Climate Change Effects On Height-Diameter Allometric Relationship Vary With Tree Species And Size For Larch Plantations In Northern And Northeastern China

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Climate change effects on height-diameter allometric relationship vary with tree species and size for larch plantations in northern and northeastern China

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Abstract:

Background: Tree height-diameter relationship is very important in forest investigation, understanding forest ecosystem structure and estimating carbon storage. Climate change may modify the relationship. However, our understanding of the effects of climate change on height-diameter allometric growth is still limited at large scale.

Methods: In this study, we explore how the climate change effects on height-diameter allometric relationship vary with tree species and size for larch plantations in northern and northeastern China. Based on the repeated measurement data of 535 plots from the 6th to 8th national forest inventory of China, climate-sensitive tree height-diameter models of *Larix* plantations in north and northeast China were developed by two-level nonlinear mixed effect (NLME) method. The final model was used to analyze the height-diameter relationship of different *Larch* species under RCP2.6, RCP 4.5, and RCP8.5 climate change scenarios from 2010 to 2100.

Results: The values of R^2_{adj}(adjusted coefficient of determination), MAE(mean absolute error) and RMSE(root mean squared error) of the NLME models for calibration data were 0.92, 0.76m and 1.06m, respectively. The inclusion of climate variables MAT (Mean annual temperature), CMD (Hargreaves climatic moisture deficit) with random effects was able to increase R^2_{adj} by 19.5% and reduce the AIC (Akaike's information criterion), MAE and RMSE by 22.2%, 44.5% and 41.8%, respectively. The climate sensitivity was ranked as *L. gmelinii* > the unidentified species group > *L. pincipis-rupprechtii* > *L. kaempferi* > *L. olgensis* under RCP4.5, but *L. gmelinii* > *L. pincipis-rupprechtii* > the unidentified species group > *L. olgensis* > *L. kaempferi* under RCP2.6 and RCP8.5.

Conclusion: According to the climate sensitivity, tree species could be classified as group I(*L. gmelinii*, *L. pincipis-rupprechtii* and the unidentified species group) with large ΔH (from -4.77% to 18.17%) and group II (*L. kaempferi* and *L. olgensis*) with small ΔH (from -6.37% to 9.4%).Large trees were more sensitive to climate change than small trees.
Key words: nonlinear mixed-effects model; height-diameter model; climate change; climate-sensitive growth model

Background

Tree height-diameter (H-D) models are one of the most useful tools in forest management. Because tree height measurement is time-consuming, expensive and difficult in over-crowed and dense forests, a small number of trees are typically subsampled in practice to measure tree height, while D is measured precisely for all trees in a plot (Zell 2018). Thus, H-D models are often constructed to predict missing total height measurements for the rest of the trees. Numerous H-D models have been developed (Fang and Bailey 1998; Huang, Price et al. 2000; Jayaraman and Zakrzewski 2001; Calama and Montero 2004; Sharma and Yin Zhang 2004; Sharma and Parton 2007; Kroon, Andersson et al. 2008; Hulshof, Swenson et al. 2015; Zang, Lei et al. 2016; Zell 2018; Zhang, Chhin et al. 2019; Bronisz and Mehtätalo 2020; Ciceu, Garcia-Duro et al. 2020; Santiago-García, Jacinto-Salinas et al. 2020; Zhang, Sajjad et al. 2020). Models showed that the H-D relationship was context-dependent, and dependent on genetic characteristics (Kroon, Andersson et al. 2008), stand age (Sánchez, Varela et al. 2003), site condition (Sharma and Yin Zhang 2004; Sharma and Parton 2007; Krisnawati, Wang et al. 2010; Zhang, Sajjad et al. 2020), competition status (Calama and Montero 2004; Sharma and Yin Zhang 2004; Sharma and Parton 2007; Ciceu, Garcia-Duro et al. 2020) , silvicultural treatment (Saunders and Wagner 2008; Russell, Amateis et al. 2010) and climate (Wang, Fang et al. 2006; Hulshof, Swenson et al. 2015; Fortin, Van Couwenberghe et al. 2019; Zhang, Chhin et al. 2019).

Under the background of global change, the effects of climate change on forest growth were attained great concerns (Hasenauer, Nemani et al. 1999; Kirschbaum 2000; Yang, Watanabe et al. 2006; Hartl-Meier, Dittmar et al. 2014; Charney, Babst et al. 2016). However, how climate change alerts H-D relationships has only recently been considered (Albert and Schmidt 2010; Hulshof, Swenson et al. 2015;

Fortin, Van Couwenberghe et al. 2019; Zhang, Chhin et al. 2019; Ng'andwe, Chungu et al. 2021). For example, Hulshof, Swenson et al. (2015) developed mixed-effects models to test H-D allometric differences due to climate and functional groups, and models showed that temperature, and some extent precipitation, in part explained tree allometric variation. Climate variables can significantly explain the variation of the relationship between tree height and diameter, and adding climate variables can improve the prediction practicability of the model in the context of climate change. Zhang, Chhin et al. (2019) developed tree level NLME model to explore height-diameter allometry of Chinese fir in relation to climate and found that temperature was a key climate factor shaping height-diameter allometry, and showed that tree heights increased with increasing mean annual temperature. Fortin, Van Couwenberghe et al. (2019) developed generalized H-D models of 44 tree species across France and found that the temperature effect was significant for 33 species and the precipitation effect was significant only for 7 species. They estimated that two-thirds of climate sensitive species are expected to be generally shorter under RCP2.6 scenario.

However, the direction and magnitude of climatic effects on H-D relationships has further exploration space. For example, Hulshof, Swenson et al. (2015) showed that the coefficient of MAT was negative but the model developed by Zhang, Chhin et al. (2019) showed MAT has positive effects on H-D allometry. Feldpausch, Banin et al. (2011) found that annual precipitation coefficient of variation, dry season length, and mean annual air temperature were key drivers of variation in H-D allometry at the pantropical and region scales. Ng'andwe, Chungu et al. (2021) found that temperature negatively modulate H-D allometry in *Pinus merkusii* and *P. michoacana* in Zambia. Furthermore, how these climatic effects differ among tree species and sizes of Larch are not well understood. The climate effects on H-D relationship are likely to have an impact on tree stability, height estimation, yield prediction and forest management decision, thus making it necessary to examine it under climate change.

Larch is an economically and ecologically important genus of tree species in China, especially in the northern and northeastern Provinces. The area and volume of larch forests in Chinese forests amount to 6.50 and 6.77 per cent, respectively (State Forestry Administration 2014). Both empirical and process-based models found that future climate change would affect stand growth, productivity, and biological rotation of larch plantations (Shen, Lei et al. 2015; Lei, Yu et al. 2016; Zang, Lei et al. 2016; Xie, Wang et al. 2017; Xie, Lei et al. 2020), but how climate change will modify the H-D relationship is unknown yet. Therefore, the objectives of the study were: 1) to develop a climate-sensitive H-D model for larch plantations in north and northeast China; 2) to examine the effects of future climate change on H-D relationship among larch species and tree sizes. Quantifying the effects of climate change will help better understand the H-D allometric relationship and adaptive forest management under climate change.

