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Allometric Equations for Applying Plot Inventory and Remote Sensing Data to Assess Coarse Root Biomass Energy in Subtropical Forests

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Abstract Coarse root biomass (CRB) is an important store of carbon (C) and forest residue for renewable energy, but is often overlooked due to the lack of a simple and effective way to estimate its magnitude. In this study, we developed allometric equations for three functional groups using data from 133 tree samples, with a diameter at breast height (DBH) ranging from 2.6 to 52.0 cm. The functional groups included evergreen coniferous (*Pinus massoniana*), deciduous broad-leaved (*Alniphyllum fortunei*, *Choerospondias axillaris*, *Liquidambar formosana* and *Quercus fabri*) and evergreen broad-leaved (*Castanopsis carlesii*, *Cyclobalanopsis glauca*, *Litsea coreana* and *Schima superba*) species. Allometric equations that related CRB to plot inventory data (e.g. DBH or tree height (H)) and their combinations significantly fitted ($P < 0.0001$) for the functional groups and all tree species. The equations using DBH or DBH-H as predictor variables were the best fit ($R^2 \geq 0.90$) and produced good predictions with little bias (less than 21%) for local sites and at regional scales. Allometric equations related to easily obtained remote sensing data (i.e. crown width (CW) and H) were also significantly fitted ($P < 0.0001$, $R^2 \geq 0.76$), and predictions were close to the observed CRB, despite a high bias (larger than 98.0%). In conclusion, the use of these equations to estimate CRB is essential to the harvest process and helps to formulate new policies for managing the feedstock supply to bioenergy production in subtropical forests.

Keywords Coarse root biomass · Bioenergy · Allometric equations · Functional groups · Remote sensing · Subtropical forests

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Introduction

Ever-increasing levels of environmental pollution and energy demands have stimulated global research into alternative energy resources [1]. Forest biomass is widely recognized as an important energy source with the potential to reduce greenhouse gas emissions and to minimize environmental pollution [2]. Forest ecosystems are often seen as potentially enormous carbon (C) sinks and plant biomass providers [3]. Forest biomass includes all parts of the tree, not only the stem but also bark, branches, needles or leaves and even roots. As a non-negligible part of forest biomass, tree roots account for approximately 30% of the total tree biomass, of which most is held in coarse roots [4]. Previous studies have concluded that coarse roots could be a significant fuelwood resource to supply emerging fuelwood chains [3]. This process has proven to be technically feasible and economically profitable [5, 6]. One idea that has received considerable attention is the large-scale

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removal of coarse root biomass (CRB) from forests. However, the removal of CRB leads to a loss of soil organic C and nutrients [7]. Assessment of nutrient losses due to root harvesting requires accurate CRB estimates [3]. In addition, increases in the use of CRB for energy also need to occur in ways that maintain productivity and environmental sustainability to ensure long-term production. Thus, to ensure the sustainable use of CRB in subtropical forests, there is a need to quantify the actual amount of CRB available.

Coarse roots are difficult to quantify in the field because of the large size of the portion hidden in soil and the cost and labour requirements needed to harvest the whole root system. Many investigators have used indirect techniques to estimate their biomass. An allometric equation is the most commonly used indirect method to estimate CRB [8, 9]. The equations usually relate the CRB to some easily measured variables, such as the diameter at breast (DBH), tree height (H) or a combination of such parameters [4, 10–12]. Species-specific allometric equations are preferred, but this is impractical for forests composed of diverse tree species. Allometric equations for functional groups (e.g. angiosperm or gymnosperm, evergreen or deciduous), which include functional traits (e.g. wood density), are alternative approaches [13]. Nevertheless, it is necessary to test the effects of tree species before functional groups are aggregated.

The increasing need to quantify CRB has prompted the development and compilation of allometric equations for boreal [4, 14], temperate [15, 16] and tropical forests [17–19]. However, CRB has not been estimated in subtropical forests because only a few equations are available. To the best of our knowledge, only a few studies have developed allometric equations for multiple species at local [11, 20] and regional scales [13]. Moreover, it has not yet been confirmed that these equations could be applied to other sites or species. Xiang et al. [21] developed general allometric equations for *Pinus massoniana* roots based on 197 samples across 20 sites in subtropical forests. Despite this work, the high diversity of tree species in subtropical forests [22] makes it impractical to develop general allometric equations for each species [23]. Therefore, accurate and simple methods to estimate CRB are required in subtropical forests.

Together with forest inventory data, allometric equations have been used to estimate forest biomass. Remote sensing has gradually become the primary tool used to monitor forest structure and estimate stand biomass C stocks [24]. The high resolution of light detection and ranging (LiDAR) remote sensing allows the estimation of three-dimensional forest structure and offers an effective measurement of tree crown width (CW) and H in forests [25, 26]. Although the LiDAR technique can rapidly and accurately obtain CW and H data in forests [27], the effective use of these data to estimate forest biomass, and in particular belowground CRB, is challenging due to the paucity of allometric equations using CW and H as predictive variables.

China has the fifth largest forest resource in the world, and its forest area accounts for 5% of the global total [28]. Together with the other large forested counties, China has the opportunity to develop forest-based energy solutions to mitigate C emissions [29]. Subtropical forests in China hold a tremendous potential to provide the feedstock necessary to meet emerging renewable energy goals. Accurate estimates of CRB will improve the accuracy of forest C storage estimates and its potential for bioenergy. China has detailed permanent plot data collected by each 5-year national forest resource inventory. The plot data includes tree DBH and H [11]. In addition, the application of remote sensing enables forest biomass to be determined. The use of this forest resource inventory data and remote sensing techniques to estimate CRB in subtropical forests makes it imperative to develop CRB allometric equations and test their applications. Hence, we selected nine common tree species that represent three functional groups (evergreen coniferous, deciduous broad-leaved and evergreen broad-leaved species) to develop CRB allometric equations. The objectives of this study were to (1) test whether tree species affect the allometric relationship within a given functional group; (2) develop and extend functional group allometric equations to predict CRB using forest inventory data at local and regional scales; and (3) assess the usefulness of remote sensing imagery data to estimate CRB in subtropical forests.

