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

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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

54 Nations 2015). Fertilizer is an important factor affecting oil palm production and
55 represents 40%–50% of the total field upkeep costs (Ng 2002). Fertilizer requirements
56 in oil palm plantations were determined by leaf nutrient contents analysis, as is typical
57 for many other crops (Pritts and Heidenreich 2012; Memon, Memon, and Hassan 2005).
58 To determine leaf nutrient contents, leaf samples are annually collected for analysis
59 (Chapman and Gray 1949; Fairhurst and Mutert 1999). Leaf samples are taken
60 periodically from leaf number 17 for adult palms and leaf number 9 for young palms.
61 Commonly, the sampled leaves are grouped in leaf sampling units (LSUs) that consist
62 of 30–40 selected palms each. One LSU is assigned for every 30–40 ha (Foster and
63 Choong 1976; Uexkull, Fairhurst, and von Uexkull 1991). A common problem is the
64 accuracy of determining the leaf for sampling. To identify leaf number 17, workers
65 must first identify leaf number 1, the youngest fully-expanded leaf, and then count
66 backwards. However, there can be some ambiguity in determining the youngest fully-
67 expanded leaf. Therefore, an improved technique is needed that can be used to quickly
68 monitor leaf nutrients in oil palm plantations. Remote sensing techniques based on the
69 reflectance values of leaves have the potential to meet this demand.
70 Remote sensing techniques based on reflectance values have been used for the
71 detection and prediction of plant nutrient states. Albayrak (2008) measured reflectance
72 levels for determining nitrogen (N), phosphorus (P), potassium (K), acid detergent fibre,
73 and neutral detergent fibre contents in a sainfoin pasture and found a strong relationship
74 between plant nutrient content and canopy reflectance, with coefficient of determination
75 (R^2) values in the 0.68–0.93 range. Cohen *et al.* (2010) estimated leaf N levels in potato
76 using spectral data and simulated bands from the VENμS satellite that indicated N
77 fertilizer treatment levels, obtaining an R^2 value of 0.95, an 80.5% overall accuracy and
78 a kappa coefficient (κ) value of 74%. Özyigit and Bilgen (2013) showed significant

79 relationships between spectral reflectance and the leaf nutrient contents of N, P, and K
80 in rangeland plants with R^2 values of 0.85, 0.43, and 0.84, respectively. Menesatti *et al.*
81 (2010) estimated the plant nutritional status using a visible to near infra-red (NIR)
82 spectrophotometric analysis of orange leaves and obtained high R^2 values of 0.91, 0.43,
83 0.99, 0.95, 0.94, 0.92, 0.93, and 0.89 for N, P, K, calcium (Ca), magnesium (Mg), iron
84 (Fe), manganese (Mn), and zinc (Zn), respectively.
85 Using NIR reflectance spectroscopy, Rothman *et al.* (2009) showed that
86 wavelengths in the 1100–2498 nm range had strong correlations with the nutritional
87 values of foods eaten by mountain gorillas, with R^2 values of 0.73–0.99. Başayiğit,
88 Dedeoğlu, and Akgül (2015) showed that wavelengths of 540–560 nm (green visible)
89 and 990–1010 nm (NIR) were correlated with active Fe levels in apple, cherry, and
90 peach, with coefficients of the accuracy of 76.70%, 75.28%, and 78.69%, respectively.
91 The coefficient of accuracy is a statistical parameter for methods comparisons (Lin and
92 Torbeck 1998). Stein *et al.* (2014) predicted macronutrient contents from loblolly pine
93 reflectance. They found that the important wavelengths in the partial least squares
94 regression reflectance model for leaf N status were visible, red edge, and NIR regions,
95 while the visible and red-edge regions were the important wavelengths for determining
96 leaf P, K, and Mg. Min and Lee (2005) identified wavelengths of 448, 669, 719, 1,377,
97 1,773, and 2,231 nm as significant for N detection in citrus. Özyigit and Bilgen (2013)
98 found that wavelengths of 609, 647, 651, 654, 669, 675, 676, 680, 721, 727, and 760 nm
99 were suitable for estimating the N levels in rangeland plants; those of 675 and 680 nm
100 were suitable for estimating P levels; and those of 410, 411, 417, 422, 460, 463, 468,
101 646, 651, 658, 669, 670, 674, 676, and 682 nm were suitable for estimating K levels.
102 Thus, reflectance values from spectrometry data at different suitable wavelengths can be
103 used to determine leaf nutrient contents in different plants. However, oil palm nutrient

