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Height-diameter relationship for *Pinus koraiensis* in Mengjiagang Forest Farm of Northeast China using nonlinear regressions and artificial neural network models

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Abstract: Korean pine (*Pinus koraiensis* Sieb. et Zucc.) is one of the highly commercial woody species in Northeast China. In this study, six nonlinear equations and artificial neural network (ANN) models were employed to model and validate height-diameter (H-DBH) relationship in three different stand densities of one Korean pine plantation. Data were collected in 12 plots in a 43-year-old even-aged stand of *P. koraiensis* in Mengjiagang Forest Farm, China. The data were randomly split into two datasets for model development (9 plots) and for model validation (3 plots). All candidate models showed a good perfomance in explaining H-DBH relationship with error estimation of tree height ranging from 0.61 to 1.52 m. Especially, ANN models could reduce the root mean square error (RMSE) by the highest 40%, compared with Power function for the density level of 600 trees. In general, our results showed that ANN models were superior to other six nonlinear models. The H-DBH relationship appeared to differ between stand density levels, thus it is necessary to establish H-DBH models for specific stand densities to provide more accurate estimation of tree height.

Keywords: forest measurement; nonlinear growth functions; artificial intelligence technology; Korean pine plantation

Tree diameter at breast height (DBH) and tree height (H) are the most important variables used in forest inventory and management (Lei et al. 2009), particularly for estimating total tree and stand volumes (Sharma et al. 2004). In addition, tree sizes at the individual tree and stand levels are underlying variables for determining site index, timber volume, and forest structures and dynamics (Parresol, Bernard 1992; Lauri et al. 2015; Ahmadi et al. 2016). In forest inventory field, the measurement of tree height is time-consuming and costly because of the low visibility of tree tops in dense stands while diameter at breast height of a tree can be measured quickly, easily, and accurately by basic instruments such as tree calipers and diameter tape (Staudhammer, Lemay 2000; Colbert et al. 2002; Sharma, Parton 2007; Mengesha et al. 2018). To save time and effort in forest inventory, foresters often predict tree height using height-diameter (H-DBH) models instead of direct measurement of height (Ahmadi et al. 2013).

Previous studies have used linear and nonlinear growth equations to develop H-DBH relationships for several tree species (Colbert et al. 2002; Emanuel et al. 2018; Mengesha et al. 2018). The nonlinear growth functions have been widely used

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to fit tree height-diameter models, however they may produce large extrapolation errors when applying beyond the range of model development data, thus the predictive capability of model should be carefully validated before application (Zhang 1997). Artificial neural networks (ANNs) are computing systems in artificial intelligence technology which is based on the structures and functions of biological neural networks (Ashraf et al. 2015). Recently, ANN models have been applied in many aspects of forest management, especially in forest modelling such as the estimation of tree volume (Diamantopoulou, Milios 2010), prediction of tree diameter and height (Shao, Reynolds 2006; Vieira et al. 2018), and forest cover types (Blackard, Dean 1999) because of its strong capacity of nonlinear mapping, high accuracy and robustness (Sheela, Deepa 2013). However, few studies have developed height-diameter (H-DBH) models using artificial neural networks (Özçelik et al. 2013). The H-DBH relationship of one tree species could vary with environmental gradients (Sharma et al. 2004; Özçelik et al. 2014), thus the development of H-DBH model for specific site conditions is needed to provide more accurate estimation of tree height. Korean pine (*Pinus koraiensis* Sieb. et Zucc.) is widely distributed in Northeast China and it is one of the most valuable and commercially important timber and nut production species (Jin et al. 2017; Nguyen et al. 2018). However, the information on H-DBH relationship in this species is limited (Zang et al. 2016). Therefore, this study aimed to develop H-DBH models using basic nonlinear growth equations and artificial neural networks (ANN) models to describe the height-diameter relationship in *P. koraiensis* in Mengjiagang Forest Farm, China.

MATERIAL AND METHODS

Study area and data description

The study was carried out in Mengjiagang Forest Farm (46°32'16''N, 129°10'36''E) in Heilongjiang Province, China. The climate is East Asian continental monsoon with long winter and dry seasons. In the study site, mean annual temperature is 2.7°C and mean annual precipitation is 550 mm. Average annual maximum and minimum temperatures are 35.6°C in July and –34.7°C in January, respectively.