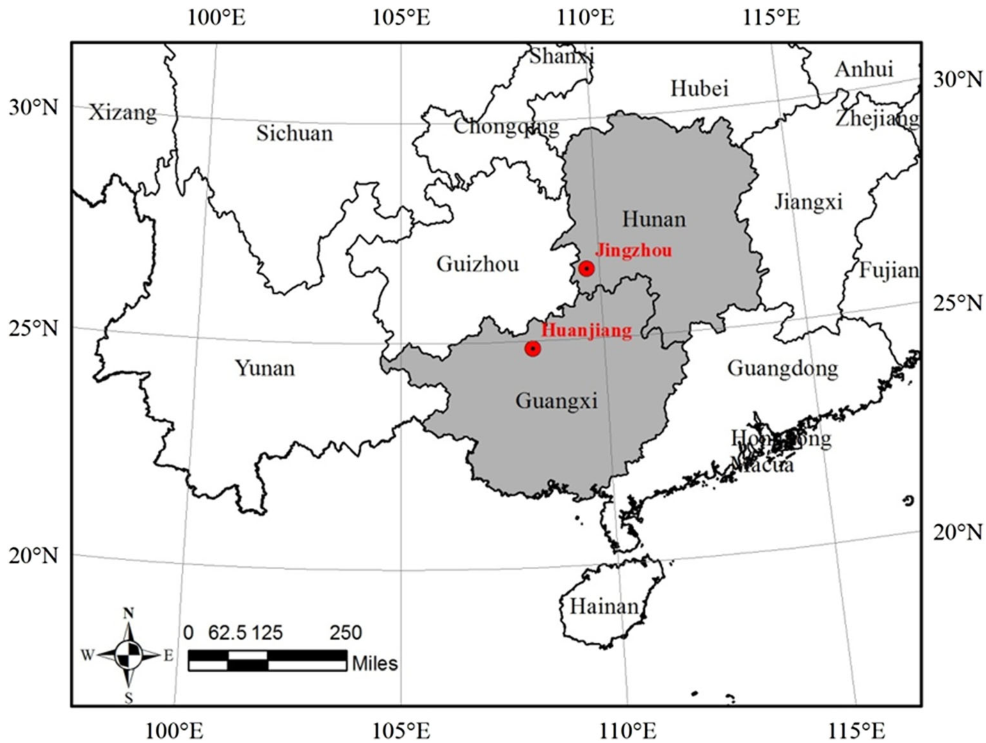
Materials and Methods

Study Site Description

The study was conducted at two sites in southern China. One site was located at the Paiyashan Forest State Farm (latitude 26°24′N-26°35′N, longitude 109°27′E-109°38′E) in Jingzhou County, Hunan Province. The other site was located at the Huaijiang Ecosystem Research Station (24°43′N-24°45′N, 108°18′E-108°20′E), Huanjiang County, Guangxi Zhuang Autonomous Region. Both sites are characterized by a subtropical humid monsoon climate (Fig. 1).

The Paiyashan Forest State Farm is characterized by a low and medium mountainous topography, with elevation ranging from 330 to 1075 m above mean sea level. The average annual rainfall is 1250 mm, and the average annual temperature is 16.7 °C, ranging from an average of 5.7 °C during the coolest month (January) to 26.8 °C during the warmest month (July). The soil parent material is purple sand shale, and the soil type is designated as a red soil at altitudes below 600 m and yellow soil at altitudes higher than 600 m. The soil is classified as Alliti-Udic Ferrosols in Chinese Soil Taxonomy, which

Fig. 1 Location of the study sites



corresponds to Acrisol in the World Reference Base for Soil Resources [30]. Forest types on the farm include *Cunninghamia lanceolata* plantations and secondary forests dominated by different tree species [31].

At Huanjiang Station, the topography is a typical karst fengcong depression, with elevation ranging from 272 to 674 m above mean sea level. Average annual temperature is 19.9 °C, ranging from an average of 10.1 °C during the coolest month (January) to 27.9 °C during the warmest month (July). The mean annual precipitation is 1389 mm, mostly occurring between April and August. The geology can be described as soluble and porous limestone and dolomite, and the soil type is mainly rendzina, which is equivalent to Luvisols in the World Reference Base for Soil Resources [30]. The zonal vegetation in the station is subtropical mixed evergreen and deciduous broadleaf forest.

Tree Sampling and Root Biomass Measurement

Following the procedure described by Xiang et al. [31], 133 tree samples of nine common species were selected at two sites (Tables 1 and 2). Tree samples selected for each species represent the size range in the forests investigated, and trees with severe defects were excluded. Among the 133 trees, the size range was from 1.8 to 52.0 cm in DBH, from 2.0 to 30.2 m in H and from 0.9 to 16.5 m in CW (Tables 1 and 2). The nine tree species were categorized into three functional groups according to morphological and phenological traits in subtropical forests, including evergreen coniferous (*P. massoniana*), deciduous broad-leaved (*Alniphyllum fortunei*, *Choerospondias axillaris*, *Liquidambar formosana* and *Quercus fabri*) and evergreen broad-leaved (*Castanopsis carlesii*, *Cyclobalanopsis glauca*, *Litsea coreana* and *Schima superba*) species.

The sampled trees were destructively harvested in October 2014 using a chainsaw, and stems were felled at the ground surface. The excavation method was performed to determine CRB, with an excavation cylinder having an extended radius of 1.5 m distance from the tree stump and a depth down to 1.5 m. The root stump and as many lateral roots as possible within the cylinder were collected. The root stump was manually excavated at a soil depth of 1.5 m, and the resulting roots were washed using water and then weighed in the field using a weighing beam to obtain their fresh weight. For CRB, only roots with a diameter >2 mm were considered [9], and all CRB weights were expressed on an oven-dried and ash-free basis. To determine the dry weight of the coarse root, root samples were collected, placed in cloth bags and transported to the laboratory. The root samples were oven-dried at 65 °C to a constant weight. The average moisture content was calculated and used to determine the CRB dry weight.

