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Research Article

Non-Destructive Prediction of Moisture and Oil Content in Palm Fresh Fruit Bunches Using Electrical Capacitance

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Abstract

Rapid, non-destructive techniques for evaluating the internal quality of fresh oil palm fruit bunches (FFB) are needed to improve harvesting and postharvest management. This study aimed to develop predictive models for the moisture and oil content of fresh oil palm fruit bunches using electrical capacitance and chemometric analysis. Electrical capacitance (Cp) measurements were obtained using an inductance-capacitance-resistance (LCR) meter from fruit samples representing five maturity levels. The capacitance data were analyzed using Partial Least Squares Regression (PLSR) with several data preprocessing techniques, including Original, Baseline Correction, Standard Normal Variate (SNV), and Multiplicative Scatter Correction (MSC). Model performance was evaluated using the coefficient of determination (R^2), the correlation coefficient (r), the standard error of prediction (SEP), the residual predictive deviation (RPD), and the consistency (%) parameter. Among the evaluated preprocessing methods, MSC produced the best model performance. The optimal model for moisture content was obtained using MSC with three latent factors, yielding R^2 = 0.74 r = 0.86, SEP = 5.02%, RPD = 1.81, and consistency = 86.12%. The optimal model for oil content prediction was also obtained using MSC with four latent variables, achieving R^2 = 0.88, r = 0.94, SEP = 3.84%, RPD = 2.36 and consistency = 93.84%. These results indicate that electrical capacitance combined with PLSR has potential as a rapid and non-destructive method for the chemical quality evaluation of oil palm FFB, particularly for oil content prediction, while moisture content prediction showed limited predictive capability.

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1. Introduction

Oil palm (Elaeis guineensis Jacq.) is one of the most important plantation crops and the largest contributor to global vegetable oil production (Murphy et al., 2021). As the leading producer of palm oil, Indonesia relies heavily on the quality of oil palm fresh fruit bunches to ensure optimal crude palm

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oil yield and processing efficiency (Hasibuan, 2020). The internal quality of oil palm fresh fruit bunches (FFB) plays a critical role in determining oil extraction performance, where key parameters, such as moisture content, oil content, and free fatty acid (FFA) content, are closely associated with fruit maturity and directly influence oil recovery during milling processes (Basyuni et al. 2017; Tan et al. 2023). Among these parameters, moisture and oil content are particularly important because they reflect compositional changes during fruit maturation and directly affect oil extraction efficiency.

In recent years, rapid, non-destructive techniques for evaluating the internal quality attributes of agricultural products have been developed. Optical-based methods, such as near-infrared spectroscopy (NIRS) and hyperspectral imaging, have shown promising results in predicting the chemical composition and maturity of agricultural commodities (Novianty et al. 2020; Guo et al. 2023; Budiastra et al. 2024). However, these approaches are often sensitive to surface properties, light scattering and environmental conditions. This sensitivity reduces their robustness when applied to heterogeneous biological materials, such as fresh FFB from oil palms, which possess complex internal structures.

Electrical sensing techniques, particularly capacitance-based measurements, provide an alternative approach for the nondestructive evaluation of biological materials. The electrical response of plant tissues is influenced by their dielectric properties, which depend on the composition and distribution of water, lipids, and ionic components within the tissue (Rehman et al. 2011; Cheng et al. 2022; Van Haeverbeke et al. 2023). Biochemical changes occur in the mesocarp tissue during oil palm fruit maturation, including progressive oil accumulation and changes in water distribution. These compositional changes affect the dielectric properties because water has a relatively high dielectric constant, whereas lipids exhibit much lower dielectric values (Nelson 2008; Salimi et al. 2025).

Capacitance, a dielectric-related electrical parameter, reflects the ability of a material to store electrical charge under an applied electric field. Changes in the moisture content generally increase the capacitance owing to the high dielectric constant of water, whereas an increase in the oil content tends to reduce the overall dielectric response. This relationship forms the basis for using capacitance as an indicator of compositional changes in biological materials (Ishak et al. 2021). Recent developments in capacitive sensing technology have further confirmed that variations in the dielectric constant directly influence the capacitance response, enabling the rapid detection of moisture-related changes (Petrashin et al. 2025).

