RESEARCH AND EVALUATION OF GROWTH RATE MODEL FOR NATIVE CHINESE MOSO BAMBOO

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Abstract. Tree height growth assessment is important to understand forest dynamics that can reflect the health, productivity, and sustainability of a forest. Tree growth models are important tools to provide a reliable set of information for forest management. Accurate prediction of plant height from time is important for estimating future production. In this study, we used 80 native Moso bamboo and fit 9 models to predict bamboo height as a function of time since sprouting. Our results showed that Logistic growth model was the most suitable for predicting bamboo height (r=0.969), and can be used for predicting the growth and yield of mature native Moso bamboo, and provide a basis for the calculating biomass and carbon storage.
Keywords: *Phyllostachys heterocycla, tree growth, height, growth time, optimal model*

Introduction

Forest ecosystems account for 30% of the global terrestrial ecosystem. It is the most biologically and genetically diverse ecosystem providing not only habitat to more than 50% of the world's flora and fauna (Aerts and Honnay, 2011; Keenan et al., 2015; Miura et al., 2015), but also served human all through human history by providing food, water resources and other valuable timber products (Morales et al., 2015; Miura et al., 2015). Forest ecosystems also play an irreplaceable role in curbing global climate change, carbon cycle, soil and water conservation, and sustainable supply and regulation of forest products (Piao et al., 2018). The research and development of the forest growth model can timely and accurately understand the quantity, quality and dynamic changes of forest resources, and provide a basis for the analysis and assessment of forest growth, biomass and forest yield (Köhl et al., 2015).

Tree growth is an important facet of forest dynamics and can reflect the health, productivity, and sustainability of the forest (Zhang et al., 2019), therefore, it is very important to measure it on a regular basis. Tree growth models are important tools in providing reliable information for decision making regarding forest management (Liu et al., 2017). Many tree growth models that can effectively project changes in forest resources have been developed (Cortini et al., 2011; McCullagh et al., 2017). Tree height is the most important factor in forest resource inventory surveys, production and management of forest resources and for research on forest ecosystems (Vargas-Larreta et al., 2009; Xuan et al., 2016). Accurate estimation of tree height is important in the

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development of forest growth models and can be used to estimate stock volume, biomass and carbon stocks (Li et al., 2015).

Tree growth is a complex process that depends on multiple and interacting factors. It is influenced by site conditions (Lévesque et al., 2016), climatic variables (Zell, 2018), and management (Biging and Dobbertin, 1995). Observation of tree height (H) from the ground is usually affected by the complexity of the distribution of understory vegetation, forest density and topography of the terrain (Temesgen et al., 2014). Moreover, the procedure to measure H is both time and cost expansive. Due to these reasons estimation of H is relatively more tricky and difficult that DBH (D) measurement. Because of this difficulty and to reduce the costs associated with field inventories, it is common practice to fit tree models based on D to predict H (Saunders and Wagner, 2008; Paulo et al., 2011). Further, an improved understanding of the H–D relationship is needed for reliable regional and global estimates of forest biomass and carbon storage. An allometric power relationship between H and D is often assumed in estimating H, although this approach neglects the possible large deviation in estimating biomass by allometry (Feldpausch et al., 2011; Stark et al., 2013). Besides this, non-linear theoretical functions are often used, such as the Chapman-Richards (Song et al., 2011), Hossfeld (Yen et al., 2010), Logistic, and Gompertz (Richards, 1959; Huang et al., 1992; Zeide, 1993; Cieszewski, 2001).

Bamboo is an important forest resources in many parts of the world. There are more than 70 genera of bamboo that are mainly distributed in tropical and subtropical regions (Zhou, 1992). Bamboo is particularly import in China, which is known as the "kingdom of bamboo". There are more than 40 genera and 400 species of bamboo in China. The Chinese bamboo forest covers 6.01 million ha, mainly distributed in Fujian, Jiangxi, Zhejiang, Hunan, Sichuan, Guangdong, Guangxi, and Anhui provinces (State Forestry Administration, 2014).

