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Species-Specific Allometric Models for Aboveground Biomass Estimation in Two *Cinchona* Species in the Peruvian Andes

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ABSTRACT

Accurate estimation of aboveground biomass is an essential component for assessing carbon sequestration and ecological dynamics of forest ecosystems. This study aims to determine the aboveground biomass content using specific allometric models in two species of the genus Cinchona (*C. micrantha* and *C. pubescens*) in the Peruvian Andes. A total of 51 individuals of *C. micrantha* and 60 individuals of *C. pubescens* (diameter at breast height (DBH) > 5 cm) were sampled non-destructively. For each species, 25 combinations resulting from applying five mathematical forms (linear, exponential, logarithmic, polynomial, and power) to five independent variables (DBH, H, DBH × H, $DBH^2 \times H$, $DBH \times H^2$) were evaluated. Second-order polynomial models with the composite variable $DBH^2 \times H$ presented the best predictive performance with an $R^2 = 0.95$ for *C. micrantha* and 0.97 for *C. pubescens*, along with low errors (RMSE < 4.35 for *C. micrantha* and < 9.02 for *C. pubescens*) and reduced Akaike information criterion (AIC) values. The results reveal morpho-functional differences between species, highlighting the importance of fitting specific models to optimize the precision of the estimates. Furthermore, the effectiveness of non-destructive sampling in conservation contexts is confirmed. This study provides robust quantitative tools for forest monitoring and ecological restoration in areas of high ecological vulnerability.

1. INTRODUCTION

The genus Cinchona is composed of 24 species [1] recognized for its high medicinal value, highlighting the presence of alkaloids such as quinine in its bark. This compound has been used as the only effective treatment against malaria for more than three centuries [2, 3]. In Peru, there are few forest remnants of *C. micrantha* and *C. pubescens* distributed mainly in the regions of Cajamarca and Piura [4-6]. However, these species have been decimated by anthropogenic activities (agriculture, cattle ranching, logging) [7, 8], which has led to severe population declines and placed several *Cinchona* species at high risk of local or regional extinction in the Peruvian Andes due to historical overexploitation for medicinal purposes and ongoing habitat degradation, recent studies indicate that the genus faces extinction risks from overexploitation, deforestation, and limited protected coverage, prompting national reforestation action plans (2020–2022) targeting *Cinchona* species [9, 10]. This critical conservation status underscores the imperative to adopt non-destructive approaches in ecological and biomass studies, as destructive sampling would further compromise already vulnerable populations and undermine ongoing restoration and monitoring efforts [9, 11].

The estimation of aboveground biomass is a key indicator to assess forest carbon sequestration [12]; in addition to this, the estimation of carbon stocks is necessary to understand the flow of carbon between forest stands and the atmosphere [13]. Although biomass calculated from field data measurement is the most reliable, this approach is unrealistic for large-scale studies [14].

Obtaining accurate biomass estimates that reflect reality is essential for understanding ecosystem dynamics and addressing critical environmental challenges, such as quantifying carbon stocks. These data can be used for the restoration of degraded ecosystems, biodiversity conservation, and sustainable resource management [15]. The rigorous estimation of biomass allows optimizing forest conservation strategies by allowing a more efficient allocation of resources and adequately targeting ecological restoration actions, especially in the face of increasing pressures from deforestation and climate change [16]. Furthermore, accurate quantification of biomass remains a priority in ecological and environmental studies [17], as it constitutes a key indicator for estimating carbon stocks, mitigating climate change, and assessing the functional state of ecosystems [18]. In this regard, it is critical to develop and apply robust methodological approaches that ensure accurate and reliable measurements of tree volume and aboveground biomass [15].

The destructive method is widely recognized for its high accuracy in estimating biomass in different plant organs [19, 20]. Several studies highlight the importance of having an adequate sample size to ensure the reliability of the models; for example, Roxburgh et al. [20] suggest a minimum sample size between 17 and 79 individuals to develop robust models based on stem diameter. Despite its accuracy, this methodology has significant limitations: (1) high operational costs, (2) irreversible damage to sampled organisms, and (3) ethical and ecological incompatibility with the study of rare, threatened, or endangered species, where removing even a few individuals can significantly reduce population viability, genetic diversity, or recovery potential [9].

In the specific case of *Cinchona* species in Peru—nationally symbolic, medicinally iconic, and facing documented extinction risks from overexploitation and habitat loss—destructive sampling is particularly unacceptable, as it would directly conflict with national conservation priorities, reforestation plans, and international commitments for biodiversity protection and climate mitigation [10]. These limitations highlight the urgency of exploring and implementing alternative non-destructive methods that balance precision with sustainability, allowing repeated monitoring without compromising the viability of the populations studied [15]. Non-destructive techniques (e.g., increment borers for density, morphometric measurements for volume) enable longitudinal studies, support REDD+ initiatives, facilitate carbon stock monitoring in protected or restoration areas, and align directly with ethical imperatives for conserving endangered tree species in high-biodiversity hotspots like the Peruvian Andes [21].

