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Hypsometric relationship of *Schizolobium parahyba* var. *amazonicum* in plantations integrated with livestock in eastern Amazonia: applications of different modeling methods

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FOREST MANAGEMENT

ABSTRACT

Backgrounds: Research on how obtaining basic variables from the forest inventory supports the accurate estimation of planted forest production. Therefore, this work aimed to select the best modeling method for estimating the heights of trees in a *Schizolobium parahyba* forest and livestock integration system in the countryside of Pará state, Brazil; hence it was established to compare specific and general regression equations for the different management types, and to analyze whether there is a gain in precision with the increased complexity of the regression models and artificial neural networks (ANNs). Three hypsometric regression models were tested: Curtis, Stoffels & Van Soest, and Petterson, using linear, mixed, nonlinear, and covariate models. The ANNs were of the Multilayer Perceptron type with one and two variables in the input layer.

Results: The linear Stoffels & Van Soest hypsometric models showed the best regression adjustment, followed by the Curtis model. The linear and nonlinear regression models performed similarly; hence, the linear ones were more efficient based on their simplicity of adjustment. The specific equations performed better than the general equation except for stratum II. The artificial neural networks with two input variables resulted in better estimates of tree heights.

Conclusion: The linear equation models were selected, including the specific strata I and III, and the general equation for stratum II. The increase in the complexity of the regression models did not indicate better estimates, unlike the ANNs.

Keywords: Artificial neural networks; forest inventory; production forests; regression models; silvopastoral system.

HIGHLIGHTS

The simplest regression models provided better estimates of the height of *paricá* trees.
Two models with covariates detected the differences among planting strata.
Artificial neural networks showed bias problems in estimating heights.
The regression models had the same trend regardless of the fitting type.

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INTRODUCTION

Forest plantations represent a sustainable alternative to reducing timber extraction from native forests, aiding their preservation and protection. Fast-growing species, well-suited to edaphoclimatic conditions, are ideal for planted forests. In the Amazon region, *Schizolobium parahyba* var. *amazonicum* (Huber ex Ducke) Barneby, commonly known as *paricá*, has gained prominence due to its ability to meet these requirements. The species can reach heights ranging from 15 to 40 m and diameters up to 100 cm, with a straight, cylindrical trunk, high adaptability, and significant potential for timber production (Rabelo et al., 2023; Santos et al., 2023; Cordeiro et al., 2020). This adaptability and productivity have attracted interest from the Brazilian forestry sector.

As reported by the *Indústria Brasileira de Árvores* (2023), *paricá* is one of the most planted native forest species in Brazil, alongside *Araucaria angustifolia* (Bertol.) Kuntze, commonly known as *araucária*. In 2014, these two species were cultivated over a total area of 365,000 ha. By 2022, this figure had risen to 381,000 ha, marking a 4% increase within 8 years (IBGE, 2024). *Paricá* wood has an average basic density of 0.30 g cm^{-3}, making it particularly suited for veneering and laminated panels, constituting its most profitable market segment (Silva et al. 2020). Furthermore, the wood demonstrates promise for sawdust production, energy generation, cellulose, and paper manufacturing applications. Economically, *paricá* is highly valuable due to its versatility in packaging, civil construction, and utensils (Mascarenhas et al. 2021; Setter et al. 2021; Terezo et al. 2021).

A noteworthy ecological advantage of *paricá* is its status as a pioneer species, which allows it to be used in restoring degraded areas and promoting reforestation, both in homogeneous plantations and agroforestry systems (Delarmelina et al. 2023; Sales et al. 2021). Among agroforestry systems, silvopastoral systems combine forest plantations and livestock farming within the same area. These systems offer benefits such as providing thermal comfort to cattle, enhancing soil nutrient cycling, and facilitating carbon sequestration (Silva et al., 2021a). Additionally, diversifying production through silvopastoral systems ensures a more stable income for rural properties than relying solely on homogeneous plantations or livestock farming (Minini et al. 2024). However, further research is essential to understand the growth and productive behavior of *paricá* in such integrated systems.

Forest management strives to optimize timber production by relying on knowledge and controlling timber stocks within forest stands (Xinmei et al. 2020). Achieving this goal requires accurately quantifying the variables influencing stock availability to better plan forest production and management activities (Petris et al. 2022). Among these variables, tree height is critical for estimating forest production. However, direct measurement of tree height can be costly and time-intensive (Shen et al., 2023; Jurjević et al., 2020). Consequently, an alternative methodology involves establishing a mathematical relationship between tree height and diameter at breast height (DBH), measured 1.3 m above the ground, based on a selected sample. Using this relationship alongside management techniques, it becomes possible to estimate the heights of the remaining trees within acceptable precision and error margins (Andrade et al. 2023; Nie and Liu 2023).

This mathematical relationship, called the hypsometric relationship in forestry science, allows for estimating forest stand dynamics, growth, and productivity (Terra et al., 2022; Fernandes et al., 2021). Furthermore, it enables the evaluation of planting site quality (Zea-Camaño et al. 2020) and supports decision-making in forest management practices, such as thinning (Jha et al. 2023; Zhang et al. 2020). Sociological position, location, species, age, canopy size, density, and silvicultural practices can influence the hypsometric relationship (Acosta et al., 2020). Thus, each plantation necessitates a specific model to characterize this relationship and minimize estimation errors (Cunha et al., 2022; Lanssanova et al., 2021; Hofiço et al., 2020; Morais et al., 2020). Regression analysis, a statistical method used to evaluate the relationship between dependent and independent variables, is typically employed for this purpose (Nascimento et al., 2020). Linear regression is the most frequently used among regression types, as it seeks to establish a line of best fit for observed data (Bonfatti Júnior and Lengowski 2022).

