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Population-Specific Nonlinear Models for Predicting Height and Diameter Growth of *Ficus variegata* Blume Plantations in Indonesia

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ABSTRACT

Ficus variegata Blume is a species that has the prospect of being developed for forest plantation. Its wood products can be used for woodworking, furniture, and light construction materials. This study aimed to develop models of height and diameter growth of this species based on age. In this study tree height was measured at 0.5; 1; 2; 3; 4 and 10 years, while stem diameter was measured at breast height (DBH) at 1; 2; 3; 4 and 10 years of age from 2 populations of *F. variegata* progeny trials with genetic material from the West Nusa Tenggara (WNT) population (n trees = 395) and the Cilacap-Pangandaran (C-P) (n trees = 393). Five nonlinear regression models were tested, with model accuracy verified by 4 criteria: root mean square error (RMSE), coefficient of determination (R^2), adjusted coefficient of determination (adjusted R^2), and Akaike Information Criterion (AIC). The Weibull ($R^2 = 0.881$; RMSE =1.034) model was the best model for tree height estimation for WNT and Chapman Richards ($R^2 = 0.822$; RMSE =1.288) for C-P. Weibull ($R^2 = 0.767$; RMSE = 2.853) and Gompertz ($R^2 = 0.767$; RMSE =2.853) models were the best models for tree diameter estimation for the WNT population, and Weibull ($R^2 = 0.765$; RMSE = 2.834) and Logistic ($R^2 = 0.765$; RMSE =2.835) for the C-P population. Our findings demonstrate that growth models are population-dependent, necessitating the use of distinct optimal models for reliable growth prediction and management in different genetic sources of *F. variegata.*

1. INTRODUCTION

Tree growth models play an important role in forest management and tree breeding by providing accurate predictions of tree growth over time. They are particularly useful in assessing site productivity [1], biomass prediction [2], and harvest cycle planning [1, 3]. In tree breeding, these models are useful for identifying ages for selecting superior genotypes by analyzing how traits at youth correlate with those at maturity to aid breeding strategies [4-6], guiding the selection of important traits for productivity improvement, thereby supporting the long-term sustainability of forest resources [7, 8].

In forest growth and yield studies, models predicting the height and diameter growth of individual trees are essential elements and valuable tools for planning sustainable forest management [9]. These models can predict forest growth flexibly [10]. Forest growth models illustrate how tree dimensions or other tree characteristics, as well as stand-level factors, change over time with age [3]. Forest managers use stand growth predictions to determine the optimal timing for thinning, pruning, and felling and to analyze the economics of silviculture [11].

Tree height and diameter at breast height (DBH) are important for developing various growth and yield models [12]. DBH can be measured quickly, easily, and accurately, whereas total tree height measurements are relatively complex, time-consuming, and expensive. Tree height growth models are often used as site index indicators, as tree height tends to be less affected by competition than diameter or volume [13]. Height growth models can be combined with diameter growth models to estimate individual tree volume or total stand volume.

Various growth models have been developed for various tree species, mainly using nonlinear models, which better describe biological growth patterns than linear approaches. These models help quantify the relationship between variables such as height, diameter, and age, allowing for better forest management. Commonly used nonlinear models such as Chapman-Richards [14], Gompertz [15], von Bertalanffy [15], Weibull [16], and Logistic [15] models describe the growth of tree height and diameter over time with high accuracy. These models have been widely applied to commercial species such as *Anthocephalus macrophyllus* (Roxb.) Havil. [17], *Pinus merkusii* Jungh. et de Vriese [7], *Eucalyptus* spp. [18], *Peronema canescens* [19], *Picea mariana* (Mill.) B.S.P., and *Pinus banksiana* Lamb. [20]. However, despite the many growth model studies on these species, a similar growth model for *Ficus variegata* has not been conducted. The application of different growth models to different species and environments is crucial, making this research important.

F. variegata is a fast-growing tree species whose wood is used for woodworking, furniture, and light construction materials [21-23]. The natural distribution of this species covers tropical and subtropical regions [24]. Its rapid growth in height and diameter gives it high potential for plantation forest development. Despite this potential, until now, no growth model has been developed to describe the development of height and diameter with age. Qirom and Supriyadi [25] have developed a model to estimate the volume of *F. variegata* based on height and diameter variables, without knowing the age of the tree. The absence of such a model limits accurate predictions of growth performance, thus affecting breeding efforts and other silvicultural measures to maximize economic benefits.

This study aimed to (1) develop and compare nonlinear growth models for height and diameter, and (2) identify the best-fitting models for two distinct populations of *F. variegata*.

