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Mixed-species allometric equations and estimation of aboveground biomass and carbon stocks in restoring degraded landscape in northern Ethiopia

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Abstract

Accurate biomass estimation is critical to quantify the changes in biomass and carbon stocks following the restoration of degraded landscapes. However, there is lack of site-specific allometric equations for the estimation of aboveground biomass (AGB), which consequently limits our understanding of the contributions of restoration efforts in mitigating climate change. This study was conducted in northwestern Ethiopia to develop a multi-species allometric equation and investigate the spatial and temporal variation of C-stocks following the restoration of degraded landscapes. We harvested and weighed 84 trees from eleven dominant species from six grazing exclosures and adjacent communal grazing land. We observed that AGB correlates significantly with diameter at stump height D_{30} ($R^2 = 0.78$; $P < 0.01$), and tree height H ($R^2 = 0.41$, $P < 0.05$). Our best model, which includes D_{30} and H as predictors explained 82% of the variations in AGB. This model produced the lowest bias with narrow ranges of errors across different diameter classes. Estimated C-stock showed a significant positive correlation with stem density ($R^2 = 0.80$, $P < 0.01$) and basal area ($R^2 = 0.84$, $P < 0.01$). At the watershed level, the mean C-stock was 3.8 (±0.5) Mg C ha^{-1}. Plot-level C-stocks varied between 0.1 and 13.7 Mg C ha^{-1}. Estimated C-stocks in three- and seven-year-old exclosures exceeded estimated C-stock in the communal grazing land by 50%. The species that contribute most to C-stocks were *Leucaena sp.* (28%), *Calpurnia aurea* (21%), *Euclea racemosa* (20.9%), and *Dodonaea angustifolia* (15.8%). The equations developed in this study allow monitoring changes in C-stocks and C-sequestration following the implementation of restoration practices in northern Ethiopia over space and time. The estimated C-stocks can be used as a reference against which future changes in C-stocks can be compared.

1. Introduction

Tropical forests play a major role in regulating the earth's climate through sequestering atmospheric CO_2 [1, 2]. However, tropical forests have become the second largest atmospheric source of CO_2 due to increased deforestation, large-scale land-use changes, and global climate change induced tree mortality [3–5]. Forest degradation is severe in Sub-Saharan Africa (SSA) [6–8] and is amplifying climate change-related risks such as drought and flooding in the region [9, 10]. Partly in response to these threats, significant attention has been paid to the consequences of tropical forest degradation on regional and global scales in recent years [11, 12]. Most notably, this attention has led to the establishment of an international policy framework, increased collaboration between states, and global initiatives to reduce deforestation and promote the recovery of degraded landscapes [13, 14]. In this line, the African Forest Landscape Restoration Initiatives (AFR100) targeted to restore 100 million hectares of degraded landscapes by 2030 in order to boost food security, sustain ecosystem benefit of trees, and improve the resilience of local communities towards the impacts of global climate change [15, www.afr100.org].

Ethiopia has been implementing extensive watershed management measures since the 1980s and has restored several degraded areas [16]. However, the contribution of these restored areas to mitigate climate change through carbon sequestration is not well understood. This gap partly stems from lack of biomass estimation methods, which are required to investigate the temporal and spatial changes in C-stocks following the implementation of restoration measures. Such information gap potentially affects collaboration between states and transnational organizations, as well as future efforts to increase the geographical coverage of restored landscapes [12, 17].

Generalized biomass equations have been used to estimate tropical forest carbon dynamics, and have played a significant role in improving data availability [18, 19]. However, the accuracy of aboveground biomass (AGB) estimation still falls behind what is required, especially in SSA [20, 21]. The main reasons for persistent inaccuracy were lack of site-specific biomass estimation models which can represent the heterogeneity of the study population in terms of species composition and tree-size variation [21–24]. To date, there is no mixed-species allometric model for small-size trees in SSA, including Ethiopia, leading to a high level of uncertainty in estimated AGB in the region. Thus, it is urgent and timely to develop site-specific allometric equations for mixed-species forest stands and to investigate carbon dynamics in restoring landscapes. The present study was conducted to derive various mixed-species allometric equations for small-sized trees and to identify the best allometric equation for the restoring landscape. We then applied the best equation to estimate AGB and compared the distribution of C-stocks in grazing exclosures and adjacent communal grazing land (CGL) to understand the importance of grazing exclosures in recovering the C-sequestration potential of degraded landscape in northern Ethiopia.

2. Materials and methods

2.1. Study area and climate characteristics

The study was conducted in 'Gomit watershed', located in South Gondar administrative zone, in the upper Blue Nile River catchment in northwestern Ethiopia (figure 1(*a*)). This watershed stretches to the east of Lake Tana and covers an area of 1483 ha (figure 1(*c*)). It contains six exclosures[7]: *Atikurit* (ATK. 37.905°E, 12.116°N, age = 1 year); *Markos* (MAR, 37.897°E, 12.098°N, age = 2 years); *Kikibe* (KIK, 37.907°E, 12.103°N, age = 3 years); *Enkurofej* (ENK, 37.894°E, 12.115°N, age = 4 years); *Tinkish* (TIN, 37.896°E, 12.121°N age = 5 years), and *Deldalit* (DEL, 37.899°E, 12.101°N, age = 7 years). The exclosures are located close to the communal grazing land (hereafter, CGL, 37.898°E, 12.110°N) (SI appendix, figure S1 available at stacks.iop.org/ERL/13/024022/mmedia). We assume that before establishment, exclosures and the communal grazing land were in similar condition, because the exclosures were established on the same type of communal grazing land used for livestock grazing.

In the study watershed, major land use types include cultivated lands (23% of the land area), degraded secondary forest lands (53%), communal grazing land (18%), and other uses (6%) [25]. In the highlands of Ethiopia, including the upper Blue Nile Basin, the cattle population represents more than 75% of livestock population [26]. According to the Global Livestock Production and Health Atlas, the Amhara region cattle population density ranges from 64.7–93.8 (heads km^{-2}) (http://kids.fao.org/glipha/#). In this line, livestock population in the upper Blue Nile Basin is one of the main land-use change drivers and shows increasing trends of 1.5% per year [26, 27]. In the Ethiopian highlands, livestock pressure also affects the hydrological system and exacerbates water-related problems [28].