Regression models have evolved with advances in modeling techniques to improve adjustment efficiency and applicability (Cerqueira et al., 2020). For instance, mixed-effects modeling combines fixed variables that describe overall effects, such as the allometric relationship between DBH and various heights, with random variables associated with localized conditions or variability-blocking factors (Leite et al., 2021). Nonlinear models are often preferred, as they more accurately describe biological phenomena by integrating parameters directly into the model (Abreu Neto et al., 2021). Covariates can also be incorporated into nonlinear models to identify other independent variables that improve estimates of the dependent variable (Silva et al., 2024; Lacerte et al., 2021).

Alternatively, the use of artificial intelligence (AI) has been highlighted in forestry science (Soares et al., 2021), such as predicting DBH and tree height through sensor images (Silva et al., 2021b), production projection (Casas et al., 2022), productivity modeling (Freitas et al., 2020), biomass prediction (Domingues et al., 2020), estimating conicity and volume (Șahin, 2024), and hypsometric relationship (Shen et al., 2020; Almeida et al., 2022; Costa et al., 2022). Artificial neural networks (ANNs) are an AI method that can be used as an alternative to traditional modeling techniques, such as regression models, because they are more generalizable and less sensitive to noise and outliers (Bayat et al., 2020). The strong nonlinear modeling capacity explains this fact without any predetermined functions, no statistical assumptions required between variables, and the possibility of processing a large amount of data (Ercanli, 2020; Ma et al., 2020; Proto et al., 2020).

Thus, the present study aimed to identify the most suitable modeling approach for estimating tree heights within a *Schizolobium parahyba* forest and livestock integration system in Pará state, Brazil. The research involved comparing specific and general regression equations across different management approaches and analyzing potential gains in precision using increasingly complex regression models and ANNs.

MATERIAL AND METHODS

Study area

The work was carried out at Fazenda Cinco Águas, which spans 254 ha, located in Abel Figueiredo, within the mesoregion of southeastern Pará state, Brazil. The farm is located at the coordinates 05° 21' 42" S e 48° 47'36" W (Figure 1), with main access via BR-222, 1,473 km away from Brasilia, the capital of Brazil. The predominant soil is a yellow latosol, characterized by good physical properties, a medium clayey texture, and an undulating slope ranging from 8 to 20% (Santos et al., 2018). The region's climate is classified as Aw, indicating a hot and humid tropical savanna, according to the Köppen-Geiger classification (Alvares et al., 2013). The vegetation is characterized as a submontane-dense ombrophilous Forest, and the average annual precipitation ranges from 1,000 to 2,000 mm, with an average temperature of 26 °C (Nascimento et al., 2022).

The farm has two forest plantations, one of *which is Eucalyptus grandis*, occupying 120 ha. The other comprises a silvopastoral system, consisting of a *paricá* plantation, implemented with seedlings from seeds and occupying an area of 46 ha. Due to several crosses, the herd has 40 heads of cattle of no defined breed. The pasture was formed with the forage species *Panicum maximum*. The area of the silvopastoral system was divided into three strata (Figure 1), as follows: Stratum I: 12.33 ha of *paricá* planted in 2020 with a spacing of 4 x 2 m with pasture; Stratum II: 9.91 ha of *paricá* planted in 2020 with a spacing of 4 x 2 m without pasture; and Stratum III: 23.83 ha of *paricá* planted in 2019 with and spacing of 3.5 x 3.5 m with pasture. Despite the presence and absence of pasture in the strata, cattle moved freely throughout the farm area.

Data collection

Data from a 2024 forest inventory with temporary plots were used. Forty-six circular plots of 500 m^2 were installed and systematically distributed among the strata, with 80 m separating them. Based on the stratum size, 14, 11, and 24 plots were allocated to stratum I, II, and III, respectively (Figure 1).

The diameter at 1.3 m above the ground (DBH) was measured using a Haglof Suta Mantax Blue with a diameter of 1,300 mm. Two measurements were taken, one perpendicular to the other, and the average between the two diameters was used. The total individual height of the trees was obtained using a Haglöf SWEDEN AB hypsometer, with all the trees in the central row of each plot being measured. A total of 84 trees were sampled in stratum I, 73 in stratum II and 89 in stratum III. In stratum I, the mean DBH was 13.84 cm, with a standard deviation (SD) of 3.92 cm. The mean DBH was 14.16 cm, with an SD of 3.98 cm in stratum II, and 17.36 cm, with an SD of 4.17 cm in stratum III. The mean height was 16.30 m and the standard deviation (sd) was 3.83 m in stratum I, the mean height was 18.15 m and the sd was 5.03 m in stratum II, and the mean height was 18.18 m and the sd was 4.05 m in stratum III.

