



HOKKAIDO UNIVERSITY

Title	A simple method for detection and counting of oil palm trees using high-resolution multispectral satellite imagery
Author(s)	Santoso, Heri; Tani, Hiroshi; Wang, Xiufeng
Citation	International journal of remote sensing, 37(21), 5122-5134 https://doi.org/10.1080/01431161.2016.1226527
Issue Date	2016-11
Doc URL	https://hdl.handle.net/2115/67153
Rights	This is an Accepted Manuscript of an article published by Taylor & Francis in International Journal of Remote Sensing on Published online: 23 Sep 2016, available online: http://www.tandfonline.com/10.1080/01431161.2016.1226527 .
Type	journal article
File Information	Int. J. Remote Sens.37-21_5122-5134.pdf



**A simple method for detection and counting of oil palm trees using
high resolution multispectral satellite imagery**

Heri Santoso ^{a, b, *}, Hiroshi Tani ^c, Xiufeng Wang ^c

^a Indonesian Oil Palm Research Institute, Medan 20158 Indonesia;

^b Graduate School of Agriculture, Hokkaido University, Sapporo 060-8589 Japan

^c Research Faculty of Agriculture, Hokkaido University, Sapporo 060-8589 Japan

* Corresponding author: heri@env.agr.hokudai.ac.jp; hs_jmp@yahoo.com.

Phone: +8111-706-3659

*This is an Accepted Manuscript of an article published by Taylor & Francis Group
in International Journal of Remote Sensing on 23/09/2016, available
online: <http://dx.doi.org/10.1080/01431161.2016.1226527>*

A simple method for detection and counting of oil palm trees using high resolution of multispectral satellite imagery

Abstract

In the past, oil palm density has been determined by manually counting trees every year in oil palm plantations. The measurement of density provides important data related to palm productivity, fertilizer needed, weed control costs in a circle around each tree, labourers needed and needs for other activities. Manual counting requires many workers and has potential problems related to accuracy. Remote sensing provides a potential approach for counting oil palm trees. The main objective of this study is to build a robust and user-friendly method that will allow oil palm managers to count oil palm trees using a remote sensing technique. The oil palm trees analysed in this study have different ages and densities. QuickBird imagery was applied with the six pansharpening methods and was compared with panchromatic QuickBird imagery. The black and white imagery from a false colour composite of pansharpening imagery was processed in three ways: (1) oil palm tree detection, (2) delineation of the oil palm area using the red band, and (3) counting oil palm trees and accuracy assessment. For oil palm detection, we used several filters that contained a Sobel edge detector, texture analysis co-occurrence, and dilate, erode, high-pass, and opening filters. The results of this study improved upon the accuracy of several previous research studies that had an accuracy of about 90–95%. The results in this study show (1) modified intensity-hue-saturation (IHS) Resolution Merge is suitable for 16-year-old oil palm trees and have rather high density with 100% accuracy; (2) Colour Normalized (Brovey) is suitable for 21-year-old oil palm trees and have low density with 99.5% accuracy; (3) Subtractive Resolution Merge is suitable for 15- and 18-year-old oil palm trees and have a rather high density with 99.8% accuracy; (4) PC Spectral Sharpening with 99.3% accuracy is suitable for 10-year-old oil palm trees and have low density; and (5) for all study object conditions, Colour Normalized (Brovey) and Wavelet Resolution Merge are two pansharpening methods that are

suitable for oil palm tree extraction and counting with 98.9% and 98.4% accuracy, respectively.

Keywords: filter, oil palm, oil palm counting, pansharpening, remote sensing, segmentation

1. Introduction

Oil palm density, age, management, and parent material all affect oil palm production. Oil palm tree density is one of the parameters used to determine if replanting is needed and affects oil palm production (Ng, 1972; Corley, 1973; Breure et al., 1990; Corley and Tinker, 2003; Huth et al., 2014; Bonneau et al., 2014). Therefore, one way to increase oil palm production has been to develop new varieties that are suitable for planting at high densities (Breure, 2010). Managers of oil palm plantations typically measure oil palm density manually every year. This important data can be used to estimate oil palm productivity, the amount of fertilizer needed, periodic weeding costs, and the number of workers needed, and is related to other activities (Ng, 1972; Kiama et al., 2014). Of course, counting oil palm trees manually requires many workers and has the potential problem of inaccurate counting.

In the past few years, several studies have dealt with the monitoring and mapping of oil palm using remote sensing in the various contexts. The Moderate Resolution Imaging Spectroradiometer (MODIS) has been used for studies on the primary productivity of oil palm trees as it is related to the global carbon balance (Cracknell et al. 2013; Tan, Kanniah, and Cracknell 2014; Cracknell et al. 2015). Tan, Kanniah, and Cracknell (2013) studied the age of oil palm trees using the Disaster Monitoring Constellation 2 and Advanced Land Observing Satellite phased array L-band synthetic aperture radar. Moreover, remote sensing has been applied for the identification and monitoring of basal stem rot disease (Lelong et al. 2010; Helmi Z M

Shafri et al. 2011; Liaghat et al. 2014; Helmi Zulhaidi Mohd Shafri and Hamdan 2009; Santoso et al. 2011); several research studies have used remote sensing for oil palm tree detection and counting. Jusoff and Pathan (2009) used airborne hyperspectral sensing with linear spectral mixture analysis, along with a mix to a pure converter and Euclidean norm techniques to map individual oil palm trees. Shafri et al. (2011) achieved 95% accuracy using high spatial resolution airborne imagery with several steps to discriminate oil palms from non-oil palms using spectral analysis, texture analysis, edge enhancement, a segmentation process, morphological analysis and blob analysis. Kattenborn et al. (2014) using unmanned aerial vehicle imagery with point cloud classification (reconstruction of oil palm trees using 3D processing) and achieved a mapping accuracy to 86.1% for the entire study area and 98.2% stands of dense oil palm. Srestasathiern and Rakwatin (2014) using QuickBird imagery with 90% accuracy. They used a vegetation index for distinguishing oil palms from the background, and then applied rank transformation, a non-maximal suppression algorithm and semi-variogram analysis to determine the appropriate window size. In addition, Wong-in et al. (2015) achieved 90% accuracy using aerial images with several steps such as removing non-tree components from an image, distinguishing oil palms from other components using a low-pass filter and normalized cross correlation, identifying individual oil palm trees, and counting the number of oil palms. Korom et al. (2014) segmented the shape of oil palm canopies/crowns using WorldView-2 imagery based on watershed segmentation and achieved an accuracy of about 77%.

Based on previous research, oil palm plantation managers (oil palm practitioners) need a simple method that is easy to implement for counting oil palm trees in plantations. The main objective of this study is to build a robust and easy-to-use method for counting oil palms using remote sensing.

