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Exploring allometric relationships in immature oil palm in Southern Benin's smallholdings

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ABSTRACT

Accurate estimation of oil palm aboveground biomass is essential for understanding growth dynamics, carbon accumulation, and resource-use efficiency, particularly during the immature stage when management practices strongly influence future productivity. However, few studies have developed non-destructive allometric equations specifically adapted to immature oil palms under African smallholder conditions. This study investigated the relationships between morphometric traits and total aboveground biomass of immature oil palm trees managed by smallholders in southern Benin. Morphometric measurements were conducted on 15 immature oil palm trees aged 2 to 3 years intercropped with maize or cassava. Tree height (H_max), girth circumference (Girth), and crown diameter (Crown_diameter) were measured on standing trees. Frond-related variables included petiole and rachis length (L), dry weights (DW) of petiole, rachis, and leaflets, dry weight of a 0.30 m rachis fragment sampled at the midpoint, and petiole cross-sectional dimensions. A total of 278 fronds were analysed. To predict the aboveground biomass, both linear regression and random forest (RF) models were applied. Results showed that maximum frond biomass is reached at frond rank 10, after which it gradually declines. Unlike the existing equations, frond biomass was poorly predicted by rachis biomass and petiole cross-section ($R^2 < 0.40$). the petiole length emerged as the best predictor of frond biomass ($R^2 = 0.64$). Similarly, the petiole length if the frond 10 was the most relevant predictor of total aboveground biomass in immature oil palms ($R^2 = 0.94$; $RMSE_{LOOCV} = 0.94$ kg). The INEAC vigour index was also a relevant predictor of total aboveground biomass, but to a lesser extent than simple morphometric variables such as frond length and height. Although the proposed equations should be interpreted cautiously because of the limited sample size and single-site design, this study provides an initial framework for rapid and non-destructive biomass estimation in immature oil palms under smallholder conditions. These results could support future assessments of biomass accumulation, carbon sequestration, and the effects of management practices such as intercropping on young oil palm development.

1. Introduction

Biomass accumulation, defined as the net gain of organic matter within a plant, is a key indicator of plant growth and ecosystem functioning. In agricultural systems, accurate biomass estimation is essential for assessing crop productivity, nutrient-use efficiency, and residue recycling potential, thereby supporting sustainable management practices. In ecological contexts, biomass also underpins the understanding of carbon sequestration, nutrient cycling, and primary production dynamics.

In recent decades, the oil palm (*Elaeis guineensis Jacq.*) sector has received increasing scientific attention due to its economic importance and its environmental implications, particularly in relation to carbon dynamics and land-use change associated with tropical deforestation

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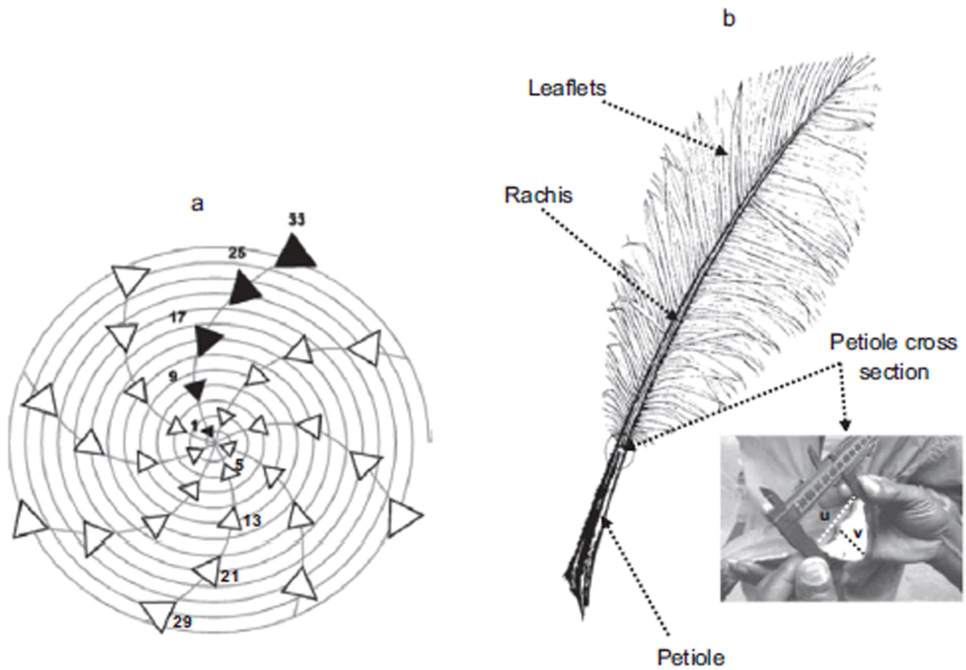

Fig. 1. (a) Labelled frond pattern indicating the frond rank numbering and crown phyllotaxis ; (b) demonstration of the PCS (petiole cross sectional area) where the letter *u* correspond to the thickness and the letter *v to the* width of the petiole at point C *;* a rachis fragment is taken from the rachis midpoint as shown in red (Adapted from Aholoukpè *et al*., 2013).

(Carlson et al., 2012; Rival and Levang, 2014). Beyond these concerns, robust biomass estimates are required to better understand plantation growth dynamics and resource allocation within agroecosystems.

Leaf diagnosis is widely used to assess the nutritional status of oil palms through nutrient concentrations measured in leaflets at rank 17 (Caliman et al., 2002; Woittiez et al., 2018). However, while useful for nutritional monitoring, this approach does not directly capture whole-plant growth or biomass accumulation, which are essential for evaluating plant performance and predicting productivity.

Direct biomass measurement in perennial crops such as oil palm is challenging because destructive sampling is labor-intensive, costly, and impractical at plantation scale (Jaffré and Namur, 1983; Syahrinudin, 2005). As a result, allometric equations have been widely developed as non-destructive tools to estimate biomass from easily measured morphometric traits (Chave et al., 2014; Pilli et al., 2006). In oil palm, variables such as frond number, stem height, stem girth, and other morphological traits have been shown to reflect growth and biomass production (Caliman et al., 2002), as they are linked to carbon assimilation and dry matter accumulation.

However, most existing allometric models for oil palm biomass estimation were developed for mature palms grown under homogeneous industrial plantation systems in Southeast Asia (Henson et al., 2012; Lewis et al., 2020). These environments differ markedly from smallholder systems in West Africa, where climatic constraints and management heterogeneity are more pronounced. In southern Benin, annual rainfall ranges from 900 to 1200 mm, whereas optimal oil palm development requires approximately 1800 mm of well-distributed rainfall (Allé, 2014; Corley and Tinker, 2016). Such limitations, combined with diverse cropping systems, fertilization practices, and intercropping strategies, are likely to influence growth patterns and biomass allocation.

In addition, existing models often rely heavily on stem-related variables, which may be less informative in immature palms, where trunk development remains limited and biomass accumulation is predominantly driven by frond development (Corley and Tinker, 2016). Consequently, the applicability of these models to immature palms in smallholder systems of West Africa remains poorly documented. Overall, there is a clear lack of locally calibrated allometric models for estimating biomass of immature oil palms under heterogeneous smallholder conditions in West Africa.

Our study aimed to develop locally calibrated allometric models for estimating the aboveground biomass of immature oil palms cultivated under smallholder conditions in southern Benin. We investigated the link between easily measured morphometric traits and biomass components in smallholder plantations in southern Benin. We hypothesized that: (i) locally developped models would improve biomass estimation compared with existing Asian plantation models; (ii) easily measured frond traits would be reliable predictors of aboveground biomass ; and (iii) an integrated vigour index based on selected morphometric traits would effectively predict the aboveground biomass of immature oil palms under smallholder conditions in southern Benin.

2. Materials and methods

2.1. Study area

The study was conducted on the Allada Plateau in southern Benin (2° to 2°30′E; 6°25′-7°30′N) in the Atlantique department, southern Benin. The climate is Sudano-Guinean with a bimodal distribution that characterises a sub-equatorial climate. The first (long) rainy season extends from April to July and peaks in mid-June. The second (short) rainy season extends from September to November and peaks in early October. Annual air temperature varies from 25 °C to 29 °C. The average inter-annual rainfall in the study region is 1100 mm between 1951 and 2010 (Allé, 2014). Rhodic Ferralsols (FAO, 2006) are dominant in this region. These soils are weakly desaturated, red, deep, and originate from sandy-clayey sediments of the Continental Terminal called "terre de barre" (Azontonde et al., 2010; Djegui, 1992).

2.2. Plant materials and management

Oil palm (*Elaeis guineensis*, Jacq.) is a monocotyledon belonging to the *Arecaceae* family. From a botanical perspective, the oil palm is a giant herb (Corley and Tinker, 2016). However, oil palm is often

Table 1
Cropping management history of each palm plantations.

Plantations	Variety	Number of oil palm	Age (years)	Land use before the planting	Management of the plantation		
					Year1	Year2	Year3
1 (P1 to P9*)	Tenera (Deli x La Mé)	9	2	Maize	Two cycles of intercropping with corn: no fertilizer added to either the palm tree or the corn.	No intercropping	-
2 (P10 to P15*)	Tenera (Deli x La Mé)	6	3	Cassava	One cycle of intercropping with corn; no fertilizer added to either the palm tree or the corn.	Intercropping with cassava; no fertilizer added to either the palm tree or the cassava.	No intercropping

* P1 to P15 are the trees in order of dissection.

Table 2
Performances of the random forest models for the fronds and tree biomass predictors.

