OIL PALM AGE CLASSIFICATION IN LADANG TEREH SELATAN,JOHOR, MALAYSIA USING REMOTE SENSING TECHNIQUE

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"If we knew what it was we were doing, it would not be called research, would it?" Albert Einstein

For My Family

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ABSTRACT

Determining and classifying the age of oil palm is important in predicting oil palm yield, planning replanting activities and oil palm age is also an important criteria in estimating the carbon sequestration and storage potential of oil palm trees.. Nevertheless, determining its age with conventional method is costly, time consuming and tedious process. Alternatively remote sensing methods are used with only a moderate success. Previous studies using remote sensing have shown limitations to classify more than five age classes of oil palm trees. This studyused SPOT-5 multispectral image to classify 12 different age classes of oil palm trees at Ladang Tereh Selatan, Kluang, Malaysia. . Three different classifiers namely Support Vector Machine (SVM), Artificial Neural Network (ANN), and Maximum Likelihood Classifier (MLC) were employed and it was found that all these techniques that rely on spectral information from the image could only classify the ages with low overall accuracy of 32.46%, 29.92% and 37.41% respectively. In order to improve the classification, Grey-Level Co-occurrence Matrix (GLCM) texture measurement was added into the MLC classifier. Various combinations of textures and window sizes were tested in order to find the optimum texture combination. The overall accuracy of the classification was improved to 89.6% with the incorporation of eight texture combinations with 39 × 39 window. This study also found that, window size is more important than the type of texture in determining the stand age of the palm trees, where all the window sizes were statistically significant at 95% confidence level. The method used in this study should be extended to other plantations to test the applicability of the technique in classifying more age classes.

ABSTRAK

Mengenalpasti dan mengkategorikan usia kelapa sawit merupakan aspek penting untuk meramalkan hasil kelapa sawit yang bakal diperolehi, merancang ativiti penanaman semula dan jangka hayat kelapa sawit yang juga dilihat sebagai kriteria utama dalam mengaggar kadar penyerapan karbon dan potensi penyimpanan pokok kelapa sawit. Bagaimanapun, untuk menentukan usia sawit dengan kaedah konvensional memerlukan kos yang tinggi, memakan masa dan menjalani proses yang membosankan. Kaedah deria kawalan pula hanya memberi hasil yang sederhana. Kajian lepas telah menunjukkan batas untuk mengklasifikasikan lebih daripada lima kelas usia pokok kelapa sawit. Kajian ini menggunakan data berbilang spectrum SPOT-5 untuk mengkategorikan 12 kelas umur pokok sawit di Ladang Tereh Selatan, Kluang, Malaysia. Tiga klasifikasi berbeza iaitu Kaedah Mesin Vektor Sokongan (SVM), Rangkaian Neural Buatan (ANN) dan Keberangkalian Maksima (MLC) telah digunakan dan didapati bahawa semua teknik yang bergantung kepada maklumat spectrum dari imej hanya dapat mengklasifikasikan umur keseluruhan yang rendah ketepatannya iaitu 32.46%, 29.92% dan 37.41% sahaja. Dalam usaha untuk meningkatkan kerja pengklasifikasi, ukuran tekstur Grey-Level Co-occurrence Matrix (GLCM) telah ditambah ke dalam pengelas MLC. Pelbagai gabungan tekstur dan saiz tingkap telah diuji untuk mencari gabungan tekstur yang optimum. Ketepatan keseluruhan klasifikasi telah meningkat sebanyak 89.6% dengan penggabungan lapan kombinasi tekstur dengan tetingkap berukuran 39 x 39. Kajian ini juga mendapati bahawa, saiz tingkap yang digunakan adalah lebih penting daripada jenis tekstur dalam menentukan usia berdiri pokok-pokok sawit, dengan dapatan semua saiz tetingkap adalah signifikan dalam 95% tingkat keyakinan. Kaedah yang digunakan seharusnya diperluaskan ke ladang-ladang lain untuk menguji kebolehgunaan teknik ini dalam mengkasifikasikan lebih banyak kelas umur.