Modeling methods

The hypsometric models proposed by Curtis (1967) (Crt), Stoffels & Van Soest (1953) (SVS), and Petterson (1967) (Ptt) were selected due to their ability to provide adjustments in both arithmetic and nonlinear forms. Four adjustment approaches were applied: 1) Linear regression: Hypsometric equations were adjusted using the selected models in their linear form, with one equation fitted for each stratum and one general equation for the entire plantation using the least squares method; 2) Nonlinear regression: A general equation was fitted for the entire plantation, as well as one for each stratum, using the selected models

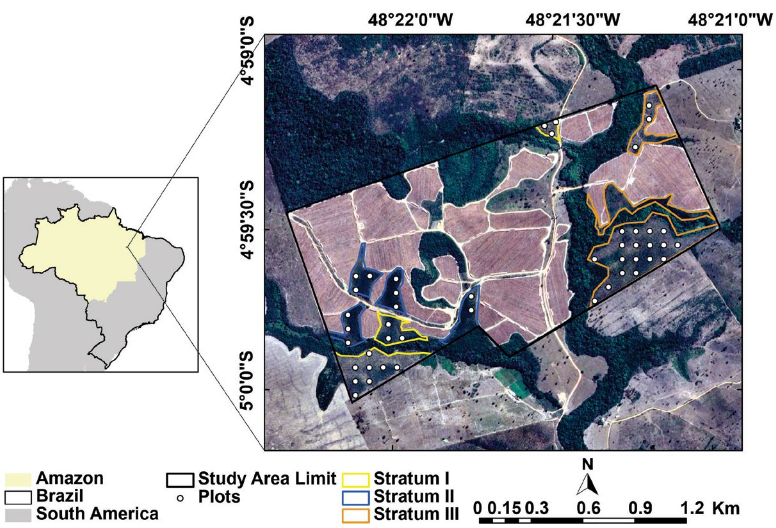

Figure 1: Cinco Águas farm location within the Amazon (highlighted) in Brazil (Source: IBGE, SIRGAS 2000).

in their nonlinear form with the parameters obtained by weighted least squares estimation; 3) Mixed Effect Models: The selected models were adjusted in their linear form, using the maximum likelihood method, incorporating plantation strata as a random effect, and; 4) Models with covariates: The selected models were adjusted in their nonlinear form, by the generalized least squares method, adding plantation strata as covariates to both parameters estimated in the regression. The strata were coded as random effects in the mixed-effects models, representing inherent variation within each group (Table 1). This treatment allowed for adjusting inherent differences among strata while maintaining cohesion in data modeling. In the case of nonlinear regressions, covariates were incorporated as fixed terms and evaluated for their interaction with other explanatory factors, enhancing the predictive capacity of the models.

The dataset was divided randomly into two equal subsets—one for fitting and one for validation—each containing 50% of the measurements. This division was implemented due to the intrinsic inter-individual variability of the seminal stand. Allocating more data to the validation set increases the likelihood of detecting errors when the model is extrapolated across the entire area, thereby either validating or challenging the accuracy of the estimations. Furthermore, dividing the dataset equally ensures that the training and validation subsets adequately represent the data's variability (Raj, 1968), thereby reducing potential bias that could emerge from disproportionate set sizes.

Table 1: Structure of linear, non-linear, linear mixed-effects and non-linear regression models with covariates.

Abbreviation	Adjustment model	
	Linear model	
Crt	$H = \beta_0 + \beta_1 \frac{1}{D} + \varepsilon_i$	(1)
SVS	$ln(H) = \beta_0 + \beta_1 ln(D) + \varepsilon_i$	(2)
Ptt	$\frac{1}{H+1,3} = \beta_0 + \beta_1 \frac{1}{D}$	(3)
	Non-linear model	
Crt	$H = e^{\left[\beta_0 + \beta_1\left(\frac{1}{D}\right)\right]} + \varepsilon_i$	(4)
SVS	$H = \beta_0 D^{\beta_1} + \varepsilon_i$	(5)
Ptt	$H = \left\{\frac{1}{\left[\beta_0 + \beta_1\left(\frac{1}{D}\right)\right]}\right\} - 1,3 + \varepsilon$	(6)
	Linear mixed-effects model	
Crt	$H = \beta_0 + \beta_{0_{Est}} + \left(\beta_1 + \beta_{1_{Est}}\right)\frac{1}{D} + \varepsilon_i$	(7)
SVS	$ln(H) = \beta_0 + \beta_{0_{Est}} + \left(\beta_1 + \beta_{1_{Est}}\right) ln(D) + \varepsilon_i$	(8)
Ptt	$\frac{1}{H+1,3} = \beta_0 + \beta_{0_{Est}} + \left(\beta_1 + \beta_{1_{Est}}\right)\frac{1}{D} + \varepsilon_i$	(9)
	Non-linear models with covariates	
Crt	$H = e^{\left[\beta_0 + \beta_{0_{Est}} + \left(\beta_1 + \beta_{1_{Est}}\right)\left(\frac{1}{D}\right)\right]} + \varepsilon_i$	(10)
SVS	$H = (\beta_0 + \beta_{0_{Est}}) D^{\left(\beta_1 + \beta_{1_{Est}}\right)} + \varepsilon_i$	(11)
Ptt	$H = \left\{\frac{1}{\left[\beta_0 + \beta_{0_{Est}} + \left(\beta_1 + \beta_{1_{Est}}\right)\left(\frac{1}{D}\right)\right]}\right\} - 1,3 + \varepsilon$	(12)

Where: H is the total individual height of the trees; D is the diameter at 1.3 m from the ground; βi are the adjusted parameters of the models; Est is the planting strata.

For the Curtis, Stoffels & Van Soest linear models with mixed effects, the Meyer Correction Factor was employed to refine the estimates, as the models utilize a logarithmic transformation (Heberle et al., 2022). Regression model analysis for the fitted data employed statistical criteria (Table 2), including the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), as well as graphical residual analysis. Efficiency Evaluation (EE) and Average Residual Error in percentage (RE%) were employed for graphical analysis of the validation dataset estimates. All analyses were performed using RStudio version 4.3.2 (2023), with the "lme4" package used for fitting mixed models and the "nlme" package for models with covariates.

