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Modeling the dominant-height growth and site index for *Rhizophora apiculata* plantations in Ca Mau province, Vietnam

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Abstract: Site classification is crucial aspect of forest management, particularly for assessing the productivity potential of forest stands. Forest productivity potential is often expressed as the dominant height of a stand at a given index age, commonly referred to as the site index (SI). Site index information is critical for forest management and silvicultural decision-making, including determining optimal thinning schedules and clear-cutting timings, as well as predicting stand development patterns. This study aimed to develop an SI for *Rhizophora apiculata* plantations in Ca Mau province, Vietnam. Fitting data were collected from 97 temporary sample plots (N = 1237), with ages ranging from 5 to 24 years. Using a 10-fold cross-validation method, six well-established growth models were applied to the dominant height-age data. Fifteen trees were destructively harvested for stem analysis and were used for model validation. The models were evaluated using six statistical metrics: a: adjusted R^2 ($R^2_{adj.}$), mean bias (MB), the root mean square error (RMSE), mean absolute bias (MAB), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The results revealed that the Gompertz equation outcompeted other candidate models resulting in the highest adjusted R^2 ($R^2_{adj.}$ = 0.946) and least mean absolute bias (MAB = 1.125) when used in stem analysis data. Therefore, Gompertz equation with asymptote or shape parameter expansion is recommended for generating family of site index curves.

Keywords: Index age, 10-fold cross validation, guide curve, destructive sampling, *Rhizophora apiculata*

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Introduction

The assessment of forest productivity is an important tool for the planning and sustainable management of even aged forests. This can be quantified directly or indirectly using the geocentric or phytocentric approach (Vanclay, 1994). Site productivity, usually quantified as site index (SI), estimates the potential of a particular forest stand to produce above ground wood (Clutter et al., 1983; Riofrío et al., 2023; Stefanello et al., 2024). Site quality is influenced by topographic, climatic, edaphic and biological factors (Subedi et al., 2024). One of the most reliable indicators of site quality is the dominant-height of a stand at a given age, which correlates strongly with the productivity for a specific species (Clutter et al., 1983; Manso et al., 2021; Sharma et al., 2002).

In Vietnam, mangrove forests have undergone dramatic changes in recent decades due to natural and anthropogenic disturbances. In seven decades, Vietnam has witnessed approximately 7% decline per decade in Mangrove forests (from 400,000 ha in 1943 to about 270,000 ha in 2015). Majority of the forests located in the southern regions of the Mekong Delta and the Can Gio Estuary (FAO, 2015; Hong & San, 1993). Ca Mau province, represents the largest mangrove forest in Vietnam accounting for about 39% (~93000 ha) of total mangrove forest in Vietnam (Hawkins & Trends, 2010; Nguyen et al., 2023). These forests once spanned approximately 200,000 hectares, providing essential ecosystem services such as habitat for marine life and protection against storm surges (Benthem et al., 1999). However, significant degradation has occurred due to anthropogenic activities, particularly shrimp farming, which caused a 90% reduction in dense mangrove areas from 1988 to 2018 (Hong et al., 2019). The mangrove plantations in Ca Mau are predominantly composed of *Rhizophora apiculata*, a species of economic importance that is used for firewood, charcoal, and construction materials.

Given the importance of these plantations, site productivity measurement is essential for their sustainable management. Dominant-height growth models, commonly used in forestry, provide an efficient and accurate way to assess site productivity and guide silvicultural decisions (Lanner, 1985; Manso et al., 2021; Skovsgaard & Vanclay, 2008). However, limited research has focused on developing site index models specifically for *R. apiculata* in plantation forests in Vietnam. Existing models, such as the Gompertz and Chapman–Richards models, have proven effective for various species (Mahanta et al., 2019; Manso et al., 2021; Park et al., 2019; Stefanello et al., 2024), but their application to mangrove species remains underexplored.

The main objective of this study is to use the guide curve approach to model site index curves and classify areas of *R. apiculata* stands. The specific objectives are to a) model dominant height data of a *R. apiculata* as a function of tree age in the Ca Mau province, Vietnam, and validate using time-series data obtained from stem-analysis. b) prepare site index classification of *R. apiculata* planted forests based on the guide curve approach and discuss management implications.

