SAR Data Application for the Smallholder's Oil Palm Plantation Management in Indonesia

(インドネシアにおける小規模オイルパーム農園管理のための SAR データ活用手法の検討)

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SAR Data Application for the Smallholder's Oil Palm Plantation Management in Indonesia

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Declaration

This thesis is submitted for the degree of Doctor of Philosophy at the United Graduate School of Agricultural Sciences, Tottori University. This dissertation is the result of my own work and has not been and is not being, in part or wholly, submitted for another degree, diploma, or similar qualification.

Lissa Fajri Yayusman

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Table of contents

List of Figures

List of Tables

List of Abbreviation

ALOS	: Advanced Land Observing Satellite
ASTER GDEM	: Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model
AVNIR-2	: Advanced Visible and Near Infrared Radiometer type 2
B	: Backscatter
BA	: Backscatter arithmetical bands
ENL	: Equivalent Number of Look
FAO	: Food and Agriculture Organization
FBD	: Fine Beam Dual Polarization
FD3	: Freeman and Durden 3-components Decomposition
GLCM	: Gray Level Coocurrence Matrix
GPS	: Global Positioning System
H/A/α	: Entropy/Anisotropy/Alpha decomposition
HH	: Horizontal-Horizontal polarized SAR
HV	: Horizontal-Vertical polarized SAR
JAXA	: Japanese Aerospace Exploration Agency
PA	: Producer's Accuracy
PALSAR	: Phased Array L-band Synthetic Aperture Radar
PCA	: Principal Component Analysis
PD3	: Polarimetric Decomposition
PLR	: Full Polarimetric
PolSAR	: Polarimetric SAR Data Processing and Educational Tool
RBF	: Radial Basis Function
SRTM	: Shuttle Radar Topography Mission
SVM	: Support Vector Machine
UA	: User's Accuracy
UTM	: Universal Transverse Mercator
VH	: Vertical-Horizontal polarized SAR
VV	: Vertical-Vertical polarized SAR
WGS84	: World Geodetic System 84
Y4	: Yamaguchi 4-components Decomposition

Chapter 1

Introduction

1.1 Research Background

Agricultural sector still plays as the key role of Indonesian economy as it contributes as the main income to majority of the household. As a tropical country, Indonesia possesses favorable condition of both climate and soil elements to support agricultural activities. Sufficient average rainfall and sunshine along the year, as well as abundant fertile soils in this country make Indonesia as the major producer of various agricultural products, such as rubber, palm oil, cocoa, and coffee.

Among the main commodities of this country, palm oil is considered as the product with greatest potential for further development because of the rising demand of palm oil which is marked as the world's most traded vegetable oil. The palm oil is extracted from the fruit of oil palm tree and is mainly used as substances in food, cooking oil, hygiene products, and a source of bio-fuel (Budidarsono et al. 2013, Verheye 2010). In addition to its high market prospect, the production cost of palm oil is known to be cost- and area-effective compared to other oil crops such as soybean and sun flower (Dislich et al. 2016). The production of palm oil also requires labor intensive works, which means the development of oil palm plantation would widely open the job opportunity for people in rural area where the cultivation is normally taken place. On the other hand, the labor wage in Indonesia is much lower compared to those in other countries, and consequently, reduces the production cost. These factors make oil palm as one of the most profitable cash crops as well as the most efficient oil crop across the world, while at the same time, contribute to the rural area development (Corley and Tinker 2016).

The oil palm (*Elaeis guineensis* Jacq.) is an African origin perennial crop that grown throughout the low-land equatorial tropics, mainly in Africa, South East Asia, as well as South and Central America. The high profit of palm oil leads to the expansion of oil palm cultivation in Indonesia in recent decades. During the last 20 years, the harvested area of oil palm fruits has been expanded from about 1.8 million ha in 1994 to more than 10 million ha in 2014 throughout the country, and is projected to continue increasing (Ministry of Agriculture of Indonesia 2015). In 2014, Indonesia produced 126.68 million tons of oil palm fruits and shared 46% of total world's production (FAO 2017). The expansion has becoming wilder and has brought both pro and contra within various stakeholders, scientists and environmentalists. This issue is considered as a serious threat to the tropical rainforest and biodiversity as well as land-use management (Fitzherbert et al. 2008, Vijay et al. 2016, Wilcove and Koh 2010), while some others claim that oil palm brings great impacts to rural household and Indonesian income, and stores more carbon than most of other alternative agricultural land uses (Basiron and Weng 2004, Lamade and Bouillet 2005, Sayer et al. 2012).

As the optimum oil palm cultivation is constrained by specific conditions, such as rainfall, land altitude, and type of soil, its establishment in Indonesia is particularly concentrated in Sumatra, Kalimantan, and Sulawesi Islands. Among these islands, Sumatra is especially favorable due to its rich volcanic soils and suitable climate. However, the shortage of good and available resources of mineral soil, advancements in technology, and the high demand of agroforestry products have driven the oil palm planting on peat soil (Corley and Tinker 2016). Miettinen et al. (2012) estimated more than 1 Mha or about 15% of total peatland in Sumatra and about 258.000 ha or 4% of

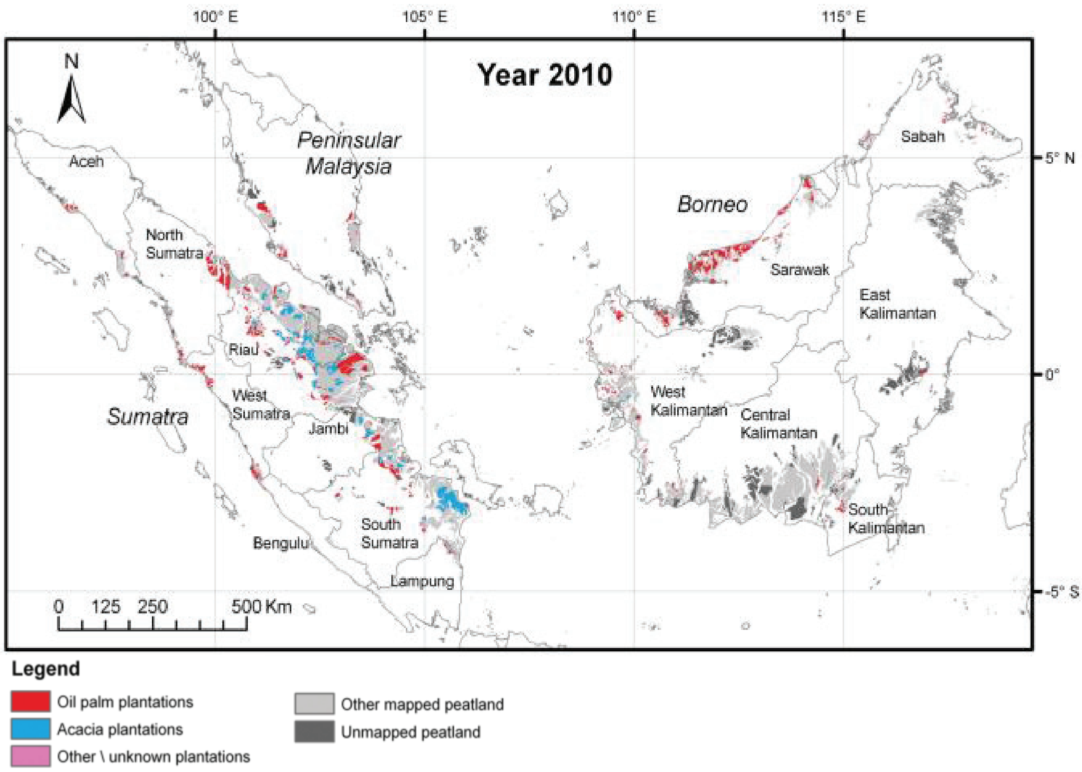

Figure 1.1 Extent of oil palm plantations on peatland in 2010 (Miettinen et al. 2012)

peatland in Kalimantan have been developed for industrial oil palm plantation in 2010 (Fig. 1.1). This fact has drawn even more controversy because land conversion on peatland might harm the environment more than on mineral soil. Tropical peatland store abundant of carbon density, contain large amount of organic matters and has high water holding capacity (Page et al. 2011). These characteristics make peatland become less suitable for any agricultural activities and require additional treatments of peat management before the cultivation, such as drainage and compaction, to control the water table condition (Melling et al. 2011). On the other hand, drying effect from any disturbances to this ecosystem might cause peat become more vulnerable to fire and enhanced CO_2 loss from decomposition process (Miettinen et al. 2012, Page et al. 2002).

Development of oil palm plantation was originally initiated by the Indonesian government not only for the domestic consumption purpose, but also as one of export commodities along with rubber and cocoa. Hence, the state or private companies were commonly entrusted to manage such kind of industrial plantations in large-scale area, while the smallholders were more focused on the traditional agriculture crops cultivation, such as rice, soybean, maize, and vegetables. However, the involvement of the smallholders to the oil palm expansion has been significantly increased and has taken about 40% of the total oil palms area in recent years (McCarthy 2010). While this activity was started with the support provided by the government through nucleus estate and smallholder (NES) schemes in 1980s, the development by smallholders nowadays is mainly occurred independently, without any contract or direct support from state or company (Euler et al. 2015). The later type of plantation is commonly termed as independent smallholder. Cultivation by this smallholders usually follows the existence of large plantations complemented with palm oil mills, because oil palm fruits must be processed within 48 hours after they are harvested (Budidarsono et al., 2013). This kind of expansion is more uncontrollable and might be more harmful to environment and land-use management because any household could attempt to cultivate oil palms anywhere, regardless the size of their owned land. The plantations are usually randomly distributed, covering small area, with average size from 2 ha up to 5 ha, and situated between various land covers (Lee et al. 2014). Therefore, the location of independent smallholders' oil palm plantations is almost undetectable and hard to differentiate among the other types of land cover.

On the other hand, due to the lack of management practice and access to the oil palm mill, independent smallholders commonly earns lower oil palm yields and incomes compared to the private estate and scheme plantations (Lee et al., 2013). This problem becomes more complex for the farmers who grow oil palms on peatland area, considering the characteristic of peatland that is not really suitable for oil palm cultivation. Peat management procedures prior the planting are hardly applied by smallholders because of their limited financial condition to carry out such high-cost process, inadequate knowledge regarding to the peat characteristics, and sometimes poor management ability. Cultivation under this condition may lead to higher tendency of oil palms to lean as the trees grow and more tree toppling in early stage, and as a result, yield production will decrease significantly (Corley and Tinker 2016).

While uncontrolled expansion caused by independent smallholders should be avoided, improvement and recovery for the existed oil palm to increase the yield production are still important to enhance socio-economic condition of smallholders, and at the same time to overcome the environmental problems. As the effort, comprehensive study on the identification of smallholders' oil palms expansion area is necessary for detail monitoring of small-scale plantations. On the other hand, spatial mapping of the distribution of tree conditions in existed oil palms planted on peatland is essential to support rehabilitation process, control, and implementation of best management practices for sustainable oil palm plantation (Lim et al., 2012).

Considering the wide distribution and large area of oil palms expansion, remote sensing has become the most suitable method to support this study. This technology provides the ability to monitor land cover in various scales. Identification of specific land covers such as oil palm plantation has been proven by several studies. Miettinen, et al. (2010) had succeeded to discriminate the oil palm plantation with other woody plantations using backscatter data of ALOS PALSAR mosaic, while Santos and Messina (2008) has applied RADARSAT texture information, Landsat ETM+, and digital video data fusion for modeling African oil palm in Ecuadorian Amazon. However, the previous studies are mainly attempted to carry out the classification for private estate oil palms, which covering large area. On the other hand, while the application of remote sensing for land use and land cover monitoring in tropical peatland has also widely done (Jaenicke 2010, Koh et al. 2011), there are still limited studies about classifying the vegetation conditions, especially for smallholders' oil palms. Thus, the identification of small-scale smallholder's plantation and its tree condition are still practically hard to do using currently available data, and any further study regarding to this will be helpful for monitoring the land use change caused by smallholder's oil palm expansion and rehabilitation for increase the yield of smallholder's plantations cultivated on peatland area.

Multi-sensor and multi-scale images acquired by Advanced Land Observing Satellite (ALOS) are considered as the proper data to conduct the study related to smallholder's oil palm plantations. Penetration ability through tree canopy and backscatter characteristic of Phased Array type L-band Synthetic Aperture Radar (PALSAR) data offer potential tool for vegetation type identification. Fully polarimetric PALSAR data is particularly useful as it provides more information related to the object scattering (Negri et al. 2016). Considering the frequent cloud cover in the tropics, active remote sensing is very much useful for monitoring purpose. On the other hand, the multispectral image derived by AVNIR-2 sensor offers wide range of spectral information for identifying other land cover types. Thus, further studies using these data are considered to be effective for improving smallholders' oil palm management.

1.2 Research Objectives

The main purpose of this study is to explore the methodology of ALOS PALSAR and ALOS PALSAR-2 application for identification and mapping of areal distribution and tree conditions of smallholders' oil palm plantations. In order to achieve this purpose, this study focused on the following specific objectives:

(1) to explore the characteristic of oil palm plantation that can be identified by remote sensing data,

(2) to examine the ability of dual and full polarization of ALOS PALSAR data in discriminating oil palms from other land cover types,

(3) to identify the best integration methodology of ALOS-Sensor data to detect smallholders' oil palm plantations,

(4) to investigate the most effective backscatter and polarimetric parameter for identifying oil palm tree conditions on peatland area

1.3 Outline of Dissertation

This dissertation is organized into five chapters. This chapter has described the general background of this study, motivation of the research, as well as several targets to be achieved by conducting the study.

Chapter 2 provides information about the main object of this study, which is the smallholder's oil palm plantation, from the plant characteristic up to the explanation of smallholder's oil palm expansion in Indonesia. Moreover, a brief explanation about general methodology used in this study, consist of polarimetric SAR and textural analysis, are also described.

Chapter 3 mainly discusses the methodology to discriminate smallholder's plantations from other land cover type. This chapter includes the study using the integration of bot SAR and optical sensor of ALOS satellite data, as well as examination of fully polarimetric SAR ability to detect this object.

In chapter 4, the exploration of ALOS-2 PALSAR-2 data was explained. In this study, the analysis was conducted for more detail target, which is the oil palm tree condition by using combination of textural and polarimetric decomposition method.

General discussion about overall result of the study was explained in chapter 5. This chapter also describes various limitations of the current study and some recommendation for future study focusing on smallholder's oil palm plantation.

Chapter 2

Theoretical Framework

2.1 The Oil Palm

As the main object of this study, extensive understanding about oil palm tree and smallholder's oil palm plantation are essential. Comprehensive knowledge about the physical growth and requirements for oil palm cultivation will be useful for understanding the characteristic of oil palm tree, as well as for designing the best methodology to discriminate oil palm from other land cover. On the other hand, information about variety of oil palm managements and factors affecting expansion are necessary for better understanding of oil palm development pattern by the smallholders.

2.1.1 The origin and growth of oil palm

Oil palm is a tropical crop which mainly grown in the flat and lowland area. It is originated from Africa, in particular to West Africa, and was originally cultivated by independent small farmers (Budidarsono et al. 2013). Various physical evidences found in this area have convinced the use of oil palm for human activities from thousands years ago. Since that time, oil palm has been expanded throughout the equatorial tropics. The oil palm (*Elaeis guineensis* Jacq.) is a species of Arecaceae or Palmae family which include many plants with enormous economic importance. It is also grouped together with the coconut under Cocoideae subfamily, while the genus *Elaeis* is derived from Greek word *elaion*, which means oil. The other species of this genus is called *Elaeis oleifera* or American oil palm. Unlike *E. guineensis*, *E. oleifera* is rarely planted commercially, and therefore, the term oil palm is commonly referred as *E. guineensis* instead.

The early growth stage of oil palm tree is begun with the formation of wide stem base and a few of leaves produced in spiral succession from meristem. The number of leaves produced increase after 2 years of planting as much as 40 opened leaves per year, but then it declines as the tree grows, stabilizing after 8-12 years. The un-branched tree trunk is started to be formed after three years of planting, with the rate of grow is about 25 to 50 cm per year, depending on the environmental and hereditary factors. The height may reach 20 m height at the age of 25 years old, and is considered to be not effective for production anymore, because the fruit harvesting process at this height is very difficult and time consuming. Therefore, regeneration process by replanting new trees is usually carried out to the oil palms after 25-30 years of planting (Corley and Tinker 2016, Sheil 2009, Verheye 2010).

