# Health Status Detection of Oil Palm Tree Using an Unmanned Aerial Vehicle Multispectral Image Based on Picterra Platform

HONG LAY

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF

THE REQUIREMENTS FOR THE MASTER DEGREE OF SCIENCE

IN GEOINFORMATICS

FACULTY OF GEOINFORMATICS

BURAPHA UNIVERSITY

2021

COPYRIGHT OF BURAPHA UNIVERSITY

การตรวจหาสถานะสุขภาพของปาล์มน้ำมันโดยใช้ภาพถ่ายหลายช่วงคลื่นจากอากาศยานไร้คนขับด้วยพิกเทอร์ราแพลตฟอร์ม

HONG LAY

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรวิทยาศาสตรมหาบัณฑิต
สาขาวิชาภูมิสารสนเทศศาสตร์
คณะภูมิสารสนเทศศาสตร์ มหาวิทยาลัยบูรพา
2564
ลิขสิทธิ์เป็นของมหาวิทยาลัยบูรพา

# Health Status Detection of Oil Palm Tree Using an Unmanned Aerial Vehicle Multispectral Image Based on Picterra Platform

HONG LAY

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE MASTER DEGREE OF SCIENCE
IN GEOINFORMATICS
FACULTY OF GEOINFORMATICS
BURAPHA UNIVERSITY
2021

COPYRIGHT OF BURAPHA UNIVERSITY

The Thesis of Hong Lay has been approved by the examining committee to be partial fulfillment of the requirements for the Master Degree of Science in Geoinformatics of Burapha University

Advisory Committee

Principal advisor

............................................................

(Professor Zhenfeng Shao)

Co-advisor

............................................................

(Doctor Kitsanai Charoenjit)

Examining Committee

............................................................ Principal examiner

(Associate Professor Xiaobin Cai)

............................................................ Member

(Professor Zhenfeng Shao)

............................................................ Member

(Doctor Kitsanai Charoenjit)

............................................................ Member

(Professor Doctor Li Xi)

............................................................ Dean of the Faculty of Geoinformatics

(Doctor Kitsanai Charoenjit)

............................................................

This Thesis has been approved by Graduate School Burapha University to be partial fulfillment of the requirements for the Master Degree of Science in Geoinformatics of Burapha University

............................................................ Dean of Graduate School

(Associate Professor Dr. Nujjaree Chaimongkol)

............................................................

62910208: MAJOR: GEOINFORMATICS; M.Sc. (GEOINFORMATICS)

KEYWORDS: Oil palms; Multispectral remote sensing image; Object extraction; UAV; Vegetation indices

HONG LAY : HEALTH STATUS DETECTION OF OIL PALM TREE USING AN UNMANNED AERIAL VEHICLE MULTISPECTRAL IMAGE BASED ON PICTERRA PLATFORM. ADVISORY COMMITTEE: ZHENFENG SHAO, Ph.D., KITSANAI CHAROENJIT, Ph.D. 2021.

Oil palm plantations are a significant export crop for Cambodia, providing employment opportunities and economic growth. An Unmanned Aerial Vehicle (UAV) was used to capture two plots of oil palm area for this research. Oil palm trees were extracted from high-resolution images using the Picterra platform. Furthermore, oil palm trees are counted both automatically and manually, with the effect demonstrating a high overall accuracy.

In addition, also used the multispectral image to assess the health of oil palm trees based on the Parrot Sequoia camera. The camera has occurred in three bands like Green, Red, Red Edge, and Near-Infrared. Thereby, the health of an oil palm tree is determined using vegetation indices such as NDRE, GNDVI, and NDVI. On the other hand, maximum, low, mean, and standard deviation in vegetation and chlorophyll content were contrasted with the vegetation indices. The NDVI indices are superior to the NDRE and GNDVI indices.

There are two objectives of the research as the following; 1) to detect and count oil palm trees of very high-resolution images from UAV with Picterra platform and 2) to evaluate and compare oil palm trees health by Using NDRE, GNDVI, and NDVI indices in vegetation and chlorophyll content. Oil palm trees were detected and counted using UAV-based high-resolution imagery, and their health was assessed using multispectral images.

According to the Picterra platform, the output of counting is Plot-1 has 3456 oil palm trees, and Plot-2 has 3477 oil palm trees. The accuracy of oil palm detection using the F-score of Plot-1 is 100%, and Plot-2 is 98.97%. In this research, Picterra is a high-performance platform that can use to retrieve objects from UAV imagery.

The results of the health assessment of oil palm trees reveal from Normalized Difference Red Edge that Plot-1 has three classes: low chlorophyll (0.14–0.29) of 22.92%, medium chlorophyll (0.29–0.33) of 48.64%, and high chlorophyll (0.33–0.44) of 28.44%, and Plot-2 has three classes: low chlorophyll (0.13–0.26) of 22.93%, medium chlorophyll (0.26–0.31) of 48.27%, and high chlorophyll (0.31–0.40) of 28.80%.

Plot-1 has three classes: unhealthy (0.41–0.65) of 10.22%, moderately healthy (0.65–0.71) of 43.30%, and very healthy (0.71–079) of 46.48%, while Plot-2 has two classes: moderately healthy (0.46–0.69) of 40.91% and very healthy (0.69–0.78) of 59.09%, according to Green Normalized Difference Vegetation Index calculations.

Whereas Normalized Difference Vegetation Index shows that Plot-1 has three classes: unhealthy (0.33–0.71) of 4.34%, moderately healthy (0.71–0.81) of 37.12%, and very healthy (0.81–0.88) of 58.54%, while Plot-2 has two classes: moderately healthy (0.54–0.81) of 22.56% and very healthy (0.81–0.88) of 77.44%.

In this thesis, the vegetation index is extracted from multispectral images of the UAV platform, and the oil palm tree is classified. The results have been published in an international academic conference and applied in Cambodia's MRICOP Company. Therefore, the Picterra platform is helpful for object extraction and geospatial analysis since the F-score has resulted in high accuracy assessment.

## ACKNOWLEDGEMENTS

At first, I would like to express my gratitude to my supervisor Professor Zhenfeng Shao, who has advised me in writing a dissertation. I would like to thanks Dr. Hor Sanara who has provided a drone (DJI Matrice 100) for collecting data in the field. Moreover, I would like to thank the Director of MRICOP that give me permission for collecting the oil palm area, especially give a good chance to present my proposal there. Subsequently, I would like to thanks all the lecturers who taught me at Wuhan University, Burapha University, and GISTDA for all who gave us an extraordinary education.

My special thanks to all my family members, my dear parents, my younger brother, my grandparent, my uncles and aunts that trusted in me, supported me, motivated me, given me motivation, and given me good advice.

I would also like to thank my classmate, Suwatcharapong Surasanpreedee, Anurak Chakpor, Arpakorn Wongsit, Nittaya Katekaew, Mot Ly, Sopaphan Chinnabut, Phorn Nayelin for their support in class and group meetings.

Also, I am grateful to the staff of LIESMARS, BUU, and GISTDA who without their support, this Dissertation would not have been possible.

Especially, my appreciation also extends to SCGI Master Program to fulfill my dream of being a student graduation in Geoinformatics and giving me a good chance to study both in Thailand for the first year and China for the second year.

Funding: This work is supported by the National Key Research and Development Program of China with grant number 2018YFB2100501, the National Natural Science Foundation of China with grant numbers 41890820, 42090012, 41771452, and 41771454, the Key Research and Development Program of Yunnan province in China with grant number 2018IB023, Consulting research project of Chinese Academy of Engineering with grant number 2020ZD16.

Hong Lay

# TABLE OF CONTENTS

**Page**

# List of tables

**Page**

# List of figures

**Page**

# List of acronyms and abbreviations

| | | |
|---|---|---|
| **AI** | : | Artificial Intelligence |
| **DL** | : | Deep Learning |
| **UAV** | : | Unmanned Ariel Vehicle |
| **NDRE** | : | Normalized Difference Red Edge |
| **GNDVI** | : | Green Normalized Difference Vegetation Index |
| **NDVI** | : | Normalized Difference Vegetation Index |
| **MI** | : | Multispectral Image |
| **UAS** | : | Unmanned Aircraft Systems |
| **RGB** | : | Red, Green, Blue |
| **NIR** | : | Near-Infrared |
| **RE** | : | Red Edge |
| **GPS** | : | Global Positioning System |
| **LAI** | : | Leaf Index Area |
| **$Km^2$** | : | Square kilometer |
| **P** | : | Plot |
| **ELCs** | : | Economic Land Concession |
| **RGC** | : | Royal Government of Cambodia |
| **MAFF** | : | Ministry of Agriculture, Forestry and Fisheries (Cambodia) |
| **Ha** | : | Hectare |
| **MRICOP** | : | Mong Reththy Investment Cambodia Oil Palm Co., Ltd |
| **US$** | : | Dollar |
| **FAOUN** | : | Food and Agriculture Organization of the United Nations |
| **R&D** | : | Research and Development |
| **MP** | : | Megapixel |
| **LAI** | : | Leaf Index Area |
| **VI** | : | Vegetation Indices |
| **MI** | : | Multispectral Image |
| **RoI** | : | Region of Interest |

# CHAPTER 1
# INTRODUCTION

This chapter provides an overview of the oil palms at Mong Reththy Investment Cambodia Oil Palm Co., LTD (MRICOP) in Cambodia, the use of Unmanned Aerial Vehicle (UAV) in agriculture, the use of vegetation indices in estimating agriculture health using the multispectral band, and an explanation of the research's significance and scope of the study.

## 1.1 Background

Oil palms are the product of the agriculture sector in Cambodia. Oil palm plantations occupy 1188,00 ha of Cambodia's Economic Land Concessions, according to the study (Colchester, Chao, Dan, & Villanueva, 2011). The report (Saing, Hem, Ouch, Phann, & Pon, 2012) shows that Mong Reththy Investment Cambodia Oil Palm Co., LTD (MRICOP) is the first company to invest in oil palm plantations covering 11000 ha in Cambodia since 1995. Oil palm trees have been cultivated on four plantations (Estates A, B, C, and D). As of 2016, oil palm trees have been planted on 15173 ha.

In this era, Unmanned Ariel Vehicle (UAV) is widely used in estimating oil palm trees. UAV has become an application in Photogrammetry and Remote Sensing (RS) (Yu, Wu, Luo, & Ren, 2017). In addition, the multispectral bands of the Parrot Sequoia Multispectral camera sensor have been demonstrated in agriculture using a UAV. The sensor has been delivered Green band, Red band, Red Edge band, Near-Infrared band, and RGB imagery. In the same way, (Raeva, Šedina, & Dlesk, 2019) assess those vegetation indices (NDRE, GNDVI & NDVI) with multispectral imagery from UAV. Mostly, the Near-Infrared band emittances absorption at the region of the electromagnetic spectrum (Olukayode, Blesing, Rotimi, & Oguntol, 2018). Therefore, multispectral imagery can be used in estimating oil palm tree health from UAV based on vegetation and chlorophyll content.

UAV is useful for estimating oil palm trees because it can be used in multispectral imagery, and it can also deliver very high-resolution images. The use of very high-resolution images from drones is appropriate for detecting and counting oil palm trees. The oil palm trees were used Convolution Neural Networks (CNNs) and Faster-RCNN approach to extract the information from imagery, according to (Mubin, Nadarajoo, Shafri, & Hamedianfar, 2019), (X. Liu, Ghazali, Han, & Mohamed, 2021). In this study, the Picterra platform will be used to extract and count oil palm trees in both plots.

For delivering into vast oil palm areas, UAV-based multispectral and very high-resolution imagery is critical, as seen above. The health of the oil palm tree will be determined by analyzing each tree and determining where it will be located. Additionally, the Picterra platform was used to detect and count oil palm trees using UAV-based very high-resolution imagery. In order, to estimate the health of oil palm trees using a multispectral camera with four bands (Green, Red, Red Edge, and Near-Infrared), the Normalized Different Red Edge (NDRE), Green Normalized Different Vegetation Index (GNDVI), and Normalized Different Vegetation Index (NDVI) were used to access oil palm tree health.

UAV significance to apply multispectral imagery in estimating oil palm trees, also it has been delivered very high-resolution imagery. In detecting and counting oil palm trees appropriate to use very high-resolution imagery from drones. Otherwise, the oil palm trees were used Convolution Neural Networks (CNNs) and Faster-RCNN approach in detecting and counting, according to (Mubin et al., 2019), (X. Liu et al., 2021). In this study, an online Artificial Intelligence (AI) is going to extract and count oil palm trees of two plots.

As shown above, UAV-based multispectral and very high-resolution imagery are essential for delivering into large oil palms area. The oil palm tree health is going to analyze a single tree and find where is allocated. Moreover, this study has applied UAV-based multispectral images to be detected and counted oil palm trees by using an online AI platform. In order, to estimate oil palm trees health from a multispectral camera that includes four bands have such as Green, Red, Red Edge, and Near-Infrared bands to be used Normalized Different Red Edge (NDRE), Green Normalized Different Vegetation Index (GNDVI), and Normalized Different Vegetation Index (NDVI).

## 1.2 Problem statement

Oil palm plantations occupy a vast area, making it impossible for the owner to monitor and count them. The owner will be considered in replacing the dead tree and harvest. Therefore, the only way to address this issue is to use UAV-based multispectral and high-resolution imagery that is suitable for large-scale applications. In estimating oil palm tree health and counting and detecting oil palm trees, all factors are taken into consideration. Moreover, the Picterra platform has achieved high accuracy, and vegetation indices have been used to estimate the health of oil palm trees based on multispectral bands.

## 1.2 Research objectives and research questions

### 1.3.1 Research objectives

There are two objectives of this study is:

(1) To detect and count oil palm trees of very high-resolution images from UAV with Picterra platform

(2) To evaluate and compare oil palm trees health by using NDRE, GNDVI, and NDVI indices in vegetation and chlorophyll content

### 1.3.2 Research questions

There are four research questions for this study on research:

(1) Can Picterra platforms be detected and counted from very high-resolution images?

(2) What are the advantages of using multispectral bands to assess the health of oil palm trees from UAV?

(3) What is the difference between NDRE, GNDVI, and NDVI indices in vegetation and chlorophyll content?

(4) Which vegetation index is most useful for estimating the health of oil palm trees?

## 1.4 Hypotheses

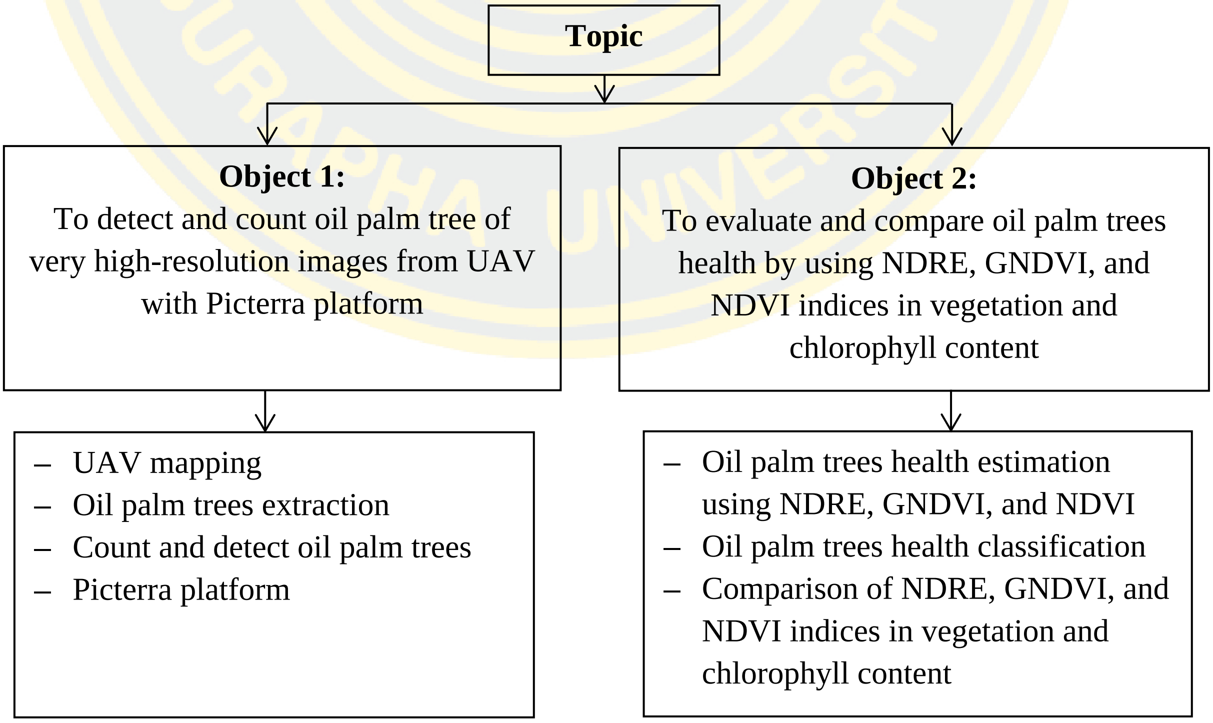
(1) The Picterra platform detects and counts oil palm trees in very high-resolution imagery captured by a UAV, resulting in a high-accuracy assessment.

(2) The multispectral camera can be used to assess agriculture stress and monitor the health of oil palms.

(3) Oil palm tree health can be estimated using multispectral bands such as NDRE, GNDVI, and NDVI.

## 1.5 The scope of the study

The study's goal is to extract objects and determine the health of oil palm trees. NDRE, GNDVI, and NDVI are used to estimate the health of oil palms, and the Picterra platform is used to extract objects. Furthermore, the vegetation indices will compare vegetation and chlorophyll content in both plots. However, the work must be completed within the timeframe set by Wuhan University and must be of high quality, so the study on “Health Status Detection of Oil Palm Tree Using an Unmanned Aerial Vehicle Multispectral Image Based on Picterra Platform”.




Figures 1 Detailed the scope of the study

### 1.6 Research design

Tables 1 Summary of research design

| Specific objectives | Respective research question | Techniques of analysis | Data collection | Data analysis and software |
|---|---|---|---|---|
| (1) To detect and count oil palm tree of very high-resolution images from UAV with Picterra platform | - Can Picterra platforms be detected and counted high-resolution images? | Picterra platform | - Training sample<br>- UAV Imagery | - DJI Matrice 100<br>- DroneDeploy<br>- Pix4Dmapper<br>- ArcGIS Pro 2.7 |
| (2) To evaluate and compare oil palm trees health by using NDRE, GNDVI, and NDVI indices in vegetation and chlorophyll content | - What are the advantages of using multispectral bands to assess the health of oil palm trees from UAV?<br>- What is the difference between NDRE, GNDVI, and NDVI indices in vegetation and chlorophyll content?<br>- Which vegetation index is most useful for estimating the health of oil palm trees? | - NDRE, GNDVI, and NDVI<br>- Georeferencing<br>- Zonal Statistics as Table<br>- Join Field<br>- Buffer | - Oil palm tree extraction<br>- Multispectral images (Red, Green, Red Edge, and Near-Infrared bands)<br>- Shapefile<br>- NDRE, GNDVI, NDVI mean value | - ArcGIS Pro 2.7<br>- ArcGIS 10.5 |

# CHAPTER 2
# LITERATURE REVIEW

This chapter expresses the concept related to the research title that has such as an overview of oil palms, oil palm plantations in Cambodia, UAV, multispectral camera, vegetation index trend, remote sensing, Deep Learning algorithm, previous research, Artificial Intelligence, and Picterra platform (AI-powered). The importance of multispectral sensors in agriculture.

## 2.1 Overview of Oil Palms

Oil palm has been contributed to the ecosystem, environment, economy, and without proper monitoring and management of the oil palm industry is important (Shaharum et al., 2020). The research (Hartley, 1967) explains that oil palm has been expanded to Malaysia since 1963. Therefore, the oil palm boom has contributed to economic growth in Southeast Asia (Qaim, Sibhatu, Siregar, & Grass, 2020). Presently, Southeast Asia is the dominant region of production with Malaysia being the leading producer and exporter of palm oil (Wahid, Abdullah, & IE, 2005). Malaysia produces about 47% of the world's supply of palm oil (Sumathi, Chai, & Mohamed, 2008).

### 2.1.1 Oil Palm world plantation

Palm oil production has boomed over the last decade, resulting in an expansion of the global oil palm planting area from 10 to 17 Million hectares between 2000 and 2012 (Pirker, Mosnier, Kraxner, Havlík, & Obersteiner, 2016). Many planters will find the section on herbicide control of circle and interrow weeds of great practical use since the mechanics of herbicide spraying are covered in great detail (Turner & Gillbanks, 1974). Oil palm plantations support much fewer species than do forests and often also fewer than other tree crops (Fitzherbert et al., 2008). In contrast, the emission from forest conversion exceeds the potential carbon fixation of oil palm plantings (Germer & Sauerborn, 2008). For the latter, palm oil mills are fast becoming generators of renewable energy from their biomass and biogas (Basiron & Weng, 2004). Therefore, oil palm has been planted by MRICOP since 1995 which the first company starts to invest in an oil palm plantation in Cambodia.

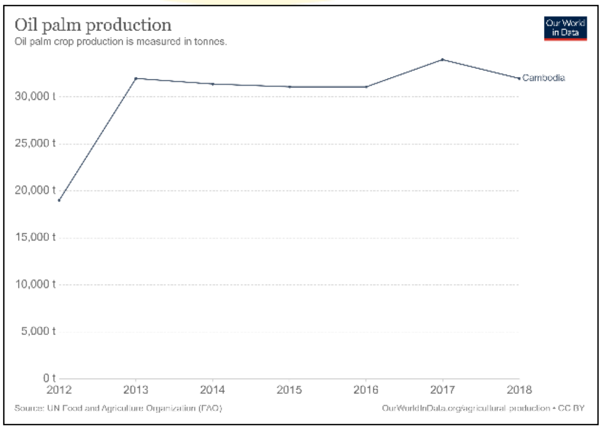
### 2.1.2 Oil Palms plantation in Cambodia

According to (Sokhannaro, 2011) MRICOP is the first company in Cambodia that has been invested in commercially cultivated oil palm. The company has been obtained 11,000 ha of LECs from RGC. The period of investing in oil palm is 70 years that start to plant since 1995.  The company has been invested US$ 36 million that includes the development of the refinery. Moreover, the oil palm plantation is located in Sihanoukville Province. The seeds have been imported from outside the country, have such as Costa Rica, Thailand, and Malaysia.

Figures 2 Oil palms plantation at MRICOP, Sihanoukville Province, Cambodia

#### *2.1.2.1 Oil Palms production*

Previous projections showed that our yields would reach approximately 270,000 t in 2020, but in reality, a figure of up to 300,000 t is possible. Regrettably, our two palm oil mills are not capable of handling all the raw palm fruit, which leaves enough fruit to produce 5,000 t of palm oil to rot in the plantation, leading to a massive waste of money, said Reththy, reported from (The Phnom Penh Post, 2020). However, according to (Figure 3) show that Cambodia has been exported oil palm about 20,000 t for 2012, an increase in 2013 over 30,000 t until 2018.




Figures 3 Oil palm production in Cambodia from 2012 to 2018 (FAOUN, 2020)

## 2.2 Unmanned Aerial Vehicle

Unmanned Aerial Vehicles (UAV) have been utilized in military applications by various developed countries since 1990 (Renduchintala, Jahan, Khanna, & Javaid, 2019). In recent years, the UAV has been used in remote sensing, agriculture monitoring, vegetation index mapping, agriculture estimation with multispectral sensors (Lu, Fan, Ghimire, & Deng, 2020), agricultural research applications of crop growth (Shafian et al., 2018). Moreover, (Khaliq et al., 2019) recommend that UAV has been provided very high-resolution imagery in considering evaluated relations tween the Normalized Difference Vegetation Index (NDVI) and crop vigor. The application of UAV is important for crop monitoring and management.

### 2.2.1 Multispectral sensor

The multispectral sensor has been used in crop monitoring and growing, among agricultural chemicals and nitrogen (Lee & Searcy, 2000). UAV in combination with multispectral sensor increase utilization vegetation index and manage crop production (Iqbal, Lucieer, & Barry, 2018) of multispectral sensors typically used for remote sensing (Mamaghani & Salvaggio, 2019). The integration of multispectral sensor with UAV which data output are meaningful. Moreover, the multispectral sensor has been applied to agriculture which drones allow managing crops, soil, fertilizing, and irrigation more effectively. There are four bands for estimating vegetation index and crop monitoring, such as reflectance of green, red, red edge, and near-infrared.

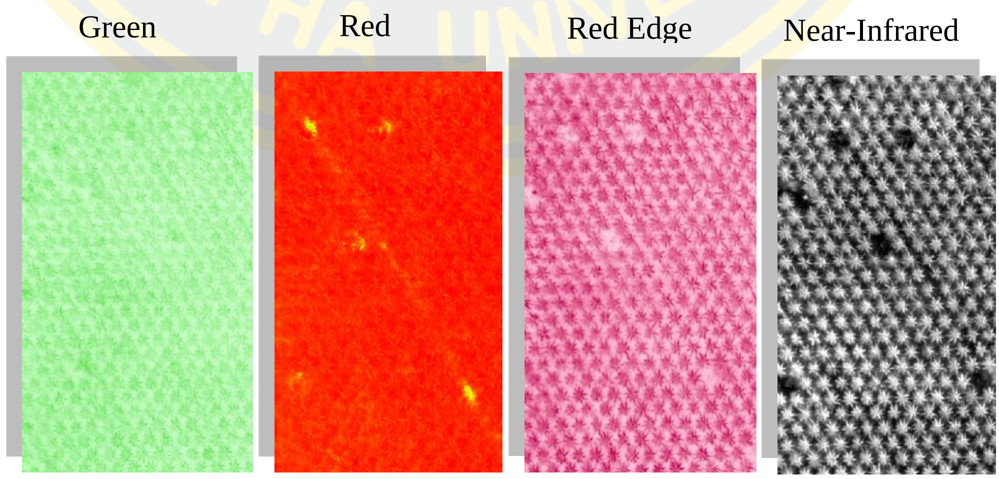
### 2.2.2 Parrot Sequoia Multispectral Sensor

The Parrot Sequoia has been utilized to capture crops that have delivered four bands have green, red, red edge, and near-infrared, Parrot Sequoia multispectral sensor uses onboard a UAV (Handique et al., 2017). (Handique et al., 2020) mentions that the Parrot Sequoia sensor has been delivered built-in GPS module. According to (Kurbanov & Litvinov, 2020) shows that Parrot Sequoia expresses two sensors, a multispectral camera has 41.2 MP monochrome cameras: green, red, red edge, near-infrared, and 16 MP RGB cameras. Therefore, the Parrot Sequoia has been applied for refine fertilization, detection of leaf problem at a field, crop yield estimation, water stress, and vegetation stress. The details of the camera mention in (Figure 4) below:


Figures 4 Parrot Sequoia Multispectral camera sensor

2.2.3 Multispectral Vegetation Bands

There are four bands in estimating vegetation has Green, Red, Red Edge, and Near-Infrared band (Figure 5). The green band has been used for estimating leaf and chlorophyll plants that reflected energy in the 500 to nm. The red band has been utilized for leaf index area, soil moisture, plant stress, classify crop type, and humidity which strong chlorophyll absorption and reflected energy in the 600 to 700 nm spectral band. Red Edge has been applied for evaluating plant stress and chlorophyll that reflected band from 700 to 730 nm. In the same way, the Near-Infrared band is widely used VI in agriculture, monitor crop health, and leaf cellular structure.