Materials and Methods

Study Site

Ca Mau province, located at the southern tip of Vietnam's Mekong River Delta, lies between latitudes 8°30' to 9°10'N and longitudes 104°80' to 105°5'E (Fig. 1). The province boasts a unique

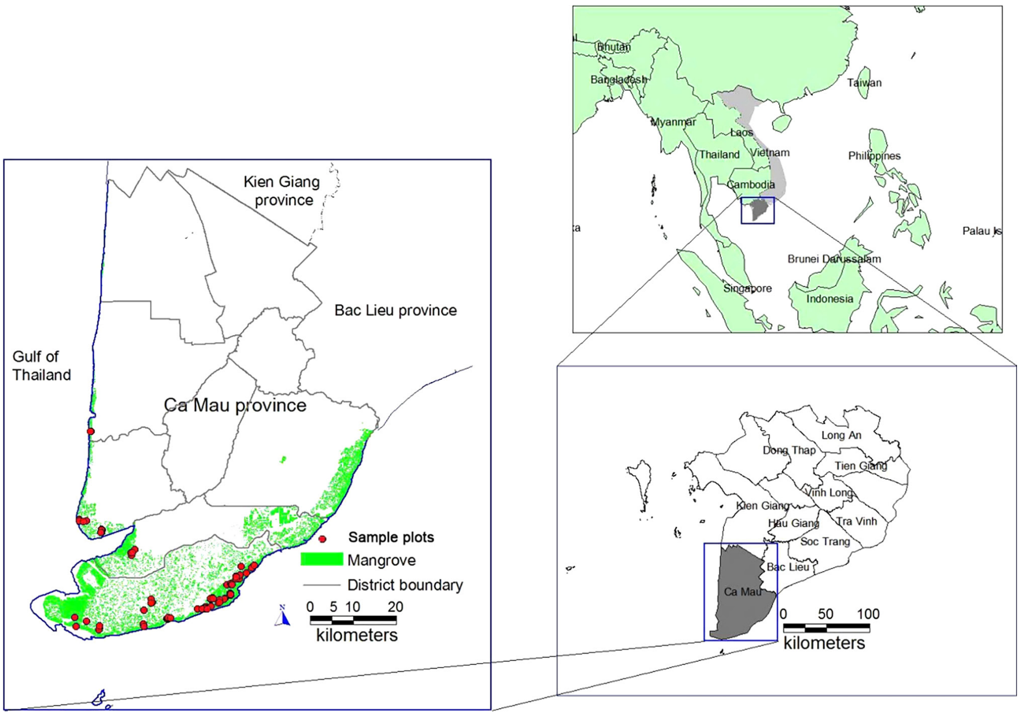

Fig. 1. Ca Mau province of the Mekong Delta of Vietnam

coastal geography, with 107 km of coastline along the eastern sea and 147 km along the western sea. It is characterized by a dense network of rivers, canals and creeks, making it a critical area for forestry, fishery and agriculture (Tinh et al., 2009). Covering an area of 5,392 km^2, Ca Mau represents more than 13% of the Mekong Delta's total land area of the Mekong Delta and about 1.6% of the total land area (CMSO, 2016).

The province's terrain is flat and low-lying, with an elevation of only 0.75 meters above mean sea level. It experiences a complex interaction between saline and freshwater due to the influence of two tidal regimes: large-amplitude semidiurnal tides from the east sea and smaller-amplitude diurnal tides from the west sea (SIWRP, 2008). These tidal patterns, combined with local topography and geology, create a unique environment conducive to mangrove growth. However, agricultural activities have led to 75% decline in forest area between 1988 and 2018 (Hong et al., 2019).

Ca Mau has a tropical monsoon climate, with two distinct seasons: a dry season from December to April, driven by east-northeast winds, and a rainy season from May to November, dominated by west-southwest winds. The region supports a population of over 1.3 million and has experienced a notable annual GDP growth rate of 12% over the past 15 years (Quach et al., 2017). This combination of geographic and climatic conditions makes Ca Mau an important region for mangrove research and forest management.

Data Collection and Analysis

Data Collection

A total of 97 temporary sample plots were established in *R. apiculata* dominated mangrove plantations using a stratified random sampling method with proportional allocation. Stratification was performed on the basis of the age class. Within each age stratum, the sampling plots were randomly allocated in proportion to the area represented by that class. This approach ensured that all age classes were represented and that the sampling accurately reflected the spatial distribution of the plantations in the Ca Mau Province. The number of plots per age class and their spatial locations are presented in Table 2 and Figure 1, respectively. The plot sizes ranged from 0.01 ha to 0.1 ha to ensure that each plot contained at least 30 trees. Plantation records were the basis for age determination. Within each plot, all trees were identified at the species level and subjected to measurement of total height (H) and diameter at breast height (DBH). DBH was measured at a standard height of 1.3 meters from the ground and H was measured at 0.1 m precision using a Criterion RD 1000 instrument. Data from all plots were combined and sorted by the largest DBH and H and only the top 20% data were selected (N = 1760) for modeling the dominant-height growth of *R. apiculata*. Given the nature of the data, we could only apply guide curve approach, we also sample 15 trees at 20 years of age were destructively sampled to estimate their height and diameter at earlier ages.