Figure 2.1 Oil palm tree (Elaeis guineensis)

The oil palm tree is categorized as a monocotyledon species with male and female inflorescences form separately on the same palm. The cluster fruits of oil palm are developed on the short stems close to the trunk, and will be ready for harvesting after 5-6 months after flowering. A bunch of mature oil palm fruits may contain 1,000 to 4,000 fruits with 15-25 kg weights, depending on the tree's age and vigor (Verheye 2010). Product of oil palm tree, the palm oil, is produced by extracting the fruit and seed of oil palm. The oil produced from both parts has different fatty acid, and therefore has different uses. Crude palm oil (CPO) produced from the outer mesocarp is usually used in food, while palm-kernel oil, extracted from the endosperm, is mostly used for non-edible products, such as soap, detergents, cosmetics, as well as industrial and agricultural chemicals. About 5 to 7 tons/ha/year of oil yield can be produced from oil palms planted under good condition. This yield is 3-8 times higher than any other oil seed crop, which makes oil palm as the most area-effective vegetable oil crop (Sheil 2009, Wahid et al. 2005).

2.1.2 Requirements for oil palm cultivation

2.1.2.1 Climatic requirements

As a tropical crop, oil palm demands high and stable temperature with plenty rainfall and sunshine throughout the year. The tree may be growing with daily temperature range from 21 °C to 32 °C, with optimal mean between 24-28 °C. Cultivation at high altitude or at places beyond 15 °N/S is still possible, however, slow vegetative growth might be happened due to the low mean temperature. On the other hand, high temperature above about 38 °C is also unfavorable as it may affect the photosynthesis.

The other important factors supporting oil palm growth is supply of water. Sufficient amount of rainfall is particularly crucial as it affects to soil water content, surface run-off, as well as evapotranspiration. Average rainfall of 150 mm/month with a minimum 100 mm/month, and annual mean ranging from 1,800 mm to 2,500 mm are considered as the best condition. Decrease in potential of oil palm yield might be occurred due to deficit of water when the dry periods happen for more than 2 consecutive months, while severe stress would be arisen after exceeding 3 months. However, temporary flooding or sudden increase in amount of water may also cause high damage on young or immature oil palms, while mature palms are less affected.

Even though water availability and nutrients usually give higher effects, a high level of solar radiation is also necessary. It has been proven that solar penetration through the canopy affects the growth rate and fruit bunch production, as the oil palms planted in the open field generally grow faster and produce higher yields than those planted under closed canopy. Shading palms make the growth become slower for all ages and reduce the production of female inflorescences for mature palms. As an approach to measure solar radiation, sunshine hours are used as they are normally well-correlated. Several experiments regarding this matter indicate 5 hours/day of sunshine is required for oil palm cultivation (Verheye 2010).

Corley and Tinker (2016) stated that Adiwiganda et al. (1999) has classified 11 agroclimatic zones in Indonesia based on the suitability for oil palms cultivation, in regard to rainfall, sunshine hours, and length of dry periods, as shown on table 2.1.

Table 2.1 Agroclimatic zones for oil palm cultivation in Indonesia

Zone	Characteristics	Distribution	ASU
I	Rf = 1750-3000mm; < 1 dry months; sd = 6 h/day	Eastern part of North Sumatra; eastern of Aceh; northern of Riau; northern and southern part of Kepala Burung Papua; north coast and southern part of Papua	AS1 ‐ n
II	Rf = 1750–3000 mm; 1–2 dry months; sd = 6 h/day	Most of Riau; eastern Jambi; most of northern part of South Sumatra; most of Central Kalimantan; Aru Islands of Papua; small part of southern Papua	AS1 ‐ k1
III	Rf >3000 mm; < 1 dry months; sd = 5.0–5.5 h/day	Western part of Aceh; western part of North Sumatra, Nias Island, northern part of West Sumatra	AS2 ‐ m2
IV	Rf >3000 mm; 1–2 dry months; sd = 6 h/day	West Kalimantan; most of western part of Papua	AS2 ‐ h1k1
V	Rf >3000 mm; 1–2 dry months; sd = 5.5–6.0 h/day	Southern part of West Sumatra; northern part of Bengkulu	AS2 ‐ h1k1m1
VI	Rf = 1450–1750 mm; 1–2 dry months; sd = 5.0–5.5 h/day	Small area of northern part of East Kalimantan; Central Sulawesi (except Palu and surroundings); northern part of Maluku	AS2 ‐ h1k1m2
VII	Rf = 1450–1750 mm; 2–3 dry months; sd = 5.0–5.5 h/day	Southern part of South Sumatra, Bangka and Belitung; eastern Lampung; most of East Kalimantan; small area of eastern part of Central Kalimantan; most of South Sulawesi; southern part of Papua borders with Papua New Guinea	AS3 ‐ h1k2m2
VIII	Rf = 1750–3000 mm; 3–4 dry months; sd = 5.0–5.5 h/day	Western part of Lampung; small area of western part of West Java	AS3 ‐ k2m2
IX	Rf = 1250–1450; 3–4 dry months; sd = 5.5–6.0 h/day	Palu and surroundings; most of Sulawesi Tenggara; central Maluku; South Maluku; East Timor	AS3 ‐ h2k2m1
X	Rf = 1250–1450 mm; >4 dry months; sd = 6 h/day	Eastern part of West Java; central Java; East Java; Bali; southern part of South Sulawesi; southern part of Sulawesi Tenggara	ANS ‐ h2k3
XI	Rf <1250 mm; >4 dry months; sd = 6 h/day	West Nusa Tenggara; East Nusa Tenggara	ANS ‐ h3k3

Source: Adiwiganda *et al*. (1999) in Corley and Tinker (2016)

ANS: agroclimatically not suitable; AS: agroclimatically suitable; ASU: agroclimatic suitability unit; h: rainfall as limiting factor; k: dry month as limiting factor; m: sunshine duration as limiting factor; n: normal (without any limiting factor).

Rf: Rainfall; sd: sunshine duration; 1: light intensity; 2: moderate intensity; 3: strong intensity

2.1.2.2 Soil condition

In case of soil requirements, oil palm has quite high toleration for wide range of soil variations. The suitability of soil mainly depends on its physical properties which determine the stability of soil structure, rather than chemical properties or nutrient supply, which can be managed by an appropriate application of fertilizer. The optimal soil for oil palms is the one with fine structure, has little gravel, has a texture that good enough for drainage, and contains sufficient soil organic matter. Soils with high clay content, loam, or silt-dominant are particularly suitable to produce good yields (Pirker et al. 2016).

Corley and Tinker (2016) also mentioned that wetness is one of soil suitability criteria designated for South East Asia by Paramananthan (2000). The wetness criterion means the soil water content and moisture conditions which should be neither excessively or insufficiently drained nor prone to flooding. Even though mature oil palms can tolerate temporary flooding, a high water table or low hydraulic conductivity may cause anoxic condition in the soil, and affect the palms growth and productivity.

2.1.2.3 Other requirements

The other requirements for oil palm cultivation consist of the topographic condition and land clearing. Planting oil palms on steep slopes is highly not recommended as it may increase erosion risk, as well as the effort and cost of establishment, maintenance, and harvesting. While oil palms can still be grown on the land with slope up to 16˚, flat land with 0 – 4˚ slope inclination is considered as the most favorable for the cultivation (Pirker et al. 2016).

As oil palms are usually planted on the land which previously used for other vegetation, land clearing is one of the important procedures prior to the development. The initial vegetative cover should be eliminated, and the soil must be freed-up from pests, diseases, and other hazard that might be harmful for the crop. This procedure is more complex when it is applied to forest concession area, because evacuation of huge amount of vegetative matters requires long time and much labor work. Several techniques, such as manual uprooting for low vegetation, and mechanical down-pulling of the old trees using bulldozer are generally applied in large oil palm estate. However, land clearing by burning the previous land cover is still used, particularly by the smallholders, because this method is considered as an easy and low-cost tool comparing to other techniques (Verheye 2010). Application of this method, especially during dry season, has drawn global attention and has been forbidden as the amount of smoke from the fire cause high air pollution and become serious threat for environment as well as public health.

2.1.3 The expansion of oil palm plantation in Indonesia

The initial oil palm seedlings brought to South East Asia were planted at Buitenzorg (currently known as Bogor) Botanic Garden in Java Island, Indonesia in 1848. The seeds from these palms were then distributed to other areas, particularly to Sumatra Island, and were originally planted as ornamental plants. Commercialization of the crop was started to be developed about over 60 years later and established mainly in east coast area of Sumatra (Corley and Tinker 2016).

Along with growing global demand for palm oil, in late 1690s, Indonesian government began to focus on the development of oil palm plantations through state-owned companies which was integrated with transmigration program to provide labor workers. The state-owned plantations played crucial role in oil palm cultivation until several policy changes triggered the establishment by private companies and smallholders. Statistical data provided by The Ministry of Agriculture of Indonesia show rapid expansion of private estate and smallholder's oil palms since early 1990s, while no significant increase of state-owned plantation area can be seen (Fig. 2.2).

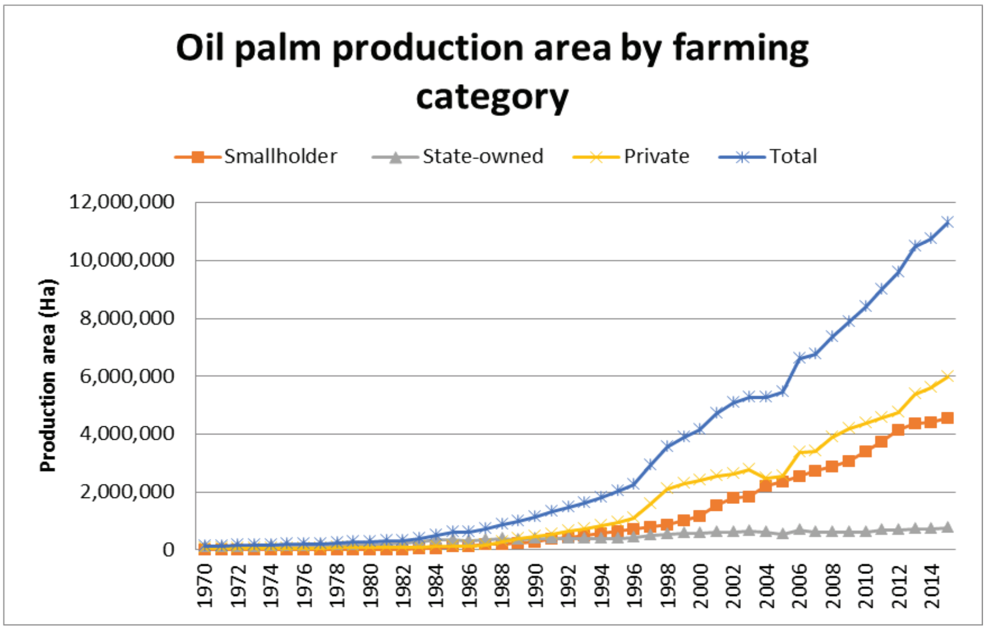

Figure 2.2 Oil palm production area by farming category (Source: Ministry of Agriculture of Indonesia 2015)

Indonesia has the largest and the most rapid growth of harvested oil palm areas among other countries. The harvested area of oil palm fruits has been increased by more than ten times, as much as 1 million ha in 1990 to 10.8 million ha in 2014 (Ministry of Agriculture of Indonesia 2015). Distribution of oil palm plantations in Indonesia itself is mainly concentrated in Sumatra Island, with the largest area could be found in Riau Province (Fig.2.3). However, large investment from both local and foreign private companies, as well as high interest of smallholders to cultivate oil palms has driven the expansion in other areas, such as Kalimantan, Sulawesi, and Papua Islands.

On the contrary of its contribution to the national income and development of rural area, expansion of oil palm has drawn much controversy because of the rapid land conversion to oil palm (Fitzherbert et al. 2008, Wilcove and Koh 2010). While some studies found that generally the land converted to oil palm was initially either degraded or other agricultural land, the expansion on conservation area, such as pristine and peat swamp forest, which have rich biodiversity and store huge amount of carbon, are still occurred mainly in some part of Sumatra and Kalimantan Islands.

2.1.4 Smallholders' oil palm plantation in Indonesia

The smallholder oil palm farmers started to develop their own plantation not long after the oil palms plotted as cash crop. After the establishment of state-owned plantation, the government encouraged the smallholders to grow oil palms through a scheme called *Perkebunan Inti Rakyat* (*PIR*) or Nucleus Estate Scheme (NES). The farmers, which is named as smallholder-plasma farmers, received several supports from

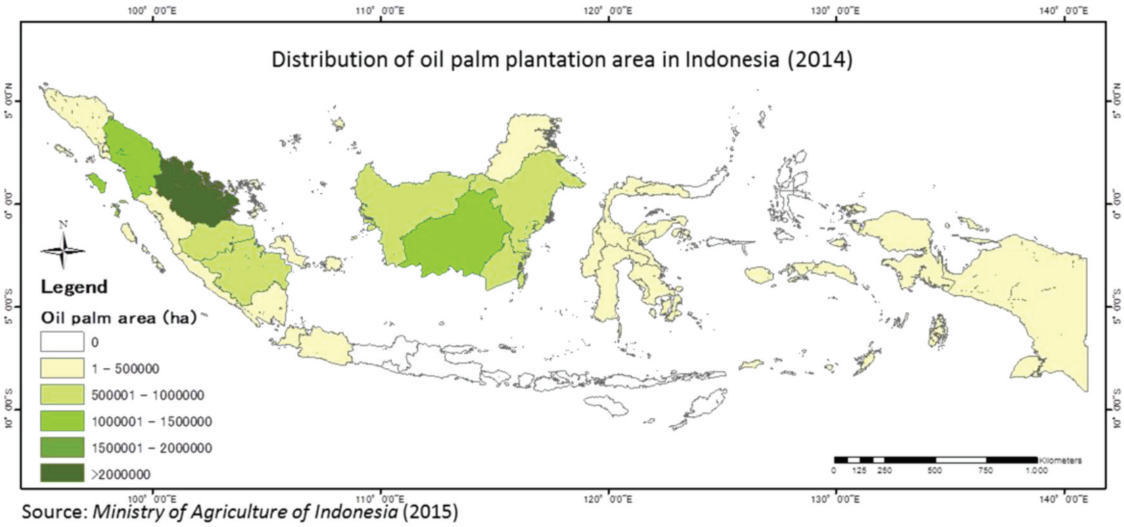

Figure 2.3 Oil palm distribution map in Indonesia

the state-owned companies, including seedlings, technical assistance, finance, as well as guaranteed support price for fruits supplied by them. However, In 1990s governmental role started to decrease over time and replaced by the partnership with private enterprise after the new scheme, called Primary Cooperative Credit for Members (*Koperasi Kredit Primer untuk Anggota* - KPPA), was enforced. With the new policy of decentralization system, local communities and farmers, whose crop production was unsuccessful, could transform their land to oil palm plantations. This situation caused more smallholder to cultivate independently, separate from the companies' and plasma plantation (Budidarsono et al. 2013, Glenday and Paoli 2015).

Unlike the state-owned or private estate, which are developed at the 1000ha or larger, smallholders' oil palm plantations are generally cover only a few hectare area (Corley and Tinker 2016, Lee et al. 2014). It is stated in The Ministry of Agriculture of Indonesia's Decree No. 98/2013 that one can be qualified as 'smallholder farmer' if only the farmer plantations less than 25 ha in size. In case of plantations managed by plasma-farmers in association with private company or state, the plantations of several farmers are usually arranged and located in the same area close to the company's plantation. On the other hand, the independent smallholders, are generally develop oil palms in much smaller area, ranged about 2-5 ha of land (Glenday and Paoli 2015). This type of farmers is not locked in to formal partnerships and is free to sell their fruit bunch to any agents (Vermeulen and Goad 2006). Therefore, independent smallholder could establish their plantation anywhere as long as they can make sure to sell their fruits to be processed within 48 hours after harvesting.