The plots were established in 1973 and they were planted in a random block arrangement with 3 density levels: 400 trees·ha^{-1} (N1); 600 trees·ha^{-1} (N2) and 800 trees·ha^{-1} (N3). In summer of 2016, 4 plots (40 × 25 m each) were selected to develop H-DBH models for each density level. Diameter at breast height (DBH), tree height (H) of 758 pine trees within 12 plots (4 plots × 3 density levels) were measured. For each tree, two perpendicular diameters (outside-bark 1.3 m above ground level) were measured to the nearest 0.1 cm and were then averaged to obtain DBH (cm). Total H (m) was

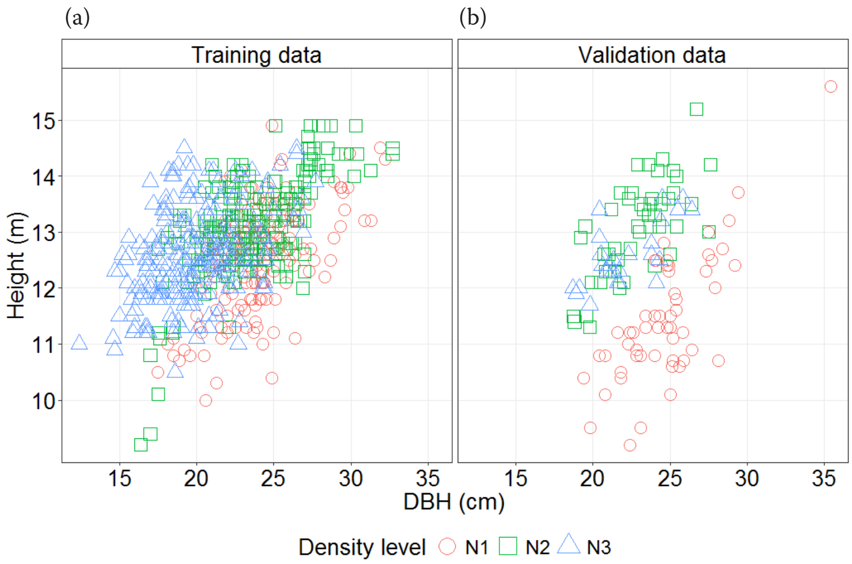

Fig. 1. Height diameter relationship in different density levels for: (a) training and (b) validation datasets

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Table 1. Summary statistics for the training and the evaluation data sets

Attributes	Training data set (n = 630 trees in 9 plots)		Validation data set (n = 128 trees in 3 plots)	
	DBH (cm)	H (m)	DBH (cm)	H (m)
Min	12.4	9.2	18.7	9.2
Max	32.7	14.9	35.4	15.6
Mean	22.29	12.77	23.51	12.22
Standard deviation	3.44	0.91	2.70	1.18

DBH – diameter at breast height, H – tree height

measured to the nearest 0.5 m, using a Vertex IV® (Haglof, Sweden). In order to evaluate the performance of developed H-DBH models, the data were randomly divided into a training dataset (9 plots) and a validation dataset (3 plots). Two datasets are described in Fig. 1 and summary statistics also are shown in Table 1.

Model development and comparison

Nonlinear growth functions. A set of 6 nonlinear growth functions was selected from previously studies on H-DBH models (Table 2) because of their appropriate features such as sigmoid shape and flexibility. Besides, the parameters of these functions can be biologically interpreted (e.g., upper asymptote and change rate) as documented in the literature (Huang 1999). In this study, we employed only functions that do not transform tree height variable to avoid problem of back transformation bias. We used *nls* function in R version 3.5.1 (R Core Team 2018) to fit 6 candidate models. For estimating the parameters, the initial values were obtained by using the package *lmfor* (Mehtatalo 2015).

Artificial neural networks. In this study, we used multilayer neural networks to develop H-DBH model in *P. koraiensis.* A proposed ANN model was designed using MATLAB Neural Network Toolbox (MathWorks, Natick, USA) and using multilayer perceptrons (MLP). In our study, the proposed neural network had one input layer, one hidden layer and one output layer. In each density level, the data of the input layer were DBH values and the data of output layer were height values in three plots used for ANN model training (Fig. 2). One remaining plot of each density level was used to validate the ANN models. The type and the

Table 2. A list of candidate H-DBH models

Model	References
Chapman-Richards: $\mathrm{H} = 1.3 + a(1 - e^{-b\mathrm{DBH}})^c$	Richards (1959); Huang et al. (1992)
Prodan: $\mathrm{H} = 1.3 + \dfrac{\mathrm{DBH}^2}{a + b\mathrm{DBH} + c\mathrm{DBH}^2}$	Strand (1959)
Ratskowky: $\mathrm{H} = 1.3 + ae^{\frac{-b}{\mathrm{DBH}+c}}$	Ratkowsky (1990); Huang et al. (1992)
Logistic: $\mathrm{H} = 1.3 + \dfrac{a}{1 + be^{-c\mathrm{DBH}}}$	Pearl, Reed (1920); Huang et al. (1992)
Gompertz: $\mathrm{H} = 1.3 + ae^{-be^{-c\mathrm{DBH}}}$	Gompertz (1832); Huang et al. (1992)
Power: $\mathrm{H} = 1.3 + a\mathrm{DBH}^b$	Stoffels; Van Soest (1953)

H – tree height; DBH – tree diameter at breast height; a, b, c – parameters of the equation

