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MACHINE LEARNING CLASSIFICATION OF MACRONUTRIENT LEVELS IN OIL PALM TREES WITH LANDSAT-8 IMAGERY

KOK ZHI HONG

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May 2021

Chair : Prof. Sr. Gs. Abdul Rashid bin Mohamed Shariff, PhD
Faculty : Engineering

Optimized fertilizer application is essential in ensuring the best yields and profits. In the last two decades, fertilizer application in the palm oil industry of Malaysia has increased by 169% and more than 200% in amount and value respectively. The excessive use of fertilizer is seen as a deterrent to sustainable agriculture, both environmentally and economically. Unfortunately, current nutrient monitoring methods for better fertilizer management are inefficient, desctructive and only adoptable for industrial plantations. This suggests the need for a more conventional and efficient approach for fertilizer management. Remote sensing (RS) and machine learning (ML) have provided possibilities to monitor crop nutrient in a more efficient approach. Therefore, this study aims to assess the feasibility of Landsat-8 OLI/TIRS RS imageries in classifying oil palm tree macronutrient levels on a plot basis with ML models such as Support Vector Machine (SVM), Multilayer Perceptron (MLP) and Random Forest (RF). The study consisted of 36 plots in which fertilizer applications and foliar analyses of palm leaves from Frond 17 (i.e. Nitrogen(N), Phosphorus(P), Potassium(K), Magnesium(Mg) and Calcium(Ca)) were conducted for 5 consecutive years (2013 - 2017). Plot surface reflectance was acquired from specific scenes of respective years by applying filters, overlay extraction and vegetation indices (VI). The study explored the effects of the applied methodology with four scenarios as input for the models via a 50:50 calibration and validation data split for 30 iterations: 1.) initial spectral data; 2.) filtered spectral data; 3.) filtered spectral features with selection; and 4.) all filtered spectral features. Using the Jeffries-Matusita (J-M) distance, Rank filter was found to be the best filter for image filtering. VIs related to soil background or atmospheric correction were selected as predictors for N (i.e. EVI, SARVI, ARVI, GARI, MSAVI, EVI2), while those related to NIR for K (i.e. NDVI, TVI, IPVI). The best mean classification accuracy

for N, K, Mg and Ca of each model at validation stage are as follow: SVM at 79.7%, 76.6%, 63.5% and 87% respectively; MLP at 76.1%, 73.4%, 61% and 87% respectively; and RF at 76.9%, 73.6%, 62.1% and 86.4% respectively. SVM, RF and MLP experienced improvement in performance with the use of filters or feature selection, with MLP benefiting the most. with the use of filters or feature selection or both (Scenario 2 and 3). However, uneven sample distribution led to misleading results for Ca and occasional overfitting by models for other nutrients. SVM was reported with the best model performance, followed by RF and MLP; while RF for model stability, followed by SVM and MLP. Accounting both factors, the study concluded the potential of applying Landsat-8 images in classifying plot N level excessiveness with RF while possibly K level excessiveness with SVM or RF.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Master Sains

KLASIFIKASI PEMBELAJARAN MESIN TAHAP MAKRONUTRIEN DALAM POKOK KELAPA SAWIT DENGAN IMEJAN LANDSAT-8

Oleh

KOK ZHI HONG

Mei 2021

Pengerusi **: Prof. Sr. Gs. Abdul Rashid bin Mohamed Shariff, PhD**
Fakulti   **: Kejuruteraan**