104 contents studies using remote sensing techniques have been limited. We believed that
105 oil palm leaf nutrient contents could also be predicted using these techniques. Fertilizer
106 recommendations can also be derived from leaf spectral measurements. Cilia *et al*.
107 (2014) produce a pixel-based variable-rate N fertilization map from hyperspectral
108 sensors in maize. Amaral, Trevisan, and Molin (2017) proposed variable-rate N
109 fertilization in sugarcane based on readings from the crop canopy reflectance sensor
110 Crop Circle ACS-430 (Holland Scientific Inc. Lincoln, NE, USA).
111 Therefore, the objective of this study was to determine suitable reflectance
112 wavelengths to predict leaf nutrient contents, especially those of N, P, K, Ca, Mg, boron
113 (B), copper (Cu), and Zn. In oil palm trees, N, P, K, Ca, and Mg are major nutrients that
114 are required for annual vegetative dry matter production and fresh fruit-bunch
115 production. In addition, the micronutrients B, Cu, and Zn are required by mature oil
116 palms (Ng 2002). Ng (2002) found that sulfur (S), as major nutrient, and Mn and Fe are
117 also required for oil palm growth; but establishing their levels is not necessary for
118 determining fertilizer requirements. The S levels in common fertilizers (ammonium
119 sulfate, superphosphate, and kieserite) are sufficient for oil palm growth and production.
120 Oil palm in Indonesia are mostly grown in soil with low pH values (Nelson *et al*. 2002),
121 which means that the amounts of available Mn and Fe were high. Therefore, Mn and Fe
122 were omitted when determining the fertilizer requirements for oil palm.

123 **2. Materials and Methods**

124 Oil palm leaf reflectance data were collected, and leaf nutrient analyses were performed.
125 Predicting leaf nutrient contents in oil palm using reflectance data will increase the
126 efficiency of management practices in oil palm plantations. In particular, monitoring
127 leaf nutrient states will help determine fertilizer requirements, decreasing costs and
128 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

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

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

183 ***2.3. Data analyses***

184 The wavelengths were divided into nine groups (Table 1) as described by Hatchell
185 (1999). The analyses in this study were carried out using R software (RStudio 2015) as
186 described below.

187 Table 1. Wavelength ranges

188 *2.3.1. Variable screening to construct normalised differences and simple ratio*
189 *models*

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

197 *2.3.2. Vegetative indices*

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

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

204 Table 2. Vegetative indices used in this study
205

206 *2.3.3. Variables selected using a stepwise regression and the generalized linear*
207 *model (*GLM*) formulae*

208 Stepwise methods with the GLM formula were applied to dataset 2 to determine the
209 variables suitable for predicting leaf nutrient contents. The stepwise method has been
210 commonly used in research for selecting variables suitable for predicting or simulating
211 leaf nutrient contents in several plants (Starks *et al.* 2006; Albayrak 2008; Joffre *et al.*
212 1992; Başayiğit, Dedeoğlu, and Akgül 2015; Serusi *et al.* 2010; Min and Lee 2005;
213 Basayigit and Senol 2009; Özyigit and Bilgen 2013). In this study, stepwise processing
214 was performed with the MASS package in RStudio software (Ripley *et al.* 2015) using
215 the GLM formula (RStudio 2015). The parameters set for the GLM formula were
216 Gaussian for family. The stepwise processing was based on Akaike's Information
217 Criterion (AIC) value with forward and backward directions. The stepwise processing
218 was applied to the nine wavelength ranges, and all variables selected as output from
219 stepwise processing were tested for significant covariates. Therefore, the final variables
220 selected were all significant at $p = 0.05$ for inclusion in the model to predict leaf nutrient
221 contents (Bursac *et al.* 2008). The function of automated model selection based on the
222 *p*-value was adopted from Meys (2013). The parameters of goodness-of-fit were the
223 adjusted coefficient of determination (R^2_a) and R^2 between the reference and predicted
224 values from the output of the model predicting the nutrient contents. Root mean squared
225 error (RMSE) was also used to evaluate the model by summarizing the differences
226 between the actual (observed) and predicted values.

227 Principal component regression (PCR) was applied to the model that was
228 produced from the stepwise processes. PCR is a method that addresses multicollinearity,
229 according to Fekedulegn *et al*. (2002) and Alibuhtto and Peiris (2015), and is based on
230 principal component analysis. Variables in the stepwise model were transformed to
231 uncorrelated variables called principal components of the correlation matrix. Then some
232 of the principal components were eliminated to effect a reduction in variance, which
233 was performed using ordinary least squares estimation (Fekedulegn *et al*. 2002; Graham
234 2009). We used the "analogue package" to perform PCR that included scaling data and
235 cross validation. The PCR performances were R^2, maximum bias of the model residuals,
236 and RMSE. The regression coefficients for the PCR were used to build the final
237 predictive model of leaf nutrient contents (Simpson and Oksanen 2016).

238 **3. Results**

239 ***3.1. Leaf nutrient analysis***

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

248 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:

$$\text{N-ND}_{(X1423\_X1877)} = \frac{(X1423 - X1877)}{(X1423 + X1877)}, \quad (1)$$

$$\text{N-SR}_{(X1423\_X1877)} = \frac{X1423}{X1877}, \quad (2)$$

$$\text{Ca-ND}_{(X1164\_X1238)} = \frac{(X1164 - X1238)}{(X1164 + X1238)}, \text{ and} \quad (3)$$

$$\text{Ca-SR}_{(X1164\_X1238)} = \frac{X1164}{X1238}. \quad (4)$$

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.