The potential for harvesting forest species can be assessed through forest inventories, which provide essential data for estimating the volume, biomass, and carbon stocks in forest ecosystems [22]. Accurate quantification of these resources requires rigorous assessment of tree and forest density and structure. The accuracy of these estimates depends not only on the technical, human, and financial resources available but also on the methodological quality, the tools employed, and the management and analysis of the data collected [23].

In this context, regression models are a key tool for biomass and carbon estimation as they allow the fitting of reliable allometric equations [12, 21, 22, 24]. These models are commonly employed to predict aboveground biomass, establishing relationships between direct measurements obtained from a subsample and structural variables easily measured non-destructively, such as stem diameter and tree height, which facilitates their application in large-scale forest inventories through non-invasive measurements, facilitating biomass estimation, albeit with an associated degree of uncertainty. Scientific literature supports the development and application of allometric models for forest biomass estimation [20, 25].

The objectives of this research were to: i) determine the non-destructive shape density of *C. micrantha* and *C. pubescens*, ii) test the efficacy of various predictor variables to optimize the trade-off between ease of measurement and accuracy of biomass predictions of *C. micrantha* and *C. pubescens*.

2. METODOLOGY

2.1 Location

The study was carried out in the community of La Cascarilla, province of Jaen, Cajamarca region, located in the jungle (Figure 1) between the coordinates 5.671994° S, 72.898198° W at an altitude of 1968 m a.s.l., with an annual rainfall of 1730 mm, minimum temperature of 13 ℃, and maximum of 20.5 ℃.

Individuals with a diameter at breast height (DBH) greater than 5 cm were selected using a stratified random sampling approach to cover the entire observed diameter range and ensure representativeness of size classes in the remnant Cinchona forests. A total of 51 individuals of *C. micrantha* (DBH range: 5–12.1 cm, mean 6.7 cm) and 60 individuals of *C. pubescens* (DBH range: 5–20.37 cm, mean 8.8 cm) were sampled. These specimens were identified in Cinchona forest remnants within the community's jurisdiction. For each individual, the following variables were recorded: DBH in cm, commercial height in m, and basic wood density (g/cm^3) was determined from stem samples.

2.2 Density determination

Wood density was determined by a non-destructive method using a Pressler auger (diameter = 0.43 cm). The extraction of the samples (dowels) was performed at a height of 1.30 m from the ground [26]. Once the wood sample was extracted, it was weighed and stored in a plastic container to preserve its integrity during transport to the Forestry and Environmental Engineering Laboratory of the National University of Jaén.

The samples were placed in an oven at 105 ℃ for 48 hours until they reached constant weight, thus eliminating moisture. Finally, the dry weight was recorded, and the basic density (g/m^3) was calculated using the following formula:

$$\delta = P/V \qquad (1)$$

where, δ = basic density of the wood (g/cm^3), P = dry weight of the wood (g) and V = volume of the wood in green state (cm^3).