The study watershed is mountainous and characterized by a monsoonal unimodal rainfall pattern [29]. The rainy season occurs from June to September and accounts for 80% of the total annual rainfall. Based on data from the National Meteorological Agency of Ethiopia, the catchment received a mean annual rainfall of 1109.7 (±164.5 SD) mm over the period 1952–2014 (figure 1(*b*)). Monthly mean maximum and minimum temperatures ranged from 22.6 °C–28.8 °C and from 11.2 °C–15.4 °C, respectively.

2.2. Vegetation inventory

A vegetation survey was conducted on six exclosures and adjacent CGL located in the study watershed. In each exclosure and CGL, three transects were established perpendicular to the main slope of the terrain. To consider topographic variations, each transect was further divided into three landscape positions, namely foot slope (FS), mid (MS) and upper (US) slopes. Then, sampling plots of 20 m × 20 m size were established in each landscape position along with each transect. In total, 61 sample plots, ~21 in each of the three landscape positions were established across the study

[7] Exclosures are areas socially fenced from wood cutting, grazing by domestic animals and other agricultural activities with the goal of promoting natural regeneration of plants and rehabilitating formerly degraded communal grazing land [16].

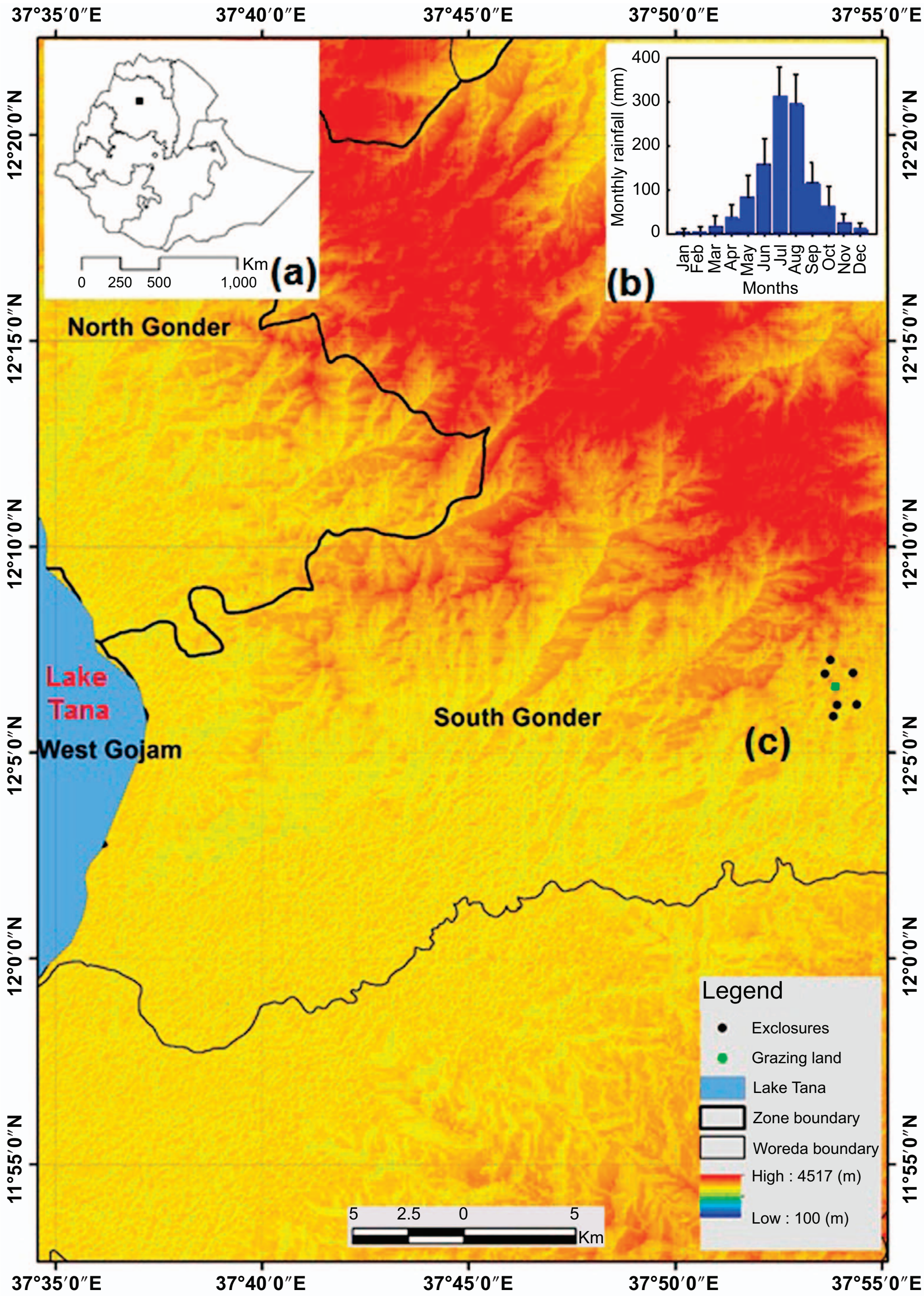

Figure 1. (*a*) Location of the study area in Ethiopia (black dot), (*b*) rainfall characteristics of the study area, (*c*) details of the topography and location of the studied exclosures and communal grazing land.

watershed. Tree species encountered in each plot and their stem diameter (D_{30}) at 30 cm above the ground and total tree height (H, m) were recorded using a caliper and measuring tape, respectively. Since small-size trees dominate the area, we opted to measure the diameter at 30 cm above the ground [30, 31].

2.3. Tree harvesting and determination of above-ground biomass

To determine AGB and C-stocks, we first identified eleven dominant woody species using our vegetation inventory data following the approach used in [32]. To determine total AGB, we collected two to seven representative tree species from each study site. After measuring D_{30} and H, the total aboveground components of the trees were harvested. The felled tree individuals were separated into the stem, twig, and foliage components. The fresh AGB of each component was weighed on the site using a spring balance ($\pm$0.01 kg) [33]. To determine the dry matter contents of the sampled trees, representative sub-samples were collected randomly from each component of the tree.