Dominant-Height Modeling

We fitted six anamorphic models (Table 1) using dominant height and plantation age data. These model forms are Chapman-Richards (M1), Schumacher (M2), Cilliers-Van Wyk (M3), Johnson-Schumacher (M4), Gompertz (M5) and Verhulst (M6). Each model has three parameters to be estimated; therefore, each model can result in three sets of site-index curves that make each model parameter dependent on the reference time (base age), which is the value of dominant height at a given base age.

We fitted selected models (M1–M6) using 10-fold cross-validation (k = 10) for model fitting by randomly dividing the training data set into 10 equal subsets (also known as fold) based on tree IDs. These models (M1 to M6) were trained using 9 folds (k – 1 folds), and validation was performed using the remaining fold. This process was repeated 10 times so that each fold served once as the validation set (Pokhrel et al., 2025). The stem analysis dataset was used to test the best performing model. The summary statistics of modeling dataset is presented in Table 2.

Table 1. Models selected to estimate the dominant height/age curves for *R. apiculata* trees

Model form	Model name	Model designation	References
$H = \beta_0[1 - \exp(-\beta_1 A)]^{\beta_1}$	Chapman-Richards	M1	Richards, 1959, Chapman, 1961
$H = \beta_0 \exp(-\beta_1 A^{-\beta_2})$	Schumacher	M2	Schumacher, 1939
$H = \beta_0[1 - \exp(-\beta_1(A - \beta_2))]$	Cilliers-Van Wyk	M3	Cilliers-Van Wyk, 1938
$H = \beta_0 \exp(-\frac{\beta_1}{A + \beta_2})$	Johnson-Schumacher	M4	Johnson, 1935, Schumacher, 1939
$H = \beta_0 \exp[-\beta_1 \exp(-\beta_2 A)]$	Gompetz	M5	Gompertz, 1825
$H \frac{\beta_0}{1 + \beta_1 \exp(-\beta_2 A)}$	Verhulst	M6	Verhulst, 1838

H – dominant height (m), A – age (years), β_0, β_1, β_2 – model parameters to be estimated.

Table 2. Summary statistics of DBH and total height

Age (year)	Number of plot	DBH (cm)			Total-height (m)		
		Minimum	Maximum	Mean (SD)	Minimum	Maximum	Mean (SD)
5	10	1.30	7.00	3.66(0.77)	1.5	6.0	4(0.56)
8	6	2.50	15.30	5.3(1.8)	3.3	9.5	6.3(1.35)
10	15	2.90	14.00	6.63(1.83)	2.0	11.3	7.4(1.51)
11	7	2.90	17.80	6.83(1.81)	4.6	13.4	8.1(1.33)
12	6	3.50	14.60	7.58(1.43)	4.2	11.7	9(1.22)
14	3	4.40	24.30	9.06(3.22)	4.2	13.7	10.2(2.02
15	9	4.80	20.40	10.22(1.9)	6.0	16.6	11.5(1.44)
17	3	2.90	20.10	11.28(3.33)	6.0	20.6	13.2(2.21)
20	21	4.80	26.70	11.97(4.46)	5.6	20.1	13.7(3.21)
23	11	7.30	26.70	12.89(4.17)	5.8	19.3	14.6(3.09)
24	6	6.40	25.80	13.52(3.98)	5.0	19.5	16(2.75)

Model Selection and Validation

To select the best model for predicting dominant-height growth and site index, several statistical criteria were employed such as mean bias (MB; Equation (7)), mean absolute bias (MAB; Equation (8)), root mean square error (RMSE; Equation (9)), adjusted R2 (Adj.R2; Equation (10)), Akaike Information Criterion (AIC; Equation (11)), and Bayesian Information Criterion (BIC; Equation (12)).

$$MB = \tfrac{1}{k}\sum_{j=1}^{k}[\tfrac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)] \quad (7)$$

$$MAB = \tfrac{1}{k}\sum_{j=1}^{k}[\tfrac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|] \quad (8)$$

$$RMSE = \tfrac{1}{k}\sum_{j=1}^{k}\sqrt{\tfrac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (9)$$

$$\text{Adj.}R^2 = \tfrac{1}{k}\sum_{j=1}^{k}\left(1 - \frac{(n-1)\sum_{1}^{n}(y_i - \hat{y}_i)^2}{(n-p)\sum_{1}^{n}(y_i - \bar{y}_i)^2}\right) \quad (10)$$

$$AIC = \tfrac{1}{k}\sum_{j=1}^{k}(nln\left(\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}\right) + 2p) \quad (11)$$

$$BIC = \tfrac{1}{k}\sum_{j=1}^{k}(nln\left(\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}\right) + pln(n)) \quad (12)$$

where: n is the number of samples; $\bar{y}$ is mean observed value, $\hat{y}$ represents the observed value; represent the predicted value, p is the number of parameters, and k is the number of folds/subsets (k = 1, 2, ..., 10).

