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Construction of Additive Allometric Biomass Models for Young Trees of Two Dominate Species in Beijing, China

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Abstract: The traditional volume-derived biomass method is limited because it does not fully consider the carbon sink of young trees, which leads to the underestimation of the carbon sink capacity of a forest ecosystem. Therefore, there is an urgent need to establish an allometric biomass model of young trees to provide a quantitative basis for accurately estimating the carbon storage and carbon sink of young trees. The destructive data that were used in this study included the biomass of the young trees of the two dominant species (*Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière) in China, which was composed of the aboveground biomass (B_a), belowground biomass (B_b), and total biomass (B_t). Univariate and bivariate dimensions were selected and five candidate biomass models were independently tested. Two additive allometric biomass model systems of young trees were established using the proportional function control method and algebraic sum control method, respectively. We found that the logistic function was the most suitable for explaining the allometric growth relationship between the B_a, B_t, and diameter at breast height (D) of young trees; the power function was the most suitable for explaining the allometric growth relationship between the B_b and D of young trees. When compared with the independent fitting model, the two additive allometric biomass model systems provide additive biomass prediction which reflects the conditions in reality. The accuracy of the B_t models and B_a models was higher, while the accuracy of the B_b models was lower. In terms of the two dimensions—univariate and bivariate, we found that the bivariate additive allometric biomass model system was more accurate. In the univariate dimension, the proportional function control method was superior to the algebraic sum control method. In the bivariate dimension, the algebraic sum control method was superior to the proportional function control method. The additive allometric biomass models provide a reliable basis for estimating the biomass of young trees and realizing the additivity of the biomass components, which has broad application prospects, such as the monitoring of carbon stocks and carbon sink evaluation.

Keywords: young tree; forest carbon sink; allometric growth; additive model

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1. Introduction

The assessment of the carbon sink capacity must be based on an accurate biomass, which is then converted into the carbon content and carbon dioxide equivalent. The volume-derived biomass method is used for the evaluation of forest carbon sinks and considers trees with a diameter at breast height >5 cm. However, the volume-derived biomass method has not been able to assess the carbon sink of young trees, which leads to the underestimation of the carbon sink capacity of forest ecosystems [1]. The assessment of the carbon sink capacity of forest ecosystems has received extensive global attention [2–4]. To address the limitations of the volume-derived biomass method, it is necessary to evaluate the carbon sink of young trees.

The lack of allometric biomass models of young trees affects the accuracy of assessing the available forest biomass, forest fuel load, and carbon sink [5]. Due to the small size of young trees, not calculating the volume of a few young trees will not have a significant impact on the estimation of the carbon stock. However, young trees contribute significantly to the carbon sink because they grow faster than large-diameter trees [6,7]. In addition, reliable biomass models of young trees are particularly important in fire-prone forest ecosystems. For example, in the *Pinus brutia* Ten. forests in Turkey, nearly 15% of the forest area is dominated by young trees (D ranges from 0.1 to 8) [1].

There are differences in the definition of a young tree in different regions. In Turkey, trees with a diameter at breast height of <8 cm are considered to be young trees and are not measured in conventional forest inventory applications such as industrial round-wood production [1]. In China, trees with a diameter at breast height of <5 cm are considered to be young trees and are not measured in forest resource inventories [6]. The biomass estimation of young trees in Turkey mainly targeted the crown biomass component and was based on a small sample size [8]. Due to the difficulty of obtaining biomass samples, the development of an allometric biomass model of young trees in China has been limited to a few studies.

The main methods for estimating the forest biomass include the model and remote sensing inversion methods. The most reliable way to determine the forest biomass would be to cut and weigh all the trees in the forest. However, this would be destructive, time-consuming, costly, and could only be conducted on a small scale [9]. The model method can be used to estimate the forest biomass non-destructively. It estimates the forest biomass using readily measurable tree factors [9,10]. In the model method, the biomass can be estimated either by tree volume and biomass expansion factor or by the allometric biomass model. Biomass estimation on a large spatial scale can be realized using the remote sensing inversion method but atmospheric interference can affect the estimation accuracy of satellite data [11]. Therefore, using allometric biomass models is often the best choice for estimating the forest biomass if there is information on individual trees.

The allometric relationship of young trees is different from that of old trees [12,13]. Bond-Lamberty et al. (2002) found that when using data samples with a large diameter at breast height, the allometric biomass models were significantly biased in estimating the biomass of small-diameter trees [14]. Small-diameter trees play an important role in estimating forest biomass because they account for a large number of the individual trees that make up the biomass [12]. Therefore, it is necessary to separately develop an allometric biomass model of young trees. However, only a few studies have modeled the biomass of young trees [12,15,16].

The selection of the predictor is particularly important when developing an allometric biomass model. Many allometric biomass models were established between tree biomass and easily measured tree variables, such as the diameter at breast height, tree height, crown width, and wood density [17–19]. For these developed models, the diameter at breast height is the most commonly used and reliable predictor [20,21]. It has also been suggested that adding tree height as a predictor to allometric biomass models can significantly improve model performance [22,23].

Model form selection is an important uncertainty in estimating tree biomass. The power function is the most commonly used to model allometric biomass [24,25]. The exponential growth of biomass based on individual size is described in a power function form [26,27]. However, due to resource competition, the continuous acceleration and infinite growth of individual tree biomass in forest ecosystems is not valid. The logistic model is a classical method for predicting population size. The logistic model has similar rapid growth to the power function, which then gradually flattens out and finally approaches the asymptotic value [28]. The logistic model and power function have the same statistical validity, but the logistic model has better ecological significance and can better estimate shrub biomass [29].

For the modeling of tree biomass, the additivity of the biomass components should be ensured, that is, the total biomass of the trees should be equal to the sum of the biomass of each component. The total biomass of the trees is usually divided into different components based on their physiological function, such as the trunk, branch, leaf, and root biomass. When more than two tree components are involved, if the biomass model of each component is fitted separately, the intrinsic correlation between the tree components is not considered. In some studies, mathematical models were selected for the different tree components, parameter fitting was carried out independently, and allometric biomass models of each component were developed. When these models were used for prediction, there was a non-additivity problem between the predicted total biomass of the trees and the predicted biomass of each component [14,30–32].

To solve the additivity problem, different models and estimation methods have been proposed, such as the generalized moment method (GMM) [33], error-in-variable simultaneous equations method (EIV) [34], proportional function control method, and algebraic sum control method [35,36]. Among these methods, there is no unified conclusion on the best method. Zheng et al. (2022) showed that the prediction accuracy of the proportional function control method was higher [37]. Moreover, Xiong et al. (2023) showed that the GMM method had a better fitting performance [25]. Fu et al. showed that the EIV method has more advantages and potential [38].

