



Research article

Enhancing jatropha genotype selection for wood chemical composition and calorific value using near-infrared spectroscopy

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Abstract

Importance of the work: Near-infrared (NIR) spectroscopy has great potential as a high-throughput characterizing tool, especially for improving wood qualities in jatropha breeding work.

Objectives: To characterize jatropha wood qualities across various genotypes and to investigate the relationship between chemical composition and calorific value based on evaluating the chemical composition and calorific value of jatropha wood using NIR spectroscopy.

Materials and Methods: Analysis was conducted on 365 wood samples from various jatropha genotypes. Neutral detergent fiber (NDF), acid detergent fiber (ADF), lignin, cellulose, hemicellulose and calorific value were all predicted using partial least squares (PLS) regression models.

Results: The correlation coefficient (r) values of these models ranged from 0.65** to 0.81**, where ** indicates significance at $p < 0.01$, with low standard error of calibration and of prediction. In addition, there were significant effects of harvest age and re-harvesting, along with notable genotypic variations in all quality parameters that the PLS models anticipated, with significant correlations between calorific value and NDF ($r = 0.65^{**}$), ADF ($r = 0.42^{**}$) and lignin ($r = 0.91^{**}$).

Main finding: The NIR spectroscopy models developed had modest predictive performance for calorific value and wood chemical components of jatropha, indicating that NIR has potential as a rapid and non-destructive tool for preliminary screening and comparative evaluation of genotypes based on wood quality.

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Introduction

The physic nut, *Jatropha curcas* L., has attracted considerable interest as a promising energy crop because its seed oil is suitable for biodiesel production (Muakrong and Srinives, 2020). In addition, jatropha has potential as a fast-growing tree for biomass generation due to its rapid growth, tolerance to heavy pruning and consistent annual fruit yield (Arunyanark et al., 2022; 2024). The main biomass component of jatropha is wood (Arunyanark et al., 2023a; 2023b). However, the relatively low density and high moisture content of jatropha wood can reduce its calorific value during combustion (Muakrong et al., 2014). Accordingly, improvement of jatropha for biomass energy should consider not only biomass yield, but also wood quality traits that determine fuel value, particularly chemical composition and calorific value.

The genetic variation of *J. curcas* is relatively narrow, limiting the phenotypic diversity available for cultivar improvement. Therefore, interspecific hybridization is relevant not only for increasing biomass productivity but also for improving wood quality traits associated with biomass utilization efficiency. Broadening the genetic base through interspecific hybridization is a promising strategy in jatropha breeding (Muakrong and Srinives, 2020). In several fast-growing tree species, interspecific hybridization has been used successfully to improve biomass yield, including willow (Gramlich et al., 2018), poplar (Barghini et al., 2015), eucalypts (Sumathi and Ramasamy, 2017) and leucaena (Brewbaker, 2013). Similarly, hybridization between jatropha and related species, especially *Jatropha integerrima* Jacq. (Phithakhongsa et al., 2023), may increase genetic diversity, introduce useful traits and improve the probability of obtaining superior cultivars. In addition, hybrid vigor may contribute to enhanced yield potential in jatropha hybrids (Arunyanark et al., 2022; 2023a). Therefore, interspecific hybrids between *J. curcas* and *J. integerrima* may provide a useful breeding population for improving both biomass quantity and wood quality.

Wood is an important resource for bioenergy production; however, its quality varies with the types and proportions of organic and inorganic compounds present (Nasser and Aref, 2014). Wood properties are influenced by genotype, environment and their interaction, resulting in variation in chemical composition and physical characteristics that affect energy value (Li et al., 2017; Dadile et al., 2020). Furthermore, plant age influences wood tissue properties and may alter both biomass yield and feedstock quality (Silva et al., 2019).

Therefore, evaluation of jatropha hybrids for biomass use requires assessment of key wood composition traits. The present study used neutral detergent fiber (NDF) and acid detergent fiber (ADF) as integrative indicators of cell wall structure. In contrast, lignin, cellulose and hemicellulose represent the major structural components of lignocellulosic biomass (Pasangulapati et al., 2012). Generally, NDF reflects the total cell wall fraction, whereas ADF represents mainly cellulose and lignin (Jung and Lamb, 2004). Cellulose and hemicellulose are the principal polysaccharide fractions of biomass, while lignin is a more aromatic polymer that is closely associated with energy density and combustion behavior (Pasangulapati et al., 2012; Wang et al., 2020). Together, these traits provide a practical basis for evaluating biomass quality in jatropha wood.

Selection for biomass yield in jatropha hybrids requires a comprehensive breeding approach, particularly when wood-quality traits, such as chemical composition and calorific value, are also considered. Conventional methods for measuring these traits are laborious, time-consuming and costly, making direct selection difficult (Arunyanark et al., 2023a; 2023b). In addition, plant breeders must evaluate many traits simultaneously within limited timeframes. Consequently, rapid and effective phenotyping remains a major challenge in breeding programs for quantitative traits, including chemical composition (Fonseca et al., 2020; Danzi et al., 2022). Therefore, efficient phenotyping is essential for identifying desirable genotypes in complex breeding populations (Theerawitaya et al., 2022). This limitation affects breeding decisions directly because large hybrid populations cannot be screened efficiently for wood chemical composition and calorific value using conventional analytical methods alone. As a result, early-stage selection, parent choice and simultaneous ranking for biomass yield and fuel quality become inefficient.

Near-infrared (NIR) spectroscopy is a rapid, simple and cost-effective method for evaluating chemical constituents with minimal sample preparation (Jiang, 2020). It provides rapid responses, automated measurement, ease of operation and simultaneous analysis of multiple traits (Alamu et al., 2021). Therefore, NIR spectroscopy is well suited to the demands of plant breeding for rapid phenotypic assessment and biomass composition analysis (Zhang et al., 2017). Tsuchikawa and Kobori (2015) showed that NIR could be used effectively to assess the chemical, physical, mechanical and morphological characteristics of wood materials, especially when the cellular structure was retained; in addition, it could evaluate wood quality more rapidly than conventional techniques (Loureiro

et al., 2022). More importantly, NIR provides a practical tool for high-throughput phenotyping, enabling large numbers of genotypes to be screened rapidly for compositional traits in breeding populations (Gebreselassie et al., 2017; Zhang et al., 2017). Nevertheless, to date, no published studies have applied NIR spectroscopy to determine the chemical composition and calorific value of jatropha wood for the selection of superior hybrid genotypes based on wood quality. Therefore, the present study aimed to determine the chemical composition and calorific value of jatropha wood using NIR spectroscopy, to identify quality differences among genotypes and to examine the relationship between chemical composition and calorific value. Specifically, the study focused on NDF, ADF, lignin, cellulose, hemicellulose and calorific value as key indicators for rapid wood-quality screening and breeding-oriented genotype evaluation in jatropha.

Materials and Methods

Plant materials

In total, 365 wood samples were collected from diverse *Jatropha* genotypes, consisting of established *J. curcas* varieties, *J. integerrima* and hybrids developed through a dedicated breeding program. The hybrid materials comprised both interspecific and intraspecific crosses of jatropha. The interspecific crosses consisted of 150 F₁ samples, 50 F₂ samples, 50 polycross samples and 50 backcross samples, whereas the intraspecific crosses contributed 65 samples. These samples were selected from multiple genotypes and harvest conditions to maximize variation in wood characteristics within the dataset. Samples were obtained from experimental plots at Kasetsart University, Kamphaeng Saen Campus, Nakhon Pathom, Thailand (7.25 m above mean sea level; 14°01'21.97" N, 99°58'42.04" E). Most genotypes were established from seed, with one plant representing one genotype. In general, one sample represented chipped wood from a single plant. For biomass harvesting, the stem of each jatropha plant was cut at 30 cm above ground level, with only the trunk and branches retained after leaf removal. After mechanical chipping, the wood chips were thoroughly mixed to obtain a homogeneous composite sample, from which a 0.5 kg subsample was randomly collected. The subsample was oven-dried at 80°C for 72 h and then ground into a fine powder for chemical analysis, calorific value determination and NIR spectral measurement.