To correct for coarse roots that were unharvested, we first measured the average diameter of all lateral roots at each breakage point for individual trees. Based on the measured diameter, we then harvested all lateral roots of this size from every tree to determine the percentage of roots growing beyond a distance of 1.5 m from the stump. From these samples, the ratios of root lengths and fresh mass of 1.5 m long roots to entire roots were determined to calculate the CRB.

Table 1 Number (*N*) and ranges in diameter at breast height (DBH), height (H) and crown width (CW) of the sample trees that were used to build the equations (92 trees)

Site	Functional group	Tree species	Number	DBH (cm)		H (m)		CW (m)	
				Mean	Range	Mean	Range	Mean	Range
Hunan	Evergreen coniferous	*Pinus massoniana*	7	32.1	5.9–52.0	17.0	8.5–20.0	5.9	1.2–8.8
	Deciduous broad-leaved	*Alniphyllum fortunei*	8	22.6	3.8–39.5	15.4	6.4–21.5	6.0	1.6–9.8
	Deciduous broad-leaved	*Choerospondias axillaris*	5	15.5	7.8–24.5	13.7	11.9–15.9	4.6	1.8–7.2
	Deciduous broad-leaved	*Liquidambar formosana*	7	31.1	10.0–47.2	23.5	12.9–30.2	7.9	5.1–10.1
	Evergreen broad-leaved	*Schima superba*	8	15.8	3.0–28.5	12.5	6.0–18.2	5.5	1.5–9.0
	Evergreen broad-leaved	*Litsea coreana*	10	23.0	2.6–45.5	13.2	3.5–21.5	7.1	0.9–16.5
	Evergreen broad-leaved	*Cyclobalanopsis glauca*	8	29.4	6.2–50.9	18.5	10.7–22.8	7.9	3.5–12.4
Guangxi	Evergreen coniferous	*Pinus massoniana*	10	16.5	1.8–27.2	14.7	2.1–21.8	3.2	1.1–4.8
	Deciduous broad-leaved	*Liquidambar formosana*	8	16.2	6.3–24.3	12.5	6.3–21.1	4.8	3.1–6.4
	Deciduous broad-leaved	*Quercus fabri*	5	20.5	9.7–35.5	15.1	8.6–21.6	4.4	2.8–7.6
	Deciduous broad-leaved	*Castanopsis carlesii*	4	18.3	5.3–32.8	11.0	5.6–17.2	4.0	1.6–5.8
	Evergreen broad-leaved	*Cyclobalanopsis glauca*	9	9.4	3.5–16.4	8.9	2.0–13.6	2.7	1.1–4.7
	Evergreen broad-leaved	*Schima superba*	3	11.5	7.5–14.0	11.6	10.9–12.3	3.2	1.0–4.8

Model Formulation and Statistical Analysis

We used a power function and an exponential function to develop the allometric relationship of CRB against DBH [32]. After a comparison of the performance of the two functions, we found that the power function had a higher coefficient of determination (R^2) as well as a lower root mean square error (RMSE), Furnival index (FI) and Akaike information criterion (AIC) (Table S1). Thus, we used the power function to develop the allometric equation in this study.

We performed an analysis of covariance (ANCOVA), using species as a categorical factor and DBH as a continuous covariate, to determine whether tree species affected the allometric relationship within a given functional group. If there was no significant effect, we aggregated the tree species data to develop the allometric equations of each functional group. Otherwise, we developed species-specific allometric equations and functional group equations based on the allometric similarities of the species. The difference was significant ($P < 0.05$), and pairwise comparisons were tested by a Tukey honestly significant difference test.

We used the data from 92 trees to develop allometric equations (Table 1) and the data from the remaining 41 trees to validate the equations (Table 2). For each functional group, approximately one third of the trees were randomly selected for the validation, whereas the data from the remaining trees

Table 2 Number (*N*) and ranges in diameter at breast height (DBH), height (H) and crown width (CW) of the sample trees that were used for validation (41 trees)

Site	Functional group	Tree species	Number	DBH (cm)		H (m)		CW (m)	
				Mean	Range	Mean	Range	Mean	Range
Hunan	Evergreen coniferous	*Pinus massoniana*	3	19.8	12.2–25.0	17.3	14.9–20.5	5.2	2.5–7.0
	Deciduous broad-leaved	*Alniphyllum fortunei*	2	18.9	6.6–31.1	15.1	8.9–21.2	4.7	1.3–8.0
	Deciduous broad-leaved	*Choerospondias axillaris*	5	10.4	3.3–18.7	11.0	5.6–13.7	4.0	1.4–8.6
	Deciduous broad-leaved	*Liquidambar formosana*	3	18.6	6.9–29.0	17.8	8.0–25.3	6.4	3.2–8.9
	Evergreen broad-leaved	*Schima superba*	2	23.4	13.0–33.8	16.6	14.6–18.5	6.0	3.9–8.0
	Evergreen broad-leaved	*Cyclobalanopsis glauca*	2	21.1	11.2–31.0	17.1	13.1–21.0	9.2	7.2–11.1
Guangxi	Evergreen coniferous	*Pinus massoniana*	6	20.0	2.0–31.7	17.0	2.8–25.3	4.0	1.5–6.3
	Deciduous broad-leaved	*Liquidambar formosana*	3	12.3	7.6–19.6	11.8	8.2–17.6	4.6	3.1–6.1
	Deciduous broad-leaved	*Quercus fabri*	3	11.9	8.0–14.1	10.8	8.5–15.2	2.9	1.9–4.2
	Deciduous broad-leaved	*Castanopsis carlesii*	3	13.7	10.6–18.5	11.2	10.1–12.6	4.4	2.4–5.7
	Evergreen broad-leaved	*Cyclobalanopsis glauca*	7	9.4	6.2–12.6	9.1	2.0–11.6	3.1	2.0–5.5
	Evergreen broad-leaved	*Schima superba*	2	22.6	8.8–36.5	15.7	10.5–20.8	4.5	2.9–6.1