Then, the sub-samples were weighed in the field, sealed in plastic bags, and transported to *Adet* Agricultural Research Center to determine their moisture contents. Samples were then oven-dried at 65 °C until constant weight was attained. The total oven-dried samples were weighed and the fresh-to-oven-dry weight ratios calculated. These ratios were used to convert the total fresh weights of sample trees measured in the field into total oven-dry weights [33, 34]. The carbon content in the AGB was estimated by multiplying the values of AGB by the default IPCC carbon fraction value of 0.47 [35].

2.4. Biomass model development and cross-validation test

Biomass estimation models were developed using non-linear regression equations based on either stump diameter (D_{30}) alone or in combination with their total tree height (H) as independent variables [33, 34]. Model cross-validation was conducted following a split-sample approach [36, 37] by randomly dividing the 84 sample trees into two equal parts. (Both halves of the dataset were used as a 'training data set' for model calibration (hereafter, F1/2D and S1/2D, $n = 42$ each), and as a 'test data set' for model-validation (hereafter, CVD_F1/2D and CVD_S1/2D, $n = 42$ each). Finally, the full dataset (FD, $n = 84$) was used to build the final biomass estimation models. Model performance was checked using various goodness-of-fit statistics, such as coefficient of determination (R^2), standard error of estimate *(SEE)*, index of agreement (D), mean absolute bias (MAB), percent bias ($PBIAS$), root mean square error ($RMSE$), prediction residuals sum of squares ($PRESS$), percent relative standard error ($PRSE$) and weighed Akaike information criterion (AIC_{iw}) [29, 33, 38]. We also performed outlier and influence diagnostic test statistics, including Cook's distance and Leverage point [39] (SI appendix: Materials and Methods). We compared the performance of our best model with seven previously published biomass estimation models from Ethiopia and elsewhere in the tropics. Finally, we used our best model to convert forest inventory data to AGB and C-stocks in the exclosures and CGL.

2.5. Statistical analysis

Pearson correlation tests were conducted to identify which plant biometric variables (D_{30} or H) were most strongly correlated with measured total AGB of harvested trees. A correlation analysis was conducted between independent variables (D_{30} and H). Pearson's correlations were computed between estimated C-stock, stem density and basal area for each exclosure and CGL, as well as for different landscape positions, and at the watershed level. The differences among exclosures and communal grazing land and between plots at different landscape positions (FS, MS, US) in aboveground biomass and C-stock were assessed using one-way analysis of variance. The significance of differences between exclosures and CGL in mean AGB and C-stock was tested using the least significant difference test (LSD) with $p < 0.05$.

3. Results

3.1. Harvested tree species and their dendrometric relationship

The harvested dominant tree species, their dendrometric information (D_{30}, H) and the range of oven-dry biomass per plant species are presented in (SI appendix, table S1). The D_{30}, H and measured AGB of the harvested trees ranged from 2.0–10.1 cm, 1.3–5.0 m, and 0.6–20.6 kg tree^{-1}, respectively. The correlations between AGB-D30 and AGB-H were significantly positive ($P < 0.01$) (figures 2(*a*) and (*b*)). We found only a weak correlation between H and D_{30} (figure 2(*c*)). Similarly, H-D_{30} correlations were weak for non-harvested trees measured across all sites ($R^2 = 0.27$, $P < 0.01$) and varied between sites and across diameter classes for trees from the same site (SI appendix, figure S2).

3.2. Development and validation of a boveground biomass estimation models

Models developed for predicting AGB and their performances are presented in table 1. In all model forms, the influence of coefficients was significant ($P < 0.001$). Model performance analysis (table 1) and further cross-validation test results (SI appendix, table S2) showed that Y8 is the best model, given the set of eight candidate models with an AIC_{iw} of 60%. The cross-validation test showed that model estimates were stable for the two 'test datasets' (F1/2D and S1/2D) (figures 3(*a*) and (*b*)). The parameter estimates for the coefficients a and b for model Y8 using F1/2D and S1/2D dataset showed negligible differences from those parameter estimates using the full dataset (FD, $n = 84$) (SI appendix, table S3). The *PRSE*, the regression, and influence diagnostic analysis further confirmed that parameter estimates were stable and reliable for model Y8 (SI appendix, figure S3). The biomass of the cross-validation dataset ($n = 42$, CVD_F1/2D or CV_S1/2D) estimated by model Y8 using F1/2D or S1/2D training dataset, showed negligible differences compared to biomass estimated using the 'full dataset' (FD) (figures 3(*a*) and (*b*)). The deviations of estimated averages from observed average AGB per tree, were −4.8% [−2.58%] and +4.3% [+2.3%] when using the 'training' dataset F1/2D [FD] and S1/2D [FD] equations, respectively (figures 3(*a*) and (*b*)).

3.3. Comparison of aboveground biomass equations with previously published equations

Model Y8 produced the lowest average relative error (*PBIAS* %) compared to the error produced using previously published equations (figures 4(*a*)–(*h*)). The equations used by Negash [33] and Ali [40] underestimated the total AGB by 18.6% and 70.3%, while the equation used by Ketterings [41], Kuyah [34],

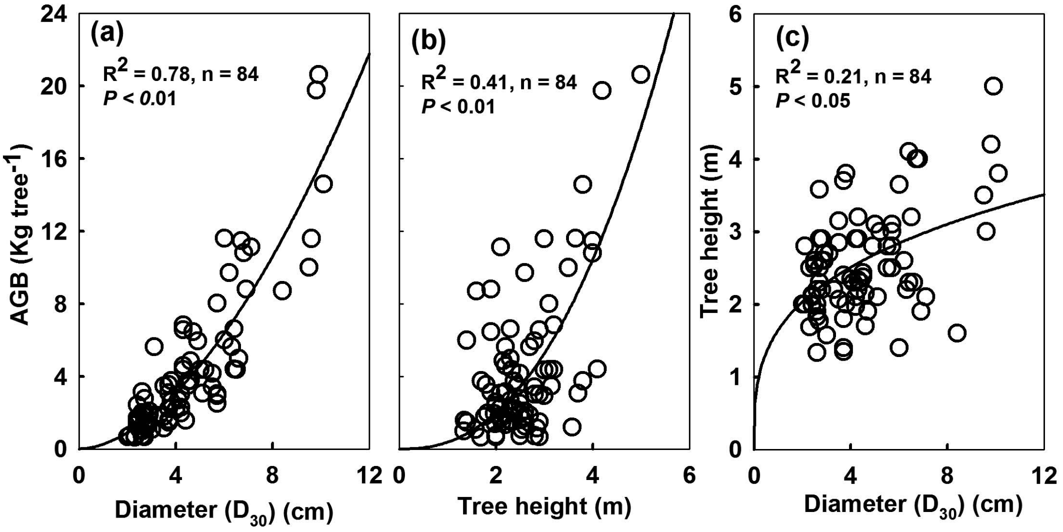

Figure 2. Aboveground biomass of harvested trees as a function of diameter at stump height (D_{30}) (*a*), total tree height (*b*), and regression of tree height as a function of diameter at stump height (D_{30}) (*c*).