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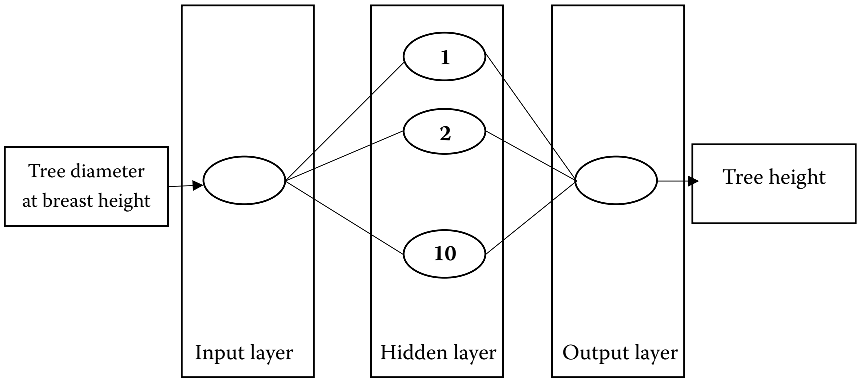

Fig. 2. Artificial neural network architectures (the model has three layers, for each density level, ten models are constructed by correspondingly varying the number of neurons in the hidden layer from 1 to 10)

complexity of the ANN model can be determined by the number of the neurons in the hidden layer. Several studies have revealed that the number of neurons in the hidden layer can not be determined directly. Generally, it should meet the following Eq. 1 (Yu, Jia 2012):

$$i = \sqrt{j + m} + R \quad (1)$$

where:
i – number of neurons in the hidden layer;
j – number of neurons in the output layer;
m – number of neurons in the input layer;
R – any number ranging from 0 to 10.

As the input layer in our study had one neuron and the output layer had one neuron, the number of neurons of the hidden layer meets the condition: $1 \leq i < 11$. Thus, in our study, the number of neurons in the hidden layer was set from 1 to 10 to search for the best ANN models. The activation function used in the hidden layer was hyperbolic tangent sigmoid transfer function and training algorithm was the Levenberg-Marquardt Backpropagation. We set the target error as 0.01 and learning rate as 0.01 and the networks were trained for 1,000 epochs for all models as there was very negligible reduction of the root mean square error (RMSE) values after 1,000 epochs.

Model performance criteria. In the present study, three good-ness of fit statistics obtained from the residuals were examined to compare the performance of ANN models and six nonlinear models. These criteria were root mean square error (RMSE), which indicates the precision of the estimates; the coefficient of determination (R^2), which is used to determine the relative correlation between the estimated and the measured data; and Akaike's information criterion (AIC), which is an index used to select the best model from a group of candidate models (Akaike 1974). The RMSE, R^2 and AIC were defined as in the following Eqs (2–4):

$$R^2 = 1 - \frac{\sum\left(y_i - \widehat{y_i}\right)^2}{\sum\left(y_i - \overline{y}\right)^2} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2}{n}} \quad (3)$$

$$\text{AIC} = n\ln(\text{RMSE}) + 2\text{p} \quad (4)$$

where:
y_i – observed height value of the tree i^{th};
$\widehat{y_i}$ – estimated height value of the tree i^{th};
$\overline{y}$ – mean value of observed height;
n – sample size,
p – number of model parameters to be estimated;
RMSE – root mean square error.

For each ANN model, the AIC value can be calculated by using the Eqs (5, 6) of Panchal et al. (2010) and D'Emilio et al. (2018).

$$AIC = n\ln\left(\frac{RSS}{n}\right) + 2K \quad \text{if } n/K \geq 40 \quad (5)$$

$$AIC = n\ln\left(\frac{RSS}{n}\right) + 2K + \frac{2K(K+1)}{n-K-1} \quad \text{if } n/K < 40 \quad (6)$$

where:
n – number of observations,
K – number of free parameters,
RSS – residual sum of square.

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RESULTS

Evaluation of nonlinear models

For six nonlinear regression models (Table 3), we found that the coefficient estimates varied among density levels. The asymptotically maximum estimated height varied approximately from 12 to 14 m. Among nonlinear models, the Power function showed a statistical significance in all coefficient estimates. Except for the parameter *c*, all coefficient estimates of Prodan model were not statistically significant. The results of goodness of fit statistics for the training and validation datasets are shown in Fig. 3. In all six nonlinear models, there was a small difference in RMSE values between training and validation data. Power model exhibited a smaller RMSE values in the validation dataset, compared with other nonlinear models. In general, Power model had the highest value of R^2, except for N3 density level where Ratskowky model showed the highest R^2 for the both training (0.742) and validation data (0.612). The AIC values of Power model were slighly smaller than those of other nonlinear models for both training and validation data, and for all stand density levels.

ANN models

In this study, the number of neurons in the hidden layer of ANN models used for training process ranged from 1 to 10. In training dataset of N1 and N3 density levels, the AIC values tended to increase with the number of neurons in the hidden layer. In validation dataset, however, the AIC values increased with the neuron number for N1 and N2 density levels (Fig. 3). We observed that the coefficient of determination (R^2) of all models varied from 0.61 to 0.77, and the differences in R^2 values were found between the six nonlinear models and ANN models in each stand density level (Fig. 3).

