

Article

Development of Compatible Biomass Models for Chinese Fir, Poplar, and Oak in Hunan Province

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Abstract

Direct adoption of nationwide generalized biomass models often causes systematic prediction errors when applied to forest biomass estimation in Hunan Province. This study developed localized multi-component compatible biomass model systems for Chinese fir, poplar and oak based on 461 felled-tree specimens sampled from 14 administrative cities of Hunan Province during 2022–2023. Individual allometric equations were first fitted via weighted least squares, and hierarchical compatible model structures were further established by algebraic component summation and proportional scaling under simultaneous equation constraints. The final total-biomass compatible equations were: Chinese fir: $B_{\text{total}} = 0.065662D^{1.750420}H^{0.780381} + 0.024760(D^2H)^{0.774387}$; Poplar: $B_{\text{total}} = 0.046471D^{2.171796}H^{0.462424} + 0.013116 \cdot (D^2H)^{0.822310}$; Oak: $B_{\text{total}} = 0.0927573(D^2H)^{0.89013} + 0.018969(D^2H)^{0.89162}$. R^2 values for total and aboveground biomass exceeded 0.92 and prediction accuracy exceeded 96%, with TRE within $\pm 3\%$ for all species. Root biomass models reached prediction accuracy higher than 78% with $R^2 > 0.78$. Stem, wood and bark sub-models achieved distinctly better fitting performance than branch and foliage sub-models, and strict hierarchical compatibility was guaranteed among total and component biomass predictions. Calibrated exclusively with local field data, these models effectively eliminate regional systematic estimation bias and only require readily measurable DBH and tree height as input variables, serving as reliable tools for regional forest biomass assessment and routine forest resource monitoring across Hunan Province.

Keywords: Hunan Province; biomass and carbon monitoring; compatibility; representative commercial timber species

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1. Introduction

Forests, as the dominant component of terrestrial ecosystems, play an irreplaceable role in global carbon cycling, biodiversity conservation, soil and water retention, and climate regulation [1–3]. As a core indicator of forest ecosystem productivity and carbon stocks, the dynamic changes in forest biomass are central to global carbon cycle research; their accurate estimation is critical for understanding ecosystem functioning, evaluating

forest resource values, formulating carbon management and climate change response strategies, and fulfilling obligations under the United Nations Framework Convention on Climate Change [4–6]. Biomass models establish quantitative relationships between tree morphological attributes (e.g., DBH, total height, and crown width) and biomass, providing a practical and scientifically rigorous approach for large-scale forest biomass estimation and carbon accounting; they thus serve as essential tools in forest resource monitoring and ecological research [7,8].

Biomass modeling research has progressively evolved from independent single-species equations toward the development of multi-component compatible model systems. Early studies primarily relied on single-variable or single-component allometric equations and often overlooked the additive relationships among biomass components. Consequently, the sum of predicted component biomasses frequently deviated from the predicted total biomass, resulting in biologically inconsistent estimates. To address this issue, Parresol [9] was among the first to establish the theoretical framework for additive compatible biomass modeling by integrating simultaneous equation systems with seemingly unrelated regression (SUR) techniques, thereby ensuring strict algebraic additivity among biomass components. This pioneering work laid the methodological foundation for the development of compatible biomass model systems worldwide. Subsequently, biomass modeling expanded from species-specific and regional applications toward broader-scale generalization. Chave et al. [10] developed continental-scale allometric equations for tropical forests based on extensive destructive sampling datasets, substantially improving the consistency and applicability of large-scale biomass estimation. However, the generalized nature of these models may limit their ability to accurately represent regional variations in growth patterns, stand conditions, and biomass allocation strategies, particularly for subtropical plantation species. As a result, direct application of generalized biomass equations may introduce systematic estimation biases when used outside their original calibration domains. In recent years, advances in statistical methodologies, increased availability of large biomass datasets, and improved understanding of biomass allocation mechanisms have accelerated the development of compatible biomass model systems. Current research increasingly emphasizes not only high predictive accuracy, but also biological consistency, hierarchical compatibility, and regional adaptability, making the construction of localized compatible biomass models an important direction in forest biomass assessment and carbon accounting.

In China, biomass model research dates to the 1970s; the nonlinear joint estimation approach proposed by Zeng et al. [11] established the foundational framework for compatible model construction in China. In recent years, Chinese researchers have continued to refine biomass model systems for regionally important tree species. For instance, Xie et al. [12] developed regional additive biomass models for Mongolian oak, enhancing both consistency among biomass components and regional adaptability; and Zhu et al. [13] developed power-function models for volume and aboveground biomass of Xinjiang spruce (*Picea schrenkiana*), demonstrating the superiority of power functions over other model forms in terms of goodness-of-fit. In summary, both domestic and international research has continuously expanded the theoretical and methodological basis of biomass modeling, emphasizing not only biological plausibility and algebraic consistency but also regional-scale adaptability, remote sensing applicability, and generalizability across stand types—collectively providing critical support for forest ecosystem carbon stock assessment and ecological management. However, existing regional compatible biomass models targeting Hunan's dominant commercial tree species remain scarce, restricting precise local forest resource inventory.

As a key forestry province in southern China, Hunan Province has long relied on national-scale biomass models promulgated in 2010. However, owing to pronounced

regional differences in climate, soil conditions, and stand structure, forest biomass estimation errors attributable to these national models can reach 15%–20%, rendering them inadequate for accurately capturing local growth patterns [14,15]. This phenomenon has also been documented in studies on coniferous forests in northern Hunan: for example, Luo et al. [16] found that applying the national general-purpose models to Chinese fir and loblolly pine produced estimates that were significantly either overestimated or underestimated. Furthermore, multi-scale regression analyses of subtropical forests in China indicate that regional estimation errors can reach 30% or higher when relying solely on national or broad ecological-zone models [17]. Regional factors such as soil nutrients, growth environment, and silvicultural management significantly influence species-specific biomass allocation patterns, underscoring the urgent need to develop regionalized and precision-calibrated biomass models [18].

Chinese fir (*Cunninghamia lanceolata*), Poplar (*Populus* spp.), and Oak (*Quercus* spp.) are the dominant commercial timber species in Hunan Province and constitute important components of its forest resources. Chinese fir, as China's indigenous fast-growing high-quality timber species, is widely distributed in the hilly and montane areas of western and southern Hunan; its plantation forests are extensive, exhibiting rapid growth, superior wood quality, and dual functions of timber production and ecological protection [19]. Poplar, owing to its fast growth rate, short rotation cycle, and high economic returns, has developed into large-scale fast-growing high-yield plantation forests along the plains of Dongting Lake and riparian zones; it is an important raw material source for Hunan's wood-processing industry [20]. Oak broadleaved timber species play an important role and hold significant value in Hunan's forestry production [21].

This study focuses on developing species-specific and multi-component compatible biomass model systems for Chinese fir, Poplar, and Oak in Hunan Province. Based on destructively sampled tree data collected from representative forest stands, nonlinear regression and simultaneous equation modeling were employed to construct localized compatible biomass models incorporating strict additive constraints among components. We hypothesize that: (1) localized biomass models developed using regional data significantly outperform national-scale generalized models in terms of predictive accuracy in Hunan Province; and (2) incorporating simultaneous equation constraints ensures strict additivity among biomass components and improves model consistency and biological interpretability. Leave-one-out cross-validation (LOOCV) was used to evaluate model performance and predictive accuracy, ensuring robustness and reliability. The resulting models provide a scientific basis for precise regional forest resource inventory and support improved biomass estimation and sustainable forest management in Hunan Province.

2. Materials and Methods

2.1. Study Area

Hunan Province (108°47'–114°15' E, 24°38'–30°08' N) is located in central China within the middle Yangtze River basin, occupying a transitional zone between the Yunnan–Guizhou Plateau to the west and the Jiangnan Hills and Jiangnan Plain to the east. Terrain slopes from west to east in a stepwise manner. The total land area is approximately 218,000 km². The province falls within a typical subtropical monsoon climate zone, characterized by a warm and humid climate with a mean annual temperature of 16–18 °C, mean annual precipitation of 1450 mm, synchronous occurrence of high temperature and rainfall, and four well-defined seasons. Major landform types include mountains (>800 m a.s.l.), hills (200–800 m a.s.l.), and plains (<200 m a.s.l.), collectively covering more than 90% of the provincial forest area. The dominant soil types are red soils (Ferralsols) and yellow soils (Cambisols). The regional forest vegetation belongs to the mid-subtropical evergreen broad-leaved forest zone; however, precipitation is unevenly distributed in

space and time due to topographic and climatic variability, with high interannual variation in annual precipitation (1200–1800 mm) [22–24].

2.2. Data Sources

Based on the spatial distribution of Chinese fir, poplar, and oak resources in Hunan Province, a total of 461 felled-tree samples were collected by stratified random sampling across 14 prefecture-level cities and autonomous prefectures between 2022 and 2023, incorporating variation in landform type (mountainous, hilly, and plain areas), site conditions, stand age, silvicultural management intensity, and growth status. The sample comprised 154 Chinese fir, 150 poplar, and 157 oak trees. Each species was sampled with proportional allocation across eight diameter classes (4–32 cm) to ensure broad coverage and representativeness. Basic tree metrics and descriptive statistics (maximum, minimum, mean and standard deviation of DBH, tree height and component dry biomass) for each species are summarized in Table 1, where total sample numbers and the subset of trees with complete root excavation are also specified.

Component biomass measurements for each sample tree were conducted as follows: (1) Stem biomass was determined by sectional weighing, with stem discs collected at each section to determine the wood-to-bark ratio and representative subsamples taken for moisture content measurement; (2) crown biomass was measured by fresh-weight stratified sampling of the upper, middle, and lower crown layers, with total crown biomass estimated using the standard-branch method, and subsamples collected for drying treatment; (3) root biomass was determined by whole-root excavation, with roots classified by root diameter into root collar (>25 mm), coarse roots (2–25 mm), and fine roots (<2 mm) for separate weighing. Root subsamples were also collected, and root sampling covered one-third of all sample trees. All collected subsamples were oven-dried at 80 °C to constant weight (the weight difference between two consecutive measurements was less than 0.5%). Moisture content was calculated to convert fresh weight to dry biomass, and all biomass data in this study refer to dry biomass.

Table 1. Summary statistics of tree dimensions and component biomass for Chinese fir, poplar and oak.

Species	Total Samples (Root Samples)	Component Index	Min	Max	Mean	Sd
Chinese fir	154 (74)	DBH (cm)	2.2	35.3	19.88	7.77
		Tree height (m)	2.5	25.6	14.25	5.38
		Stem wood biomass (kg)	0.27	320.04	85.16	74.69
		Stem bark biomass (kg)	0.03	55.51	13.90	11.44
		Branch biomass (kg)	0.04	89.72	12.64	15.06
		Foliage biomass (kg)	0.05	51.25	10.31	9.69
		Root biomass (kg)	0.20	77.14	20.55	16.65
Poplar	150 (36)	DBH (cm)	2.2	37.9	17.13	8.95
		Tree height (m)	3.7	29.6	16.39	6.81
		Stem wood biomass (kg)	0.37	391.49	86.95	92.86
		Stem bark biomass (kg)	0.15	66.41	12.87	13.30
		Branch biomass (kg)	0.10	128.10	17.94	20.98
		Foliage biomass (kg)	0.03	31.97	3.11	4.17
Oak	157 (50)	Root biomass (kg)	0.55	91.13	20.37	22.86
		DBH (cm)	3.5	38.9	16.69	8.87
		Tree height (m)	3.7	24.7	12.93	4.70
		Stem wood biomass (kg)	1.25	667.73	120.91	133.47
		Stem bark biomass (kg)	0.25	121.89	20.97	25.40

Branch biomass (kg)	0.06	184.03	39.79	41.68
Foliage biomass (kg)	0.09	41.01	7.81	7.64
Root biomass (kg)	0.84	189.40	45.61	49.94

2.3. Methods

2.3.1. Biomass Model Development

1. Independent Model

With individual-tree biomass as the response variable and tree attributes—including DBH, total height, crown width, crown length, and stem volume—as potential predictor variables, scatter plots were first generated to examine correlations among variables. Crown width, crown length, and stem volume showed weak or redundant correlations with biomass in scatter plots and were excluded for parsimony, leaving only DBH and total height as core predictors. Based on biological principles and prior research findings [7,16], appropriate model structures were designed. WLS combined with the Marquardt or Newton algorithm was used to fit nonlinear regression models and estimate model parameters. The study adopted allometric (relative growth) equations as the basis for independent biomass model construction, with two candidate model structures as follows:

$$B = c_0(D^2H)^{c_1} \quad (1)$$

$$B = c_0D^{c_1}H^{c_2} \quad (2)$$

where B is individual-tree biomass (kg); D is DBH (cm); H is total tree height (m); and c_0 , c_1 , c_2 are model parameters to be estimated (the same notation applies throughout).

2. Compatible Models

(1) Total-biomass compatible model system

The compatible model system for total tree biomass comprises sub-models for total biomass, aboveground biomass, and root biomass, structured as the following simultaneous equation system:

$$\begin{cases} B_{total} = f(x_1) + f(x_2) \end{cases} \quad (3)$$

$$\begin{cases} B_{aboveground} = f(x_1) \end{cases} \quad (4)$$

$$\begin{cases} B_{root} = f(x_2) \end{cases} \quad (5)$$

where B_{total} , $B_{aboveground}$, and B_{root} are total tree biomass, aboveground biomass, and root biomass (kg), respectively; $f(x_1)$ and $f(x_2)$ denote Model (1) or (2), as appropriate (same notation below).

(2) Aboveground-biomass compatible model system

The aboveground-biomass compatible model system includes sub-models for aboveground biomass, stem biomass, crown biomass, and the organ-level components: wood, bark, branch, and foliage biomass. The model structures are as follows:

I. Algebraic sum-of-components control based on stem biomass

Aboveground biomass is expressed as the sum of stem and crown biomass:

$$\begin{cases} B_{aboveground} = f(x_3) + f(x_4) \end{cases} \quad (6)$$

$$\begin{cases} B_{stem} = f(x_3) \end{cases} \quad (7)$$

$$\begin{cases} B_{crown} = f(x_4) \end{cases} \quad (8)$$

where B_{stem} and B_{crown} are stem and crown biomass (kg), respectively.

II. Proportional scaling based on stem and crown total biomass

Stem biomass is further partitioned into wood and bark biomass, and crown biomass into branch and foliage biomass, using proportional scaling functions:

$$B_{wood} = \frac{1}{1 + g(x_5)} \cdot f(x_3) \quad (9)$$

$$B_{bark} = \frac{g(x_5)}{1 + g(x_5)} \cdot f(x_3) \quad (10)$$

$$B_{branch} = \frac{1}{1 + g(x_6)} \cdot f(x_4) \quad (11)$$

$$B_{foliage} = \frac{g(x_6)}{1 + g(x_6)} \cdot f(x_4) \quad (12)$$

where $g(x_5)$ and $g(x_6)$ are the simplified ratio functions for stem and crown components, respectively.

2.3.2. Model Evaluation and Validation

Considering the large numerical differences and inconsistent dimensions between aboveground and belowground biomass, the coefficient of variation of parameter estimates (Cv) was selected to evaluate model stability. As a dimensionless statistic, Cv is independent of data magnitude and enables fair comparisons of parameter stability across aboveground, belowground, and different component models, with $Cv \leq \pm 50\%$ defined as the criterion for stable parameters. Overall model performance was comprehensively assessed using the coefficient of determination (R^2), residual standard error (S), total relative error (TRE), mean systematic error (MSE), mean percentage standard error ($MPSE$), and prediction accuracy (p).

The calculation formulas for each metric are as follows:

$$Cv = \frac{\sigma}{\mu} \times 100 \quad (13)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (14)$$

$$S = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n - p}} \quad (15)$$

$$TRE = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)}{\sum_{i=1}^n \hat{y}_i} \times 100 \quad (16)$$

$$MSE = \frac{1}{n} \times \sum_{i=1}^n \frac{y_i - \hat{y}_i}{\hat{y}_i} \times 100 \quad (17)$$

$$MPSE = \frac{1}{n} \times \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{\hat{y}_i} \right| \times 100 \quad (18)$$

$$P = 1 - t_{\alpha} \times \frac{S}{\hat{y}} \div \sqrt{n} \times 100 \quad (19)$$

where $S_{\hat{\theta}}$ denotes the standard deviation of the parameter estimate, $\hat{\theta}$ denotes the parameter estimate, y_i is the observed value, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the mean of observed values, $\hat{\bar{y}}$ is the mean of predicted values, n is the sample size, p is the number of parameters, and t_{α} is the t-value at significance level α ($\alpha = 0.05$).

In addition, residual plots were generated and LOOCV was applied to assess model applicability; the same six evaluation metrics were used to comprehensively evaluate model reliability and applicability.

3. Results

3.1. Total-Biomass Compatible Model System

3.1.1. Data Pre-Analysis

As revealed in Figures 1–3, aboveground biomass and root biomass of Chinese fir, poplar, and oak each exhibited significant positive correlations with D, H, and D²H, confirming the scientific validity and applicability of Models (1) and (2) adopted in this study.

3.1.2. Independent Model Development for Whole-Tree Biomass

Prior to constructing the total-biomass compatible model systems for Chinese fir, poplar, and oak, Models (1) and (2) were independently fitted to aboveground biomass and root biomass data for each species to identify the optimal base models for subsequent simultaneous equation formulation. Results are presented in Tables 2–7.