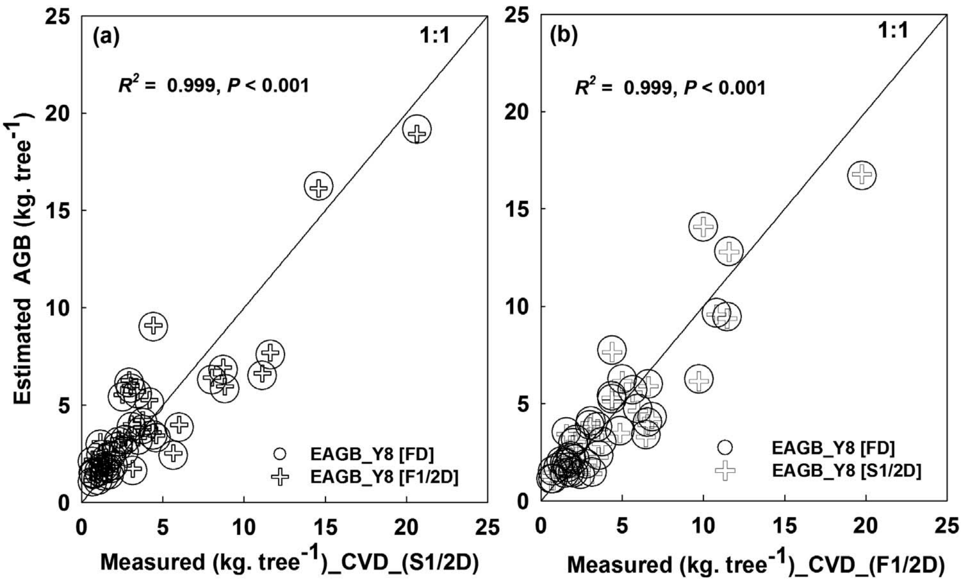

Figure 3. Relationships between estimated and measured total aboveground biomass of the cross-validations 'test' dataset. In figure (*a*) and (*b*), circles are the biomass estimates using the full dataset (FD, $n = 84$) equation, the crosses are the estimates calculated using the model developed by the first halves of 'training' dataset (F1/2D) and second halves of 'training' dataset (S1/2D), $n = 42$ each. The 1:1 lines indicate the cross-validation data (CVD), CVD_S1/2D (*a*) and CVD_F1/2D (*b*). The R^2 values in figures 3(*a*) and (*b*) show the relationships between estimated AGB using the half and the full data set, respectively.

Brown [42], Mugasha [43] and Zewdie [44] overestimated total AGB by 6.4%, 17.2%, 33.4%, 34.6%, and 94.3%, respectively (figures 4(*b*)–(*h*)). More importantly, the spread of error in estimated AGB was stable across different diameter classes in Y8, ranging from −5.2% to 8.7%, however, it was considerably higher in previously published biomass estimation models (SI appendix, figure S4).

3.4. Estimated aboveground biomass and carbon stocks in restoring landscape

Table 2 shows a summary of forest inventory results and estimated biomass and carbon stocks. Stem density, basal area (BA) and tree-size (D_{30}, H) varied between sites and plots across landscape positions (table 2). Tree size-class distribution profiles revealed that the diameter-class ranging from 3–6 cm constituted about 97% of the total population. They also contributed the largest proportion of basal area (BA) and total aboveground C-stocks (figures 5(*a*)–(*c*)). Large-diameter trees ($D_{30} > 9$ cm) were also scarce in the CGL and accounted for only 10%, they, however, stocked approximately 80% of the total estimated C-stocks in the CGL (figure 5(*c*)).

Estimated C-stock showed a significant positive correlation with stem density ($R^2 = 0.80$, $P < 0.01$)

Table 1. Equations and goodness-of-fit performance statistics for estimating biomass (kg dry matter/plant) of multiple tree species grown in the exclosures and communal grazing land across the upper Blue Nile River Catchment.

Models	Coefficient			Performance statistics										PRSE			Rank
	a	b	c	R^2	SEE	MAB	PBIAS%	PRESS	RMSE	D	AIC	r_iAIC	AICiw	a	b	c	
$Y1 = a^*(D_{30})^b$	0.2655***	1.7737***	–	0.78	1.88	1.36	−0.82	332.42	1.86	0.94	110.43	12.45	0.0	22.2	6.2		2
$Y2 = a^*(D_{30})^2$	0.1681***	–	–	0.78	1.92	1.35	−6.86	329.06	1.90	0.94	112.21	14.23	0.0	3.8			5
$Y3 = a^*(D_{30})^b*(H)^c$	0.2430***	1.5041***	0.5511***	0.82	1.73	1.27	−0.16	279.99	1.70	0.95	98.80	0.82	0.4	19.5	7.8	25.0	4
$Y4 = a^*(D_{30})^2*(H)^b$	0.1257***	0.2539***		0.78	1.88	1.32	−9.73	323.31	1.85	0.94	111.67	13.69	0.0	14.4	46.2		6
$Y5 = a^*(D_{30})^b*(H)^2$	0.1282***	0.886***		0.66	2.34	1.61	−12.98	494.98	2.31	0.91	148.88	50.90	0.0	26.3	14.6		7
$Y6 = a^*(D_{30}*H)^2$	0.0115***			0.47	2.90	2.18	−41.73	796.90	2.88	0.88	183.95	85.97	0.0	6.1	0		8
$Y7 = a^*(D_{30}*H)^b$	0.2567***	1.1213***		0.78	1.87	1.36	−0.35	305.98	1.85	0.94	111.34	13.36	0.0	20.1	5.5		3
$Y8 = a^*(D^2{}_{30}*H)^b$	0.2451***	0.7038***		0.82	1.73	1.28	0.01	267.29	1.71	0.95	97.98	0.00	0.6	19.2	5.2		1

SEE, Bias, MAB are in kg per plant, $n = 84$. Y, D_{30}, H, are aboveground biomass (kg/plant), diameter at stump height (30 cm) and total tree height (m), respectively. *** is significant at $P < 0.001$. **Bold** PRSE values indicate unreliable parameter estimates. A positive and negative PBIAS (%) indicates over- and underestimation of AGB. Model performance ranking was performed based on goodness-of-fit statistics (this table) and outlier and influence diagnostic test statistics, (Cook's distance and Leverage point) (SI appendix, figure S3).