Considering that the growth of young trees is different from that of old trees, it needs to be confirmed that the conclusions made in previous literature based on the allometric biomass model are applicable to young trees. In this study, based on the measured destructive data of young trees of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière, the additive allometric biomass model system was established with the diameter at breast height and tree height as the predictors to ensure the additive relationship between the total biomass, aboveground biomass, and belowground biomass. We compared two additive methods, namely the proportional function control method and the algebra sum control method, to determine which method was better. We hypothesized that (1) the bivariate additive allometric biomass model system is more accurate; (2) when compared with the power function, the logistic model can better estimate the allometry of young trees; and (3) among the two additive methods, the proportional function control method is superior to the algebra sum control method.

2. Materials and Methods

2.1. Study Site and Data

2.1.1. Study Site

Beijing is located at the junction of the Inner Mongolia Plateau and the North China Plain. The elevation is ≤100 m and the elevation of most areas ranges between 30 and 50 m. The climate is a warm temperate semi-humid continental monsoon climate with four distinct seasons, a hot and rainy summer and a cold and dry winter. The average annual temperature is about 11.5 °C and the frost-free period is 5 to 6 months annually. The annual average precipitation is 585 mm, with the summer precipitation accounting for about 74% of the annual precipitation. According to zonal vegetation types, Beijing belongs to the warm temperate deciduous broad-leaved forest area [39].

2.1.2. Data Collection

We obtained data during the peak annual biomass accumulation period from September to October 2021. A total of 44 plantation plots of 30 m × 30 m were investigated, and all the young trees with diameters below 5 cm and heights above 130 cm were measured (Table S1).

Table 1 shows the descriptive statistics of the data. The data was collected from 167 young trees: 104 *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll trees and 63 *Populus* × *tomentosa* Carrière trees. The factors that were measured for each tree included the diameter at breast height, tree height, aboveground biomass, belowground biomass, and total biomass. For each tree, the fresh weight of the trunk, branches, and leaves were weighed and samples were taken. The sample was dried in the oven at 105 °C to obtain the dry mass. According to the proportion of the fresh mass and dry mass of the sample, the dry mass of each component was calculated, and then the parts of the tree were added together to obtain the aboveground biomass. The belowground biomass was determined using the full excavation method. The whole root system was dug out manually, the soil on the root was cleared, and then the total fresh weight of the rhizome (≥5 mm), coarse roots (2–5 mm), and fine roots (<2 mm) were weighed. The sample was dried in the oven at 105 °C to obtain the dry mass. According to the proportion of the fresh mass and dry mass of the sample, the dry mass of each component was calculated, and then the parts of the tree were added together to obtain the belowground biomass. The total biomass of the tree was obtained by adding the aboveground and belowground biomass.

Table 1. Statistics of the tree characteristics (N, D, and H) and biomass components (B_a, B_b, and B_t) of two tree species (*Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière).

Tree Species	N	D (Mean ± S.D.)	H (Mean ± S.D.)	B_a (Mean ± S.D.)	B_b (Mean ± S.D.)	B_t (Mean ± S.D.)
Betula pendula subsp. *mandshurica* (Regel) Ashburner & McAll	104	3.0 ± 1.0	4.4 ± 1.4	2.095 ± 1.425	0.631 ± 0.540	2.727 ± 1.778
Populus × *tomentosa* Carrière	63	3.1 ± 1.0	4.5 ± 1.4	1.650 ± 1.184	0.445 ± 0.389	2.095 ± 1.513

Note: S.D.—Standard deviation, N—number of samples, D—diameter at breast height (cm), H—tree height (m), B_a—aboveground biomass (kg), B_b—belowground biomass (kg), B_t—total biomass (kg).

2.2. Statistical Analysis

2.2.1. Independent Fitting Model

Many biomass models have been widely used to assess the carbon sink of global forest ecosystems [29,32,40,41]. In this study, five kinds of biomass models commonly used in the past were tested. Univariate and bivariate combinations were considered: (1) diameter at breast height (D); and (2) D and tree height (H). Among them, the three model forms of logistics function (Model 1), quadratic polynomial function (Model 2), and power function (Model 3) only include D.

Model 1: $B = a_0 / \left(1 + e^{a_1 + a_2 \cdot D}\right)$

Model 2: $B = a_0 + a_1 D + a_2 D^2$

Model 3: $B = a_0 D^{a_1}$

Model 4: $B = a_0 D^{a_1} H^{a_2}$

Model 5: $B = \exp\left[a_0 + a_1 \cdot \ln\left(H \times D^2\right)\right]$

Model 5: The Akaike information criterion (AIC) statistics were used to assess the model complexity and its goodness of fit, with preference being given to the model with a smaller AIC value. Using the AIC minimization criterion, the optimal model form for the aboveground biomass, belowground biomass, and total biomass in terms of the univariate and bivariate combinations was selected.

2.2.2. Proportional Function Control Method

The basic principle of the proportional function control method is to directly fit the total biomass model and then assign the total biomass to the aboveground biomass and the belowground biomass. The method is specified below.

Steps: based on the optimal model form for the total biomass (B_t) in Section 2.2.1, $B_t = f_1(D)$ and $B_t = f_2(D, H)$ were developed to obtain the estimated value of the total biomass under two dimensions. Then, the scale function under two dimensions was set to: $g_1(D) = b_1 D^{c_1}$ and $g_1(D, H) = d_1 D^{e_1} H^{f_1}$. With the estimated total biomass as the control, the biomasses of the two components were combined into a simultaneous equations system, and the parameters of the system were estimated by nonlinear seemingly unrelated regression. The univariate and bivariate additive allometric biomass model systems were expressed as follows:

$$\begin{cases} B_a = \frac{1}{1+g_1(D)} \times f_1(D) + \varepsilon_1 \\ B_b = \frac{g_1(D)}{1+g_1(D)} \times f_1(D) + \varepsilon_2 \end{cases}$$

$$\begin{cases} B_a = \frac{1}{1+g_1(D,H)} \times f_2(D,H) + \varepsilon_1 \\ B_b = \frac{g_1(D,H)}{1+g_1(D,H)} \times f_2(D,H) + \varepsilon_2 \end{cases}$$

2.2.3. Algebraic Sum Control Method

The basic principle of the algebraic sum control method is that the aboveground biomass, belowground biomass, and total biomass are combined into equations, and the total biomass model is obtained by adding the two-component models. The regression model of each component contains its own independent variables. The method is specified below.