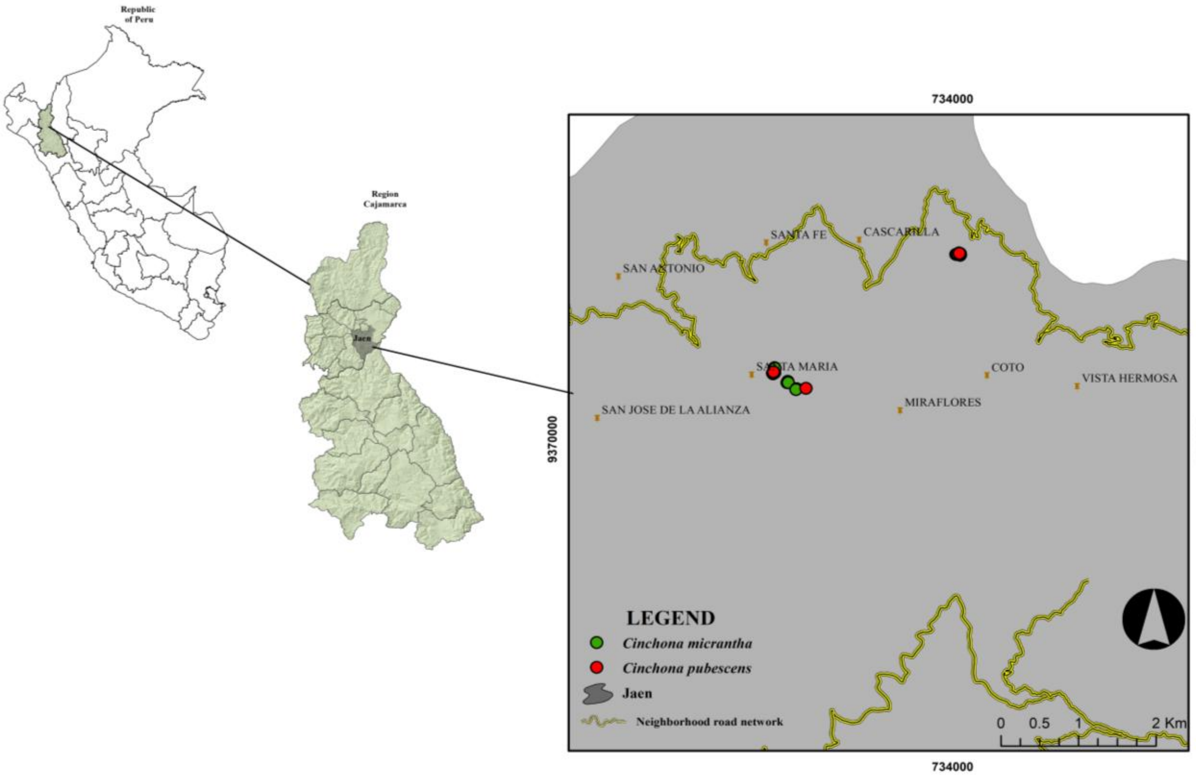

Figure 1. Location map of the study area

2.3 Biomass content of the stem

Biomass was estimated indirectly by the product of stem volume and basic wood density, obtained by non-destructive methods (Pressler) [12, 21, 27]. A form factor of 0.79 was used, recommended for hardwoods [28].

2.4 Allometric regression models used for the estimation of biomass

The allometric models evaluated (Table 1) were selected from functional forms widely reported in the scientific literature [28, 29], complemented with morphometric combinations adapted to the structural characteristics of *C. micrantha* and *C. pubescens*. These forms include linear, exponential, logarithmic, polynomial, and potential regressions, and were applied following the methodological criteria suggested by studies [21, 25]. The predictor variables used were DBH (in cm), individual height (H, in m), and the combination of both.

Although the extensive use of bilateral logarithmic transformations (i.e., log-log) in allometric models to stabilize variance and linearize nonlinear relationships has been documented in the literature [28, 29], in this study, we chose to keep the variables in their original scale (linear and untransformed) for two main reasons. First, because the natural scale equations allow a direct and transparent interpretation of the results by technical users and forest managers, facilitating their practical application in the field. Second, because the approach focused on evaluating the actual predictive fit to the data without introducing distortions associated with back-transformation of logarithms, which can induce biases if not properly corrected, e.g., using smearing correction factors such as the one proposed by the study [30].

Table 1. Allometric models proposed to estimate the biomass content in the stems of *C. micrantha* and *C. pubescens*

No.	Equation of the Models	Variable	Model
a	$y = ae^{bx}$	DBH	Exponential
b	$y = ax + b$	DBH	Linear
c	$y = a\ln(x) + b$	DBH	Logarithmic
d	$y = ax^2 - bx + c$	DBH	Polynomial
e	$y = ax^b$	DBH	Potential
f	$y = ae^{bx}$	H	Exponential
g	$y = ax + b$	H	Linear
h	$y = a\ln(x) + b$	H	Logarithmic
i	$y = ax^2 - bx + c$	H	Polynomial
j	$y = ax^b$	H	Potential
k	$y = ae^{bx}$	DBH × H	Exponential
l	$y = ax + b$	DBH × H	Linear
m	$y = a\ln(x) + b$	DBH × H	Logarithmic
n	$y = ax^2 - bx + c$	DBH × H	Polynomial
o	$y = ax^b$	DBH × H	Potential
p	$y = ae^{bx}$	$DBH^2 \times H$	Exponential
q	$y = ax + b$	$DBH^2 \times H$	Linear
r	$y = a\ln(x) + b$	$DBH^2 \times H$	Logarithmic
s	$y = ax^2 - bx + c$	$DBH^2 \times H$	Polynomial
t	$y = ax^b$	$DBH^2 \times H$	Potential
u	$y = ae^{bx}$	$DBH \times H^2$	Exponential
v	$y = ax + b$	$DBH \times H^2$	Linear
w	$y = a\ln(x) + b$	$DBH \times H^2$	Logarithmic
x	$y = ax^2 - bx + c$	$DBH \times H^2$	Polynomial
y	$y = ax^b$	$DBH \times H^2$	Potential

*DBH: Diameter at breast height, H: Commercial height.

2.5 Data analysis

Once the field and laboratory data were collected, violin plots were used to graphically represent the distribution of density and biomass of the analyzed species. Subsequently, the proposed mathematical models were applied with the selected variables to estimate the biomass in the stems. The evaluation of model performance was based on the calculation of the root mean square error (RMSE) and the Akaike information criterion (AIC). The selection of the optimal allometric model was based on the combination of a higher coefficient of determination (R^2) and lower RMSE and AIC values. Additionally, the average absolute bias (ABL) was calculated to identify possible deviations between the estimated and observed values, considering that a lower ABL value indicates a lower tendency to bias, reflecting a better model fit.