For N1 and N2 density levels, the best model performance was achieved by using 10 neurons in the hidden layer, showing the smallest RMSE values for both training dataset (0.745 and 0.564, respectively) and validation dataset (1.277 and 0.610, respectively). Meanwhile, in N3 density level, the best model performance was observed in the ANN model using 7 neurons in hidden layer for both training dataset (RMSE = 1.279) and validation dataset (RMSE = 0.743).

In N1 density level, the RMSE values of validation data ranged from 0.743 to 0.745 and from 0.750 to 0.763 in ANN models and nonlinear models, respectively. In N2 density level, we found that the RMSE values of the ANN model using 10 neurons in the hidden layer were reduced by approximately 17 and 40% for validation and training data, respectively, compared to Power model. In N3 density level, the RMSE of the ANN model with 7 neurons in the hidden layer was slightly lower than those of nonlinear models for both training and validation data.

DISCUSSION

Tree height is fundamental variable in forest management for developing growth model, biomass estimation, and for determining stand structure and dynamics (Diamantopoulou, Özçelik 2012; Navroodi et al. 2016). In our study, six non-linear growth functions selected for estimating total tree height performed quite well with small RMSE values (0.651 to 1.517) and fairly well of R^2 values (0.592–0.744) for all stand density levels. Overall, our results supported the findings of previous studies, indicating the appropriateness of nonlinear models in describing H-DBH relationship (Diamantopoulou, Özçelik 2012; Özçelik et al. 2014; Mengesha et al. 2018; Emanuel et al. 2018). In general, H-DBH relationship has been considered to approach a sigmoidal shape (Özçelik et al. 2014; Costa et al. 2016; Ferraz et al. 2018), however the best fit model appeared to vary with tree species and site conditions. For example, the best model was the logistic growth function for *Pinus kesiya* in Benguet province, Philippines (Lumbres et al. 2013); was the Gompertz function for three economically important tree species of southern Turkey (Özçelik et al. 2014); was the Weibull function for *Cupressus lusitanica* in Gergeda Forest, Ethiopia (Mengesha et al. 2018). In previous study on H-DBH model of Korean pine, Richards equation with four parameters appeared to explain well H-DBH relationship in Nature forest of Jilin province, China (Deng et al. 2001). Zang et al. (2016) used Chapman-Richards function to describe the H-DBH relationship for *Pinus koraiensis* in mixed Mongolian oak-deciduous stands and mixed spruce-fir-deciduous stands in Wangqing Forestry Bureau, Jilin Province of Northeast China. On the contrary, our study demonstrated that Power model was the best fit model among

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Table 3. Parameter estimates for the basic H-DBH nonlinear models

Model	Parameter estimates											
	a				*b*				*c*			
	Estimate	SE	*t*-value	*P*-value	Estimate	SE	*t*-value	*P*-value	Estimate	SE	*t*-value	*P*-value
N1 density level												
Chapman-Richards	12.517	0.453	27.611	< 2e–16***	0.182	0.061	2.983	0.003**	7.410	8.061	0.919	0.35929
Prodan	25.994	14.548	1.787	0.075763	–1.263	1.217	–1.038	0.300	0.095	0.025	3.768	0.000227***
Ratskowky	13.904	0.923	15.057	< 2e–16***	2.426	1.383	1.754	0.081	–11.946	2.879	–4.150	5.26e–05***
Logistic	12.432	0.393	31.615	< 2e–16***	13.543	14.486	0.935	0.351	0.208	0.060	3.455	0.000697***
Gompertz	12.501	0.434	28.785	< 2e–16***	8.060	8.230	0.979	0.328	0.185	0.058	3.195	0.001**
Power	2.927	0.441	6.642	4.00e–10***	0.425	0.047	8.986	4.78e–16***				
N2 density level												
Chapman-Richards	13.686	0.773	17.694	< 2e–16***	0.108	0.047	2.306	0.0221*	1.676	1.227	1.367	0.173
Prodan	8.565	7.500	1.142	0.255	–0.009	0.655	–0.014	0.989	0.069	0.014	4.857	2.3e–06***
Ratskowky	13.236	0.256	51.673	< 2e–16***	0.908	0.240	3.781	0.000203***	–14.328	0.668	–21.463	< 2e–16***
Logistic	13.559	0.623	21.778	< 2e–16***	2.913	1.672	1.742	0.08292	0.129	0.040	3.195	0.001**
Gompertz	13.502	0.587	23.008	< 2e–16***	2.331	1.368	1.705	0.08969	0.124	0.040	3.115	0.002**
Power	3.623	0.343	10.580	< 2e–16***	0.375	0.030	12.580	< 2e–16***				
N3 density level												
Chapman-Richards	14.032	8.829	1.589	0.113	0.029	0.146	0.200	0.841	0.264	0.419	0.631	0.529
Prodan	1.010	5.330	0.190	0.85	0.233	0.559	0.416	0.678	0.074	0.015	5.105	6.77e–07***
Ratskowky	13.098	1.218	10.751	< 2e–16***	2.283	2.681	0.851	0.395	–4.226	8.344	–0.507	0.613
Logistic	12.913	2.086	6.191	2.58e–09***	0.686	0.348	1.973	0.049*	0.079	0.089	0.884	0.377
Gompertz	12.862	1.956	6.574	3.04e–10***	0.587	0.351	1.670	0.096	0.076	0.089	0.858	0.392
Power	6.301	0.590	10.685	< 2e–16***	0.195	0.031	6.226	2.12e–09***				

