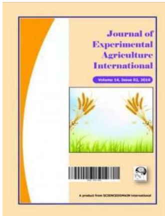

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Application of Spectroscopy for Nutrient Prediction of Oil Palm

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Authors' contributions

This work was carried out in collaboration between all authors. Author HAJJ designed the study, performed the statistical analysis, wrote the protocol and the first draft of the manuscript. Authors NMN, VJR and XA managed the analyses of the study. Authors WIWI and ARMS contributed with minor corrections. All authors read and approved the final manuscript.

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ABSTRACT

Oil palm crop has been an important source of income to Malaysian economy, thus it is important to ensure the crops obtain optimum nutrient supply to achieve a higher productivity. This study aimed to investigate the ability of near-infrared reflectance spectroscopy for predicting nutrient deficiency of oil palm tree based on its leaf samples. Near-infrared spectral data was measured using a full range spectroradiometer with wavelength ranging from 350 to 2500 nm from three different frond numbers, namely frond 3, frond 9 and frond 17. Partial least square method was used to develop calibration and prediction models data for the prediction of nitrogen, phosphorus and potassium of oil palm. The result indicated that the full range spectrometer can be used to predict the nutrient deficiency of oil palm tree based on 30 leaf samples. Frond 17 was found to have a better prediction accuracy than frond 3 and frond 9. The value of coefficient of determination (R^2) for frond 17 for values of nitrogen, phosphorus and potassium of 0.98, 0.98 and 0.98 while frond 3 results with 0.21, 0.12 and 0.19 and frond 9 had values of 0.05, 0.49 and 0.48 respectively. In terms of Root Mean

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Square Error of Prediction for frond 17 ranged between 1.40 and 1.55 while frond 3 and frond 9 ranges from 0.01 to 0.15 and 0.01 to 0.21 respectively. In summary, spectroradiometer can be used to predict nutrient deficiency in oil palm frond frond17 using partial least square analysis.

Keywords: Oil palm; nutrients; deficiency; spectrometer; partial least square.

1. INTRODUCTION

Oil palm (*Elaeis guineensis Jacq.)* which originates from West Africa [1] is a lucrative commercial crop which is mainly cultivated in countries such as Nigeria, Malaysia and Indonesia, the latter two being the largest producers and exporters [2]. Palm oil has become a very important crop with its wide uses not only in the food industry but cosmetics and pharmaceuticals as well, making it crucial that palm oil yield is maximised in all possible ways. A healthy palm is necessary to maximise yield, and it is possible to maintain good healthy palm through regular application of fertiliser.

In general, fertilizers account for about 40-50 percent of the in-field production costs in the oil palm industry [3]. However, since the fertiliser cost is increasing, the industry is aiming to optimize the use of fertilizer for sustaining high yields and profits per unit area through balanced fertilization and improved fertilizer efficiency [4]. Hamdan et al. [5] studied the effects of Nitrogen (N), Phosphorus (P) and Potassium (K) fertilizers on oil palm bunch components and found that a lack of N could significantly affect the number of bunch, bunch weight and total oil per bunch. In short, the deficiency symptoms of N include pale gree or yellow lower fronds, purplish brown leaflet tips and reduced fronds and yield; K symptoms are chlorotic and necrotic spots on older fronds, orange spotting, small frond size and late crowning; P symptoms include stunted growth, small diameter of palm trunk and short fronds [6]. This finding signifies the importance of regular fertiliser application for best results in its productivity and yield Nevertheless, application of fertiliser is very costly with high yearly maintenance, thus precision agricultural practice [7] was introduced to minimise wastage and cost by only applying the required amount of nutrition for the palm tree [8]. In this way, wastage of fertiliser can be avoided. In order to apply only the required amout of fertiliser, the actual amount of fertiliser needed by crop need to be studied. In the plantation industry, nutrient requirements are commonly determined by obtaining a part of the palm for chemical analysis, which uses destructive methods and is very much time consuming.

