OIL PALM DETECTION AND DELINEATION USING LOCAL MAXIMA, TEMPLATE MATCHING AND SEEDED REGION GROWING

CHONG KHAI LOONG

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Master of Philosophy (Remote Sensing)

Faculty of Built Environment and Surveying
Universiti Teknologi Malaysia

JANUARY 2020

DEDICATION

To my beloved mother and father

ACKNOWLEDGEMENT

In the preparation of this thesis, first of all, I would like to thank my supervisor, Professor Dr. Kasturi Devi Kanniah for her continuous guidance along my postgraduate journey. I would also like to thank Prof. Christine Pohl, as my previous supervisor, for her valuable insight and willingness to give me an opportunity to pursue my Master of Philosophy degree in Universiti Teknologi Malaysia.

I would also like to thank my families for supporting my every decision and also provided me with aids in any form. Without them, it would not possible for me to finish the studies. Besides, I am blessed to have met with many experienced friends and researchers along my research journey. Their advice and guidance had benefited me tremendously and their determination had taught me to persevere in this journey no matter the difficulties.

Last but not least, I would like to thank Universiti Teknologi Malaysia to provide me with necessary facilities to complete my research and the writing of the thesis.

ABSTRACT

Oil palm (*Elaeis guineensis Jacq.*) is recognized as a golden crop and it contributes significantly to the economic development of Malaysia. Oil palm detection and delineation are important stepping stones for the practice of precision agriculture in the oil palm industry and it could be done so with remote sensing applications. This research aims to develop a semi-automatic, streamlined approach of oil palm detection and delineation using a combination of template matching, local maxima and seeded region growing with Worldview-2 data. The performance of the proposed methods was assessed in various aspects while taking into consideration the different planting conditions, age, and height. The proposed methods of oil palm detection managed to achieve high accuracy with overall precision and recall rate of 83% and 90% respectively and planimetric accuracy of 0.84 m root mean square error. The overall accuracy index is recorded at 71.2%. It was found that different planting conditions affect the detection accuracy to a certain degree where oil palms in optimal planting conditions are the most accurately detected with an accuracy index of 89.5%. Meanwhile, the parameters of age and height were found to have no significant effect on the planimetric accuracy or its positional accuracy. Oil palm delineation scored a high segmentation accuracy with only a 25% error rate. The proposed methods are feasible for oil palm detection with their simple, streamlined and user-friendly features and the application of this approach can be extended to other regions of oil palms with similar conditions.

ABSTRAK

Kelapa sawit (*Elaeis guineensis Jacq*.) telah diiktiraf sebagai tanaman emas dan ia banyak menyumbang kepada pembangunan ekonomi Malaysia. Pengesanan dan penyempadanan pokok kelapa sawit adalah batu loncatan penting bagi amalan pertanian teliti dalam industri kelapa sawit dan boleh dilakukan dengan aplikasi penderiaan jauh. Penyelidikan ini bertujuan untuk membangunkan kaedah pengesanan dan penyempadanan pokok kelapa sawit secara semi-automatik dan garis alir dengan gabungan teknik padanan templat, maksima tempatan dan penumbuhan kawasan pembenihan dengan data Worldview-2. Prestasi kaedah yang dicadangkan dinilai daripada pelbagai aspek dengan mengambil kira keadaan penanaman, usia dan ketinggian. Kaedah yang dicadangkan dalam pengesanan pokok kelapa sawit ini berjaya mencapai ketepatan yang tinggi dengan kejituan keseluruhan dan kadar ingatan masing-masing sebanyak 83% dan 90% serta ketepatan planimetri sebanyak 0.84 m daripada min selisih punca kuasa dua. Indeks ketepatan keseluruhan direkodkan pada 71.2%. Didapati keadaan penanaman yang berbeza memberi kesan kepada ketepatan pengesanan kelapa sawit ke darjah tertentu, di mana kelapa sawit dalam keadaan penanaman yang optimum paling tepat dikesan dengan indeks ketepatan 89.5%. Sementara itu, parameter usia dan ketinggian didapati tidak memberi kesan yang bererti ke atas ketepatan planimetrik atau ketepatan kedudukannya. Sementara itu, penyempadanan kelapa sawit telah mencatat ketepatan segmentasi yang tinggi dengan hanya kadar ralat 25%. Kaedah yang dicadangkan adalah sesuai untuk pengesanan kelapa sawit dengan ciri-cirinya yang mudah, garis alir dan mesra pengguna dan aplikasi kaedah ini boleh diperluas ke kawasan kelapa sawit lain yang mempunyai keadaan yang serupa.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

NDVI	-	Normalized Difference Vegetation Index
GDP	-	Gross Domestic Product
GSD	-	Ground Sample Distance
UAV	-	Unmmaned Aerial Vehicle
MPOB	-	Malaysian Palm Oil Board
RSPO	-	Roundtable of Sustainable Palm Oil
NIR	-	Near Infra-red
LIDAR	-	Light Detection and Ranging
SVM	-	Support Vector Machine
NCC	-	Normalized Cross Correlation
CNN	-	Convolutional Neural Network
GNSS	-	Global Navigation Satellite System
MS	-	Multispectral
Pan	-	Panchromatic
AI	-	Accuracy index
RMSE	-	Root Mean Square Error

LIST OF SYMBOLS

μ	-	Mean
cm	-	Centimeter
nm	-	Nanometer

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Background of Research

The oil palm (*Elaeis Guineensis Jacq.*) is a worldwide commodity known for its vegetable oil, also known as palm oil. Among other major oil crops like soybean, sunflower, rapeseed etc., oil palm has the highest oil yield per area, thus making it a lucrative crop to grow. Oil palm trees are planted commercially at large scale to make use of its high oil-yielding capability. The Malaysian Palm Oil Board (MPOB) (2017) states that 5,811,145 hectares of oil palms covered the land of Malaysia as of December of 2017, which constitutes about 17.68% of 32.86 million hectares total landmass of Malaysia. In the annual Gross Domestic Product (GDP) report published by the Department of Statistics Malaysia, the oil palm industry contributed to the GDP with RM 38,490 million at current prices in 2013, which constitutes of 41.91% share of the agricultural sector, or 3.9% of percentage share of the total GDP (Hasan, 2014).

Palm oil has become one of the major sources of edible oil. According to the trend of global edible oil demand, expansion of oil palm cultivation is inevitable, additional areas of oil palm are forecasted to increase globally by 12 to 19 Mha by 2050 (Corley, 2009). However, in Malaysia, there is only a maximum potential increase of 28% of total oil palm areas (ETP, 2010). Due to the limited land bank in Malaysia, it is important that the land is utilized optimally to achieve highest production possible. In this context, constant monitoring of oil palm is essential to safeguard the production of existing oil palms while progressing towards the evolution of the industry with incorporation of technological advancement like remote sensing.