3. RESULTS

3.1 Density and biomass

Figure 2 presents violin plots illustrating the aboveground biomass distributions of *C. micrantha* and *C. pubescens*, based on field measurements taken in a tropical montane ecosystem. Both species show right-skewed distributions with modes close to zero, reflecting a prevalence of smaller individuals. In the case of *C. micrantha*, the distribution is narrower, extending to a maximum of ≈ 100 kg, while *C. pubescens* has a longer tail, reaching up to ≈ 300 kg. These patterns highlight the greater potential of *C. pubescens* for biomass accumulation, which may confer competitive advantages in resource allocation and invasion dynamics within shared habitats.

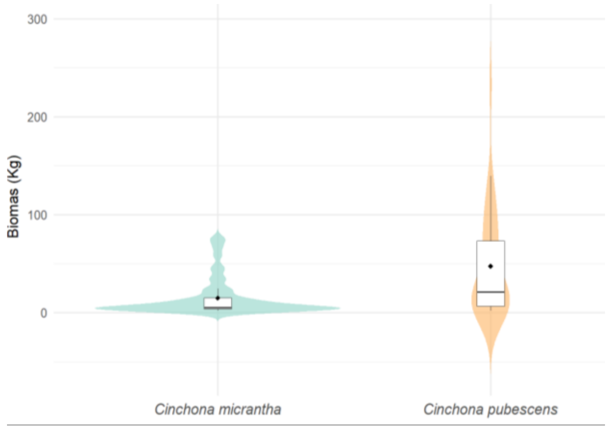

Figure 2. Violin plot showing biomass values of *C. micrantha* and *C. pubescens*

3.2 Stocks of tree components and equations developed to estimate the aboveground biomass of individual trees

The stem biomass in individuals of *C. micrantha* and *C. pubescens* averaged 14.78 kg and 47.25 kg, respectively. In *C. micrantha*, values ranged from 1.65 to 76.55 kg, while in *C. pubescens*, they ranged from 1.77 to 232.87 kg.

Figure 3 shows the relationship between observed stem biomass and two dendrometry variables: DBH (Figure 3(a)) and height (Figure 3(b)) in individuals of *C. micrantha* and *C. pubescens*. A clear positive trend is observed in both species, where increasing diameter and height are associated with higher biomass values, although the dispersion is more pronounced in *C. pubescens*, especially in the higher values, suggesting greater structural variability within this species. Observations also reveal that *C. pubescens* reaches significantly higher maximum biomass values than *C. micrantha*, reflecting differences in biomass accumulation potential between species. These results confirm the usefulness of simple morphometric variables for modeling biomass, although they also underscore the need to consider the species factor in the formulation of accurate allometric equations.

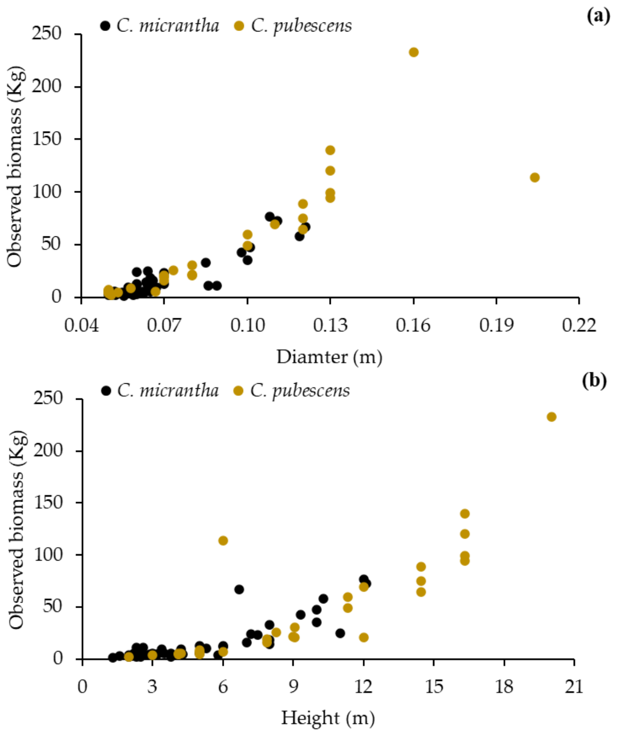

Figure 3. Scatter plot of (a) diameter and (b) height versus biomass observed for *C. micrantha* and *C. pubescens*

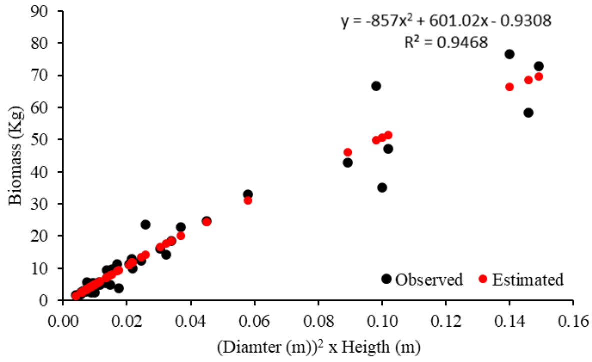

Figure 4. Observed stem biomass versus DBH² × H for *C. micrantha,* with fitted second-order polynomial model and 95% confidence interval