Figures 5 The multispectral bands for oil palm trees health estimation

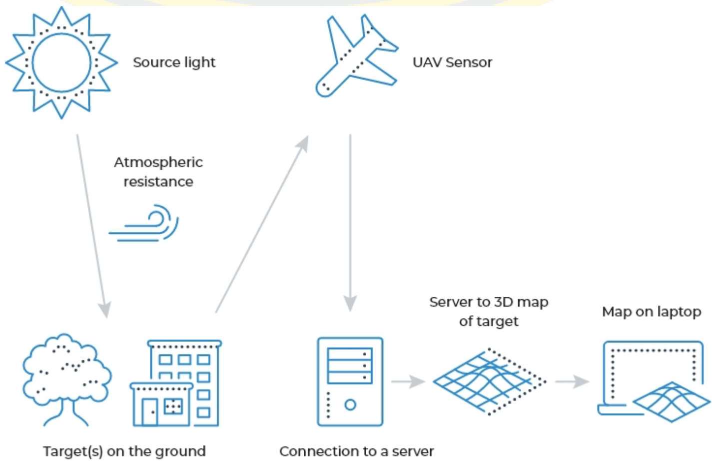
### 2.2.4 Agriculture UAV Types

Tables 2 Types of agriculture UAV applications

| **Agriculture UAV** | **Advantages** | **Disadvantages** | **UAV types** |
|---|---|---|---|
| Agriculture Harvesting | – Fast to harvest yield on the large scale<br>– Decrease labor and save income | – Difficult to control with a short plant<br>– Need to charge more battery's |  |
| Agriculture Mapping | – Detect chlorophyll and count plants<br>– Predict crop yield and agriculture stress estimation | – High cost of the production<br>– Difficult to teach farmer how to monitor |  |
| Agriculture Spraying | – Provide fertilizer into the crop<br>– Control by human and reduce labor | – The effect of weather like wind and rain<br>– Small storage |  |

## 2.3 Photogrammetry concept

The research (Baek, 2020) expresses that Photogrammetry is the science and technology of collecting accurate knowledge about physical objects and the atmosphere by observing, calculating, and analyzing photographs, variations of electromagnetic radiant imagery, and other phenomena. Photogrammetry refers to methods for measuring real-world structures and surface characteristics from photographs according to (Aber, Marzolff, Ries, & Aber, 2019).




Figures 6 Basics of Photogrammetry concept

## 2.4 Remote Sensing technique in agriculture

Remote sensing is art or science that tells something about an object on Earth without touching it, according to (Fischer, Hemphill, & Kover, 1976). There are two types of sensors, passive and active remote sensing. (Navalgund, Jayaraman, & Roy, 2007) mentions that remote sensing has been applied for agriculture, forestry, water resources, land use, urban sprawl, geology, environment, coastal zone, marine resources, snow and glacier, disaster monitoring and mitigation, infrastructure development, etc.

The application of remote sensing in agriculture is characterized by several phenological, land management, and economic features (Steven & Clark, 2013). According to (Huang, Chen, Tao, Huang, & Gu, 2018) shows that agricultural remote sensing data are characteristics of big data. Therefore, in recent years, the application in agriculture is used for crop monitoring and management, yield estimation, and vegetation health.

## 2.5 Vegetation Index

According to (Bannari, Morin, Bonn, & Huete, 1995) mentions that VI is used for estimating vegetation in the field of remote sensing applications. The VI has been used in RS applications from airborne and satellite recent advanced using UAV (Xue & Su, 2017). Therefore, VI has provided the equation in estimating agriculture health and chlorophyll based-multispectral bands, the VI has such as Green Normalized Different Vegetation Index (GNDVI), Normalized Different Red Edge (NDRE), and Normalized Different Vegetation Index (NDVI) all of these incorporated the Near-Infrared (NIR) band.

### 2.5.1 The Normalized Difference Red Edge

RDRE refers to Normalized Different Red Edge which is similar to the NDVI index. The multispectral camera provides Red Edge and Near-Infrared for estimating chlorophyll of oil palm tree's leaf. The NDRE estimates the tree's leaf that it identify chlorophyll absorption of Red wavelengths with the higher reflectance of NIR wavelengths, and the Red Edge (REDGE) wavelength to indicate chlorophyll content, according to (Carlson & Ripley, 1997). NDRE equation (1) below:

NDRE = (NIR - REDGE) / (NIR - REDGE) (1)

Where:

NIR = It refers to Near-Infrared band that reflectance at NIR spectrum

REDGE = It refers to Red Edge band that reflectance at REDGE spectrum

2.5.2 The Green Normalized Difference Vegetation Index

According to (ESRI, 2020) Green Normalized Difference Vegetation Index (GNDVI) is a vegetation index that has been used in NIR and Green bands in estimating photosynthetic activity. Therefore, it is a commonly used vegetation index to determine water and nitrogen uptake into the plant canopy. See detail equation (2) below:

GNDVI = (NIR - Green) / (NIR + Green) (2)

Where:

NIR = It refers to Near-Infrared band that reflectance at NIR spectrum

Green = It refers to the Green band that reflectance at the Green spectrum

2.5.3 The Normalized Difference Vegetation Index (NDVI)

The well-known NDVI used for estimating green vegetation that refers to Normalized Different Vegetation Index (Rouse, Haas, Schell, & Deering, 1974). The green leaf scattering in NIR wavelength that it combines with chlorophyll absorption in RED wavelengths. The equation is below (3):

NDVI = (NIR - Red) / (NIR + Red) (3)

Where:

NIR = It refers to Near-Infrared band that reflectance at NIR spectrum

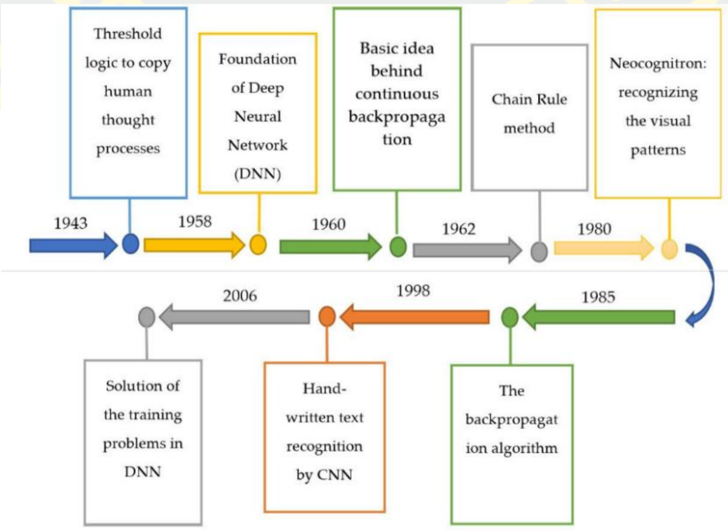
RED = It refers to Red band that reflectance at RED spectrum (Karaburun, 2010)

According to (Figure 7) shows the value range of NDVI for accessing trees such as health such as dead plants or inanimate objects is 0 to -1, the unhealthy plant is 0 to 0.33, moderately healthy plant is 0.33 to 0.66, and very healthy plant is 0.66 to 1.


Figures 7 The value range of the Normalized Difference Vegetation Index

## 2.6 Deep Learning algorithm

In recent years, deep learning is the fastest-growing trend in big data analysis, according to (Xiao Xiang Zhu, 2017). The research (Hargrave, 2020) said that deep learning is a subset of machine learning in AI of the human brain processing. Moreover, the previous research papers mention that method was used deep learning architectures have such as DNN, DBN, RNN, and CNN. All architectures have applied to many fields that include computer vision, machine vision, speech recognition, natural language processing, audio recognition, machine translation, bioinformatics, and drug design. (J. Hu, Niu, Carrasco, Lennox, & Arvin, 2020), (Ciregan, Meier, & Schmidhuber, 2012), (Krizhevsky, Sutskever, & Hinton, 2012).




Figures 8 The revolution of deep learning from 1943–2006
(Saleem, Potgieter, & Mahmood Arif, 2019)

2.6.1 Object extraction

Object extraction is a technique for extracting imagery from satellites and UAVs. In extracting oil palm tree automatically that was applied the method Faster-RCNN (X. Liu et al., 2021), Convolutional Neural Network (CNN) (Arce et al., 2021), and R-CNN model and feature pyramid network (FPN) (Ocer, Kaplan, Erdem, Kucuk Matci, & Avdan, 2020) from UAV imagery with high overall accuracy assessment. Therefore, the oil palm tree extraction is used for counting the number in estimating yield every year.

2.6.2 Previous studies on Deep Learning

Many researchers have been applied Deep Learning for detecting and counting objects. Some algorithms were used in the previous studies, such as CNN, UHT-Net, Deep Convolutional Autoencoder (DCAE), Multi-Scale-Dilation network, etc. According to (Table 3) shows that previous research paper using deep learning algorithms, and their advantages and disadvantages. Moreover, the algorithms have been applied in different fields as the following agriculture, land use classification, car detection based-imagery of very high-resolution, and image classification.

Tables 3 Previous studies propose a method for detecting an object

| N | Paper | Methodology |
|---|---|---|
| 1 | Fast and Adaptive Deep Fusion Learning for Detecting Visual Objects<br>(Doulamis & Doulamis, 2012) | – Implementing a novel fast (a real-time) and fusion strategy for detecting an object<br>– Tracking object movement |
| 2 | Benchmarking Deep Learning Frameworks for the Classification of Very High-Resolution Satellite Multispectral Data<br>(Papadomanolaki, Vakalopoulou, Zagoruyko, & Karantzalos, 2016) | – Convolutional Neural Networks (CNN) for classifying land use of multispectral remote sensing data that occurs high overall accuracy<br>– Compare method were proposed |

| | | |
|---|---|---|
| 3 | Deep Learning-Based Oil Palm Tree Detection and Counting for High-Resolution Remote Sensing Images (W. Li, Fu, Yu, & Cracknell, 2017) | – Counting oil palm trees based-CNN that occurs accuracy more than 96%<br>– Collect training sample through sliding window technique |
| 4 | A Deep Learning-based Approach for Banana Leaf Diseases Classification (Amara, Bouaziz, & Algergawy, 2017) | – Propose LeNet architecture as a CNN for detecting and classifying banana plant diseases |
| 5 | Deep Learning Approach for Car Detection in UAV Imagery (Ammour et al., 2017) | – Automatic detecting and counting car from UAV imagery with CNN and SVM |
| 6 | Deep learning for remote sensing image classification: A survey (Y. Li, Zhang, Xue, Jiang, & Shen, 2018) | – Remote sensing data classification based on CNN, deep belief network, pixel-wise classification, scene classification, and auto-encoder |
| 7 | Deep Learning-based Hyperspectral Image Classification with Application to Environmental Geographic Information Systems (Song & Kim, 2017) | – Land cover classification of Hyperspectral image for combining AI and spatial data with CNN |
| 8 | Spectral–Spatial Classification of Hyperspectral Imagery with 3D Convolutional Neural Network (Y. Li, Zhang, & Shen, 2017) | – Implementing for classifying hyperspectral image of the area of interest with 2D CNN, 3D CNN, and 3D structure |
| 9 | A Deep Convolution Neural Network Method for Land Cover Mapping: A Case Study of Qinhuangdao, China (Yunfeng Hu, Zhang, Zhang, & Yan, 2018) | – Deep Convolutional Neural Network (DCNN) model for classifying land use/land cover with |

| | | |
|---|---|---|
| | | multispectral and hyperspectral satellite imagery |
| 12 | Convolutional Neural Networks for Detection and Classification of Maritime Vessels in Electro-Optical Satellite Imagery (Rice, 2018) | – Apply open-source CNN pre-trained on a large dataset<br>– Use CNN for detecting and classifying ship in satellite imagery |
| 13 | Deep Learning Based Fossil-Fuel Power Plant Monitoring in High Resolution Remote Sensing Images: A Comparative Study (H. Zhang & Deng, 2019) | – Propose deep learning for detecting power plant based on remote sensing data of the region of interest (RoI) |
| 14 | Detecting Building Changes between Airborne Laser Scanning and Photogrammetric Data (Z. Zhang et al., 2019) | – Apply CNN and Siamese Networks for extracting building changes that deliver overall accuracy of F1-score of 76.13% |
| 15 | CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision Agriculture (Zheng et al., 2019) | – Apply YOLOv3 Network and DCNN for detecting species classification and detection dataset that occurs accuracy over 99% |
| 16 | Deep Learning for Generic Object Detection: A Survey (L. Liu et al., 2020) | – Use CNN and Object recognition of generic object detection |
| 17 | A Strictly Unsupervised Deep Learning Method for HEp-2 Cell Image Classification (Vununu, Lee, & Kwon, 2020) | – Implementing Deep Convolutional Autoencoder (DCAE) for detecting and classifying HEp-2 Cell Image |

## 2.7 Artificial Intelligence

According to (Frankenfield, 2021) said that Artificial intelligence (AI) refers to the simulation of human intelligence in machines, artificial intelligence doesn't begin with human intelligence as a model (Dick, 2019). The study (Ongsulee, 2017) mentions that AI is intelligence displayed by machines. There are two subsets of AI Deep Learning (DL) and Machine Learning (ML). In the same way, AI has been applied to the field of computer science and spatial data.

Extracting information from imagery using Deep Learning has been reached great success in the field of AI (W. Hu & Huang, 2020). There are ten applications of AI such as E-commerce, navigation, robotics, human resource, healthcare, agriculture, gaming, automobiles, social media, and marketing according to (Biswal, 2021). Moreover, AI-powered algorithm has been used in the field of spatial data (Bala, 2020).

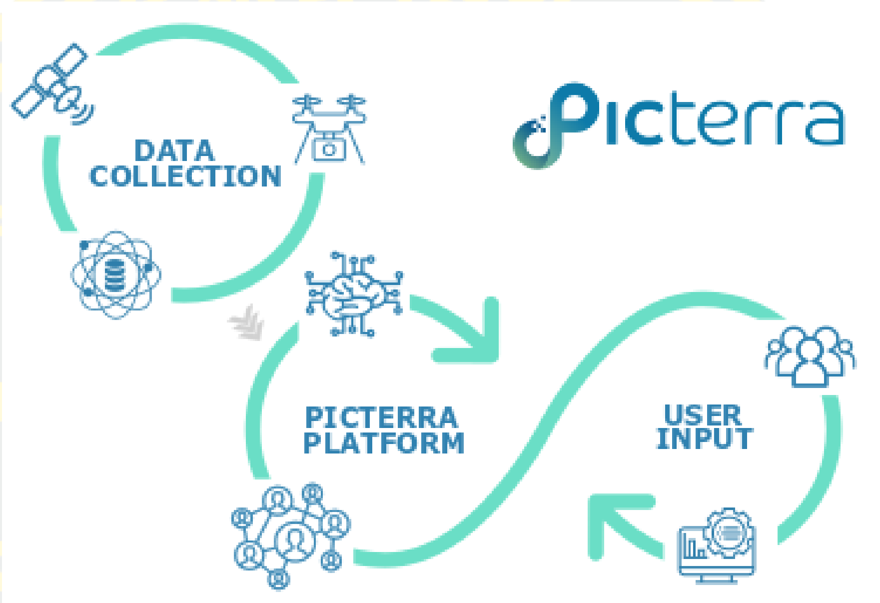
### 2.7.1 Geospatial Artificial Intelligence

Geospatial artificial intelligence abbreviates (geoAI) that combine AI method in machine learning, data mining, and high-performance computing for extracting information from spatial big data (VoPham, Hart, Laden, & Chiang, 2018), (Yingjie Hu, Gao, Newsam, & Lunga, 2018). In recent years, object extraction is exciting to automation has been delivered AI, DL, and GeoAI. Object detection has been applied to DL and AI that provide high performance of accuracy assessment.

### 2.7.2 Picterra platform

The Picterra form has been developed self-service AI platform for extracting and delivering information from satellite and UAV imagery. The platform accepts all users for uploading imagery and analyzes using an AI-powered toolkit. Moreover, there are three steps of the Picterra platform in extracting the information from the imagery of satellite and UAV platform, has such as Train, Detect, and Analyze (Picterra, 2020).

According to (Figure 9) shows that user collects imagery from satellite and UAV platform and put it into Picterra platform, and analyze. After that the acquisition of aerial images over an urban scene, an ortho mosaic has been uploaded to Picterra to localize and map seven categories of objects. The detections can be exported in a range of popular GIS formats (KML, GeoJSON, Shapefile) and PDF reports can also be generated.



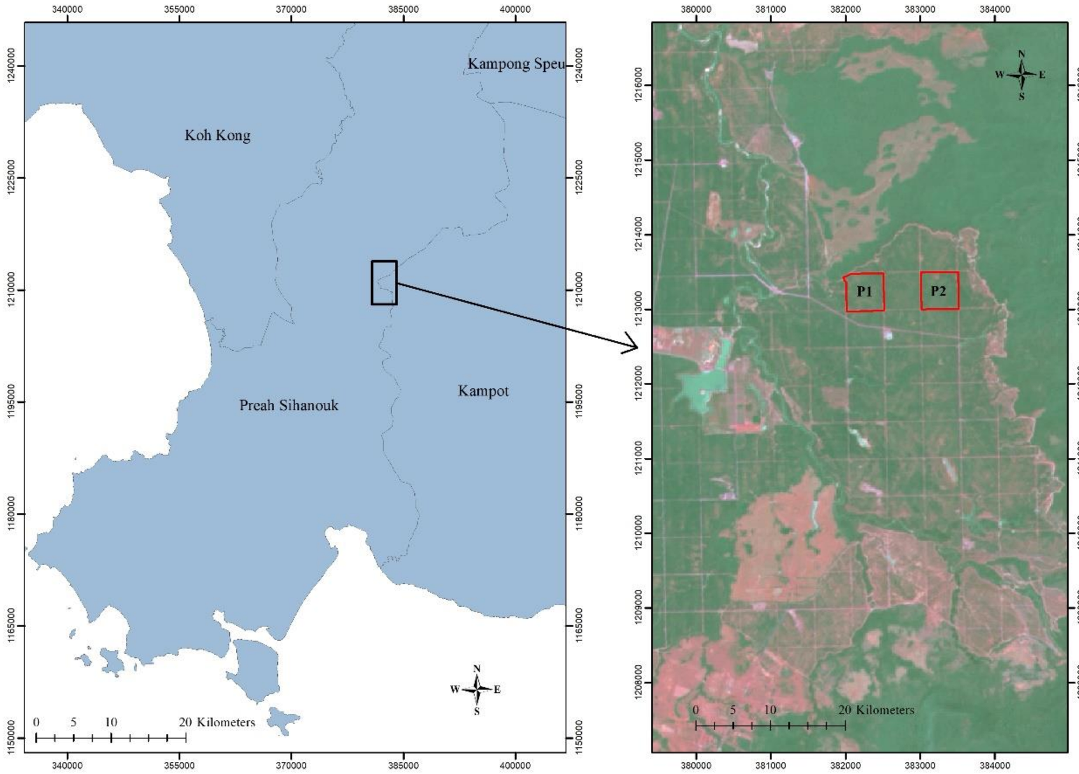

Figures 9 The detail of the Picterra platform for Object-Detection

# CHAPTER 3
# RESEARCH METHODOLOGY

This chapter will explain the approach, which involves a study area, research framework, data collection, data processing, data analysis, Picterra platform, accuracy assessment, and vegetation indices equation. Material and equipment, software applications, UAV flight plans, and raw image mosaicking are all included.

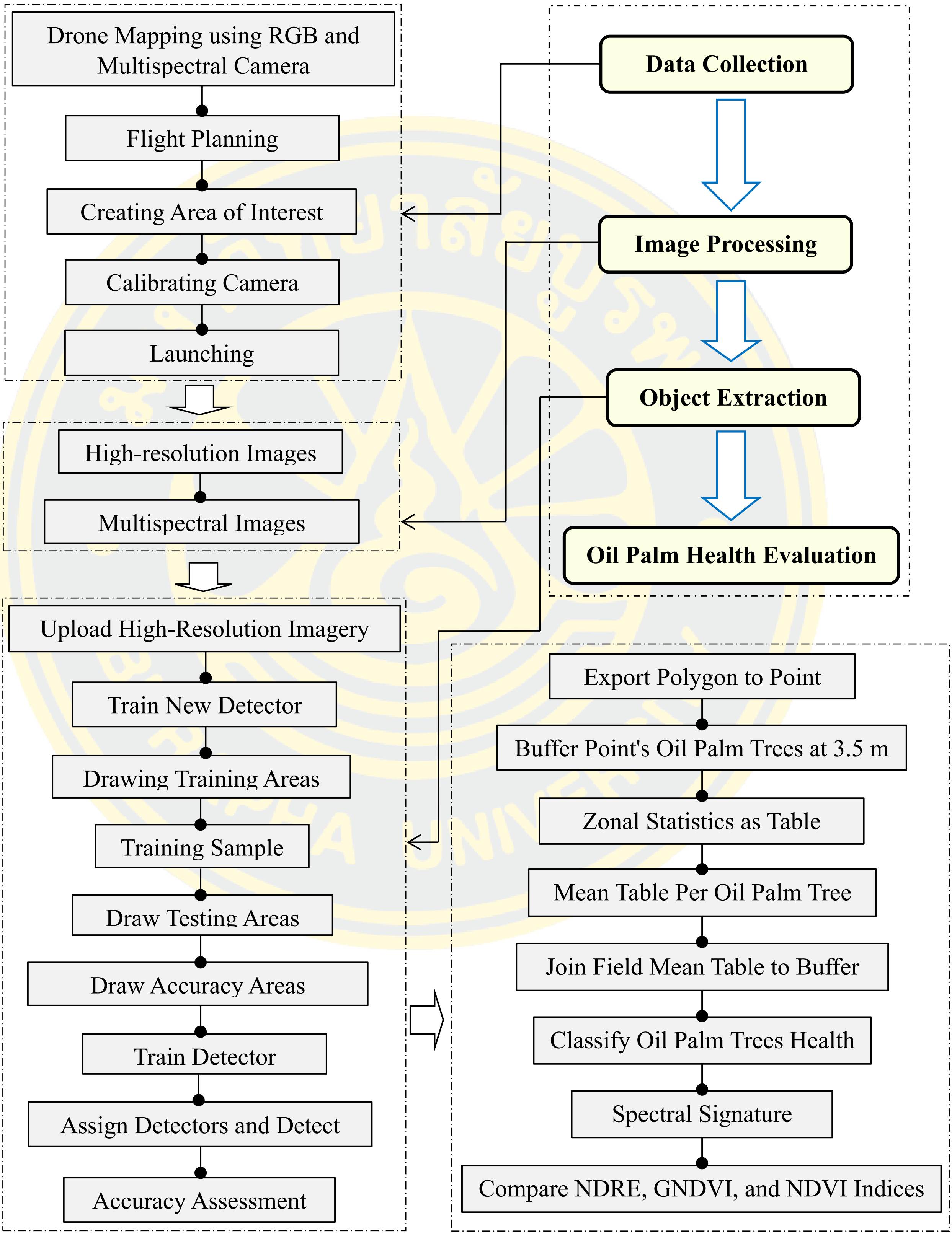
## 3.1 Study area

The oil palm plantations cover the largest land in Cambodia, and the study cannot cover the whole region. So, the analysis will collect two plots of oil palm plantations using the UAV (DJI Matrice 100) at Mong Reththy Investment Cambodia Oil Palm Co., LTD, Sihanoukville, Cambodia. The UTM coordinates for the study area are 383000 North and 1212000 East.




Figures 10 The study area of this case study in Sihanoukville Province, southwest Cambodia; P1) The red rectangle shows plot one of oil palm trees, P2) The red rectangle shows plot two of oil palm trees

**3.2 Research framework**




Figures 11 Workflow of the research

### 3.3 Data acquisition

Application of an unmanned aerial vehicle (UAV) (DJI Matrice 100) to capture raw images of oil palm trees obtained from RGB (Red, Green, and Blue bands) and a multispectral camera. Drone Pilots and Operators are required for two oil palm plots that have been captured.

3.3.1 UAV mapping using RGB and multispectral camera

It has two kinds of cameras: RGB cameras and Parrot Sequoia Multispectral Sensor. RGB is used to capture high-resolution images of oil palm trees being detected and counted in each plot. The Parrot Sequoia Multispectral Sensor is used to capture multispectral images for accessing oil palm tree health using vegetation indices.