Researches on oil palm monitoring have been growing in recent decades since oil palm makes a huge impact economically and environmentally. Remote sensing is a handy tool to provide accurate information to monitor oil palm in a sustainable manner. Remote sensing is able to retrieve information from afar without coming into contact with the object of interest (Jensen and Lulla, 1987). By obtaining images of the oil palm plantations from above, valuable information like tree counts, terrain information, yield, palm age, etc. can be derived (Chong et al., 2017). Remote sensing is a stepping stone towards precision agriculture. Many remote sensing applications like land use classification, pest and disease detection, change detection etc. could be carried out for oil palm which will be discussed further in Chapter 2.

As an industrial crop, oil palm trees are planted commercially with standard triangular planting pattern of 9 meters apart to maximize the penetration of sunlight in order to maximize production (Basiron, 2007). This planting pattern, together with the unique shape of oil palm, makes them readily distinguishable from above (Shafri, Hamdan and Saripan, 2011). These characteristics and its importance as a profitable crop, make oil palm to be a frequent subject for object detection studies (Kattenborn et al., 2014; Li et al., 2017; Norzaki and Tahar, 2018; Srestasathiern and Rakwatin, 2014). In those studies, they aimed to detect and delineate oil palms automatically with various image processing techniques, which will be discussed further in Chapter 2.

1.2 Statement of the problem

Tree counting is a costly and a labour-intensive practice to be carried out on field level (Pouliot et al., 2002). In industrial practice of oil palm planting, most plantations have resorted to estimating the figures by multiplying total area with standard planting density (around 148 oil palms per hectare) (Basiron, 2007), which obviously is not accurate due to heterogeneity of the land surface (hilly, undulated or flat) and features (river, land or forest). Therefore, an automatic oil palm counting approach is very much desirable to solve this issue and the information would be invaluable to the plantation’s owner (Kattenborn et al., 2014).

A fully automatic tree counting system does not required user intervention at any stage of processing and it applies to estate of any conditions; while a semi-automatic approach does require user intervention at some stage of processing and the result may affected by different conditions of an estate. At current stage, a fully automated oil palm counting has not yet achievable, while a semi-automatic one is quite feasible and had been much studied (Kattenborn et al., 2014; Shafri et al., 2011; Wong-in et al., 2015). However, most of the approaches are complex and knowledge demanding which are not easily transferable to the actual users, making them less adoptable to the actual commercial practice. There is a lack of simple, accurate and reliable approach which could streamline the whole process of oil palm counting, from detection to delineation.

Delineation of oil palm could help to indicate the size of the individual oil palm crown. It can be performed by object-based image segmentation based on the features of an object like size, shape, and texture (Ahmed et al., 2018). The process segments images into smaller groups with similar features. However, common segmentation techniques introduce noises and overlapping of crowns tend to happen causing oil palm to lose its individuality which highlights the importance of the individual starting seeds (Erikson, 2003; Fan et al., 2005). Seeded region growing in this case reuses the detection result and could potentially produce a more accurate segmentation result, while retaining the identity of individual crowns, provided that the seeds are correctly placed.

In most oil palm detection and delineation studies, the accuracy assessment is often inconclusive and biased as they did not take into consideration of the effect of different planting conditions on an actual setting. This is understandable as different settings could introduce additional errors to their result. Nevertheless, the algorithm should be tested for every situation and every condition so that the result could be evaluated impartially and accepted universally. This way, the weakness of the technique could be learnt and improved upon, and the goal to automatic oil palm counting will be one step closer.

1.3 Objectives of the study

This study aims to devise an efficient way to detect and delineate individual oil palm crowns with high accuracy and lean towards the lower end on the spectrum of complexity. It involved streamlining the process of detection and delineation by using template matching and seeded region growing techniques and providing both information of the oil palm location and crown size in one go. The application of automatic detection and delineation of oil palm is beneficial to both the industry and the environment as it provides crucial information for the decision making of higher management.

Having stated the context and significance of oil palm tree detection and individual delineation, the objectives of this research are as follows:

(a) To develop a semi-automatic, streamlined approach to detect and delineate individual oil palm trees.

(b) To assess the accuracy of the oil palm detection and delineation using different metrics under different planting conditions, age and height.

1.4 Research Questions

From the research background, problem statement and the objectives, the following research questions are drawn:

i. Is a semi-automatic, streamlined oil palm tree detection and delineation applicable?

ii. Do different settings like planting conditions, age and height affect the accuracy of oil palm detection?

1.5 Study Area

The study area of the current research located is located at MPOB Research Station Kluang, Johor. It was established in September 1979 and formerly known as the Palm Oil Research Institute of Malaysia research station. The study site covers an area of 486 ha. It is located 13 km and 115 km from Kluang and Johor Bahru, respectively (see figure 1.1).