However, electrical signals obtained from biological materials are often complex and nonlinear, requiring advanced data analysis techniques to extract meaningful relationships from them. Chemometric approaches, such as Partial Least Squares Regression (PLSR), are widely applied to model multivariate relationships between sensor data and chemical properties (Erler et al. 2020). In addition, recent advancements in agricultural sensing have emphasized the integration of electrical

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sensing with data-driven modeling techniques to improve prediction accuracy (Mellyana et al. 2024; Mellyana et al. 2025).

Despite these advancements, studies specifically investigating the application of electrical capacitance combined with chemometric modeling to predict the internal quality attributes of oil palm fresh fruit bunches remain limited. In particular, limited research has addressed the simultaneous prediction of moisture and oil content in intact oil palm FFB using capacitance measurements combined with multivariate calibration. Therefore, this study aimed to evaluate the potential of electrical capacitance, integrated with multivariate analysis, as a non-destructive method for predicting the moisture and oil content in oil palm fresh fruit bunches.

2. Material and Methods

2.1 Research Materials

Fresh fruit bunches of oil palm were obtained from the Cikabayan Plantation in Bogor, Indonesia. These samples represented five ripeness stages: unripe, under-ripe, ripe I, ripe II, and overripe stages. The classification was based on external fruit color and the number of detached fruitlets, following the maturity criteria reported by Hasibuan (2020), namely unripe (reddish-black fruit with no detached fruitlets), under-ripe (red fruit with no detached fruitlets), ripe I (1-3 detached fruitlets), ripe II (5-10 detached fruitlets), and overripe (20-40 detached fruitlets). Each maturity stage comprised 10 intact bunches, yielding a total of 50 samples for analysis.

2.2 Electrical Capacitance Measurement

The electrical capacitance was measured using an LCR meter (GW Instek LCR-819, Good Will Instrument Co., Ltd., Taipei, Taiwan) connected to a pair of custom-made copper plate electrodes. These electrodes were mounted on an elliptical frame designed to accommodate the irregular shapes of the oil palm fresh fruit bunches. The dimensions of the copper electrodes were 60 cm × 52 cm × 2 mm (length × width × thickness). The gap between the two electrode plates ranged from 14 to 18 cm and was adjusted according to the size of each FFB sample. The FFB was positioned between the two electrodes.

During the measurement, an intact FFB was placed between the two copper electrodes, with the entire bunch enclosed within the gap, and the electric field generated by the LCR meter interacted with all the fruit tissues. To minimize the effects of sample orientation and structural heterogeneity, each FFB was measured at four orientations by rotating the bunch by 90° about its longitudinal axis within the electrode frame. At each orientation, the capacitance was measured three times, and the final capacitance value used for modelling was calculated as the average of all 12 measurements (4 orientations × 3 repetitions).

Capacitance measurements were conducted at 14 logarithmically spaced frequency points ranging from 50 Hz to 100 kHz under ambient laboratory conditions (temperature: 25 ± 2°C; relative humidity:

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65 ± 5%). The capacitance values obtained at each frequency were used as predictor variables in the moisture and oil content models. The measurement configuration and electrode setup are shown in Figure 1.

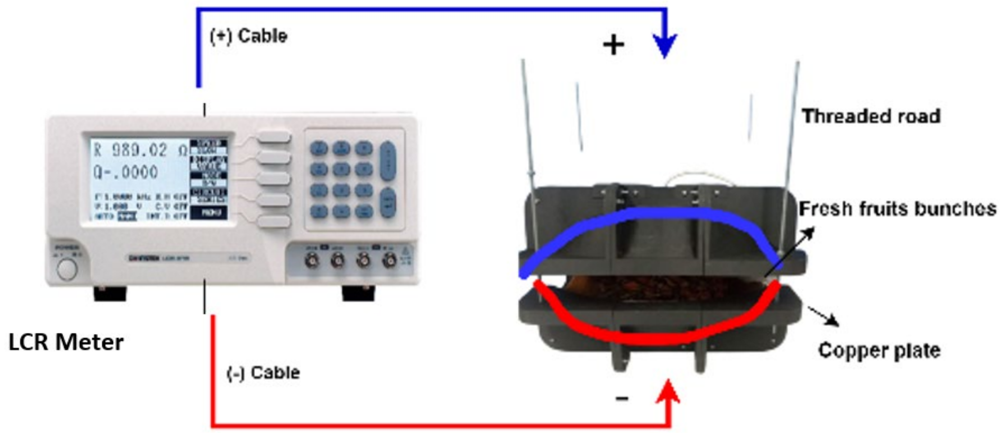

Figure 1. Electrical capacitance measurement system consisting of an LCR meter connected to custom-made copper plate electrodes used for measuring intact oil palm fresh fruit bunches (FFB).