Non-destructive methods should replace the conventional destructive analysis method to determine the nutrient level and this can be accomplished by using spectroscopic method [9]. The spectrometer takes spectral radiance measurements of study object to learn about its properties without destroying it. This unique ability of spectrometer has become a tool for data acquisition in all kinds of field including the agricultural field. Its application on agricultural products is important to achieve a non-destructive method to determine properties of the agricultural product. This includes the usage of spectrometer to determine taste characterization of Valencia oranges [10] and sugar content in sugarcane internodes [11].

Spectrometer is also widely used for palm oil in various applications. CheMan and Mirghani [12] applied the spectroradiometer to determine the moisture content in crude palm oil while Ammawath et al. [13] used the infrared spectrometer to determine Butylated Hydroxytoluene (BHT) in palm olein and palm oil with known levels, and also to determine iodin levels in palm oil [14]. Besides that, it can also be used to detect diseases in palm tree, such as Ganoderma [15,16].

This study focuses on the application of spectrometer to determine nutrient deficiency in oil palm trees based on reflectance data of leaf samples. The specific objectives of the studies were to investigate the feasibility of using spectrometer 1) to determine N, P and K prediction with statistics analysis using Partial least square (PLS); also 2) to compare nutrient levels of different fronds, samples frond 3 (F3), frond 9 (F9) and frond 17 (F17) [17,18].

2. MATERIALS AND METHODS

2.1 Leaf Samples

Different aged palm tree has different levels of critical deficiency content (CDC) of nutrients at which maximum yield is obtained [19]. For a start, leaf samples were taken from 5 year old oil palm trees at the United Plantation (UP) farm situated at Jenderata, Teluk Intan, Malaysia. Twenty palms had no N fertilizer application with partial application of P, while 10 remainder palms had no aplocation of P with partial levels of N. All 30 palms had other nutrient application in the normal levels. A normal oil palm tree has between 40 and 60 fronds. However, in this study, there were three fronds of interest from each tree, namely F3, F9 and F17 [17,18]. A total of 30 samples were taken for each frond type, in accordance to the leaf sampling unit (LSU) palm system [6,20].

The F17 has been the main choice for nutrient assessment was based on pioneer researches as good representation because it is the center frond of an oil palm tree [21,22,23]. Furthermore, F3 and F9 were selected to represent as control for this experiment since both the fronds were usually used in occasional leaf analysis for micronutrients representations for palms below age of 3 years [17,6]. A comparison was later done in another experiment between palm of 5, 10 and 20 years old for frond 17 as it's the only frond that was consistently available for palm of all three ages. Palm of age 5 years was selected because after the age of 6 and above, nutrient variation are minimal due to an established canopy, however this age is crucial since a healthy palm tree starts to fruit after 3 years old.

Leaf sampling indicates nutritional status of the crop while soil sampling determines nutrient availability and supply [22]. Therefore, leaf sampling is the subject of interest. A sum of 30 leaf samples of each fronds (F3, F9 and F17) were randomly collected from 30 trees [20]. Both left and right leaflets from the mid-section of the oil palm fronds were cut for scan as in Fig. 1.

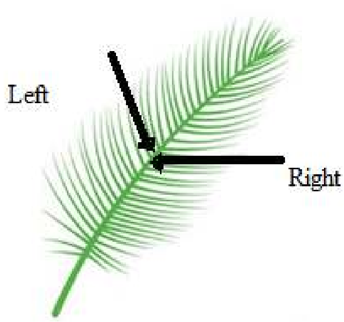

Fig. 1. Oil palm frond mid-section

Since the leaflets were exposed to harsh weather conditions, its cuticles were filled with dirt and moss. Hence, there is a cleansing step required prior to commence of data acquisition using the spectroradiometer, to reduce errors. The cut leaflets were cleansed with a clean piece of cloth that was dipped into distilled water. Only a slight pressure was applied on the leaflet during the cleansing action to ensure its cuticles and upper epidermis was unharmed. Then, each leaflet were scanned from the top at its mid-section. Once the reflectance data was acquired from leaflets using the spectroradiometer, they were bagged individually and placed in a cooling storage box to reduce biological activity changes before they were taken to the laboratory (2 to 8 km away) for a conventional chemical analysis [24].