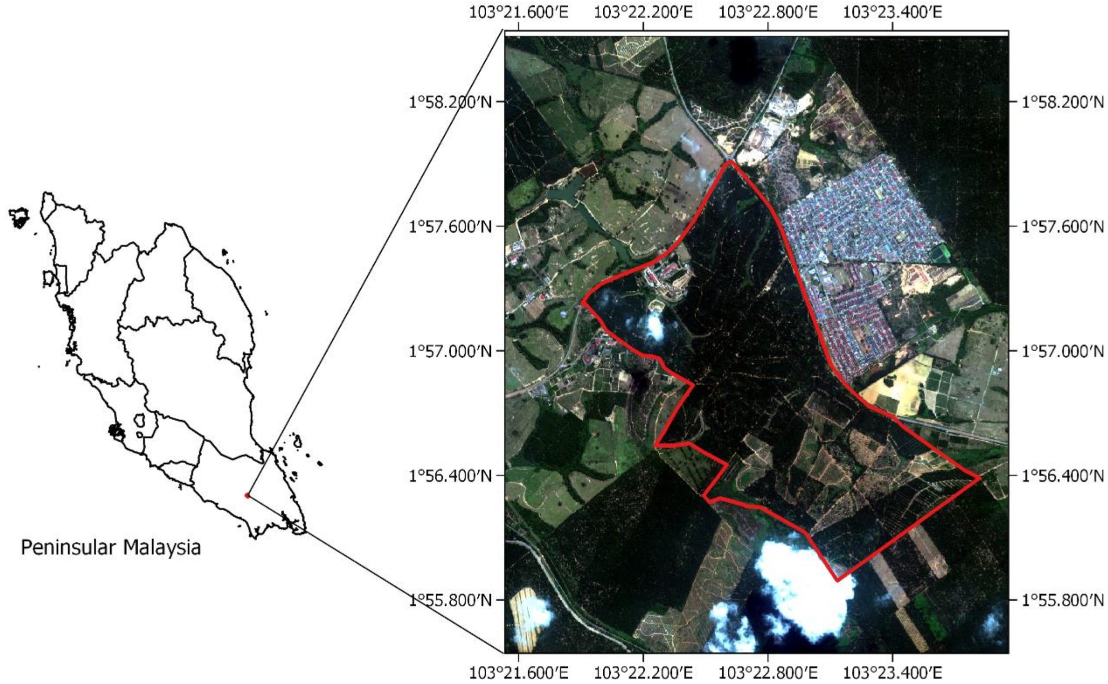

Figure 1.1 Test site of the research station located at Kluang, Johor, Malaysia indicated by red polylines

1.6 Scope of the Study

There are several types of imagery for the application of tree counting. For an accurate result, the oil palm should be discernible on the image and thus a very high resolution imagery of 50 cm ground sample distance (GSD) or higher is required as the ratio of pixel spacing to crown diameter affects the result of object detection in general (Pouliot et al., 2002). This can be taken by low altitude aircraft or UAV.

Currently, many satellites also offer images of this resolution, e.g. WorldView-1, Worldview-2, WorldView-3, GeoEye, Quickbird, etc. These images also come in multiple spectral bands which can further assist in detecting oil palms. This study is tested on a research site (MPOB) in this research (see figure 1.1), where the configuration of planting conditions may differ from the actual commercial plantation, in which the planting conditions will be denser and more uniform.

In the application of object detection techniques, local maxima and template matching were chosen to be applied in oil palm scenario. Both techniques are simple and can be executed quite easily while showing promising result on oil palm and other plantation crops (Larsen et al., 2011; Norzaki et al., 2018). There are several methods of object segmentation techniques. In this study, seeded region growing technique was found to be compatible to the research approach and had been chosen to streamline the detection and delineation process. Region growing techniques are commonly applied for the segmentation of forest trees but has not yet attempted on oil palm delineation (Erikson, 2003). Oil palm develops distinct features on the image which can be effectively delineated using region growing.

1.7 Significance of the study

Oil palm is the dominant and leading vegetable oil crop in the world. It has a global market share of 34% according to impact report released by Roundtable on Sustainable Palm Oil (RSPO) in 2014. Oil palm trees have been planted extensively in Malaysia, which made our country the largest producer of palm oil in the world. Hence, for Malaysia to remain competitive in the palm oil industry, the productivity of oil palms had to be measured and monitored.

Precision agriculture is a key to future management of oil palms as it emphasised on maximum profit with minimum efforts. Oil palm tree detection is a stepping stone for the implementation of precision agriculture as it indicates the precise location of the oil palms and the number of oil palms planted in an area. With this information at hand, precise treatment plan could be derived which includes fertilization program, weeding program, pruning program etc. These site-specific and tree-specific treatments of oil palms can improve yield and reduce costs of maintenance. While eliminating over-spending problems, it reduces the wastage of fertilizers and chemicals (pesticides and herbicides) which is beneficial in terms of environmental protection.

Oil palm detection plays a key role in helping the management of oil palm plantations. It is an important and necessary practice for yield estimation and monitoring, precision agriculture, replanting layout planning, etc. With delineation of individual oil palm, their health condition could be monitored as the size of the crown often indicate the robustness of the oil palm. With their size in check, abnormal oil palm could be pinpointed and thus treatment plan could be derived for these stunted oil palms.

1.8 Organization of chapters

Chapter 1 provides an insight on the research objectives and the motivation of the study. The rest of the thesis are organized in the following structures. Chapter 2 is the review of past literatures on oil palm tree detection and delineation studies as well as other oil palm remote sensing applications on precision agriculture. Chapter 3 is the methodology of the thesis which describes every technique and process in details. Chapter 4 provides the result and discussion of the outcome of this research. Chapter 5 is the conclusion which summarizes the research and offers recommendation for future studies.

REFERENCES

Adams, R., & Bischof, L. (1994). Seeded region growing. *IEEE Transactions on Pattern analysis and machine intelligence, 16*(6), 641-647.

Ahmed, A. A., Pradhan, B., Sameen, M. I., & Makky, A. M. (2018). An optimized object-based analysis for vegetation mapping using integration of Quickbird and Sentinel-1 data. *Arabian Journal of Geosciences, 11*(11), 280. doi:10.1007/s12517-018-3632-1

Aziz, N., Omar, W., Kassim, R., & Kamarudin, N. (2012). Remote Sensing Measurement for Detection of Bagworm Infestation in Oil Palm Plantation. *MPOB Information Series, 589*.

Basiron, Y. (2007). Palm oil production through sustainable plantations. *European Journal of Lipid Science and Technology, 109*(4), 289-295. doi:10.1002/ejlt.200600223

Briechle, K., & Hanebeck, U. D. (2001). Template matching using fast normalized cross correlation. *Proc. SPIE 4387 on Optical Pattern Recognition XII.* March 20, 2001. Orlando, FL, United States. doi:10.1117/12.421129

Candiago, S., Remondino, F., De Giglio, M., Dubbini, M., & Gattelli, M. (2015). Evaluating multispectral images and vegetation indices for precision farming applications from UAV images. *Remote Sensing, 7*(4), 4026-4047.

Cheevasuvit, F., Maitre, H., & Vidal-Madjar, D. (1986). A robust method for picture segmentation based on a split-and-merge procedure. *Computer Vision, Graphics, and Image Processing, 34*(3), 268-281.

Chemura, A., van Duren, I., & van Leeuwen, L. M. (2015). Determination of the age of oil palm from crown projection area detected from WorldView-2 multispectral remote sensing data: The case of Ejisu-Juaben district, Ghana. *ISPRS Journal of Photogrammetry and Remote Sensing, 100*(0), 118-127. doi:10.1016/j.isprsjprs.2014.07.013

Cheng, Y., Yu, L., Xu, Y., Liu, X., Lu, H., Cracknell, A. P., Kanniah, K., & Gong, P. (2018). Towards global oil palm plantation mapping using remote-sensing data. *International Journal of Remote Sensing, 39*(18), 5891-5906. doi:10.1080/01431161.2018.1492182

Chong, K. L., Kanniah, K. D., Pohl, C., & Tan, K. P. (2017). A review of remote sensing applications for oil palm studies. *Geo-Spatial Information Science, 20*(2), 184-200. doi:10.1080/10095020.2017.1337317

Chong, K.-P., & Alexander, A. (2016). Early detection and management of ganoderma basal stem rot disease: a special report from Sabah. *Transactions on Science and Technology, 3*(3), 517-523.