2. MATERIALS AND METHODS

2.1 Location and sample

Data were obtained from two open-pollinated *F. variegata* progeny trials established in 2012 in the area of Forestry Service Agency, Yogyakarta Special Province, Indonesia (Figure 1). Geographical location, site conditions, and climate were described by Haryjanto et al. [26]. The trials consisted of genetic materials from two populations: (1) 17 families from West Nusa Tenggara (WNT) and (2) 19 families from Cilacap-Pangandaran (C-P), with a plant spacing of 5 × 5 m. The trial was established in a randomized complete block design with six replications. Each family was represented by two types of non-contiguous plot (NCP): a five-tree plot for WNT and a four-tree plot for C-P. NCP has multiple trees from the same family randomized within each block [6].

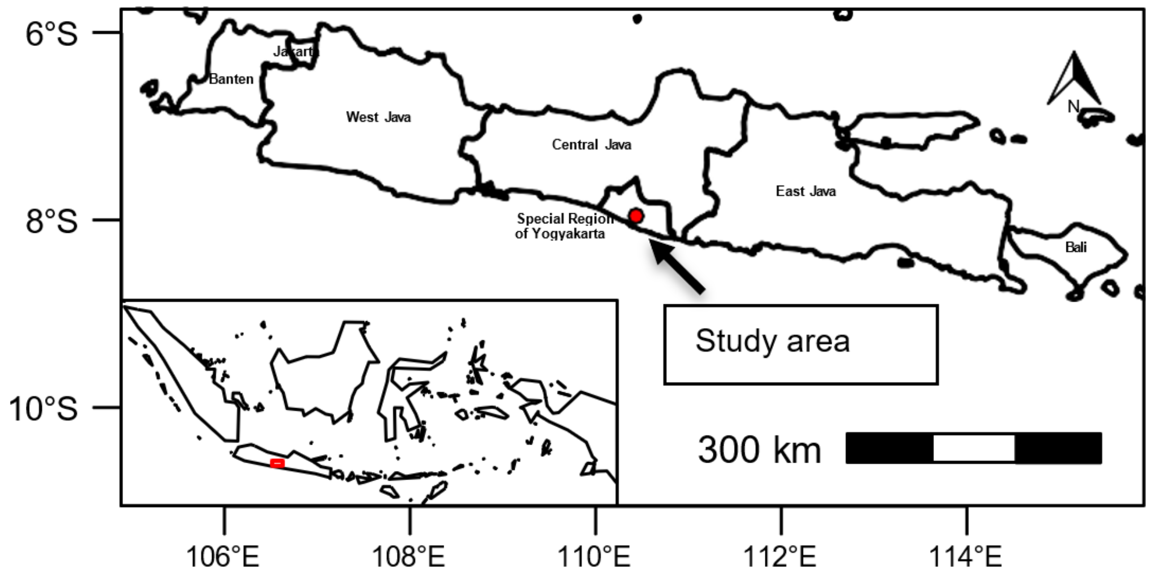

Figure 1. Study area (marked by arrow)

Table 1. Statistical characteristics of tree height and DBH of *F. variegata* for the WNT and C-P populations

WNT						
Height/ Age (year) (N = 2358)						
	0.5	**1**	**2**	**3**	**4**	**10**
Mean (m)	1.44	1.79	3.46	4.93	5.92	9.74
Min (m)	0.50	0.65	1.80	2.36	2.77	5.34
Max (m)	2.56	3.10	5.56	7.97	9.04	14.13
SD	0.41	0.49	0.62	1.03	1.19	1.76
DBH/ Age (year) (N = 1965)						
Mean (cm)	-	2.76	4.58	8.21	10.25	17.61
Min (cm)	-	0.90	1.13	2.23	2.87	6.05
Max (cm)	-	5.00	8.76	14.95	18.47	39.49
SD	-	0.77	1.38	2.59	2.98	4.72
C-P						
Height/Age (year) (N = 2370)						
	0.5	1	2	3	4	10
Mean (m)	0.94	1.26	3.20	4.57	5.77	9.05
Min (m)	0.19	0.25	0.73	1.10	1.75	5.04
Max (m)	2.54	3.39	6.75	9.33	11.50	16.10
SD	0.43	0.54	0.93	1.42	1.60	1.99
DBH/Age (year) (N = 1975)						
Mean (cm)	-	1.91	3.40	6.27	8.96	16.10
Min (cm)	-	0.63	0.86	0.95	2.55	7.17
Max (cm)	-	4.59	8.65	14.64	19.27	34.71
SD	-	0.74	1.53	2.86	3.28	4.29

Note: N = Number of observations

Periodic measurements were taken of tree height (in meters) measured from ground level to the top of the tree at ages 0.5, 1, 2, 3, 4, and 10 years using a measuring pole. Stem diameter (in cm) at 1.3 m above ground level (diameter at breast height, DBH) at ages 1, 2, 3, 4, and 10 years using a phi-band meter. A total of 393 plants from the WNT population and 395 plants from the C-P population were measured. Periodic measurements were taken of tree height in meters, measured from ground level to the top of the tree, at ages 0.5, 1, 2, 3, 4, and 10 years, using a measuring pole. Stem diameter (in centimeters) at 1.3 meters above ground level (diameter at breast height, DBH) was measured at ages 1, 2, 3, 4, and 10 using a phi-band meter. A total of 393 plants from the WNT population and 395 plants from the C-P population were measured. These trees were observed from initial observation until 10 years later, and the statistical characteristics of the data are summarized in Table 1.

