Allometric Models for Aboveground Biomass of Six Common Subtropical Shrubs and Small Trees

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Research

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Abstract

Background: The aboveground biomass (AGB) of shrubs and small trees is the main component for the productivity and carbon storage of understory vegetation in subtropical natural secondary forests. However, few allometric models exist for shrubs and small trees, even though they can accurately evaluate understory vegetative biomass.

Methods: To estimate the ABG of six common shrub and small tree species, we utilized harvesting to sample 206 individuals, and developed species-specific and multi-species allometric models based on four predictors including height (H), stem diameter (D), crown area (Ca), and wood density (ρ).

Results: As expected, these six shrub and small tree species possessed greater biomass in their stems in contrast to branches, with the lowest biomass in the leaves. Species-specific allometric models that employed D and the combined variables of D^2H and ρDH as predictors, could accurately estimate the components and total AGB, with R^2 values ranging from between 0.602 and 0.971. A multi-species shrub allometric model revealed that ρDH was the best predictor, with R^2 values ranging from between 0.809 and 0.890.

Conclusions: These results indicated that H and D were effective predictors for the models to estimate the AGB of the six shrub and small tree species, and the introduction of ρ improved their accuracy. The optimal model selected in this study could be applied to estimate the biomass of shrubs and small trees in the subtropical regions.

1. Introduction

Shrubs (stem ramifications < 1.3 m, < 5 m high) and small trees (stem ramifications > 1.3 m, < 8 m high) (Mbow et al. 2014, Bayen et al. 2020) are important components of understory vegetation (MacDonald et al. 2012, Flade et al. 2020). Shrubs and small trees are the main carbon sinks of forest vegetation, particularly in the early stages of forest stand succession, which can quickly absorb and release nutrients within the soil, thereby accelerating the carbon cycle between vegetation and soil (Cavard et al. 2011, Kumar et al. 2018). Consequently, an accurate assessment of the biomass of shrubs and small trees is critical for the estimation of carbon storage in ecosystems.

The most accurate technique for estimating the biomass of individual trees or shrubs is direct harvesting and weighing. However, this strategy is only suitable at a small-scale due to its being labor intensive and time-consuming (MacDonald et al. 2012, Ali et al. 2015). Furthermore, the large-scale harvesting of shrubs and small trees reduces vegetation coverage, increases the risk of soil erosion, and destroys wildlife habitats (Cavard et al. 2011, Donato et al. 2012, Brantley et al. 2016). Allometric models with easily measurable predictors can be used to quickly estimate the aboveground and belowground biomass of plants without damaging them (Djomo et al. 2010, Roxburgh et al. 2015, Bayen et al. 2020, Brassard et al. 2011).

As the primary component of forest carbon storage, large trees have been studied by many researchers toward the establishment of allometric models (Cairns et al. 2009, Cavanaugh et al. 2014, Jagodzinski et al. 2019). Due to the morphological differences in growth between large trees, small trees, and shrubs, large tree equations are not suitable for calculating the biomass of shrubs and small trees (Bond-Lamberty et al. 2002). Consequently, it is necessary to generate allometric equations that can approximate their biomass (Chave et al. 2005).

When estimating the biomass of multi-branched shrubs, stem height (H) is typically regarded as a quantifiable measurement factor for the development of allometric equations (Chaturvedi et al. 2013, Chave et al. 2014). Some researchers have also considered the stem diameter (D) and crown area (Ca) of shrubs, whereas others have included the combined variable, D^2H, as a predictor (Elzein et al. 2011, Liu et al. 2015, Huff et al. 2018). Moreover, the addition of wood density (ρ) might significantly improve the estimation of tree biomass (Ali et al. 2015). In particular, generalized allometric models that included D, H, and ρ have been reported to have more stability and less uncertainty, particularly for mixed species models (Alvarez et al. 2012).

Generally, the regression equation of a biomass allometric model is constructed by employing power (Paul et al. 2013), linear, and power exponential functions (Sharma et al. 2011, Dou et al. 2019) with measurement factors as variables. Nonlinear models are more likely to accurately fit the relationship between the measurement factors and biomass than linear models (Chapagain et al. 2014).

