POTENTIAL OF HYPERSPECTRAL REMOTE SENSING DATA IN ASSESSING CHLOROPHYLL CONTENT OF MATURE OIL PALM WITH LINEAR DISCRIMINANT ANALYSIS CLASSIFIER

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ABSTRACT: Chlorophyll (chl) is a fundamental biotic indicator in sustaining plant productivity, including *Elaeis guineensis.* Traditionally, chl is quantified via a series of wet chemical routine that is destructive, time-consuming and impractical for the oil palm plantation. Thus, a rapid tool or instrument which is cost-effective and environmental friendly that is capable to quantify the chl content is highly desirable for sustaining the oil palm industry. The availability of hyperspectral remote sensing has raised the interest of non-destructive measurement of chl content. Therefore, the aims of this study are to 1) develop the chl a and SPAD reading sufficiency classes using the Jenks Natural Breaks Classification (JNBC), 2) identify the chl-sensitive wavelengths of oil palm using hyperspectral remote sensing data and 3) evaluate the capability of Linear Discriminant Analysis (LDA) algorithm in classifying the chls sufficiency classes. Hence, a field experiment was carried out on mature *Tenera* palm stands (15 years old) with nitrogen treatments varied from 0 to 2 kg. The JNBC was proposed to determine the chl sufficiency classes. Meanwhile, feature selection was performed to select the chl-sensitive wavelengths while the LDA algorithm was used to classify the chl sufficiency levels using the previously selected wavelengths. The results of this study depicted that the chl a- and SPAD reading-sensitive wavelengths were frond-dependent. Generally, the SPAD reading classification accuracy tends to decrease as frond gets older. The LDA performed a moderate classification in discriminating the chl sufficiency levels of oil palm with accuracy ranging from 55.41 to 77.39%. In the nutshell, the factor of frond number should be considered in monitoring chls content of oil palm.

1. INTRODUCTION

Chlorophyll is an essential pigment for photosynthesis as well as plant functioning. The chl is traditionally quantified using destructive wet chemical procedures which generated chemical wastage and time consuming especially for plantation scale such oil palm. In contrast to the conventional method, hyperspectral remote sensing (HRS) has offered a non-destructive analysis for assessing chlorophyll. In addition, the spectral feature of HRS offers worthy information regarding the chl status in the plant. According to Gitelson and Merzlyak (1994), the spectral feature positioned near the 550 and 705 nm and above 750 nm was sensitive to the variations in chlorophyll content. A similar finding is also confirmed by Gitelson et al. (2003), where the spectral feature located from 525 to 555 nm and from 695 to 725 nm were capable to predict chl content of hardwood trees species with the coefficient of determination (R^2) above 0.94.

There were several techniques have been explored for evaluating chl content via HRS including spectral analysis, vegetation index, and machine learning. Machine learnings such support vector machine (SVM), Discriminant Analysis (DA), Decision Tree (DT) and Partial Least Square (PLS) have presenting their ability in estimating nutrients and chl of various type of crops (Gómez-Casero et al., 2007; Zhai et al., 2013; Amirruddin and Muharam, 2019). For chl study in oil palm, Golhani et al. (2019) tested the Interval Partial Least Squares (iPLS) regression to assess the relationship between HRS data and SPAD readings of oil palm seedlings as the proxy for detection of Orange Spotting (OS) disease. They reported that the iPLS model capable to predict the chl content with correlation coefficients of r = 0.72 and root mean square error (RMSE) value of 3.70%.

However, there is still lacking of the chl study in mature oil palm using HRS and machine learning. Hence, the objectives of this study were to 1) develop the chl a and SPAD reading sufficiency classes using the Jenks Natural Breaks Classification (JNBC), 2) identify the chl-sensitive wavelengths of oil palm using hyperspectral remote sensing data and 3) evaluate the capability of Linear Discriminant Analysis (LDA) algorithm in classifying the chls sufficiency classes.

2. MATERIALS AND METHODS

2.1 Study Area and Treatments

The study was conducted in a 15 years old *Tenera* plot belong to the United Malacca Berhad oil palm plantation located in Malacca, Malaysia (2°22′49.35” N and 102°14′16.84” E). The experiment was designed in Randomized Completely Block (RCB) layout with three levels of nitrogen (N) treatments. Three levels of N; 0, 1, and 2 kg N $palm^{-1}$ $year^{-1}$ were formulated and ammonium chloride (NH_4ClO) was applied as the source of N for three consecutive years.

2.2 Data Collection

During the field campaign, leaflets from frond 9 and frond 17 were chosen for the measurement of chls content and also spectral reflectance. SPAD readings were measured on the leaflets from each selected palm by SPAD Minolta 502. The spectroradiometer FieldSpec®4 Standard-Res model was used to measure the reflectance of the same leaflets used in SPAD readings measurement. After spectral measurements, the leaflets were subjected to chl content analysis using the method proposed by Coombs et al. (1985).