Models	Predictors	Final value of *mtry*	R^2	RMSE LOOCV (kg)
RFF	L_Total; L_petiol, L_Rachis, Linear_Density, Width_PC, Thickness_PC, Num_Leaflets, DW_Frag_Rachis	7	0.81	0.056
RFT_Direct	H_max, Girth, Crown_diameter, L_Petiol_10, L_Rachis_10, Width_PC_10, Thickness_PC_10, Num_Leaflets_10	3	0.92	1.22
RFT_Comp	IV_Ineac, L_Total_10, Linear_Density_10, PCS	3	0.91	1.43
RFT_Mix	IV_Ineac, L_Total_10, H_max, Num_Leaflets_10	4	0.94	1.09

referred to as tree based on its arborescent architecture, perennial nature and functional role within agroforestry and biomass assessment frameworks (Abnisa et al., 2013; Aholoukpe et al., 2013). In this study, the words "oil palm" and "tree" will be used interchangeably.

The palm leaves are inserted into the crown following a regular spiral-shaped phyllotaxis in which the position of each frond determines its rank (Fig. 1a). All leaves emerge from a central growing apex, referred to as the basal cabbage (Lewis et al., 2020). From the centre of the crown to its periphery, non-functional newly formed leaves (spears) and then functional leaves follow one another. The rank "1″ frond corresponds to the youngest fully open functional frond, and older fronds are assigned sequentially higher numbers. An oil palm frond is composed of a petiole whose base is embedded in the crown of the palm, a rachis in the extension of the petiole, and leaflets inserted on the rachis (Fig. 1a). On the palm frond, point C marks the border between the petiole and the rachis (Fig. 1b).

In this study, 15 immature oil palm trees were selected from two smallholder plantations with the formal consent of the farmers. The plantations were two and three years old, respectively, and the palms had been established at a planting density of 143 trees per hectare. All palms were planted on the same date within each plantation. The two-year-old plantation was predominantly intercropped with maize, whereas the three-year-old plantation was managed under a sequential intercropping system involving maize followed by cassava. No fertilizers were applied to the oil palms (Table 1). The plant material in the two plantations is selected material of "Tenera" fruit form, belonging to the widely distributed Deli x La Mé genetic origin marketed by the *Centre de Recherches Agricoles Plantes Pérennes* (CRA-PP/INRAB) to the palm growers in Benin. (Fig.1)

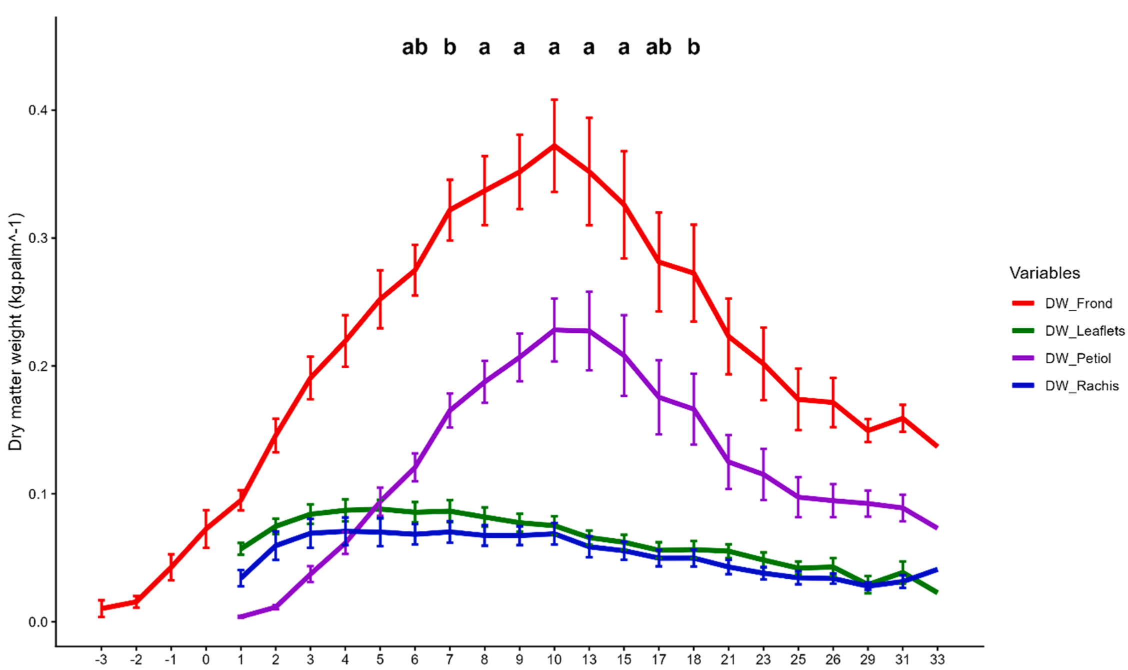

Fig. 2. Differences in frond biomass according to frond rank. Bars sharing the same letter are not significantly different at the 5% significance level, based on Dunn's post hoc test. Graphs for individual palms are available in Supplementary Material S2.

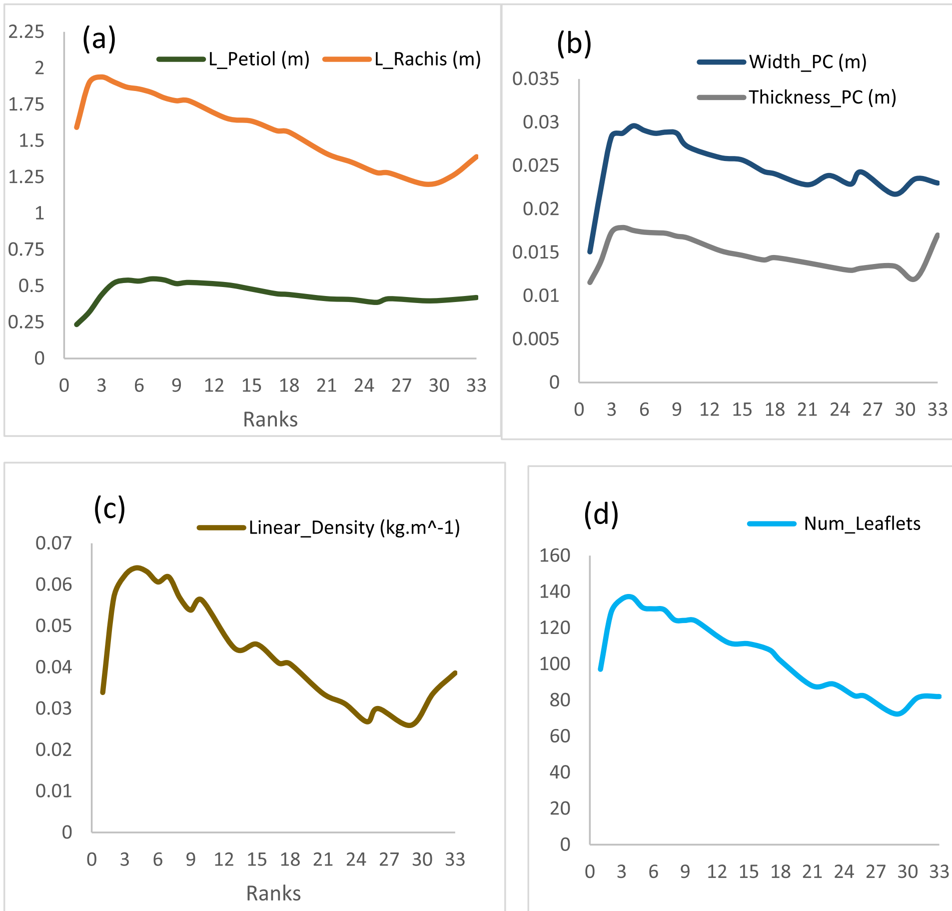

Fig. 3. Difference in frond morphometrics as a function of frond rank. (a) petiole and rachis lengths ; (b) width and thickness of petiole; (c) Linear density ;(d) number of leaflets. Units are shown in the legend.

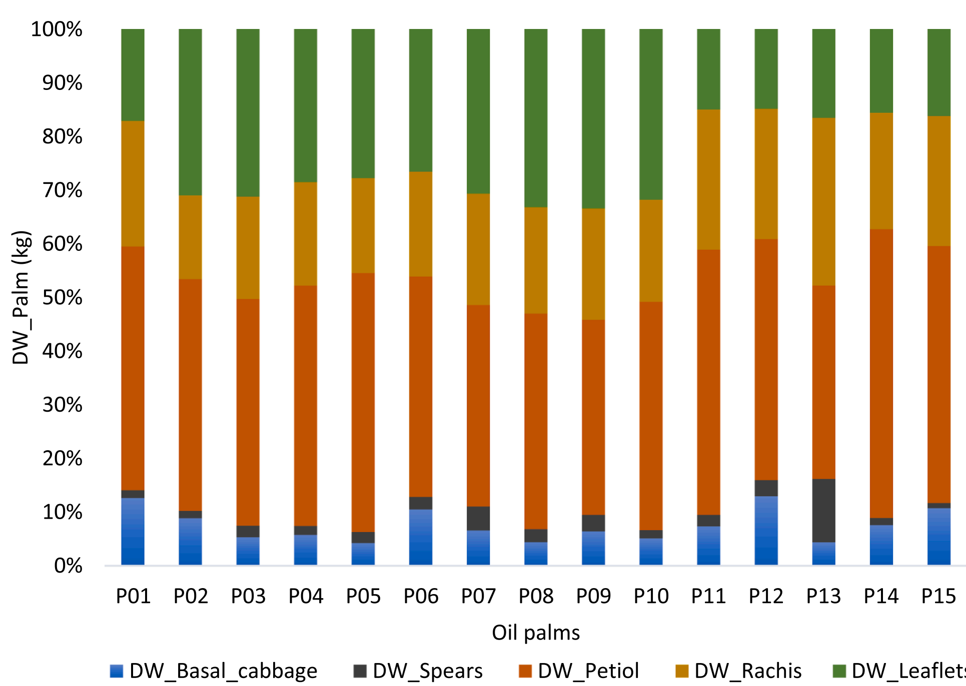

Fig. 4. Mean proportions of biomass component dry weights (kg) for the 15 sampled oil palms.