99 2. Methods

100 This study analysed oil palms at an oil palm estate in Medan, North Sumatra, Indonesia
101 ($3^{\circ}1.58' - 3^{\circ}13.92'N$ and $99^{\circ}5.49' - 99^{\circ}13.44'E$; Fig. 1), with several oil palm densities.
102 Basal stem rot disease in trees infected by *Ganoderma boninense* caused the observed
103 heterogeneity of oil palm density. QuickBird imagery archived on 4 August 2008 was
104 used in this study with bands consisting of visible red (630–690 nm), green (520–600
105 nm) and blue (450–520 nm), NIR (near infrared, 760–900 nm) and panchromatic (450–
106 900 nm). Fig. 2 provides a map of the oil palm density conditions in this study area.
107 Study sites 1, 2, 3 and 4 had 16 (Fig. 2(a)), 21 (Fig. 2(b)), 15 and 18 (Fig. 2(c)), and 10
108 (Fig. 2(d)) year-old oil palms, respectively. Various conditions surrounding oil palm
109 trees, such as the density of grass and other weeds, will affect oil palm tree detection
110 and counting (Jusoff and Pathan, 2009; Shafri, et al., 2011; Kattenborn et al., 2014;
111 Wong-in et al., 2015). Therefore, the main target in the present study is to build a robust
112 method for oil palm detection and counting under any oil palm conditions and densities.

113 Fig. 3 shows the flow of the three-part method proposed in the present study: 1)
114 oil palm tree detection, 2) delineation of the oil palm area, and 3) oil palm tree counting
115 and accuracy assessment. ENVI 5.2, ERDAS Imagine 2015, and ArcGIS 10.2.2 were
116 the types of software used in this study. As a common standard for digital image
117 processing, converting a digital number into radiance was done using ENVI 5.2. In this
118 research study, pansharpening was used for oil palm detection because this allows the
119 shape of the oil palm canopy to be detected into detail. Johnson et al. (2012) reported
120 that a pansharpened image has more spatial information and minimizes the distortion of
121 spectral information of a multispectral image with lower resolution. Lin et al. (2015)
122 reported that pansharpening can improve and increase the classification accuracy of
123 land use and land cover using WorldView-2 imagery.

Several pansharpening methods were used and compared with each other in the present study to determine the best pansharpening method for oil palm detection. Panchromatic imagery was also used in this study. Colour Normalized (Brovey), Gram-Schmidt Spectral Sharpening, and PC Spectral Sharpening methods were processed with ENVI 5.2. Meanwhile, Subtractive Resolution Merge, Modified HIS Resolution Merge, and Wavelet Resolution Merge were processed with ERDAS Imagine 2015.

2.1 Oil palm detection

First, a pre-processing step was employed. All processing steps in the first part were completed using ENVI 5.2. The false colour composite RGB 432 (NIR-R-Green) images were built from pansharpening imagery and were then converted to a grayscale image (Korom, et al., 2014). The pre-processing step continued using ENVI colour tables with a grayscale image as an input file. We chose a black and white linear colour table and then adjusted the stretch bottom slider to the right side and stretch top slider to the left until 70–75% of a wide slider (ENVI, 2014). The image became light in the background, black in the foreground (oil palm canopy), and then the new image was saved (Guijarro et al., 2011; Muller-Lunow et al., 2015). The further steps conducted after pre-processing are described below:

- Edge enhancement. The oil palm canopy shape was detected using a Sobel edge detector with approximately 75–85% of an image added back.
- Texture analysis in this study used co-occurrence with a mean parameter, 5×5 of processing windows and 3×3 of co-occurrence shift.
- Morphology analysis in this study consisted of two filters, a dilate filter with a 3×3 kernel size and an erode filter with a 5×5 kernel size.

- In the extracting objects step, a high-pass filter with a 9×9 kernel size was used and then we continued using an opening filter with a 5×5 kernel size. When the detected object was an oil palm tree, it was converted to a polygon.

Fig. 1. The study site is on an oil palm plantation in North Sumatra, Indonesia; A) vicinity map showing the vicinity of the study site on the island of Sumatra; 2) map of the study site (Source map: Indonesian Geospatial Board-
<http://www.bakosurtanal.go.id/download/>)

Fig. 2. Oil palm density condition in this study showing parts of (a) study site 1 (150.16 ha); (b) study site 2 (139.31 ha); (c) study site 3 (130.49 ha); (d) study site 4 (128.99 ha)

Fig. 3. The study flow chart: (I) oil palm tree detection; (II) delineation of oil palm area, and (III) oil palm tree counting and accuracy assessment

The second part of the delineation of the oil palm area, a pre-processing step, was needed; this was done in the same way as the first part, but using the red band (Santoso et al., 2011) from pansharpening imagery as an input file. The image had become lighter in the foreground (oil palm area) and darker (black) in the background. After pre-processing, the morphology operation in this part was a closing filter with a 5×5 or a 7×7 kernel size. The object that was detected was the oil palm area and should be converted to polygon format as a masking polygon. In the final part in this study, oil palm tree counting was done in ArcGIS 10.2.2 using an overlay of both polygons from first and second parts; then the conversion processes were completed using polygons from overlay results as point features.

2.2 Accuracy assessment

An accuracy assessment was applied for the oil palm feature extraction (as a point feature layer in GIS) and compared with the result of manual counting (Shafri, et al., 2011) using on-screen digitization in five square polygons (each square polygon is 1 ha), four of which were distributed in the fourth corners of every site area plus one polygon in the centre. The number of oil palms counted manually and the number extracted digitally from QuickBird imagery were selected in the five (5) square polygons using ArcGIS 10.2.2; the results of these two counting methods were compared with each other to determine the accuracy of oil palm detection and extraction.

3. Results and discussion

The proposed methods for oil palm tree detection and counting in the present study were tested in several areas with different oil palm ages and densities. Fig. 4 shows an example of the results of each process in the proposed method that was used in the present study. Fig. 4(a) shows the shape of the oil palm canopy as dark-black with the light areas indicating the background. An oil palm canopy takes on a star-like shape; there are outer angular shapes around the centre of the canopy. The Sobel edge detector, texture analysis, and dilate filter were applied to minimize the outer shape of the oil palm canopies (see Fig. 4(b), 4(c), and 4(d)). The erode filter produced an oil palm canopy outline as a square shape (Fig. 4(e)) and the high-pass filter sharpened this square shape (Fig. 4(f)). Moreover, the opening filter converted the square shape into the object that was selected and the background is erased or left empty (Fig. 4(g)).