*significant at $P < 0.05$; **significant at $P < 0.005$ level; ***significant at $P < 0.0005$ level; SE – standard errors; *a*, *b*, *c* – parameters of the equation

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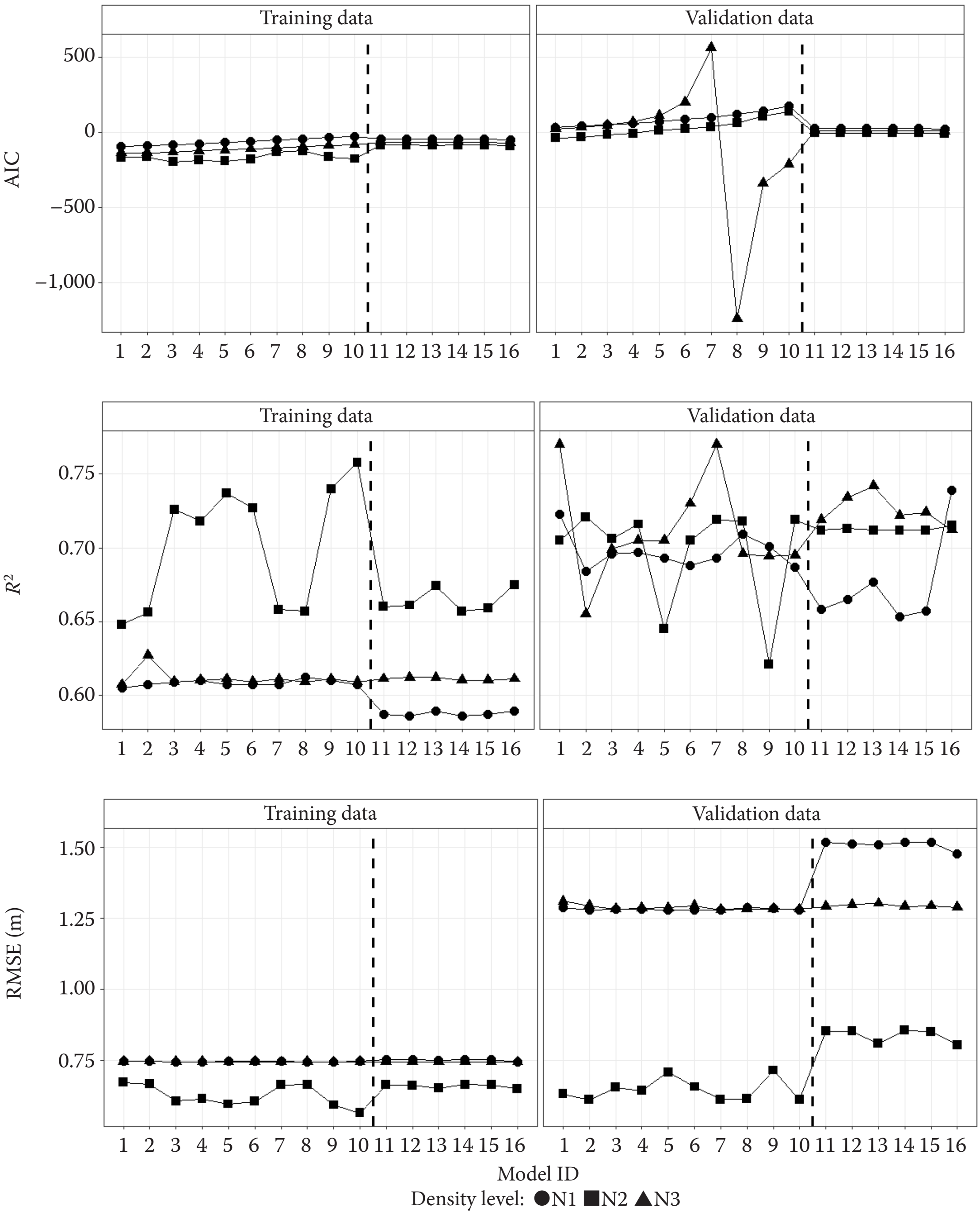

Fig. 3. Goodness of fit statistics for 10 ANN models and 6 nonlinear models.The statistic values are shown for both training and validation datasets. Model ID from 1 to 10 refers to ANN models with corresponding neuron number in the hidden layer. Model ID from 11 to 16 refers to the model of Chapman-Richards, Prodan, Ratskowky, Logistic, Gompertz and Power, respectively. RMSE, R^2, AIC are root mean square error, coefficient of determination and Akaike's Information Criterion, respectively.