2.2 Spectral Reflectance Measurements

The device used for data acquisition was the Analytical Spectral Devices (ASD) Fieldspec 4, a full range spectroradiometer (FRS) that has wavelength from 350 to 2500 nm which provides uniform visible (vis), near infrared (NIR) and short wave infrared (SWIR) manufactured by Boulder, US. This device is equipped with superior signal throughput, signal-to-noise, and radiometric performance; this device ensures data integrity in unpredictable atmospheric conditions with wavelength accuracy of 0.5 nm and wavelength reproducibility of 0.1 nm.

A total of 10 readings were taken (which was then averaged into one) facing the upper epidermis of each leaflet at its midsection. The left and right side readings were also averaged into one reading per frond. Theoretically, one oil palm tree (same target) will have three observations (F3, F9 and F17). Measurements were easily taken using a clip-on probe with very high accuracy for non-destructive functionality of live oil palm leaflet, that scans in just 100 milliseconds with 1000 W quartz-halogen lamp and highly regulated power supply, there is no room for imparity. This device was used to obtain the reflectance spectra of oil palm leaves [25]. Relative reflectance spectra were computed by dividing sample radiance with reference radiance from spectral on white reference panel (made of Labsphere Spectralon plaque) for each wavelength. All spectral data were transformed into ASCII format and processed using the View Spec software for Windows, designed with Graphical User Interface (GUI) [26].

2.3 Pre-processing Method

Before starting on the PLS analysis, 50 nm of the first and last data points were removed from the original reflectance spectra to avoid noise interruption, resulting in 400 nm to 2450 nm region of wavelength [27]. The spectral data was then tested for pre-processing for optimal performance including the Multiplicative Scatter Correction (MSC), first and second derivatives and Standard Normal Variate (SNV), Gaussian Filter, normalisations and Savitzky Golay Smoothing with Multiplicative Scatter Correction (MSC) being the best pre-processing technique for this study [28].

All the types of pre-processing techniques were tested with a few types of possibilities for instance area, range maximum and mean normalization were explored to seek for the best method of pretreatment. The PLS was performed to build the calibration and validation models for all three fronds. To evaluate among the pre-processing techniques, coefficient of determination (R^2) value and root mean square error of prediction (RMSEP) of the PLS model were taken into consideration [10]. As a result, multiplicative scatter correction (MSC) was found to be the best pre-processing technique for this study.

2.4 Statistical Analysis- Partial Least Squares

In general, PLS regression reduces the predictors to a smaller set of uncorrelated components and then performs least squares regression on these components, instead of on the original data. In PLS regression, emphasis is given in developing predictive models. PLS regression generalizes and combines features from principal component analysis (PCA) and multiple regression (MR) to predict or analyse a set of dependent variables from a set of independent variables or predictors.

This prediction is achieved by extracting from the predictors a set of orthogonal factors called latent variables (LV) which consist of the best predictive power. Before developing the calibration models, the sample data was randomly divided into calibration set (75 % of the whole samples) and prediction set (25 % of the whole samples) [29]. PLS regression constructs an orthogonal basis of LV, in such a way that they are oriented along directions of maximal covariance between the spectra matrix X and the response value Y [10,30]. The maximum number of LV was set at 10 after experimenting with 7 and 13 [31]. Results of any number higher than this did not represent the actual data.

Samples for prediction models were selected by taking one of every four samples from the entire sample set, to ensure the entire range of data was covered, mainly because the data consist of different nutrient treatments [29]. Then PLS with full cross validation was used to evaluate quality and prevent over-fitting of graph to obtain the calibration models while the prediction set evaluates the models. All three fronds (F3, F9 and F17) had 30 samples each where 23 samples were used for calibration while 7 samples were used for prediction. One (5%) outliers were removed from the sample group as suggested by the PLS model results to generate calibration and prediction model that better represent the data from the sample group.