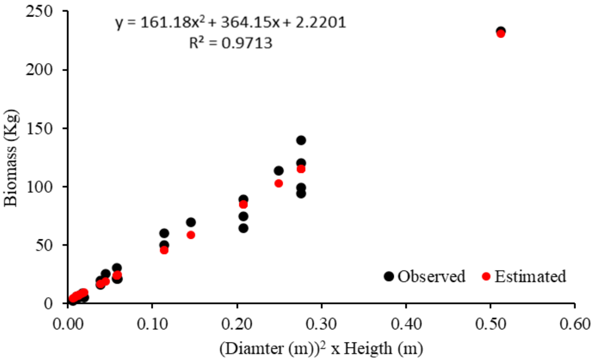

Figure 5. Observed stem biomass versus DBH² × H for *C. pubescens*, with fitted second-order polynomial model and 95% confidence interval

Twenty-five allometric models were evaluated to estimate stem biomass in the *Cinchona* species analyzed (Tables 2 and 3). The equations identified as "s" (Figure 4 and Figure 5) (second-order polynomial with $DBH^2 \times H$) showed the best statistical performance for both species, with coefficients of determination (R^2) of 0.95 for *C. micrantha* and 0.97 for *C. pubescens*. These models also presented the lowest values in the error metrics: MAE (2.30 and 6.08), MSE (18.95 and 81.33), RMSE (4.35 and 9.02), and AIC (154.03 and 135.95), indicating a robust and accurate fit to the observed data.

In particular, when considering the composite variable $DBH^2 \times H$, second-order polynomial regression models were identified as the most appropriate to describe the relationship with stem biomass. The selected models were: $y = -857x^2 + 601.02x - 0.9308$ for *C. micrantha* and $y = 161.18x^2 + 364.15x + 2.2201$ for *C. pubescens* (where $x = DBH^2 \times H$), which reflect specific patterns of biomass accumulation as a function of tree structural dimensions. These results show the importance of adjusting species-specific models, incorporating composite morphometric variables that significantly improve the predictive capacity of allometric equations.

Table 2. Parameter estimates of 25 mathematical combinations estimating *C. micrantha* biomass, coefficient of determination (R^2), mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and Akaike information criterion (AIC)

Code	Model	Variable	R^2	MAE	MSE	RMSE	AIC
a	$y = 0.3482e^{47.033x}$	DBH (m)	0.79	5.80	95.53	9.77	236.53
b	$y = 920.92x - 46.816$		0.83	5.27	59.28	7.70	212.19
c	$y = 69.911\ln(x) + 206.11$		0.79	5.99	73.18	8.55	222.94
d	$y = 8581.7x^2 - 482.12x + 5.6304$		0.86	4.96	51.63	7.19	205.15
e	$y = 204361x^{3.704}$		0.84	5.11	58.60	7.66	211.61
f	$y = 1.8118e^{0.3117x}$	H (m)	0.76	4.29	89.74	9.47	233.34
g	$y = 5.3368x - 10.841$		0.71	6.69	102.64	10.13	240.19
h	$y = 24.392\ln(x) - 19.107$		0.58	8.72	147.92	12.16	258.83
i	$y = 0.5535x^2 - 1.5846x + 4.7014$		0.77	4.59	82.66	9.09	229.15
j	$y = 0.9458x^{1.5451}$		0.75	5.60	116.79	10.81	246.78
k	$y = 2.8871e^{2.8649x}$	DBH × H (m)	0.80	6.25	186.64	13.66	270.69
l	$y = 54.591x - 4.8588$		0.91	3.38	31.19	5.58	179.45
m	$y = 21.58\ln(x) + 43.858$		0.76	6.76	84.53	9.19	230.30
n	$y = 14.049x^2 + 36.861x - 1.8311$		0.92	2.76	28.90	5.38	175.55
o	$y = 46.333x^{1.2951}$		0.92	2.70	30.86	5.55	178.90
p	$y = 4.0171e^{23.805x}$	$DBH^2 \times H$ (m)	0.77	7.27	253.22	15.91	286.25
q	$y = 484.17x + 0.5367$		0.94	2.49	20.22	4.50	157.34
r	$y = 17.844\ln(x) + 87.657$		0.83	5.75	59.32	7.70	212.23
s	**$y = -857x^2 + 601.02x - 0.9308$**		**0.95**	**2.30**	**18.95**	**4.35**	**154.03**
t	$y = 566.62x^{1.0403}$		0.94	2.57	23.29	4.83	164.54
u	$y = 4.4606e^{0.2243x}$	$DBH \times H^2$ (m)	0.68	7.78	366.30	19.14	305.08
v	$y = 4.4676x + 2.9155$		0.88	3.22	44.41	6.66	197.46
w	$y = 11.68\ln(x) + 14.291$		0.69	7.68	109.43	10.46	243.46
x	$y = -0.0422x^2 + 5.0361x + 2.3635$		0.88	3.14	43.88	6.62	196.86
y	$y = 7.8524x^{0.7167}$		0.87	3.91	57.67	7.59	210.80