Results indicated that Model (2) yielded slightly higher fitting accuracy than Model (2.1) for Chinese fir and poplar aboveground-biomass, with all parameter Cv values $\leq 20\%$ (Chinese fir: $Cv_1 = 7.19\%$, $Cv_2 = 18.74\%$), consistent with known tree growth patterns. For root biomass, Model (2) produced a negative height effect for poplar ($C_2 = -1.0167$) and oak ($C_2 = -0.0225$), which violates basic allometric principles; therefore, Model (1) was adopted for root biomass of both species, yielding parameter $Cv \leq 30\%$ (poplar: $Cv_0 = 30.4\%$, $Cv_1 = 4.35\%$) and more randomly distributed residuals (Figure 2d–f). The optimal model for oak aboveground biomass was Model (1), reflecting the fact that as a broad-leaved species, oak biomass allocation is more sensitive to D²H, making Model (1) more appropriate for capturing its growth characteristics. Furthermore, MPSE $< 1.3\%$ and TRE $< \pm 3\%$ for the three species' aboveground biomass independent models indicate that the independent models are sufficiently reliable to serve as core models for compatible model construction.

Table 2. Parameter estimates and coefficients of variation for Chinese fir aboveground and root biomass independent models.

Component	Model No.	C_0/Cv_0 (%)	C_1/Cv_1 (%)	C_2/Cv_2 (%)
Aboveground biomass	(1)	0.064994/10.59	0.847226/1.46	—
	(2)	0.065662/10.77	1.75042/7.19	0.780381/18.74
Root biomass	(1)	0.054293/20.39	0.697909/3.52	—
	(2)	0.056700/20.22	1.654444/14.80	0.383954/74.27

Table 3. Parameter estimates and coefficients of variation for poplar aboveground and root biomass independent models.

Component	Model No.	C_0/Cv_0 (%)	C_1/Cv_1 (%)	C_2/Cv_2 (%)
Aboveground biomass	(1)	0.034074/7.71	0.916078/1.02	—
	(2)	0.046471/10.66	2.171796/3.88	0.462424/23.98
Root biomass	(1)	0.012354/30.40	0.840814/4.35	—
	(2)	0.051601/31.53	2.952456/7.53	−1.016725/29.68

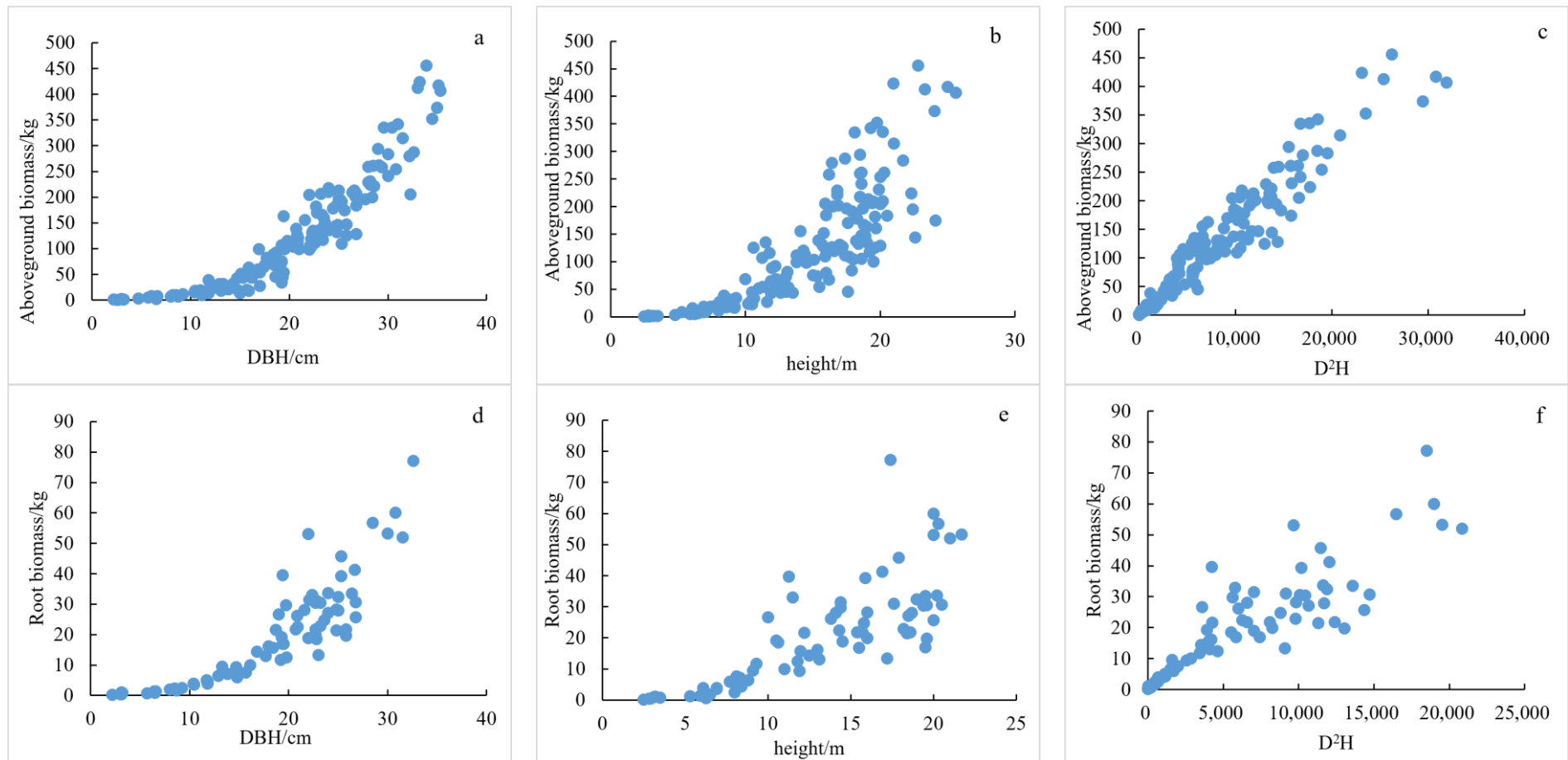


Figure 1. Scatter plots of relationships between DBH, total height, D²H, and biomass for Chinese fir. Panels (a–c) show relationships with aboveground biomass; panels (d–f) show relationships with root biomass.

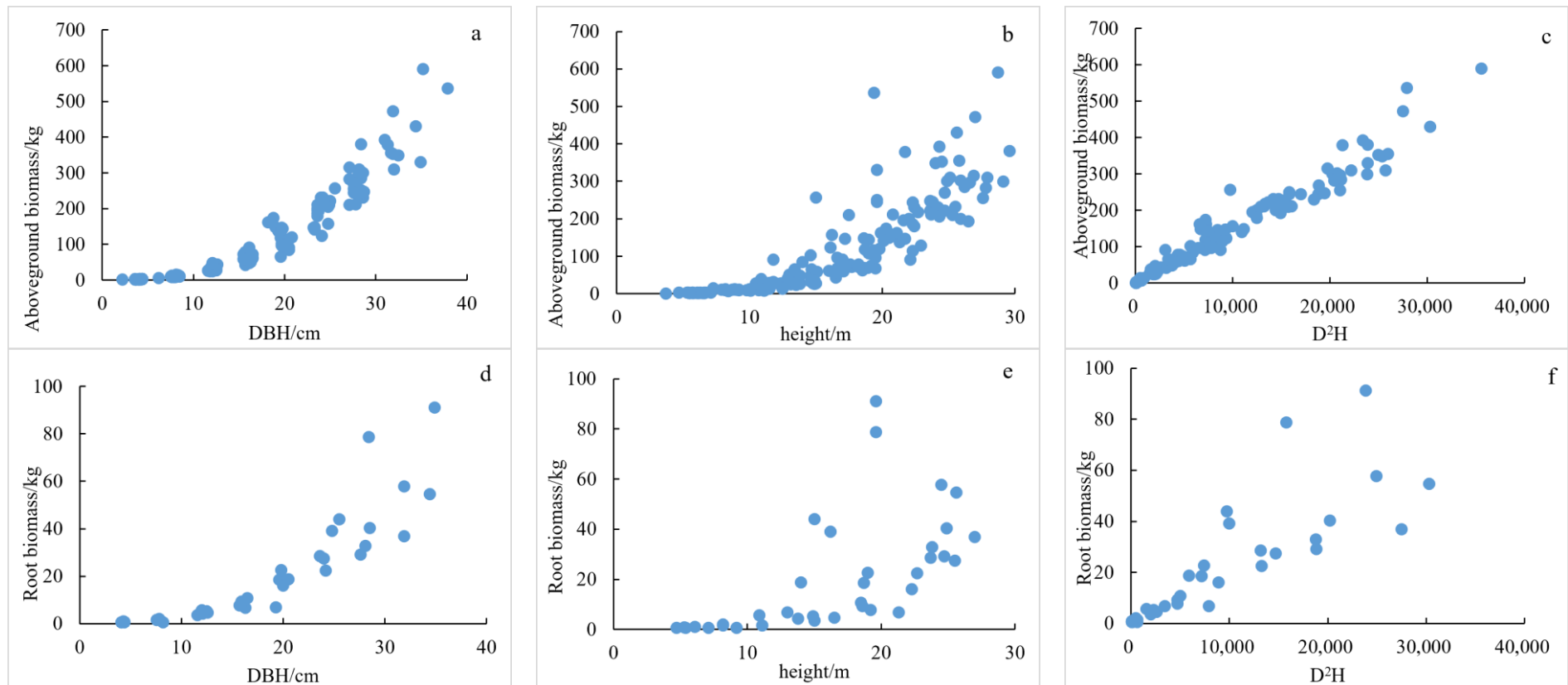


Figure 2. Scatter plots of relationships between DBH, total height, D^2H , and biomass for poplar. Panels (a–c) show relationships with aboveground biomass; panels (d–f) show relationships with root biomass.

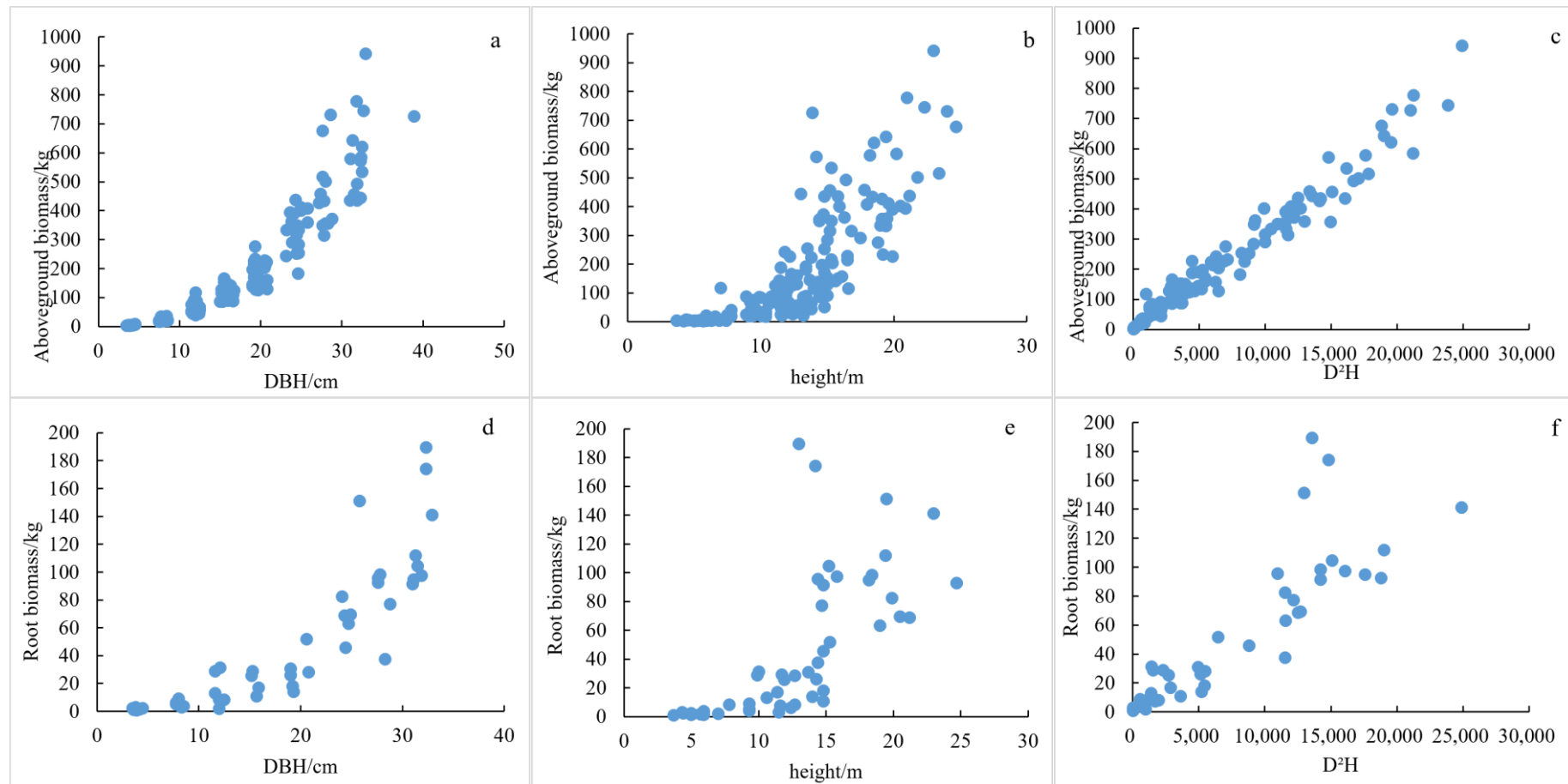


Figure 3. Scatter plots of relationships between DBH, total height, D²H, and biomass for oak. Panels (a–c) show relationships with aboveground biomass; panels (d–f) show relationships with root biomass.

Table 4. Parameter estimates and coefficients of variation for oak aboveground and root biomass independent models.

Component	Model No.	C_0/Cv_0 (%)	C_1/Cv_1 (%)	C_2/Cv_2 (%)
Aboveground biomass	(1)	0.092757/9.66	0.890130/1.36	—
	(2)	0.130914/10.99	2.134897/2.85	0.368370/24.05
Root biomass	(1)	0.074786/28.19	0.756961/4.60	—
	(2)	0.137383/38.84	1.990382/11.65	−0.022496/−1575.79

Table 5. Statistical evaluation metrics for Chinese fir aboveground and root biomass independent models.

Component	Model No.	R ²	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
Aboveground	(1)	0.9223	29.40	−1.09	−6.81	21.09	96.28
	(2)	0.9242	29.13	−0.97	−6.81	21.02	96.31
Root	(1)	0.7570	8.27	−8.60	−13.14	30.50	91.48
	(2)	0.7839	7.85	−7.13	−12.91	29.90	91.77

Table 6. Statistical evaluation metrics for poplar aboveground and root biomass independent models.

Component	Model No.	R ²	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
Aboveground	(1)	0.9590	25.57	−1.37	−4.32	16.03	96.63
	(2)	0.9625	24.54	−1.60	−3.84	15.34	96.78
Root	(1)	0.6901	12.91	−12.64	−16.23	34.77	81.24
	(2)	0.9154	6.85	−2.98	−7.63	20.07	88.94

Table 7. Statistical evaluation metrics for oak aboveground and root biomass independent models.

Component	Model No.	R ²	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
Aboveground	(1)	0.9634	38.48	−2.79	−5.81	17.33	96.88
	(2)	0.9362	50.97	−4.36	−4.65	16.85	95.93
Root	(1)	0.7560	24.92	−12.80	−19.93	37.84	86.45
	(2)	0.8065	22.43	−11.07	−18.06	34.91	87.56

3.1.3. Compatible Model Development for Whole-Tree Biomass

Based on the results above, simultaneous equation systems (Models (3)–(5)) were used to construct total-biomass compatible model systems for Chinese fir, poplar, and oak:

- (1) Chinese fir total-biomass compatible model:

$$\begin{cases} B_{total} = C_0 D^{C_1} H^{C_2} + C_3 (D^2 H)^{C_4} \cdot I & (20) \\ B_{aboveground} = C_0 D^{C_1} H^{C_2} & (21) \\ B_{root} = C_3 (D^2 H)^{C_4} \cdot I & (22) \end{cases}$$

- (2) Poplar total-biomass compatible model:

$$\begin{cases} B_{total} = C_0 D^{C_1} H^{C_2} + C_3 (D^2 H)^{C_4} \cdot I & (23) \\ B_{aboveground} = C_0 D^{C_1} H^{C_2} & (24) \\ B_{root} = C_3 (D^2 H)^{C_4} \cdot I & (25) \end{cases}$$

- (3) Oak total-biomass compatible model:

$$\begin{cases} B_{total} = C_0 (D^2 H)^{C_1} + C_2 (D^2 H)^{C_3} \cdot I & (26) \\ B_{aboveground} = C_0 (D^2 H)^{C_1} & (27) \\ B_{root} = C_2 (D^2 H)^{C_3} \cdot I & (28) \end{cases}$$

where I is a dummy variable used to control sample contribution to root parameter estimation ($I = 0$ for trees without root samples; $I = 1$ for trees with root samples), and C_0 – C_4 are model parameters.