These metrics were chosen based on comparing models with different forms of adjustment and several equation parameters. Thus, AIC and BIC allow for better comparison between adjustment methods by considering the estimation error and the number of parameters in the same evaluation metric (Dziak et al., 2020). EE and RE% are similar to the Adjusted Coefficient of Determination (R^2_{aj}) and Residual Standard Error (Syx%) statistics, but these metrics are applied only to those adjusted by the least squares method. Thus, for application in other adjustment methods, the EE and RE% metrics were used (Nascimento et al., 2020).

The Artificial Neural Networks (ANNs) were of the Multilayer Perceptron type, chosen for their superior analytical capacity compared to other neural network structures. These networks feature hidden layers that capture nonlinearities in the data (Oliveira Neto et al., 2022). Ercanlı (2020) developed an initial network and iteratively modified certain components until achieving a configuration with the smallest error. Key components of the tested networks included: Input layer variables: Either one (DBH) or two (DBH and plantation strata, with strata coded into binary categorical variables), consistent with the regression models described earlier; Number of hidden layers: One or two layers were tested; Number of neurons per layer: Configurations tested included three, four, and five neurons, with optimal combinations balancing result accuracy and computational efficiency. The number of neurons was calculated as twice the number of hidden layers minus one (Heaton, 2008); Activation functions: Hyperbolic tangent and logistic functions were examined; Training algorithms: Resilient backpropagation with weight propagation ("rprop+"), smallest absolute gradient ("sag"), and smallest learning rate ("slr") were tested. The error function stopping criterion was set at 0.01, with a maximum of 10,000,000 combinations to ensure rigorous network evaluation. Supervised training was applied to validate the fit of the training and validation datasets (Hao et al., 2020). The training of the ANNs was divided into architectures with one and two hidden layers with the logistic activation function and the "rprop+" algorithm. After this training, the ANN with the lowest error among those tested was selected, alternating the activation function and the algorithm. Of the 18 ANNs tested, the 6 best were selected for analysis.

Evaluation metrics for the neural networks included Efficiency Evaluation (EE), Average Residual Error in percentage (RE%), and graphical analysis of estimates. Additional criteria included network error and the number of combinations required to achieve the results. ANNs were processed using RStudio version 4.3.2 (R Core Team, 2024) with the support of the "neuralnet" package.

RESULTS

Regarding the linear models, the Stoffels & Van Soest model provided the best statistics for adjusting the general equation. In the fit for each stratum, the Stoffels & Van Soest model was also the best for strata I and II, while the Curtis model was the best for stratum III. The separate fit of strata I and III showed better statistics than the general equation (Table 3).

The graphs of the observed and estimated heights indicated similarity in the dispersion pattern of the results among the three models, both for the fit and validation data (Figure 2). In all adjustments, the Stoffels & Van Soest model was the one that indicated the lowest tendency for estimation errors. The trend lines of the validation data for stratum I indicated the worst results, corroborating the adjustment statistics, when compared with the other strata.

Table 2: Evaluation metrics for regression models and artificial neural networks.

Statistical criteria	Formulas	
AIC	$2n\sigma^2$	(1)
BIC	$(\theta)+\frac{p}{2}\log n$	(2)
EE	$1-\left\{\left[\frac{\sum(y-\hat{y})^2}{\sum(y-\bar{Y})^2}\right]\left[\frac{(n-1)}{(n-p)}\right]\right\}$	(3)
RE%	$\frac{\sqrt{\sum_{i=1}^{n}\frac{(y_i-\hat{y}_i)^2}{n}}}{\bar{Y}}100$	(4)

Where: AIC is the Akaike Information Criterion, BIC is the Bayesian Information Criterion (BIC), EE is the Efficiency Evaluation, RE% is the Average Residual Error in percentage, y_i is the observed value; $\hat{y}_i$ is the estimated value, θ_j is the maximum likelihood of parameters, σ^2 is the variance of the observed data, n is the number of observations, L is the is the joint density of the estimates, p is the number of parameters, and $\bar{Y}$ is the arithmetic mean of the dependent variable.

Table 3: Adjusted coefficients and evaluation metrics for the fit and validation data of the linear models.

Models	β_0	β_1	Fit		Validation	
			AIC	BIC	EE	RE (%)
General equation						
Crt	3.4064*	-8.0912*	1.0098	1.0113	0.9934	17.59
SVS	1.0349*	0.6666*	1.0043	1.0058	0.9935	17.54
Ptt	0.0232*	0.4679*	1.0125	1.0140	0.9930	17.64
Stratum I						
Crt	3.4194*	-8.1636*	0.7197	0.7017	0.9857	20.16
SVS	0.8671*	0.7377*	0.6680	0.6501	0.9866	18.13
Ptt	0.0202*	0.4936*	0.6865	0.6686	0.9864	18.58
Stratum II						
Crt	3.5038*	-8.5738*	1.2466	1.2220	0.9729	17.27
SVS	0.8840*	0.7496*	1.2107	1.1860	0.9775	17.53
Ptt	0.0213*	0.4584*	1.2608	1.2361	0.9665	18.52
Stratum III						
Crt	3.4515*	-9.7617*	1.0009	0.9855	0.9802	15.10
SVS	0.7988*	0.7254*	1.0035	0.9881	0.9791	16.88
Ptt	0.0197*	0.5752*	1.0016	0.9862	0.9788	16.34

Where: Ct is the Curtis model, SVS is the Stoffels & Van Soest model, Pt is the Petterson model, AIC is the Akaike information criterion, BIC is the Bayesian information criterion, EE is the efficiency evaluation, RE is the mean residual error (%), and * are the parameters significant at 5%.