Methods

Tree height-diameter Data

Tree H-D data used in this study were from 6^{th} (year 2000), 7^{th} (year 2005)and 8^{th}(year 2010) National Forest Inventories in 7 provinces (Beijing, Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, and Inner Mongolia) in north and northeast China. We selected only pure larch plantation plots to develop the H-D model. The larch species presented in these plots are *L. gmelinii.*, *L. olgensis*, *L. kaempferi*, *L. principis-rupprechtii*. In addition, there were trees are not identified to specific species which were recorded as larch. According to the protocol of NFI, heights of 3-5 medium trees were measured in each plot. In total, 7304 pairs of H–D measurements in 535 plots were obtained across seven Provinces. Data were split into two parts for model calibration and validation by the following method: each plot was randomly allocated to a number between 1 and 535, and plots whose number were less than 20th percentile of all plots were assigned as validation data (1609 pairs in 107 plots) and the rest were fitting data (5695 pairs of H–D measurements in 428 plots). Summary statistics of tree and stand variables can be found in Table 1. The scatter plot can be found in Figure 1.

Table 1 Summary statistics for tree and stand variables by Provinces

Data	Province	Number of Plots	Number of tree observations	D (cm)	H (m)	AGE (a)	N (trees•ha^{-1})	BA (m^2•ha^{-1})
Calibration	Beijing	7	37	14.7(4.6)	9.3(2.3)	32.9(10.6)	561.9(418.5)	9.1(9.9)
	Hebei	72	3326	10.7(4.5)	7.9(2.2)	21.7(6.7)	1072.6(540.9)	9.3(7.3)
	Heilongjiang	96	706	14.5(5.3)	13(3.9)	27.9(9.7)	653.9(520.5)	4.6(4.6)
	Jilin	132	1058	12.9(4.7)	11.4(4.4)	25.2(9.9)	1032.2(565.3)	9.0(5.6)
	Liaoning	52	406	14.4(4.8)	13.5(4.5)	23.6(10.2)	1292.3(631.7)	13.5(8.6)
	Inner Mongolia	35	188	12.2(3.7)	10.1(3.2)	25.8(7.1)	855.1(617.7)	8.0(6.4)
	Shanxi	34	195	11.1(3.1)	8.7(2.8)	26.5(9.3)	1297.8(627.3)	9.4(7.7)
	total	428	5916	11.9(4.8)	9.6(3.8)	23.6(8.5)	977.2(610.6)	8.5(6.9)
Validation	Beijing	3	18	12.6(1.7)	9.2(1.6)	25.8(3.1)	816.8(469.2)	11.5(10.7)
	Hebei	12	620	11.4(3.8)	8.9(2.3)	24.8(7.6)	994.9(607.2)	8.5(5.4)
	Heilongjiang	27	193	15.2(5.0)	13.1(3.8)	29.5(9.8)	559.3(548.7)	6.0(6.3)
	Jilin	38	351	13.5(4.4)	11.9(4.0)	28.4(11.1)	904.2(532.9)	8.2(4.9)
	Liaoning	12	97	12.2(4.5)	11.3(5.4)	23.2(9.3)	1207.8(651.1)	17.7(7.0)
	Inner Mongolia	11	53	11.1(4.4)	9.1(4.1)	28(9.9)	1135.5(835.4)	7.3(6.4)
	Shanxi	4	21	9(1.8)	6.7(2.0)	17.9(4.2)	848.6(622.8)	7.3(6.3)
	total	107	1353	12.5(4.4)	10.4(3.8)	26.3(9.4)	902.6(626.8)	8.6(6.8)

Note: D, diameter at breast height; H, tree height; N, tree number per hectare; BA, basal area per hectare; the numbers within parentheses are the standard deviation.

Figure 1 Scatter plot of tree height-diameter allometry by Larch species in 7 provinces.

Climate data

The current climatic data for model calibration were downloaded from ClimateAP, which is an application for dynamic local downscaling of historical and future climate data in Asia Pacific (Wang, Wang et al. 2017). Seasonal and annual climate variables (averaged from 1980 to 2010) for a plot were produced based on latitude, longitude, and elevation (Table 2).

Table 2. Descriptions of the candidate climatic variables

Variable	Description
AHM	Annual heat:moisture index
CMD	Hargreaves climatic moisture deficit
DD_0	Degree-days below 0°C
DD_18	Degree-days below 18°C
DD18	Degree-days above 18°C
DD5	Degree-days above 5°C
EMT / °C	Extreme minimum temperature over a 30-year period
EXT / °C	Extreme maximum temperature over a 30-year period
EREF	Hargreaves reference evaporation
MAP / mm	Mean annual precipitation (mm)
MAT / °C	Mean annual temperature
MCMT / °C	Mean coldest month temperature
MWMT / °C	Mean warmest month temperature
NFFD	The number of frost-free days
PAS / mm	Precipitation as snow between August in previous year and July in current year
TD / °C	Temperature difference between MWMT and MCMT, or continentality

For projections of future H-D relationship under expected climate change, we used the latest climate-change scenarios of the 5^{th} Assessment Report from the IPCC using a downscaled global climate model (GCM) applied in three representative concentration pathways (RCPs), RCP2.6, RCP4.5, and RCP8.5 (Van Vuuren, Edmonds et al. 2011). These pathways represent the scenarios with low, medium and high concentrations of greenhouse gases and predictive radiative forcing. The GCM model for future climate scenarios used in the study was CNRM-CM5 (The Centre National de Recherches Météorologiques Coupled global climate Model) (Voldoire, Sanchez-Gomez et al. 2013). Future climate data for the time periods 2025 (average for 2010-2040), 2055 (average for 2040-2070) and 2085 (average for 2070-2100) were also downloaded from the ClimateAP.

Selection of climate variables

Principal Component Analysis (PCA) (Wold, Esbensen et al. 1987) can be an exploratory method used for evaluation of the climatic variability and can be robust as an auxiliary technique when used in combination with other statistical techniques (Scolforo, Maestri et al. 2013).We first used PCA method to analyze the data for all climate variables. Owing to climate variables with different units, all variables were standardized prior to PCA. Components explaining more than 80% of the variance were retained. For each component, variables with large loading were selected for further analysis. These variables with strong correlations with H and the least multicollinearity among them were served as options for modelling.

Basic H-D models

The basic H-D model was from Zang et al. (2016) for the same tree species in the region and modified as Eq. (1) which was a generalized H-D model with the inclusion of competition effects besides tree diameter.

$$H = 1.3 + (a_0 + a_1 BAL) \times (1 - exp(-(b_0 + b_1 BAL) \times D))^c + \varepsilon \quad (1)$$

Where H is the total tree height (m), D is the diameter at breast height (cm), BAL is the sum of basal area larger than a subject tree, a_0, a_1, b_0, b_1 and c are model parameters, which have their own biological characteristics, and ε is random error.