Steps: based on the optimal model form from Section 2.2.1, the optimal model form of the aboveground biomass (B_a) in two dimensions was determined as follows: $B_a = m_1(D)$ and $B_a = m_2(D,H)$, and the optimal model form of the belowground biomass (B_b) under the two dimensions was calculated as follows: $B_b = n_1(D)$ and $B_b = n_2(D,H)$. The two biomass components and the total biomass were combined into a set of equations, and the parameters of the equations were estimated by nonlinear seemingly uncorrelated regression. The univariate and bivariate additive allometric biomass model systems were expressed as follows:

$$\begin{cases} B_a = m_1(D) + \varepsilon_1 \\ B_b = n_1(D) + \varepsilon_2 \\ B_t = m_1(D) + n_1(D) + \varepsilon_3 \end{cases}$$

$$\begin{cases} B_a = m_2(D,H) + \varepsilon_1 \\ B_b = n_2(D,H) + \varepsilon_2 \\ B_t = m_2(D,H) + n_2(D,H) + \varepsilon_3 \end{cases}$$

2.2.4. Model Evaluation

The coefficient of determination (R^2) represents the ratio of the proportion of the variance that is explained by the independent variable to the variance of the dependent variable. When R^2 is close to 1, it indicates that the model can explain the change in the dependent variable well. The root mean square error (*RMSE*) measures the average deviation between the observed and predicted values. The smaller the *RMSE*, the better the predictive ability of the model. The formulae for the R^2 and *RMSE* are specified below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(M_i - \hat{M}_i\right)^2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(M_i - \hat{M}_i\right)^2}{\sum_{i=1}^{n}\left(M_i - \overline{M}\right)^2}$$

where, M_i is the measured value (%), $\hat{M}_i$ is the predicted value (%), $\overline{M}$ is the average measured value (%), and n is the sample number.

Figure 1 shows the data collection and analysis process. All the statistical calculations were performed using R 4.3.1 [42]. The systemfit package was used to estimate the parameters of the simultaneous equations [43]. The ggplot2 package (version 3.4.4) was used to display the data [44].

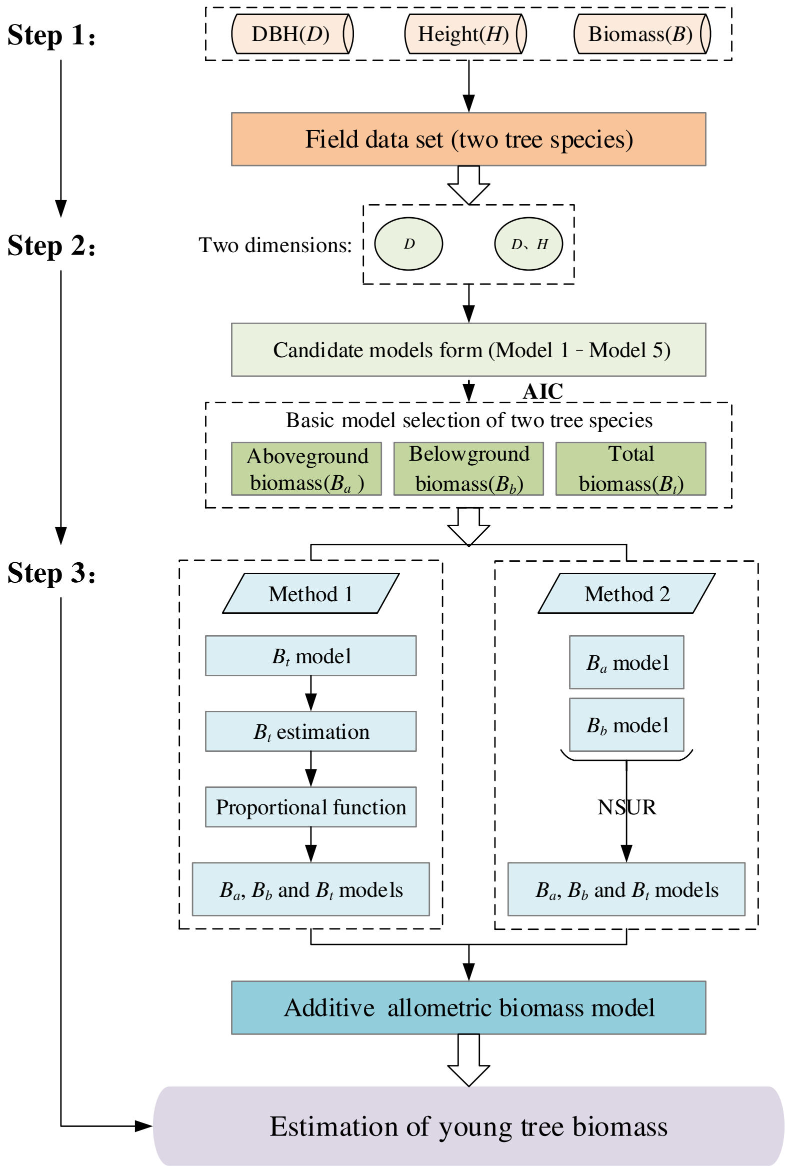

Figure 1. Flowchart of the data collection and analysis.

3. Results

3.1. Correlation Analysis of Variables

The correlation analysis results are shown in Figure 2. Both D and H were positively correlated with B_a, B_b, and B_t. The correlation coefficient of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll ranged from 0.3 to 0.97. The correlation coefficient of *Populus* × *tomentosa* Carrière ranged from 0.52 to 0.99.

The stacked kernel density of B_a, B_b, and B_t is shown in Figure 3. Skewness is a measure of the asymmetry degree in data distribution. The skewness of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll ranged from 0.4973 to 2.0447, and that of *Populus* × *tomentosa* Carrière ranged from 0.7338 to 2.0037. The asymmetry degree of B_b is higher, and the asymmetry degree of B_a and B_t is lower.