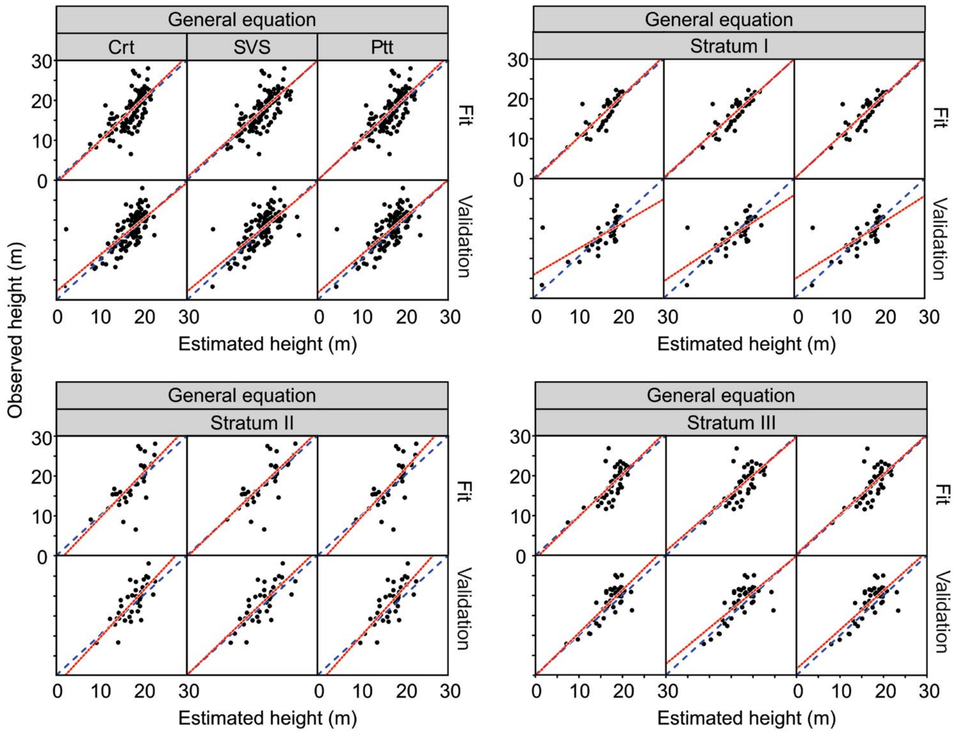

Figure 2: Observed and estimated individual heights using linear models in a *paricá* plantation within a silvopastoral system. Where: Crt is the Curtis model, SVS is the Stoffels & Van Soest model, Ptt is the Petterson model, blue line is the 1:1 line, and the red line is the trend line of estimates.

Considering the general equation of the nonlinear models, the Petterson model showed the best statistics. The Stoffels & Van Soest model was the best among those tested in stratum I. In strata II and III, statistics from the fit database for the Stoffels & Van Soest models were similar, while for the validation database, the best fit was achieved with the

Curtis model. Concerning the fit of the linear models, the strata I and III equations indicated better results than the general equation (Table 4).

The graphs of the observed and estimated heights of the non-linear models maintained the same pattern as the models in their linear form for all fitted data (Figure 3).

Table 4: Adjusted coefficients and evaluation metrics for the fit and validation data of the nonlinear models.

Models	β_0	β_1	Fit		Validation	
			AIC	BIC	EE	RE (%)
General equation						
Crt	3.4609*	-8.6606*	1.0034	1.0049	0.9943	17.43
SVS	3.1452*	0.6321*	1.0000	1.0015	0.9933	17.24
Ptt	0.0222*	0.4592*	0.9970	0.9985	0.9939	17.11
Stratum I						
Crt	3.4695*	-8.7307*	0.7132	0.6953	0.9863	20.66
SVS	2.4463*	0.7317*	0.6668	0.6488	0.9864	18.35
Ptt	0.0187*	0.5047*	0.6785	0.6606	0.9867	19.02
Stratum II						
Crt	3.6390*	-10.1210*	1.2272	1.2025	0.9823	16.59
SVS	2.3254*	0.7734*	1.2026	1.1780	0.9808	17.07
Ptt	0.0140*	0.5257*	1.2076	1.1830	0.9821	16.84
Stratum III						
Crt	3.5085*	-10.5364*	0.9958	0.9804	0.9838	14.72
SVS	2.6639*	0.6669*	0.9990	0.9836	0.9781	16.21
Ptt	0.0204*	0.5443*	0.9940	0.9786	0.9807	15.46

Where: Ct is the Curtis model, SVS is the Stoffels & Van Soest model, Pt is the Petterson model, AIC is the Akaike information criterion, BIC is the Bayesian information criterion, EE is the efficiency evaluation, RE is the mean residual error (%), and * are the parameters significant at 5%.

