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Determination of the Optimum Harvest Window and Quality Attributes of Oil Palm Fresh Fruit Bunch Using Non-Destructive Shortwave Infrared Spectroscopy

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Abstract. Determination of the optimum harvest window (OHW) plays a key role in the agro-food chain because the quality of fruit depends on the right harvesting time. In palm oil industry, indices based on destructive measurements are used for this purpose, through visual observation of the number of detached fruitlets. In this study, we proposed a reflectance shortwave infrared (SWIR) method for the evaluation of the OHW of the oil palm fresh fruit bunch (FFB), as well as its standard quality attributes. The experiment involved 150 FFBs in five different maturity stages, followed by a biochemical analysis to determine samples' quality indices. Reflectance data of the FFB was studied and correlated to its standard quality attributes (ripeness, oil content, free fatty acids (FFA) level, the deterioration of bleachability index (DOBI), and carotene content) based on oil extracted from its mesocarp. The harvest date, as well as the fruits' quality attributes were modeled using Principal Component Analysis (PCA) and Partial Least Square (PLS). The models showed significant relationships with biochemical changes during FFB maturation and ripening. The investigations showed that the OHW for FFB was indicated by the characteristic drop of reflectance value of certain wavelengths within the SWIR region. Furthermore, the SWIR spectroscopy data could be modeled using PLS regression to determine oil extraction rate (OER), FFA, DOBI and carotene of FFB non-destructively. In this study, five non-destructive evaluation (NDE) models were successfully developed to determine FFB's OHW, OER, FFA, DOBI and carotene by utilizing the SWIR reflectance. The models delivered rapid results with high accuracy and proven to be a time- and cost-saving solution for NDE of FFB.

INTRODUCTION

Indonesia is the largest producer of oil palm since 2006. In 2018, the country contributed 47.437 million tons of the total world oil palm market [1]. Part of the commodity (13.5 million tons) consumed domestically, as edible processed products [1]. In addition, 12.41% of the country's total export are generated from this commodity [2]. Although the plantation area of oil palm in Indonesia reached 16 million hectares in 2018 [1], on average, the productivity is still lower than expected. With only slightly higher than 2 tons of palm oil per hectare [3], there is certainly room for improvement. As an edible vegetable oil, palm oil is extracted from the fleshly part (mesocarp) of the fruit of the oil palms. The mesocarp is a reddish pulp in nature and contain high percentage of the oil [4]. The fruits form a fresh fruit bunch (FFB) and harvested according to visual evaluation [5]. However, even a trained and experienced grader may find difficulties to identify fully ripe FFB.

In an ideal condition, up to 9 tons of palm oil can be derived from every hectare of oil palm plantation [3]. However, accurate determination of optimum harvest window (OHW) for FFB is difficult. Untimely or premature harvest of the FFB is recurrent. It causes the oil to partially accumulate in the mesocarp [5]. The condition is common in Indonesia, due to unskilled labor generally employed in oil palm plantation to reduce the production cost. When oil palm mills received and processed the unripe FFB, the production cost will increase due to lower oil yield [6].

Several methods have been proposed to accurately determine OHW for FFB [4]. Manual inspection is the most common choice. However, human vision has limitation due to the resemblance of unripe FFB with the ripe one [7]. In addition, visual inspection alone cannot properly determine the oil content of the FFB [8]. Furthermore, while

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higher oil yield is desirable, the quality of the oil strongly influences the market price of the palm oil [9]. The quality attributes include the free fatty acids (FFA) level, the deterioration of bleachability index (DOBI), and carotene content of the oil. The yield as well as the quality of the oil currently determined through destructive chemical analysis, which is costly, time consuming, and required significant amount of resources.