6 candidate nonlinear equations evaluated in terms of RMSE and AIC values for Korean pine plantation in Mengjiagang Forest Farm, China. The inconsistency between our study and others could be explained by the differences in site condition and in stand structure and age, which can affect the H-DBH relationship (Özçelik et al. 2014).

Our data showed that coefficient estimates and model performance criteria varied among three stand density levels. The performance of H-DBH models

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tended to differ between density levels, and this could be explained by the variation in local environment and stand conditions (Sharma et al. 2004). Stand density is an important factor affecting tree growth in coniferous species (Mäkinen, Isomäki 2004). Low stand density may reduce the competition among individual trees, which results in advantageous conditions for tree growth (Woodruff et al. 2000). Moreover, low tree density might increase soil moisture availability and generate favorable physiological responses, whereby affecting tree growth (Nguyen et al. 2018). In accordance with previous studies (Krieger 1998; Ritchie et al. 2012), our data indicated that H-DBH relationship of *P. koraiensis* could be conditioned on stand density.

Compared with stand density of 600 trees·ha^{-1} and 800 trees·ha^{-1}, tree height in the stand density of 400 trees·ha^{-1} tended to be smaller. Similary, Zeide, Vanderschaaf (2002) documented that Loblolly pine trees in higher density stand were taller than those in lower density stand. It is likely that the competition for light between a tree and its neighbors may promote the height growth (Dorn et al. 2000). According to Lauri et al. (2015), this phenomenon can be explained by the biological growth rhythm of trees in dense stands that they firstly focus on height growth to compete for light, and then use their resources to increase diameter . This strategy may result in a higher height variation in small-diameter stand compared with those of large-diameter stand. The influence of stand density on the H-DBH relationship was also found in many studies (e.g. Krieger 1998; Staudhammer, LeMay 2000; Ritchie et al. 2012). For instance, Krieger (1998) constructed H-DBH models for 6 stand density levels (from 100 to 1,100 trees·ha^{-1}) for white spruce species. In our study, the difference between AIC and RMSE values for model performance were observed (Fig. 3). The contradiction of RMSE and AIC has been also reported in previous work (Kingston et al. 2008; Luo et al. 2018). Compared with other model performance criteria, RMSE is commonly implemented to select the best model (Özçelik et al. 2013; Costa et al. 2016, Zang et al. 2016; Ferraz et al. 2018), thus in this study, we determined RMSE as the main goodness of fit statistic for mode evaluation. Based on the RMSE values, we suggest using the ANN model with 10 neurons in the hidden layer for stand density of 400 trees·ha^{-1} and 600 trees·ha^{-1}, and the ANN model with 7 neurons in the hidden layer for stand density of 800 trees·ha^{-1} for H-DBH relationship of Korean pine in our study site. In the present study, ANN models performed superior to non-linear growth functions in explaining H-DBH relationship in *P. koraiensis*, as indicated by small RMSE for all stand density levels, This finding is consistent with previous studies indicating that ANN models can be an effective alternative to regression analysis, providing an accurate tree height estimation for forest inventory (Özçelik et al. 2013; Zhi, Gan 2017; Vieira et al. 2018). Besides, the model developed in this study showed the better overall performance in terms of RMSE compared with other approaches in previous studies such as using nonlinear regression for estimating tree height of Crimean juniper with RMSE values ranging from 1.28 to 1.89 (Özçelik et al. 2013), and using nonlinear mixed effects models for *Pinus koraiensis* with RMSE values ranging from 1.40 to 2.65 and from 0.95 to 2.67 in training data and validaton data, respectively (Zang et al. 2016). Although our study referred only to the specific three stand density levels in Mengjiagang Forest Farm, the obtained results could be a basis for further research by highlighting the applicability of ANN models in tree height prediction and this would provide forest managers and researchers with useful guidelines for predicting tree height of *Pinus koraiensis* in the research site.

CONCLUSIONS

Nonlinear growth functions have been commonly used for modeling tree height-diameter relationship. This study used 6 non-linear functions and ANN models to describe H-DBH relationship of *P. koraiensis* in three different stand densities in Mengjiagang Forest Farm, China. Based on RMSE and R^2 statistics, we showed that the ANN models were superior to all examined nonlinear models. Our data suggest that it is necessary to establish H-DBH models for different stand densities of *P. koraiensis* to provide more accurate estimates of tree height. The ANN models provide a new approach for tree height estimation and could be implemented at individual tree and stand levels for *P. koraiensis* in this studied region.

References

Ahmadi K., Alavi S.J, Kouchaksaraei M.T, Aertsen W. (2013): Non-linear height-diameter models for oriental beech (*Fagus orientalis* Lipsky) in the Hyrcanian forests,

https://doi.org/10.17221/5/2019-JFS

Iran. Biotechnologie, Agronomie, Société et Environnement, 17: 431–440

Ahmadi K., Alavi S.J. (2016): Generalized height diameter models for *Fagus orientalis* Lipsky in Hyrcanian forest, Iran. Journal of Forest Science, 62: 413–421.