During oil palm tree extraction, several oil palm canopy/trees were not extracted and some objects were also extracted that were not oil palms (Fig. 4(i)). This is caused when some of the vegetation that surrounds oil palm trees has the same radiance values

as the radiance values of oil palms. Moreover, some areas were classified as noise. In a further step, the noise was reduced using the oil palm area extraction areas with the red band. Meanwhile, a part of the oil palm canopy was not extracted; this was caused when the oil palm canopy had some different pixel radiance values while only a small part of a particular tree had the same values with oil palm radiance; however, in these cases, the majority of the oil palms had the same values as the surrounding radiance values. Moreover, the small part of the pixel values of oil palm radiance were erased by some kernel/window size areas in filters applied in this study (Hosoi, et al., 2012; Warner et al., 2006). In addition, this change affected the accuracy assessment. The oil palm area extraction results will affect the accuracy of oil palm tree counting because they are used to reduce noise during oil palm tree extraction.

3.1 Oil palm tree counting and accuracy assessment

After using a red band to reduce noise during oil palm area extraction, oil palm trees could be counted from the results of the converted polygon of oil palm extraction to create a point layer. The present study encompassed a total area of 548.95 ha for testing the proposed methods, which were divided into four different study sites areas to determine oil palm density and age. Tables 1–4 show the ability of the method to count oil palm trees and the count accuracy assessment for study sites 1–4. We assumed the manually counted values were accurate because we used QuickBird pansharpening imagery to manually count trees based on screen digitized imagery of oil palm trees in five square areas where each area covered 10,000 m². Each area and pansharpening method used in this study resulted in different oil palm tree counts. The research results from Wyczalek and Wyczalek (2014) produced similar results while using a different method of pansharpening that will affect the classification results. Tables 1–4 show the potential of the four pansharpening methods for counting oil palm trees using PC

Spectral Sharpening, Colour Normalized (Brovey), Subtractive Resolution Merge, and Modified Resolution Merge, at study sites 1–4, respectively.

Fig. 4. Example results of the proposed methods in this study: (a) black and white imagery; (b) image from Sobel applied; (c) image after texture analysis; (d) image after dilate filter; (e) image after erode filter; (f) image after high-pass filter; (g) image after opening filter; (h) oil palm object extraction; (i) polygon of oil palm extraction with pansharpening imagery as background

The potential of using the pansharpening method for counting oil palm trees in different areas is shown in Table 5. Study sites 1, 2, 3, and 4 had 16, 21, 15/18, and 10-year-old oil palm trees, respectively. Study sites 1, 2, 3, and 4 had rather high, low, rather high, and low oil palm density, respectively. With these conditions, the best pansharpening methods for study sites 1, 2, 3, and 4 were Modified IHS Resolution Merge pansharpening (100% accuracy), Colour Normalized (Brovey) pansharpening (99.5%), Subtractive Resolution Merge pansharpening (99.8%), and PC Spectral Sharpening (99.3%), respectively. Two pansharpening methods employed for oil palm tree extraction and counting in this study had 98.4% and 98.9% accuracy and were Wavelet Resolution Merge and Colour Normalized (Brovey), respectively (Table 6; Fig. 5).

When compared with the accuracy of oil palm tree counting in previous research studies that used several methods, the methods proposed in the present study are potentially useful for oil palm planters and plantation managers and could be adopted and implemented as part of oil palm management practices. This proposed method is simple and all the steps and filter are available in ENVI software. In addition, it is possible to use different image processing software that has a grayscale convert function,

a foreground and background stretching function, a Sobel edge detector, and texture analysis co-occurrence, as well as dilate, erode, high-pass, and opening filters.

We believe the accuracy achieved using the methods employed in the present study is adequate for estate managers to use so they can employ remote sensing to rapidly determine oil palm density. In oil palm management, if the estate has planting records, especially stand maps of oil palm plantations, monitoring oil palm trees individually in the field is very easy. However, sometimes oil palm plantation managers need a second opinion and can accurately monitor oil palm density using imagery based on remote sensing.

Table 1. Capability and accuracy assessment for study site 1

Table 2. Capability and accuracy assessment for study site 2

Table 3. Capability and accuracy assessment for study site 3

Table 4. Capability and accuracy assessment for study site 4

Table 5. The potential of the pansharpening method for oil palm tree extraction in different areas

Table 6. Accuracy assessment of oil palm tree extraction

Fig. 5. Oil palm extraction and counting using Colour Normalized (Brovey) in study site 2 (a) and using Wavelet Resolution Merge in study site 3 (b)

4. Conclusions

The pansharpening method used with multispectral satellite imagery such as a QuickBird image has potential for use in oil palm tree detection and counting. The different pansharpening methods provided different results for oil palm tree counting. The methods proposed in the present study exhibited about 98% accuracy and provide potential methods for oil palm tree detection and counting as part of oil palm management. The methods proposed in the present study are easy to use with ENVI or other image processing software that have a grayscale conversion function, stretching foreground and background functions, a Sobel edge detector, texture analysis co-occurrence, as well as dilate, erode, high-pass, and opening filters. The proposed methods will be tested using images from unmanned aerial vehicles that many oil palm companies currently operate for surveillance and monitoring of oil palm coverage.

Acknowledgement

This work was supported by the Director of the Indonesian Oil Palm Research Institute.

References

- Bonneau, Xavier, Pieter Vandessel, Maxwell Buabeng, and Charles Erhahuyi. 2014. "Early Impact of Oil Palm Planting Density on Vegetative and Oil Yield Variables in West Africa." *Ocl* 21 (4): A401. doi:10.1051/ocl/2014009.
- Breure, C. J. 2010. "Rate of Leaf Expansion: A Criterion for Identifying Oil Palm (*Elaeis Guineensis* Jacq.) Types Suitable for Planting at High Densities." *NJAS - Wageningen Journal of Life Sciences* 57 (2). Royal Netherlands Society for Agriculture Sciences: 141–147. doi:10.1016/j.njas.2010.03.001.
- Breure, C. J., T. Menendez, and M. S Powell. 1990. "The Effect of Planting Density on the Yield Components of Oil Palm (*Elaeis Guineensis*)." *Experimental Agriculture* 26 (01): 117–124. doi:10.1017/S0014479700015453.
- Corley, R. H. V. 1973. "Effects of Plant Density on Growth and Yield of Oil Palm." *Experimental Agriculture* 9 (02): 169. doi:10.1017/S0014479700005639.
- Corley, R H V, and P B Tinker. 2003. *The Oil Palm. World Agriculture Series*. Vol. No. 3/24. doi:10.1002/9780470750971.