To satisfy the compatibility requirement, the aboveground–biomass model was fitted independently, while total–biomass and root biomass model parameters were estimated jointly using simultaneous estimation: predicted values from the aboveground–biomass model were first substituted into the total biomass model, which was then jointly fitted with the root biomass model to obtain root biomass parameter estimates, thereby constituting the complete three–component compatible model system.

Fitting results (Tables 8–10) showed that, with the exception of the oak total–biomass parameter C_2 ($Cv = 68.08\%$) and the poplar root biomass parameter C_3 ($Cv = 65.27\%$), all remaining parameter Cv values were $\leq 50\%$ (Chinese fir: $Cv_3 = 44.54\%$, $Cv_4 = 6.16\%$), indicating that model parameters were minimally influenced by species–specific characteristics and environmental heterogeneity; only a few root biomass parameters exhibited marginal variation attributable to soil nutrient differences. Overall, the biases for aboveground and root biomass components in the three–species total–biomass models were small, satisfying compatibility requirements.

Table 8. Parameter estimates and coefficients of variation for the Chinese fir total–biomass compatible model.

Model	C_0	C_1	C_2	C_3	C_4	$Cv_0\%$	$Cv_1\%$	$Cv_3\%$	$Cv_4\%$
(20)	0.065662	1.750420	0.780381	0.024760	0.774387	10.77	7.19	44.54	6.16
(21)	0.065662	1.750420	0.780381	—	—	10.77	7.19	—	—
(22)	—	—	—	0.024760	0.774387	—	—	44.54	6.16

Table 9. Parameter estimates and coefficients of variation for the poplar total–biomass compatible model.

Model	C_0	C_1	C_2	C_3	C_4	$Cv_0\%$	$Cv_1\%$	$Cv_3\%$	$Cv_4\%$
(23)	0.046471	2.171796	0.462424	0.013116	0.822310	10.66	3.88	65.27	8.07
(24)	0.046471	2.171796	0.462424	—	—	10.66	3.88	—	—
(25)	—	—	—	0.013116	0.822310	—	—	65.27	8.07

Table 10. Parameter estimates and coefficients of variation for the oak total–biomass compatible model.

Model	C_0	C_1	C_2	C_3	$Cv_0\%$	$Cv_1\%$	$Cv_2\%$	$Cv_3\%$
(26)	0.092757	0.890130	0.018969	0.891620	9.66	1.36	68.08	7.98
(27)	0.092757	0.890130	—	—	9.66	1.36	—	—
(28)	—	—	0.018969	0.891620	—	—	68.08	7.98

Residuals for Chinese fir and poplar total, aboveground, and root biomass models were randomly distributed with respect to both D and H (Figures 4 and 5), with no obvious systematic bias. For oak, root biomass residuals were slightly elevated in larger diameter classes ($DBH > 30$ cm) and taller trees ($H > 20$ m) (Figure 6c,f); this is presumably attributable to the deep root systems of large–diameter oak trees penetrating deep red soil layers, where excavation difficulty increases measurement error. However, overall residuals remained within an acceptable range.

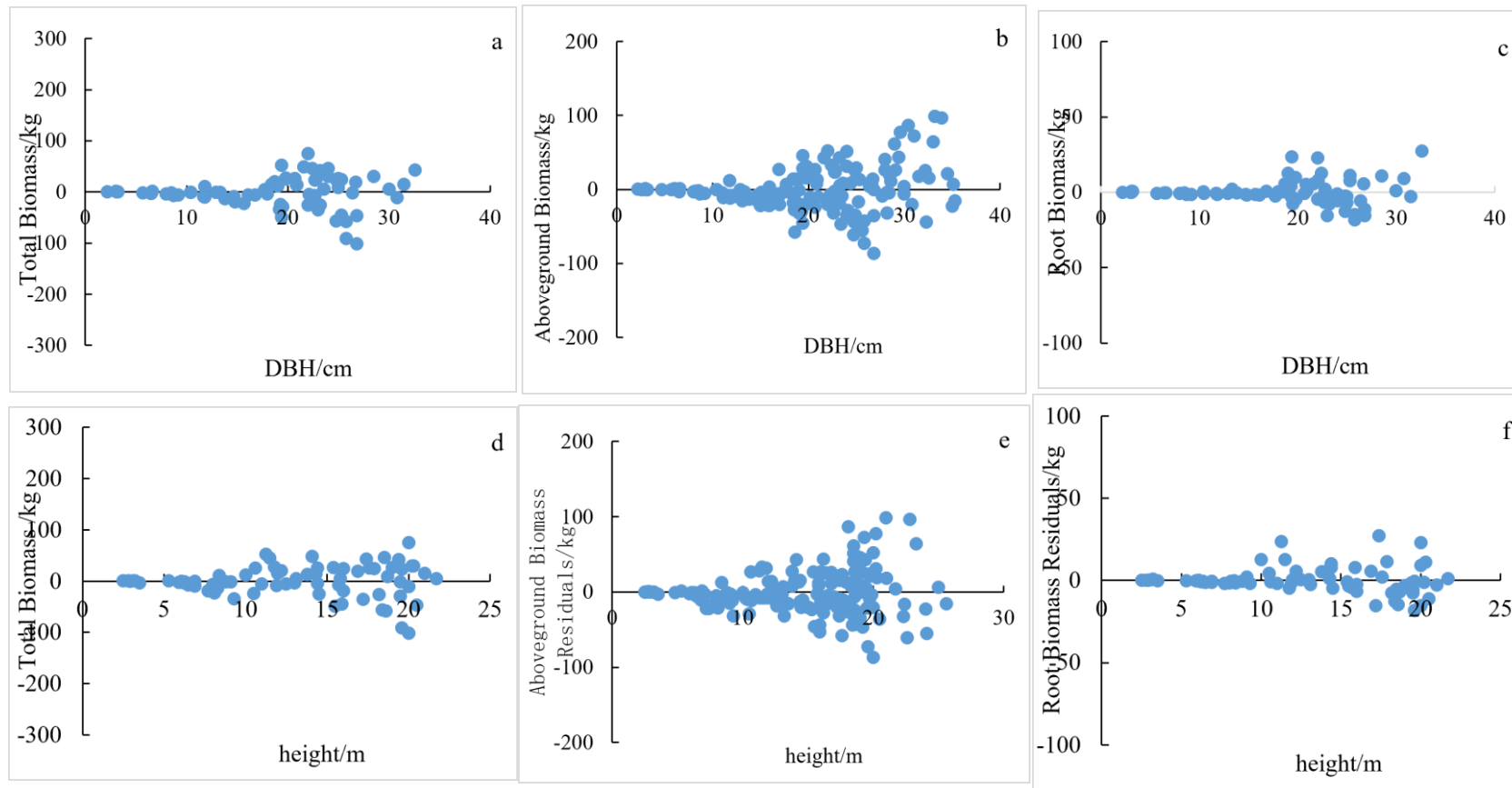


Figure 4. Residual plots of Chinese fir total-biomass compatible models against DBH and total height. Panels (a–c): residuals of total, aboveground, and root biomass models vs. DBH; panels (d–f): residuals vs. total height.

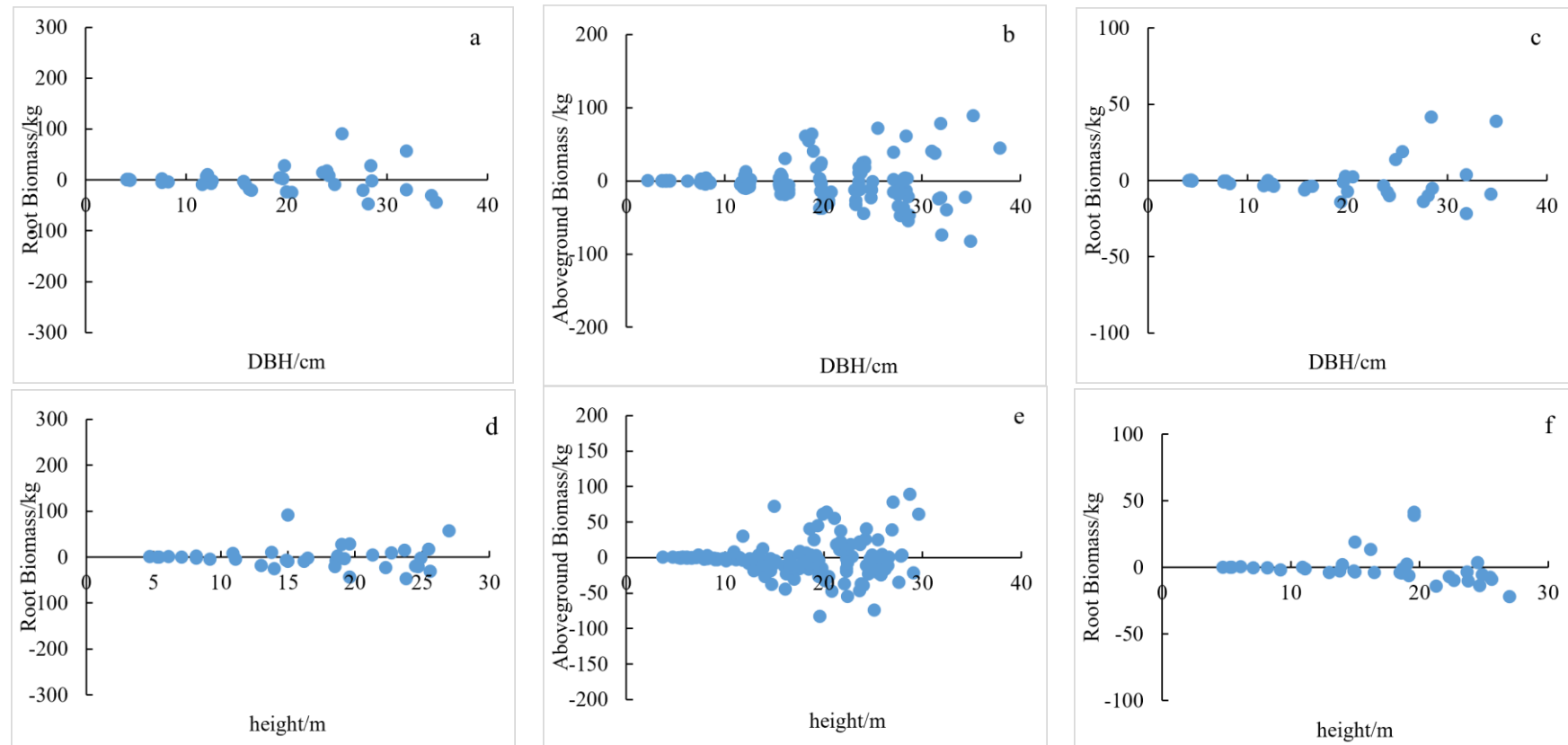
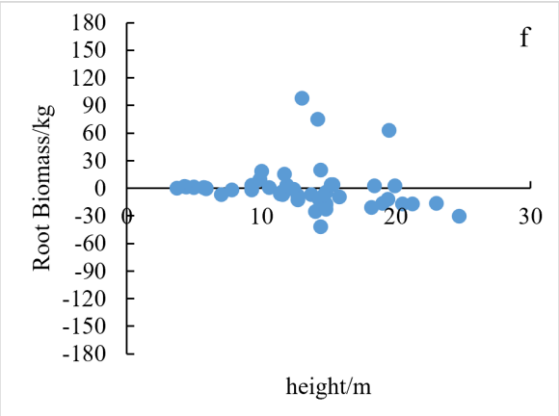
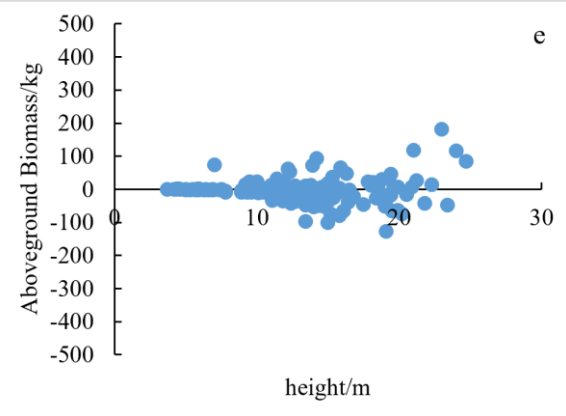
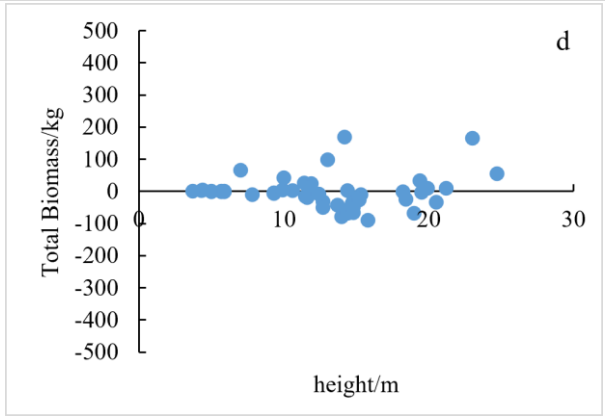
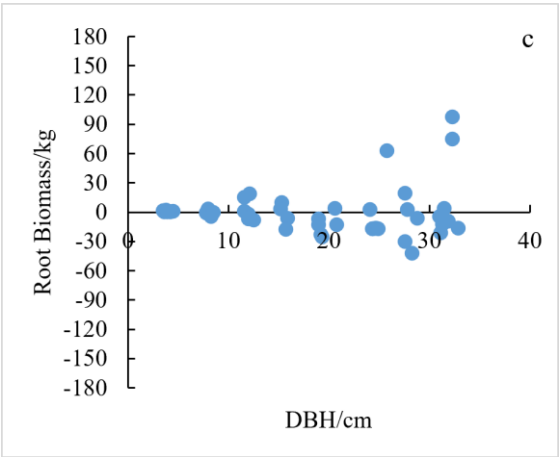
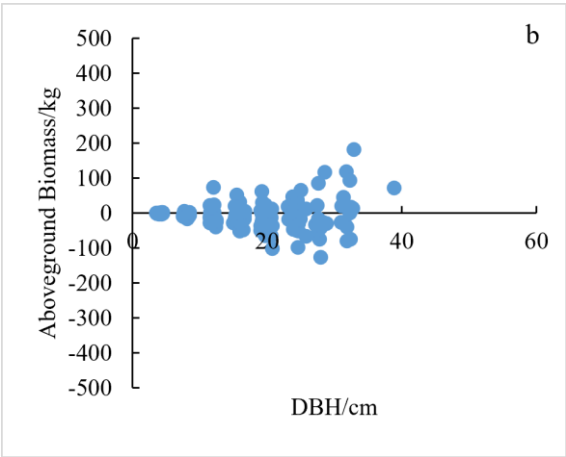
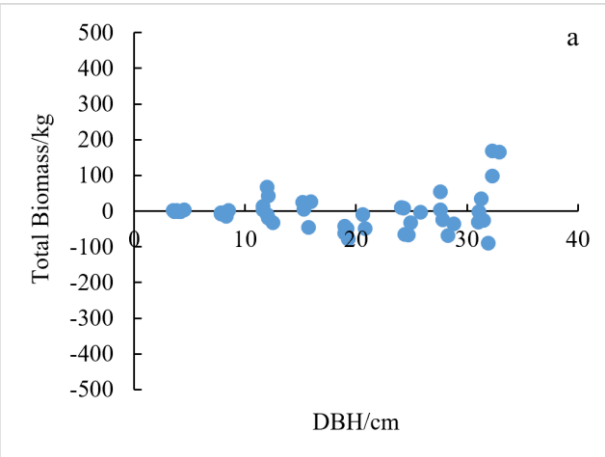


Figure 5. Residual plots of poplar total-biomass compatible models against DBH and total height. Panels (a–c): residuals of total, aboveground, and root biomass models vs. DBH; panels (d–f): residuals vs. total height.



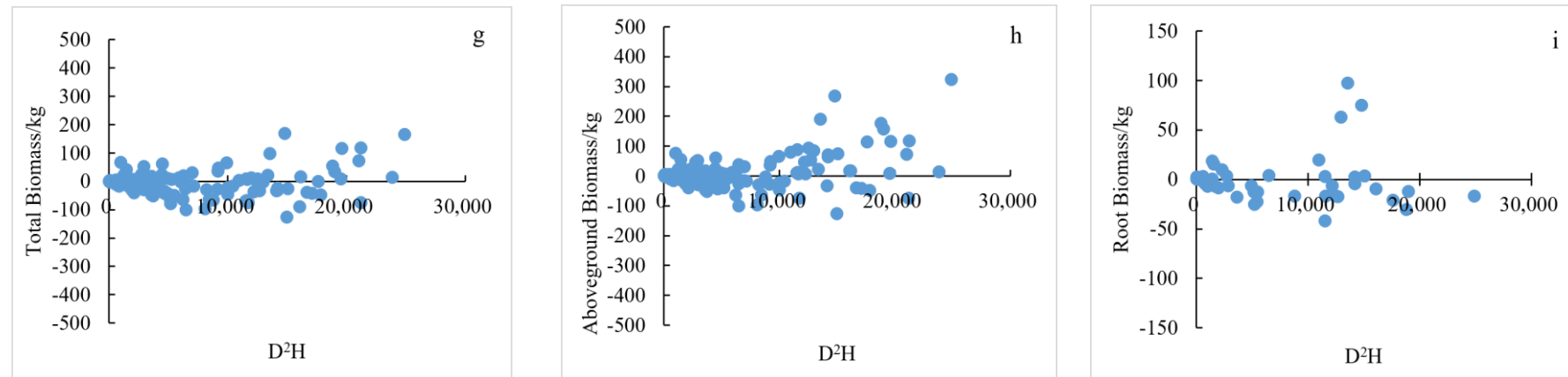


Figure 6. Residual plots of oak total-biomass compatible models against DBH, total height, and D^2H . Panels (a–c): residuals vs. DBH; panels (d–f): residuals vs. total height; panels (g–i): residuals vs. D^2H .

