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ORIGINAL RESEARCH ARTICLE

A model of cross-sectional growth of *Cunninghamia lanceolata* plantation in Hunan province with climate effects

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ABSTRACT

Objective: The influence of climate on forest stands cannot be ignored, but most of the previous forest stand growth models were constructed under the presumption of invariant climate and could not estimate the stand growth under climate change. The model was constructed to provide a theoretical basis for forest operators to take reasonable management measures for fir under the influence of climate. **Methods:** Based on the survey data of 638 cedar plantation plots in Hunan Province, the optimal base model was selected from four biologically significant alternative stand basal area models, and the significant climate factors without serious covariance were selected by multiple stepwise regression analysis. The optimal form of random effects was determined, and then a model with climatic effects was constructed for the cross-sectional growth of fir plantations. **Results:** Richards formula is the optimal form of the basic model of stand basal area growth. The coefficient of adjustment (R_a^2) was 0.8355; the average summer maximum temperature (T_{max}) and the water vapor loss (C_{MD}) in Hargreaves climate affected the maximum and rate of fir stand stand growth respectively, and were negatively correlated with the stand growth. The adjusted coefficient of determination (R_a^2) of the fir stand area break model with climate effects was 0.8921, the root mean square error (RMSE) was 3.0792, and the mean relative error absolute value (MARE) was 9.9011; compared with the optimal base model, R_a^2 improved by 6.77%, RMSE decreased by 19.04%, and MARE decreased by 15.95%. **Conclusion:** The construction of the stand cross-sectional area model with climate effects indicates that climate has a significant influence on stand growth, which supports the rationality of considering climate factors in the growth model, and it is important for the regional stand growth harvest and management of cedar while improving the accuracy and applicability of the model.

Keywords: Fir Plantation Forest; Climate Factor; Stand Area Cut-Off Growth Model; Mixed-Effects Model

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1. Introduction

Broken area is one of the important indexes for evaluating forest quality and calculating yield[1,2], which has the advantages of easy measurement and accurate data, and is the basis for developing forest management measures and harvesting plans. As an indicator reflecting the growth process of forest stands also affects the stand stock[3], and its model accuracy is more directly related to the prediction accuracy of the overall model of the whole forest, so it has become one of the hot spots of domestic and international research[3].

Cunninghamia lanceolata is one of the main silvicultural and timber species in Southern China[5], and is also an excellent timber species unique to the subtropical region of China[6]. The eighth national forest resources inventory showed that the existing plantation area of fir plantations is about 1.24×10^3 million hm^2, accounting for about 26.6% of the national plantation area, and its share in commercial timber is about 1/4. It has an important position and role in meeting the national economic development and people's demand for multiple benefits of forests[7].

Stand age, stand quality and stand density are the variables used to construct the stand area model, and most of the current simulations of stand area models are limited to factors such as topography and geomorphology[8,9]. Gao *et al.*[10] used a dummy variable approach to construct a stand break area growth model for Pinus sylvestris based on the average height of the dominant wood as the stand index; Hu[3] used a mixed-effects model approach to construct a stand break area growth model for oak natural forests in Hunan, using the dominant height of the stand at a standard age of 20 a as the stand index. Yan *et al.*[11] chose the base model without stand index taking into account the errors arising from the complexity of the stand, and constructed a stand area model for poplar and oak. Although the above models solve the corresponding problems, most of them assume a constant climate and cannot estimate the stand growth under the influence of climate factors. In contrast, the *Second National Assessment Report on Climate Change* shows that the average annual temperature and annual precipitation in China will increase by 3.5 ℃ and 4.2% respectively[12]. The IPCC also suggested in the *Fifth Assessment Report* that the warming rate in the past 50 a is almost twice as high as that in the past 100 a[13,14], and the rate of climate change has increased significantly. Considering the sensitivity of fir to climate, this study added climatic factors such as temperature and precipitation in the subsequent modeling process based on using the average height of dominant trees in the stand as an index of stand quality, and analyzed their effects on the growth of fir stands in the cross-sectional area, which provided a theoretical basis for the fir management measures adopted by forest operators under the influence of climate.