To evaluate the differences in height-diameter allometry among larch species, dummy variables S_m were created: (1) $S_1 = 1$ denotes the *L. gmelinii.* and 0 the rest of cases; (2) $S_2 = 1$ denotes the *L. olgensis* and 0 the rest of cases; (3)$S_3 = 1$ denotes the *L. principis-rupprechtii.* and 0 the rest of cases; (4) $S_4 = 1$ denotes the *L. kaempferi*; and (5) the category which can not be identified was represent by $S_1 = S_2 = S_3 = S_4 = 0$ as the reference.

Therefore, the model could be written as:

$$H = f(\beta, S_m, D, BAL) + \varepsilon \quad (2)$$

Where β is the fixed-effect parameter vector, S_m was dummy variable denoting tree species, and other variables are defined as above.

Nonlinear mixed-effects climate-sensitive H-D model

To quantify the climatic effects on the H-D allometry, the selected climate variables were added into the model by reparameterization for parameters in basic H-D model, and it could be written as:

$$H = f(\beta, BAL, Climate, S_m, D) + \varepsilon \tag{3}$$

Where $Climate$ was the climate variable vector selected by PCA and correlation analysis, and other variables were the same as mentioned above.

Owing to the correlated H-D observations in plots violating the principle of independence of error terms and the strong predictive ability of mixed effects model in forestry data (Calama and Montero 2004; Sharma and Parton 2007), the nonlinear mixed effected model can be an appropriate way to develop the climate sensitive H-D model which can be written as:

$$H_{ijk} = f\left(\beta, D_{ijk}, BAL, Climate, S_m, u_i, u_{ij}\right) + \varepsilon_{ijk} \tag{4}$$

$$u_i \sim N(0, \sigma_{province}^2),\ u_{ij} \sim N(0, \sigma_{plot}^2).$$

Where H_{ijk} and D_{ijk} is the k^{th} individual tree height nested within j^{th} plot in the i^{th} province, u_i and u_{ij} is the province- and plot-level random effects, and ε_{ijk} is the random error. Other variables were the same as mentioned above.

The estimated random effect parameter $\boldsymbol{u_i}$ were calculated as follows:

$$\boldsymbol{\hat{u}_i} = \boldsymbol{\hat{\Psi}\hat{Z}_i^T(\hat{Z}_i\hat{\Psi}\hat{Z}_i^T + \hat{R}_i)^{-1}e_i} \tag{5}$$

Where $\boldsymbol{\hat{u}_i}$ is the estimated prediction vector for random parameters, $\boldsymbol{\hat{\Psi}}$ is the estimated $\mathrm{q} \times \mathrm{q}$ variance-covariance matrix for among-unit variability, where q is the number of random effects parameters in the model, $\boldsymbol{\hat{R}_i}$ is the estimated $\mathrm{k} \times \mathrm{k}$ variance-covariance matrix for within-unit variability, $\boldsymbol{\hat{Z}_i}$ is the partial derivatives matrix with respect to the random parameters and $\boldsymbol{e_i}$ is the residual vector determined by the difference between the observed and predicted heights using model which only has fixed effects.

To account for the within-unit heteroscedasticity and autocorrelation in variance-covariance matrix ($\boldsymbol{R_i}$), the variance-covariance matrix was determined as:

$$\boldsymbol{R_i} = \sigma^2 \boldsymbol{G_i}^{0.5} \Gamma_{\boldsymbol{i}} \boldsymbol{G_i}^{0.5} \tag{6}$$

Where σ^2 is the value of residual variance of the estimated model, $\boldsymbol{G_i}$ is a diagonal matrix explaining the variance of within unit heteroscedasticity, $\Gamma_{\boldsymbol{i}}$ is a diagonal matrix accounting for within tree autocorrelation structure of errors, and AR(1) was used to reflect the within-tree autocorrelation structure of errors for matrix Γ_i. To reduce the heterogeneity in variance, the variance power equation was determined as:

$$\text{var}(\varepsilon_{ijk}) = \sigma^2 \hat{H}_{ijk}^{2\gamma} \quad (7)$$

where, $\widehat{H}_{ijk}$ is the estimated height of k^{th} tree nested in j^{th} plot in i^{th} province using fixed part of the mixed-effects model; γ is the parameter to be estimated; and σ^2 is the same as defined in Eq.6. Parameters in NLME models were estimated by restricted maximum likelihood implemented with 'nlme' package in R software (Pinheiro, Bates et al. 2013).

When a new subject is available(for example, the one in the validation set), the model needs to be calibrated for this subject by using information about the subject to estimate the empirical best linear unbiased predictors (EBLUPs) of the random effects parameters (Meng and Huang 2009). The methods from Gordan was reference to compose the predict function in R (Nigh 2012; Team 2013).

Model evaluation and validation

The following statistics were employed for model evaluation and validation: the adjusted coefficient of determination (R_{adj}^2), Akaike's information criterion (AIC), the mean absolute error (Scolforo, Maestri et al.), the root mean square error (RMSE).

$$R_{adj}^2 = 1 - \frac{\sum_{i=1}^{n_i}\sum_{j=1}^{n_{ij}}\sum_{k=1}^{n_{ijk}}(H_{ijk}-\hat{H}_{ijk})^2}{\sum_{i=1}^{n_i}\sum_{j=1}^{n_{ij}}\sum_{k=1}^{n_{ijk}}(H_{ijk}-\bar{H})^2} \times \frac{n-1}{n-p-1} \quad (8)$$

$$MAE = \frac{\sum_{i=1}^{n_i}\sum_{j=1}^{n_{ij}}\sum_{k=1}^{n_{ijk}}|H_{ijk}-\hat{H}_{ijk}|}{n} \quad (9)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n_i}\sum_{j=1}^{n_{ij}}\sum_{k=1}^{n_{ijk}}(H_{ijk}-\hat{H}_{ijk})^2}{n}} \quad (10)$$

$$AIC = -2\log L\,ik + 2k \quad (11)$$

Where n is the number of observations, $\hat{H}_{ijk}$ is k^{th} tree estimated height of nested in j^{th} plot nested in i^{th} province ; H_{ijk} is the k^{th} tree observed height nested in j^{th} plot nested in i^{th} province. $\bar{H}$ is the observed mean height for all data, n_i, n_{ij}, n_{ijk} are the total number of the province, the plots nested in i^{th} province, k^{th} trees nested in the j^{th} plot nested in i^{th} province, p is the number of model parameters; and LL is the log-likelihood.

