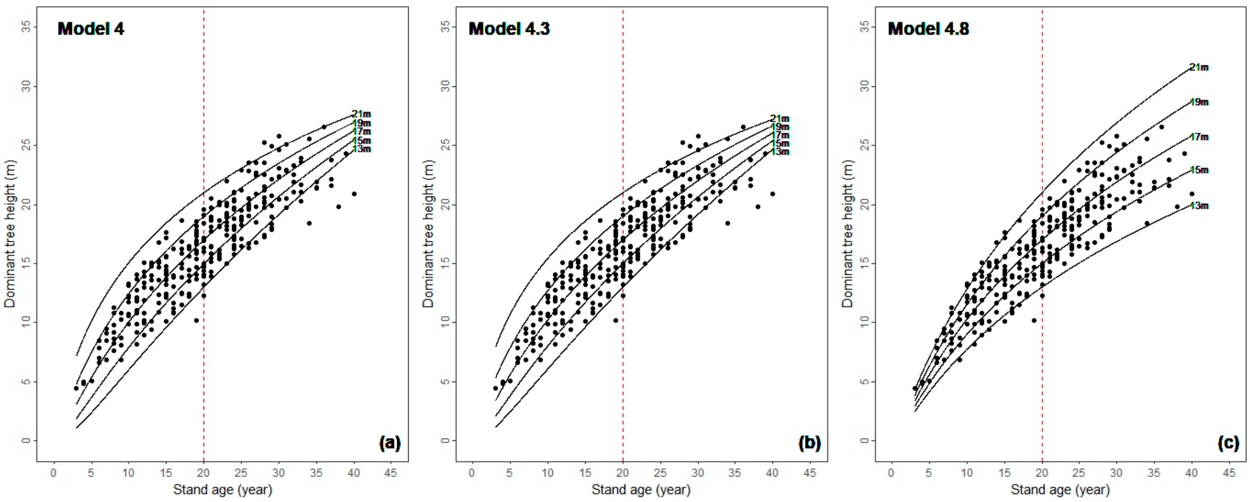

Figure 5. Polymorphic site index curves of Masson pine for different site classes ((**a**) represents M4; (**b**) represents M4.3; (**c**) represents M4.8).

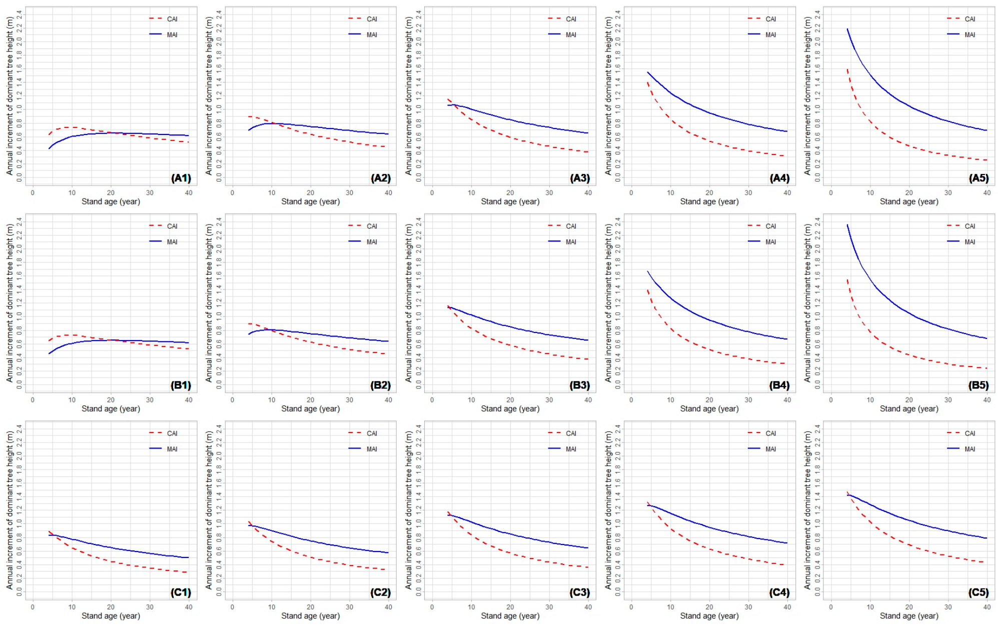

Figure 6. Relationship between current annual increment and mean annual increment about Masson pine stand dominant height ((**A1**–**A5**) represents M4 with a site index range from 13 to 21 m; (**B1**–**B5**) represents M4.3 with a site index range from 13 to 21 m; (**C1**–**C5**) represents M4.8 with a site index range from 13 to 21 m).