2. Overview of the study area

Hunan is located in the transition zone from the Yunnan-Guizhou plateau to the hills of Jiangnan and from the Nanling Mountains to the Jianghan Plain. It is surrounded by mountains on three sides, with a horseshoe-shaped landscape opening toward the north, located at 24°38′–30°08N′, 108°47′–114°15′E. It seats east of Jiangxi, west of Chongqing and Guizhou, south of Guangdong and Guangxi, and north of Hubei, with a total area of 211,800 km^2. The climate type is subtropical monsoon humid climate, with variable temperature in spring and autumn, cold winter and hot summer, rainy spring and summer, and dry autumn and winter. The average daily temperature is stable in most areas, the average annual temperature is 16–19°C, the frost-free period is 253–311 d, and the average annual precipitation in the province is 1,200–1,700 mm, with abundant rainfall and sufficient water and heat.

3. Materials and methods

3.1 Data sources

The data used for constructing the model in this study were obtained from the 1980 cedar plantation sample plot survey data from various cities and counties in Hunan Province, with a sample plot size of about 667 m^2, which mainly distributed in the east (Changsha, Zhuzhou, Xiangtan), north (Changde, Yiyang), and south (Yongzhou, Chenzhou, Hengyang) of Hunan Province. Latitude and longitude coordinates, elevation, soil texture, slope position, average diameter at breast height of stand, slope shape, gradient, soil thickness, stand age, number of plants per hectare, average height of dominant trees, etc. were the main sample plot survey factors, of which 638 sample plots have complete data that required. Based on the latitude and longitude coordinates and elevation of each site, climate data were obtained from ClimateAP (2019) wrote by Wang *et al.*[12], which can extract climate data for the Asia-Pacific region, with 12 types of climate factors (**Table 1**).

Table 1. Definition of climate variables

Variable	Description
T_{MA}(℃)	Average annual temperature
T_{MWM}(℃)	Average temperature in the hottest month
T_{MCM}(℃)	Average temperature in the coldest month
$T_D(°C)$	Average temperature difference
$P_{MA}(mm)$	Annual precipitation
A_{HM}	Dryness index= $(T_{MA}+10)/(P_{MA}/1000)$
$D_{D5}(°C)$	Growth accumulated temperature
C_{MD}	Hargreaves climate water vapor deficit
$T_{ave}(°C)$	Average summer temperature
$T_{max}(°C)$	Average summer maximum temperature
$T_{min}(°C)$	Average summer minimum temperature
$P_{PT}(mm)$	Summer precipitation

In order to improve the accuracy of modeling and the rationality of model evaluation, this study divided the sample plot data into 478 groups of modeling data and 160 groups of testing data according to the ratio of 3:1, which were used to simulate and test the fir plantation stand cross-area growth model, and the relevant statistics are shown in **Table 2**.

Table 2. Modeling and verifying data statistics*

Variable	Modeling data				Validation data			
	Min	**Max**	**Max**	**Stand error**	**Min**	**Max**	**Mean**	**Stand error**
T/a	11	26	19.6	3.3	11	26	19.8	3.2
H_D/m	7.6	18.7	12.6	2.3	7.7	19.1	12.8	2.1
N/(plant/hm^{-2})	750	5,175	2,150.6	704.1	1,035	4,275	2,118.1	685.2
SDI	695.9	2,844.5	1,369.1	365.1	722.8	2,454.1	1,351.5	355.4
B_A/(m^2/hm^{-2})	10.6	52.9	27.6	9.4	9.8	54.9	27.3	9.6
T_{MCM}/℃	1.6	8.0	5.9	0.9	3.3	8.0	6.0	1.0
P_{PT}/mm	349	811	496.6	71.6	388	656	495.7	60.8
T_{max}	22.6	33.1	30.3	2.6	24.1	32.9	30.6	2.0
C_{MD}	0	185	97.9	56.3	0	184	93.7	54.6

*T, H_D, B_A and N represent stand age, average height of dominant trees, per hectare basal area and number of trees per hectare respectively.

3.2 Research methods

3.2.1 Screening of independent variables

In this study, multivariate stepwise regression analysis was used to screen the independent variables for climate factors, and factors with severe covariance were excluded according to the variance inflation factor (VIF), thus retaining factors with weak covariance and significant effects as follows[3].

1) Given the significance α, the corresponding critical values are noted as $F^{(1)}$. The i independent variables X_i in the regression model were subjected to one-way linear regression analysis with the dependent variable respectively. The test F statistic $F_i^{(1)}$ of the regression coefficients of the respective variables is calculated and the maximum value $F_{il}^{(1)}$ is selected, and is introduced into the regression model X_{il} when $F_{il}^{(1)} \geq F^{(1)}$.