We evaluated and ranked the fitting and validation statistics for each growth model. For MB, MAB, RMSE, AIC, and BIC, model ranks were assigned in ascending order, with lower values indicating better performance and receiving lower ranks. For adjusted R^2, ranks were assigned in descending order, so that models with higher adjusted R^2 values received lower ranks. For each model, the rank values from the fitting and validation datasets were summed to obtain a total rank score. These total scores were then re-ranked in ascending order to determine the overall performance of the models (Pokhrel et al., 2025; Subedi et al., 2018). Model selection was based on the consistency between fitting and validation rankings, the number of model parameters (complexity), and the ease of model fitting (simplicity). Finally, when the best model was found, the parameters were refitted using all training data (all folds). Validation was performed on dataset obtained from stem analysis.

Development of Site Index Equations

The selection of an appropriate index age, or base age, is a critical factor in the development of site index equations. Several factors must be considered when choosing this reference age. Curtis et al. (1974) emphasized that the index age should closely approximate the rotation age, as the primary goal is often to maximize total volume production during the rotation period. In contrast, Trousdell (1974) suggested that the index age should be selected after the period of rapid growth has passed and should ideally be somewhat shorter than the typical rotation age for the species in question.

Choosing an index age too low can introduce significant bias, as stands may not yet be fully mature and could still be in the juvenile growth phase. On the contrary, selecting an index age that is too high may lead to excessive extrapolation, as much of the observed variation in dominant height with age may occur outside the chosen range. To balance these considerations, it is essential to choose an index age close to the average observed age of the sample plots, ensuring accurate predictions across a range of site conditions.

In this study, an index age of 20 years was selected. This age falls within the range of most sample plot measurements, ensuring that the site index corresponds to the dominant height of a stand at 20 years of age. This choice is appropriate for *R. apiculata* plantations in the region and provides a solid basis for the evaluation of site productivity. The guide curve method offers an effective means of developing the site index equations for *R. apiculata* in the Ca

Mau province, allowing accurate predictions of site productivity based on dominant-height growth at the selected index age of 20 years.

For the development of site index equations, a mathematical modeling approach was employed instead of a graphical method. While graphical methods can be useful, they are often limited by subjectivity and the difficulty of performing statistical tests to assess the goodness of fit (Onyekwelu, 2005; Onyekwelu & Fuwape, 1998). On the contrary, mathematical models provide a more objective and statistically rigorous approach for generating site index curves. Specifically, the guide curve method was used in this study, as it is well suited to even-aged single species forest stands and works effectively with temporary sample plots (Nanang & Nunifu, 1999).

Results

Parameter estimation, fit statistics and model selection

Anamorphic dominant height -age models were fitted using 10-fold cross-validations using data collected from sample plots. Parameter estimates associated standard error and p-values of selected models (Table 1) for *R. apiculata* are presented in Table 3

The parameters of models M1, M4, M5, and M6 are statistically significant at the <5% level. Notably, the parameters of Models M4, M5, and M6 are statistically significant at the <0.1% level.

To validate the selected models, six criteria were used for selecting the most suitable prediction model. Average fit and cross-validation statistics and their respective rank of dominant-height models are reported in Table 4. Among the six models, M5 performed the best (the lowest total rank in the fit and validation statistics) followed by M6. MB, MAB, and RMSE of each model with standard deviation (Table 4).

Table 3. Parameter estimates, standard error (SE), t value, and p-values on selected models (Table 1)

Model	Parameter	Estimate	SE	t value	p-value
M1	β_0	49.449	15.150	3.419	0.003
	β_1	0.019	0.008	2.223	0.035
	β_2	0.984	0.062	15.757	<0.0001
M2	β_0	363347.654	3097608.766	0.196	0.845
	β_1	11.736	5.447	2.312	0.036
	β_2	0.096	0.055	1.727	0.096
M3	β_0	50.325	8.822	5.766	<0.0001
	β_1	0.018	0.004	4.431	<0.0001
	β_2	−0.218	0.343	−0.631	0.538
M4	β_0	50.397	3.714	13.593	<0.0001
	β_1	34.459	3.452	9.993	<0.0001
	β_2	9.410	1.113	8.454	<0.0001
M5	β_0	23.694	0.815	29.128	<0.0001
	β_1	2.576	0.051	50.607	<0.0001
	β_2	0.092	0.005	18.779	<0.0001
M6	β_0	20.020	0.383	52.319	<0.0001
	β_1	7.374	0.280	26.341	<0.0001
	β_2	0.167	0.006	27.762	<0.0001