was used to fit equations. Natural logarithms were used to normalize and linearize the data. A correction factor (CF) was introduced for all allometric equations to correct the systematic bias [33]. Instead of evaluating all possible forms of allometric equations using different predictor variables, we selected the four most common models relating to DBH, H and their combination [4, 11, 16, 21] to develop allometric equations for three functional groups and all tree species. In addition, two regression models were selected to fit equations relating to CW and H that were easily derived from LiDAR imagery [24]. The allometric equations are as follows:

$$\ln(\mathrm{CRB}) = \mathrm{a} + \mathrm{b} \times \ln(\mathrm{DBH}) \tag{1}$$

$$\ln(\mathrm{CRB}) = \mathrm{a} + \mathrm{b} \times \ln(\mathrm{H}) \tag{2}$$

$$\ln(\mathrm{CRB}) = \mathrm{a} + \mathrm{b} \times \ln\left(\mathrm{DBH}^2 \times \mathrm{H}\right) \tag{3}$$

$$\ln(\mathrm{CRB}) = \mathrm{a} + \mathrm{b} \times \ln(\mathrm{DBH}) + \mathrm{c} \times \ln(\mathrm{H}) \tag{4}$$

$$\ln(\mathrm{CRB}) = \mathrm{a} + \mathrm{b} \times \ln(\mathrm{CW}) \tag{5}$$

$$\ln(\mathrm{CRB}) = \mathrm{a} + \mathrm{b} \times \ln(\mathrm{H}) + \mathrm{c} \times \ln(\mathrm{CW}) \tag{6}$$

where a, b and c are the fitted parameters, CRB (kg) is the coarse root biomass, DBH (cm) is the diameter at breast height, H (cm) is the tree height and CW (m) is the crown width.

For each equation, all parameters were tested for significance at $P < 0.05$. The criteria used to evaluate the performance and fitness of the six models were the R^2, RMSE, FI and AIC [34, 35].

Comparison of Allometric Equations with Other Published Equations

To examine their predictive ability and to compare errors among the allometric equations developed for each functional group in this study, we calculated the CRB for three functional groups using data from 41 tree samples and our allometric equations relating to DBH, DBH-H and CW-H as well as allometric equations developed by Li et al. [11] and Lai et al. [20]. The bias (%) of each equation compared to the actual CRB was calculated using the following formula:

$$\mathrm{Bias}(\%) = \frac{1}{N}\sum_{I=1}^{N}\left(\frac{D_{\mathrm{obs}} - D_{\mathrm{pred}}}{D_{\mathrm{obs}}}\right) \times 100 \tag{7}$$

where D_{obs} and D_{pred} represent the observed and predicted CRB (kg) and N is the number of tree samples. A one-way analysis of variance (ANOVA) was used to test the differences in bias among the six equations.

Concurrently, we examined the accuracy of our allometric equations using DBH as the predictor variable to estimate the CRB reported by Xiang et al. [21] and Lai et al. [20] for 356 trees in subtropical forests in nine provinces. The data for these 356 trees is available online in an open-access format, and their DBH ranged from 1.1 to 56.5 cm. In addition, we also adopted the average bias method to evaluate the efficiency of equations for four different DBH classes (0–10, 10–20, 20–30 and ≥30 cm). We compared all estimated CRB values to the observed data using linear regression methods. Statistical analyses in this study were performed using the statistical software R 3.3.1.

Results

CRB Allometric Equations Using DBH and H as Predictor Variables

For deciduous broad-leaved species, no significant species effects were found in the allometric equations (Table S2), and we developed functional group equations accordingly. For evergreen broad-leaved species, tree species significantly affected ($P < 0.05$) the relationship between DBH and CRB (Table S2). However, the pairwise comparison showed that with exception of *L. coreana*, there was no significant difference among the other three tree species (Table S3). Thus, we developed a species-specific allometric equation for *L. coreana*, and the functional group aggregated the other three evergreen broad-leaved species.

Allometric equations using DBH, H and their combination as predictor variables significantly fitted ($P < 0.0001$) with our data for the three functional groups and all species (Table 3). The R^2 ranged from 0.66 to 0.98 for all equations. For a given functional group, allometric equations using DBH as the only predictor variable fitted well with a high R^2 (0.90–0.97) and low RMSE, FI and AIC, whereas equations using H as the only predictor variable were the poorest fit with the lowest R^2 (0.67–0.68) and had the largest RMSE, FI and AIC (Table 3). Adding H as the second predictor variable did not improve the fitness of equations relating to $(\mathrm{DBH})^2 \times \mathrm{H}$, as R^2 decreased and RMSE, FI and AIC increased compared to DBH equations. When separately related to DBH and H, the equations also fitted well with the data and had similar, or only slightly different, R^2, RMSE, FI and AIC (Table 3).

The allometric equations differed among the three functional groups and all species combined (Fig. 2). At a given DBH, the values of CRB were the highest for evergreen broad-leaved species and the lowest for evergreen coniferous species. Deciduous broad-leaved species and all species combined had intermediate CRB values (Fig. 2).

