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**Predicting Oil Palm Leaf Nutrient Contents in Kalimantan, Indonesia
by Measuring Reflectance with a Spectroradiometer**

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Predicting Oil Palm Leaf Nutrient Contents in Kalimantan, Indonesia by Measuring Reflectance with a Spectroradiometer

Abstract

Leaf nutrients are needed for oil palm growth and production, and the nutrient contents of oil palm leaves can be determined by the chemical analyses of the number 9 and 17 leaves for young and adult palms, respectively. However, the accurate selection of the proper leaf for sampling is problematic. Remote sensing techniques based on the reflectance values of leaves may easily monitor leaf nutrients in oil palm plantations. We studied leaf nutrient contents using spectral reflectance data to determine suitable wavelengths for predicting the contents of the most important leaf nutrients: nitrogen, phosphorus, potassium, calcium, magnesium, boron, copper, and zinc. The samples were taken from one oil palm plantation in Pundu, Central Kalimantan, Indonesia. The proposed vegetative indices, several common vegetative indices, and a stepwise regression that continued with a principal component regression were used to build models for predicting leaf nutrient contents. The proposed vegetative indices performed better than the common vegetative indices. For each of the leaf nutrients, models that included all of the significant variables from the stepwise regression and continued with principal component regression from the ultraviolet A and green to far red wavelength groups had better performance levels than models that included individually selected variables selected from each wavelength group. For total leaf nutrient content predictions, variables from the green wavelength group were always selected and contributed more to the models than any other group. Thus, our proposed vegetative indices and multivariate model may be used to predict leaf nutrient contents in oil palm plantations.

Keywords: macronutrient, micronutrient, oil palm, spectral, reflectance, spectroradiometer

1. Introduction

Oil palm (*Elaeis guineensis* Jacq) is an economically important crop in Indonesia and Malaysia (World Growth 2011; Basiron 2007), which are now the largest exporters of vegetable oil in the world (OECD/Food and Agriculture Organization of the United

Nations 2015). Fertilizer is an important factor affecting oil palm production and represents 40%–50% of the total field upkeep costs (Ng 2002). Fertilizer requirements in oil palm plantations were determined by leaf nutrient contents analysis, as is typical for many other crops (Pritts and Heidenreich 2012; Memon, Memon, and Hassan 2005). To determine leaf nutrient contents, leaf samples are annually collected for analysis (Chapman and Gray 1949; Fairhurst and Mutert 1999). Leaf samples are taken periodically from leaf number 17 for adult palms and leaf number 9 for young palms. Commonly, the sampled leaves are grouped in leaf sampling units (LSUs) that consist of 30–40 selected palms each. One LSU is assigned for every 30–40 ha (Foster and Choong 1976; Uexkull, Fairhurst, and von Uexkull 1991). A common problem is the accuracy of determining the leaf for sampling. To identify leaf number 17, workers must first identify leaf number 1, the youngest fully-expanded leaf, and then count backwards. However, there can be some ambiguity in determining the youngest fully-expanded leaf. Therefore, an improved technique is needed that can be used to quickly monitor leaf nutrients in oil palm plantations. Remote sensing techniques based on the reflectance values of leaves have the potential to meet this demand.

Remote sensing techniques based on reflectance values have been used for the detection and prediction of plant nutrient states. Albayrak (2008) measured reflectance levels for determining nitrogen (N), phosphorus (P), potassium (K), acid detergent fibre, and neutral detergent fibre contents in a sainfoin pasture and found a strong relationship between plant nutrient content and canopy reflectance, with coefficient of determination (R^2) values in the 0.68–0.93 range. Cohen *et al.* (2010) estimated leaf N levels in potato using spectral data and simulated bands from the VENμS satellite that indicated N fertilizer treatment levels, obtaining an R^2 value of 0.95, an 80.5% overall accuracy and a kappa coefficient (κ) value of 74%. Özyigit and Bilgen (2013) showed significant

relationships between spectral reflectance and the leaf nutrient contents of N, P, and K in rangeland plants with R^2 values of 0.85, 0.43, and 0.84, respectively. Menesatti *et al.* (2010) estimated the plant nutritional status using a visible to near infra-red (NIR) spectrophotometric analysis of orange leaves and obtained high R^2 values of 0.91, 0.43, 0.99, 0.95, 0.94, 0.92, 0.93, and 0.89 for N, P, K, calcium (Ca), magnesium (Mg), iron (Fe), manganese (Mn), and zinc (Zn), respectively.

Using NIR reflectance spectroscopy, Rothman *et al.* (2009) showed that wavelengths in the 1100–2498 nm range had strong correlations with the nutritional values of foods eaten by mountain gorillas, with R^2 values of 0.73–0.99. Başayığit, Dedeoğlu, and Akgül (2015) showed that wavelengths of 540–560 nm (green visible) and 990–1010 nm (NIR) were correlated with active Fe levels in apple, cherry, and peach, with coefficients of the accuracy of 76.70%, 75.28%, and 78.69%, respectively. The coefficient of accuracy is a statistical parameter for methods comparisons (Lin and Torbeck 1998). Stein *et al.* (2014) predicted macronutrient contents from loblolly pine reflectance. They found that the important wavelengths in the partial least squares regression reflectance model for leaf N status were visible, red edge, and NIR regions, while the visible and red-edge regions were the important wavelengths for determining leaf P, K, and Mg. Min and Lee (2005) identified wavelengths of 448, 669, 719, 1,377, 1,773, and 2,231 nm as significant for N detection in citrus. Özyigit and Bilgen (2013) found that wavelengths of 609, 647, 651, 654, 669, 675, 676, 680, 721, 727, and 760 nm were suitable for estimating the N levels in rangeland plants; those of 675 and 680 nm were suitable for estimating P levels; and those of 410, 411, 417, 422, 460, 463, 468, 646, 651, 658, 669, 670, 674, 676, and 682 nm were suitable for estimating K levels. Thus, reflectance values from spectrometry data at different suitable wavelengths can be used to determine leaf nutrient contents in different plants. However, oil palm nutrient

contents studies using remote sensing techniques have been limited. We believed that oil palm leaf nutrient contents could also be predicted using these techniques. Fertilizer recommendations can also be derived from leaf spectral measurements. Cilia *et al.* (2014) produce a pixel-based variable-rate N fertilization map from hyperspectral sensors in maize. Amaral, Trevisan, and Molin (2017) proposed variable-rate N fertilization in sugarcane based on readings from the crop canopy reflectance sensor Crop Circle ACS-430 (Holland Scientific Inc. Lincoln, NE, USA).

Therefore, the objective of this study was to determine suitable reflectance wavelengths to predict leaf nutrient contents, especially those of N, P, K, Ca, Mg, boron (B), copper (Cu), and Zn. In oil palm trees, N, P, K, Ca, and Mg are major nutrients that are required for annual vegetative dry matter production and fresh fruit-bunch production. In addition, the micronutrients B, Cu, and Zn are required by mature oil palms (Ng 2002). Ng (2002) found that sulfur (S), as major nutrient, and Mn and Fe are also required for oil palm growth; but establishing their levels is not necessary for determining fertilizer requirements. The S levels in common fertilizers (ammonium sulfate, superphosphate, and kieserite) are sufficient for oil palm growth and production. Oil palm in Indonesia are mostly grown in soil with low pH values (Nelson *et al.* 2002), which means that the amounts of available Mn and Fe were high. Therefore, Mn and Fe were omitted when determining the fertilizer requirements for oil palm.