The objective of this study was to develop species-specific and multi-species allometric models for the prediction of branch, stem, leaf, and total aboveground biomass for the most dominant species of the forest understorey in subtropical China. To ensure the accuracy of the models, we measured as many samples (206) of shrubs and small trees as possible when collecting data. When developing models, we selected single variable D, H, Ca, ρ, and complex variables D^2H and ρDH and compared the resulting models for their predictive power.

2. Materials And Methods

2.1. Study Area

The plant component AGB was derived from shrubs and small trees growing in the natural secondary forests of Qiaomu Township, located 22 km northeast of Qingyang County (30°19'N to 30°50' and 117°40' to 118°07'E), in Anhui Province, China. This region is home to a subtropical humid monsoon climate with average temperatures of 28°C and 3°C during the summer and winter months, respectively, which is suitable for the support of a rich and sustainable carbon sink (Yu et al. 2014). The elevation of this area ranges from 44.6–104.1 m, with an average annual precipitation of 1374.7 mm. The soil type is brown calcareous (IUSS Working Group WRB 2014) and the thicknesses ranges from 20 cm to 100 cm.

The vegetation type of the study area is subtropical deciduous broadleaved forest, and the typical overstorey is dominated by *Liquidambar formosana*, *Quercus acutissima Carruth*, and *Castanea mollissima*. Common understorey shrubs and herbaceous species in the study area include *Lindera fruticosa*, *Diospyros rhombifolia*, *Acer ginnala*, *Liriope graminifolia*, *Liriope muscari*, and *Microlepia marginata*.

2.2. Sampling design

Five shrub species (*Acer ginnala*, *Diospyros rhombifolia*, *Rhododendron ovatum*, *Camellia cuspidate*, and *Lindera fruticosa*) and one small tree species (*Dendrobenthamia japonica*), which are widely distributed in subtropical natural secondary broadleaved mixed forests, were selected to develop allometric biomass models. We sampled 24 stands from natural secondary broadleaved mixed forests following the cessation of anthropogenic disturbances (e.g., selective harvesting, firewood collection, and grazing) to allow for regrowth (Yang et al. 2021). In each stand, we established a 20 × 20 m^2 plot and the distance between the sample plots was > 100 m. For each species, we selected ~ 35 individuals and a total of 206 individuals of six species from the 24 plots. Individuals were selected to represent the range of heights and diameters of the entire population as closely as possible. All field surveys were conducted in mid-August 2020.

2.3. Field data collection

Prior to the harvesting of any shrub or small tree, we measured the height (H), crown area (Ca), and stem diameter (D). H was defined as the distance between the ground and the highest point of the canopy. Ca encompassed two directions, the maximum diameter of the crown (d1), and perpendicular diameter to d1 (d2).

$$Ca = \pi \times \frac{d1 \times d2}{4} \quad (1)$$

D was different for shrubs and small trees, where the stem diameter was measured at 130 cm and 10 cm above the root collar for small trees and shrubs, respectively. Each harvested sample was separated into stems, branches, and leaves, stored in sealed bags, and then transferred to the laboratory for analysis within three days.

2.4. Laboratory analysis

All laboratory analyses were completed at Anhui Agricultural University in Heifei, Anhui, China. The fresh weight (0.01g) of each component was measured using an electronic balance. To determine the specific wood density (ρ = dry weight/green volume in g cm^{-3}) 2–6 wood samples were extracted from the transverse sections of the trunks and branches of each tree (Yepes et al. 2016). All samples were then dried at 105°C in a drying oven for 48–72 hours to a constant weight. The dry weight (0.01g) of each component of each species was weighed using an electronic balance. Finally, we obtained the biomass of each component (leaf biomass (LB); branch biomass (BB); stem biomass (SB)); total aboveground biomass (AGB, Table 1); and plant component aboveground biomass as a percentage of the AGB per plant species.