CRB Allometric Equations Using CW and H as Predictor Variables

For the three functional groups and all species combined, allometric equations relating CRB to CW were significantly fitted ($P < 0.0001$), but the goodness of fit was

Table 3 Allometric equations for estimations of coarse root biomass (CRB)

Functional group	Predictor variables	a (Se)	b (Se)	c (Se)	R^2	*P* value	RMSE	CF	FI	AIC
Evergreen coniferous	DBH	−4.44 (0.33)	2.48 (0.11)		0.97	<0.0001	0.35	1.06	2.67	16.90
	H	−5.03 (1.44)	2.94 (0.53)		0.67	<0.0001	1.21	2.08	9.11	58.68
	$(DBH)^2 \times H$	−5.01 (0.57)	0.92 (0.07)		0.93	<0.0001	0.56	1.17	4.21	32.41
	DBH and H	−3.70 (0.33)	3.01 (0.19)	−0.87 (0.26)	0.98	<0.0001	0.26	1.03	1.97	8.67
	CW	−0.58 (0.48)	2.67 (0.34)		0.81	<0.0001	0.93	1.54	6.98	49.63
	H and CW	−3.71 (0.74)	1.55 (0.34)	1.89 (0.28)	0.92	<0.0001	0.58	1.18	4.39	35.86
Deciduous broad-leaved	DBH	−4.17 (0.46)	2.54 (0.16)		0.90	<0.0001	0.51	1.14	3.99	53.76
	H	−5.35 (1.08)	3.18 (0.39)		0.68	<0.0001	0.91	1.51	7.04	91.19
	$(DBH)^2 \times H$	−4.93 (0.55)	0.96 (0.06)		0.88	<0.0001	0.55	1.16	4.29	58.54
	DBH and H	−4.13 (0.64)	2.56 (0.32)	−0.04 (0.46)	0.90	<0.0001	0.51	1.14	3.99	55.76
	CW	−0.96 (0.63)	2.55 (0.37)		0.61	<0.0001	1.00	1.65	7.77	97.71
	H and CW	−4.57 (0.99)	2.10 (0.49)	1.29 (0.42)	0.76	<0.0001	0.79	1.37	6.13	84.07
Evergreen broad-leaved	DBH	−4.11 (0.28)	2.64 (0.10)		0.96	<0.0001	0.43	1.10	3.35	41.08
	H	−4.94 (1.02)	3.16 (0.41)		0.67	<0.0001	1.19	2.03	9.19	105.72
	$(DBH)^2 \times H$	−4.91 (0.37)	1.00 (0.05)		0.94	<0.0001	0.51	1.14	3.97	51.90
	DBH and H	−4.19 (0.38)	2.59 (0.19)	0.09 (0.27)	0.96	<0.0001	0.43	1.10	3.34	42.96
	CW	−0.75 (0.42)	2.53 (0.27)		0.74	<0.0001	1.04	1.72	8.09	97.50
	H and CW	−3.18 (0.89)	1.48 (0.49)	1.68 (0.37)	0.80	<0.0001	0.91	1.51	7.06	90.82
All species	DBH	−4.02 (0.24)	2.50 (0.08)		0.92	<0.0001	0.53	1.15	4.19	132.70
	H	−4.83 (0.64)	3.01 (0.24)		0.66	<0.0001	1.09	1.81	8.62	250.86
	$(DBH)^2 \times H$	−4.70 (0.30)	0.94 (0.04)		0.89	<0.0001	0.61	1.20	4.79	154.55
	DBH and H	−3.82 (0.32)	2.64 (0.16)	−0.23 (0.23)	0.92	<0.0001	0.53	1.15	4.17	133.73
	CW	−0.70 (0.28)	2.49 (0.18)		0.71	<0.0001	1.00	1.65	7.89	236.45
	H and CW	−3.56 (0.51)	1.61 (0.25)	1.n (0.20)	0.81	<0.0001	0.81	1.39	6.42	204.61

a, b and c are allometric coefficients with standard errors in parentheses

R^2 coefficient of determination, *RMSE* root mean square error, *FI* Furnival index, *AIC* Akaike information criterion

relatively poor, with an R^2 lower than 0.81 (Table 3). When allometric equations were related to the combination of CW and H (model 6), the fitness was improved and R^2 was larger than 0.80, except for deciduous broad-leaved species (R^2 = 0.76). Including H as the second predictor variable in the equations decreased the RMSE, FI and AIC for all equations (Table 3).

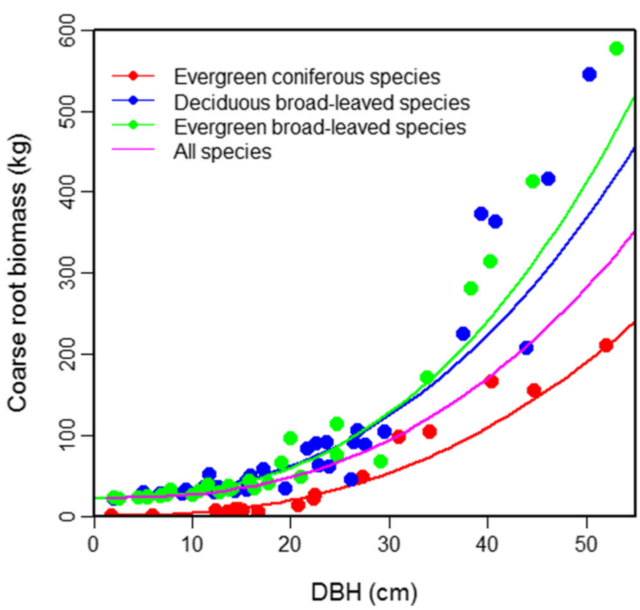


Fig. 2 Allometric relationships between diameter at breast height (DBH) and coarse root biomass (CRB) (model 1) together with the fitted curves for all species (in *purple*) and three functional groups consisting of evergreen coniferous species (in *red*), deciduous broad-leaved species (in *blue*) and evergreen broad-leaved species (in *green*)

Accuracy of CRB Prediction and Errors in the Allometric Equations

The equations relating to DBH (model 1), DBH-H (model 4) and CW-H (model 6) had better fit, and therefore, we used these three equations for each functional group and the equations developed by Li et al. [11] and Lai et al. [20] to compare their predictive ability. A comparison between the predicted and observed CRB of 41 trees indicated that models 1 and 4 had the best predictive ability, with a bias lower than 21% (Fig. 3 and Table 4). The CRB predicted by model 6 was overestimated compared to the observed CRB for evergreen coniferous, deciduous broad-leaved species and evergreen broad-leaved species (Fig. 3). The biases of model 6 were 98.8–172.1% (Table 4). The equations of Li et al. [11] poorly predicted CRB for our data, with an overestimation for evergreen coniferous species and an underestimation for deciduous and evergreen broad-leaved species (Fig. 3), whereas the equations of Lai et al. [20] predicted CRB well, except for evergreen coniferous species. The biases of the equations of Li et al. [11] and Lai et al. [20] were higher for evergreen coniferous species (73.2 and 108.9%), but were lower for the other two functional groups (less than 46.6%) (Table 4).