2. Materials and Methods

Oil palm leaf reflectance data were collected, and leaf nutrient analyses were performed. Predicting leaf nutrient contents in oil palm using reflectance data will increase the efficiency of management practices in oil palm plantations. In particular, monitoring leaf nutrient states will help determine fertilizer requirements, decreasing costs and environmental contamination.

2.1. Study site and leaf sampling methods

The study was conducted in one oil palm plantation belonging to a company in Pundu, East Kotawaringin District, Central Kalimantan, Indonesia (Fig. 1 *a, b*). Leaf samples were collected during 14–15 March 2015 from three different age groups of oil palms: 5, 12, and 17 years old. Symptoms of K and Mg deficiencies in oil palms appear in older leaves, N deficiency symptoms occur in younger and older leaves, and micronutrient deficiencies commonly appear in younger leaves (Corley and Tinker 2003; Von Uexkull and Fairhurst 1999). Therefore, leaf samples were taken from leaf number 9 (young), 17 (middle), 25 (old), and 33 (older) in every age group (Fig. 2). A total of 42 leaf samples was collected for leaf nutrient analyses.

Fig. 1. Study site was on Kalimantan Island (*a*); map of the study site's area (*b*).

Fig. 2. Leaf sampling: leaf numbers 9, 17, 25, and 33 (*a*); leaf collection in the field (*b*); spectral leaf measurement (*c*); and cleaning oil palm leaflets before leaf analysis (*d*).

2.2. Oil palm leaf nutrient analyses

The leaf nutrient analyses were performed at the Leaf Laboratory of the Indonesian Oil Palm Research Institute in Medan, North Sumatra, Indonesia. Before leaf samples were processed in the laboratory for analysis, they were cleaned or wiped using Aquadest (distilled water) to remove dust. Leaf samples were analysed for N, P, K, Ca, Mg, B, Cu, and Zn. The N content was measured by the Kjeldahl method. K, Ca, Mg, Cu, and Zn were measured by atomic absorption spectrometry. P and B were measured by inductively coupled plasma atomic emission spectrometry and direct current plasma emission spectrometry. All procedures in the analyses were adopted from Kalra (1998) and Sulaeman, Suparto, and Eviati (2005).

2.3. *Reflectance measurements of oil palm leaves*

The reflectance of oil palm leaves was measured using a portable spectroradiometer [FieldSpec3; Analytical Spectral Devices (ASD), Inc., Boulder, CO, USA] with a plant probe having a wavelength range of 350–2500 nm. In total, 42 leaf samples from three groups of oil palms of different ages were collected. The reflectance measurements were applied to leaflets that were taken from three sections of every leaf (bottom, middle, and upper) and each leaf included three leaflets. Thus, there were 378 leaflets for leaf reflectance measurement. The reflectance was measured on the surface of the leaflets at 10 positions per leaflet, resulting in 3780 reflectance data measurements. The measurements were periodically calibrated with a white reference panel or white reference standard. The spectral resolution output data from the ASD operating system was 1 nm along the whole spectrum. The digital number values from the measurement were converted to spectral reflectance values using ViewSpecPro version 6.2.0 from ASD. We calculated the mean values of the 42 leaf samples' reflectance from the 90 reflectance measurements taken per sample. The mean values of the reflectance measurements with 1-nm resolution were labelled as dataset 1. Data selected every 3 nm for wavelengths in the range of 350–1000 nm and every 10 nm for wavelengths of 1001–2500 nm were labelled as dataset 2 (Hatchell 1999). Therefore, there were 42 data points of observation (leaf nutrient analysis), with 2151 spectral measurements as variables for dataset 1 and 367 spectral measurements as variables for dataset 2.

Figure 3 shows the mean reflectance values of oil palm leaves from dataset 2 with standard deviations. This reflectance pattern is a common vegetative spectral pattern (Hoffer 1984). The oil palm reflectance was low in the visible wavelengths and high in the NIR wavelengths. It started to decrease at approximately 1150 nm and sharply decreased at approximately 1300 nm (Fig. 3). Low reflectance in visible

wavelengths is to the result of chlorophyll absorption, and the low reflectance values at approximately 1450 and 1900 nm are the result of water absorption (Hoffer 1984).

Fig. 3. Mean reflectance values of oil palm leaves with standard deviations calculated from spectral measurements.

2.3. Data analyses

The wavelengths were divided into nine groups (Table 1) as described by Hatchell (1999). The analyses in this study were carried out using R software (RStudio 2015) as described below.

Table 1. Wavelength ranges

2.3.1. Variable screening to construct normalised differences and simple ratio models

Dataset 1 was used for variable screening to construct normalised differences (NDs) and simple ratio (SR) formulae. The script from Sonobe and Wang (2016) was adopted and used in this study to investigate the 2,151 variables that could be used to predict leaf nutrient contents based on R^2 values. The R^2 values calculated from predicted values of the ND and SR formulae were compared with leaf nutrient analyses (reference values). Thus, we identified different suitable variables for each type of nutrient content in the leaves.

2.3.2. Vegetative indices

Vegetative indices have been used for estimating and monitoring leaf nutrient contents in plants, including studies in a sainfoin pasture by Albayrak (2008), in potato by Cohen *et al.* (2010), Munoz-Huerta *et al.* (2013), in wheat by Mahajan *et al.* (2014), and in loblolly pine by Stein *et al.* (2014). The vegetative indices used in this study are shown

in Table 2. The vegetative indices calculated from dataset 1 were used as variables for correlation analyses against the reference values. The goodness-of-fit parameter was R^2 .

Table 2. Vegetative indices used in this study

2.3.3. Variables selected using a stepwise regression and the generalized linear model (GLM) formulae

Stepwise methods with the GLM formula were applied to dataset 2 to determine the variables suitable for predicting leaf nutrient contents. The stepwise method has been commonly used in research for selecting variables suitable for predicting or simulating leaf nutrient contents in several plants (Starks *et al.* 2006; Albayrak 2008; Joffre *et al.* 1992; Başayığit, Dedeoğlu, and Akgül 2015; Serusi *et al.* 2010; Min and Lee 2005; Basayigit and Senol 2009; Özyigit and Bilgen 2013). In this study, stepwise processing was performed with the MASS package in RStudio software (Ripley *et al.* 2015) using the GLM formula (RStudio 2015). The parameters set for the GLM formula were Gaussian for family. The stepwise processing was based on Akaike's Information Criterion (AIC) value with forward and backward directions. The stepwise processing was applied to the nine wavelength ranges, and all variables selected as output from stepwise processing were tested for significant covariates. Therefore, the final variables selected were all significant at $p = 0.05$ for inclusion in the model to predict leaf nutrient contents (Bursac *et al.* 2008). The function of automated model selection based on the p -value was adopted from Meys (2013). The parameters of goodness-of-fit were the adjusted coefficient of determination (R^2_a) and R^2 between the reference and predicted values from the output of the model predicting the nutrient contents. Root mean squared error (RMSE) was also used to evaluate the model by summarizing the differences between the actual (observed) and predicted values.