2.5. Data analysis

We compared the biomass of aboveground plant components (e.g., leaves, branches, stems, and aboveground parts) with selected independent variables (D, H, Ca, D^2H, and ρDH) using graphs and correlation coefficients to determine the nature of the correlation. Correlation analysis indicated that D, D^2H, and ρDH explained most of the biomass variations (Fig. S1).

Linear and nonlinear regression analyses were employed for examining the relationships between aboveground biomass components and the measured variables, including D, H, Ca, ρ, D^2H, and ρDH, which were performed using the '*basictrendline*' Package (Mei et al. 2018). By comparing the regression coefficients (R^2) and Akaike Information Criterion (AIC) of the regression model (Ruiz-Peinado et al. 2012), the following equations were presented for describing the relationships between the aboveground biomass components:

$W = ax + b$ (8)

$W = ax^2 + bx + c$ (9)

$W = ax^b$ (10)

where W is the dependent variable (LB, BB, SB, and AGB), x is the independent variable (D, H, Ca, ρ, D^2H, or ρDH), and a, b, and c are the allometric coefficients. All statistical analyses were performed in R (version 4.0.4).

3. Results

3.1. Aboveground biomass allocation

The distribution ratios of the total biomass of leaves, branches, and stems of the six shrub and small tree species were evaluated. Comparatively, these six species allocated the most biomass to stems, with the least biomass in the leaves. In contrast to other species, *Dendrobenthamia japonica* better reflected this phenomenon; however, the distribution of *Acer ginnala* in each component was relatively even (Fig. 1).

3.2. Allometric biomass model

We employed linear regression and nonlinear regression models to estimate the biomass of each species. The higher R^2 and lower AIC values of all optimization models indicated that the model had improved utility. For the species-specific model, the single variable D and complex variables D^2H and ρDH had the best predictive effects for the biomass of the six species (Table 3). For *Acer ginnala*, *Diospyros rhombifolia*, and *Dendrobenthamia japonica*, D^2H was the best predictor of SB and AGB (R^2 = 0.858 ~ 0.971 and R^2 = 0.908 ~ 0.961; $P < 0.001$, respectively). D had the best predictive effect for the leaf biomass of the five species (R2 = 0.602 ~ 0.93; $P < 0.001$) and also performed well for the AGB of *Lindera fruticosa* and *Diospyros rhombifolia* (R^2 = 0.937 and R^2 = 0.892; $p < 0.001$). For *Rhododendron ovatum*, ρDH accounted for more than 90% of the variations in the BB (R = 0.904; $P < 0.001$), SB (R = 0.945; $P < 0.001$), and AGB (R = 0.961; $P < 0.001$).

Similar to the species-specific allometric models, ρDH was the best predictor for biomass with the pooled data of all shrub

inclusion of ρ to the independent variable improved the prediction accuracy of

the model (Fig. 2). As the best predictor for multi-species aboveground biomass regression models ρDH explained 80.9%, 85.1%, 88.3%, and 89.0% of the variations of LB ($R = 0.809$; $P < 0.001$), BB ($R = 0.851$; $P < 0.001$), SB ($R = 0.883$; $P < 0.001$), and AGB ($R = 0.890$; $P < 0.001$), respectively (Table 3).

4. Discussion

During plant growth and development, biomass is accumulated in the form of organic matter through plant photosynthesis, where additional biomass is distributed into the stems to increase their length to obtain more light, toward potentially gaining a competitive advantage over other trees (Nam et al. 2018, Bayen et al. 2020). In this study, the biomass of the stems of six shrub and small tree species exceeded that of the branches and leaves, and accounted for more than 50% of the total aboveground biomass, except for *Acer ginnala*, which was consistent with many previous results (Singh et al. 2011, Bayen et al. 2020).