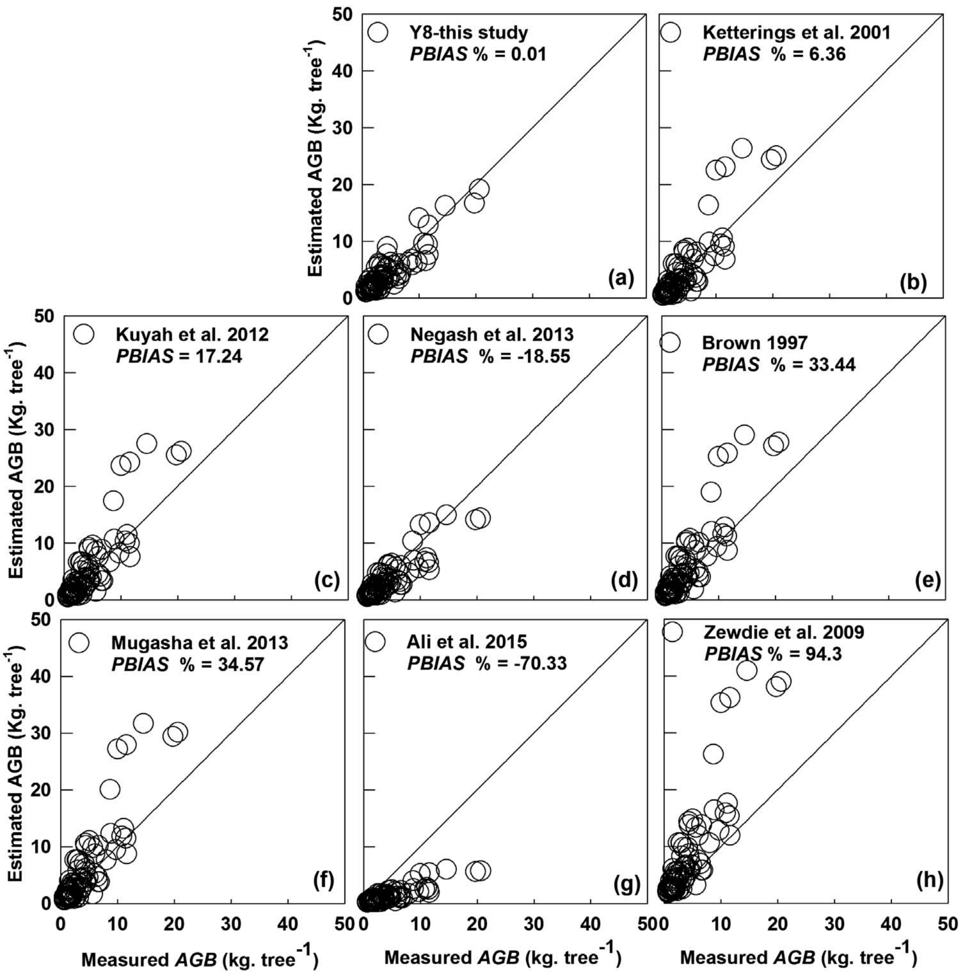

Figure 4. Relationships between estimated and measured total aboveground biomass of sample trees ($n=84$). (*a*) refers to the best model (Y8) of this study. (*b*)–(*h*) represent previously published biomass estimation models. *PBIAS%* shows error produced in the estimation of biomass. The diagonal lines show a 1:1 relation. A positive and negative *PBIAS* % indicates over- and underestimation of AGB, respectively.

and basal area ($R^2=0.84$, $P<0.01$) (SI appendix, figures S5(*a*)–(*f*)). Estimated C-stocks varied between sites and plots across landscape positions within the same exclosures and CGL (table 2). Plots located at the FS position displayed higher values of estimated C-stocks in MAR, KIK and CGL. In contrast, plots at MS position showed higher values of C-stocks in ATK, ENK, TIN and DEL (table 2). Site wise, the estimated C-stock was higher in the 7 year s old exclosure (DEL = 4.7 Mg C ha^{-1}), while the lowest was found in the CGL (2.12 Mg C ha^{-1}) (table 2, figure 5(*d*)). At the watershed level, estimated C-stocks at the FS and MS landscape positions were significantly higher than estimated C-stock at the upper slope positions (figure 5(*e*)). The most important species in terms of C-stocks were *Leucaena sp.* (28%), *Calpurnia aurea* (21%), *Euclea racemosa* (20.9%) and *Dodonaea angustifolia* (15.8%). Site wise, *Euclea racemosa* in ATK and DEL; *Calpurnia aurea* in MAR, *Leucaena spp.* in KIK and ENK; *Dodonaea angustifolia* in TIN exclosures and *Croton macrostachyus* in CGL, were the most important species in terms of C-stocks. Each of these species represented 57, 64, 45, 86, 67, 27, and 82% of total estimated C-stocks in respective exclosures and CGL, respectively (SI appendix, figure S6).

4. Discussion

4.1. Aboveground biomass and dendrometric relationship across grazing exclosures

The relationship between stem diameter and tree height varied considerably across sites, as well as between different diameter classes within the same site, suggesting that tree-size differences and micro-site conditions may influence the H-D_{30} relationships in the studied site. This is in line with previous studies that reported tropical tree H-D_{30} correlations considerably vary from region to region due to variations in forest type and structure, climate and environmental conditions [45]. Such differences may also influence the coefficient values of biomass estimation models, and thus have important implications for the estimation of biomass and the carbon storage potential of tropical forests [41, 46, 47]. The highest correlation between D_{30} and AGB (figure 2(*a*)) indicates that stem

Table 2. Summary of forest inventory results and estimated aboveground biomass and carbon stocks in the exclosures and communal grazing land.