Unfortunately, due to lack of management practice, yields of smallholder's oil palms are usually lower than estate yields. Vermeulen and Goad (2006) showed that scheme smallholders in Indonesia generally produced 90% of estate yields, while the independent smallholders' yields only 57%, mainly because of the poor availability of good quality seed stock, access to the oil palm mills, financial problem, and sometimes lack of technical knowledge of oil palm cultivation (Corley and Tinker 2016, Papenfus 2000). However, in spite of their lower productivity, as shown in Fig. 2.2, smallholders currently still play very important role in the palm oil industry of Indonesia as they manage up to 40% of total oil palms area in recent years (McCarthy 2010). It is therefore, management improvement of smallholder sector is necessary in order to achieve sustainable development of oil palm plantation.

2.2 Basic Theory of Polarimetric Synthetic Aperture Radar (PolSAR)

Remote sensing is defined as the science and art of obtaining information about object, area, or phenomenon through analysis of the data that acquired by device and is not in direct contact with the target (Lillesand et al. 2008). Based on the sensor type being used, the acquisition method in satellite remote sensing is divided to passive and active methods. In passive remote sensing system, data acquisition highly depends upon existed energy sources such as the sun or earth itself. The sensor only receives the reflectance of the energy from objects. On the other hand, the sensor in active system radiates the electromagnetic energy and receives the energy scattered back to sensor by itself. This system has ability to measure anytime because it does not depend on the sun light. In addition, the long wave that commonly used in this system is particularly useful for measurement at any weather conditions as it is able to penetrate cloud cover (Murai et al. 1993, CCRS 2014, Richards and Jia 2006).

2.2.1 Polarimetric Synthetic Aperture Radar (PolSAR)

Synthetic Aperture Radar (SAR), the most common radar system being used, transmits microwave in the range direction at right angles to the flight direction (azimuth direction), receives the backscattering from the object and measures the delay time between those two processes with a small antenna. In SAR imaging process, the most significant factors of microwave characteristics are frequency range (or wavelength) and polarization.

Polarization is defined as the oscillating direction involved in an electrical field. While microwave is usually transmitted and received either in horizontal (H) or vertical (V) polarization, four combinations of polarizations could be applied in SAR system which have different backscattering characteristic respect to the polarization. Those combinations are HH, HV, VH, and VV, where each letter represents the polarization while transmitted and received by sensor, respectively. In this study, dual and fully polarimetric SAR data were used to detect the target object. Dual-polarized SAR detects the object target using scattering from either combination of HH and HV or VH and VV. On the other hand, fully polarimetric data provide more scattering information from the object using four types of linear polarization and their combination.

SAR polarimetric offers the ability to interpret different representations of electromagnetic scattering mechanisms without in-situ information. For fully polarimetric radars, scattering properties of image pixels are directly described by the 2 × 2 scattering matrix [S] which connecting the vectors representing the incident and scattered waves:

$$[\boldsymbol{S}] = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \qquad \text{(Eq. 2.1)}$$

The elements of this matrix express the change due to scattering interaction of horizontal (*H*) and vertical (*V*) wave components. However, since the real process involves dynamic environments, scattering processes are interpreted using the higher-order matrices, covariance matrix (C) and coherency matrix (T), which has taken into account the environment condition (Alberga et al. 2008).

2.2.2 Polarimetric Decomposition Theorems

Polarimetric target decomposition has been developed to provide interpretation based on sensible physical constraints by observing the coherency or covariance matrix of polarization (Lee and Pottier 2009). Among several decomposition methods for extracting the information of scattering mechanism, this study focused on using three decomposition theorems as follows (Alberga et al. 2008, Lee and Pottier 2009):

a. Eigenvalue-eigenvector decomposition (Cloude and Pottier 1997)

This decomposition was proposed to extract average parameters from experimental data using eigenvector analysis of coherency matrix, which provides a basis invariant description of the scatterer with a specific decomposition into types of scattering process (the eigenvectors) and their relative magnitudes (the eigenvalues). The method is free of physical constraints and provides information about polarimetric scattering with matrix-characterizing such as polarimetric entropy (H), Anisotropy (A), and average or mean scattering angle, alpha (α).

- Entropy (H) indicates the randomness of the scatterer represented in a value ranged from 0 to 1. An H value equal to 0 indicates a deterministic scatteing process, while H equal to 1 means a degenerated eigenvalues spectrum with high random scattering.
- Anisotropy (A) shows the relationship between secondary scattering processes. It measures the relative importance of the second and third eigenvalues of the decomposition.
- Alpha (α) is an angle ranging from 0 to $\pi/2$ and indicates the mean scattering

mechanism. Among the mean parameters (α , β , δ , and γ), α is determined as the main parameter for identifying the dominant scattering.

b. Freeman-Durden 3 components decomposition (Freeman and Durden 1998)

This decomposition theorem defines the technique of physically-based scattering mechanisms, including odd, double-bounce, and volume scatterings (Fig. 2.4). This scattering model is known for its simplicity because it decomposes Pol-SAR image under reflection symmetry condition of covariance matrix:

$$< S_{HH}S_{HV}^{*} > \approx < S_{VV}S_{HV}^{*} > \approx 0 \qquad \text{(Eq. 2.2)}$$

In this method, odd scattering is produced from the Bragg small roughness model that describes co-polarized polarization from the object. This scattering is also called as surface scattering (s) as it principally represents the scattering information from moderately rough surface such as soil. On the other hand, double-bounce scattering (d) is usually modeled the reflection from tree trunk and ground, while volume scattering (v) describe the random distribution of very thin, cylinder-like scatterers in response to branch of canopy cover.

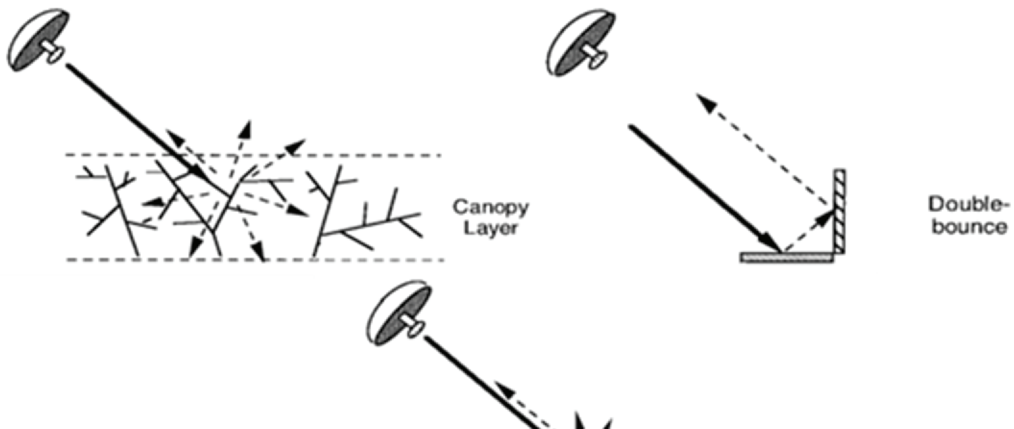

Figure 2.4 Scattering mechaninsm used in Freeman-Durden decomposition model (Freeman and Durden 1998)

c. Yamaguchi 4 components decomposition (Yamaguchi et al. 2005)

Yamaguchi decompositions mainly modeled the similar characteristics as Freeman-Durden model. However, unlike the previous one, this model considering the Pol-SAR analysis for urban area in which the reflection symmetry condition does not apply. Therefore, this model tried to approach the Freeman-Durden model with new condition of $< S_{HH}S_{HV}^{*} > \neq 0$ and $< S_{VV}S_{HV}^{*} > \neq 0$ in the covariance matrix. In this case, additional helix scattering, which corresponds to non-symmetry condition, was proposed as the fourth component for characterizing scatter in man-made or urban area.

2.3 Texture Analysis

Texture is defined as representation of local tonal variations that is repeated in the larger spatial domain and determines visual smoothness or coarseness of image features (Lilesand & Kiefer 1994, Srinivasan & Shobha 2008). Rosenfeld and Kak (1982) described texture as a similarity grouping of complex visual pattern composed of entities that have characteristic of brightness, color, size, etc. In digital image, texture determines the pixel relation with its neighbor pixel within a small area centered on the pixel (Murray, et al. 2010). It is therefore the analysis of texture requires mathematical function that could characterize the variation of tonal primitive properties and the spatial dependence between them.

Texture characteristics measurement could be approached through various sides, based on the dimension and statistical model being used. Haralick (1979) mentioned there are at least eight statistical approaches to the measurement and characterization of image textures. Recently, the statistical approaches has been explored and compared with each other to find the most applicable model. Murray et al. (2010) summarized the comparison of two texture classes, structural and statistical method, for classification purpose. The structural techniques, which classify texture by looking for repeating patterns and other structural characteristics in the image, is best applied for artificial environment. Otherwise, the statistical techniques, that performing statistical operations for classifying the image and commonly focusing on a small moving window, are best work with natural environment. Among all of the texture approaches, statistical Grey

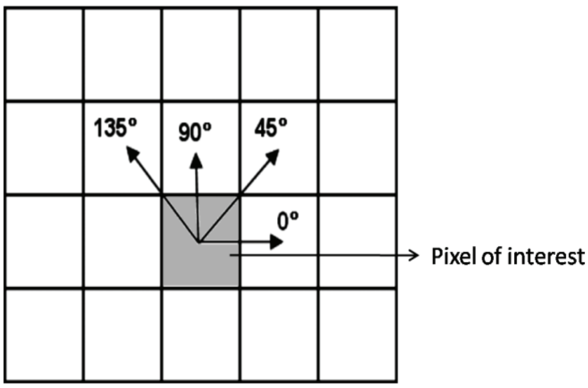

Figure 2.5 Four directional angles for GLCM computation (Abolghasemi et al. 2010)

Level Co-occurrence Matrix (GLCM) proposed by Haralick et al. (1973) is one of the most widely used texture measurement.

GLCM, or sometimes called grey-tone spatial-dependency matrix, is a square matrix which has same number of row and column as N quantization level of the image and symmetrical around a diagonal (Murray et al. 2010, Basile Giannini et al. 2012). In GLCM, the texture information of digital image is principally defined by the adjacency relationships for a pair of pixels with certain grey tone value which are separated by a fixed spatial relationship (Gadkari 2004). It is computed by assuming p(i,j) as the frequency of occurrence of two cells of grey tone i and j, separated by distance d with specific direction that generally corresponding to four angles of 0º, 45º, 90º, and 135º as illustrated in Figure 2.5 (Tso & Mather 2009).

As an example, the texture feature of an image (Figure 2.6(a)) with 4 quantization levels (has grey tone 0-3) will be calculated. The 4 x 4 GLCM (Figure 2.6(b)) calculates how often the grey tone *i* which is contained in the pixel of interest could be paired up with grey tone *j* in the image with distance 1 pixel from the pixel of interest and four directional angles. The results are presented in the Figure 2.6 (c) to (f) for directions with angles 0º, 90º, 135º, and 45º, respectively. Each matrix is normalized by dividing each cell by the total number of pairs (Tso & Mather 2009). The texture

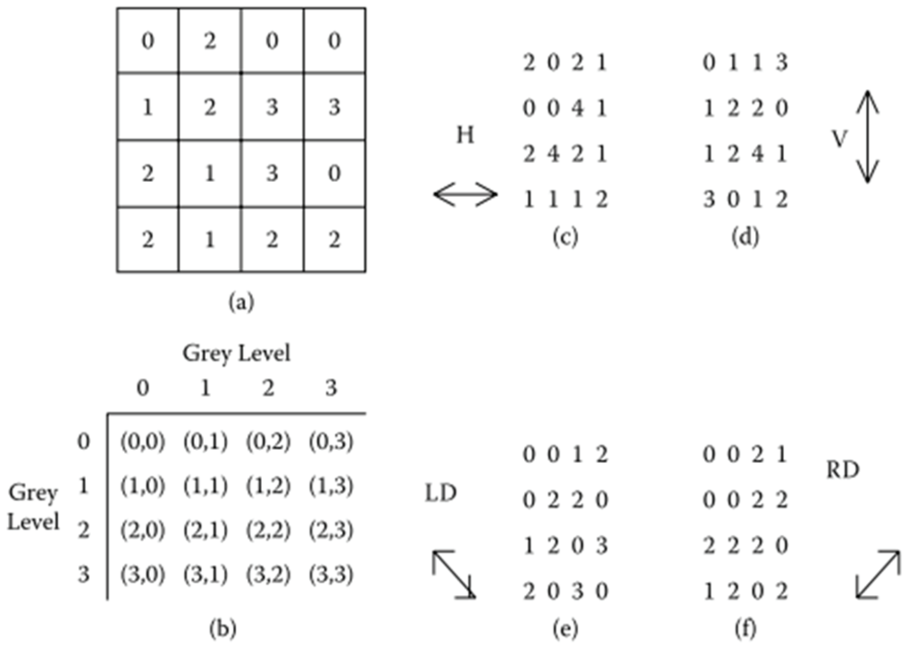

Figure 2.6 An example of GLCM computation; (a) 4 quantization level digital image; (b) 4x4 form of GLCM with grey level 0-3; (c)-(f) results of GLCM computation with four directional angles 0º, 90º, 135º, and 45º, respectively (Tso & Mather, 2009)

features are calculated by averaging over the four directional co-occurrence matrices.

There are various types of GLCM features which are formulated based on the most significant texture factors being measured. Santos and Messina (2008) has summarized eight features from Haralick (1973) that will be used in this study as describe on Table 2.2

Table 2.2 GLCM texture features used in the study

Feature	Formula	Explanation
Mean	$\mathrm{MEAN} = \mu = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} i \,.\, p(i,j)$	Measures both of tone and texture information; calculates the average grey level inside the moving window
Variance	$\mathrm{VAR} = \sigma^2 = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-\mu)^2\, p(i,j)$	Image heterogeneity measurement
Entropy	$\mathrm{ENT} = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p\,(i,j)\log(p(i,j))$	Measures the image disorder. Large values mean small values of GLCM measurement due to the image texture that not uniform
Angular Second Moment	$\mathrm{ASM} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \{p(i,j)\}^2$	A measure of textural uniformity. Value will be large when there is less local texture variation; when the grey level distribution is constant
Contrast	$\mathrm{CON} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)\,.\,(i-j)^2$	Measures the contrast or amount of local variation present in the image; High values indicate contrasting grey tones in the image
Correlation	$\mathrm{COR} = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i.j)p(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y}$	Measures grey tone linear dependencies in the image; expressed by the correlation coefficient between grey-levels and the probability densities at each of the grey –level pairs.
Dissimilarity	$\mathrm{DIS} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)\ .\,\lvert i-j\rvert$	Measurement of the difference grey tone in the image
Homogeneity	$\mathrm{HOM} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{p(i,j)}{1+(i-j)^2}$	A measure of homogeneity; high value if the difference in pairs of grey-levels are small

(Haralick, et al. 1973, Santos & Messina 2008)

Where : N = Number of distinct gray levels in the quantized image

$p(i,j)$ = $(i,j)^{th}$ entry in a normalized gray-tone spatial-dependence matrix

$p_x(i)$ = $\sum_{j=0}^{N-1} i\, p(i,j)$ $\quad$ $p_y(j)$ = $\sum_{i=0}^{N-1} i\, p(i,j)$

$\mu_x\mu_y$ = means of p_x and p_y $\quad$ $\sigma_x\sigma_y$ = standard deviations of p_x and p_y

It has been proved that there is no exact feature will be effective for all kind of applications. The suitable feature will be different depends on the object of interest. Beside the feature types, previous studies indicated that window size is the other important part to be considered when applying GLCM. It is believed that the final result will much relies on the size of moving window. Too small window size will lead to less textural information of each category. Otherwise, too big size of moving window will cause overlap measurement with other land cover types and produce errors in classification at the boundaries between classes because the specific characteristic that could differentiate each class could not be obtained. Therefore, the ideal window size also important to be examined as it will depends on the resolution of the image and the size of object being explored (Murray et al. 2010, Haralick et al. 1973).