The statistical software program for multivariate calibration called the 'The Unscrambler' (version 10.2, Camo Process AS, Oslo, Norway) was used to perform pre-processing and model developments. Two statistical parameters of Root Mean Square Error of Prediction (RMSEP), and coefficient of determination (R^2) were used to measure the performance of the three types of calibration and prediction models.

3. RESULTS AND DISCUSSION

The Fig. 2 shows spectral curves for 30 oil palm leaf samples for F17 of 5 year old oil palm tree, in the range of 400-2450 nm. The spectral graph shows the shape of leaf reflectance taken from the top of each leaflet. Wavelength with the range of 640 to 780 nm indicates the chlorophyll content of green leaf [32]. The higher reflectance lines shows leaves with less moisture contents while the lower lines shows leaves, having higher moisture contents, especially in the SWIR (1300 nm to 2500 nm) region [33].

Table 1 shows the performance of PLS regression prediction models for frond number F3, F9 and F17 of oil palm leaf samples. The data has been pre-processed using MSC, selected as the best method for these range of data. There are three macronutrients of interest namely N, P and K. It was observed that the prediction value indicated by R^2 is the highest for all three nutrients for F17 compared to F3 and F9.

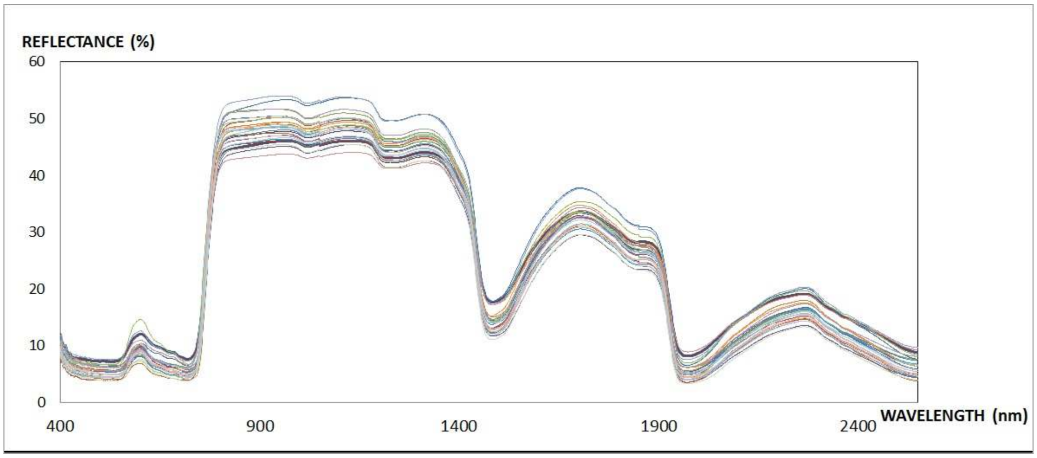

Fig. 2. Typical spectral curve of oil palm reflectance of F17, using full range spectroradiometer

Table 1. PLS with MSC model performance for N, P and K of F3, F9 and F17

Wave-length (nm)	Frond 3 (F3)				Frond 9 (F9)				Frond 17 (F17)			
	Calibration		Prediction		Calibration		Prediction		Calibration		Prediction	
	R^2	RMSEC	R^2	RMSEP	R^2	RMSEC	R^2	RMSEP	R^2	RMSEC	R^2	RMSEP
N	0.82	0.05	0.21	0.15	0.91	0.04	0.05	0.21	0.94	0.02	0.91	0.34
P	0.95	0.00	0.12	0.01	0.96	0.00	0.49	0.01	0.79	0.00	0.72	0.00
K	0.95	0.01	0.19	0.06	0.95	0.01	0.48	0.04	0.90	0.01	0.90	0.03

Results from F3 for the calibration were very good as indicated by the R^2 values of 0.82, 0.95 and 0.95 for N, P and K respectively. However, the prediction performance of F3 for N, P and K were poor, with the R^2 representation values of 0.21, 0.12 and 0.19 respectively, although it had a pretty good calibration model. This result indicates that F3 has almost no relationship with N, P and K nutrients.

