UNIVERSITI PUTRA MALAYSIA

SPECTRAL AND FOLIAR ANALYSIS USING MULTIPLE MACHINE LEARNING CLASSIFIERS FOR MATURE OIL PALM TREATED WITH NITROGEN FERTILIZER

AMIRATUL DIYANA BINTI AMIRRUDDIN

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By

AMIRATUL DIYANA BINTI AMIRRUDDIN

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

March 2021

DEDICATION

To my lovely parents and my beloved, Nur Halim Mazlan who always kept praying for me day and night to achieve my goal

To my family members

and

all my friends who supported me all these years.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

SPECTRAL AND FOLIAR ANALYSIS USING MULTIPLE MACHINE LEARNING CLASSIFIERS FOR MATURE OIL PALM TREATED WITH NITROGEN FERTILIZER

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Chair : Assoc. Prof. Farrah Melissa Muharam, PhD
Faculty : Agriculture

In assessing the leaf biochemical properties, spectral analysis has been explored as the non-invasive alternative to destructive leaf analysis. This study aims to develop spectral-based classification models to estimate oil palm's chlorophyll (chl) and nutrient status via machine learning (ML). In this study, different nitrogen (N) rates were applied to 8 and 11 years old. The leaf nitrogen (N), phosphorus, potassium, magnesium, calcium, chl a, chl b, total chl content, and relative chl content were measured from frond 9 and 17. Meanwhile, spectral reflectance in visible (Vis) and near-infrared (NIR) were measured at three spatial scales: leaf (spectroradiometer), canopy (unmanned aerial vehicle (UAV)), and scene (SPOT-6 satellite).

The objectives of this study are to; 1) evaluate the leaf spectral data and ML (Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM)) in classifying N status; 2) examine SPOT-6-derived spectral indices (SIs) in monitoring N using LDA and SVM; 3) discriminate chls status via spectroradiometer and ML (Random Forest (RF) and Decision Tree (DT)); 4) classify nutrients status via integration of spectroradiometer, ML (Logistic Model Tree (LMT) and Naïve Bayes) and imbalance approaches (Synthetic Minority Over-Sampling TEchnique (SMOTE), Adaptive Boosting (AdaBoost) and combination of SMOTE and AdaBoost (SMOTE+AdaBoost)); while 5) assess leaf and canopy spectral models in discerning the chls and nutrients status via LMT-AdaBoost.

In objective 1, there is a clear trade-off between the number of the sensitive-N spectral features with LDA accuracy and the N-sensitive features responses

were palm age-dependent. For objective 2, the Vis index (Blue Green Red Index ($BGRI_1$ and $BGRI_2$)) (79.55%) and Vis+NIR index (Normalized Difference Vegetation Index, Normalized Green, Infrared Percentage Vegetation Index, and Green Normalized Difference Vegetation Index) (81.82%)) were the best SIs to assess N status of young- and prime-mature palms, respectively via SVM. The SVM was superior to LDA in categorizing the N status and the N-sensitive SIs tested were palm age-dependent. Results from objective 3 showed that chl-sensitive features are often positioned at the red edge and RF outperformed the DT in discriminating the chl status (96.05 to 98.08%). Meanwhile, the best discrimination of nutrients status (objective 4) was achieved via the LMT-SMOTE+AdaBoost (76.13 to 100.00%). Also, the effect of frond-age was prominent in both chls and nutrients studies via spectroradiometer. The UAV study (objective 5) highlighted the capability of SIs was greater than the raw band in assessing the chls and nutrients status of oil palm (74.64 to 100.00%). In comparing the competency of leaf and canopy spectral models, the former manifested robust accuracies (98.53 to 100.00%), yet, the latter model offered wide coverage with a lesser number of spectral features, elucidating by the maximum difference of 25.36%.