Reference methods

The finely ground wood samples were analyzed for calorific value and chemical composition. NDF, ADF and ADL were determined using fiber bag technology with an ANKOM 200 Fiber Analyzer (ANKOM Technology; Macedon, NY, USA) according to Van Soest et al. (1991). Samples were digested in neutral detergent solution for NDF and in acid detergent solution for ADF under boiling conditions for 60 min. For ADL determination, the ADF residue was treated further with 72% sulfuric acid. Hemicellulose was calculated as NDF minus ADF, cellulose as ADF minus ADL and lignin was expressed as the ADL fraction. Calorific value was determined using a PARR 1261 Bomb Calorimeter (Parr Instrument Company; Moline, IL, USA), according to the standard method (International Organization for Standardization, 1998).

Near infrared measurement and calibration development

Before spectral collection, homogenized ground samples, previously oven-dried at 80°C for 72 h, were allowed to cool to room temperature in a desiccator. For each sample, 4 g was placed in a 30 mL glass beaker, which was positioned on the window of a Buchi NIRFlex FT-NIR spectrometer (model N-500; Buchi Labortechnik AG; Flawil, Switzerland). Diffuse reflectance spectra were collected from 32 randomly selected positions on each sample surface and the spectra were averaged to obtain a representative spectrum for each sample. This procedure was used to reduce the influence of sample heterogeneity in ground wood material under the instrument's diffuse reflectance mode. Each sample was measured three times over the wavelength range of 1000–2500 nm at a spectral resolution of 1 nm. The integration time was set at 23 s for each measurement, representing the spectral acquisition time automatically optimized under the operating conditions of the instrument. All measurements were performed after the samples had equilibrated to room temperature in an air-conditioned laboratory maintained at 25 ± 2°C.

Subsequently, a calibration model was developed using the full spectrum (1000–2500 nm). Raw spectral data were preprocessed by applying log₁₀ absorbance transformation, Savitzky–Golay smoothing, standard normal variate (SNV) correction and second-derivative transformation to resolve overlapping peaks, correct for baseline offset and minimize scattering effects. Calibration models for predicting wood chemical composition and calorific value were constructed by correlating the processed spectra with the corresponding

reference values using NIRCal software (version 5.4, Build 3000; BÜCHI Labortechnik AG; Flawil, Switzerland). Because no NIR method has been published for determining the chemical composition in *Jatropha curcas* wood, calibration development in the present study followed the test-set validation approach recommended in ISO 12099:2017 (International Organization for Standardization, 2017). This standard recommends a minimum of 120 samples for calibration and 20 samples for validation. In the present study, the number of samples used in the calibration set was in the range 220–242, whereas the number of samples used in the validation set was in the range 107–123, depending on the trait. Multivariate calibration was performed using PLS regression. The optimal number of latent variables, or PLS factors, was selected using the automatic optimization procedure of the NIRCal software, following the manufacturer's recommended calibration settings and standard NIR calibration guidelines (Workman and Weyer, 2012; International Organization for Standardization, 2017).

For each trait, the available samples were divided randomly into calibration and validation sets, with approximately two-thirds assigned for calibration and the remaining one-third assigned for independent validation. No internal cross-validation was applied during model development; instead, model performance was evaluated using a single external validation set. The number of samples included in each model varied among traits because only samples with both usable spectra and complete reference data were retained for each calibration. The recommended procedure provided by the BUCHI NIRFlex N-500 manufacturer was followed for the parameter settings used in the calibration development and the final settings were obtained from the instrument's automatic optimization.

Application of developed near infrared models for evaluating wood quality among jatropha genotypes

The developed NIR calibration models were applied to predict wood chemical composition and calorific value and to evaluate genotypic variation among the *jatropha* genotypes under different harvest ages and regrowth conditions. The experiment was arranged as a split-plot in a randomized complete block design with four replications, in which the main plots were assigned to three harvest ages (12 mth after planting, MAP; 18 MAP, 24 MAP) and the subplots to 16 *jatropha* genotypes.

Harvest age was assigned as the main-plot factor because it involved destructive harvesting by severe pruning at different

times. This arrangement facilitated field management and minimized interference between previously harvested regrowth plants and adjacent unharvested plants with longer harvest ages. In addition, it reduced potential border advantages for plants growing near previously harvested plots, where increased space and reduced competition could affect plant growth. Each main plot consisted of 16 genotype subplots. Each subplot comprised three rows of six plants, giving 18 plants per subplot; therefore, each main plot contained 288 plants, excluding guard rows and border plants. A schematic layout of the split-plot arrangement, showing replications, main plots and subplots, has been provided as Supplementary Fig. S1. Based on a planting spacing of 1.0 m × 1.5 m, the net area of each subplot was 27 m² and the net area of each main plot was 432 m², excluding alleys, guard rows and border plants.

Different main plots were allocated to each harvest age. In contrast, only the plants in the 12 mth harvest treatment were harvested again in the second year, at 12 mth intervals, to evaluate regrowth biomass. The genotypes consisted of 13 F₁ interspecific hybrids between *J. curcas* and *J. integerrima* (KUBJL 1, KUBJL 2, KUBJL 3, KUBJL 4, KUBJL 5, KUBJL 6, KUBJL 7, KUBJL 8, KUBJL 10, KUBJL 11, KUBJL 12, KUBJL 13, KUBJL 14), together with the parental lines *J. curcas* (JcM10) and *J. integerrima* (Ji2 and Ji1). Wood biomass was collected after severe pruning at harvest and samples were selected randomly for the NIR spectral analysis. The chemical composition and calorific value of these samples were predicted using the developed PLS calibration models. Conventional reference analyses were used for model calibration and independent validation, as described above, but were not repeated for all samples in the genotype evaluation experiment. Border effects were minimized by excluding border-row plants from sampling and by planting an additional guard row of KUBJL 14 around the experimental area. Detailed planting and harvesting practices are described in Arunyanark et al. (2022; 2023b).

Statistical analysis

The calibration models developed to predict wood chemical composition and calorific value were evaluated based on the validation set. Model performance was assessed using the correlation coefficient (*r*), standard error of calibration (SEC), standard error of prediction (SEP), ratio of prediction to deviation (RPD), slope and bias. These statistics were calculated using Equations 1–6, respectively:

$$r = \frac{\sum_{i=1}^n [(y_i - \bar{y})(\hat{y}_i - \hat{\bar{y}})]}{\{[\sum_{i=1}^n (y_i - \bar{y})^2][\sum_{i=1}^n (\hat{y}_i - \hat{\bar{y}})^2]\}^{1/2}} \quad (1)$$

$$SEC = [\sum_{i=1}^{n^c} (y_i - \hat{y}_i)^2 / (n^c - p - 1)]^{1/2} \quad (2)$$

$$Bias = \sum_{i=1}^{n^v} (\hat{y}_i - y_i) / n^v \quad (3)$$

$$SEP = \{[\sum_{i=1}^{n^v} (\hat{y}_i - y_i) - Bias]^2 / (n^v - 1)\}^{1/2} \quad (4)$$

$$RPD = SD_v / SEP \quad (5)$$

$$Slope = \sum_{i=1}^n [(y_i - \bar{y})(\hat{y}_i - \hat{\bar{y}})] / \sum_{i=1}^n (y_i - \bar{y})^2 \quad (6)$$

where y_i is the reference value, $\hat{y}_i$ is the NIR-predicted value, $\bar{y}$ and $\hat{\bar{y}}$ are the respective means of the reference and NIR-predicted values, n is the number of samples in the relevant calibration or validation set, n^c is the number of calibration samples, n^v is the number of validation samples, p is the number of PLS factors and SD_v is the standard deviation of the reference values in the validation set.

SEC and SEP were retained as reported by the NIR calibration software and represent the calibration and prediction errors of the models. These equations and model evaluation criteria followed standard NIR calibration and validation procedures (Williams and Sobering, 1996; Workman and Weyer, 2012; International Organization for Standardization, 2017).

Predicted values obtained based on NIR spectroscopy were analyzed using the R software (version 4.5.3; R Core Team, 2026), a language and environment for statistical computing and graphics. Analysis of variance (ANOVA) for the experiment on the wood quality of the jatropha genotypes was performed as a split-plot in a randomized complete block design (RCBD), with harvest age as the main plot and genotype as the subplot. In addition, a combined ANOVA was performed for the 12 mth harvest data collected over two consecutive years using RCBD, following the combined analysis procedure for experiments conducted over years (Gomez and Gomez, 1984). Mean comparisons were performed using Duncan's new multiple range test with the agricolae package (version 1.3-7;

de Mendiburu, 2023) at a significance test level of $p < 0.05$ and simple correlation coefficients were calculated between the predicted wood chemical composition traits and calorific value.