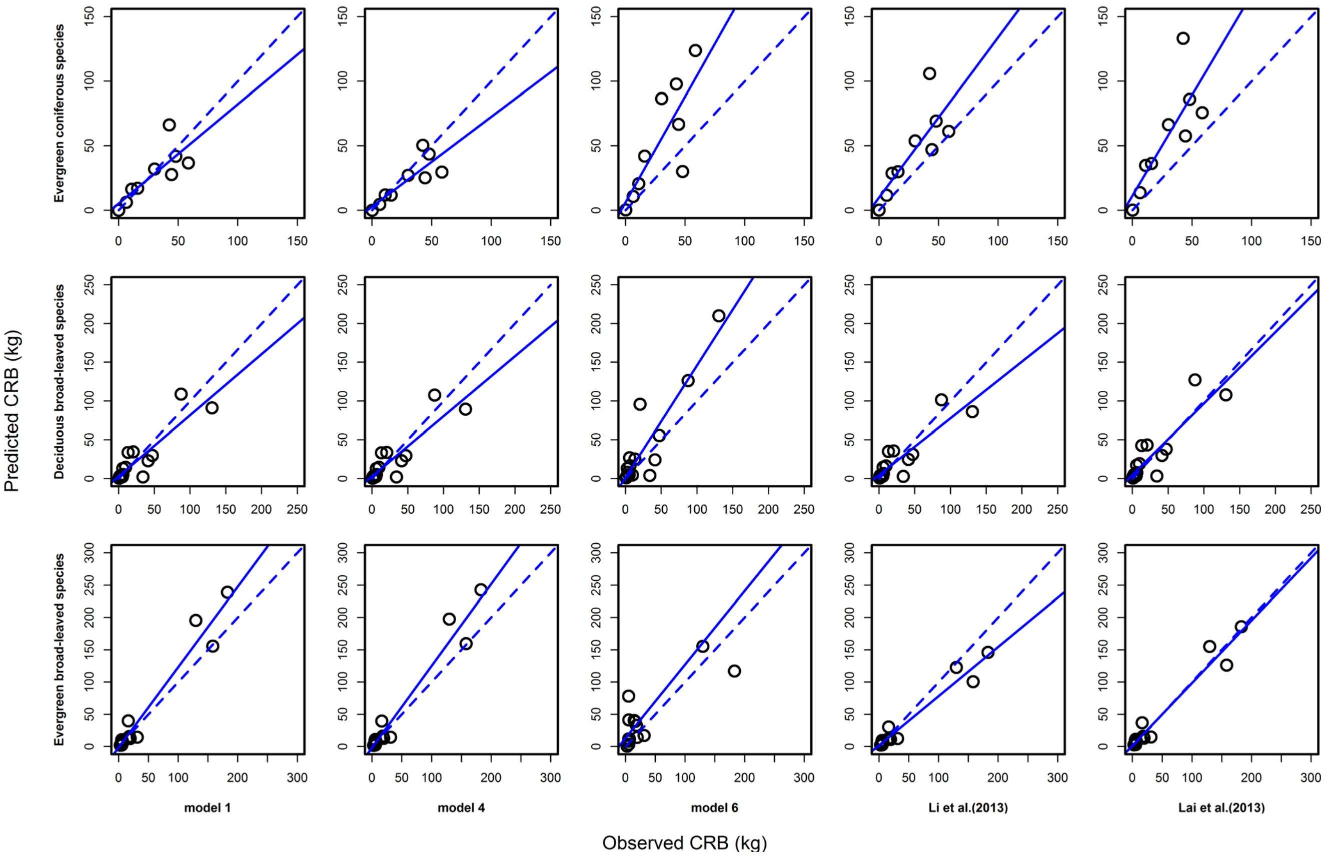


Fig. 3 Relationship between observed coarse root biomass and predicted coarse root biomass estimated by models 1, 4 and 6, and allometric equations developed in previous studies by Li et al. [11] and Lai et al. [20]. The *full line* is a fitted curve, while the *dashed line* indicates the 1:1 relationship. The Li et al. [11] and Lai et al. [20] equations are all species combined models

Lai et al. [20] only incorporated DBH and CRB data, and therefore, we used model 1 to predict CRB. Model 1 poorly predicted CRB for evergreen coniferous species, whereas the prediction for evergreen broad-leaved species was relatively good (Fig. 4). When used to estimate CRB for different DBH classes, the evergreen coniferous species equation had a relatively low average bias for the 0–10-cm (6.68%) and 10–20-cm (8.72%) classes, but with relatively higher stand deviations (Fig. 5) than for the 20–30- and ≥30-cm classes. For evergreen broad-leaved species, DBH classes of 0–10 and 20–30 cm had relatively low average bias and stand deviations (Fig. 5).