Development of nondestructive evaluation (NDE) for quality inspection of food and agricultural products promotes simpler [10] and lower-cost results [11] as compared to chemical analysis. This technique delivers results more rapidly, while still providing acceptable results [12]. Several physical and chemical attributes of agricultural products can be precisely determined using NDE [12-13], particularly when spectroscopic methods are employed [13]. Previous studies suggested that NDE such as visible and near infrared spectroscopy (wavelength at 340-1000 nm) can be utilized for the determination of FFB quality attributes [5, 8]. Nevertheless, it showed some limitation when used to determine multiple parameters particularly FFA, DOBI and carotene level. Other study reported that, short-wave infrared reflectance (SWIR) spectroscopy (1000-2500 nm) could be used to perform simultaneous determination of edible vegetable oil quality parameters in less than a minute [14].

In this study, we developed models for determining oil palm FFB ripeness and quality attributes nondestructively using SWIR spectroscopy. The developed models were used to determine OHW for FFB according to its spectral response. The models were validated using different set of FFB samples.

MATERIALS AND METHODS

The study was performed in the oil palm plantation in west Sumatra, Indonesia (coordinates 0°08'23.7"S 100°00'24.6"E). The oil palm trees were 8 to 10 years old, of the *Marihat* cultivar. The female flowers were observed from anthesis until it fully developed into FFB, then harvested at five different observation-days (120, 140, 160, 180 and 190 days after anthesis (DAA)) [4]. Thirty replications were made for every harvest time-frame. 150 FFBs were used as samples, 100 for model calibration and 50 for model validation. After harvest, the FFB were immediately weighed and sterilized in-situ. The FFB then were re-weighed to measure additional moisture content introduced by the sterilization process. The fruits were gently hand-picked (to avoid damage and bruises) from the FFB, and grouped according to its hemispherical location (apical, equatorial and basal) and relative-position on the spikelet (inner and outer fruits). The fruits then weighed and separated for spectral measurements and chemical analysis. 5 sets of 20 fruits (obtained equally from all FFB parts) then weighed and placed on a 100 mm glass petri dish. An FT-NIR spectrometer (NIRFlex N-500, Buchi, Germany) was used to measure the diffused reflectance (1000-2500 nm) of the fruits. Fruits then rolled 180° to have all fruits' surface recorded. The measurements then replicated 5 times using different sets of samples.

The mesocarps were then separated from the kernel to determine its weight. Mesocarps were dried in 105 °C oven to determine its moisture content. The oil was then extracted from the mesocarps using butt and Soxhlet extraction apparatus. The oil extraction rate was determined according to Makky *et al*. [8]. The oil quality attributes (FFA, DOBI and carotene) were determined according to these standard methods [15], [16] and [17], respectively.

The recorded spectral data were pretreated using three smoothing point [18]. Principal component analysis (PCA) was used to identify principal components [19], coefficient and loading score for grouping the FFB according to its spectral data and harvest time. Furthermore, partial least square (PLS) regression used to calibrate models for determination Oil Content, FFA, DOBI, and carotene according to the spectral data. The models calibrated using 2/3 of the samples and validated by the rest of 1/3 samples.

RESULTS AND DISCUSSION

The physicochemical characteristic of the FFB samples is presented in Table 1. From the observation, the physical properties such as color, shape and dimension between unripe and ripe FFB were visually similar. OER, DOBI and carotene of oil in mesocarp were influenced by the FFB development stages (Figure 1). In addition, FFA only significantly increased when the FFB was over-matured, suggesting rapid senescence process at this stage.

TABLE 1. The physicochemical attributes of FFB as observed according to the occurrence of Anthesis

			Oil Content (OER %)		FFA (%)		DOBI		Carotene (ppm)	
Observation	**Samples**	**Ripeness**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
120 DAA	30	Under Ripe	4.391a	2.546	1.031a	0.651	0.734a	0.033	157.860a	87.323
140 DAA	30	Unripe	15.610b	3.614	1.130a	0.618	0.998a	0.205	327.199b	69.611
160 DAA	30	Unripe	20.481bc	4.450	1.270ab	0.552	1.944b	0.959	455.934b	109.467
180 DAA	30	Ripe	23.433c	10.036	1.213ab	0.740	3.092c	0.255	758.913c	126.675
190 DAA	30	Over Ripe	21.130bc	6.419	1.591b	0.562	1.528a	0.573	415.849b	80.077

^{z} Means followed by the same letter within column are non-significant at P = 0.05 by Duncan's multiple range tests.