2) Given the significance α, the corresponding critical value is noted as $F^{(2)}$, a binary regression model of the dependent variable and the subset of independent variables is established, and the value of F test statistic $F_j^{(2)}$ of the regression coefficient of the independent variable is calculated, and the maximum $F_{j2}^{(2)}$ of which is selected, and when $F_{j2}^{(2)} \geq F^{(2)}$, introduce X_{j2} into the regression model, otherwise terminate it[3].

3) Repeat step 2 and substitute the respective variables into the model one by one for F test, and when the original independent variables become no longer significant due to the later introduced independent variables, they are removed to ensure that the model contains only significant variables[3].

3.2.2 Construction of the model for stand area break

The growth and development of a stand is strongly influenced by its stand age, stand quality, and the degree of utilization of the stand resources[15,16], so three variables, stand quality index, density index, and stand age, need to be included in the construction of a stand area break growth model[17]. In this study, four commonly used models were selected as candidate base models, and in the construction of the base model, the stand quality index was selected as the average height of the dominant tree HD in the stand. The density index was selected from the stand density index SDI and the number of plants per hectare *N* after comparing the differences in the accuracy of the base models[7], and the specific model form was as follows.

$$B_A = aH_D^b\left(1 - e^{(-cT(SDI/1000))^d}\right)^f \tag{1}$$

$$B_A = aH_D^b\left(1 - e^{(-cT(N/1000))^d}\right)^f \tag{2}$$

$$B_A = H_D^{(a+b/T)}(SDI/1000)^{(c+d/T)}e^{(f+g/T)} \tag{3}$$

$$B_A = H_D^{(a+b/T)}(N/1000)^{(c+d/T)}e^{(f+g/T)} \tag{4}$$

Where: *T*, B_A, SDI, H_D are stand age, stand cross-sectional area, stand density index, and mean height of dominant trees in the stand respectively; *a*, *b*, *c*, *d*, *f*, and *g* are all model fixed parameters.

3.2.3 Construction of the mixed-effects model

The model built based on the regression relationship of the regression function depending on both fixed effect parameters and random effect parameters is called mixed effects model, and its general form[3,18] is as follows.

$$y_i = f(\beta, \mu_i, x_i) + \varepsilon_i \tag{5}$$

Where: y_i and x_i are the vector of dependent and independent variables for the *i* sample respectively; ε_i is the error term; β and μ_i are the vector of fixed effect parameters and the vector of random parameters respectively.

In the process of constructing the mixed-effects model, the key step is the parameter construction of the two major effects of the model—random effects and fixed effects, that is, all the independent variables related to the research object are added to each parameter of the model in the form of permutation and combination as random effects fit, and the model is evaluated according to AIC, BIC, and the smaller the value of AIC and BIC, the better the model fits. However, surplus independent variables as well as parameters can cause non-convergence of the model[19,20]. In order to avoid this problem and select a parametric construction with fewer parameters and convergent form, this study first conducts the significance factor screening of the study object and then conducts a multi-parameter effect simulation test using the optimal base model[3].

3.3 Evaluation of model accuracy

In this study, model evaluation was performed using adjusted coefficients of determination R_a^2, root mean square error RMSE, mean relative error absolute value MARE, Akaike info criterion AIC, and Bayesian information quantity BIC, with the following formula.

$$\mathrm{AIC} = -2\ln l + 2 \tag{6}$$

$$\mathrm{BIC} = -2\ln l + \ln np \tag{7}$$

$$R_a^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2}\left(\frac{n-1}{n-p}\right) \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n - P}} \tag{9}$$

$$\mathrm{MARE} = \frac{1}{n}\sum_{i=1}^n \left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{10}$$

Where: y_i is the *i*-th sample measured value; $\hat{y}_i$ is the *i*-th sample predicted value; $\bar{y}$ is the average measured value; *p* is the number of parameters in the model; *n* is the number of samples; and *l* is the maximum likelihood function value of the model.

4. Results and analysis

4.1 Climate factor screening and classification

The annual mean temperature (T_{MA}), annual cumulative temperature (D_{D5}), hottest monthly mean temperature (T_{MWM}), coldest monthly mean temperature (T_{MCM}), mean temperature difference (T_D), annual precipitation (P_{MA}), dryness index (A_{HM}), Hargreaves climate water vapor deficit

(C_{MD}), summer mean air temperature (T_{ave}), summer mean maximum temperature (T_{max}), summer mean minimum temperature (T_{min}), summer mean precipitation (P_{PT}), and other 12 climatic factors affecting cedar growth were selected. The independent variables with severe covariance VIF > 5 were excluded by using variance expansion factor[21]. As shown in **Table 3**, the climate factors with weak covariance and high contribution were T_{MCM}, P_{PT}, T_{max} and C_{MD}, whose corresponding standardized coefficients were 0.268, 0.135, -0.597 and -0.322 respectively. It can be concluded that T_{MCM} and P_{PT} is positively correlated with the growth of section area, while T_{max} and C_{MD} is negatively correlated with the growth of section area.