SITE NAME	Site-code	Exclosures age	Landscape position	Stem density ($Plot^{-1}$)	Mean D_{30} (cm)	Mean H (m)	BA ($m^2\ ha^{-1}$)	AGB ($Mg\ ha^{-1}$)	C-stock ($Mg\ ha^{-1}$)
ATIKURIT	ATK	1	FS_1	74	3.1	2.1	1.4	3.7	1.7
			FS_2	157	2.8	2.0	2.5	6.8	3.2
			FS_3	72	2.8	2.0	1.1	3.1	1.5
			MS_1	183	3.0	2.0	3.5	8.8	4.1
			MS_2	321	3.0	2.0	5.6	14.8	7.0
			MS_3	195	3.0	1.9	3.4	8.7	4.1
			US_1	97	2.9	2.1	1.6	4.5	2.1
			US_2	16	2.5	1.8	0.2	0.5	0.3
Average				139	2.9	2.0	2.4	6.4	3.0
MARKOS	MAR	2	FS_1	62	3.7	2.4	1.9	4.7	2.2
			FS_2	450	3.1	2.5	8.8	26.6	12.5
			FS_3	27	3.3	2.4	0.6	1.7	0.8
			MS_1	134	3.6	2.4	3.6	9.3	4.4
			MS_2	37	2.6	2.2	0.5	1.5	0.7
			MS_3	75	3.5	2.3	1.9	5.0	2.4
			US_1	44	3.3	2.8	1.1	3.1	1.5
			US_2	14	2.5	2.2	0.2	0.5	0.3
			US_3	6	3.7	2.6	0.2	0.5	0.2
Average				94	3.3	2.4	2.1	5.9	2.8
KIKIBE	KIK	3	FS_1	234	4.2	2.9	8.4	23.7	11.1
			FS_2	115	4.3	3.2	4.6	13.5	6.4
			FS_3	39	3.5	2.2	1.0	2.6	1.2
			MS_1	63	3.9	2.5	2.1	5.0	2.4
			MS_2	48	3.2	2.1	1.0	2.6	1.2
			MS_3	487	3.4	2.2	11.4	29.1	13.7
			US_1	90	3.9	2.9	2.9	8.3	3.9
			US_2	9	2.9	1.8	0.2	0.4	0.2
			US_3	21	3.5	2.4	0.6	1.4	0.7
Average				123	3.6	2.5	3.6	9.6	4.5
ENKUROTEJI	ENK	4	FS_1	3	2.9	2.0	0.1	0.1	0.1
			FS_2	17	3.1	2.1	0.3	0.9	0.4
			FS_3	202	4.6	4.1	8.7	29.1	13.7
			MS_1	87	4.9	4.1	4.4	14.1	6.6
			MS_2	203	4.1	3.5	7.0	22.8	10.7
			MS_3	94	4.1	3.3	3.3	10.5	5.0
			US_1	59	3.5	2.8	1.6	4.5	2.1
			US_2	16	5.2	3.1	1.0	2.3	1.1
			US_3	33	3.9	2.4	1.2	3.0	1.4
Average				79	4.0	3.0	3.1	9.7	4.6
TINKISH	TIN	5	FS_1	49	3.8	2.5	1.8	4.5	2.1
			FS_2	18	3.2	2.3	0.4	1.0	0.5
			FS_3	21	3.4	2.8	0.5	1.5	0.7
			MS_1	187	3.6	2.2	5.6	13.6	6.4
			MS_2	328	3.5	2.1	8.3	20.8	9.8
			MS_3	164	3.4	2.1	3.8	9.5	4.5
			US_1	210	3.6	2.1	5.6	13.4	6.3
			US_2	185	3.5	2.1	4.8	11.6	5.4
			US_3	183	3.5	2.0	4.5	10.7	5.0
Average				149	3.5	2.2	3.9	9.6	4.5
DELDALIT	DEL	7	FS_1	104	3.6	2.5	3.7	8.5	4.0
			FS_2	423	3.4	2.3	10.1	26.9	12.6
			FS_3	52	3.9	2.7	1.9	4.7	2.2
			MS_1	259	3.5	3.3	6.4	21.8	10.3
			MS_2	184	3.1	2.2	3.5	9.5	4.5
			MS_3	182	3.2	2.3	3.9	10.7	5.0
			US_1	14	4.4	2.5	0.6	1.4	0.6
			US_2	27	3.6	2.6	0.8	2.1	1.0
			US_3	75	3.3	2.6	1.7	4.9	2.3
Average				147	3.6	2.6	3.6	10.1	4.7

Table 2. *Countinued.*

SITE NAME	Site-code	Exclosures age	Landscape position	Stem density (Plot^{-1})	Mean D_{30} (cm)	Mean H (m)	BA (m^2 ha^{-1})	AGB (Mg ha^{-1})	C-stock (Mg ha^{-1})
			FS_1	30	6.9	2.5	7.2	11.4	5.4
			FS_2	44	6.0	1.9	9.0	7.0	3.3
			FS_3	13	8.9	2.2	5.4	3.4	1.6
			MS_1	32	2.5	1.5	0.4	1.0	0.5
GRAZING_LAND	CGL	n/a	MS_2	43	4.2	1.8	3.4	6.1	2.9
			US_1	27	4.7	1.5	3.8	3.3	1.5
			US_2	31	4.0	1.8	2.0	3.0	1.4
			US_3	28	2.5	1.6	0.4	0.9	0.4
Average				31	5.0	1.9	4.0	4.5	2.1