Chung, G. F. (2012). 6 - Effect of Pests and Diseases on Oil Palm Yield. In O.-M. Lai, C.-P. Tan, & C. C. Akoh (Eds.), *Palm Oil* (pp. 163-210): AOCS Press.

Clinton, N., Holt, A., Scarborough, J., Yan, L., & Gong, P. (2010). Accuracy Assessment Measures for Object-based Image Segmentation Goodness. *Photogrammetric Engineering & Remote Sensing, 76*(3), 289-299. doi:10.14358/PERS.76.3.289

Clinton, N., Holt, A., Scarborough, J., Yan, L., & Gong, P. (2010). Accuracy Assessment Measures for Object-based Image Segmentation Goodness. *Photogrammetric Engineering & Remote Sensing, 76*(3), 289-299. doi:10.14358/PERS.76.3.289

Corley, R. H. V. (2009). How much palm oil do we need?. *Environmental Science & Policy, 12*(2), 134-139. doi:10.1016/j.envsci.2008.10.011

De Alban, J., Connette, G., Oswald, P., & Webb, E. (2018). Combined Landsat and L-Band SAR Data Improves Land Cover Classification and Change Detection in Dynamic Tropical Landscapes. *Remote Sensing, 10*(2), 306. doi:10.3390/rs10020306

Dong, X., Quegan, S., Yumiko, U., Hu, C., & Zeng, T. (2015). Feasibility Study of C- and L-band SAR Time Series Data in Tracking Indonesian Plantation and Natural Forest Cover Changes. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 8*(7), 3692-3699. doi:10.1109/JSTARS.2015.2400439

Edwards, D. P., Hodgson, J. A., Hamer, K. C., Mitchell, S. L., Ahmad, A. H., Cornell, S. J., & Wilcove, D. S. (2010). Wildlife-friendly oil palm plantations fail to protect biodiversity effectively. *Conservation Letters, 3*(4), 236-242.

Erikson, M. (2003). Segmentation of individual tree crowns in colour aerial photographs using region growing supported by fuzzy rules. *Canadian Journal of Forest Research, 33*(8), 1557-1563. doi:10.1139/x03-062

ETP. (2010). Economic Ttransformation Programme (ETP). *Handbook Chapter 9 - Roadmap of Malaysia Palm Oil Industry*.

Eynck, C., Shrestha, D., Vollmann, J., Falk, K. C., Friedt, W., Singh, H. P., & Obeng, E. (2013). Sustainable Oil Crops Production. *Biofuel Crop Sustainability* (pp. 165-204): John Wiley and Sons.

Fairhurst, T., Rankine, I., Kerstan, A. G., McAleer, V., Taylor, C., & Griffiths, W. (2003). A conceptual framework for precision agriculture in oil palm plantations. *Oil Palm: Management for Large and Sustainable Yields, PPI-PPIC-IPI*, 321-332.

Fan, J., Zeng, G., Body, M., & Hacid, M.-S. (2005). Seeded region growing: an extensive and comparative study. *Pattern Recognition Letters, 26*(8), 1139-1156. doi:10.1016/j.patrec.2004.10.010

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. doi:10.1016/j.tree.2008.06.012

Glinskis, E. A., & Gutiérrez-Vélez, V. H. (2019). Quantifying and understanding land cover changes by large and small oil palm expansion regimes in the Peruvian Amazon. *Land Use Policy, 80*, 95-106. doi:10.1016/j.landusepol.2018.09.032

Hasan, A. R. (2014). *Annual Gross Domestic Product 2005-2013*. Malaysia.

Hu, Y., Tao, V., & Croitoru, A. (2004). Understanding the rational function model: methods and applications. *International archives of photogrammetry and remote sensing,* 20(6), 663-668.

Izzuddin, M., Idris, A., Wahid, O., Nishfariza, M., & Shafri, H. (2013). Field spectroscopy for detection of Ganoderma disease in oil palm. *MPOB Information Series, 532*(4).

Jensen, J. R., & Lulla, K. (1987). Introductory digital image processing: a remote sensing perspective. *Geocarto International,* 2(1), p. 65. doi:10.1080/10106048709354084

Kattenborn, T., Sperlich, M., Bataua, K., & Koch, B. (2014). Automatic Single Tree Detection in Plantations using UAV-based Photogrammetric Point clouds. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XL-3*, 139-144. doi:10.5194/isprsarchives-XL-3-139-2014

Ke, Y., & Quackenbush, L. J. (2011). A review of methods for automatic individual tree-crown detection and delineation from passive remote sensing. *International Journal of Remote Sensing, 32*(17), 4725-4747. doi:10.1080/01431161.2010.494184

Kee, Y. W., Shariff, A. R. M., Sood, A. M., & Nordin, L. (2018). Application of SAR data for oil palm tree discrimination. *IOP Conference Series: Earth and Environmental Science, 169*, 012065. doi:10.1088/1755-1315/169/1/012065

Khosrokhani, M., Khairunniza-Bejo, S., & Pradhan, B. (2018). Geospatial technologies for detection and monitoring of Ganoderma basal stem rot infection in oil palm plantations: a review on sensors and techniques. *Geocarto International, 33*(3), 260-276. doi:10.1080/10106049.2016.1243410

Laben, C. A., & Brower, B. V. (2000). Process for enhancing the spatial resolution of multispectral imagery using pan-sharpening: Google Patents.

Larsen, M., Eriksson, M., Descombes, X., Perrin, G., Brandtberg, T., & Gougeon, F. A. (2011). Comparison of six individual tree crown detection algorithms evaluated under varying forest conditions. *International Journal of Remote Sensing, 32*(20), 5827-5852. doi:10.1080/01431161.2010.507790

Laurance, W. F., Koh, L. P., Butler, R., Sodhi, N. S., Bradshaw, C. J., Neidel, J. D., Consunji, H., & Vega, J. M. (2010). Improving the performance of the roundtable on sustainable palm oil for nature conservation. *Conservation Biology*, *24*(2), 377-381.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*, 436. doi:10.1038/nature14539

Levine, M. D., & Nazif, A. (1982). An experimental rule-based system for testing low level segmentation strategies. *Multicomputers and Image Processing: Algorithms and Programs*, 149-160.