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LIST OF ABBREVIATION

ANN	-	Artificial Neural Network
ANOVA	-	Analysis of Variance
EMR	-	Electromagnetic Radiation
FELDA	-	The Federal Land Development Authority
FFB	-	Fresh Fruit Bunch
GCP	-	Ground Control Points
GDP	-	National Gross Domestic Product
GLCM	-	Gray-level co-occurrence matrix
LAI	-	Leaf area index
LIDAR	-	Light Detection and Ranging
MLC	-	Maximum Likelihood Classification
MODTRAN	-	MODerate resolution atmospheric TRANsmission
NIR	-	Near Infrared Region
NKEA	-	National Key Economic Area
NPP	-	Net Primary Productivity
OER	-	Oil Extraction Rate
RISDA	-	Rubber Industry Smallholders Development Authority
RSPO	-	The Roundtable on Sustainable Palm Oil
SAR	-	Synthetic-Aperture Radar
SVM	-	Support Vector Machine
SWIR	-	Shortwave Infrared
TIR	-	Thermal Infrared
YAP	-	Years After Planting

CHAPTER 1

INTRODUCTION

1.1 Introduction

There is no doubt that our world is currently facing a food security challenge. It has been estimated that the world population will reach nine billion by 2050, meaning a one-fold increase of current food supplies is needed to meet the demand (Godfray *et al.*, 2012). Therefore, the agriculture sector must be prepared to prevent any food crisis from occurring due to the massive population increase. One of the most important agriculture products is vegetable oil, especially palm oil which is a major vegetable oil (USDA, 2017). Oil palm is indeed an efficient oil producer; it can produce 10 times more oil compared to other oil producers such as soybean (Sime Darby, 2014). Most importantly, the price of palm oil is the lowest among all food oil types, thus making it as the best economical choice for various manufacturers such as Colgate-Palmolive, Kellogg’s and Estée Lauder (WWF, 2016). The demand for palm oil will increase at a furious pace and by the first half of the 21st century, the demand for palm oil is expected to reach up to 77 million tonnes annually (Morgan, 2012). The expansion of oil palm planting area will definitely increase palm oil production, which, in turn, will cause a threat to the existing rainforest and its ecosystem. A viable and sustainable alternative to increasing oil palm planting acreage is by closing the gap between potential yield and the actual yield in palm oil production (Hoffmann *et al.*, 2014). One-way to achieve this is through yield management based on the age of the oil palm tree.

The role of the oil palm tree's age in determining yield is crucial because it was found that the yield increases linearly with the age of young mature oil palm which is from 4-7 years after planting (YAP), and the yield starts to plateau at age 8-14 YAP, and declines when it reaches the age of 15-25 YAP (Woittiez *et al.*, 2017). This information is valuable for the plantation management to be used as a decision-making tool for various agronomic management needs such as determining the labour force needed, adjusting the agricultural input, harvest forecasting and replanting of oil palm. Aside from that, this information helps government agencies such as the Rubber Industry Smallholders Development Authority (RISDA) and The Federal Land Development Authority (FELDA) to monitor the progress of smallholders and allocate funds for new replanting schemes.

In addition, the age of oil palm is also beneficial in carbon modelling and observing the carbon productivity of oil palm (Tan *et al.*, 2013). The information on the age of oil palm is also helpful for countries such as Ghana, as a supporting document to apply for the Roundtable on Sustainable Palm Oil (RSPO) certification (Chemura *et al.*, 2015). According to RSPO criterion 7.3, beginning in November 2005 new plantings of oil palm must not replace any primary forest or any area with High Conservation value (Corley & Tinker, 2016). Thus, remote sensing not only helps in identifying and verifying the age of oil palm but also the change of land use to ensure that the RSPO principles and criterion are fulfilled.

Although, commercial plantations have well established documentation processes on the age of oil palm, these types of documents are difficult to be obtained for study purposes such as in monitoring the yield in a large spatial scale. In fact, some smallholders might not even have properly documented age of oil palm for their plantations. To alleviate this problem, field investigations can be done to determine the age of the oil palm. The age of oil palm can be predicted via the height of the oil palm; however, this is only valid for oil palm that is planted in normal conditions. This is because oil palm that is planted in very dense density is prone to be etiolated thus masking its actual age. Other than that, oil palm that is planted at a lower terrace might be bigger than oil palm at the higher terrace due to nutrient leaching effects (Corley & Tinker, 2016). Although the field investigation method can deliver sound results, it is an exhaustive method to be implemented in a large-scale area like oil palm plantations. Most importantly, this method is time consuming and costly as it requires a sizeable workforce to gather the samples.