Model evaluation and applicability assessment (Tables 11–16) further confirmed that R^2 values for total-biomass compatible models exceeded 0.92 and p exceeded 96% for all three species. Poplar achieved the highest total-biomass model accuracy ($R^2 = 0.9671$, $p = 96.97\%$), attributable to its fast-growing nature, more regular growth patterns, and stronger correlations between biomass and D and H. Oak, with a higher proportion of natural forest individuals (approximately 62% of the sample), exhibited slightly greater growth heterogeneity, resulting in a marginally lower R^2 (0.9651) than poplar; yet, it is still significantly superior to the national general-purpose model.

Table 11. Statistical evaluation metrics for the Chinese fir total-biomass compatible models.

Model	R^2	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
(20)	0.9208	31.06	−0.87	−6.21	20.82	96.34
(21)	0.9242	29.13	−0.97	−6.81	21.02	96.31
(22)	0.8762	5.39	0.44	—	—	91.11
(22)*	0.7734	7.98	0.45	3.68	29.31	90.96

(22)*: results calculated from Model (22) fitted parameters using measured root samples.

Table 12. Statistical evaluation metrics for the poplar total-biomass compatible models.

Model	R^2	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
(23)	0.9671	23.98	−1.62	−4.25	15.13	96.97
(24)	0.9625	24.54	−1.60	−3.84	15.34	96.78
(25)	0.8239	5.94	−1.95	—	—	80.78
(25)*	0.7146	12.39	−1.95	−8.34	33.68	79.79

(25)*: results calculated from Model (25) fitted parameters using measured root samples.

Table 13. Statistical evaluation metrics for the oak total-biomass compatible models.

Model	R^2	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
(26)	0.9651	41.25	−2.65	−4.85	17.31	96.89
(27)	0.9634	38.48	−2.79	−5.81	17.33	96.88
(28)	0.8592	13.28	−0.80	—	—	85.75
(28)*	0.7778	23.78	−0.80	14.34	47.64	85.29

(28)*: results calculated from Model (28) fitted parameters using measured root samples.

Table 14. LOOCV applicability assessment for Chinese fir total-biomass compatible models.

Model	R^2	TRE (%)	MSE (%)	MPSE (%)	p (%)
(20)	0.9204	−0.85	−0.84	20.84	96.33
(21)	0.9215	−0.93	−6.52	21.60	96.24
(22)	0.8647	0.66	—	—	90.68

Table 15. LOOCV applicability assessment for poplar total-biomass compatible models.

Model	R^2	TRE (%)	MSE (%)	MPSE (%)	p (%)
(23)	0.9672	−1.64	−4.27	15.14	96.98
(24)	0.9604	−1.56	−3.66	15.75	96.69
(25)	0.7863	−2.55	—	—	78.96

Table 16. LOOCV applicability assessment for oak total-biomass compatible models.

Model	R^2	TRE (%)	MSE (%)	MPSE (%)	p (%)
(26)	0.9652	−2.69	−4.86	17.33	96.89
(27)	0.9623	−2.78	−5.72	17.61	96.83

(28)	0.8435	−1.36	—	—	85.06
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Based on integrated assessment of parameter Cv , residual analysis, and model fitting and applicability evaluation, the final total-biomass compatible models for Chinese fir, poplar, and oak are as follows:

① Chinese fir total-biomass compatible model:

$$\begin{cases} B_{total} = 0.065662D^{1.750420}H^{0.780381} + 0.024760 (D^2H)^{0.774387} \end{cases} \quad (29)$$

$$\begin{cases} B_{aboveground} = 0.065662D^{1.750420}H^{0.780381} \end{cases} \quad (30)$$

$$\begin{cases} B_{root} = 0.024760 (D^2H)^{0.774387} \end{cases} \quad (31)$$

② Poplar total-biomass compatible model:

$$\begin{cases} B_{total} = 0.046471D^{2.171796}H^{0.462424} + 0.013116 (D^2H)^{0.82231} \end{cases} \quad (32)$$

$$\begin{cases} B_{aboveground} = 0.046471D^{2.171796}H^{0.462424} \end{cases} \quad (33)$$

$$\begin{cases} B_{root} = 0.013116 (D^2H)^{0.82231} \end{cases} \quad (34)$$

③ Oak total-biomass compatible model:

$$\begin{cases} B_{total} = 0.0927573 (D^2H)^{0.89013} + 0.018969 (D^2H)^{0.89162} \end{cases} \quad (35)$$

$$\begin{cases} B_{aboveground} = 0.0927573 (D^2H)^{0.89013} \end{cases} \quad (36)$$

$$\begin{cases} B_{root} = 0.018969 (D^2H)^{0.89162} \end{cases} \quad (37)$$

3.2. Aboveground-Biomass Compatible Model System

3.2.1. Independent Model Development for Aboveground Components

Models (1) and (2) were independently fitted to aboveground-biomass component data for each of the three species, the optimal models were selected, and simultaneous equation systems for aboveground biomass compatible models were formulated. Parameter estimation results are presented in Tables 17–19; goodness-of-fit evaluation results are in Tables 20–22.

Overall, R^2 values for stem biomass models exceeded 0.93 for all three species (Chinese fir: 0.9340; poplar: 0.9665; oak: 0.9570). R^2 for wood and bark models exceeded 0.93 and 0.85, respectively, with $TRE < \pm 3\%$ (Chinese fir wood $TRE = -1.58\%$; bark $TRE = -6.98\%$). Stem, wood, and bark components account for the majority of aboveground biomass (70%–85%) with low variability ($Cv < 15\%$) and minimal environmental sensitivity, resulting in high model fitting stability.

R^2 for crown biomass ranged from 0.58 to 0.74, while those for branch and foliage biomass ranged from 0.35 to 0.64. Notably, the poplar foliage model produced a negative R^2 (−0.2728), indicating relatively poor prediction performance. This is partly caused by localized leaf abscission in some young saplings, which introduced systematic bias into the measured foliage biomass data. These components account for a small proportion (15%–20%) of aboveground biomass and are strongly affected by canopy closure and light conditions (e.g., foliage biomass Cv in oak natural forests reached 44.41%), resulting in lower model accuracy. Nevertheless, MPSE values were below 50% for all components, representing an acceptable precision level for regional biomass estimation.

The optimal model for Chinese fir and poplar stem, wood, and bark was Model (1), as these components exhibit stronger correlations with D^2H . The optimal model for crown, branch, and foliage biomass was Model (2), as branch and foliage growth responds more independently to individual D and H .

Table 17. Parameter estimates and coefficients of variation for Chinese fir aboveground-biomass component models.

Component	Model No.	C_0/Cv_0 (%)	C_1/Cv_1 (%)	C_2/Cv_2 (%)
Stem	(1)	0.028346/9.91	0.915219/1.27	—
	(2)	0.027709/10.05	1.716931/6.35	1.051406/12.02

Wood	(1)	0.020980/9.78	0.930745/1.23	—
	(2)	0.020132/9.89	1.671260/6.45	1.159958/10.80
Bark	(1)	0.009711/13.77	0.824581/1.97	—
	(2)	0.010046/13.43	1.974690/7.10	0.443998/35.94
Crown	(1)	0.064819/24.04	0.689828/4.05	—
	(2)	0.074053/22.93	2.371474/12.09	−0.485220/68.92
Branch	(1)	0.047398/32.74	0.677439/5.55	—
	(2)	0.051230/31.92	2.188299/18.34	−0.300051/154.93
Foliage	(1)	0.032647/25.83	0.681962/4.45	—
	(2)	0.037790/25.08	2.270510/13.54	−0.395012/90.76

Table 18. Parameter estimates and coefficients of variation for poplar aboveground–biomass component models.

Component	Model No.	C_0/Cv_0 (%)	C_1/Cv_1 (%)	C_2/Cv_2 (%)
Stem	(1)	0.020363/7.32	0.948885/0.93	—
	(2)	0.023415/10.69	2.049174/4.11	0.746873/14.84
Wood	(1)	0.014955/6.93	0.967131/0.87	—
	(2)	0.016480/10.17	2.039635/3.92	0.826678/12.74
Bark	(1)	0.006857/10.87	0.849033/1.53	—
	(2)	0.010170/15.03	2.123521/5.53	0.277820/55.59
Crown	(1)	0.019059/18.84	0.817021/2.80	—
	(2)	0.052923/24.31	2.711249/7.02	−0.654003/38.58
Branch	(1)	0.006535/17.24	0.910831/2.31	—
	(2)	0.013588/23.11	2.647536/6.93	−0.193463/124.46
Foliage	(1)	0.029369/34.11	0.616080/7.01	—
	(2)	0.491749/45.89	3.520553/9.71	−2.800228/16.79

Table 19. Parameter estimates and coefficients of variation for oak aboveground–biomass component models.

Component	Model No.	C_0/Cv_0 (%)	C_1/Cv_1 (%)	C_2/Cv_2 (%)
Stem	(1)	0.041501/8.62	0.946206/1.15	—
	(2)	0.047684/10.99	2.013783/2.88	0.760891/11.27
Wood	(1)	0.037925/9.66	0.939897/1.29	—
	(2)	0.045217/12.18	2.032270/3.10	0.706369/13.22
Bark	(1)	0.004790/9.13	0.971509/1.81	—
	(2)	0.004778/12.03	1.940675/3.63	0.974988/10.56
Crown	(1)	0.077255/18.35	0.772094/2.97	—
	(2)	0.175308/18.93	2.433772/4.38	−0.541935/−28.65
Branch	(1)	0.041676/20.39	0.822372/3.09	—
	(2)	0.096076/22.23	2.462761/4.85	−0.415571/−42.55
Foliage	(1)	0.080056/22.83	0.577783/4.91	—
	(2)	0.189430/22.91	2.344827/5.68	−1.099897/−17.24

Table 20. Statistical evaluation metrics for Chinese fir aboveground–biomass component models.

Component	Model No.	R ²	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
Stem	(1)	0.9340	22.14	−2.09	−5.59	18.16	96.58
	(2)	0.9304	22.81	−2.36	−5.55	18.21	96.49
Wood	(1)	0.9385	18.58	−1.58	−5.61	18.18	96.65
	(2)	0.9327	19.50	−2.03	−5.50	18.25	96.50
Bark	(1)	0.8566	4.34	−6.98	−8.52	22.16	95.46
	(2)	0.8709	4.14	−6.20	−8.24	21.61	95.64

Crown	(1)	0.5833	14.55	−20.32	−27.14	43.66	92.12
	(2)	0.6381	13.60	−18.17	−25.08	40.80	92.43
Branch	(1)	0.3487	12.19	−32.76	−42.05	57.95	89.88
	(2)	0.4438	11.30	−30.67	−40.87	55.73	90.32
Foliage	(1)	0.4224	7.39	−23.61	−26.38	43.11	91.45
	(2)	0.4162	7.45	−22.92	−24.98	40.65	91.30

Table 21. Statistical evaluation metrics for poplar aboveground–biomass component models.

Component	Model No.	R ²	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
Stem	(1)	0.9665	19.47	−0.14	−4.03	15.33	96.86
	(2)	0.9667	19.48	−0.39	−3.93	15.46	96.86
Wood	(1)	0.9678	16.72	−0.41	−3.58	14.70	96.91
	(2)	0.9676	16.84	−0.61	−3.54	14.86	96.89
Bark	(1)	0.9313	3.50	−1.62	−8.48	21.60	95.69
	(2)	0.9415	3.24	−1.61	−7.65	20.98	96.00
Crown	(1)	0.5250	16.46	−21.78	−19.26	36.28	90.13
	(2)	0.5856	15.43	−18.93	−15.43	32.00	90.41
Branch	(1)	0.5714	13.78	−19.78	−17.13	34.89	90.06
	(2)	0.5900	13.52	−18.92	−14.83	31.89	90.14
Foliage	(1)	−0.8894	5.73	−51.23	−43.22	59.10	85.48
	(2)	−0.2728	4.74	−39.35	−32.67	50.20	85.08

Table 22. Statistical evaluation metrics for oak aboveground–biomass component models.

Component	Model No.	R ²	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
Stem	(1)	0.9570	32.90	−2.58	−4.70	15.29	96.43
	(2)	0.9456	37.11	−3.23	−4.54	15.84	96.00
Wood	(1)	0.9562	28.02	−3.75	−5.60	16.53	96.47
	(2)	0.9412	32.59	−4.51	−5.34	17.15	95.93
Bark	(1)	0.9018	7.99	−1.08	−6.34	21.29	94.04
	(2)	0.9020	8.00	−1.06	−6.35	21.29	94.03
Crown	(1)	0.7431	24.35	−14.37	−16.90	33.77	93.07
	(2)	0.7416	24.50	−14.22	−11.54	27.93	93.02
Branch	(1)	0.7342	21.56	−15.83	−18.53	35.55	92.79
	(2)	0.7259	21.96	−15.65	−14.01	30.90	92.64
Foliage	(1)	0.3889	5.99	−22.99	−25.89	44.41	90.66
	(2)	0.4034	5.94	−21.40	−17.38	35.27	90.54

3.2.2. Compatible Model Development for Aboveground Components

Based on the foregoing analysis, simultaneous equation systems (Models (3)–(12)) were used to formulate aboveground–biomass compatible model systems for Chinese fir, poplar, and oak:

- ① Chinese fir aboveground–biomass compatible model (Equations (38)–(44)):

$$\left\{ \begin{array}{l} B_{\text{aboveground}} = C_0(D^2H)^{C_1} + C_2D^{C_3}H^{C_4} \\ B_{\text{stem}} = C_0(D^2H)^{C_1} \\ B_{\text{crown}} = C_2D^{C_3}H^{C_4} \\ B_{\text{wood}} = \frac{1}{1 + a_0(D^2H)^{a_1}} \cdot C_0(D^2H)^{C_1} \\ B_{\text{bark}} = \frac{a_0(D^2H)^{a_1}}{1 + a_0(D^2H)^{a_1}} \cdot C_0(D^2H)^{C_1} \\ B_{\text{bark}} = \frac{1}{1 + b_0D^{b_1}H^{b_2}} \cdot C_2D^{C_3}H^{C_4} \\ B_{\text{foliage}} = \frac{b_0D^{b_1}H^{b_2}}{1 + b_0D^{b_1}H^{b_2}} \cdot C_2D^{C_3}H^{C_4} \end{array} \right. \quad \begin{array}{l} (38) \\ (39) \\ (40) \\ (41) \\ (42) \\ (43) \\ (44) \end{array}$$

② Poplar aboveground-biomass compatible model (Equations (45)–(51)):

$$\left\{ \begin{array}{l} B_{\text{aboveground}} = C_0(D^2H)^{C_1} + C_2D^{C_3}H^{C_4} \\ B_{\text{stem}} = C_0(D^2H)^{C_1} \\ B_{\text{crown}} = C_2D^{C_3}H^{C_4} \\ B_{\text{wood}} = \frac{1}{1 + a_0(D^2H)^{a_1}} \cdot C_0(D^2H)^{C_1} \\ B_{\text{bark}} = \frac{a_0(D^2H)^{a_1}}{1 + a_0(D^2H)^{a_1}} \cdot C_0(D^2H)^{C_1} \\ B_{\text{branch}} = \frac{1}{1 + b_0D^{b_1}H^{b_2}} \cdot C_2D^{C_3}H^{C_4} \\ B_{\text{foliage}} = \frac{b_0D^{b_1}H^{b_2}}{1 + b_0D^{b_1}H^{b_2}} \cdot C_2D^{C_3}H^{C_4} \end{array} \right. \quad \begin{array}{l} (45) \\ (46) \\ (47) \\ (48) \\ (49) \\ (50) \\ (51) \end{array}$$

③ Oak aboveground-biomass compatible model (Equations (52)–(58)):

$$\left\{ \begin{array}{l} B_{\text{aboveground}} = C_0(D^2H)^{C_1} + C_2(D^2H)^{C_3} \\ B_{\text{stem}} = C_0(D^2H)^{C_1} \\ B_{\text{crown}} = C_2(D^2H)^{C_3} \\ B_{\text{wood}} = \frac{1}{1 + a_0(D^2H)^{a_1}} \cdot C_0(D^2H)^{C_1} \\ B_{\text{bark}} = \frac{a_0(D^2H)^{a_1}}{1 + a_0(D^2H)^{a_1}} \cdot C_0(D^2H)^{C_1} \\ B_{\text{branch}} = \frac{1}{1 + b_0(D^2H)^{b_1}} \cdot C_2(D^2H)^{C_3} \\ B_{\text{foliage}} = \frac{b_0(D^2H)^{b_1}}{1 + b_0(D^2H)^{b_1}} \cdot C_2(D^2H)^{C_3} \end{array} \right. \quad \begin{array}{l} (52) \\ (53) \\ (54) \\ (55) \\ (56) \\ (57) \\ (58) \end{array}$$

where a_0 – a_2 , b_0 – b_2 , and c_0 – c_4 are model parameters.