Bamboo is the main food for giant pandas, which are a unique and protected species in China (Mertens et al., 2008). Bamboo provides food for humans too. Further, it is a green material that can be used as a substitute and supplement for wood where it is widely used in construction, transportation, papermaking, furniture, and handicraft manufacturing (Tang et al., 2016). *Phyllostachys heterocycla* (Moso bamboo), which is characterized by its fast growth and rapid biomass accumulation is an important forest type in Southern China (Zhao et al., 2016). These forests cover 4.43 million ha in China, accounting for about 70% of the national bamboo forest area. The main forest products from Moso bamboo forests are timber and shoots for human consumption. Moso bamboo can reach a height of 20 m when mature and can grow between 30 and 100 cm per day during the growing season (Jiang et al., 2002; Chen, 2011). Thus, it has a higher annual carbon sequestration than other common timber trees (Song et al., 2011), suggesting a high potential for carbon storage (Yen et al., 2010).

For these reasons, there is a need to monitor and accurately estimate the biomass of Moso bamboo forests in China. The growth patterns of bamboo are different from trees; its unique characteristics include fast growth, high production and rapid maturation from shoot to culm (Scurlock et al., 2000). Few researchers have addressed the H–D relationship of bamboo using an allometric power equation (Inoue et al., 2011). The H-D relationship of Moso bamboo has only been studied by Inoue (2013), who used reduced major axis regression. Previous studies have mostly focused on biomass and carbon storage, and did not systematically study bamboo height. In this paper we use the bamboo height data to develop a growth model for Moso bamboo. Such an equation is useful for quantifying bamboo biomass and carbon storage.

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Materials and methods

Study area

The study area is located near Yixing City and Wuxi City in southwest Jiangsu Province, adjacent to the Zhuhai Scenic Area (N 31°25′and E 119°73′). The area has a higher elevation and mountainous in the south and lower in elevation and relatively flat in the north, the range of the DEM is -137~614 m (*Fig. 1*). The area called “the ocean of bamboo” in Chinese. The area falls within the subtropical monsoon climate region, with abundant rainfall all year round. The average annual number of rainy days is 136.6, and the annual average precipitation is 1177 mm (Wu and Ming, 2007). The rainfall is concentrated in spring and summer, although it is warm and humid throughout much of the year. The annual average temperature is 15.7°C, the average frost-free period is more than 240 days, and the growth period is up to 250 days. The rivers cris-cross the study area and the average annual precipitation is 1177 mm. The soil is mainly yellow in colour with abundant organic matter providing excellent conditions for the growth of bamboo (Peng and Zou, 2011).