Based on the established six specific species and one mixed species model, D, D^2H, and ρDH were the best factors for forecasting the aboveground biomass of shrubs. As distinct from Vu Thanh Nam's method (2018), we employed a single independent variable (single variable D, H, Ca, ρ; compound variables D^2H, ρDH) as a predictor in the model, which made the process simpler and more convenient in operation. We observed from the optimal model, even though we employed a single variable, that it still had a satisfactory prediction accuracy, and the R^2 of all models was > 0.6 (Table 3).

In terms of model fitting accuracy, Ca did not perform well (Table. S1), and was shown to be inconsistent with some research (Conti et al. 2013, She et al. 2015, Yang et al. 2017). This was because, unlike desert shrubs and subtropical grassland plants (She et al. 2015, Bayen et al. 2020), the crown structures of subtropical shrubs and small trees are irregular in their natural state, which translates to a decrease in the capacity of Ca to predict the biomass of shrub branches and leaves (Poorter et al. 2012, Liu et al. 2015). However, the addition of H to the models developed for the shrubs was reasonable; it improved model accuracy when combined with D and ρ, although the correlation between the H and biomass was lower than Ca (Table 2, Table 3 and Fig. S1). Consistent with previous studies, D^2H was one of the best predictors of shrub and small tree biomass (Alvarez et al. 2012, Liu et al. 2015, Dou et al. 2019).

When another variable (ρDH) was employed to predict biomass, the model was better than D and H, particularly for shrub mixed multi-species models. According to previous studies, ρ was one of the most important characteristics of tree species, which had obvious differences between various species. We introduced ρ as a predictor directly into the model with reference to previous research methods; however, the results were not satisfactory (Table. S1). Compared with D and H, the intraspecies variation in ρ was negligible and could be regarded as almost constant (Francis et al. 2017, Nelson et al. 2020). Thus, we attempted to create a new combined entity (ρDH) as a predictor variable.

From the results, the introduction of ρ reduced SEE and increased R^2, which indicated that the inclusion of ρ enhanced the accuracy of the model, which aligned well with the work of Ali (2015). Many studies have indicated that ρ is an essential factor for improving model accuracy (Yepes et al. 2016, Kebede et al. 2018). Furthermore, it was indicated that ρ had enhanced relevance in mixed models, as it was believed to augment the differences in the physiological structures and functional characteristics of tree species (Xu et al. 2015, Nam et al. 2018). Taking ρ as a portion of the independent variable can reduce the errors caused by D and H in the measurement to a certain extent, as well as the influences of morphological differences on the accuracy of multi-species models (Pilli et al. 2006, Zeng et al. 2017).

Comparing the accuracy of a model in estimating the biomass of a component of the same tree species, the allometric model possessed a higher predictive ability for wood organs (stems and branches) than leaves. Some studies attributed the low predictive power of leaf biomass models to the ephemeral nature of leaves and their destruction by herbivores (Roxburgh et al. 2015, Sanquetta et al. 2015, Bayen et al. 2020). The accuracy of the allometric leaf model of evergreen shrubs in this

ubs, which appeared to confirm this assumption.

Due to the difficulties involved with fully excavating the root biomass (particularly fine roots), only the aboveground biomass was considered in our research, which might have translated to limitations in the application of the equations. We acknowledge that our developed models were based on a small number of individual samples (i.e., 32 to 38 individuals per species). Therefore, we do not recommend the use of predictive models for tree species beyond the range of predictor variables, which will likely cause significant errors in the estimated values.

5. Conclusion

This study sampled six common subtropical shrubs and small trees to develop an allometric species-specific and multi-species shrub model for biomass organs (e.g., leaves, branches, stems, and total aboveground biomass), where D, H, and ρ were employed as easily measurable predictors. Variables that had strong correlations with biomass might be used as basic indicators to establish allometric models. The species-specific allometric models developed in this study, with D and D^2H as predictors, accounted for a high variation (60.2–97.1%) in the AGB of shrubs and small trees.