Discussion

Functional Group Allometric Equations Based on Forest Plot Data

An accurate estimation of tree CRB in forests is critically important for effective predictions of stand production and energy biomass in forests used by local communities [36]. From an economic perspective, there is also a need for a better quantification of belowground biomass [37]. However, there have been few allometric biomass equations developed

Table 4 Average bias (%) of coarse root biomass (CRB) estimated for three functional groups using our allometric equations that relate to DBH (model 1), DBH¯H (model 4) and CW-H (model 6) as well as the equations of Li et al. [11] [CRB = 1.16 × exp. (−3.47 + 2.31 ln(DBH))] and Lai et al. [20] [CRB = 1.15 × 0.031(DBH)$^{2.38}$]

Functional groups	Tree number	Average bias (%)					*P* value
		Model 1	Model 4	Model 6	Li et al. [11]	Lai et al. [20]	
Evergreen coniferous	9	−1.83*a	−19.09a	99.97b	73.18b	108.88b	<0.001
Deciduous broad-leaved	16	19.97	18.81	98.78	38.91	46.63	0.255
Evergreen broad-leaved	16	19.14*ab	20.61ab	172.10a	1.74b	20.16ab	<0.05

Differences in average bias denoted with asterisks are significant at $P = 0.05$

DBH diameter at breast height, *H* height, *CW* crown width

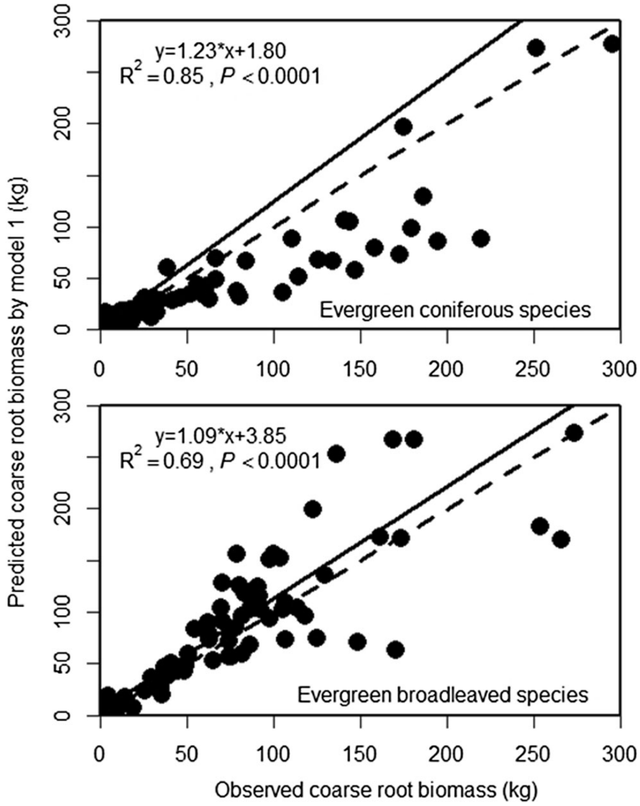


Fig. 4 Coarse root biomass (CRB) estimation accuracy when applying model 1 to the data from Xiang et al. [21] and Lai et al. [20]. The two figures show predicted vs observed values for evergreen coniferous (n = 255) and evergreen broad-leaved (n = 101). For the two figures, the *dashed line* corresponds to a 1:1 relationship, whereas the *solid line* is a regression spline fit to the data points to highlight how predictive accuracy varies with tree size. The bias of each set of predictions is reported in the lower right-hand corner

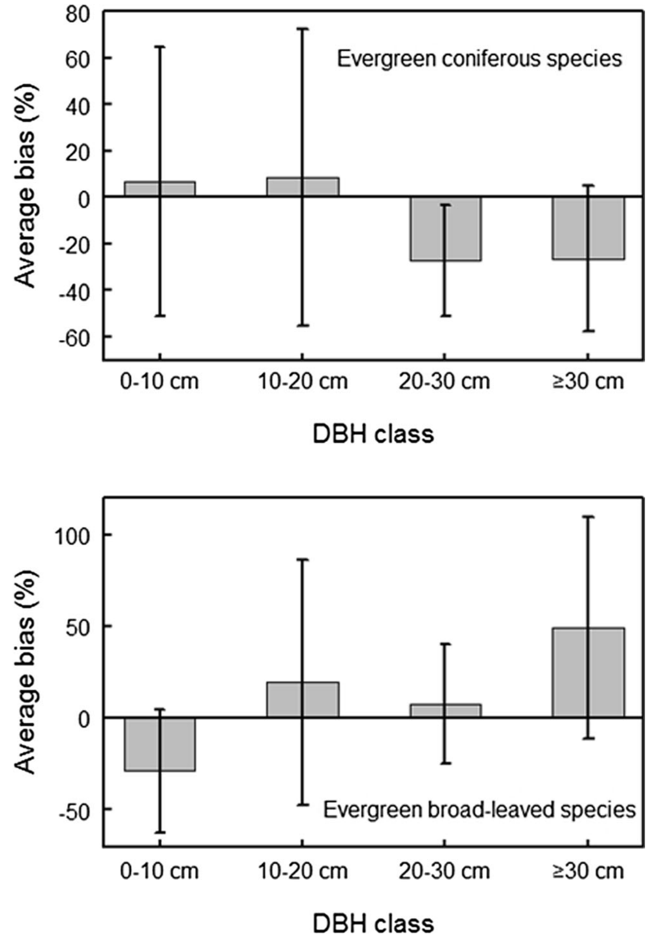


Fig. 5 Bias (with *rectangles* representing mean values and *bars* representing standard deviations) for different diameter at breast height (DBH) classes (0–10, 10–20, 20–30 and ≥30 cm) when applying model 1 to the data from Xiang et al. [21] and Lai et al. [20]. The number of evergreen coniferous species and evergreen broad-leaved species was 255 and 101, respectively

specifically for coarse roots in subtropical forests. Previous studies have usually aggregated the data at the functional group or all species levels, ignoring the difference in the allometric relationships between tree species [13, 23, 24, 31]. Even though the aggregated equations are convenient for biomass estimates, in particular for situations where there are no tree species records, these often lead to large uncertainties. Therefore, it is important to test whether tree species significantly affects the allometric relationships before developing equations for a functional group. Excluding *L. coreana*, no significant effect was found within a given functional group in this study. This result implies that developing a functional group allometric equation is practical.