Li, H., Jing, L., & Tang, Y. (2017). Assessment of Pansharpening Methods Applied to WorldView-2 Imagery Fusion. *Sensors*, *17*(1), 89. doi:10.3390/s17010089

Li, L., Dong, J., Njeudeng Tenku, S., & Xiao, X. (2015). Mapping Oil Palm Plantations in Cameroon Using PALSAR 50-m Orthorectified Mosaic Images. *Remote Sensing, 7*(2), 1206-1224. doi:10.3390/rs70201206

Li, W., Dong, R., Fu, H., & Yu, L. (2018). Large-Scale Oil Palm Tree Detection from High-Resolution Satellite Images Using Two-Stage Convolutional Neural Networks. *Remote Sensing, 11*(1), 11. doi:10.3390/rs11010011

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. doi:10.3390/rs9010022

Liaghat, S., & Balasundram, S. K. (2010). A review: The role of remote sensing in precision agriculture. *American journal of agricultural and biological sciences, 5*(1), 50-55.

Lim, K., Treitz, P., Wulder, M., St-Onge, B., & Flood, M. (2003). LiDAR remote sensing of forest structure. *Progress in Physical Geography, 27*(1), 88-106.

Liu, T., Yuan, Z., Sun, J., Wang, J., Zheng, N., Tang, X., & Shum, H.-Y. (2011). Learning to detect a salient object. *IEEE Transactions on Pattern analysis and machine intelligence, 33*(2), 353-367.

Loh, S. K., Azman, I., Hishamuddin, E., Ong-Abdullah, M., Razmah, G., & Sundram, S. (2018). Oil palm economic performance in Malaysia and R & D progress in 2017. *Journal of Oil Palm Research*, *30*(2), 163-195.

MPOB (2017). Oil Palm Planted Area 2017. *Economics and Industry Development Division, Malaysia Palm Oil Board.* Retrieved from http://bepi.mpob.gov.my/images/area/2017/Area_summary.pdf.

Manandhar, A., Hoegner, L., & Stilla, U. (2016). Palm tree detection using circular autocorrelation of polar shape matrix. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences, 3*, 465-472.

McBratney, A., Whelan, B., Ancev, T., & Bouma, J. (2005). Future directions of precision agriculture. *Precision Agriculture, 6*(1), 7-23.

Mehnert, A., & Jackway, P. (1997). An improved seeded region growing algorithm. *Pattern Recognition Letters, 18*(10), 1065-1071. doi:10.1016/S0167-8655(97)00131-1

Norzaki, N., & Tahar, K. N. (2018). A comparative study of template matching, ISO cluster segmentation, and tree canopy segmentation for homogeneous tree counting. *International Journal of Remote Sensing*, 1-23. doi:10.1080/01431161.2018.1524182

Oil World (2016). Global Palm Oil Production 2015. from ISTA Mielke GmbH

Padwick, C., Deskevich, M., Pacifici, F., & Smallwood, S. (2010). WorldView-2 pan-sharpening. *Proceedings of the ASPRS 2010 Annual Conference*. April 26-30, 2010. San Diego, CA, USA.

Phillips, T.-Y., Rosenfeld, A., & Sher, A. C. (1989). O(log n) bimodality analysis. *Pattern Recognition, 22*(6), 741-746. doi:10.1016/0031-3203(89)90010-1

Phua, M. -H., Chong, C. W., Ahmad, A. H., & Hafidzi, M. N. (2017). Understanding rat occurrences in oil palm plantation using high-resolution satellite image and GIS data. *Precision Agriculture, 19,* 42–54. doi:10.1007/s11119-016-9496-z

Pohl, C., & Loong, C. K. (2016). In-situ data collection for oil palm tree height determination using synthetic aperture radar. *IOP Conference Series: Earth and Environmental Science, 34,* 012027. doi:10.1088/1755-1315/34/1/012027

Pouliot, D. A., King, D. J., Bell, F. W., & Pitt, D. G. (2002). Automated tree crown detection and delineation in high-resolution digital camera imagery of coniferous forest regeneration. *Remote Sensing of Environment, 82*(2–3), 322-334. doi:10.1016/S0034-4257(02)00050-0

Pouliot, D., & King, D. (2005). Approaches for optimal automated individual tree crown detection in regenerating coniferous forests. *Canadian Journal of Remote Sensing, 31*(3), 255-267.

Rendana, M., Rahim, S. A., Lihan, T., Idris, W. M. R., & Rahman, Z. A. (2015). A Review of Methods for Detecting Nutrient Stress of Oil Palm in Malaysia. *J. Appl. Environ. Biol. Sci, 5*(6), 60-64.

Rizeei, H. M., Shafri, H. Z. M., Mohamoud, M. A., Pradhan, B., & Kalantar, B. (2018). Oil Palm Counting and Age Estimation from WorldView-3 Imagery and LiDAR Data Using an Integrated OBIA Height Model and Regression Analysis. *Journal of Sensors, 2018,* 13. doi:10.1155/2018/2536327

Santoso, H., Gunawan, T., Jatmiko, R. H., Darmosarkoro, W., & Minasny, B. (2011). Mapping and identifying basal stem rot disease in oil palms in North Sumatra with QuickBird imagery. *Precision Agriculture, 12*(2), 233-248. doi:10.1007/s11119-010-9172-7

Selvaraja, S., Balasundram, S., Vadamalai, G., & Husni, M. (2013). Use of spectral reflectance to discriminate between potassium deficiency and orange spotting symptoms in oil palm (Elaeis guineensis). *Life Science Journal, 10*(4), 947-951.

Shafri, H. Z. M., Anuar, M. I., Seman, I. A., & Noor, N. M. (2011). Spectral discrimination of healthy and Ganoderma-infected oil palms from hyperspectral data. *International Journal of Remote Sensing, 32*(22), 7111-7129. doi:10.1080/01431161.2010.519003

Shafri, H. Z. M., Hamdan, N., & Izzuddin Anuar, M. (2012). Detection of stressed oil palms from an airborne sensor using optimized spectral indices. *International Journal of Remote Sensing, 33*(14), 4293-4311. doi:10.1080/01431161.2011.619208

Shafri, H. Z. M., Hamdan, N., & Saripan, M. I. (2011). Semi-automatic detection and counting of oil palm trees from high spatial resolution airborne imagery. *International Journal of Remote Sensing, 32*(8), 2095-2115. doi:10.1080/01431161003662928

Srestasathiern, P., & Rakwatin, P. (2014). Oil Palm Tree Detection with High Resolution Multi-Spectral Satellite Imagery. *Remote Sensing, 6*(10), 9749-9774. doi:10.3390/rs6109749

Tan, K. T., Lee, K. T., Mohamed, A. R., & Bhatia, S. (2009). Palm oil: Addressing issues and towards sustainable development. *Renewable and Sustainable Energy Reviews, 13*(2), 420-427. doi:10.1016/j.rser.2007.10.001

Teillet, P. M. (1986). Image correction for radiometric effects in remote sensing. *International Journal of Remote Sensing, 7*(12), 1637-1651. doi:10.1080/01431168608948958

Ulaby, F. T., Moore, R. K. and Fung, A. K. (1981) Microwave remote sensing: active and passive. Volume I: Microwave remote sensing fundamentals and radiometry. *Addison-Wesley Publishing Company Advanced Book Program/ World Science Division*. Lawrence, KS, United States: Kansas Univ.