*3.3.1.1 Flight planning*

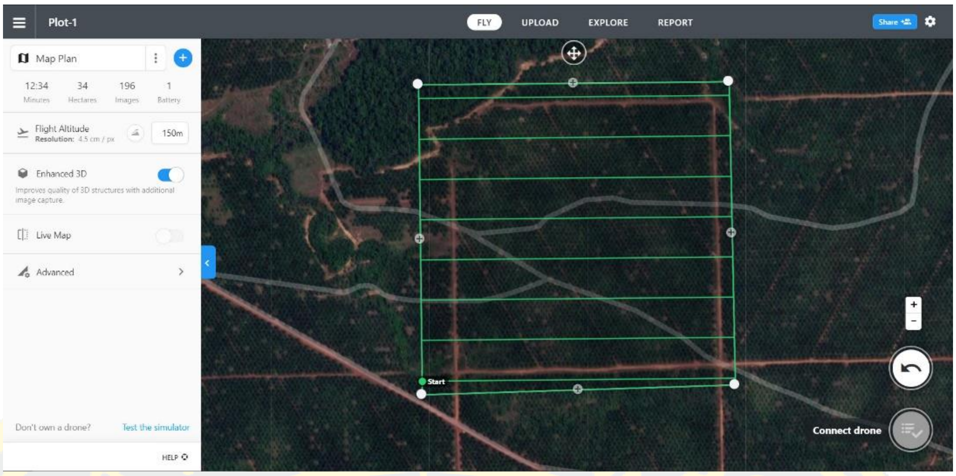
Both plots set a flight plan depending on the area conditions and the battery used, according to (Table 4). The image resolution output is 0.06m, with a height of 150m, side/front overlap of Parrot Sequoia camera is 80%, side/front overlap of RGB camera is 70%, and coverage area of 25 ha in both plots.

Tables 4 DJI Matrice 100 flight planning

| **Plot** | **Height** | **Parrot Sequoia** | **RGB Camera** | **Coverage (ha)** | **Resolution** |
|---|---|---|---|---|---|
| P1 | 150m | 80% | 75% | 25 | 0.06m |
| P2 | 150m | 80% | 75% | 25 | 0.06m |

*3.3.1.2 Creating area of interest (AOI)*

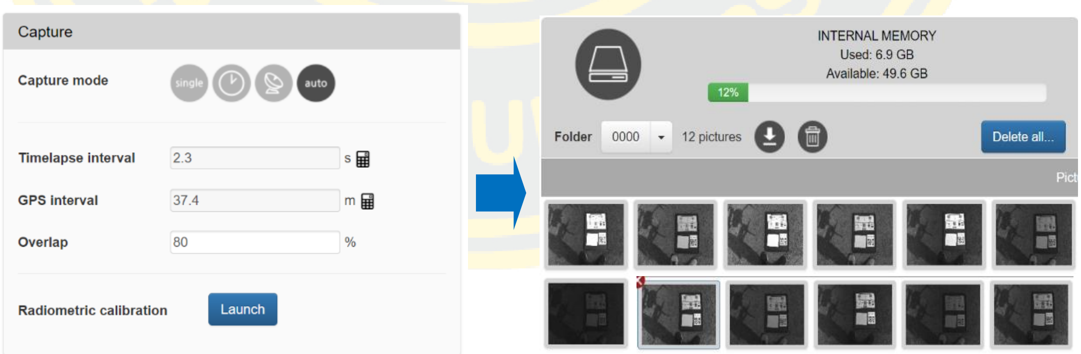
Two plots generated in the shapefile were uploaded by the research field. Then, by exporting the shapefile to KML, uploading it to the DroneDeploy app. For instance, P1 has nine lines that run from east to west. The AOI in the process of being created was visible in (Figure 12).




Figures 12 Drone flight plan in DroneDeploy app

*3.3.1.3 Calibrating camera*

The RGB camera was calibrated to know satellite and GPS while capturing raw images of oil palms. After that, the multispectral sensor was calibrated using sunlight panel reflectance. Furthermore, before deploying the UAV, all GPS cameras must attach to the satellite. The reflectance factor is 0.7. According to Parrot Sequoia camera calibration expresses that speed 12m/s, height 150m, and overlap wanted 80%, the output of reflectance listed below:




Criteria of Parrot Sequoia calibration Reflectance output

Figures 13 Parrot Sequoia camera calibration with panel reflectance

*3.3.1.4 UAV Launching*

After the camera was calibrated, a DJI controller was used to launch and control the UAV. The DJI controller ensures that the signal on the DroneDeploy app is right. The drone is controlled by pilot and spotter.

3.3.2 Image processing

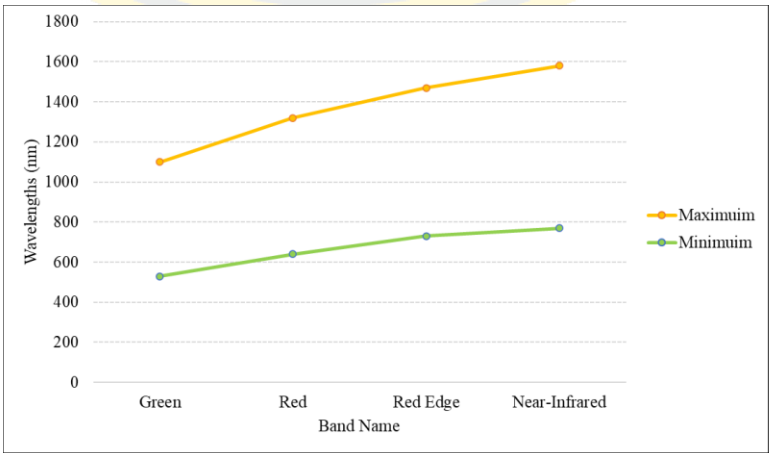
UAV with RGB and multispectral camera was used to capture oil palm raw images. The raw images are kept separate from the RGB and multispectral cameras in a different folder. For P1 and P2, the raw images were merged.

Pix4Dmapper was used to mosaic RGB raw images, the result of mosaicking occurs in high-resolution images. Both plots of oil palm are clipped in using the Extract by Mask tool. The images were cropped so that oil palm trees could be easily detected.

The multispectral image was merged and the multispectral bands' reflectance was calibrated. Green has a reflectance factor of 0.7, Red has a reflectance factor of 0.7, Red Edge has a reflectance factor of 0.7, and Near-Infrared has a reflectance factor of 0.7. The NDVI index is calculated automatically.

*3.2.2.1 Wavelength each band of multispectral*

The wavelength of multispectral bands maximums and minimums such as Green (530nm – 570nm), Red (640nm – 680nm), Red Edge (730 – 740), and Near-Infrared (770 – 810).

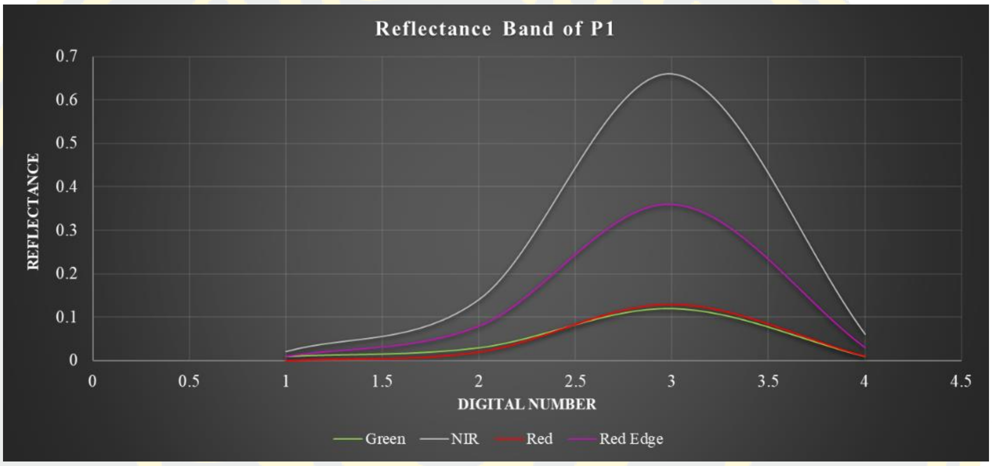



Figures 14 The wavelength of each band of a multispectral camera

*3.2.2.2 Reflectance multispectral bands from UAV*

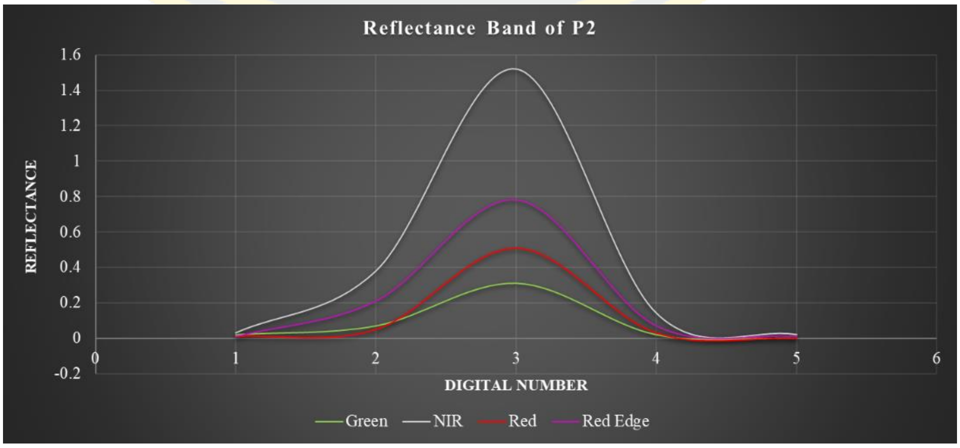
Tables 5 Reflectance band of P1

| Band | Min | Avg | Max | Stdev | Var |
|---|---|---|---|---|---|
| Green | 0.01 | 0.03 | 0.12 | 0.01 | 0.00 |
| NIR | 0.02 | 0.14 | 0.66 | 0.06 | 0.00 |
| Red | 0.00 | 0.02 | 0.13 | 0.01 | 0.00 |
| Red Edge | 0.01 | 0.08 | 0.36 | 0.03 | 0.00 |




Tables 6 Reflectance band of P2

| Band | Min | Avg | Max | Stdev | Var |
|---|---|---|---|---|---|
| Green | 0.02 | 0.07 | 0.31 | 0.02 | 0.00 |
| NIR | 0.03 | 0.38 | 1.52 | 0.14 | 0.02 |
| Red | 0.01 | 0.05 | 0.51 | 0.03 | 0.00 |
| Red Edge | 0.01 | 0.21 | 0.78 | 0.07 | 0.01 |




Figures 16 Reflectance band of P2

The factor of reflectance is based on the values of the panel. According to reflectance generation, both plots show that the NIR band is higher than other bands. The lowest reflectance is the Green band. Therefore, the health of oil palm trees uses NIR band calculation with Green, Red, and Red Edge bands.

## 3.4 Data processing

### 3.4.1 Materials and equipment

Data collection was used materials and equipment for supporting fieldwork. According to (Table 7), the materials and equipment have such as DJI Matrice 100 used to capture raw images of oil palm. GPS was used to collect ground-truthing. Arial photographs of oil palm apply for object extraction and oil palm tree estimation. A camera was used to take the situation of oil palm trees in both plots.

Tables 7 The list of materials and equipment

| **Materials and equipment** | **Goals** |
|---|---|
| DJI Matrice 100 | To capture raw images of oil palm |
| Aerial photograph of oil palm | To extract object and estimate oil palm health |
| GPS | To collect ground-truthing |
| Camera | To take a picture and video |

### 3.4.2 Software application

For detecting and counting oil palm trees, a software application was used on the Picterra platform. The index value was extracted using ArcGIS Pro 2.7. A map design was created using ArcGIS 10.5 software. DJI Controller and DroneDeploy Ranging of sensors that detect movement of the drone, as well as user commands. Pix4Dmapper mosaic raw images are also available. (Table 8) explains it in detail:

Tables 8 list of software application

| Software name | Purpose of application |
|---|---|
| Picterra platform | Detect and count oil palm trees |
| ArcGIS Pro 2.7 | Extract NDRE, GNDVI, and NDVI mean value, identify spectral signature profile, and create coefficient ($R^2$) |
| ArcGIS 10.5 | Mapping of the study area and oil palm trees health classification |
| DJI Controller and DroneDeploy | Ranging of sensors that detect movement of the drone, as well as user commands |
| Pix4Dmapper | Raw images processing |

**3.5 Oil palms extraction by Picterra platform**

A Swiss company has been created the Picterra platform, which has provided an AI-powered that can be used as a geospatial cloud-based platform for deep learning-based detectors, quickly and securely (Picterra, 2020). The platform provides easy steps such as:

- Trian: User can build & train own detectors that it is based on scale and anywhere
- Detect: Based on the area, the user can be detected objects and patterns
- Analyze: The user can visualize and share results online that export data to Excel or GIS workbench, or use many integrations.

3.5.1 Upload high-resolution imagery

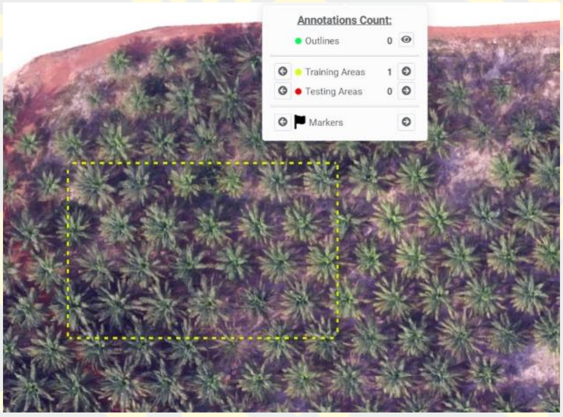
The oil palm imagery P1 and P2 were uploaded into the Picterra platform after creating a new folder on the platform's interface. The following move is to build a new “Train New Detector”. We have to choose the “Count” for object extraction.

3.5.2 Train new detector

Train New Detector is very important to create training sample after that go to modify on the new detector. Use tools and creates an outline of objects on the Picterra platform online interface. Training sample based on the area detection.

3.5.3 Drawing training areas

Before the Picterra platform detects oil palm trees at scale in the project, needs to train a new detector by giving it areas with objects where will learn, these are called Training Areas. Use the “Training Areas” are from the toolbox to place the first training area. This area should contain a few examples of the objects or patterns that Picterra platforms want to detect and some context around them.




Figures 17 Drawing training areas yellow rectangle on the oil palm trees

3.5.4 Training sample

Use the circle tool to outline all the objects or patterns contained within the first training area that will detect. Training sample in the 5 Training Areas, but need to follow such as:

- Every object of interest inside the Training Area should be outlined
- Objects partially inside the area should also be outlined
- Can be edited the outlines by clicking on them
- Can copy and paste annotations by using the “enter cloning mode” function in edit mode.

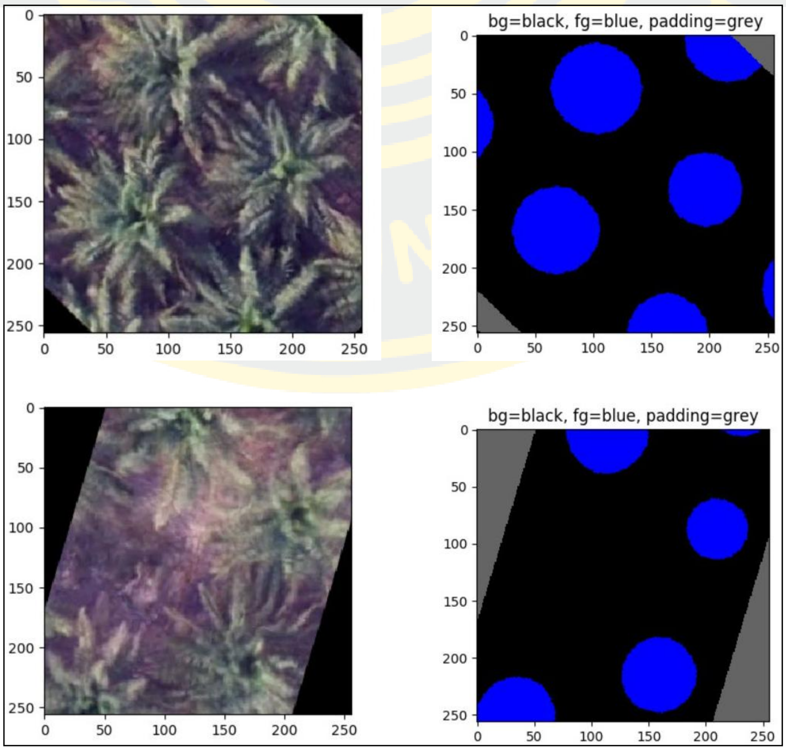

Figures 18 Training sample of the oil palm trees

*3.5.4.1 Picterra training report of P1*

Tables 9 Detector settings of P1

| Detector name | Oil Palm Tree P1 |
|---|---|
| Training steps | 500 |
| Detection type | Count |
| Output type | Polygon |
| Size filter type | Auto filter |
| Custom size filter min | None |
| Custom size filter max | None |
| Target resolution | None |

The first column shows an example of images that the detector is 'seeing' during training. The second column shows the label that the detector is learning to output. In the second column, bg means background and fg foreground.



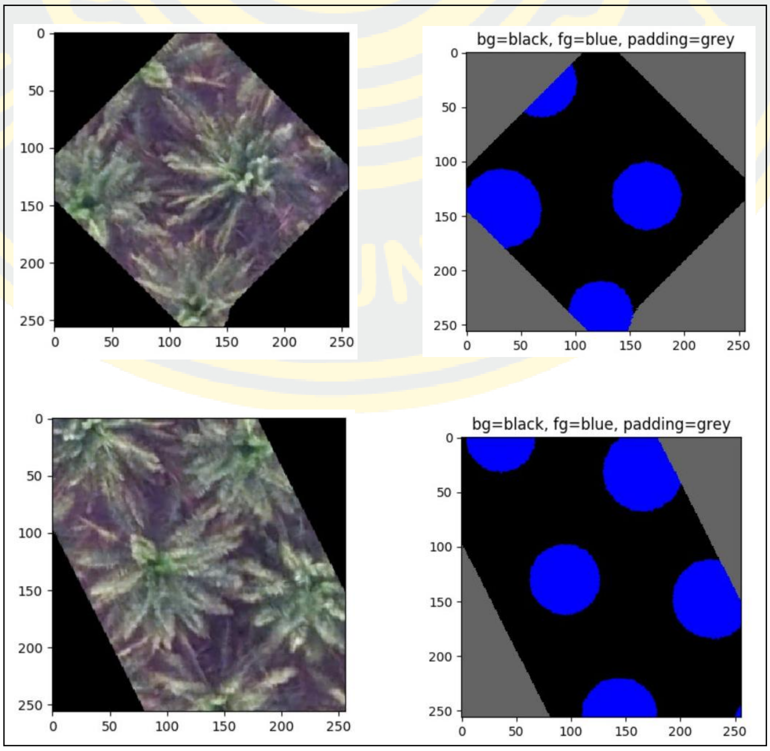

Figures 19 The output training sample of P1

*3.5.4.2 Picterra training report of P2*

Tables 10 Detector settings of P2

| Detector name | Oil Palm Tree P2 |
|---|---|
| Training steps | 500 |
| Detection type | Count |
| Output type | Polygon |
| Size filter type | Auto filter |
| Custom size filter min | None |
| Custom size filter max | None |
| Target resolution | None |

The first column shows an example of images that the detector is 'seeing' during training. The second column shows the label that the detector is learning to output. In the second column, bg means background and fg foreground.




Figures 20 The output training sample of P1

3.5.5 Draw testing areas

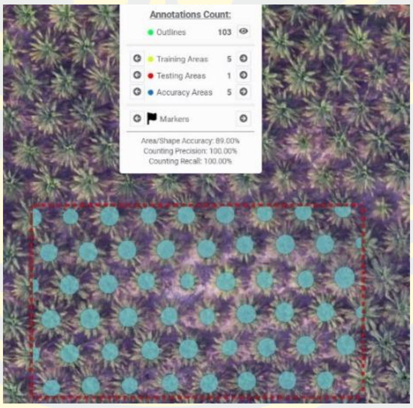
It is now time to decide where the detector will be tested. Use the 'Testing' area tool to draw a few areas where the detector will output a preview of results after training.

– Do not need to outline the objects inside testing areas

– The larger the testing areas, the longer the training of your detector. Try to balance the number and coverage of testing areas to assess the detector in the most efficient way

– Testing areas may or may not overlap with some of the training areas

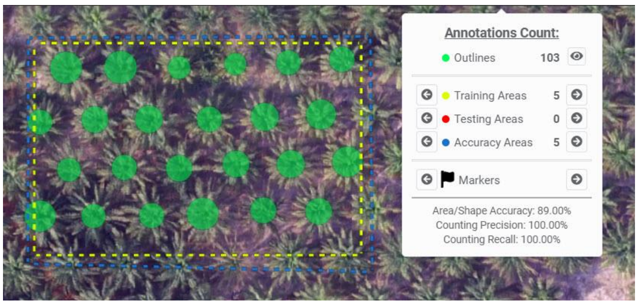
– Can assess detector on multiple images if the place testing areas in each of them.



Figures 21 Oil palm trees detection in a red circle by using draw testing areas tool

3.5.6 Draw accuracy areas

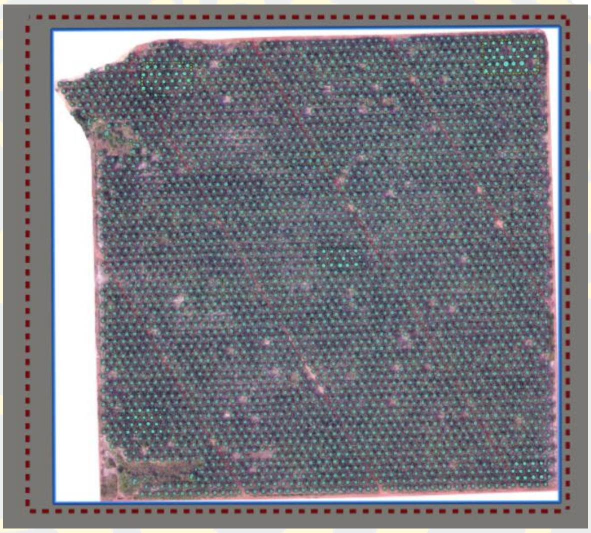
The accuracy areas need to draw 5 rectangles on the Training Areas before the platform detects oil palm trees. After the train detector, the accuracy will appear at detectors. In drawing accuracy areas must be covered all Training Areas that have been created.




Figures 22 Draw accuracy areas at blue rectangle on the Training Areas

3.5.7 Train detector

Before the platform detects oil palm trees, need to create a Train Detector at first. This window has displayed a Train Detector that covers the oil palm tree of P1 with an output of object detections. The output has occurred in the shapefile extension of object extraction.



Figures 23 The oil palm trees detection using tool Train Detector

3.5.8 Assign detectors and detect oil palm trees

The platform detects oil palm trees from high-resolution imagery, it must be assigned a detector. And then click on the bottom Run to detect the oil palm trees, wait a moment to get the result of the oil palm trees detection. Just click on the bottom view detection result and download shapefile data.

3.5.9 Accuracy assessment

In object detection of oil palm trees, used F-score in measuring accuracy assessment. Recall and precision of the test calculated for F-score, where the precision is the number of correctly identified positive results divided by the number of all positive results. The F-score equation is shown (4) below:

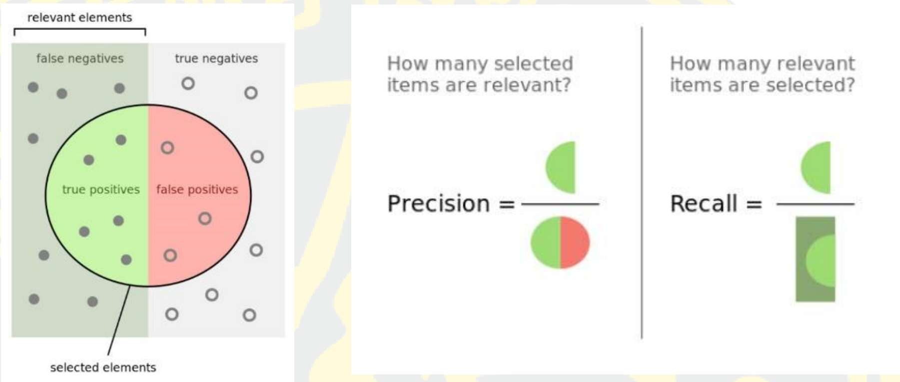
$$F1 = 2 / recall^{-1} + precision^{-1} \quad (4)$$

Where:

– F1-score is the coincidence mean of the precision and recall

– Precision is the number of true positives that have been divided by the number of false positives plus true positives

– Recall is the number of true positives that have been divided by the number of true positives plus false negatives.