Table 3. Results of multiple stepwise regression analysis of climate factors

Variables	Unstandardized coefficients	Stand error	Standardized coefficients	*t* test	*P* value	Tolerance	VIF
VIF	0.319	0.084	0.109	3.808	<0.001	0.764	1.309
T_{MCM}	2.667	0.298	0.268	8.951	<0.001	0.705	1.417
P_{PT}	0.018	0.005	0.135	3.696	<0.001	0.470	2.129
T_{max}	-2.561	0.138	-0.597	-18.608	<0.001	0.613	1.631
C_{MD}	-0.054	0.006	-0.322	-9.564	<0.001	0.555	1.802
T_{ave}	-2.638	0.845	-0.382	-3.121	0.002	0.042	23.807
T_{min}	4.911	0.905	0.668	5.428	<0.003	0.042	24.024

The significant climate factors obtained from the screening were selected and scaled into classes according to their respective ranges of values (**Table 4**). The final coldest monthly mean temperature (T_{MCM}) was classified as level 8, the Hargreaves climate moisture deficit (C_{MD}) was classified as level 10, the average summer precipitation (P_{PT}) was classified as level 9, and the average summer maximum temperature (T_{max}) was classified as level 12.

Table 4. The division of climatic factors grades

Climate factors	Symbol	Grade division
Mean coldest month temperature	T_{MCM}	One level per degree Celsius
Hargreaves climatic moisture deficit	C_{MD}	The division of climatic factors grades per 20 units
Summer mean precipitation/mm	P_{PT}	Every 50 mm
Summer mean maximum temperature	T_{max}	One level per degree Celsius

4.2 Base model

4.2.1 Calculation of stand density index

The stand density index (SDI) is one of the common density indices used in the construction of the stand sectional area or accumulative growth model[22], and its expression is as follows.

$$\mathrm{SDI} = N(D_0/D)^{\beta} \tag{11}$$

Where: SDI is the stand density index; N is the number of plants per hectare in the stand; D_0 is the standard average diameter at breast height; D is the average diameter at breast height in the stand; and β is the natural thinning rate.

In order to determine the SDI value, β must be estimated first. In this study, β was estimated using the method of quadratic exclusion of sample plots with insufficient stand size[23]. First took all samples to build the regression equation $\ln N = a_1 - b_1 \ln D_g$, and excluded sample plots of $\ln N < a_1 - b_1 \ln D_g$. Then the remaining sample plots are used to establish the regression equation $\ln N = a_2 - b_2 \ln D_g$, and the sample plots of $\ln N < a_2 - b_2 \ln D_g$ are excluded. Finally, the regression equation was established with the remaining sample plots[23].

$$\ln N = \alpha - \beta \ln D \tag{12}$$

The regression equation was finally obtained by taking all the sample data and fitting each regression model nonlinearly in Forstat 2.2 software according to the abovesteps, with the following expressions for the above regression equation and its adjusted coefficient of determination $R_a^2 = 0.71$.

$$\ln N = 4.5273 - 0.9605 \ln D \tag{13}$$

Combine the natural thinning rate $\beta =$

-0.96053 with the relevant variables, and substituted into the SDI expression to calculate the stand density index for each site.

4.2.2 Selection of the model

The above basic models (1) to (4) were fitted nonlinearly with R software, and the final results of fitting and accuracy evaluation are shown in **Table 5**. Models (1) and (3) outperformed models (2) and (4) in all indices, indicating that the stand density index would be more appropriate than using the number of plants per hectare to express the density index. Among them, model (1) has the best simulation effect, the highest modeling data, and the lowest error index, so model (1) is chosen as the base model for simulating the growth of stand cross-sectional area.