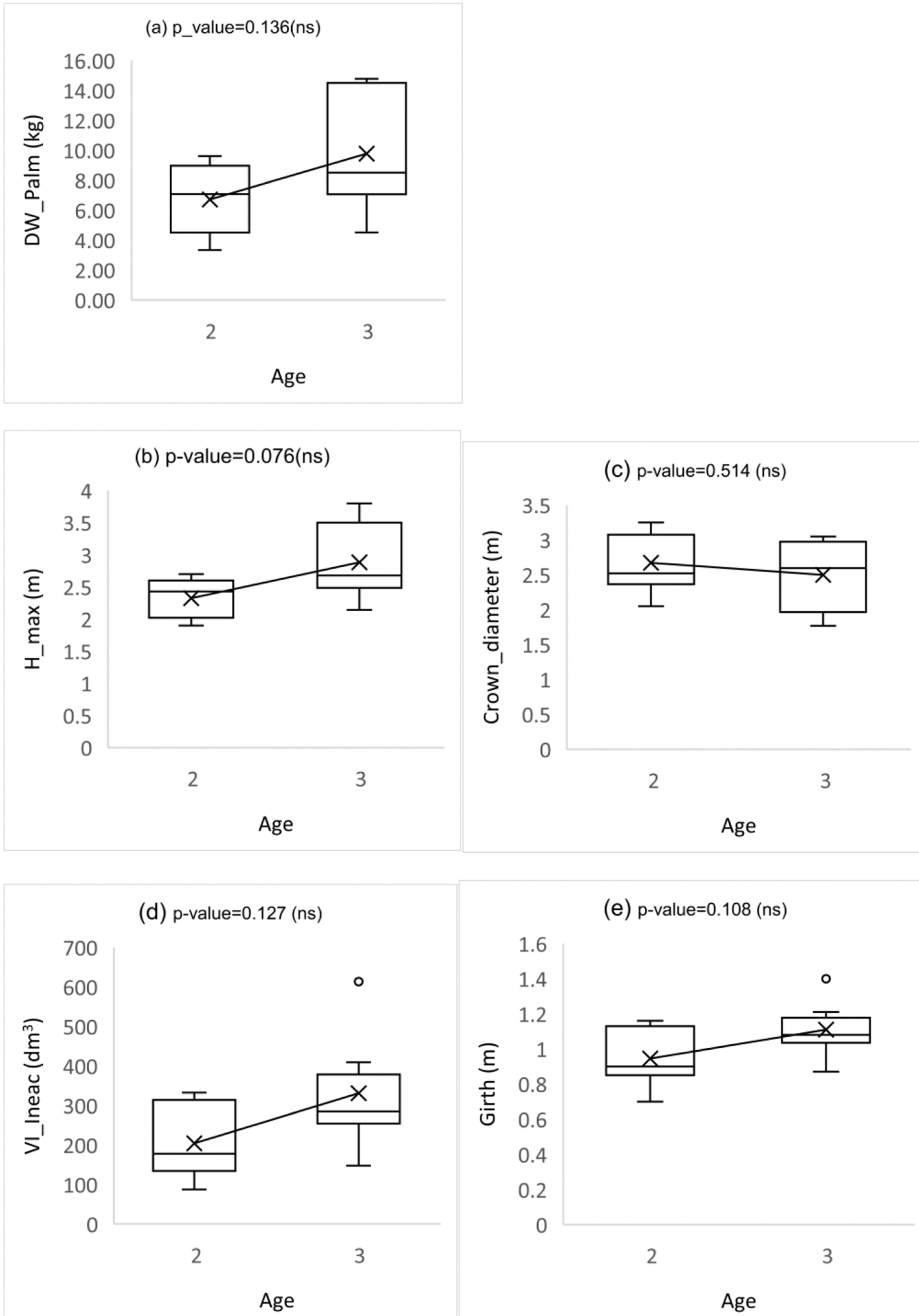

Fig. 5. Effect of the age on the oil palm variables. (a) oil palm aboveground biomass ; (b) maximum height; (c) crown diameter ; (d) Ineac's Vigour index ; (e) Girth ($n = 15$).

2.3. Data collection

Palms were selected at random at least 20 m from the plantation border, all were selected in the different plantations. Severely leaning or recovered palms were not considered. Data collection was conducted a single occasion for each individual palm and organised into two principal stages. The first stage comprised morphometric measurements taken prior to the tree felling and subsequent dissection.

Step 1: Morphometric measurements before felling the oil palms

The following variables were collected on the 15 standing palm trees:

Number of photosynthetically active fronds (Nb_Fronds)

Height of the tree (H_max)

Average crown diameter (Crown_diameter)

Girth circumference (Girth)

The height of the tree (H_max) was measured from the ground to the tip of the tallest frond using a graduated wooden ruler. The average crown diameter (Crown_diameter) was calculated from the average of two perpendicular diameters of the horizontal projection of the crown to the ground using a plumb line. Crown diameters were measured at the tips of the longest leaves in a north–south and east–west orientation. The girth circumference (Girth) was measured using a rope wound around the base of the stipe.

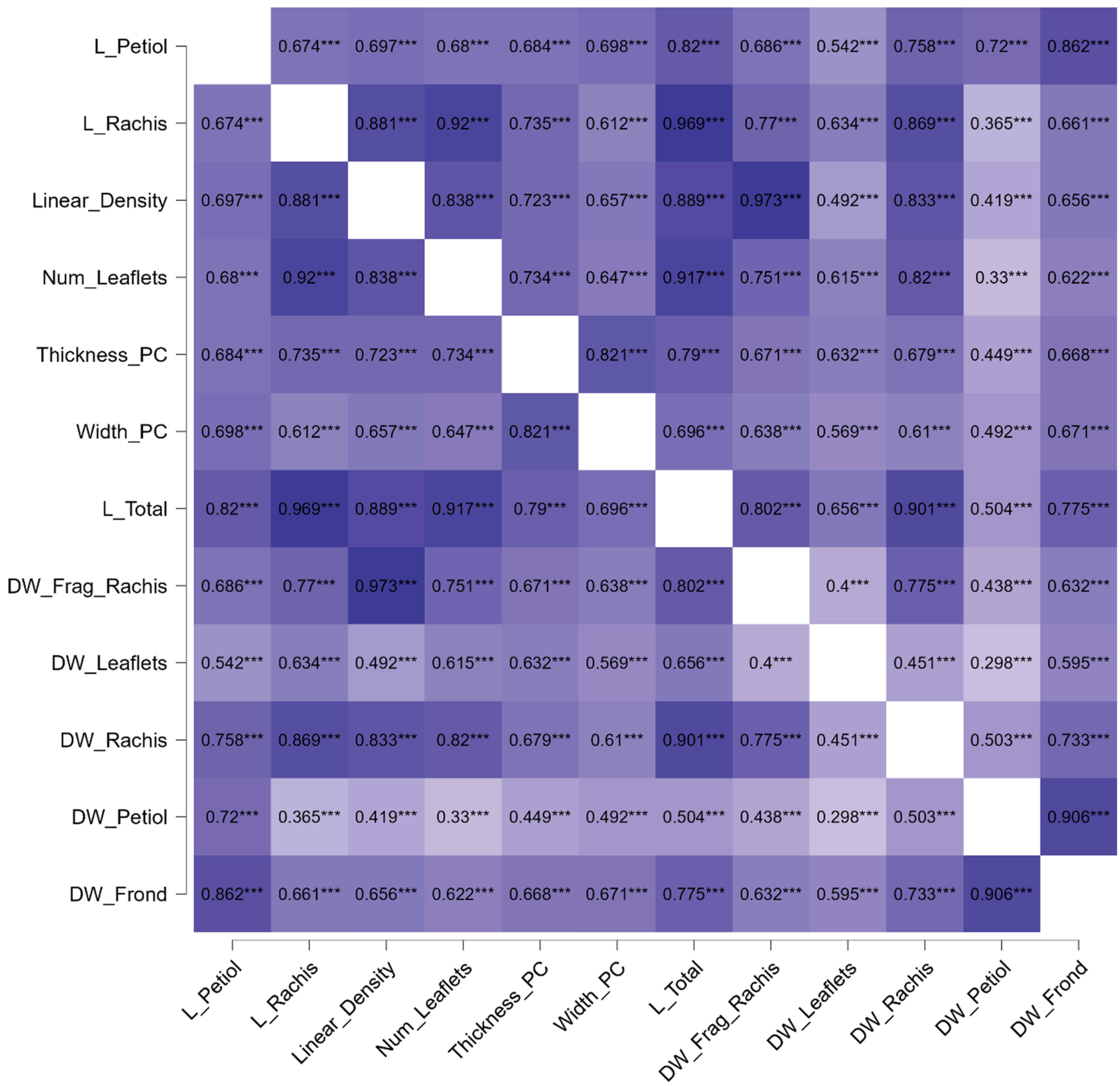

Fig. 6. Spearman's *Rho* correlation heatmap of fronds variables.

Step 2: Felling and dissection of the trees.

The felling of the young oil palms was carried out at ground level, avoiding mutilating the lowest leaves of the palm. Each palm tree was then dissected to extract the entire petiole of the frond and obtain precise measurements. A method adapted from Aholoukpè et al.(2013) was used to select the fronds to be measured: In addition to fronds at the head of all spires (ranks 1 to 8), all the fronds located on spire 1 (1, 9,17, 25…), 2 (2, 10, 18, 26…), 5 (5, 13, 21, 29…), and 7 (7, 15, 23, 31…) were considered for data collection. A total of 278 leaves were sampled for measurements. All fresh weights were measured and recorded as close to the time of felling as possible, with particular attention paid to leaflets. Samples were promptly transferred to the laboratory oven to avoid bias in dry weight (DW) measurements due to decomposition or moisture loss during handling.