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

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

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

308 ***3.3. Vegetative indices***

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

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

319

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

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

327 ***3.4. Multivariate analysis***

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

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

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

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

Table 7. Results of a multivariate analysis using PLSR

Table 8. Results of a multivariate analysis using PCR

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 *X*553–*X*707 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 *X*1423 and *X*1877 had strong positive correlations with the N leaf nutrient analysis ($R^2 = 0.53$), while *X*1164 and *X*1238 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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References

Abdel-Rahman, Elfatih M., Onisimo Mutanga, John Odindi, Elhadi Adam, Alfred Odindo, and Riyad Ismail. 2017. "Estimating Swiss Chard Foliar Macro- and Micronutrient Concentrations under Different Irrigation Water Sources Using Ground-Based Hyperspectral Data and Four Partial Least Squares (PLS)-Based (PLS1, PLS2, SPLS1 and SPLS2) Regression Algorithms." *Computers and Electronics in Agriculture* 132 (November 2016). Elsevier B.V.: 21–33. doi:10.1016/j.compag.2016.11.008.

Albayrak, Sebahattin. 2008. "Use of Reflectance Measurements for the Detection of N, P, K, ADF and NDF Contents in Sainfoin Pasture." *Sensors* 8 (11): 7275–7286. doi:10.3390/s8117275.

Alibuhtto, M C, and T S G Peiris. 2015. "Principal Component Regression for Solving Multicollinearity Problem." In *5th International Symposium 2015 of the South Eastern University of Sri Lanka*, 231–238. Oluvil: South Eastern University of Sri Lanka. http://www.seu.ac.lk/intsym2015/.

Amaral, Lucas R., Rodrigo G. Trevisan, and José P. Molin. 2017. “Canopy Sensor Placement for Variable-Rate Nitrogen Application in Sugarcane Fields.” *Precision Agriculture*. Springer US, 1–14. doi:10.1007/s11119-017-9505-x.

Başayiğit, Levent, Mert Dedeoğlu, and Hüseyin Akgül. 2015. “The Prediction of Iron Contents in Orchards Using VNIR Spectroscopy.” *Turkish Journal of Agriculture and Forestry* 39 (1): 123–134. doi:10.3906/tar-1406-33.

Basayigit, Levent, and Huseyin Senol. 2009. “Prediction of Plant Nutrient Contents in Deciduous Orchards Fruits Using Spectroradiometer.” *International Journal of ChemTech Research* 1 (2): 212–224.

Basiron, Yusof. 2007. “Palm Oil Production through Sustainable Plantations.” *European Journal of Lipid Science and Technology* 109 (4): 289–295. doi:10.1002/ejlt.200600223.

Behera, S. K., B. N. Rao, K. Suresh, K. Ramachandrudu, and K. Manorama. 2016. “Soil Fertility, Leaf Nutrient Concentration and Yield Limiting Nutrients in Oil Palm (Elaeis Guineensis) Plantations of Surat District of Gujarat.” *Indian Journal of Agricultural Sciences* 86 (3): 409–413.

Bursac, Zoran, C Heath Gauss, David Keith Williams, and David W Hosmer. 2008. “Purposeful Selection of Variables in Logistic Regression.” *Source Code for Biology and Medicine* 3: 17. doi:10.1186/1751-0473-3-17.

Capolupo, Alessandra, Lammert Kooistra, Clara Berendonk, Lorenzo Boccia, and Juha Suomalainen. 2015. “Estimating Plant Traits of Grasslands from UAV-Acquired Hyperspectral Images: A Comparison of Statistical Approaches.” *ISPRS Int. J. Geo-Inf* 4: 2792–2820. doi:10.3390/ijgi4042792.

Chapman, G. W., and H. M. Gray. 1949. “Leaf Analysis and the Nutrition of the Oil Palm (Elaeis Guineensis Jacq.).” *Annals of Botany* 13 (4): 415–433. http://aob.oxfordjournals.org/content/13/4/415.short.

Cilia, Chiara, Cinzia Panigada, Micol Rossini, Michele Meroni, Lorenzo Busetto, Stefano Amaducci, Mirco Boschetti, Valentina Picchi, and Roberto Colombo. 2014. “Nitrogen Status Assessment for Variable Rate Fertilization in Maize through Hyperspectral Imagery.” *Remote Sensing* 6 (7): 6549–6565. doi:10.3390/rs6076549.

Cohen, Y., V. Alchanatis, Y. Zusman, Z. Dar, D. J. Bonfil, A. Karnieli, A. Zilberman, et al. 2010. “Leaf Nitrogen Estimation in Potato Based on Spectral Data and on

Simulated Bands of the VENμS Satellite." *Precision Agriculture* 11 (5): 520–537. doi:10.1007/s11119-009-9147-8.

Corley, R H V, and P B Tinker. 2003. *The Oil Palm*. *Blackwell Science Ltd*. Fourth Edi. Malden, MA: Blackwell Science Ltd,. doi:10.1002/9780470750971.

Fairhurst, T, and E Mutert. 1999. "Interpretation and Management of Oil Palm Leaf Analysis Data." *Better Crops International* 13, No 1: 48–51.

Fekedulegn, B Desta, J J Colbert, R R Hicks, and Michael E Schuckers. 2002. *Coping with Multicollinearity : An Example on Application of Principal Components Regression in Dendroecology*. *United States Department of Agriculture*. Newtown Square PA: USDA Forest Service. http://www.fs.fed.us/ne.