2.3 Data Analysis

In order to classify the chls content into the group, the JNBC has been proposed to determine the number of the classes. This approach is similar to the work done by Rodriguez-Moreno and Llera-Cid (2012) for the classification of N content of wheat. The goodness of variance fit (GVF) was used as the indicator of the class’s fitness of the JNBC which ranging from 0 to 1. The GVF of 0 and 1 signifies worst and good class, respectively. For the spectral analysis, the spectra starting from 400 to 2500 nm were analysed in this study. Prior to the feature selection and classification of chls content status, spectral data were separated by the ratio 70:30, purposely for training and validation. Both training and validating data sets were used to evaluate LDA classification. The classification with accuracy below 40.00%, between 40.00 to 80.00% and above 80.00%, were considered as a poor, moderate and good model, correspondingly (Unger Holtz, 2005). The feature selection and classification of chls content were carried out by using the Waikato Environment for Knowledge Analysis (WEKA) 3.8.2 software.

3. RESULTS AND DISCUSSION

Table 1 shows the best chls sufficiency classes; low, medium and high as obtained from the JNBC according to the types of chl content. The chl a and SPAD reading sufficiency levels generated from the JNBC have high GVF of 0.77 and 0.88, respectively. These classes were then used for feature selection and classification of chls content. Meanwhile, Table 2 depicts the significant spectral bands gained from feature selection for chls content classification, where a major number of the significant spectral bands were located in the NIR region. Besides, the red-edge bands ranging from 680 to 730 nm also recorded in both palm fronds. This discovery is parallel to the finding by Sims and Gamon (2002) (forest trees), Gitelson et al. (2003) (beech, wild vine, maple and chestnut) and Gitelson (2011) (beech) which reported that the reflectance in red-edge regions were sensitive to a wide range of chl content. The feature selection dictated that the chls response were frond-specific since each frond number has its own sensitive bands. This result was concurrent with Ding et al. (2009), where the sensitivity of spectral bands to chl content depended on plant genotype, phenotype and leaf characteristics.

Table 1: Sufficiency classes of chl a and SPAD reading obtained from the JNBC approach.

Types of chlorophyll	Class	Range	GVF
Chl a (mg cm^{-2})	Low	10.48 – 19.13	0.77
	Medium	19.26 – 22.89	
	High	22.96 – 34.96	
SPAD reading (SPAD unit)	Low	61.00 – 72.20	0.88
	Medium	72.50 – 77.50	
	High	77.60 – 83.50	

Table 2: The chl-sensitive spectral bands selected from the feature selection.

Types of chlorophyll	Frond	Selected spectral bands (nm)
Chl a	9	549, 550, 708,710, 719, 730, 731, 733, 1317, 1372, 1391, 1893
	17	550, 702, 714, 717, 720, 1385, 1388, 1399, 1407, 1423, 1870, 1876, 2109, 2110, 2380, 2381, 2427
SPAD reading	9	438, 646, 647, 702, 705, 717, 724, 734, 744, 1337, 1400, 1411, 1488, 1515, 1955, 2137, 2140, 2338, 2366, 2367, 2421, 2422
	17	423, 452, 715, 720, 723

Most of the LDA classification belonged to moderate accuracy and there is no classification above 80.00%, regardless types of chl, as well as frond numbers, was observed in this study (Table 3). This might be due to the characteristics of our datasets that were non-normally distributed since LDA is designed and performed better with linear datasets as reported by Curram and Mingers (1994). The SPAD reading classification accuracy tended to decrease as frond gets older. This decreasing pattern in frond number is not in agreement with finding made by Lamade et al. (2009). The authors reported that the SPAD reading of oil palm tends to increase as the frond number increased. This might be due to the influenced of other factors such as variety (Gholizadeh et al., 2009), growing condition (Simorte et al., 2001), and genotype (Peng et al., 1993).

Table 3: Linear Discriminant Analysis classification accuracy for mature oil palm.

Types of chlorophyll	Frond	Classification accuracy (%)	
		Training	Validation
Chl a	9	64.03	66.12
	17	65.54	77.39
SPAD reading	9	64.07	77.34
	17	55.41	56.69

< 40.00%, 40.00 – 80.00% and > 80.00%, were considered as a poor, moderate and good.

4. CONCLUSION

Based upon the results discussed earlier, remote sensing measurement has potential in assessing chls content of oil palm. The proposed classes according to the JNBC approach could be a reference to classify the chls content of oil palm. However, consideration of the factor of frond number should be taken in monitoring chls content of oil palm. Further evaluation using other machine learning should be explored in order to get a robust model for monitoring the chl status of oil palm.

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6. DECLARATION

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