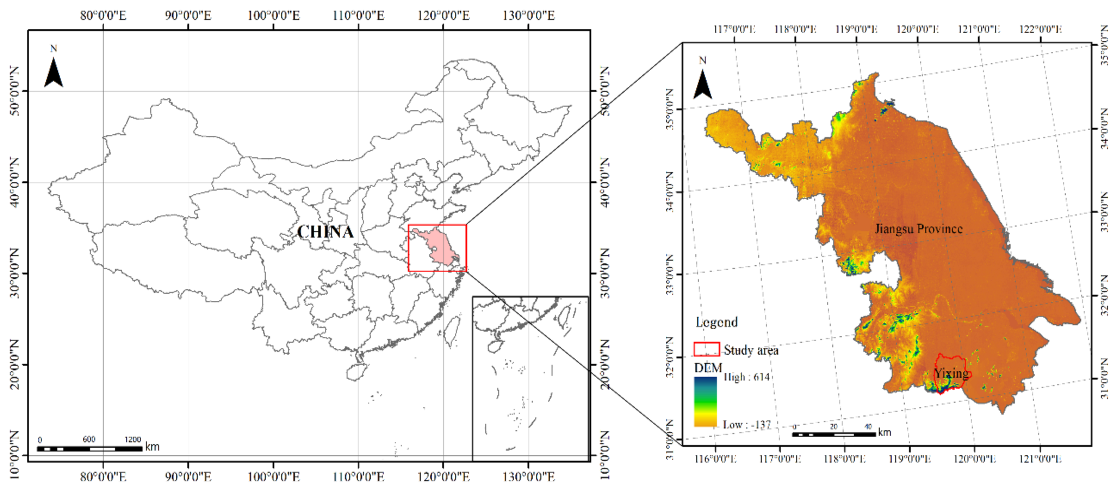

Figure 1. *Location and digital elevation model (DEM) of the study area*

Data acquisition

Five plots (15*15 m) were set up in the study area, and 20 bamboo shoots were randomly selected from each sample plots. Shoots that died or which were damaged by animal foraging or vandalism were removed from the data set, eighty bamboo shoots were left from sample plots in the study area as measurement samples, shoots were identified for measurement on March 26, 2015, and visited at regular intervals. By May 22, the shoots began to grow in height. Height growth was completed after 56 days. When the shoot height was less than 2 m, height was measured by a tape; when the shoot height exceeded 2 m, the height references were accurately measured by total station (Leica Flexline TS06plus Total Station) with accuracy to the millimetre level. The complete height recorded after the growth ranged from 10.71m to 16.06 m.

The models used were nonlinear and fit using the statistical package SPSS 20.0 (SPSS for Windows version 20.0) and the Levenberg-Marquardt (LM) method.

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Tree height models assessment

We selected nonlinear models such as tree growth empirical equations and theoretical equations to compare the performance of the model. All model formulas refer to the reference (Meng, 2006). The model formulas were shown in *Table 1*.

Table 1. *Selected tree height models*

Number	Model	Formula
Model 1	Logistic	$h=\frac{A}{1+\mathrm{be}^{-ct}}$
Model 2	Richard	$h=A(1-e^{-bt})^{c}$
Model 3	Gompertz	$h=Ae^{-be^{-rt}}$
Model 4	Schumacher	$h=Ae^{-b/t}$
Model 5	Sloboda	$h=Ae^{-be^{-ct^{d}}}$
Model 6	Rоляср	$h=At^{b}e^{-ct}$
Model 7	Weibull	$h=A(1-e^{-bt})^{c}$
Model 8	Power function	$h=At^{b}$
Model 9	Korf	$h=Ae^{-bt^{-c}}$

H: Moso bamboo’s height, m; t: time, day; a-d are parameters

Model evaluation

In order to verify the accuracy of the forecasting accuracy of the above methods, we validated the models. Usually the model is validated by independent data sets, which is the best way to validate the model at present (Zhang et al., 2019). The majority of the data (80%) was used for model calibration, and the remaining (20%) data was used for verifying the consistency of the models. At present, this method of model validation has been applied in many model validation, such as the biomass model, DBH growth model and carbon storage model (Zhang et al., 2019). Model evaluation mainly used the following indicators: root mean squared error (RMSE), adjusted coefficient of determination (R^2_{adj}), and other criteria (Montgomery, 2013). RMSE combines the variation of mean deviation and deviation, and can directly and clearly evaluate the accuracy of the model. RMSE and R^2 are important evaluation factors in this paper. The closer the R^2 value is to 1, the better the fitness of the model is (Peng et al., 2001). However, Cameron and Windmeijer (1997) suggested that the coefficient of determination (R^2) is not suitable for model evaluation of non-linear functions. Therefore, this paper uses six indicators to evaluate it comprehensively (Burnham and Anderson, 2002) including: root of mean square error (RMSE), coefficient of determination (R^2) and adjusted coefficient of determination (R^2_{adj}), bias (BIAS) and relative bias ($BIAS_{rel}$), residual sum of squares (RSS), Akaike’s Information Criterion (AIC). The smaller the RMSE value, the higher the predicted accuracy. The large of R^2 and R^2_{adj} value, and correlation is stronger. AIC is an information standard commonly used to choose the best model. The expressions of the statistics are shown as follows:

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$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(h_i - \hat{h}_i)}{n-p-1}} \quad \text{(Eq.1)}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(h_i - \hat{h}_i)^2}{\sum_{i=1}^{n}(h_i - \bar{h}_i)^2} \quad \text{(Eq.2)}$$

$$R_{\text{adj}}^2 = 1-(1-R^2)\times\frac{n-1}{n-p-1} \quad \text{(Eq.3)}$$

$$Bias = \frac{\sum_{i=1}^{n}(\hat{h}_i - h_i)}{n} \quad \text{(Eq.4)}$$

$$Bias_{\text{rel}} = \frac{\sum_{i=1}^{n}(\hat{h}_i - h_i)/h_i}{n}\times 100 \quad \text{(Eq.5)}$$

$$RSS = \sum_{i=1}^{n}(h_i - \hat{h}_i)^2 \quad \text{(Eq.6)}$$

$$AIC = n\ln(RSS) + 2(p+1) - n\ln(n) \quad \text{(Eq.7)}$$

where h_i is the observation value; $\hat{h}_i$ is the forecast value and $\bar{h}_i$ is the average value; n is the total number of data used to the fitted model; and p is the number of independent variables.

Results

Non-linear regression analysis was performed by SPSS. The model estimated all the parameters by using the calibration data, and obtained the parameters and R^2 values of each model (*Table 2*). Except for model 9, all of them showed relatively satisfying results. Therefore, it can be seen that model 9 is not suitable for this data. As shown in *Table 2*, Model 1-8 uses all the data to estimate the parameters by nonlinear regression. All parameters are significant ($p < 0.05$), and the parameters of each model are easily obtained by calculation except model 9.

Table 2. *Parameter estimates and fitting statistics of the models using all data*

Parameter	a	b	c	d	R^2
Model 1	1553.94	142.43	0.135		0.969
Model 2	1946.97	7.73	0.06		0.964
Model 3	1891.38	10.05	0.066		0.965
Model 4	5506.07	72.04			0.961
Model 5	2181.55	51.33	0.596	0.523	0.963
Model 6	0.389	2.206	0.011		0.953
Model 7	2357.07	0.000	2.482		0.960
Model 8	0.893	1.859			0.949
Model 9	605.285	4.867	1637.086		0.06

a-d are model’s parameters

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According to the above test formula, each test index value is calculated using the calibration data and the verification data, and the results are shown in *Table 3*.

Table 3. *Calibration data and validation data adaptive statistics for models*

No.	Variables	Fitting data				Validation data			
		bias(m)	RMSE(m)	AIC	Adj. R^2	bias(m)	RMSE(m)	AIC	Adj. R^2
1	h,t	-0.66	4.26	187.55	0.9689	-0.96	3.05	38.73	0.9836
2	h,t	-2.38	4.57	196.42	0.9643	-2.68	3.52	43.25	0.9782
3	h,t	-2.88	4.52	195.07	0.965	-3.17	3.44	42.55	0.9792
4	h,t	-1.37	4.75	201.54	0.9613	-1.66	3.72	45.04	0.9757
5	h,t	-2.61	4.63	198.03	0.9634	-2.90	3.60	44.01	0.9772
6	h,t	-0.45	4.75	215.40	0.9613	-0.75	4.34	50.01	0.9668
7	h,t	-0.22	4.63	204.26	0.9634	-0.07	3.75	45.33	0.9752
8	h,t	1.80	5.3	219.08	0.9519	1.50	4.45	50.77	0.9652

Model fitting and evaluation

Using the Origin8.1, the growth model was fitted by the Levenberg-Marquardt (LM) method. The fitting effects of Model 1, Model 2, Model 3, Model 4 and Model 8 were good (*Fig. 2*). Other models adopt nonlinear regression, and the fitting results werenon-convergence, which was not suitable for the prediction of this data. In the subsequent statistics, the statistical results of the unconverging model were removed.

