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Modeling height-diameter relationship for artificial monoculture *Metasequoia glyptostroboides* in sub-tropic coastal megacity Shanghai, China

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ABSTRACT

Tree height is a key variable in forest monitoring studies and for forest management. However, tree height measurement is time consuming, and the recommended procedure is to use estimates from tree height (H) - diameter at breast height (DBH) models. Increasingly, H-DBH models are being developed for urban forests, providing tools to forest management and ecosystem services estimation. Here, we compared model forms and approaches for predicting H as a function of DBH and additional stand level covariates variables. Four model forms were evaluated: (i) basic models (which only used DBH as predictor variable); (ii) generalized models (which used DBH and other predictor variables based on the best basic model); (iii) a mixed-effects model based on the best basic model; and (iv) a mixed-effects model based on the generalized model. Several sampling designs aimed at minimizing height measurement were tested in terms of accuracy and applicability. Taking predicted accuracy and investigation cost into account, we recommend generalized non-linear mixed-effects model (NLME) when there were two or less tree height measurements taken in a given stand. The basic NLME model could be calibrated when there were 3 or more tree height measurements, depending on the required level of accuracy and investigation cost. Additionally, we first reported that soil pH as a covariate variable in H-DBH model and our generalized NLME model implied that the difference in the H-DBH relationship caused by pH varies among different stands. This finding may be attributable to differing biological properties of the similar alkaline tolerance species.

1. Introduction

Individual diameter at breast height outside bark (DBH, measured 1.3 m above ground level) and tree height (H) are key variables in forestry applications and are used to study forest structure (Curtis, 1967), to estimate timber volume and carbon storage (Curtis, 1967; McPherson and Peper, 2012), site index and other important variables (Peng et al., 2001). Information on the height of urban trees is essential for tree management (McPherson and Peper, 2012), but is often ignored in municipal tree layer inventories (Rust, 2014). To save time and expense, tree height is usually measured in a subsample of trees first, and then the species-specific H-DBH models would be used to overcome the lack of information about unmeasured tree height (Gómez-García et al., 2015; Monteiro et al., 2016; Zang et al., 2016a).

There are two basic types of models to describe the relationship between H and DBH (Lei et al., 2009; Zang et al., 2016a): one is basic model, assuming that tree height is completely dependent on DBH (Soares and Tomé, 2002; Gómezgarcía et al., 2014; Mehtätalo et al., 2015), and the other is generalized model, assuming that tree height is not only dependent on DBH but also dependent on other tree and stand-level variables (Soares and Tomé, 2002; Temesgen and Gadow, 2004; Newton and Amponsah, 2007; Huang et al., 2009). Stand-level variables incorporated into generalized H-DBH models include i.e. stand age, density, basal area, crown competition factor, site index, dominant height and geographic coordinates, etc (Curtis, 1967; Temesgen and Gadow, 2004; Temesgen et al., 2007; Dahle and Grabosky, 2009; Schmidt et al., 2011; Dahle et al., 2014; Gómez-García et al., 2015; Zang et al., 2016a; Adamec and Drápela, 2017; Dahle et al., 2017).

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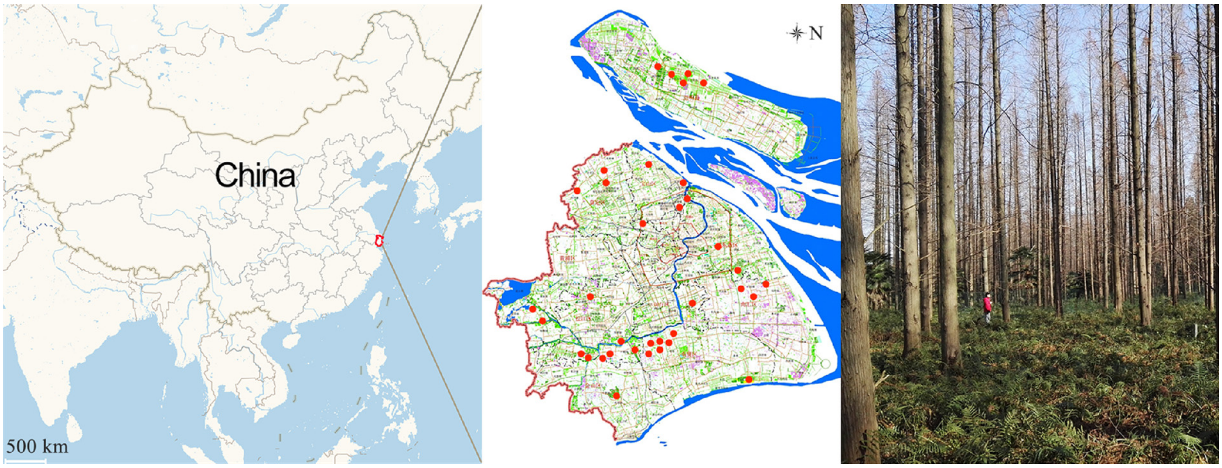