Table 5. Parameter fitting and precision evaluation of candidate models

Data	Index	Model (1)		Model (2)		Model (3)		Model (4)	
		Estimated value	Stand error	Estimated value	Stand error	Estimated value	Stand error	Estimated value	Stand error
Parameter	*a*	6.1818	0.7593	1.7035	3.5770	0.8707	0.2158	1.0022	0.3929
	b	0.8016	0.0409	1.3405	0.0726	-1.2246	4.0778	7.0178	7.2819
	c	0.0012	0.0004	<0.0001	<0.0001	1.0061	0.1395	0.2327	0.2031
	d	9.8364	3.8411	9.5872	12.1026	-0.9635	2.5781	6.0671	3.7699
	e	0.1016	0.0414	0.0591	0.0753	0.8885	0.5540	0.6033	1.0797
	g					1.6024	10.2745	-22.1470	19.7498
Modeling data	R_a^2	0.8355		0.5145		0.8331		0.5199	
	RMSE	38.035		65.392		38.296		65.026	
	MARE	117.796		214.470		119.299		212.944	
Validation	RMSE	41.842		72.176		42.006		71.856	
	MARE	130.976		237.118		132.269		235.809	

Table 6. Evaluation results of the random effects of climatic factors*

Random effects position					Index	
a	***b***	***c***	***d***	***f***	**AIC**	**BIC**
X	C				2,583.301	2,616.658
X	P+C				2,586.629	2,624.156
	X+P+C				2,587.294	2,624.820
	M+X+P+C				2,583.632	2,625.329
	X+P+C		M		2,583.672	2,625.368
M+P	X+C				2,584.186	2,625.882
X	P+C		M		2,584.203	2,625.899
M+X	P+C				2,584.216	2,625.912
	M+X+C				2,599.808	2,637.335
X	M+C				2,599.846	2,637.373
	C	P			2,617.770	2,651.127
	X+P		M		2,615.220	2,652.746
	P+C	M			2,619.189	2,656.716
	X+P				2,628.985	2,662.341
	X		M		2,635.018	2,668.375

**M, X, P* and *C* respectively represent the random effects of climate factors T_{MCM}, T_{max}, P_{PT} and C_{MD}; *a, b, c, d* and *f* are the five parameters of the optimal foundation model.

4.3 Construction of mixed-effects model

In order to compare and analyze the effects of each of the four significant climate factors and their comprehensive differences on the stand area growth, a stand area growth model with random effects was constructed for model (1).

Using the hybrid model module of R software, the four climate factors T_{MCM}, P_{PT}, T_{max}, C_{MD} and their combinations, which had no serious covariance and had significant effects on area break, were screened as random effects, and the effects were added to the parameters *a*, *b*, *c*, *d*, *f* and their combinations (1,150 types) for random effects simulation, and the non-converging types were excluded, and each model was evaluated according to AIC and BIC. The results are shown in **Table 6**.

As shown in **Table 6**, the best mixed-effects model was constructed by adding T_{max} to parameter a, C_{MD} to parameter b in the random effects construction. Therefore, the final expression of the stand cross-sectional area growth model with climate random effects was constructed as follows:

$$B_{Aij} = (a_0 + a_{i0})H_{Dij}^{(b_0+b_{oj})}\left(1 - e^{\left(-cT_{ij}(\mathrm{SDI}_{ij}/1000)^d\right)}\right)^f + \varepsilon_{ij} \quad (14)$$

Where: B_{Aij}, H_{Dij}, T_{ij}, and SDI_{ij} denotes the stand area, mean height of dominant wood, stand age and stand density index for the mean summer maximum temperature (T_{max}) at level i, the water vapor deficit (C_{MD}) at level j in Hargreaves climate, a_{i0} and b_{i0} are the random effect parameters for T_{max} and C_{MD} respectively, and a, b, c, d, and f are model fixed parameters.

4.4 Model simulation analysis

The non-linear mixed-effects simulation of model (14) was performed using R software, and the obtained parameter fitting results and model testing results are shown in **Table 7**.

Table 7. Fitting results of model parameters

Data	Index	Model (1)		Model (14)	
		Estimated value	**Stand error**	**Estimated value**	**Stand error**
Parameter	a	6.1818	0.7593	6.2813	0.6408
	b	0.8016	0.0409	0.7451	0.0365
	c	1.24E-05	3.97E-05	0.0002	0.0004
	d	9.8364	3.8421	7.9746	2.7091
	f	0.1016	0.0415	0.1218	0.0456
Estimate	AIC	2,640.35		2,583.30	
	BIC	2,665.36		2,616.66	
Modeling data	R_a^2	0.8355		0.8921	
	RMSE	3.8035		3.0792	
	MARE	11.7796		9.9011	
Validation data	RMSE	4.1842		3.4665	
	MARE	13.0978		11.4833	

From **Table 7**, the results of fitting the parameters of each model are significant. Comparing AIC and BIC, it can be seen that the fitting effect of the model (14) after adding the random effect is better than the base model (1), and the effect of random effect is obvious. From R_a^2, RMSE, and MARE, the model (14) after adding random effects outperforms the base model (1) in terms of modeling and testing accuracy. The adjusted coefficient of determination R_a^2 of the modeled sample increased from 0.8355 to 0.8921, an increase of 6.77%; the root mean square error RMSE decreased by 19.04%, and the mean relative error MARE decreased by 15.95% in absolute value; the root mean square error RMSE of the test sample decreased by 17.15%, and the mean relative error MARE decreased by 12.33%.