2.3 Chemical Quality Analysis

2.3.1 Moisture Content

The moisture content was determined using the oven-drying method based on SNI 01-2891-1992 (Badan Standardisasi Nasional 1992). Approximately 5 g of homogenized mesocarp sample was dried in an oven at 105°C until a constant weight was achieved. The dried sample was then cooled in a desiccator and weighed again. The moisture content was calculated using Equation (1).

$$Moisture(\%) = \frac{W0-W1}{W0} \times 100 \quad (1)$$

Where W0 is the initial sample weight (g) and W1 is the final weight after drying (g).

2.3.2 Oil Content

Oil content (OC), expressed as crude fat content, was determined using the Soxhlet extraction method according to SNI 01-2891-1992 (Badan Standardisasi Nasional 1992). Approximately 1–2 g of homogenized mesocarp sample was placed in an extraction thimble and extracted using n-hexane for approximately 6 h. After extraction, the solvent was evaporated, and the extraction flask containing the extracted fat was dried at 105 °C to a constant weight. The oil content was calculated using Equation 2.

$$OC(\%) = \frac{W2-W1}{W} X100 \quad (2)$$

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Where W is the sample weight (g), W_1 is the weight of the empty flask (g), and W_2 is the weight of the flask plus the extracted fat (g).

2.4 Data Preprocessing

Capacitance data obtained at different frequencies were pre-processed prior to model development to improve the signal quality and reduce systematic variations unrelated to the sample composition. The preprocessing methods evaluated in this study included original data, Baseline Correction, Standard Normal Variate, and Multiplicative Scatter Correction (Barra et al. 2022).

2.5 Prediction Model Development

The relationship between electrical capacitance and chemical quality parameters was analyzed using PLSR. The capacitance values measured at 14 frequencies were used as predictor variables (X), whereas the moisture and oil contents obtained from laboratory analyses were used as response variables (Y).

A total of 50 samples were used in this study. To ensure that the calibration and validation sets were representative, the dataset was divided using a stratified random sampling approach based on maturity levels and the range of chemical values of interest. Specifically, the samples were sorted by maturity and chemical content before being partitioned into calibration (70%, 35 samples) and external validation (30%, 15 samples) sets. This approach aims to maintain a balanced distribution of sample variations across both subsets, thereby supporting a more consistent evaluation of the model performance on independent data. Data preprocessing and PLSR model development were performed using Unscrambler X software (Camo Analytics AS, Oslo, Norway).

2.6 Model Evaluation

The model performance was evaluated using the correlation coefficient (r), coefficient of determination (R^2), standard error of calibration (SEC), standard error of prediction (SEP), coefficient of variation (CV), and ratio of performance to deviation (RPD). The coefficient of determination (R^2) indicates the proportion of variance in the reference data explained by the model, whereas SEC and SEP represent the calibration and prediction errors, respectively. Lower SEC and SEP values indicate better predictive accuracies (Vibhute et al. 2018). An ideal predictive model is characterized by r values approaching 1, lower SEC, SEP, and CV values, and an RPD ≥ 2 (Nicolaï et al. 2007).

To ensure model stability and prevent overfitting, the consistency (%) parameter was calculated by comparing the SEC and SEP values as follows Equation 3.

$$Consistency(\%) = \frac{SEC}{SEP} X100\% \quad (3)$$

According to Lengkey et al. (2013), the acceptable range for a robust model is 80-110%. A consistency value exceeding 110% indicates potential model overfitting, whereas a value below 80% suggests abnormal measurement errors or instability between the calibration and validation datasets.