Fig. 1. Geographical location of the study area and scenery of *M. glyptostroboides* within one plot. Red circles represent permanent plots in SUFRN. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

However, due to the hierarchical structure of the datasets used to construct H-DBH models (i.e. trees within plots within stands), the classical regression assumption that measurements are independent is untenable (Neter et al., 1985). The mixed model technique, as an alternative approach, usually deals with this problem successfully (Castaño-Santamaría et al., 2013). From a practical point of view, linear and nonlinear mixed-effects models have been reported to estimate a more accurate and precise relationship of tree height and DBH than both conventional linear and nonlinear models (Trincado et al., 2007; Temesgen et al., 2008; Castaño-Santamaría et al., 2013; Gómez-García et al., 2015; Zang et al., 2016a).

Compared to the breadth and depth of modelling in the fields of nature forests, urban forests modelling is in its early phase (McPherson and Peper, 2012). Unlike in nature forests, models for urban forests are rare (Rust, 2014). In addition, models developed for nature forests cannot be directly transferred to urban forests (McHale et al., 2009), because the urban areas are warmer (Oke, 2010) and more polluted (Monn et al., 1995), especially in low quality soils (Jim, 1998). These characters of urban environment would influence tree growth (Jim, 1998; Monteiro et al., 2016).

In recent decades, the speed of urbanization has intensified globally and over 10% of the world's population now lives in megacities of 10 million or more (e.g. New York, Shanghai) (Roberts, 2011; UN, 2012). However, rapid urbanization is associated with problems such as nature ecosystem destruction and environmental degradation (Bloom et al., 2008). In addition, this land use change coupled with high nitrogen (N) deposition also changed nutrient cycling in soils (Chen et al., 2014), which would reduce the stability of structure and function of urban forests (He et al., 2016). The Shanghai municipality is a typical example with environmental problems associated with rapid urbanization in China (Huang et al., 2013). To improve the situation of the unbalanced urbanization, Shanghai's urban forest areas rapidly increased with the implementation of key forest projects in the last 20 years. As a consequence, forest coverage increased from 3.17% in 1999 to 14% in 2014 (Wang et al., 2013). Particularly, *Metasequoia glyptostroboides* (Hu and Cheng) plantation, as ecological public welfare forests, accounted for 5.7% of Shanghai's forest area in 2014. *M. glyptostroboides* is a species considered extinct and only present in fossil records until its discovery for the scientific world in 1948 (Chu and Cooper, 1950). In order to prevent its extinction, seedlings from the seed lot collected from several population in China had been planted throughout the world (Satoh, 1998; Williams et al., 2003). In addition to its quick growth (Wilczyński et al., 2014), its relative adaptation to air pollution (Zhang et al., 2014) and amelioration of alkaline soil have(Li et al., 2008) made this tree species an obvious choice of urban foresters (Kim and Lee, 2016).

Urban forests can potentially mitigate the deterioration of environmental problems accompanying rapid urbanization via a range of forest ecosystem benefits and services (Roy et al., 2012). Managing urban forests to provide more ecosystem services are becoming important facets of municipal forestry (Young, 2010). Therefore, it has become an increasingly important part of ecological studies to conduct research on the structure, function and factors that influence urban forests (Dwyer et al., 1992; McPherson et al., 1997; Dahle et al., 2014; Zheng et al., 2018). However, as far as we know, there are rarely impressive models used in total tree height estimation for *M. glyptostroboides* (Mu et al., 2017), more specially even-aged plantation in urban. This resulted in a lack of inventory and management tools for this species. Furthermore, up to now, there has not been any study that considered site characteristics like soil pH and fertility as candidate variables in nonlinear generalized H-DBH model.