Principal component regression (PCR) was applied to the model that was produced from the stepwise processes. PCR is a method that addresses multicollinearity, according to Fekedulegn *et al.* (2002) and Alibuhitto and Peiris (2015), and is based on principal component analysis. Variables in the stepwise model were transformed to uncorrelated variables called principal components of the correlation matrix. Then some of the principal components were eliminated to effect a reduction in variance, which was performed using ordinary least squares estimation (Fekedulegn *et al.* 2002; Graham 2009). We used the “analogue package” to perform PCR that included scaling data and cross validation. The PCR performances were R^2 , maximum bias of the model residuals, and RMSE. The regression coefficients for the PCR were used to build the final predictive model of leaf nutrient contents (Simpson and Oksanen 2016).

3. Results

3.1. Leaf nutrient analysis

Leaf nutrients had low to high variability in the order P, N, K, Ca, Zn, Mg, B, and Cu according to the leaf nutrient content analysis (Table 3). The leaf nutrient contents found in this study were highly variable. This may have resulted from the different ages of samples leaves: young (leaf number 9), middle (number 17), old (number 25), and older (number 33). Leaf age is one factor that affects leaf nutrient concentrations (Fairhurst and Mutert 1999). The variability of the leaf nutrient contents in this study was important for determining the correlations with leaf reflectance spectra (Starks *et al.* 2006).

Table 3. Summary of the leaf nutrient contents analysis

3.2. ND and SR formulae

The selected variables from the leaf reflectance spectra used to build the ND and SR formulae for predicting leaf nutrient contents are shown in Table 4. Both ND and SR formulae used the same selected variables (Table 4). N had the highest R^2 value (0.53), and B had the lowest value (0.33). Like the results of Mukaka (2012), the r values in the 0.70–0.90 range achieved for both ND and SR in the current study showed that spectral numbers X_{1423} and X_{1877} were highly positively correlated with the N leaf nutrient analysis (reference value) and that X_{1164} and X_{1238} were highly positively correlated with the Ca leaf nutrient analysis. The ND and SR equations for N and Ca leaf nutrient contents are as follows:

$$N\text{-}ND_{(X_{1423}\text{-}X_{1877})} = \frac{(X_{1423} - X_{1877})}{(X_{1423} + X_{1877})}, \quad (1)$$

$$N\text{-}SR_{(X_{1423}\text{-}X_{1877})} = \frac{X_{1423}}{X_{1877}}, \quad (2)$$

$$Ca\text{-}ND_{(X_{1164}\text{-}X_{1238})} = \frac{(X_{1164} - X_{1238})}{(X_{1164} + X_{1238})}, \text{ and} \quad (3)$$

$$Ca\text{-}SR_{(X_{1164}\text{-}X_{1238})} = \frac{X_{1164}}{X_{1238}}. \quad (4)$$

P, K, Mg, B, Cu, and Zn had moderately positive correlations with ND and SR formulae, and the variables selected are provided in Table 4. The formats of the equations for P, K, Mg, B, Cu, and Zn of ND were the same as those of equations (1) and (3), and the formats of the equations for SR were the same as those of equations (2) and (4). Different spectra were selected for the different variables: NIR 1 (G8) was used for determining P and Ca; NIR 1 (G8) and NIR 2 (G9) were used for N and B; shortwave (SW)-NIR (G7) was used for Mg and Cu; green (G3) and red (G5) were used for K; and far-red (G6) and SW-NIR (G7) were used for Zn.

Table 4. Normalised difference (ND) and simple ratio (SR) models for dataset 1.

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273 The wavelengths selected from the ND and SR models, including those for
274 predicting N, P, Ca, B, and Cu contents, were in the 1005–1877 nm range (NIR or
275 SWIR to SWIR2 or NIR2). This is in accordance with the results of Pimstein *et al.*
276 (2011), indicating that N and K had correlations with the visible and SWIR
277 wavelengths. They proposed a new ND equation for N, with wavelength numbers X_{870}
278 and X_{1450} for Equation 1 and X_{1645} and X_{1715} for Equation 2, that produced better
279 results than those of the common vegetative indices. Mahajan *et al.* (2014) proposed
280 new a vegetative index for predicting the P content using wavelength numbers X_{1080}
281 and X_{1460} . The wavelength number selected for the ND and SR models to predict N
282 and P contents was selected from the NIR region, which is in accordance with the
283 results of Pimstein *et al.* (2011); they found interactions for both N and P with
284 wavelengths in the NIR region. Ca in oil palm leaves is correlated with the leaf lignin
285 content (Nur Sabrina, Sariah, and Zaharah 2012). In Yao *et al.* (2010), the wavelength
286 numbers X_{1164} and X_{1238} in the ND and SR formulae used to predict Ca content in
287 leaves were correlated with those in the NIR to determine the lignin content in *Acacia*
288 trees. In oil palms, B functions in the translocation of N and P, and in pollen viability.
289 The Cu in oil palms is needed for N metabolism and pollen viability (Tengoua *et al.*
290 2015). Therefore, the variables selected for predicting B and Cu by ND and SR were
291 similar to those selected for N and P.

292 The different wavelength numbers selected from ND and SR for K, Mg, and Zn
293 were in the X_{530} – X_{773} range. In oil palm, K is important for proper stomatal
294 functioning in leaves, the transport of assimilates from photosynthesis, enzyme
295 activation, and oil synthesis. Mg is a constituent of chlorophyll and is essential for
296 efficient photosynthesis (Rankie and Fairhurst 1999), while Zn has important roles in
297 catalysing enzyme activity, especially in oil synthesis (Ng 2002). In addition, deficiency

symptoms for K, Mg, and Zn in the field can be seen in middle to older leaves. Indeed, the wavelength numbers selected were close to NIR, especially for Mg and Zn, while for K they were in the green and red spectra. For K, the wavelength number X_{530} was close to the peak of the green region, and X_{707} occurred where reflectance started to increase, close to NIR. In addition, for Mg and Zn, the selected wavelength numbers were close to the peak of reflectance in the NIR region. Therefore, X_{1423} and X_{1877} , X_{1215} and X_{1317} , X_{530} and X_{707} , X_{1164} and X_{1238} , X_{753} and X_{773} , X_{1005} and X_{1033} , and X_{744} and X_{764} can be used for predicting leaf nutrient content of N, P, K, Ca, Mg, B, Cu, and Zn, respectively, although the correlation coefficients (r) were low to moderate by ND and SR formulae.

3.3. Vegetative indices

The relationships of vegetative indices with leaf nutrient contents are shown in Table 5, with R^2 in the 0–0.37 range, with the highest R^2 value occurring for the modified chlorophyll absorption reflectance index 1 (MCARI1) in predicting the Ca leaf contents. The ND used spectral numbers 870 and 1450 (termed N870_1450) and predicted the N, P, and K contents with $R^2 = 0.347$, 0.209, and 0.347, respectively. The green normalised difference vegetation index predicted the B and Zn contents with $R^2 = 0.296$ and 0.086, respectively. MCARI1 predicted the Ca contents with $R^2 = 0.373$, while MCARI predicted Mg contents with $R^2 = 0.293$, and the transformed chlorophyll absorption reflectance index predicted the Cu content with $R^2 = 0.244$.

Table 5. Relationships (R^2 values) between vegetative indices and leaf nutrient contents.

The results were in accordance with those of Pimstein *et al.* (2011) and Mahajan *et al.* (2014), especially for the R^2 of vegetative indices used for predicting leaf nutrient

contents. The ND and SR results (Table 4) in this study had greater R^2 values than did the common vegetative indices (Table 5). Different plant types respond differently to the vegetative indices applied to predict leaf nutrient contents. Furthermore, leaf reflectance is affected by leaf structure, leaf conditions, moisture, maturity, and culture practices (Hoffer 1971; Hoffer 1984).