The inclusion of ρ as a predictive variable improved the accuracy of the multi-species shrub model. Further, ρDH played a significant role in the allometric models of specific and multiple species. The good predictive capacities of the allometric equations used in this study might be extended to the allometric models of other tree species. In the absence of a specific allometric equation, the multi-species allometric equation was an appropriate choice (under the condition of confirming the variable range). In contrast to species-specific allometric models, optimal multi-species estimation models also had a fit accuracy for all components and total shrub biomass. This indicated that the multi-species model might expedite the estimation of shrub biomass, which can translate to savings in time and manpower. In short, the results of this investigation might facilitate the rapid non-destructive acquisition of biomass estimates for subtropical shrubs and small trees.

Abbreviations

H: total height (m); D: stem diameter; Ca: canopy area; ρ: basic wood density; LB: leaf biomass; BB: branch biomass (kg); SB: stem biomass; AGB: aboveground biomass; A.g: *Acer ginnala*; D.r: *Diospyros rhombifolia*; R.o: *Rhododendron ovatum*; C.c: *Camellia cuspidate* ; L.f: *Lindera fruticose*; D.j: *Dendrobenthamia japonica*; AIC: Akaike information criterion; SEE: standard error of the estimation; CF: correction factor.

Declarations

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Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Competing interests

The authors declare no competing interests.

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Tables

Table 1. Summary of the range values (min-max) of biometric variables of the six woody species.

Species	n	D (cm)	H (m)	Ca (m^2)	ρ (g/ cm^3)	LB (kg)	BB (kg)	SB (kg)	AGB (kg)
Acer ginnala	32	0.42 - 4.03	0.84 - 4.60	0.02 - 2.79	0.51(0.01)	0.001 - 0.167	0.003 - 0.343	0.001 - 0.397	0.003 - 0.884
Diospyros rhombifolia	35	0.60 - 2.45	1.04 - 3.78	0.03 - 2.24	0.55(0.01)	0.004 - 0.062	0.001 - 0.291	0.009 - 0.411	0.015 - 0.760
Rhododendron ovatum	36	0.99 - 4.79	1.42 - 3.47	0.10 - 2.26	0.65(0.01)	0.009 - 0.177	0.011 - 0.509	0.027 - 0.887	0.056 - 1.563
Camellia cuspidata	33	0.81 – 4.93	0.72 - 4.90	0.11 - 6.18	0.70(0.02)	0.007 - 0.516	0.006 - 1.076	0.017 - 1.607	0.031 - 3.120
Lindera fruticosa	38	0.24 - 2.57	0.51 - 4.23	0.02 - 4.54	0.39(0.02)	0.002 - 0.097	0.001 - 0.235	0.001 - 0.354	0.002 - 0.678
Dendrobenthamia japonica	33	1.35-5.82	2.05-7.23	0.17-7.69	0.43(0.01)	0.005-0.451	0.015-0.739	0.044 - 2.369	0.081 - 3.560

Note: n, number of individuals per species; H, total height (m); D, stem diameter (cm); Ca, canopy area (m^2); ρ, basic wood density (g/m^3); LB, leaf biomass (kg); BB, branch biomass (kg); SB, stem biomass (kg); AGB, measurement of all aboveground biomass (kg). Values in brackets represent the standard deviation (SD).

Table 2. Best fit species-specific regression models for the prediction of the aboveground biomass.