Tables 23–31 show that wood and bark models achieved high goodness-of-fit (Chinese fir $a_1 = -0.1095$, $C_v = 17.85\%$), and branch and foliage parameters remained stable (poplar $b_1 = 0.7461$, $C_v = 34.39\%$). In the compatible models, the R^2 values of stem, wood, and bark sub-models decline by less than 0.01 relative to their independent counterparts, while the decline is less than 0.05 for branch and foliage sub-models. This indicates that the compatibility constraint does not significantly compromise the prediction accuracy at the component level.

Parameter C_v values were $<50\%$ for the Chinese fir and poplar wood and bark models, as well as for the oak crown model; C_v values exceeded 50% for all other component models. Overall, parameter stability was markedly higher for stem, wood, and bark models than for crown, branch, and foliage models.

Table 23. Parameter estimates and C_v for the Chinese fir aboveground compatible model (Models (38)–(40)).

Component	Model	$C_0/C_{v0}\%$	$C_1/C_{v1}\%$	$C_2/C_{v2}\%$	$C_3/C_{v3}\%$	$C_4/C_{v4}\%$
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Aboveground	(38)	0.028346/9.91	0.915219/1.27	0.010420/57.79	2.584360/9.35	−0.097926/240.92
Stem	(39)	0.028346/9.91	0.915219/1.27	—	—	—
Crown	(40)	—	—	0.010420/57.79	2.584360/9.35	−0.097926/240.92

Table 24. Parameter estimates and Cv for the Chinese fir stem component models (Models (41)–(42)).

Component	Model	$C_0/Cv_0\%$	$C_1/Cv_1\%$	$a_0/Cva_0\%$	$a_1/Cva_1\%$
Wood	(41)	0.028346/9.91	0.915219/1.27	0.450883/18.79	−0.109522/17.85
Bark	(42)	0.028346/9.91	0.915219/1.27	0.450883/18.79	−0.109522/17.85

Table 25. Parameter estimates and Cv for the Chinese fir crown component models (Models (43)–(44)).

Component	Model	$C_2/Cv_2\%$	$C_3/Cv_3\%$	$C_4/Cv_4\%$	$b_0/Cvb_0\%$	$b_1/Cvb_1\%$	$b_2/Cvb_2\%$
Branch	(43)	0.010420/57.79	2.584360/9.35	−0.097926/240.92	6.153479/94.00	−1.531182/26.69	1.015387/40.01
Foliage	(44)	0.010420/57.79	2.584360/9.35	−0.097926/240.92	6.153479/94.00	−1.531182/26.69	1.015387/40.01

Table 26. Parameter estimates and Cv for the poplar aboveground compatible model (Models (45)–(47)).

Component	Model	$C_0/Cv_0\%$	$C_1/Cv_1\%$	$C_2/Cv_2\%$	$C_3/Cv_3\%$	$C_4/Cv_4\%$
Aboveground	(45)	0.020363/7.32	0.948885/0.93	0.052969/69.03	2.367568/8.07	−0.362405/60.28
Stem	(46)	0.020363/7.32	0.948885/0.93	—	—	—
Crown	(47)	—	—	0.052969/69.03	2.367568/8.07	−0.362405/60.28

Table 27. Parameter estimates and Cv for the poplar stem component models (Models (48)–(49)).

Component	Model	$C_0/Cv_0\%$	$C_1/Cv_1\%$	$a_0/Cva_0\%$	$a_1/Cva_1\%$
Wood	(48)	0.020363/7.32	0.948885/0.93	0.267126/21.97	−0.062730/35.65
Bark	(49)	0.020363/7.32	0.948885/0.93	0.267126/21.97	−0.062730/35.65

Table 28. Parameter estimates and Cv for the poplar crown component models (Models (50)–(51)).

Component	Model	$C_2/Cv_2\%$	$C_3/Cv_3\%$	$C_4/Cv_4\%$	$b_0/Cvb_0\%$	$b_1/Cvb_1\%$	$b_2/Cvb_2\%$
Branch	(50)	0.052969/69.03	2.367568/8.07	−0.362405/60.28	38.06164/86.43	0.746138/34.39	−2.594870/13.16
Foliage	(51)	0.052969/69.03	2.367568/8.07	−0.362405/60.28	38.06164/86.43	0.746138/34.39	−2.594870/13.16

Table 29. Parameter estimates and Cv for the oak aboveground compatible model (Models (52)–(54)).

Component	Model	$C_0/Cv_0\%$	$C_1/Cv_1\%$	$C_2/Cv_2\%$	$C_3/Cv_3\%$
Aboveground	(52)	0.041501/8.62	0.946206/1.15	0.053232/48.15	0.795255/6.39
Stem	(53)	0.041501/8.62	0.946206/1.15	—	—
Crown	(54)	—	—	0.053232/48.15	0.795255/6.39

Table 30. Parameter estimates and Cv for the oak stem component models (Models (55)–(56)).

Component	Model	$C_0/Cv_0\%$	$C_1/Cv_1\%$	$a_0/Cva_0\%$	$a_1/Cva_1\%$
Wood	(55)	0.041501/8.62	0.946206/1.15	0.117400/35.58	0.044437/83.67
Bark	(56)	0.041501/8.62	0.946206/1.15	0.117400/35.58	0.044437/83.67

Table 31. Parameter estimates and Cv for the oak crown component models (Models (57)–(58)).

Component	Model	$C_2/Cv_2\%$	$C_3/Cv_3\%$	$b_0/Cvb_0\%$	$b_1/Cvb_1\%$
Branch	(57)	0.053232/48.15	0.795255/6.39	2.847114/52.15	−0.296384/−18.84

Foliage	(58)	0.053232/48.15	0.795255/6.39	2.847114/52.15	−0.296384/−18.84
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As shown in Figures 7–9, residuals of aboveground–biomass component models in the compatible system were more concentrated than those from the independent models (Figures 7d–l, 8d–l and 9a–g); for example, the residual range of the Chinese fir foliage model narrowed from −15 to +12 kg (independent) to −10 to +8 kg (compatible), reflecting the effective integration of component information within the simultaneous equation framework and the consequent reduction in random error. Minor systematic biases in component model residuals were observed at some diameter classes, but residuals were generally randomly distributed.

Tables 32–37 further confirm that R^2 values for aboveground–biomass compatible models exceeded 0.93 for all three species (Chinese fir: 0.9317; poplar: 0.9631; oak: 0.9653), with $TRE < \pm 2\%$ and $p > 96\%$. Oak achieved the highest aboveground–biomass model accuracy ($p = 96.92\%$), owing to its more stable aboveground–biomass allocation pattern (wood 65%–70%, bark 10%–15%, branch and foliage 15%–20%), which facilitated more precise fitting of the proportional scaling functions. Overall, the aboveground biomass compatible models performed well, with stem, wood, and bark sub-models outperforming crown, branch, and foliage sub-models, primarily because stem and wood biomass is large and less variable under equivalent DBH and height conditions.

Table 32. Statistical evaluation for the Chinese fir aboveground–biomass compatible models.

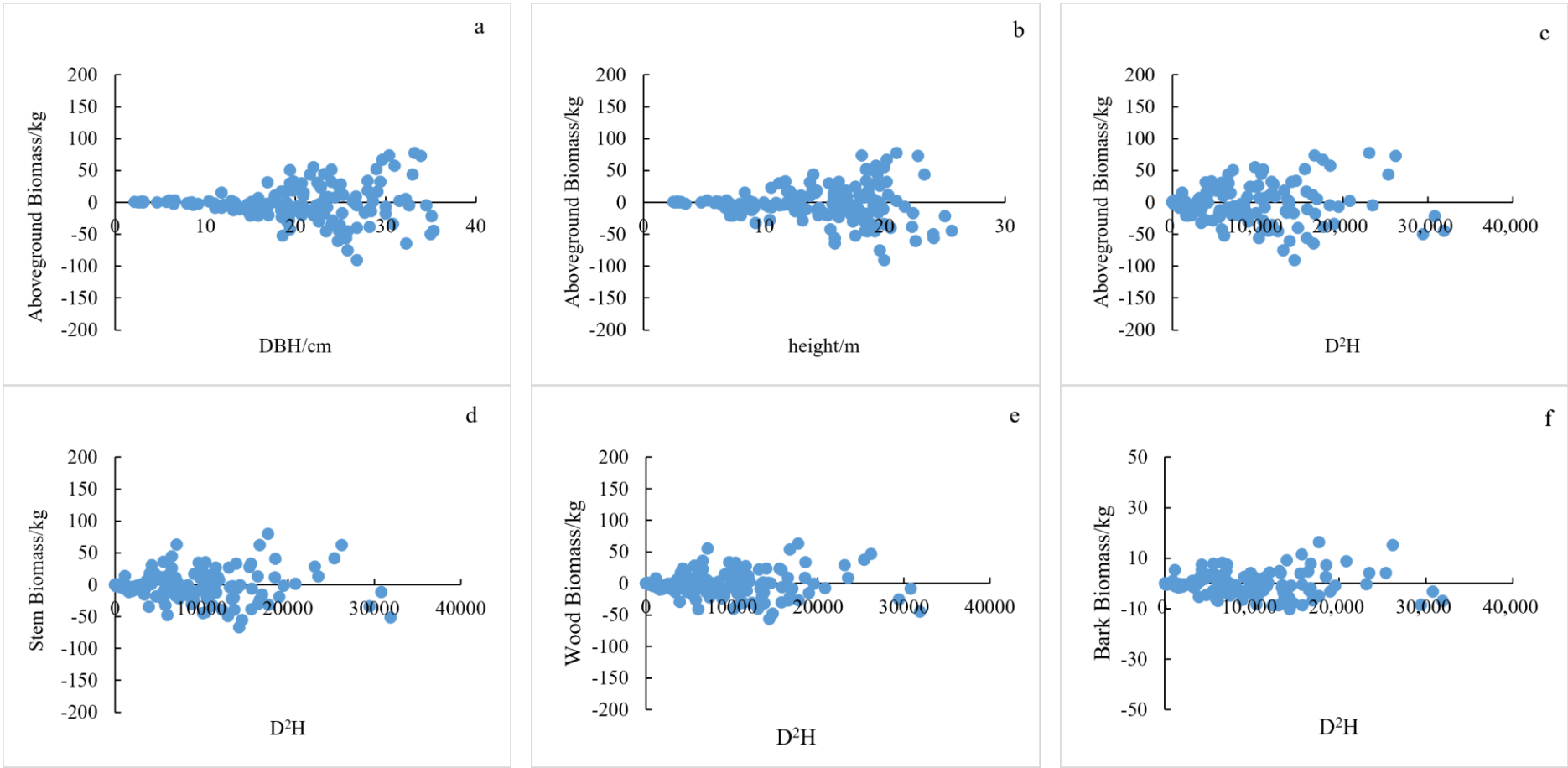
Component	Model	R^2	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
Aboveground	(38)	0.9317	27.67	−1.95	−2.12	21.05	96.53
Stem	(39)	0.9340	22.14	−2.09	−5.59	18.16	96.58
Crown	(40)	0.7004	12.37	−1.34	11.19	53.46	91.69
Wood	(41)	0.9384	18.60	−2.10	−5.89	18.20	96.66
Bark	(42)	0.8668	4.19	−2.00	−3.73	21.63	95.39
Branch	(43)	0.6002	9.58	−1.83	37.72	94.54	88.38
Foliage	(44)	0.5653	6.43	−0.73	4.41	48.37	90.33

Table 33. Statistical evaluation for the poplar aboveground–biomass compatible models.

Component	Model	R^2	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
Aboveground	(45)	0.9631	24.32	−0.14	−4.05	15.21	96.76
Stem	(46)	0.9665	19.47	−0.14	−4.03	15.33	96.86
Crown	(47)	0.7042	13.04	−0.16	−3.56	33.37	90.02
Wood	(48)	0.9672	16.88	−0.20	−4.69	15.16	96.87
Bark	(49)	0.9343	3.42	0.26	−0.53	19.87	95.70
Branch	(50)	0.7053	11.47	−0.41	−2.86	33.90	89.73
Foliage	(51)	0.4639	3.08	1.30	−2.06	50.32	83.82

Table 34. Statistical evaluation for the oak aboveground–biomass compatible models.

Component	Model	R^2	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
Aboveground	(52)	0.9653	37.51	−1.76	−3.18	16.84	96.92
Stem	(53)	0.9570	32.90	−2.58	−4.70	15.29	96.43
Crown	(54)	0.7917	21.92	0.79	0.65	33.60	92.66
Wood	(55)	0.9564	27.96	−2.33	−4.21	16.33	96.43
Bark	(56)	0.9054	7.84	−4.01	−7.40	21.40	94.33
Branch	(57)	0.7942	18.97	−1.06	3.15	35.97	92.38
Foliage	(58)	0.5345	5.23	−0.59	−4.97	45.92	89.47



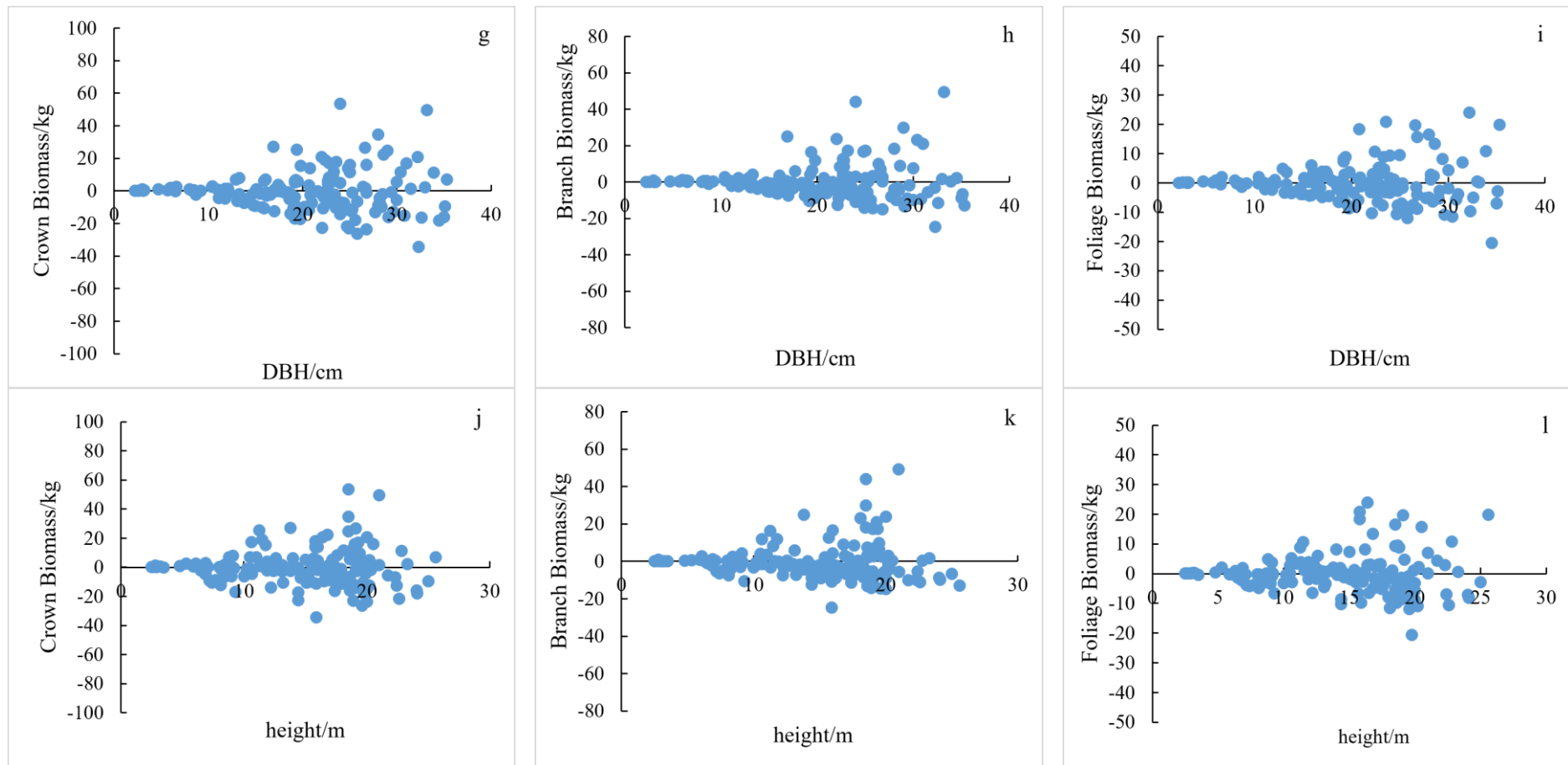
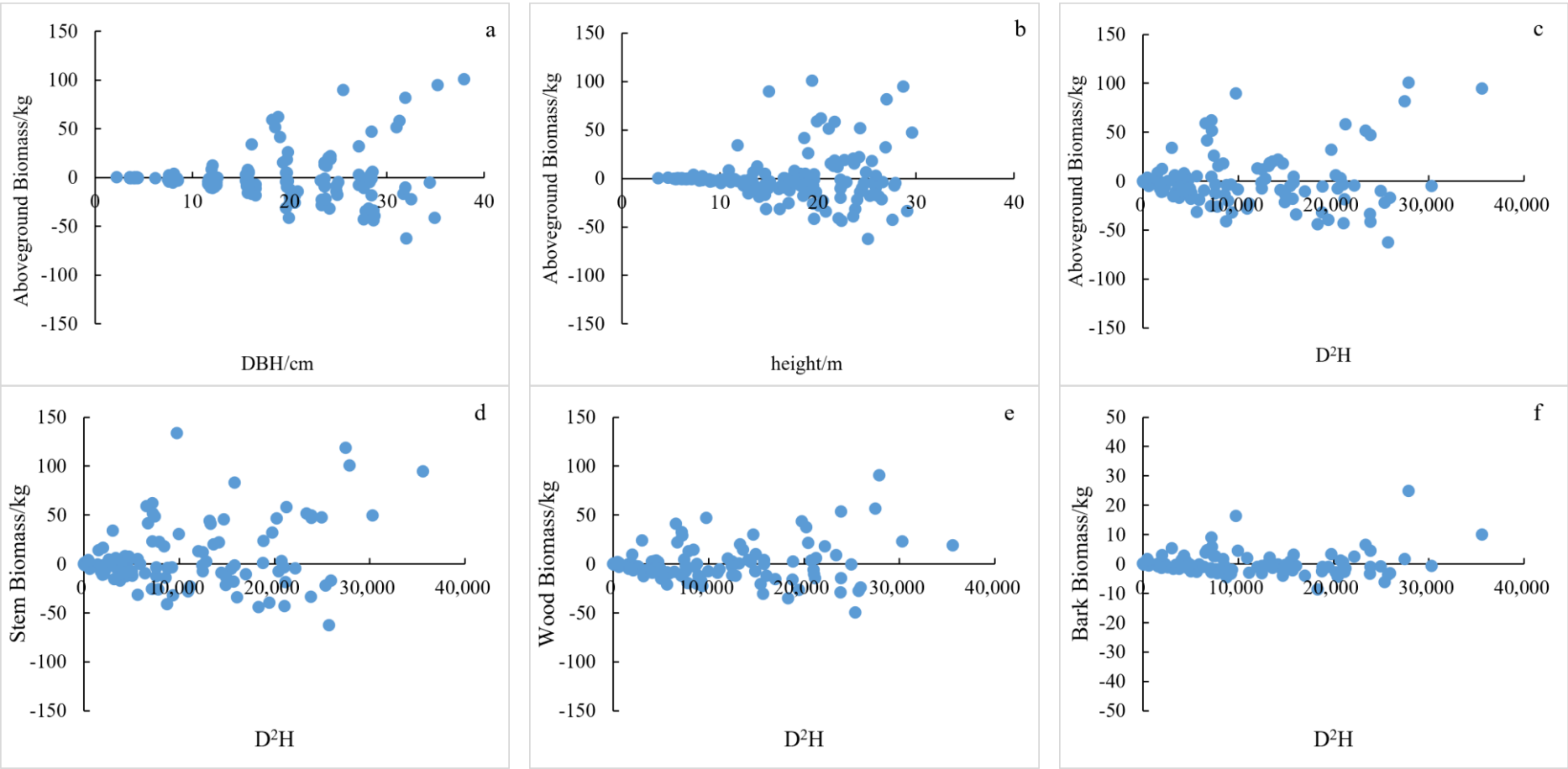