2.2 Model

The growth models employed in this study are summarized in Table 2. These models represent sigmoid curves, which are commonly used to describe asymptotic biological growth [8]. A sigmoid model characterizes growth that begins slowly, accelerates rapidly, and then gradually slows as it approaches a maximum value.

For all models, ω = dependent variable (height, diameter), t = independent variable (age in years), α, β, k, and m are estimated parameters, exp = an exponential function, and ε = random error.

2.3 Data analysis

The nonlinear least squares method was used to obtain the best-fitting model. Model selection, aimed at describing the relationship between tree height, diameter, and age, was based on four criteria presented in Table 3. The F-test was used to evaluate the significance of the nonlinear regression model at a 95% confidence level. The best model is the one with the lowest average values of root mean square error (RMSE) and Akaike information criterion (AIC), and the highest average values of coefficients of determination (R^2) and adjusted coefficient of determination (adjusted R^2) [19, 27, 28]. AIC is a commonly used metric for comparing models of varying complexity based on a given dataset [29]. R^2 values range from 0 to 1, with higher values indicating that a greater proportion of the variance in the data is explained by the model [30]. Since the model is nonlinear, RMSE is a useful additional measure of accuracy alongside R^2 [29]. If two or more models have identical values for a given criterion, they are considered to have the same ranking [31]. Data were analyzed using nonlinear regression with the NLIN procedure in SAS On Demand for Academics [32].

Table 2. Nonlinear mathematical models used in the study

No.	Model	Equation	Source
1	Chapman-Richards	$\omega(t) = \alpha(1 - \beta \exp(-kt))^{1/(1-m)} + \varepsilon$	[14, 33]
2	Weibull	$\omega(t) = (\alpha - \beta \exp(-kt^{m})) + \varepsilon$	[16]
3	von Bertalanffy	$\omega(t) = (\alpha^{1-m} - \beta \exp(-kt))^{1/(1-m)} + \varepsilon$	[15]
4	Gompertz	$\omega(t) = \alpha \exp(-\beta \exp(-kt)) + \varepsilon$	[15, 33]
5	Logistic	$\omega(t) = \alpha / (1 + \beta \exp(-kt)) + \varepsilon$	[15]

Table 3. Best model criteria

No.	Function Name	Equation
1	Root mean square error (RMSE)	$RMSE = \sqrt{\sum \frac{(y_i - \hat{y}_i)^2}{n}}$
2	Coefficient of determination (R^2)	$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$
3	Adjusted Coefficient of determination (adjusted R^2)	$adjusted\ R^2 = 1 - (1 - R^2)\frac{(n-1)}{(n-k)}$
4	Akaike information criterion (AIC)	$AIC = 2k + n\,ln\frac{\sum(y_i - \hat{y}_i)^2}{n}$

where, y_i, $\hat{y}_i$, $\bar{y}$ = y measured, estimated, and mean values of the dependent variables, respectively, k = number of parameters of the estimated models, and n is the number of observations.

A key methodological limitation of this study is that the data were analyzed using standard nonlinear regression, which does not account for the hierarchical structure of the data (trees nested within families and blocks) or the temporal autocorrelation inherent in repeated measurements from the same individuals. This approach may lead to underestimated standard errors of the parameter estimates and, consequently, an overstatement of their statistical precision and significance.

3. RESULTS AND DISCUSSION

3.1 Tree height and diameter correlation

The relationship between tree height and DBH is widely applied in forest inventory analyses [34, 35]. In this study, the correlation between tree height and DBH was very strong, with coefficients of determination (R^2) of 0.921 and 0.863 for the WNT and C-P populations, respectively (Figure 2). This strong correlation is useful for indirectly estimating tree height by measuring only DBH [36]. Measuring tree height is often difficult and prone to large errors, especially in forests with tall trees and dense crowns [2], and it generally requires more time [35]. In contrast, DBH is easier to measure, offers high precision, and involves lower costs. In the context of tree breeding, a strong correlation between tree height and DBH is valuable for assigning trait weights during genetic selection using a multi-trait selection index [17]. Because of this correlation, selecting for DBH will also positively affect tree height, making the breeding program more efficient.