2.4 SAR and Texture-Analysis Studies on Vegetation Mapping

Availability of reliable and up-to-date land use and land cover information is substantial for planning, management, and monitoring systems. While land use and land cover classification using satellite remote sensing and GIS has been developed for a long time, identification methods, particularly for vegetation, still remain difficult due to various considerations and techniques involved. In term of vegetation classification at community and species level, interpretation of spectral elements from each pixel only is considered to be inadequate, and therefore, spatial context by taking into account the spatial properties of a region in the image need to be developed.

Texture analysis, as one of the methodology that measure relationship of pixel values in large spatial domain of the image, has been applied in several studies to improve the vegetation mapping. Murray et al. (2010) has stated the importance of selecting appropriate data, GLCM texture features, and moving window in vegetation classification based on the objects. In the study, it was found that the combination of all multispectral IKONOS bands with texture extracted using mean, dissimilarity, and entropy features provided the most robust methodology to classify sub-Antarctic vegetation communities. Textural approach has also been applied for forest structure mapping as demonstrated by Franklin et al. (2001) and Shamsoddini (2012). On the other hand, study by Rakwatin et al. (2012) proved the ability of 50-m resolution dual polarization ALOS PALSAR backscatter data for tropical forest mapping in central Sumatra, Indonesia by applying multi-scale texture. However, classification of plantations in this study still remains unsolved as significant confusions were found between acacia and oil palm plantations with natural forest and clear cuts, respectively.

Improvement of oil palm classification has been achieved in several studies by employing textural analysis using the image integration from both optical and SAR sensors. A study by Laurin et al. (2013) demonstrated GLCM application to the integration of ALOS PALSAR, Landsat TM, and ALOS AVNIR-2 data for land cover mapping in tropical site in West Africa, which included large scale oil palm plantations. In this study, mean, entropy, correlation, variance, and second-moment GLCM features were extracted from Landsat TM (band 4 and 5) and AVNIR-2 (band 3 and 4) which are known to be useful for detecting vegetation, as well as from HH and HV polarization of ALOS PALSAR image. Overall accuracy as much as 95.6% of land cover classification was obtained by combining these data. The highest accuracy at 99.6% and 98.9% of producer's and user's accuracy, respectively, were also achieved for the oil palm class. Another study by Santos and Messina (2008) has successfully applied the fusion of C-band SAR and Landsat ETM+ assisted by ground-based digital video data for modeling African Oil Palm in the Ecuadorian Amazon. This study also successfully detected the diseased oil palms that existed in the plantation. Highest accuracies were obtained by combining the mean, variance, contrast, and correlation features of SAR image and Landsat ETM+ band 1, 2, 3, 4, 5, and 7. Since both of these oil palm studies were conducted in large scale oil palm plantations, further development to identify oil palms planted in small scale area still need to be observed.

Beside the multi-sensors data integration method, interpretation of scattering mechanism of SAR polarizations allows the identification of vegetation even in more detail analysis. Lee and Pottier (2009) explain about various applications regarding to vegetation mapping that can be explored using polarimetric information of SAR data. Polarization bands and parameters obtained after decompositions were proved to be useful for land cover classification, forest mapping, until crop classification. Study by Chowdhury et al. (2013) also successfully applied polarimetric decomposition to estimate Growing Stoke Volume (GSV) in a Siberian forest without applying multi-temporal data. This study also found the significant correlation of double-bounce and volume scattering powers with GSV. These previous studies proved the potential ability of PolSAR in detail analysis such as tree growth and tree conditions even within same species.

Chapter 3

ALOS Data Integration and Fully Polarimetric SAR for Identification of Smallholders' Oil Palm Plantations in Southern Sumatra, Indonesia

3.1 Introduction

High global demand for palm oil has driven massive oil palm expansion in the tropics (Sayer et al. 2012, Gaskell 2015). Indonesia and Malaysia have become the major location of this activity due to availability of supporting factors such as favorable climate, suitable soils, and lower labor cost comparing to other countries (Clay 2004, Kongsager and Reenberg 2012). Known as the most area-effective and the highest yielding oil crop, cultivation of oil palms has turned into a vital economic strategy for both countries, as it highly contributes to national income as well as becomes a strong driver of economic development in rural areas, where the cultivation is commonly taken place. Moreover, the product of palm oil itself is useful as an alternative source of bio-fuel (Comte et al. 2012, Gatto et al. 2015, Susanti and Burgers 2011). Unfortunately, this phenomenon has also attracted controversy as it leads to biodiversity loss (Fitzherbert et al. 2008, Wilcove and Koh 2010), deforestation (Vijay et al. 2016), and increased greenhouse gas emission (Germer and Sauerborn 2008). While state and private-owned oil palm plantations have given high contribution to those impacts, it has been proven that besides those plantations, oil palm plantations managed by smallholdings also play important role, especially in Indonesia, making the careful monitoring and management of this type of plantation also necessary (Lee et al. 2014).

Mesuji District of Lampung Province in Southern Sumatra, Indonesia is known as one of the locations of smallholders' oil palms development. The smallholders in this area tend to establish oil palm by converting rubber or agricultural lands which are considered to be less profitable. This expansion is feared to be uncontrolled, with a larger conversion of land cover especially in protected areas. For a more detailed monitoring of the environmental impacts of oil palm expansion regarding to land use conversion to oil palm plantation, and better land cover management, a comprehensive spatial planning and mapping are necessary for this area. However, the small-scale area and randomly distributed characteristics of smallholders' plantations make the works become more complicated.

The identification of oil palm plantation using remote sensing has been proved for several studies. Miettinen et al. (2010) have successfully discriminated woody plantations from palm plantations using backscatter information of ALOS PALSAR data. On the other hand, Santos and Messina (2008) have performed texture analysis to model the African oil palm using C-band SAR, and Landsat ETM+ data. Nonetheless, those studies were predominantly performed for private-owned and large-scale oil palm properties. The identification of small scale oil palm plantations is believed to be practically hard using the currently available remote sensing data. It is therefore further studies regarding the detection of smallholder's oil palm plantations using remote sensing data is then necessary.

It has been suggested that the integration of multi-sensor, multi-temporal, or multi-modal images may provide more informative and reliable imagery to improve the interpretation capabilities for object detection (Pohl and Van Genderen 1998, Bedi and Khandelwal 2013). Laurin et al. (2013) also described the beneficial combination of optic and SAR data as optical data is useful to measure the reflectance of the topmost layer of the vegetation, while SAR data provides geometric information and volume scattering detection without the effect of weather conditions. Combining those advantages with texture analysis, they have successfully performed forest and land cover mapping for a tropical site in West Africa, characterized by very complex landscape, fragmented in small patches of different land use and land cover types.

On the other hand, fully polarimetric of SAR data offers more information about scattering mechanism from the object target. Four types of linear polarization and their combination, as well as other parameters, such as the amplitude, phase, and orientation, are helpful to improve separability between objects, and consequently, improve accuracy of classification result (Negri et al., 2016). A study by Bagan et al. (2010) has proved the effectiveness of using polarimetric data for land cover classification in Kalimantan, Indonesia. The study also proved that using combination of polarimetric through polarimetric coherency T3 matrix combine with intensity data yielded higher accuracy than using only the original four bands polarization data. Moreover, in order to improve classification result, classifier algorithm is also affected, depends on the object target, availability and distribution of training samples. Support Vector Machine (SVM) is one of common classification tools for classification and detection (Zhang et al., 2010). The ability of this classifier has been proved in several land cover classification.

Trisasongko (2017) has examined the ability of SVM for stand age of rubber plantation mapping using ALOS-2 polarimetric SAR, and proved that the higher overall accuracy was obtained by using SVM, compared with other classifier. Moreover, application of SVM for classifying the oil palm plantation using Landsat ETM+ data has also been performed by Nooni et al. (2014) and its superiority over MLC has been proven.

By referring to these studies, we tried to apply a texture analysis to solve the problem in the detection of smallholder's oil palm plantation, while the integration of both SAR and optical sensor data is believed to be improving the analysis. In addition, classification using fully polarimetric SAR and alternative classification algorithm is also examined. In this study, multi-sensor and multi-scale images acquired by the ALOS were considered adequate to detect small oil palm plantations managed by smallholders. Medium resolution of both images is considered to be good enough for identifying the small scale plantation. Given the frequent cloud cover present in tropical countries, radar data was mainly examined, with optical imagery used as supporting data and for result comparison. This study aimed to explore the ability of ALOS data integration and fully polarimetric ALOS PALSAR to discriminate oil palms from other vegetation covers and to develop an effective methodology to accurately detect smallholder's oil palm plantations in Southern Sumatra.

3.2 Study Area and Data

3.2.1 Study Area

The study area is located in Simpang Pematang Sub-District, Mesuji Regency, Lampung Province, in the southern part of Sumatra Island, Indonesia (Fig. 3.1). Mesuji Regency was part of Tulang Bawang Province that seceded in 2008. It is situated in the north-east area of Lampung Province, which is adjacent to South Sumatra Province in the north and west side, separated by Mesuji River. The study was performed to 5 × 5 km area in the border of Mesuji Regency of Lampung Province and Mesuji Sub-District of Ogan Komering Ilir Regency in South Sumatra Province. It covers the area surrounding the Lintas Timur national road which connecting the two provinces.

In terms of meteorological condition, Mesuji Regency is generally favorable for oil palm development. This area has two distinct seasons with tropical rainforest climate and receives average sunshine for about 5 until 5.5 hours per day. It experiences abundant rainfall during rainy or wet season from November to May, while during June

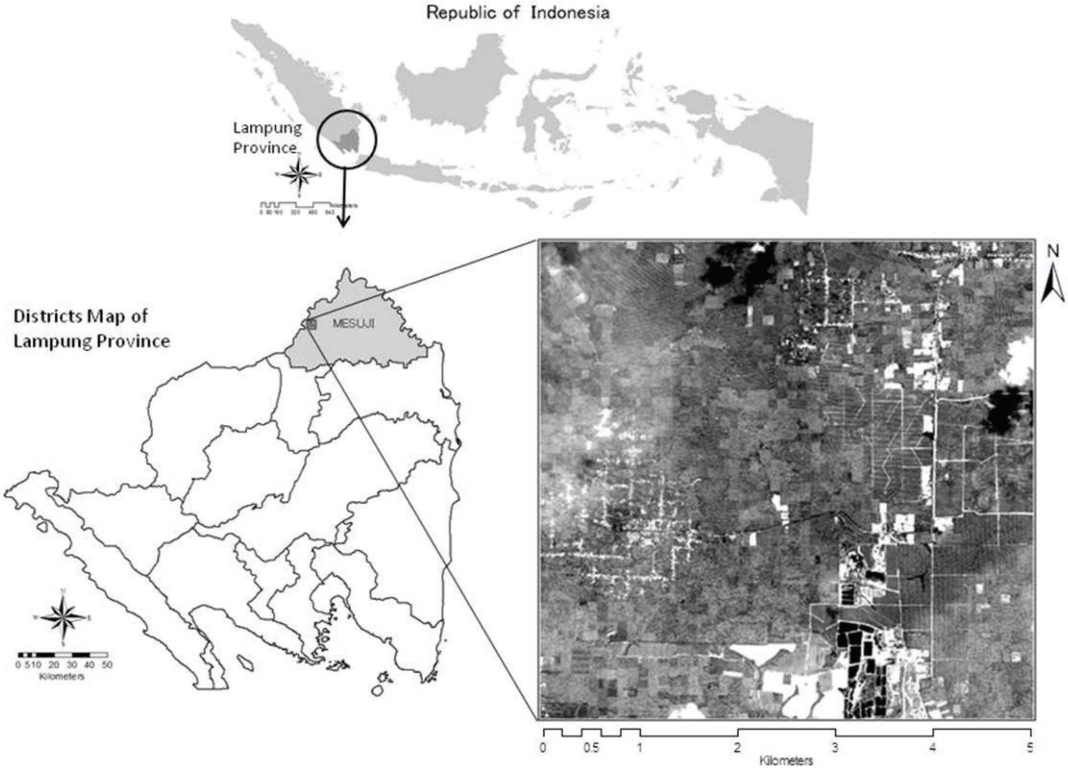

Figure 3.1 Location and Worldview-1 scene of study area

to October the dry season is occurred with limited rainfall. The average rainfall is about 175 mm of per year, with average temperature ranges from 26˚C to 28˚C. Based on the requirements of oil palm cultivation on Section 2.1.2, the above conditions can be considered as suitable condition for oil palms. Moreover, the classification of agroclimatic zones for oil palm cultivation in Indonesia as mentioned on the Chapter 2 (Table 2.1), this eastern side of Lampung Province region is classified as an Agroclimatically Suitable (AS) region with AS3-h1k2m2 unit, which means agroclimatically suitable with strong intensity of limiting factors – light intensity of rainfall limitation (h1) with moderate intensities of both dry month and limitation of sunshine duration (k2m2) (Corley and Tinker 2016). As for topography condition, Mesuji Regency has relatively flat topography, with slope is ranged between 3 to 30 %. The study area is located as a part of the Mesuji River Basin area, the main river basin in Mesuji regency, and is generally covered by dry soil (Ministry of Manpower and Transmigration of Republic of Indonesia 2007).

As shown on Worldview-1 image (Fig. 3.1), among total of 25 km^2 of study area is mainly used as rubber plantation, and about 30% is covered by oil palm plantations, both managed by private estate and smallholders. The private estate located on the south-east part of the area is belonged to PT Lambang Jaya, who started to develop the oil palm in this area since 1998. Meanwhile, smallholder's oil palm plantations were established following the existence of the private estate. According to the information derived during field survey activity, smallholder's plantations are usually planted on small area, located in random places, and surrounded by rubber plantation or acacia. Those areas mainly developed in irregular shape. Even though there are several plantations that are located next to each other, the planting age are not always same, because the smallholders sometimes start to grow oil palm based on their financial condition. Smallholders who cultivate oil palms are generally residents who came to this area through a program which relocate some residents from densely populated area, such as Java Island, to less populated one, or so called transmigration program. The remaining area is comprised of settlement area with some mixed garden crops located in their neighborhood, as well as agricultural and grass land. The main commodities of this area beside oil palm and rubber are included maize and cassava, meanwhile, paddy field area has been gradually decreasing due to its conversion to oil palm plantation.

3.2.2 Data

The data used for the analysis consist of primary and secondary data. The primary data comprise ALOS images, while the secondary or ancillary data include the other satellite image and field survey data (Table 3.1).

Table 3.1 List of data used for the analysis

Data	Type of data / processing level	Acquisition date	Resolution (m)
ALOS PALSAR FBD	Primary / 1.5	14 September 2010	12.5
ALOS PALSAR PLR	Primary / 1.1	25 October 2010	12.5
ALOS AVNIR-2	Primary / 1.5	20 June 2008	10
Worldview-1 (panchromatic)	Secondary	26 September 2011	0.46
SRTM DEM	Secondary	-	90
Field data	Secondary	18 April – 20 May 2013	

3.2.2.1 Primary data

In order to detect smallholders' oil palm plantation, remote sensing images acquired by ALOS are used for the analysis. ALOS, or called 'Daichi' in Japanese, is a remote sensing satellite developed by Japan Aerospace Exploration Agency (JAXA) which carried three sensors, a radar sensor named PALSAR, and two optical sensors called Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) and Advanced Visible and Near Infrared Radiometer type 2 (AVNIR-2). Each of sensor has different spatial and radiometric resolution, and therefore, images acquired by three of them can be use simultaneously to complement each other information.

The ALOS PALSAR data acquired in Fine Beam Dual (FBD) and Polarimetry (PLR) modes were used as the main data to analyze the characteristic of smallholders' oil palm plantations. The FBD image used in this study consist of Horizontal-Horizontal (HH) and Horizontal-Vertical (HV) polarizations. The data has been processed in level 1.5 before used as the main source for texture extraction and combined with the optical image for smallholders' oil palms detection. On the other hand, the PLR or fully polarization SAR image has four bands polarizations, including HH, HV, VH, VV polarizations. This image was analyzed independently from data processing level 1.1. However, due to the coverage of available data for the study area, the PLR data could not fully cover all over 5×5 km^2 area. Some missing part on the north-east area will then be neglected from this analysis. The two images used in this study were taken at relatively close date to minimize the temporal distortion.