Akaike H. (1974): A new look at the statistical model identification. IEEE Transactions on Automatic Control, 19: 716–723.

Ashraf M.I, Meng F.R, Bourque C.P.A, MacLean D.A. (2015): A novel modelling approach for predicting forest growth and yield under climate change. PLoS ONE 10: 1–18.

Blackard J.A., Dean D.J. (1999): Comparative accuracies of artificial neural networks and discriminant analysis in predicting forest cover types from cartographic variables. Computers and Electronics in Agriculture, 24: 131–151.

Colbert K.C, Larsen D.R, Lootens J.R. (2002): Height–diameter equations for thirteen midwestern bottomland hardwood species. Northern Journal of Applied Forestry, 19: 171–176.

Costa E.A, Schroder T., Finger C.A. (2016): Height-diameter relationships for *Araucaria angustifolia* (Bertol.) Kuntze in Southern Brazil. CERNE, 22: 493–500.

D'Emilio A., Aiello R., Consoli S., Vanella D., Iovino M. (2018): Artificial neural networks for predicting the water retention curve of sicilian agricultural soils. Water, 10: 1431.

Deng H.B, Hao Z., Wang Q.L. (2001): Study on height growth model of *Pinus koraiensis*. Journal of Forestry Research, 12: 192.

Diamantopoulou M.J., Milios E. (2010): Modelling total volume of dominant pine trees in reforestations via multivariate analysis and artificial neural network models. Biosystems Engineering, 105: 306–315.

Diamantopoulou M.J, Özçelik R. (2012): Evaluation of different modeling approaches for total tree-height estimation in Mediterranean Region of Turkey. Forest Systems, 21: 383–397.

Dorn L.A., Pyle E.H., Schmitt J. (2000): Plasticity to light cues and resources in *Arabidopsis thaliana*: testing for adaptive value and costs. Evolution, 54: 1982–1994.

Emanuel A.C., André F.H. , Daniel R.K., César A.G.F. (2018): Height-diameter models for *Araucaria angustifolia* (Bertol.) Kuntze in natural forests. Journal of Agricultural Science, 10: 133–145.

Ferraz F., Antonio C., Mola Y., José R.S, Loos R.A, Scolforo H.F. (2018): Height-diameter models for *eucalyptus* sp. plantations in Brazil. CERNE, 24: 9–17.

Gomperzt B. (1832): On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies. Philosophical Transactions of the Royal Society of London, 115: 513 –585.

Huang S., Titus S.J, Wiens D.P. (1992): Comparison of nonlinear height-diameter functions for major Alberta tree species. Canadian Journal of Forest Research, 22: 1297–1304.

Huang S.M. (1999): Ecoregion-based individual tree height–diameter models for lodgepole pine in Alberta. Western Journal of Applied Forestry, 14: 186–193.

Jin X.J, Pukkala T., Li F.R, Dong L.H. (2017): Optimal management of Korean pine plantations in multifunctional forestry. Journal of Forestry Research, 28: 1027–1037.

Krieger C. (1998): The effects of tree spacing on diameter, height and branch size in white spruce. Management Notes, 13: 1–12.

Kingston G.B., Maier H.R., Lambert M.F. (2008). Bayesian model selection applied to artificial neural networks used for water resources modeling. Water Resources Research, 44: 1–12.

Lauri M., Sergio M., Timothy G. (2015): Modeling height–diameter curves for prediction. Canadian Journal of Forest Research, 45: 826–837.

Lei X.D, Peng C.H, Wang H.Y, Zhou X.L. (2009): Individual height-diameter models for young black spruce (*Picea mariana*) and jack pine (*Pinus banksiana*) plantations in new brunswick, canada. Forestry Chronicle, 85: 43–56.

Lumbres R.I, Lee Y.J, Calorajr F., Parao M. (2013): Model fitting and validation of six height-DBH equations for *Pinus kesiya* royle ex gordon in benguet province, philippines. Forest Science and Technology, 9 : 45–50.

Luo Z., Song Q., Wang T., Zeng H., He T., Zhang H., Wu W. (2018): Direct impacts of climate change and indirect impacts of non-climate change on land surface phenology variation across Northern China. ISPRS International Journal of Geo-Information, 7: 1–14.

Mäkinen H., Isomäki A. (2004): Thinning intensity and growth of Scots pine stands in Finland. Forest Ecology and Management, 201: 311–325.

Mehtatalo L. (2015): Lmfor: Functions for forest biometrics. R package version. 1. Available at https://CRAN.R–project.org/package=lmfor

Tsega M., Guadie A., Teffera Z.L., Belayneh Y., Niu D. (2018): Development and validation of height-diameter models for *Cupressus lusitanica,* in Gergeda forest, Ethiopia. Forest Science and Technology, 14: 1–7.