Figure 7. Residual plots of Chinese fir aboveground-biomass compatible models. Panels (a–c): residuals of aboveground, stem, wood, and bark models vs. DBH, height, and D^2H ; panels (d–f): stem, wood, and bark model residuals vs. D^2H ; panels (g–i): crown, branch, and foliage model residuals vs. DBH; panels (j–l): crown, branch, and foliage model residuals vs. total height.



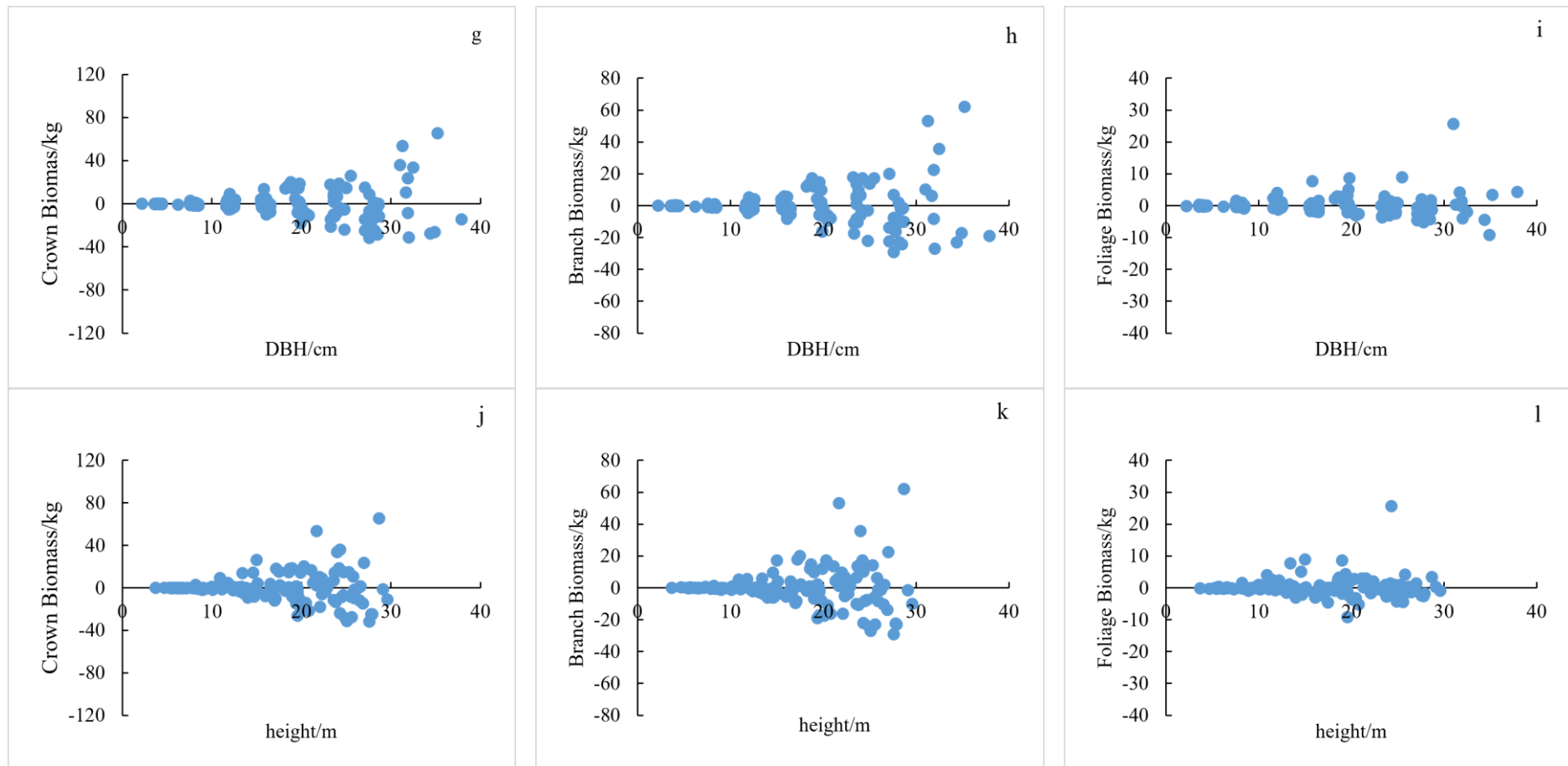


Figure 8. Residual plots of poplar aboveground-biomass compatible models. Panel arrangement follows that of Figure 7.

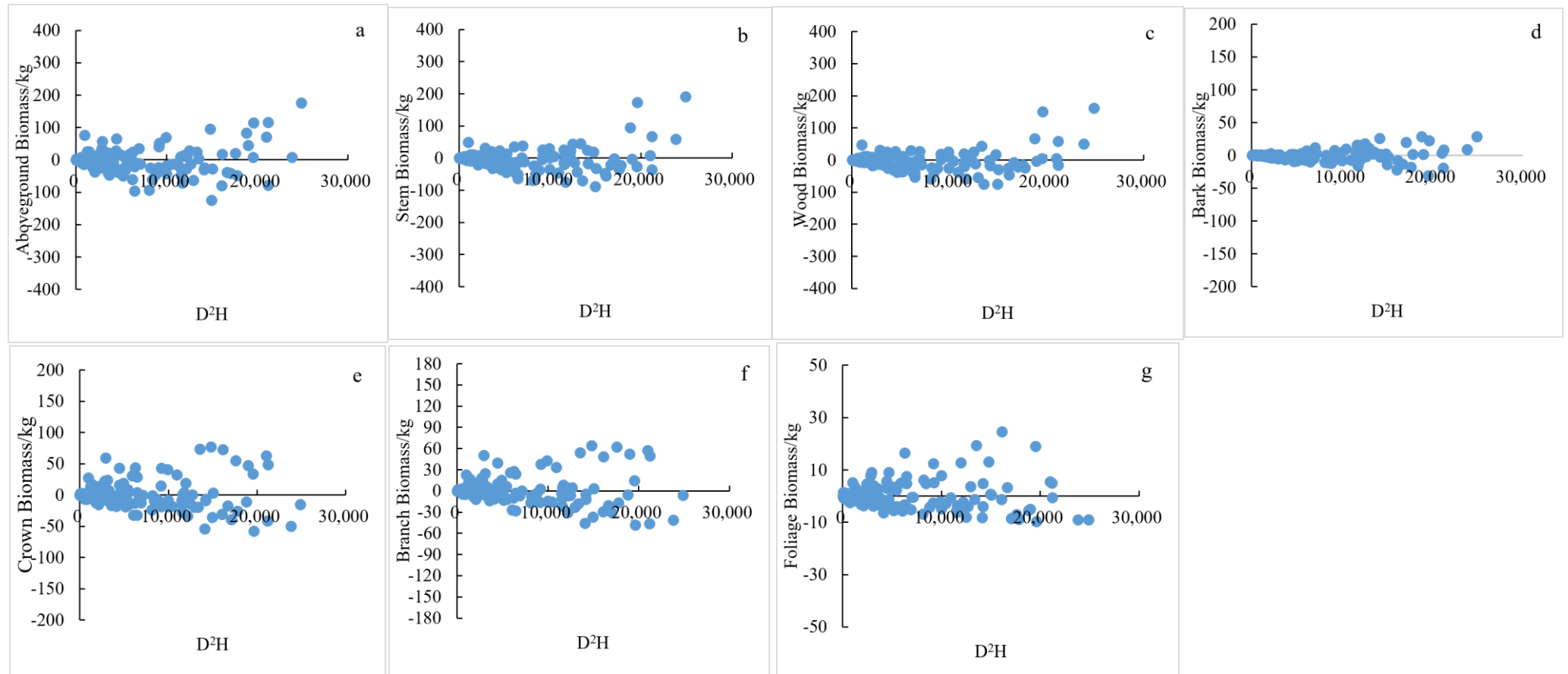


Figure 9. Residual plots of oak aboveground-biomass compatible models. Panels (a–g): residuals of aboveground, stem, wood, bark, crown, branch, and foliage models vs. D^2H .

Table 35. LOOCV applicability assessment for Chinese fir aboveground compatible models.

Component	Model	R ²	TRE (%)	MSE (%)	MPSE (%)	p (%)
Aboveground	(38)	0.9305	−1.98	−2.12	21.14	96.50
Stem	(39)	0.9326	−2.08	−5.36	18.54	96.55
Crown	(40)	0.6785	−1.49	11.54	54.14	91.41
Wood	(41)	0.9384	−2.11	−5.90	18.20	96.66
Bark	(42)	0.8652	−2.00	−3.69	21.69	95.37
Branch	(43)	0.5908	−1.95	37.87	94.89	88.21
Foliage	(44)	0.5371	−0.57	4.83	48.99	90.07

Table 36. LOOCV applicability assessment for poplar aboveground compatible models.

Component	Model	R ²	TRE (%)	MSE (%)	MPSE (%)	p (%)
Aboveground	(45)	0.9628	−0.21	−4.05	15.28	96.74
Stem	(46)	0.9655	−0.10	−3.88	15.63	96.81
Crown	(47)	0.6604	−0.56	−3.16	34.29	89.38
Wood	(48)	0.9672	−0.20	−4.70	15.16	96.88
Bark	(49)	0.9321	0.32	−0.47	19.96	95.63
Branch	(50)	0.7009	−0.56	−2.91	33.88	89.64
Foliage	(51)	0.3970	2.16	−1.10	51.51	82.96

Table 37. LOOCV applicability assessment for oak aboveground compatible models.

Component	Model	R ²	TRE (%)	MSE (%)	MPSE (%)	p (%)
Aboveground	(52)	0.9646	−1.75	−3.15	16.94	96.90
Stem	(53)	0.9554	−2.56	−4.64	15.52	96.36
Crown	(54)	0.7796	0.81	0.93	34.13	92.45
Wood	(55)	0.9563	−2.32	−4.19	16.35	96.42
Bark	(56)	0.9025	−4.09	−7.42	21.53	94.25
Branch	(57)	0.7935	1.08	3.18	35.98	92.37
Foliage	(58)	0.5216	−0.65	−4.81	46.33	89.33

Based on comprehensive assessment of parameter Cv, residual analysis, goodness-of-fit evaluation, and LOOCV applicability testing, the final aboveground-biomass compatible models for Chinese fir, poplar, and oak with fully parameterized equations are provided.

① Chinese fir aboveground-biomass compatible model

$$B_{\text{aboveground}} = 0.028346(D^2H)^{0.915219} + 0.010420D^{2.584360}H^{-0.097926} \quad (59)$$

$$B_{\text{stem}} = 0.028346(D^2H)^{0.915219} \quad (60)$$

$$B_{\text{crown}} = 0.010420D^{2.584360}H^{-0.097926} \quad (61)$$

$$B_{\text{wood}} = \frac{1}{1 + 0.450883(D^2H)^{-0.109522}} \cdot 0.028346(D^2H)^{0.915219} \quad (62)$$

$$B_{\text{bark}} = \frac{0.450883(D^2H)^{-0.109522}}{1 + 0.450883(D^2H)^{-0.109522}} \cdot 0.028346(D^2H)^{0.915219} \quad (63)$$

$$B_{\text{branch}} = \frac{1}{1 + 6.153479D^{-1.531182}H^{1.015387}} \cdot 0.010420D^{2.584360}H^{-0.097926} \quad (64)$$

$$B_{\text{foliage}} = \frac{6.153521D^{-1.531183}H^{1.015386}}{1 + 6.153479D^{-1.531182}H^{1.015387}} \cdot 0.010420D^{2.584360}H^{-0.097926} \quad (65)$$

② Poplar aboveground-biomass compatible model

$$\left\{ \begin{array}{l} B_{\text{aboveground}} = 0.020363(D^2H)^{0.948885} + 0.052969D^{2.367568}H^{-0.362405} \end{array} \right. \quad (66)$$

$$\left\{ \begin{array}{l} B_{\text{stem}} = 0.020363(D^2H)^{0.948885} \\ B_{\text{crown}} = 0.052969D^{2.367568}H^{-0.362405} \end{array} \right. \quad (67)$$

$$\left\{ \begin{array}{l} B_{\text{wood}} = \frac{1}{1 + 0.267126(D^2H)^{-0.062730}} \times 0.020363(D^2H)^{0.948885} \end{array} \right. \quad (68)$$

$$\left\{ \begin{array}{l} B_{\text{bark}} = \frac{0.267126(D^2H)^{-0.062730}}{1 + 0.267126(D^2H)^{-0.062730}} \times 0.020363(D^2H)^{0.948885} \end{array} \right. \quad (69)$$

$$\left\{ \begin{array}{l} B_{\text{branch}} = \frac{1}{1 + 38.06164D^{0.746138}H^{-2.59487}} \times 0.052969D^{2.367568}H^{-0.362405} \end{array} \right. \quad (70)$$

$$\left\{ \begin{array}{l} B_{\text{foliage}} = \frac{38.06164D^{0.746138}H^{-2.59487}}{1 + 38.06164D^{0.746138}H^{-2.59487}} \times 0.052969D^{2.367568}H^{-0.362405} \end{array} \right. \quad (71)$$

③ Oak aboveground-biomass compatible model

$$\left\{ \begin{array}{l} B_{\text{aboveground}} = 0.041501(D^2H)^{0.946206} + 0.053232(D^2H)^{0.795255} \end{array} \right. \quad (72)$$

$$\left\{ \begin{array}{l} B_{\text{stem}} = 0.041501(D^2H)^{0.946206} \\ B_{\text{crown}} = 0.053232(D^2H)^{0.795255} \end{array} \right. \quad (73)$$

$$\left\{ \begin{array}{l} B_{\text{wood}} = \frac{1}{1 + 0.11740(D^2H)^{0.044437}} \cdot 0.041501(D^2H)^{0.946206} \end{array} \right. \quad (74)$$

$$\left\{ \begin{array}{l} B_{\text{bark}} = \frac{0.11740(D^2H)^{0.044437}}{1 + 0.11740(D^2H)^{0.044437}} \cdot 0.041501(D^2H)^{0.946206} \end{array} \right. \quad (75)$$

$$\left\{ \begin{array}{l} B_{\text{branch}} = \frac{1}{1 + 2.847114(D^2H)^{-0.296384}} \cdot 0.053232(D^2H)^{0.795255} \end{array} \right. \quad (76)$$

$$\left\{ \begin{array}{l} B_{\text{foliage}} = \frac{2.847114(D^2H)^{-0.296384}}{1 + 2.847114(D^2H)^{-0.296384}} \cdot 0.053232(D^2H)^{0.795255} \end{array} \right. \quad (77)$$

3.3. Full Compatible Model System: Total and Component Biomass

Building upon the foregoing analyses, separate model systems were established for (i) the three species' total, aboveground, and root biomass, and (ii) aboveground-biomass partitioned among stem and crown, stem partitioned between wood and bark, and crown partitioned between branch and foliage. Because both model systems involve aboveground-biomass as a linkage component, inconsistencies may arise when estimating biomass for the same tree using the two systems independently. To resolve this incompatibility, the total-biomass compatible model was designated as the core, and an algebraic sum-of-components control approach was applied to construct a new model system in which wood, bark, branch, and foliage biomass sum exactly to aboveground biomass. Parameters were estimated through nonlinear errors-in-variables simultaneous equation estimation, achieving full compatibility between total and component biomass.