Comparisons of H-D relationships among larch species under future climate change

For each plot, we produced 37 simulated trees with diameter from 5 cm (minimum value of D in calibration data) to 41 cm (maximum value of D in calibration data), and these diameter values were set to be evenly distributed. The values of BAL were obtained by mean value of each D with interval of 1cm in calibration data. According to final nlme model with the inclusion of climate variables, tree heights for a given D of all plots under different climate change scenarios were predicted. After the corresponding H of each D is averaged, the H-D curves of different larch species under climate change scenarios were generated. For observe how the climate change effect the H-D allometry in details, the relative change of tree height △H was defined for comparisons with a given D (Eq. 12). Similarly, after the corresponding △H of each D is averaged, the △H-D curves of different larch species were generated.

$$\triangle \mathrm{H} = \sum_{1}^{n}(H_{change} - H_{current})/\mathrm{n} \times H_{current} \quad (12)$$

Where n was the number of simulated trees. H_{change} and $H_{current}$ represent tree height value predicted under future and current climate scenarios, respectively.

Results

Selected climate variables

Three principal components described 95.27% of the variability of the climate data (Table 3). For component 1, the variables with absolute loading values > 0.3 were MAT, DD_0, DD5, DD_18 and NFFD, so the component 1 mainly represents the temperature variability. For component 2, the variables which absolute loading values >0.3 were TD, MAP, AHM and CMD, so the component 2 represents the moisture variability. For component 3, TD and PAS were chosen.

According to the loading, the most two important climate variables were selected which include MAT, DD_18, CMD, MAP, TD, PAS. Table 4 presents the correlation between these climate variables and tree height. Because of the collinearity between MAT, DD_18, MAP, TD and PAS. Finally, only MAT and CMD were selected for further reparameterization using NLME. Summary statistics of MAT and CMD can be found in Table 5.

Table 3 PCA analysis result of the climate variables

	Comp.1	**Comp.2**	**Comp.3**
MAT	0.331	0.000	0.000
MWMT	0.265	0.248	-0.229
MCMT	0.282	-0.172	0.272
TD	-0.114	0.341	-0.43
MAP	0.000	0.394	0.338
AHM	0.147	-0.387	-0.262
DD_0	-0.302	0.104	-0.238
DD5	0.301	0.185	-0.14
DD_18	-0.329	0.000	-0.104
DD18	0.269	0.243	-0.183
NFFD	0.311	0.150	0.000
PAS	-0.172	0.265	0.388
EMT	0.287	-0.128	0.21
EXT	0.250	0.171	-0.357
Eref	0.249	-0.215	0.000
CMD	0.000	-0.444	-0.238
Accumulated variance	56.050	81.680	95.27

Table 4 Pearson correlation coefficient matrix between H and climatic variables

Variables	CMD	TD	PAS	MAP	DD_18	MAT	H
CMD	1.000	-	-	-	-	-	-
TD	-0.424***	1.000	-	-	-	-	-
PAS	-0.673***	0.193***	1.000	-	-	-	-
MAP	-0.841***	0.141***	0.566***	1.000	-	-	-
DD_18	-0.041***	0.435***	0.421***	-0.358***	1.000	-	-
MAT	-0.004	-0.347***	-0.412***	0.390***	-0.995***	1.000	-
H	-0.503***	0.404***	0.329***	0.414***	0.070***	-0.029***	1.000

Note: *,$p<0.05$;**,$p<0.01$;***,$p<0.001$.

Table 5 Mean value of MAT and CMD under 3 climate change scenarios

MAT	Period:2010-2040	Period:2040-2070	Period:2070-2100
RCP2.6	3.95(2.40)	4.41(2.41)	4.53(2.43)
RCP4.5	3.92(2.43)	4.87(2.44)	5.70(2.42)
RCP8.5	4.14(2.42)	5.69(2.42)	7.44(2.36)
CMD	Period:2010-2040	Period:2040-2070	Period:2070-2100
RCP2.6	180.96(88.22)	164.38(75.68)	164.34(87.09)
RCP4.5	158.82(82.30)	142.16(77.02)	180.26(83.53)
RCP8.5	160.62(83.16)	186.03(82.88)	187.04(82.78)

Note: The numbers within parentheses are the standard deviation

Final NLME h-d model with climatic variables

When climate variables were selected into the model, all the explanatory variables were determined. Then, we tested all the combinations of dummy variables representing different species, climate variables and Province- and plot- level random effects to parameters from the basic model (Eq. 1). The final model with good convergence and the lowest AIC value was chosen for simulations. The climate variables were set into parameter a and b, the tree species dummy variables and random effects were set into parameter a.

Therefore, the equations 2 to 4 can be rewritten representing basic H-D model, climate-sensitive H-D model, and climate-sensitive mixed-effect H-D model (Eq. 13-15).

$$H_{ijk} = 1.3 + (a_0 + a_1 BAL + \sum_{m=1}^{4} f_m S_m)[1 - e^{b_0 D_{ijk} + b_1 BAL}]^c + \varepsilon_{ijk} \quad (13)$$

$$H_{ijk} = 1.3 + (a_0 + a_1 \mathrm{BAL} + a_2 MAT + a_3 CMD + \sum_{m=1}^{4} f_m S_m)[1 - e^{(b_0 + b_1 BAL + b_2 MAT + b_3 CMD) D_{ijk}}]^c + \varepsilon_{ijk} \quad (14)$$

$$H_{ijk} = 1.3 + \left(a_0 + a_1 \mathrm{BAL} + a_2 MAT + a_3 CMD + \sum_{m=1}^{4} f_m S_m + u_i + u_{ij}\right)[1 - e^{(b_0 + b_1 BAL + b_2 MAT + b_3 CMD) D_{ijk}}]^c + \varepsilon_{ijk} \quad (15)$$

Where $f_1 \sim f_4$, $a_0 \sim a_3$, $b_0 \sim b_3$, c are the model parameters to be estimated; other variables are defined as above.

Model comparison and evaluation

The fitting and validation results of the models are shown in Table 6. The base model (Eq.13) described 76% part of the variations in the height-diameter relationship when fitted the training data(R_{adj}^2=0.76). When tree species dummy variable and province-specific, plot-specific random effects were included in the base model, the climate variables contributed significantly to the variance of tree heights and R_{adj}^2 increased from 0.77 to 0.92 (Table 6). Training dataset showed similar results, and the inclusion of climate variables (Eq. 14) resulted in the increase R_{adj}^2 by 3% and the reduce of AIC by 3%. Mixed effect model (Eq. 15) also removed the heteroscedasticity of residuals (Figure 2).