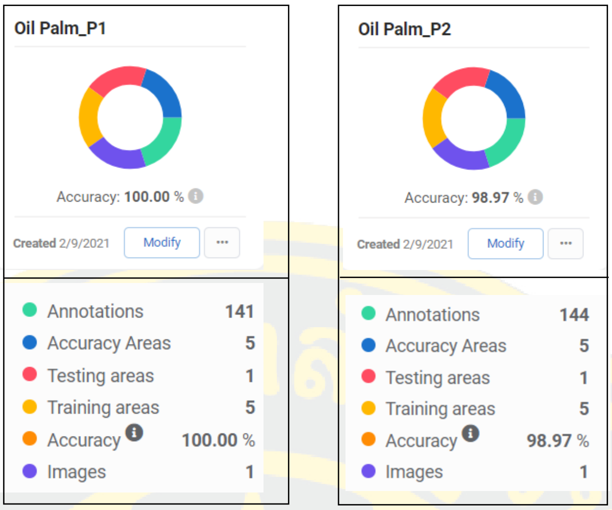

Figures 24 The detailed Precision and Recall functions

*3.5.9.1 Accuracy assessment of P1 and P2*

The assessment of accuracy is according to F-score, the shows that P1 of annotations is 141, accuracy areas is 5, testing areas is 1, training areas is 5, and overall accuracy is 100%. Regarding P2 shows that annotations are 141, accuracy areas are 1, testing areas are 5, and overall accuracy is 98.97%. By mean of (Table 11) and (Figure 25) below:

Tables 11 Detail the oil palm trees detection of P1 and P2

| Plot | Annotations | Accuracy areas | Testing areas | Training areas | Accuracy (%) |
|---|---|---|---|---|---|
| P1 | 141 | 5 | 1 | 5 | 100 |
| P2 | 140 | 5 | 1 | 5 | 98.97 |



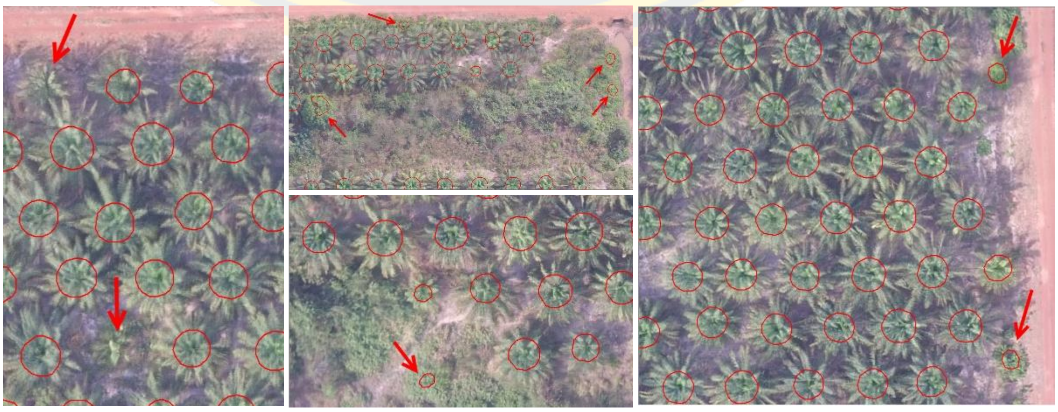

Figures 25 The accuracy assessment of oil palm trees detection by using the Picterra platform; a) accuracy of P1, b) accuracy of P2

*3.5.9.2 Missing and detect different objects of P1 and P2*

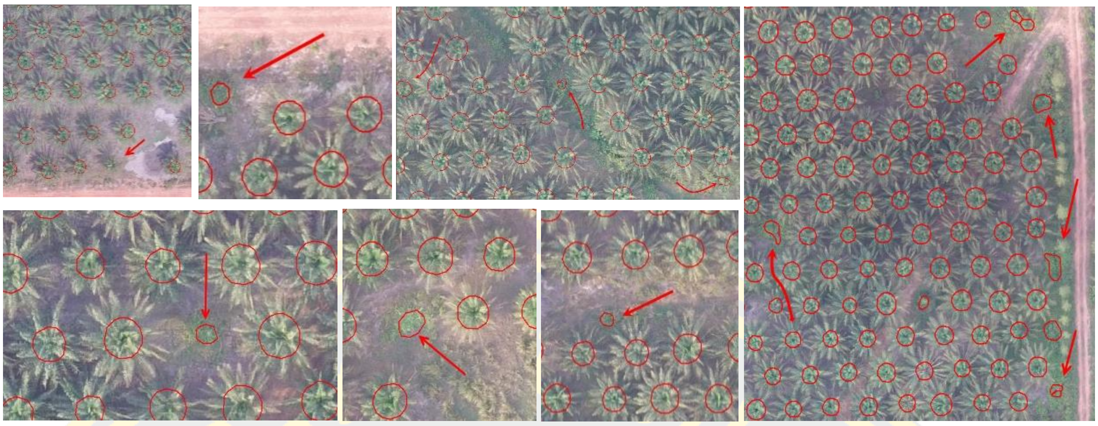
According to (Table 12), the result of object extraction occurred P1 is 2 for missing detection and 7 for detecting different objects. As for P2 is 1 for missing detection and 14 for detecting different objects. See detailed at (Figure 26) and (Figure 27).

Tables 12 The detail missing and detect the different object of P1 and P2

| Plot | Missing detection | Detect different objects |
|---|---|---|
| P1 | 2 | 7 |
| P2 | 1 | 14 |



Figures 26 Show missing and detect different objects of P1



Figures 27 Show missing and detect different objects of P2

**3.6 Vegetation indices for estimating oil palm trees health**

After the result of oil palm tree extraction in the single tree from very high-resolution images. From UAV, the multispectral images were used to calculate oil palm tree health using vegetation indices. There are three vegetation indices as NDRE, GNDVI, and NDVI.

**3.7 Mean value of NDRE, GNDVI, and NDVI extraction**

In extracting vegetation value, it was used a mean value of vegetation indices to join every single tree by using Zonal Statistics as Table tool. The shapefile was exported from the polygon of oil palm detection which needs to convert to a point. After that buffer point of oil palm trees to polygon by input the value of radius at 3.5m. In extracting the raster value from vegetation indices, used Zonal Statistics as Table tool that can be used single statistic, the result as a table instead of an output raster (ESRI, 2016). The value of vegetation indices is based on the Mean table and then joins the field Mean value to the polygon buffer of each oil palm tree.

# CHAPTER 4
# EXPERIMENT RESULT

This chapter summarizes the findings of the experiment from Chapter 3's implementation methods and refers to research objects, research questions, and hypotheses. The result includes mapping of UAV-based imagery for detecting and counting oil palm trees using the Picterra platform, mapping of oil palm tree health estimation, and classification from multispectral bands. Moreover, based on three vegetation indices, a spectral signature was generated to classify oil palm health.

## 4.1 Detecting and counting oil palm trees

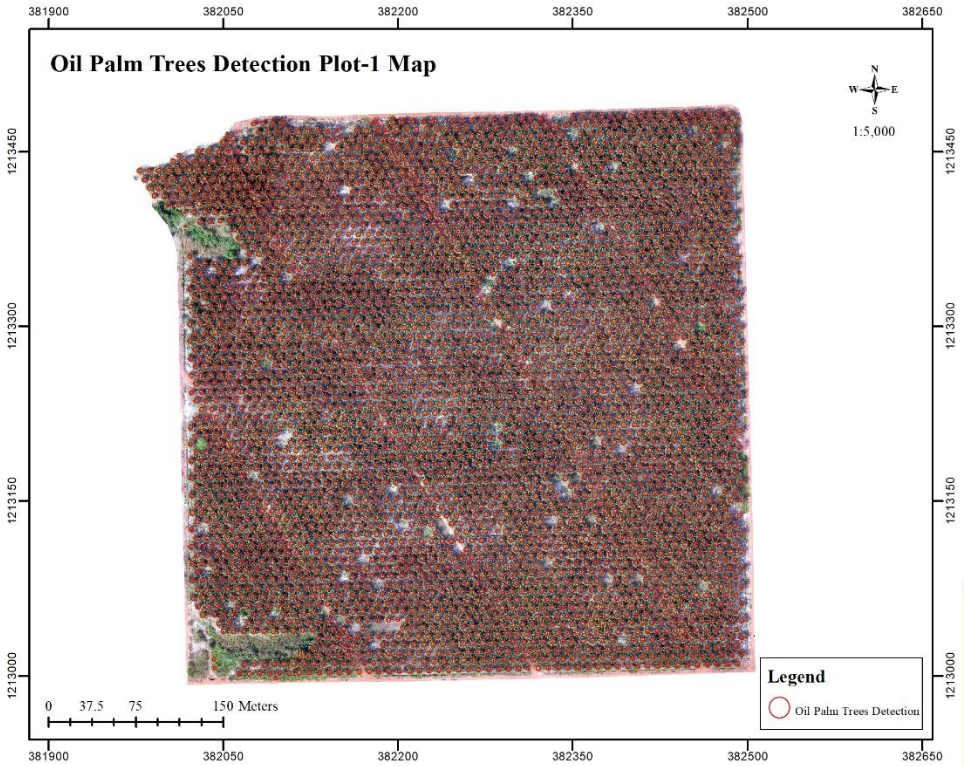
The Picterra platform is used to count and detect oil palm trees based on high-resolution images, which has a high overall accuracy assessment. Using the Zonal Statistics as Table tool on ArcGIS 10.5 desktop, the object extraction was exported to shapefile extension to create an oil palm tree health classification and extract value to the table. Similarly, oil palm tree extraction is demonstrated on the platform and with the help of an internet connection.

4.1.1 Oil palm trees detection

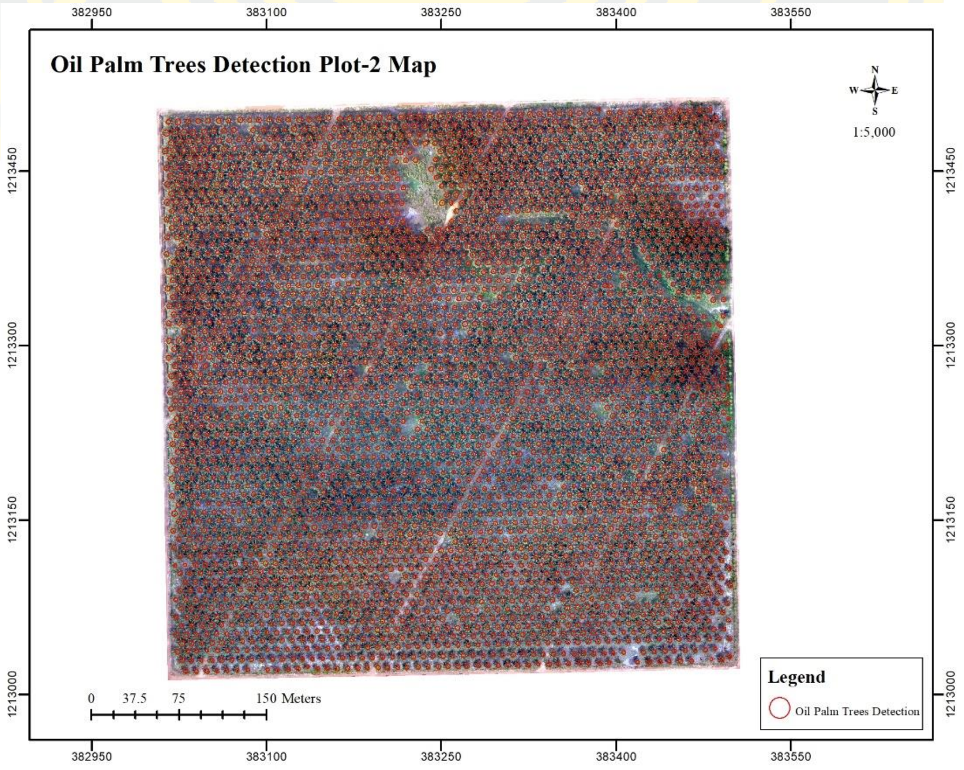
Oil palm trees were extracted using the Picterra platform, according to the map (Figure 28) and (Figure 29). The platform has a high overall accuracy of 100 percent for P1 and 98.97 percent for P2. Meanwhile, P1 has a total oil palm extraction of 4.70 ha, while P2 has a total oil palm extraction of 4.10 ha (Table 14). Even though the overall accuracy of the oil palm tree detection appears to be high, it indicates missed detection and identifies different objects. One oil palm tree is without detection, which detects seven different objects on the unknown trees of P1. Whereas P2 was displayed one palm tree and fourteen different objects on the unknown trees show as incomplete detection.

Tables 13 Oil palm trees extraction of P1 and P2

| Plot | Area (ha) | Oil palm tree extraction (ha) | Missing objects | Different objects | Overall accuracy |
|---|---|---|---|---|---|
| P1 | 25 | 4.70 | 2 | 7 | 100% |
| P2 | 25 | 4.10 | 1 | 14 | 98.97% |




Figures 28 Oil palm trees detection map of P1



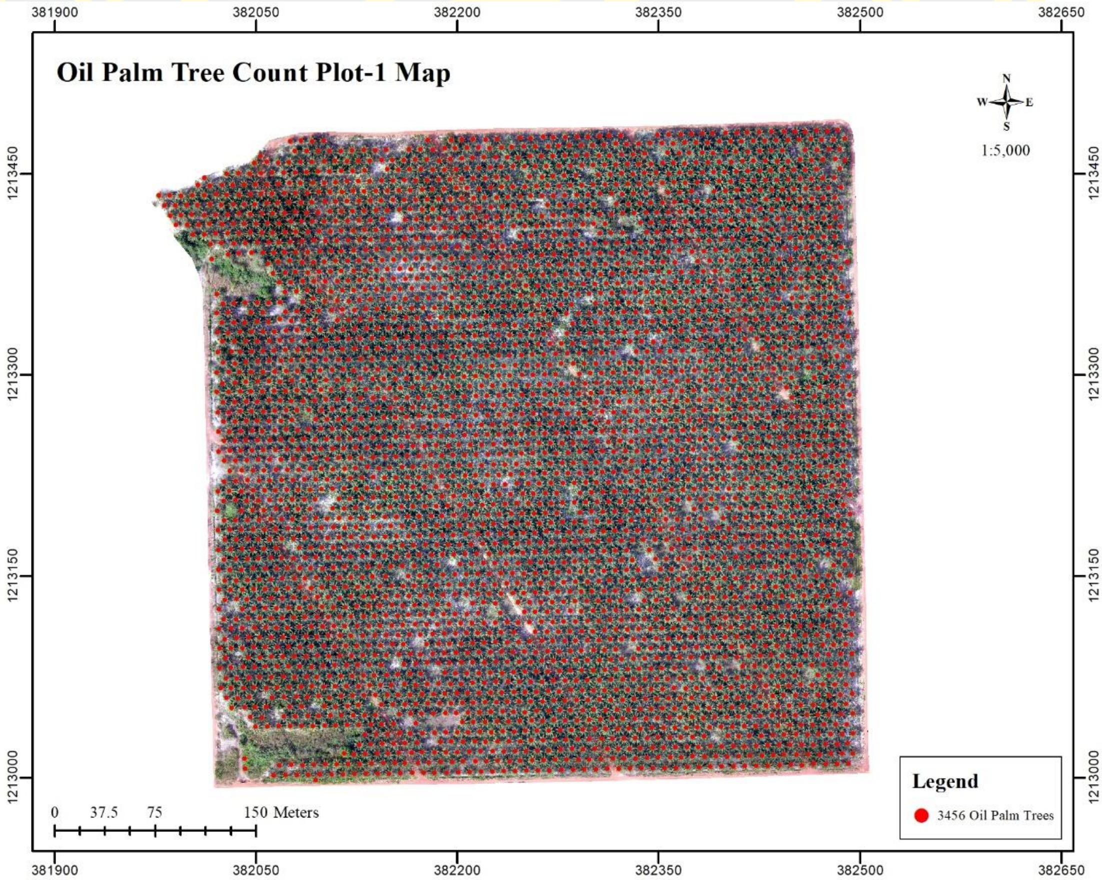

Figures 29 Oil palm trees detection map of P2

4.1.2 Oil palm trees counting

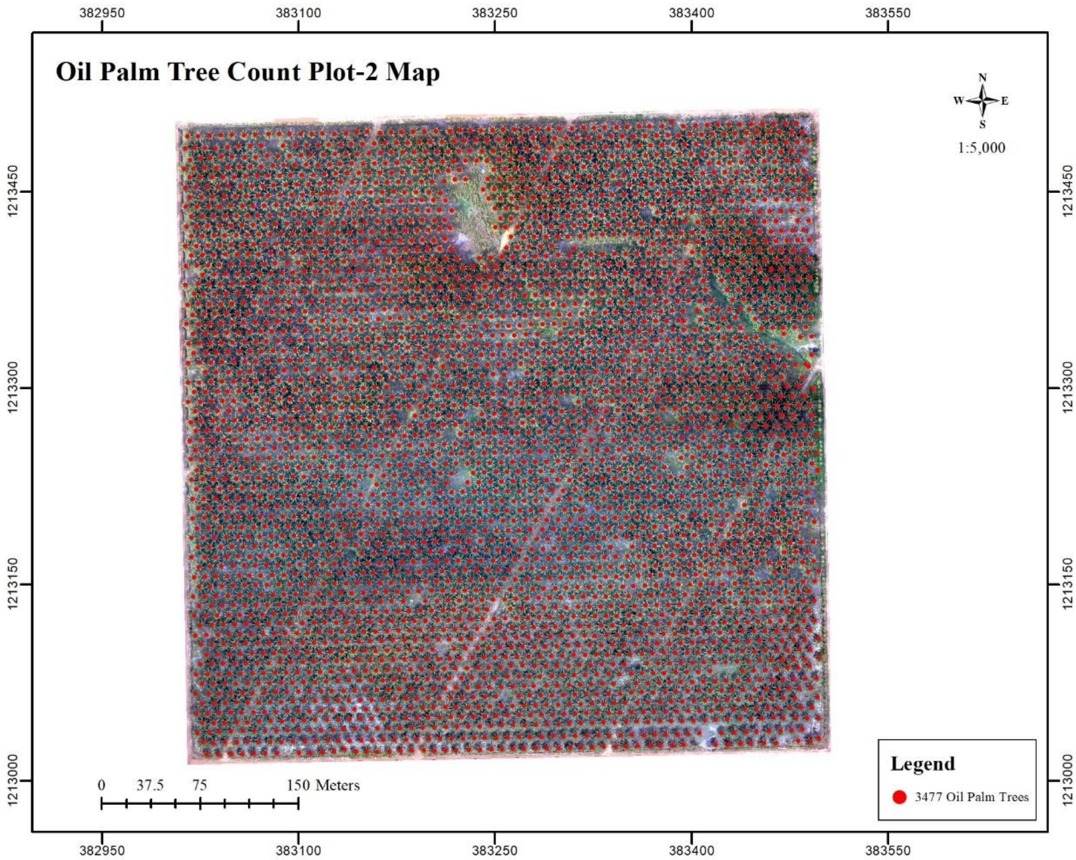
Following the extraction of oil palm trees, the next step is to count the number of oil palm trees in both fields. UAV-based very high-resolution imagery is used to count oil palm trees. The result is that oil palm trees are counted by using the Picterra platform, minus missed detection, and different objects are detected, as seen below (Table 15). Furthermore, the number of oil palm trees manually counted in P1 is 3447 trees, while P2 has 3462 trees, as seen on the map (Figure 30) and (Figure 31).

Tables 14 Counting oil palm trees of P1 and P2

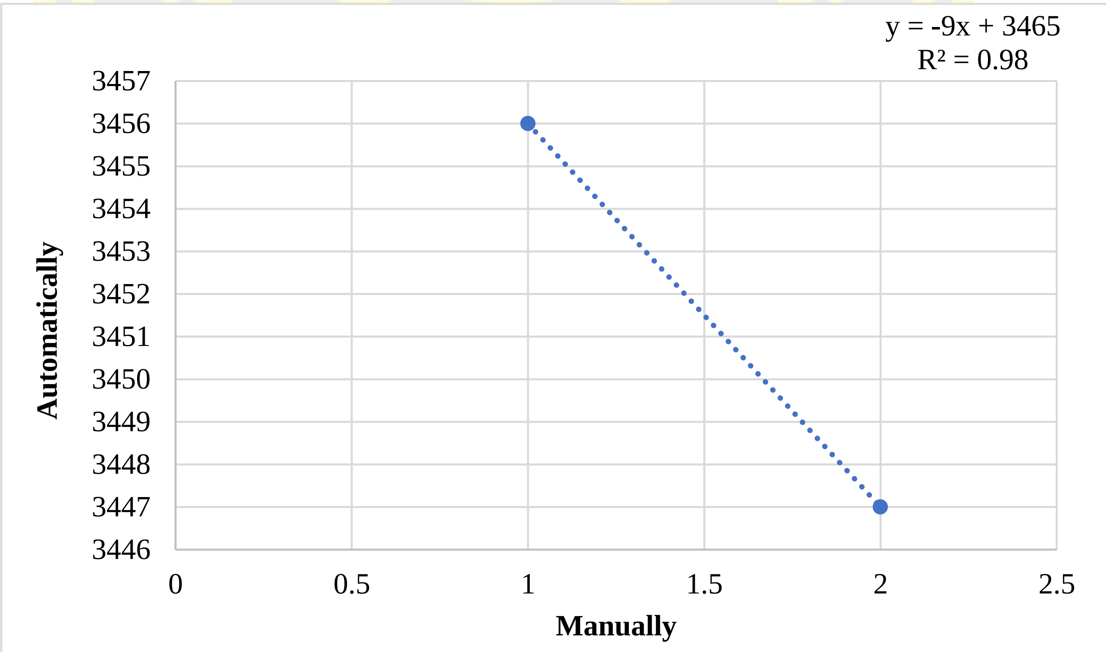
| Plot | Area (ha) | Automatically | Manually | Different |
|---|---|---|---|---|
| P1 | 25 | 3456 | 3447 | 9 |
| P2 | 25 | 3477 | 3462 | 15 |



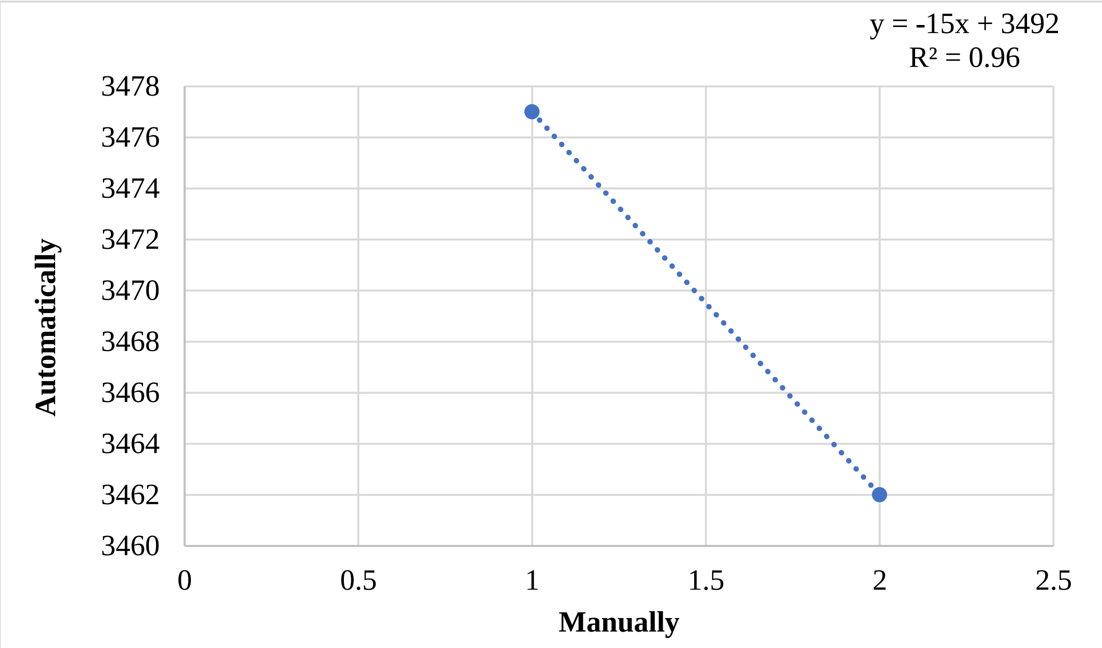

Figures 30 Oil palm tree count map of P1




Figures 31 Oil palm tree count map of P2




(P1)




(P2)

Figures 32 The result of scatter plot analysis between count by automatically and manually (P1) and (P2)

## 4.2 Oil palm trees health estimation and classification

The vegetation indices with Normalized Difference Red Edge (NDRE), Green Normalized Difference Vegetation Index (GNDVI), and Normalized Difference Vegetation Index (NDVI) were used to estimate oil palm tree health and were compared. The NDRE was used to classify the chlorophyll reflectance of an oil palm leaf, which absorbs at the Red Edge and Near-Infrared wavelengths. GNDVI examines water and nitrogen absorption in the plant canopy and absorbs in the green and near-infrared spectrums. Reflectance is used to calculate NDVI, which absorbs in the red and near-infrared bands. However, a multispectral image was used to extract the mean value and derive the value depending on the pixel. In both plots, the value of VI was used to classify the health of the oil palm trees. The health classification of oil palm trees on the map that links to point was extracted. The VI interval and percentage have been used to classify and compare the health of oil palm trees.