The multispectral image derived by optical sensor, ALOS AVNIR-2, has four bands electromagnetic corresponding to blue wave (band 1), green wave (band 2), red wave (band 3), and Near Infrared wave (band 4) with 10 meter spatial resolution in each scene. The image was selected with less than 20% of cloud coverage on the study area.

3.2.2.2 Secondary data

The high resolution image taken by Worldview-1 satellite, Digital Elevation Model (DEM) derived by ASTER satellite, and information from field survey were used as secondary data. The Worldview-1 is an earth observation satellite owned by DigitalGlobe, which offers panchromatic imaging system with image taken under half-meter resolution. By examining this image, detail land cover in the study area can be clearly seen, and accurate information for training sample of classification and accuracy assessment procedure, while the Digital Elevation Model (DEM) derived by Shuttle Radar Topographic Mission (SRTM) data were used for terrain correction process as a part of SAR pre-processing.

Field survey activity was conducted on 18 April until 20 May 2013 to gain information about real condition of land cover in the present time. Ground truth data of several smallholders' oil palm plantations and other land cover types were acquired using GPS receiver and map sketches. In particular area of smallholders' plantations, oil palm tree's structural parameters was measured to obtain general knowledge about tree's characteristics in each growing stages. Additionally, interview with local communities and residents was performed to gain information related to oil palm development system by local smallholders and issues caused by oil palm expansion. All of the information obtained from the field survey activity was used as one of the basic knowledge for analysis as well as complementary data for training sampling and accuracy assessment.

3.3 Methodology

Methodology of this study is divided into two main parts. Firstly is the detection of smallholders' oil palm plantation using ALOS- sensor data integration, consisted of ALOS PALSAR FBD and ALOS AVNIR-2 data, which mainly discuss about the methodology to figure out characteristic of oil palm plantations that can be detected by satellite image, to assess the ability of PALSAR data only and the effect of data integration on identification of smallholders' oil palms. On the other hand, the second part of methodology is mainly focused on the exploration of fully polarimetric PALSAR data and the effect of SVM classifier for oil palm detection.

3.3.1 ALOS-Sensor data integration analysis

3.3.1.1 Image pre-processing

Pre-processing procedures was carried out to satellite image in order to reduce error and distortions from internal and external factors. Geometric correction was performed to PALSAR FBD and AVNIR-2 images by transforming the images to the local coordinate of Universal Transverse Mercator (UTM) projection zone 48 South of datum World Geodetic System 1984 (WGS 1984). Both of the images were co-registered to Worldview-1 image and four Ground Control Points (GCPs) from field survey using affine transformation method. Additionally, terrain correction was performed to the PALSAR data using DEM of SRTM. This step was carried out in order to reduce geometric and brightness distortions over elevated and sloping terrain due to the nature of SAR's side looking scan system. On the other hand, as an image derived by optical sensor, cloud existence also sometimes affects the AVNIR-2 image. In this case, ISODATA classification was applied to AVNIR-2 data in order to remove clouds along with the shadows from the image.

3.3.1.2 Determination of classification criteria

Even though the main target of this analysis is detecting the smallholders' oil palm plantation, the image classification must be conducted for land cover exists on all over the study area. Therefore, understanding of each land cover classes characteristics should be done prior to the classification. In this study, seven land cover classes according to the condition and the objective of the study area were formed and described on Table 3.2. Oil palm plantation, as the main target of this analysis, is particularly divided into two classes. Because, based on visual interpretation on the reference data and the information from field data, characteristics of oil palm tree, such

Table 3.2 Description of land cover criteria

No.	Class Name	Criteria
1.	Agriculture	Includes all areas covered by agricultural activities, such as corn, cassava, and paddy field. Additionally, grassland, which has similar feature with agricultural land cover, also been included.
2.	Bare land	Represented by bare land areas that has just opened or agriculture area that has not been cultivated yet.
3.	Mature oil palm	Oil palm plantation that older than 5 years when the oldest image was acquired. The trees are normally higher than 3 meter.
4.	Young oil palm	Oil palm plantation that has been planted less than 5 years before the oldest image acquired. The tree's height is generally less than 3 meter.
5.	Other woody vegetation	Included all kinds of woody vegetation beside oil palm. Dominated by rubber plantation. The others are consisted of acacia, cajuput trees and the yard areas surround the settlement that has mix plantations of acacia, rubber, banana, and coconut trees.
6.	Settlement	Characterized by all of artificial features, such as houses, roads, and other buildings.
7.	Water bodies	Represented by the pound that exist in oil palm mill factory as water supply for the oil palm processing and waste container from the process. No natural water body existed in this area.

as tree height and crown cover, are very distinguishable when the tree is still just planted (young stage) and when tree has grown up (mature stage). Therefore, the oil palm land cover class was discriminate as young oil palm and mature oil palm. Picture condition of each class in the study can be seen in Appendix A.

3.3.1.3 Texture analysis

In order to detect smallholder's oil palm plantation, particular feature that will be helpful for discriminating oil palms from other land cover should be explored. By studying the oil palm cultivation system, it is known that oil palm plantation has unique characteristic of its planting pattern. The design of planting pattern affects yield of plantations because the palm does not grow irregularly as does a dicotyledonous tree, and the canopy is almost covering in circular area. Therefore, in order to make sure that all plants could obtain sufficient nutrients, sunlight, and water supply, oil palm trees are planted in very clear pattern with certain distance between each tree. While the pattern usually can be either in square or triangular shape, it has been examined that the equilateral triangular planting pattern with 9 × 9 meter interval (Figure 3.2) is the most effective method (Corley and Tinker 2016, Verheye 2010).

Based on the knowledge that electromagnetic energy reflected by objects will give different signature with respect to the land cover type, the backscatter or reflectance value from ground and oil palm tree also will be different to each other (Murai et al. 1993). With such interval of oil palm, the planting pattern will construct similar regular pattern of tonal distribution covering wide area in the image. Therefore,

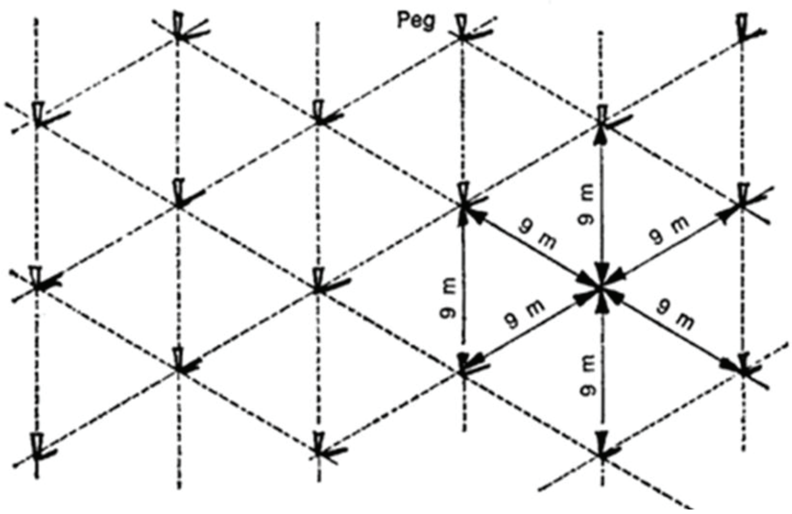

Figure 3.2 Oil palm equilateral triangular planting pattern

it was hypothesized that smooth textural features of this plantation could be identified in remote sensing imagery by examining the spatial distribution of neighboring backscatter or reflectance value within certain area size.

Based on the hypothesis, textural analysis was considered as the most appropriate methodology to detect the regular planting pattern, because this method provide the ability to measure the tonal distribution through its statistical calculation within certain area of moving window. Accordingly, textural analysis procedure was performed to extract land cover information from PALSAR data. The most commonly used texture processing method, the GLCM, was used to detect the planting pattern signature the image.

Before extracting texture feature, radiometric conversion was firstly performed to ALOS PALSAR image. In this step, pixel value was converted to radar backscattering coefficient (σ^{O}) in decibel (dB) unit, using the following formula (Shimada 2002):

$$\sigma^{o} = 20 * \log_{10}[\,I\,] + CF \qquad \text{(Eq. 3.1)}$$

where, I is pixel value of each pixel and CF is an offset conversion factor (- 86 dB).

A synthetic band of HH-HV polarization band was produced from the original PALSAR data by subtacting the backscatter coefficient value of each pixel on HH band with the value in the same pixel on HV band. This method was carried out following the study of Miettinen et al. (2010) who obtained significant improvement in separating palms from other woody plantations using this synthetic band. A new composite ALOS PALSAR image was generated from the two original polarization bands and the additional synthetic band.

As mentioned on the Chapter 2, there is no exact suitable window size and texture feature for all land cover classification. Specific pairs of those parameters always different according to the target object. Therefore, selection process is important in order to produce accurate classification results.

Total of 48 texture images were extracted using eight texture features from the backscatter image of the new composite ALOS PALSAR. The features, consisted of contrast, correlation, dissimilarity, entropy, homogeneity, mean, second moment, and variance, were extracted using 3 × 3, 5 × 5, 7 × 7, 9 × 9, 11 × 11, and 13 × 13 moving window sizes, in 64 quantization levels, and same separation parameters (d=1 and θ=45°or shifting △X=1 and △Y=1). The 13 × 13 window size was selected as the highest threshold by considering the characteristic of smallholder's plantations that usually covering on small area. The ability of each texture feature-window size pair on detecting smallholder's oil palm was evaluated by assessing classification images produced by Maximum Likelihood method. Training sample been used in this process were taken from the reference image of Worldview-1 and ground truth data.

Albregtsen (2008) stated that within the several texture features available, some are strongly correlated with each other. Therefore, a suitable combination of several texture features to classify the target object must be selected. The selection procedure applied involved the image classification to determine the features that gave the smallest classification errors. As the main target of this study, the classification result of each pair was mainly evaluated based on the smallest classification errors of mature and young oil palms, as well as the overall accuracy.

Firstly, the MLC was applied to the 48 images extracted from each single texture features. Based on the producer's and user's accuracy for young and mature oil palm classes for all moving window sizes, the texture features that showed high accuracy were selected as potential texture features, from which several combinations were formed. New texture extractions were then produced from PALSAR image using the selected feature combinations from each window size. The MLC was applied to all combinations and accuracy was assessed to obtain the best feature combination result for a specific window size in the detection of smallholder's oil palms using only the ALOS PALSAR.

3.3.1.4 Optical image processing

The AVNIR-2 image was processed to examine the ability of optical imagery for oil palm discrimination and to prepare the integration with the texture features derived from the ALOS PALSAR. The processing included Principal Component (PC) extraction and optical image classification.

The ortho-rectified and cloud-free ALOS AVNIR-2 image was re-sampled from 10 to 12.5 m pixels, to match the size of the PALSAR data, as the same spatial resolution is required for data integration. Moreover, to prevent any processing problem caused by data format differences, the original 8-bit data of AVNIR-2 image, which differed from the texture image, were converted to single float data as demonstrated by

Santos and Messina (2008). In addition, the multispectral images, such as ALOS AVNIR-2, consist of several bands that might be correlated, potentially caused redundant information that will significantly reduce the accuracy of the classification (Murray et al. 2010). In order to reduce this possibility, Principal Component Analysis (PCA) was used.

Principle component was extracted using IDRISI Selva software. Percentage of variance value from each principle component will be shown in the covariance matrix. This result could be used for deciding the significant PCs should be included in classification process. Whilst the correlation between each extracted principle component and ALOS AVNIR-2 bands could be examined from the degree of correlation matrix in order to analyzed the most correlated band with each PC.

Both of the full bands of AVNIR-2 image and its PCs were classified using MLC to the same category as texture analysis and the results were assessed for accuracy. The results were compared to analyze the effect of reducing dimensionality of AVNIR-2 data for detecting oil palm plantation.

3.3.1.5 Classification of integrated ALOS data

Satellite image provides data in different portions based on the sensor type, coverage of electromagnetic spectrum range of the sensor, spatial resolutions, and temporal resolutions. In some cases, an analysis could not be optimally done because of limited specifications of the data. On purpose of increasing the exploitation of multisource data for certain analysis, advanced analytical and numerical data integration techniques are being developed. By combining several data with different characteristics, image integration or image fusion could increase interpretation and analytical capabilities for more reliable results and give more thorough information about observed object (Pohl and Van Genderen 1998). In order to explore more information to classify small scale oil palm plantation, the integration of SAR and multispectral data was performed.

The selected PALSAR texture data were enriched by integrating with multispectral information from AVNIR-2 image. This process was carried out at pixel level, when both of data types were not extracted either into any feature kind or classified image yet. In this step, the texture image from ALOS PALSAR extracted using best combination of two texture features and window size, consisted whether the original two polarization bands (HH and HV) or three polarization bands (HH, HV, and HH-HV) were combined with all ALOS AVNIR-2 bands or principle components (PCs) bands of the optical image. Finally, the MLC was applied once again to detect oil palm plantations from the integrated ALOS data. This analysis was determined the most significant combination to detect smallholder's oil palm plantation in the study area.

3.3.1.6 Accuracy Assessment

All of accuracy assessment processes were performed by deriving 625 points from the center of 200 meter mesh in size in WorldView-1 image with additional information from the field surveys (Figure 3.3). The results were obtained for each confusion matrix, examining the user's, producer's, and overall accuracies, as well as the kappa statistics.

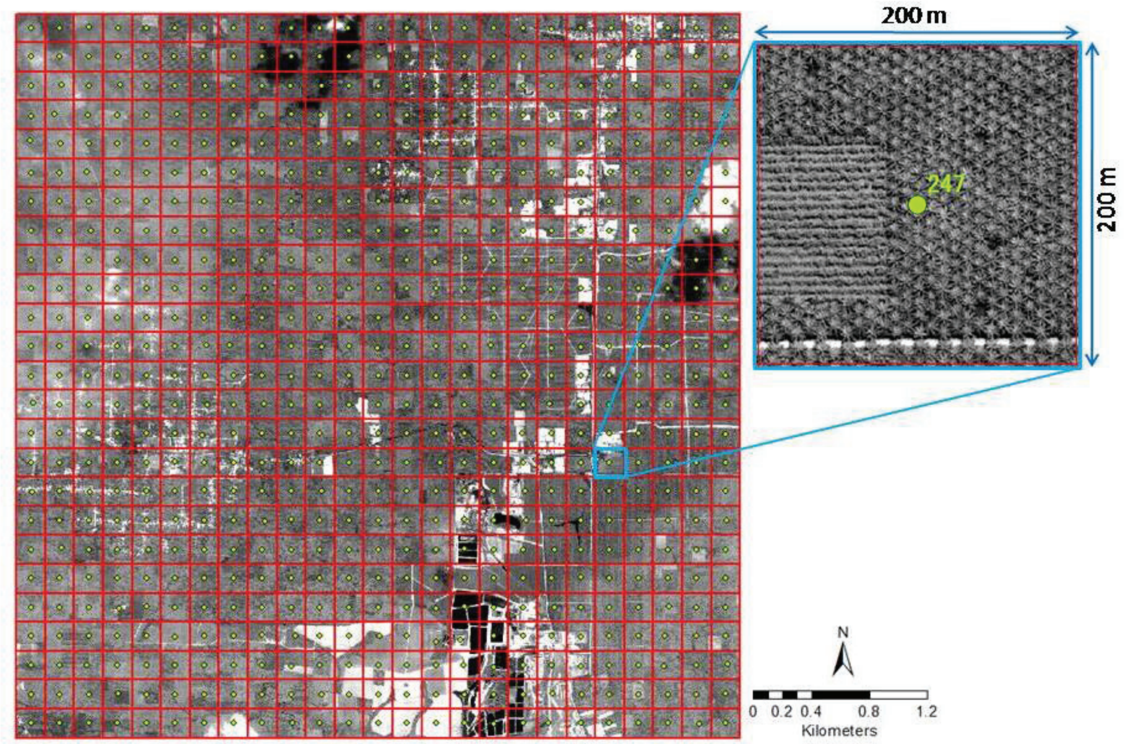

Figure 3.3 Accuracy assessment method

The error matrix is generally used to presenting accuracy in which the accuracy of each class are described with both errors of inclusion (commission errors) and errors of exclusion (omission errors) present in the classification. This matrix has square array of rows and columns which express the number of sample being used for accuracy assessment process. The columns present the reference data while the rows show the classified data generated from remote sensing image classification. The overall accuracy of the produced map from classification process is computed by dividing the total correctly classified pixels by the total number of samples. Producer's accuracy indicates the probability of a reference pixel being correctly classified in the produced map. It is calculated by dividing the total number of correct pixels in a class by the total number of the same class that derived from reference data. On the other hand, user's accuracy indicates the probability of a pixel that classified on the produced map actually represent the right object or class on the ground. This accuracy is computed by dividing the total number of correct pixels in a class by the total number of pixels that were classified in the same class (Congalton 1991).