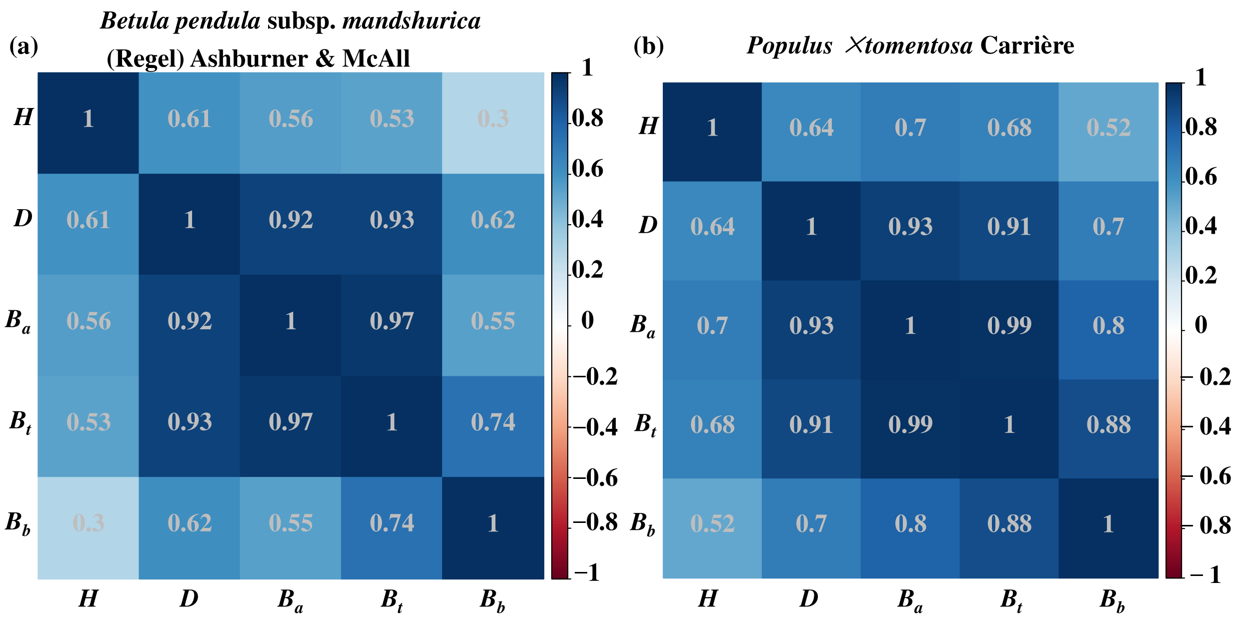

Figure 2. Correlation heat map of five variables (diameter at breast height [D], tree height [H], aboveground biomass [B_a], belowground biomass [B_b], and total biomass [B_t]). Blue indicates positive correlation. Red indicates negative correlation. (**a**) *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll. (**b**) *Populus* × *tomentosa* Carrière.

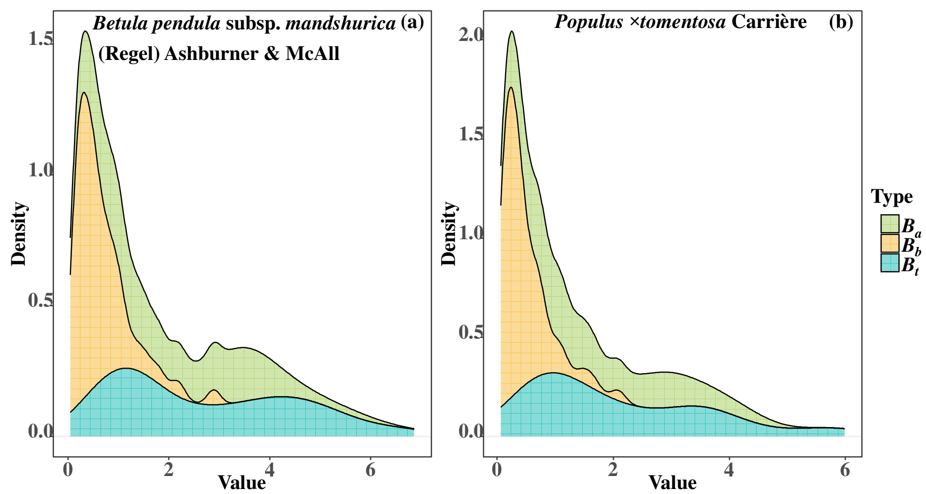

Figure 3. Stacked kernel density plot of three biomass components (aboveground biomass [B_a], belowground biomass [B_b], and total biomass [B_t]). (**a**) *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll. (**b**) *Populus* × *tomentosa* Carrière.

3.2. Analysis of the Independent Fitting Model

Based on the AIC minimization principle, the optimal model form was selected from the five candidate models. In the univariate dimension, the optimal model form for the aboveground biomass of the two species was Model 1, the optimal model form for the belowground biomass was Model 3, and the optimal model form for the total biomass was Model 1 (Figure 4, Table 2). In the bivariate dimension, the optimal model form for the aboveground biomass, belowground biomass, and total biomass of the two species was Model 4 (Table 3).