On each frond, the following variables were obtained:

Number of leaflets (Num_Leaflets)
Length of the rachis (L_Rachis)
Length of the petiole (L_Petiol)
Thickness of the petiole cross-section at C (Thickness_PC) (Fig. 1b)
Width of the petiole cross-section at C (Width_PC) (Fig. 1b)
Dry weight of a 0.30m-fragment of rachis (DW_Frag_Rachis) (Fig. 1b)
Dry weight of the rachis (DW_Rachis)
Dry weight of the leaflets (DW_Leaflets)
Dry weight of the petiole (DW_Petiol)

The total length of a frond (L_Total) was calculated as the sum of rachis and petiole lengths. Frond dry biomass (DW_Frond, kg frond^{-1}) was obtained by summing the oven-dried weights of its three components: leaflets, rachis, and petiole.

Total frond dry weight was summed across all fronds counted on each palm (Nb_Fronds). For fronds that were not directly measured, dry weight was estimated using a rational function model:

Dw_Frond = (a + b × frond_rank) / (1 + c × frond_rank + d × frond_rank^2).

The model was fitted individually for each palm using the nls function in R version 4.5.1 (R Core Team, 2025). Model fit was consistently high (R^2 = 0.91–0.99), with root mean square error (RMSE) values below 40 g for individual frond dry weight predictions. Parameter estimates for each palm are provided in Supplementary Material S1.

Total aboveground biomass per palm (DW_Palm, kg palm^{-1}) was then calculated as the sum of the dry weight of all spears and fronds (including both measured and model-estimated fronds), plus the dry weight of the remaining basal cabbage (DW_Basal_cabbage, kg palm^{-1}).

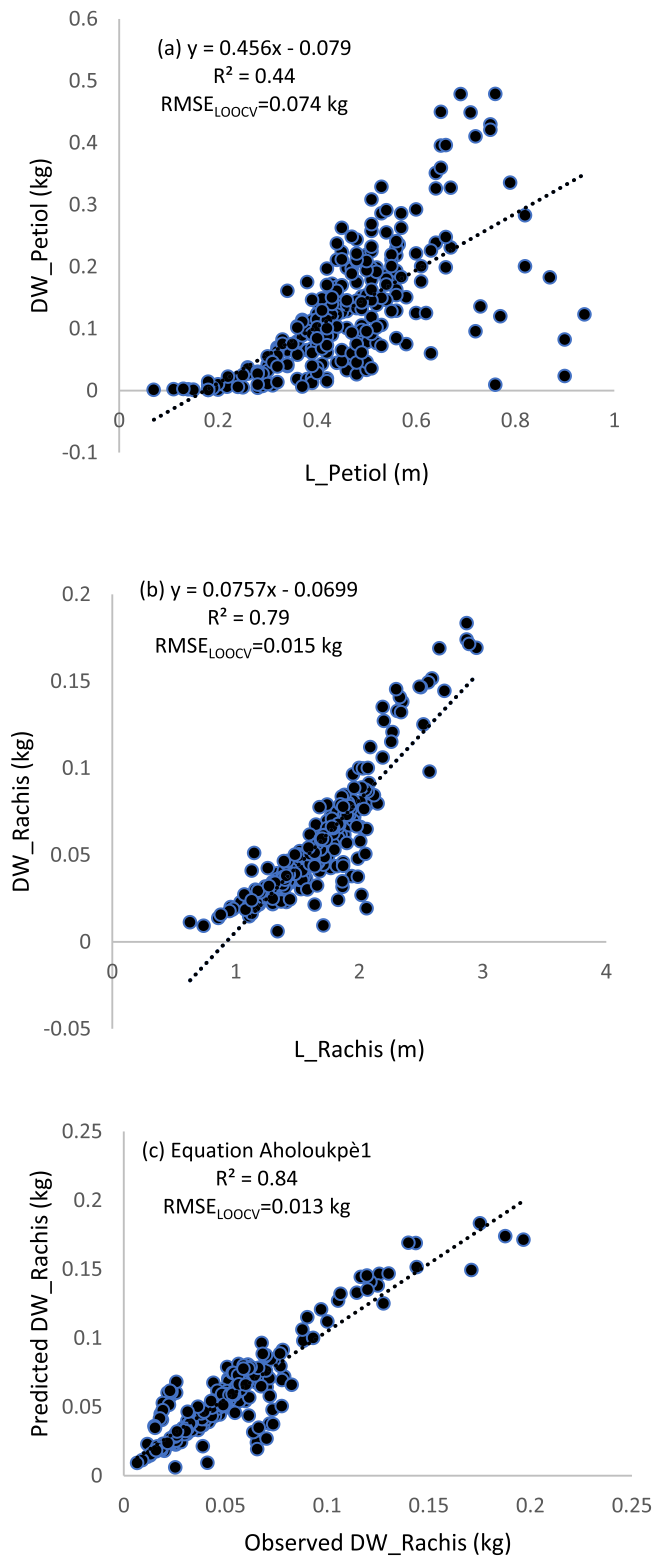

Fig. 7. Fronds components biomass as a function of their lenght. (a) petiole biomass as a function of its length ; (b) rachis biomass as a function of its length; (c) Frond biomass as predicted by the Aholoukpè's Eq. (1) (n = 278).

2.4. Data analysis

2.4.1. Testing existing allometric equations

The Aholoukpè Eq. (1) is designed to predict rachis biomass (Aholoukpè et al., 2013). The equation is:

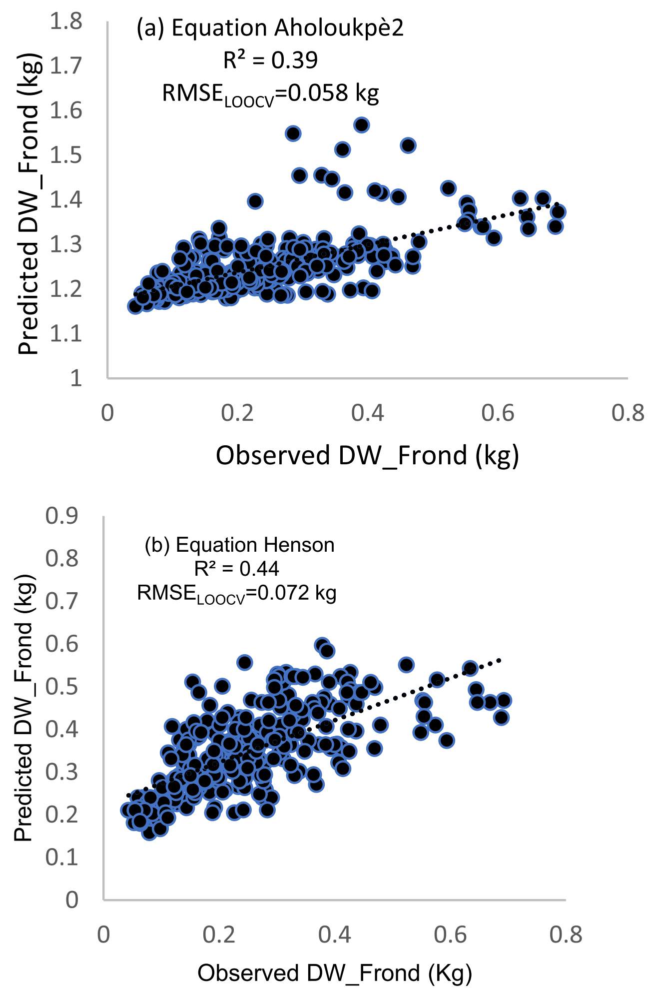

Fig. 8. Test of the existing equations (a) Frond biomass predicted by the Aholoukpè's Eq. (2) versus observed ; (b) Frond biomass predicted by the Henson Equation versus observed.

$$DW\_Aholoukpè1 = 1.133 \times Linear\_Density \times L\_Rachis \qquad (1)$$

Where *DW_Aholoukpè1* is the dry weight of the rachis of a frond as calculated by Aholoukpè Eq. (1) in kg; Linear_Density is the linear density of the rachis, corresponding to the ratio of the dry weight of a central fragment of the rachis (*DW_Frag_Rachis*) to the length of the fragment, which is 0.30 m in this study (Fig. 1b). *L_Rachis* is the length of the rachis.

Afterwards, the Aholoukpè Eq. (2) is applied to estimate the whole frond biomass (Aholoukpè et al., 2013):

$$DW\_Aholoukpè2 = 1.147 + 2.135 \times DW\_Aholoukpè1 \qquad (2)$$

Where *DW_Aholoukpè2* is the dry biomass of a frond as calculated by Aholoukpè Eq. (2), in kg.

Henson's (2003) equation for palms less than seven years old is written as:

$$DW\_Henson = \beta\ PCS + \alpha \qquad (3)$$

Where *DW_Henson* is the dry biomass of a frond as calculated by Henson's equation, in kg; *PCS* is the petiole cross-sectional area (cm^2) equal to the product of the width and thickness of the petiole measured at point C of the frond; β is equal to the value 0.0101t + 0.0284, and α to the value 0.00394t − 0.0076; t corresponds to the age of the palm grove expressed in years.