In a nutshell, the leaf scale is portrayed as the best platform in discriminating the chls and nutrients status followed by canopy and scene. The canopy and scene scales could assess the leaf biochemical properties with satisfactory accuracy. It is also suggested that the LMT-SMOTE+AdaBoost was the finest classifier in evaluating the chls and nutrients of oil palm.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

ANALISA SPEKTRAL DAN DAUN MENGGUNAKAN BEBERAPA PEMBELAJARAN MESIN UNTUK POKOK KELAPA SAWIT MATANG YANG DIBERI RAWATAN NITROGEN

Oleh

AMIRATUL DIYANA BINTI AMIRRUDDIN

Mac 2021

Pengerusi : Prof. Madya Farrah Melissa Muharam, PhD
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Dalam mengukur kandungan biokimia daun, analisis spektral telah diterokai sebagai alternatif yang tidak invasif kepada analisis daun yang merosakkan. Fokus kajian ini adalah untuk membangunkan model pengelasan spektral bagi mengukur status klorofil dan nutrien tanaman sawit melalui pembelajaran mesin (ML). Dalam kajian ini, beberapa kadar nitrogen (N) diberikan kepada tanaman sawit yang berumur 8 dan 11 tahun. Kandungan N, fosforus (P), kalium (K), magnesium (Mg), kalsium (Ca), klorofil a (chl a), klorofil b (chl b), klorofil total (TCC) dan klorofil relatif (RCC) daun diukur dari pelepah 9 dan 17. Selain itu, pantulan spektral dari kawasan boleh dilihat (Vis) dan infra-merah (NIR) diukur pada tiga skala spasial: daun (spektroradiometer), kanopi (kenderaan udara tanpa pemandu (UAV)) dan pemandangan (satelit SPOT-6).

Objektif kajian ini adalah untuk; 1) menilai potensi spektral daun dan ML (Analisis Diskriminasi Linear (LDA) dan Mesin Sokongan Vektor (SVM)) dalam pengelasan status N; 2) mengkaji indeks spektral SPOT-6 dalam memantau N dengan menggunakan LDA dan SVM; 3) mendiskriminasikan status klorofil melalui spektradiometer dan ML seperti Hutan Rawak (RF) dan Pohon Keputusan (DT); 4): mengelaskan status nutrient-nutrien melalui integrasi spektroradiometer, ML (Model Pohon Logistik (LMT) dan Naïve Bayes (NB)) dan kaedah data tidak seimbang (Teknik Pensampelan Minoriti Sintetik (SMOTE), Peningkatan Adaptif (AdaBoost) dan kombinasi SMOTE dan AdaBoost (SMOTE+AdaBoost)); manakala 5) menilai model spektral daun dan kanopi dalam mengelaskan status chl dan nutrien melalui model LMT-AdaBoost.

Dalam objektif 1, terdapat pertukaran yang jelas di antara bilangan ciri-ciri spektral N dengan akurasi LDA, dan respon ciri-ciri spektral N tergantung kepada umur tanaman sawit. Untuk objektif 2, indeks Vis (Indeks Merah Hijau Biru ($BGRI_1$ dan $BGRI_2$)) (79.55%) adalah indeks terbaik untuk menilai status N tanaman sawit matang muda dan indeks Vis+NIR (Indeks Vegetasi Perbezaan Normalisasi (NDVI), Normalisasi Hijau (NG), Indeks Vegetasi Peratusan Inframerah (IPVI) dan Indeks Vegetasi Perbezaan Normalisasi Hijau (GNDVI)) (81.82%) bagi tanaman sawit prima, melalui SVM. SVM mengungguli LDA dalam mengklasifikasikan status N dan SI yang sensitif terhadap N bergantung pada usia tanaman sawit. Keputusan daripada objektif 3 menunjukkan kebanyakan ciri-ciri spektral yang sensitif terhadap klorofil berada di kawasan pinggir merah dan RF mengatasi DT dalam membezakan status klorofil (96.05 to 98.08%). Sementara itu, diskriminasi status nutrient-nutrien yang terbaik (objektif 4) dicapai melalui model LMT-SMOTE+AdaBoost (76.13 sehingga 100.00%). Selain itu, kesan faktor usia pelepah adalah ketara dalam kajian klorofil dan nutrien melalui spektroradiometer. Kajian UAV (objektif 5) membuktikan bahawa prestasi model SI lebih baik berbanding model spektral mentah dalam pengelasan klorofil dan nutrien (74.64 sehingga 100.00%). Dalam membandingkan kompetensi model spektra daun dan kanopi, model spektra daun menunjukkan ketepatan yang teguh (98.53 sehingga 100.00%), walaubagaimanapun, model spektral kanopi menawarkan kelebihan melalui liputan kawasan lebih luas dengan bilangan ciri spektral yang lebih rendah berbanding model spektrum daun dengan perbezaan akurasi yang maksimum sebanyak 25.36%.