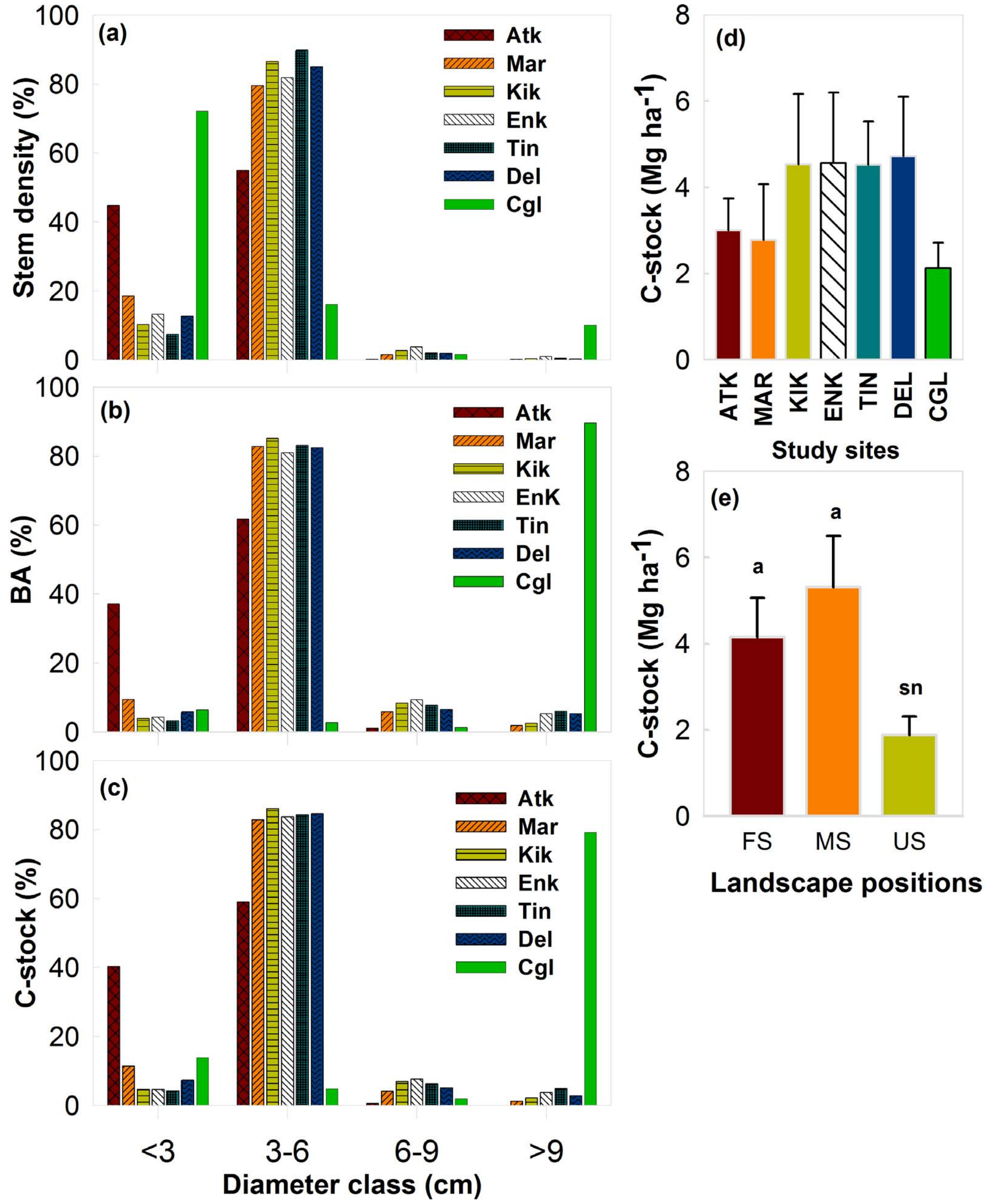

Figure 5. Proportions of stem density (*a*), basal area (*b*), and C-stock (*c*) across diameter classes in study landscape. Estimated C-stocks variation between sites (*d*) and between landscape positions (*e*). The letter, 'sn' indicates a significant difference, whereas 'a' indicates no significant difference.

diameter is one of the main predictors of tree biomass in the studied grazing exclosures and CGL. To this line, similar conclusions were reported in previous studies [30, 33, 34, 43, 48].

4.2. Multi-species biomass estimation models and their performances

The predictive performance of different models using the full dataset ranged from 47%–82%. This variation might be attributed to allometric differences and predictors included in the models [39]. Based on cross-validation and performance statistics test, model Y8 that included D_{30} and H as predictors are the best from the given set of model forms. It explained 82% of the variance in measured AGB and produced the lowest average relative error (0.01%), implying that using D_{30} and H together as predictor may increase model robustness, as it can partially help to capture the effects of site-specific H-D_{30} relationship on biomass allometric equations [47, 49]. Moreover, the performance of our best model to make an accurate prediction is not an artifact of overfitting, because the value of the RMSE in the cross-validation test is close to the standard error (SE) of the full dataset (table 1, appendix, table S2).

In addition, the parameter values in the regression equations and cross-validations were stable across subsets of the 'test' dataset for our best model. The *PRSE*, the regression and the influence diagnostic analysis provided evidence that the parameter estimates were reliable in model Y8. This further supports our argument that Y8 is robust and can reliably be used to estimate the AGB in restoring degraded landscape and CGL. Moreover, the dominant tree species that are used for model development also occur dominantly in the degraded dry Afromontane forest areas and grazing exclosures in the study region [8, 16, 32, 50–57], indicating that model Y8 is representative for larger areas of northern Ethiopia. The diameter-alone model (Y1) is the second-best model and explained 78% of the variation in measured AGB, with an associated error of 0.82%. This model also produced acceptable *PRSE* values ($PRSE < 25\%$), as well as outliers and influential points lower than 10% (table 1, SI appendix, figure S3). Hence, Y1 can be considered as a potential AGB estimation model for the study area and other similar regions when data for tree height are not available.

4.3. Model comparison and importance of site-specific allometric equation

Compared to other generalized biomass estimation models, our site-specific allometric equation produced the lowest estimation error for the study area. A stable spread of error produced across different diameter-classes indicated that Y8 is able to capture the heterogeneity of the studied tree population in terms of species composition and tree-size variation [45, 47]. Our result is in line with several studies, which have concluded that site-specific AGB estimation models are more robust and reliable to convert forest inventory data to AGB [41, 43]. Assessing forest C-stock is an integral part of understanding global climate change impacts in the tropics [19, 58]. Thus, our model could play a considerable role in reducing biomass estimation uncertainties, which resulted from the lack of allometric equations for small-size trees [48]. More importantly, in northern Ethiopia, the foundation trees species[8] (i.e. *Juniperus procera and Olea europaea)* of the dry Afromontane forest areas failed to regenerate and other pioneer species are overtaking the open spaces [51, 54]. Most of these pioneer species are similar to those species used to develop our model, thus, our mixed-species model is crucial to calculate the contribution of understory trees and shrubs to total C-stocks in degraded secondary Afromontane forests. It might also facilitate a paradigm-shifting towards restoring landscapes from the focus on values of remnant degraded secondary forests and woodlands alone.