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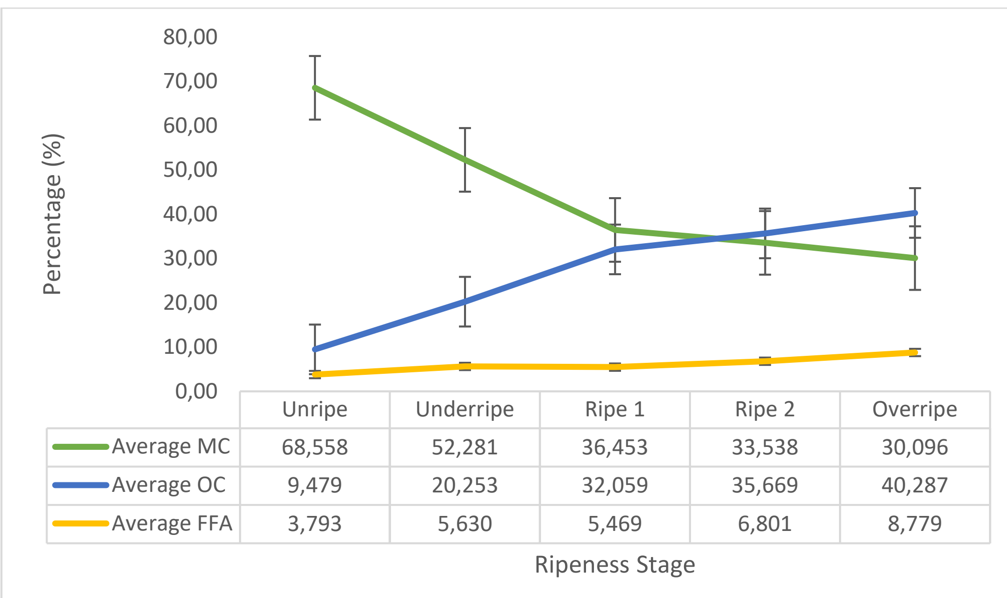
Furthermore, RPD values were categorized to assess predictive ability according to Bellon-Maurel et al. (2010): values below 1.4 indicate poor performance, values between 1.4 and 1.8 indicate fair performance, values between 1.8 and 2.0 indicate good predictive capability, and values above 2.0 indicate very good to excellent predictive performance. Internal validation was performed to rigorously evaluate the performance and reliability of the prediction model.

3. Results and Discussion

3.1 Variability of Chemical Quality Parameters at Different Maturity Stages

A statistical summary of the chemical quality parameters of oil palm fruit at different maturity stages is presented in Figure 2. The results demonstrated clear variations in moisture content, oil content, and FFA levels across maturity stages, indicating significant biochemical and structural changes in the mesocarp tissue during fruit development.

The moisture content in oil palm fresh fruit bunches decreased progressively from the unripe to overripe stages, indicating a reduction in water content during maturation. In contrast, crude fat content increased with advancing maturity, suggesting a shift in the compositional balance between the water and lipid fractions within the mesocarp tissue. This indicates changes in the internal composition of the fruit during development.



	Unripe	Underripe	Ripe 1	Ripe 2	Overripe
Average MC	68,558	52,281	36,453	33,538	30,096
Average OC	9,479	20,253	32,059	35,669	40,287
Average FFA	3,793	5,630	5,469	6,801	8,779

Figure 2. Variability of chemical quality parameters at different maturity stages.

FFA values increased toward the later maturity stages, particularly in fully ripe and overripe fruits, indicating triglyceride hydrolysis during fruit deterioration. This process is associated with lipase activity, which accelerates lipid breakdown and contributes to an increase in FFA levels (Ngando

Ebongue et al. 2006). A similar increase in FFA, accompanied by changes in moisture content under postharvest conditions, was reported by Akbar et al. (2025), supporting the trend observed in this study. Although FFA was not included as a target variable in the prediction models, its variation across maturity stages provides additional evidence of biochemical changes occurring during fruit ripening. This supports the interpretation of moisture and oil content dynamics.

These compositional changes are important because the moisture and lipid fractions exhibit contrasting dielectric properties. Water has a high dielectric constant, whereas lipids have relatively low dielectric constants (Nelson 2008). Therefore, variations in the moisture and oil contents are expected to influence the electrical capacitance response measured in this study. As fruit maturity progresses, decreases in moisture content and oil accumulation alter the dielectric characteristics of the mesocarp tissue, thereby affecting its capacitance response. This relationship provides the basis for developing capacitance-based prediction models for the non-destructive evaluation of the moisture and oil content in oil palm fresh fruit bunches.

3.2 Effect of Frequency on Electrical Capacitance at Different Maturity Stages

Figure 3 shows how the capacitance changes with frequency at different maturity stages of oil palm fresh fruit bunches. The capacitance decreased markedly with increasing frequency at all maturity stages. The highest Cp values appeared at low frequencies and dropped to very low values at higher frequencies. This pattern shows that the dielectric response of oil palm fruit tissue is determined by frequency-dependent polarization within the biological structure of the mesocarp.