Table 3. Parameter estimates of 25 mathematical combinations estimating *C. pubescens* biomass, coefficient of determination (R^2), mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and Akaike information criterion (AIC)

Code	Model	Variable	R^2	MAE	MSE	RMSE	AIC
a	$y = 1.4636e^{30.857x}$	DBH (m)	0.246	34.21	15404.32	124.11	293.27
b	$y = 1209.1x - 59.787$	DBH (m)	0.773	13.53	643.56	25.37	198.01
c	$y = 112.29\ln(x) + 329.33$	DBH (m)	0.757	17.85	687.90	26.23	200.01
d	$y = -3401.5x^2 + 1942x - 92.928$	DBH (m)	0.787	15.67	603.38	24.56	196.08
e	$y = 49496x^{3.0641}$	DBH (m)	0.534	16.74	2545.09	50.45	239.26
f	$y = 2.2224e^{0.2481x}$	H (m)	0.832	13.99	744.16	27.28	202.37
g	$y = 9.1303x - 37.917$	H (m)	0.700	18.63	848.54	29.13	206.31
h	$y = 67.613\ln(x) - 93.219$	H (m)	0.550	24.16	1274.71	35.70	218.51
i	$y = 0.8391x^2 - 8.1835x + 30.625$	H (m)	0.816	13.17	521.88	22.84	191.72
j	$y = 0.2844x^{2.1035}$	H (m)	0.797	12.65	672.83	25.94	199.34
k	$y = 5.1413e^{1.5315x}$	DBH × H (m)	0.702	26.98	7403.91	86.05	271.29
l	$y = 63.426x - 13.852$	DBH × H (m)	0.901	11.11	280.36	16.74	173.08
m	$y = 47.113\ln(x) + 67.718$	DBH × H (m)	0.701	20.66	847.40	29.11	206.27
n	$y = 12.361x^2 + 30.444x - 1.3845$	DBH × H (m)	0.926	7.95	208.27	14.43	164.16
o	$y = 41.016x^{1.384}$	DBH × H (m)	0.923	8.42	225.37	15.01	166.53
p	$y = 7.7936e^{9.5014x}$	$DBH^2 \times H$ (m)	0.598	37.95	20421.97	142.91	301.73
q	$y = 426.76x - 0.3329$	$DBH^2 \times H$ (m)	0.968	6.16	91.12	9.55	139.37
r	$y = 34.245\ln(x) + 148.15$	$DBH^2 \times H$ (m)	0.740	19.44	735.67	27.12	202.02
s	**$y = 161.18x^2 + 364.15x + 2.2201$**	**$DBH^2 \times H$ (m)**	**0.971**	**6.08**	**81.33**	**9.02**	**135.95**
t	$y = 407.9x^{0.9837}$	$DBH^2 \times H$ (m)	0.967	6.39	95.86	9.79	140.89
u	$y = 8.9439e^{0.0726x}$	$DBH \times H^2$ (m)	0.585	37.80	16866.17	129.87	295.99

v	$y = 3.3001x + 5.3591$	DBH × H^2 (m)	0.879	10.25	343.85	18.54	179.21
w	$y = 28.335\ln(x) + 0.6921$	DBH × H^2 (m)	0.652	21.67	985.84	31.40	210.80
x	$y = 0.0083x^2 + 2.8922x + 7.3017$	DBH × H^2 (m)	0.881	10.58	337.60	18.37	178.66
y	$y = 5.5645x^{0.8498}$	DBH × H^2 (m)	0.873	9.98	376.90	19.41	181.96

4. DISCUSSION

Although the Pressler increment borer provides a reliable estimate for many species, its small core diameter (0.43 cm) may limit representativeness in heterogeneous hardwoods like Cinchona, where radial variations in density occur due to differences between sapwood and heartwood, or the presence of tension/stress wood. To mitigate potential bias, future studies could consider extracting multiple cores from different radial orientations (e.g., north-south-east-west) and averaging values, or combining with resistance drilling for validation [31-33]. In this study, a single core per tree was used due to conservation constraints on these threatened species.

