

Application of Spectroscopy for Nutrient Prediction of Oil Palm

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 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]. Tarmizi 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. 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 [6] was introduced to

minimise wastage and cost by only applying the required amount of nutrition for the palm tree [7]. In this way, wastage of fertiliser can be avoided. In order to apply only the required amount 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 [8]. 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 [9] and sugar content in sugarcane internodes [10].

Spectrometer is also widely used for palm oil in various applications. CheMan and Mirghani [11] applied the spectroradiometer to determine the moisture content in crude palm oil while Ammawath et al.[12] used the infrared spectrometer to determine Butylated Hydroxytoluene (BHT) in palm olein and palm oil with known levels, and also to determine iodine levels in palm oil [13]. Besides that, it can also be used to detect diseases in palm tree, such as Ganoderma [14,15].

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).

2. MATERIALS AND METHODS

2.1 Leaf Samples

Leaf samples were taken from 5 year old oil palm trees at the United Plantation (UP) farm situated at Jenderata, Teluk Intan, Malaysia. 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. The frond samples were randomly collected from 30 trees, resulting to 90 samples in total. Both left and right leaflets from the mid-section of the oil palm fronds were cut for scan as in Figure 1.

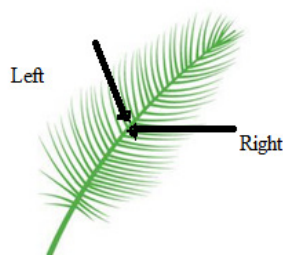


Fig 1: Oil palm frond mid-section

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 [16].

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) facing the upper epidermis. 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. Relative reflectance spectra were computed by dividing sample radiance with reference radiance from spectral on white reference panel for each wavelength. All spectral [17] data were transformed into ASCII format and processed using the View Spec software for Windows, designed with Graphical User Interface (GUI).

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, resulting in 400 nm to 2450 nm region of wavelength. 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 and Savitzky Golay Smoothing, with Multiplicative Scatter Correction (MSC) being the best pre-processing method for this study. Then PLS was performed to build the calibration and validation models for all three fronds.

2.4 Statistical Analysis- Partial Least Squares

PLS regression reduces the predictors to a smaller set of uncorrelated components and performs least squares regression on these components, instead of on the original data. In PLS regression, the emphasis is on 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 [18]. 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). 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 [9,19]. The maximum number of LV was set at ten. Samples for prediction models were selected by taking one of every four samples from the entire sample set, to ensure the entire range of date was covered [20]. Then PLS with cross validation based on 10 segments were used for obtaining 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. 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 calibration and prediction models.

3. RESULTS AND DISCUSSION

Figure 2 shows a typical spectral curve for oil palm leaf samples in the range of 400-2450 nm. In the wavelength range of 400 to 700 nm shows the chlorophyll content of green leaf. The higher reflectance lines shows older more mature leaves with less moisture contents while the lower lines shows newer younger leaves, having higher moisture contents, especially in the SWIR (1300 nm to 2500 nm) region.

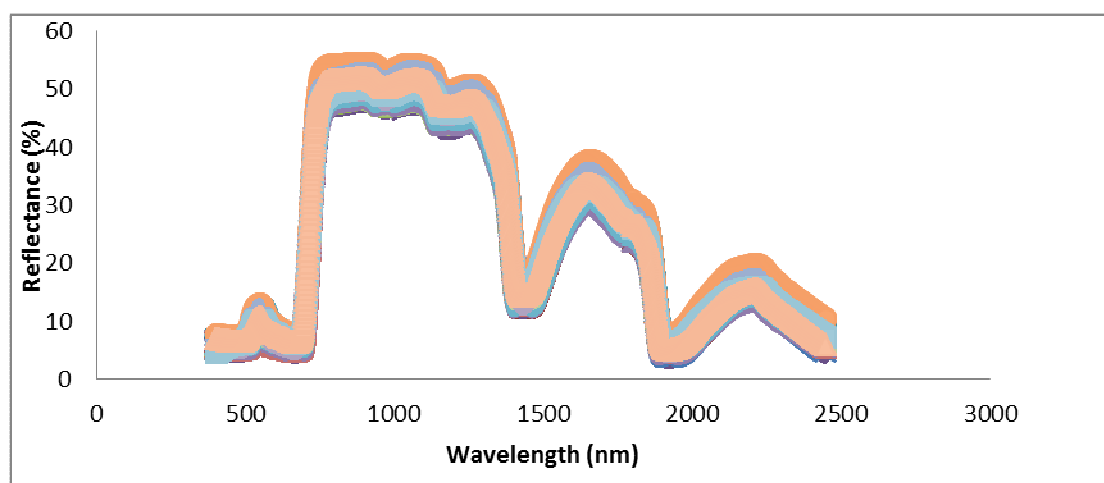


Fig 2: Typical spectral curve of oil palm reflectance of F17, using full range spectroradiometer