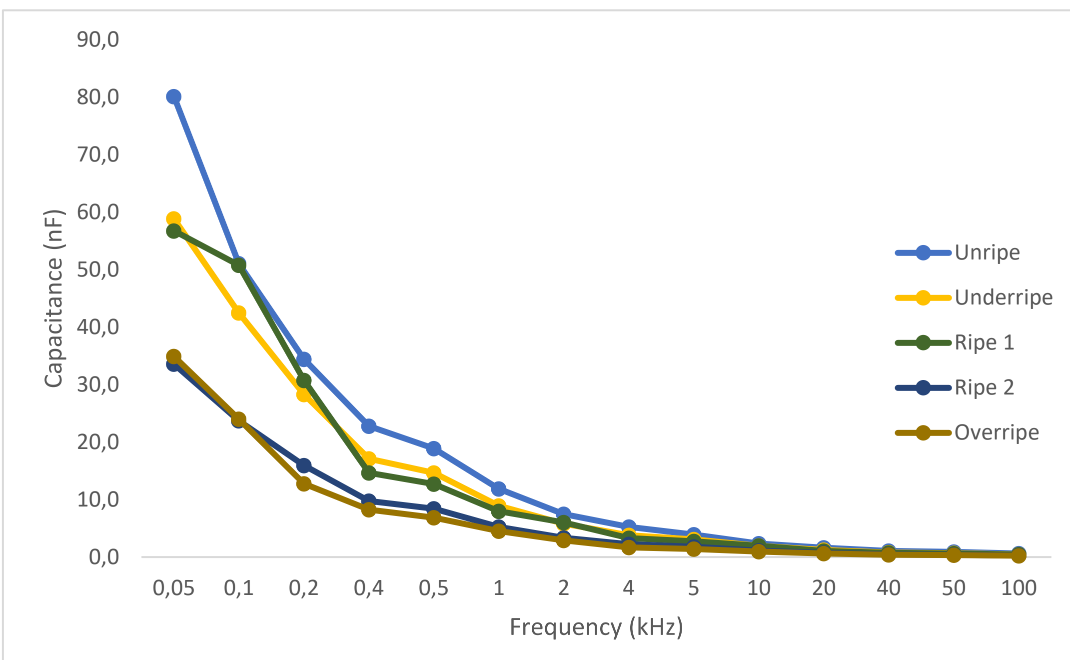


Figure 3. Effect of frequency on electrical capacitance at different maturity stages.

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This decrease in capacitance with increasing frequency is common in biological materials because of dielectric relaxation. At low frequencies, interfacial polarization, ionic conduction, and dipole orientation play significant roles, as mobile ions and polar molecules can respond to a changing field. As the frequency increases, the field changes too quickly for dipoles and charge carriers to keep up, reducing the polarization and capacitance (Lizhi et al. 2008; Biasio dan Cametti 2011). Other agricultural and biological materials exhibit similar frequency-dependent behavior owing to Maxwell-Wagner interfacial polarization in their heterogeneous cellular structures (Kafarski et al. 2018). The capacitance differences between the maturity stages were most evident at low frequencies. Immature fruits (unripe and under-ripe) showed higher capacitance than ripe and overripe fruits. This trend aligns with Figure 3, where moisture decreases and oil increases as the fruit matures. The high dielectric constant of water means that tissues with greater water content exhibit higher capacitance (Ellison 2007; Grimnes and Martinsen 2014). The lower dielectric permittivity of oil reduces its contribution to capacitance.

As fruits mature, oil increases in the mesocarp, whereas water decreases. These changes lower the tissue dielectric response and capacitance, especially at low frequencies, where polarization occurs. The observed capacitance trends in Figure 3 match the moisture and oil changes in Figure 2. This result shows that electrical capacitance is sensitive to these compositional changes and supports its use as a quick, non-destructive method for estimating the moisture and oil content in oil palm fruit (Jha et al. 2011).

3.3 Relationship Between Capacitance and Chemical Properties

As shown in Table 1, the regression analysis demonstrated that the electrical capacitance was closely associated with the chemical properties of the oil palm fresh fruit bunches. Capacitance exhibited a positive relationship with moisture content and a negative relationship with oil content across the evaluated frequency range. These relationships are consistent with the compositional changes occurring during fruit maturation and the contrasting dielectric characteristics of water and lipids in the mesocarp tissue (Figure 2).