3.4. Multivariate analysis

The multivariate analysis used a stepwise regression with the GLM formula, and improved R^2 and R^2_a for common vegetative indices and for the proposed ND and SR. No variables were selected from wavelengths in G2 and G7–G9 when applying the stepwise regression (Table 6). In the stepwise regression, variables were added or deleted from the model one at a time until the stop criterion (in this case the AIC value) was reached. Wavelength numbers in G2 and G7–G9 were not selected for constructing the leaf nutrient contents prediction model. The stepwise regression was ceased if the AIC value was very low in the initial analysis. We also applied stepwise regressions to all of the selected variables of wavelengths in G1 and G3–G6; this group is referred to as group C (Table 6).

The partial least squares regression (PLSR) model can also be used as a powerful multivariate analysis for leaf nutrient prediction (Li *et al.* 2016; Capolupo *et al.* 2015; Cohen *et al.* 2010; Stein *et al.* 2014; Abdel-Rahman *et al.* 2017; Galvez-Sola *et al.* 2015; Serusi *et al.* 2010). For comparison, the PLSR model was applied in this study using the backward selection of predictors, leave-one-out cross-validation and the orthogonal scores algorithm method. The model was selected based on two approaches. One was based on significance, and the other was based on combining significance with the variable importance in the projection approach. The results of the PLSR method are shown in Table 7. All of the wavelength groups had positive responses, but the number

347 of variables selected was greater and the R^2 value lower than with the GLM method, in
348 general.

349 Table 6. Results of a multivariate analysis using the GLM method

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356 Table 7. Results of a multivariate analysis using PLSR

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365 Table 8. Results of a multivariate analysis using PCR

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For the two multivariate results, we considered the results from the stepwise variables selection and then we applied a PCR to build the final model. The PCR calculated principal components of a linear combination of the original variables but not for a feature selection method. The results of the multivariate analysis using PCR are shown in Table 8. In general, the R^2 for all model predictions of leaf nutrient contents were higher than the multivariate analysis using a stepwise GLM and PLSR. All of the leaf nutrient contents model predictions have R^2 values in the 0.86-0.94 range for the macro nutrients (N, P, K, Ca, and Mg) and in the 0.77-0.084 range for micro-nutrients B, Cu, and Zn. The RMSE values were less than zero for P, Mg, Ca, N, and K and in the 1 to 3.6 range for Cu, Zn, and B.

The correlation between the N content in leaves and the leaf nutrient analysis (reference value) from the PCR had R^2 values in the 0.55-0.94 range, with the greatest R^2 values occurring in G3 (green). The P content correlation with the leaf nutrient analysis (reference value) had R^2 values in the 0.49–0.0.90 range, with the greatest R^2 values occurring in G5 (red). For K, Ca, Mg, B, Cu, and Zn, the R^2 values were in the 0.61–0.85, 0.69–0.86, 0.36–0.91, 0.61–0.84, 0.59–0.84, and 0.36–0.77 ranges, respectively. The greatest R^2 values occurred in G3 (green) for K, Ca, Mg, B, and Cu and in G5 (red) for B and Zn.

The PCR was applied to all variables selected from G1 and G3–G6 to produce a new model of the correlation between leaf nutrient contents and leaf reflectance. The R^2 values were more strongly correlated in each wavelength group. The R^2 values for N, P, K, Ca, Mg, B, Cu, and Zn were 0.997, 0.92, 0.97, 0.96, 0.99, 0.97, 0.86, and 0.92, respectively. Separating all of the selected variables in the model from G1 and G3–G6 showed that wavelengths in G3 (green) contributed the most to the model. The relative contributions of each wavelength group are shown in Table 9. Plant photosynthesis is

strongly affected by the chlorophyll content. Gitelson *et al.* (1996) found that the green group had the maximum sensitivity for a wide range of chlorophyll concentrations and proposed that the green normalised difference vegetative index had a wider dynamic range than the normalised difference vegetative index.

Table 9. Variable separation based on wavelength groups in group C

The final equations from the models constructed from the PCR and based on the greatest R^2 value from G1–G9 (model 1: N1, P1, K1, Ca1, Mg1, B1a, B1b, Cu1, and Zn1) and from group C (model 2: N2, P2, K2, Ca2, Mg2, B2, Cu2, and Zn2) are shown in Table 10. Model 2 had an improved RMSE, which was less than that for model 1. Predictions of the B and Zn contents had RMSE values > 1 ; they were 2.47, 2.45, 1.01, 2.49, and 1.58 for B1a, B1b, B2, Zn1, and Zn2, respectively. The RMSEs were 0.004–0.95 for the contents of all other leaf nutrients. An RMSE value close to zero is one indicator of the good predictive value of a model. These results are consistent with those of Albayrak (2008), which showed that spectral reflectance in the visible to NIR range could be used for leaf nutrient predictions in a sainfoin pasture. Min and Lee (2005) found high r between absorbance levels at each wavelength number and the leaf N concentration of citrus for wavelength numbers in the X553–X707 range. Stein *et al.* (2014) showed that N, P, K, Ca, and Mg contents in the leaves of loblolly pine are correlated with the visible spectrum (500–600 nm) and at approximately 700 nm.

Table 10. Final model of variables selected by PCR to predict leaf nutrient contents

4. Discussion

In this study, the oil palm leaf nutrient contents, especially N, P, K, Ca, Mg, and B, were similar to those of oil palm found growing under several conditions in Malaysia,

Gujarat, Ghana, and Colombia. Differences in irrigation conditions, terrains, and planting materials in Malaysia resulted in N, P, K, Ca, Mg, and B leaf contents in the ranges of 2.49-2.81, 0.159-0.180, 0.96-1.15, 0.68-1.02, 0.19-0.26, and 13.7-15.8, respectively (Lee *et al.* 2011). Oil palm in low and high yield conditions in the Surat District of Gujarat had N, P, K, Ca, Mg, and B leaf contents in ranges of 2.45-2.75, 0.16-0.17, 0.59-0.72, 0.66-0.59, and B 20.7-20.8 , respectively (Behera *et al.* 2016). Oil palm growing in different soil in Ghana that received fertilizer had N, P, K, Ca, and MG leaf contents in the range of 2.25-2.91, 0.133-0.15, 75-1.09, 0.67-0.97, and 0.31-0.36, respectively (Vossen 1970). In Colombia, oil palm from Malaysia planted in Colombia had N, P, K, Ca, Mg, and B leaf contents in the range of 2.12-2.73, 2.43-2.73, 0.72-1.07, 0.69-0.88, 0.23-0.3, and 15-22.6, respectively (Navia, Restrepo, and Romero 2014). Fertilizer requirements could be determined based on the leaf nutrient contents, soil analysis, or a combination of soil and leaf analyses.