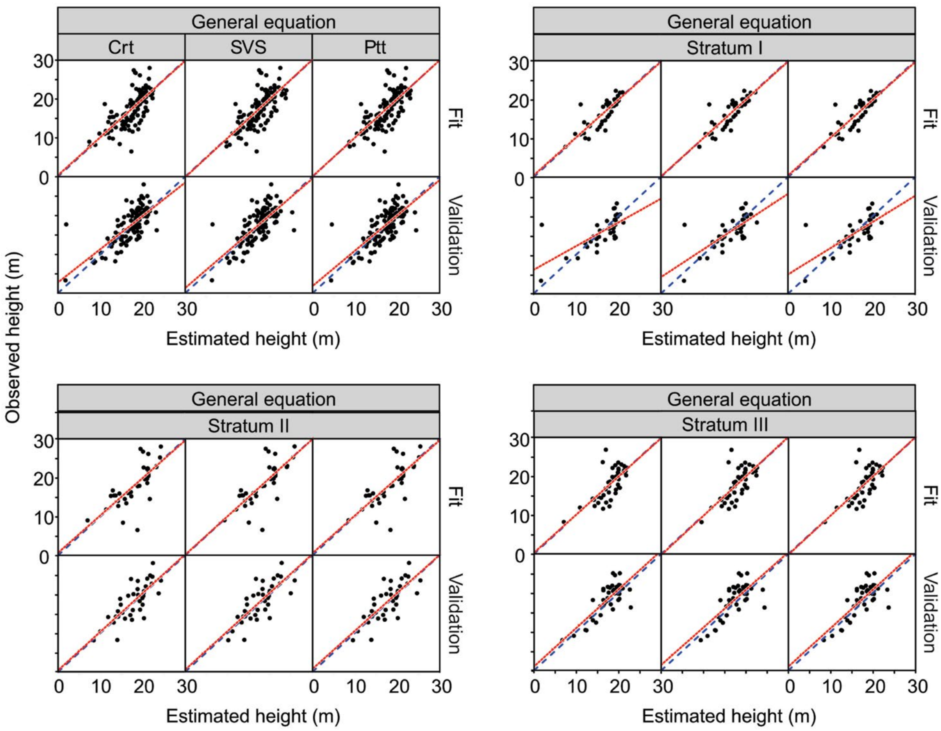

Figure 3: Observed and estimated individual heights by nonlinear models in a *paricá* plantation in a silvopastoral system. Where: Crt is the Curtis model, SVS is the Stoffels & Van Soest model, Ptt is the Petterson model, blue line is the 1:1 line, and the red line is the trend line of estimates.

The Stoffels & Van Soest model provided the best fit and validation statistics among the mixed models. When analyzing the random effect, the tested models indicated a difference among the strata only in the estimated β_1 (Table 5). The strong correlation between the data explains the lack of differentiation of the estimated coefficients, with the correlation index being -0.80 for the Curtis model, -0.96 for Stoffels & Van Soest, and -0.83 for the Petterson model.

The similarity between the pattern of the distribution of estimated heights is once again noticeable in the mixed-effect models (Figure 4). With the exception of the Stoffels & Van Soest model in the fitting data, the results were underestimated up to a height of 15 m. From there, the results were overestimated. In the validation data, all models indicated overestimation of the results up to a height of 20 m.

In the models with covariates, Petterson's model had the best statistics. The estimated coefficients of the strata were not significant in any of the equations tested (Table 6).

The Curtis model showed the same fit pattern as the linear, nonlinear, and mixed models (Figure 5). Although the coefficients of the covariates were not significant, the Stoffels & Van Soest and Petterson models were able to capture the differences in the height/DBH ratio of each stratum. The Stoffels & Van Soest and Peterson models underestimated all results, both for the adjustment and validation data. The Curtis model did not indicate trends for the adjustment data. In the validation data, the results were underestimated up to a height of 20 m. After this height, the results showed a tendency to overestimate.

The neural networks tested with two variables in the input layer (Net_3, Net_5, and Net_6) demonstrated better performance in estimating the height of the trees than the networks with only one variable (Net_{12}, Net_{17}, and Net_{18}). Net_{12}, with a hidden layer of five neurons, logistic activation function, and "rprop+" activation algorithm, showed the best statistics for estimating the height of the *paricá* trees (Table 7).

Except for Net_{12}, the estimated values were concentrated at 14, 16 and 20 m, with notable differences in Net_5 and Net_6 (Figure 6). Despite the results of the network adjustments, there was no tendency to underestimate or overestimate the results of the adjustment data. In the validation data, up to a height of 15 m, a tendency to underestimate the results is observed. Between 15 and 30 m, there is a tendency to overestimate the results. This pattern was observed in all tested networks, especially in Net_{12} and Net_{17}.

DISCUSSION

Hypsometric relationship equations are fundamental in conducting forest inventories, which explains the considerable research effort dedicated to developing methodologies for accurately estimating tree heights. When comparing linear and nonlinear models, the evaluation metrics (EE, AIC, BIC, and RE) were closely aligned, and the graphical distributions of the estimates appeared similar. Among the models tested, the Stoffels & Van Soest equation exhibited the most favorable metrics in both modeling approaches, with the nonlinear models performing slightly better overall. In terms of the general equation, mixed linear models outperformed others in EF and ER metrics, whereas linear models demonstrated higher AIC and BIC values. While nonlinear models with covariates presented better evaluation metrics than standard nonlinear models, the non-significance of their coefficients rendered them unsuitable for selection.

Table 5: Adjusted coefficients and evaluation metrics for the linear mixed fit and validation models.