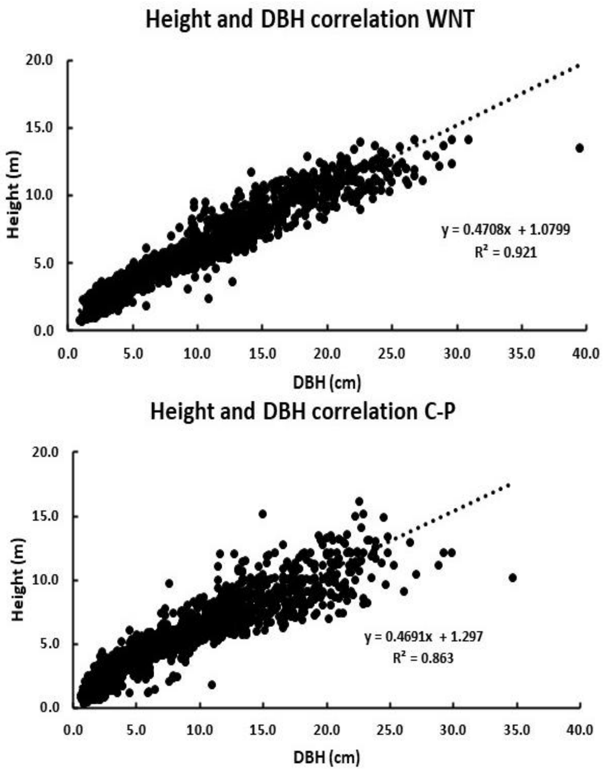

Figure 2. Tree height and DBH correlation for *F. variegata*

3.2 Growth curve

Growth curves are usually divided into four stages: exponential, linear, logarithmic, and asymptotic, which depict accelerating rates, constant rates, slowing rates, and no significant increase [19].

3.2.1 Height curve

The height-age curve shown in Figure 3 is a sigmoid curve (resembling the letter S). It begins with a rapid growth phase, resulting in an exponential shape, followed by a constant growth rate forming a linear pattern. Eventually, the growth slows down, taking on a logarithmic shape, and nearly stops as it approaches its maximum limit (asymptotic), causing the curve to level off horizontally.

During the early growth (ages 0.5–2 years) phase, the models diverge significantly in their portrayal of initial growth vigor. For the WNT population, the Logistic model (with the highest k value of 0.629) predicts the most aggressive early height accumulation, followed closely by the Gompertz. In contrast, the Weibull and von Bertalanffy models depict a more gradual initial ascent. This divergence is critical for managers assessing early survival and weed competition, as the choice of model would lead to different conclusions about first-year growth performance. For the C-P population, a similar pattern is observed, where the Logistic model shows the steepest initial slope, but the overall predicted heights in this phase are lower than for WNT across all models, aligning with the observed data in Table 1.

Mid-rotation growth and inflection (ages 2–5 years), this period encompasses the inflection point (point of maximum growth rate) and is where the biological interpretation of parameters β and m becomes visually apparent. For WNT, the Chapman-Richards model (with m = 0.587) shows an inflection point occurring at a greater proportion of the final asymptotic height compared to other models, leading to a more sustained period of rapid growth. The Weibull model, identified as the best-fit, presents a slightly more symmetric S-shape. For C-P, the Chapman-Richards model (best-fit) has a lower m value (0.552), visually shifting its inflection point slightly earlier relative to its asymptote compared to the WNT Chapman-Richards curve. The Logistic model curves for both populations exhibit their characteristic symmetric inflection around the midpoint, which appears less representative of the data spread shown in Figure 3.

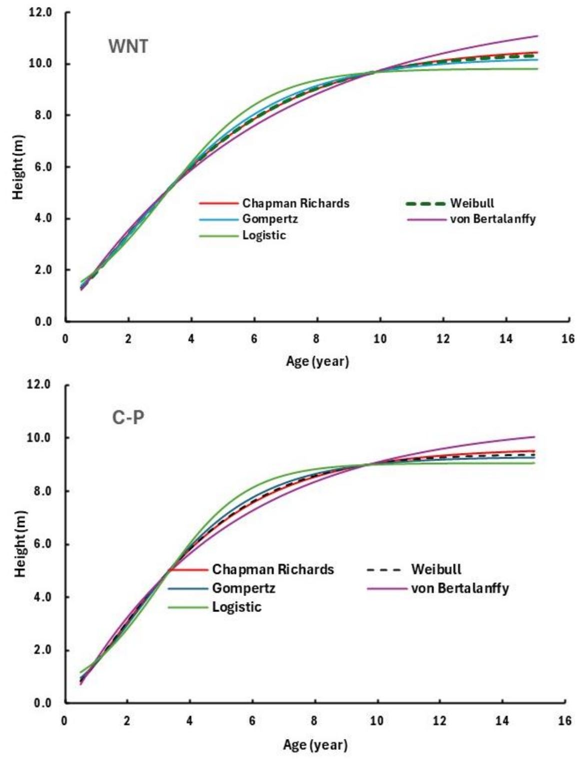

Figure 3. Height–age growth model curves of *F. variegata* for the WNT and C-P populations

Approaching the asymptote (ages 5–10 years), all models converge towards their respective asymptotes (α), but at different rates. The von Bertalanffy model, with its very small m parameter, approaches its asymptote (which is notably higher than other models) most gradually, whereas the Logistic model tends to level off more abruptly after its inflection. The best-performing models (Weibull for WNT, Chapman-Richards for C-P) show a steady, realistic deceleration, which is ecologically realistic for a light-demanding species approaching canopy closure and resource limitation [37].