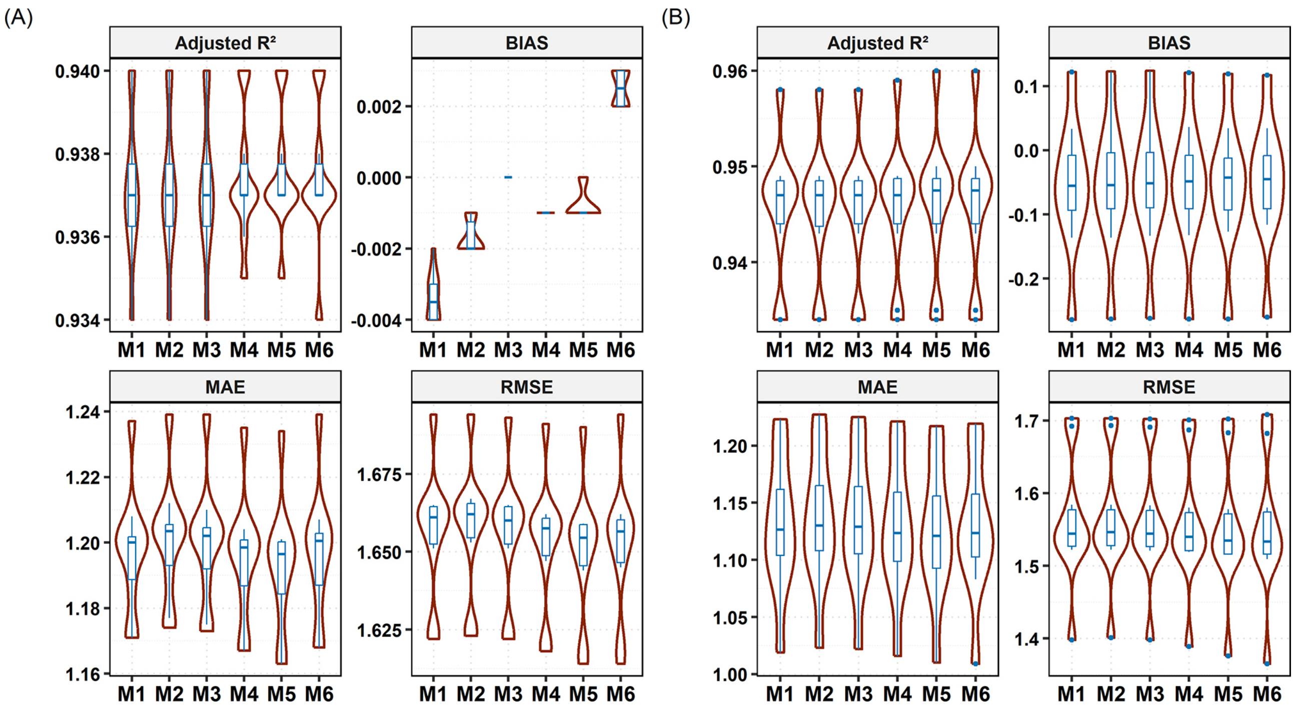

Fig. 2. The boxplot of fitting statistics across the folds for the training dataset (A) and testing datasets (B) for selected models overlaid with violin plots