The positive relationship between capacitance and moisture content indicates that samples with higher water content tend to produce stronger dielectric response. Conversely, the inverse relationship between capacitance and oil content reflects the gradual replacement of water by accumulated lipids during fruit maturation, resulting in a lower overall dielectric response of the fruit tissue. Similar relationships between dielectric properties, moisture content, and lipid content have been reported for various agricultural and biological materials (Chin-Hashim et al. 2022; Mellyana et al. 2025).

Table 1. Linear regression between electrical capacitance and fruit chemical properties at selected frequencies.

Parameter	Frequency (kHz)	Linear Regression	R	R^2
Moisture content	0.4	$C_p = 3.02x + 1.51$	0.96	0.92
	1	$C_p = 5.91x - 0.14$	0.96	0.92
	5	$C_p = 16.84x + 1.95$	0.94	0.88
	20	$C_p = 43.86x - 1.12$	0.96	0.92
	50	$C_p = 78.52x - 1.34$	0.94	0.88
Oil content	0.4	$C_p = -2.17x + 62.18$	-0.94	0.88
	1	$C_p = -4.25x + 63.39$	-0.93	0.86
	5	$C_p = -11.98x + 61.55$	-0.9	0.81
	20	$C_p = -31.48x + 64.05$	-0.94	0.88
	50	$C_p = -56.30x + 64.17$	-0.92	0.85

The strength of the relationship between the capacitance and chemical properties varied with the measurement frequency. Frequencies in the low- to mid-frequency region (0.4–1 kHz) and around 20 kHz generally exhibited stronger and more stable relationships with both moisture and oil content. This finding suggests that the dielectric polarization mechanisms operating within these frequency ranges are particularly sensitive to compositional changes in the mesocarp tissue. Therefore, capacitance measurements at these frequencies may provide useful information for characterizing internal quality attributes and developing predictive models for the moisture and oil content in oil palm fresh fruit bunches.

3.4 Prediction of Chemical properties Using PLSR model

3.4.1 Moisture Content Prediction

The performances of the PLSR models for moisture content prediction using various pretreatment methods are summarized in Table 2. Among the evaluated methods, the MSC method with three latent factors was selected as the most effective and robust. This model achieved an R2 of 0.74 and RPD of 1.81.

The selection was based on an assessment of both the predictive accuracy and model stability. The Consistency parameter was used to evaluate the model reliability across the calibration and validation datasets. As shown in Table 2, a trade-off was observed: while the MSC five-factor model achieved a higher RPD (1.98), it exhibited low stability, with a consistency value of 62.69%. According to the criteria proposed by Lengkey et al. (2013), the acceptable consistency range for a robust model is 80-110%. Consequently, the 5-factor model was deemed to be susceptible to overfitting. Conversely, the MSC three-factor model provided a more favorable balance, maintaining a high consistency of 86.12%

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while delivering a satisfactory RPD of 1.81. Therefore, the model with three latent factors was prioritized as the most reliable.

The improvement observed after MSC preprocessing indicates that this method effectively reduces signal variability unrelated to the sample composition, such as differences in the sample structure and measurement conditions. By correcting additive and multiplicative distortions, the MSC enhances the information relevant to the moisture content. The relationship between the predicted and measured values obtained from the three-latent-factor MSC model is illustrated in Figure 4. The distribution of data points around the 1:1 regression line indicates a reasonable agreement, which is consistent with the dielectric properties of water in biological tissues (Brantlov et al. 2025).

Table 2. Performance of PLS models for moisture prediction.

Treatment	Factor	R^2	R	SEC (%)	SEP (%)	CV (%)	RPD	Consistency (%)
Original	6	0.63	0.80	10.02	11.41	24.67	1.59	87.83
	7	0.60	0.78	8.40	11.63	25.13	1.56	72.26
Baseline	6	0.63	0.79	10.01	11.45	24.99	1.58	87.43
	7	0.61	0.78	11.19	11.70	25.53	1.54	95.60
Standard Normal Variate	6	0.58	0.76	0.39	0.33	19.76	1.47	118.5
	7	0.52	0.72	0.38	0.34	20.61	1.41	112.3
Multiplicative Scatter Correction	**3**	**0.74**	**0.86**	**4.32**	**5.02**	**11.45**	**1.81**	**86.12**
	4	0.73	0.86	2.95	4.67	10.64	1.94	63.20
	5	0.75	0.86	2.78	4.58	10.45	1.98	62.69