The parameter α is defined in some literature [38, 39] as the maximum value attainable by the dependent variable, influenced by site productivity. Therefore, when modeling the relationship between peak height and age, α is set as the maximum value of the response variable observed in the data. In this study, α represents the maximum achievable height at the study site. For the WNT population, α ranged from 9.831 to 12.193 m across the five models, while for the C-P population, it ranged from 9.068 to 10.623 m (Table 4).

The shape and rate parameters (β, k, and m) control how quickly growth occurs and when the maximum growth rate occurs. The parameter β is a shape or scaling parameter that influences the inflection point, or when the maximum growth rate occurs, and sometimes the initial size relative to the asymptote. In the Logistic model (Table 4), the WNT population (β = 7.260) reached the inflection point earlier than the C-P population (β = 9.715), meaning the C-P trees reached the maximum growth rate later. In the Chapman-Richards model, β < 1 (here, 0.668–0.787) affects curvature, and a lower β often indicates a longer, slower growth phase after the inflection point. For the von Bertalanffy model, a value of β near α (11.871 versus 10.930 in the C-P model) indicates that inflection occurs earlier in the WNT model for height growth. A higher β value in the logistic model (C-P > WNT) aligns with a later inflection point in the C-P population.

The parameter k is generally related to the intrinsic growth rate, or the rate at which the tree approaches its asymptotic height. Biological meaning: a larger k value indicates faster early growth and an earlier slowdown. k values are generally higher in C-P models than in WNT models (e.g., 0.289 vs. 0.341 in the Chapman-Richards model) (Table 4), indicating slightly faster early growth in C-P.

The parameter m is an additional shape parameter that allows for greater flexibility in the location of inflection relative to the asymptotic height. In the Chapman-Richards model, parameter m is 0.587 and 0.552 for WNT and C-P, respectively (Table 4). This means that inflection occurs earlier in the C-P model than in the WNT model.

Differences between WNT and C-P populations in these parameters suggest different growth strategies or environmental adaptations. C-P shows somewhat faster early growth (higher k) but may reach inflection later in age (higher β in Logistic), whereas WNT inflects at a greater proportion of final height (Chapman-Richards m closer to 0.6).

Table 4. Parameter estimates and reliability values for each height growth model of *F. variegata* for the WNT and C-P population

Model	α	β	k	m	R^2	Adjusted R^2	RMSE	AIC	Sig.	Rank
Height/WNT										
Chapman-Richards	10.669	0.668	0.289	0.587	0.881	0.880	1.034	165.556	**	2
Weibull	10.431	9.556	0.123	1.329	0.881	0.881	1.034	164.514	**	1
von Bertalanffy	12.193	11.871	0.158	1.293E-04	0.880	0.879	1.039	187.340	**	4
Gompertz	10.237	2.415	0.384	-	0.880	0.880	1.036	171.816	**	3
Logistic	9.831	7.260	0.629	-	0.877	0.877	1.049	231.195	**	5
Height/C-P										
Chapman-Richards	9.615	0.787	0.341	0.552	0.822	0.822	1.288	1209.346	**	1
Weibull	9.411	9.021	0.137	1.377	0.822	0.822	1.289	1209.969	**	2
von Bertalanffy	10.623	10.930	0.197	1.04E-04	0.820	0.820	1.295	1233.732	**	4
Gompertz	9.305	2.856	0.461	-	0.821	0.821	1.291	1218.296	**	3
Logistic	9.068	9.715	0.742	-	0.816	0.816	1.308	1280.063	**	5

** Significant at $p < 0.01$

All five models successfully fitted the height data curves in both populations over time, showing high coefficients of determination and adjusted coefficients of determination (R^2 and adjusted R^2 = 0.816–0.881) for both the four- and three-parameter models. This indicates that more than 81% of the variation in tree height can be explained by tree age, with the remaining variation attributed to other factors. The RMSE for the WNT population ranged from 1.034 to 1.049, while the C-P population was higher, between 1.288 and 1.308 (Table 4). In general, the WNT population's height data had a smaller standard deviation than that of the C-P population (Table 1). These two metrics are closely related, as both measure the dispersion of data relative to the mean: standard deviation reflects the spread of the original data, while RMSE indicates the dispersion of prediction errors relative to the true values. All models tested had p-values < 0.01 (Table 4), indicating a less than 1% probability that the model outcomes occurred by chance. In other words, tree height growth models can be used with high confidence for prediction. Furthermore, the parameters of the nonlinear models had a significant effect on the response variable—tree height—in this study.