Foster, H L, and Chang Kwong Choong. 1976. "Palm Leaf Nutrient Levels." *MARDI Res. Bull.* 5, 2: 74–90.

Galvez-Sola, L., F. García-Sánchez, J.G. Pérez-Pérez, V. Gimeno, Josefa M. Navarro, J.J. Martínez-Nicolás, and M. Nieves. 2015. "Rapid Estimation of Nutritional Elements on Citrus Leaves by near Infrared Reflectance Spectroscopy." *Frontiers in Plant Science* 6 (July): 1–8. doi:10.3389/fpls.2015.00571.

Gitelson, Anatoly A., Yoram J. Kaufman, and Mark N. Merzlyak. 1996. "Use of a Green Channel in Remote Sensing of Global Vegetation from EOS-MODIS." *Remote Sensing of Environment* 58 (3): 289–298. doi:10.1016/S0034-4257(96)00072-7.

Graham, Michael H. 2009. "Statistical Confronting Multicollinearity in Ecological" 84 (11): 2809–2815.

H.R. Von Uexkull and T.H. Fairhurst. 1999. "Some Nutritional Disorder in Oil Palm." *Better Crop International* 13, No 1: 16–21.

Hatchell, D.C. 1999. "Analytical Spectral Devices, Inc. (ASD) Technical Guide. 3rd Ed." *Inc. ASD Technical Guide*.

Hoffer, R. M. 1984. "Remote Sensing of the Distribution and Structure of Vegetation-Chapter 5." In *The Role of Terrestrial Vegetation in the Global Carbon Cycle: Measurement by Remote Sensing*, edited by G.M. Woodwell, 131–159.

Hoffer, Roger M. 1971. *The Importance of "Ground Truth" Data in Remote Sensing*. LARS Print 120371. Sao Jose' dos Campos, Sao Paulo., Brazil. doi:Paper presented at the "United Nations Panel Meeting on the Establishment and Implementation of Research Programs in Remote Sensing. Held at the National Institute for Space Research. November 29 - December 10, 1971.

Joffre, R., D. Gillon, P. Dardenne, R. Agneessens, and R. Biston. 1992. “The Use of Near-Infrared Reflectance Spectroscopy in Litter Decomposition Studies.” *Annales Des Sciences Forestieres* 49 (5): 481–488. doi:10.1051/forest:19920504.

Kalra, Yash P. 1998. *Handbook of Reference Methods for Plant Analysis*. Edited by Yash P. Kalra. *Soil and Plant Analysis Council, Inc.* Boca Raton, FL: CRC Press, Taylor & Francis Group. doi:10.2135/cropsci1998.0011183X003800060050x.

Lee, Chin-Tui, Zaharah Abdul Rahman, Mohamed Hanafi Musa, Mohd Shahkhirat Norizan, and Choon-Check Tan. 2011. “Leaf Nutrient Concentrations in Oil Palm as Affected by Genotypes, Irrigation and Terrain.” *Journal of Oil Palm and the Environment* 2 (5): 38–47. doi:10.5366/jope.2011.05.

Li, Zh, Ch Nie, Ch Wei, X Xu, X Song, and J Wang. 2016. “Comparison of Four Chemometric Techniques for Estimating Leaf Nitrogen Concentrations in Winter Wheat (Triticum Aestivum) Based on Hyperspectral Features.” *Journal of Applied Spectroscopy* 83 (2). Russian Original: 240–247. doi:10.1007/s10812-016-0276-3.

Lin, L, and L D Torbeck. 1998. “Coefficient of Accuracy and Concordance Correlation Coefficient: New Statistics for Methods Comparison.” *PDA J Pharm Sci Technol* 52 (2): 55–59.

Mahajan, G. R., R. N. Sahoo, R. N. Pandey, V. K. Gupta, and Dinesh Kumar. 2014. “Using Hyperspectral Remote Sensing Techniques to Monitor Nitrogen, Phosphorus, Sulphur and Potassium in Wheat (Triticum Aestivum L.).” *Precision Agriculture* 15 (5): 499–522. doi:10.1007/s11119-014-9348-7.

Memon, N, K S Memon, and Zia-ul Hassan. 2005. “Plant Analysis as a Diagnostic Tool for Evaluating Nutritional Requirements of Bananas.” *International Journal of Agriculture & Biology* 7 (5): 824–831.

Menesatti, P., F. Antonucci, F. Pallottino, G. Roccuzzo, M. Allegra, F. Stagno, and F. Intrigliolo. 2010. “Estimation of Plant Nutritional Status by Vis-NIR Spectrophotometric Analysis on Orange Leaves [Citrus Sinensis (L) Osbeck Cv Tarocco].” *Biosystems Engineering* 105 (4): 448–454. doi:10.1016/j.biosystemseng.2010.01.003.

Meys, Joris. 2013. “Stepwise Regression Using P-Values to Drop Variables with Nonsignificant p-Values.”

http://stackoverflow.com/questions/3701170/stepwise-regression-using-p-values-to-drop-variables-with-nonsignificant-p-value.