Table 4. Summary of statistical criteria of dominant-height models

Model	Fit Statistics							Validation Statistics							Total ranking
	MB	MAB	RMSE	$R^2_{adj.}$	AIC	BIC	Rank	MB	MAB	RMSE	$R^2_{adj.}$	AIC	BIC	Rank	
M5	−0.001 (2)	1.193 (1)	1.650 (1)	0.938 (1)	4216.883 (1)	4236.885 (1)	7.0	−0.054 (3.5)	1.125 (1)	1.551 (2)	0.946 (1.5)	4216.883 (1)	4236.885 (1)	10.0	17.0 (1)
M4	−0.001 (3)	1.195 (2)	1.653 (3)	0.937 (2.5)	4220.529 (3)	4240.530 (3)	16.5	−0.054 (3.5)	1.128 (3)	1.555 (3)	0.946 (3)	4220.529 (3)	4240.530 (3)	18.5	35.0 (3)
M6	0.002 (5)	1.197 (3)	1.652 (2)	0.937 (2.5)	4219.119 (2)	4239.120 (2)	16.5	−0.051 (1)	1.127 (2)	1.551 (1)	0.946 (1.5)	4219.119 (2)	4239.120 (2)	9.5	26 (2)
M3	0.000 (1)	1.200 (5)	1.656 (4)	0.937 (5)	4224.777 (4)	4244.778 (4)	23.0	−0.053 (2)	1.133 (5)	1.559 (4)	0.946 (4.5)	4224.777 (4)	4244.778 (4)	23.5	46.5 (4)
M1	−0.003 (6)	1.197 (4)	1.656 (5)	0.937 (5)	4225.133 (5)	4245.135 (5)	30.0	−0.057 (6)	1.130 (4)	1.560 (5)	0.946 (4.5)	4225.133 (5)	4245.135 (5)	29.5	59.5 (5)
M2	−0.002 (4)	1.201 (6)	1.658 (6)	0.937 (5)	4226.724 (6)	4246.725 (6)	33.0	−0.055 (5)	1.134 (6)	1.561 (6)	0.945 (6)	4226.724 (6)	4246.725 (6)	35.0	68.0 (6)

Note: The values in parentheses represent the rankings for the corresponding fit and validation statistics. The rank columns indicate the total sum of rankings for each model.

Mean Bias, MAB, RMSE, and $R^2_{adj.}$ obtained for validation dataset in each fold in 10-fold cross validation are shown in Figure 2. Among the models, M5 demonstrated the best overall performance, with the highest $R^2_{adj.}$ and the lowest bias, MAB, and RMSE across both datasets. M4 and M6 also performed well, showing relatively low error metrics and $R^2_{adj.}$ but with higher variation among folds. In contrast, M1 and M2 showed the weakest performance, characterized by lower $R^2_{adj.}$ 2 values and higher MAB and RMSE (Fig. 2, Table 4).

The selected dominant height/age model for *R. apiculata* in the study (a Gompertz function) was then re-fitted to the entire data set (training+testing dataset). The estimated parameters from the re-fitted models (Table 5) were used to predict the site index at base age of 20 years (Fig. 3).

Table 5. Parameter estimates of the best-fitted model using combined data (training + validation)

Model	Parameter	Estimate	SE	Pr(>|t|)	Expanded parameter	Site index equation*
M5	β_0	23.7472	0.7205	<0.0001	β_0	$SI = H\dfrac{\exp[-\beta_1 \exp(-\beta_1 A)]}{\exp[-\beta_1 \exp(-\beta_1 A_0)]}$
	β_1	2.5776	0.0448	<0.0001		
	β_2	0.0917	0.0043	<0.0001	β_2	$\beta_0(\exp - \beta_1\left(\dfrac{-\ln\left(\dfrac{H_0}{\beta_0}\right)}{\beta_1}\right)^{\frac{A}{A_0}})$