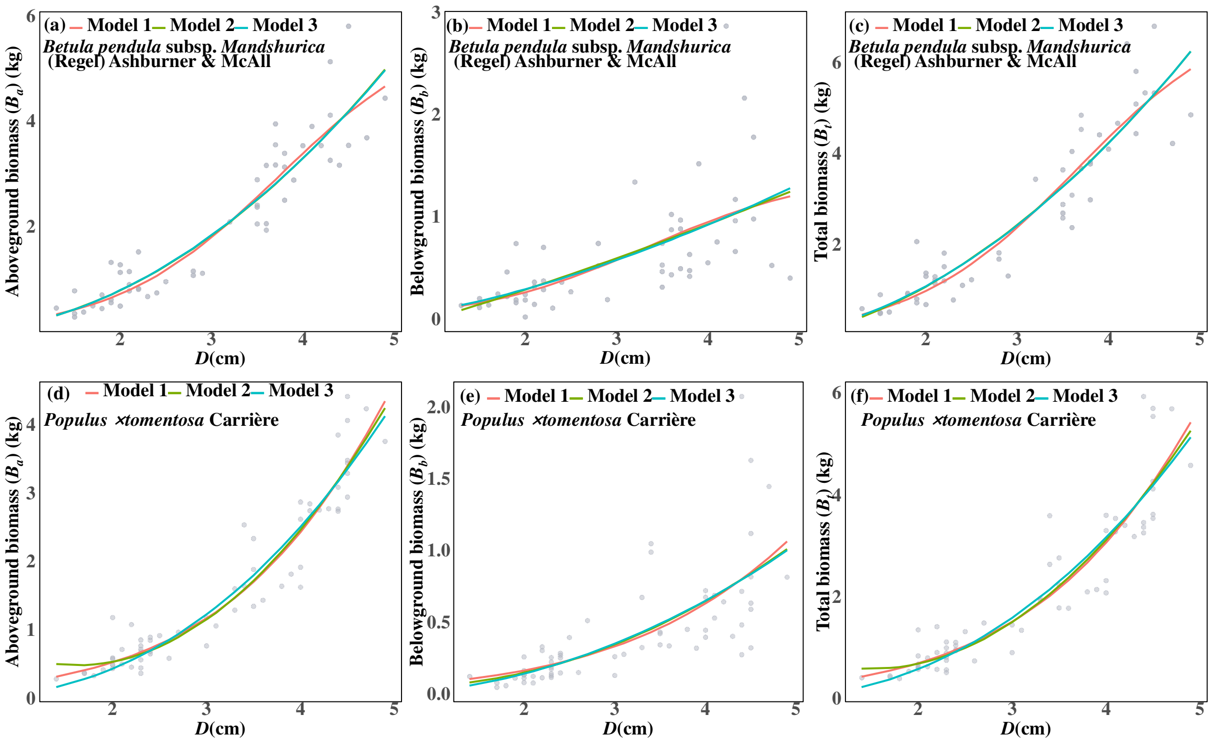

Figure 4. Comparative analysis of three univariate candidate models (Model 1, Model 2, and Model 3) with two tree species and three biomass components (aboveground biomass [B_a], belowground biomass [B_b], and total biomass [B_t]). (**a**–**c**) is the result of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll. (**d**–**f**) is the result of *Populus* × *tomentosa* Carrière.

Table 2. Parameter estimation (a0, a1, and a2) and Akaike information criterion (AIC) results for three univariate candidate models (Model 1, Model 2, and Model 3) with two tree species (*Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière) and three biomass components (aboveground biomass [B_a], belowground biomass [B_b], and total biomass [B_t]).

Tree Species	Component	Model	a0	a1	a2	AIC
Betula pendula subsp. *mandshurica* (Regel) Ashburner & McAll	B_a	(1)	6.0309	4.1417	−1.1056	160.28
	B_a	(2)	0.0385	−0.034	0.215	166.39
	B_a	(3)	0.2085	2.0017	NA	164.41
	B_b	(1)	1.4627	3.5013	−1.0489	123.81
	B_b	(2)	−0.2264	0.2456	0.0122	125.17
	B_b	(3)	0.107	1.5734	NA	123.23
	B_t	(1)	7.4355	3.9978	−1.0944	202.02
	B_t	(2)	−0.1882	0.212	0.2272	210.81
	B_t	(3)	0.3099	1.8962	NA	208.64
Populus × *tomentosa* Carrière	B_a	(1)	16.5001	4.9433	−0.8015	54.30
	B_a	(2)	1.4302	−1.1264	0.3487	55.26
	B_a	(3)	0.0877	2.4293	NA	56.36
	B_b	(1)	4.6766	4.5959	−0.6928	24.74
	B_b	(2)	0.0914	−0.0682	0.053	24.78
	B_b	(3)	0.038	2.0698	NA	22.81
	B_t	(1)	22.3301	4.9061	−0.7718	114.68
	B_t	(2)	1.5216	−1.1946	0.4017	115.44
	B_t	(3)	0.124	2.3484	NA	114.84

Note: NA indicates no parameter.

Table 3. Parameter estimation (a0, a1, and a2) and Akaike information criterion (AIC) results of two bivariate candidate models (Model 4 and Model 5) with two tree species (*Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière) and three biomass components (aboveground biomass [B_a], belowground biomass [B_b], and total biomass [B_t]).

Tree Species	Component	Model	a0	a1	a2	AIC
Betula pendula subsp. *mandshurica* (Regel) Ashburner & McAll	B_a	(4)	0.2157	2.0291	−0.0442	166.14
	B_a	(5)	−1.6713	0.6432	NA	220.91
	B_b	(4)	0.1879	2.0841	−0.7946	117.52
	B_b	(5)	−2.299	0.4976	NA	135.52
	B_t	(4)	0.3538	2.0019	−0.1724	206.67
	B_t	(5)	−1.2791	0.6106	NA	273.25
Populus × *tomentosa* Carrière	B_a	(4)	0.0649	2.2219	0.3585	41.19
	B_a	(5)	−2.6711	0.8104	NA	67.90
	B_b	(4)	0.0268	1.8741	0.3782	22.78
	B_b	(5)	−3.6567	0.7321	NA	22.82
	B_t	(4)	0.0905	2.1431	0.3649	106.15
	B_t	(5)	−2.3654	0.7943	NA	120.52

Note: NA indicates no parameter.

3.3. Analysis of the Two Additive Allometric Biomass Models

According to the estimation results of the optimal total biomass that was selected in Tables 2 and 3, the proportional function was set and the equations were combined into simultaneous equations. The parameter estimation of the proportional function control method is shown in Table 4. According to the optimal model forms for the aboveground and belowground biomass that were selected in Tables 2 and 3, the equations were combined into simultaneous equations. The parameter estimation using the algebraic sum control methods is shown in Table 5.

Table 4. Parameter results of the total biomass model and proportional function for two tree species (*Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière) using the univariate and bivariate proportional function control method.

Species	Dimension	Model	Total Biomass			Proportional Function		
			a0	a1	a2	b0	b1	b2
Betula pendula subsp. *mandshurica* (Regel) Ashburner & McAll	Univariate	1	7.4355	3.9978	−1.0944	0.5107	−0.4223	/
	Bivariate	4	0.3538	2.0019	−0.1724	0.9139	−0.0397	−0.6976
Populus × *tomentosa* Carrière	Univariate	1	22.3301	4.9061	−0.7718	0.3929	−0.2906	/
	Bivariate	4	0.0905	2.1431	0.3649	0.3879	−0.3167	0.0305

Table 5. Parametric results of the aboveground biomass and belowground biomass model for two tree species (*Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière) using the univariate and bivariate algebraic sum control method.

Species	Dimension	Model	Aboveground Biomass			Model	Belowground Biomass		
			b0	b1	b2		c0	c1	c2
Betula pendula subsp. *mandshurica* (Regel) Ashburner & McAll	Univariate	1	5.9573	4.1662	−1.1197	3	0.1086	1.5628	/
	Bivariate	4	0.2153	2.0213	−0.0366	4	0.1867	2.0909	−0.7964
Populus × *tomentosa* Carrière	Univariate	1	12.2232	4.7389	−0.8437	3	0.0374	2.0816	/
	Bivariate	4	0.0642	2.2329	0.3555	4	0.0247	1.9306	0.3798

Figure 5 shows the logistic function results in Table 4. Both coefficients of the logistic function have ecological significance; a0 refers to the equilibrium biomass and −a2 is the growth rate relative to the equilibrium biomass. A larger −a2 value indicates that individual trees will rapidly increase in biomass at a younger stage, which is known as the equilibrium growth rate.