Kesimpulannya, skala daun merupakan plafform yang terbaik untuk mengklasifikasikan status klorofil dan nutrien diikuti dengan kanopi dan pemandangan. Model spektral kanopi dan pemandangan mampu menilai status klorofil dan nutrien dengan ketepatan yang memuaskan Pengelasan dengan LMT-SMOTE+AdaBoost juga dicadangkan sebagai pengelasan terbaik dalam menilai klorofil dan nutrien kelapa sawit.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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I hereby confirm that:

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Declaration by Members of Supervisory Committee

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) are adhered to.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

FFB	Fresh fruit bunch
Vis	Visible
NIR	Near-infrared
SWIR	Shortwave near-infrared
SI	Spectral index
LDA	Linear Discriminant Analysis
SVM	Support Vector Machine
RF	Random Forest
NB	Naïve Bayes
LMT	Logistic Model Tree
DT	Decision Tree
SMOTE	Synthetic Minority Over-sampling TEchnique
AdaBoost	Adaptive Boosting
D	Deficient
O	Optimum
AUC	Area under Receiver Operating Curve (ROC)
GM	Geometric mean
BAcc	Balance accuracy

CHAPTER 1

INTRODUCTION

1.1 Background

Oil palm is the main source of vegetable oils consumed in the world that contributes more than 40% of the global total production in 2019 (FAS/USDA, 2020). Together Malaysia and its neighbouring country, Indonesia, are the key players of the oil palm industry which produce and export about 85 and 90% of palm oil worldwide, respectively (FAS/USDA, 2020). Due to the low prices and high yield per area basis, oil palm has become the largest source of edible oils and fats in the world (Sime Darby, 2013; Yoshizaki et al., 2013). The demands for Malaysian palm oil have increased yearly along with the increment of the global population, particularly from India, China, the European Union (EU), Vietnam and Turkey (Khadir, 2020). According to Mielke (2017), the global demand for palm oil has increased from 11.56 in 1992 to 63.84 million tonnes in 2017 and will continue to rise in the forthcoming years. Considering the increment trend of palm oil consumption, good agriculture practices including appropriate nutrient and pest management are essential for sustaining optimum oil palm production to satiate the global demand.

In oil palm agronomic practices, efficient nutrient management is important for sustaining oil palm production and preserving the environment. Oil palm requires a huge amount of (N), phosphorus (P), potassium (K), magnesium (Mg) and calcium (Ca) for optimal growth and high yield production. According to Sung (2016), oil palm required about 125, 20, 251, 35 and 40 kg of N, P, K, Mg and Ca, respectively to produce 30 tonnes of fresh fruit bunch (FFB) ha^{-1} $year^{-1}$.

Chl also plays an important role in monitoring oil palm growth and health status. Chl is a green pigment contains in the chloroplast and essential for photosynthesis. During the process of photosynthesis, carbon dioxide (CO_2) and water (H_2O) are converted into carbohydrates (CH_2O) and oxygen (O_2) using the solar radiation absorbed by the plant pigments, chl. Generally, chl a and chl b are the main pigments for photosynthesis which mainly absorbed the red and blue light, respectively (Li et al., 2018). Chl also provides worthy information on crop physiological status, productivity, photosynthesis capacity and served as a proxy for nutrient assessment (Ling et al., 2011).