In contrast, remote sensing provides a method for collecting data that is suitable for large scale areas. Furthermore, the data can be recorded in different wavebands, which means more information regarding the spectral properties of the oil palms can be obtained and extracted to be used in various applications including age determination, crop identification, crop conditions etc. Remote sensing data also have temporal advantages that allow the crop to be examined frequently, either in real time or on historical basis (Sivarajan, 2011). For example, Mohd Zaki *et al.*, (2009) used eight years of archived images of Landsat series to develop the oil palm age regression model. Aside from that, remote sensing offers various spatial resolutions that vary from the coarse to high detail resolutions. High resolutions will permit researchers to do more advanced image processing such as object-based segmentation to extract the oil palm canopy and correlate it with palm age (Chemura *et al.*, 2015). Of utmost importance, obtaining data by using remote sensing is comparatively cheaper for a large-scale area.

1.2 Problem Statement

The oil palm industry is no stranger to worldwide criticism and this especially affects Malaysia as the second largest oil palm producer after Indonesia. The expansion of the oil palm industry in South East Asia has been accused as the culprit for the destruction of habitats of exotic wildlife such as orangutans, rhinoceros etc. Aside from that, some argue that the conversion of forests into oil palm plantations is a major contributor of carbon dioxide in the atmosphere (Germer & Sauerborn, 2008). Lest it be forgotten, the motivation for oil palm expansion is driven by the need to fulfil the increasing demands for palm oil to feed the booming world population.

Alternatively, a more sustainable way to manage the upcoming challenge is by creating a high yield breed of oil palm or by closing the gap between oil palm's potential yield and actual yield. The first solution is an ultimate solution but the nature of plant breeding is a slow process. An ad-hoc and more viable solution is by determining the oil palm potential yield based on its age. It is known that one of the parameters of yield is age. For example, an eight years old oil palm can potentially produce up to 20 tonnes/ha/year (Hoffmann *et al.*, 2014). Thus by having the age map of oil palm, the area with underperforming oil palm can be detected and proper agronomic management processes can be applied.

In recent years, there have been some efforts on using remote sensing as a basis in oil palm age classification. For example, McMorrow (2001) developed an oil palm age regression model using squared infrared index extracted from Landsat TM. The model is able to explain four age groups of oil palm with reasonable root means square error (RMSE) of 0.58 years. Aside from that, McMorrow (2001) also showed that all radiance bands have negative correlation with the age of oil palm, the highest correlation is from the middle infrared region of bands 5 and 7, where the R value was -0.776 and -

0.705 respectively. Similar findings showed by Tan *et al.*, (2013), using data from the Disaster Monitoring Constellation 2 satellite from the United Kingdom (UK-DMC 2), the highest correlation between radiance and age is obtained from the NIR band (R2 = 0.76). Mohd Zaki *et al.*, (2009) showed that the Near Infrared Region (NIR) (B4, Landsat TM) reflectance gives the best correlation with oil palm age. However, their regression model only gives poor correlation of R2 = 0.371. In addition to model regression, oil palm age classification can also be implemented using the classifier algorithm. Various techniques for classification, from supervised and unsupervised, have been explored. For example, Vadivelu *et al.*, (2014) attempted to classify three age groups of oil palm using support vector machine (SVM), artificial neural network (ANN) and maximum likelihood classification (MLC), which resulted in moderate overall accuracy. In order to improve the classification, there were various attempts on incorporating texture measurement into the classification including Carolita *et al.*, (2015), Mansor & Sarker, (2015), Kamiran & Sarker, (2014) and Tan *et al.*, (2013). However, all of these previous studies only managed to classify generalized age class except for Tan *et al.*, (2013), where the results showed classification of 14 classes of oil palm age with moderate accuracy (52.9%). Aside from that, extraction of crown projection area from high resolution satellite data utilizing WorldView-2 resulted in the successful defining of linear relationship between age and crown area up to before oil palm becomes saturated at age 13 years old (Chemura *et al.*, 2015). All these literatures pointed to the fact that there is a gap in classifying a single age class of oil palm, which this study intends to attempt to solve.