Min, M, and WS Lee. 2005. "Determination of Significant Wavelengths and Prediction of Nitrogen Content for Citrus." *Transactions of the ASAE* 48 (1998): 455–461. doi:10.13031/2013.18308.

Mukaka, M. M. 2012. "Statistics Corner: A Guide to Appropriate Use of Correlation Coefficient in Medical Research." *Malawi Medical Journal* 24 (3): 69–71.

Munoz-Huerta, Rafael F., Ramon G. Guevara-Gonzalez, Luis M. Contreras-Medina, Irineo Torres-Pacheco, Juan Prado-Olivarez, and Rosalia V. Ocampo-Velazquez. 2013. "A Review of Methods for Sensing the Nitrogen Status in Plants: Advantages, Disadvantages and Recent Advances." *Sensors (Basel, Switzerland)* 13 (8): 10823–10843. doi:10.3390/s130810823.

Navia, Edwin A., Edwin F. Restrepo, and Hernán Mauricio Romero. 2014. "Response of Six Sources of Oil Palm Planting Materials from Malaysia Planted in the Eastern Plains of Colombia to Bud Rot." *Journal of Oil Palm Research* 26 (MAR): 73–83.

Nelson, By Paul N, Tiemen Rhebergen, Suzanne Berthelsen, Michael J Webb, Murom Banabas, Thomas Oberthür, Chris R Donough, Kooseni Indrasuara, and Ahmad Lubis. 2002. "Soil Acidification under Oil Palm : Rates and Effects on Yield." *Better Crops* 95 (4). Sigapore: 22–25. http://www.ipni.net/publication/bettercrops.nsf/0/EC3F3750369330DA8525797C00796675/$FILE/Better Crops 2011-4 p22.pdf.

Ng, Sk. 2002. "Nutrition and Nutrient Management of Oil Palm-New Thrust for the Future Perspective." *In: Pasricha, N.S., Bansal, S.K. (Eds.), Potassium for Sustainable Crop Production. International Symposium on Role of Potassium in India. Potash Research Institute of India, and International Potash Institute, New Delhi.*, 415–429. http://www.ipipotash.org/udocs/Nutrition and Nutrient Management of the Oil Palm.pdf.

Nur Sabrina, A. A., M. Sariah, and A. R. Zaharah. 2012. "Suppression of Basal Stem Rot Disease Progress in Oil Palm (Elaeis Guineensis) after Copper and Calcium Supplementation." *Pertanika J. Trop. Agric. Sci.* 35 (S): 13–24. http://www.pertanika.upm.edu.my/Pertanika PAPERS/JTAS Vol. 35 (S) Dec. 2012/02_page 13-24.pdf.

OECD/Food and Agriculture Organization of the United Nations. 2015. *OECD-FAO Agricultural Outlook 2015-2024*. OECD Publishing, Paris. doi:http://dx.doi.org/10.1787/agr_outlook-2015-en.

Özyigit, Y., and M. Bilgen. 2013. "Use of Spectral Reflectance Values for Determining Nitrogen, Phosphorus, and Potassium Contents of Rangeland Plants." *Journal of Agricultural Science and Technology* 15 (SUPPL): 1537–1545.

Pimstein, Agustin, Arnon Karnieli, Surinder K. Bansal, and David J. Bonfil. 2011. "Exploring Remotely Sensed Technologies for Monitoring Wheat Potassium and Phosphorus Using Field Spectroscopy." *Field Crops Research* 121 (1): 125–135. doi:10.1016/j.fcr.2010.12.001.

Pritts, Marvin, and Cathy Heidenreich. 2012. "Leaf and Soil Analysis Special Edition." *New York Berry News. Cornell University. College of Agriculture and Life Sciences.* 11 (8).

Rankie, Ian, and T.H. Fairhurst. 1999. "Management of Phosphorus, Potassium and Magnesium in Mature Oil Palm." *Better Crops International* 13, No 1: 10–15.

Ripley, Brian, Bill Venables, Douglas M Bates, Kurt Homik, Albrecht Gebhardt, and David Firth. 2015. "Package ' MASS ,'" 167.

Rothman, Jessica M., Colin A. Chapman, Julie L. Hansen, Debbie J R Cherney, and Alice N. Pell. 2009. "Rapid Assessment of the Nutritional Value of Foods Eaten by Mountain Gorillas: Applying near-Infrared Reflectance Spectroscopy to Primatology." *International Journal of Primatology* 30 (5): 729–742. doi:10.1007/s10764-009-9372-z.

RStudio. 2015. "Integrated Development Environment (IDE) for R Code." Boston, MA: RStudio, Inc. https://www.rstudio.com/products/rstudio/.

Serusi, Simona, W Dr. Verhoef, J Dr. Clevers, and M Dr. Schlerf. 2010. "Estimation of Leaves Nutrient Content in Seagrass Using Spectral Data The Case of Halodule Uninervis." *Master of Thesis. International Institute for Geo-Information and Earth Observation. Enschede, The Netherlands*. Master of Thesis. ITC. International Institute for Geo-Information and Earth Observation. Enschede, The Netherlands.

Simpson, Gavin L, and Jari Oksanen. 2016. "Package ' Analogue .'" London: CRAN. https://github.com/gavinsimpson/analogue.