Results and Discussion

Chemical composition and calorific value

Reference values for NDF, ADF, lignin, hemicellulose, cellulose and calorific value obtained based on the standard chemical analyses are presented in Table 1. Wide and well-distributed reference values are important for developing reliable calibration models. Accordingly, each parameter was summarized by its minimum and maximum values, mean and SD. NDF was in the range 60.95–84.07% (SD = 3.76%), ADF in the range 47.80–71.05% (SD = 3.58%), lignin in the range 4.94–25.84% (SD = 3.20%), hemicellulose in the range 11.60–20.32% (SD = 1.75%) and cellulose in the range 35.08–55.48% (SD = 2.93%). The calorific value was in the range 3,973–4,830 cal/g (SD = 113.59 cal/g). Furthermore, the calibration and validation sets had comparable ranges and SD values, indicating good consistency of the dataset.

The wide ranges observed in this study were reasonable for jatropha because the dataset included diverse genetic backgrounds, such as parental lines and hybrid populations, along with samples from various harvest conditions. Similarly, other studies have reported considerable variation in biomass and wood-related traits among jatropha genotypes and harvest regimes, especially in hybrid materials and regrowth populations (Muakrong et al., 2014; Arunyanark et al., 2022, 2023a, 2023b). Therefore, the broad variation observed here likely reflected real biological differences in jatropha wood.

A wide range of chemical composition and calorific values is beneficial for calibration development, although extreme values may complicate NIR prediction because outliers can

Table 1 Chemical composition and calorific value in the wood of jatropha genotypes for the full samples based on reference methods.

Component	Full set				Calibration set				Validation set			
	<i>n</i>	Range	Mean	SD	<i>n</i>	Range	Mean	SD	<i>n</i>	Range	Mean	SD
NDF (%)	365	60.95–84.07	74.62	3.76	228	60.95–84.07	74.53	3.85	110	62.56–81.71	74.80	3.56
ADF (%)	365	47.80–71.05	59.57	3.58	231	47.80–71.05	59.55	3.68	111	48.57–68.26	59.61	3.38
Lignin (%)	365	4.94–25.84	13.42	3.20	236	4.94–25.84	13.51	3.29	117	5.57–22.83	13.25	3.02
Hemicellulose (%)	365	11.60–20.32	15.39	1.75	227	11.60–20.32	15.39	1.80	123	11.84–19.41	15.39	1.67
Cellulose (%)	365	35.08–55.48	43.00	2.93	220	35.08–55.48	42.99	2.96	107	35.50–50.90	43.01	2.87
Calorific value (cal/g)	365	3,973–4,830	4,524	113.59	242	3,973–4,830	4,524	116.40	121	4,214–4,768	4,525	108.0

n = number of samples, NDF = neutral detergent fiber, ADF = acid detergent fiber.

distort calibration models (Workman and Weyer, 2012). Therefore, while broad variation improves model robustness, the influence of outliers should be considered to maintain predictive accuracy and generalizability. Overall, the dataset was suitable for calibration development because it captured substantial variation in jatropha wood properties, while maintaining comparable distributions between the calibration and validation set

Near infrared spectral analysis

Fig. 1 shows the NIR spectra of 365 ground jatropha wood samples before and after spectral preprocessing. In the raw spectra (Fig. 1A), the absorption curves were highly overlapped and no clearly separated spectral classes were visible. The spectra were divided into calibration and validation sets and

the validation spectra were encompassed within the spectral range of the calibration set, indicating that both sets originated from the same material matrix and that extrapolation during prediction was avoided. After preprocessing with $\log_{10}(1/R)$ transformation, Savitzky-Golay smoothing, SNV and second derivative, the baseline variation was reduced and peak resolution was enhanced (Fig. 1B). The preprocessed spectra revealed absorption regions associated with major wood constituents, including bands around 1410–1440 nm related mainly to O–H stretching, bands between 1685 and 1790 nm related mainly to C–H stretching in lignin, hemicellulose and cellulose, a strong feature around 1907–1942 nm associated with hemicellulose and water and bands around 2080–2110 and 2267–2332 nm corresponding to combination bands of cellulose, hemicellulose and lignin (Schwanninger et al., 2011; Workman and Weyer, 2012; Rushing et al., 2016; Fonseca

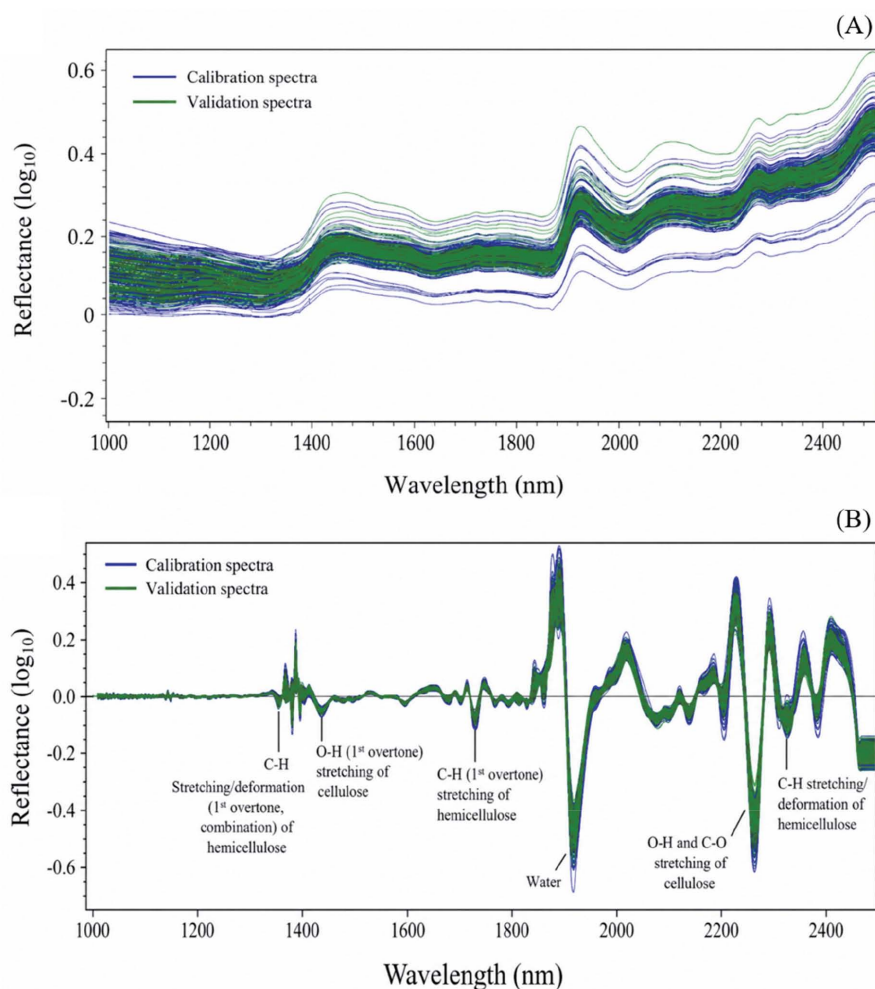


Fig. 1 Comparative near infrared spectra of jatropha wood samples (A) before spectral preprocessing; (B) after spectral preprocessing, where raw spectra transformed to $\log_{10}(1/R)$ and preprocessed using Savitzky-Golay smoothing, standard normal variate and second derivative, with major absorption regions in preprocessed spectra associated with O–H, C–H and C=O vibrations related to water, lignin, cellulose and hemicellulose.

et al., 2020). Based on these results, spectral preprocessing improved the interpretability of the NIR spectra and highlighted absorption bands relevant to the chemical composition of jatropa wood.

The PLS models were developed to predict the chemical composition and calorific value of jatropa wood using various spectral pre-treatments. The optimal pre-treatment for each trait was selected based on model performance. For the calibration set, the correlation coefficients (r) ranged from 0.65 to 0.81, and all correlations were significant at $p < 0.01$, with SEC values in the range 1.37–2.72% for chemical traits and a calorific value of 68.75 cal/g (Table 2). For the validation set, r was in the range 0.45**–0.76**, while SEP was in the range 1.58–2.55% for chemical traits and calorific value was 82.85

cal/g. Bias values were low, in the range -0.09% to 0.37% for chemical traits, with a calorific value of 3.89 cal/g.