Figure 2 Residuals vs predicted values for different H-D models based on calibration data

Table 6 Parameter estimates and statistics for equations (13)-(15)

	parameter	parameter definition	Eq.(13)	Eq.(14)	Eq.(15)
fixed-effects parameters	a_0		21.382(0.000)	21.460(0.000)	19.772(0.000)
	b_0		0.078(0.000)	0.088(0.000)	0.106(0.000)
	c_0		1.616(0.000)	1.545(0.000)	2.083(0.000)
	a_1	BAL	-0.137(0.000)	-0.085(0.000)	-0.111(0.000)
	a_2	MAT		1.322(0.000)	0.259(0.0381)
	a_3	CMD		-0.021(0.000)	-0.030(0.000)
	b_1	BAL	0.001(0.000)	0.001(0.000)	0.005(0.000)
	b_2	MAT		-0.005(0.000)	0.003(0.0024)
	b_3	CMD		0.000(0.07)	0.000(0.000)
	f_1	*L. gmelinii*	-5.137(0.000)	-3.790(0.000)	0.216(0.898)
	f_2	*L. olgensis*	3.234(0.000)	3.317(0.000)	1.879(0.013)
	f_3	*L. kaempferi*	-4.944(0.000)	-2.951(0.000)	0.865(0.050)
	f_4	*L. principis-rupprechtii.*	2.557(0.000)	2.319(0.000)	0.226(0.735)
Variance components	$\sigma_{province}$				1.349
	σ_{plot}				2.700
model performance					
	γ				0.674
	AIC		23007.83	22368	17911.4
Fitting set R^2_{adj}			0.77	0.79	0.92
Fitting set MAE(m)			1.37	1.28	0.76
Fitting set RMSE(m)			1.82	1.72	1.06
Validation set MAE(m)			1.5	1.44	1.38
Validation set RMSE(m)			2.03	1.93	1.8

Note: $\sigma_{province}$ and σ_{plot} are the variance for the random parameters u_i and u_{ij}, respectively; γ is the parameter of correlation structure. AIC was the Akaike's information criterion.

H-D relationships among larch tree species and tree sizes under future climate change

Results showed different effects of climate variables on parameters a_0 and b_0, denoting the maximum and relative change of tree height with diameter (Table 6). Parameter a_1 was significantly negative indicating the increasing BAL will reduce the maximum height. The coefficient a_2 of MAT for parameter a was significantly positive which means that the rising MAT will increase the maximum tree height. This was also shown in Figure 3 where all H-D curves of different species became steeper under RCP2.6 and RCP 4.5 from 2010 to 2070. However, parameter b_2 was negative indicating that the rising MAT will lower the tree height with the same diameter and there is a threshold for the effect of temperature on H-D relationship of larch species. Parameter a_3 was significantly negative indicating the decreasing precipitation will reduce the maximum height. Both CMD and BAL showed marginal effects on H-D relationship since b_1 and b_3 were nearly zero.

Table 6 showed that all parameters of tree species dummy variables f_1~f_4 were positive, but f_1 and f_4 were not significant, indicating that *L.olgensis* and *L.Kaempfer* had significant difference with unidentified group, which was also illustrated in Figure. 3. Coefficient f_2 was the largest indicating that the maximum of tree height is the largest for *L.olgensis*.

MAT increases with the time and the temperature under RCP8.5 is largest followed by RCP4.5 and RCP2.6. The precipitation under RCP8.5 is smallest and has the steepest slope followed by RCP4.5 and RCP2.6. Figure 4 showed the ΔH-D curve of larch species under climate scenarios RCP2.6, RCP4.5 and RCP8.5. Generally, tree species can be obviously classified as two groups in terms of ΔH, which are group I (*L. gmelinii* group, *L. pincipis-rupprechtii* and the unidentified larch species) and group II (*L. kaempferi* and *L. olgensis*). They showed strong (ΔH from -4.77% to 18.17%) and weak (ΔH from -6.37% to 9.40%) responses to climate change, respectively. The values of ΔH for Group I were positive which indicated that future climate change increased tree height compared with current climate with the exception of RCP 2.6 from 2010 to 2040 and RCP8.5 from 2040-2100. However, the values of ΔH were complicated varying from negative to positive with the increasing diameter for Group II.

It can be observed that ΔH varied with tree diameter. Generally, large trees showed large ΔH values, but there were different responses to climate among larch species. For tree species group I, the ΔH increased with the increase of tree DBH in small and medium sizes and kept stable in large size. For group II, the absolute ΔH increased with the increase of tree DBH, but changed from negative to positive

Mean abosolute ΔH value of tree height with diameter among larch species under different climate scenarios in period 2010 to 2100(mean value of the absolute ΔH in period 2010 to 2040, 2040 to 2070 and 2070 to 2100) was shown in Figure 5. It can be observed that the climate sensitivity of larch species was ranked as *L. gmelinii* > *L. pincipis-rupprechtii* > the unidentified species group > *L. olgensis* > *L. kaempferi* under RCP2.6 and RCP8.5, and the sensivity was larger under RCP8.5 than that under RCP2.6. However, the sensitivity was ranked as *L. gmelinii* > the unidentified species group > *L. pincipis-rupprechtii* > *L. kaempferi* > *L. olgensis* under RCP4.5.

Figure 3 Relationship between tree height and DBH of larch species under different climate change scenarios

Figure 4 Relative change of tree height with diameter among larch species under different climate scenarios

Figure 5 Mean absolute ΔH values of height with diameter among larch species under different climate scenarios

Discussion

Climate-sensitive H-D model

The climate-sensitive H-D allometry model with a two-level NLME approach at the province and plot levels was developed for larch plantations in the study. Results showed that a two-level mixed-effects model with the inclusion of climate variables provided better performance compared to fixed-effects model without climate variables, which could also be found in other reports (Sharma and Parton 2007; Zang, Lei et al. 2016; Zhang, Chhin et al. 2019; Bronisz and Mehtätalo 2020; Ciceu, Garcia-Duro et al. 2020). In this study, using mixed-effects model and including climate variables was able to increase R^2_{adj} by 19.5% and reduce the AIC, MAE and RMSE by 22.2%, 44.5% and 41.8% for fitting set, respectively. The residual heterogeneity was also reduced. Owing to the correlation among tree height-diameter observations, fixed-effect model would lead to biased variance of the parameter estimates and thus invalidate the hypothesis tests (Pinheiro, Bates et al. 2013). Mixed effect modelling approach can be an appropriate solution to this problem (Calama and Montero 2004; Sharma, Vacek et al. 2016). Similarly, Vizcaíno-Palomar, Ibáñez et al. (2017) reported that inclusion of climate variables and random effects reduce the AIC by 9.0%. Sharma, Vacek et al. (2016) reported that inclusion of random effects was able to increase the R^2_{adj} by 9.2% and reduce the AIC and RMSE by 7.8% and 25%, respectively.

The climate variables including MAT and CMD significantly affected H-D relationship but the effect was not very strong which was in line with the previous studies (Hulshof, Swenson et al. 2015; Fortin, Van Couwenberghe et al. 2019; Zhang, Chhin et al. 2019).Temperature usually affects the growth season and growth rate of tree height. Low temperature will hinder the division and specialization of cambium and meristem cells, thus accumulating more nutrients and carbohydrates and distributing them to the trunk, therefore the shape of tree changed (Kilpeläinen, Peltola et al. 2006). Fortin, Van Couwenberghe et al. (2019) pointed out that the mean temperature from March to September affected H-D relationship of most French species. Temperature was not a marginal effect that can be overlooked and its effect was also quadratic so that an optimal temperature existed. Ng'andwe, Chungu et al. (2021) also found that increasing temperature beyond the optimum for *Pinus merkusii* and *P. michoacana* will reduce the tree growth and increase the rotation age. Similarly, in this study, MAT modified parameters a_2 and b_2 positively and negatively, respectively, which also indicated that there was an optimal temperature for larch tree height. Zhang, Chhin et al. (2019) reported that MAT was the dominant climatic factor in modulating height-diameter allometry of Chinese fir, and the effect of MAT and MWMT were positively associated with tree height. Larch in the region begins to grow in May, and the growth speed reaches the maximum in July, then gradually slows down until it stops growing (Wang, Wang et al. 1992). Therefore, the temperature in May and the precipitation in the previous year are very important for the height growth of larch. Our results showed that CMD had significant effects on H-D relationship. The coefficient of CMD, a_3, was negative which indicated that the height decreases with the increase of water deficiency. This was consistent with previous study (Zhou, Lei et al. 2019) which found that the precipitation from the previous October to the current April significantly promoted the height growth of Mongolian pine. Sang, Sebastian - Azcona et al. (2019) also found that the negative and positive effects of CMD on the height of white spruce trees in northern Canada.