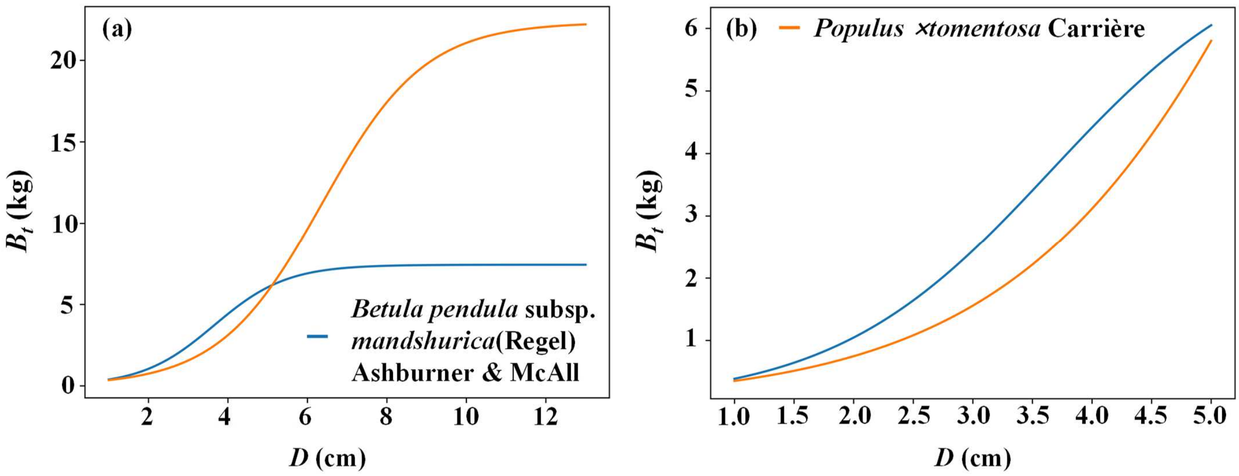

Figure 5. Visualizations of logistic function in Table 4. (**a**) Comparative analysis of the equilibrium biomass of two tree species (*Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière). (**b**) Comparative analysis of the equilibrium growth rate of two tree species (*Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière).

The results showed that the equilibrium biomass of B_t and B_a of *Populus* × *tomentosa* Carrière was higher than that of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll. The equilibrium growth rate of B_t and B_a of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll is higher than that of *Populus* × *tomentosa* Carrière (Tables 4 and 5).

The parameter estimation processes of the two additive allometric biomass models were different but the accuracy performance of the models was similar. For the proportional function control method, the R^2 of the total biomass model and aboveground biomass model was higher (0.861–0.9292) when compared with the R^2 of the belowground biomass model (0.3899–0.5101). For the algebraic sum control methods, the R^2 of the total biomass model and aboveground biomass model was high (0.8604–0.9293), while the R^2 of the belowground biomass model was low (0.3795–0.5100; Table 6).

Table 6. Precision index (R^2 and *RMSE*) results of the proportional function control and algebraic sum control methods in the univariate and bivariate dimensions with two tree species (*Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière) and three biomass components (aboveground biomass [B_a], belowground biomass [B_b], and total biomass [B_t]).

Species	Dimension	Additive Method	Total Biomass		Aboveground Biomass		Belowground Biomass	
			R^2	*RMSE*	R^2	*RMSE*	R^2	*RMSE*
Betula pendula subsp. *mandshurica* (Regel) Ashburner & McAll	Univariate	1	0.8756	0.6272	0.8683	0.5247	0.3899	0.4257
	Univariate	2	0.8749	0.6289	0.8681	0.5252	0.3795	0.4293
	Bivariate	1	0.8795	0.6174	0.8748	0.5091	0.4221	0.4164
	Bivariate	2	0.8804	0.6150	0.8753	0.5106	0.4239	0.4157
Populus × *tomentosa* Carrière	Univariate	1	0.8610	0.5643	0.9128	0.3552	0.4943	0.2809
	Univariate	2	0.8604	0.5655	0.9127	0.3584	0.4941	0.281
	Bivariate	1	0.8786	0.5273	0.9292	0.3229	0.5101	0.2788
	Bivariate	2	0.8786	0.5272	0.9293	0.3227	0.5100	0.2789

Combining the prediction accuracy of the three biomasses, the two dimensions were compared. The bivariate additive allometric biomass model system was the most accurate (Table 6). Then, the two additive methods were compared. In the univariate dimension, the proportional function control method was superior to the algebraic sum control method. In the bivariate dimension, the algebraic sum control method was superior to the proportional function control method (Table 6).

For *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll, the model performance was optimal when the algebraic sum control methods were used in the bivariate dimension (total biomass model: R^2 = 0.8804, aboveground biomass model: R^2 = 0.8753, belowground biomass model: R^2 = 0.4239). For *Populus* × *tomentosa* Carrière, the model performance was optimal when the algebraic sum control methods were used in the bivariate dimension (total biomass model: R^2 = 0.8786, aboveground biomass model: R^2 = 0.9293, belowground biomass model: R^2 = 0.5100; Figure 6).