Kappa statistic is commonly used for assessing the total agreement whether the classification result could represent the real condition or not. Kappa is calculated based on the number of agreement that actually present the real condition compared to the agreement would be expected to be present just by chance. Interpretation of kappa statistic is described as on Table 3.3 (Viera & Garrett 2005).

Table 3.3 Interpretation of kappa statistics

Kappa	Agreement
< 0	Less than chance agreement
0.01 – 0.20	Slight agreement
0.21 – 0.40	Fair agreement
0.41 – 0.60	Moderate agreement
0.61 – 0.80	Substantial agreement
0.81 – 0.99	Almost perfect agreement

(Source : Viera & Garrett, 2005)

The assessment was mainly focused on the accuracy of young and mature oil palm plantation classes. However, even though the main target of this analysis is the smallholder's plantation, its evaluation was performed simultaneously with the private-owned plantation since the characteristics of both types are similar.

3.3.2 Fully Polarimetric PALSAR image classification using SVM

3.3.2.1 Image pre-processing

In this study, the fully polarimetric ALOS PALSAR data was mainly used as the primary data. A level 1.1 PALSAR image was firstly multilooked and extracted to intensity data [S2] and polarimetric coherency matrix for polarimetric decomposition process. The intensity data, which consisted of four bands corresponding to each polarization type, were converted to backscatter coefficient (σ^{o}) using the Equation 3.1 and then corrected by terrain flattening to get the gamma nought data (γ^{o}). These data will be used as four bands backscatter parameters (B) for further classification process.

The speckle filtering process was performed using lee filter to both intensity and polarimetric data. Total of 18 additional backscatter data were produced using arithmetical operations of each bands, such as addition, subtraction, multiplication, and division. These additional bands will be mentioned as backscatter bands from arithmetical process (BA). On the other hand, decomposition processes were carried out to produce various kind of combination from polarimetric data before terrain corrected and geocoded to UTM projection zone 48S datum WGS 84 using SRTM DEM.

3.3.2.2 Polarimetric decomposition

Total of 18 parameters of polarimetric decomposition (PD) comprises of 3 components of Freeman-Durden decomposition (FD3), 4 components of Yamaguchi decomposition (Y4), and 11 parameters of eigenvalue-eigenvector (H/A/α) decomposition theorem were produced and tested for this analysis. Besides the main parameters of entropy, anisotropy, and alpha, all of the decomposition parameters of H/A/α theorem, as mentioned on the Table 3.4 below, were also used in this part in order to analyze the effect of cumulative parameters.

Table 3.4 List of H/A/α deocmposition parameters

Alpha (α)	Combination 1-HA	Entropy (H)
Anisotropy (A)	Combination H(1-A)	gamma
Beta	Combination HA	lambda
Combination 1-H1-A	delta	

3.3.2.3 Image classification using Support Vector Machine (SVM)

Support Vector Machine classifier is based on statistical or binary function, which is considered as an alternatives classifier to improve classification. This is because the SVM has tendency to minimize classification error by determining the unknown probability distribution. Accuracy of classification using SVM depends on the type of kernel function used because the kernel function assigns new classes into one class or other (Nooni et al., 2014). The kernel function that commonly used for classification is Gaussian Radial Basis Filter (RBF). In this study, RBF is mainly used.

The application of Gaussian RBF kernel requires two parameters that should be determined, including cost or penalty parameter (C) and specific function parameter (γ). The penalty parameter controls the trade-off between allowing training errors and forcing rigid margins. Increasing value on this parameter will make SVM create more accurate model. While γ is a floating value greater than or equal to 0.01, and usually the inverse number of input bands.

The analysis in this study will address three conditions that might affect the classification result:

a. Determination of potential polarimetric parameter

This process aims to find the most suitable parameter from PD for detecting the smallholder's oil palm. The input parameter comprises of all of grouped parameter (for example 4 parameters of Y4), combination between the linear polarization or intensity data (I) with one of PD, and the combination of all data. In this process, Gaussian RBF was applied using default parameter in ENVI software, C = 100 and γ = 1/number of bands. The amount of sample polygon used here are 225 samples, with each class has 30 samples except for water body (20) and settlement (25), because of the small area exist.

b. Changing on RBF parameter condition

In this condition, the PD parameters with potential of high accuracy based on the (a) conditions will be tested using various of penalty and gamma parameters

c. Changing on sample number

In this case, the input bands are similar to b case but test will be conducted using several numbers of samples. The sample tested here are 155, 225, and 350

3.3.2.4 Accuracy Assessment

Accuracy assessment of this study was carried out using the same method as the study on ALOS-Sensor data integration on section 3.3.1.6. The assessment was carried out at every stage of classification

3.4 Results and Discussions

3.4.1 Results of Smallholders' Oil Palm Detection using ALOS-Sensor Data Integration

a. ALOS PALSAR texture image classification

The classification result of each texture feature from three ALOS PALSAR composite bands for six types of moving window sizes is presented in Fig.3.4. The graph shows that mean feature was consistently resulting good accuracy if compared to other features. Low accuracy results are only shown in producer's accuracy using 9x9 and 11x11 window sizes. The superiority of the mean feature resulted from its characteristics which calculating the average grey-level value inside a moving window. Oil palm trees are normally planted covering a certain area at the same time. This uniform planting age will make SAR sensor receive identical signature of backscatter value and construct similar value distribution pattern in certain area of the image so that the average value in window size will be similar to each other within one window size oil palm plantation area. This was followed by variance that showed relatively high accuracy, especially for big window sizes.

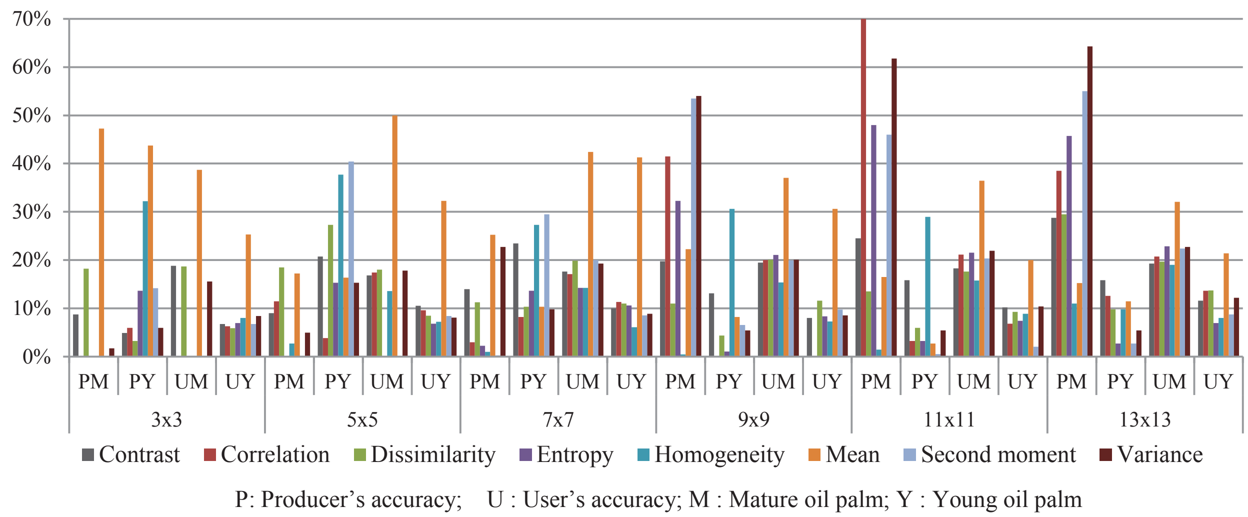

Figure 3.4 Accuracy oi oil palm classification in single texture feature

Fig. 3.4 also shows that only mean feature was effective for small window size, but not the others. Thus, to extract the morphological characteristic in texture, 9 x 9 or more window size is required. Based on these results, the combination of mean and variance features was selected as potential combination. The other features, such as entropy, correlation, second moment, and homogeneity which showed good accuracy for big window sizes were also examined for alternative combinations.

Among those selections, however, there were several combinations that could not be extracted in this process. Successful combinations were classified and the result was summarized in Table 3.5. The highest overall accuracy (55.68%) and kappa statistics (0.4095) were produced by an 11 x 11 mean and variance combination, even though the same combination for a 9 x 9 window size showed higher accuracy for all oil palm classes. This result agrees with Santos and Messina (2008) who found that the combination between mean and variance is effective to detect African palm trees, since it provides significant structural information from the radar images. On the other hand, correlation and variance combination also showed a very high producer's accuracy for mature oil palm, but not for other oil palm and land cover classes.

By this result, mean and variance combination in 11 x 11 window size was concluded as the most significant feature and window size parameter for oil palm detection and land cover classification for the study area as shown by land cover map result in Fig. 3.5. The 9 x 9 window size was not selected because for further analysis, good accuracy for the general land cover also considered as important parameter to avoid wrong classifications due to confusion with other land cover types.

Table 3.5 proves that sufficient statistical result and improvement were obtained by combining two texture features. Because each texture feature contains very voluminous data and should be extracted for all types of polarization bands, combination using more types of texture features was not performed in this study in

Table 3.5 Statistical results of texture feature combination test

Window Size	Feature Combination		Mature Oil Palm		Young Oil Palm		Overall Accuracy	Kappa Statistics
			PA	UA	PA	UA		
9 x 9	Mean	Variance	82.11%	60.48%	56.82%	44.64%	52.16%	0.3814
	Mean	Entropy	42.50%	47.89%	20.77%	40.00%	39.76%	0.2375
11 x 11	Correlation	Mean	42.11%	51.06%	59.18%	48.33%	55.20%	0.4019
	Correlation	Variance	81.58%	24.73%	12.24%	26.09%	29.44%	0.1347
	Mean	Variance	75.44%	48.59%	44.90%	47.83%	55.68%	0.4095
13 x 13	Correlation	Mean	28.07%	50.00%	44.90%	45.83%	45.76%	0.298
	Correlation	Variance	85.09%	25.39%	12.24%	27.27%	29.28%	0.1331
	Mean	Variance	67.54%	43.06%	46.67%	49.90%	55.34%	0.4081

PA : Producer's Accuracy; UA : User's Accuracy order to simplify the process and avoid the large amount of data. Nevertheless, that combination should be examined for future verification.

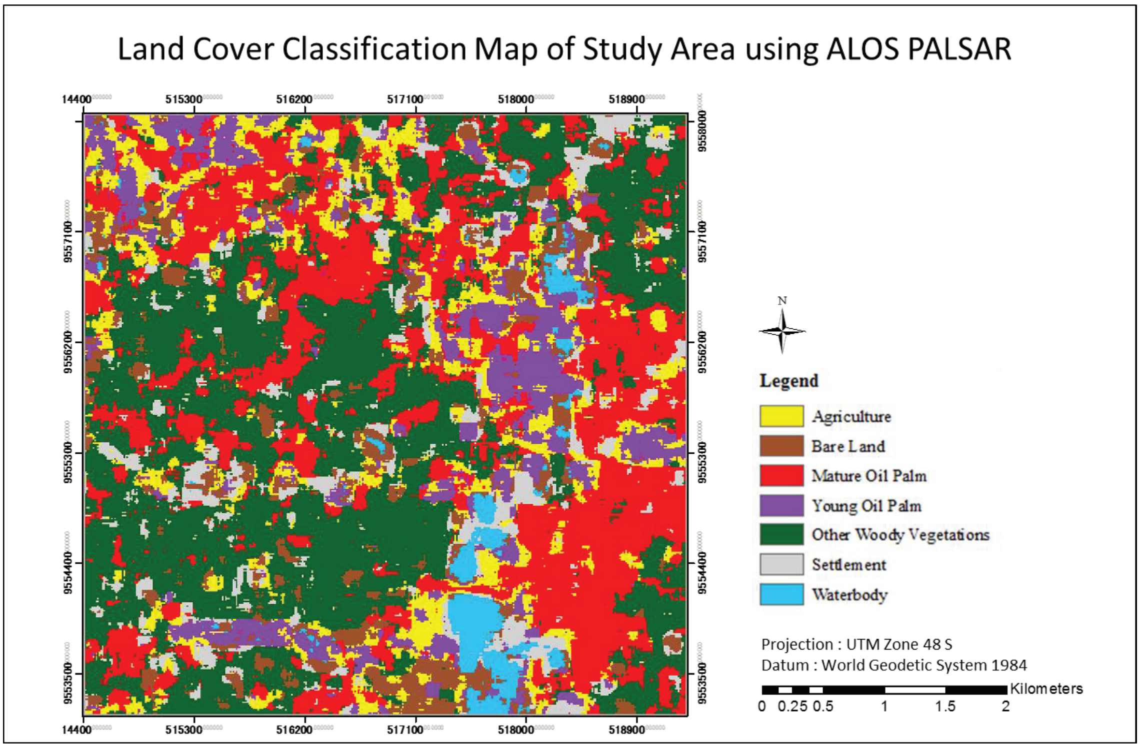

Figure 3.5 Land cover classification map using mean-variance of ALOS PALSAR texture features in 11 x 11 moving window sizes

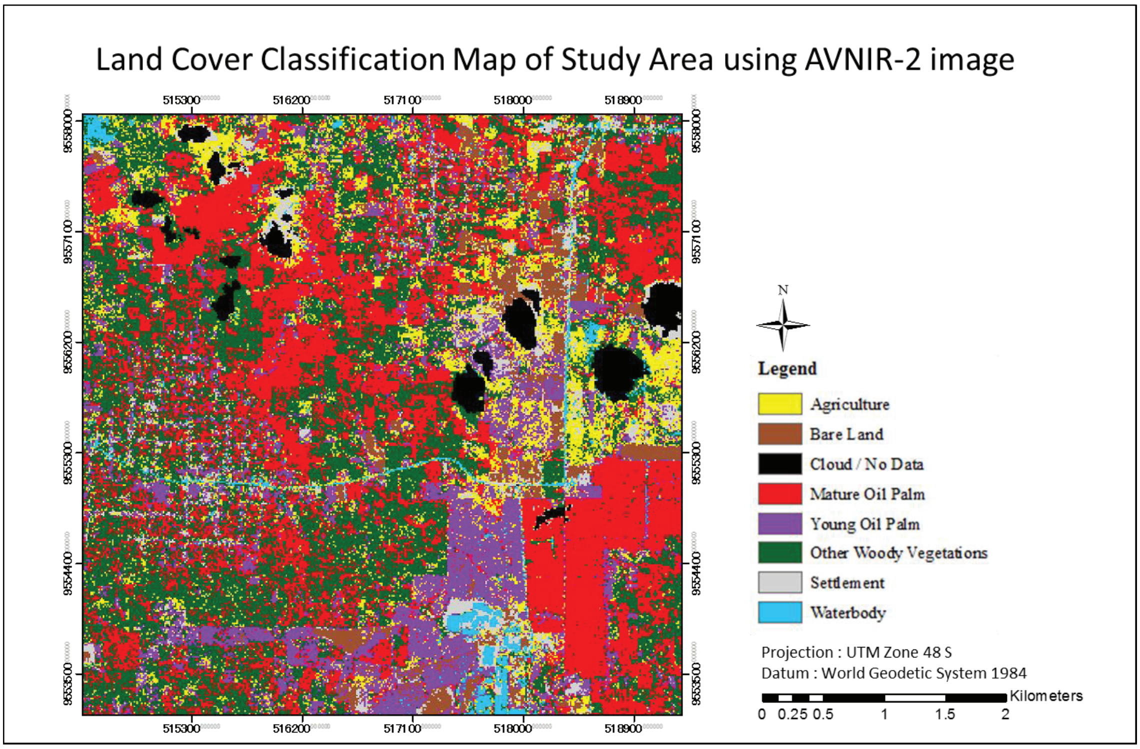

Figure 3.6 Land cover classification map using all ALOS AVNIR-2 bands

b. Optical image classification

All four bands of the ALOS AVNIR-2 image were transformed using PCA. The first two PCs accounted 97.16% of the variance, and 99.28% if accumulated with the third PC. The correlation matrix between generated PC and the original bands showed that PC1 was strong correlation with bands 1, 2, and 3, while PC2 was only strongly correlated with band 4. Finally, the PC3 correlated primarily with band 3 and 4 in small amount.

