Allometric models for aboveground biomass of six common subtropical shrubs and small trees

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Abstract  The aboveground biomass (AGB) of shrubs and small trees is the main component for the productivity and carbon storage of understory vegetation in subtropical secondary forests. However, few allometric models exist to accurately evaluate understory biomass. To estimate the AGB of five common shrub (diameter at base < 5 cm, < 5 m high) and one small tree species (< 8 m high, tree’s seedling), 206 individuals were harvested and species-specific and multi-species allometric models developed based on four predictors, height (H), stem diameter (D), crown area (Ca), and wood density (ρ). As expected, the six species possessed greater biomass in their stems compared with branches, with the lowest biomass in the leaves. Species-specific allometric models that employed stem diameter and the combined variables of D2H and ρDH as predictors accurately estimated the components and total AGB, with $R^2$ values from 0.602 and 0.971. A multi-species shrub allometric model revealed that wood density × diameter × height (ρDH) was the best predictor, with $R^2$ values ranging from between 0.81 and 0.89 for the components and total AGB, respectively. These results indicated that height (H) and diameter (D) were effective predictors for the models to estimate the AGB of the six species, and the introduction of wood density (ρ) improved their accuracy. The optimal models selected in this study could be applied to estimate the biomass of shrubs and small trees in subtropical regions.

Keywords  Aboveground biomass · Allometric models · Shrubs · Small trees · Subtropical forests

Introduction

Shrubs (diameter at base < 5 cm, < 5 m high) and small trees (< 8 m high, tree’s seedling) (Mbou 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 components of carbon sinks of forest vegetation in the forest succession and can rapidly absorb and release nutrients within the soil, thereby accelerating the carbon cycle between vegetation and soil (Cavard et al. 2011). 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 tree or shrub species is direct harvesting and weighing. However, this 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, large-scale harvesting of shrubs and small trees reduces vegetation cover, 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 destructive harvesting (Djomo et al. 2010; Roxburgh et al. 2015; Bayen et al. 2020). As the primary component of forest carbon storage, large trees have been studied by many researchers for the development 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 shrub and small tree biomass. Consequently, it is necessary to generate more specific allometric equations that can approximate their biomass (Chave et al. 2005).

When estimating the biomass of multi-branched shrubs, stem height (H) is regarded as a quantifiable measurement for the development of allometric equations (Chaturvedi and Raghubanshi 2013; Chave et al. 2014). Some researchers have also considered stem diameter (D) and crown area (Ca) of shrubs, whereas others have included the combined variable, D2H, 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 small tree and shrub 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).

Allometric models that address the need to accurately measure the impacts of forest restoration and succession on the biomass of populations are required in subtropical forests. A number of allometric models have recently been developed by Liu et al. (2015) and Yang et al. (2017) for desert and subalpine small trees and shrubs; however, these models are not suitable for subtropical forests. Ali et al. (2015) developed a set of six mixed-species equations for woodlands based on studies in the Tiantong National Forest Park community in Zhejiang Province, China, which provided a reference for our research in terms of research methods but did not include the regional variations of our study area in terms of tree species composition (Guedes et al. 2018).

The specific objectives of this study were to: (1) assess and compare the patterns of biomass allocation to aboveground components between species; (2) develop species-specific and multi-species allometric models to facilitate the prediction of branch, stem, leaf, and total aboveground biomass (AGB) for the most dominant species of the forest understory; (3) to quantify any bias of the recommended models and test against direct measurements of AGB obtained across a range of contrasting sites; and, (4) compare the modeling method and model accuracy of this study with the established multi-species model. To ensure the accuracy of the models, 206 shrubs and small trees samples were measured when collecting data. When developing the models, single variables D, H, Ca, ρ, and complex variables D2H and ρDH were selected and compared with for their predictive power.

Materials and methods

Study area

The aboveground biomass (AGB) component was derived from shrubs and small trees growing in the natural secondary forests of Qiaomu Township, 22 km northeast of Qingshanyang County (30°19′ to 30°50′ N and 117°40′ to 118°07′ E), Anhui Province, China. This region has a subtropical humid monsoon climate with average temperatures of 28 °C and 3 °C during the summer and winter months, respectively, suitable for the support of a rich and sustainable carbon sink (Yu et al. 2014). Elevations range from 44.6 to 104.1 m, with an average annual precipitation of 1374.7 mm. The soil type is brown calcareous and depth ranges from 20 to 100 cm.