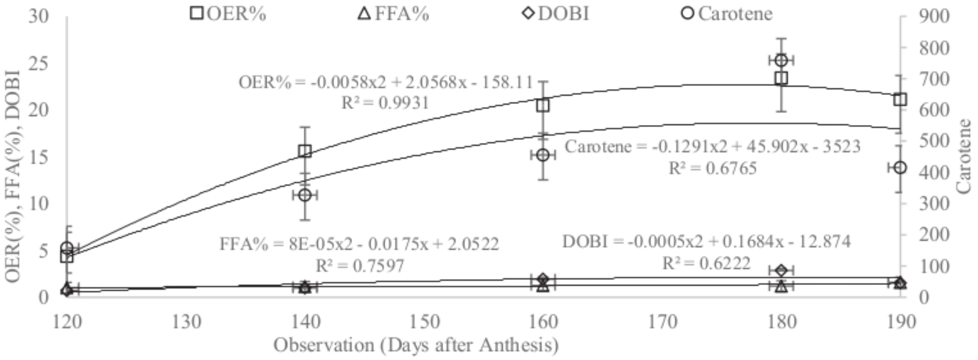


FIGURE 1. Progress of chemical properties in the mesocarp's oil of the FFB according to its aging process

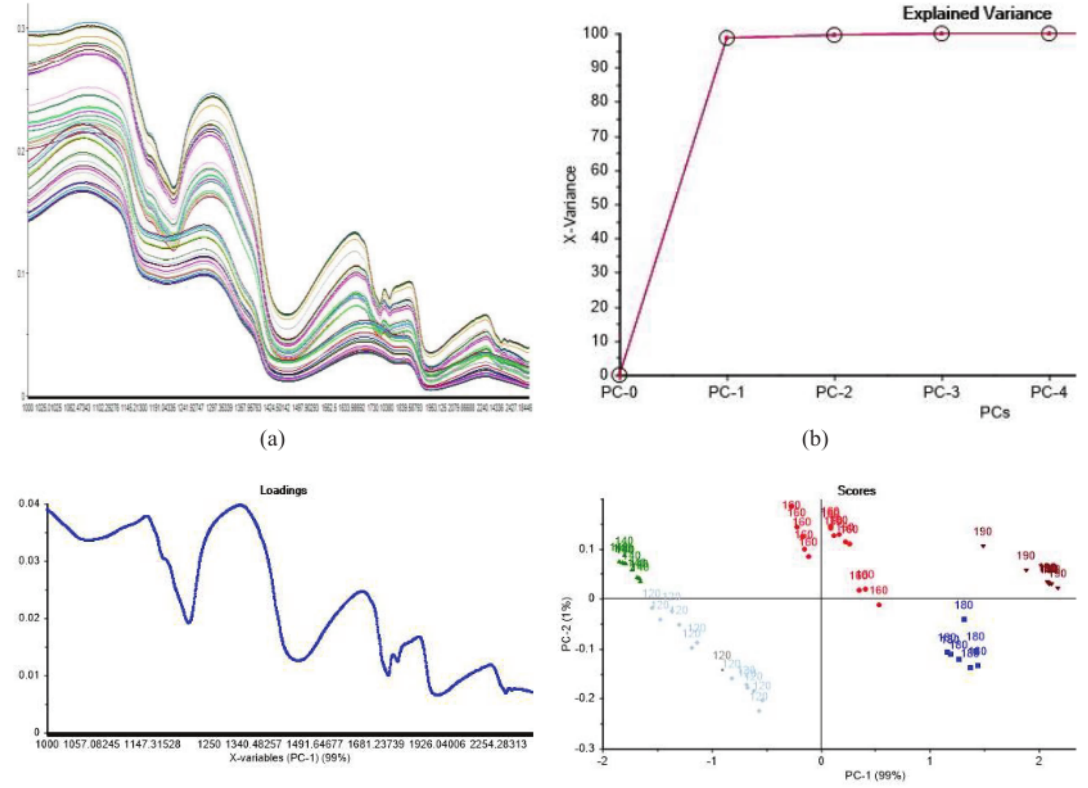
The oil palm FFB started to develop immediately after the mantled pistillate flower anthesis [20]. Female flowers inflorescenced at anthesis, after the opening of its peduncular bract and prophyll [21]. The female rachillae carried pistillate flowers at maturity, with exposed stigmas, which immediately followed by pollination [21]. During initial development stage, the fruits mesocarp contained high moisture and chlorophyll [4]. The kernel was small, and its shell was still liquid. Along the aging process, oil started to form in the fruits mesocarp, replacing the water. The carotene, a distinctive pigment in the oil, influenced the color of the fruits [8]. With the accumulation of oil and carotene in the mesocarp, the fruit exocarp color became redder [7]. The aging fruit hardened the shell protecting the kernel which was now rich in oil.