The overall objective of this research was to select suitable plot-specific H-DBH models for *M. glyptostroboides*. The basic, generalized and mixed-effects models were used to develop the H-DBH model based on the data from the permanent plots established in *M. glyptostroboides* plantations over a wide range of growing conditions in Shanghai. The specific objectives of this study were as follows: (1) to compare basic, generalized and mixed-effects models; and (2) to test several sampling designs for minimizing the height measurement effort in terms of accuracy and applicability.

2. Materials and methods

2.1. Study site

The Shanghai Urban Forest Research Network (SUFRN) was established in 2011 to monitor the forest ecosystem service, comprising 95 permanent plots (Fig. 1). These monitored plantations originate from planting and are monoculture with little understory. There was no treatment on these plantations before and after the plots establishment. Located at the elevation of 5 m above sea level, these plots are in plain region with annual precipitation ranged from 606 to 1481 mm and annual temperatures ranging from 14.6 to 16.2 °C. Paddy soil (or anthrosols based on FAO/UNESCO classification) and tidal soil (or fluvisols) are the main soil type distributed in the SUFRN landscape (Xu et al., 2011).

2.2. Data collection

The trees layer inventory was carried out in 2016 and soil sampling

Table 1
Summary statistics of plots.

Data type	Variable	Mean	Standard deviation	Min.	Max.
Fitting data	H	16.0	6.69	3.5	38.0
	DBH	17.8	7.50	5.1	39.6
	AGE	21.0	5.86	16.0	35.0
	CB	4.1	1.44	1.0	8.7
	DEN	1357	831.24	383	2467
	D_a	17.82	6.29	10.96	30.81
	BA	25.67	4.14	19.83	35.32
	pH	7.93	0.92	5.73	8.56
	CN	9.50	2.64	6.80	16.04
	CP	1.84	0.75	0.94	3.49
	NP	0.19	0.05	0.13	0.34
Validation data	H	12.5	3.42	3.8	24.0
	DBH	13.5	4.85	5.3	35.3
	AGE	22.0	7.56	17.0	35.0
	CB	2.6	0.74	0.9	6.2
	DEN	2894	848.68	1517	3850
	D_a	13.52	3.21	10.66	18.10
	BA	53.54	19.24	24.46	70.67
	pH	7.98	0.54	7.51	8.81
	CN	11.17	4.31	7.30	17.53
	CP	1.55	0.42	1.17	2.12
	NP	0.15	0.02	0.10	0.16

H: Height/m, DBH: Diameter at breast height/cm, AGE: plantation age, CB: Crown breadth/m, DEN: Density/trees hm^{-2}, D_a: Average DBH of each plot/cm, BA: Basal area/m^2 hm^{-2}, CN/CP/NP: soil CN/CP/NP ratio.

in 2011. Soil organic carbon (SOC), total nitrogen (TN), total phosphorous (TP) concentrations at the depths (0–10 cm) and soil pH were measured. The field inventory and SOC, TN, TP, pH measuring methods were based on the National Standards of the People's Republic of China for "Methodology for field long-term observation of forest ecosystem research" (GB/T 33027-2016). All free standing woody plants with DBH larger than 5 cm (at 1.3 m above the ground) were mapped and tagged. The DBH of each stem was measured with flexible tape (with a precision of 0.1 cm) and the height and crown breadth of each stem was measured using radar distance measurement (Vertex IV, Haglöf Sweden AB). The dataset presented in this paper were obtained from 17 plots (each 20 m × 30 m), comprising 1121 stems of *M. glyptostroboides.* Data were split into two parts for model fitting and validation by the following method (Zang et al., 2016a): each plot was randomly allocated to a number between 1 and 17 (e.g. plot1, plot2), and plots whose number were 1,2 and 3 were assigned as validation data (358 stems in 3 plots) and the rest were fitting data (763 stems in 14 plots). More details of the plots included in this study can be found in Table 1.

2.3. Analytical framework

The approach taken to achieve our goals was described in the following sections (a–e).

2.3.1. Selection of the basic nonlinear height-diameter model

The 27 models were evaluated as candidate models in this study, including the Weibull-type function, the Chapman-Richards function, the modified logistic function, the Korf-type function and Gompertz-type function (details of the models can be found in (Huang et al., 1992, 2000; Li and Fa, 2011)). All functions were fitted using nonlinear least squares regression (NLS). The best fitted model for the fitting data was selected on the following criteria: (i) statistical significance of the estimated parameters and (ii) goodness-of-fit statistics (Gómez-García et al., 2015).