In this study, the variables selected in the ND and SR equations were in accordance with the results of previous research (Mahajan *et al.* 2014; Pimstein *et al.* 2011; Yao *et al.* 2010). The ND and SR equations predicted the leaf nutrient contents better than existing vegetative indices. Validation is an important step before any model can be applied to the field. For the proposed ND and SR equations, the appropriate method for calibrating and determining the wavelength number that matched the proposed models' selected wavelength number used both hyperspectral and multispectral imagery as data. The multivariate analysis using PCR to two variables from ND and SR equations found that the R^2 values were 0.65, 0.66, 0.61, 0.69, 0.64, 0.61, 0.70, and 0.56 for N, P, K, Ca, Mg, B, Cu, and Zn, respectively. We have applied the PCR to all variables (16 variables) from ND and SR equations, and the R^2 values were 0.89, 0.82, 0.82, 0.82, 0.87, 0.83, 0.90, and 0.76 for N, P, K, Ca, Mg, B, Cu, and

Zn, respectively. The complete results of the PCR using variables from ND and SR equations are shown in Table 11. Therefore, the variables from ND and SR can be used for leaf nutrition content predictions with a multivariate analysis.

Table 11. Results of PCR analysis to predict leaf nutrient contents using variables from ND and SR equations

The multivariate analysis using the GLM method and continued with the PCR of dataset 2 showed that wavelengths in G3 (green) were the most important in this study. Variables selected from G3 had strong effects in all of the proposed models for predicting leaf N, P, K, Ca, Mg, B, Cu, and Zn contents. A limitation of the model constructed using the multivariate analysis in this study was that many variables were selected to create the model. The number of variables selected from the GLM method could be reduced by applying an automated model selection based on $p = 0.01$ for inclusion in the model and then applied with the PCR to build a model for predicting leaf nutrient contents. Generally, a multivariate model has a better predictive power compared with a simple regression. Here, the model involving variables from visible wavelengths (G1 and G3–G6) performed well.

The results of the present study are in accordance with previous results showing that visible wavelengths contribute highly to predicting leaf nutrient contents (Özyigit and Bilgen 2013; Stein *et al.* 2014; Min and Lee 2005; Albayrak 2008) because of the different spectral resolutions in the spectroradiometer and hyperspectral image data, the next challenge will be to implement the proposed multivariate model using hyperspectral imagery.

Another challenge in developing new techniques to improve agricultural management, especially for predicting leaf nutrient contents in oil palm plantations, is

adapting robust models and methods to the specific characteristics of the plantations. In Indonesia, oil palm plantations are commonly very large, with a single estate covering 2000–3000 ha. Leaf nutrient monitoring to determine fertilizer needs in oil palm plantations is based on the leaf nutrient contents of LSU's that may each represent 30 ha. Furthermore, the characteristics of the leaf samples taken from the 30 selected trees in each LSU depend on the homogeneity of oil palm conditions (tree age, vigour, soil nutrient status, and land topography). Thus, the proposed model provides a preliminary version of the kind of robust model and method that will be needed for validation using data collected under different conditions including soil type, topography, territory (area), and climate, and to precisely calculate leaf nutrient contents based on spectral values from remote sensing.

5. Conclusions

The ND and SR models using wavelength numbers $X1423$ and $X1877$ had strong positive correlations with the N leaf nutrient analysis ($R^2 = 0.53$), while $X1164$ and $X1238$ had strong positive correlations with the Ca leaf nutrient analysis ($R^2 = 0.50$). The P, K, Mg, B, Cu, and Zn analyses had moderately positive correlations, with R^2 values in the 0.33–0.49 range. Several vegetative indices commonly used for predicting leaf nutrient contents had lower R^2 values than the proposed ND and SR models in this study. A multivariate analysis with PCR using two variables each ND and SR equations showed R^2 values in the 0.56–0.70 range and using sixteen variables from all variables of ND and SR equations have R^2 in the 0.76–0.90 range. A multivariate analysis using a stepwise regression with the GLM formula that continued with PCR resulted in greater R^2 values than those for the proposed ND and SR models, as well as several existing vegetative indices. Wavelengths in the G2 (blue), G7 (SW-NIR), G8 (SWIR1), and G9 (SWIR2) did not contribute to the final models for predicting leaf nutrient contents. For

all leaf nutrient elements, models that involved variables selected from G1 and G3–G6 had better performances than those that involved variables selected from each group of wavelengths individually. Variables from G3 (green) were always selected and contributed the most to constructing the final models. Variables from G4 (yellow) were the second most important group selected for constructing the models. The wavelengths in the proposed vegetative indices and the multivariate model proposed should be studied further using hyperspectral sensors or remote sensing satellites.

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Table 1. Wavelength ranges

Group	Symbol	Wavelengths (nm)
Ultra Violet A	G1	350–400
Blue (B)	G2	401–525
Green (G)	G3	526–605
Yellow (Y)	G4	606–655
Red (R)	G5	656–725
Far Red (Re)	G6	726–750
Shortwave NIR (SW-NIR)	G7	751–1100
SWIR 1/NIR 1	G8	1101–1800
SWIR 2/NIR 2	G9	1801–2500

Table 2. Vegetative indices used in this study

Vegetation index	Formula ^a	Reference
Normalised difference vegetation index (NDVI)	$(R_{\text{NIR}} - R_{\text{red}})/(R_{\text{NIR}} + R_{\text{red}})$	Rouse <i>et al.</i> (1974)
Green normalised difference vegetation index (GNDVI)	$(R_{800-900} - R_{540-560})/(R_{800-900} + R_{540-560})$	Gitelson, Kaufman, and Merzlyak (1996)
Simple ratio (SR)	$R_{800-900}/R_{650-700}$	Birth, Gerald S.; McVey (1968)
Modified chlorophyll absorption reflectance index (MCARI)	$[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})] \times (R_{700}/R_{670})$	Daughtry (2000)
Transformed chlorophyll absorption reflectance index (TCARI)	$3[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})] \times (R_{700}/R_{670})$	Haboudane <i>et al.</i> (2002)
MCARI1	$1.2[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]$	Haboudane <i>et al.</i> (2004)
MCARI2	$1.2[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]/[(2 \times R_{800} + 1)^2 - (6 \times R_{800} - 5(R_{650}^{0.5}))^{0.5} - 0.5]$	Haboudane <i>et al.</i> (2004)
N870_1450	$(R_{870} - R_{1450})/(R_{870} + R_{1450})$	Pimstein <i>et al.</i> (2011)
N1645_1715	$(R_{1645} - R_{1715})/(R_{1645} + R_{1715})$	Pimstein <i>et al.</i> (2011)
P1080_1460	$(R_{1080} - R_{1460})/(R_{1080} + R_{1460})$	Mahajan <i>et al.</i> (2014)

^a The letter “R” followed by a three or four-digit number indicates the wavelength of the respective reflectance value.

Table 3. Summary of the leaf nutrient contents analysis

Nutrient	Min	Max	Mean	SD	CV (%)
N (%)	1.80	3.22	2.51	0.31	12.36
P (%)	0.16	0.20	0.17	0.01	6.63
K (%)	0.86	1.49	1.04	0.17	16.29
Ca (%)	0.42	0.93	0.67	0.12	18.11
Mg (%)	0.16	0.39	0.23	0.06	28.22
B (ppm)	7.52	25.82	16.10	4.60	28.58
Cu (ppm)	1.52	9.43	5.29	1.77	33.40
Zn (ppm)	7.98	26.97	14.17	3.98	28.05

Abbreviations: Min, minimum; Max, maximum; SD, standard deviation; CV, the coefficient of variation.

Table 4. Normalised difference (ND) and simple ratio (SR) models for dataset 1.