Sonobe, Rei, and Quan Wang. 2016. “Assessing the Xanthophyll Cycle in Natural Beech Leaves with Hyperspectral Reflectance.” *Functional Plant Biology*, 438–447. doi:10.1071/FP15325.

Starks, Patrick J., Duli Zhao, William A. Phillips, and Samuel W. Coleman. 2006. “Development of Canopy Reflectance Algorithms for Real-Time Prediction of Bermudagrass Pasture Biomass and Nutritive Values.” *Crop Science* 46 (2): 927–934. doi:10.2135/cropsci2005.0258.

Stein, Beth R., Valerie a. Thomas, Laura J. Lorentz, and Brian D. Strahm. 2014. “Predicting Macronutrient Concentrations from Loblolly Pine Leaf Reflectance across Local and Regional Scales.” *GIScience & Remote Sensing* 51 (3): 269–287. doi:10.1080/15481603.2014.912875.

Sulaeman, Suparto, and Eviati. 2005. *Analisis Kimia Tanah, Tanaman, Air, Dan Pupuk*. Edited by Fahmuddin Agus. 2nd ed. Bogor: Indonesian Soil Research Institute. http://balittanah.litbang.pertanian.go.id/eng/.

Tengoua, F. F., M. M. Hanafi, A. S. Idris, and S. R. Syed-Omar. 2015. “Screening for Optimum Concentrations of Boron, Copper and Manganese for the Growth of Three-Month Old Oil Palm Seedlings in Solution Culture.” *Pertanika Journal of Tropical Agricultural Science* 38 (1): 113–126.

Uexkull, H.R. von, T.H. H Fairhurst, and H R von Uexkull. 1991. *Fertilizing for High Yield and Quality the Oil Palm*. *IPI-Bulletin*. Vol. 12. Bern/Switzerland: International Potash Institute.

Vossen, Ham Van Der. 1970. “Nutrient Status and Fertilizer Responses of Oil Palms on Different Soils in the Forest Zone of Ghana.” *Ghana Journal of Agricultural Science* 3: 109–129. http://www.cabdirect.org/abstracts/19710307810.html.

World Growth. 2011. *The Economic Benefit of Palm Oil to Indonesia. A Report by World Growth February 2011*. *World Growth Palm Oil Green Development Campaign*. http://worldgrowth.org/site/wp-content/uploads/2012/06/WG_Indonesian_Palm_Oil_Benefits_Report-2_11.pdf.

Yao, Sheng, Guofen Wu, Mian Xing, Shuke Zhou, and Junwen Pu. 2010. “Determination of Lignin Content in Acacia Spp. Using near-Infrared Reflectance Spectroscopy.” *BioResources* 5 (2): 556–562.

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)	$(R_{NIR} - R_{red})/(R_{NIR} + R_{red})$	Rouse *et al.* (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 *et al.* (2002)
MCARI1	$1.2[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]$	Haboudane *et al.* (2004)
MCARI2	$1.2[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]/[((2 \times R800 + 1)^2 - (6 \times R_{800} - 5(R_{650})^{0.5}))^{0.5} - 0.5]$	Haboudane *et al.* (2004)
N870_1450	$(R_{870} - R_{1450})/(R_{870} + R_{1450})$	Pimstein *et al.* (2011)
N1645_1715	$(R_{1645} - R_{1715})/(R_{1645} + R_{1715})$	Pimstein *et al.* (2011)
P1080_1460	$(R_{1080} - R_{1460})/(R_{1080} + R_{1460})$	Mahajan *et al.* (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	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^2_a = adjusted R^2. Highlighted data indicate the results of the greatest R^2_a 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}	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	062	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 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.

	N			P			K			Ca			Mg			B			Cu			Zn		
G	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.