Species	Variate	Equations	x	a	b	c	R^2	AIC	SEE	CF
Acer ginnala	LB	$Y = ax^b$	ρDH	0.0107	1.2995		0.717***	-144	0.0241	1.000
	BB	$Y = ax^b$	ρDH	0.0281	1.2997		0.883***	-113	0.039	1.000
	SB	$Y = ax^b$	D^2H	0.0127	0.8865		0.905***	-118	0.0357	1.000
	AGB	$Y = ax^2+bx+c$	D^2H	-0.0002	0.0264	0.0014	0.908***	-64	0.0823	1.003
Diospyros rhombifolia	LB	Y = ax+b	D	0.0269	0.0115		0.602**	-216	0.0105	1.000
	BB	$Y = ax^b$	D	0.0258	2.3461		0.762***	-138	0.032	1.001
	SB	Y = ax+b	D^2H	0.0204	0.0067		0.858***	-120	0.0413	1.001
	AGB	$Y = ax^b$	D	0.0855	2.3190		0.892***	-95	0.0592	1.001
Rhododendron ovatum	LB	Y = ax+b	D	0.0411	-0.0360		0.753***	-172	0.0196	1.000
	BB	$Y = ax^2+bx+c$	ρDH	-0.0011	-0.0622	-0.0584	0.904***	-131	0.0348	1.001
	SB	$Y = ax^2+bx+c$	ρDH	-0.0013	0.1041	-0.0843	0.945***	-111	0.0461	1.001
	AGB	$Y = ax^2+bx+c$	ρDH	-0.0026	0.1850	-0.1480	0.961***	-86	0.0662	1.002
Camellia cuspidate	LB	$Y = ax^b$	D	0.0222	2.0255		0.930***	-117	0.0385	1.001
	BB	$Y = ax^2+bx+c$	ρDH	-0.0018	0.0970	-0.1205	0.868***	-47	0.0110	1.006
	SB	$Y = ax^2+bx+c$	D^2H	-0.0001	0.0263	0.0048	0.952**	-53	0.1010	1.005
	AGB	$Y = ax^2+bx+c$	D^2H	-0.0002	0.0533	-0.0199	0.947***	-5	0.2080	1.022
Lindera fruticosa	LB	Y = ax+b	D	0.0432	0.0212		0.680***	-213	0.0139	1.001
	BB	$Y = ax^b$	D	0.0192	2.6443		0.913***	-207	0.015	1.000
	SB	$Y = ax^b$	D^2H	0.0359	0.7234		0.925***	-178	0.022	1.000
	AGB	$Y = ax^2+bx+c$	D	0.0774	0.0786	-0.0530	0.937***	-136	0.0379	1.001
Dendrobenthamia japonica	LB	$Y = ax^b$	D	0.0057	2.4503		0.862***	-127	0.0333	1.001
	BB	$Y = ax^b$	D^2H	0.0118	0.7686		0.861***	-79	0.0686	1.002
	SB	$Y = ax^b$	D^2H	0.0267	0.8168		0.971***	-66	0.0844	1.004
	AGB	$Y = ax^b$	D^2H	0.0420	0.8099		0.962***	-28	0.1490	1.011

Note: H, total height; D, diameter of the longest stem; ρ, wood density; LB, leaf biomass; BB, branch biomass; SB, stem

a, b, c, allometric coefficients; R^2, coefficient of determination; AIC, Akaike

information criterion; SEE, standard error of the estimation; CF, correction factor. ***, $p < 0.001$; **, $p < 0.01$

Table 3. Best fitted multi-species regression models for the prediction of aboveground biomass.

Species	Variety	Equations	x	a	b	R^2	AIC	SEE	CF
Multi-species	LB	$Y = ax^b$	ρDH	0.0132	1.3146	0.809**	-674	0.034	1.001
	BB	$Y = ax^b$	ρDH	0.0338	1.2282	0.851***	-461	0.063	1.001
	SB	$Y = ax^b$	ρDH	0.0523	1.2398	0.883***	-357	0.085	1.005
	AGB	$Y = ax^b$	ρDH	0.0994	1.2464	0.890***	-140	0.160	1.013

Note: H, total height; D, diameter of the longest stem; ρ, wood density; LB, leaf biomass; BB, branch biomass; SB, stem biomass; AGB, total aboveground biomass; a, b, allometric coefficients; R^2, coefficient of determination; AIC, Akaike information criterion; SEE, standard error of the estimation; CF, correction factor. ***, $p < 0.001$