Besides climate, H-D relationship was affected by multiple biotic and abiotic variables, for example genetic characteristics (Kroon et al., 2008), stand age (Sάnchez et al., 2003), site condition (Sharma and Yin Zhang, 2004; Sharma and Parton, 2007; Zhang et al., 2020), competition status (Calama and Montero, 2004; Sharma and Yin Zhang, Ciceu et al., 2020). Considering the inclusion of other stand factors will aggravate the model complexity, we only use diameter and BAL as the independent variable for ensuring more stable convergence. Other methods like machine learning were worthy of further exploration in future study.

The impact of climate change on H-D relationship by larch species and tree size

Our model simulations showed that the effects of climate change on H-D relationship varied with larch species. Generally, *Δ*H-D curves of larch species can be obviously classified as two groups, which are group I (*L. gmelinii* group, *L. pincipis-rupprechtii* group and the unidentified species group) and group II *(L. kaempferi* and *L. olgensis*). They showed strong (*Δ*H from -4.77% to 18.17%) and weak (*Δ*H from -6.37% to 9.40%) response to future climate change, respectively. Under warmer and drier climatic conditions, *L.kaempferi* and *L.ogensis* will grow thicker and shorter than the rest of the tree species group, and their *Δ*Hs are lower than those of group I for a given tree diameter. This may due to these two tree species are moisture loving species (Wang *et al*., 1992). Under drought stress, the hydraulic conductivity of the xylem of the trunk suffers irreversible loss. Therefore, the lack of water during the growing season allows to allocate more resources for the growth of diameter (Ryan and Yoder 1997). Compared with group II, group I is more resistant. As the temperature increases, more resources will be allocated to the growth of the height than the diameter, thus trees would be higher. Previous studies also supported this result (Aiba and Kitayama 1999; THORNLEY 1999; Schelhaas 2008; Zhang, Wang et al. 2020).

*Δ*H also varied with tree diameter under future climate change. For tree species group I, *Δ*H increased for small and medium sizes and kept stable for large sizes. This may be resulted from the limited height growth of trees with large diameter because of the limits to tree height (Koch, Sillett et al. 2004). For tree species group II, *Δ*H increased with the increasing DBH, but changed from negative to positive, indicating that small trees will grow short but large trees high. Campbell, Magnussen et al. (2021) reported that large trees were most sensitive to annual climate fluctuations. From the perspective of competition, larger trees in a stand have more competitive advantages than smaller trees while the smaller neighbor trees do not influence the growth of larger trees (Cannell *et al.*, 1984). Under the warmer and drier climate in the future, due to the developed root system of the big trees, their growth will not be affected by the lack of water, and the growth of small trees may face drought stress. McDowell, Pockman et al. (2008) pointed out that plants can avoid water damage caused by drought through stomatal closure, leading to carbon starvation and a cascade of down-stream effects. Seedlings or small trees are more likely to inhibit growth or even die due to hydraulic failure. The phenomena of changing from negative to positive for ΔH of *L. kaempferi* and *L. olgensis* along with increasing diameter support this conclusion.

Conclusions

Two-level climate-sensitive NLME model was developed for larch planatations in north and northeast China in this study which showed biological and statistical reasonability. MAT, CMD, was the dominant climatic factor in modulating height-diameter allometry of larch plantations. Model simulation showed that the climate sensitivity of H-D allometry varied with tree species and diameter. According to the climate sensitivity, tree species could be classified as group I(*L. gmelinii*, *L. pincipis-rupprechtii* and the unidentified species group) with large ΔH (from -4.77% to 18.17%) and group II (*L. kaempferi* and *L. olgensis*) with small ΔH (from -6.37% to 9.4%). Large trees were more sensitive to climate change than small trees.

Declarations

Ethics approval and consent to participate

The authors declare that the study was not conducted on endangered, vulnerable or threatened species. The authors declare that they obtained the informed consent from human participants involved in this study.

Consent for publication

All authors gave their informed consent to this publication and its content.

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Availability of data and material

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Authors' contributions

Q.G. Xu: Data preparation, Data analysis, Writing, review & editing; X. D. Lei: Conceptualisation, Funding, Writing, review & editing; H. Zeng and W. S. Zeng: Data collection, review & editing.

Competing interests

The authors declared that they have no conflicts of interest to this work.