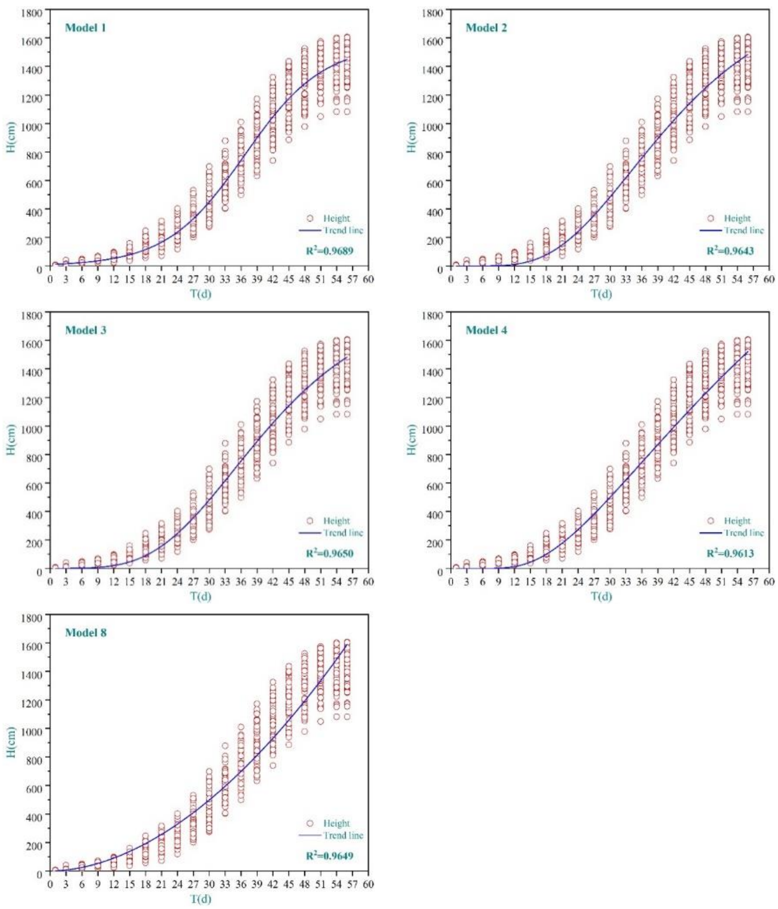

Figure 2. *Models fitting trend line*

It can be seen from the above trend graph that bamboo's height and the growth time have a high correlation, and models 1, 2, 3, 4 and 8 have higher R^2 values: 0.9689, 0.9643, 0.9650, 0.9613 and 0.9649, respectively. The correlation coefficient of Model 1 was the highest observed, and the result obtained in the fitting of the calibration data has the highest precision, which is suitable for the estimation of bamboo's height growth and conforms to the law of tree growth curve.

As shown in *Fig. 3*, the models 1, 2, 3, 4, and 8, respectively, use the calibration data to obtain the residual of the predicted height, and most of the data points are distributed around y=0. These models show the full uniformity of the predicted values and the independence of the residuals. The residual distribution of model 1 in the figure is relatively small, which reveals model 1 is the best model in the study.