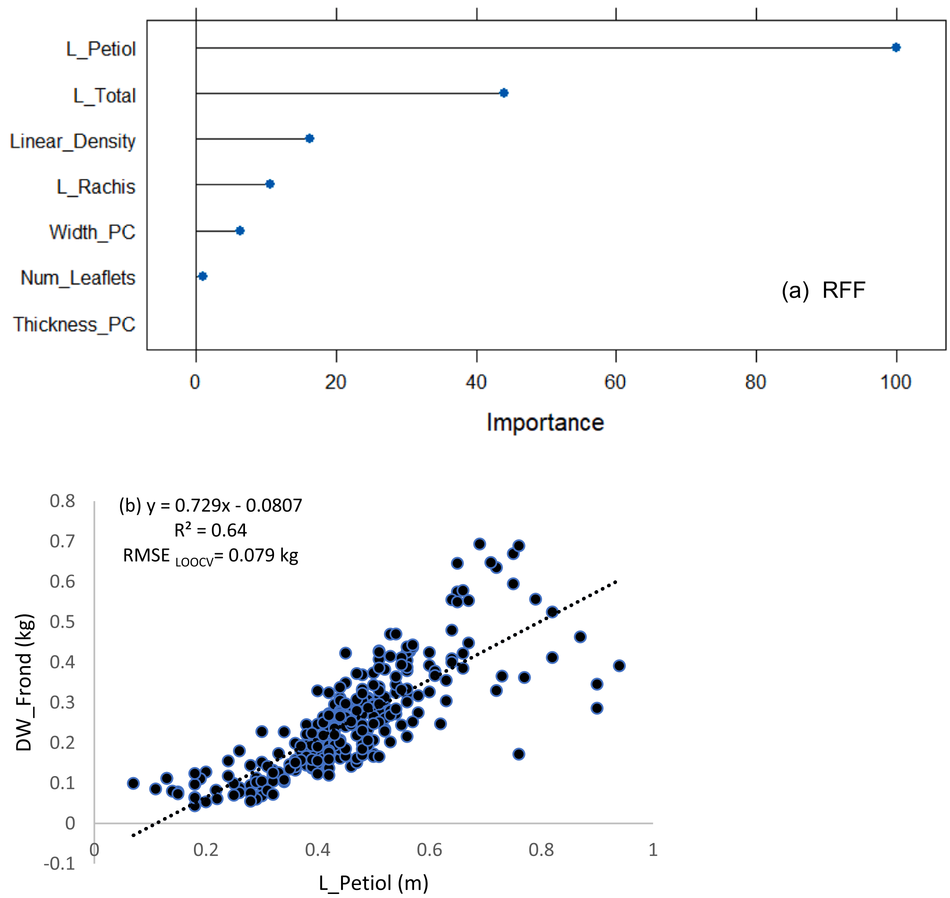

Fig. 9. (a) Random forest model for the selection of the fronds biomass predictors (RFF). (b) Observed frond biomass as a function of the petiol lenght.

The vigour index (VI) formula was proposed by the *Institut National pour l'Étude Agronomique du Congo Belge* (INEAC, Yangambi in DRC) (Caliman et al., 2002; De Berchoux and Lecoustre, 1986). Variables such as crown diameter, Height and girth were combined to account for canopy development within the VI.

The formula is written as follows:

$$VI\_Ineac = Girth^2 \Big/ 4\pi \times \sqrt{Crown\_diameter^2 / 4 + H\_max^2} \quad (4)$$

Where *VI_Ineac* is the vigour index; Girth is the girth circumference; H_max is the height of the tip of the highest leaf; Crown_diameter is the average crown diameter. As a volume measurement the VI_Ineac is express in dm^3. The VI corresponds to the volume of a cylinder whose base equals the cross-sectional area of the stem, and whose height corresponds to the hypotenuse of a right triangle defined by H_max and half of the crown diameter.

2.4.2. Analysing the effect of the fronds' rank, age and management histories on the aboveground biomass

The effect of age on the oil palm total aboveground biomass was assessed using students two-sample Welch's *t*-test. The non-parametric Kruskal–Wallis rank sum test was used to assess the effect of frond rank and palm age when the normality of the residuals and the homoscedasticity conditions for ANOVA were not met. These conditions were assessed using the Shapiro - Wilk and Breusch-Pagan tests, respectively. Once significant effects were detected, the Dunn's multiple comparisons test, adjusted with the Bonferroni method, was used as a *post-hoc* test to identify the significance of the differences. Differences were considered statistically significant when $p \leq 0.05$. Biomass was compared across age classes and management histories of the plantations. Age was not included as a predictor in the predictive models; given the partial confounding between age and management history, results were interpreted cautiously and without causal attribution.

2.4.3. Predicting frond and tree aboveground biomass

All statistical analyses were conducted using R software version 4.5.1 (R Core Team, 2025). Spearman's rho and Kendall's tau correlation coefficients were first examined to assess the strength of bivariate relationships between oil palm morphometric and weight variables. Following commonly used guidelines, correlation coefficients (*rho* or *tau*) greater than 0.70 were considered indicative of very strong associations (Kpienbaareh et al., 2022).

Two complementary modelling approaches were then used to identify the best predictors of oil palm frond dry biomass (DW_Frond) and aboveground dry biomass (DW_Palm). First, Random Forest (RF) regression models were implemented to capture potential non-linear relationships and rank predictor importance. The RF models (Breiman, 2001; RColorBrewer and Liaw, 2018) were fitted using the "ranger" and "caret" packages. Random forests are ensemble tree-based methods derived from CART (Classification and Regression Trees), where the data are recursively partitioned into homogeneous subsets of the response variable and predictions are averaged across all trees (Scornet, 2023). This approach is robust to multicollinearity, overfitting, and outliers, and is computationally efficient (Darst et al., 2018; Kaveh et al., 2023).

Variable importance was assessed using the increase in out-of-bag (OOB) prediction error (%IncMSE), obtained by permuting each predictor while keeping others unchanged (Verikas et al., 2011). Predictors directly constituting biomass components (DW_Frag_Rachis, DW_Rachis, DW_Petiol, DW_Leaflets, DW_Frond) were excluded to avoid target

Table 3
Diagnostic tests of linear regression models. Residuals versus fitted-value plots are presented in Supplementary Material S3.

Models (Response ~ Predictor)	Shapiro-Wilk W	Shapiro-Wilk p-value	BP statistic	BP p-value
Fronds models				
DW_Rachis ~ L_Rachis	0.93	6.59×10^{-10} (Non-Normal)	26.88	2.17×10^{-7} (Heteroscedastic)
DWrachAhol1 ~ DW_Rachis	0.82	$< 2.2 \times 10^{-16}$ (Non-Normal)	3.34	0.07 (Homoscedastic)
DW_Petiol ~ L_Petiol	0.96	1.56×10^{-7} (Non-Normal)	91.89	$< 2.2 \times 10^{-16}$ (Heteroscedastic)
DW_Frond ~ L_Petiol	0.96	2.7×10^{-6} (Non-Normal)	66.54	3.43×10^{-16} (Heteroscedastic)
DWFrondAhol2 ~ DW_Frond	0.80	$< 2.2 \times 10^{-16}$ (Non-Normal)	6.59	0.01 (Heteroscedastic)
DWFrondhens ~ DW_Frond	0.98	6.55×10^{-4} (Non-Normal)	5.84	0.02 (Heteroscedastic)
Trees models				
Models (Response ~ Predictor)	Shapiro-Wilk W	Shapiro-Wilk p-value	BP statistic	BP p-value
DW_Palm ~ L_Total_10	0.95	0.58 (Normal)	1.44	0.23 (Homoscedastic)
DW_Palm ~ IV_Ineac	0.91	0.14 (Normal)	2.54	0.11 (Homoscedastic)
DW_Palm ~ Num_Leaflets_10	0.93	0.31 (Normal)	4.10	0.04 (Homoscedastic)
DW_Palm ~ H_max	0.89	0.08 (Normal)	0.76	0.38 (Homoscedastic)

Shapiro-Wilk W: Shapiro–Wilk statistic value; BP p-value: Breusch–Pagan test statistic value; BP p-value: Breusch–Pagan test p-value; SW p-value: Shapiro–Wilk test p-value; BP p-value: Breusch–Pagan test p-value.

leakage. For DW_Palm, three RF configurations were evaluated: (i) a full model including all morphometric variables (RFT_Direct), (ii) a model including only composite variables (RFT_Comp), and (iii) a mixed model (RFT_Mix) combining the most important foliar and whole-tree variables from RFT_Direct with the top-ranked composite predictors from RFT_Comp (Table 2), as identified by the varImpPlot () function in R software. All RF models were fitted using 500 trees (ntree = 500), with hyperparameters tuned via repeated cross-validation by minimizing the root mean square error (RMSE). A fixed random seed ensured reproducibility.

Based on RF outputs, the most influential predictors were retained for subsequent inferential analyses using simple linear regression models. These models were fitted to assess linear relationships between selected structural traits and biomass components. All regressions were restricted to the observed range of predictor values to ensure biological plausibility and to define the domain of applicability. The assumptions of normality and homoscedasticity were evaluated prior to model interpretation using residual diagnostics. When these assumptions were violated, model performance was assessed using predictive metrics (R^2 and $RMSE_{LOOCV}$), whereas statistical inference based on regression coefficients, confidence intervals, and significance tests was treated with caution.

All statistical tests were considered significant at $\alpha = 0.05$. Model performance was evaluated using RMSE and R^2, while unbiased predictive error was estimated using leave-one-out cross-validation ($RMSE\__{LOOCV}$). In this procedure, each observation is sequentially excluded, the model is trained on the remaining data, and the omitted value is predicted. This approach provides a robust estimate of model generalisation, particularly in datasets with limited field observations (Allen, 1971; Brovelli et al., 2008).

3. Results

3.1. Difference in frond-related variables as a function of frond rank

Fig. 2 shows the synchronic variation in average frond dry weight according to rank. Three groups of fronds can be distinguished:

The youngest fronds (up to rank 7), for which dry weight significantly increases with frond rank (df=20; Kruskal–Wallis chi-squared = 121.56, p-value < 0.001),
Fronds from ranks 8 to 15, for which dry weight, although increasing up to rank 10 and decreasing thereafter, form a plateau whereby they do not appear significantly different from each other,
Fronds above rank 15, for which dry weight decreases with rank and reaches a value similar to that of the dry weight at rank 2 for the oldest fronds.