Tables 15 Class intervals of vegetation indices NDRE with respective areas, as a percentage of P1 and P2

| P1 | | | | P2 | | | |
|---|---|---|---|---|---|---|---|
| Class | Class intervals | Area (ha) | Percentage | Class | Class intervals | Area (ha) | Percentage |
| Low Chlorophyll | 0.14 to 0.29 | 3.03 | 22.92 | Low Chlorophyll | 0.13 to 0.26 | 3.05 | 22.93 |
| Medium Chlorophyll | 0.29 to 0.33 | 6.43 | 48.64 | Medium Chlorophyll | 0.26 to 0.31 | 6.42 | 48.27 |
| High Chlorophyll | 0.33 to 0.44 | 3.76 | 28.44 | High Chlorophyll | 0.31 to 0.40 | 3.83 | 28.80 |

Tables 16 Class intervals of vegetation indices GNDVI with respective areas, as a percentage of P1 and P2

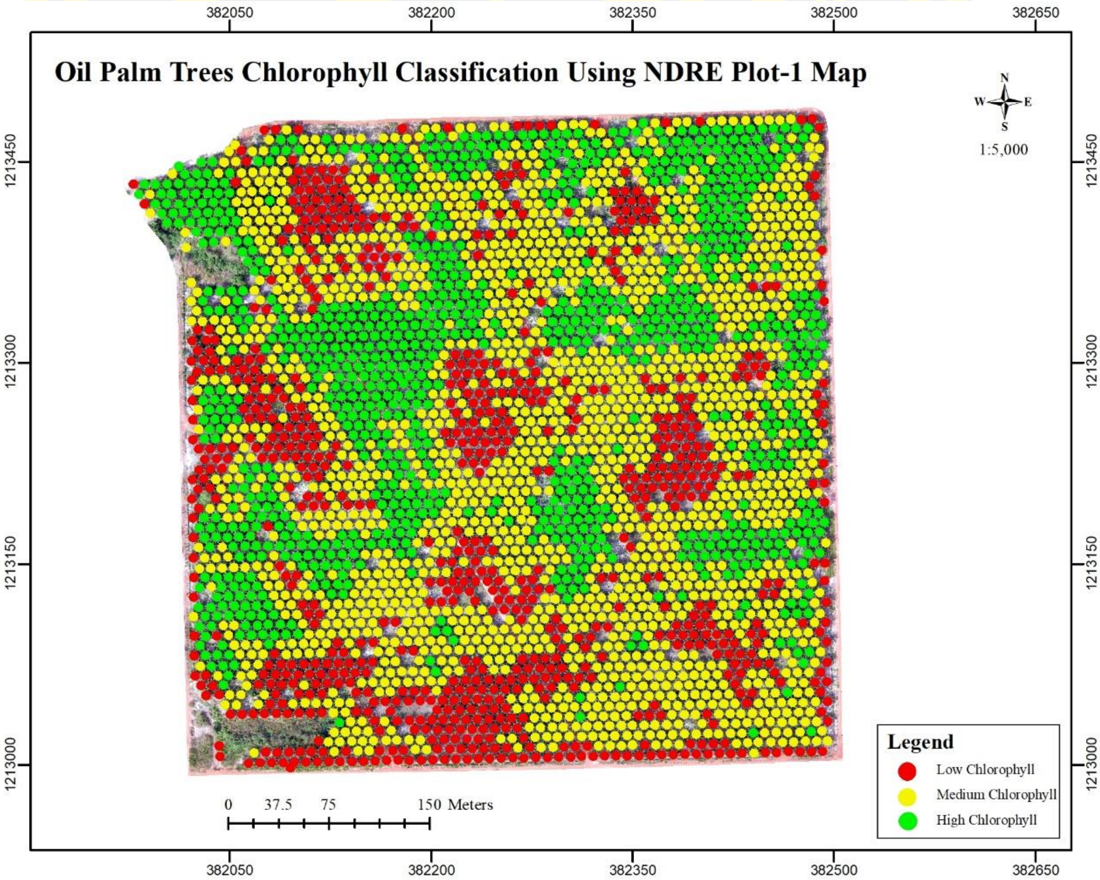
| P1 | | | | P2 | | | |
|---|---|---|---|---|---|---|---|
| Class | Class intervals | Area (ha) | Percentage | Class | Class intervals | Area (ha) | Percentage |
| Unhealthy | 0.41 to 0.66 | 1.35 | 10.22 | Unhealthy | n/a | n/a | n/a |
| Moderately Healthy | 0.66 to 0.72 | 5.72 | 43.30 | Moderately Healthy | 0.46 to 0.69 | 5.4 | 40.91 |
| Very Healthy | 0.72 to 0.79 | 6.14 | 46.48 | Very Healthy | 0.69 to 0.78 | 7.8 | 59.09 |

Tables 17 Class intervals of vegetation indices NDVI with respective areas, as a percentage of P1 and P2

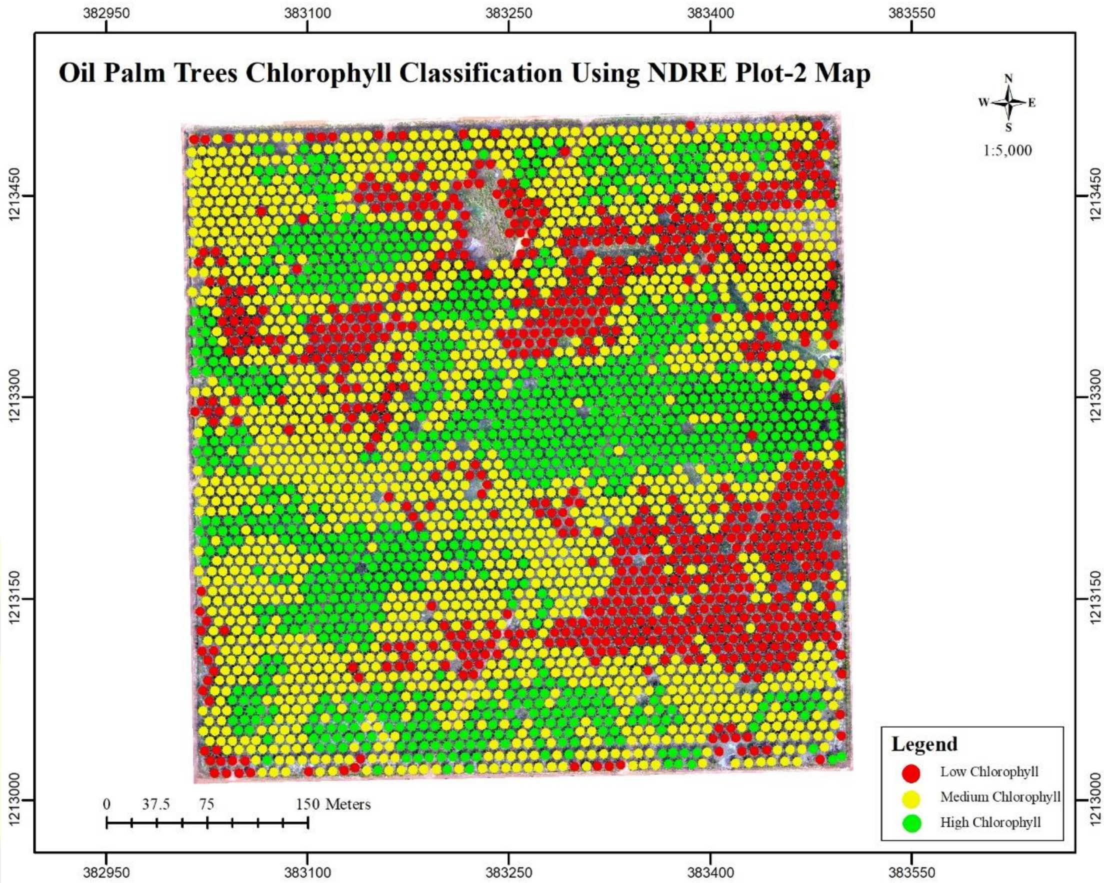
| P1 | | | | P2 | | | |
|---|---|---|---|---|---|---|---|
| Class | Class intervals | Area (ha) | Percentage | Class | Class intervals | Area (ha) | Percentage |
| Unhealthy | 0.33 to 0.71 | 0.6 | 4.34 | Unhealthy | n/a | n/a | n/a |
| Moderately Healthy | 0.71 to 0.81 | 5.13 | 37.12 | Moderately Healthy | 0.54 to 0.81 | 3 | 22.56 |
| Very Healthy | 0.81 to 0.88 | 8.09 | 58.54 | Very Healthy | 0.81 to 0.88 | 10.3 | 77.44 |

4.2.1 Oil Palm trees chlorophyll estimation using NDRE

The NDRE is used to describe the chlorophyll of an oil palm leaf, which absorbs and reflectance Near-Infrared and Red Edge radiation. The chlorophyll estimation of P1 (Figure 33) and P2 (Figure 34) are the three classes of oil palm trees. Low chlorophyll (0.14 – 0.29), medium chlorophyll (0.29 – 0.33), and high chlorophyll (0.33 – 0.44) are all found in P1. In this way, the P2 result indicates low chlorophyll (0.13 – 0.26), medium chlorophyll (0.26 – 0.31), and high chlorophyll (0.31 – 0.40).



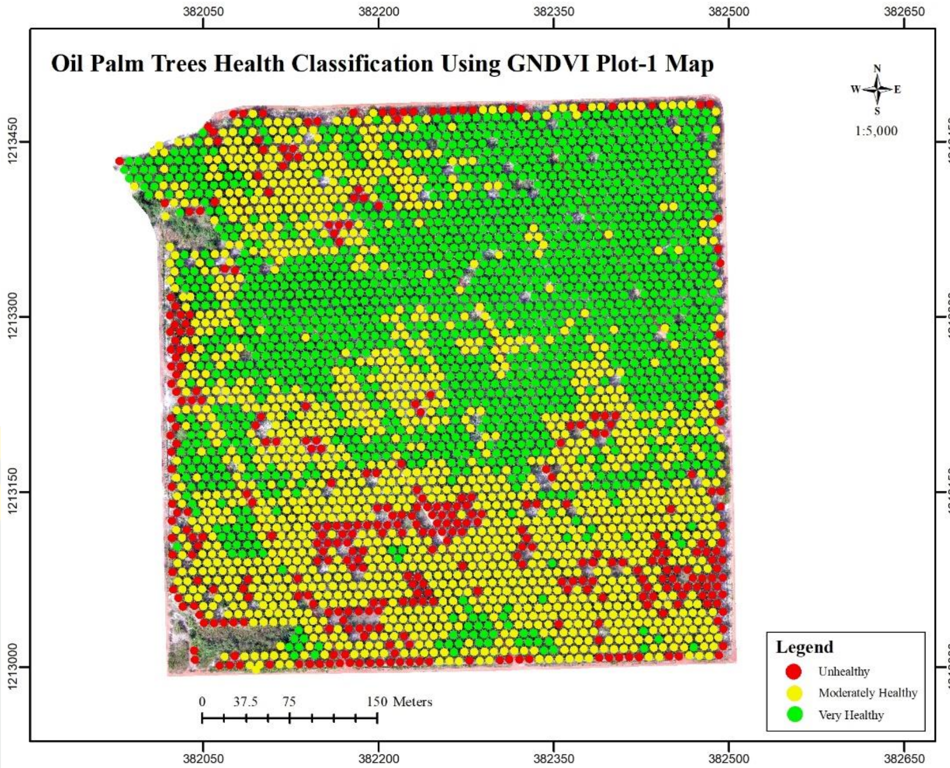

Figures 33 Mapping of oil Palm trees chlorophyll classification using NDRE of P1



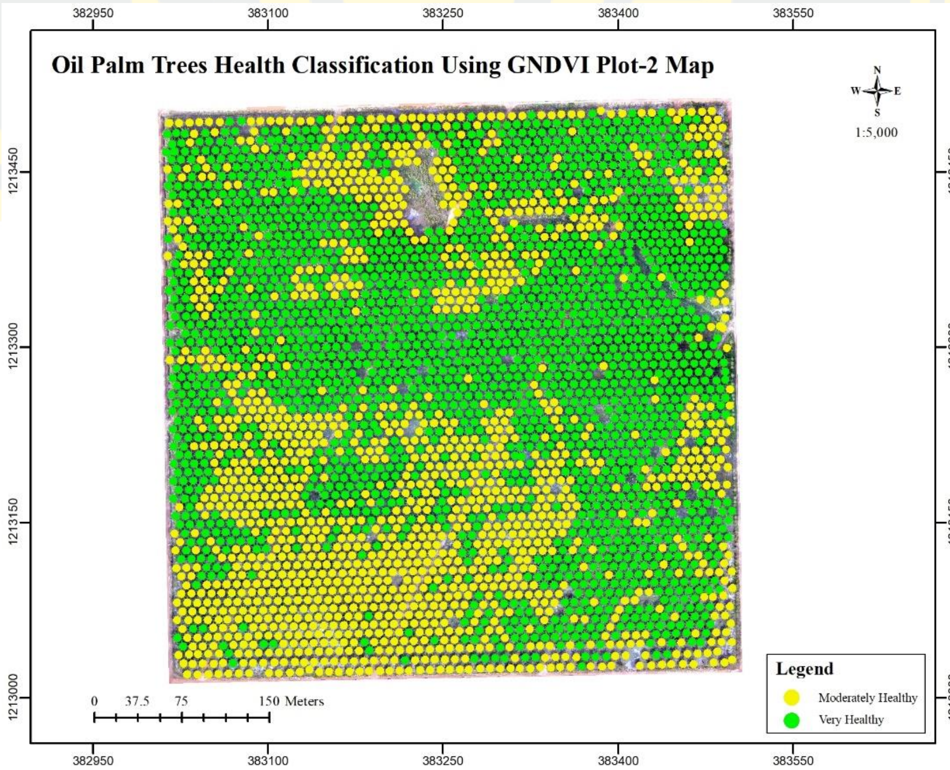

Figures 34 Mapping of oil palm trees chlorophyll classification using NDRE of P2

4.2.2 Oil palm trees health estimation using GNDVI

GNDVI monitors water and nitrogen uptake in the plant canopy reflectance and absorbs at the Green and Near-Infrared wavelengths. P1 is classified into three classes, and P2 is classified into three classes of oil palm tree health estimation. P1 is classified as unhealthy (0.41 – 0.65), moderately healthy (0.65 – 0.71), and very healthy (0.71 – 079) according to (Figure 35). In addition, P2 on the map (Figure 36) reveals that it is moderately healthy (0.46 – 0.69) and very healthy (0.69 – 0.78).



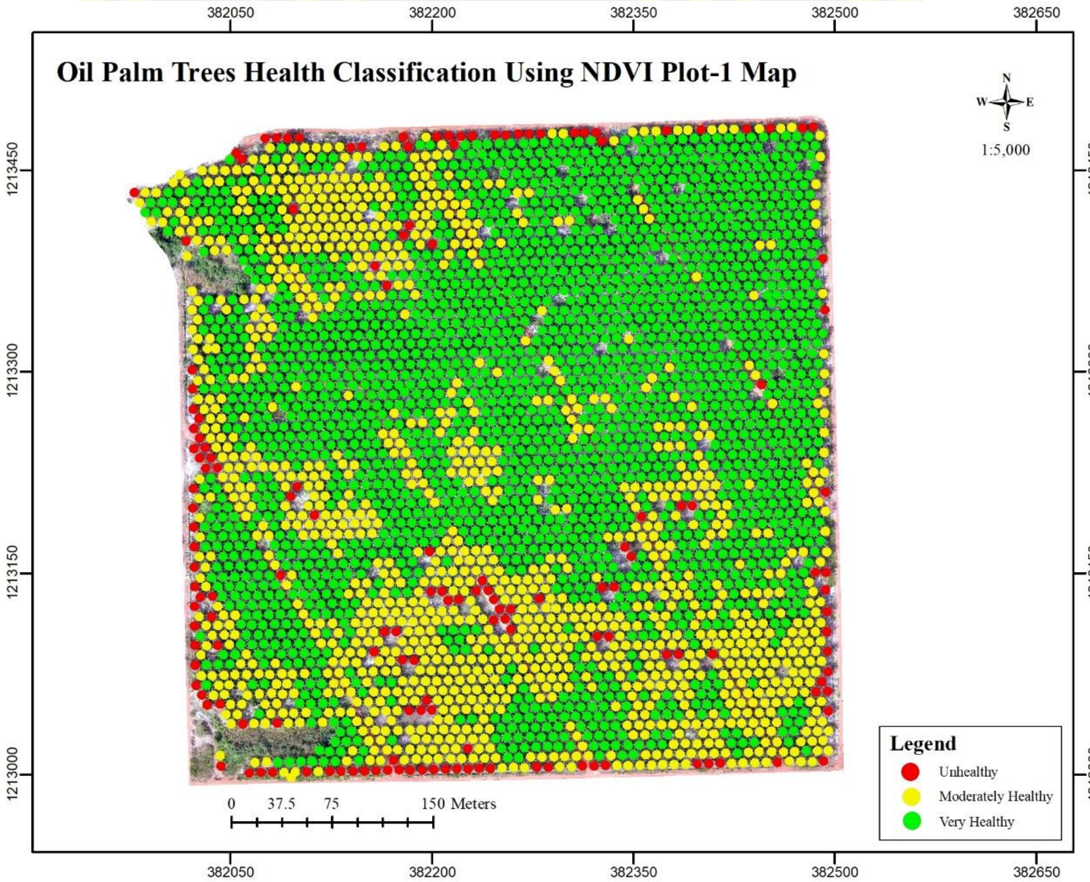

Figures 35 Mapping of oil palm trees health classification using GNDVI of P1



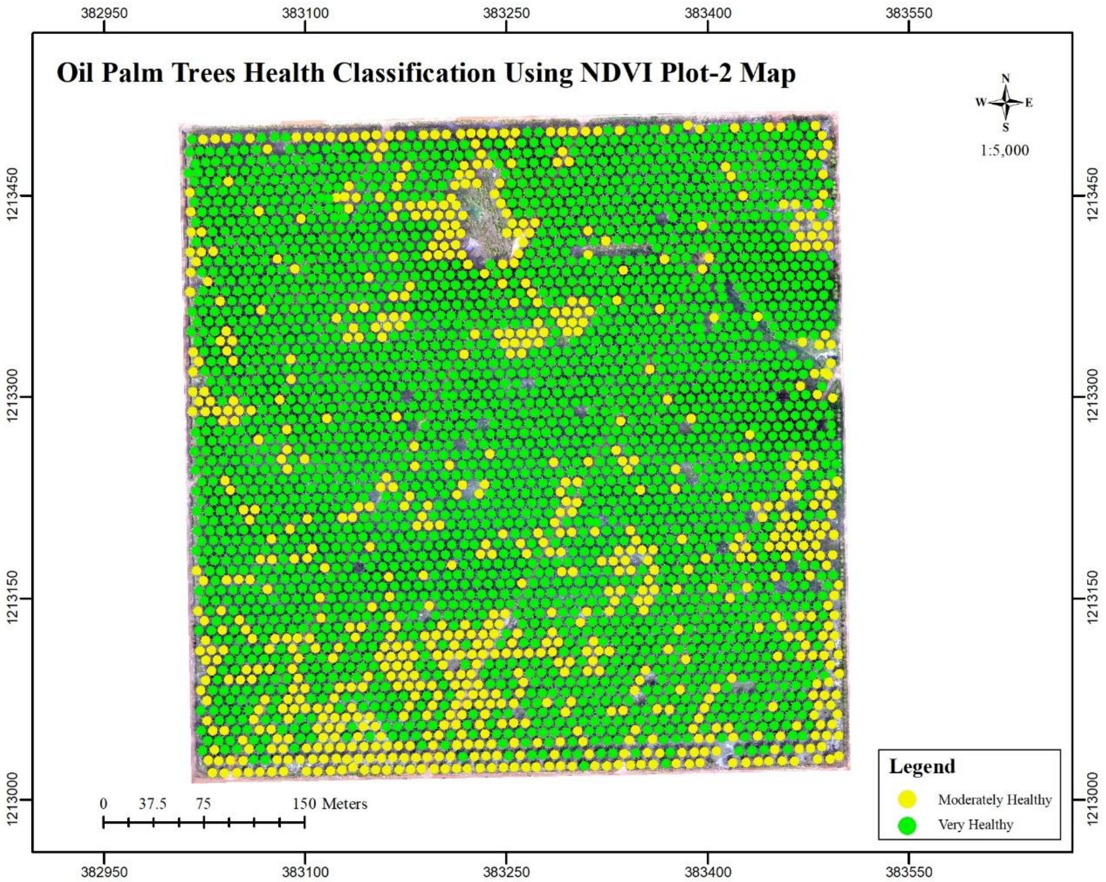

Figures 36 Mapping of oil palm trees health classification using GNDVI of P2

4.2.3 Oil palm trees health estimation using NDVI

NDVI is calculated using reflectance and absorbs in the Red and Near-Infrared ranges. P1 is classified into three classes, while P2 is classified into two classes of oil palm tree health estimation. P1 has unhealthy (0.33 – 0.71), moderately healthy (0.71 – 0.81), and very healthy (0.81 – 0.88), according to (Figure 37). And P1 the result occurs (Figure 38) that moderately healthy (0.54 – 0.81) and very healthy (0.81 – 0.88).




Figures 37 Mapping of oil palm trees health classification using NDVI of P1

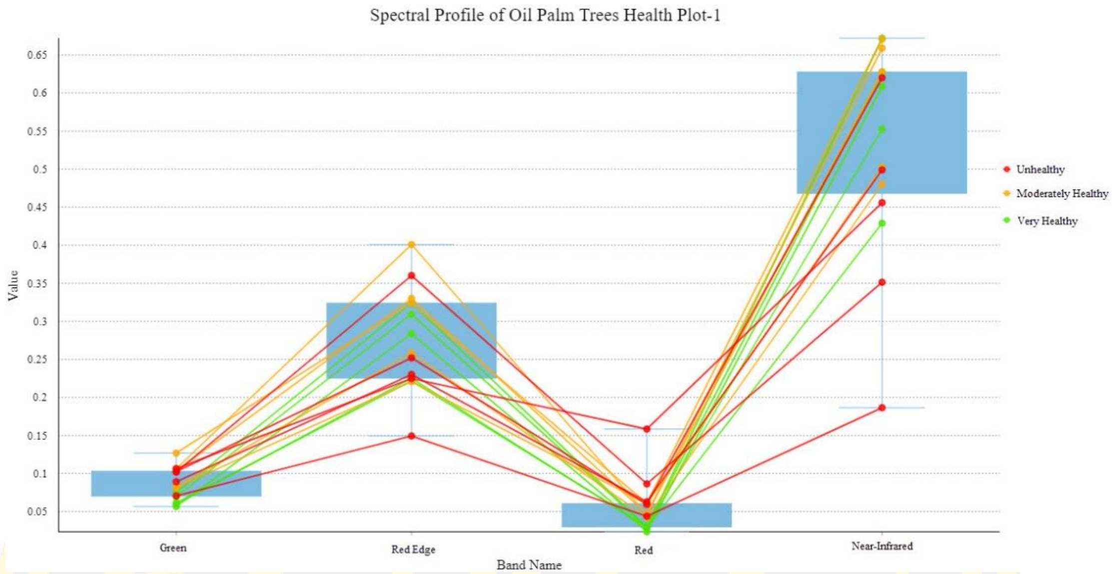



Figures 38 Mapping of oil palm trees health classification using NDVI of P2

4.2.4 Spectral signature of multispectral bands

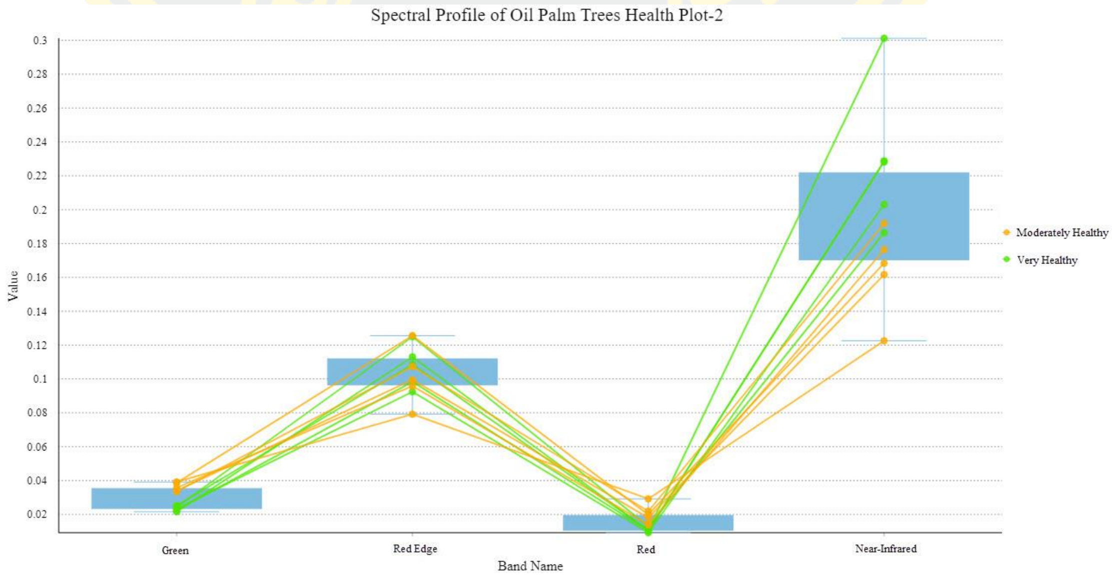
The compression of the Green band, Red Edge band, Red band, and Near-Infrared band in the spectral signature of oil palm tree health based on GNDVI and NDVI indices. Use ten oil palm trees per one classify to compare the spectral profile of absorbs and emittance of each band. The result of P1 (Figure 39) shows that unhealthy absorbs low at Green and Red bands, and emittances low at the Red Edge and Near-Infrared bands. Moderately healthy absorbs medium Green and Red bands, and emittances medium at the Red Edge and Near-Infrared bands. Very healthy absorbs high at Green and Red bands, and emittances high at the Red Edge and Near-Infrared bands.

BURAPHA UNIVERSITY

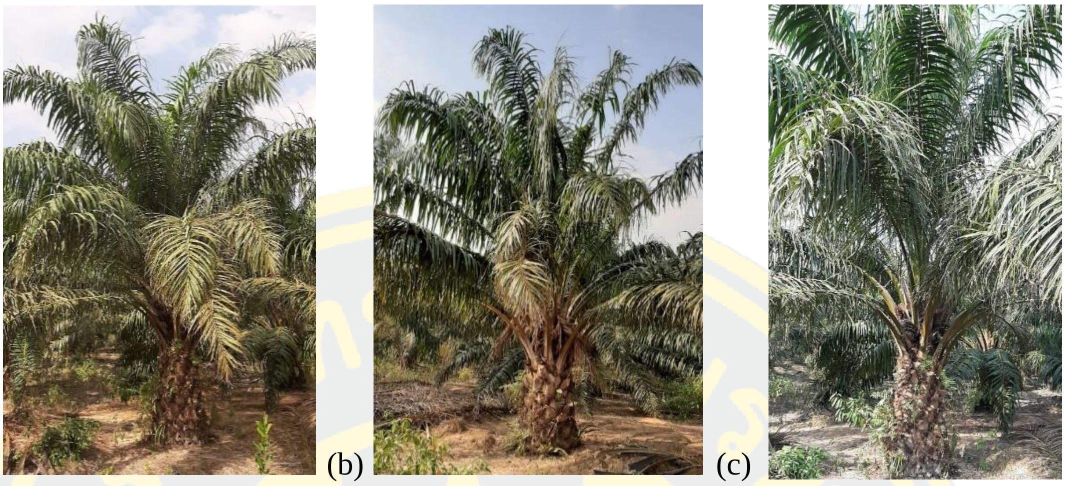



Figures 39 Comparison spectral signature of oil palm trees health of P1

Spectral signature uses to identify object reflectance and emittances. ArcGIS Pro has been performed to create a signature profile of oil palm health. There are ten oil palm trees per one classify for comparing the spectral profile of absorbs and emittance of each band. The result of P2 (Figure 40) shows that moderately healthy absorbs medium Green and Red bands and emittances medium at the Red Edge and Near-Infrared bands. Very healthy absorbs high at Green and re bands, and emittances high at Red Edge and Near-Infrared bands.