- Cracknell, Arthur Philip, K D Kanniah, K P Tan, and L Wang. 2013. "Evaluation of MODIS Gross Primary Productivity and Land Cover Products for the Humid Tropics Using Oil Palm Trees in Peninsular Malaysia and Google Earth Imagery." *International Journal of Remote Sensing* 34 (20): 7400–7423. doi:10.1080/01431161.2013.820367.
- Cracknell, Arthur Philip, Kasturi Devi Kanniah, Kian Pang Tan, and Lei Wang. 2015. "Towards the Development of a Regional Version of MOD17 for the Determination of Gross and Net Primary Productivity of Oil Palm Trees." *International Journal of Remote Sensing* 36 (1): 262–289. doi:10.1080/01431161.2014.995278.
- ENVI. 2014. "ENVI Classic Help." Exelis-ENVI52-Classic.
- Guijarro, M., G. Pajares, I. Riomoros, P. J. Herrera, X. P. Burgos-Artizzu, and A. Ribeiro. 2011. "Automatic Segmentation of Relevant Textures in Agricultural Images." *Computers and Electronics in Agriculture* 75 (1). Elsevier B.V.: 75–83. doi:10.1016/j.compag.2010.09.013.
- Hosoi, Fumiki, Hiroaki Matsugami, Kenichi Watanuki, Yo Shimizu, and Kenji Omasa. 2012. "Accurate Detection of Tree Apexes in Coniferous Canopies from Airborne Scanning Light Detection and Ranging Images Based on Crown-Extraction Filtering." *Journal of Applied Remote Sensing* 6 (1): 063502. doi:10.1117/1.JRS.6.063502.
- Huth, Neil I, Murom Banabas, Paul N Nelson, and Michael Webb. 2014. "Development of an Oil Palm Cropping Systems Model: Lessons Learned and Future Directions." *Environmental Modelling & Software* 62 (0). Elsevier Ltd: 411–419. doi:http://dx.doi.org/10.1016/j.envsoft.2014.06.021.
- Johnson, Brian, Ryutaro Tateishi, and Nguyen Hoan. 2012. "Satellite Image Pansharpening Using a Hybrid Approach for Object-Based Image Analysis." *ISPRS International Journal of Geo-Information* 1 (3): 228–241. doi:10.3390/ijgi1030228.
- Jusoff, Kamaruzaman, and Mubeena Pathan. 2009. "Mapping of Individual Oil Palm Trees Using Airborne Hyperspectral Sensing : An Overview." *Applied Physics Research* 1: 15–30.
- Kattenborn, T., M. Sperlich, K. Bataua, and B. Koch. 2014. "Automatic Single Palm Tree Detection in Plantations Using UAV-Based Photogrammetric Point Clouds." *International Archives of the Photogrammetry, Remote Sensing and Spatial*

334 *Information Sciences - ISPRS Archives* 40 (3): 139–144.
 335 doi:10.5194/isprsarchives-XL-3-139-2014.

336 Kiama, J W, V Raman, and T H H Patrick. 2014. “Low-Cost RFID-Based Palm Oil
 337 Monitoring System (PMS): First Prototype.” *IOP Conference Series: Earth and
 338 Environmental Science* 18: 012054. doi:10.1088/1755-1315/18/1/012054.

339 Korom, Alexius, M-H Phua, Y Hirata, and T Matsuura. 2014. “Extracting Oil Palm
 340 Crown from WorldView-2 Satellite Image.” *IOP Conference Series: Earth and
 341 Environmental Science* 18: 6. doi:10.1088/1755-1315/18/1/012044.

342 Lelong, Camille C D, Jean Michel Roger, Simon Brégand, Fabrice Dubertret, Mathieu
 343 Lanore, Nurul a. Sitorus, Doni a. Raharjo, and Jean Pierre Caliman. 2010.
 344 “Evaluation of Oil-Palm Fungal Disease Infestation with Canopy Hyperspectral
 345 Reflectance Data.” *Sensors* 10: 734–747. doi:10.3390/s100100734.

346 Liaghat, Shohreh, Reza Ehsani, Shattri Mansor, Helmi Z.M. Shafri, Sariah Meon,
 347 Sindhuja Sankaran, and Siti H.M.N. Azam. 2014. “Early Detection of Basal
 348 Stem Rot Disease (Ganoderma) in Oil Palms Based on Hyperspectral
 349 Reflectance Data Using Pattern Recognition Algorithms.” *International Journal
 350 of Remote Sensing* 35 (10): 3427–3439. doi:10.1080/01431161.2014.903353.

351 Lin, Chinsu, Chao-Cheng Wu, Khongor Tsogt, Yen-Chieh Ouyang, and Chein-I Chang.
 352 2015. “Effects of Atmospheric Correction and Pansharpening on LULC
 353 Classification Accuracy Using WorldView-2 Imagery.” *Information Processing
 354 in Agriculture* 2 (1). China Agricultural University: 25–36.
 355 doi:10.1016/j.inpa.2015.01.003.

356 Müller-Linow, Mark, Francisco Pinto-Espinosa, Hanno Scharr, and Uwe Rascher. 2015.
 357 “The Leaf Angle Distribution of Natural Plant Populations: Assessing the
 358 Canopy with a Novel Software Tool.” *Plant Methods* 11 (1): 11.
 359 doi:10.1186/s13007-015-0052-z.

360 Ng Siew Kee. 1972. *The Oil Palm, Its Culture, Manuring and Utilisation*. International
 361 Potash Institute. [http://www.ipipotash.org/udocs/the_oil_palm-its_culture-
 362 manuring_and_utilisation.pdf](http://www.ipipotash.org/udocs/the_oil_palm-its_culture-manuring_and_utilisation.pdf).

363 Santoso, Heri, Totok Gunawan, Retnadi Heru Jatmiko, Witjaksana Darmosarkoro, and
 364 Budiman Minasny. 2011. “Mapping and Identifying Basal Stem Rot Disease in
 365 Oil Palms in North Sumatra with QuickBird Imagery.” *Precision Agriculture* 12:
 366 233–248. doi:10.1007/s11119-010-9172-7.