Aplikasi baja optimum adalah mustahak dalam memastikan hasil dan keuntungan maksimum..Dalam dua dekad terakhir, penggunaan baja dalam industri kelapa sawit di Malaysia didapati meningkat sebanyak 169% dalam jumlah dan lebih daripada 200% dalam nilai. Penggunaan baja yang berlebihan dilihat sebagai penghalang kepada pertanian lestari dari segi persekitaran dan ekonomi. Malangnya, kaedah pemantauan nutrien semasa untuk pengurusan baja yang lebih baik adalah kurang effisien, merosakkan dan hanya dapat digunakan oleh pengusaha sawit secara industri. Ini menunjukkan keperluan kaedah yang lebih efisien untuk pengurusan baja. Penderiaan jauh (RS) dan pembelajaran mesin (ML) telah memberikan kemungkinan untuk menentukan cara pemantauan nutrien tanaman yang lebih cekap. Oleh itu, kajian ini bertujuan menilaikan penggunaan imejan Landsat-8 OLI / TIRS dalam mengklasifikasikan tahap makronutrien pokok kelapa sawit berdasarkan plot dengan model ML seperti Support Vector Machine (SVM), Multilayer Perceptron (MLP) dan Random Forest (RF) akan dinilaikan. Kajian ini terdiri daripada 36 petak yang melibatkan aplikasi baja dan analisis daun kelapa sawit dari pelapah nombor ke-17 (iaitu bagi Nitrogen(N), Fosforus(P), Potasium(K), Magnesium(Mg) dan Kalsium(Ca)) dilakukan selama 5 tahun berturut-turut (2013 - 2017). Refleksi permukaan plot diperolehi daripada imejan tertentu pada tahun masing-masing dengan menggunakan teknik penapisan, pengekstrakan lapisan dan indeks tumbuh-tumbuhan (VI). Bagi memahami kesan metodologi yang diaplikasikan, empat senario digunakan sebagai input untuk model melalui pembelahan data secara 50:50 bagi tahap penentukuran dan pengesahan data yang dijalankan sebanyak 30 lelaran: 1.) data spektrum asli; 2.) data spektrum yang ditapis; 3.) ciri spektrum yang ditapis dengan pemilihan; dan 4.) semua ciri spektrum yang ditapis. Dengan penggunaan jarak Jeffries-Matusita (J-M), teknik penapisan Rank didapati sebagai tapis yang paling berkesan bagi proses penapisan imejan. VI yang berkaitan dengan latar tanah atau atmosfera dipilih sebagai peramal untuk N (i.e. EVI, SARVI, ARVI, GARI, MSAVI, EVI2) sementara yang berkaitan

dengan NIR dipilih untuk K (i.e. NDVI, TVI, IPVI). Secara keseluruhan, nilai purata ketepatan klasifikasi terbaik untuk N, K, Mg dan Ca setiap model pada tahap pengesahan adalah seperti berikut: SVM masing-masing pada 79.7%, 76.6%, 63.5% dan 87%; MLP masing-masing pada 76.1%, 73.4%, 61% dan 87%; dan RF masing-masing pada 76.9%, 73.6%, 62.1% dan 86.4%. SVM, RF dan MLP mengalami peningkatan purata dengan penggunaan teknik penapisan atau pemilihan ciri atau kedua-dua (Senario 2 dan 3), dengan MLP yang mendapat paling banyak manfaat. Dalam kajian ini, taburan sampel yang tidak rata menyebabkan keputusan yang tidak tepat untuk Ca, sementara semua model mengalami peningkatan berlebihan sekali-sekala (overfitting) bagi nutrien lain. SVM mempunyai prestasi model terbaik, diikuti oleh RF dan MLP; sementara RF adalah model yang paling stabil, diikuti SVM dan MLP. Dengan mengambil kira kedua-dua faktor tersebut, kajian ini mencapai konklusi bahawa imejan Landsat-8 berpotensi untuk mengklasifikasikan kelebihan tahap plot N dengan RF sementara dengan kemungkinan, mengklasifikasikan kelebihan tahap K melalui RF atau SVM.

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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 Master of Science. The members of the Supervisory Committee were as follows:

Abdul Rashid bin Mohamed Shariff, PhD
Professor
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Siti Khairunniza binti Bejo, PhD
Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Member)

ZALILAH MOHD SHARIFF, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 09 September 2021

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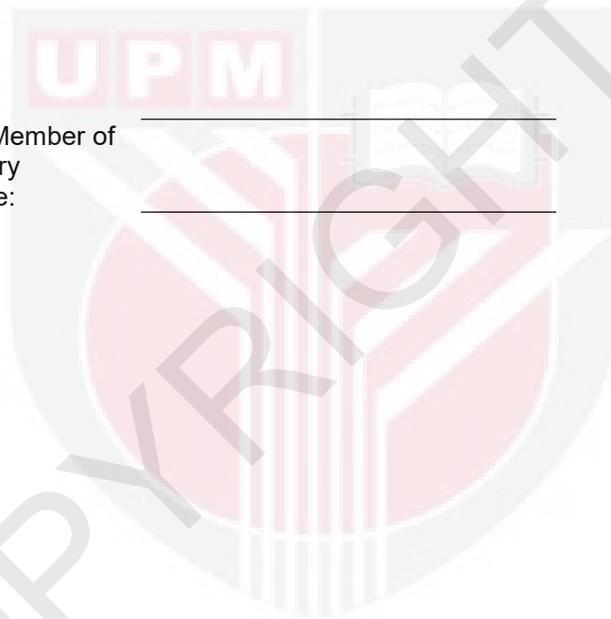