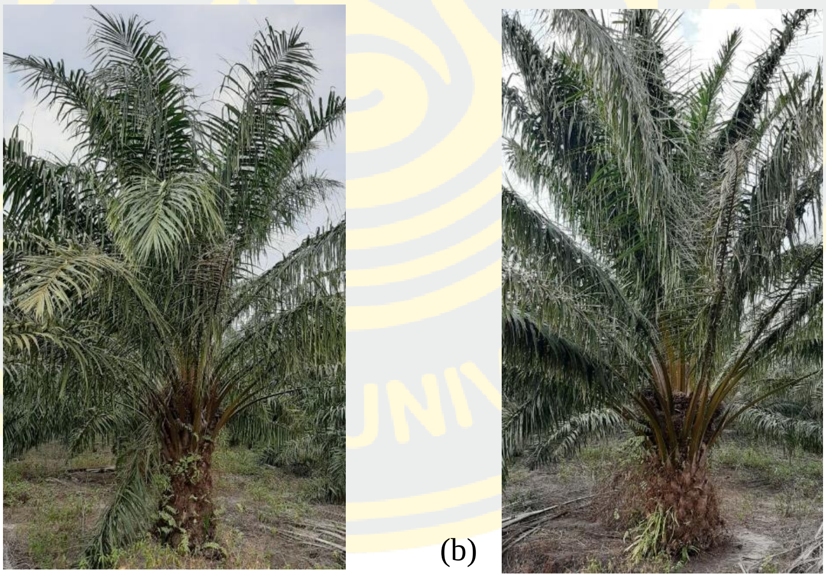



Figures 40 Comparison spectral signature of oil palm trees health of P2



(a) (b) (c)

Figures 41 The situation of a single oil palm tree of P1; a) Unhealthy, b) Moderately Healthy, c) Very Healthy



(a) (b)

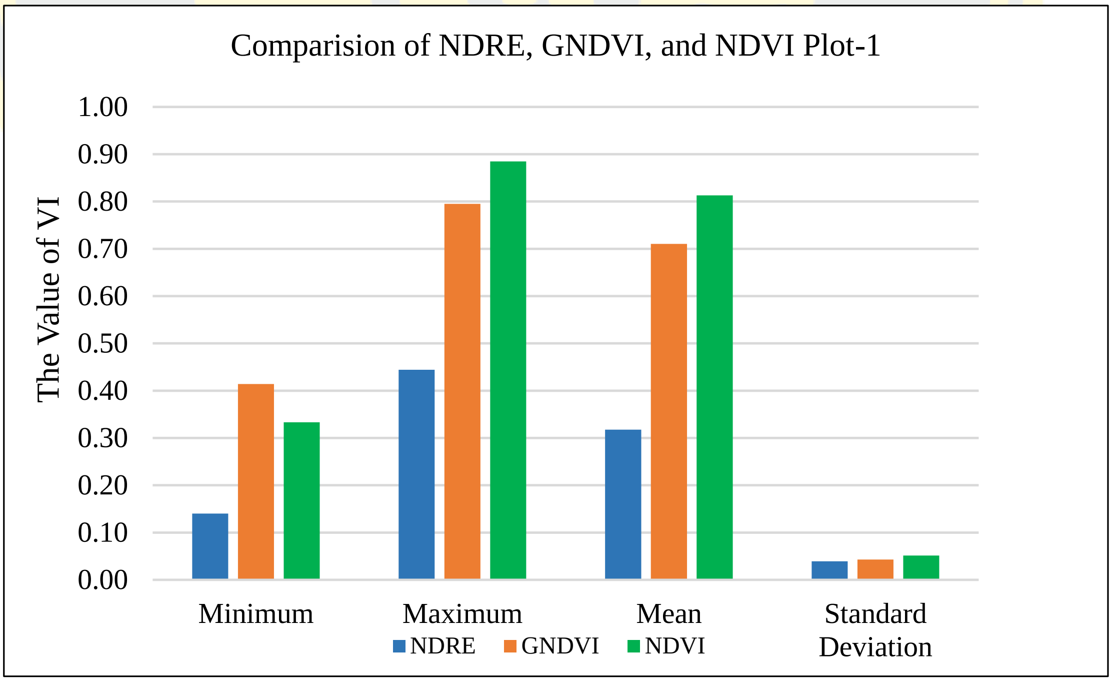
Figures 42 The situation of a single oil palm tree of P2; a) Moderately Healthy, b) Very Healthy

4.2.5 Comparison of NDRE, GNDVI, and NDVI indices

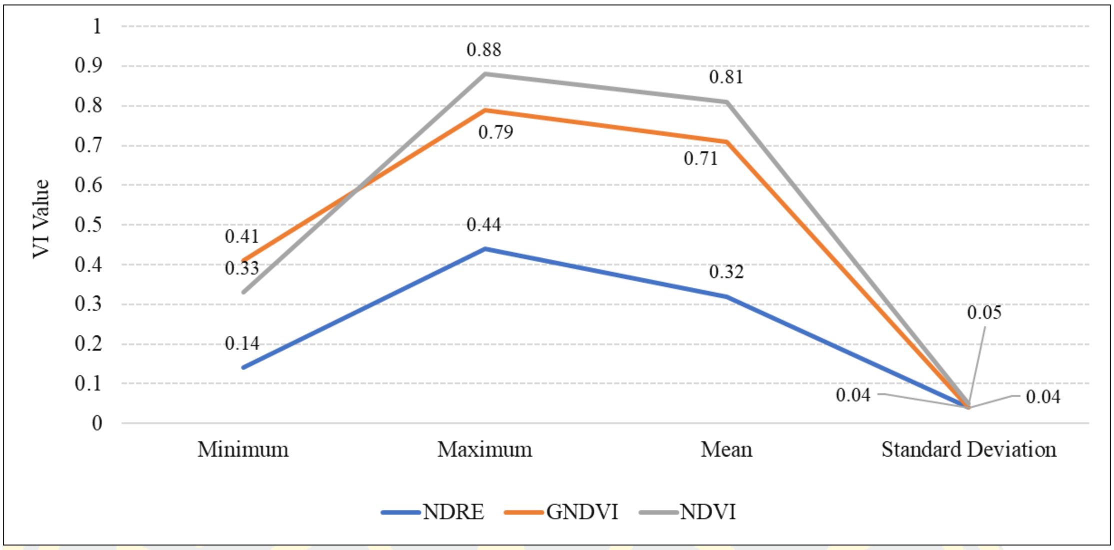
After use vegetation index to estimate chlorophyll and health of oil palm trees. The result of P1 (Table 19) and (Figure 43) shows that NDRE value Minimum is 0.14, Maximum is 0.14, Mean is 0.32, and Std Dev is 0.04. The value of GNDVI shows that the Minimum is 0.41, Maximum is 0.79, Mean is 0.71, and Std Dev is 0.04. And the value of NDVI has such as Minimum is 0.33, Maximum is 0.88, Mean is 0.81, and Std Dev is 0.05.

Tables 18 The value of vegetation indices (Min, Max, Mean, StDev) of P1

| VI | Minimum | Maximum | Mean | Standard Deviation |
|---|---|---|---|---|
| NDRE | 0.14 | 0.44 | 0.32 | 0.04 |
| GNDVI | 0.41 | 0.79 | 0.71 | 0.04 |
| NDVI | 0.33 | 0.88 | 0.81 | 0.05 |




Figures 43 Comparison of vegetation indices of P1

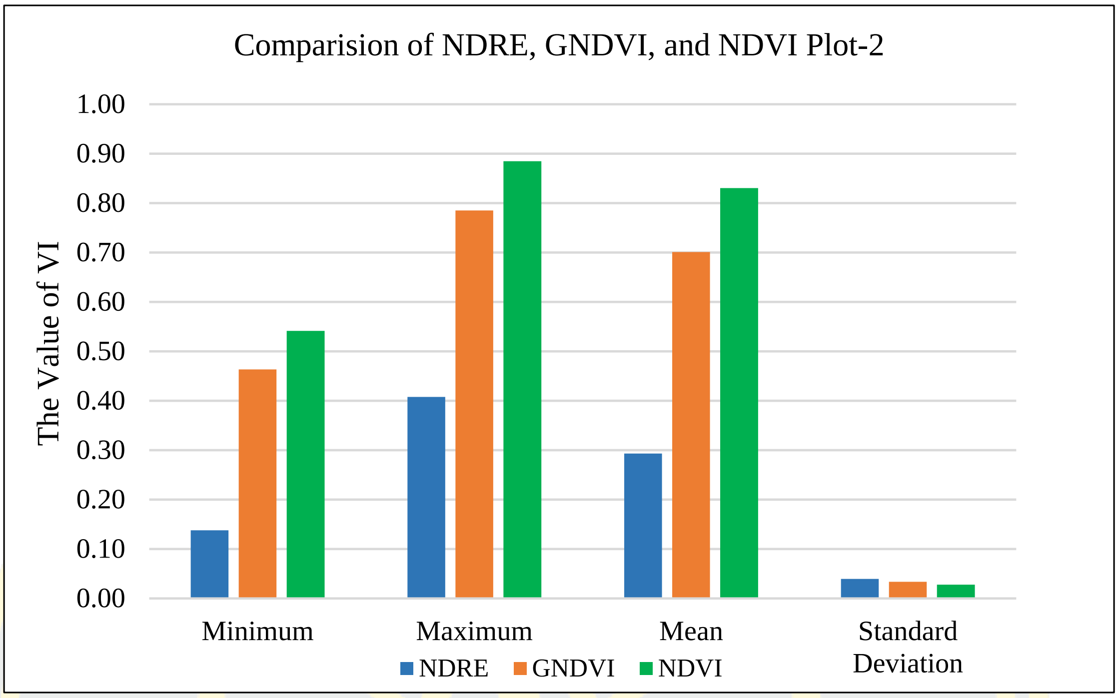



Figures 44 Comparison of min, max, mean, and St Dev of P1

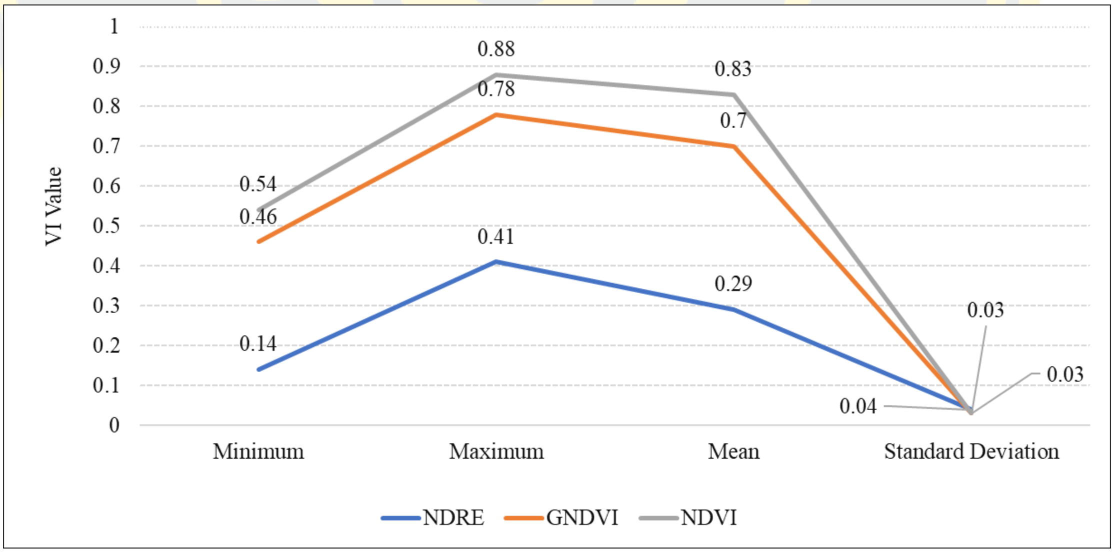
The result of P2 (Table 20) and (Figure 45) shows that the value of NDRE has such as Minimum is 0.14, Maximum is 0.41, Mean is 0.29, and Std Dev is 0.04. The value of GNDVI has such as Minimum is 0.46, Maximum is 0.78, Mean is 0.70, and Std Dev is 0.03. And the value of NDVI has such as Minimum is 0.54, Maximum is 0.88, Mean is 0.83, and Std Dev is 0.03. The value of NDVI is higher than NDRE and GNDVI.

Tables 19 The value of vegetation indices (Min, Max, Mean, StDev) of P2

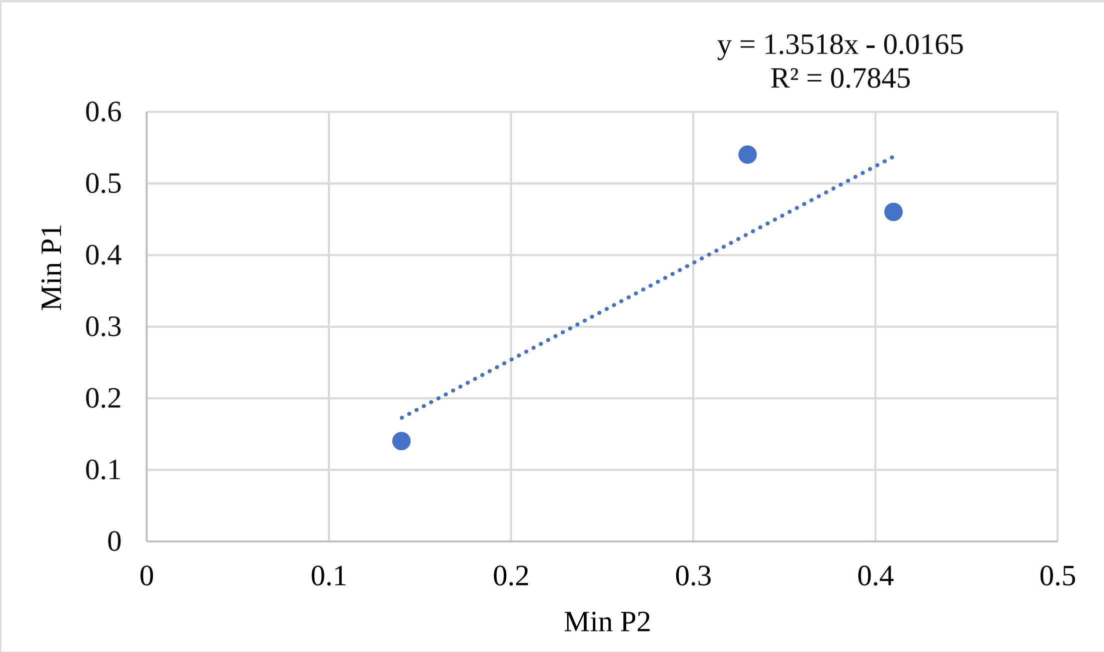
| VI | Minimum | Maximum | Mean | Standard Deviation |
|---|---|---|---|---|
| NDRE | 0.14 | 0.41 | 0.29 | 0.04 |
| GNDVI | 0.46 | 0.78 | 0.70 | 0.03 |
| NDVI | 0.54 | 0.88 | 0.83 | 0.03 |



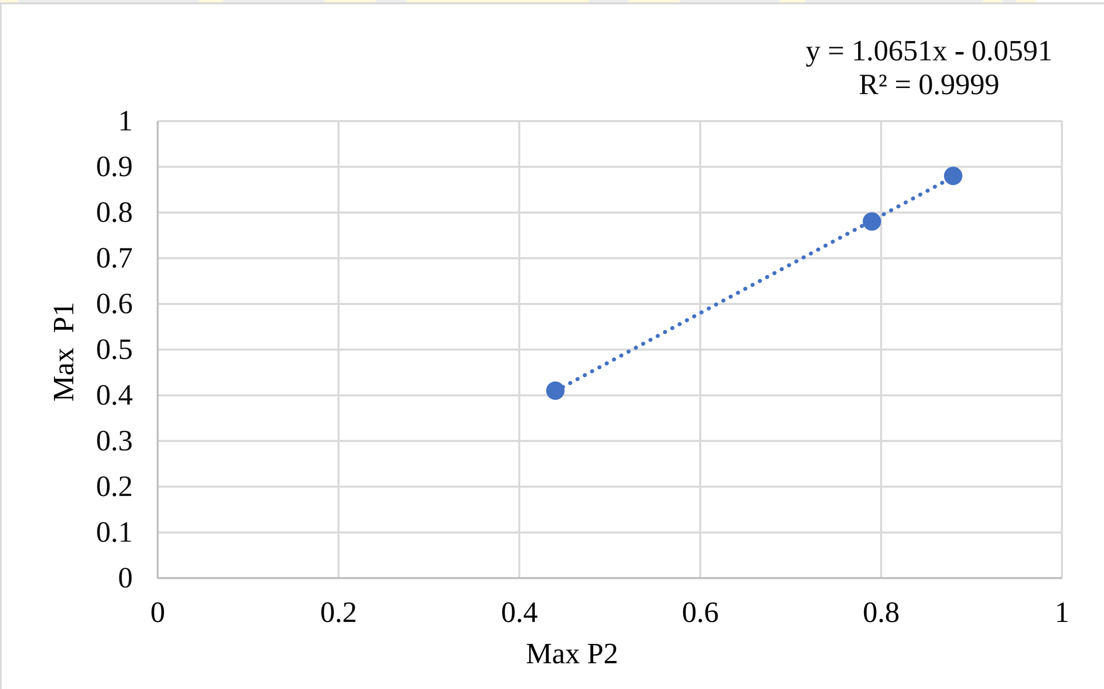

Figures 45 Comparison of vegetation indices of P1



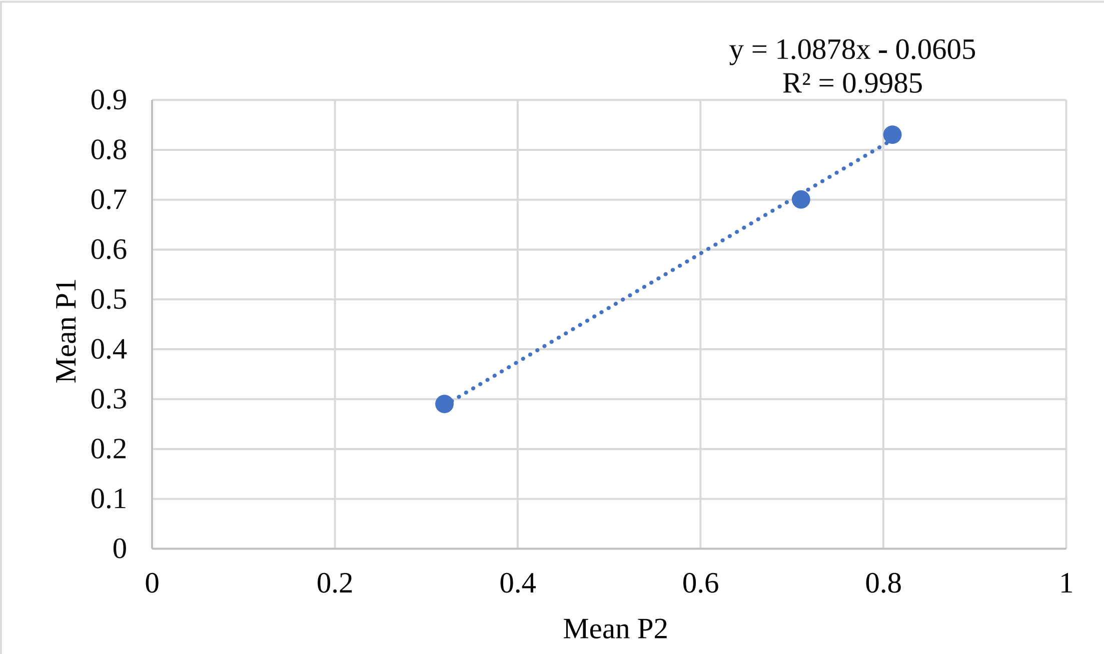

Figures 46 Comparison of min, max, mean, and St Dev of P2


y = 1.3518x - 0.0165
R² = 0.7845
0.6
0.5
0.4
0.3
0.2
0.1
0
Min P1
0
0.1
0.2
0.3
0.4
0.5
Min P2

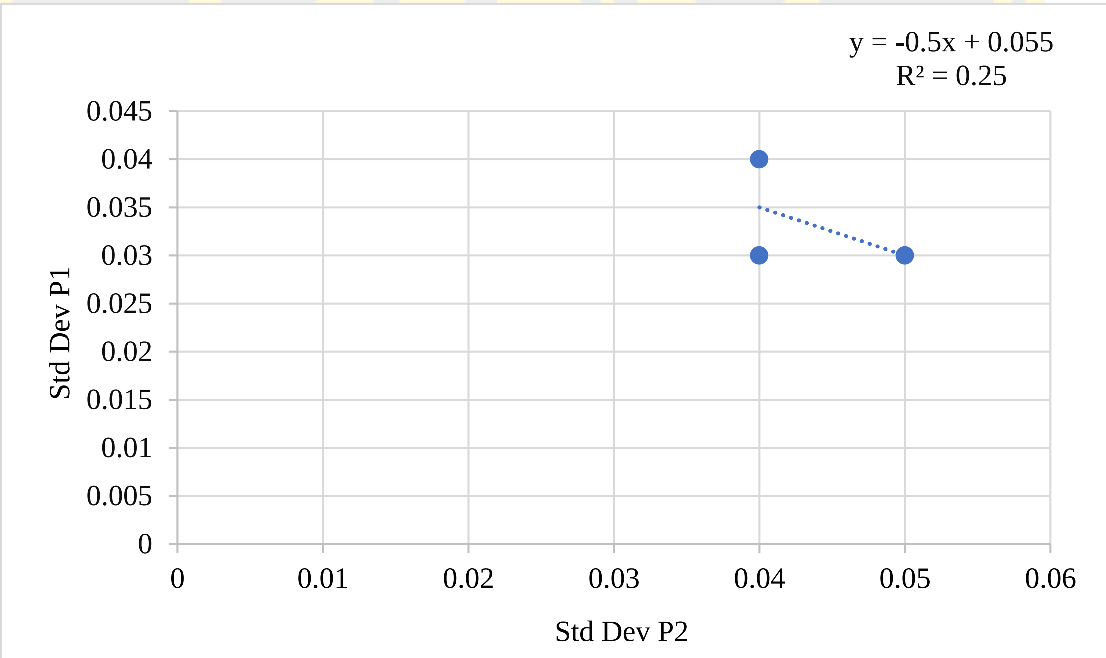
(a)


y = 1.0651x - 0.0591
R² = 0.9999
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Max P1
0
0.2
0.4
0.6
0.8
1
Max P2

(b)




(c)




(d)

Figures 47 The result of scatters plot analysis between NDRE, GNDVI, and NDVI. (a) Min P1 and Min P2; (b) Max P1 and Max P2; (c) Mean P1 and Mean P2; (d) Std Dev P1 and P2

# CHAPTER 5
# CONCLUSION AND DISCUSSION

## 5.1 Conclusion

In this study, there are two plots of oil palm trees were detected and counted UVA-based very high-resolution images. The high-resolutions were used to detect oil palm trees using the Picterra platform that brings AI-powered. At Mong Reththy Investment Cambodia Oil Palm Co., LTD in Sihanoukville Province, Cambodia, a multispectral image was used to assess the health of oil palm trees. Furthermore, the Picterra platform has good performance detection and counting objects. The NDRE, GNDVI, and NDVI indices in vegetation and chlorophyll content were compared.

**Oil palm tree counting and detection**

The outcome of the oil palm tree extraction reveals that the Picterra platform performs well in this study when it comes to detecting areas of interest. The platform has delivered high accuracy assessment in both plots, but it had issues with missed detection and detecting different objects. Several trees have the same texture and pattern as the oil palm trees, and a few objects are so small and blurry. Therefore, oil palm tree extraction produces a polygon that encompasses every oil palm tree.

While using the Picterra platform to count the number of oil palm trees, high-resolution imagery is critical. Oil palm trees were counted in this study using UAV-based imagery that provided 0.06 m in both plots. However, the platform offers high-accuracy assessments focused on training areas. The training sample is suitable for oil palm extraction.

**Oil palm trees estimation and classification**

All vegetation indices can be evaluated healthy of the oil palm trees, according to the results of the oil palm trees health estimation. The oil palm tree's chlorophyll was examined using the NDRE. Oil palm tree estimation that occurs water and nitrogen absorption into the plant canopy were identified using GNDVI analysis. Whereas, based on the index's value set, NDVI was used to measure oil palm tree health. Besides this, after comparing vegetation indices, it was discovered that NDVI outperformed NDRE and GNDVI.

## 5.2 Discussion

The Picterra platform can be detected objects from very high-resolution imagery of UAV according to study implementation. The platform helps count the object on large-scale farming. Especially it is a simple platform on the online interface that can be used for the user. In addition, it can be extracted the object from satellite imagery and generated the result shapefile extensions.

The advantages of the multispectral image have such as oil palm health estimation, chlorophyll prediction, and crop nitrogen. The NDRE, GNDVI, and NDVI are different reflectance for accessing the health of oil palm trees in vegetation and chlorophyll content. Therefore, according to the study implementation show that NDVI is useful for the health of oil palm trees estimation.

**Recommendation**

The application of high-resolution images from UAV is very important for counting oil palm trees. The Picterra platform is useful for extracting, it is too simple. The platform occurs high accuracy assessment after used to detect oil palm trees in both plots. In this way, the platform can be used a large area on the online interface with an internet connection.

The farm can apply the vegetation index to calculate the whole of oil palm areas by using multispectral images. UAV can apply the whole oil palm area in estimating at MRICOP its health based on multispectral images. Therefore, the farmer can manage and estimate the yield of oil palm trees to produce it for the consumer. Especially they can be replaced dead oil palm tree after used high-resolution imagery from UAV.

**Proposal for the next study**

The approach of this study can be used with high-resolution imagery from satellites in future studies by contrasting accuracy assessment. For object retrieval, a deep learning algorithm and cognitive architecture should be used. For evaluating the health of oil palm trees, researchers should compare more vegetation indices and variables. Therefore, potential research should be predicted oil palm tree yield and soil moisture. The researcher may incorporate additional variables such as temperature, soil moisture, and water availability.

# REFERENCES


Aber, J. S., Marzolff, I., Ries, J., & Aber, S. E. W. (2019). *Small-format aerial photography and UAS imagery: Principles, techniques and geoscience applications*: Academic Press.

Amara, J., Bouaziz, B., & Algergawy, A. (2017). A deep learning-based approach for banana leaf diseases classification. *Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband*.

Ammour, N., Alhichri, H., Bazi, Y., Benjdira, B., Alajlan, N., & Zuair, M. (2017). Deep learning approach for car detection in UAV imagery. *Remote Sensing, 9*(4), 312.

Arce, L. S. D., de Arruda, M. d. S., Furuya, D. E. G., Osco, L. P., Paula, A., Ramos, M., . . . Li, J. (2021). Mapping Single Palm-Trees Species in Forest Environments with a Deep Convolutional Neural Network.

Baek, J. (2020). A Piece of Space: Exploring photographic space as a visualized form of spatial experience and thinking about how a designer can position it in reality.

Bala, V. (2020). The Rise of AI-powered Geospatial Analytics. Available online: https://blog.gramener.com/. (Accessed on 05 April 2021)

Bannari, A., Morin, D., Bonn, F., & Huete, A. (1995). A review of vegetation indices. *Remote sensing reviews, 13*(1-2), 95-120.