Leaf nutrients	Model	Variables ^a	R^2 ^b
N	SR	X_{1423}, X_{1877}	0.53
	ND	X_{1423}, X_{1877}	0.53
P	SR	X_{1215}, X_{1317}	0.45
	ND	X_{1215}, X_{1317}	0.45
K	SR	X_{530}, X_{707}	0.38
	ND	X_{530}, X_{707}	0.38
Ca	SR	X_{1164}, X_{1238}	0.50
	ND	X_{1164}, X_{1238}	0.50
Mg	SR	X_{753}, X_{773}	0.43
	ND	X_{753}, X_{773}	0.43
B	SR	X_{1439}, X_{1883}	0.33
	ND	X_{1439}, X_{1883}	0.33
Cu	SR	X_{1005}, X_{1033}	0.49
	ND	X_{1005}, X_{1033}	0.49
Zn	SR	X_{744}, X_{764}	0.34
	ND	X_{744}, X_{764}	0.34

^a Variables selected; the letter “X” followed by a three or four-digit number indicates the wavelength of the respective reflectance value.

^b R^2 = coefficient of determination.

Table 5. Relationships (R^2 values) between vegetative indices and leaf nutrient contents.

Vegetation indice	Leaf nutrient contents							
	N	P	K	Ca	Mg	B	Cu	Zn
NDVI	0.20	0.12	0.15	0.33	0.00	0.21	0.26	0.05
GNDVI	0.14	0.10	0.15	0.27	0.01	0.30	0.19	0.09
SR	0.20	0.07	0.07	0.32	0.00	0.16	0.31	0.07
MCARI	0.05	0.00	0.01	0.14	0.293	0.01	0.24	0.07
TCARI	0.05	0.00	0.01	0.14	0.291	0.02	0.24	0.07
MCARI1	0.27	0.13	0.12	0.37	0.01	0.15	0.34	0.02
MCARI2	0.27	0.10	0.08	0.36	0.01	0.13	0.36	0.04
N870_1450	0.35	0.21	0.35	0.25	0.02	0.02	0.10	0.03
N1645_1715	0.01	0.04	0.01	0.00	0.04	0.00	0.07	0.01
P1080_1460	0.31	0.18	0.31	0.22	0.03	0.02	0.08	0.02

Bold text indicates the greatest R^2 value in each column.

Table 6. Results of a multivariate analysis using the GLM method.

G	N		P		K		Ca		Mg		B		Cu		Zn									
	NV	R^2	R^2_a	NV	R^2	R^2_a	NV	R^2	R^2_a	NV	R^2	R^2_a	NV	R^2	R^2_a	NV	R^2	R^2_a	NV	R^2	R^2_a			
G1	2	0.31	0.27	3	0.24	0.18	6	0.42	0.32	6	0.57	0.50	4	0.28	0.21	4	0.43	0.36	5	0.48	0.40	2	0.13	0.09
G2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
G3	13	0.88	0.82	11	0.78	0.70	7	0.72	0.67	10	0.74	0.66	9	0.83	0.78	8	0.71	0.63	11	0.70	0.59	6	0.43	0.33
G4	6	0.68	0.63	5	0.67	0.62	3	0.46	0.42	7	0.56	0.47	5	0.73	0.69	5	0.51	0.44	2	0.41	0.38	5	0.49	0.42
G5	7	0.72	0.66	10	0.80	0.74	9	0.65	0.55	8	0.65	0.57	7	0.80	0.76	11	0.71	0.60	8	0.55	0.44	9	0.60	0.49
G6	3	0.32	0.27	4	0.29	0.22	4	0.38	0.31	5	0.48	0.41	5	0.63	0.57	4	0.37	0.30	3	0.35	0.30	2	0.33	0.29
G7	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
G8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
G9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C*	22	0.99	0.99	13	0.85	0.78	17	0.93	0.89	20	0.92	0.84	23	0.97	0.94	17	0.95	0.92	11	0.74	0.64	13	0.84	0.76

GLM = generalized linear model; NV = number of variables selected; R^2 = coefficient of determination from a linear relationship; R_a^2 = adjusted R^2 . Highlighted data indicate the results of the greatest R_a^2 and R^2 values for G1–G9.

* Stepwise regression applied to all selected variables of wavelengths in G1–G9.

Table 7. Multivariate analysis using PLSR.

G	N		P		K		Ca		Mg		B		Cu		Zn									
	NV	R^2	R^2_{CV}	NV	R^2	R^2_{CV}	NV	R^2	R^2_{CV}	NV	R^2	R^2_{CV}	NV	R^2	R^2_{CV}	NV	R^2	R^2_{CV}	NV	R^2	R^2_{CV}	NV	R^2	R^2_{CV}
G1	2	0.16	0.06	13	0.22	0	15	0.18	0	11	0.56	0.43	15	0.20	0	3	0.21	0.14	3	0.35	0.28	13	0.17	0
G2	16	0.47	0.36	12	0.80	0.68	42	0.31	0.05	22	0.59	0.47	33	0.06	0	37	0.12	0.01	7	0.41	0.31	37	0.05	0
G3	10	0.58	0.41	27	0.26	0.16	27	0.34	0.25	6	0.55	0.45	27	0.74	0.44	11	0.71	0.55	27	0.43	0.35	3	0.084	0
G4	7	0.67	0.55	14	0.64	0.44	16	0.42	0.33	16	0.49	0.42	9	0.60	0.42	9	0.62	0.44	3	0.41	0.36	16	0.12	0
G5	24	0.26	0.14	5	0.53	0.38	9	0.43	0.31	7	0.39	0.30	12	0.76	0.64	5	0.38	0.27	21	0.34	0.24	9	0.30	0.13
G6	6	0.34	0.25	8	0.27	0.1	4	0.14	0.01	7	0.35	0.26	6	0.46	0.36	8	0.26	0.08	7	0.32	0.21	8	0.45	0.24
G7	5	0.53	0.45	12	0.51	0.41	5	0.59	0.43	74	0.42	0.36	23	0.63	0.48	93	0.10	0	9	0.65	0.55	6	0.34	0.21
G8	10	0.45	0.35	10	0.58	0.41	8	0.32	0.11	6	0.49	0.40	56	0.12	0	11	0.67	0.57	17	0.73	0.62	56	0.07	0
G9	27	0.85	0.77	9	0.72	0.63	32	0.51	0.29	70	0.52	0.27	70	0.47	0.23	12	0.59	0.44	18	0.68	0.57	56	0.06	0
C*	63	0.76	0.61	7	0.58	0.43	25	0.39	0.23	18	0.62	0.48	45	0.51	0.40	133	0.29	0.03	27	0.79	0.70	115	0.41	0.10

PLSR = partial least squares regression; NV = number of variables selected; R^2 = coefficient of determination of calculation; R^2_{CV} = R^2 of leave-one-out cross-validation. Highlighted data are the results of the greatest R^2 and R^2_{CV} values of leave-one-out cross-validation for G1–G9.

* Stepwise regression applied to all selected variables of wavelengths in G1–G9.

Table 8. Multivariate analysis using PCR.