Based on overall model performance criteria, the Weibull model was identified as the best-fitting model for the WNT population, whereas the Chapman-Richards model performed best for the C-P population (Table 4). In contrast, the Logistic model ranked lowest in predictive accuracy for tree height in both the WNT and C-P populations. A separate study [1] found that the Gompertz and Meyer growth models were the most accurate for predicting teak (*Tectona grandis*) height in Nigeria. The selection of the best model is influenced by species-specific traits and site characteristics.

3.2.2 Diameter curve

The diameter based on DBH is widely used in tree measurements to estimate tree volume, assuming the base area is circular [19]. The diameter-age curve is presented in Figure 4. The shape of the diameter growth curve is similar to that of the height growth curve—sigmoidal.

Early growth phase (ages 1–3 years), predicting time to merchantable size. The early DBH growth trajectories are crucial for scheduling the first thinning or assessing wood quality in short-rotation cycles. The Logistic model again predicts the most rapid initial diameter expansion. However, the Weibull model (best-fit for both populations) depicts a much slower start, particularly for C-P (k=0.035). This profound difference has direct operational consequences: using the Logistic model would predict an earlier attainment of a minimum pulpwood or pole diameter than the Weibull model, potentially leading to premature and uneconomic harvest plans [11].

In the mid-late rotation phase (ages 4–10 years), the dominance of the near-linear increment is observed. This is the most critical phase for volumetric yield accumulation. The most striking visual feature is the near-linear growth trajectory of the Chapman-Richards model, a direct mathematical consequence of its shape parameter m being extremely close to 1 (0.963 for WNT, 0.974 for C-P). In growth analysis, an m value of 1 in the Chapman-Richards function simplifies to a monomolecular curve with no inflection, explaining the linear appearance [39]. This indicates that, according to this model, diameter increment remains strong and relatively constant, a highly desirable trait for sustained biomass production. The Weibull model curves also show strong, sustained increases but with a gentle, concave-down shape, indicating a very slow decline in growth rate. This pattern suggests that radial growth in *F. variegata* is highly persistent and does not exhibit a classic, pronounced sigmoidal slowdown until very late, aligning with the growth strategy of fast-growing pioneer species that prioritize structural expansion [40]. The von Bertalanffy model is a clear outlier, its curve failing to capture the data's central tendency and predicting an implausibly high asymptote, which corroborates its consistently poor statistical ranking (highest AIC).

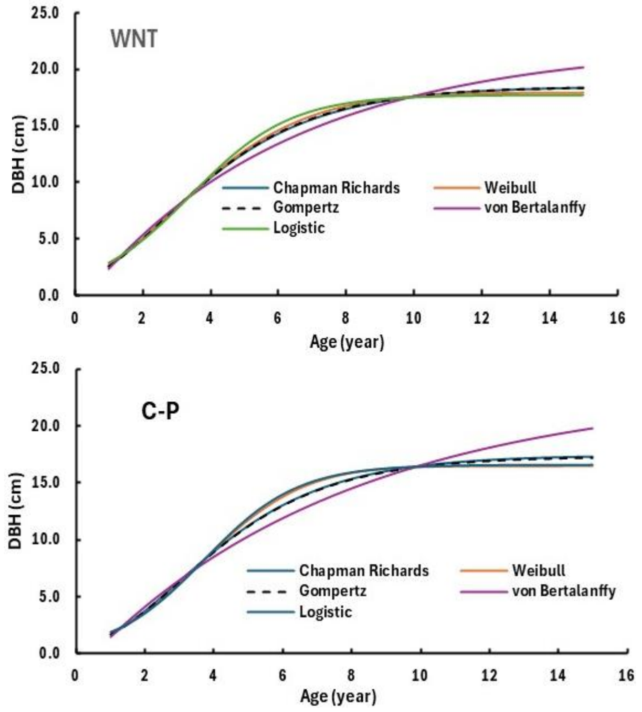

Figure 4. DBH–age growth model curves of *F. variegata* for the WNT and C-P populations

The parameter α represents the maximum average DBH that the population approaches. In the WNT population, it ranges from 17.774 cm (Logistic) to 22.227 cm (von Bertalanffy), and in the C-P population, it ranges from 16.532 cm (Weibull/Logistic) to 23.323 cm (von Bertalanffy). Consistent models (Chapman-Richards and Gompertz) suggest that the WNT population reaches a slightly larger DBH than the C-P population (18.528 cm vs. 17.417 cm), indicating potentially better growing conditions or genetic potential at WNT.