The classification using only the optical sensor data was not better than with the PALSAR texture analysis. All bands of the AVNIR-2 image classification had a high producer's accuracy (85.85%) for mature oil palms and a moderate accuracy (57.78%) for young oil palms. However, the results of user's accuracy for both stages were still under 50% and were considered as low accuracy. From Fig.3.6, we could see that mature oil palms mainly contaminated woody plantations. This is because spectral information of the AVNIR-2 sensor could detect the presence of vegetation, but lack of ability for distinguishing the vegetation types which has similar characteristic. The reflectance from oil palm and woody plantations were regarded as dense vegetation, but the unique characteristic of oil palm plantations were not detected as well as with the texture analysis. More salt and paper was also found in the classification image, especially for the mature oil palms. Moreover, young oil palms were detected in oil palm mill areas because of the land cover change from agriculture and grassland areas into ponds and roads. These changes occurred after the AVNIR-2 data was acquired (two years before the PALSAR data).

c. Object detection using integrated ALOS-Sensor

The texture feature combination of the ALOS PALSAR integrated with ALOS AVNIR-2 image produced six combinations. All of these digital data combinations produced improved accuracies over the results derived from each sensor only as much as 18.56% and 16.80% comparing with the individual classification of AVNIR-2 and PALSAR, respectively. This also resulted in a 0.6326 kappa statistic value which is considered as a substantial agreement of classification result (Viera and Garrett 2005). As described in Table 3.6, the highest accuracy was achieved by combining all polarization bands of mean-variance features in 11 x 11 window size with all AVNIR-2 bands (Combination 1). This result indicated the significance of adding synthetic

HH-HV band instead of using the original HH and HV bands only to support oil palm discrimination. The use of both HH and HV polarization improved the classification because each polarization has different backscatter in response to different biophysical characteristics. The HH shows the surface scattering while depolarization HV measures the volume scattering of vegetation. However, adding HH-HV band improved the detection because of the unique canopy structure of palm trees, which have no branch stem with leave clusters, thereby creating an open space right below the canopy. This is believed to lower the HV backscatter and increase the HH-HV backscatter value from oil palm as explained by Miettinen et al. (2010). The classification using all AVNIR-2 bands was more effective in detecting oil palms, whereas the use of PCs still resulting in a lower accuracy.

Table 3.6 Accuracy assessment results of ALOS data integration

No.	PALSAR Texture	AVNIR -2	Total band	Mature Oil Palm		Young Oil Palm		Overall Accuracy	Kappa Stat.
				PA	UA	PA	UA		
1	Mean and Variance (all bands)	All bands	10	92.45%	66.67%	64.44%	63.04%	**72.48%**	**0.632**
2		PC 1,2	8	87.74%	56.36%	53.33%	57.14%	67.84%	0.570
3		PC 1,2,3	9	90.57%	57.14%	53.33%	60.00%	69.28%	0.590
4	Mean and Variance (HH & HV)	All bands	8	89.62%	66.90%	64.44%	65.91%	71.84%	0.620
5		PC 1,2	6	89.62%	56.89%	53.33%	53.33%	67.84%	0.570
6		PC 1,2,3	7	90.57%	54.86%	62.22%	66.67%	68.80%	0.584

PA : Producer's Accuracy; UA : User's Accuracy; PC : Principle Component

Table 3.7 Error matrix of combination 1

Classified Data	Reference Data								Row Total	Producer's Accuracy	User's Accuracy
	AG	BR	MO	YO	WD	ST	WB	CL			
Agriculture (AG)	**55**	3	4	10	26	3	1	0	102	57.89%	53.92%
Bare land (BR)	4	**20**	0	0	1	2	0	0	27	71.43%	74.07%
Mature Oil Palm (MO)	3	0	**98**	3	41	2	0	0	147	**92.45%**	**66.67%**
Young Oil Palm (YO)	9	3	1	**29**	3	1	0	0	46	**64.44%**	**63.04%**
Other Woody Veg. (WD)	19	1	1	3	**206**	8	0	1	239	72.03%	86.19%
Settlement (ST)	5	0	2	0	7	**15**	1	0	30	46.88%	50.00%
Water body (WB)	0	1	0	0	2	1	**9**	0	13	81.82%	69.23%
Cloud (CL)	0	0	0	0	0	0	0	**21**	21	95.45%	100.00%
Column Total	95	28	106	45	286	32	11	22	**625**		
Overall Accuracy	**72.48%**										
Kappa Statistic	**0.6326**										

By examining the error matrix of combination 1 (Table 3.7), It could be observed that low user's accuracy for mature oil palm is mainly caused by confusion with other woody vegetation. It caused many woody plantations, which is dominated by rubber, detected as mature oil palm. Visual comparison between classified data (Fig. 4) and reference image revealed that the error also occurred for mixed vegetation from yards or gardens surrounding the settlement areas. These confusions mainly occurred due to their similarity of vertical structure vegetation in L-Band, as mentioned by Laurin et al. (2013) for their texture classification results using ALOS PALSAR data. The existence of similar kind of vegetation with oil palm in the yard also determined as one of the error factor. This fact is supported by field survey data that describe about existence of coconut trees and a few oil palm trees (less than 0.5 Ha) planted adjacent to various kinds of vegetation and houses. Comparing with the results of using only texture data, the error for the yard area was indeed reduced by its combination with optical data. The detection of young oil palm, however, mainly confused with agriculture or grassland because both of them have similarity that lack of woody component and the reflecting the electromagnetic energy come from the ground as the size of vegetation is small.

The 11 x 11 was identified as the most suitable window size for detecting smallholder's plantations in the Mesuji area. It proved that increasing window size would not always improve the accuracy. As in case of this study, the object of interest is smallholder's plantation which generally has very small size of 1 Ha until medium size area. Fig. 3.7 illustrates the comparison between the classification result of 11 x 11 (Fig. 3.7-a) and 13 x 13 window size (Fig. 3.7-b) for a very small oil palm plantation (presented with the blue box). Based on the reference image (Fig. 3.7-c), classification result of 11 x 11 window size (a) shows good result as it could detect 66 of the 72 pixels, or 91.67% of oil palm plantation. Oppositely, for the 13 x 13 window size (b), 15 of the 72 pixels of the area were detected as agriculture or other woody vegetation, and only 79.17% was well detected. It is might be caused by the effect of the backscatter value from the area surrounding the oil palms. Nevertheless, applying window size suitable for the size of the object of interest results in more effective measurements since enough characteristic information is obtained.

Additionally, this classification method was not only useful to detect smallholder's oil palm from its surrounding land cover, but also to differentiate between different oil palm growing stages. It is shown by the small error between young and mature oil palm occurred (Table 3.7). This was possible because of the different vertical structure of vegetation signature obtained by PALSAR, and also the gap between canopy's difference between young and mature oil palm. These factors are beneficial to distinguish the growing stage of oil palm even though both of them have the same planting pattern.

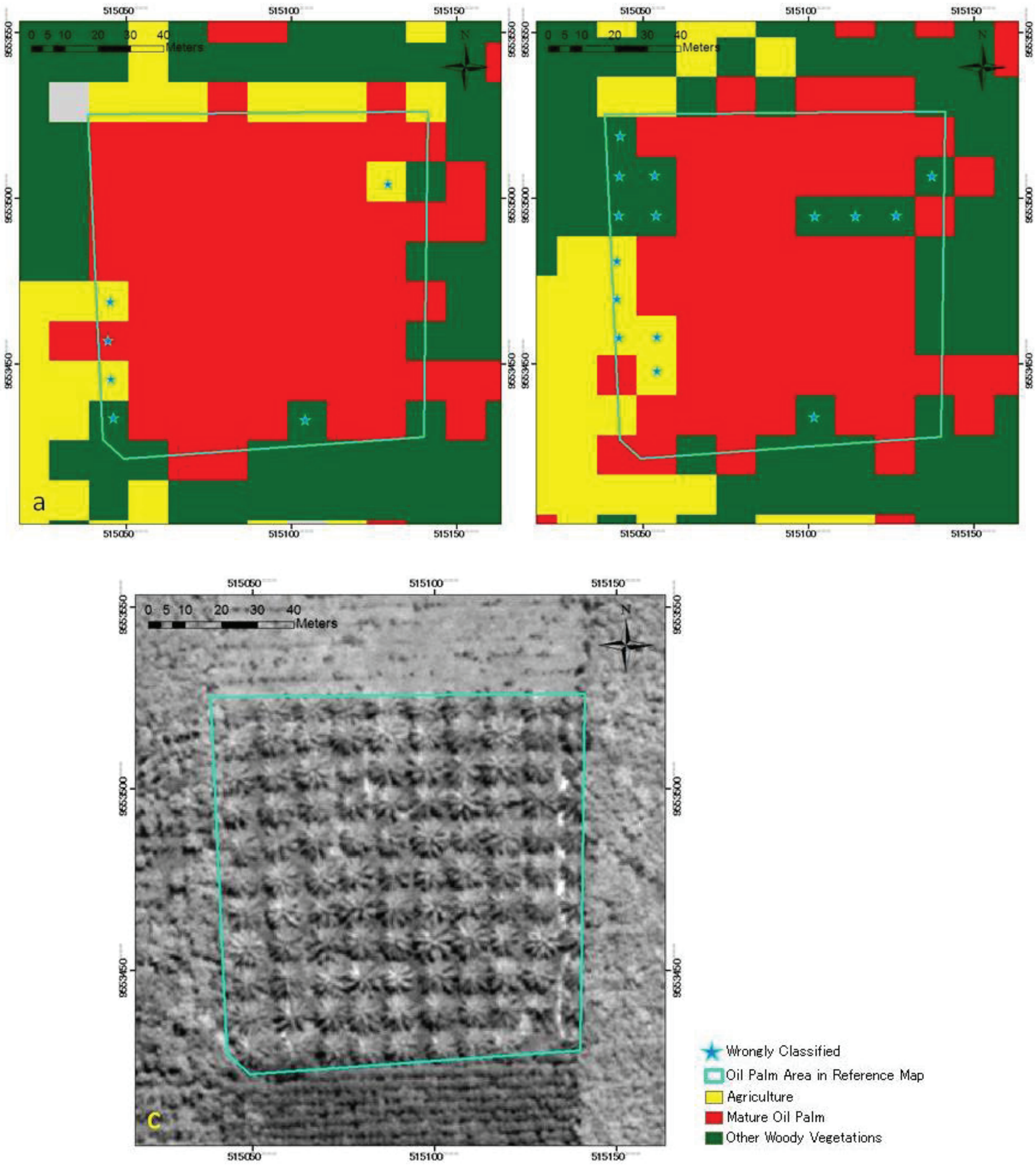

Figure 3.7 Comparison of oil palm plantation classification using (a) mean-variance in (b) 11 x 11 and (c) 13 x 13 window sizes based on reference image

3.4.2 Result of Classification using Fully Polarimetric PALSAR Data

a. Suitable PD parameters for smallholder's oil palm detection

This process was carried out to the 10 kinds of PD parameter combinations. By examining the results on figure 3.8, it can be seen that the highest overall accuracy was achieved by using H/A/ α parameters and combination of intensity and H/A/α. From the Table 3.8, it is also clear that both of parameters yield relatively higher accuracy for mature and young oil palms.

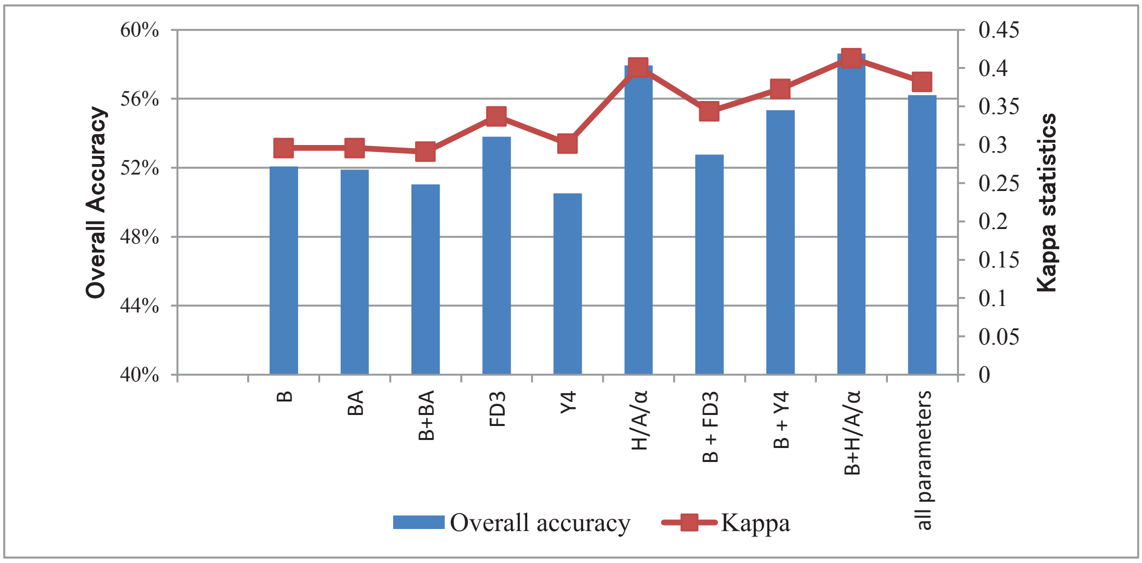

Figure 3.8 Overall accuracy and kappa statistics of each parameter and its combination

Table 3.8 Producer's and User's accuracies for oil palm classes

No.	Bands	Mature Oil palm		Young Oil palm	
		PA	UA	PA	UA
1	**Backscatter (B)**	37.63%	43.21%	40%	35.56%
2	**Bacscatter-arithmatic (BA)**	37.63%	41.18%	25%	40%
3	**Backscatter + BA (B+BA)**	34.41%	40.51%	37.50%	34.88%
4	**Freeman-Durden dec. (FD3)**	19.35%	35.29%	62.50%	34.25%
5	**Yamaguchi dec. (Y4)**	6.45%	60%	60%	36.36%
6	**H/A/α**	50.54%	54.02%	75%	40.54%
7	**Backscatter and Freeman-Durden (B + FD3)**	41.94%	41.05%	57.50%	34.85%
8	**Backscatter and Yamaguchi dec. (B + Y4)**	39.78%	46.25%	65%	41.94%
9	**Backscatter and H/A/α (B+H/A/α)**	51.61%	51.61%	72.50%	42.03%
10	**all parameter**	46.24%	50%	72.50%	40.85%

b. Effect of changing Gaussian RBF parameter

This process was carried out by changing the parameter as can be seen on Table 3.9. This result indicated no changes in term of classification accuracy.

Table 3.9 Accuracy assessment after changing parameter

No.	Parameter (C-gamma)	Bands	OA	Kappa statistics	Mature Oil palm		Young Oil palm	
					PA (%)	UA (%)	PA (%)	UA (%)
1	100-0	**B**	52.07%	0.2957	37.63	43.21	40	35.56
2		**H/A/α**	57.93%	0.4008	50.54	54.02	75	40.54
3		**B + H/A/α**	58.62%	0.413	51.61	51.61	72.5	42.03
4	100-1	**B**	52.07%	0.2957	37.63	43.21	40	35.56
5		**H/A/α**	57.93%	0.4008	50.54	54.02	75	40.54
6		**B + H/A/α**	58.62%	0.413	51.61	51.61	72.5	42.03
7	100-2	**B**	52.07%	0.2957	37.63	43.21	40	35.56
8		**H/A/α**	57.93%	0.4008	50.54	54.02	75	40.54
9		**B + H/A/α**	58.62%	0.413	51.61	51.61	72.5	42.03
10	200-0	**B**	52.41%	0.3	39.78	43.53	37.5	34.88
11		**H/A/α**	57.24%	0.3918	49.46	52.27	72.5	40.28
12		**B + H/A/α**	57.24%	0.3946	50.54	47.47	70	41.18

c. Effect of the number of training sample

The number of polygon samples was changed to the lower and higher number then the samples used for test (a). Based on the result on table 3.10, increasing number of sample polygons will increase the overall accuracy and accuracy of oil palm classes.