G	N			P			K			Ca			Mg			B			Cu			Zn		
	R^2	MB	RMSE	R^2	MB	RMSE	R^2	MB	RMSE	R^2	MB	RMSE	R^2	MB	RMSE	R^2	MB	RMSE	R^2	MB	RMSE	R^2	MB	RMSE
G1	0.55	0.69	0.26	0.49	0.02	0.01	0.65	0.28	0.13	0.76	0.15	0.08	0.36	0.13	0.06	0.65	7.07	3.44	0.69	3.71	1.26	0.3	12.3	3.66
G2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
G3	0.94	0.16	0.11	0.88	0.01	0.01	0.85	0.23	0.09	0.86	-0.07	0.06	0.91	0.03	0.03	0.84	-	2.47	0.84	1.56	0.95	0.6	8.29	2.97
G4	0.82	-0.27	0.17	0.82	0.01	0.01	0.68	0.24	0.12	0.75	-0.13	0.08	0.86	0.07	0.03	0.72	6.39	3.18	0.64	3.06	1.34	0.7	8.26	2.81
G5	0.85	-0.23	0.16	0.90	0.00	0.01	0.81	0.17	0.10	0.81	-0.11	0.07	0.89	0.04	0.03	0.84	3.77	2.45	0.74	2.94	1.17	0.7	7.78	2.49
G6	0.57	-0.67	0.25	0.54	0.02	0.01	0.61	0.26	0.13	0.69	0.15	0.09	0.79	0.07	0.04	0.61	-	3.61	0.59	2.93	1.41	0.5	9.13	3.22
G7	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
G8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
G9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C*	0.99	0.02	0.02	0.92	0.01	0.00	0.97	-0.05	0.04	0.96	-0.03	0.04	0.99	0.01	0.01	0.97	0.94	1.01	0.86	1.40	0.89	0.9	2.72	1.58

PCR = principal component regression; MB = maximum bias of the model residuals; R^2 = coefficient of determination of calculation; Highlighted data are the results of the greatest R^2 for all variables selected in G1–G9; RMSE = Root mean squared error.

* Group of all selected variables of wavelengths in G1–G9.

1 Table 9. Variable separation based on wavelength groups in group C.

Nutrient	Number of variables	Number of variables selected from wavelength group					R^2	MB	RMSE
		G1	G3	G4	G5	G6			
N	22	6	12	4	-	-	0.997	0.02	0.02
P	13	-	7	-	6	-	0.92	0.01	0.004
K	17	2	9	2	-	4	0.97	-0.05	0.04
Ca	20	-	10	3	6	1	0.96	-0.03	0.04
Mg	23	-	12	3	5	3	0.99	0.01	0.01
B	17	5	7	4	-	1	0.97	0.94	1.01
Cu	11	-	7	2	2	-	0.86	1.40	0.89
Zn	13	-	5	5	-	3	0.92	2.72	1.58

2 R^2 = coefficient of determination; MB = maximum bias of the model residuals; RMSE = root mean square
3 error.

4

5 Table 10. Final model of variables selected by PCR to predict leaf nutrient contents.

Model ^a	Equation ^b	R ²	RMSE
N1	467.26X527-684.82X533+3383.43 X554-3716.2X557-1448.32 X563+3663.97X566-1504.24X569 -2331.04X572+4116.12X575-1758.35X581-3567.07X596+4866.74X602-1480.22X605	0.94	0.11
N2	17.77X350-48.81X356+66.53X359-49.29X362-23.21X371+29.58X386- 140.99X5331092.57X560-1734.08X563+1220.42X566+2687.89X572- 5640.11X575+4687.8X581-6064.36X584+3474.07X587-864.06X593+3647.23X596- 1482.66X602-4400.71X614+6228.86X620-6652.4X638+3951.21X641	0.997	0.02
P1	61.442X659-164.28X665+173.01X674-140.27X683+62.41X686+110.94X695- 209.82X698+119.5X701-14.03X710+1.63X722	0.90	0.01
P2	33.92X527-36.77X530+82.72X560-85.66X563+32.01X575- 115.32X584+82.28X587+148.20X662-166.33X665+29.98X674-30.55X698+30.46X701- 4.60X710	0.92	0.004
K1	-227.96 X545+2961.11 X560-2211.65 X563-1826.20 X566+1625.65 X572-1581.21 X584+1269.91 X587	0.85	0.09
K2	-18.62 X353+23.08 X356+490.53 X542-821.79 X545+2794.28 X560-1411.02 X563-2414.27 X566+1564.46 X572-1706.45 X584+1686.52 X587-829.77 X602+992.97 X608-337.00 X629- 1668.25 X737+3210.41 X740-2952.70 X746+1405.87 X749	0.97	0.04
Ca1	-740.54 X545+1449.71 X548-1749.59 X557+692.92X563+1325.2X566-2672.93 X572+2078.8 X575-455.39 X590-987.01X599 +1059.25 X602	0.86	0.06
Ca2	181.69 X527-487.65 X536+1083.14 X548-1781.10 X557+834.17 X563+1390.81 X566-3256.21 X572+2143.30 X575-975.56 X599+986.45 X602-736.40 X638+1398.38 X644-840.93 X647+867.32 X671-1454.06 X674+620.45 X677+635.77 X713-2213.57 X719+1733.62 X722- 130.24 X737	0.96	0.04
Mg1	-313.49 X545+706.57 X548-283.18 X551-639.89 X554+876.32 X557-442.20 X563+224.29 X590+303.02 X602-431.43 X605	0.91	0.03
Mg2	-362.16 X545+520.12X548-216.32 X551+471.20 X557-462.81 X563-497.47 X569+821.73 X575- 300.62 X578+336.62 X596-772.09 X590+1184.26 X602-727.48 X605+201.40 X620-408.32 X644+592.45 X650-507.81 X656+225.97 X677-111.48 X683+56.64 X704-429.07 X722+774.28 X728-436.19 X734+46.93 X749	0.99	0.01
B1a	13993.71 X527-24088.92 X530+23742.10 X536-18657.09 X539+15175.42 X551-33592.47 X563+28364.63 X569-4906.56 X593	0.84	2.47
B1b	22895.74 X659-94173.64 X665+84370.24 X668-16611.98 X677+32892.43 X695-40800.64 X698+16039.03 X707+46137.37 X716-137101.43 X719+123958.43 X722-37785.88 X725	0.84	2.45
B2	589.16 X377+1538.81 X383-3068.97 X386-1877.26 X395+3340.11 X398+19929.74 X536+ 38269.38 X539+48398.6 X551 -53011.6 X563+21088.2 X572+32501.8 X599-32303.4 X602+32411.2 X620-41840.0 X623 +58478.1 X638-47856.9 X641-99 X749	0.97	1.01
Cu1	-6023.45 X530+8493.37 X533-9279.56 X542+8900.35 X548-11739.27 X572+16234.38 X578- 17964.27 X584+28034.34 X590-22428.39 X593+19608.02 X599-13923.31 X602	0.84	0.95
Cu2	-6609.20 X530+6941.42 X533-1141.54 X551+13489.36 X590-17502.34 X593+19399.09 X599- 15227.43 X602-11751.35 X632+12344.1 X635-532.28 X722 +570.72 X725	0.86	1.40
Zn1	-30405.63 X668+74156.81 X674-76207.32 X680+65150.69 X686-37410.03 X689+41547.49 X704-46237.16 X707+25245.86 X719-15708.24 X722	0.77	2.49
Zn2	-14322.23 X530+20355.71 X533+50406.23 X563-47384.64 X557-71712.84 X602 +40321.98 X608+97905.02 X614 -47719.94 X617 -79472.88 X629+51667.07 X635-6885.324 X728+8627.049 X731-1711.676 X749	0.92	1.58

6 R² = coefficient of determination; RMSE = root mean square error.

7 ^a The equations from the models built using the stepwise regression and based on the greatest R² from
8 wavelength groups: N1, P1, K1, Ca1, Mg1, B1, Cu1, and Zn1. The equations using variables
9 selected from each wavelength groups in model 2 are as follows: N2, P2, K2, Ca2, Mg2, B2, Cu2,
10 and Zn2. Leaf nutrients: N, nitrogen; P, phosphorus; K, potassium; C, calcium; Mg, magnesium; B,
11 boron; Cu, copper; and Zn, zinc.