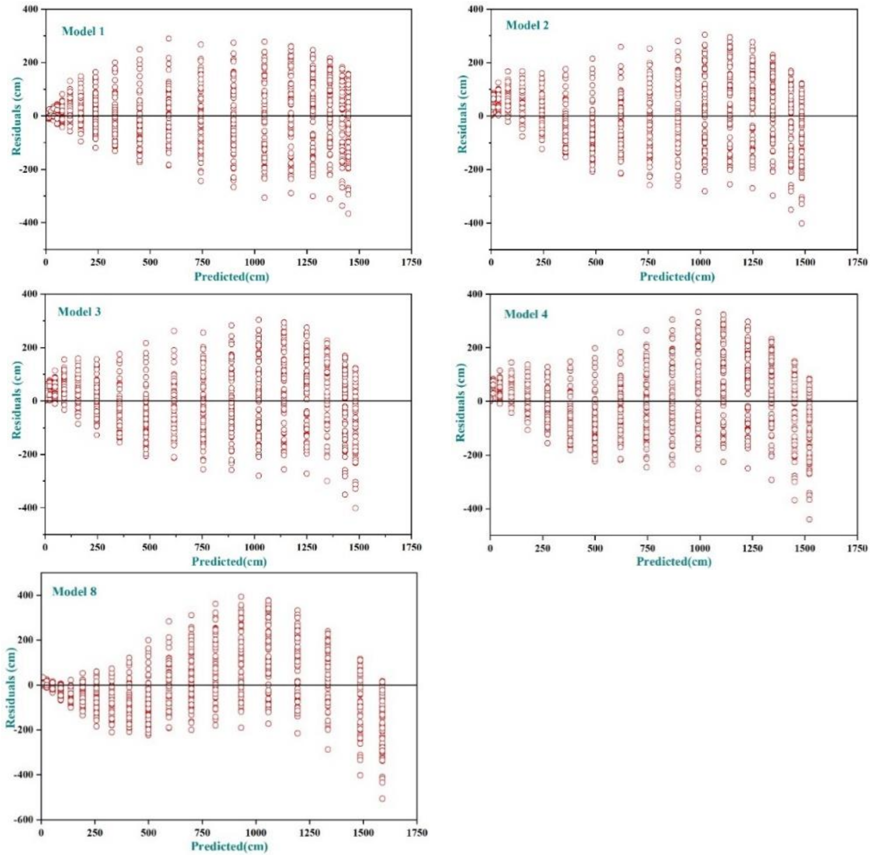

Figure 3. *Residual plots in the calibration dataset for the models (Model 1; Model 2; Model 3; Model 4; Model 8)*

As shown in *Fig. 4*, the models 1, 2, 3, 4, and 8 use the verification data to obtain the average deviation value and RMSE of the bamboo height through the growth period. The standard deviations of models 1, 2, 3, 4 and 8 are mainly distributed around y=0, in which the standard deviation of model 8 is 1.61 m, and deviations of most model are less than 1 m, accounting for 93% of all deviations. The RMSE values of models 1, 2, 3, 4 and 8 are between 0.049-1.86, the RMSE of model 8 varies greatly, the RMSE value of model 1 changes little, and the model is relatively stable. According to the above analysis, the model 1 is the most suitable model in the calibration data and the verification data among the five models.

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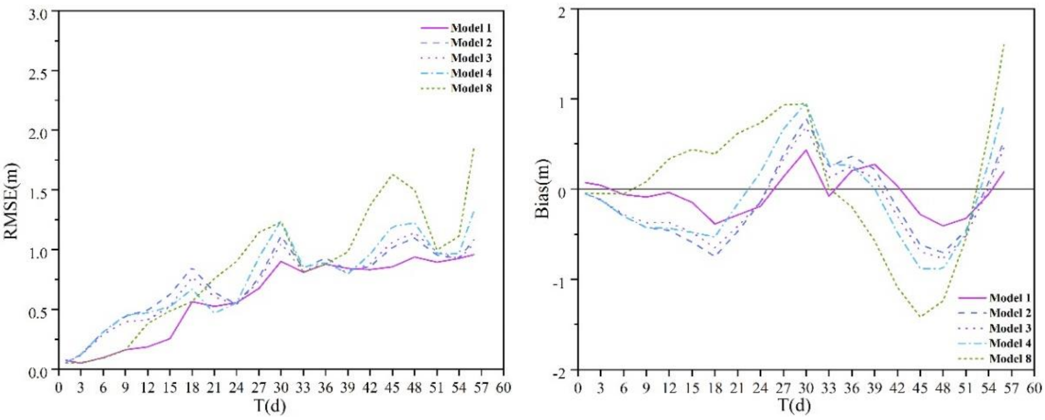