2.3.2. Inclusion of stand variables in the model

Considering the number of parameters and their biological interpretation (Peng et al., 2001) and the variance of the relationship between height and DBH among forest stands, a generalized model was constructed through merely re-parameterizing the asymptote parameter in the best basic model as the functions of covariates variables (Gómez-García et al., 2015; Zang et al., 2016a). The re-parameterizing progress was done using linear regression analysis over the candidate covariates stand variables for each plot. These stand variables were CB (crown breadth, m), Density (trees per hectare, stems/hm^2), D_a (arithmetic mean DBH of each plot, cm), BA (basal area, m^2/hm^2), pH (soil pH), AGE (plantation age), CN (soil CN ratio), CP (soil CP ratio), NP (soil NP ratio). In the analysis, different combinations of these stand variables were tested. Linear models including different stand variables were fitted to explain the variation in the model parameters calculated for each plot(Adame et al., 2008). The linear model selected was that which showed the minimum RMSE (root mean square error) and BIC (Bayesian Information Criteria).

2.3.3. Mixed-effects basic and generalized models

Once the best basic and generalized H-DBH model were selected, a mixed-effects modelling approach (NLME) was used to fit the models. A general formula for the mixed-effects model is expressed as Eqs. (1) and (2) (Lindstrom and Bates, 1990). All parameters in the basic and generalized H-DBH models were tested to incorporate random effects first (Pinheiro and Bates, 1998), and the model that passed the convergence test with the lowest BIC was selected as the final model. The heteroscedasticity of the residuals in the mixed-effects models was only taken into account because there was no remeasured height in our dataset. The maximum likelihood method was used to estimate the parameters in mixed-effects models. The estimation of random components of the model parameters (namely calibration process) is expressed as Eq. (3) (Davidian and Giltinan, 1995). A comprehensive and detailed description of the prediction of random effects parameters can be found in the literature (Davidian and Giltinan, 1995; Calama and Montero, 2004; Wang et al., 2007; Castaño-Santamaría et al., 2013).

$$y_i = f(\varnothing_i, X_i) + e_i \; e_i \sim N(0, R_i) \tag{1}$$

$$\varnothing_i = A_i\beta + B_i u_i \; u_i \sim N(0, D) \tag{2}$$

$$\hat{u}_i = \hat{D}\hat{Z}_i(\hat{R}_i + \hat{Z}_i\hat{D}{Z_i}^T)^{-1}\hat{e}_i \tag{3}$$

where y_i is the ($n_i \times 1$) observation vector of tree heights taken from the *ith* plot, *f*(.) is a nonlinear function, ϕ_i is a ($r \times 1$) parameter vector (r is the number of parameters in the model), X_i is the ($n_i \times r$) predictor matrix for the *i*th plot, and R_i is a ($n_i \times n_i$) positive-definite variance–-covariance matrix for the error term, $\hat{u}_i$ is the estimated prediction ($q \times 1$) vector for random parameters (where q is the number of random effects parameters in the model), $\widehat{D}$ is the estimated $q \times q$ variance-covariance matrix for among-unit variability, $\widehat{Z}_i$ is the partial derivatives matrix with respect to the random parameters, $\widehat{R}_i$ is the estimated $k \times k$ variance-covariance matrix for within-unit variability (k is the number of sampled trees for calibration), $\hat{e}_i$ is the residual ($n_i \times 1$) vector determined by the difference between the observed and predicted heights using the model, including only fixed effects.

2.3.4. Model assessment and comparison

Statistical and graphical analyses were used to compare model performance. Three statistical criteria were examined: the adjusted coefficient of determination (${R_a}^2$) (Eq. (4)), the root mean square error (RMSE) (Eq. (5)), and the BIC.

$$R_a^2 = 1 - \frac{\sum_{i=1}^{n}(est_i - obs_i)^2}{\sum_{i=1}^{n}(est_i - \overline{obs})^2} \times \frac{n-1}{n-p-1} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(est_i - obs_i)^2}{n-p}} \tag{5}$$

where est_i, *i*th estimated value; obs_i, *i*th observed value; n, number of observations; p, number of parameters of the model

2.3.5. Sampling design and validation

When validating the mixed effects model, the new sampling data of the DBH and tree height should be used to estimate the random parameters. Since the random parameters obtained by different tree-sampling designs were not the same, the prediction accuracy varied greatly when estimating the height of the trees not being measured in the sample plots. According to some preliminary studies with different tree-sampling designs (Gómez-García et al., 2015; Zang et al., 2016b; Adamec and Drápela, 2017), arithmetic mean DBH tree-sampling design was selected. Using this method, 1 to 4 trees within ± 2 cm from the arithmetic mean DBH were randomly selected per plot in the validation dataset (Table 1).