A form factor of 0.79 was applied, as this is a commonly recommended general value for hardwoods in tropical and subtropical forests when species-specific measurements are unavailable [34, 35]. This value approximates the ratio of actual stem volume to the cylinder volume ($DBH^2 \times H \times \pi/4$), and has been widely used in biomass studies of broadleaf species. However, it is not derived from direct measurements on *Cinchona* spp. or closely related Andean hardwoods, which may introduce uncertainty (typically ±10–20% in volume estimates). Species-specific form factors, if developed in future work through destructive sampling on non-threatened analogs or advanced non-destructive techniques (e.g., terrestrial LiDAR), would improve precision.

One notable limitation of this study is the relatively small sample size (n = 51 for *C. micrantha* and n = 60 for *C. pubescens*) and the narrow DBH ranges sampled (5–12.1 cm for *C. micrantha*, mean = 6.7 cm; 5–20.37 cm for *C. pubescens*, mean = 8.8 cm), which primarily represent juvenile or small-diameter trees in remnant Andean forests. This constraint arises from the critically endangered status of these *Cinchona* species, driven by historical overexploitation and habitat fragmentation, necessitating non-destructive sampling to minimize further population impacts [9, 10]. Consequently, the allometric models developed here may exhibit reduced predictive accuracy when extrapolated to larger individuals (e.g., DBH > 30 cm), where allometric scaling relationships often shift due to changes in tree architecture, wood density gradients, or biomechanical constraints [28, 36]. Such extrapolation could lead to systematic biases in biomass estimates, potentially over- or underestimating carbon stocks in mature stands and compromising applications in REDD+ programs or large-scale ecological restoration [27, 37]. To address this, future research should prioritize expanding datasets to include broader DBH classes through collaborative inventories in protected areas, while adhering to non-destructive protocols such as terrestrial laser scanning (TLS) for volume validation or integrating remote sensing data (e.g., LiDAR) for independent model testing [38, 39]. Additionally, bootstrapping or cross-validation techniques could be employed to quantify uncertainty in current models, ensuring robust applicability across ontogenetic stages [37].

Accurate estimation of aboveground biomass is a fundamental tool for assessing the carbon stocks of forest ecosystems, especially in threatened species or species with ecological and medicinal relevance, such as *Cinchona micrantha* and *C. pubescens*. This study demonstrates that allometric equations adjusted specifically for each species allow modeling stem biomass with high accuracy, as evidenced by high R^2 values (up to 0.95 for *C. micrantha* and 0.97 for *C. pubescens*) and low prediction errors (RMSE and AIC). These results are consistent with previous work highlighting the importance of locally calibrated models to improve the accuracy of biomass estimates in tropical forests [25, 28]. Unlike classical approaches that seek only the best-fit equation, this study emphasizes the empirical validation of specific models for little-studied species of the genus Cinchona, whose biocultural and ecological relevance has been underestimated. The novelty lies in the conservationist approach based on non-destructive methods and in the applicability of the models in REDD+ programs and carbon monitoring in vulnerable high Andean ecosystems.

The superior performance of models based on the composite variable $DBH^2 \times H$ stems from strong theoretical and geometric foundations in plant allometry. $DBH^2 \times H$ approximates the volume of a cylindrical stem (basal area × height), which directly scales with biomass assuming relatively constant wood density and taper across individuals. This variable integrates the two primary dimensions of tree structure, horizontal expansion (DBH^2 captures cross-sectional area) and vertical extension (H), better than single predictors like DBH or H alone, which fail to account for the three-dimensional allocation of biomass in stems, branches, and foliage [21, 40]. In tropical trees, where biomass is not uniformly distributed but follows scaling principles influenced by mechanical stability, hydraulic constraints, and resource allocation, composite variables like $DBH^2 \times H$ reduce residual variance by capturing volumetric proportionality more effectively than simpler forms (e.g., DBH alone often yields $R^2 < 0.90$ in heterogeneous stands). This is particularly relevant in montane Andean contexts, where environmental stresses (e.g., wind, slope) may alter taper and height-diameter relationships, making volume proxies especially robust [41].

The high R^2 values obtained here (0.95–0.97) indicate excellent model fit and are superior to or comparable to those reported in many pantropical and regional studies. Pantropical generic models, e.g., research [21], typically achieve R^2 around 0.80–0.93 when validated across diverse sites, with higher uncertainty in montane or secondary forests due to site-specific allometry. In younger secondary tropical forests, improved models incorporating DBH, H, and wood density reach adjusted $R^2 \geq 0.96$ [42], similar to our results. In Andean montane forests, local equations often yield $R^2 = 0.90$–0.96, but generic pantropical models applied without calibration show larger biases (e.g., overestimation by 20–50% in high-elevation sites). Our species-specific, non-destructive models outperform many generalized approaches, likely due to the focus on threatened remnant populations with limited structural variability and the use of polynomial forms on composite variables, which better capture non-linear scaling in these Andean hardwoods. This underscores the value of locally fitted equations for precise carbon accounting in vulnerable ecosystems, where generic models may introduce substantial errors.