1.2 Problems Statement

Conventionally, wet chemistry has been long practised to determine the leaf biochemical properties including chls and nutrients content of crops. Whilst these practices are accurate, a few drawbacks of this technique have been issued including invasive, laborious, time consuming, expensive and produce chemical wastage (Muñoz-Huerta et al., 2013; Navarro-Cerrillo et al., 2014). Furthermore, these traditional approaches are not applicable to monitor the spatial and temporal dynamics of nutrient and chl status (Zhai et al., 2013) in the oil palm plantation since oil palms are commonly cultivated in plantation scale involving hundreds to thousands hectare of land.

In the oil palm industry, fertilizers are the most expensive agriculture inputs yet mandatory for high FFB production, and they account for about 46 to 85% of the plantation total cost production (Goh and Härdter, 2003; Silalertruksa et al., 2012; Pardon et al., 2016). According to the estimation made by Goh (2011), the oil palm plantation could suffer an annual economic loss of RM 1.24 and 0.15 billion resulted from the insufficient fertilizer application and over-application of ammonium nitrate of 0.25 kg palm^{-1} year^{-1}, respectively. Additionally, the yield response to the fertilizer application may take up 8 months or even a few years to be perceived, hence delaying fertilizer application might cause a reduction in fresh fruit bunch (FFB) production and result in the economic loss to the oil palm sector (Goh and Teo, 2011; Corley and Tinker, 2015a) . Therefore, there is an urgency for a rapid method for monitoring the nutrients and chls status to ensure the sustainability of oil palm growth and production, so that proper nutrient management and mitigation plans could be executed promptly by the oil palm plantation management to prevent economic losses.

As an alternative to the traditional methods, spectral analysis is a powerful technique for appraising leaf biochemical properties in crops. This approach offers non-invasive measurement, periodic assessment, immediate analysis and wide coverage. A plethora of studies using the spectral analysis has been explored in appraising the chl and nutrients content of various types of perennial crop such as apple (Ding et al., 2009; Ye et al., 2020), hardwood trees (Yoder and Pettigrew-Crosby, 1995; Navarro-Cerrillo et al., 2014), citrus (Liu et al., 2016; Osco et al., 2019), olive (Zarco-Tejada et al., 2004; Rubio-Delgado et al., 2020); avocado (Abdulridha et al., 2018) and oil palm (Khorramnia et al., 2014; Golhani et al., 2019; Yadegari et al., 2020). Besides, the machine learnings (ML) such as Naïve Bayes (NB), Support Vector Machine (SVM), Artificial Neural Network (ANN), Linear Discriminant Analysis (LDA), Partial Least Square Regression (PLSR) and Random Forest (RF) also exhibited promising results in assessing the leaf biochemical status of crops (Goel et al., 2003; Muhammad Asraf et al., 2012a, 2012b; de Fátima da Silva et al., 2014; James et al., 2018; Santoso et al., 2019; Prado Osco et al., 2019).
To overcome the limitation of the traditional methods for assessing chl and nutrient contents of oil palm as well as to sustain the FFB production, this study attempted to develop a rapid method to facilitate in appraising leaf biochemical status of oil palm via spectral analysis from different spatial scales including leaf, canopy and scene in conjunction with ML classifiers.

1.3 Objectives of the Study

The main focus of this study is to develop the classification model to estimate the chl and nutrients nutrition status of oil palm via the integration of spectral analysis and ML classifier from different spatial scales.

1.3.1 Specific Objectives

The specific objectives of this study are:

1. To evaluate the potential of spectral measurements obtained from leaf scale and machine learning approaches as a rapid tool for quantifying oil palm N status.

2. To examine the potential of the SI derived from satellite sensors as a tool in monitoring the N nutrition status of mature oil palm.

3. To discriminate the chls sufficiency status of mature oil palm using hyperspectral data obtained from leaf measurement.