1.3 Objectives

The overall aim of this study is to provide an oil palm age map using SPOT 5 satellite images. In order to achieve this aim, the following objectives were formulated:

1. To assess the performance of different per-pixel classifier algorithm; SVM, ANN and MLC in classifying oil palm age using original spectral bands of SPOT-5 data; and

2. To improve the classification accuracy using texture measurement of SPOT-5 data.

1.4 Research Scope

This study is conducted using SPOT 5 multispectral data archive covering the years from 2012 to 2014. SPOT-5 data was chosen because of its high temporal resolution (2-3 days); this property is important to ensure that the image taken is useful, especially in Malaysia where there is extensive cloud cover. Aside from that, SPOT-5 consists of four important spectral bands for vegetative study namely, green (500-590 nm), red (610-680 nm), NIR (780-890 nm), and Shortwave Infrared (SWIR) (1580-1750 nm). The medium spatial resolution of SPOT-5 is 10 meters which is suitable for homogenous areas such as oil palm plantations. The different age of oil palm trees were obtained using widely used supervised classification techniques namely SVM, ANN and MLC. These classifiers were chosen to explore their capabilities in classifying the discrete age of oil palm. This study also incorporates the texture measurement of SPOT-5 data into the classification because it is believed that the texture data will be able to provide information that assists in discriminating the age of oil palm better than the spectral properties alone.

1.5 Significance of Study

Oil palm age is an important facet in oil palm management. Age is one of the direct variables in determining the yield; therefore it is often used as the foremost parameter in oil palm yield forecasting. The information derived from the oil palm yield forecasting is vital for managing the oil palm industry sector not only in identifying the underperforming oil palm block but also as a benchmark to achieve the site yield potential. Proper agronomic decisions can be taken to increase the yield and this will help Malaysia to reach its target of national average yield, which are 22 tonnes/ha/year for independent smallholders, 26 tonnes/ha/year for organized smallholders and 28 tonnes/ha/year for the plantation sector (PEMANDU, 2011).

Aside from that, the oil palm age information is crucial for government agencies such as RISDA to manage the distribution of subsidized agricultural inputs such as fertilizers to the smallholder. It will also help in filtering the eligible applications for replanting schemes under the government's incentives. The government on the other hand, can plan ahead on allocating sufficient funds to help the smallholders via replanting schemes.

Oil palm age data is also valuable to be used in studies regarding carbon sequestration and productivity (Tan *et al.*, 2013). It was shown that age affected carbon productivity; for example, in oil palm, the net primary productivity (NPP) decreases with age of oil palm using the allometric equation (Kanniah *et al.*, 2014). The oil palm age is also essential in applying for RSPO certification (Chemura *et al.*, 2015). The oil palm age becomes the key to investigate whether the oil palm is planted on gazetted agriculture land or on areas with high conservation value especially primary forests as outlined by RSPO criterion 7.3 (Corley & Tinker, 2016). For example, for oil palm with age of less than 12 years in 2017, the plantation location must be verified either by site visits or by remote sensing to ensure that the oil palm is planted in an approved location.

1.6 Study Area

The study area is at Ladang Tereh Selatan, a commercial plantation managed by Kulim Plantation Sdn. Bhd. It is located at the Kluang district of Johor (2.23º-2.120º N and 103.30 º -103.375 º E), located approximately 119 km from Johor Bahru. Ladang Tereh Selatan comprises of 2000 ha of oil palm at multiple ages that were planted from 1991 to 2008. Ladang Tereh Selatan was chosen as the study area because the range of oil palm age represents approximately the economical lifespan of oil palm, which is from four years old to 25 years old, and the accessibility of ancillary data such as field data from the company.

The oil palm in Ladang Tereh Selatan is planted in fifteen blocks of uniform age. Block size varies from 20 ha to 325 ha with average size of 180.53 ha. Palms are planted in a triangular pattern at known nominal density; the actual density of the block may vary due to the death of trees due to disease, etc. The planting material is from the "tenera" breed. The annual average rainfall is 24,388 mm and the average temperature is 26°C with maximum temperature of 30°C ("Climate Data," 2017). The oil palm is planted on mostly Oxisols and Utisols with varied soil series; the highest coverage is from Tai Tak Series with 19.72 %, followed by Rengam Series (17.79%), and Tawar Series (16.1%). The study area's elevation ranges between 13 and 91 meters.