Furthermore, our model can be used to illustrate the magnitude of possible uncertainties in biomass estimation associated with the omission of small diameter trees from tropical forest inventories and C-stock estimation [59]. For example, the magnitude of AGB underestimation when small-size trees are not considered in biomass estimation, accounted for nearly 30% [60], between 12 and 49% [59], 25 and 45% [61] of total forest AGB. This, in turn, signifies the impotence of small-size trees in forest carbon storage [62]. Therefore, it is obvious that reliable biomass estimation might have considerable implications in allocations of funds among various priorities and application and attribution of international climate-change mitigation funds for restoration measures. It might as well assist to evaluate the attainments of globally and regionally recognized sustainability goals, such as the Sustainable Development Goals, particularly the land degradation neutrality target [63] and the African Forest Landscape Restoration Initiative achievements [15]. Therefore, our biomass estimation model produced for small-size trees is relevant to monitor temporal and spatial changes in C-stocks and to improve the accuracy of AGB estimations, specifically in the context of monitoring carbon dynamics in grazing exclosures and their potentials in providing ecosystem services like mitigating climate change through sequestering atmospheric CO_2 in northern Ethiopia.

4.4. Spatial and temporal variation in AGB and C-stocks across the study watershed

Tree-size, stem density, and basal area considerably varied along landscape positions within the same exclosures and CGL. The highest AGB values were recorded in the plots located in foot slope and mid-slope

[8] Foundation species are species whose architecture and functional and physiological characteristics define forest structure and alter microclimates, while their biomass and chemical makeup contribute substantially to ecosystem processes [80–82].

positions. This might be attributed to the mass translocation from upper to lower landscape positions (e.g. soil, water, and organic materials such as leaves and branches), which create a favorable microclimate and nutrient input in lower topographic positions [47, 64, 65]. The high number of small-size trees in the study sites points towards a positive impact of exclosures to recover degraded landscapes [66, 67]. The magnitude of C-stock variation was considerably higher between plots in the same exclosures and CGL than between sites, indicating that micro-site conditions and landscape position play a significant role in forest C-stock dynamics [68, 69]. This further stresses that carbon pool investigations across different landscape positions are crucial for accurate estimations of C-stock on watershed levels and that they are needed to understand C-fluxes after the implementation of restoration practices. More importantly, together with remote sensing data, the estimated hectare-level C-stock might provide a great opportunity to monitor the dynamics of AGB and C-stock in restoring landscapes at a regional- or national-scale [70].

The significant positive relationships between estimated C-stocks, stem density and basal area (SI, appendix, figures S5(*a*)–(*f*)), together with similar patterns of diameter class distribution in terms of stem density, basal area and C-stocks shown by the exclosures further supports the important role of small-sized trees in carbon storage in the exclosures and young secondary forest (figures 5(*a*)–(*c*)). The relative contribution of small-size trees to AGB stocks depends on forest type and severity of the disturbance [71]. For instance, in secondary forest, trees $<$10 cm stem diameter (dbh) accounted for 19% [62] and 24% [72]. Another study also found that understory woody plants (dbh $<$4 cm) contributes 30% of total AGB in an old field succession and 17% in a young secondary forest [73]. Although trees $<$10 cm dbh can contribute considerably to AGB stocks in secondary and highly disturbed old growth forests, they are usually missing from the forest inventories (e.g. [8, 74]), lead to underestimate the forest biomass when forest inventory data are used, particularly in young secondary forest dominated by small-size trees [8, 59, 62]

The magnitude of estimated C-stocks in 3–7 years old exclosures exceeds the C-stock estimates in the CGL by about 50%, indicating the importance of exclosures to restore the degraded landscapes across the upper Blue Nile river catchment [16, 66, 75]. Estimated C-stocks in our study area were similar to estimated C-stocks in other grazing exclosures in northern Ethiopia [32, 66]. The estimated C-stocks were not linearly related to exclosure age, suggesting that landscape carbon pool recovery does not only depend on the duration of altered management, but it may also depend on other features of the biophysical and social systems within which they are implemented [67, 76]. Another study indicated that the legacy of the initial vegetation coverage at the site plays a considerable role in restoring the degraded landscapes and ecosystem process rates during tropical forest successions [76]. Among other species, *Leucaena sp.* is a dominant species in terms of carbon stock, especially in the KIK (3 yrs) and ENK (4 yrs) exclosure sites. Although *Leucaena sp.* is a multipurpose tree species, it is considered as an invasive species and is aggressively replacing indigenous trees in many parts of the world [77–79]. Hence, future management options should consider limiting the expansion of this species and, if possible, replace this species by indigenous tree species. Concerning carbon pool comparison between exclosures and CGL, future studies should consider increasing the number of observations from CGL, thereby evaluating the effectiveness of grazing exclosures in recovering degraded landscapes across the region.

5. Conclusions

This study presents the first mixed-species allometric equations for small-size trees in northern Ethiopia. The best model explained 82% of the variation in measured AGB. It produced the lowest bias and narrow ranges of errors across different diameter classes, compared to other generalized biomass estimation models from Ethiopia and elsewhere in Africa. This confirms that our model is robust and reliably estimates AGB and C-stock in grazing exclosures and young secondary forests dominated by small-size trees. Furthermore, the model has potential for application in other regions, where agro-ecological zones, tree-size distribution, species composition and site characters are similar to our study area. Exclosures accumulated large AGB and C-stocks than CGL, indicating the importance of grazing exclosures in assisting the processes of recovering the degraded landscapes and hence their suitability in mitigating climate change through sequestering atmospheric CO_2. Reported C-stock values can be used as a reference against which future estimates can be compared, thereby helping to investigate aboveground forest carbon dynamics in space and time under possibly different future climate conditions. Finally, future studies should also try to develop a mixed-species biomass estimation model for the remnant old growth and degraded secondary forests, thereby improving regional carbon assessment and accurate data availability.

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