With aboveground biomass as the baseline and DBH and height as explanatory variables, the general structure of the component biomass models is:

$$\left\{ \begin{array}{l} B_{\text{wood}} = \frac{1}{1 + g_1(D, H) + g_2(D, H) + g_3(D, H)} \cdot f_{\text{aboveground}}(D, H) \end{array} \right. \quad (78)$$

$$\left\{ \begin{array}{l} B_{\text{bark}} = \frac{g_1(D, H)}{1 + g_1(D, H) + g_2(D, H) + g_3(D, H)} \cdot f_{\text{aboveground}}(D, H) \end{array} \right. \quad (79)$$

$$\left\{ \begin{array}{l} B_{\text{branch}} = \frac{g_2(D, H)}{1 + g_1(D, H) + g_2(D, H) + g_3(D, H)} \cdot f_{\text{aboveground}}(D, H) \end{array} \right. \quad (80)$$

$$\left\{ \begin{array}{l} B_{\text{foliage}} = \frac{g_3(D, H)}{1 + g_1(D, H) + g_2(D, H) + g_3(D, H)} \cdot f_{\text{aboveground}}(D, H) \end{array} \right. \quad (81)$$

where $f_{\text{aboveground}}(D, H)$ is the aboveground-biomass model function, and $g_1(D, H)$ – $g_3(D, H)$ are relative proportional functions (with wood biomass proportion set to unity as the reference).

Based on prior independent model evaluation and aboveground-biomass compatible model construction results, the Chinese fir branch biomass model based on Model (2) produced biologically implausible parameter behavior, which was resolved when Model

(1) was used as the base model. Therefore, Model (1) was adopted as the base model for all Chinese fir aboveground–biomass component compatible models.

Prior to parameter estimation, to remove heteroscedasticity, preliminary fitting of each component model (wood, bark, branch, foliage) was performed using nonlinear least squares with each component model as its own weighting function. Simultaneous estimation of all model parameters was then performed using a nonlinear errors-in-variables simultaneous equation system, with the Newton–Tang algorithm for parameter estimation, Lagrange multipliers for error variable correction, and a TSEM variance structure specification. Component biomass model parameter estimates for the three species are given in Table 38.

Table 38. Parameter estimates for aboveground–biomass component models of the three species.

Species	a ₀	a ₁	a ₂	a ₃	a ₄	a ₅
Chinese fir	0.435670	−0.102711	1.647491	−0.255865	1.201560	−0.246443
Poplar	0.361090	−0.099037	0.388146	−0.057509	1.872978	−0.410280
Oak	0.167591	−0.010266	0.926661	−0.109533	1.654142	−0.358421

Results of the integrated model assessment (Tables 38 and 39) demonstrated that, after simultaneous equation correction, the proportional scaling function parameters for wood, bark, branch, and foliage were more precisely estimated for all three species. R^2 values for total biomass, aboveground biomass, and wood models all exceeded 0.92, and TRE was within $\pm 3\%$ (Chinese fir total biomass $R^2 = 0.9208$, TRE = -0.87% ; poplar wood $R^2 = 0.9596$, TRE = -0.43%). Root biomass models, constrained by sample size (only 54 trees with measured root samples), yielded slightly lower R^2 (Chinese fir: 0.7734; poplar: 0.7146), but TRE was controlled within $\pm 2\%$ (oak root biomass TRE = -0.80%), satisfying accuracy requirements for root carbon stock estimation in carbon accounting. Overall, total biomass, aboveground biomass, and wood biomass models for all three species performed well. Root, bark, and —for poplar and oak—branch models also achieved satisfactory fitting; foliage models showed relatively lower precision, primarily due to small foliage biomass and high variability, and improvements would require larger samples with optimized sampling design.

Compared with directly constructed independent aboveground–biomass compatible models, accuracy was essentially equivalent for all models except the poplar foliage model (slightly lower). The full compatible model system presented in this section is therefore preferred for production applications, as it ensures complete consistency between total and component biomass estimates.

Table 39. Statistical evaluation for full compatible biomass models of the three species.

Species	Model Type	R^2	S (kg)	TRE (%)	MSE (%)	MPSE (%)	p (%)
Chinese fir	Total biomass	0.9208	31.06	−0.87	−6.21	20.82	96.34
	Aboveground biomass	0.9242	29.13	−0.97	−6.81	21.02	96.31
	Root biomass	0.8762	5.39	0.44	—	—	91.11
	Root biomass (measured samples)	0.7734	7.98	0.45	3.68	29.31	90.96
	Wood biomass	0.9377	18.95	−0.01	−4.70	18.62	96.53
	Bark biomass	0.8685	4.21	−2.85	−4.91	21.68	95.40
	Branch biomass	0.4965	10.85	−4.36	−17.82	57.89	87.18
	Foliage biomass	0.5543	6.58	−1.88	−5.63	43.73	90.23
Poplar	Total biomass	0.9671	23.98	−1.62	−4.25	15.13	96.97
	Aboveground biomass	0.9625	24.54	−1.60	−3.84	15.34	96.78
	Root biomass	0.8239	5.94	−1.95	—	—	80.78
	Root biomass (measured samples)	0.7146	12.39	−1.95	−8.34	33.68	79.79

Oak	Wood biomass	0.9596	19.00	−0.43	−3.43	16.03	96.49
	Bark biomass	0.9346	3.46	4.31	−0.51	20.53	95.47
	Branch biomass	0.6810	12.05	−8.68	−6.80	32.87	90.10
	Foliage biomass	0.2592	3.65	−12.04	−8.37	54.70	83.31
	Total biomass	0.9651	41.25	−2.65	−4.85	17.31	96.89
	Aboveground biomass	0.9634	38.48	−2.79	−5.81	17.33	96.88
	Root biomass	0.8592	13.28	−0.80	—	—	85.75
	Root biomass (measured samples)	0.7778	23.78	−0.80	14.34	47.64	85.29
	Wood biomass	0.9551	28.75	−3.28	−4.90	16.30	96.36
	Bark biomass	0.8618	9.60	9.97	−1.33	22.43	92.04
	Branch biomass	0.7854	19.63	−6.75	−8.68	34.13	92.72
	Foliage biomass	0.5294	5.32	−4.52	−7.44	45.45	89.70

Note: Root biomass model metrics are computed from dummy-variable model predictions; root biomass (measured samples) metrics are computed from measured root sample data.

The final comprehensive compatible biomass model systems for Chinese fir, poplar, and oak (with numerical parameter values) are presented in the original Chinese text (Section 3.3 final equations), incorporating total biomass, aboveground biomass, root biomass, wood, bark, branch, and foliage sub-models for each species within a fully additive compatible framework.

① Chinese fir aboveground-biomass compatible model

$$\begin{cases} B_{\text{total}} = 0.065662D^{1.750420}H^{0.780381} + 0.024760(D^2H)^{0.774387} \\ B_{\text{aboveground}} = 0.065662D^{1.750420}H^{0.780381} \end{cases} \quad (84)$$

$$B_{\text{root}} = 0.024760(D^2H)^{0.774387} \quad (85)$$

$$B_{\text{wood}} = \frac{1}{1 + 0.43567(D^2H)^{-0.102711} + 1.647491(D^2H)^{-0.255865} + 1.20156(D^2H)^{-0.246443}} \times 0.065662D^{1.75042}H^{0.780381} \quad (86)$$

$$B_{\text{bark}} = \frac{0.43567(D^2H)^{-0.102711}}{1 + 0.43567(D^2H)^{-0.102711} + 1.647491(D^2H)^{-0.255865} + 1.20156(D^2H)^{-0.246443}} \times 0.065662D^{1.75042}H^{0.780381} \quad (87)$$

$$B_{\text{branch}} = \frac{1.647491(D^2H)^{-0.255865}}{1 + 0.43567(D^2H)^{-0.102711} + 1.647491(D^2H)^{-0.255865} + 1.20156(D^2H)^{-0.246443}} \times 0.065662D^{1.75042}H^{0.780381} \quad (88)$$

$$B_{\text{foliage}} = \frac{1.20156(D^2H)^{-0.246443}}{1 + 0.43567(D^2H)^{-0.102711} + 1.647491(D^2H)^{-0.255865} + 1.20156(D^2H)^{-0.246443}} \times 0.065662D^{1.75042}H^{0.780381} \quad (89)$$

② Poplar aboveground-biomass compatible mode

$$\begin{cases} B_{\text{total}} = 0.046471D^{2.171796}H^{0.462424} + 0.013116 \cdot D^2H^{0.822310} \\ B_{\text{aboveground}} = 0.046471D^{2.171796}H^{0.462424} \end{cases} \quad (91)$$

$$B_{\text{root}} = 0.013116(D^2H)^{0.82231} \quad (92)$$

$$B_{\text{wood}} = \frac{1}{1 + 0.361090(D^2H)^{-0.099037} + 0.388146(D^2H)^{-0.057509} + 1.872978(D^2H)^{-0.410280}} \times 0.046471D^{2.171796}H^{0.462424} \quad (93)$$

$$B_{\text{bark}} = \frac{0.361090(D^2H)^{-0.099037}}{1 + 0.361090(D^2H)^{-0.099037} + 0.388146(D^2H)^{-0.057509} + 1.872978(D^2H)^{-0.410280}} \times 0.046471D^{2.171796}H^{0.462424} \quad (94)$$

$$B_{\text{branch}} = \frac{0.388146(D^2H)^{-0.057509}}{1 + 0.361090(D^2H)^{-0.099037} + 0.388146(D^2H)^{-0.057509} + 1.872978(D^2H)^{-0.410280}} \times 0.046471D^{2.171796}H^{0.462424} \quad (95)$$

$$B_{\text{foliage}} = \frac{1.872978(D^2H)^{-0.410280}}{1 + 0.361090(D^2H)^{-0.099037} + 0.388146(D^2H)^{-0.057509} + 1.872978(D^2H)^{-0.410280}} \times 0.046471D^{2.171796}H^{0.462424} \quad (96)$$

③ Oak aboveground-biomass compatible model

$$\left\{ \begin{array}{l} B_{\text{total}} = 0.0927573 (D^2H)^{0.89013} + 0.018969 (D^2H)^{0.89162} \end{array} \right. \quad (98)$$

$$B_{\text{aboveground}} = 0.0927573 (D^2H)^{0.89013} \quad (99)$$

$$B_{\text{belowground}} = 0.018969 (D^2H)^{0.89162} \quad (99)$$

$$B_{\text{wood}} = \frac{1}{1 + 0.167591(D^2H)^{-0.010266} + 0.926661(D^2H)^{-0.109533} + 1.654142(D^2H)^{-0.358421}} \times 0.0927573(D^2H)^{0.890130} \quad (100)$$

$$B_{\text{bark}} = \frac{0.167591(D^2H)^{-0.010266}}{1 + 0.167591(D^2H)^{-0.010266} + 0.926661(D^2H)^{-0.109533} + 1.654142(D^2H)^{-0.358421}} \times 0.0927573(D^2H)^{0.890130} \quad (101)$$

$$B_{\text{branch}} = \frac{0.926661(D^2H)^{-0.109533}}{1 + 0.167591(D^2H)^{-0.010266} + 0.926661(D^2H)^{-0.109533} + 1.654142(D^2H)^{-0.358421}} \times 0.0927573(D^2H)^{0.890130} \quad (102)$$

$$B_{\text{foliage}} = \frac{1.654142(D^2H)^{-0.358421}}{1 + 0.167591(D^2H)^{-0.010266} + 0.926661(D^2H)^{-0.109533} + 1.654142(D^2H)^{-0.358421}} \times 0.0927573(D^2H)^{0.890130} \quad (103)$$

4. Discussion

4.1. Model Accuracy and Applicability

For root biomass models, the total relative error was within 8% and prediction accuracy reached around 80%. Nevertheless, obvious systematic biases existed. These biases mainly stemmed from the high sensitivity of tree roots to soil and environmental conditions as well as limited sample quantity, leading to higher MSE and MPSE values (Tables 11–13). This finding is consistent with the research of Wang et al. [25], who pointed out that environmental heterogeneity and insufficient sampling are the dominant factors triggering poor stability of root biomass models. Consistently, Lehtonen et al. [26] confirmed that soil property, thermal condition and site environment exert prominent regulation effects on root biomass accumulation. Even when incorporating multiple stand variables, nearly half of the variation in fine root biomass remained unexplained, further demonstrating roots' strong dependence on site environments. Although root biomass typically represents less than 20% of total-biomass, limiting its effect on total biomass estimates, root biomass is of critical value in carbon flux and ecological function assessments. We therefore suggest increasing root sampling in future studies to improve the stability and applicability of root models.

The aboveground-biomass compatible models overall showed good fitting performance, with stem, wood, and bark sub-models clearly outperforming crown, branch, and foliage sub-models (Tables 32–37), primarily because these major biomass components have larger stock and lower variability at given DBH and tree height.

Removing crown-related variables slightly improved a few statistical metrics for branch and foliage models but reduced R^2 and increased residual standard deviation (S). Foliage biomass is influenced not only by tree vigor but also by stand structure and canopy closure, increasing variability and MPSE—this result coincides with the research findings of Forrester et al. [27], who illustrated that specific leaf area and wood density substantially regulate foliage biomass allocation patterns. Conversely, stem, wood, and bark components, by virtue of their large biomass and low variability, consistently exhibited superior model fit relative to branch and foliage models. Therefore, the adoption of compatible models that integrate different components through proportional scaling relationships not only ensures that component biomass sums equal total aboveground biomass but also enhances model stability and biological coherence [28].

The present study adopted a two-variable approach using only DBH and total height; crown and environmental covariates were not incorporated. However, more variables introduce increased information redundancy, and a balance must be struck based on the intended application context [29]. Consistent with previous research conclusions, González-Benecke et al. [30] found that adding crown area or stand-level parameters to DBH–height core models improved goodness-of-fit, though practical implementability must be weighed against precision gains. For branch and foliage biomass models, crown

width and branch density may have statistically significant effects [31], but given their minor contribution to total aboveground biomass, these variables may reasonably be omitted in production applications. For scientific research or actuarial applications, however, models incorporating crown variables for improved foliage precision are still recommended. Similarly, Zou et al. [32] verified that crown width (CW) and crown length (CL) improve predictive accuracy for crown biomass, particularly in research contexts, and the inclusion of these variables can be calibrated to specific application requirements. Xiang et al. [33] demonstrated that stand age also improves the fit of generalized allometric equations for Chinese fir. In summary, to balance operational feasibility and accuracy, we recommend maintaining streamlined core models using only DBH and height, while optionally incorporating crown variables to enhance component-level precision in specific application scenarios.

4.2. Model Comparison

This study found that for Chinese fir and poplar aboveground biomass, the use of Model (2) produced a biomass decrease with increasing height at a given DBH, which violates biological principles. When the power-function form, Model (1), was adopted, this biologically anomalous behavior was corrected, suggesting that simple power models still have limitations in mechanistic interpretation. This finding is consistent with Li et al. [28], who noted that power functions, while commonly used, may produce anomalous height-effect behaviors without appropriate structural corrections. In addition, our observation that stem, wood and bark models feature more stable parameters than crown, branch and foliage equations is consistent with Wang et al. [25], who confirmed components accounting for high biomass share and low inherent variability generally develop more robust allometric models.

In the compatible aboveground-biomass model system, precise compatibility between total and component biomass was achieved by constraining the sum of wood, bark, branch, and foliage to equal aboveground-biomass and estimating all component parameters through nonlinear errors-in-variables simultaneous equation estimation. This compatibility approach is particularly important for whole-tree biomass and carbon stock estimation, as it substantially reduces the risk of large divergences between predicted and observed values [34,35]. Residual analysis by diameter class showed occasional systematic biases but no significant heteroscedasticity, with residuals generally randomly distributed, indicating good overall fit, especially for wood components [36]. Our finding that species-specific biomass models have limited cross-regional adaptability is consistent with Lü et al. [34], who reported distinct regional differences in Chinese fir biomass equations. Compared with directly constructed independent aboveground biomass models, compatible models did not show reduced accuracy (with marginal differences only for the poplar foliage biomass model) but markedly enhanced biological consistency and interpretability. Despite increased model complexity, compatible models represent the preferred choice for production applications where consistency between total and component biomass and accurate representation of tree structural patterns are required [27,37].