The total dry weight of the frond follows the same trend as the petiole dry weight. Unlike the petiole, the rachis and leaflet biomass increase until rank 3, then slightly decrease with increasing rank. The petiole length increases tremendously until rank 4, slightly decreases, and then markedly decreases after rank 13 (Fig. 3a). The rachis length (Fig. 3a), thickness, width at point C, (Fig. 3b), and linear density (Fig. 3c) and number of leaflets (Fig. 3d) also increase until rank 3, but then slightly decrease, as do the rachis and leaflet biomass (Fig. 2).

3.2. Morphometric variables and total aboveground biomass distribution according to the age of the oil palm

As shown in Fig. 4, the petiole compartment contributed the most to the oil palm aboveground biomass. The petiole biomass accounted for 40% to 50%, while the biomass of the rachis accounted for 15% to 35% of the oil palm aboveground biomass. The biomass of the leaflets constituted between 18% and 35% of the total oil palm aboveground biomass. The basal cabbage provided <15% of the total. Total aboveground biomass was, on average, 6.72 kg (Standard Error=0.78) for two-year-old palms and 9.77 kg (Standard Error=1.64) for three-year-old palms. The increase with respect to age and management history although close to 3 kg was not found to be significant (df=7.26; t-value= −1.67; p-value>0.05, Fig. 5). The three-year-old oil palms (2.88 m) were not significantly taller than the two-year-old ones (2.32 m) (df=6.76; t-value = −2.09; p-value > 0.05, Fig. 5). The crown diameter of three-year-old palms (2.50 m) was not significantly larger than that of two-year-old palms (2.67 m) (df=9.24; t-value = 0.68; p-value > 0.05, Fig. 5). The girth circumference (Girth) did not differ significantly by the age of the oil palm (df=10.62; t-value = −1.76; p-value > 0.05, Fig. 5). As a result, the INEAC's vigour index (VI_Ineac) did not differ significantly by the age of the oil palm (df =7.35; t-value = −1.72; p-value > 0.05, Fig. 5). (Fig. 4), (Fig. 5)

3.3. Frond morphometric bivariate relationships and biomass predictors

All the 278 fronds were considered in this analysis. The length of the rachis was highly correlated with the number of leaflets and petiole thickness at point C. The number of leaflets was also highly correlated with the dry weight of a rachis fragment and petiole thickness at point C. Petiole thickness was highly correlated with width at point C (rho > 0.70; Fig. 6). Frond biomass was highly correlated with both petiole length and total frond length (rho > 0.70), although the correlation with petiole length was stronger (rho = 0.86 vs. 0.77). Among all frond components, petiole biomass showed the strongest correlation with frond biomass. Conversely, rachis length was most strongly correlated

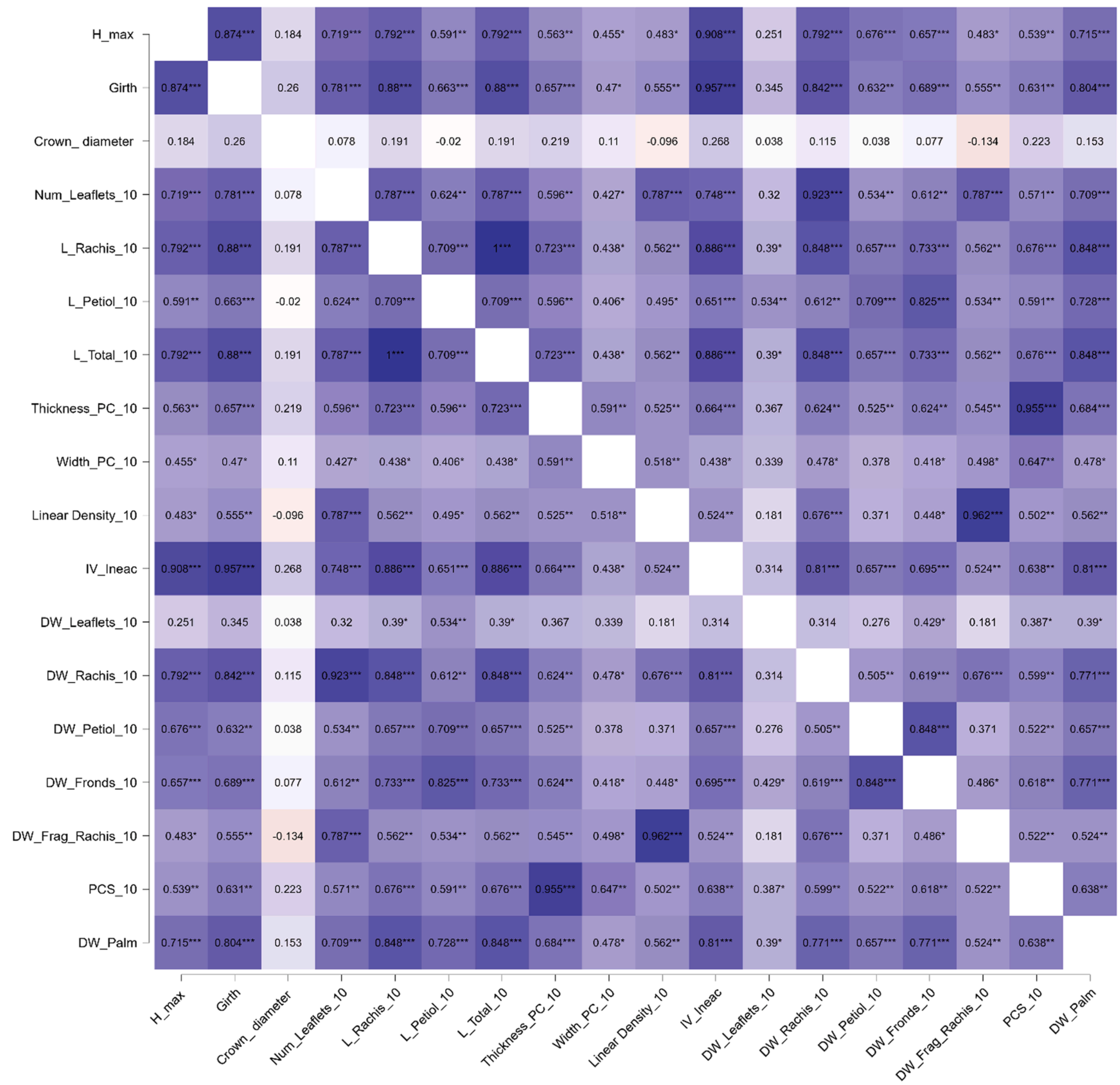

Fig. 10. Kendall's *Tau* correlation heatmap of tree variables.

with frond length (Fig. 6). Rachis biomass was highly correlated with rachis length, petiole length, and the number of leaflets. Petiole biomass was also correlated with petiole length (Fig. 6). All correlations were significant (p-value < 0.001; Fig. 6). Rachis linear density was correlated with petiole thickness, number of leaflets, and total frond length (rho > 0.70; Fig. 6).

Unlike the petiole, rachis length was a good predictor of rachis dry biomass using a linear regression model ($R^2 = 0.79$; $RMSE_{LOOCV} = 0.015$ kg; Fig. 7a,b). However, Aholoukpè's Eq. (1) showed slightly better predictive performance than the rachis length-based model ($R^2 = 0.84$ vs. 0.79; Fig. 7b,c). In contrast, both Aholoukpè's and Henson's equations performed poorly in predicting frond biomass ($R^2 < 0.50$; Fig. 8a, b). The random forest model exhibited strong predictive performance, explaining 81% of the variance in frond biomass ($R^2 = 0.81$; Fig. 9a). Its prediction error was relatively low ($RMSE_{LOOCV} = 0.056$ kg; Table 2). Likewise, petiole length was a strong predictor of frond dry biomass in the linear regression model ($R^2 = 0.84$; $RMSE_{LOOCV} = 0.08$ kg; Fig. 9b). Nevertheless, although these models showed good predictive performance, residual diagnostics revealed significant violations of the assumptions of normality and homoscedasticity (Shapiro–Wilk test, $p < 0.05$; Breusch–Pagan test, $p < 0.05$; Table 3 and Supplementary material 3). (Fig. 6; Fig. 7; Fig. 8; Fig. 9; Table 3)

3.4. Oil palm morphometric variables relationships and biomass predictors

The total and rachis length, and the number of leaflets of frond 10 were highly correlated with the tree's girth and height as well as the INEAC's Vigour Index (*tau* > 0.70, Fig. 8). The rachis biomass of frond 10 were also correlated with tree girth and heigh (*tau* > 0.70, Fig. 10). Girth was highly correlated with height, but no correlation was found between crown diameter and the other tree morphometric variables (*tau* > 0.70, Fig. 10).

The RF model with the mix of direct and composite variables (RFT_Mix) showed the best performance in predicting the tree dry biomass (R^2=0.93 and $RMSE_{LOOCV}$=1.11 kg; Fig. 11a and Table 2). The performances of the RFT_Mix model were slightly better than that of the RFT_Direct, the model with only the directly measured variables (R^2=0.92 and $RMSE_{LOOCV}$ =1.22 kg; Fig. 11b and Table 2) and the performance of the RFT_Comp model with the composite variables, as well (R^2=0.91 and $RMSE_{LOOCV}$ =1.43 kg; Fig. 11c and Table 2).