The OHW for harvesting the oil palm FFB was when the pulpy mesocarp was saturated in oil [4]. While visually impossible to determine when exactly the mesocarp saturated with oil, spectroscopy evaluation of the fruits could provide valuable information, showing indication of oil concentration in this part. Spectral response of the fruits as recorded by FT-NIR (1000-2500 nm) spectroscopy showed that (Figure 2), developmental stages of the FFB could be differentiated through PCA. The method successfully grouped the FFB according to its age using the raw diffused reflectance spectral data.

The PCA statistical procedure used orthogonal transformation to convert the raw diffused reflectance spectral data (Figure 2a) of the FFB into several linearly uncorrelated principal components. From 150 FFB samples with 1500 spectra variables, the number of principal components (PC) determined by the PCA were 4 (Figure2b), explaining more than 99.99% of data variance. The transformation was defined in such a way that the first PC (PC-1) had 98.8 possible variability in the data and succeeding PCs in turn had lesser variance under the constraint that it was orthogonal to the preceding components.

The PCA was used as a tool to explain raw spectral data for making predictive models of FFB age. The loadings were a set of weight by which each standardized original spectral data was multiplied to get the component score. In this analysis there were 10 distinguished loadings weight (eigenvectors) for spectral wavelength of 1051, 1140, 1212, 1313, 1450, 1639, 1728, 1850, 1932, and 2199 nm. The eigenvectors were 0.0336, 0.0378, 0.0192, 0.0398, 0.0126, 0.0247, 0.0100, 0.0168, 0.0066, and 0.0118, respectively (Figure 2c). Plotting the component scores of two confusion PC (PC-1 and PC-2) in principal axes, resulting in a five distinctive groups membership of the FFBs in relation to its age upon harvest. The groups distinguished FFB spectral data harvested at 120, 140, 160, 180 and 190 DAA (Figure 2d).

The PCA results depended on the scaling of samples raw spectral data. The PCA could not further apply to describe the quality attributes of the FFB (OER, FFA, DOBI, Carotene) since it was limited by assumptions made in its derivation. The PCA had another limitation where the signals were non-negative. The mean-removal in PCA process would force the mean of some spectral data to be zero. Consequently, the data became unphysical negative fluxes. Furthermore, forward modeling had to be performed to recover the true magnitude of the spectral signals.