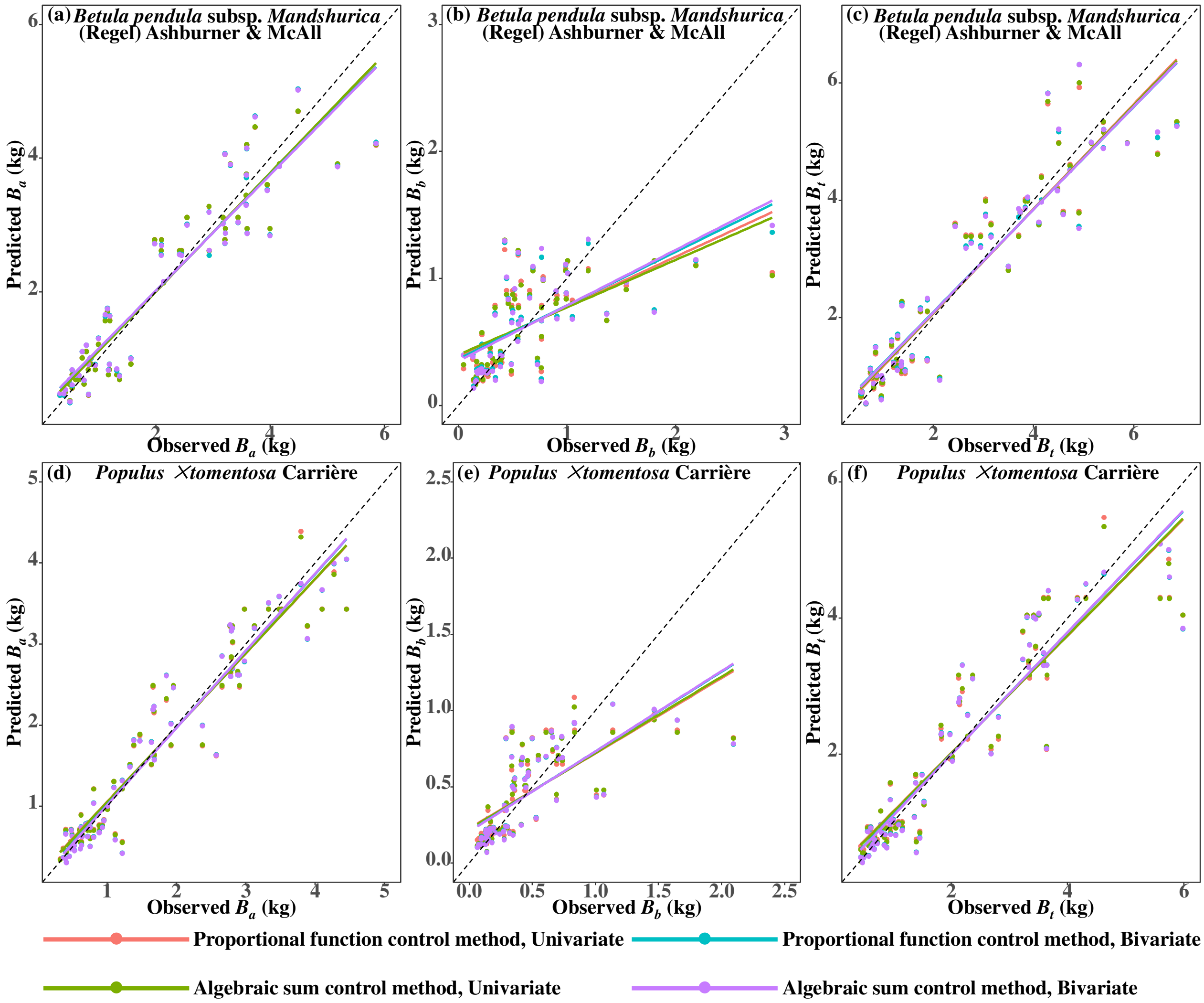

Figure 6. Regression results of the observed values and the predicted values of the proportional function control and algebraic sum control methods in the univariate and bivariate dimensions with two tree species and three biomass components (aboveground biomass [B_a], belowground biomass [B_b], and total biomass [B_t]). (**a**–**c**) is the result of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll. (**d**–**f**) is the result of *Populus* × *tomentosa* Carrière.

In addition, we conducted validation and found that the two additive allometric biomass models were additive and met the needs of practical applications, and the independent regression models were not additive (Figure 7).

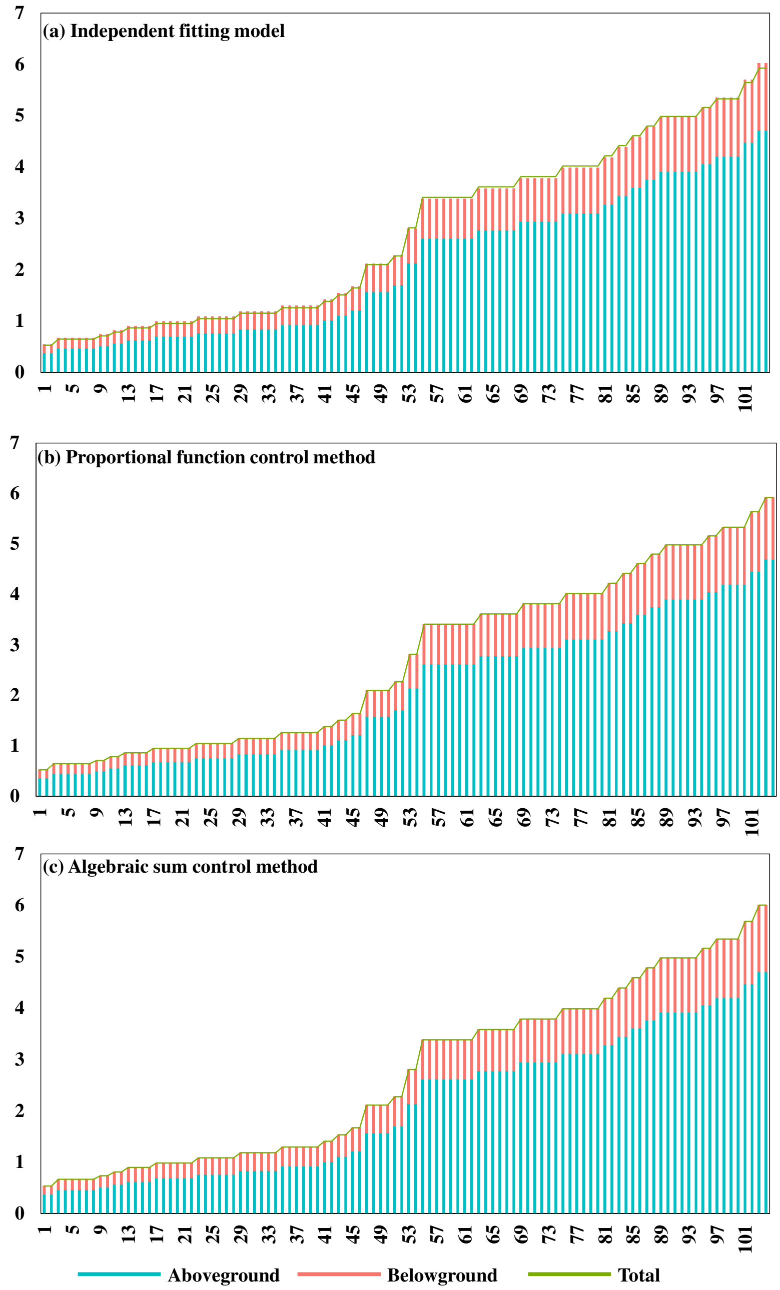

Figure 7. Additivity verification of the independent fitting model and two additive allometric biomass models (proportional function control method and algebraic sum control method). (**a**) Independent fitting model. (**b**) Proportional function control method. (**c**) Algebraic sum control method.