The assumptions of normality and homoscedasticity were met for all the tree linear regression models (LMT), indicating constant variance and normally distributed residuals (Shapiro–Wilk p-value > 0.05; Breusch–Pagan p-value > 0.05; Table 3 and Supplementary material 3). The total length of the frond 10 (L_Total_10) showed the best

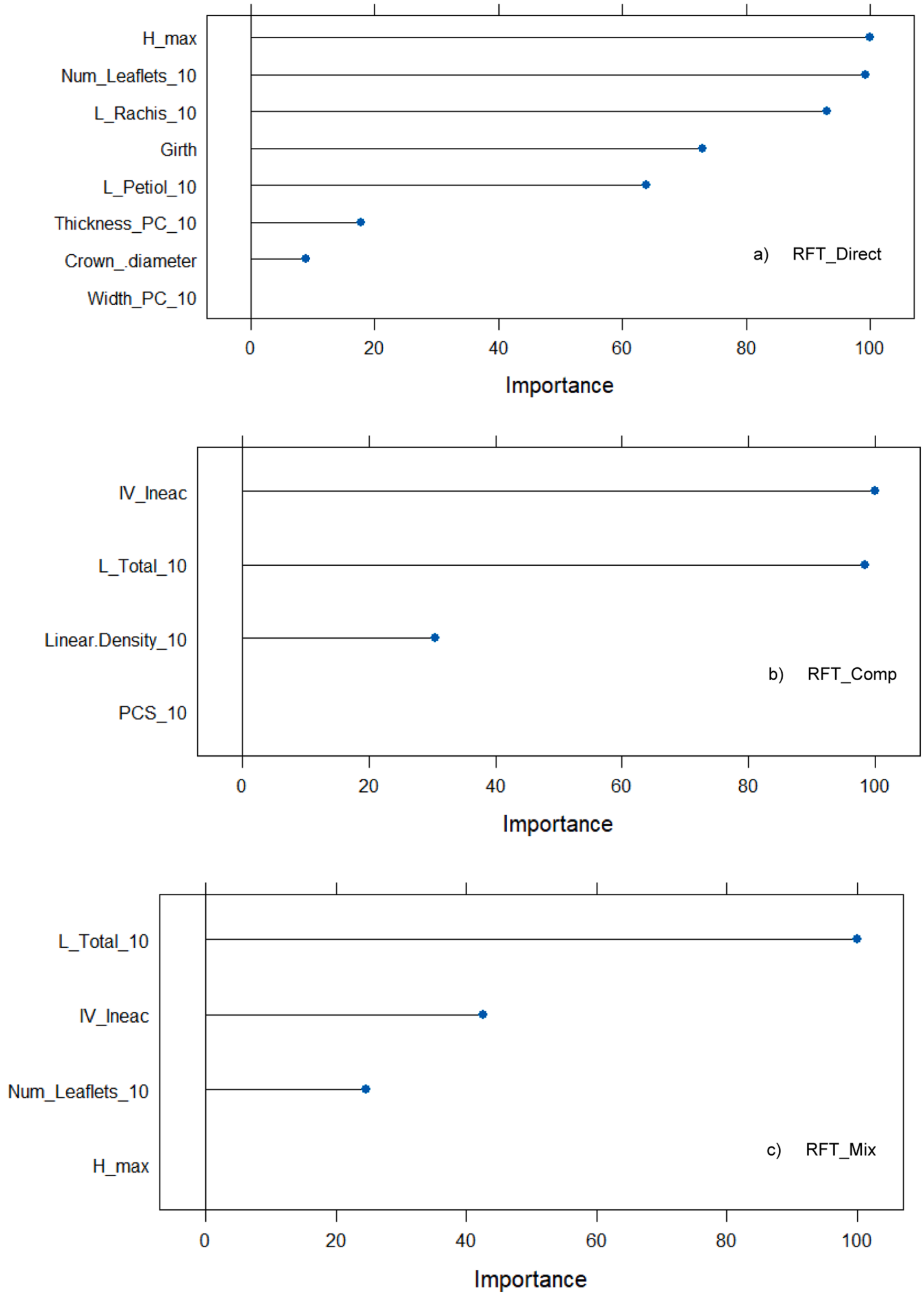

Fig. 11. Random forest models for the selection of the tree biomass predictors (n = 15). (a) Random forest model for the selection of the best tree biomass predictors using direclty measured variables as independants variables (RFT_Direct). (b) Random forest model for the selection of the best tree biomass predictors using composited variables as independants variables (RFT_Comp) ; (c) Random forest model for the selection of the best tree biomass predictors using best independants variables from the RFT_Direct and RFT_Comp (RFT_Mix).

performances in predicting the tree aboveground biomass in the random forest model (RFT_Mix; Fig. 11). When L_Total_10 was retained as the sole predictor of the tree aboveground biomass in a simple linear regression, the resulting equation was: DW_Palm = 8.616 L_Total_10 - 11.86 (LMT1, R^2=0.94, Fig. 12).

The INEAC's vigour index showed better performance than the height and the number of leaflets of the frond 10 in the RFT_Mix model (Fig. 12c and d). However, in linear regression, the height performed better than the INEAC's vigour index (Fig. 12a and c). The $RMSE_{LOOCV}$ in the regression valued 0.94 kg for the L_Total_10. This value represents <1 kg deviation from the measured aboveground dry biomass. (Fig. 10; Fig. 11,;Fig. 12)

4. Discussion

4.1. Differences in immature oil palm frond biomass according to the rank

Unlike adult palms that reach their highest frond biomass level at rank 10 and almost stabilise around a constant value (Aholoukpè et al., 2013), we found that immature oil palm frond biomass increases up to rank 10 and then gradually decreases. The developmental conditions of the fronds in the early stage could explain this pattern. The fronds

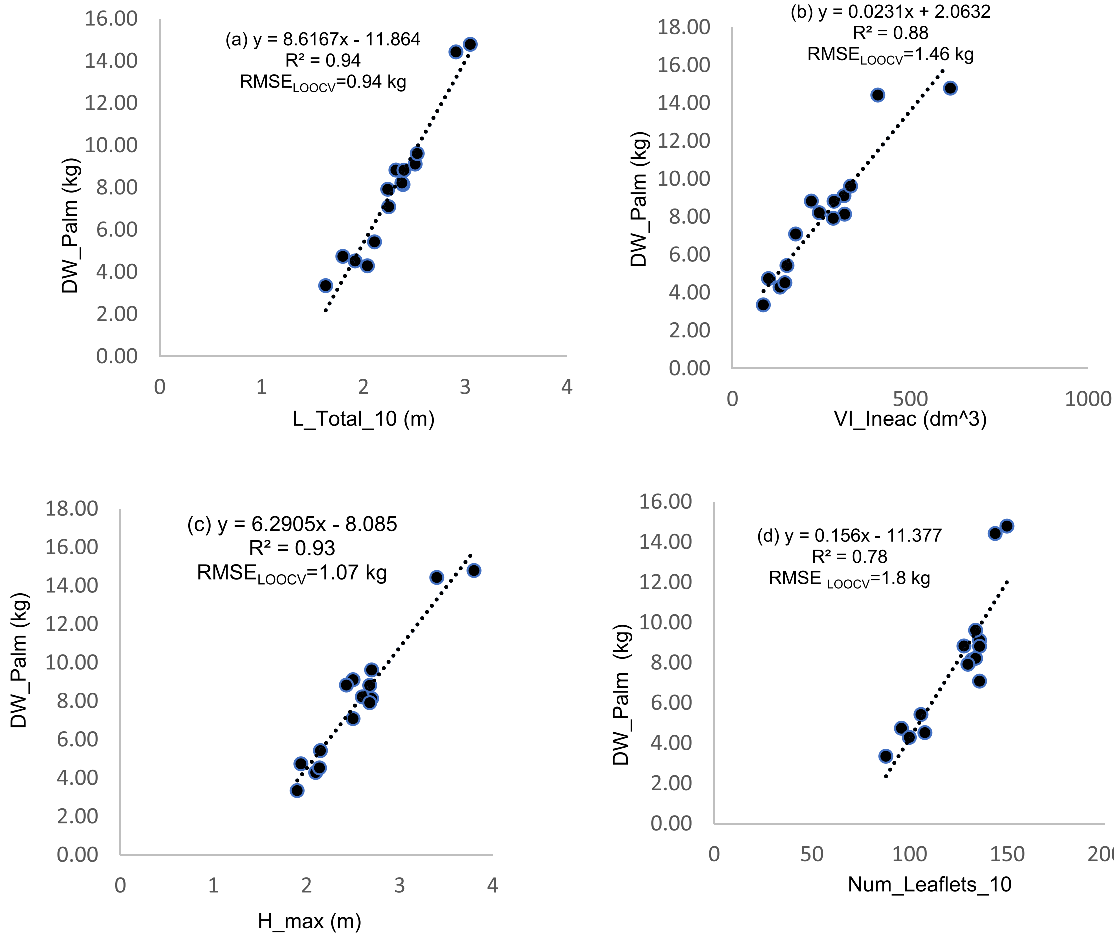

Fig. 12. Linear regression models for the selection of the tree biomass predictors. (a) oil palm dry biomass as a function of the frond 10′s petiole length. (b) oil palm dry biomass as a function of the INEAC's Vigour Index ; (c) oil palm biomass as a function of the tree's total height ; d) oil palm biomass as a function of the frond 10′s number of leaflets.

beyond rank 10 were produced several months before the rank-1 frond. In that early stage, the palm tree was younger and possessed a much smaller leaf area, implying more limited assimilate production capacity. Consequently, the resources available to sustain frond growth were reduced, leading to smaller final frond size at the end of their development. Furthermore, the carbon assimilate allocation processes could concomitantly be hypothesized as the stipe is non-existent for immature palms. The fronds of immature palms likely play a central role in temporary carbon storage and allocation dynamics. However, these mechanisms remain inferred from growth patterns rather than directly measured in this study. These reserves may then be mobilised by the plant to buffer variations in assimilation rates during periods of insufficient supply.