Table 1 shows the performance of both calibration and 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 nutrients of interest namely N, P and K.

From Table 1, it was observed that the calibration value indicated by R^2 is the highest for all three nutrients of F17 compared to F3 and F9. F3 has calibration values of N, P and K as 0.82, 0.95 and 0.95 respectively. The prediction performance for N, P and K were poor, for which the R^2 values were 0.21, 0.12 and 0.19 respectively.

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

Wavelength (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	0.8	0.05	0.2	0.15	0.9	0.04	0.0	0.21	0.9	0.20	0.9	1.46
P	2	0.00	1	0.01	1	0.00	5	0.01	9	0.19	8	1.53
K	0.9	0.01	0.1	0.06	0.9	0.01	0.4	0.04	0.9	0.19	0.9	1.40
	5		2		6		9		9		8	
	0.9		0.1		0.9		0.4		0.9		0.9	
	5		9		5		8		9		8	

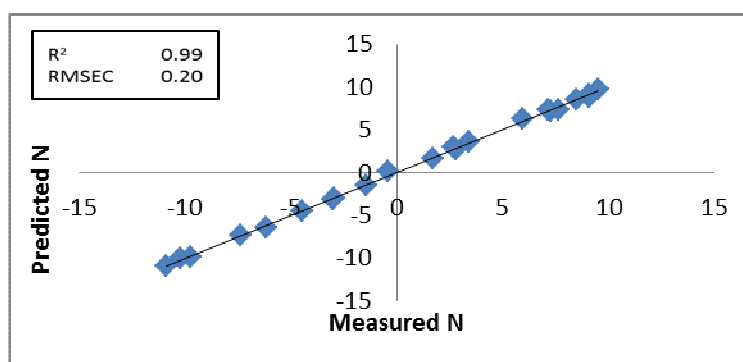
Table 1 also shows the performance of both calibration and prediction models for F9 of oil palm leaf samples. There are three nutrient of interest of N, P and K from the table, it was observed that the calibration performance as indicated by R^2 is good for all three nutrients of 0.91, 0.96 and 0.95 respectively with relative low Root Mean Square Error of Calibration (RMSEC) ranging from 0.00 to 0.04. The prediction results for R^2 were lower than the calibration models ranging between 0.05 to 0.48, while the RMSEP were slightly higher than RMSEC, ranging between 0.01 and 0.21.

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, P and K of 0.99, 0.99 and 0.99 respectively. The prediction performance results for R^2 value of N, P and K, were 0.98, 0.98 and 0.98 respectively. The result of F17 was relatively low RMSEC ranging from 0.19 to 0.20. The RMSEP were slightly higher than RMSEC, ranging between 1.40 and 1.53.

From the results, it is observed that frond number F17 gives better results compared to F3 and F9 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. In addition, the spectrometer gives better prediction for P and K compared to N.

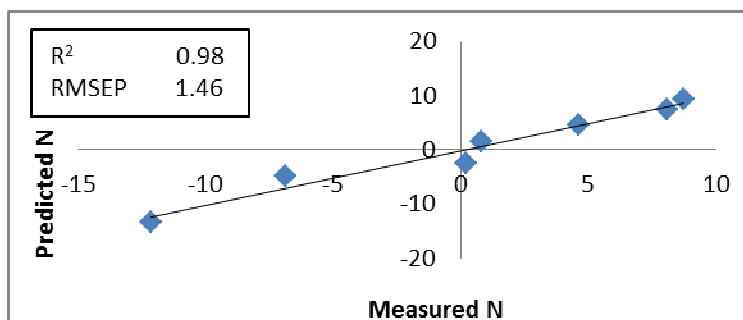
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(a)