- Shafri, Helmi Z. M., Nasrulhapiza Hamdan, and M. Iqbal Saripan. 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.
- Shafri, Helmi Z M, Mohd I Anuar, Idris a Seman and M Noor. 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, Helmi Zulhaidi Mohd, and Nasrulhapiza Hamdan. 2009. "Hyperspectral Imagery for Mapping Disease Infection in Oil Palm Plantation Using Vegetation Indices and Red Edge Techniques." *American Journal of Applied Sciences* 6 (6): 1031–1035. doi:10.3844/ajassp.2009.1031.1035.
- Srestasathiern, Panu, and Preesan Rakwatin. 2014. "Oil Palm Tree Detection with High Resolution Multi-Spectral Satellite Imagery." *Remote Sensing* 6 (10): 9749–9774. doi:10.3390/rs6109749.
- Tan, Kian Pang, K D Kanniah, and a P Cracknell. 2013. "Use of UK-DMC 2 and ALOS PALSAR for Studying the Age of Oil Palm Trees in Southern Peninsular Malaysia." *International Journal of Remote Sensing* 34 (November 2013): 7424–7446. doi:10.1080/01431161.2013.822601.
- Tan, Kian Pang, Kasturi Devi Kanniah, and Arthur Philip Cracknell. 2014. "On the Upstream Inputs into the MODIS Primary Productivity Products Using Biometric Data from Oil Palm Plantations." *International Journal of Remote Sensing* Vol. 35, N (August 2014): 37–41. doi:10.1080/01431161.2014.889865.
- Warner, Timothy A., James B. McGraw, and Rick Landenberger. 2006. "Segmentation and Classification of High Resolution Imagery for Mapping Individual Species in a Closed Canopy, Deciduous Forest." *Science in China, Series E: Technological Sciences* 49 (SUPPL. 1): 128–139. doi:10.1007/s11431-006-8114-0.
- Wong-in, Teerawut, Tonphong Kaewkongka, Nagul Cooharajanone, and Rajalida Lipikorn. 2015. "Automatic Oil Palm Detection and Identification from Multi-Scale Clustering and Normalized Cross Correlation." In , 403–410. Springer Berlin Heidelberg. doi:10.1007/978-3-662-47200-2_43.

399 Wyczalek, Ireneusz, and Wyczalek Elzbieta. 2013. "Studies on Pansharpening and
400 Object-Based Classification of Worldview-2 Multispectral Image." *Archives of*
401 *Photogrammetry, Cartography and Remote Sensing*, no. Monograph: 109–117.

426 Table 1. Capability and accuracy assessment for study site 1

Method	Area (ha)	Total of oil palm extraction	Polygon test (ha)	Oil palm counted manually	Oil palm extraction	Difference	Accuracy (%) (compared with counted manually data)
Panchromatic	150.16	15,421	5	514	529	(15)	97.2
Gram Schmidt Spectral Sharpening	150.16	13,306	5	514	483	31	94.0
PC Spectral Sharpening	150.16	12,125	5	514	439	75	85.4
Colour Normalized (Brovey)	150.16	14,107	5	514	485	29	94.4
Subtractive Resolution Merge	150.16	13,216	5	514	475	39	92.4
Modified Intensity-Hue-Saturation Resolution Merge	150.16	14,471	5	514	514	-	100.0
Wavelet Resolution Merge	150.16	13,601	5	514	486	28	94.6

427

428

429 Table 2. Capability and accuracy assessment for study site 2

Method	Area (ha)	Total of oil palm extraction	Polygon test (ha)	Oil palm counted manually	Oil palm extraction	Difference	Accuracy (%) (compared with counted manually data)
Panchromatic	139.31	11,263	5	400	433	(33)	92.4
Gram Schmidt Spectral Sharpening	139.31	9,604	5	400	370	30	92.5
PC Spectral Sharpening	139.31	9,564	5	400	375	25	93.8
Colour Normalized (Brovey)	139.31	10,703	5	400	398	2	99.5
Subtractive Resolution Merge	139.31	9,668	5	400	369	31	92.3
Modified Intensity- Hue-Saturation Resolution Merge	139.31	10,957	5	400	415	(15)	96.4
Wavelet Resolution Merge	139.31	10,111	5	400	392	8	98.0

430

431

432 Table 3. Capability and accuracy assessment for study site 3

Method	Area (ha)	Total of oil palm extraction	Polygon test (ha)	Oil palm counted manually	Oil palm extraction	Diffe- rence	Accuracy (%) (compared with counted manually data)
Panchromatic	130.49	12,869	5	471	495	(24)	95.2
Gram Schmidt Spectral Sharpening	130.49	11,629	5	471	454	17	96.4
PC Spectral Sharpening	130.49	12,261	5	471	465	6	98.7
Colour Normalized (Brovey)	130.49	13,000	5	471	495	(24)	95.2
Subtractive Resolution Merge	130.49	12,297	5	471	472	(1)	99.8
Modified Intensity- Hue-Saturation Resolution Merge	130.49	12,817	5	471	493	(22)	95.5
Wavelet Resolution Merge	130.49	12,399	5	471	469	2	99.6

433

434

435 Table 4. Capability and accuracy assessment for study site 4

Method	Area (ha)	Total of oil palm extraction	Polygon test (ha)	Oil palm counted manually	Oil palm extraction	Diffe- rence	Accuracy (%) (compared with counted manually data)
Panchromatic	128.99	13,183	5	449	514	(65)	87.4
Gram Schmidt Spectral Sharpening	128.99	11,414	5	449	464	(15)	96.8
PC Spectral Sharpening	128.99	11,137	5	449	446	3	99.3
Colour Normalized (Brovey)	128.99	12,127	5	449	476	(27)	94.3
Subtractive Resolution Merge	128.99	11,272	5	449	444	5	98.9
Modified Intensity- Hue-Saturation Resolution Merge	128.99	12,722	5	449	499	(50)	90.0
Wavelet Resolution Merge	128.99	11,579	5	449	458	(9)	98.0

436

437

Table 5. The potential of the pansharpening method for oil palm tree extraction in different areas

Method	Accuracy (%) (compared with counted manually data)			
	Area 1	Area 2	Area 3	Area 4
Panchromatic	97.2	92.4	95.2	87.4
Gram Schmidt Spectral Sharpening	94.0	92.5	96.4	96.8
PC Spectral Sharpening	85.4	93.8	98.7	99.3
Colour Normalized (Brovey)	94.4	99.5	95.2	94.3
Subtractive Resolution Merge	92.4	92.3	99.8	98.9
Modified Intensity-Hue-Saturation Resolution Merge	100.0	96.4	95.5	90.0
Wavelet Resolution Merge	94.6	98.0	99.6	98.0

Highlighted are the results of highest accuracy in the same column.