Overall, these results suggest that frond biomass variation with rank is primarily driven by developmental stage rather than fixed structural constraints. The implication of this finding is that the biomass of fronds at the immature stage, with ranks below and beyond 10, could be assessed by linear interpolation. This would be done between the biomass of fronds considered to have negligible mass (rank 0) and mature fronds at rank 10, similarly to the approach recommended for young fronds in adult palm trees in Benin (Aholoukpè et al., 2013).

4.2. Importance of the morphometric variables in predicting the immature oil palm frond and tree biomass

Frond 10 morphometric traits (leaflet number, rachis length, and total frond length) were strongly correlated with tree-level variables such as height and girth, indicating close coupling between frond development and overall plant architecture at the immature stage. This suggests that early growth in oil palm is largely driven by elongation processes, particularly in the petiole and rachis. Similar patterns have been reported during juvenile stages of oil palm development (De Berchoux et al., 1986), where frond length increases with age until approximately 10–13 years. In this study, simple morphometric variables provided reliable estimates of frond and tree biomass. In contrast to findings in adult palms, where combining multiple structural components improves prediction accuracy (Aholoukpè et al., 2013), petiole length alone was sufficient to explain a large proportion of biomass variation at the immature stage. These results indicated that the morphometric variables that are directly measurable are sufficient to predict the biomass of immature oil palm.

4.3. Petiole as the largest contributor to the biomass of the immature oil palm

The petiole contributed substantially to the overall biomass of the immature palms in southern Benin. As highlighted by Henson et al. (2012), frond bases which were not separated from the petiole could have made the greatest contribution. Lewis et al. (2020) reported similar findings in Malaysian peatlands. The frond width was strongly correlated with its thickness at point C as shown by Ruer and Varéchon (1964). Like in the case of adult oil palms, Aholoukpè's variable, based on linear density and rachis length, has good performance in predicting the rachis biomass. Nevertheless, both Aholoukpè's and

Henson's equations poorly predicted the frond biomass. The petiole length predicted frond biomass better than the rachis-based variables used as independent variables in equations of Henson and Dolmat (2003); Lewis et al.(2020) and Aholoukpè et al.(2013) for <6 years old and adult oil palm in Malaysia and Benin. These differences may be partly explained by variations in ecological conditions and planting material, which are not fully detailed in the studies of Henson and Lewis et al., potentially influencing allometric relationships. In our study, which focused on immature oil palms, the rachis has not yet fully accumulated biomass, which may explain its weaker predictive performance. In contrast, the discrepancies observed with Aholoukpè et al. (2013) may also relate to differences in developmental stage and biomass allocation patterns during early palm growth.

Using remote sensing in Malaysia, Korom et al.(2016) found that oil palm aboveground biomass can be consistently estimated using the crown diameter measurement at all ages. Unlike Korom et al.(2016), a poor relationship was found between the oil palm aboveground biomass and the crown diameter values in this study. Crown diameter was not significantly correlated with tree morphometric variables such as girth and height. In contrast, the VI_Ineac index showed strong positive associations with girth and height, while remaining only weakly associated with crown diameter. This pattern may be partly explained by the mathematical structure of the index, in which height and girth contribute more strongly due to their relative scale and variability compared to crown diameter. As a result, crown diameter may have a reduced influence on the overall index variation, particularly when its variance is lower or less coupled with other structural traits. In particular, intercropping systems have been shown to affect vegetative growth parameters in oil palm (Koussihouèdé et al., 2020), which may partly explain the observed independence of crown diameter from other structural variables in this study. As Henry et al. (2011) highlighted, the relevance of an allometric equation to a given study depends on various factors, such as cropping practices and ecological differences in the study regions.

4.4. The vigour index predicts aboveground biomass, but frond 10 morphometric traits perform better

The total length of frond 10 emerged as the strongest single predictor of aboveground biomass, highlighting the relevance of frond-level morphometric traits as practical indicators of structural development in immature oil palms. Under linear modeling, tree height generally performed stronger than the composite VI_Ineac index, suggesting that simple morphometric measurements can provide robust first-order approximations of biomass variation under linear assumptions. The relatively lower performance of VI_Ineac in linear models may be related to its composite mathematical structure, which integrates multiple variables with different scales and variance structures. In particular, the contribution of crown diameter appears less strongly reflected in biomass variation, which is consistent with its weak correlation with individual tree morphometric variables in this dataset. However, this interpretation remains statistical rather than mechanistic, as the index aggregates traits in a non-independent manner. In contrast, the Random Forest (RF) model showed improved performance of the VI_Ineac index relative to height alone. This suggests that the relationship between palm structural traits and biomass is likely non-linear and involves interactions among variables that are not captured by linear regression models. Machine learning approaches may therefore better accommodate the multivariate and non-additive nature of biomass accumulation in immature oil palms. These results are consistent with previous studies showing that combining multiple structural traits can improve biomass prediction in tropical trees (Picard et al., 2015; Djomo and Chimi, 2017; Kenzo et al., 2009). However, the benefit of composite indices appears to be method-dependent in the present study, being more evident under non-linear modeling frameworks. Importantly, predictive performance should be interpreted in light of the study design. The dataset originates from a single immature plantation system, and model validation was performed using internal cross-validation rather than independent external datasets. As a result, the reported performance metrics likely reflect within-site predictive ability rather than broader spatial generalisability. Overall, these findings suggest that while simple morphometric variables such as frond length and height provide reliable and interpretable biomass estimates under linear assumptions, composite indices such as VI_Ineac may better capture structural complexity when non-linear relationships are accounted for. Nevertheless, external validation across contrasting ecological and management conditions is required before generalizing these models beyond immature oil palm systems in southern Benin.

4.5. Limitations and ways forward

Although several frond biomass regression models exhibited violations of the assumptions of normality and homoscedasticity, their predictive performance remained satisfactory, as indicated by the R^2 and $RMSE_{LOOCV}$ values. These metrics primarily assess model fit and predictive accuracy and are therefore less sensitive to departures from these assumptions than inferential statistics (Kutner et al., 2005; Montgomery et al., 2021). Furthermore, the relatively large frond sample size (n = 278 fronds) provides additional support for the robustness of the predictive performance estimates. Nevertheless, the observed heteroscedasticity and non-normality may affect the reliability of parameter estimates, confidence intervals, and significance tests (Chatterjee and Simonoff, 2013; James et al., 2023). Consequently, the relationships identified by the regression models should be interpreted primarily from a predictive perspective, whereas inferences regarding the magnitude and statistical significance of regression coefficients should be treated with caution. Additional limitations arise from the study design. The proposed equations were developed from a limited number of immature palms sampled within a single site, which may constrain their broader applicability (Williams et al., 2013). Environmental variability, plantation management practices, and genetic differences among oil palm cultivars were not explicitly accounted for and may influence biomass allocation and accumulation patterns. As highlighted by Henry et al. (2011), the applicability of allometric equations is strongly influenced by ecological conditions and management contexts. Future research should therefore validate the proposed relationships using independent datasets collected under similar smallholder conditions. Larger and more diverse datasets, including stratified sampling across agroecological zones, management systems, and oil palm genotypes, would improve the robustness and generalizability of biomass prediction models. Additional studies are also needed to quantify biomass accumulation across different developmental stages of oil palm, fertilizer regimes, and intercropping systems in order to better understand how cropping practices influence immature palm growth. Methodologically, mixed-effects models accounting for plantation-level clustering could further improve model transferability and provide more realistic estimates of uncertainty across diverse management contexts. Finally, future work should consider the operational constraints of field measurements in smallholder systems to ensure that biomass estimation approaches remain practical and scalable.

5. Conclusions

This study demonstrates the potential of simple morphometric measurements for the non-destructive estimation of biomass in immature oil palms under smallholder conditions in Benin. Beyond identifying useful predictors of frond and aboveground biomass, the results highlight the value of combining traditional allometric approaches with machine-learning methods to capture the complex relationships underlying biomass accumulation in young palms. These findings contribute to improving biomass assessment in immature oil palms, a critical but often overlooked stage due to the practical difficulties associated with destructive sampling. The proposed models showed encouraging predictive performance and provide a useful basis for future studies of growth dynamics, resource-use efficiency, and carbon accumulation. However, their robustness should be interpreted in light of several limitations. The study was based on a relatively small number of sampled palms from a single site, which restricts the representativeness of the dataset and limits the generalizability of the resulting equations. In addition, some regression models exhibited departures from the assumptions of normality and homoscedasticity, indicating that uncertainty remains regarding parameter estimates and statistical inference, even when predictive performance metrics were satisfactory. The practical implementation of these models in smallholder systems also warrants consideration. Although the selected morphometric variables are relatively simple to measure, field conditions, plantation heterogeneity, and labor requirements may influence the operational feasibility and consistency of biomass assessments. Consequently, the proposed equations should be regarded as site-specific and preliminary rather than broadly applicable tools. Future research should focus on validating and refining these relationships using larger and more diverse datasets encompassing multiple sites, agroecological conditions, management practices, and oil palm genotypes. Such efforts will be necessary to quantify model uncertainty more accurately, improve transferability, and determine the extent to which these allometric relationships can be applied beyond the conditions represented in the present study.

CRediT authorship contribution statement

Hermione Koussihouèdé: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Hervé Aholoukpè:** Supervision, Resources, Project administration, Methodology, Funding acquisition. **Albert Flori:** Writing – review & editing, Validation, Methodology, Data curation. **Jeremie Adjibodou:** Investigation. **Haniel Hinkati:** Investigation. **Romuald Ayizannon:** Writing – review & editing. **Guillaume Amadji:** Supervision, Project administration. **Cathy Clermont-Dauphin:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

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.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.tfp.2026.101351.

Data availability

The data used in this study are available from the CIRAD Dataverse in https://doi.org/10.18167/DVN1/RYCBER.

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