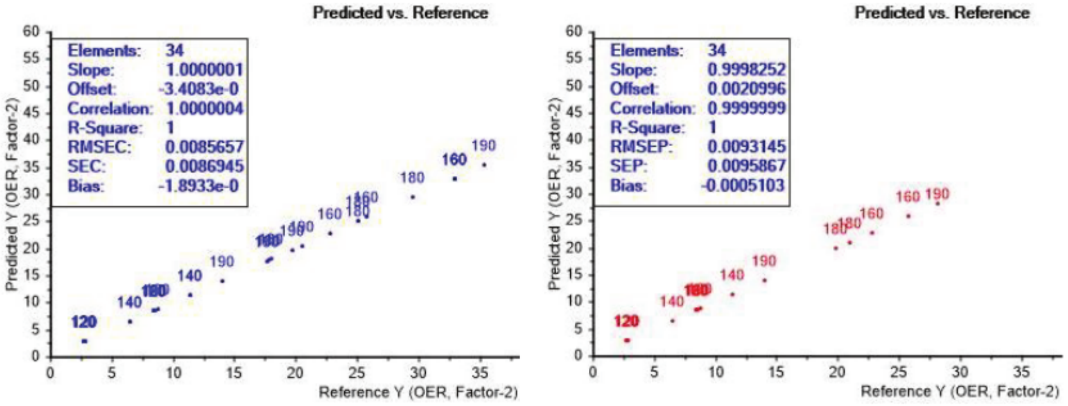


(a) (b)

(c) (d)

FIGURE 2. The figure of (a) and (b) show raw spectral data indicating differences FFB respond according to its maturity. and the coefficient of spectrum in relation to the wavelength. (c) the PCA grouping the FFB according to its age and (d) the identification of OHW

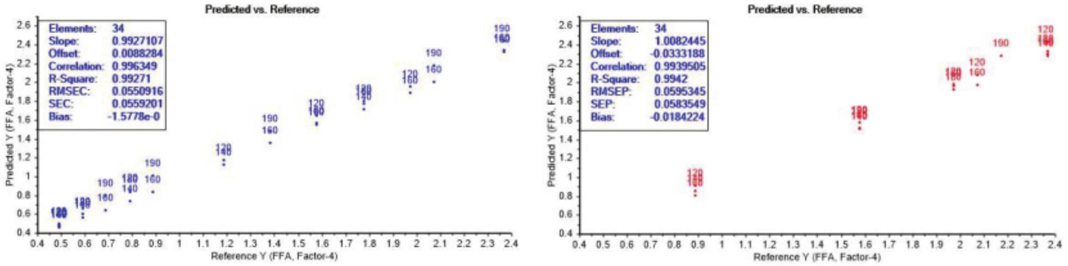
Since PCA had design limitation for modeling oil palm FFB quality attributes (OER, FFA, DOBI and carotene), the partial least squares (PLS) regression was used to develop the models. PLS was a statistical method which had certain corresponding to the PCA. The PLS was widely used in chemometrics [22], bioinformatics [23], senso-metrics, and neuroscience [24]. The PLS worked by finding linear regression model, then projecting the predicted FFB quality attributes with the attributes measured by chemical analysis. The projection placed into a new space, correlating the input and dependent variables instead of finding hyperplanes for explaining maximum variance between them. The PLS was utilized to explained fundamental relations between FFB diffused spectral response in NIR region (1000-2500 nm) with its quality indices. The latent variable approach of the PLS modeling identified the covariance structures inside the multidimensional direction. In this study, the number of measured samples were less than the recorded spectral variable. This condition in nature was better suited for PLS regression analysis as compared to the standard regression. The latter often failed to establish acceptable models in similar situation.



(a) (b)

FIGURE 3. The FFB OER as modeled by PLS regression showed (a) high correlation and consistent results upon model calibration and (b) model validation

For modeling the FFBs' OER, the PLS introduced two latent factors which explained 99.99% of variance in the FFBs' diffused reflectance near infrared spectroscopy. The calibrated model produced correlation and coefficient of determination of 1 with RMSEC and Bias of 0.0085657 and -0.18933, respectively (Figure 3a). The results were better than previous study [8]. With the regression slope of 1 the calibration model minimized the offset between predicted and measured results. Using the rest 50 data samples (1/3 of data) the OER model was validated. The results suggested that the model obtained better accuracy and consistency then the previous one [7]. The validation results (Figure 3b) produced correlation and coefficient of determination of 0.99 and 1, respectively. Model's RMSEP was 0.0093145 and its bias was -0.0005103. upon validation, model's produce offset of 0.0020996 with regression slope of 0.999. The slight difference between calibration and validation results was small, thus, neglectable.