For F9 of oil palm leaf samples, it was observed that the calibration performance as indicated by R^2 is good for all three nutrients of 0.91, 0.96 and 0.95 respectively with relative low Root Mean Square Error of Calibration (RMSEC) ranging from 0.00 to 0.04. However, the prediction accuracy of the model as indicated by R^2 were lower than the calibration model's results ranging between 0.05 to 0.48, while the RMSEP were slightly higher than RMSEC, ranging between 0.01 and 0.21. These results justifies that in occasional practices, leaf analysis from F3 and F9 are usually selectively used to determine the micronutrients, while F9 is also used for routine leaf sampling for oil palm tree of 3 years and below [6].

Table 1 also shows the performance of both calibration and prediction models for F17 of oil palm leaf samples. From the table, it is observed that the calibration performance as indicated by R^2 were very good for all three nutrients of N and K with values of 0.94 and 0.90 respectively, but slightly low for P with R^2 value of 0.79. The prediction performance results for representation of R^2 value of N, P and K, were 0.91, 0.72 and 0.90 respectively. In addition to that, the results of RMSEC value of F17 were relatively low ranging from 0.01 to 0.02 while the RMSEP values were slightly higher than RMSEC, ranging between 0.03 and 0.34. The lower results for P in both calibration and prediction models indicate that P nutrient is less found in oil palm leaf. Unlike N and K that has obvious deficiency symptoms on oil palm leaves, P deficiency was more clearly seen in stunted palm and decreased trunk diameter, giving rise to tall oil palm trees [6]. The results obtained from F17 for N, P and K showed better results for both calibration and prediction models compared to an earlier studies conducted by Khorramnia [34] with R^2 ranging from 0.58 to 0.69 and 0.12 to 0.46 for calibration and prediction respectively. This study was conducted using similar spectroscopy sensor but produced higher R^2 values most probably because one or two outliers were removed from the sample group according to the feedback obtained from PLS model, thus resulting in better calibration and prediction model.

From the results, it is observed that frond number F17 gave reasonable PLS prediction results compared to F3 and F9 for N, P and K using the spectrometer. This is most probably due to F17 being the frond number close to the mid-section of its palm tree, giving better representation of the whole palm tree, especially in terms of macronutrients. In summary, the FRS proves to provide better prediction of nutrients compared to visible and near infrared range (450-900 nm) and electromagnetic radiation (EMR) sensing system that reported insignificant results for R^2 values on reflectance data for nutrient from oil palm leaves. [20,35]. This is because of the advantage of Fieldspec 4 FRS that comes with a probe that easily clips onto the leaf sample, thus highly reducing environmental errors of sunlight scatter and equipment inadequacy.

Figs. 3, 4 and 5 shows the prediction graphs of three nutrients N, P and K of F17, respectively. In these figures, both the ordinate and abscissa represents the predicted and measured values of nutrients in percentage of dry matter (D.M.).