442 Table 6. Accuracy assessment of oil palm tree extraction

Method	Area (ha)	Total of oil palm extraction	Polygon test (ha)	Oil palm counted manually	Oil palm extraction	Difference	Accuracy (%) (compared with counted manually data)
Panchromatic	548.95	52,736	20	1,834	1,971	(137)	93.0
Gram Schmidt Spectral Sharpening	548.95	45,953	20	1,834	1,771	63	96.6
PC Spectral Sharpening	548.95	45,087	20	1,834	1,725	109	94.1
Colour Normalized (Brovey)	548.95	49,937	20	1,834	1,854	(20)	98.9
Subtractive Resolution Merge	548.95	46,453	20	1,834	1,760	74	96.0
Modified HIS Resolution Merge	548.95	50,967	20	1,834	1,921	(87)	95.5
Wavelet Resolution Merge	548.95	47,690	20	1,834	1,805	29	98.4

443 Highlighted are results of highest accuracy.

444

445

446

447

448

449

450

451

452

453

454

455

456

457

458

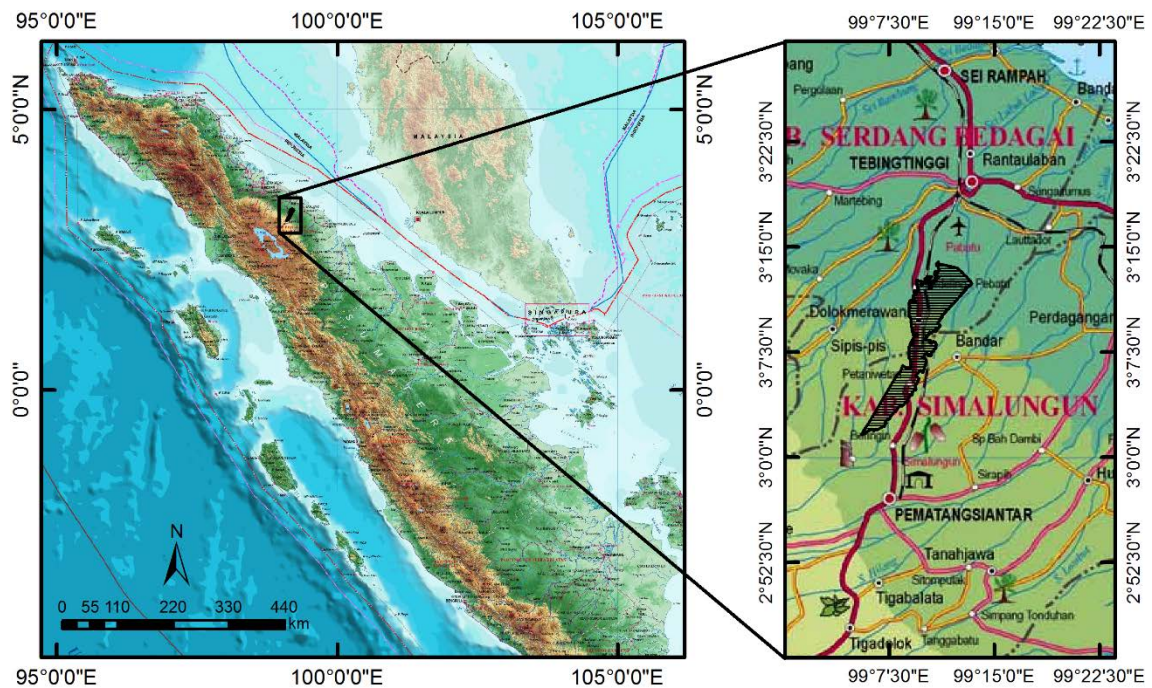


Fig. 1. The study site is on an oil palm plantation in North Sumatra, Indonesia; A) vicinity map showing the vicinity of the study site on the island of Sumatra; 2) map of the study site (Source map: Indonesian Geospatial Board-
<http://www.bakosurtanal.go.id/download/>)