4. Discussion

A robust allometric biomass model should be built from a large number of data samples. When the sample size of the biomass data is relatively small, the accuracy of the model may be reduced. Consequently, this study included 167 young trees, which was sufficient to conduct robust biomass modeling for two tree species. Wang (2006) established independent biomass models with only 10 trees per species using biomass data from *Pinus koraiensis* and *Larix gmelinii* [45]. Additionally, Zheng et al. (2022) used the biomass data from 137 young trees on the Qinghai–Tibet Plateau to establish independent biomass models with the ground diameter instead of the diameter at breast height as a predictor [37]. Wang et al. used destructive biomass data from 501 trees in three provinces of young trees in northeast China to establish a biomass model [13]. Furthermore, Dong et al. (2014) established an additive allometric biomass model system with sample sizes of 41 Pinus koraiensis and 122 *Larix gmelinii* [46]. Then, Cui et al. (2020) harvested 45 *Robinia pseudoacacia* L. in the Loess Plateau of Shaanxi Province and established an additive allometric biomass model system [22]. This study did not collect samples from different ecological regions, so this is a potential limitation. Therefore, it is suggested that young trees of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière should be sampled in different ecological zones in the future.

We found that the logistic function was the optimal model form for the aboveground biomass and total biomass, and the power function was more suitable for fitting the belowground biomass. Whether the traditional allometric biomass model (that is, the power function model) can fit all the observed biomass data well has been investigated by ecologists [24,47,48]. Although the power function has been verified statistically in previous biomass studies, it has been challenged theoretically [26,29]. Consistent with our study, Ma et al. (2021) found that the logistic function was superior to the power function for estimating the allometry relationship of shrub biomass [29]. In addition, Zhou et al. (2021) proposed the concept of a dynamic allometric scaling relationship between the trunk biomass and aboveground biomass, which was fitted to an asymptotic allometric model, and it was verified that it could fit biomass data better than a power function [26].

As hypothesized, we found that the prediction accuracy of the model that included tree height as a predictor was significantly improved. This is consistent with many other studies [22,49,50]. In contrast, Zhang et al. (2016) discovered that the addition of tree height to the biomass model did not improve the model performance as expected, especially for the branch biomass and leaf biomass [51]. Tree height is often overlooked in forest models because it is difficult to accurately measure tree height in closed-canopy forests, and there has been substantial debate on whether to use tree height as a predictor for biomass models [52]. For young trees, it is easy to measure the tree height. Therefore, in practical applications, it is more appropriate to use the bivariate additive allometric biomass model that was developed in this study.

We have verified that the sum of the predicted values of each biomass component model was different from the predicted values of the total biomass model when using the independent fitting model. The disadvantage of the independent fitting model is that additivity is not satisfied. In contrast, the two additive allometric biomass models that were developed have clear advantages. The models of the total biomass, aboveground biomass, and belowground biomass were fitted using simultaneous equations to explain the intrinsic correlation between the biomass components of the same tree. Therefore, it is crucial to emphasize the benefit of using the additive allometric biomass model in practical applications.

There are many additive modeling methods. However, we found that the proportional function control method was superior to the algebraic sum control method in the univariate dimension, and the algebraic sum control method was superior to the proportional function control method in the bivariate dimension. Many studies have used algebraic sum and proportional function control methods to construct additive allometric biomass model systems. For instance, Liu et al. (2023) conducted destructive sampling of trees on Hainan Island and established an additive allometric biomass model using the algebraic sum control method, which satisfied the additivity of the aboveground biomass, branch biomass, and leaf biomass [19]. Furthermore, Wang et al. (2018) established an additive allometric biomass model based on diameter at breast height and height in a young forest of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll in northeast China using the algebraic sum control method [13]. Moreover, Fu et al. (2016) established an additive allometric biomass model with *Pinus massoniana* Lamb. in southern China using the algebraic sum control method [38]. Then, Zhang et al. (2016) established one-, two-, and three-variable additive allometric biomass models for *Populus* × *tomentosa* Carrière in the Jiangsu Province, China using the proportional function control method [51]. Zeng et al. (2017) realized the additivity between the aboveground biomass and four biomass components, the trunk, bark, branches, and leaves [53]. The proportional function control method is first fitted to the whole tree biomass, and then the proportional function is used to allocate the tree biomass to each biomass component. The algebraic sum control method is used to directly model the biomass component, and then the total biomass is obtained by adding the biomasses of each component. In the practice of forestry production, the goal is to obtain the whole tree biomass or the aboveground biomass, so the additive model that is developed using the proportional function control method is more practical.

Whether the sample data need to be divided into modeling data and testing data is still a controversial issue. Some studies suggest that the applicability of evaluating the predictive ability of the model by calculating the evaluation index of the modeling data must be tested [54]. However, Kozak and Kozak (2003) concluded that grouping samples for suitability tests would result in the loss of part of the modeling information and would not provide additional information for model evaluation [55]. To make full use of the sample information, this study did not distinguish between modeling samples and test samples, and all the sample data were used to build the biomass models.

5. Conclusions

In this study, two additive allometric biomass model systems of young trees of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll and *Populus* × *tomentosa* Carrière were established, these provide a theoretical reference and technical support for estimating the biomass of young trees at a single tree scale. The two yield table is given for the application of the model (Tables S2 and S3). Our research results will provide a quantitative basis for the monitoring of carbon stocks and carbon sink evaluation of young trees in China. We found that the logistic function was more suitable for explaining the allometric growth relationship between the aboveground biomass, total biomass, and diameter at breast height of young trees; the power function was more suitable for explaining the allometric growth relationship between the belowground biomass and diameter at breast height of young trees. In the actual modeling process, an appropriate model form should be selected for the different biomass components since the biomass results of independent fitting models are not additive. The bivariate additive allometric model system has higher accuracy. Thus, in practical applications, we recommend the bivariate additive allometric model as the first choice. There was no consensus on which of the two additive methods was better. In the univariate dimension, the proportional function control method was superior to the algebraic sum control method. In the bivariate dimension, the algebraic sum control method was superior to the proportional function control method. In the actual modeling process, it is necessary to compare the methods and choose the best additive method.

The biomass of young trees is influenced by a variety of abiotic and biological factors, including climate, stand structure, and site conditions. Thus, it is suggested that future studies should consider including these factors as additional predictors. Mixed effect models have been shown to have advantages in improving the accuracy of model estimation. Therefore, the biomass prediction could be improved by combining the mixed effect model with the additive model.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/f15060991/s1, Table S1: Location and basic stand factors of 50 plantations plots. Table S2: Yield table of *Betula pendula* subsp. *mandshurica* (Regel) Ashburner & McAll. Table S3: Yield table of *Populus* × *tomentosa* Carrière.

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