As shown in Table 2, the ratio of prediction to deviation (RPD), calculated as the ratio of the standard deviation of the reference data in the validation set to SEP, was in the range 1.06–1.53. The best predictive performance was for lignin, with calibration and validation r values of 0.80** and 0.76**, respectively and the highest RPD (1.53), whereas the weakest performance was for hemicellulose, with a validation r of 0.45** and an RPD of 1.06. Based on these results, there was modest predictive performance overall, with better discrimination for some traits than others. Thus, the models are more suitable for preliminary screening and comparative evaluation of jatropa genotypes than for precise analytical or

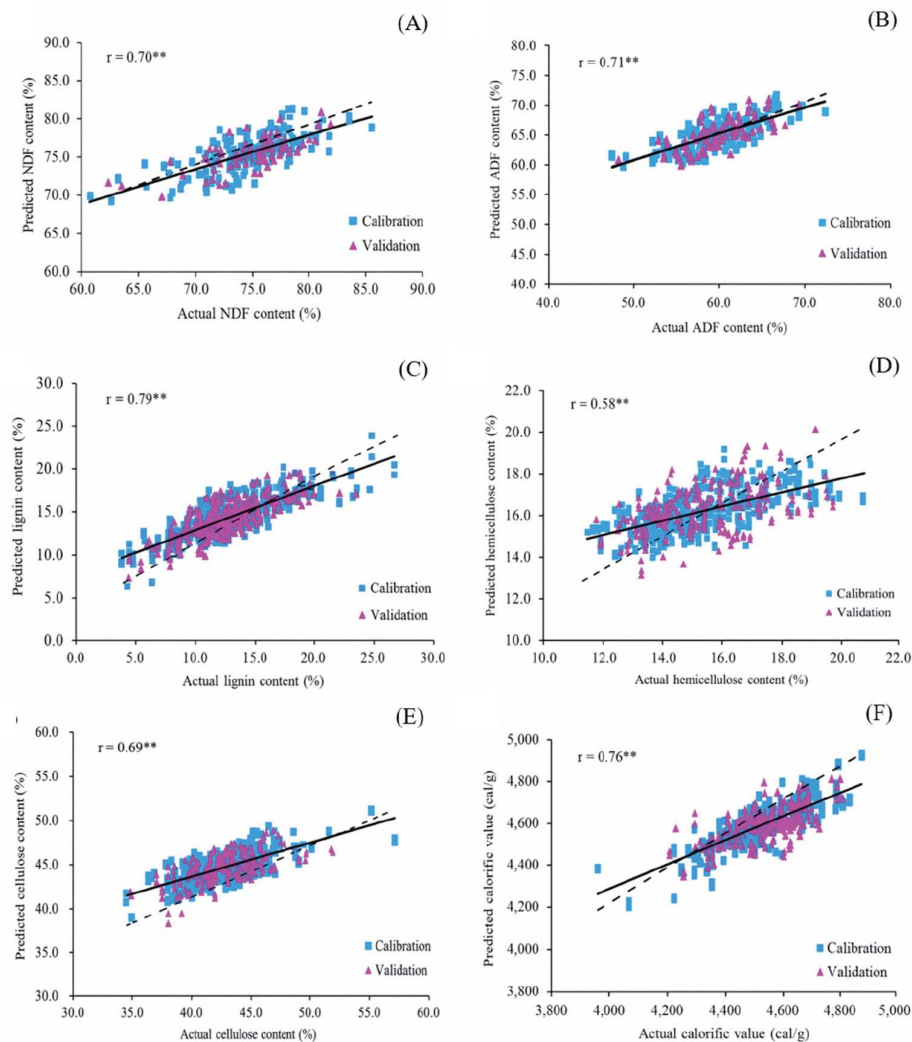


Fig. 2 Relationships between actual and near infrared-predicted values of jatropa wood for: (A) neutral detergent fiber (NDF); (B) acid detergent fiber (ADF); (C) lignin; (D) hemicellulose; (E) cellulose; (F) calorific value, where solid black line indicates fitted regression and dashed black line represents 1:1 relationship between actual and predicted values, r = correlation coefficient; ** = significant at $p < 0.01$.

Table 2 Calibration and validation statistics for models developed to predict chemical composition and calorific value in the wood of *Jatropha* genotypes.

Compositions	PLS	Calibration			Validation				
	factors	slope	<i>r</i>	SEC	slope	<i>r</i>	SEP	Bias	RPD
NDF (%)	8	0.50	0.71**	2.72	0.45	0.70**	2.55	0.37	1.40
ADF (%)	9	0.50	0.71**	2.59	0.58	0.72**	2.38	0.09	1.42
Lignin (%)	10	0.65	0.80**	1.95	0.65	0.76**	1.97	0.01	1.53
Hemicellulose (%)	8	0.42	0.65**	1.37	0.35	0.45**	1.58	-0.09	1.06
Cellulose (%)	10	0.50	0.70**	2.10	0.49	0.66**	2.17	0.15	1.32
Calorific value (cal/g)	8	0.65	0.81**	68.75	0.49	0.65**	82.85	3.89	1.30

NDF = neutral detergent fiber; ADF = acid detergent fiber; *r* = correlation coefficient; SEC = standard error of calibration; SEP = standard error of prediction; Bias = average error of prediction; RPD = ratio of prediction to deviation; PLS factors (latent variables) = number of latent variables used in the partial least squares calibration model.

** = significant at $p < 0.01$.

quality control applications.

Based on the paired *t* test comparing the values obtained from the standard chemical analyses with those predicted by the calibration models, there was no significant differences at the 95% confidence level for all properties examined (data not shown). The linear regression plots of predicted versus reference values in Fig. 2 represent the validation results, with correlation coefficients in the range 0.58**–0.79**. These values were consistent with the validation statistics in Table 2, indicating moderate predictive ability for several traits. The present study was the first to apply NIR spectroscopy to the evaluation of *jatropha* wood properties, extending its previous use from *jatropha* seed traits and seed oil properties (Lengkey et al., 2013; Posom and Sirisomboon, 2014, 2015) to wood-based traits relevant to biomass quality.

Compared with the NIR studies in other biomass materials, the present models had lower to moderate predictive performance. Often, other studies on other wood and lignocellulosic biomasses have reported stronger calibrations when the sample composition was less heterogeneous or when

the trait-specific models were better defined (Tsuchikawa and Kobori, 2015; Loureiro et al., 2022). In the present study, the inclusion of diverse genetic backgrounds and harvest conditions likely increased biological variation and sample heterogeneity, thereby reducing the model precision for some traits. Nevertheless, the models still captured meaningful variation in *jatropha* wood and may be useful for rapid, non-destructive screening in breeding programs, particularly for lignin, NDF and ADF. Further refinement of calibration sets and spectral preprocessing may improve model performance in future studies.

Effectiveness of near infrared spectroscopy in assessing jatropha wood genotypes

The ANOVA indicated that harvesting age significantly influenced NDF, ADF, lignin, hemicellulose, cellulose and calorific value ($p < 0.01$; Table 3). Significant differences were also observed among genotypes for all traits ($p < 0.01$). A significant interaction between harvesting age and genotype

Table 3 Mean squares from analysis of variance in split-plot design of near infrared predicted values for chemical composition and calorific value in wood of *jatropha* genotypes at different harvesting ages.

Source of variance	df	NDF		ADF		Lignin		Hemicellulose		Cellulose		Calorific value	
Replication	3	15.29		12.35		7.22		0.71		10.63		18,256	
Harvesting age (H)	2	31.59	**	165.98	**	63.76	**	89.47	**	104.44	**	205,164	**
Error A	6	1.22		1.21		0.85		0.54		0.81		3,294	
Genotype (G)	15	23.09	**	20.13	**	27.56	**	1.82	**	10	**	61,806	**
H × G	30	3.82	*	3.49		2.43	**	0.78		3.37	*	4,481	**
Error B	135	2.81		2.5		1.09		0.52		1.94		1,622	

df = degrees of freedom; NDF = neutral detergent fiber; ADF = acid detergent fiber; Error A = main-plot error (replication × harvesting age); Error B = subplot error (residual error).