Basiron, Y., & Weng, C. K. (2004). The oil palm and its sustainability. *Journal of Oil Palm Research, 16*(1).

Biswal, A. (2021). AI applications: Top 10 Artificial Intelligence Applications. Available online: https://www.simplilearn.com/. (Accessed on 05 April 2021)

Carlson, T. N., & Ripley, D. A. (1997). On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote sensing of Environment, 62*(3), 241-252.

Ciregan, D., Meier, U., & Schmidhuber, J. (2012). *Multi-column deep neural networks for image classification*. Paper presented at the 2012 IEEE conference on computer vision and pattern recognition.

Colchester, M., Chao, S., Dan, V. T., & Villanueva, J. (2011). Oil Palm Expansion in South East Asia. *Bogor, Moreton-in-Marsh: Forest People Programme and Perkumpulan Sawit Watch*.

Dick, S. (2019). Artificial intelligence. Available online:https://www.investopedia.com/. (Accessed on 30 March 2021)

Doulamis, N., & Doulamis, A. (2012). *Fast and adaptive deep fusion learning for detecting visual objects.* Paper presented at the European Conference on Computer Vision.

ESRI. (2020). Band Indices. Available online: https://pro.arcgis.com/. (Accessed on 20 February 2021)

FAOUN. (2020). Palm Oil. Available online: https://ourworldindata.org/. (Accessed on 01 March 2021)

Fischer, W. A., Hemphill, W., & Kover, A. (1976). Progress in remote sensing (1972–1976). *Photogrammetria, 32*(2), 33-72.

Fitzherbert, E. B., Struebig, M. J., Morel, A., Danielsen, F., Brühl, C. A., Donald, P. F., & Phalan, B. (2008). How will oil palm expansion affect biodiversity? *Trends in ecology & evolution*, *23*(10), 538-545.

Frankenfield, J. (2021). Artificial Intelligence (AI). Available online: https://www.investopedia.com/. (Accessed on 17 March 2021)

Germer, J., & Sauerborn, J. (2008). Estimation of the impact of oil palm plantation establishment on greenhouse gas balance. *Environment, Development and Sustainability*, *10*(6), 697-716.

Handique, B., Goswami, C., Gupta, C., Pandit, S., Gogoi, S., Jadi, R., . . . Raju, P. (2020). Hierarchical classification for assessment of horticultural crops in mixed cropping pattern using UAV-borne multi-spectral sensor. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 43*, 67-74.

Handique, B., Khan, A. Q., Goswami, C., Prashnani, M., Gupta, C., & Raju, P. (2017). Crop discrimination using multispectral sensor onboard unmanned aerial vehicle. *Proceedings of the National Academy of Sciences, India Section A: Physical Sciences*, *87*(4), 713-719.

Hargrave, M. (2020). How deep learning can help prevent financial fraud. *Investopedia. com*.

Hartley, C. W. S. (1967). The oil palm. *The oil palm.*

Hu, J., Niu, H., Carrasco, J., Lennox, B., & Arvin, F. (2020). Voronoi-based multi-robot autonomous exploration in unknown environments via deep reinforcement learning. *IEEE Transactions on Vehicular Technology*, *69*(12), 14413-14423.

Hu, W., & Huang, F. (2020). *Review of Deep Learning Parallelization and Its Application in Spatial Data Mining.* Paper presented at the 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE).

Hu, Y., Gao, S., Newsam, S. D., & Lunga, D. D. (2018). GeoAI 2018 workshop report the 2nd ACM SIGSPATIAL international workshop on GeoAI: AI for geographic knowledge discovery seattle, WA, USA-November 6, 2018. *ACM SIGSPATIAL Special*, *10*(3), 16.

Hu, Y., Zhang, Q., Zhang, Y., & Yan, H. (2018). A deep convolution neural network method for land cover mapping: A case study of Qinhuangdao, China. *Remote Sensing*, *10*(12), 2053.

Huang, Y., Chen, Z.-x., Tao, Y., Huang, X.-z., & Gu, X.-f. (2018). Agricultural remote sensing big data: Management and applications. *Journal of Integrative Agriculture*, *17*(9), 1915-1931.

Iqbal, F., Lucieer, A., & Barry, K. (2018). Simplified radiometric calibration for UAS-mounted multispectral sensor. *European Journal of Remote Sensing*, *51*(1), 301-313.

Karaburun, A. (2010). Estimation of C factor for soil erosion modeling using NDVI in Buyukcekmece watershed. *Ozean journal of applied sciences*, *3*(1), 77-85.

Khaliq, A., Comba, L., Biglia, A., Ricauda Aimonino, D., Chiaberge, M., & Gay, P. (2019). Comparison of satellite and UAV-based multispectral imagery for vineyard variability assessment. *Remote Sensing*, *11*(4), 436.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, *25*, 1097-1105.

Kurbanov, R., & Litvinov, M. (2020). *Development of a gimbal for the Parrot Sequoia multispectral camera for the UAV DJI Phantom 4 Pro.* Paper presented at the IOP Conference Series: Materials Science and Engineering.

Lee, W., & Searcy, S. (2000). *Multispectral sensor for detecting nitrogen in corn plants.* Paper presented at the ASAE Annual International Meeting, Midwest Express Center, Milwaukee, Wisconsin.

Li, W., Fu, H., Yu, L., & Cracknell, A. (2017). Deep learning based oil palm tree detection and counting for high-resolution remote sensing images. *Remote Sensing*, *9*(1), 22.

Li, Y., Zhang, H., & Shen, Q. (2017). Spectral–spatial classification of hyperspectral imagery with 3D convolutional neural network. *Remote Sensing*, *9*(1), 67.

Li, Y., Zhang, H., Xue, X., Jiang, Y., & Shen, Q. (2018). Deep learning for remote sensing image classification: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *8*(6), e1264.

Liu, L., Ouyang, W., Wang, X., Fieguth, P., Chen, J., Liu, X., & Pietikäinen, M. (2020). Deep learning for generic object detection: A survey. *International journal of computer vision*, *128*(2), 261-318.

Liu, X., Ghazali, K. H., Han, F., & Mohamed, I. I. (2021). Automatic Detection of Oil Palm Tree from UAV Images Based on the Deep Learning Method. *Applied Artificial Intelligence*, *35*(1), 13-24.

Lu, H., Fan, T., Ghimire, P., & Deng, L. (2020). Experimental Evaluation and Consistency Comparison of UAV Multispectral Minisensors. *Remote Sensing*, *12*(16), 2542.

Mamaghani, B., & Salvaggio, C. (2019). Multispectral sensor calibration and characterization for sUAS remote sensing. *Sensors*, *19*(20), 4453.

Mubin, N. A., Nadarajoo, E., Shafri, H. Z. M., & Hamedianfar, A. (2019). Young and mature oil palm tree detection and counting using convolutional neural network deep learning method. *International Journal of Remote Sensing*, *40*(19), 7500-7515.

Navalgund, R. R., Jayaraman, V., & Roy, P. (2007). Remote sensing applications: An overview. *Current Science*, 1747-1766.

Ocer, N. E., Kaplan, G., Erdem, F., Kucuk Matci, D., & Avdan, U. (2020). Tree extraction from multi-scale UAV images using Mask R-CNN with FPN. *Remote Sensing Letters*, *11*(9), 847-856.

Olukayode, O., Blesing, L., Rotimi, A., & Oguntol, E. (2018). Assessment of plant health status using remote sensing and GIS techniques. *Advances in Plants & Agriculture Research*, *8*(6), 517-525.

Ongsulee, P. (2017). *Artificial intelligence, machine learning and deep learning.* Paper presented at the 2017 15th International Conference on ICT and Knowledge Engineering (ICT&KE).

Papadomanolaki, M., Vakalopoulou, M., Zagoruyko, S., & Karantzalos, K. (2016). Benchmarking deep learning frameworks for the classification of very high resolution satellite multispectral data. *ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences, 3*(7).

Picterra. (2020). Our Misssion. Available online: https://picterra.ch/.
(Accessed on 13 February)

Pirker, J., Mosnier, A., Kraxner, F., Havlík, P., & Obersteiner, M. (2016). What are the limits to oil palm expansion? *Global Environmental Change, 40*, 73-81.

Qaim, M., Sibhatu, K. T., Siregar, H., & Grass, I. (2020). Environmental, Economic, and Social Consequences of the Oil Palm Boom. *Annual Review of Resource Economics, 12*(1), 321-344. doi:10.1146/annurev-resource-110119-024922

Raeva, P. L., Šedina, J., & Dlesk, A. (2019). Monitoring of crop fields using multispectral and thermal imagery from UAV. *European Journal of Remote Sensing, 52*(sup1), 192-201.

Renduchintala, A., Jahan, F., Khanna, R., & Javaid, A. Y. (2019). A comprehensive micro unmanned aerial vehicle (UAV/Drone) forensic framework. *Digital Investigation, 30*, 52-72.

Rice, K. (2018). *Convolutional neural networks for detection and classification of maritime vessels in electro-optical satellite imagery*. Retrieved from

Rouse, J., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA special publication, 351*(1974), 309.

Saing, C. H., Hem, S., Ouch, C., Phann, D., & Pon, D. (2012). Foreign investment in agriculture in Cambodia. *Phnom Penh, Rome: Cambodia Development Resource Institute (CDRI), Food and Agriculture Organization of the United Nations (FAO).*

Saleem, M. H., Potgieter, J., & Mahmood Arif, K. (2019). Plant Disease Detection and Classification by Deep Learning. *Plants (Basel), 8*(11). doi:10.3390/plants8110468

Shafian, S., Rajan, N., Schnell, R., Bagavathiannan, M., Valasek, J., Shi, Y., & Olsenholler, J. (2018). Unmanned aerial systems-based remote sensing for monitoring sorghum growth and development. *PloS one, 13*(5), e0196605.

Shaharum, N. S. N., Shafri, H. Z. M., Ghani, W. A. W. A. K., Samsatli, S., Al-Habshi, M. M. A., & Yusuf, B. (2020). Oil palm mapping over Peninsular Malaysia using Google Earth Engine and machine learning algorithms. *Remote Sensing Applications: Society and Environment, 17*. doi:10.1016/j.rsase.2020.100287

Sokhannaro, H. (2011). Palm oil development in Cambodia.

Song, A., & Kim, Y. (2017). Deep learning-based hyperspectral image classification with application to environmental geographic information systems. *Korean Journal of Remote Sensing, 33*(6_2), 1061-1073.

Steven, M., & Clark, J. A. (2013). *Applications of remote sensing in agriculture*: Elsevier.

Sumathi, S., Chai, S., & Mohamed, A. (2008). Utilization of oil palm as a source of renewable energy in Malaysia. *Renewable and sustainable energy reviews, 12*(9), 2404-2421.

The Phnom Penh Post. (2020). CEO: Up to 300,000 tonnes of palm oil 'possible' this year. Available online: https://www.phnompenhpost.com/business/ceo-300000-tonnes-palm-oil-possible-year. (Accessed on 10 March 2021)

Turner, P. D., & Gillbanks, R. (1974). Oil palm cultivation and management. *Oil palm cultivation and management.*

VoPham, T., Hart, J. E., Laden, F., & Chiang, Y.-Y. (2018). Emerging trends in geospatial artificial intelligence (geoAI): potential applications for environmental epidemiology. *Environmental Health, 17*(1), 1-6.

Vununu, C., Lee, S.-H., & Kwon, K.-R. (2020). A Strictly Unsupervised Deep Learning Method for HEp-2 Cell Image Classification. *Sensors, 20*(9), 2717.

Wahid, M. B., Abdullah, S. N. A., & IE, H. (2005). Oil palm. *Plant Production Science, 8*(3), 288-297.

Xiao Xiang Zhu, D. T., Lichao Mou, Gui-Song Xia, Liangpei Zhang, Feng Xu, Friedrich Fraundorfer. (2017). Deep Learning in Remote Sensing A Review. *IEEE GEOSCIENCE AND REMOTE SENSING MAGAZINE, IN PRESS.*

Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. *Journal of sensors, 2017*.

Yu, X., Wu, X., Luo, C., & Ren, P. (2017). Deep learning in remote sensing scene classification: a data augmentation enhanced convolutional neural network framework. *GIScience & Remote Sensing*, *54*(5), 741-758.

Zhang, H., & Deng, Q. (2019). Deep learning based fossil-fuel power plant monitoring in high resolution remote sensing images: A comparative study. *Remote Sensing*, *11*(9), 1117.

Zhang, Z., Vosselman, G., Gerke, M., Persello, C., Tuia, D., & Yang, M. Y. (2019). Detecting building changes between airborne laser scanning and photogrammetric data. *Remote Sensing*, *11*(20), 2417.

Zheng, Y.-Y., Kong, J.-L., Jin, X.-B., Wang, X.-Y., Su, T.-L., & Zuo, M. (2019). CropDeep: The crop vision dataset for deep-learning-based classification and detection in precision agriculture. *Sensors*, *19*(5), 1058.

# APPENDICES

มหาวิทยาลัยบูรพา
BURAPHA UNIVERSITY

## Appendix A Data Collection by Using UAV

UAV Pilot log: Unmanned Aerial Vehicle Logbook for Drone Pilots and Operators

FLIGHT ID/NO: **P1** Month **January** Day **31** Year **2021**

FLIGHT LOCATION: **10.973034, 103.922482** Weather: **33.8$^{0}$C, 1.5m/s**

UNMANNED AERIAL VEHICLE:

MANUFATURE: **DJI Matrice 100**

MODEL NUMBER: .......................

CREW:

PILOT: **LAY Hong**

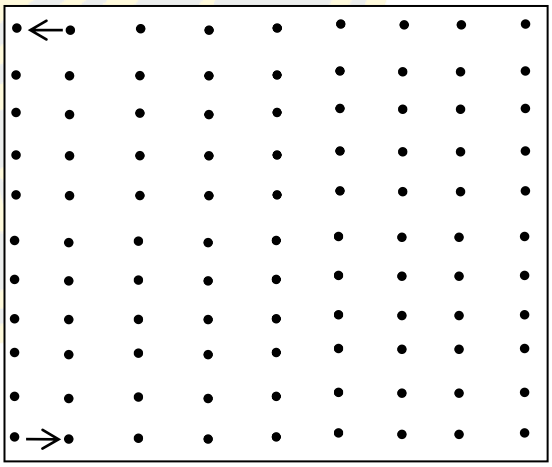
SPOTTER: **MOL Pheng Kheang**

PREFLIGHT CHECKLIST

- ☑ Batteries Charged & Secure
- ☑ Props OK &Tight
- ☑ Compass Calibration
- ☑ Aircraft Hardware OK
- ☑ Software / Firmware Update
- ☑ Camera / PPV ON
- ☑ Equipment & Gear OK
- ☑ Transmitter Control Power ON
- ☑ Satellite Connection
- ☑ Transmitter Controls OK
- ☑ Aircraft Power ON
- ☑ Applications / Systems ON

| SESSION INTERVAL | FLIGHT TIMES START | STOP | TOTAL |
|---|---|---|---|
| P1 | 14:40 | 14:52 | 12 min |
| - | - | - | - |
| - | - | - | - |
| TOTAL HOURS FOR SESSION | | | |
| TOTAL FORWARD | | | |
| TOTAL TO DATE | | | |

*End* FLIGHT MAP



*Start*

POSTFLIGHT NOTES / JOURNAL ENTRIES:

I CERTIFY THAT THE FORWARD ENTRIES ARE TRUE AND CORRECT:

PILOT: **LAY Hong** SPOTER: **MOL Peng Kheang**

UAV Pilot log: Unmanned Aerial Vehicle Logbook for Drone Pilots and Operators

FLIGHT ID/NO: **P2** Month **February** Day **01** Year **2021**

FLIGHT LOCATION: **10.973463, 103.931413** Weather: **39.5$^{0}$C, 1.5m/s**

UNMANNED AERIAL VEHICLE:

MANUFATURE: **DJI Matrice 100**

MODEL NUMBER: .......................

CREW:

PILOT: **LAY Hong**

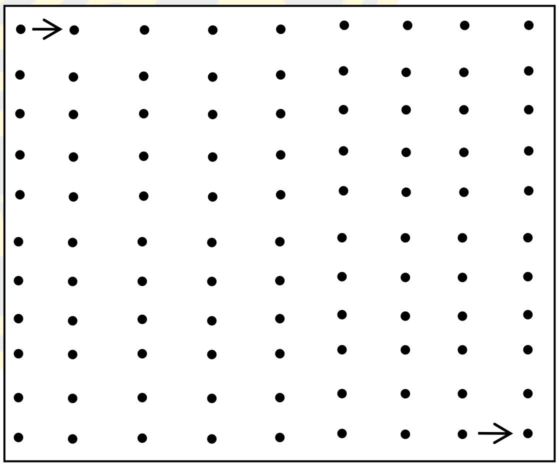
SPOTTER: **MOL Pheng Kheang**

PREFLIGHT CHECKLIST

- ☑ Batteries Charged & Secure
- ☑ Props OK &Tight
- ☑ Compass Calibration
- ☑ Aircraft Hardware OK
- ☑ Software / Firmware Update
- ☑ Camera / PPV ON
- ☑ Equipment & Gear OK
- ☑ Transmitter Control Power ON
- ☑ Satellite Connection
- ☑ Transmitter Controls OK
- ☑ Aircraft Power ON
- ☑ Applications / Systems ON

| SESSION INTERVAL | FLIGHT TIMES | | |
|---|---|---|---|
| | START | STOP | TOTAL |
| P2 | 14:30 | 14:42 | 12 min |
| - | - | - | - |
| - | - | - | - |
| TOTAL HOURS FOR SESSION | | | |
| TOTAL FORWARD | | | |
| TOTAL TO DATE | | | |

*Start* FLIGHT MAP



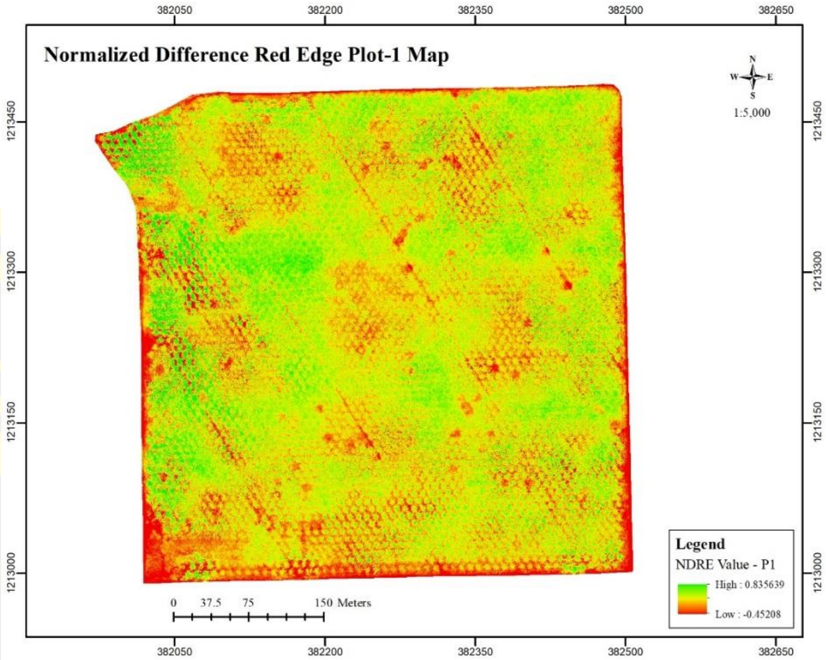
*End*

POSTFLIGHT NOTES / JOURNAL ENTRIES:

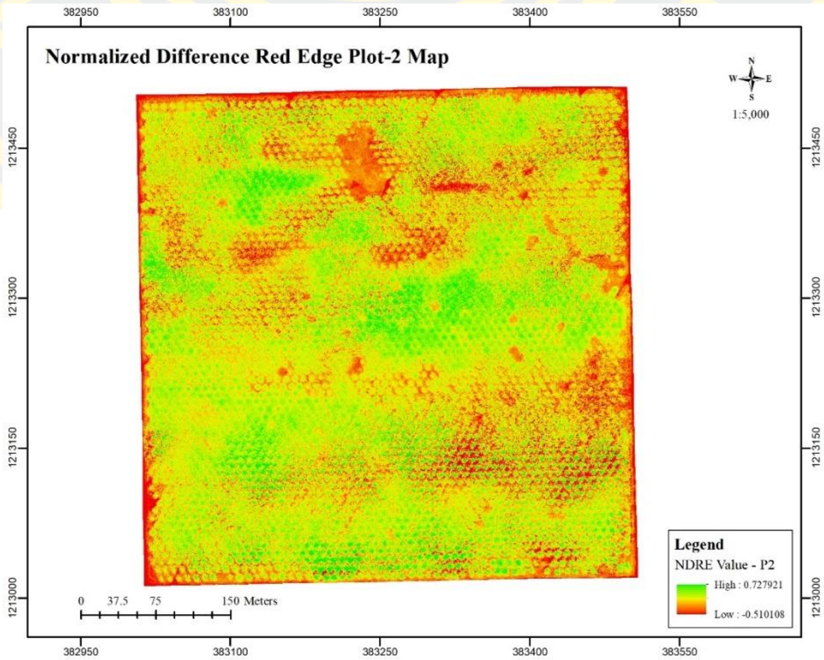
I CERTIFY THAT THE FORWARD ENTRIES ARE TRUE AND CORRECT:

PILOT: **LAY Hong** SPOTER: **MOL Peng Kheang**

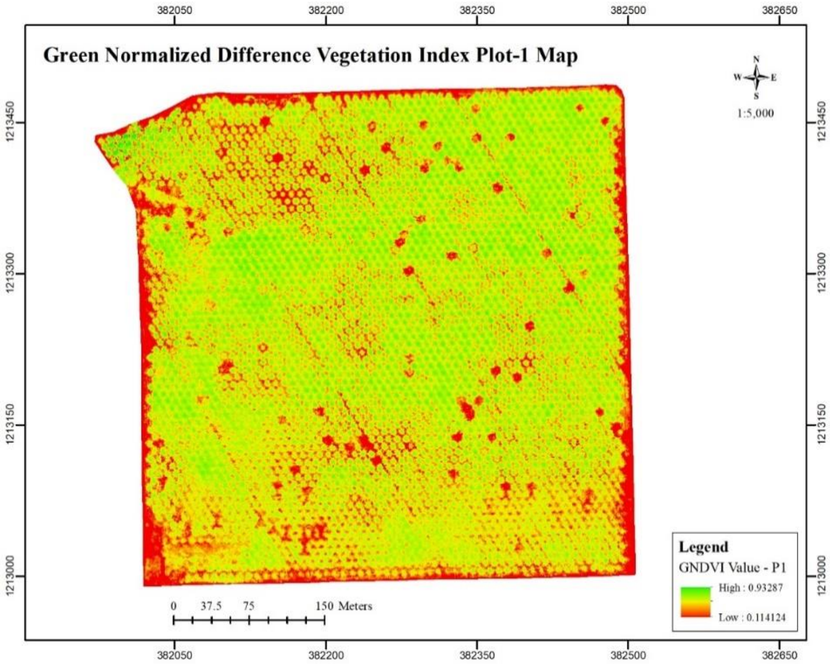
## Appendix B Vegetation Calculation (NDRE, GNDVI, AND NDVI)



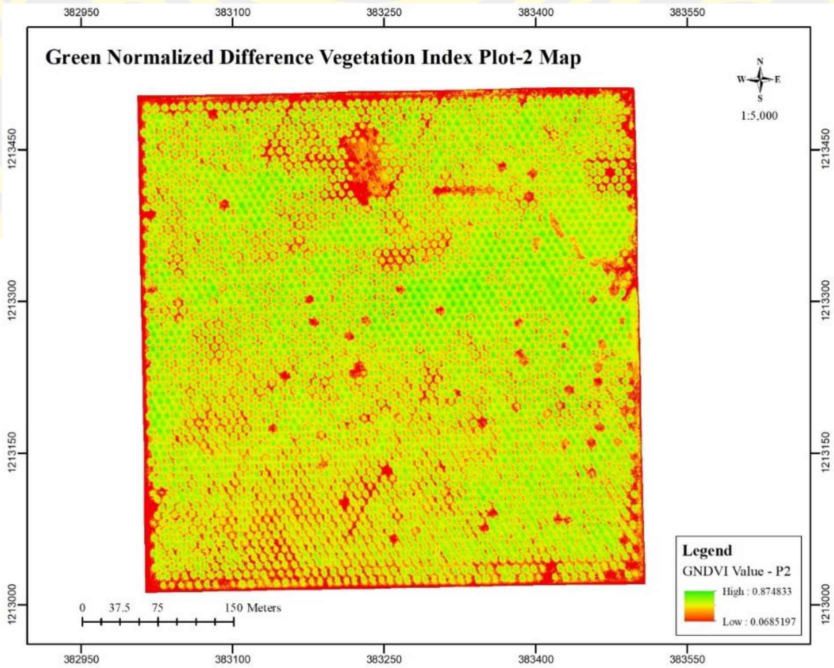

Figures 48 Oil Palm trees chlorophyll estimation using NDRE of P1



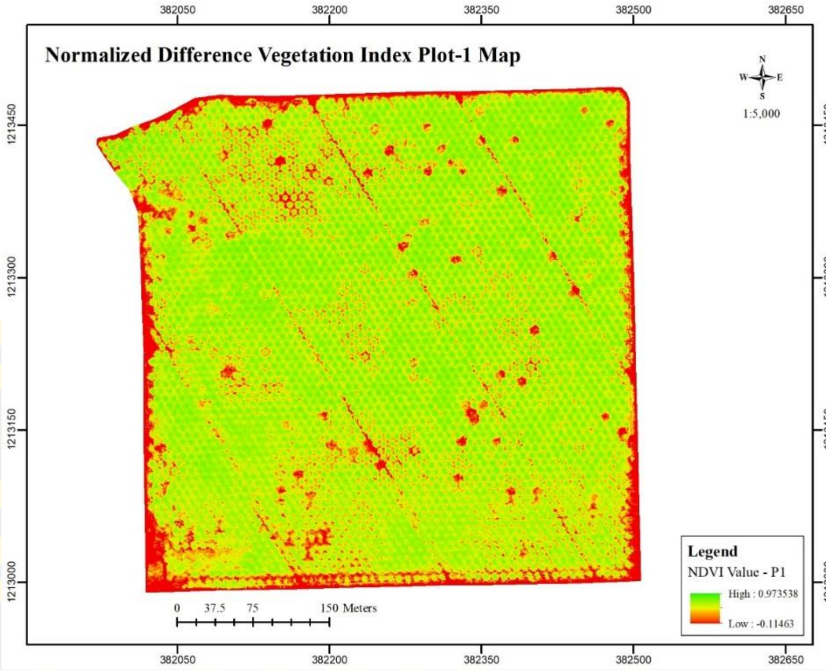

Figures 49 Oil Palm trees chlorophyll estimation using NDRE of P2



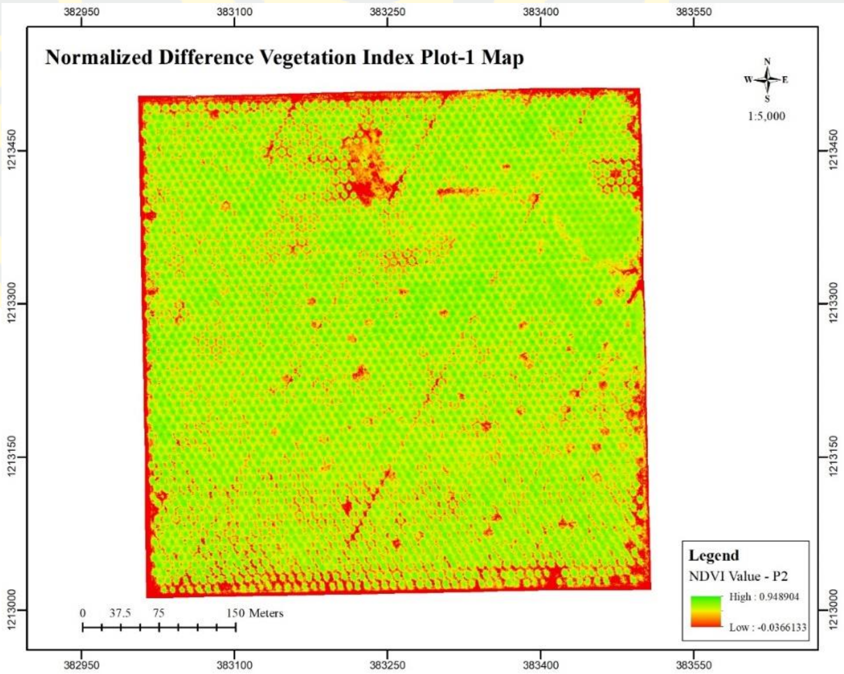

Figures 50 Oil palm trees health estimation using GNDVI of P1




Figures 51 Oil palm trees health estimation using GNDVI of P2




Figures 52 Oil palm trees health estimation using NDVI of P1




Figures 53 Oil palm trees health estimation using NDVI of P2

## Appendix C Permission Letter

测绘遥感信息工程国家重点实验室（武汉大学）

LIESMARS

State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (Wuhan University)

To Director

Mong Reththy Investment Cambodia Oil Palm Co., LTD

**Subject:** **Request for data of below-mentioned study area**

Sir/MS

Being a full professor and supervisor of Mr. Lay Hong, I am glad to write this letter to you that Mr. Lay Hong is doing MSc (Photogrammetry & Remote Sensing) from State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (LIESMARS), Wuhan University, China. He has already defended his MSc dissertation proposal. His MSc dissertation topic is **"Health Status Detection of Oil Palm Tree Using an Unmanned Aerial Vehicle Multispectral Image Based on Picterra Platform"**

In recently, UAV is useful in smart agriculture. This research will be evaluated by using Normalized Different Vegetation Index (NDVI), Normalized Difference Red Edge (NDRE), and Green Normalized Difference Vegetation Index (GNDVI).