4. Discussion

4.1. The Effect of Stand Density on the Dominant Height of Forests

Stand density reflects the current degree of full utilization of forest land productive potential and is an important indicator of stand competitive status. Stand density determines the distribution of light and nutrients within a region and is an important factor affecting stand growth [33]. However, scholars generally believe that stand density has little effect on the stand dominant height [5,6,34]. In this study, we conducted a one-way ANOVA analysis using close-to-natural transformed forests (25a) under different reserve densities and found that the impact of stand density on the dominant height of the Masson pine forest was not significant (Table 4). Pienaar et al. established a growth model using the average dominant height of a 36-year-old slash pine (*Pinus elliottii* Engelm.) plantation in South Africa with different initial densities (150–1200 plants/acre) and found that the initial planting density had little effect on the dominant height of the stand [35]. The results of this study are similar to those of previous research.

On the other hand, Tymińska-Czabańska et al. found that stand density has an impact on the top height growth of Scottish pine, with higher stand density stimulating the growth of the top height, especially in production sites where the top height increases by about 10% [36].

According to the forest succession stage division proposed by Lu, forest growth can be divided into five stages: group building stage, competitive growth stage, quality selection stage, close-to-natural forest stage, and natural sustainable forest stage. Among them, a higher stand density during the competitive growth stage may promote the height growth of the forest [12,37,38]. Woodruff et al. measured coastal Douglas fir (*Pseudotsuga menziesii* (Mirb.)) with initial planting densities of 300, 1360, and 2960 trees/ha and found that in the fifth year after planting, both height and diameter growth increased with increasing density, and decreased with decreasing density in the seventh year [39]. Therefore, when establishing a single tree or stand growth model, in order to ensure the rationality and universality of the model, it is necessary to fully consider the impact of stand density on tree growth.

4.2. The Effect of Management Mode on the Dominant Height of Forests

In this study, we selected some 25-year-old Masson pine sample plots with the same initial planting density and terrain (altitude, slope, and aspect) as the close-to-natural transformed forest plot from 80 conventional management plots of Masson pine. We conducted a one-way ANOVA analysis on the stand dominant height under conventional management modes compared to the close-to-natural transformed forest plot of Masson pine. We found that the management mode had no significant impact on the Masson pine stand dominant height in this study (Table 5). The difference between conventional management (rotation period management) and close-to-natural transformation is mainly reflected in the intensity of thinning. The intensity of thinning directly affects the forest density, while as discussed above, the stand density has no significant impact on the Masson pine stand dominant height. The results of two one-way ANOVA analyses also mutually confirm this conclusion. In addition, the mixture effects of understory replanting on dominant height growth are weak [40]. And, compared to radial growth, dominant height growth has more species and site specificity and does not have as much elasticity [41]. Therefore, although the management mode does not have a significant impact on the stand dominant height in this study, specific analysis is needed for different tree species, close-to-natural transformation methods, and management locations.

It is worth noting that the forest stands formed extensive forest windows after clearcutting, the canopy competition effect between trees and their neighbors was weakened, and the radial growth was more vigorous, which is a significant difference in the growth of trees under the close-to-natural management mode compared with the conventional management [30,42].

4.3. Model Comparison and the Influence of Terrain Factors

The Bayesian approach has been widely applied to the estimation of stand growth models [20,43,44]. The Bayesian approach allows for the natural integration of prior knowledge into the estimation process and improves the accuracy of estimates with limited sample data, which is also reflected in this study. Compared to nonlinear least squares and nonlinear mixed-effects models, the Bayesian approach exhibits better biological characteristics in the range with less data distribution (stand age $\leq$ 10 and stand age $\geq$ 30) (Figure 5), especially when the site index is large (Figure 6). Another advantage of the Bayesian approach is that it has narrower confidence intervals, which implies higher confidence and less decision risk [45]. However, we noticed that the use of the Bayesian approach in the GADA model caused a slight decrease in the model accuracy (R^2 decreased by 1.30%) compared to the least squares method, which may be related to data distribution.