Signature:
Name of Member of
Supervisory
Committee:

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LIST OF ABBREVIATIONS

A.)Applicable to All

I) General

ACD	Above Carbon Density
ANN	Artificial Neural Network
ATP	Adenosine Triphosphate
BSR	Basal Stem Rot
Ca	Calcium
CART	Classification and Regression Tree
CNN	Convolutional Neural Network
CoV	Coefficient of Variance
CPO	Crude Palm Oil
Def	Deficient
DN	Digital Number
DNN	Deep Neural Network
DOS	Dark Object Subtraction
Ex	Excessive
FFB	Fresh Fruit Bunch
FFT	Fast Fourier Transform
J-M	Jeffries-Matusita
K	Potassium
LAI	Leaf Area Index
Mar Def	Marginally Deficient
Mar Ex	Marginally Excessive
Mg	Magnesium

MKL	Multiple Kernel Learning
ML	Machine Learning
MLP	Multilayer Perceptron
MSAVI	Modified Soil Adjusted Vegetation Index
MSC	Multiplicative Scatter Correction
MYR	Malaysian Ringgit
N	Nitrogen
NDVI	Normalized Difference Vegetation Index
NH_4^+	Ammonium ion
NNI	Nitrogen Nutrient Index
NO_3^-	Nitrate ion
OA	Overall Accuracy
Opt	Optimum
P	Phosphorus
PA	Precision Agriculture
PO_4^{3-}	Phosphate
r	Correlation coefficient
R^2	Coefficient of Determination
RBF	Radial Basis Function
RF	Random Forest
RGB	Red, Green, Blue
ROI	Region of Interest
RuBisCO	Ribulose-1,5-bisphosphate carboxylase-oxygenase
RuBP	Ribulose 1,5-bisphosphate
S	Sulphur

S-G filter	Savtizky-Golay filter
SMLR	Stepwise Multiple Linear Regression
SVM	Support Vector Machine
TLB	Total Leaf Base
UAV	Unmanned Aerial Vehicle
VI/Is	Vegetation Index/Indices

II) Spectral

ARVI	Atmospherically Resistance Vegetation Index
B	Blue
EVI	Enhanced Vegetation Index
EVI2	2-Band EVI (EVI2)
G	Green
GARI	Green Atmospherically Resistant vegetation Index
GNDVI	Green NDVI
IPVI	Infrared Percentage Vegetation Index
IR	Infrared
MSAVI	Modified SAVI
MSR	Modified Simple Ratio
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
NIR/G	NIR/G ratio
NIR/R	NIR/R ratio
OSAVI	Optimized SAVI
R	Red
RDVI	Renormalized Difference Vegetation Index

SARVI	Soil adjusted and Atmospherically Resistant Vegetation Index
SAVI	Soil Adjusted Vegetation Index
SWIR	Shortwave Infrared
TVI	Transformed Vegetation Index
VNIR	Visible and Near Infrared

III) Satellite and sensors

ALOS-PALSAR	Advanced Land Observation Satellite - Phased Array type L-band Synthetic Aperture Radar
HJ-1A/1B	Huan Jing - 1A/1B
Landsat-8 OLI/TIRS	Landsat-8 Operational Line Imager / Thermal Infrared Sensor
LiDAR	Light Detection and Ranging
MODIS	Moderate Resolution Imaging Spectroradiometer
Sentinel-2 MSI	Sentinel-2 Multispectral Instrument
Sentinel-3 OLCI	Sentinel-3 Ocean and Land Colour Instrument
Terra-SAR	Terra - Synthetic Aperture Radar
QuickBird	Very high (<1m) resolution satellite imaging
WorldView	Very high (<1m) resolution satellite imaging

B.)Applicable to Table Only

ANOVA	Analysis of Variance
Bag	Bagging
BGNIR	Blue, Green, Near Infrared
CorrAn	Correlation Analysis
CR	Continuum Removal
Cu	Copper