Your dataset is particularly acknowledged in his MSc dissertation, and we would like to share our research results of oil tree healthy and detections with you in any form.

**Study area: Mong Reththy Investment Cambodia Oil Palm Co., LTD**

We need all these types of data;

1. Drone capturing 2 plots of oil palm farm
2. Field-photographs of oil palm farm
3. Ground truthing by using GPS
4. And GIS data (Shapefile)

Supervisor's Signature:

Zhenfeng Shao

Dated: 2021/01/11

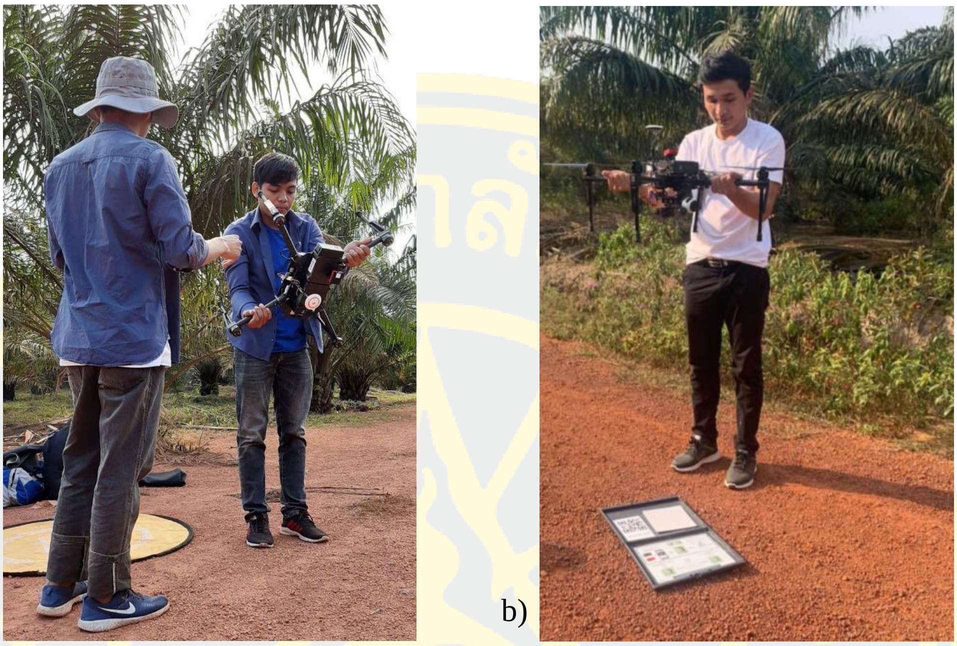
测绘遥感信息工程国家重点实验室（武汉大学）

地址：武汉市珞喻路129号，430079
Tel:027-68778969 Fax:027-68778969

Add: 129 Luoyu Road, Wuhan, P.R.China
Postal Code: 430079

Figures 54 The permission letter for collecting data at the oil palm area

## Appendix D Activities of Data Collection at Field Work



a) b)

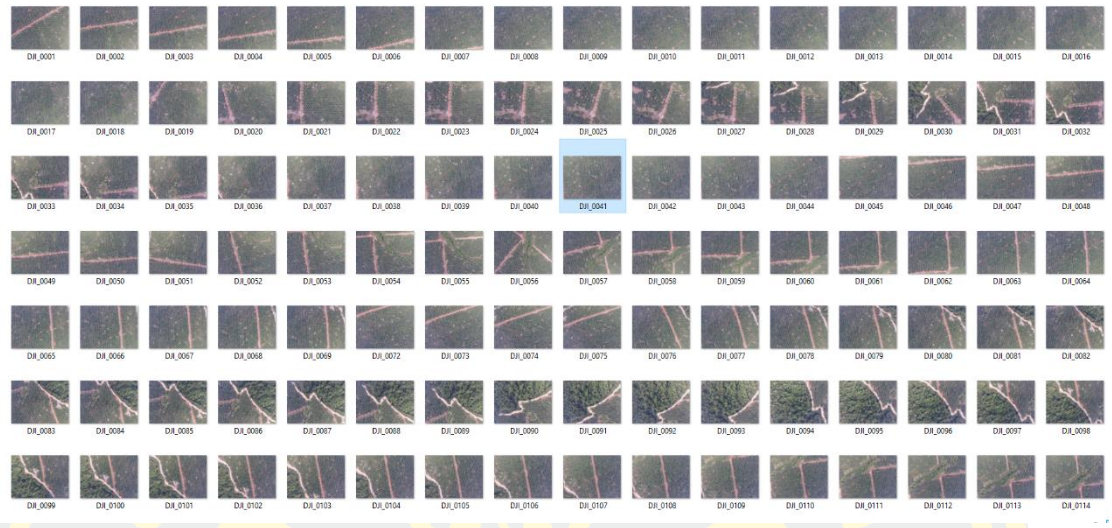
Figures 55 Camera calibration; a) Calibrating RGB camera b) Calibrating Sequoia camera

Figures 56 The activity of launching DJI Matrice 100 for capturing oil palm raw images

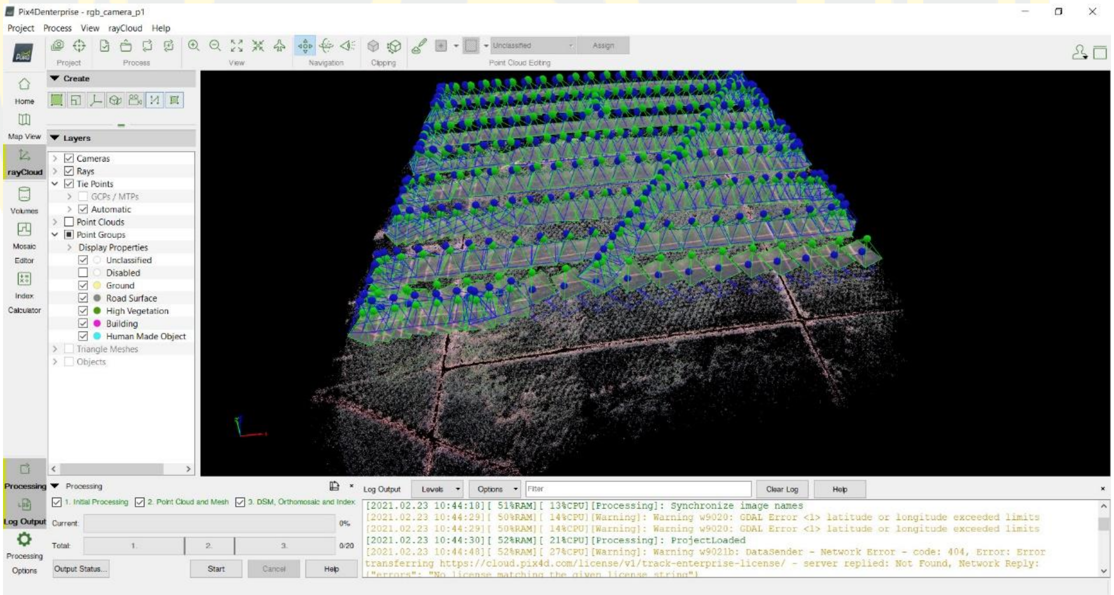
Figures 57 The activity of data collection at oil palm areas

Figures 58 The activity of data requirement and purpose presentation of the research

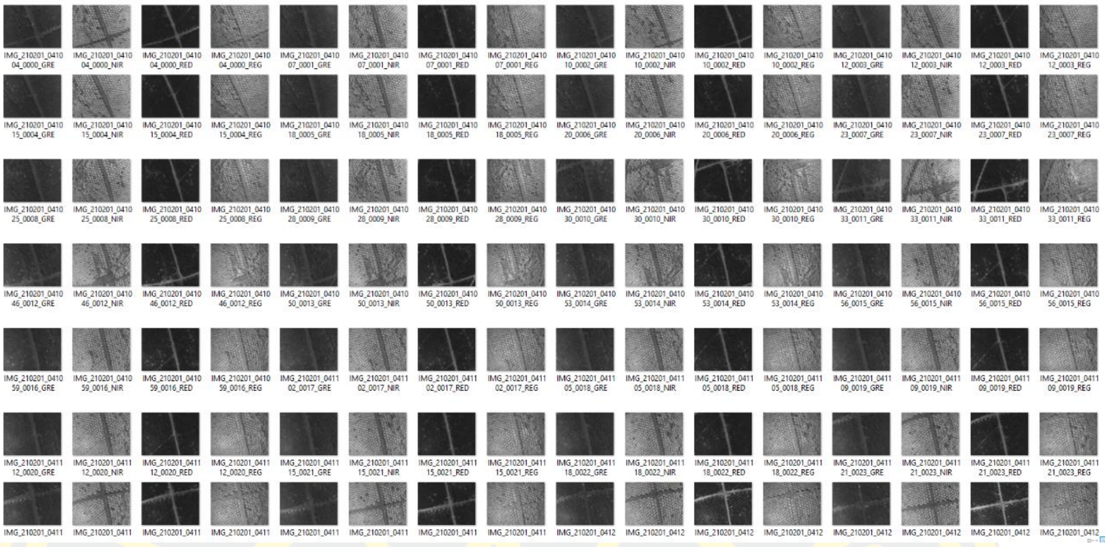
## Appendix E Data Processing



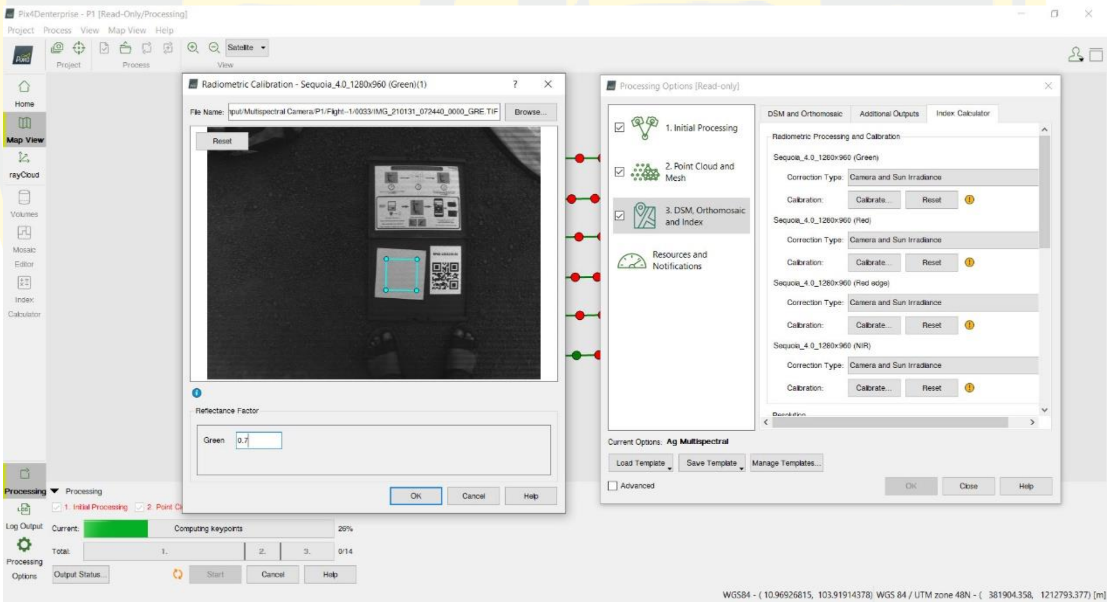
Figures 59 RGB camera's raw image of oil palms



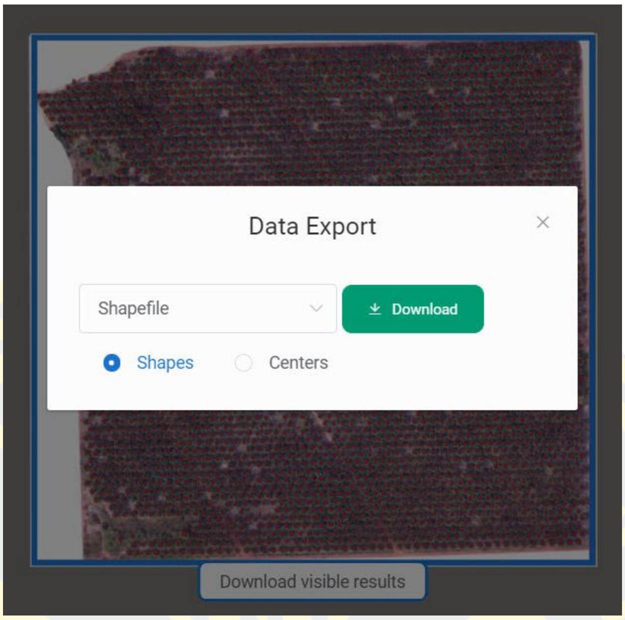

Figures 60 Mosaicking oil palm raw images from RGB camera in Pix4Dmapper



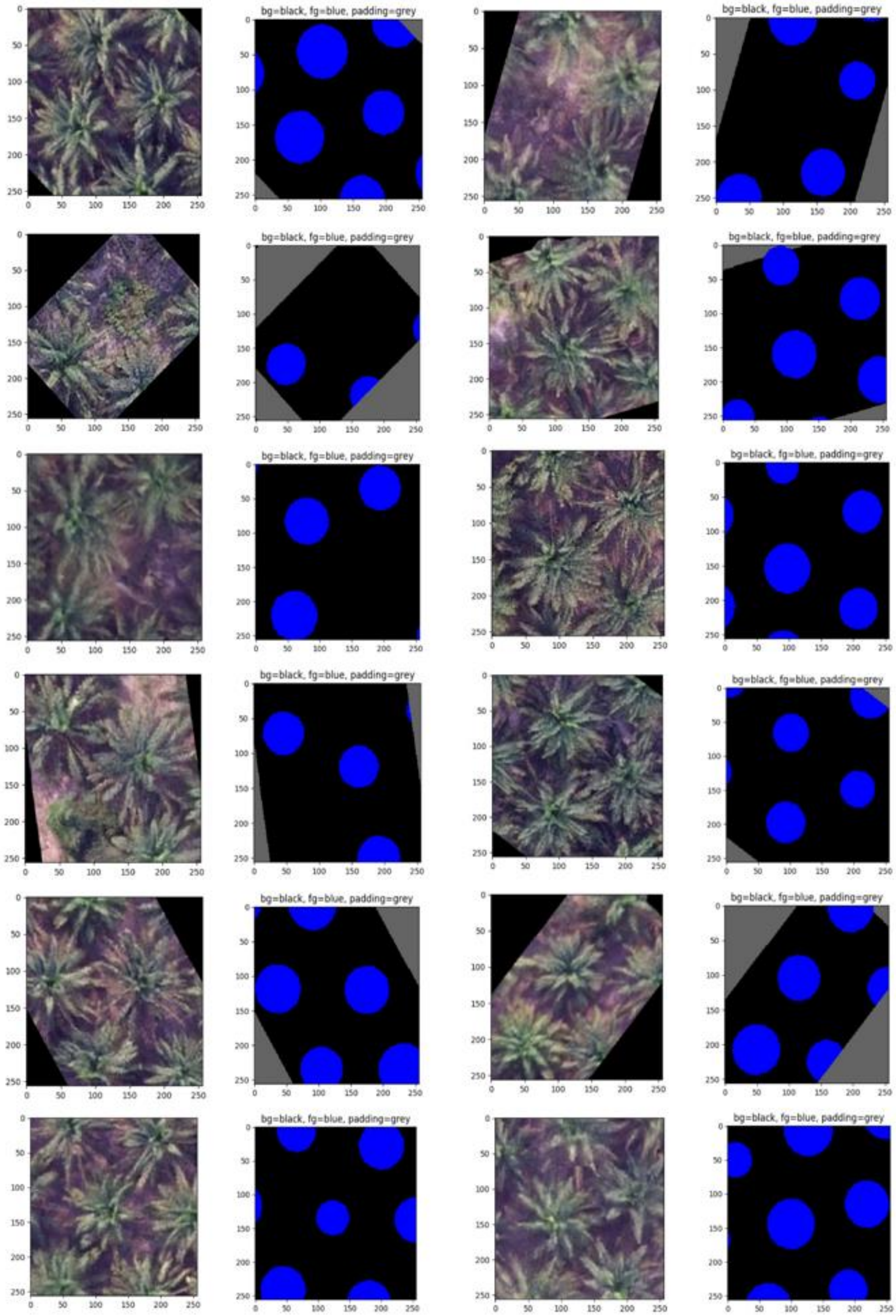
Figures 61 Parrot Sequoia camera's raw image of oil palms




Figures 62 Mosaicking and calibrating reflectance factor (Green, Red, Red Edge, and Near-Infrared) of oil palm raw images from Sequoia camera in Pix4Dmapper

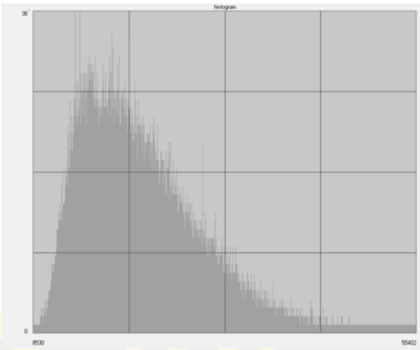



Figures 63 Export oil palm extraction to shapefile

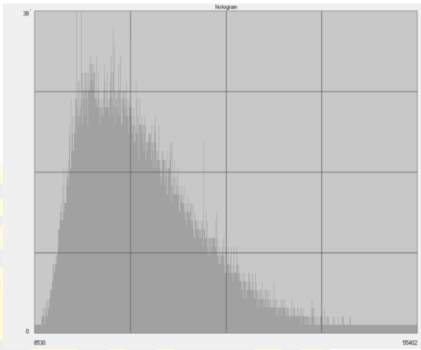



Figures 64 Example input images from Picterra training report

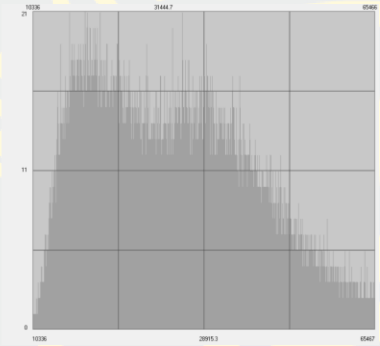
## Appendix F Multispectral Image Statistics



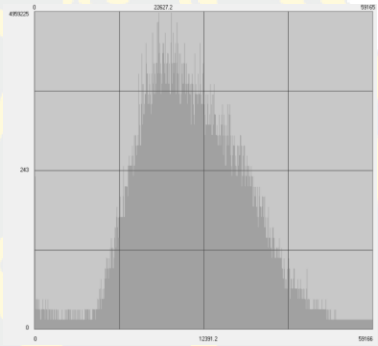
Green



Red Edge

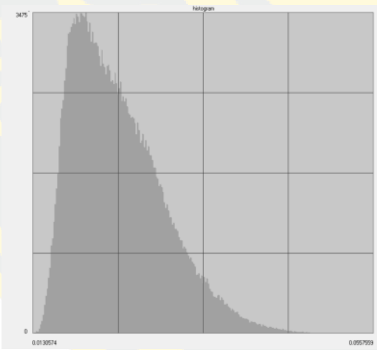


Red

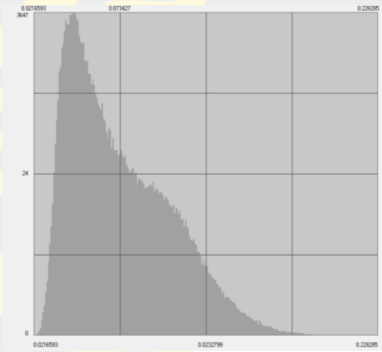


Near-Infrared

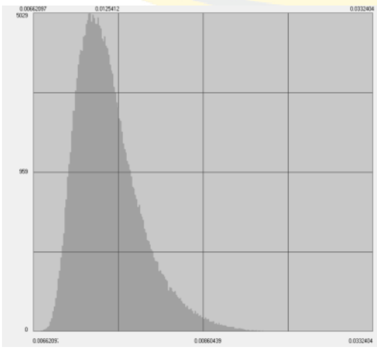
Figures 65 Image Histograms of P1



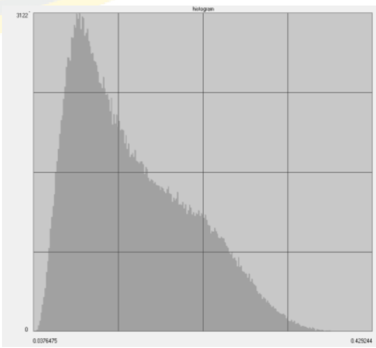
Green



Red Edge



Red



Near-Infrared

Figures 66 Image Histograms of P2

## LIST OF PUBLICATIONS AND PAPERS PRESENTED

**1.** Haoran Zhang, Tanita Suepa, Lay Hong, Mot Ly & Phorn Nayelin (2020). Visualization Analysis of COVID-19 to Respond Infectious Disease Outbreaks Using Geoinformatics Techniques in Thailand: Opportunities and Challenges. 7$^{th}$ International Online Conference on HealthGIS 2020, Bangkok, Thailand.

**2.** Lay Hong, Zhenfeng Shao & Hor Sanara (2021). Application of UAV-Based Multispectral Images for Accessing Oil Palm Trees Health Using Online AI Platform. 2$^{nd}$ Intercontinental Geoinformation Days (IGD), 155-158, Mersin, Turkey.

# BIOGRAPHY

| | |
|---|---|
| **NAME** | Hong Lay |
| **DATE OF BIRTH** | 04 May 1995 |
| **PLACE OF BIRTH** | Kirivong District, Takeo Province, Cambodia |
| **PRESENT ADDRESS** | |
| **POSITION HELD** | 2018 - 2019: GIS Specialist of Commune Land Use Planning (CLUP), at SBK Research and Development Co., Ltd.<br>2017 - 2019: Volunteer of Regional Planning, at Provincial Department of Land Management, Urban Planning and Construction, Kandal Province, Cambodia |
| **EDUCATION** | 2019 - 2021: Double Master Degree of Science in Geoinformatics, Burapha University, Thailand and Wuhan University, China<br>2013 - 2018: Bachelor of Science in Land Management and Land Administration, Royal University of Agriculture, Phnom Penh, Cambodia |
| **AWARDS OR GRANTS** | Best Paper Award<br>"Visualization Analysis of COVID-19 to Respond to Infectious Disease Outbreaks Using Geoinformatics Techniques in Thailand: Opportunities and Challenges", The 7th International Conference on Health GIS 2020<br><br>SCGI Masters Programme Scholarship<br>Funded by Geo-Informatics and Space Technology Development Agency (Public Organization), Thailand |