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Figures

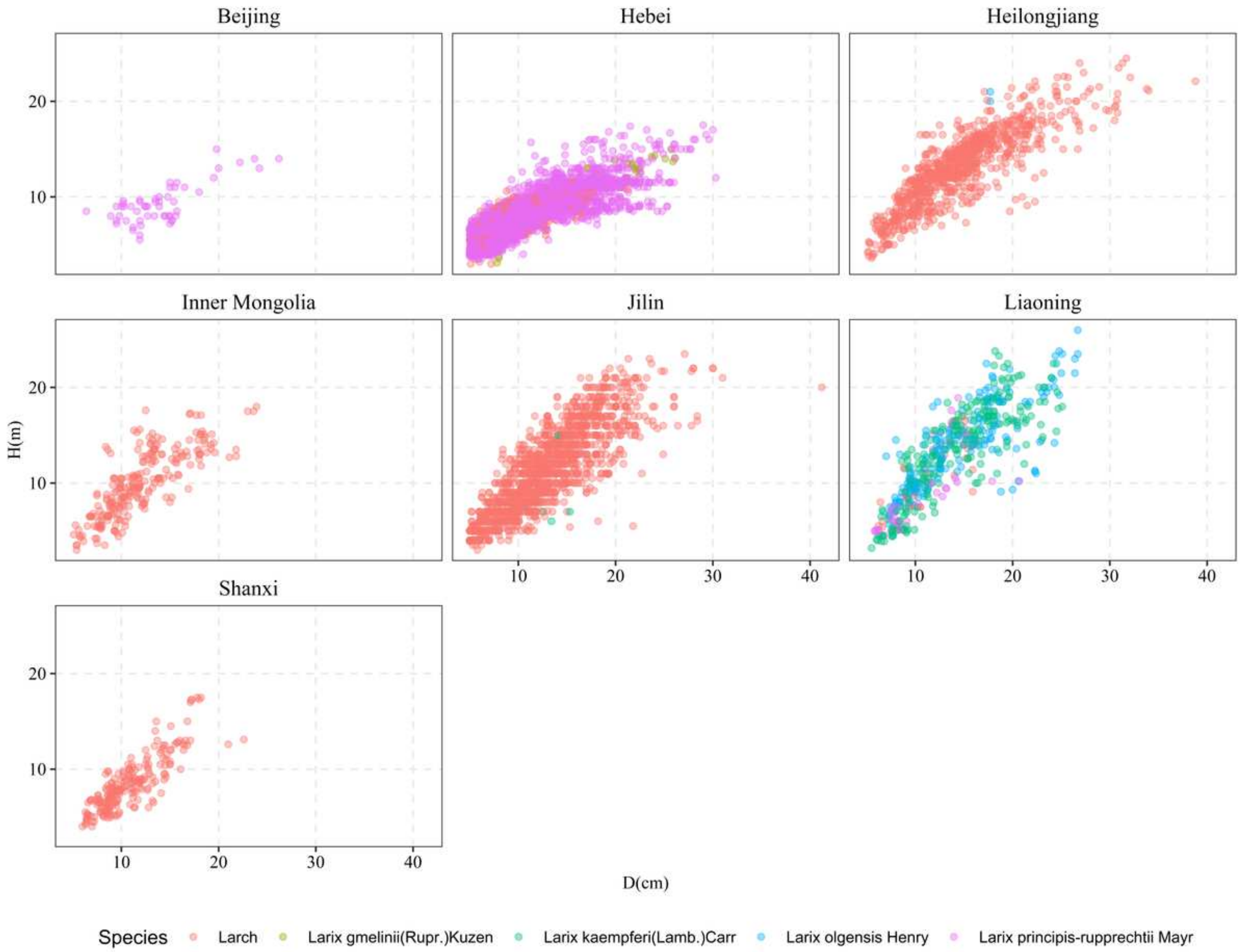

Figure 1

Scatter plot of tree height-diameter allometry by Larch species in 7 provinces.