4.3. Limitations and Prospects

Although we sampled trees across diverse DBH classes and growth conditions, the sampling design was not optimized for individual biomass components. As a result, crown, branch and foliage samples are less representative than stem samples, leading to lower fitting accuracy for branch and foliage models. This trend aligns well with Poudel et al. [38], who demonstrated that crown biomass is controlled by multiple canopy-related factors, and inadequate sampling representativeness severely restricts the precision of crown and branch biomass estimation. If precision for foliage and branch components

comparable to that of wood components is desired, sample sizes for these components should be significantly increased. Nevertheless, given that branch and foliage biomass merely accounts for 15%–20% of the total aboveground biomass, the current model accuracy is acceptable for routine forest production and management applications.

In this study, we selected DBH and total tree height as core predictors. Correlation analysis showed that both variables have strong correlations with tree biomass ($R^2 > 0.85$ for all three species). By contrast, crown width, crown length and stand volume show weak correlations or serious multicollinearity with biomass data, so we excluded redundant variables to keep models simple and field-applicable. It should be clearly stated that all model evaluations relied solely on leave-one-out cross-validation using local samples, and no independent external datasets were applied for further validation. This restricts the extrapolation ability of our models to regions with distinct site and stand conditions. In addition, root samples only accounted for one-third of all felled trees. Combined with the high environmental heterogeneity of underground parts, the limited root dataset resulted in relatively poor performance of root biomass models. Similarly, branch and foliage biomass are highly affected by canopy structure and light conditions. Constrained by sampling representativeness, their R^2 values only ranged from 0.35 to 0.74, much lower than those of stem and wood models. These inherent limitations should be fully considered in practical applications. We suggest expanding sampling for roots, branches and foliage, and collecting external samples for model validation in future research.

Regarding model selection and structural refinement, this study found that Model (2) generally produced better residual distributions than Model (1) for aboveground and root biomass, but Model (2) still exhibited biologically anomalous negative height effects in some cases—an issue not fully resolved by comparison with Model (1) and requiring further verification of biological validity in height interpretation mechanisms. Future model development should therefore include systematic testing of variable combinations (DBH, height, crown width, etc.) and comprehensive model diagnostics to ensure that model structure is fully consistent with biological mechanisms, thereby guaranteeing model reliability and interpretability.

For root biomass models, parameter C_v values generally exceeded 50%; although Model (22) achieved a relatively high R^2 , only a small number of sample trees were available for root biomass measurement, leading to sparse root dataset. Such modeling characteristics are consistent with the existing research conclusion [39], which confirmed root growth features are highly susceptible to environmental fluctuation and display obvious spatial divergence across different regions. Root excavation is labor-intensive and costly, and currently we only sample roots for part of the felled trees. Nevertheless, roots are a critical component of total biomass. We recommend conducting synchronous root sampling in future field surveys to improve root model stability and applicability.

We also conducted a comparison against the National Standard GB/T 43648–2024 (Biomass Models and Carbon Accounting Parameters for Major Tree Species). For Chinese fir and loblolly pine, the national models produced errors of $\pm 3\%$ to $\pm 5\%$ for total and aboveground biomass, while errors for branch and foliage exceeded 20%. For poplar, errors of total, aboveground and root biomass reached around 25%. These results reflect the poor cross-provincial transferability of national general models. Accordingly, future regional research in Hunan should supplement field measurements of branch, foliage and root biomass to develop locally calibrated models with improved adaptability and prediction accuracy.

In addition, this study did not quantitatively assess the uncertainty propagation from individual component biomass equations to total biomass estimates. Since errors from wood, bark, branch, foliage and root sub-models will accumulate and jointly affect the accuracy of total biomass prediction, future studies are suggested to conduct uncertainty

analysis across the full model system to further improve the reliability of model outputs for carbon accounting.

5. Conclusions

Based on 461 felled-tree samples from 14 prefecture-level cities and autonomous prefectures in Hunan Province, we established complete compatible biomass model systems for Chinese fir, Poplar and Oak via independent model screening and nonlinear errors-in-variables simultaneous equation fitting. These models effectively resolve the systematic estimation errors caused by direct application of national generalized models in this region. Most model parameters have a coefficient of variation (C_v) below 50%, and residuals are randomly distributed, indicating good statistical performance and biological rationality.

Stem, wood and bark (accounting for 70%–85% of aboveground biomass) show excellent model performance with $R^2 > 0.85$ and prediction accuracy over 95%. By comparison, branch and foliage models have lower R^2 (0.35–0.74) due to strong influences from the canopy environment, though MPSE values remained below 50%, which is acceptable for regional branch and foliage biomass estimation given their inherently large variability. Root biomass models yield R^2 values of 0.71–0.88 owing to environmental complexity and sampling difficulties; after dummy variable correction, their prediction accuracy exceeds 80%, which is adequate for regional belowground biomass estimation. All models only adopt easily measured DBH and tree height as predictors, avoiding complex field surveys and lowering inventory costs.

The compatible model system was locally calibrated for Chinese fir plantations, Poplar fast-growing plantations, and Oak natural forests in Hunan Province. It can provide a technical basis for accurate regional forest biomass estimation and forest resource monitoring.

Meanwhile, this study still has several limitations. All models were calibrated using samples collected only in Hunan Province. Therefore, additional adaptability tests are required before applying these models to areas with different site conditions. Expanding sampling coverage across more regions in future work will effectively enhance the general applicability of the proposed compatible model system.

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References

1. Beugnon, R.; Albert, G.; Hähn, G.; Yu, W.; Haider, S.; Hättenschwiler, S.; Davrinche, A.; Rosenbaum, B.; Gauzens, B.; Eisenhauer, N. Improving forest ecosystem functions by optimizing tree species spatial arrangement. *Nat. Commun.* **2025**, *16*, 6286. <https://doi.org/10.1038/s41467-025-61389-7>.
2. Sugiyama, A.; Game, E.T.; Wright, S.J. Planting exceptional tropical tree species to increase long-term carbon storage in assisted secondary succession. *J. Appl. Ecol.* **2024**, *61*, 7–12. <https://doi.org/10.1111/1365-2664.14533>.
3. Sun, X.; Wang, Z.; Chu, C.; Zhang, Y.; Chen, H. Contrasting controls on symbiotic and asymbiotic nitrogen fixation rates along altitudinal gradients in subtropical forests. *For. Ecosyst.* **2025**, *14*, 100335. <https://doi.org/10.1016/j.fecs.2025.100335>.
4. IPCC. 2022 IPCC Sixth Assessment Report; Cambridge University Press: Cambridge, UK, 2022. <https://doi.org/10.1017/9781009157926>.
5. Zhou, L.; Zhou, X.; He, Y.; Fu, Y.; Du, Z.; Lu, M.; Sun, X.; Li, C.; Lu, C.; Liu, R.; et al. Global systematic review with meta-analysis shows that warming effects on terrestrial plant biomass allocation are influenced by precipitation and mycorrhizal association. *Nat. Commun.* **2022**, *13*, 4914. <https://doi.org/10.1038/s41467-022-32671-9>.
6. Fang, J.Y.; Chen, A.P.; Peng, C.H.; Zhao, S.; Ci, L. Changes in forest biomass carbon storage in China between 1949 and 1998. *Science* **2001**, *292*, 2320–2322.
7. Zeng, W.S. Developing tree biomass models for eight major tree species in China. In *Biomass Volume Estimation and Valorization for Energy*; InTech: London, UK, 2017; pp. 3–21.
8. Luo, Y.; Wang, X.; Ouyang, Z.; Lu, F.; Feng, L.; Tao, J. A review of biomass equations for China's tree species. *Earth Syst. Sci. Data* **2020**, *12*, 21–40.
9. Parresol, B.R. Additivity of nonlinear biomass equations. *Can. J. For. Res.* **2001**, *31*, 865–878. <https://doi.org/10.1139/x00-202>.
10. Chave, J.; Réjou-Méchain, M.; Búrquez, A.; Chidumayo, E.; Colgan, M.S.; Delitti, W.B.; Duque, A.; Eid, T.; Fearnside, P.M.; Goodman, R.C.; et al. Improved allometric models to estimate the aboveground biomass of tropical trees. *Glob. Change Biol.* **2014**, *20*, 3177–3190. <https://doi.org/10.1111/gcb.12629>.
11. Zeng, W.S.; Luo, Q.B. On Method of Mathematical Modeling for Forestry Tables. *Cent. South For. Inventory Plan.* **2001**, *(2)*: 1–4. (Original in Chinese)
12. Xie, L.F.; Li, F.R.; Dong, L.H. Constructing biomass models for natural *Quercus mongolica* based on Bayesian seemingly unrelated regression. *Chin. J. Appl. Ecol.* **2022**, *33*, 1937–1947. <https://doi.org/10.13287/j.1001-9332.202207.019>.
13. Zhu, Y.L.; Zhang, J.L.; Zhang, H.F.; Gao, J.; Bao'erhan, D. Fitting Analysis of Spruce Accumulation and Aboveground Biomass Model in Xinjiang. *Chin. Wild Plant Resour.* **2024**, *43*, 100–106.
14. Yang, C.; Shi, Y.; Sun, W.; Zhu, J.; Ji, C.; Feng, Y.; Ma, S.; Guo, Z.; Fang, J. Updated estimation of forest biomass carbon pools in China 1977–2018. *Biogeosciences* **2022**, *19*, 2989–2999.
15. Zhu, Y.; Feng, Z.; Lu, J.; Liu, J. Estimation of Forest Biomass in Beijing (China) Using Multisource Remote Sensing and Forest Inventory Data. *Forests* **2020**, *11*, 163.
16. Luo, H.; Chen, J.; He, J.; Li, J.; Li, J.; Kang, W. Biomass Models and Ecosystem Carbon Density: A Case Study of Two Coniferous Forests in Northern Hunan, China. *Forests* **2023**, *14*, 814. <https://doi.org/10.3390/f14040814>.
17. Peng, S.; He, N.; Yu, G.; Wang, Q. Aboveground biomass estimation at different scales for subtropical forests in China. *Bot. Stud.* **2017**, *58*, 45. <https://doi.org/10.1186/s40529-017-0199-1>.
18. Wang, T.; Dong, L.; Liu, Z. Factors driving carbon accumulation in forest biomass and soil organic carbon across natural forests and planted forests in China. *Front. For. Glob. Change* **2024**, *6*, 1333868. <https://doi.org/10.3389/ffgc.2023.1333868>.
19. Zhu, G.; Hu, S.; Chhin, S.; Zhang, X.; He, P. Modelling site index of Chinese fir plantations using a random effects model across regional site types in Hunan province, China. *For. Ecol. Manag.* **2019**, *446*, 143–150. <https://doi.org/10.1016/j.foreco.2019.05.039>.
20. Wang, Z.; Yan, W.; Peng, Y.; Wan, M.; Farooq, T.H.; Fan, W.; Lei, J.; Yuan, C.; Wang, W.; Qi, Y.; et al. Biomass production and carbon stocks in poplar-crop agroforestry chronosequence in subtropical central China. *Plants* **2023**, *12*, 2451. <https://doi.org/10.3390/plants12132451>.
21. Yang, H.; He, H.M.; Huang, L.; You, W.; Tang, W.; Zhu, G. Crown diameter model of Hunan *Quercus* natural forest based on competition and site effect. *J. Cent. South Univ. For. Technol.* **2024**, *44*, 92–101, 155. <https://doi.org/10.14067/j.cnki.1673-923x.2024.06.009>.
22. Zhang, Y.; Liu, S.; Wang, Y.; Gao, H.; Jiang, Y.; Wei, D. Forest management practices and policies exert strong impacts on the spatio-temporal variations of forest disturbance in Hunan Province, China over the last three decades. *For. Ecol. Manag.* **2023**, *544*, 121167. <https://doi.org/10.1016/j.foreco.2023.121167>.

23. Li, Z.; Zheng, K.; Zhong, Q. Comprehensive Evaluation and Spatial–Temporal Pattern of Green Development in Hunan Province, China. *Sustainability* **2022**, *14*, 6819. <https://doi.org/10.3390/su14116819>.
24. Chen, L.C.; Guan, X.; Li, H.M.; Wang, Q.-K.; Zhang, W.-D.; Yang, Q.-P.; Wang, S.-L. Spatiotemporal patterns of carbon storage in forest ecosystems in Hunan Province, China. *For. Ecol. Manag.* **2019**, *432*, 656–666. <https://doi.org/10.1016/j.foreco.2018.09.059>.
25. Wang, P.F.; Dong, L.H.; Xie, L.F.; Miao, Z. Biomass model construction for artificial *Larix olgensis* plantations using hierarchical Bayesian seemingly unrelated regression. *Chin. J. Appl. Ecol.* **2025**, *36*, 1298–1308. <https://doi.org/10.13287/j.1001-9332.202505.006>.
26. Lehtonen A, Palviainen M, Ojanen, P.; Kallioikoski, T.; Nöjd, P.; Kukkola, M.; Penttilä, T.; Mäkipää, R.; Leppälammi–Kujansuu, J.; Helmisaari, H.-S. Modelling fine root biomass of boreal tree stands using site and stand variables. *For. Ecol. Manag.* **2016**, *359*, 361–369.
27. Forrester, D.I.; Tachauer, I.H.H.; Annighoefer, P.; Barbeito, I.; Pretzsch, H.; Ruiz–Peinado, R.; Stark, H.; Vacchiano, G.; Zlatanov, T.; Chakraborty, T.; et al. Generalized biomass and leaf area allometric equations for European tree species incorporating stand structure, tree age and climate. *For. Ecol. Manag.* **2017**, *396*, 160–175. <https://doi.org/10.1016/j.foreco.2017.04.011>.
28. Li, J.Y.; Ruan, H.Y.; Qiu, S.Y.; Liang, R.; Zhu, Z.; Wen, Y.; Wang, C.; Wang, Y.; Sun, Y. Comparative study on biomass estimation of Chinese fir plantations based on empirical and process-based models. *Acta Ecol. Sin.* **2024**, *44*, 3502–3514. <https://doi.org/10.20103/j.stxb.202304250868>.
29. Yu, Y.; Zhou, Z.; Sharma, R.P.; Zhang, L.; Du, M.; Zhang, H. Comparing crown ratio models for spruce–fir broadleaved mixed forests using beta regression and random forest algorithm. *Comput. Electron. Agric.* **2024**, *225*, 109302. <https://doi.org/10.1016/j.compag.2024.109302>.
30. González–Benecke, C.A.; Fernández, M.P.; Gayoso, J.; Pincheira, M.; Wightman, M.G. Using Tree Height, Crown Area and Stand–Level Parameters to Estimate Tree Diameter, Volume, and Biomass of *Pinus radiata*, *Eucalyptus globulus* and *Eucalyptus nitens*. *Forests* **2022**, *13*, 2043. <https://doi.org/10.3390/f13122043>.
31. Liu, B.; Bu, W.; Zang, R. Improved allometric models to estimate the aboveground biomass of younger secondary tropical forests. *Glob. Ecol. Conserv.* **2023**, *41*, e02359. <https://doi.org/10.1016/j.gecco.2022.e02359>.
32. Zou, W.T.; Zeng, W.S.; Zhang, L.J.; Zeng, M. Modeling Crown Biomass for Four Pine Species in China. *Forests* **2015**, *6*, 433–449. <https://doi.org/10.3390/f6020433>.
33. Xiang, W.; Li, L.; Ouyang, S.; Xiao, W.; Zeng, L.; Chen, L.; Lei, P.; Deng, X.; Zeng, Y.; Fang, J.; et al. Effects of stand age on tree biomass partitioning and allometric equations in Chinese fir (*Cunninghamia lanceolata*) plantations. *Eur. J. For. Res.* **2021**, *140*, 317–332. <https://doi.org/10.1007/s10342-020-01333-0>.
34. Lü, Z.; Duan, A. Biomass and Carbon Storage Model of *Cunninghamia lanceolata* in Different Production Areas. *Sci. Silvae Sin.* **2024**, *60*, 1–11.
35. Lin, Z.; Hong, T.; Hong, W.; Wu, C. Compatible Models of Carbon Content of Individual Trees on a *Cunninghamia lanceolata* Plantation in Fujian Province, China. *PLoS ONE*, **2016**, *11*, e0151527.
36. Zhao, D.; Lynch, T.B.; Westfall, J.A.; Coulston, J.W. Additional biomass estimation alternatives: Nonlinear two- and three-stage least squares and full information maximum likelihood for slash pine. *Can. J. For. Res.* **2022**, *52*, 780–793. <https://doi.org/10.1139/cjfr-2021-0335>.
37. Zhao, H.B.; Zhou, G.Y.; Li, Z.J.; Qiu, Z.; Wu, Z.; Wang, X. Biomass allocation characteristics and allometric growth models for four common tree species in south subtropical evergreen broad-leaved forests. *Sci. Silvae Sin.* **2022**, *58*, 23–31.
38. Poudel, K.P.; Temesgen, H.; Gray, A.N. Evaluation of sampling strategies to estimate crown biomass. *For. Ecosyst.* **2015**, *2*, 1. <https://doi.org/10.1186/s40663-014-0025-0>.
39. Carvalho, J.I.; Carayugan, M.B.; Tran, L.T.N.; Hernandez, J.O.; Bin Youn, W.; An, J.Y.; Park, B.B. Variation in Root Biomass and Distribution Based on the Topography, Soil Properties, and Tree Influence Index: The Case of Mt. Duryun in Republic of Korea. *Plants* **2024**, *13*, 1340. <https://doi.org/10.3390/plants13101340>.

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