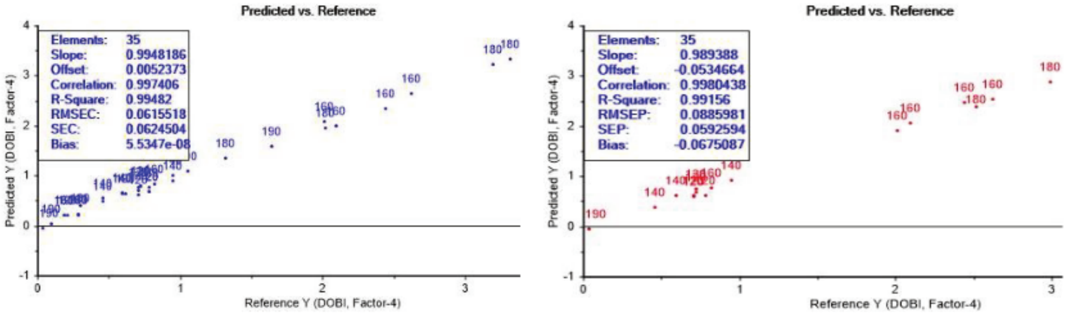
(a) (b)

FIGURE 4. The (a) model calibration and validation, and (b) high correlation with consistent results as modeled by PLS regression

The quality attribute for oil extracted from FFB, among other, was FFA. The FFA model, established by PLS, produced high-performance results. The model used 100 FFB samples as calibrator (Figure 4a) and another 50 samples for model validation (Figure 4b). Model's correlation and coefficient of determination, both in calibration and validation, obtained a number greater than 0.99. The results indicated a highly accurate and consistent model. Model's RMSEC and RMSEP was 0.055 and 0.0595, with bias of -0.15778 and -0.0184 for calibration and validation results.

The model's projection (slope) for predicting the FFA was 1, while the results offset could be ignored. 6 latent factors were introduced by the PLS to develop the model. These factors explained more than 99.9% of variance from the variables.

DOBI was another quality index of the oil extracted from FFB. Crude palm oil (CPO) extracted from FFB normally traded with several quality attributes (FFA, moisture, and impurities). The quality of CPO also had to meet good merchantable quality (GMQ). Although DOBI was not included in CPO quality specifications, the ease to bleach the oil was considered as an indicator of GMQ. Most of CPO processed into refined, bleached and deodorized (RBD) products. Analysis of FFA and DOBI could provide a good indication of the oxidative status of CPO as well as its ease in processing. Palm oil with DOBI of 2.99 – 3.24 could be considered as good [25]. Higher DOBI number indicating excellent oil quality, while poor oil had 2.3 or lower DOBI [25]. The main causes of a low DOBI in oil extracted from FFB was the entrainment of under ripe and unripe FFB in the milling line. Other causes such as delay in processing (especially during rainy season), contamination of CPO with sterilizer condensate, oxidized sludge oil, prolonged sterilization of FFB and overheating CPO (> 55 °C) in the storage tank, might also contribute to lower DOBI. However, these causes were less significant compared with the FFB quality. The black FFB bunch had oil with the lowest DOBI, while the ripe FFB had the highest DOBI. The oil extracted from FFB with optimum ripeness could have DOBI greater than 3.5 [25]. In practice, DOBI higher than 3.0 could be achieved with improvement in harvesting, particularly having the FFB harvested in OHW [26].



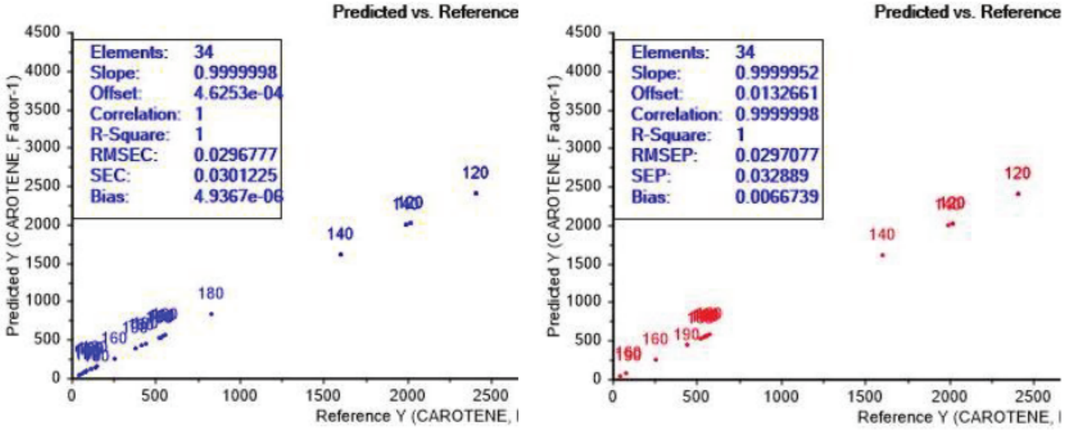
(a) (b)