Navroodi I.H, Alavi S.J, Ahmadi M.K, Radkarimi M. (2016): Comparison of different non-linear models for prediction of the relationship between diameter and height of velvet maple trees in natural forests (Case study: Asalem Forests, Iran). Journal of Forest Science, 62: 65–71.

Nguyen T.T, Tai D.T, Zhang P., Razaq M., Shen H.L. (2018): Effect of thinning intensity on tree growth and temporal variation of seed and cone production in a *Pinus koraiensis* plantation. Journal of Forestry Research, 28: doi: 10.1007/s11676–018–0690–x.

Özçelik R., Diamantopoulou M.J., Crecente C.F., Eler U. (2013): Estimating Crimean juniper tree height using

https://doi.org/10.17221/5/2019-JFS

nonlinear regression and artificial neural network models. Forest Ecology and Management, 306: 52–60.

Özçelik R., Yavuz H. , Karatepe Y., Gürlevik N., Kiriş R. (2014): Development of ecoregion-based height-diameter models for 3 economically important tree species of southern Turkey. Turkish Journal of Agriculture and Forestry, 38: 399–412.

Panchal G., Ganatra A., Kosta Y.P., Panchal D. (2010): Searching most efficient neural network architecture using Akaike's information criterion (AIC). International Journal of Computer Applications, 1: 41–44.

Parresol B.R. (1992): Baldcypress height-diameter equations and their prediction confidence intervals. Canadian Journal of Forest Research, 22: 1429–1434.

Pearl R., Reed L.J. (1920): On the rate of growth of the population of United States since 1790 and its mathematical representation. Proceedings of the National Academy of Science of the United States of America, 6: 275–288.

R Core Team (2018) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna.

Ratkowsky D.A. (1990): Handbook of Nonlinear Regression. New York, Marcel Dekker: 120.

Richards F.J. (1959): A flexible growth functions for empirical use. Journal of Experimental Botany, 10: 290–300.

Ritchie M., Zhang J., Hamilton T. (2012): Effects of stand density on top height estimation for ponderosa pine. Western Journal of Applied Forestry, 27: 18–24.

Shao G., Reynolds K.M. (2006): Computer Applications in Sustainable Forest Management. Including Perspectives on Collaboration and Integration. Dordrecht, Springer: 312.

Sharma M., Zhang S.Y. (2004): Height-diameter models using stand characteristics for *Pinus banksiana* and *Picea mariana*. Scandinavian Journal of Forest Research, 19: 442–451.

Sharma M., Parton J. (2007): Height-diameter equations for boreal tree species in Ontario using a mixed-effects modeling approach. Forest Ecology and Management, 249: 187–198.

Staudhammer C., LeMay V. (2000): Height prediction equations using diameter and stand density measures. The Forestry Chronicle, 76: 303–309.

Stoffels A., Van Soeset J. (1953): The main problems in sample plots. Nederlands Bosbouw Tijdschrift, 25: 190–199.

Strand L. (1959): The accuracy of some methods for estimating volume and increment on sample plots. Meddel. norske Skogfors, 15: 284–392. (in Norwegian with English summary)

Sheela K., Deepa S. (2013): Review on methods to fix number of hidden neuron in neural networks. Mathematical Problems in Engineering, 2013: 1–11.

Shi Y., Zhang J.Y. (2012): The Application of Artificial Neural Network Model in Estimation of Single Tree Volume Growth. In: International Conference on Remote Sensing Environment and Transportation Engineering. Nanjing, June 1–3, 2012: 1–6. doi: 10.1109/RSETE.2012.6260764.

Vieira G.C, De Mendon A.R, Da Silva G.F, Zanetti S.S, Da-Silva M.M, Dos Santos A.R. (2018): Prognoses of diameter and height of trees of eucalyptus using artificial intelligence. Science of The Total Environment, 619–620: 1473–1481.

Zang H., Lei X.D., Zhang H.R., Li C.M., Lu J. (2016): Nonlinear mixed-effects height-diameter model of *Pinus koraiensis.* Journal of Beijing Forestry University, 38: 8–16. (in Chinese with English summary)

Zeide B., Vanderschaaf C. (2002): The effect of density on the height-diameter relationship. In: General Technical Report SRS–48. Asheville, NC: US Department of Agriculture, Forest Service, Southern Research Station: 463–466.

Zhang L. (1997). Cross-validation of non-linear growth functions for modelling tree height-diameter relationships. Annals of Botany, 79: 251–257.

Zhi D.U, Gan S.S. (2017): Height-diameter models for *Cunninghamia lanceolata* and *Pinus massoniana* based on bp neural network. Central South Forest Inventory and Planning, 36: 36–39. (in Chinese with English summary)

Woodruff D.R., Bond B.J., Ritchie G.A., Scott W. (2002): Effects of stand density on the growth of young Douglas-fir trees. Canadian Journal of Forest Research, 32: 420–427.

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