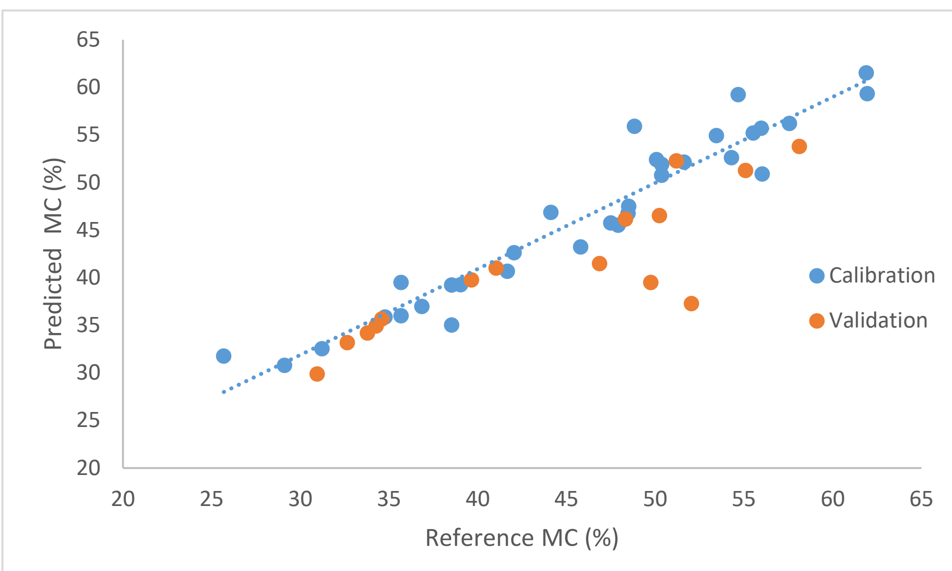

Figure 4. Predicted vs. measured moisture content using the best PLS model (MSC, three factors).

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Based on the RPD value of I.81, the model was classified as having "good" predictive capability according to the criteria established by Bellon-Maurel et al. (2010). However, given the moderate R2 value and inherent heterogeneity of biological materials, these results should be interpreted with caution. While the model successfully captured moisture-related variations, further refinement with an expanded, more diverse dataset is recommended to improve predictive precision.

3.4.2 Oil Content Prediction

The performance of the PLSR models in predicting the oil content is summarized in Table 3. Among the evaluated methods, the MSC method with three latent factors was selected as the most effective and robust. This model achieved an R2 of 0.88, R of 0.94, and RPD of 2.36.

The selection was based on a comprehensive assessment of both the predictive accuracy and model stability. The Consistency parameter was used to evaluate model reliability across the calibration and validation datasets. As shown in Table 3, a trade-off was observed: while the MSC model with four latent factors achieved a higher RPD (2.71), it exhibited low stability, with a consistency value of 62.79%. According to the criteria proposed by Lengkey et al. (2013), the acceptable consistency range for a robust model is 80-110%. Consequently, the four-factor model was deemed to be susceptible to overfitting. Conversely, the MSC model with three latent factors provided a more favorable balance, maintaining a high consistency of 93.84% while delivering robust RPD of 2.36. Therefore, the model with three latent factors was prioritized as the most reliable.

Table 3. Performance of PLS models for oil prediction.

Treatment	Factor	R^2	r	SEC (%)	SEP (%)	CV (%)	RPD	Consistency (%)
Original	6	0.61	0.78	9.05	8.24	27.67	1.56	109.90
	7	0.62	0.79	7.36	9.95	33.41	1.29	73.95
Baseline	6	0.66	0.78	9.06	8.31	28.32	1.56	108.99
	7	0.74	0.86	7.56	7.80	26.58	1.66	96.84
Standard Normal Variate	6	0.87	0.93	0.37	0.43	40.33	2.47	85.96
	7	0.86	0.93	0.37	0.43	40.19	2.48	86.25
Multiplicative Scatter Correction	**3**	**0.88**	**0.94**	**3.60**	**3.84**	**8.75**	**2.36**	**93.84**
	4	0.91	0.96	4.70	7.50	22.34	2.71	62.79

The improvement observed after MSC preprocessing suggests that this method effectively reduces signal variability unrelated to sample composition, allowing the model to capture the changes associated with lipid accumulation in the mesocarp tissue. During fruit maturation, oil accumulation modifies the dielectric properties of tissues by displacing water within the cellular structure. These

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compositional changes influenced the charge distribution and polarization behavior under an alternating electric field, as reflected in the measured capacitance response.