Mixed effect	β_0	β_1	Fit		Validation	
			AIC	BIC	EE	RE (%)
Curtis						
Intercept	3.4443	-8.6367	1.0341	1.0385	0.9936	17.57
Stratum I	3.4443	-8.4778				
Stratum II	3.4443	-8.0154				
Stratum III	3.4443	-9.4168				
Stoffels & Van Soest						
Intercept	0.8815	0.7259	1.0012	1.0056	0.9939	17.39
Stratum I	0.8815	0.7313				
Stratum II	0.8815	0.7464				
Stratum III	0.8815	0.7000				
Peterson						
Intercept	0.0212	0.4968	1.0326	1.0369	0.9931	17.64
Stratum I	0.0212	0.4850				
Stratum II	0.0212	0.4683				
Stratum III	0.0212	0.5369				

Where: AIC is the Akaike Information Criterion, BIC is the Bayesian Information Criterion, EE is the efficiency evaluation, and RE is the mean residual error (%).

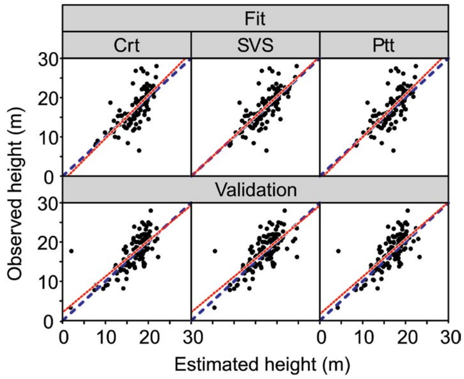

Figure 4: Observed and estimated individual heights using mixed models in a *paricá* plantation within a silvopastoral system.
Where: Crt is the Curtis model, SVS is the Stoffels & Van Soest model, Ptt is the Petterson model, blue line is the 1:1 line, and the red line is the trend line of estimates.

The choice of fitting methods was guided by the need to capture data variability and ensure model flexibility. Linear and nonlinear regression models were employed as classic approaches to describe basic relationships in the data. In contrast, mixed-effects models were adopted for their ability to handle hierarchical data structures, such as plantation strata, allowing the simultaneous capture of both intra- and inter-group variation. This approach considers the correlation between observations within the same stratum, which traditional regression methods cannot efficiently address. Additionally, models with covariates, including plantation strata, were selected to explore how these characteristics influence the estimated parameters. For example, including strata as covariates enabled the modeling of complex interactions and provided a more detailed evaluation of the impact of specific factors on the nonlinear fit.

As a result, linear models are recommended for estimating the height of trees in young *paricá* plantations under silvopastoral systems. Linear hypsometric models are particularly advantageous due to their simplicity, ease of equation adjustment (Monti et al. 2022), and straightforward interpretation (Dantas et al., 2024). These attributes make them preferable to mixed linear, nonlinear, and nonlinear models with covariates. In juvenile stands, linear models are likely to yield more accurate predictions of dendrometric variables (Santos et al., 2019). Several other studies have corroborated the superior performance of linear over nonlinear hypsometric models (Araújo et al., 2023; Dantas et al., 2024; Machado et al., 2019; Souza et al., 2017).

Across all evaluation metrics, equations developed for strata I and III outperformed the general equation in both linear and nonlinear approaches. This result can be attributed to superior data classification, as individual equations account for the specific height/DBH relationships unique to each stratum. Consistent with these findings, previous studies have advised against using a single, general hypsometric equation for diverse planting conditions. For instance, Carielo et al. (2022) assessed different Pinus species and age groups, while Murta Júnior et al. (2020) examined variations in age and thinning intensities; both studies reached similar conclusions. However, the specific equation for stratum II demonstrated inferior performance, with higher AIC and BIC values compared to strata I and III. This result suggests a weaker correlation between diameter and height in this stratum (Vendruscolo et al., 2015). Furthermore, general equations inherently benefit from being derived from larger samples (Pearl, 2014). Consequently, the general equation performed better than the specific equation for stratum II. Similarly, Figueiredo Filho et al. (2010) found that a general equation across different ages of *Araucaria angustifolia* yielded superior results compared to a

Table 6: Adjusted coefficients and evaluation metrics for the fit and validation data of the nonlinear models with covariates.

Covariates	β_0	β_1	Fit		Validation	
			AIC	BIC	EE	RE (%)
			Curtis			
Intercept	3.4695*	-8.7307*				
Stratum II	0.1694 ns	-1.3902 ns	1.0110	1.0154	0.9950	17.22
Stratum III	0.0389 ns	-1.8056 ns				
			Stoffels & Van Soest			
Intercept	2.4463*	0.7301*				
Stratum II	-0.1205 ns	0.0432 ns	0.8948	0.8992	0.9963	14.93
Stratum III	0.2175 ns	-0.0632 ns				
			Peterson			
Intercept	0.0187*	0.5047*				
Stratum II	-0.0046 ns	0.0210 ns	0.8709	0.8753	0.9963	14.59
Stratum III	0.0017 ns	0.0396 ns				

Where: Ct is the Curtis model, SVS is the Stoffels & Van Soest model, Pt is the Petterson model, AIC is the Akaike information criterion, BIC is the Bayesian information criterion, EE is the efficiency evaluation, RE is the mean residual error (%), * are the parameters significant at 5%, and ns are the non-significant parameters.

single equation. These contrasting outcomes underscore the need for further research to refine hypsometric relationships tailored to the specific conditions of each planting system (Atanazio et al., 2017).

Increasing the complexity of regression model adjustments, progressing from linear models to mixed linear models, nonlinear models with and without covariates, and ultimately to Artificial Neural Networks (ANNs), did not result in meaningful improvements in estimate accuracy. ANNs produced only marginal enhancements in EF and ER values compared to linear models, which does not justify their selection. Overfitting—where the same height is predicted for differing diameters—likely compromised the performance of most ANN models. Even the best-performing ANN (Net 12) displayed a wider error dispersion than the traditional models. Given the suitability of linear models in young stands (Santos et al., 2019), the use of more complex methods designed to facilitate biological interpretation (Dantas et al., 2024) did not yield significant benefits.