The vegetation type of the study area is subtropical deciduous broadleaved forest, and the typical overstorey
Allometric models for aboveground biomass of six common subtropical shrubs and small trees

is dominated by *Liquidambar formosana* Hance, *Quercus acutissima* Carruth., and *Castanea mollissima* Bl. Common understory shrubs and herbaceous species include *Lindera fruticose* Hemsl, *Diospyros rhombifolia* Hemsl, *Acer ginnala* Maxim, *Liriope graminifolia* (L.) Baker, *Liriope muscari* (Decaisne) L. H. Bailey, and *Microlepia marginata* (Houtt.) C. Chr.

**Sampling design**

Following the floristic description of the study region (Yang et al. 2021), six shrub and small tree species were selected that are frequently in the shrub layer. A total of 32 to 38 individuals per species were selected to incorporate the entire plant size range (Table 1). Prior to the harvesting of any materials, heights (*H*), crown areas (*Ca*), and stem diameters (*D*) were measured. *H* was defined as the distance between the ground and the highest point of the crown. *Ca* encompassed two directions, the maximum diameter of the crown (*d1*), and the perpendicular diameter to *d1* (*d2*).

D for small trees and shrubs was measured at 130 cm and 10 cm above the root collar, respectively. Each harvested sample was separated into stems, branches, and leaves, stored in sealed bags, and transferred to the laboratory for analysis within 3 days.

**Laboratory analysis**

Laboratory analyses were completed at the Anhui Agricultural University in Heifei, Anhui, China. The fresh weight (0.01 g) of each component was measured using an electronic balance. To determine the specific wood density (*ρ* = dry weight/green volume in g cm$^{-3}$), two-six 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 h to a constant weight. The dry weight (0.01 g) of each component of each species was weighed using an electronic balance. The biomass of each component, leaf biomass (LB); branch biomass (BB); stem biomass (SB); total aboveground biomass (AGB, Table 1) was obtained, and plant component aboveground biomass as a percentage of the AGB per plant species determined.

**Data analysis**

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

Linear and nonlinear regression analyses were used to examine the relationships between aboveground biomass components and the measured variables, *D, H, Ca, ρ, D^2H*,

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**Table 1** Summary of the minimum-maximum values 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|

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).
and ρDH, and were performed using the ‘basic trendline’ 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 developed to describe the relationships between the aboveground biomass components:

\[
W = ax + b \quad (2)
\]

\[
W = ax^2 + bx + c \quad (3)
\]

\[
W = ax^b \quad (4)
\]

where $W$ is the dependent variable (LB, BB, SB, and AGB), $x$ the independent variable (D, H, Ca, ρ, $D^2H$, or ρDH), and $a$, $b$, and $c$ the allometric coefficients.

\[
AIC = -2ln(L) + 2n \quad (5)
\]

where $L$ is the likelihood of data under the accorded regression model and $n$ the number of parameters in the regression model.

To test the accuracy of the allometric models, the relationships between the observed and predicted AGB were assessed for the species-specific and multi-species models. All statistical analyses were performed in R (version 4.0.4).

**Results**

**Aboveground biomass allocation**

The percentage 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 to leaves. In contrast to other species, *Dendrobenthamia japonica* reflected this phenomenon best; however, the distribution of *A. ginnala* biomass in each component was relatively even (Fig. 1).

**Allometric biomass model**

Linear and nonlinear regression models were used 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 2, Fig. 2). For *A. ginnala*, *D. rhombifolia*, and *D. japonica*, $D^2H$ was the best predictor of stem biomass 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 ($R^2 = 0.602–0.93$; $P < 0.001$) and also performed well for the AGB of *Lindera fruticosa* and *D. rhombifolia* ($R^2 = 0.937$ and $R^2 = 0.892$; $p < 0.001$). For *R. ovatum*, ρDH accounted for more than 90% of the variations in the branch biomass ($R=0.904$; $P < 0.001$), 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 of biomass with the pooled data of all shrub species, followed by D and $D^2H$ (Fig. 3). The inclusion of ρ to the independent variable improved the prediction accuracy of the model (Fig. 3). 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 leaf biomass ($R=0.809$; $P < 0.001$), branch biomass,
Allometric models for aboveground biomass of six common subtropical shrubs and small trees