Figure 4. *Values of average RMSE and Bias in relation to T in the calibration and validation datasets for the models (Model 1; Model 2; Model 3; Model 4; Model 8)*

Discussion

In this study, based on the tree-based growth model, a model suitable for bamboo height and time was selected, which is very important for predicting the change of bamboo growth height with time. Tree growth is an important manifestation of the dynamic changes of forests, which can provide a basis for forest productivity and temporal and spatial changes in forests. The tree height and DBH models are the most basic and effective models in the growth model. The choice of models should be based on the arrangement of the expression of models with calibration data and validation data (the adjusted R^2, R^2, RMSE, the absolute deviation, the relative deviation and the AIC). The model with the adjusted R^2, R^2 value closest to the highest value and a deviation (absolute and relative deviation) closest to zero is thought to be the best. The lower the value of RMSE and AIC, the higher the ranking of the model. For each model, its final ranking is the sum of the statistics of the five evaluation values. The model with the minimum sum (i.e., the highest ranking) is considered to be the functional model that is most suitable for estimating the growth of Moso bamboo. According to this analysis, the calibration data and the validation data show that model 1 is the most suitable for estimatingthe growth rate.

In comparison with previous studies, Huang et al., 1992) developed the HT-DBH functional model of the main tree species from 20 weighted nonlinear equations. It was observed that Weibull, Modified Logistic, Chapman-Richards and Schnute functions generally provided the most satisfactory results. Zhang (1997) concluded that the Schnute, Weibull and Chapman-Richards models provided the best predictive performance for 10 conifer species in the inland regions of the United States in the six nonlinear growth functions selected for HT-DBH. Peng et al. (2001) and Sharma and Parton (2007) recommended Chapman-Richards, Weibull, and Schnute nonlinear growth functions as the most satisfactory models in total height predictions in Canada. Ahmadi et al. (2013) reported that Chapman-Richards, Weibull and Schnute functions in predicting accurate total height predictions in Iranian Hyrcanian forests have shown excellent predictive performance, based on mathematical features, biological interpretation of parameters.

Furthermore, Lumbres et al. (2013) reported that the Modified Logistic nonlinear growth function was the best model for the Pinus kesiya Royle ex Gordon of Benguet in

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Philippines. Based on the result of the researchers, nonlinear growth functions are reliable in the prediction of total height of trees. In the latest study of Lumbres et al. (2015) entitled DBH-height modeling and validation for Acacia mangium and Eucalyptus pellita, the Weibull and Chapman-Richards models were observed as the best nonlinear growth functions for Acacia mangium. However, the result of our study suggested that the Logistic regression model has the highest accuracy in predicting the growth of bamboo among the nine models we selected, which is obviously different from the previous research results.

Conclusion

In this study, the bamboo was used as the object, and the measured data of the fixed sample plots were used. The nonlinear regression method was used to model 80 bamboo shoots randomly seletected in five different study plots. Considering the interrelation between the growth time of bamboo and bamboo’s height, the tree growth and empirical equations were used to establish a height growth model of bamboo. From the modeling results, the conclusions are showed as follow. Using the models 1, 2, 3, 4 and 8 to predict the bamboo height, the majority of the bamboo height determination coefficient R^2 can reach 0.9 or more, and in terms of accuracy the model 1 performance was the best. The methods and the models recommended in this study are based on statistics, which provide a reliable basis for the estimation of forest growth and survival and planting management for Chinese native Moso bamboo.

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