Uuttera, J., Haara, A., Tokola, T., & Maltamo, M. (1998). Determination of the spatial distribution of trees from digital aerial photographs. *Forest Ecology and Management, 110*(1), 275-282. doi:10.1016/S0378-1127(98)00292-8

Waser, L., Küchler, M., Jütte, K., & Stampfer, T. (2014). Evaluating the potential of WorldView-2 data to classify tree species and different levels of ash mortality. *Remote Sensing, 6*(5), 4515-4545.

Weng, C. K. (2005). Best-developed practices and sustainable development of the oil palm industry. *Journal of Oil Palm Research, 17*(C), 124.

Wong-in, T., Kaewkongka, T., Cooharojananone, N., & Lipikorn, R. (2015). Automatic Oil Palm Detection and Identification from Multi-scale Clustering and Normalized Cross Correlation. In M. Gen, J. K. Kim, X. Huang, & Y. Hiroshi (Eds.), *Industrial Engineering, Management Science and Applications 2015* (pp. 403-410). Berlin, Heidelberg: Springer Berlin Heidelberg.

Appendix A R codes for tree detection and delineation

```
##template matching
library(raster)
library(rgdal)
library(rgeos)
library(sp)

#creating template

a <- raster(file.choose(),band=1)
b<-zoom(a)
r<-crop(a,b)
plot(r)
d<-click(r,xy=T,id=T) #finding oil palm manually
df1<-d[1:2]
df2<-df1+5
df3<-df1-5
df4<- cbind(df3$x,df2$x,df3$y,df2$y)

op_temp<-NULL
for(x in (1:nrow(df4))){
  op_temp<-c(op_temp,crop(c,extent(df4[x,])))
}

#finding mean template
op_temp_raster <- list(op1,op2,op3,…)
op_temp_mat_all <- lapply(op_temp_raster,as.matrix)
op_temp_mean <- raster(Reduce('+',op_temp_mat_all/length(op_temp_raster)))

#moving template with NCC

mov_win_FNCC_fm<- function(X,px){ #X is the raster object
  j<-1
  temp <- op_temp_mean_mat_19px[(1+(19-px)/2):(19-(19-px)/2),(1+(19-px)/2):(19-
(19-px)/2)]
  zerotemp<- temp-mean(temp)
  zerotempsq<- (temp-mean(temp))^2
  v<-NULL
  while ((j+(px-1))<nrow(X)){
    i<-1
    r<-NULL
    while ((i+(px-1))<ncol(X)){
      im <-X[j:(j+(px-1)),i:(i+(px-1))]
      if(!anyNA(im)){
        tab1 <- sum(im)
        tab2 <- sum(im^2)
        nom <-sum((im-mean(im))*(zerotemp))
        deno <-sqrt((tab2-(1/ncell(im))*(tab1)^2)*(sum(zerotempsq)))
```

```
        cv<- nom/deno
        r<-c(r,cv)
      }
      i<-i+1
    }
    j<- j+1
    v<-rbind(v,r)
  }
  xymn<- xyFromCell(X,cellFromRowCol(X,(px+1)/2,(px+1)/2))
  xymx<- xyFromCell(X,cellFromRowCol(X,nrow(X)-((px-1)/2),ncol(X)-((px-
1)/2)))

return(raster(v,xmn=xymn[1],xmx=xymx[1],ymn=xymx[2],ymx=xymn[2],crs=crs(X
)))
}

##local maxima
library(raster)
library(rgdal)
library(sp)

c<- raster(file.choose(),band=1)
f<- function(X) max(X, na.rm=T)
localmax <- focal(c, fun=f, w=matrix(1,nc=17,nr=17), pad=TRUE, padValue=NA)

c1 <- c==localmax

e <- rasterToPoints(c1,fun=function(x) (x==1), spatial=T)
h <- remove.duplicates(e,zero=2.3,remove.second=T)h
writeOGR(h,dsn=getwd(),layer='op_points_5',driver='ESRI Shapefile')

## seeded region growing
library(raster)
library(rgdal)
library(rgeos)
rggw <- function(a,sp,fd){
  # a is the raster objects;
  # sp is the point layers/ seeds;
  # fd= simliarity threshold fisher distance

  ####parameter####
  pixmax = 145 #145 for 7th iteration
  t3 = 3500 #threshold for non oil palm pixel value; on b layer (nirband range 1500-
4500)
  t4 = 1500 #max-min
  #################
  point_mat<-NULL
  df<-NULL
  defcrs<-crs(sp)
  treenum<-0
```

```
  for (j in (1:length(sp))){
    # extracting value of seed cell
    seed_coord<- coordinates(sp)[j,]
    seed_cell<- cellFromXY(a,seed_coord)
    seed_value<- extract(a,seed_cell) #nir band
    adjcell_vec<- adjacent(a,seed_cell,directions=4,sorted=T,pairs=F,include=T)
    reg_member<-adjcell_vec
    iter<-1

    # circularity
    # convexity/laplacian

    if (is.na(seed_value)){
      next
    }
    if (seed_value<t3){
      next
    }
    else{
      if(seed_value>3800){
        t2<- iter*36.1-15 # 29.182*exp(0.3211*iter) ##intra-segment std deviation
(minimum)# follow units on nir band
        t4<- 1000
      }
      if(seed_value>4000){
        t2<- iter*36.1+40 # 29.182*exp(0.3211*iter) ##intra-segment std deviation
(minimum)# follow units on nir band
        t4<-1500
      }
      if(seed_value>4200){
        t2<- iter*36.1+60 # 29.182*exp(0.3211*iter) ##intra-segment std deviation
(minimum)# follow units on nir band
        t4<-1800
      }
      if(seed_value>4500){
        t2<- iter*45+100 # 29.182*exp(0.3211*iter) ##intra-segment std deviation
(minimum)# follow units on nir band
        t4<-2000
      }
      while
((sd(extract(a,reg_member),na.rm=T)<t2)&(ncell(reg_member)<pixmax)&(iter<10)
&
             ((max(extract(a,reg_member),na.rm=T)-
min(extract(a,reg_member),na.rm=T))<t4)){
        adjcell_vec<- adjacent(a,reg_member,directions=8,sorted=T,pairs=F,include=T)
        adjcell_vec<- adjcell_vec[!adjcell_vec %in% reg_member]
        regionmean<- mean(extract(a,reg_member),na.rm=T)
        regionsd<-(sd(extract(a,reg_member),na.rm=T))
        for (i in 1:length(adjcell_vec)){
          if (is.na(extract(a,adjcell_vec[i]))){
```

```
          next
        }
        if (extract(a,adjcell_vec[i])<t3){
          next
        }
        # if (((extract(a,adjcell_vec[i])-mean(extract(a,reg_member),na.rm=T))^2)/
        #     (var(extract(a,reg_member),na.rm=T))<fd){ ####
        if (((abs(extract(a,adjcell_vec[i])-regionmean))/regionsd)<fd){ ####
          reg_member<- c(reg_member,adjcell_vec[i])
        }
        else{
        }
      }
      iter<- iter+1
      #print(ttt)
    }
  }
  treenum<-treenum+1
  cat(treenum)
  point<- xyFromCell(a,reg_member)
  point_mat<- rbind(point_mat,point)
  df<-rbind(df,matrix(replicate(nrow(point),treenum),byrow=T))
  ##reg_trees[j]<-list(point)
 }
 sp_trees<-
SpatialPointsDataFrame(point_mat,data=data.frame(df,row.names=NULL),
proj4string=defcrs)
 return(sp_trees)
 #return(rasterize(sp_trees,a))
}

polygonize<- function(X,Y){  ##X is list of coordinates, Y is SPdf
 poly<-list()
 defcrs<- crs(Y)
 poly1<-lapply(X,Polygon)
 for (i in 1:length(X)) {
  poly[i]<- Polygons(poly1[i], ID=paste('polygon',i,sep=''))
 }
 df=data.frame(rep(1,length(X)))
 SP<- SpatialPolygons(poly,proj4string=crs(defcrs))
 return(SpatialPolygonsDataFrame(SP,data=df,match.ID=F))
}
```