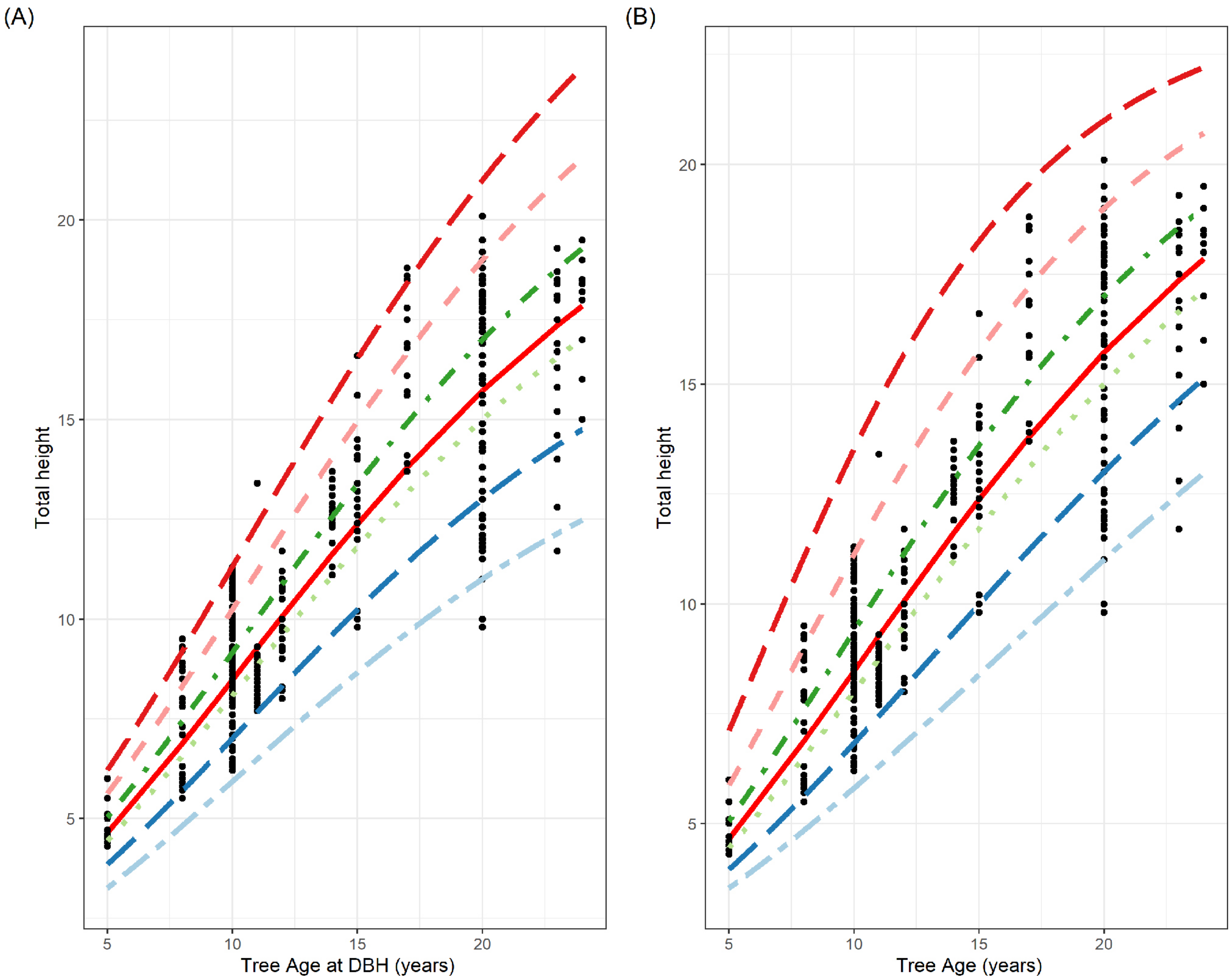

Fig. 3. The site index curves for *R. apiculata* plantations, utilizing the M5 model with an expanded parameter of β_0 (A) and β_2 (B). The solid line denotes the mean prediction line, while the dashed lines, progressing from bottom (light blue) to top (red), represent site index curves at intervals of 2 meters, ranging from 11 meters to 21 meters.

Site index curves

The dominant height age equation (M5) with estimated parameter based on combined data is selected as the best equation (Table 5). To estimate the productivity potential of the *R. apiculata* forest stand, we selected base age of 20 years which is commonly used for *R. apiculata* fuelwood plantations (Chan, 1990). We expanded asymptote (β_0) rate (β_1) and the shape parameter (β_2) of best equation. However, expanding rate parameter did not follow the growth logic and we prepared SI curves based on asymptote and shape parameter expansion (Fig. 3).

Discussion

The development of site index curves based on dominant height/age relationships remains one of the most practical and widely used methods for assessing site productivity, especially in even-aged forest plantations. In this study, we successfully constructed anamorphic site index curves for *R. apiculata* plantations in the Ca Mau region by selecting and evaluating well known growth functions. Our results show that the Gompertz function was found to be the most appropriate model to predict the growth and site index for *R. apiculata* plantations in Ca Mau, Vietnam. This function has been extensively used in forest growth and yield studies to model relationships such as height age, diameter age, basal area-age, and growth rate age (Mahanta et al., 2019; Park et al., 2019). Its popularity stems from its ability to generate sigmoid growth curves, which effectively characterize different growth stages driven by biological processes.

While several studies have confirmed the potential utility of dynamic growth models such as the Algebraic Difference Approach (ADA), and its generalization (GADA) to describe polymorphism and variable asymptotes under a wide diversity of stand situations (e.g., Manso et al., 2021; Riofrío et al., 2023; Stefanello et al., 2024; Subedi et al., 2023), such modeling requires a sufficient amount of stem analysis or permanent sample plot data taken over several intervals of measurement. Unfortunately, the database in this study did not meet these criteria due to the limited stem analysis trees (n = 15) and insufficient time-series observations. Thus, it was not possible to use GADA or other dynamic models. Yet, the current model can provide a good approximation of site index as a function of stand age. To improve the model reliability a 10-fold cross-validation technique was used. Existing stem analysis data was used to validate the model performance. The strong correlation between predicted and observed dominant height within the testing subsets and validation datasets indicates that the model demonstrates stability and generalizability for practical use in forest management. While this validation method does not entirely replace longitudinal analysis, it serves as a robust alternative when data limitations arise (Pokhrel et al., 2025; Subedi et al., 2018).