4. To classify the N, P, K, Mg and Ca sufficiency levels of mature oil palm using hyperspectral data retrieved from leaf measurement and imbalance approaches.

5. To evaluate the performance of spectral data from two different spatial scales i.e. leaf and canopy in discriminating the sufficiency levels of leaf biochemical properties of mature oil palm.

1.4 Research Framework

This thesis presented the novel method for appraising chls and nutrients sufficiency status of mature oil palm by integrating the spectral data extracted from different spatial scales with ML classifiers while addressing the imbalance problem in ML classification. Extensive foliar sampling was carried out together with in situ spectral measurement. The main goal of this study was to evaluate the applicability of the spectral model attained from the leaf, canopy and scene scales in conjunction with ML classifiers in discriminating the chls and nutrients sufficiency status of mature oil palm. The spectral measurement using the spectroradiometer represents leaf scale while the unmanned aerial vehicle (UAV) images obtained represent canopy scale and SPOT-6 satellite images considered as scene scale. The study was carried out in two different sites: i) 2°22'40” N, 102°15'56.37” E (MP05) and ii) 2°22'49.35” N, 102°14'16.84” E (MP02) belongs to United Malacca Berhad plantation located at Machap Umboo, Malacca. The MP05 and MP02 represent the 8 and 11 years old palm, correspondingly. The N treatments ranging from 0 to 6 kg palm^{-1} were applied for 3 consecutive years. Specific objective 1 and 2 were accomplished through the preliminary study utilizing the data collected from 9 and 12 years old palms after 1 year of the fertilizer program completed. On the other hand, specific objective 3, 4 and 5 were achieved using the data after completing 3 years of fertilizer application, whereby the palms age were 12 and 15 years old.

Generally, the research framework for this study was delineated into three spatial scales such as the leaf, canopy and scene (Figure 1.1). For the preliminary study, i.e. objective 1 and 2 aim were to investigate the potential of the spectral features and SI acquired from the leaf and scene scales in monitoring the N nutrition status of mature oil palm, respectively. To discriminate the N sufficiency in oil palm from the leaf and scene scales, the classifications were executed using LDA and SVM classifiers.

For further evaluation of the spectral analysis technique in appraising chls and nutrients status of mature oil palm, the spectral measurement from the leaf level using the spectroradiometer was utilized. These evaluations were carried out for objective 3 and 4. At the leaf level, the chls and nutrients content was collected from the leaflets of frond 9 and 17. From the foliar analysis, chls sufficiency levels were determined by Jenks Natural Break classification while nutrients sufficiency levels were followed by the standard reference for oil palm nutrients presented by Fairhurst et al. (2004). Further, feature selection was implemented to select the chls- and nutrients-sensitive spectral features prior to the classification. To discriminate the chls sufficiency status from the leaf scale, classification via RF and DT classifiers were performed while NB and LMT classifiers to classify the nutrients sufficiency status of mature oil palm. The best frond number in appraising leaf biochemical status via spectral analysis was also evaluated in this study.

Considering that oil palm is commonly cultivated in a plantation scale that involves hundreds to thousands of hectares of area, UAV imagery was assessed in order to improve the limitation of the leaf scale measurement. This evaluation was performed in objective 5. The performance of the raw band and SI spectral models generated from the UAV images were examined by using the LMT-AdaBoost classifier to determine the best model for appraising chls and nutrients status from the canopy scale. Then, the best spectral model obtained from the canopy level was compared to the leaf spectral model, also classified by using the LMT-AdaBoost algorithm.

Finally, the accuracies of the spectral models acquired from leaf, canopy and scene scales were compared to define the best classifier and spatial scale for appraising chls and nutrients sufficiency status of mature oil palm.