All calculations were performed using R software (R Development Core Team) and JMP software (JMP 13.0 for Mac; SAS Institute Inc., NC, USA). The basic model and generalized models were fitted by the nonlinear least squares method with the *stats* package, and the mixed-effects models were fitted with the *nlme* package. The linear modelling was performed using JMP Stepwise Regression procedure.

3. Results

3.1. Basic and generalized H-DBH model

The modified Logistic-type function was found to produce the most satisfactory basic model (Eq. (6)). The asymptote parameter $\beta_{asymptote}$ in Eq. (6) was best expanded with stand variables pH, AGE and D_a (Eq. (7), linear regression analysis results can be found in Table S1 in Supplementary Material A). Thus, the generalized model can be constructed as Eq. (8). Parameter estimates and fit statistics for both basic and generalized NLS models are listed in Table 2. The pH, AGE and D_a significantly affected the parameter β_1, β_2, β_3 in Eq. (8). The generalized H-DBH model produced better results than basic model (with BIC decreased from 3994.60 to 3523.46, R_a^2 improved from 0.76 to 0.87, RMSE decreased from 3.26 m to 2.36 m). Therefore, the generalized H-DBH model improved model performance.

Table 2
Parameter estimates and statistical criteria for four candidate models.

Item	NLS		NLME	
	Basic model	Generalized model	Basic model	Generalized model
β_0	43.41(4.31)	-8.53(1.25)	20.94(1.68)	-9.77(3.59)
β_1	0.08(0.01)	1.82(0.14)	0.15(0.013)	1.89(0.45)
β_2	26.60(2.51)	0.24(0.03)	8.85(0.79)	0.25(0.09)
β_3		0.50(0.04)		0.50(0.11)
β_4		0.11(0.01)		0.12(0.01)
β_5		8.57(0.75)		8.07(0.62)
δ_0^2			36.69	1.74
δ_2^2			5.86	
δ_3^2				5.84e-09
δ_{02}			14.37	
δ_{03}				3.03e-06
δ^2			4.68	4.72
R_a^2	0.76	0.87	0.90	0.90
RMSE	3.26	2.36	2.14	2.15
BIC	3994.6	3523.46	3463.33	3449.98
Model	1	2	3	4
df	4	7	7	10
logLik	−1984.03	−1738.50	−1708.43	−1691.80
Test		*1* vs. *2*	*2* vs. *3*	*3* vs. *4*
L.Ratio		491.05	584.45	33.26
p-value		< 0.0001	< 0.0001	< 0.0001

Note: Standard deviation in brackets. All parameter estimates statistically significant. δ_i^2 is the variance for u_i, δ_{ij} is the covariance between u_i and u_j, δ^2 is the variance for error, df is degree of freedom, logLik is log Likelihood, L.Ratio is Likelihood ratio.

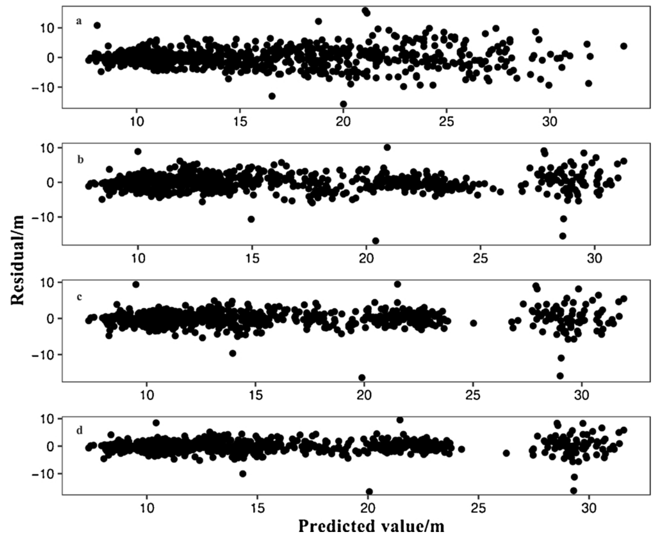

Fig. 2. Residual plots of height-diameter model for *Metasequoia glyptostroboides*. a: basic NLS model, b: generalized NLS model, c: basic NLME model, d: generalized NLME model.