In the Logistic model, the parameter β is the inflection age, which is equal to ln(β)/k. For the WNT population, ln(10.391)/0.683 ≈ 3.47. For the C-P population, β = ln(15.802)/0.742 ≈ 3.68. In the Gompertz model, inflection occurs at age = ln(ln(β))/k. Higher β values delay inflection. For the Chapman-Richards model, a very small β value (approximately 0.09–0.105) indicates that the curve starts very low relative to α and has a long, slow initial phase. For the Weibull and von Bertalanffy models, β near α indicates that inflection occurs after a delay. The C-P model generally has a slightly higher β than the Logistic and Gompertz models, meaning inflection occurs at a later age.

For the Chapman-Richards model, the inflection point is the parameter m, which is the proportion of $\alpha = m^{1/(1-m)}$. For the WNT model, m = 0.963 showed that the inflection point occurred at $\sim 0.963^{27}$, which is greater than 90% of α. This indicates a very late inflection point relative to the final size. For the C-P model, m = 0.974 showed that the inflection point occurred at >95% of α, meaning it occurred even later. These results suggest that DBH grows slowly for the curve, with the maximum growth rate occurring very close to the asymptote. For the Weibull model, m > 1 (1.738 for WNT and 2.173 for C-P), and a larger m reflects a later inflection point. The C-P model seems to have a later inflection point and a slightly smaller asymptotic DBH, possibly due to site conditions or genetic resources. The WNT curve reaches a larger DBH asymptote and may have an earlier inflection point, indicating better growing conditions for diameter development.

All five models fitted the diameter data well in both populations over the time series, with high coefficients of determination and adjusted coefficients of determination (R^2 and adjusted R^2 = 0.764–0.767) for both the 4- and 3-parameter models. This indicates that more than 76% of the variation in diameter can be explained by tree age, with the remaining variation attributed to other factors. The RMSE was relatively high in both populations (RMSE = 2.834–2.870). Since RMSE squares the differences, it gives greater weight to larger errors, making it more sensitive to outliers. Similar to the height models, all diameter growth models showed statistical significance with $p < 0.01$ (Table 4). Therefore, the tree diameter growth models can be used with high confidence for prediction purposes.

Table 5. Parameter estimates and reliability values for each DBH growth model of *F. variegata* for the WNT and C-P population

Model	α	β	k	m	R^2	Adjusted R^2	RMSE	AIC	Sig.	Rank
DBH/WNT										
Chapman-Richards	18.528	0.105	0.402	0.963	0.767	0.766	2.854	4128.863	**	2
Weibull	17.945	16.428	0.071	1.738	0.767	0.767	2.853	4128.414	**	1
von Bertalanffy	22.227	23.342	0.163	2.032E-08	0.764	0.764	2.870	4150.904	**	4
Gompertz	18.477	2.974	0.412	-	0.767	0.767	2.853	4126.726	**	1
Logistic	17.774	10.391	0.683	-	0.766	0.766	2.859	4134.583	**	3
DBH/C-P										
Chapman-Richards	17.417	0.090	0.412	0.974	0.764	0.764	2.839	4129.424	**	3
Weibull	16.532	15.145	0.035	2.173	0.765	0.765	2.834	4123.018	**	1
von Bertalanffy	23.323	24.788	0.129	1.54E-08	0.760	0.759	2.867	4168.56	**	4
Gompertz	17.379	3.544	0.419	-	0.764	0.764	2.838	4126.934	**	2
Logistic	16.602	15.802	0.742	-	0.765	0.765	2.835	4122.503	**	1

** Significant at $p < 0.01$

Based on model goodness-of-fit criteria, the Weibull and Gompertz models were the best for predicting tree diameter in the WNT population, while the Weibull and Logistic models performed best in the C-P population. In contrast, the von Bertalanffy model ranked lowest in both the WNT and C-P populations (Table 5). A previous study also found that the Gompertz, von Bertalanffy, and Chapman-Richards models performed well for predicting diameter growth in sungkai (*Peronema canescens* Jack) [19].

3.2.3 Differences in growth models between populations

The difference in growth models between the WNT and C-P populations is likely due to differences in genetic adaptation associated with their origin, as stated in studies by Klopčič et al. [37] and Wondimneh et al. [41]. The geographic origin of tree seed sources strongly influences tree growth due to genetic adaptations to local climates, soils, and elevations. This leads to differences in height and diameter when planted elsewhere. The results of the study [26] also indicate that the WNT population has a higher coefficient of additive genetic variation (CV_A) than the C-P population. CV_A is an indicator used to assess the long-term evolution of a trait and its potential for adaptation under changing environmental conditions. Thus, the WNT population is better adapted than the C-P population. This is evident in the optimal height growth models for the WNT (Weibull) and C-P (Chapman-Richards) populations. The maximum value (α) of WNT tree height is greater than that of C-P, at 10.431 m and 9.615 m, respectively. Similarly, the maximum value (α) of the WNT tree diameter is greater than that of the C-P population for the best diameter growth model of the WNT (Weibull) and C-P (Weibull) populations, namely 17.945 cm and 16.532 cm, respectively (Table 5).