Figures

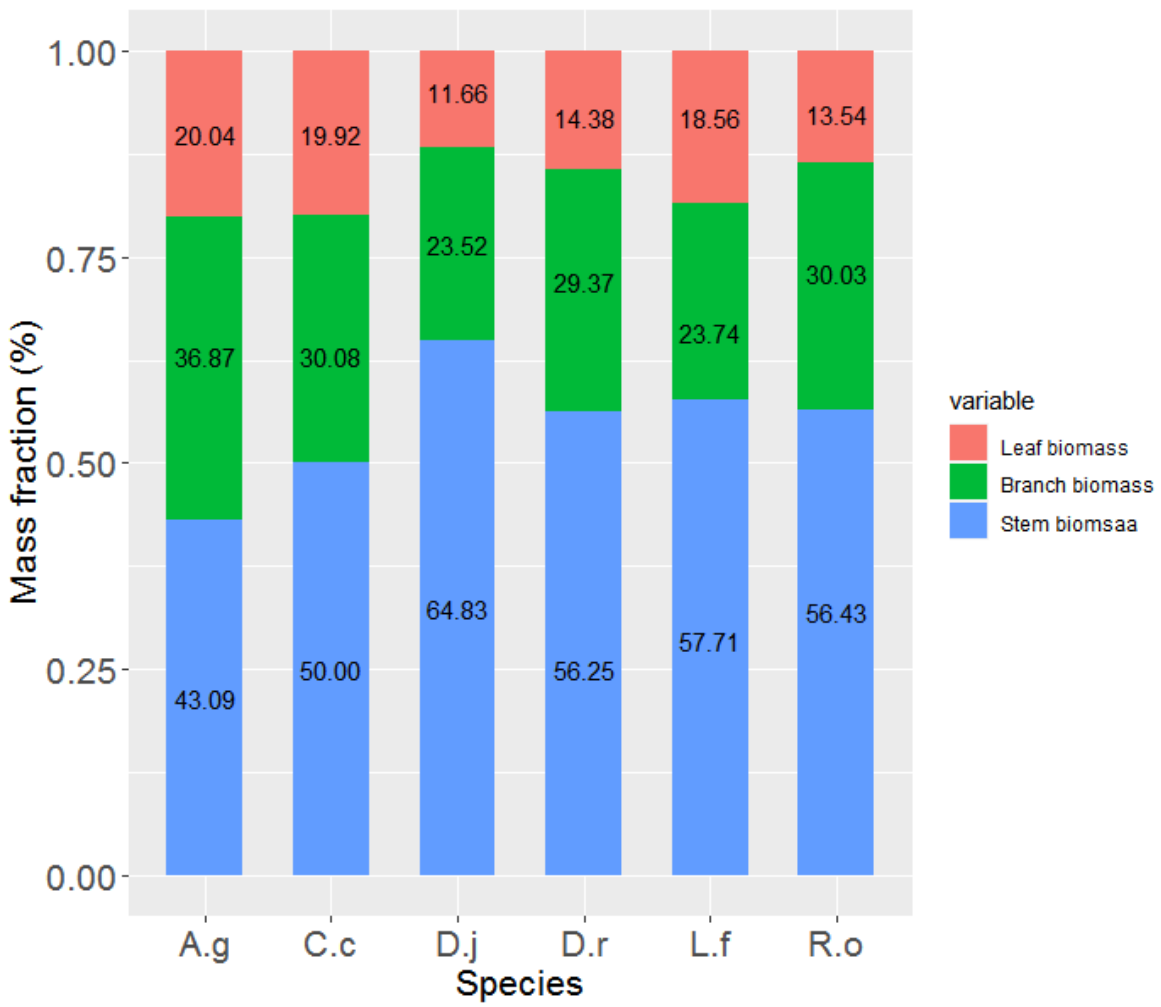

Figure 1

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Aboveground biomass allocation (%) of branches, leaves, and stems in the six shrub and tree species. A.g (Acer ginnala), D.r (Diospyros rhombifolia); R.o (Rhododendron ovatum); C.c (Camellia cuspidata); L.f (Lindera fruticosa); D.j (Dendrobenthamia japonica). Values are means ±95% bootstrapped confidence intervals.