* = significant at $p < 0.05$; ** = significant at $p < 0.01$.

was detected for nearly all characteristics, except ADF and hemicellulose. Mean comparisons across harvesting ages are presented in Fig. 3. Because significant harvesting age $\times$ genotype interactions were detected for NDF, lignin, cellulose and calorific value, the main-effect means for these traits are presented to illustrate overall trends and should be interpreted with caution. Across genotypes, NDF, ADF, lignin and calorific value were highest at 24 MAP, while lignin and calorific value increased progressively from 12 to 24 MAP. In contrast, hemicellulose was highest at 18 MAP, whereas cellulose was lowest at 18 MAP and higher at 12 MAP and 24 MAP. Based on these results, harvest age affected wood chemical composition and energy-related traits in jatropha. The observed changes may have been associated with progressive wood maturation and changes in cell-wall composition, including secondary wall development and lignification, which can increase structural fractions and enhance energy density (Jung and Lamb, 2004; Silva et al., 2019; Wang et al., 2020; Esteves

et al., 2023).

A combined analysis over 2 yr of the NIR-predicted chemical composition and calorific value in jatropha wood revealed significant ($p < 0.01$) differences between the first harvest of the initial year and the subsequent harvest in the second year for all traits (Table 4). Significant ($p < 0.01$) differences among genotypes were observed for every trait and a notable interaction between harvest year and genotype was detected for NDF and ADF. However, these year-to-year differences should be interpreted cautiously because the second-year dataset was obtained from regrowth after re-harvesting of the same plants in the 12 mth treatment. Thus, the observed differences reflect both harvest year and regrowth effects, rather than plant age alone. Comparisons of the mean values indicated that NDF, ADF, hemicellulose and cellulose were higher in the first year than in the second (data not shown), whereas the lignin content remained consistent and the calorific value was higher in the second year.

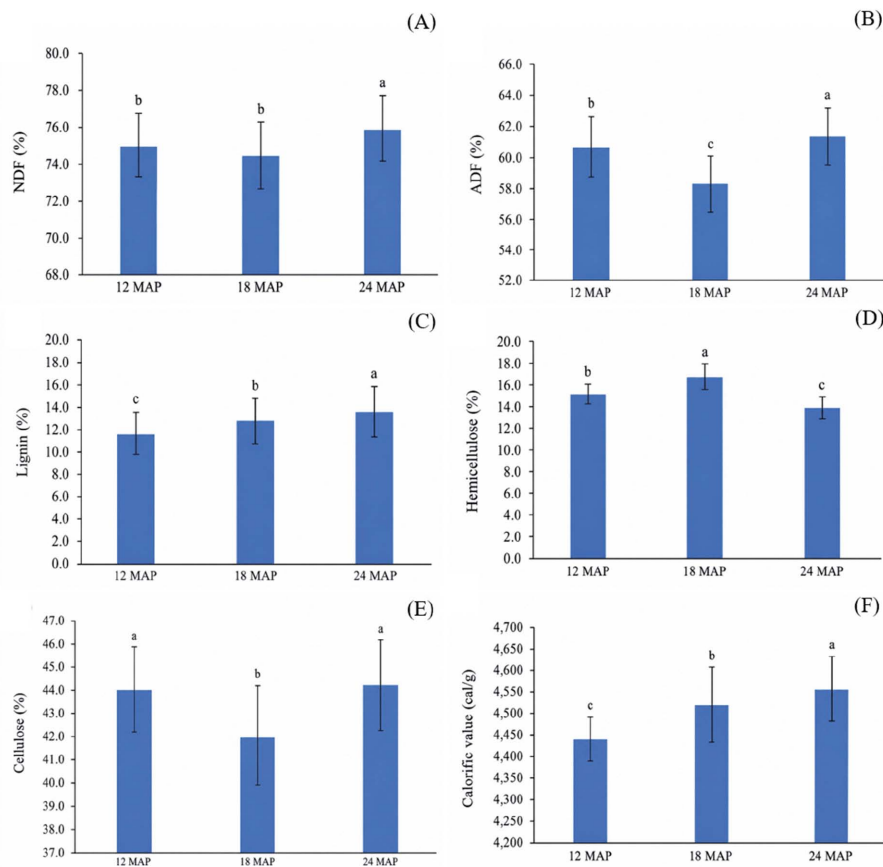


Fig. 3 Mean $\pm$ SD values of NIR-predicted wood chemical composition and calorific value of jatropha across three harvest ages (12 mth after planting (MAP, 18 MAP, 24 MAP): (A) neutral detergent fiber (NDF); (B) acid detergent fiber (ADF); (C) lignin; (D) hemicellulose; (E) cellulose; (F) calorific value, where values are overall means across genotypes. Different lowercase letters above columns indicate significant differences ($p < 0.05$) among harvest ages based on Duncan's multiple range test, and for traits showing significant harvest age $\times$ genotype interactions, main-effect means are presented to illustrate overall trends but should be interpreted with caution.

Table 4 Mean squares from the combined analysis of variance over 2 yr for near infrared-predicted chemical composition and calorific value in wood of *Jatropha* genotypes from same plants harvested at 12 mth in first year and re-harvested from regrowth in second year.

Source of variance	df	NDF		ADF		Lignin		Hemicellulose		Cellulose		Calorific value	
Year (Y)	1	179.81	**	270.57	**	0.26		20.11	**	142.32	**	439,899	**
Rep. within year	6	5.29		3.99		4.68		0.17		2.49		8,063	
Genotype (G)	15	21.38	**	16.17	**	16.17	**	0.94	**	7.84	**	27,225	**
G × Y	15	10.58	**	9.14	**	1.39		0.25		2.59		3,105	
Error	90	2.43		2.95		1.48		0.32		2.28		3,071	

df = degrees of freedom; NDF = neutral detergent fiber, ADF = acid detergent fiber.
** = significant at $p < 0.01$.

Furthermore, the combined analysis for 2 yr identified significant genotypic variation in *jatropha* wood properties, specifically, lignin from 7.93% to 14.39% (Table 5), hemicellulose from 14.17% to 15.39%, cellulose from 40.74% to 44.39% and calorific value from 4,360 to 4,653 cal/g. These findings highlight the capability of NIR spectroscopy to differentiate among *jatropha* genotypes based on wood chemical composition and energy content.

The chemical composition and calorific value of the wood

Table 5 Combined mean comparisons during 2 yr for near infrared-predicted lignin, hemicellulose, cellulose and calorific value in *jatropha* wood traits without significant genotype × year interaction.

Genotype	Lignin (%)	Hemicellulose (%)	Cellulose (%)	Calorific value (cal/g)
KUBJL 1	12.15±0.62 ^{bc}	14.55±0.50 ^{c-f}	43.68±1.63 ^{a-d}	4,512±60 ^{b-e}
KUBJL 2	11.53±1.10 ^{bcd}	14.39±0.63 ^{def}	42.91±1.71 ^{a-f}	4,470±74 ^{de}
KUBJL 3	11.79±0.56 ^{bcd}	14.86±0.44 ^{a-d}	43.21±1.57 ^{a-f}	4,501±67 ^{b-e}
KUBJL 4	10.89±1.06 ^d	14.49±0.97 ^{def}	42.52±1.23 ^{e-f}	4,465±68 ^{de}
KUBJL 5	10.82±0.93 ^d	14.33±0.59 ^{def}	44.01±1.56 ^{abc}	4,457±71 ^e
KUBJL 6	11.98±1.43 ^{bcd}	14.48±0.52 ^{def}	42.78±1.87 ^{b-f}	4,515±73 ^{bcd}
KUBJL 7	11.01±1.25 ^{cd}	14.75±0.51 ^{b-e}	42.00±1.81 ^{fg}	4,492±69 ^{b-e}
KUBJL 8	11.61±0.65 ^{bcd}	15.18±0.72 ^{ab}	40.74±2.44 ^g	4,497±67 ^{b-e}
KUBJL 10	11.01±0.90 ^{cd}	14.50±0.60 ^{def}	42.12±2.40 ^{efg}	4,483±99 ^{cde}
KUBJL 11	12.00±2.03 ^{bcd}	15.08±0.67 ^{abc}	42.34±1.44 ^{def}	4,502±118 ^{b-e}
KUBJL 12	12.23±1.19 ^b	14.63±0.60 ^{b-f}	41.97±2.37 ^{fg}	4,536±68 ^{bc}
KUBJL 13	12.02±1.11 ^{bcd}	14.51±0.65 ^{def}	43.12±1.08 ^{a-f}	4,512±105 ^{b-e}
KUBJL 14	11.58±1.02 ^{bcd}	14.17±0.59 ^f	43.53±1.70 ^{a-e}	4,504±83 ^{b-e}
JcM10	7.93±1.62 ^e	14.23±0.75 ^{ef}	43.98±1.78 ^{abc}	4,360±93 ^f
Ji 1	14.39±0.78 ^a	15.39±0.68 ^a	44.16±0.55 ^{ab}	4,543±58 ^b
Ji 2	14.08±1.73 ^a	14.50±0.77 ^{def}	44.39±2.11 ^a	4,653±71 ^a
F test	**	**	**	**
Coefficient of variation (%)	10.42	3.88	3.51	1.23