$$H = 1.3 + \frac{\beta_0}{1 + exp[-\beta_1(DBH-\beta_2)]} \quad (6)$$

$$\beta_{asymptote} = \beta_0 + \beta_1 \times pH + \beta_2 \times AGE + \beta_3 \times D_a \quad (7)$$

$$H = 1.3 + \frac{\beta_0 + \beta_1 \times pH + \beta_2 \times AGE + \beta_3 \times D_a}{1 + exp[-\beta_4(DBH-\beta_5)]} \quad (8)$$

3.2. Mixed-effects basic and generalized H-DBH model

Parameter estimates and fit statistics for both basic and generalized NLME models are listed in Table 2. Random effects of plots were found significant for both basic and generalized NLME models, which indicated the variation of the H-DBH relationship among plots. The residual plot showed homogeneous variance over the full range of the predicted values (Fig. 2). Thus, no variance functions were used in this study.

$$H = 1.3 + \frac{\beta_0 + u_0}{1 + exp[-\beta_1(DBH-\beta_2-u_2)]} \quad (9)$$

$$H = 1.3 + \frac{\beta_0 + u_0 + \beta_1 \times pH + \beta_2 \times AGE + (\beta_3 + u_3) \times D_a}{1 + exp[-\beta_4(DBH-\beta_5)]} \quad (10)$$

The NLME produced better results than NLS (Eqs. (9) and (10)). For the basic NLS and basic NLME model, BIC reduced from 3994.6 to 3463.33, R_a^2 improved from 0.76 to 0.90, RMSE reduced from 3.26 m to 2.14 m. Similar results were found for the generalized NLS and generalized NLME model, where BIC reduced from 3523.46 to 3449.98, R_a^2 improved from 0.87 to 0.90, RMSE decreased from 2.36 m to 2.15 m. In addition, the boxplots of residuals against diameter classes showed the NLME models were superior to the basic and generalized NLS models in term of estimation accuracy and stability (Fig. 3), especially with less variability from 16 to 38 diameter classes. For NLME models, in spite of the slight increase in RMSE from the basic to the generalized, BIC reduced from 3449.98 to 3463.33. In addition, Likelihood ratio test showed that the difference of goodness-of-fit between the basic NLME and the generalized NLME was significant (Model *3 vs. 4*, $p < 0.0001$) (Table 2).

3.3. Sampling designs comparison

By analyzing the relationship between the sample size and the

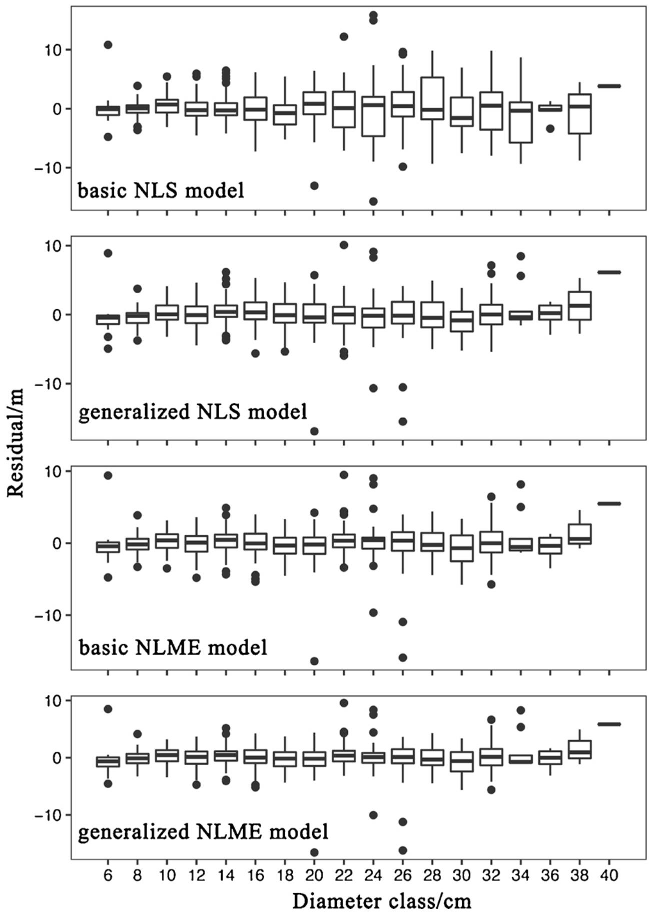

Fig. 3. Boxplots of residuals against diameter classes.