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   | MAPE (%) |
|-----------------------|---------|-------------------------|------|------|------|------|--------|-------|-------|----------|
| *Acer ginnala*        | LB      | $y=ax^b$                | 0.0107| 1.2995| 0.717***| −144 | 0.0241 | 48.86 |
|                       | BB      | $y=ax^b$                | 0.0281| 1.2997| 0.883***| −113 | 0.039  | 38.76 |
|                       | SB      | $y=ax^b$                | 0.0127| 0.8865| 0.905***| −118 | 0.0357 | 32.29 |
|                       | AGB     | $y=ax^2+bx+c$           | 0.0002| 0.0264| 0.0014| 0.908***| −64   | 0.0823| 34.48    |
| *Diospyros rhombifolia*| LB      | $y=ax+b$                | 0.0269| 2.3461| 0.762***| −138 | 0.032  | 31.27 |
|                       | BB      | $y=ax+b$                | 0.0258| 2.3461| 0.602***| −199 | 0.036  | 42.86 |
|                       | SB      | $y=ax+b$                | 0.0204| 0.0067| 0.858***| −120 | 0.0413 | 20.66 |
|                       | AGB     | $y=ax^b$                | 0.0855| 2.3190| 0.892***| −95  | 0.0592 | 18.70 |
| *Rhododendron ovatum* | LB      | $y=ax+b$                | 0.0411| −0.0360| 0.755***| −172 | 0.0196 | 25.88 |
|                       | BB      | $y=ax^2+bx+c$           | 0.0011| −0.0622| −0.0584| 0.904***| −131  | 0.0348 | 40.03    |
|                       | SB      | $y=ax^2+bx+c$           | 0.0013| 0.1041| −0.0843| 0.945***| −111  | 0.0462 | 21.05    |
|                       | AGB     | $y=ax^2+bx+c$           | 0.0026| 0.1850| −0.1480| 0.961***| −86   | 0.0662 | 18.59    |
| *Camellia cuspidate*  | LB      | $y=ax+b$                | 0.0222| 2.0255| 0.930***| −117 | 0.0358 | 24.17 |
|                       | BB      | $y=ax^2+bx+c$           | 0.0018| 0.0970| −0.1205| 0.868***| −47   | 0.0110 | 33.39    |
|                       | SB      | $y=ax^2+bx+c$           | 0.0001| 0.0263| 0.0048| 0.952***| −53   | 0.1010 | 12.94    |
|                       | AGB     | $y=ax^2+bx+c$           | 0.0002| 0.0533| −0.0199| 0.947***| −5    | 0.2080 | 15.43    |
| *Lindera fruticosa*   | LB      | $y=ax+b$                | 0.0432| −0.0212| 0.680***| −213 | 0.0139 | 47.42 |
|                       | BB      | $y=ax^b$                | 0.0192| 2.6443| 0.913***| −207 | 0.015  | 28.47 |
|                       | SB      | $y=ax^b$                | 0.0359| 0.7234| 0.925***| −178 | 0.022  | 16.87 |
|                       | AGB     | $y=ax^2+bx+c$           | 0.0774| 0.0786| −0.0530| 0.937***| −136  | 0.0379 | 22.58    |
| *Dendrobenthamia japonica* | LB      | $y=ax^b$                | 0.0057| 2.4503| 0.862***| −127 | 0.0333 | 35.87 |
|                       | BB      | $y=ax^b$                | 0.0118| 0.7686| 0.861***| −79  | 0.0686 | 28.81 |
|                       | SB      | $y=ax^b$                | 0.0267| 0.8168| 0.971***| −66  | 0.0844 | 20.31 |
|                       | AGB     | $y=ax^b$                | 0.0420| 0.8099| 0.962***| −28  | 0.1490 | 19.38 |

H, total height; D, diameter of the longest stem; $p$, wood density; LB, leaf biomass; BB, branch biomass; SB, stem biomass; AGB, total aboveground biomass; $a$, $b$, $c$, allometric coefficients; $R^2$, coefficient of determination; AIC, Akaike information criterion; SEE, standard error of the estimation; MAPE (%), mean absolute percentage error;

***, $P<0.001$; **, $P<0.01$

$(R=0.851; P<0.001)$, SB $(R=0.883; P<0.001)$, and AGB $(R=0.890; P<0.001)$, respectively (Table 3).

The relationships between the observed and predicted AGB (Fig. 4) showed that the RMSE and MAPE varied among individual species-specific models. The values of RMSE and MAPE of the multi-species allometric model were between those of species-specific models.