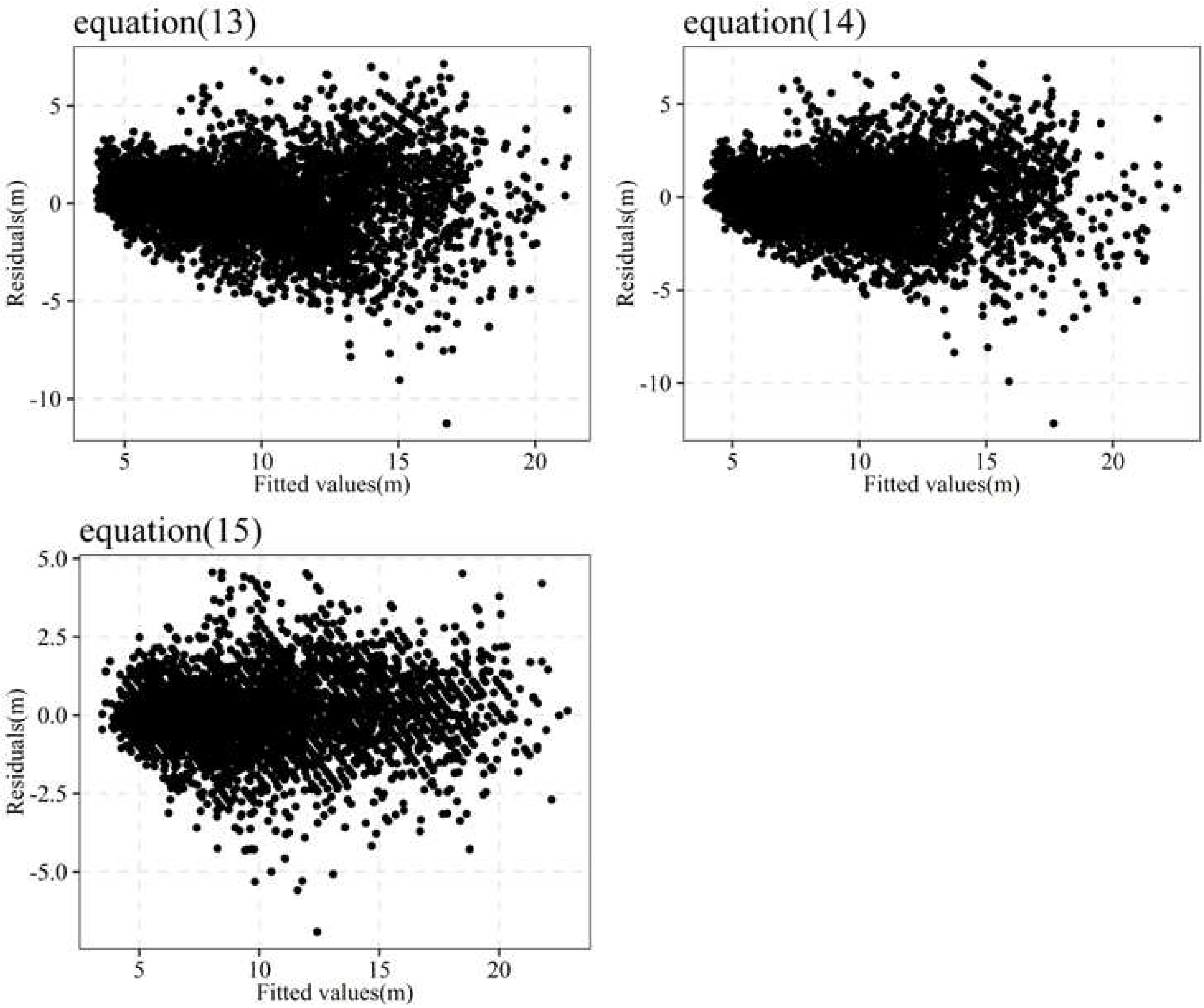

Figure 2

Residuals vs predicted values for different H-D models based on calibration data

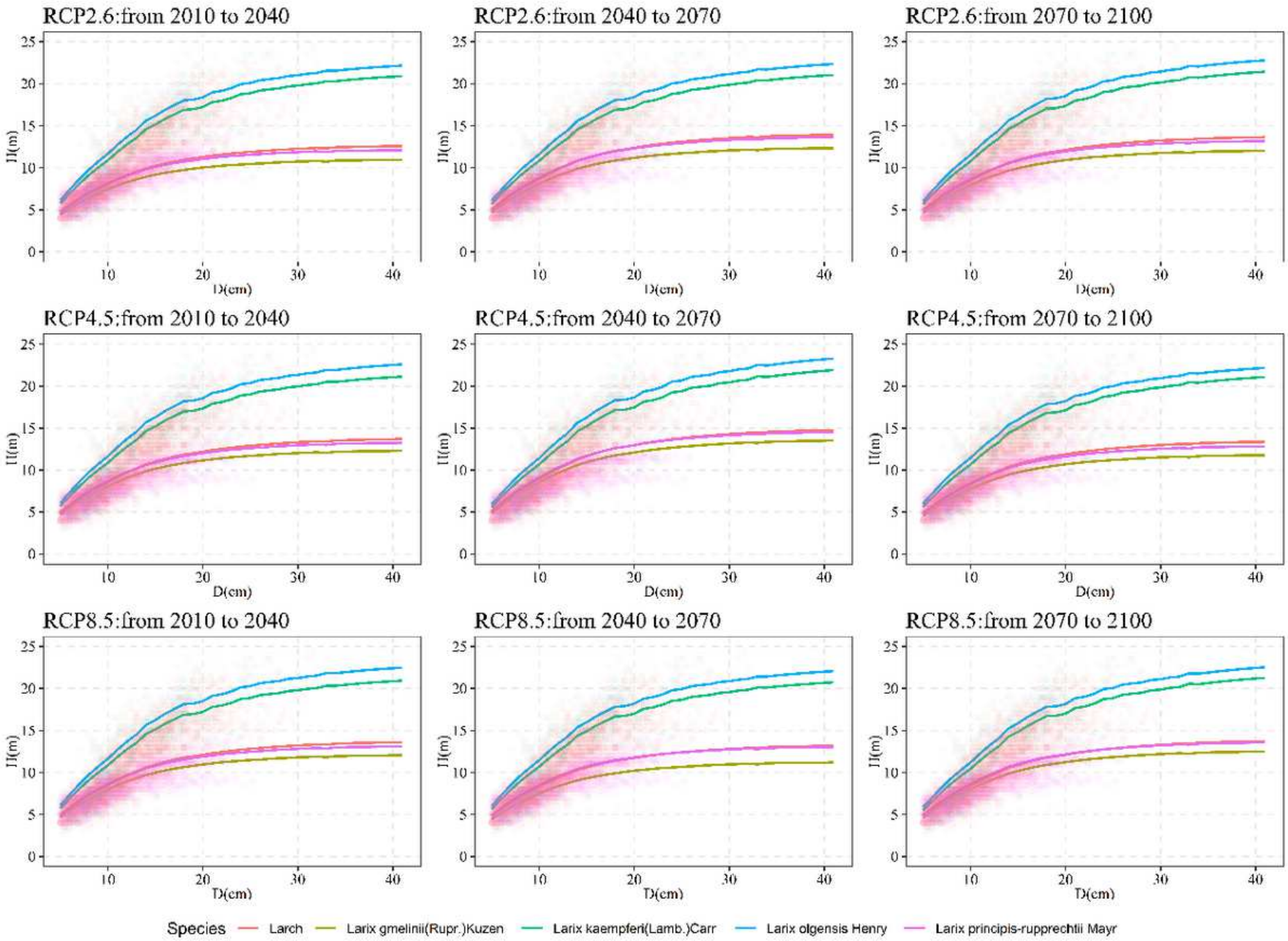

Figure 3

Relationship between tree height and DBH of larch species under different climate change scenarios

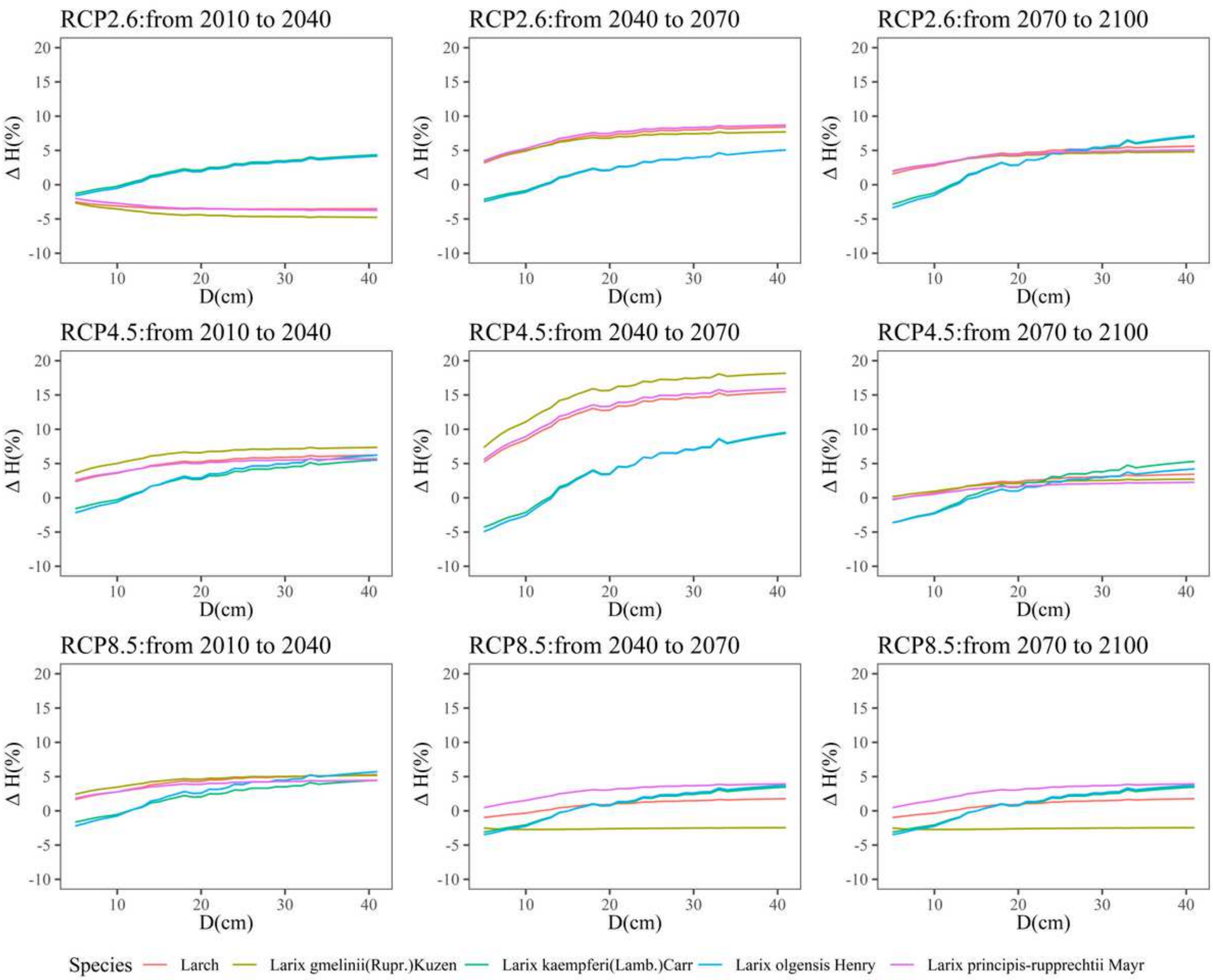

Figure 4

Relative change of tree height with diameter among larch species under different climate scenarios

Figure 5

Mean absolute ΔH values of height with diameter among larch species under different climate scenarios