The stratified random sampling design implemented in this study ensured a representative distribution of sample plots across age classes and site conditions. Similar to Parresol et al. (2017) and Sabatia and Burkhart (2014), who emphasized the importance of incorporating site-specific variation (e.g., soil depth, groundwater level, and prior land use) into site index modeling, our design allowed for age-class-specific growth modeling that reflects real-world management structures of *R. apiculata* plantations in the region. While spatial environmental covariates such as salinity, soil pH, or hydrological regime were not explicitly modeled here, future studies may benefit from integrating these variables to improve predictive capacity, especially under climate-induced changes in coastal zones. However, we acknowledge a challenge in this study that some age classes (e.g., 14 and 17 years) had limited replication due to uneven plantation history.

Model performance metrics (MB, RMSE, MAB, $R^2_{adj.}$) were in reasonable ranges and consistent with those reported in earlier site index research (Subedi et al., 2023; Subedi et al., 2024). Notably, our model was stable on several validation sets with no evident of systematic bias, suggesting generalizability across the study area setting for *R. apiculata* plantations. Extrapolation beyond the range of observed ages (>25 years) must be done cautiously and in conjunction with supporting data. The growth curves were consistent with results reported for other rapidly growing tropical species such as *Acacia mangium* and *Eucalyptus sp*. (Lumbres et al., 2018; Mahanta et al., 2019) where the growth in height slows significantly beyond 20–25 years of age. This growth can be representative of physiological aging and ecological saturation upon following mangrove site conditions such as competition for light, nutrient limitation, and salt exposure. Our evidence supports rotation age planning of 20–25 years for *R. apiculata* plantations, as promoted by current Vietnamese silviculture practice.

In comparison with Taiwania plantation studies in Taiwan (Wang et al., 2008), our findings suggest that base-age-specific models offer better accuracy and interpretability in relatively young plantations. The selection of a base age of 20 years for site index development in this study was appropriate, as it aligns with the common practice of choosing an index age close to the rotation age (Onyekwelu & Fuwape, 1998; Teshome & Petty, 2000). This ensures that the site index reflects the growth potential of a stand over a significant portion of its productive lifespan.

However, it is acknowledged that base-age-invariant approaches could offer advantages in broader-scale applications, especially when stand age varies widely or permanent plot data is more abundant. With the global threat of climate change and increasing demand for blue carbon ecosystems, site productivity measurement in mangrove forests is an essential measure for sustainable management, carbon accounting, and restoration planning. While this work presents an initial framework, it is hoped that future work will be in a position to expand the dataset both spatially and temporally, try out alternative modeling strategies including machine learning, Random Forests, and incorporate geospatial environmental covariates in order to facilitate more dynamic, spatially explicit predictions of site index (Sabatia & Burkhart, 2014; Subedi et al., 2024).

The site classification into high, moderate, and low productivity classes provides a valuable guideline for forest managers and policymakers. The site classes provide valuable information to direct forest management activities, such as the establishment of ideal thinning schedules, fertilizer application, and harvesting cycles, for more sustainable mangrove plantation management. Similar approaches of site classification have proven to apply to tropical forestry operations in Indonesia, Australia, Africa, and America (Chen & Zhu, 2012; Lumbres et al., 2018; Sabatia & Burkhart, 2014; Teshome & Petty, 2000).

Conclusions

This study developed dominant height growth models and site index curves for *R. apiculata* plantations in Ca Mau province, Vietnam. It addresses a critical knowledge gap, as few studies have focused on modeling the growth and productivity of mangrove species in Vietnam and the broader Southeast Asia region. Among the models evaluated, the Gompertz function performed the best in the model building dataset and performed well in the validation dataset obtained from stem analysis. We hope that our research offers an effective method for site quality classification, silvicultural planning and rotation age determination in mangrove management in coastal areas of Ca Mau province.

Although the guide curve is simple, the lack of temporal data hindered our ability to develop dynamic modeling approaches, such as Generalized Algebraic Difference Approaches (GADA). Nevertheless, the Gompertz model showed satisfactory performance in terms of test statistics when applied to a validation dataset comprising 15 trees obtained through stem analysis. It is recommended that future researchers augment the sample size of stem analysis data to facilitate the fitting of dynamic models.

Authors' contributions

Thi Ha Nguyen contributed to the study conception and design, data collection, and drafting of the initial manuscript.

Mukti Ram Subedi contributed to the study conception and design, data analysis, as well as manuscript editing.

Van Viet Nguyen contributed to the study conception and design, data collection, data analysis, and manuscript writing and editing.

Thi Thanh Thuy Phan contributed to manuscript writing, review, and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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