**Discussion**

During plant growth and development, biomass is accumulated as organic matter through photosynthesis, where additional biomass is distributed into stems and branches to increase their length to obtain more light, towards 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, consistent with many previous results with the exception of *A. ginnala* (Singh et al. 2011; Bayen et al. 2020).

Based on the established six specific species and one mixed species model, D, $D^2H$, and $pDH$ were the best variables for forecasting the aboveground biomass of shrubs. As distinct from the method of Nam et al. (2018), a single independent variable (single variable D, H, Ca, $p$; compound variables $D^2H$, $pDH$) was used as a predictor in the model, making the process simpler and more convenient. It was observed from the optimal model, even though a single
Fig. 2 Aboveground biomass (AGB) in relation to predictors (Note: H, total height; D, the diameter of the longest stem; ρ, wood density; $R^2$, coefficient of determination; predictors are described in Table 1.)
variable was employed, 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 (crown area) did not perform well (Table S1, Table S2), 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 species (She et al. 2015; Bayen et al. 2020), the crowns of subtropical shrubs and small trees are naturally irregular, resulting a decreased 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 beneficial and improved model accuracy when combined with D and $C$, although the correlation between the H and biomass was lower than Ca (Tables 2 and 3; Fig. S1). Consistent with previous studies, D$^2$H 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 ($\rho$DH) was used to predict biomass, the model was better than using only D and H, particularly for shrub mixed multi-species models. According to previous studies, $\rho$ is one of the most important characteristics of tree species and varies considerably between species. Wood density or $\rho$ was introduced 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 $\rho$ was negligible and could be regarded as almost constant (Francis et al. 2017; Nelson et al. 2020). Therefore, a new combined entity ($\rho$DH) was created as a predictor variable.

From the results, the introduction of $\rho$ reduced SEE and increased $R^2$, indicating that it’s enhanced the accuracy of the model, which aligned well with the work of Ali et al. (2015). Numerous studies have indicated that $\rho$ is an essential factor for improving model accuracy (Yepes et al. 2016; Kebede and Soromessa 2018). Furthermore, it was reported that $\rho$ 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 $\rho$ as a portion of the independent variable can reduce errors caused by D and H in measurements to some extent as well as influences of morphological differences on the accuracy of multi-species models (Pilli et al. 2006; Zeng et al. 2017).

In comparing the accuracy of a model in estimating the biomass of a component of the same species, the allometric model possessed a higher predictive ability for woody 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 for evergreen shrubs in this study was higher than that for deciduous shrubs, which appears to confirm this. Errors of the multi-species model were higher than some of the species-specific models (Fig. 4). This may be attributable to increased differences of H, D, Ca, and $\rho$ among samples associated with multiple species (Elzein et al. 2011; Ali et al. 2015). Nevertheless, an increase in sample size might reduce prediction errors for independent samples (Roxburgh et al. 2015; Paul et al. 2016).

Our modeling approaches to prediction errors on shrubs were compared with published models (Conti et al. 2013; Ali et al. 2015; Paul et al. 2016; Yang et al. 2017; Bayen et al. 2020) (Table 4). Researchers have focused on the AGB of shrubs with allometric models and their H, D, and Ca using linear or nonlinear regression models, or multiple-variable models. By comparing our model with previous models and model accuracy, we found that the larger the number of samples, the higher the accuracy (Paul et al. 2016). The application of multivariable and composite variables improved the performance of the model and reduced errors. These results show that the number of samples and variable selection were critical factors that impact model accuracy. Furthermore, in the multi-species allometric model, researchers have increasingly used nonlinear models, which is more aligned with the law of biomass accumulation of shrubs (Xu et al. 2020).

Due to the difficulties involved with fully excavating root biomass (particularly fine roots), only aboveground biomass was considered in our research. This might have resulted in limitations in the application of the equations. It is acknowledged that our models were based on a small number of samples (i.e., 32 to 38 individuals per species). Therefore, the use of predictive models is not recommended for tree species beyond the range of predictor variables and would likely cause significant errors in the estimated values.


Conclusions

This study sampled six common subtropical shrubs and small trees to develop an allometric species-specific and multi-species models for biomass organs (leaves, branches, stem, and total aboveground biomass).