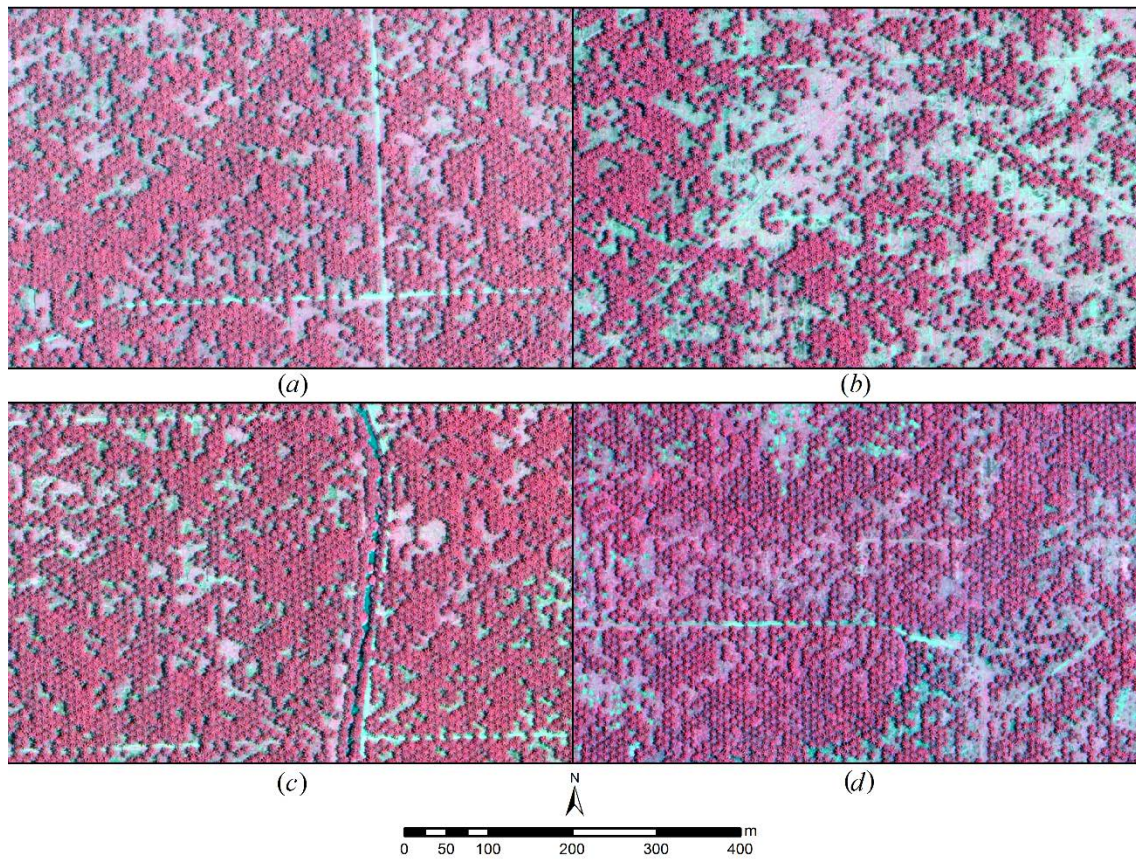
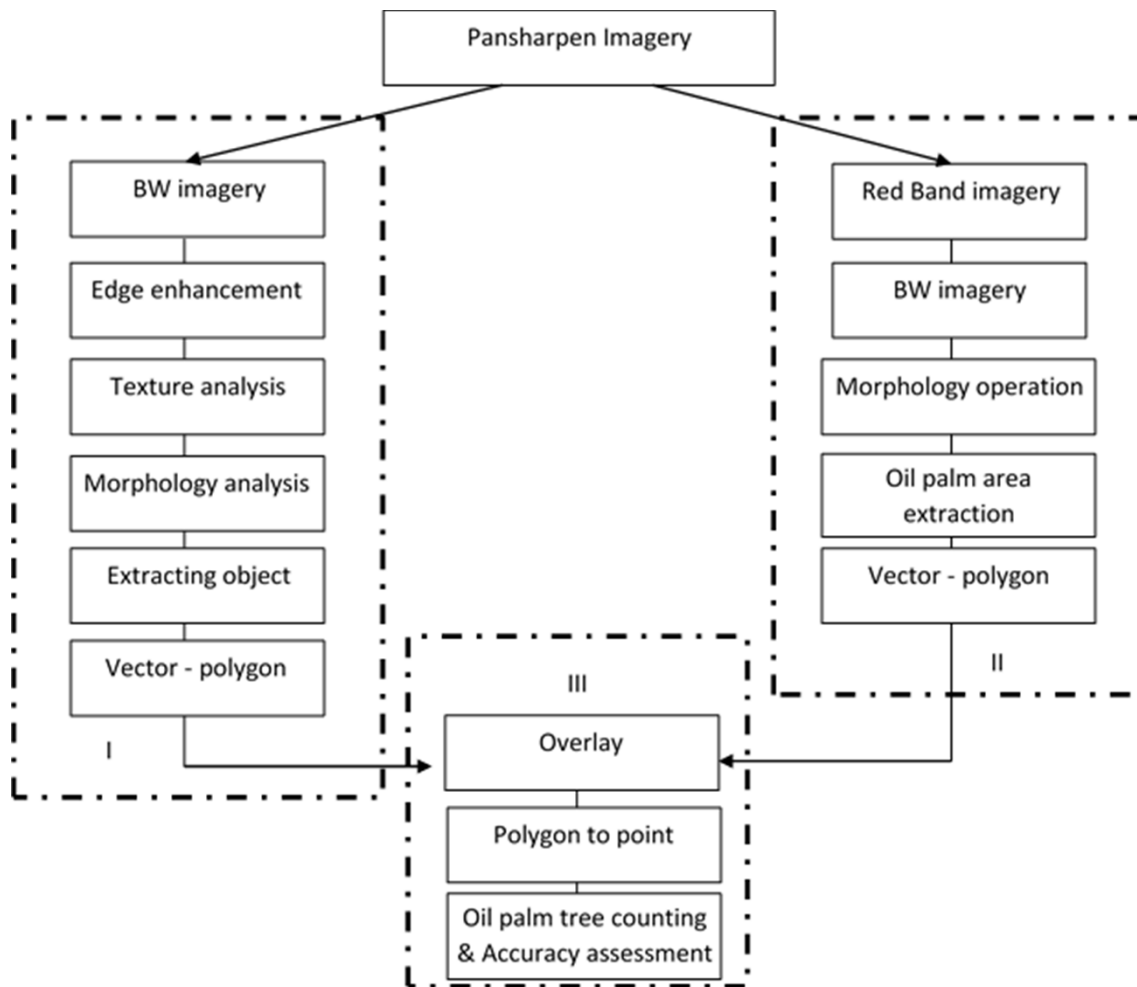


Fig. 2. Oil palm density condition in this study showing parts of (a) study site 1 (150.16 ha); (b) study site 2 (139.31 ha); (c) study site 3 (130.49 ha); (d) study site 4 (128.99 ha)



469

470 Fig. 3. The study flow chart: (I) oil palm tree detection; (II) delineation of oil palm area,
 471 and (III) oil palm tree counting and accuracy assessment