5. Conclusion and discussion

5.1 Discussion

The study of stand area growth prediction model is important for predicting forest growth and harvest, and coordinating the overall forest management, while the expression of stand age, stand quality index and density index are necessary parts for constructing stand area growth model. In this study, a hybrid model was used to add each climate factor to the base model in the form of random effects to analyze the stochastic effects of each level of climate factor on the growth of stand area. Hu[3] used the same method to analyze the effects of different stand types and stand type differences on the stand area growth of oak, and although the study objects were not consistent, the model accuracy was significantly improved; Li *et al.*[24], after comparing the traditional regression model method with the mixed model method to construct a stand area model of larch spruce fir, concluded that the mixed model method had higher accuracy. The results showed that the mixed model approach was more accurate, indicating that it was reasonable and effective to use the mixed model approach to construct the stand area model.

The final climatic factors added to the model random effects were mean maximum summer temperature T_{max} and Hargreaves climate moisture deficit C_{MD}, where T_{max} affects the maximum growth rate of the basal area and C_{MD} affects the growth rate of the basal area. The normalized coefficients of C_{MD} and T_{max} were negative, which were -0.597 and -0.322 respectively, indicating that the maximum value of the broken area and growth rate were negatively correlated with T_{max} and C_{MD} respectively, which was consistent with the research results made by Zhu[25] in the study of climatic factors on cedar tree whorls of different seed sources. It may be that because of the subtropical monsoon climate in Hunan, the temperature is generally higher during the growing season, and temperature is no longer the main requirement for tree growth. Excessive heat intensifies transpiration, and water vapor loss also intensifies water deficit in the forest, resulting in water deficit growth of fir trees being hindered. At the same time, the climatic factors with weak covariance and high contribution from multiple stepwise regression analysis in this study were T_{MCM}, P_{PT}, T_{max}, C_{MD}, which were similar to the significant climatic factors obtained by the same method in screening on the larch standing index model by Zang[12]; in the study of the distribution of suitable areas for Mongolian oak dominant species by Lv *et al.*[26], by using the knife cut method, it is concluded that the hottest monthly mean temperature, wet season precipitation, annual accumulated temperature all had significant effects on Mongolian oak, which all indicated that the climatic factors had significant effects on the growth of forest trees.

For the convenience of modeling, only the mean height of dominant trees was used to represent the stand quality index in the constructed cross-sectional area model, without directly considering the influence of topography, landform and other stand factors. In the subsequent study, we can consider using topographic and geomorphological data to construct a stand index model for cedar plantation first and obtain various status indices, and then consider climatic factors to construct a sectional area model, which may further improve the accuracy of the model.

5.2 Conclusion

In this study, the stand density index SDI (β = -0.96053) was estimated using 638 fir plantation sample plots in Hunan Province. Comparing the fitting results of different base basal area growth equations, the Richards model was determined to have the best effect ($R_a^2 = 0.8355$, RMSE = 3.8035, MARE = 11.7796). To consider the effects of different climatic factors, the climatic factors with weak covariance and high contribution were screened as T_{MCM}, P_{PT}, T_{max} and C_{MD} using multiple stepwise regression analysis, of which the first two were positively correlated with basal area growth and the last two were negatively correlated with it. The growth model of basal area distribution of Chinese fir plantation with climate random effects was constructed by using the method of mixed-effects model, thus the optimal random-effects parameter construction form was determined. Compared with the base model, the model accuracy of the model with climate random effects was significantly improved with the modeling accuracy $R_a^2 = 0.8921$, improved by 6.77%; RMSE = 3.0792, reduced by 19.04%; MARE = 9.9011, reduced by 15.95%. The results illustrate the significant influence of climate on stand growth and provide support for the rationality of adding a climate factor to the growth model, which is beneficial to the regional forest management of fir plantations while improving accuracy.

Conflict of interest

The authors declared no conflict of interest.

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