DEM	Digital Elevation Model
Dev	Derivative
FRSr	Full Range Spectroradiometer
Geo	Geometrical analysis
GLM	Generalized Linear Model
HRSr/r	Half Range Spectroradiometer/radiometer
HSI/L	Hyperspectral Imaging/ LiDAR
HSV	Hue, Saturation, Value colour model
K/PLSR	Kernel/ Partial Least Square Regression
kNN	k-Nearest Neighbour
LIF	Laser Induced Florescence
LS-Boost	Least Square - Boost
M/KELM	Multiple/Kernel Extreme Learning Machine
MANN	Model Averaged Neural Network
MARS	Multivariate Adaptive Regression Spline
MNF	Minimum Noise Fraction
Morph	Morphological analysis
MSC	Multiplicative Scatter Correction
MSI/L	Multispectral Imaging/ LiDAR
Na	Sodium
NNI	Nitrogen Nutrient Index
Norm	Normalization
PCA	Principal Component Analysis
PLS	Partial Least Square
RFFvS	Random Forest Forward variable Selection

RFVIP	Random Forest Regression and Variable Importance
SNV	Standard Normal Variate
SVM/R	Support Vector Machine/Regression
SVM-RFE	Support Vector Machine - Recursive Feature Elimination

CHAPTER 1

INTRODUCTION

1.1   General Background

Oil palm is one of the most prominent oil crops in the world. According to Shahbandeh (2020) and the Statista Research Department (2020), palm oil was the most globally consumed and exported vegetable oil, accounting for 40% and 62% of the total respectively in 2019. The success of such cultivation is attributed to its economical competitiveness with other edible oils and fats (Parsons et al., 2020; Teoh, 2013; Corley & Tinker, 2003). However, palm plantations are prone to economical losses by diseases, pests and uninformed management (Sabri, 2009). By the end of this decade (2029), the global population require a projected additional production of 25.8 million metric tonnes of edible oil to fulfil supply demands. (OECD/FAO, 2020).

In efforts to increase production, countries such as Malaysia may have encountered excessive fertilizer use in plantations, which reduces profitability. Most fertilizer costs are attributed to macronutrient fertilizers such as Ammonium Sulphate, Rock Phosphate and Muriate of Potash (Sabri, 2009). Insufficient or excessive application of macronutrient fertilizers could lead to reduction in palm tree productivity. For instance, Potassium (K) deficiency directly affects fresh fruit bunch (FFB) productivity by reducing bunch size and number while its presence in excessive amount may decrease oil content in fruits due to Boron deficiency (Rankine & Fairhurst, 1999; von Uexkull & Fairhurst, 1991). Therefore, a balanced application of fertilizer is required to prevent all forms of deficiency. Conventionally, managers or plantation staffs carry out chemical analyses on palm tree leaves periodically to diagnose nutrient requirements and determine fertilizer deployment (Su & Tan, 2019; Corley & Tinker, 2015; von Uexkull & Fairhurst, 1991).

Remote sensing involves information acquisition with images obtained from sensors via the collection of electromagnetic energy reflected from features on the Earth's surface (Campbell, 2011). With greater coverage, study of individual tree characteristics at a plantation scale with high efficiency is possible (Weiss et al., 2020; Seelan, 2003). The use of such technology in the field of agriculture has led to a specialized discipline known as Precision Agriculture (PA) - informed decision making in agriculture via results acquired from sensor data analysis (Elavarasan et al., 2018; Bongiovanni & Lowenberg-Deboer, 2004). In this context, remote sensing methods incorporating conventional approaches could be devised to aid nutrient monitoring of palm trees for effective and sustainable fertilizer applications. The approach takes leverage of advantages offered by remote sensing, such as its wide coverage with satellite imaging and the ability to detect energy beyond human vision and perception.

The process involves processing data from sensors and establishment of mathematical relationships between variables of interest. This subsequently allows for models to be derived and predictions of interested variables made at specific precisions. In this case, Jayaselan et al. (2021; 2017) demonstrated such potential for macronutrient prediction by correlating spectroscopy data at specific wavelengths with Nitrogen (N), Phosphorus (P) and Potassium (K). In modelling these variables, non-linear machine learning (ML) was applied due to its ability to extract information from non-linear data structures when compared to conventional linear models (Elavarasan et al., 2018). The approach has been applied extensively in recent agricultural application studies. For instance, Liu, B. et al. (2019) reported greater model accuracy for the non-linear Support Vector Machine (SVM) model than the Linear Discrimannt Analysis model, when both models were applied on distinguishing carrot and weed species.