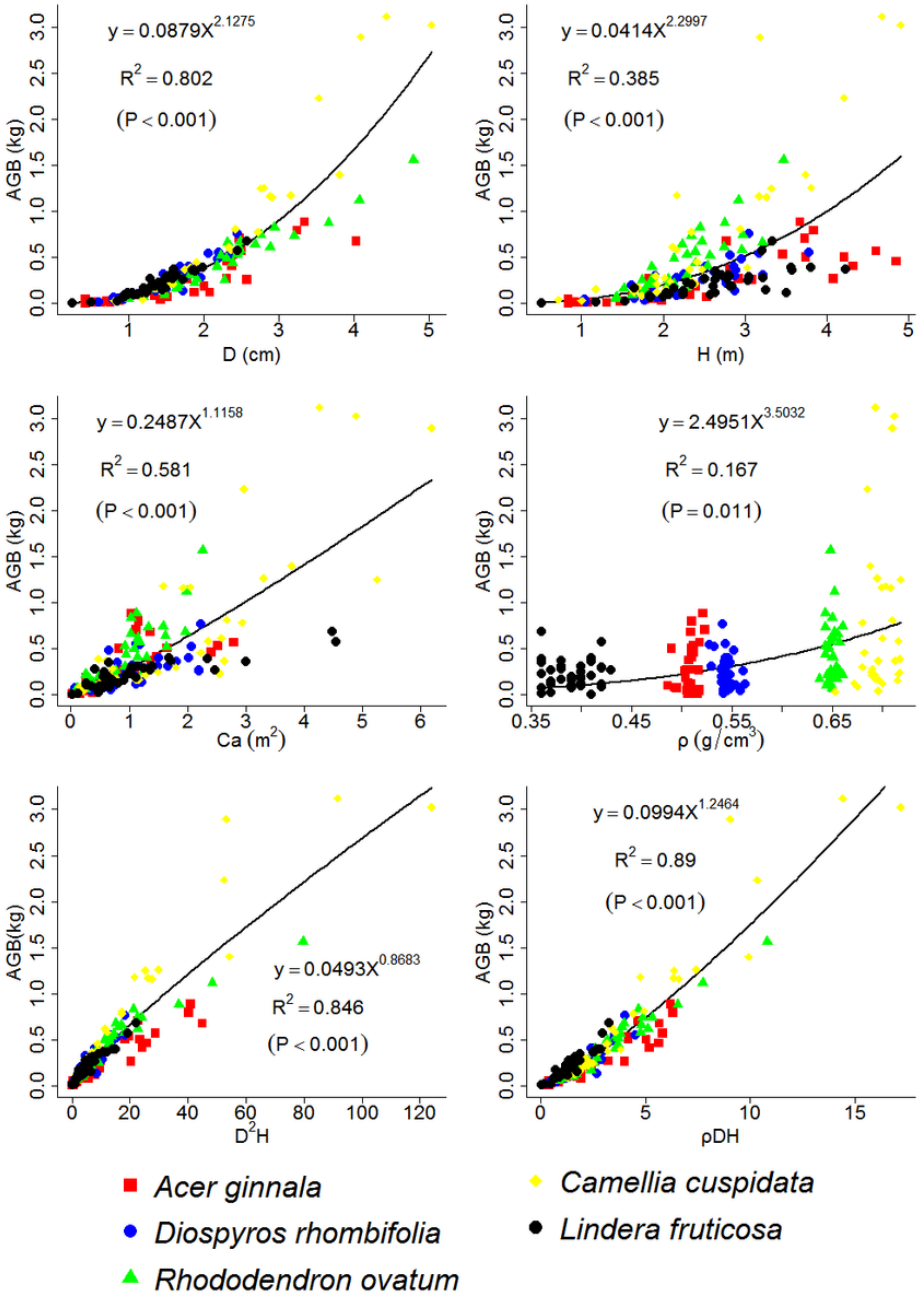

Figure 2

Relationship between ABG (the total aboveground biomass), D (diameter of the longest stem), H (height), Ca (crown area), D2H, and ρDH for the six selected shrub and small tree species. Different symbols represent individual species, whereas the trend line represents the power function (Y = axb).

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