In this study, allometric equations for three functional groups were developed. The results showed that functional group allometric equations could be used to quantify CRB for biomass energy production with acceptable accuracy. Allometric equations were significantly fitted (P < 0.0001) for three functional groups, and the predictor variables could explain more than 66% of the variability of CRB (Table 3). Among the allometric equations, we found that the equations using DBH or DBH-H as predictor variables were the best fit ($R^2 \geq 0.90$) with a high R^2 and low RMSE, FI and AIC, and their prediction biases for the trees in our study sites were less than 21% (Tables 3 and 4). The results indicate that DBH and DBH-H were good predictors of CRB.

It was found that the functional group influenced the CRB allometric equations. For a given tree diameter, the equations for all tree species combined either overestimated or underestimated CRB for each functional group (Fig. 2). Moreover, the CRB predictions of 41 trees using the equations of Li et al. [11] and Lai et al. [20] for all tree species resulted in an overestimation of CRB for evergreen coniferous species and an underestimation of CRB for other functional groups. These results confirmed that applying all species allometric equations developed at one site to other sites can introduce large errors in prediction, in particular for root biomass [4, 11]. In contrast, allometric equations using DBH alone or DBH and H separately for functional groups not only had good fits but also had low prediction biases (<21%) (Table 4). Our results were also in agreement with a previous study, which showed that the inclusion of a functional group might improve tree biomass estimates [13]. According to Niiyama et al. [17], the accuracy and precision of root biomass estimates are influenced by the quantity of data used for developing the allometric equations. Due to the high cost and labour requirements needed to excavate whole root systems, the number of sampled trees and its sizes were often limited despite the critical need for reducing uncertainty in parameter estimates [38]. Functional group models allow for increases in sample number and sample tree sizes to improve allometric equations and greatly simplify the procedures involved in making CRB estimates. In conclusion, these results support the notion that functional group classification is a trade-off that considers tree architectural traits and simplifies the procedures to develop allometric equations for more accurate CRB estimates.

Forest biomass energy is still in the initial stages of development in subtropical China [39]. Although several studies have been conducted to estimate forest CRB, the performance and predictive ability of allometric equations are still unclear in China. To validate the predictive ability of allometric equations developed in our study, we applied model 1 to the data from Xiang et al. [21] and Lai et al. [20]. The result showed that our allometric equations underestimated CRB, but the bias was 2.4% for evergreen coniferous species and 3.4% for evergreen broad-leaved species. This confirms that the equations developed using data from a variety of sites for functional group models could be extended to other subtropical sites with acceptable accuracy [38]. Previous studies have found that tree biomass allometry changes with tree size [18, 40, 41]. The size range of sampled trees in our study approximates to the sizes used by Lai et al. [20], and our equations showed a good degree of fitness for explaining the variability in CRB [42]. The lower the average bias, the better the estimates obtained from the equations [43]. The bias in this study indicated that the ability of each functional group's allometric equation to estimate CRB differed with DBH classes (Fig. 5). The equations produced relatively good CRB estimations for the 20–30- and ≥30-cm DBH classes of evergreen coniferous species and for the 0–10- and 20–30-cm DBH classes of evergreen broad-leaved species. In summary, the allometric equations using DBH as well as DBH and H as predictor variables developed for functional groups in this study could be used to estimate CRB in subtropical forests. In districts where forest plot data are available, forest managers and local policymakers can adopt the allometric equations we developed to predict CRB, providing a guide to site selection for long-term CRB supplies.

The Basis for Estimating CRB Using Remote Sensing Imagery Data

Recent progress in LiDAR technology and its application in forestry has provided a promising approach for estimating forest biomass. LiDAR technology can directly obtain tree CW and H in forests, which are important tree characteristics used in many stand growth and yield models [44]. Previous studies have found that aboveground biomass is closely related to CW and H at local and regional scales [24, 45]. However, whether this strong relationship still holds for belowground CRB remains to be determined.

The third objective of the study was to demonstrate the possibility of using remote sensing to address the problem of estimating coarse root energy at large scales. The CRB equations significantly fitted with the data from CW and H for three functional groups and could explain 76 to 92% of the variability in CRB estimates (Table 3). These results indicate that the CRB is strongly shaped by CW and H in subtropical forests because the tree architecture reflected by CW and H determines resource capture and biomass [46, 47]. In addition, the accumulation of belowground biomass is facilitated by the photosynthetic capacity of the tree aboveground canopy [48].

Although the allometric equations using CW and H as predictor variables provided a good degree of fitness, the prediction bias was larger than 98.8%. Several factors may explain this result. First, the tree architecture is variable due to the competitive environment [24, 49]. Even for a fixed tree diameter, H and CW may differ. Wang et al. [50] reported that competition intensity had a negative effect on biomass components. Consequently, competition for the aboveground and belowground environment should be considered in further studies when using CW and H to estimate CRB. Second, the error in CW measurements should be considered. The error in CW measurements may be larger than the corresponding error for DBH and H [51, 52], which could lead to a large bias in CRB estimates. Our study explored the potential for the application of remote sensing imagery data to estimate CRB in subtropical forests. The significant fit of the CW and H data in CRB equations is of great interest for the future application of remote sensing technology in monitoring forest structure and stand biomass C dynamics, but more data are required to fully fit and test the equations.

Conclusions

CRB in the subtropical forests of China has considerable potential as a renewable bioenergy source to mitigate the risk of environmental pollution and global climate change. The CRB energy resource could make a considerable contribution to future energy demand in subtropical areas and reduce the dependency on fossil fuels. The accurate projection and successful utilization of CRB for energy production requires a simple and efficient method to assess the magnitude of the root biomass. This study has shown that functional group allometric equations can be used to quantify CRB as biomass sources and for bioenergy production with acceptable accuracy in subtropical forests. Allometric equations using the DBH and DBH-H combination showed good fitness and provided accurate CRB predictions with little bias. Concurrently, although there was a large bias, allometric equations using CW and H as predictor variables significantly fitted the CRB data from three functional groups. In summary, the methods developed in this study will help forest managers better understand the limits of CRB harvesting and determine the best approaches to harvesting biomass in a sustainable way.

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