Genotype means are presented across 2 yr only for traits without a significant genotype × year interaction in combined analysis of variance. Mean ± SD values within the same column followed by different lowercase superscript letters are significantly ($p < 0.05$) different based on Duncan’s multiple range test.

were ranked as: *J. integerrima* (Ji 1 and Ji 2) > interspecific hybrids > *J. curcas* (JcM10). This ranking suggests that interspecific hybrids exhibit superior wood properties compared with pure *J. curcas*, likely due to the inheritance of favorable traits from *J. integerrima*, which exhibited the most desirable wood characteristics among the genotypes evaluated. Accordingly, *J. integerrima* may serve as a valuable parental source in breeding programs aimed at enhancing *jatropha* wood quality. Furthermore, NIR spectroscopy effectively identified interspecific hybrids—specifically, KUBJL 5, KUBJL 8, KUBJL 11 and KUBJL 12—with the most prominent wood characteristics.

Because significant genotype × year interactions were detected for NDF and ADF (Table 4), both traits were analyzed separately by year (Table 6). NDF differed among genotypes in both years, ranging from 73.38% to 76.61% in the first year and from 69.56% to 78.56% in the second year. KUBJL 14 had the highest NDF in the first year (76.61%), whereas Ji 2 had the highest value in the second year (78.56%). For ADF, genotypic differences were not significant in the first year (values ranged from 59.25% to 62.61%) but were significant in the second year ($p < 0.01$; values ranged from 54.79% to 63.98%). Ji 2 showed the highest ADF value in the second year (63.98%), whereas KUBJL 10 had the lowest values for both NDF (69.56%) and ADF (54.79%). Overall, Ji 1 and Ji 2 maintained relatively high NDF and ADF values in the second year, while KUBJL 5 and KUBJL 11 were the most promising hybrids after regrowth.

The correlation analysis between chemical composition and calorific value, based on the NIR spectroscopy, revealed significant positive relationships. Specifically, calorific value was positively correlated with NDF ($r = 0.65^{**}$), ADF ($r = 0.42^{**}$) and lignin ($r = 0.91^{**}$), as shown in Fig. 4. Among these traits, lignin had the strongest association with calorific value because it is a more energy-dense and less oxidized aromatic polymer than the structural carbohydrates in wood. Esteves et al. (2023) reported that generally, the heating value of lignin is higher than that of polysaccharides, which helps

to explain its closer relationship with wood energy content. In contrast, NDF and ADF are broader compositional indices rather than single energy-rich fractions and therefore had weaker correlations with calorific value. The present study corroborated Arunyanark et al. (2023a), affirming the efficacy of NIR spectroscopy for quantifying the relationship between wood chemical composition and energy content.

The calorific value of biomass is a critical parameter for evaluating its suitability for energy generation (Domingos et al., 2020). Wood properties—including its chemical composition, such as cellulose, hemicellulose, lignin and ash content—directly influence its heat production capacity (Börcsök and

Pásztor, 2021). In the present study, the NIR analysis revealed a strong relationship between NDF, ADF and lignin content with the calorific value of jatropha wood, with lignin having the most pronounced correlation. Consistent with Niu et al. (2014), pure lignin had a higher calorific value than cellulose or hemicellulose, underscoring its pivotal role in the biomass energy content. During combustion, the oxidation of organic

Table 6 Mean comparisons of near infrared-predicted neutral detergent fiber (NDF) and acid detergent fiber (ADF) in jatropha wood by genotype within each harvest year, following significant genotype $\times$ year interactions.

Genotype	NDF (%)		ADF (%)	
	First year	Second year	First year	Second year
KUBJL 1	74.66 $\pm$ 0.30 ^{c-f}	71.26 $\pm$ 1.32 ^{fg}	60.52 $\pm$ 0.64	56.45 $\pm$ 0.57 ^{fg}
KUBJL 2	73.79 $\pm$ 1.12 ^{ef}	71.00 $\pm$ 1.07 ^{fg}	60.09 $\pm$ 1.27	55.91 $\pm$ 1.20 ^{fg}
KUBJL 3	75.24 $\pm$ 0.71 ^{a-e}	70.43 $\pm$ 0.28 ^{fg}	60.69 $\pm$ 0.74	56.81 $\pm$ 0.67 ^{d-g}
KUBJL 4	73.38 $\pm$ 0.60 ^f	70.85 $\pm$ 1.96 ^{fg}	59.25 $\pm$ 0.77	56.79 $\pm$ 2.75 ^{d-g}
KUBJL 5	75.76 $\pm$ 1.28 ^{a-d}	76.55 $\pm$ 2.61 ^{ab}	62.51 $\pm$ 1.22	58.47 $\pm$ 0.30 ^{cde}
KUBJL 6	74.75 $\pm$ 0.86 ^{b-f}	72.86 $\pm$ 1.99 ^{def}	60.43 $\pm$ 0.82	59.02 $\pm$ 2.85 ^{bcd}
KUBJL 7	73.87 $\pm$ 0.42 ^{ef}	70.57 $\pm$ 1.72 ^{fg}	59.59 $\pm$ 1.21	56.47 $\pm$ 1.77 ^{cfg}
KUBJL 8	74.54 $\pm$ 0.94 ^{c-f}	70.53 $\pm$ 1.77 ^{fg}	59.98 $\pm$ 0.68	56.84 $\pm$ 2.30 ^{d-g}
KUBJL 10	75.32 $\pm$ 1.37 ^{a-e}	69.56 $\pm$ 0.45 ^g	60.79 $\pm$ 1.71	54.79 $\pm$ 0.13 ^g
KUBJL 11	75.98 $\pm$ 1.90 ^{abc}	75.25 $\pm$ 1.14 ^{bcd}	61.73 $\pm$ 2.04	59.38 $\pm$ 1.59 ^{bc}
KUBJL 12	74.55 $\pm$ 1.48 ^{c-f}	71.66 $\pm$ 1.84 ^{efg}	60.39 $\pm$ 1.56	57.25 $\pm$ 1.09 ^{c-g}
KUBJL 13	74.51 $\pm$ 0.29 ^{c-f}	73.94 $\pm$ 1.75 ^{cde}	60.11 $\pm$ 0.39	59.00 $\pm$ 1.10 ^{bcd}
KUBJL 14	76.61 $\pm$ 1.41 ^a	70.72 $\pm$ 0.57 ^{fg}	62.61 $\pm$ 1.21	55.61 $\pm$ 1.27 ^{fg}
JcM10	73.97 $\pm$ 1.13 ^{def}	71.84 $\pm$ 1.79 ^{efg}	59.84 $\pm$ 1.79	57.64 $\pm$ 2.30 ^{c-f}
Ji 1	76.50 $\pm$ 2.09 ^{ab}	75.83 $\pm$ 1.37 ^{bc}	61.54 $\pm$ 2.75	61.09 $\pm$ 1.19 ^b
Ji 2	75.89 $\pm$ 1.86 ^{abc}	78.56 $\pm$ 1.72 ^a	61.95 $\pm$ 2.52	63.98 $\pm$ 0.43 ^a
F test	*	**	ns	**
Coefficient of variation (%)	1.69	2.49	2.74	3.05

Because genotype $\times$ year interactions were significant for NDF and ADF in combined analysis of variance, genotype means were compared separately within each harvest year. First year refers to initial 12 mth harvest and second year refers to 12 mth regrowth harvest after re-harvesting.

Mean $\pm$ SD values within the same column followed by different lowercase superscript letters are significantly ($p < 0.05$) different based on Duncan's multiple range test. ns = not significant; * = significant at $p < 0.05$; ** = significant at $p < 0.01$.