In contrast to this study, works by Ou and Quiñónez-Barraza (2023), Skudnik and Jevšenak (2022) and Tuan et al. (2019) reported better statistical outcomes for ANNs compared to regression models. While ANNs generally excel at relating numerical and categorical variables and their distributions (Domingues et al., 2020; Binoti et al., 2013), this approach was not ideal for *paricá* trees in silvopastoral systems in this study. Lafetá et al. (2024) also found that linear models outperformed nonlinear models and ANNs when applied to a seminal stand of *Eucalyptus cloeziana* F. Muell. Variations in the success of different estimation methodologies across studies are likely attributable to differences in species, site conditions, data structure variability, and other factors (Seki 2023). The size of the database (less than a thousand observations) can influence the efficiency of ANNs, which can also explain the superiority of simpler models (Bartol et al., 2022). The random and aleatory characteristics of ANN training make it difficult to perform more in-depth analyses of the results based on the interaction between the method applied and the nature of the data (Ye et al., 2018).

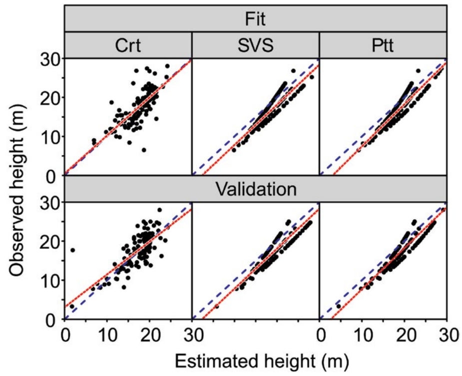

Figure 5: Observed and estimated individual heights using models with covariates in a *paricá* plantation within a silvopastoral system.
Where: Crt is the Curtis model, SVS is the Stoffels & Van Soest model, Ptt is the Petterson model, blue line is the 1:1 line, and the red line is the trend line of estimates.

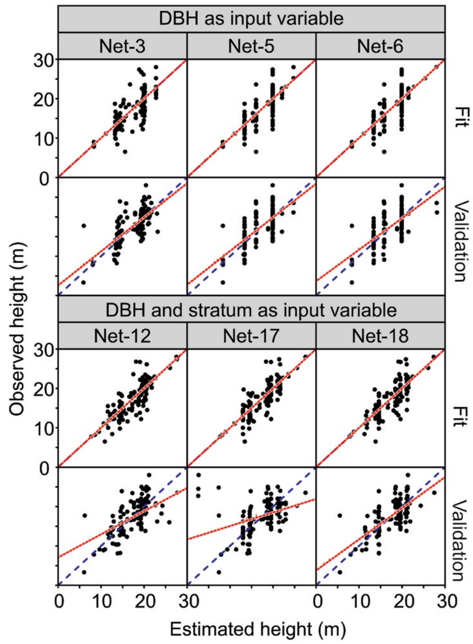

Figure 6: Observed and estimated individual heights using artificial neural networks in a *paricá* plantation within a silvopastoral system.
Where: Net is the symbol for artificial neural networks, blue line is the 1:1 line, and the red line is the trend line of estimates.

Table 7: Evaluation metrics for the fit and validation data of artificial neural networks.

Network	Combinations	Error	Fit		Validation	
			EE	RE (%)	EE	RE (%)
Net-3	78,898	506.9781	0.9938	16.75	0.9937	17.92
Net-5	1,493,455	486.9117	0.9942	16.41	0.9931	18.46
Net-6	476,629	477.9310	0.9943	16.26	0.9929	19.25
Net-12	1,075,284	375.6785	0.9961	14.42	0.9933	22.83
Net-17	2,309,468	380.6287	0.9960	14.51	0.9890	29.18
Net-18	156,972	406.9305	0.9956	15.00	0.9938	18.78

Where: EE is the efficiency evaluation, and RE is the mean residual error (%).

Within ANNs, increasing the number of hidden layers did not improve tree height estimations due to the overfitting above. However, ANNs incorporating two variables (DBH and forest stand) in their input layer outperformed those with a single variable (DBH), as evidenced in prior research (Almeida et al., 2022). The optimal configuration for ANN Net 12—comprising one hidden layer, two input variables, and five neurons—demonstrated better estimation distributions than other ANN configurations, though the evaluation metrics were comparable.

CONCLUSION

Linear models proved to be the most efficient in estimating the height of trees in *Schizolobium parahyba* var. *amazonicum* (Huber ex Ducke) Barneby plantations within a silvopastoral system located in the countryside of Pará state, Brazil. The equations tailored to each stratum of the *paricá* plantation delivered more accurate results in estimating tree height compared to the adjustments derived from general equations designed for the entire plantation.

Increasing the complexity of regression models—progressing from linear and linear mixed models to models without and with covariates, and eventually to artificial neural networks (ANNs)—did not significantly enhance the accuracy of tree height estimates. However, within the framework of ANNs, greater complexity achieved through the addition of input layer variables and an increased number of neurons in the hidden layer yielded improved tree height estimates.

Despite the similarity observed in evaluation metrics across all approaches, the computational effort required to implement ANNs is not justified for 4- and 5-year-old *paricá* stands. Nonetheless, as time progresses, these linear relationships between DBH and height may evolve, necessitating further studies to assess their accuracy and potentially revealing variations in the performance of estimation methods.

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AUTHORSHIP CONTRIBUTION

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