Appendix B Calculation of planimetric accuracy using ground reference data and detection result

Reference ID	Longitude, (P_g)	Latitude, (P_g)	Detect ID	Longitude, (P_d)	Latitude, (P_d)	Distance Error (D), m	D-squared, m^2
1407	103.3851906	1.9410789	78	103.3851918	1.9410843	0.61	0.37
1402	103.3853242	1.9410344	79	103.3853222	1.9410393	0.58	0.34
1503	103.3797677	1.9414165	74	103.3797716	1.9414137	0.52	0.27
1606	103.3793538	1.941686	66	103.3793489	1.9416801	0.85	0.71
1604	103.3793506	1.9418419	64	103.3793442	1.9418429	0.72	0.52
1505	103.3797023	1.9414587	72	103.3797041	1.9414544	0.52	0.27
1409	103.3851416	1.9409282	77	103.385147	1.940926	0.65	0.42
1701	103.3796877	1.9423717	59	103.3796898	1.9423678	0.49	0.24
1608	103.3792875	1.9417203	65	103.3792814	1.9417162	0.81	0.66
1508	103.3796369	1.9414124	73	103.3796502	1.9414136	1.49	2.22
1702	103.3796905	1.9422817	58	103.3796943	1.9422818	0.43	0.19
1509	103.3796423	1.9413266	76	103.3796413	1.9413232	0.40	0.16
1506	103.3797078	1.9413756	75	103.3796997	1.9413775	0.92	0.85
1504	103.3797009	1.9415378	69	103.379704	1.9415403	0.44	0.20
1507	103.3796355	1.941501	70	103.3796322	1.9414995	0.41	0.16
1502	103.3797691	1.9414928	71	103.379776	1.9414906	0.80	0.64
1607	103.379282	1.9418001	62	103.3792813	1.9418067	0.73	0.54
1501	103.3797677	1.9415775	68	103.3797669	1.9415856	0.90	0.81
1601	103.3794192	1.9418835	67	103.3794206	1.9418927	1.03	1.06
1602	103.3794141	1.9418038	63	103.3794207	1.9417978	1.00	0.99
1707	103.3795555	1.9422954	60	103.379555	1.9422908	0.51	0.26
1704	103.3796223	1.9423281	57	103.3796224	1.942327	0.12	0.01
1708	103.3795596	1.9422123	55	103.3795551	1.9422094	0.59	0.35
1703	103.3796959	1.9422027	56	103.3796944	1.942214	1.26	1.59
1705	103.3796264	1.9422518	61	103.3796315	1.9422456	0.88	0.78
607	103.3739343	1.9591382	95	103.3739302	1.9591335	0.70	0.49
2202	103.3733939	1.956297	3	103.3733891	1.9563113	1.68	2.81
2201	103.3733913	1.9563702	1	103.373389	1.9563792	1.02	1.05
2204	103.3733246	1.9563297	2	103.3733261	1.9563384	0.98	0.96
2104	103.372866	1.9559293	11	103.3728681	1.95594	1.21	1.47
2109	103.3728148	1.9557102	18	103.3728189	1.955723	1.48	2.19
2203	103.3734044	1.9562081	6	103.3734116	1.9562209	1.63	2.66
2102	103.3729327	1.9558874	13	103.3729356	1.9558949	0.88	0.78
2105	103.3728739	1.9558521	14	103.3728817	1.9558587	1.13	1.28
2101	103.3729223	1.9559737	10	103.372931	1.9559808	1.25	1.56
2205	103.3733325	1.9562552	5	103.3733352	1.956257	0.37	0.14
605	103.3739932	1.9591081	96	103.3739886	1.9591019	0.86	0.74
2009	103.3722009	1.9553905	88	103.3722035	1.9554013	1.23	1.51