### Table 3

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

| Species | Variety | Equations | $x$ | $a$  | $b$  | $R^2$  | AIC  | SEE | MAPE (%) |
|---------|---------|-----------|-----|------|------|--------|------|-----|----------|
| Multi-species | LB | $y = ax^b \rho DH$ | 0.0132 | 1.3146 | 0.809*** | −674 | 0.034 | 45.05 |
| | BB | $y = ax^b \rho DH$ | 0.0338 | 1.2282 | 0.851*** | −461 | 0.063 | 33.82 |
| | SB | $y = ax^b \rho DH$ | 0.0523 | 1.2398 | 0.883*** | −357 | 0.085 | 30.83 |
| | AGB | $y = ax^b \rho DH$ | 0.0994 | 1.2464 | 0.890*** | 140 | 0.160 | 27.21 |

$H$, total height; $D$, diameter of the longest stem; $\rho$, 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; $MAPE$ (%), mean absolute percentage error;

***, $P < 0.001$

### Table 4

Comparison of similar published modeling approaches to prediction errors for multiple species of shrubs

| Study          | Location                     | $n$ | Modeling approaches                          | Model                                                                 | $R^2$   | SEE   | RMSE   | MAPE (%) |
|----------------|------------------------------|-----|----------------------------------------------|-----------------------------------------------------------------------|---------|-------|--------|----------|
| Ali et al. 2015 | Tiantong National Forest Park in Zhejiang Province, China | 96  | Linear regression models and Logarithm model | $\ln (\text{AGB}) = 5.29 + 1.52 \times \ln (D) + 0.83 \times \ln (H) + 0.145 \times \ln (\text{Ca}) + 3.23 \times \rho$ | 0.730   | –     | –      | –        |
| Yang et al. 2017 | Tengger Desert in northern China | 385 | Logarithm model                             | $\ln (\text{AGB}) = -2.357 + 0.642 \times \ln (V)$                    | 0.707   | 0.810 | –      | –        |
| Bayen et al. 2020 | Sudano-Sahelian and Sahelian zones of Burkina Faso | 357 | Multiple-variables models                   | $\text{AGB} = e^{-2.14 \times D^{-0.41 \times \text{Ca}^{1.39} + e^{-2.13 \times D^{0.90 \times H^{0.51 \times \text{Ca}^{0.94} + e^{-3.16 \times D^{1.33 \times H^{0.84 \times \text{Ca}^{0.28}}}}}}}$ | 0.749   | 0.520 | 21.83  | –        |
| Paul et al. 2016 | Various ecoregions of Australia | 2383 | Logarithm model                            | $\text{AGB} = 1.128e^{(3.077 + 2.248ln (D))}$                                | 0.968   | 0.491 | 39.30  | –        |
| Conti et al. 2013 | Central-western Argentina | 245 | Linear regression models and Logarithm model | $\ln (\text{AGB}) = -9.58 + 1.06 \times \ln (\text{Ca})$                  | 0.760   | –     | 0.570  | –        |
| This study     | Anhui Province, China       | 173 | Linear regression models and Nonlinear regression model | $\text{AGB} = 0.0994 \times \rho DH^{1.2464}$                        | 0.890   | 0.160 | 0.150  | 27.21    |

$n$, number of individuals per species; $H$, total height; $D$, diameter of the longest stem; $\text{Ca}$, canopy area (m$^2$); $V$, shrub volume; $\rho$, wood density; $\text{AGB}$, total aboveground biomass; $a$, $b$, allometric coefficients; $R^2$, coefficient of determination; $SEE$, standard error of the estimation; $RMSE$, root mean square error; $MAPE$, mean absolute percentage error.
Allometric models for aboveground biomass of six common subtropical shrubs and small trees

Fig. 4 Relationships between observed aboveground biomass and predicted aboveground biomass and for species-specific models and the multi-species model. Abbreviations are root mean squared error (RMSE) and mean absolute percentage error (MAPE)

...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 D²H as predictors, accounted for a high variation (60.2–97.1%) in the aboveground biomass of shrubs and small trees.

The inclusion of ρ (wood density) as a predictive variable improved the accuracy of the multi-species shrub model. Further, pDH played a significant role in the models for 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 suggests that the multi-species model might expedite the estimation of shrub biomass, which can translate to savings in time and labour. The results of this study might also facilitate the rapid non-destructive acquisition of biomass estimates for subtropical shrubs and small trees.

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Author contributions CH and CF have contributed equally. SF, HYHC, and CF conceived and designed the study; CH, YM, SY, and WW collected data; CH and HL analyzed the data; CH, CF, SF, and HYHC wrote the manuscript.

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