12 ^b The letter “X” followed by a three-digit number indicates the wavelength of the respective reflectance
13 value.
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Table 11. Results of PCR analysis to predict leaf nutrient contents using variables from ND and SR equations.

Leaf nutrient	Variables of ND and SR			All variables of ND and SR		
	R^2	MB	RMSE	R^2	MB	RMSE
N	0.65	0.46	0.23	0.89	0.23	0.14
P	0.66	0.02	0.01	0.82	0.01	0.01
K	0.61	0.23	0.13	0.82	0.15	0.10
Ca	0.69	0.22	0.09	0.82	0.13	0.07
Mg	0.64	0.09	0.05	0.87	0.06	0.03
B	0.61	6.66	3.62	0.83	-5.05	2.51
Cu	0.70	2.46	1.24	0.90	2.18	0.77
Zn	0.56	9.19	3.26	0.76	5.24	2.55

R^2 = coefficient of determination; MB = maximum bias of the model residuals; RMSE = root mean square error; ND = normalised different; SR = simple ratio.

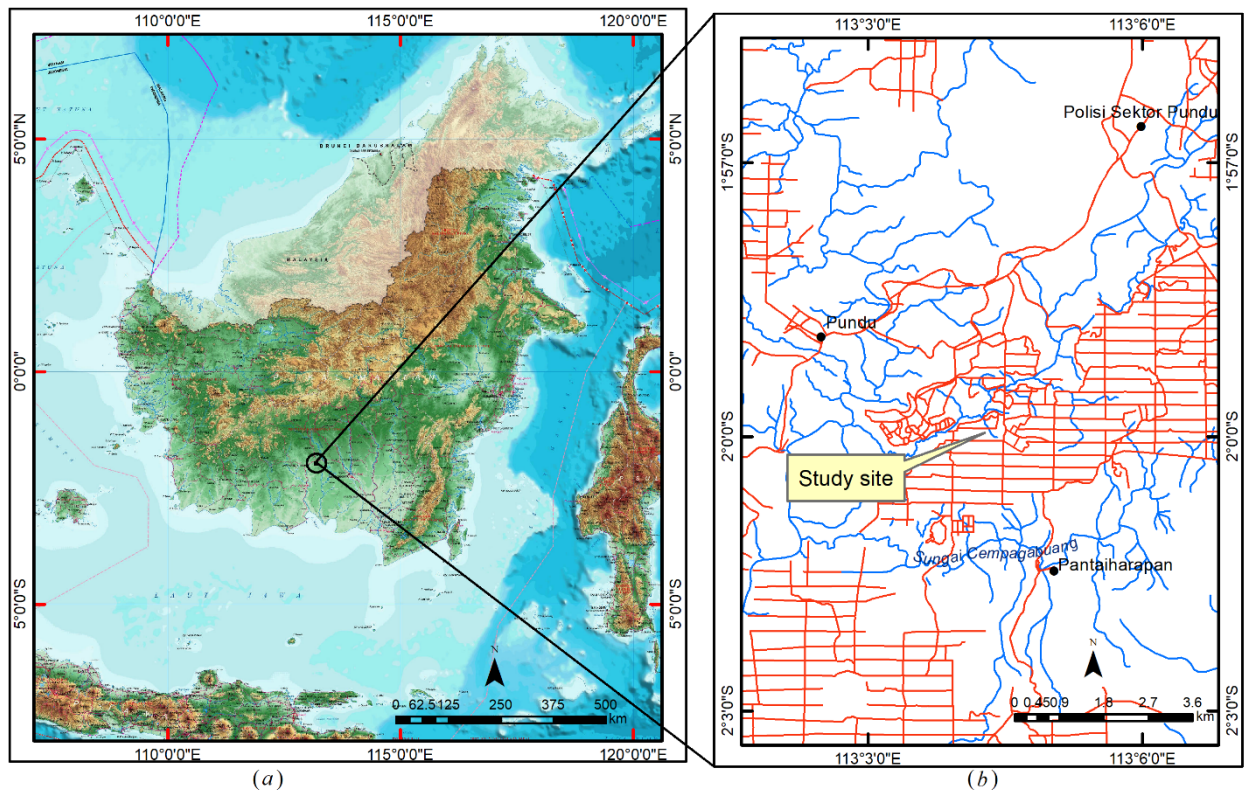


Fig. 1. Study site was on Kalimantan Island (a); map of the study site's area (b).



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52 Fig. 2. Leaf sampling: leaf numbers 9, 17, 25, and 33 (a); leaf collection in the field (b);

53 spectral leaf measurement (c); and cleaning oil palm leaflets before leaf analysis (d).

54

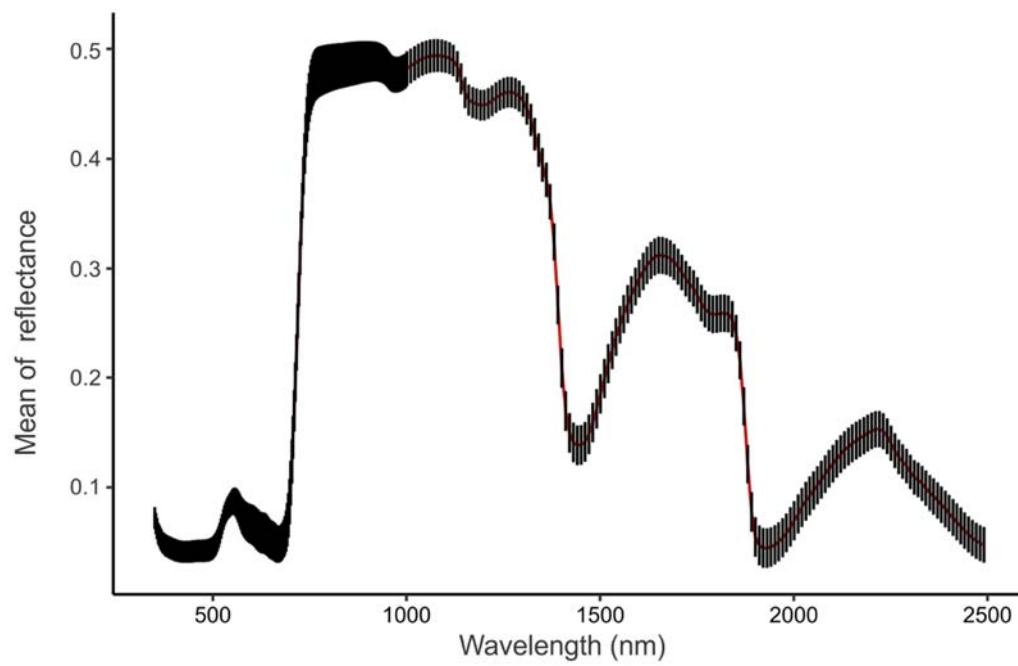


Fig. 3. Mean reflectance values of oil palm leaves with standard deviations calculated from spectral measurements.