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

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

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

Model [a]	Equation [b]	R^2	RMSE
N1	467.26*X*527-684.82*X*533+3383.43 *X*554-3716.2*X*557-1448.32 *X*563+3663.97*X*566-1504.24*X*569 -2331.04*X*572+4116.12*X*575-1758.35*X*581-3567.07*X*596+4866.74*X*602-1480.22*X*605	0.94	0.11
N2	17.77*X*350-48.81*X*356+66.53*X*359-49.29*X*362-23.21*X*371+29.58*X*386-140.99*X*5331092.57*X*560-1734.08*X*563+1220.42*X*566+2687.89*X*572-5640.11*X*575+4687.8*X*581-6064.36*X*584+3474.07*X*587-864.06*X*593+3647.23*X*596-1482.66*X*602-4400.71*X*614+6228.86*X*620-6652.4*X*638+3951.21*X*641	0.997	0.02
P1	61.442*X*659-164.28*X*665+173.01*X*674-140.27*X*683+62.41*X*686+110.94*X*695-209.82*X*698+119.5*X*701-14.03*X*710+1.63*X*722	0.90	0.01
P2	33.92*X*527-36.77*X*530+82.72*X*560-85.66*X*563+32.01*X*575-115.32*X*584+82.28*X*587+148.20*X*662-166.33*X*665+29.98*X*674-30.55*X*698+30.46*X*701-4.60*X*710	0.92	0.004
K1	-227.96 *X*545+2961.11 *X*560-2211.65 *X*563-1826.20 *X*566+1625.65 *X*572-1581.21 *X*584+1269.91 *X*587	0.85	0.09
K2	-18.62 *X*353+23.08 *X*356+490.53 *X*542-821.79 *X*545+2794.28 *X*560-1411.02 *X*563-2414.27 *X*566+1564.46 *X*572-1706.45 *X*584+1686.52 *X*587-829.77 *X*602+992.97 *X*608-337.00 *X*629-1668.25 *X*737+3210.41 *X*740-2952.70 *X*746+1405.87 *X*749	0.97	0.04
Ca1	-740.54 *X*545+1449.71 *X*548-1749.59 *X*557+692.92*X*563+1325.2*X*566-2672.93 *X*572+2078.8 *X*575-455.39 *X*590-987.01*X*599 +1059.25 *X*602	0.86	0.06
Ca2	181.69 *X*527-487.65 *X*536+1083.14 *X*548-1781.10 *X*557+834.17 *X*563+1390.81 *X*566-3256.21 *X*572+2143.30 *X*575-975.56 *X*599+986.45 *X*602-736.40 *X*638+1398.38 *X*644-840.93 *X*647+867.32 *X*671-1454.06 *X*674+620.45 *X*677+635.77 *X*713-2213.57 *X*719+1733.62 *X*722-130.24 *X*737	0.96	0.04
Mg1	-313.49 *X*545+706.57 *X*548-283.18 *X*551-639.89 *X*554+876.32 *X*557-442.20 *X*563+224.29 *X*590+303.02 *X*602-431.43 *X*605	0.91	0.03
Mg2	-362.16 *X*545+520.12*X*548-216.32 *X*551+471.20 *X*557-462.81 *X*563-497.47 *X*569+821.73 *X*575-300.62 *X*578+336.62 *X*596-772.09 *X*590+1184.26 *X*602-727.48 *X*605+201.40 *X*620-408.32 *X*644+592.45 *X*650-507.81 *X*656+225.97 *X*677-111.48 *X*683+56.64 *X*704-429.07 *X*722+774.28 *X*728-436.19 *X*734+46.93 *X*749	0.99	0.01
B1a	13993.71 *X*527-24088.92 *X*530+23742.10 *X*536-18657.09 *X*539+15175.42 *X*551-33592.47 *X*563+28364.63 *X*569-4906.56 *X*593	0.84	2.47
B1b	22895.74 *X*659-94173.64 *X*665+84370.24 *X*668-16611.98 *X*677+32892.43 *X*695-40800.64 *X*698+16039.03 *X*707+46137.37 *X*716-137101.43 *X*719+123958.43 *X*722-37785.88 *X*725	0.84	2.45
B2	589.16 *X*377+1538.81 *X*383-3068.97 *X*386-1877.26 *X*395+3340.11 *X*398+19929.74 *X*536+-38269.38 *X*539+48398.6 *X*551 -53011.6 *X*563+21088.2 *X*572+32501.8 *X*599-32303.4 *X*602+32411.2 *X*620-41840.0 *X*623 +58478.1 *X*638-47856.9 *X*641-99 *X*749	0.97	1.01
Cu1	-6023.45 *X*530+8493.37 *X*533-9279.56 *X*542+8900.35 *X*548-11739.27 *X*572+16234.38 *X*578-17964.27 *X*584+28034.34 *X*590-22428.39 *X*593+19608.02 *X*599-13923.31 *X*602	0.84	0.95
Cu2	-6609.20 *X*530+6941.42 *X*533-1141.54 *X*551+13489.36 *X*590-17502.34 *X*593+19399.09 *X*599-15227.43 *X*602-11751.35 *X*632+12344.1 *X*635-532.28 *X*722 +570.72 *X*725	0.86	1.40
Zn1	-30405.63 *X*668+74156.81 *X*674-76207.32 *X*680+65150.69 *X*686-37410.03 *X*689+41547.49 *X*704-46237.16 *X*707+25245.86 *X*719-15708.24 *X*722	0.77	2.49
Zn2	-14322.23 *X*530+20355.71 *X*533+50406.23 *X*563-47384.64 *X*557-71712.84 *X*602 +40321.98 *X*608+97905.02 *X*614 -47719.94 *X*617 -79472.88 *X*629+51667.07 *X*635-6885.324 *X*728+8627.049 *X*731-1711.676 *X*749	0.92	1.58

R^2 = coefficient of determination; RMSE = root mean square error.

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

[b] The letter "*X*" followed by a three-digit number indicates the wavelength of the respective reflectance value.

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.