Unfortunately, lower resolution approaches such as the use of satellite images for such applications in oil palm have not been confirmed, apart from Yadegari et al. (2020), which applied a high resolution image from a commercial satellite for classification of N levels. Therefore, a technique for generalizing macronutrient (i.e. N, P, K, Magnesium(Mg) and Calcium(Ca)) level classification in oil palm tree plots via correlation of freely available satellite image data (i.e. Landsat-8 OLI/TIRS) with field sample data is carried out via ML.

1.2   Problem Statement

In general, palm oil productivity may be increased with two conventional means: 1.) increase cultivation area; and 2.) improved management practices (fertilizer use, harvesting, transport, mill extraction, etc.). The former has become a less ideal method with the already expanded oil palm plantations into all remaining fertile soils. Currently, the expansion of plantation has remained stagnated in Peninsular Malaysia, thus shifting its focus to Borneo (See Section 2.1.2). Nevertheless, the idea of expansion is further impeded by its negative environmental impacts, as advocated by conservationists as a less sustainable method of food production (McCalmont et al., 2021; Glinskis & Gutiérrez-Vélez, 2019; Jackson et al., 2019; Carlson et al., 2012).

Unfortunately, increased fertilizer use also occurred partly as a result from area expansion and did not result in much improvement (IFA, 2020; Teo et al., 2010). From 2004 to 2020, the average yield from palm plantations for Malaysia in terms of Fresh Fruit Bunch (FFB) has stagnated between 17 to 20 metric tonnes/hectare (t/ha), while the total fertilizer imports have increased by 50% in amount and more than 200% in value within the stipulated period (IFA, 2020; MPOB, 2020d; Liri, 2015; Sabri 2009). Such trends of cultivation cause profits to become highly dependent on fertilizer prices. In 2008, the price of fertilizer skyrocketed due to rapidly increasing global demands, resulting in some plantations cutting down on fertilizer usage and subsequent reduced profit due

to decrease in yield throughout the period, especially when oil prices were high (Sabri, 2009).

As mentioned earlier, plantation groups resort to foliar analysis to measure the chemical compositions in leaves as diagnosis for the nutrient status of palm trees. Such methods exist in many forms, ranging from Kjedahl digestion to ion-selective electrode method for N determination, for instance (Mahajan et al., 2021; Liu, H. et al., 2019; Munoz-Huerta et al., 2013; Kalra, 1998). However, these approaches are destructive, expensive and laborious, not to mention inaccessible to smallholders.

In fact, one of the main causes for inefficient yields in smallholder sectors is insufficient fertilizer application, which could be attributed to the lack of databases to keep track of palm tree nutrient statuses (Woittiez et al., 2019; Rahman et al. 2008). Differences in management practices could lead to large disparity in terms of yields between different parties. Smallholder cultivations reported yields 30 to 60% lower than well-managed plantations (Rhebergen et al., 2018; Suharto, 2009). Macronutrient status diagnosis is essential in ensuring optimal fertilizer application and, subsequently, yield of palm trees, as nutrient deficient trees would result in low yields (Woittiez et al., 2019; 2017; Rhebergen et al., 2018; Corley & Tinker, 2015).

Notwithstanding the complexity and great challenges in smallholder implementation, devising a freely accessible model could reduce the economic constraint of smallholders to accessing fertilizer management approaches, while social constraints preventing its access could be addressed by distribution of knowledge and practice through local (e.g. government authorities, Malaysian Palm Oil Board, etc.) or private (e.g. Roundtable of Sustainable Palm Oil, etc.) piplines or joint efforts by both parties, including model's adoption through training workshops or transformative certifications or schemes implemented nationally (Apriani et al., 2020; Degli Innocenti & Oosterveer, 2020; Parveez et al., 2020; Senawi et al., 2019).

Independent smallholders play a large role due to a notable proportion of the total palm cultivation area in a country they possess cumulatively (Apriani et al., 2020; Malaysian Palm Oil Board (MPOB), 2019). Assuming proper management practices increase the productivity of smallholder plantations in Malaysia to the national average, an additional 1.2 million tonnes of Crude Palm Oil (CPO) could be generated, which is equivalent to the production from 330 thousand hectares (ha) at national average. The potential of independent smallholders as key players in the palm oil market should be acknowledged and more conventional methods for nutrient prediction be devised (Rhebergen et al., 2020; Woittiez et al., 2018).