FIGURE 5. The (a) model calibration showing strong correlation with validation of the model and (b) consistent results as modeled by PLS regression.

Using raw diffused reflectance spectra data of the FFB as recorded by spectrometer, the FFBs' DOBI were regressed by PLS to model its attributes correlation. The DOBI model established using 100 FFB samples as calibrator (Figure 5a) and another 50 samples for model validation (Figure 5b). Correlation and coefficient of determination of DOBI model, in calibration and validation, obtained a number greater than 0.99. The model's RMSEC and RMSEP were 0.06155 and 0.0886, with bias of 5.5347E-08 and -0.0675 for calibration and validation results. The model's projection (slope) for predicting the FFA was 0.99, with relatively small offset. 5 latent factors were introduced by the PLS to develop the model. These factors explained more than 99.9% of variance from the variables.

Carotene content was also an important quality control parameter for CPO. Palm oil was the richest source of natural carotenes. The β-Carotene and α-Carotene comprised of 91% of carotenoids (500–700 ppm) in CPO [27]. The major carotenes in CPO possessed high retinol, equivalent substrate to provitamin A compound with health benefit [28]. Determination of carotene in oil palm followed a lengthy and complex procedures which include sterilization, extraction and UV-Vis Spectroscopy. In this study, the carotene content of FFB was regressed with its spectral response using PLS analysis. The model's coefficient of determination of 1 in calibration and validation results (Figure 6) indicates that the PLS regression predictions perfectly fitted the data. The coefficient of determination was a statistic that inform how good the model fit the data. It was measure of how well the regression predictions approximate the real data points.

Residual was a measure of how far from the regression line data points are while the Root Mean Square Error (RMSE) was the standard deviation of the residuals (prediction errors). to measure of how spread out these residuals were. The RMSE was used in PLS regression analysis to verify the model results. RMSE of more than 25 % of the datum suggested the model was weak [29]. RMSE had direct relationship with the correlation coefficient. When the correlation coefficient was 1, the RMSE would be minimum, since most data points lied on the regression line. In the carotene model, the RMSE for model calibration (RMSEC) was 0.02968 while validating the model using different set of FFB samples delivered RMSEP of 0.0297. With minimum RMSE, the bias of the predicted data point was 4.9367 x 10^{-6} and 0.006674 for calibration and validation, respectively. The slope of model upon calibration and validation were almost 1, suggesting that a change in input variable will deliver similar respond to the prediction results. In addition, only one latent variable was introduced in this PLS regression model.



(a) (b)

FIGURE 6. The carotene content from extracted oil of the FFB samples was. The (a) model calibration showing strong correlation with validation of the model and (b) deliver consistent results as modeled by PLS regression

Oil extraction rates (OER) of the FFB could vary, and influenced by the cultivar, FFB age, number of unrecovered detached fruitlets, plant age, disease infestation, proper fertilization and good plantation practice. In Indonesia, high oil yield was desirable by mills. Mills efficiency depended on how much oil could be recovered from every kg of FFBs. It was important to know the yield for mills quality control. Lower yield increased the production cost and losses. Although in most mills there was an expert team for predicting the yields, nonetheless, in general, the prediction was based on generic calculation from previous processes. Therefore, prediction often differ from the actual results, as high as 15% [13].