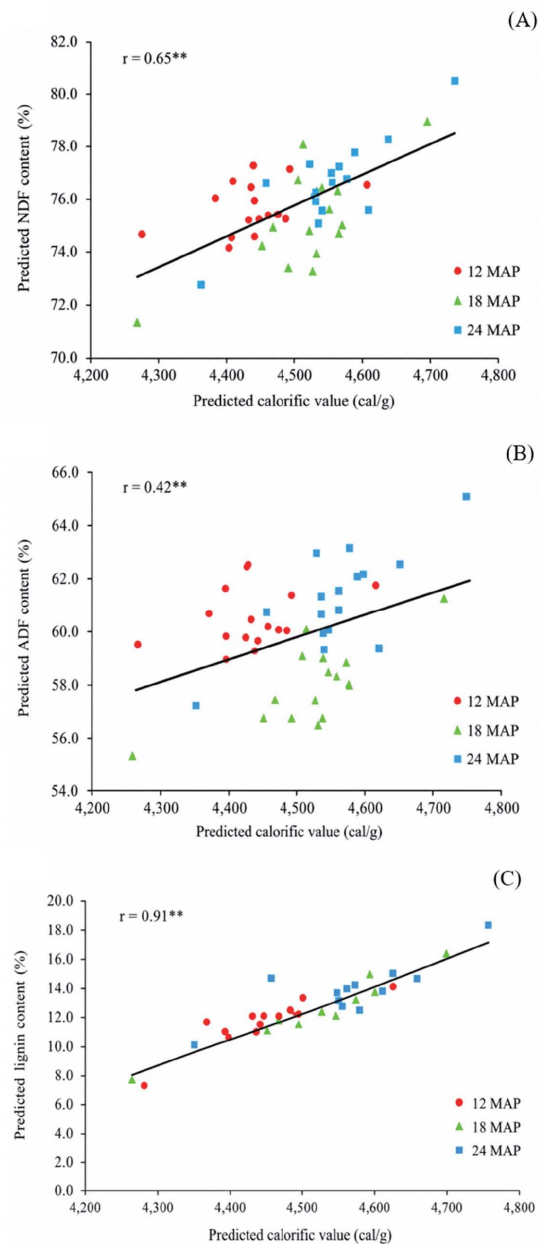


Fig. 4 Relationship between predicted values of calorific value and predicted values across three pruning ages in the wood of jatropha genotypes: (A) neutral detergent fiber (NDF); (B) acid detergent fiber (ADF); (C) lignin. MAP = month after planting; r = correlation coefficient, ** = significant at $p < 0.01$.

compounds—including cellulose, hemicellulose, lignin and starch—releases heat that is harnessed in industrial processes and high-energy applications (Posom et al., 2016; Posom and Sirisomboon, 2017).

NIR spectroscopy offers a rapid, accurate and non-invasive method for assessing the chemical, physical and mechanical properties of wood (Tsuchikawa and Kobori, 2015; Loureiro et al., 2022). The findings of the present study confirm its utility in detecting genetic variability in the chemical composition and calorific value of jatropha wood, as well as in identifying hybrids with superior wood properties. The developed present method should be an indispensable tool in jatropha research and breeding programs because its high-throughput capability enables the analysis of numerous samples, thereby increasing the efficiency of breeding operations while reducing time and costs. Consequently, NIR spectroscopy has been applied increasingly in the evaluation of wood properties, seeds, seed oils and biomass materials, supporting rapid quality assessment in biofuel and biomass applications (Posom and Sirisomboon, 2014, 2015, 2017; Tsuchikawa and Kobori, 2015; Posom et al., 2016; Loureiro et al., 2022).

Optimizing biomass energy production requires careful consideration of harvesting age as a critical factor influencing the chemical composition and calorific value of jatropha wood. Although older plants may have higher energy contents, delayed harvesting does not automatically guarantee improved economic returns. Therefore, the optimal harvesting age should be determined by considering wood quality together with biomass yield, plant health and harvest-cycle economics. Furthermore, while older wood may have a higher calorific value, the concomitant increase in the lignin content can complicate combustion due to its recalcitrance (Niu et al., 2014). Therefore, determining the optimal harvesting age necessitates balancing plant health, yield and the specific energy requirements of end-users. The significant interaction between genotype and harvest year indicated that breeding programs must consider both plant age and genetic background when optimizing wood quality. Interspecific hybrids, which amalgamate traits from different jatropha species, appear to have superior properties, rendering them promising candidates for future breeding efforts. Nevertheless, further multi-year and multi-environment evaluations are required to assess the long-term stability of these hybrids and their performance under diverse environmental conditions (Li et al., 2017; Arunyanark et al., 2022). Although the initial results are encouraging, it is imperative to evaluate these hybrids under a broader range of climatic and soil conditions to determine their suitability for

large-scale bioenergy production.

In conclusion, NIR spectroscopy showed potential as a rapid and non-destructive tool for evaluating the chemical composition and calorific value of jatropha wood. The method detected genotypic variation in wood quality traits and distinguished promising hybrids and parental lines. Although the calibration models had modest predictive performance, they were suitable for preliminary screening and comparative evaluation rather than for precise analytical applications. In addition, the variation in wood properties with harvest age and regrowth highlighted the importance of both genetic background and harvest conditions in jatropha improvement for biomass energy use. Further refinement of calibration datasets and model development may enhance the usefulness of NIR spectroscopy in future breeding programs.

Conflict of Interest

The authors declare that there are no conflicts of interest.

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References

- Alamu, E.O., Nuwamanya, E., Cornet, D., Meghar, K., Adesokan, M., Tran, T., Belalcazar, J., Desfontaines, L., Davrieux, F. 2021. Near-infrared spectroscopy applications for high-throughput phenotyping for cassava and yam: A review. *Int. J. Food Sci. Technol.* 56: 1491–1501. doi.org/10.1111/ijfs.14773
- Arunyanark, A., Tanya, P., Liangsakul, P., Srinives, P. 2022. Biomass yield stability of interspecific *Jatropha* hybrids through multiple harvest rotations with varying harvest ages. *Agric. Nat. Resour.* 56: 1215–1224.
- Arunyanark, A., Tanya, P., Liangsakul, P., Srinives, P. 2023a. Biomass productivity and wood chemical composition at different pruning ages of interspecific hybrid *Jatrophas*. *Agric. Nat. Resour.* 57: 353–362.