The relationship between the predicted and measured oil content values obtained from the three latent factor MSC model is illustrated in Figure 5. The distribution of data points around the 1:1 regression line indicates a good agreement between the predicted and reference values. Based on the RPD of 2.36, the model was classified as having good to excellent predictive capability (Bellon-Maurel et al. 2010). These results demonstrate that electrical capacitance combined with PLSR modeling holds significant potential for the non-destructive estimation of oil content in fresh fruit bunches of oil palms.

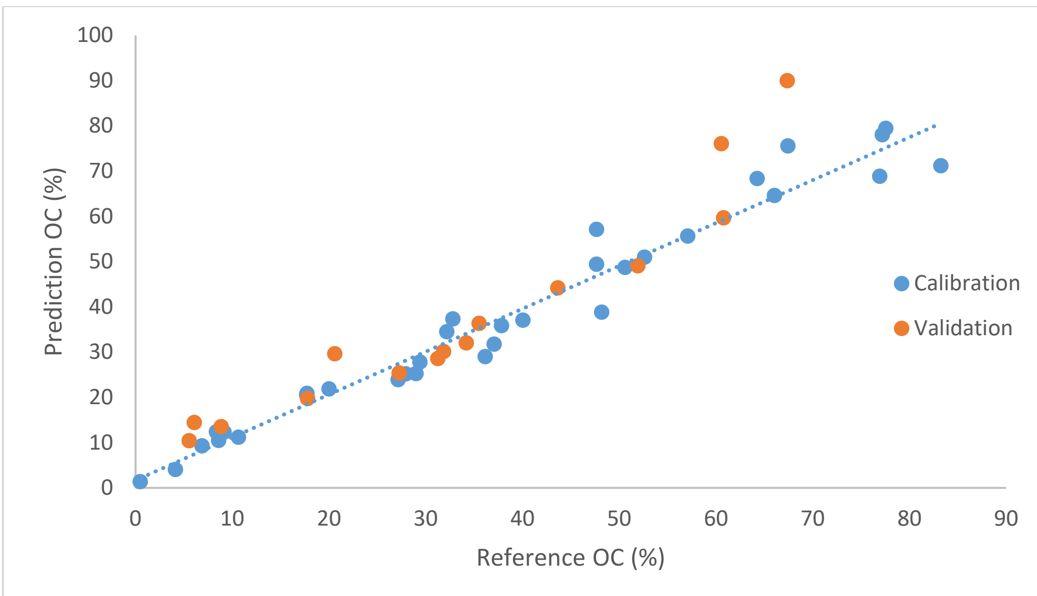

Figure 5. Predicted vs measured oil content using the best PLS model (MSC, three latent factors)

4. Conclusion

This study demonstrated that electrical capacitance combined with PLSR can be used to predict the moisture and oil content in oil palm fresh fruit bunches. Among the evaluated data preprocessing methods, MSC provided the most effective improvement in model performance, yielding the best prediction results for both moisture and oil content, whereas the other preprocessing methods showed variable effects on model accuracy.

The optimal model for moisture content was obtained using MSC with three latent factors, yielding $R^2 = 0.74$, r = 0.86, SEP = 5.02%, RPD = 1.81, and consistency = 86.12%. The optimal model for oil content prediction was also obtained using MSC with four latent variables, achieving $R^2 = 0.88$, r = 0.94, SEP = 3.84%, RPD = 2.36, and consistency = 93.84%.

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These results indicate that electrical capacitance combined with PLSR has potential as a rapid and non-destructive method for chemical quality evaluation of oil palm FFB, particularly for oil content prediction, while moisture content prediction showed limited predictive capability. These findings imply that this approach has strong potential to support the development of rapid, nondestructive, and cost-efficient sensing techniques for the quality evaluation of oil palm fresh fruit bunches.

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6. AI Writing Statement

The authors used ChatGPT (OpenAI) and Grammarly AI to assist with English language editing, grammar correction, wording refinement, and manuscript readability improvement. All manuscript content was reviewed, revised, and approved by the authors, who took full responsibility for the final version of the manuscript.

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