The morpho-structural patterns observed between the two species reflect functional differences that should be considered when selecting predictor variables. *C. pubescens* showed greater variability and biomass accumulation capacity than *C. micrantha*, with an average stem biomass of 47.25 kg vs. 14.78 kg, which coincides with its larger average size and diameter. This structural divergence highlights the need to develop species-specific allometric models, as the application of generic equations can generate significant biases [12, 24].

Likewise, the composite variable $D^2 \times H$ showed superior performance in the fitted models, supporting its use as a robust predictor in polynomial and exponential equations. As indicated by studies [20, 21], the use of variables that simultaneously integrate potential volume and vertical tree structure substantially improves the explanatory power of the model. DBH remains one of the most robust predictors for estimating aboveground biomass in trees [43]. Previous studies [28, 44-46] support this and highlight the fundamental role of DBH in the quantification of dry biomass, consolidating its use as a key variable in allometric models. Recent studies show that ecological conditions influence the selection of variables to estimate tree biomass. For example, Henry et al. [47] revealed that including tree height significantly improves the accuracy of models in humid areas, where vertical growth is determinant in biomass accumulation. Research [48, 49] has shown that environmental factors (such as water availability and temperature) can modify the relationship between diameter, height, and biomass. In particular, Daba et al. [50] highlighted that bioclimatic variables directly influence the predictive ability of metrics such as height (h) and wood density (ρ), which could explain the discrepancies between different studies. These findings indicate that there is no universal hierarchy of predictive variables, but rather that their usefulness depends on the ecological and climatic context of each region. In this study, models with the variable $DBH^2 \times H$ achieved the best fit indices for both species, suggesting their applicability to other tropical taxa with morphological characteristics.

On the other hand, the use of the non-destructive method to estimate the basic density of wood by the Pressler auger and controlled drying constitutes an efficient and replicable methodological strategy. Although destructive methods have historically been considered more accurate [19], their application is limited in conservation studies. The alternative employed in this research preserves the integrity of individuals and allows extending the assessment to populations at risk, such as those of Cinchona in the Peruvian Andes [4, 11].

In the context of global climate change, quantifying biomass and carbon stored in forest ecosystems represents a key component for assessing the balance of emissions, especially in areas subject to forest management or anthropogenic disturbances with adverse effects. Incorporating carbon content as an explanatory variable in allometric models is fundamental, as it provides critical information to more accurately estimate carbon stocks and emissions derived from forest intervention or management activities [12].

Finally, this study contributes significantly to the body of knowledge on allometric modeling in native species of biocultural and medicinal importance. In a context of climate change and anthropogenic pressure on Andean-Amazonian ecosystems, having empirically validated tools to estimate carbon and biomass is essential to strengthen conservation policies and sustainable management of forest resources. As indicated by the study [13], the accuracy of these models not only supports technical and scientific decisions but also has direct implications for compliance with international environmental commitments.

5. CONCLUSIONS

Allometric modeling based on nondestructive morphometric techniques has proven to be an effective and replicable tool for estimating stem biomass content in ecologically relevant forest species such as *Cinchona micrantha* and *C. pubescens*. The superior performance of second-order polynomial models integrating the $DBH^2 \times H$ product ($R^2 = 0.95–0.97$) evidences the potential of this composite variable to accurately capture volumetric biomass accumulation in individual trees, outperforming simpler predictors in Andean montane contexts.

The structural and functional differences observed between species highlight the importance of fitting species-specific models, avoiding generalizations that could induce substantial biases in biomass and carbon stock estimates. In addition, the implementation of non-destructive methodologies, including Pressler increment borers for wood density and morphometric measurements for volume, strengthens the applicability of these tools in threatened populations, enabling repeated monitoring without compromising the integrity of remnant Cinchona forests.

Based on these findings, the following practical recommendations are proposed:

- Adopt the presented species-specific equations (models “s” with $DBH^2 \times H$) as reference tools for non-destructive biomass estimation in future forest inventories and carbon monitoring programs targeting *Cinchona* remnants in Peru.
- Incorporate these models into national REDD+ activities, voluntary carbon projects, and ecological restoration initiatives in the Peruvian Andes, prioritizing non-destructive sampling to comply with conservation ethics and avoid further pressure on endangered populations.
- Promote the validation and expansion of these equations to other Andean Cinchona populations or related hardwood species, potentially integrating wood density variability and site-specific form factors to reduce uncertainty in large-scale carbon accounting.
- Support capacity-building programs for local communities and forest technicians in the use of non-destructive techniques and allometric tools, facilitating participatory monitoring and contributing to sustainable management of high-biodiversity montane ecosystems.

In the context of climate change and increasing anthropic pressure on Andean-Amazonian ecosystems, having empirically validated, species-specific equations represents a crucial advance for sustainable forest management, accurate carbon stock monitoring, and the effective implementation of conservation strategies for threatened Cinchona forests in the Peruvian Andes, including their integration into national reforestation plans, REDD+ mechanisms, and Peru’s Nationally Determined Contributions (NDCs) under the Paris Agreement.

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