- Arunyanark, A., Tanya, P., Liangsakul, P., Srinives, P. 2023b. Genotype performance and relationship between leaf traits, biomass yield and wood quality on interspecific hybrids of *Jatropha*. *Agric. Nat. Resour.* 57: 309–320.
- Arunyanark, A., Foytong, K., Jompuk, C., Srinives, P., Tanya, P. 2024. Plant spacing and pruning effect on yield productivity of *Jatropha*. *J. Crop Sci. Biotechnol.* 27: 501–507. doi.org/10.1007/s12892-024-00246-3
- Barghini, E., Cossu, R.M., Cavallini, A., Giordani, T. 2015. Transcriptome analysis of response to drought in poplar interspecific hybrids. *Genomics Data* 3: 143–145. doi.org/10.1016/j.gdata.2015.01.004
- Böresök, Z., Pásztor, Z. 2021. The role of lignin in wood working processes using elevated temperatures: An abbreviated literature survey. *Eur. J. Wood Wood Prod.* 79: 511–526. doi.org/10.1007/s00107-020-01637-3
- Brewbaker, J.L. 2013. ‘KX4-Hawaii’, seedless interspecific hybrid *Leucaena*. *HortScience*. 48: 390–391. doi.org/10.21273/HORTSCI.48.3.390
- Dadile, A.M., Sotannde, O.A., Zira, B.D., Garba, M., Yakubu, I. 2020. Evaluation of elemental and chemical compositions of some fuel wood species for energy value. *Int. J. For. Res.* 2020: 3457396. doi.org/10.1155/2020/3457396
- Danzi, D., De Paola, D., Petrozza, A., Summerer, S., Cellini, F., Pignone, D., Janni, M. 2022. The use of near-infrared imaging (NIR) as a fast non-destructive screening tool to identify drought-tolerant wheat genotypes. *Agriculture* 12: 537. doi.org/10.3390/agriculture12040537
- de Mendiburu, F. 2023. *agricolae*: Statistical Procedures for Agricultural Research. <https://cran.r-project.org/web/packages/agricolae/index.html>, 23 March 2024.
- Domingos, I., Ayata, U., Ferreira, J., Cruz-Lopes, L., Sen, A., Sahin, S., Esteves, B. 2020. Calorific power improvement of wood by heat treatment and its relation to chemical composition. *Energies* 13: 5322. doi.org/10.3390/en13205322
- Esteves, B., Sen, U., Pereira, H. 2023. Influence of chemical composition on heating value of biomass: A review and bibliometric analysis. *Energies* 16: 4226. doi.org/10.3390/en16104226
- Fonseca, C.E.L., Pessoa Filho, M., Braga, G.J., et al. 2020. Near-infrared reflectance spectroscopy as a tool for breeding *Andropogon gayanus* Kunth for forage quality. *J. Agric. Vet. Sci.* 13: 57–66. doi.org/10.9790/2380-1306015766
- Gebreselassie, M.N., Ader, K., Boizot, N., et al. 2017. Near-infrared spectroscopy enables the genetic analysis of chemical properties in a large set of wood samples from *Populus nigra* (L.) natural populations. *Ind. Crops Prod.* 107: 159–171. doi.org/10.1016/j.indcrop.2017.05.013
- Gomez, K.A., Gomez, A.A. 1984. *Statistical Procedures for Agricultural Research*, 2nd ed. John Wiley & Sons. New York, NY, USA.
- Gramlich, S., Wagner, N.D., Hörandl, E. 2018. RAD-seq reveals genetic structure of the F2-generation of natural willow hybrids (*Salix* L.) and a great potential for interspecific introgression. *BMC Plant Biol.* 18: 317.
- International Organization for Standardization. 2017. *Animal feeding stuffs, cereals and milled cereal products—Guidelines for the application of near infrared spectrometry*. ISO 12099:2017. International Organization for Standardization. Geneva, Switzerland.
- International Organization for Standardization. 1998. *Animal feeding stuffs, animal products and faeces or urine—Determination of gross calorific value—Bomb calorimeter method*. ISO 9831:1998(E). International Organization for Standardization. Geneva, Switzerland.
- Jiang, G.L. 2020. Comparison and application of non-destructive NIR evaluations of seed protein and oil content in soybean breeding. *Agronomy* 10: 77. doi.org/10.3390/agronomy10010077
- Jung, H.J.G., Lamb, J.F.S. 2004. Prediction of cell wall polysaccharide and lignin concentrations of alfalfa stems from detergent fiber analysis. *Biomass Bioenergy* 27: 365–373. doi.org/10.1016/j.biombioe.2004.04.001
- Lengkey, L., Budiastira, I.W., Seminar, K.B., Purwoko, B.S. 2013. Determination of chemical properties in *Jatropha curcas* L. seed IP-3P by partial least-squares regression and near-infrared reflectance spectroscopy. *Int. J. Agric. Innov. Res.* 2: 41–48.
- Li, Y., Suontama, M., Burdon, R.D., Dungey, H.S. 2017. Genotype by environment interactions in forest tree breeding: Review of methodology and perspectives on research and application. *Tree Genet. Genomes*. 13: 60.
- Loureiro, A.B., Arriel, T.G., Guedes Ramalho, F.M., Hein, P.R.G., Trugilho, P.F. 2022. NIR-based models for estimating selected physical and chemical wood properties from fast-growing plantations. *iForest*. 15: 372–380. doi.org/10.3832/ifor4030-015
- Muakrong, N., Srinives, P. 2020. Genetic potential of agronomic traits and seed physicochemical properties of novel *Jatropha* lines developed from complex interspecific hybridization. *Agrivita J. Agric. Sci.* 42: 92–109. doi.org/10.17503/agrivita.v41i0.2306
- Muakrong, N., One, K.T., Tanya, P., Srinives, P. 2014. Interspecific *Jatropha* hybrid as a new promising source of woody biomass. *Plant Genet. Resour.* 12: S17–S20. doi.org/10.1017/S1479262113000518
- Nasser, R.A., Aref, I.M. 2014. Fuelwood characteristics of six *Acacia* species growing wild in the southwest of Saudi Arabia as affected by geographical location. *BioRes.* 9: 1212–1224.
- Niu, W., Huang, G., Liu, X., Chen, L., Han, L. 2014. Chemical composition and calorific value prediction of wheat straw at different maturity stages using near-infrared reflectance spectroscopy. *Energy Fuels* 28: 7474–7482. doi.org/10.1021/ef501446r
- Pasangulapati, V., Ramachandriya, K.D., Kumar, A., Wilkins, M.R., Jones, C.L., Huhnke, R.L. 2012. Effects of cellulose, hemicellulose and lignin on thermochemical conversion characteristics of the selected biomass. *Bioresour. Technol.* 114: 663–669. doi.org/10.1016/j.biortech.2012.03.036
- Phithakhongsa, P., Tanya, P., Arunyanark, A., Phetcharat, C., Muakrong, N., Srinives, P. 2023. Discovery of male sterility from an interspecific cross between *Jatropha curcas* and *J. integerrima*. *Plant Genet. Resour.* 21: 497–504. doi.org/10.1017/S1479262123001016
- Posom, J., Sirisomboon, P. 2014. Evaluation of thermal properties of *Jatropha curcas* L. kernels using near infrared spectroscopy. *Biosyst. Eng.* 125: 45–53.
- Posom, J., Sirisomboon, P. 2015. Evaluation of the moisture content of *Jatropha curcas* kernels and the heating value of the oil-extracted residue using near-infrared spectroscopy. *Biosyst. Eng.* 130: 52–59.
- Posom, J., Shrestha, A., Saechua, W., Sirisomboon, P. 2016. Rapid non-destructive evaluation of moisture content and higher heating value of *Leucaena leucocephala* pellets using near infrared spectroscopy. *Energy* 107: 464–472.
- Posom, J., Sirisomboon, P. 2017. Evaluation of lower heating value and

- elemental composition of bamboo using near infrared spectroscopy. *Energy* 121: 147–158. doi.org/10.1016/j.energy.2017.01.020
- R Core Team. 2026. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. Vienna, Austria.
- Rushing, J.B., Saha, U.K., Lemus, R., Sonon, L., Baldwin, B.S. 2016. Analysis of some important forage quality attributes of Southeastern wildrye (*Elymus glabriflorus*) using near infrared reflectance spectroscopy. *Am. J. Anal. Chem.* 7: 642–662. doi.org/10.4236/ajac.2016.79060
- Schwanninger, M., Rodrigues, J.C., Fackler, K. 2011. A review of band assignments in near infrared spectra of wood and wood components. *J. Near Infrared Spectrosc.* 19: 287–308. doi.org/10.1255/jnirs.955
- Silva, D.A., Eloy, E., Caron, B.O., Trugilho, P.F. 2019. Elemental chemical composition of forest biomass at different ages for energy purposes. *Floresta Ambient.* 26: e20160201.
- Sumathi, M., Ramasamy, Y. 2017. Microsatellite allele length variations in inter-specific hybrids of *Eucalyptus*. *Acta Bot. Croat.* 76: 103–106.
- Theerawitaya, C., Chutteang, C., Arunyanark, A., et al. 2022. Combining high-throughput phenotyping with overall growth measurements of indica rice (*Oryza sativa* L. ssp. *indica*) cultivars over the whole life cycle. *Agric. Nat. Resour.* 56: 713–724.
- Tsuchikawa, S., Kobori, H. 2015. A review of recent application of near infrared spectroscopy to wood science and technology. *J. Wood Sci.* 61: 213–220. doi.org/10.1007/s10086-015-1467-x
- Van Soest, P.J., Robertson, J.B., Lewis, B.A. 1991. Methods for dietary fiber, neutral detergent fiber and nonstarch polysaccharides in relation to animal nutrition. *J. Dairy Sci.* 74: 3583–3597.
- Wang, S., Zou, C., Lou, C., Yang, H., Mei, M., Jing, H., Cheng, S. 2020. Effects of hemicellulose, cellulose and lignin on the ignition behaviors of biomass in a drop tube furnace. *Bioresour. Technol.* 310: 123456. doi.org/10.1016/j.biortech.2020.123456
- Williams, P.C., Sobering, D.C. 1996. How do we do it: A brief summary of the methods we use in developing near infrared calibrations. In: Davies, A.M.C., Williams, P. (Eds.). *Near Infrared Spectroscopy: The Future Waves*. NIR Publications. Chichester, UK. pp. 185–188.
- Workman, J., Jr., Weyer, L. 2012. *Practical guide and spectral atlas for interpretive near-infrared spectroscopy*. CRC Press. Boca Raton, FL, USA.
- Zhang, K., Zhou, L., Brady, M., Xu, F., Yu, J., Wang, D. 2017. Fast analysis of high heating value and elemental compositions of sorghum biomass using near-infrared spectroscopy. *Energy* 118: 1353–1360. doi.org/10.1016/j.energy.2016.11.015