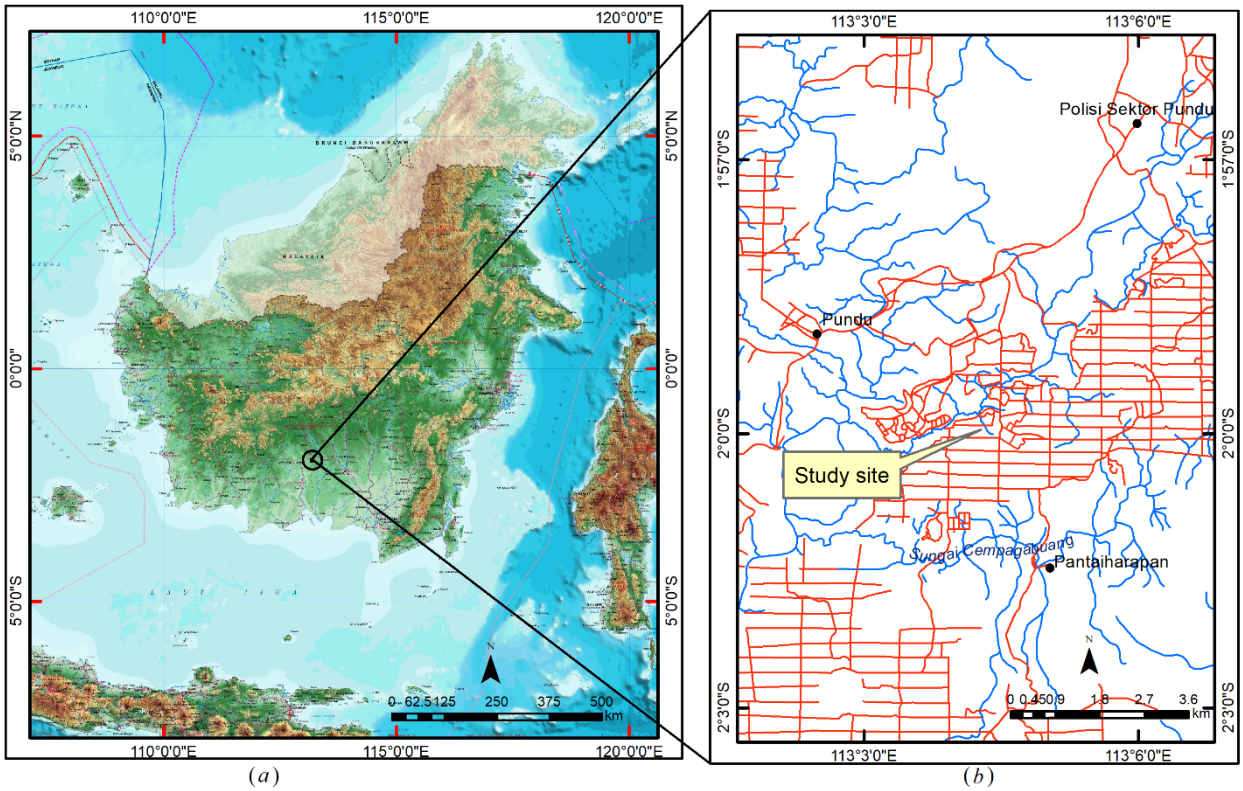

Fig. 1. Study site was on Kalimantan Island (*a*); map of the study site's area (*b*).

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*).

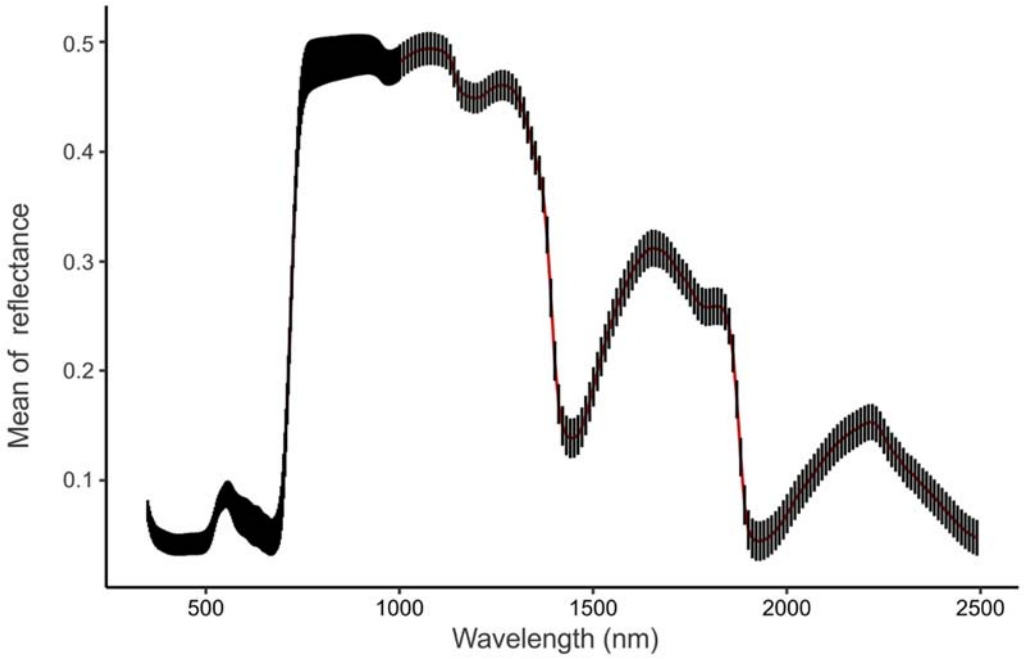

Fig. 3. Mean reflectance values of oil palm leaves with standard deviations calculated from spectral measurements.