Remote sensing might offer such possibilities. Since the 1990s, researchers such as Naert (1990) and McMorrow (1995) applied remote sensing in studying

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palm plantations as well as noted its potential. These applications fall under the umbrella of PA, whereby sensor related technologies are used for better decision making (Weiss et al., 2020, Seelan et al., 2003). Prior studies on prediction of palm tree nutrient status have been conducted with spectroradiometers (Jayaselan, 2021; 2017; Khorammnia, 2013) and high resolution satellite imaging (Yadegari et al., 2020), although these methods may remain inaccessible to smallholders and widespread application, given their commercial nature. Moderate to coarse resolution satellite imaging (i.e. MODIS, Landsat-8, Sentinel, etc.), on the other hand, could potentially offer free-source nutrient monitoring but have yet to be explored.

The following summarizes the problems stated above:

1. Nutrient diagnosis by foliar analysis is inaccessible and costly to smallholders, who also play a large role in the palm oil industry (See Section 2.1.3). Even when accessible, nutrient diagnosis methods for palm trees remain laborious, destructive and inefficient.

2. Current explored approaches for palm nutrient monitoring with remote sensing acquired potential results, although further improvements in terms of performance and accessibility are required before widespread application is achieved.

3. There is a need for a more conventional and convenient approach to diagnose nutrient status of palm trees at a large scale as the increased fertilizer use by the palm industry may lead to higher production cost and dependency of profitability on fertilizer prices in the global market (See Section 2.1.3).

1.3   Research Aim and Objectives

To address increased fertilizer use, area expansion and laborious approaches to nutrient status diagnosis, this research aims to investigate free and accessible satellite imaging in diagnosing macronutrient levels of palm trees for more informed fertilizer applications, with the following research objectives in mind:

1. Assess a series of freely available Landsat-8 OLI/TIRS images in classifying macronutrient levels in palm tree plots for subsequent years via a distance metric to measure separability between spectral data of different macronutrient level classes.

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2. Identify filters and vegetation indices (VIs) which may improve model classification accuracy as well as observe its performance differences under different scenarios.

3. Derive classification models for nutrient levels of each studied macronutrient using the selected ML algorithms (i.e. Support Vector Machine, Multilayer Perceptron and Random Forest), compare and assess their performances.There should be at least two subheadings to justify having subheadings.

1.4   Scope of Study

With reference to 1.3, the scope of the study revolves mainly on the classification of N, P, K, Mg and Ca levels in palm trees at a plot basis using Landsat-8 OLI/TIRS images and foliar analysis data. This was done via the establishment of machine learning models which related the two observations. Image processing was required before image scenes were fed into the model as input to classify the output: nutrient status. The end-products consisted of models which are able to potentially classify nutrient levels in plots.

Given data was acquired from a collaborating plantation, the study was conducted with the following inherent limitations due to the nature of the collected dataset:

1. Maintenance of palm stands contributing to changes in Leaf Area Index (LAI) or nutrient status (i.e. pruning, ablation, etc.) was assumed to be as consistent as possible for all plots

2. Chemical sampling was conducted on different period of the year for some years of data collection.

3. Palm trees are perennial crops with an industrial life cycle of 25 years, thus suggesting greater challenges for controlled experiments and monitoring than annual crops (i.e. maize, rice, etc.).

4. Given the complexity of plant-soil interactions, observations acquired may be uneven between classes of interest. Models in this study may be affected by uneven sampling between classes in a nutrient.

5. The current findings involve palm stands aged between 6.5 and 11 years old. (See Section 3.2 and 3.3 for justification of age group and experimental design)

1.5   Thesis Organization

Chapter 1 involves a general overview on the significance of oil palm trees and its fertilizer application, assessment of macronutrient status and challenges arisen from it, followed by how remote sensing may aid in addressing the aforementioned challenges.

Chapter 2 involves the literature review of this thesis. This chapter consists of three main parts. The first part consists of the historical development and morphology of oil palm, followed by an insight on the oil palm development in Malaysia. Part two focuses on remote sensing by providing a conceptual overview, followed by its application in nutrient detection and oil palms. The last part summarizes machine learning models to be applied in this study and their respective involvement in previous agricultural studies.

Chapter 3 involves methods carried out for the study. This includes descriptions on the study area and experimental design, along with explanations on data collection, processing and analysis.

Chapter 4 involves the main findings from this study and a discussion. This includes statistical descriptions of datasets, results of filtering or corrections, model performance and comparison. The discussion section comprises a critical analyses and interpretations of results from Chapter 4, including technical evaluations of experimental findings and comparisons between other closely related studies.

Chapter 5 involves concluding remarks on the study with identified limitations and general recommendations for future improvement.

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