Aside from volume, the mills need to determine the oil quality. It was strongly correlated to the market price and consumer safety. Fruit quality also significantly affects the OER performance of the mill. The quality of FFB gave the greater impact to the performance of OER produced. In general, the average OER in Indonesian mills were quite varied. However, many individual mills have obtained more than 20% OER [30]. In times of low prices of crude palm oil (CPO) as seen in the year 2018, producers were challenged to improve the performance of OER as this measurement was a management tool in assessing the profitability of a plantation enterprise.

Palm oil quality and price were dependent on the FFA content in palm oil. High content of FFA in palm oil affect the quality of palm oil and leads to various health and environmental issues. The maximum FFA content set by the Indonesian Palm Oil Association in CPO was 5%. The traditional method for determination of FFA in palm oil was through titration of the sample against potassium hydroxide in hot 2-propanol solutions by using phenolphthalein as indicator. In this study, a robust and rapid SWIR spectroscopy method was introduced for determination of FFA in palm oil is through

The FFA in palm oil determined the quality of the oil itself. Oils that are high in FFA content had poor quality and suffer significant losses during terminal process [31]. Low FFA content in CPO produced good physicochemical properties of oil products and could be useful for industrial applications. The production of FFA was performed through the hydrolysis of fatty acid during FFB milling. In addition, FFA was also released naturally in CPO and could be produced due to the action of enzyme (mainly lipase) in the palm fruits. Moreover, the damaged FFB might increase the FFA, thus affecting the quality of palm oil. An endo-genus lipase known as triacyl glycerol acyl hydrolase found in oil palm fruits [32].

The DOBI was one of the key indicators for CPO quality [33]. Good quality CPO was a pre-requisite for production of high-quality final products. A high DOBI was essential as this enabled milder processing conditions to be used for refining [26]. Mild processing conditions minimized the formation of trans fatty acids during deodorization and enabled more of the natural antioxidants (tocopherols and tocotrienols) to be preserved in the final refined oil [34]. Thus, it was important for refiners to know the quality of incoming CPO. Quality of CPO could be described by many well-established oxidation parameters, but the deterioration of bleach ability index or DOBI was the most reliable tool to predict the ease of refining [33]. The DOBI value allowed refiners to establish the required amount of bleaching earth for refining the oil to acceptable color to consumers and food manufacturers [25]. Excellent quality of CPO would have DOBI above 3.24 [25]. The DOBI value of oil extracted from dry heated oil palm fruits was higher than 3.80 [25]. Palm oil was one of the richest sources of natural carotenoids and had the highest known concentration of agriculturally-derived carotenoids [27]. The palm carotenoids concentration varied depending on the species. CPO from *Tenera* had a carotene content of 500 – 700 ppm [27]. The *Tenera* palm carotenoids consist of 91% α-and β-carotenes (including cis and trans) [27]. These major carotenes possessed high provitamin A activity. Carotenoids also possessed other important physiological properties. Consumption of carotenoids reduced the risk of cancers and diabetes and protecting human from ultraviolet light-induced erythema [28].

CONCLUSIONS

In this study, the PCA was used to model the FFB ripeness, indicating that the optimum ripeness of FFB could be determined by evaluating the fruits using SWIR spectroscopy. The procedure could be performed using NDE approached, with good results. Using this model, the OHW for harvesting FFB could be determined accurately with good reproducibility. The SWIR spectral response of the FFB positively correlated with the concentration of oil in the fruits mesocarp. Therefore, in addition to ripeness, the oil content (OER) of the FFB could also be modeled by PLS regression using its SWIR reflectance with good result. Since the SWIR responded linearly with the oil in fruits mesocarp, the oil quality could be determined using the similar procedure. Moreover, this study successfully established SWIR diffused-reflectance-based PLS regression model for FFB quality attributes such as FFA, DOBI and Carotene. All five models produced good accuracy and reproducibility when used for NDE of FFB from Marihat cultivar. The models' validation was performed to confirm that processes and activities intended to verify that models were performing as expected, in line with model objectives. So far, potential limitations of the models could not be encountered. The validation performed by FFB samples independent of model development.

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