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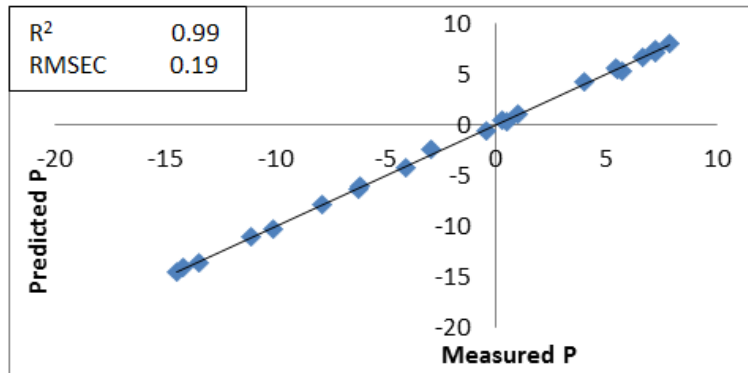
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Fig 3: Scatter plots of F17 for Nitrogen; (a) Calibration model, (b) Prediction model

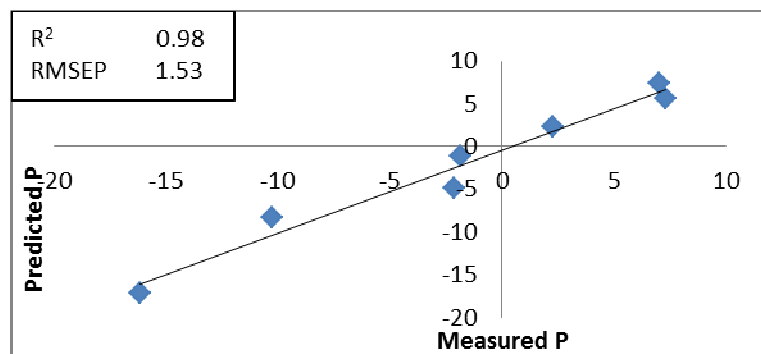
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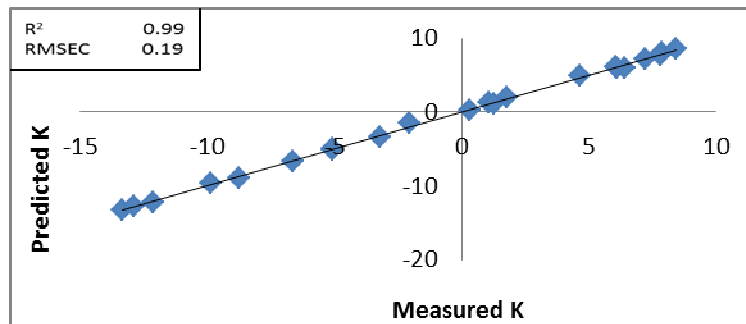
(a)



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185 (b)



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187 **Fig 4:** Scatter plots of F17 for Phosphorus ;(a) Calibration model, (b) Prediction model
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190 (a)



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193 (b)

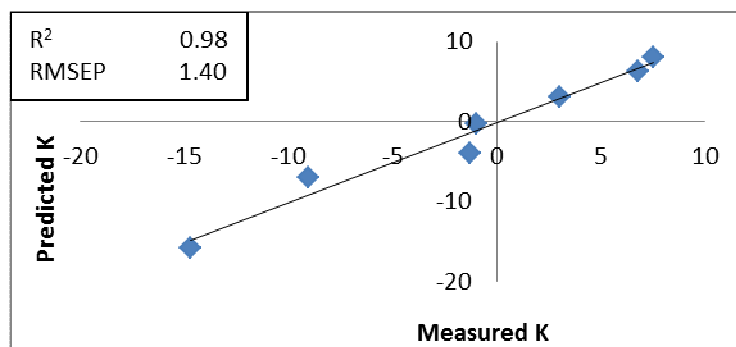


Fig 5: Scatter plots of F17 for Potassium; (a) Calibration model, (b) Prediction model

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

From the results discussed, the F17 shows better statistical relationships to all the three nutrients' calibration value compared to F3 and F9. 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. Limited number of samples could also affect the accuracy of the model. 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 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. This preliminary study suggests that nutrient deficiency can be determined fairly using spectrometer with PLS regression. 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.

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