472

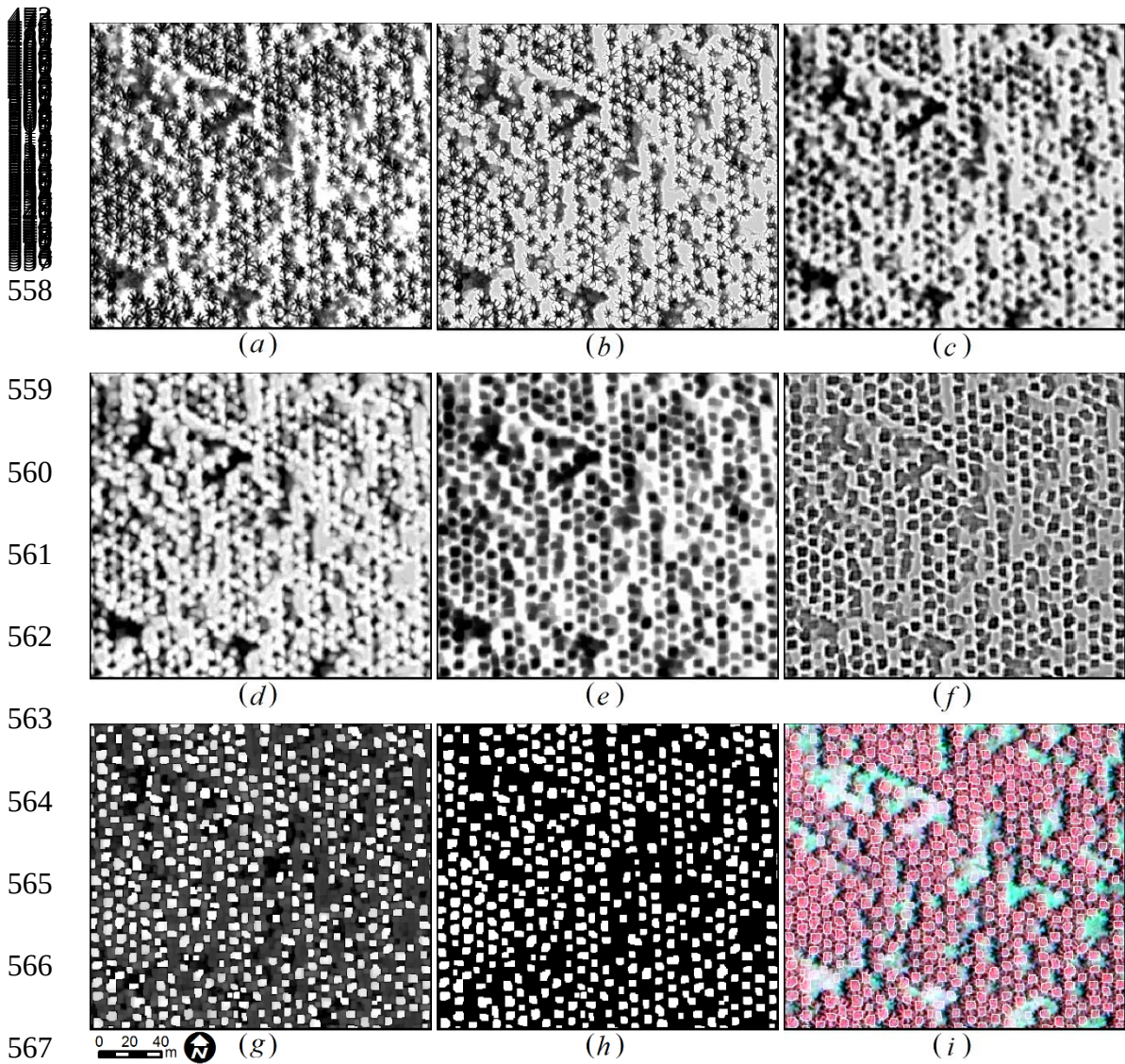
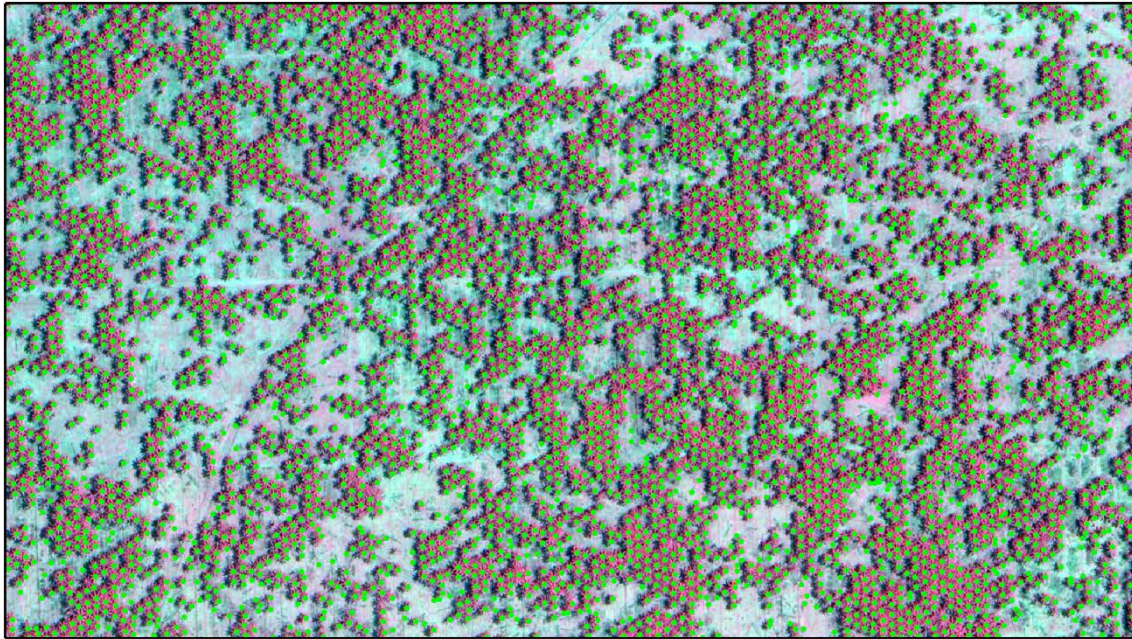
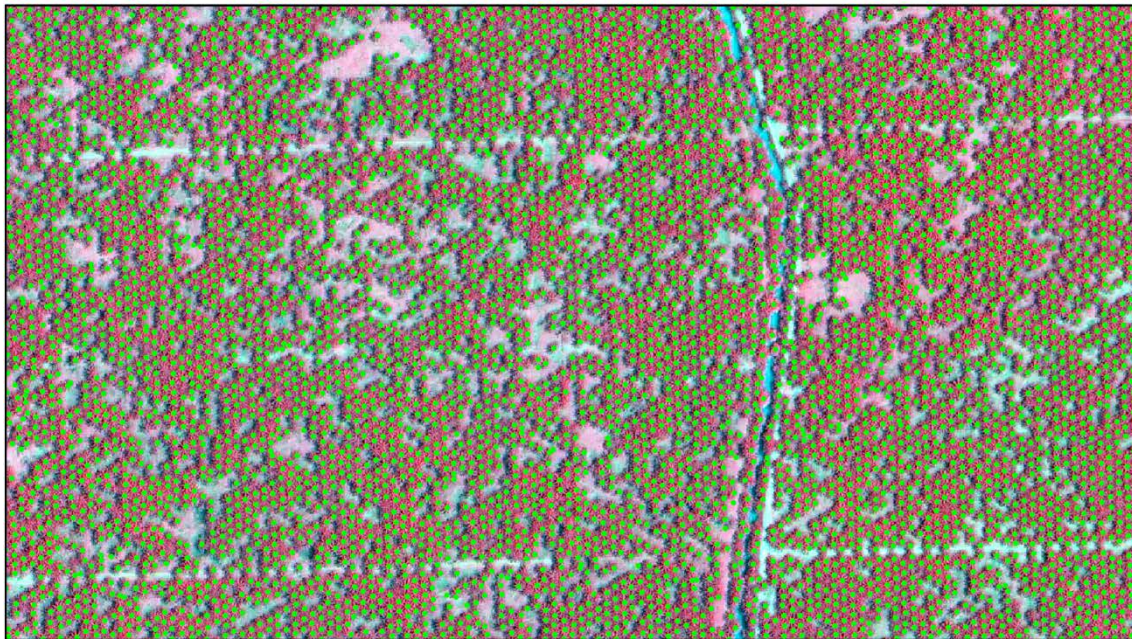


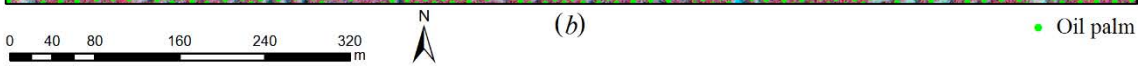
Fig. 4. Example results of the proposed methods in this study: (a) black and white (BW) imagery; (b) image from Sobel applied; (c) image after texture analysis; (d) image after dilate filter; (e) image after erode filter; (f) image after high-pass filter; (g) image after opening filter; (h) oil palm object extraction; (i) polygon of oil palm extraction with pansharpening imagery as background



(a)



(b)



Oil palm

Fig. 5. Oil palm extraction and counting using Colour Normalized (Brovey) in study site 2 (a) and using Wavelet Resolution Merge in study site 3 (b)

581

582

583

584

585

586