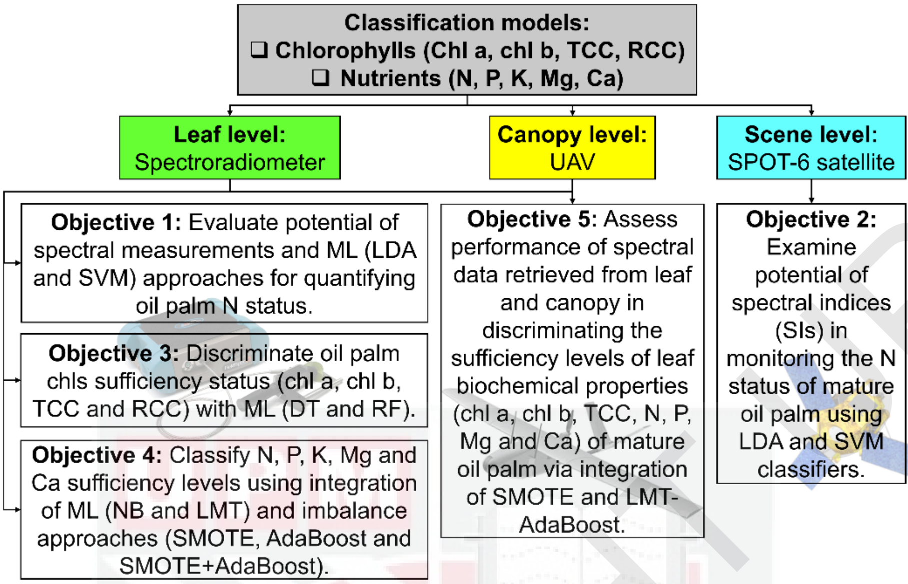

Figure 1.1: The summarized framework used in the study.

1.5 Outline of the Thesis

The thesis comprised 8 chapters and outlined as follows:

Chapter 1 describes the general overview of oil palm nutrient management and its challenges. The problem statement, research objectives and research framework also are included in this chapter.

Chapter 2 reviews the literature on oil palm growth, the importance of nutrients and chls. This chapter also encompasses comprehensive reviews on the available methods for the determination of nutrient and chl status.

Chapter 3 deliberates on the preliminary study "Assessing Leaf Scale Measurement for Nitrogen Content of Oil Palm: Performance of Discriminant Analysis and Support Vector Machine Classifiers" to accomplish the specific objective 1.

Chapter 4 is devoted for the "Evaluation of Linear Discriminant and Support Vector Machine Classifiers for Classification of Nitrogen Status in Mature Oil Palm from SPOT-6 Satellite Images: Analysis of Raw Spectral Bands and Spectral Indices" to accomplish the specific research objective 2.

Chapter 5 is dedicated to the “Hyperspectral Remote Sensing for Assessment of Chlorophyll Sufficiency Levels in Mature Oil Palm (*Elaeis guineensis*) Based on Frond Numbers: Analysis of Decision Tree and Random Forest” to complete the specific research objective 3.

Chapter 6 provides the findings on the “Hyperspectral Spectroscopy and Imbalance Data Approaches for Classification of Oil Palm's Macronutrients Observed from Frond 9 and 17” obtained to fulfil the specific research objective 4.

Chapter 7 confers “Synthetic Minority Over-Sampling TEchnique (SMOTE) and Logistic Model Tree (LMT)-Adaptive Boosting (AdaBoost) Algorithms for Classifying Imbalanced Datasets of Nutrient and Chlorophyll Sufficiency Levels of Oil Palm (*Elaeis guineensis*) Retrieved from Spectroradiometer and Unmanned Aerial Vehicle” to achieve the specific research objective 5.

Chapter 8 summarizes the findings attained from the study and the recommendations for future work regarding the assessment of chls and nutrients status of oil palm.

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LIST OF PUBLICATIONS

Journals

Amirruddin, A.D., Muharam, F.M., Mazlan, N., 2017. Assessing leaf scale measurement for nitrogen content of oil palm: Performance of Discriminant Analysis and Support Vector Machine classifiers. Int. J. Remote Sens. 38, 7260–7280. https://doi.org/10.1080/01431161.2017.1372862. Q2: Impact Factor: 2.976. (Chapter 3)

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