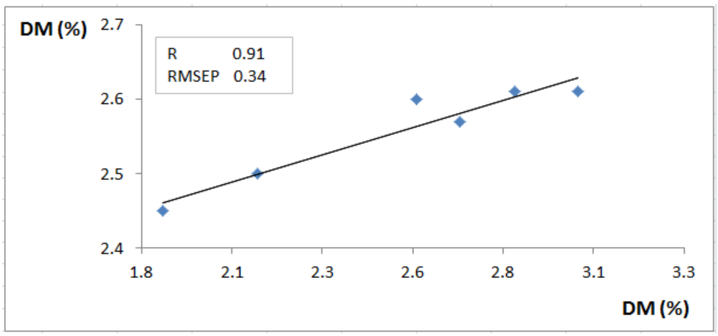

Fig. 3. Scatter plots of F17 for nitrogen for prediction model

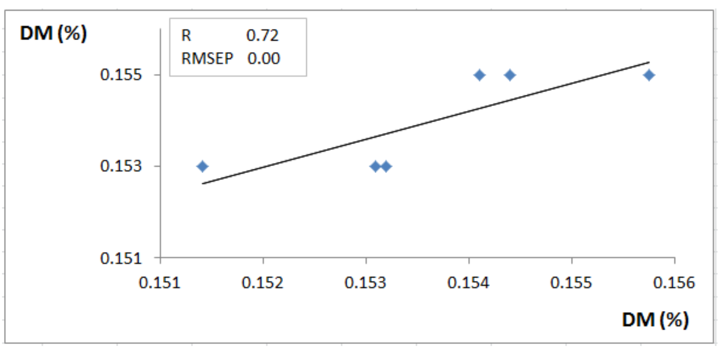

Fig. 4. Scatter plots of F17 for phosphorus for prediction model

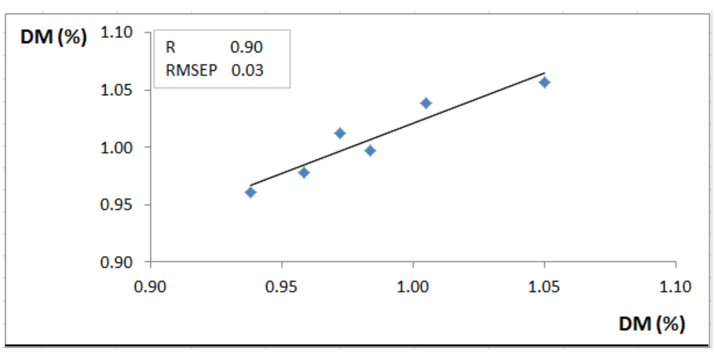

Fig. 5. Scatter plots of F17 for potassium for prediction model

From the results, the F17 shows better statistical relationships to all the three nutrients' prediction value compared to F3 and F9. The F17 has been the main frond used in leaf analysis to detect nutrient level in oil palm tree, as its gives an overall representation of the tree [21,22]. Nevertheless, it was found in this study that different fronds have different levels of nutrients, although they belong to the same tree. This is because of the canopy development which varies the intensity of sunlight radiation exposure of different frond types [22].

In general, the prediction accuracies obtained in this study are not very high, possibly due to variation between the subsamples, reflecting the heterogeneous nature of the oil palm leaflet. The level of nutrient in oil palm tree varies according to many important factors namely the rainfall, soil type, terrain, climate and other environmental factors. However, the nutrient levels can differ substantially although in the same agro-ecological environment as the dry weight of the fronds (F3, F9 and F17) depends on its environment [36,37].

Limited number of samples could also affect the accuracy of the model. Studies with larger sample group of different environmental factors and more type of nutrients is suggested for future studies. And also focus on micronutrients for F3 and F9. It is also proposed to have in-field data acquisition to avoid possible biochemical disturbance of the leaves. Overall, using the spectrometer with larger leaf sample number is suggested to improve the prediction model results.

4. CONCLUSION

As conclusion, this study shows that the spectrometer with PLS models can be applied to predict nutrient deficiency of N, P and K for oil palm from its leaf samples. The results show that the frond number F17 gives better prediction result for N, P and K than other two fronds (F3 and F9) with R^2 and RMSEP values of 0.98 to 0.98 and 1.40 to 1.53 respectively. The F17 have been commonly used in leaf analysis to detect the nutrient level of oil palm tree [20,21,22]. This preliminary study suggests that nutrient deficiency can be determined fairly using spectrometer with PLS regression on F17 of oil palm tree. Spectrometer can be used to encourage non destructive method of analysis which creates a new platform for analysis incorporation for instant in-field results in the future.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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