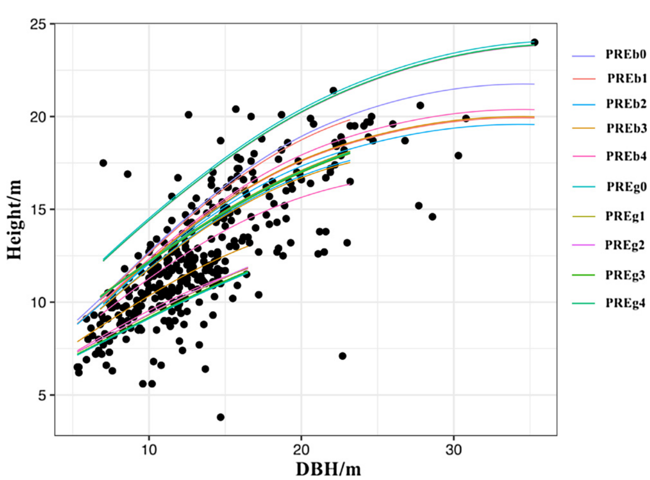

Fig. 4. Graphs of observed values (black solid dots) and fitted curves (lines in different colors) generated by the basic and generalized NLME models based on different sample sizes. PREb0, PREb1, PREb2, PREb3, PREb4 are fitted curves generated by the basic NLME models based on sample sizes from 0 to 4. PREg0, PREg1, PREg2, PREg3, PREg4 are fitted curves generated by the generalized NLME models based on sample sizes from 0 to 4.

prediction accuracy under different sampling designs, we found that the prediction accuracy could be improved obviously for basic NLME model as the sample size increases. However, the prediction accuracy of the generalized NLME almost kept the same as the sample size increases. Furthermore, when sample size less than 3, the prediction accuracy of the generalized NLME was better than the basic NLME model. When

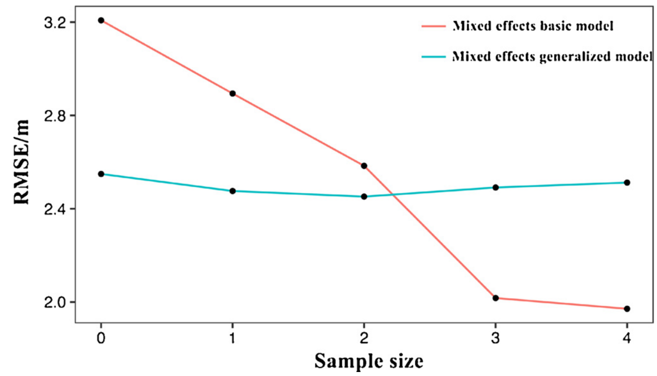

Fig. 5. Relationship between predicted accuracy and sample size under arithmetic diameter sampling design.

sample size more than 3, basic NLME model predicted better (Figs. 4 and 5).

4. Discussion

In this study, basic and generalized NLS models and their NLME models were developed and compared for *M. glyptostroboides* plantations in Shanghai. Among these models, the NLME models ranked higher in terms of their goodness-of-fit and precision. The generalized NLME model that includes stand variables captured between-stand variation and pH, AGE and D_a significantly influenced the relationship between H and DBH.

Numerous studies reported that the Chapman-Richards function demonstrated satisfactory performance in terms of fit statistics (Huang et al., 1992; Zang et al., 2016a, b). This function is versatile for modelling the H-DBH relationship and can approach the asymptote quickly when there is a weak relationship between H and DBH. However, the modified Logistic-type function was found to produce the most satisfactory NLS model in this study. Huang et al. (2000) also reported similar results with a large number of height-diameter functions evaluated using felled tree data for white spruce (*Picea glauca* (Moench) Voss) grown in Alberta's boreal forests. The logistic-type function was found to produce the most satisfactory fits (Huang et al., 2000).