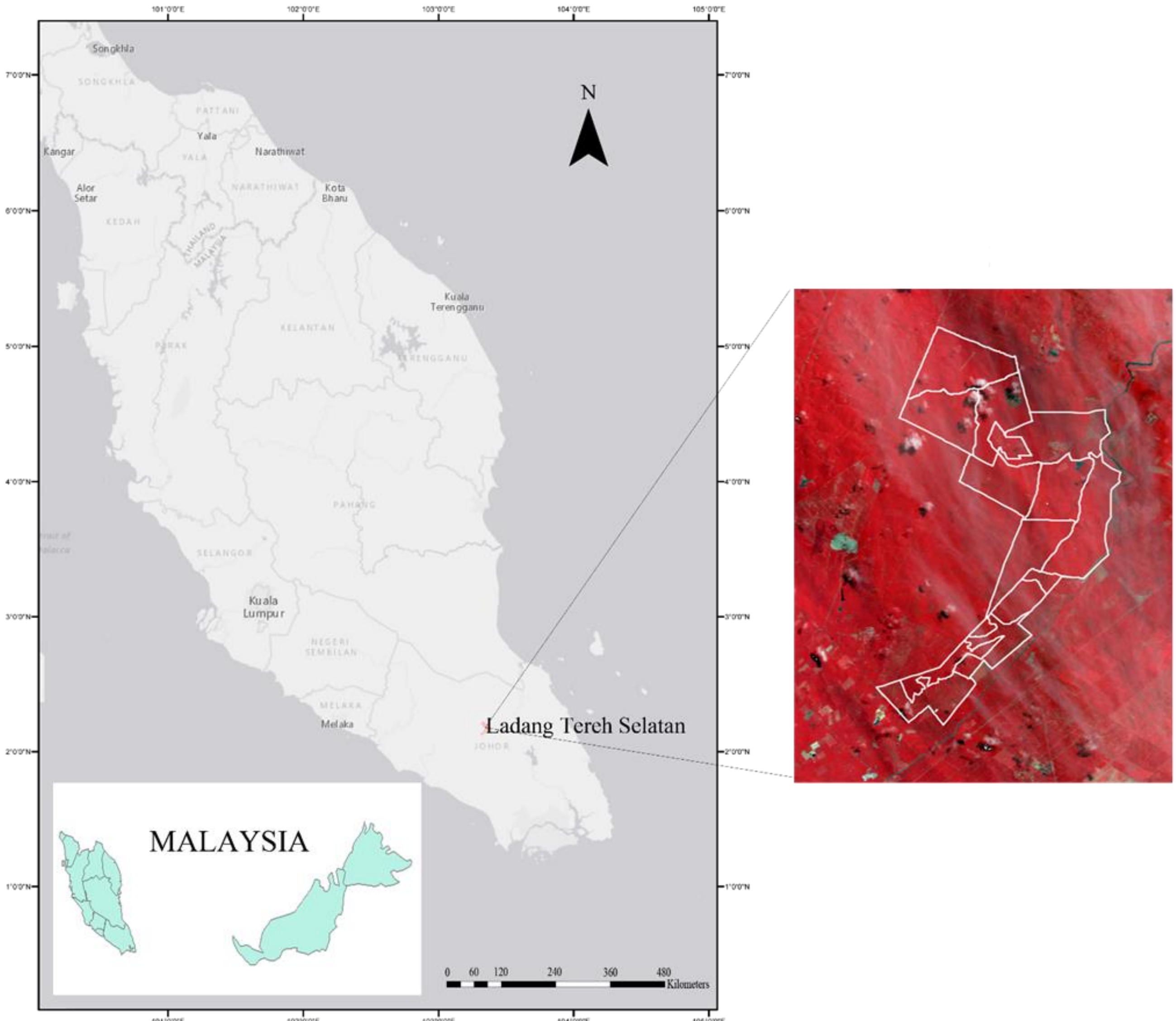

Figure 1.1: Location of Ladang Tereh Selatan

1.7 Organization of Chapters

There are five chapters in this study namely: Introduction, Literature Review, Methodology, Results and Discussion, and Conclusion. The first chapter describes the issues related to oil palm age, the research problem, and the objectives of this study. Chapter 2 provides some background information on oil palm and the method of oil palm age measurement. The methods used in achieving the objectives of the study are presented in Chapter 3. The results and discussion are explained in Chapter 4. Lastly, Chapter 5 concludes the study and provides the recommendation for future works on the matter.

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