3.2.4 Biological implications of the growth model

Each species has a different biological growth pattern influenced by its life strategy (shade-tolerant vs. light-demanding) [37], biomass allocation [40], response to the environment [42], early growth dynamics (juvenility phase), and rate of approach to the asymptote [37]. Therefore, an empirical model that is suitable for one species is not automatically suitable for another species. For *F. variegata*, the growth pattern shows a slow start (lag phase), strong acceleration in middle age, and then a more gradual approach to the maximum value. This pattern is very consistent with Weibull or Chapman–Richards.

All sigmoidal models have asymptotic parameters (α), theoretical maximum height, and diameter. The implication is that different models produce different predictions of α, thereby affecting estimates of optimal harvest age, rotation, or long-term volume predictions, as well as affecting genetic rankings, because different families may approach the asymptote at different rates.

Meanwhile, the inflection point is the age at which height/diameter growth reaches its maximum rate. The implication for *F. variegata*, for which Weibull/Chapman-Richards was selected as the best model, is that this model shows asymmetrical growth, which means that the maximum growth phase occurs earlier. This is important for determining genetic selection age and rotation.

3.3 Implications for breeding programs and plantation management of *F. variegata*

3.3.1 Breeding programs: Accelerating selection

A primary challenge in perennial tree breeding is the long generation time. Early selection—predicting mature trait performance from measurements at a juvenile age—is essential to accelerate genetic gain [6, 43]. The fitted nonlinear models provide the precise mathematical framework to implement this strategy.

The strong correlation between tree height and DBH allows selection based on just one trait—such as diameter—since diameter is highly correlated with height. This approach can save time and resources during measurement and selection. Using diameter as the primary selection trait can lead to a dual response by also improving tree height due to the strong inter-trait relationship. In indirect selection, it is important to choose a trait that is easier or more cost-effective to measure while still achieving improvements in other related traits. Indirect selection is feasible when the two traits share a high genetic correlation [6]. In the case of *F. variegata*, the genetic correlation between height and diameter is strong, indicating that selecting for diameter will positively affect tree height.

Accurately modeling height growth is essential for constructing growth curves and estimating the optimal age for selection. One of the main challenges in forest tree breeding is the lengthy selection cycle, which can span several years due to long rotation periods [43]. Growth models can support the development of age–age correlation models for estimating genetic parameters, enabling early selection [44] and thereby accelerating the breeding cycle.

For the WNT population, the Weibull height model indicates the rapid growth phase concludes around age 2-3 years (inflection point ~2.1 years). Therefore, measuring and selecting superior genotypes at age 3-4 years is recommended. At this age, tree rankings for height are largely stabilized, allowing the prediction of mature (age-10) performance with high confidence. This approach can reduce the selection cycle by 6-7 years, significantly accelerating genetic gain per unit time [4]. Breeders can apply these population-specific models to create early selection indices, weighting early height or DBH based on their genetic correlation with target mature volume.

3.3.2 Plantation management: Predicting yield and scheduling operations

For silvicultural management, the models enable dynamic yield forecasting. By integrating the best population-specific models for DBH and height (e.g., Weibull for H and Gompertz for DBH in WNT) into a standard tree volume equation, managers can project stand volume at any age. For example, a WNT plantation with 340 trees/ha at year 10 is estimated to yield approximately 41 m^3/ha. Furthermore, the DBH model parameters reveal that radial growth is sustained and near-linear for most of the rotation (inflection >90% of α). This informs critical interventions: a first thinning at age 3-4 is advised to release future crop trees precisely as height growth slows and resource allocation shifts to maximizing their diameter increment during the long linear growth phase [13]. Finally, comparing the mean annual increment curves derived from these yield projections for each population will identify the site-specific rotation age that maximizes volumetric yield, providing a scientific basis for harvest scheduling.

4. CONCLUSIONS

The main conclusions of this study are as follows: (1) Tree height and diameter are very strongly correlated, with coefficients of determination (R^2) of 0.921 for the WNT population and 0.863 for the C-P population. This is especially valuable for breeding programs, where selecting for diameter traits can positively influence height traits; (2) The Weibull model is the best for estimating tree height parameters in the WNT population, while the Chapman-Richards model performs best for the C-P population; (3) For tree diameter estimation, the Weibull and Gompertz models are most suitable for the WNT population, while the Weibull and Logistic models are best for the C-P population. The use of different models for the WNT and C-P populations underscores the critical need for adopting population-specific approaches in forest breeding and management programs. Future research should validate these models across diverse sites and incorporate stand density competition factors to enhance their general applicability for plantation management.

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