The nonlinear mixed-effects models provide flexible and powerful tools for analyzing longitudinal data, repeated observations, grouping designs, and multilevel data, and all these advantages are well suited to the needs of forestry sample design and survey data processing [46,47]. In this study, we used altitude, aspect, slope, and their combinations as random effects to fit the GADA model of the Masson pine stand dominant height. Aspect mainly affects the light exposure of plants, which, in turn, affects plant distribution and can have an impact on plant growth [48–50]. Altitude is a significant factor affecting the growth of Masson pine [51]. The impact of altitude is reflected in the hydrothermal conditions, with a gradual decrease in temperature with increasing altitude and a decreasing trend in soil moisture (influenced by gravity, vegetation type, etc.) [11,52–54]. Slope and dominant wind direction affect temperature, while slope and precipitation also determine the degree of soil erosion in the region [55–57]. All nonlinear mixed-effect models have improved accuracy, and the model has the highest prediction accuracy when aspect is used as a random effect (compared to M4, R^2 increases by 0.27%). However, based on the relationship between current annual increment and mean annual increment, we can find that the nonlinear mixed-effects model is greatly influenced by the data distribution. When the stand age is young (stand age = 5), there is a significant difference in the stand dominant height of each site index level, while when the stand age is older (stand age = 40), the difference in the stand dominant height of each site index level is relatively small. Although the nonlinear mixed-effects model takes into account the differences in stand dominant height growth of Masson pine in different terrain groups, which improves the prediction accuracy, the model fitting requires a more comprehensive data distribution.

5. Conclusions

In this study, we used survey data of Masson pine forests in the south subtropics for one-way ANOVA and found that stand density and management modes (conventional management and close-to-natural management) had no significant impact on the stand dominant height growth. Therefore, a site index model of the south subtropical Masson pine stand was established by mixing all data. Based on the fitting results and the relationship between the current annual increment and mean annual increment of the stand dominant height, we found that although the nonlinear mixed-effects model can improve the fitting accuracy and prediction performance (R^2 up to 0.27% increase), it requires a more comprehensive data distribution. However, compared to the former, the model obtained by the Bayesian approach is more elastic and biologically meaningful in cases of uneven data distribution. In summary, when the data distribution is uniform and comprehensive, introducing terrain factors into the establishment of site index models can provide a more scientific basis for estimating the productivity of southern subtropical Masson pine stands under different site conditions. When the data distribution is uneven, applying the Bayesian approach can make the site index model more biologically meaningful.

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Appendix A

#Code for NLME in R partially references the article: http://doi.org/10.3390/rs12071066.
#Code for Bayesian estimation using STAN function package in R.

```
TBB_LIB_DIR = "D:/oneapi-tbb-2021.9.0-win/oneapi-tbb-2021.9.0/lib/intel64"
Sys.setenv(LIB_TBB = TBB_LIB_DIR)
Sys.setenv(PKG_LIBS = Sys.getenv("LOCAL_LIBS"))
library(StanHeaders)
library(brms)
library(rstudioapi)
library(rstan)
options(mc.cores = parallel::detectCores())
rstan_options(auto_write = TRUE)
data_bys <- list(
N = plot_number,
t1 = data_training$t1,
t0 = data_training$t0,
h0 = data_training$h0,
h1 = data_training$h1
)
model_code <- "
data {
int<lower=0> N;
vector[N] t0;
vector[N] t1;
vector[N] h0;
vector[N] h1;
}
parameters {
real b1;
real b2;
real c;
}
transformed parameters {
vector[N] h1_pred;
for (i in 1:N) {
h1_pred[i]=exp((log(h0[i])+b1*(t0[i]^(-c)))/(1-b2*(t0[i]^(-c))))*exp(-(b1+b2*((log(h0[i])+
b1*(t0[i]^(-c)))/(1-b2*(t0[i]^(-c)))))*(t1[i]^(-c)));
}
}
model {
b1 ~ normal(-9.911901, 13.780287776761);
b2 ~ normal(2.911217, 1.258677560464);
c ~ normal(0.271303, 0.009979410609);
h1 ~ normal(h1_pred, 1);
}
"
stan_model <- stan_model(model_code = model_code) # Compiling a Stan model
fit <- sampling(stan_model, data = data_bys, iter = 500000, warmup = 100000, control
= list(max_treedepth = 15))
print(fit)
```

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