In the selected NLS model, the asymptote parameter was best expanded with stand variables pH, AGE and D_a. In previous studies, the relationship between H and DBH was found to vary at stand level due to differences in e.g. age, site index (SI) and competition status (Zang et al., 2016a). BA, which simultaneously indicates the tree size and stand density, quantified the competition status and affected the H-DBH relationship. Age was regarded as a good indicator of the mean size of the individual trees (Castedo et al., 2006) and could adequately characterize the H-DBH relationships (Zhang, 1997). However, the inclusion of stand age as a stand variable makes the use of the model suitable only to even-aged forests (Adamec and Drápela, 2017). For instance, the mixed-effects generalized model developed larch plantations implies that the difference in the H-DBH relationship caused by age varies among different species in different locations (Zang et al., 2016a). In addition, a substantial number of studies have found that dominant height and SI (site index) are good covariates in the H-DBH model and can reduce prediction errors (Castedo et al., 2006; Gómez-García et al., 2015). For instance, dominant height and BA of the stand were found to produce the most satisfactory fits in the stand model taken at 950 Spanish National Forest Inventory plots embracing six different biogeoclimatic strata (Adame et al., 2008). However, Sharma and Zhang (2004) also reported that the inclusion of SI did not increase predictive accuracy (Sharma and Zhang, 2004). Unfortunately, as no dominant height measurements and SI were available in SUFRN plots in our inventory, they were not taken into account in this study (He et al., 2009). A tree's CB affects the form of the tree and, as a result, the H-DBH relationship (Larson, 1963). Temesgen et al. (2007) reported that the inclusion of the crown competition factor in larger trees in the H-DBH model increased the accuracy of prediction for all species (Temesgen et al., 2007). However, CB did not significantly influence the relationship between H and DBH in our study. Additionally, there has been no study that reported soil pH as a significant covariate variable in H-DBH model and our generalized NLME model implied that the difference in the H-DBH relationship caused by pH varied among different stands. This finding may be attributable to differing biological properties of the similar alkaline tolerance species.

The applicability of the proposed NLME model in practice has been assessed by comparing the effect of different number of selecting trees for height measurement to be used in the calibrated conditional prediction. The results of this study confirm that the goodness-of-fit of the model increases by increasing the number of measured trees, in accordance with Zang et al. (2016b) and Adamec and Drápela (2017). Zang et al. (2016a, b) reported that arithmetic diameter tree sampling was better than others and predicted accuracy could be improved obviously when four arithmetic diameter trees were sampled per plot (Zang et al., 2016b). Adamec and Drápela (2017) reported similar results, a number (up to 6 or 9) of the required measured heights through the calibrated model kept predictability, meanwhile ensured a reduction in costs and time of data collection (Adamec and Drápela, 2017).

In previous studies, the parameters in H-DBH model have been empirically fitted, however, they could also be linked to the biophysical constraints (Watt and Kirschbaum, 2011). According to the morphology of light demanding trees, rapid height growth of conifers in even-aged stands is advantageous to access more light resource (Wickens and Horn, 1972). However, preferential carbon allocation to height is always at the expense of diameter increase (West et al., 1999). Biogeochemical studies in urban and suburban areas showed that soil C, N, P dynamics are being influenced by urbanization (Liu et al., 2011; Chen et al., 2014), which would further influence the stability of structure and function of urban forests (He et al., 2016). Watt and Kirschbaum (2011) found that CN ratio strongly influenced the slope of the logarithmic H/D relationship (Watt and Kirschbaum, 2011). However, CN, CP and NP ratio did not significantly influence the asymptote parameter in this study. Considering the characters of urban environment that influenced tree growth were complex, taking the soil fertility and even pH as candidate stand variables into the H-DBH model construction was not enough. Rainfall, spring temperature (Watt and Kirschbaum, 2011), infiltration rates in soil (Lai and Ghosh, 2017), or ozone could influence the tree growth. Testing these candidate variables combined in generalized models should be done in future study. Furthermore, NLS and NLME models with calibrated conditional predictions were compared. In addition to traditional regression and mixed-effects models, some suitable alternative methods could also be considered, among which are CART (classification and regression trees) (Adamec and Drápela, 2017), QR (quantile regression) (Zang et al., 2016a), GAM (generalized additive model) (Zang et al., 2016a). The different performance of these candidate methods would be tested in future study.

We concluded that the NLME models with calibrated conditional prediction are best suitable for the *M. glyptostroboides*. Taking predicted accuracy and investigation cost into account, we recommend generalized NLME model when there were 2 or less tree height measurements taken in a given stand. The basic NLME model could be calibrated when there were 3 or more tree height measurements, depending on the required level of accuracy and investigation cost.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ufug.2018.06.006.

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