2209	103.3732684	1.9561218	9	103.3732724	1.9561213	0.46	0.21
709	103.3803436	1.9541889	27	103.3803481	1.9541884	0.50	0.25
2206	103.3733416	1.9561689	8	103.3733443	1.9561756	0.81	0.65
2106	103.3728734	1.9557523	17	103.3728773	1.9557637	1.33	1.77
2207	103.3732618	1.9562878	4	103.3732543	1.9562886	0.84	0.71
2107	103.3727967	1.9558848	12	103.3727918	1.9558948	1.23	1.51
2008	103.3721953	1.9554737	85	103.3721944	1.9554827	1.00	0.99
2006	103.3722703	1.9554404	87	103.3722664	1.9554375	0.54	0.29
1307	103.3894637	1.9441698	48	103.3894628	1.9441723	0.29	0.09
601	103.3740612	1.9592166	93	103.3740694	1.959215	0.93	0.87
603	103.3740677	1.9590611	94	103.3740696	1.9590522	1.00	1.00
2005	103.372261	1.9555131	84	103.3722573	1.9555144	0.43	0.18
2007	103.372187	1.9555541	83	103.3721809	1.9555505	0.79	0.63
2003	103.3723369	1.955482	86	103.3723338	1.9554828	0.36	0.13
706	103.3804164	1.9542177	26	103.3804245	1.9542201	0.94	0.88
2103	103.3729442	1.9558203	15	103.3729491	1.9558271	0.93	0.87
2001	103.3723237	1.9556497	80	103.3723291	1.9556546	0.81	0.65
2004	103.3722592	1.9556041	81	103.3722572	1.9556003	0.47	0.22
609	103.3739278	1.9589879	91	103.3739303	1.9589888	0.30	0.09
2208	103.3732684	1.9562068	7	103.3732678	1.9562072	0.07	0.01
2108	103.3728059	1.9558011	16	103.3728053	1.9558043	0.36	0.13
806	103.3761849	1.9470001	104	103.3761844	1.9469947	0.61	0.37
1302	103.3896078	1.9441664	49	103.3896066	1.9441679	0.21	0.04
2002	103.3723285	1.955568	82	103.3723337	1.9555733	0.82	0.66
708	103.3803431	1.9542535	24	103.380348	1.9542517	0.59	0.35
703	103.3804895	1.9542506	25	103.3804918	1.9542518	0.29	0.08
803	103.3762333	1.9470558	103	103.3762383	1.947058	0.61	0.37
1303	103.3896006	1.9440759	52	103.3895977	1.9440775	0.37	0.13
1008	103.3778405	1.9497206	33	103.3778356	1.949732	1.37	1.87
809	103.3761232	1.9469494	105	103.3761215	1.9469539	0.53	0.28
804	103.3761742	1.9471851	98	103.3761752	1.9471846	0.13	0.02
704	103.3804205	1.9543765	20	103.3804198	1.9543829	0.71	0.50
1006	103.3779047	1.9496705	35	103.3779121	1.9496642	1.08	1.16
807	103.3761147	1.9471549	99	103.3761078	1.9471664	1.49	2.22
604	103.3739919	1.9591853	90	103.373993	1.9591923	0.79	0.62
802	103.3762468	1.9471521	100	103.3762427	1.9471485	0.60	0.36
1304	103.3895401	1.9442146	47	103.3895437	1.9442221	0.92	0.85
701	103.3804891	1.9544011	19	103.3805007	1.954401	1.29	1.65
1003	103.3779717	1.9497127	34	103.3779705	1.949714	0.20	0.04
805	103.376176	1.9471114	101	103.3761753	1.9471168	0.59	0.35
1305	103.3895325	1.944119	50	103.3895303	1.9441226	0.48	0.23
1007	103.3778372	1.9498118	30	103.3778356	1.9498133	0.25	0.06
1004	103.37791	1.94985	29	103.3779074	1.9498586	0.99	0.99
1005	103.3779089	1.949741	32	103.377912	1.9497411	0.35	0.12
608	103.3739317	1.959065	89	103.3739302	1.9590702	0.59	0.35

1308	103.3894571	1.9440851	51	103.3894539	1.9440864	0.38	0.15
1309	103.3894545	1.9440016	54	103.3894405	1.9440005	1.57	2.45
801	103.3762486	1.9472296	97	103.3762426	1.9472299	0.67	0.45
1306	103.3895271	1.9440309	53	103.3895214	1.9440277	0.73	0.53
702	103.3804835	1.9543162	22	103.3804783	1.9543241	1.05	1.11
707	103.3803431	1.9543339	21	103.3803524	1.9543376	1.12	1.25
1009	103.3778378	1.9496396	36	103.3778312	1.9496415	0.76	0.58
808	103.3761148	1.9470653	102	103.3760989	1.9470715	1.89	3.59
1001	103.3779777	1.9498843	28	103.3779748	1.9498813	0.46	0.22
1002	103.3779755	1.9498092	31	103.3779749	1.9498135	0.48	0.23
1301	103.3896115	1.9442458	46	103.3896155	1.9442448	0.46	0.21
606	103.3739958	1.9590284	92	103.3739932	1.9590205	0.92	0.85
705	103.3804085	1.9542848	23	103.3804109	1.9542924	0.88	0.77
1209	103.3850028	1.9475914	45	103.3850014	1.947591	0.17	0.03
1206	103.3851215	1.9476707	44	103.3851226	1.947668	0.32	0.10
1208	103.3850543	1.9477125	43	103.3850552	1.9477132	0.13	0.02
1203	103.3851851	1.9477234	42	103.38519	1.9477223	0.55	0.31
1202	103.3851906	1.9478033	40	103.3851899	1.9478083	0.55	0.31
1205	103.3851215	1.9477633	41	103.385127	1.9477675	0.77	0.59
1207	103.3850561	1.9478087	39	103.3850551	1.9478217	1.44	2.06
1201	103.3851924	1.9478887	37	103.3851898	1.9478942	0.67	0.45
1204	103.3851197	1.9478451	38	103.385118	1.9478398	0.61	0.37
						Sum	74.69
						Average	0.71
						RMSE:	0.84

LIST OF PUBLICATIONS

Indexed Journal

1. **Chong, K. L.**, Kanniah, K. D., Pohl, C., & Tan, K. P. (2017). A review of remote sensing applications for oil palm studies. *Geo-spatial Information Science*, 20(2), 184-200. **(Indexed by SCOPUS)**

Indexed Conference Proceedings

1. Pohl, C., & **Chong, K. L.** (2016). In-situ data collection for oil palm tree height determination using synthetic aperture radar. In *IOP Conference Series: Earth and Environmental Science* (Vol. 34, No. 1, p. 012027). IOP Publishing. **(Indexed by SCOPUS)**

Non-indexed Conference Proceedings

1. Pohl, C., **Chong, K. L.**, & van Genderen, J. (2015). Multisensor Approach to Oil Palm Plantation Monitoring Using Data Fusion and GIS. In *36th Asian Conference on Remote Sensing 'Fostering Resiient Growth in Asia'*, Manila, Philippines.