Table 3.10 Changing of samples result for classification

No.	No. of sample	Bands	OA	Mature Oil palm		Young Oil palm	
				PA	UA	PA	UA
1	225	**B**	52.07%	37.63	43.21	40	35.56
2		**H/A/α**	57.93%	50.54	54.02	75	40.54
3		**B + H/A/α**	58.62%	51.61	51.61	72.5	42.03
4	350	**B**	56.55%	44.19	48.1	44.68	43.75
5		**H/A/α**	62.58%	59.3	51.52	70.21	47.83
6		**B + H/A/α**	63.62%	65.12	53.85	74.47	47.95
7	155	**B**	49.48%	35.48	38.82	27.5	44
8		**H/A/α**	55.00%	44.09	48.81	67.5	38.03
9		**B + H/A/α**	56.03%	45.16	48.28	77.5	40.79

3.5 Conclusion

In this study, the detection of smallholder's oil palm plantations in Simpang Pematang Sub-district, Mesuji District, Lampung Province, Indonesia was performed successfully using integration of both radar and optical sensor data from the ALOS satellite. The triangular planting pattern of the plantation has been discovered as unique characteristic of oil palms. The GLCM of textural analysis was selected as the most suitable method to extract this unique pattern due to its ability to measure the correlation between grey tones. The extraction of this pattern was successful to identify the smallholder’s oil palm plantations even when surrounded by other types of vegetation cover.

Combination of mean and variance texture features from the PALSAR data was particularly useful for their detection, especially for the mature growing stage, showing that in the absence of cloud-free optical data, smallholder's oil palm plantations can still be identified using only PALSAR data. This is particularly useful for the tropical countries. The study also revealed that the integration of texture data derived from the PALSAR and multispectral data from the AVNIR-2 image highly improved the classification accuracy. The mean and variance from the HH, HV, and HH-HV bands combining with all AVNIR-2 bands resulted in the best producer’s accuracy of mature oil palm as much as 92.45%, with user’s accuracy of 66.67%. For young oil palms, the producer’s and user’s accuracy were 64.44% and 63.04%, respectively.

Fully polarimetric PALSAR classification using the SVM has resulted generally slightly greater accuracy than the classification using texture analysis of AOS PALSAR FBD data. However, direct comparison could not be explained here because the classifier used for both analysis are different. Analysis using SVM analysis also indicates that combination parameters of backscatter (B) with 11 parameter of H/A/α yielded the best accuracy for classifying smallholder’s oil palm plantation. Therefore, when the fully polarimetric data is available while cloud free image of ALOS AVNIR-2 is not, this method can be a good alternative for ALOS-Sensor data integration.

As this is one of the initial studies of smallholder's oil palm plantation detection using remote sensing, further study to improve the classification accuracy is necessary. The use of more polarization types for the texture extraction or application of other land cover classifier should be examined. The implementation of PCA to reduce redundancy while selecting combinations of integrated data or texture features is also suggested. We hope this study will improve the land cover management of the study area and general monitoring of the environmental impact associated with the expansion of oil palm plantations.

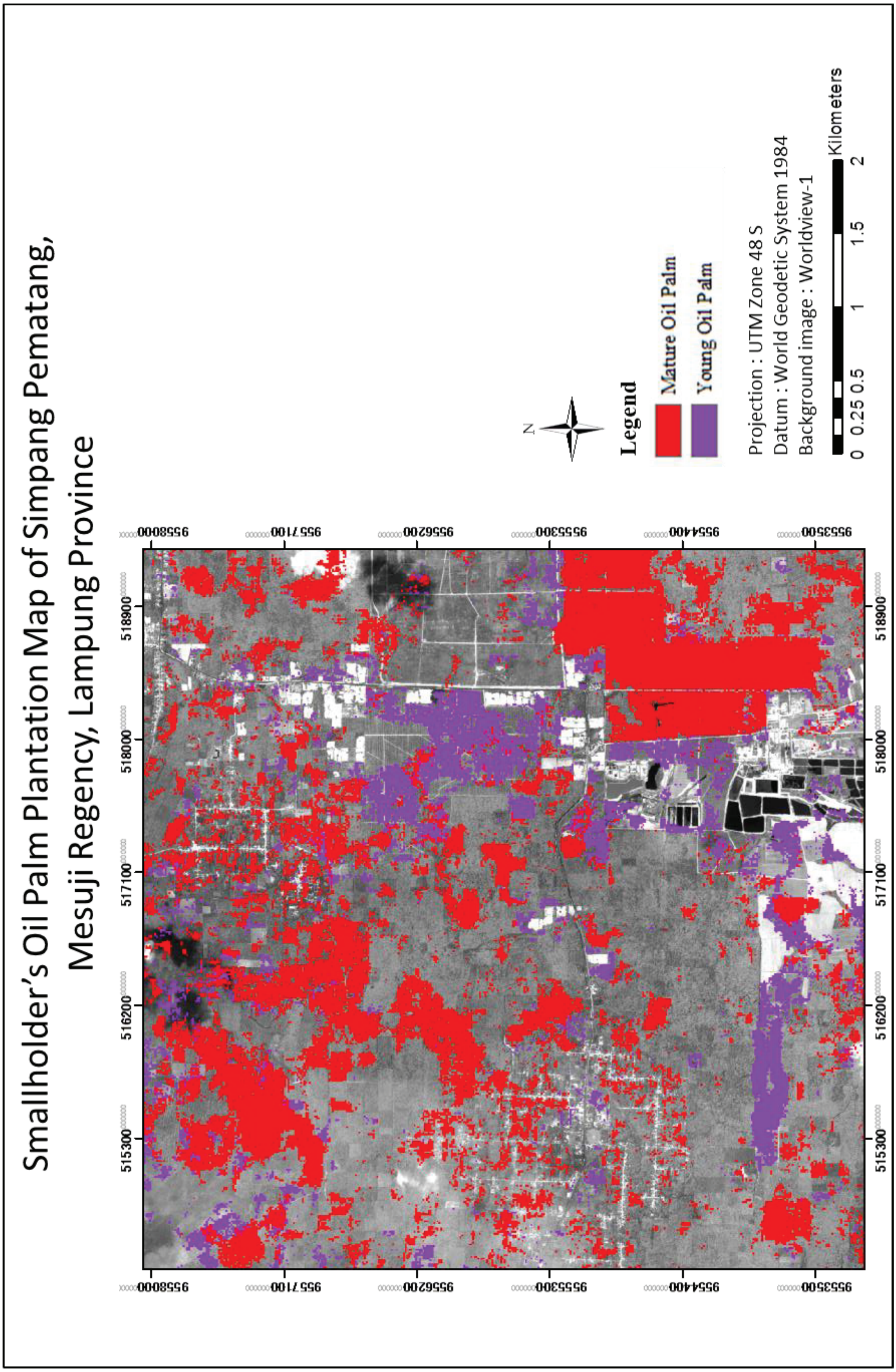

Figure 3.9 Smallholder's oil palm plantation maps using combination I

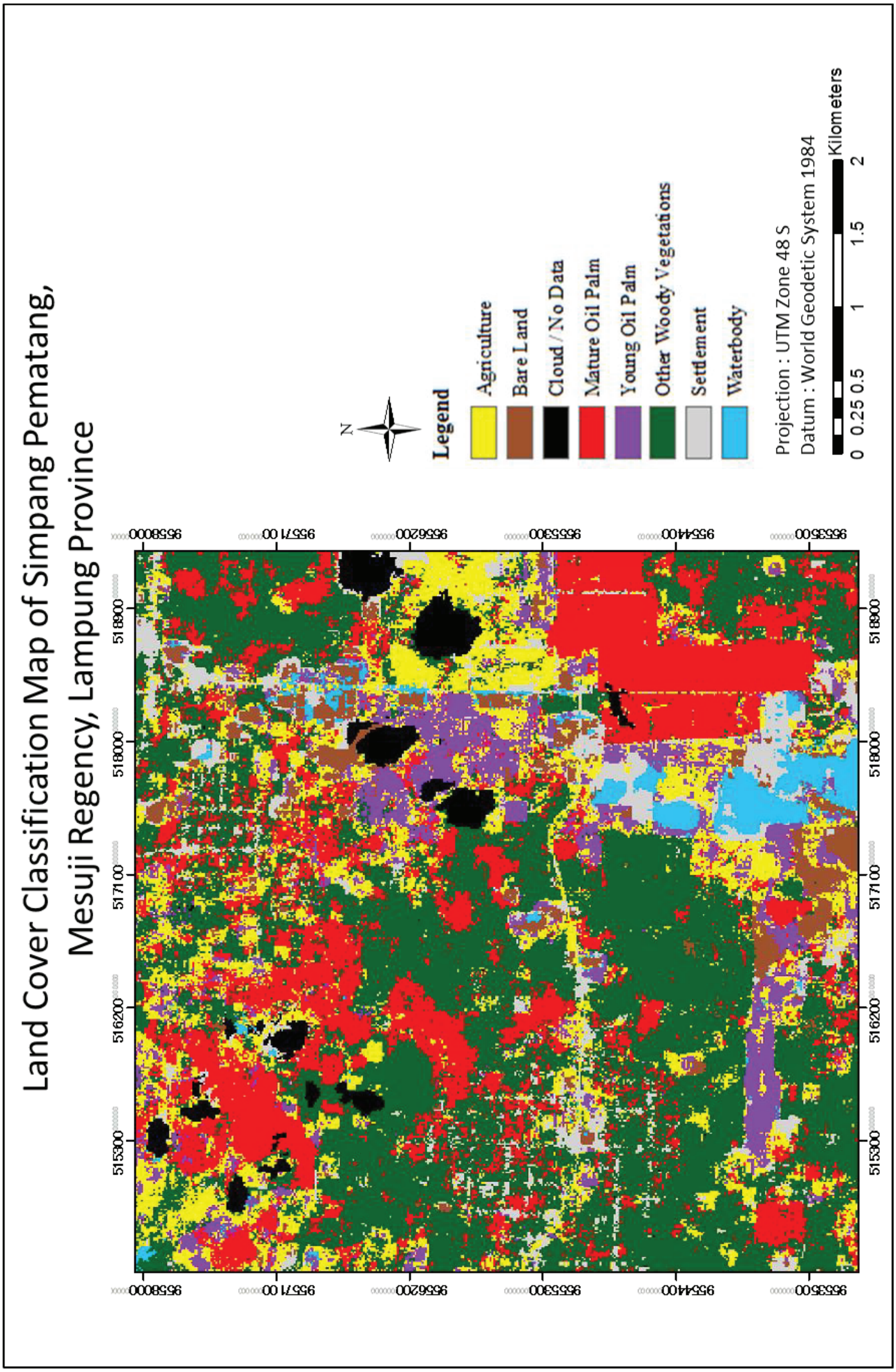

Figure 3.10 Land cover classification map of study area produced by combination I

Chapter 4

Classifying the Smallholders' Oil Palm Tree Conditions on Peatland Area using ALOS-2 PALSAR-2 data

4.1 Introduction

As one of the country's main commodities, palm oil production has been developed extensively in Indonesia. Started in Peninsular Malaysia, oil palm cultivation has been expanded to the peatland area in Sumatra and Kalimantan Islands of Indonesia, in response to the growing demand for vegetable oil (Miettinen et al. 2012).

Peatland in Indonesia is categorized as tropical peatland, where abundant carbon density is stored (Page et al. 2011). Peat has large amount of organic matter and enormous water holding capacity, but it becomes susceptible to fire when dry (Mutert et al. 1999, Page et al. 2002). However, crop production under undrained peat is usually not profitable. Thus, beside the standard planting techniques, sustainable peat soil management techniques are required prior and during the agronomic development on peatland. Proper compaction and effective drainage are the key procedures to maintain water table conditions, avoid over-drainage, and increase the bulk density and bearing capacity of the peat, which is essential for minimizing the leaning oil palm and optimizing yield (Melling et al. 2011, Melling and Chaddy 2016, Sidhu et al. 2016).

While high market demand of palm oil has become a promising strategy for poverty alleviation, limitation of available area on mineral soils has triggered the smallholders to grow oil palm in peatland area. However, peat management techniques are hardly ever applied, especially by independent smallholders; this is due to their limited financial condition to execute the high cost procedures, inadequate knowledge related to peat soil characteristics, and sometimes poor management technique. As a result, oil palm leaning in random directions is frequently found as the trees grow, and tree toppling tends to happened, even at a young planting stage. Leaning trees are known as one of the major problems for oil palms planted on peat soil as they may complicate management and harvesting, as well as decrease the yield up to 25% (Corley and Tinker 2016). Additionally, new trees have to be replanted to replace the toppling palms, which means early regeneration is carried out to several trees and results in various planting ages with diverse fruit productions occur in one plantation. Detection and mapping of such tree conditions is necessary to monitor less productive or even un-productive trees, which so that early rehabilitation, and effective implementation of best management practices in existing plantations can be realized (Lim et al. 2012).

Bandar Sei-kijang Sub-district area, Pelalawan Regency in Riau Province is one of peatland area where smallholder's oil palm plantations are being developed. Even though this area has suitable climatic condition, this area is still unfavorable for oil palms because peat soils has too high water table for oil palm. This condition causes the oil palm growth in this area become not normal and the yields remain relative low, because of the lack of peat soil management. Thus, further monitoring in this area is important for rehabilitation.

Remote sensing has been widely applied for land use/land cover classification and monitoring in tropical peatlands (Jaenicke 2010, Koh et al. 2011), while Synthetic Aperture Radar (SAR) is notably favorable to overcome cloud coverage in the tropics (Morel et al. 2011). Nonetheless, there are still limited studies about classifying the vegetation conditions, especially for oil palms. The study on Chapter 3 has successfully identified smallholders' oil palm plantations using a texture analysis of the integrated SAR backscatter and optical data. Scattering mechanisms modeled using polarimetric decompositions (PD) were proved to be effective in surface features extraction. Chowdhury et al. (2013) had applied PD to estimate growing stock volume in a Siberian forest without multi-temporal data, while Kobayashi et al. (2012) discovered the relationship between decomposition powers and tree growth of Acacia plantations in Sumatra, Indonesia. By exploiting the higher resolution offered by the PALSAR-2 sensor, better monitoring for detail analysis such as tree conditions becomes more possible. This study aimed to explore the backscatter and polarimetric decomposition from the full polarimetry data for classifying the three types of oil palm tree conditions in smallholders' plantations on peatland area.

4.2 Study Area and Materials

4.2.1 Study Area

The study was performed in Bandar Sei Kijang Sub-district, Pelalawan Regency, Riau Province of Indonesia (Fig. 4.1). Pelalawan regency area spans from the central part of Riau Province to the east coast of Sumatra Island. The study area itself, Bandar

Sei-kijang Sub-district, is located in the central part of Riau, which is close to Pekanbaru city, the capital city of Riau Province.

According to topographic condition as described by The Government of Pelalawan Regency (2014), Pelalawan Regency is mostly a low-land area. However, hilly area also can be found in some places, which mainly covered by peat soil. Therefore, some part of Pelalawan Regency has been claimed as protected area, especially the location where peat swamp forest exists. Day time temperature of this area can be as high as 33°C to 35°C, while night temperature ranged about 20°C to 23°C with average humidity about 80-88%. According to the agroclimatic zones for oil palm cultivation mentioned on Chapter 2, this area is categorized in zone II with AS1-k1 class (Corley and Tinker 2016). This class indicates that this area is agroclimatically suitable for oil palms with light intensity of rainfall and dry month duration as limiting factors. The residents of Pelalawan Regency are mainly occupied the river basin side, and area close to plantation. About 65% of them work in agricultural sectors, especially in industrial plantation, such as oil palms and acacia.

The present study is focused on about 46 km^2 area that mostly covered by oil

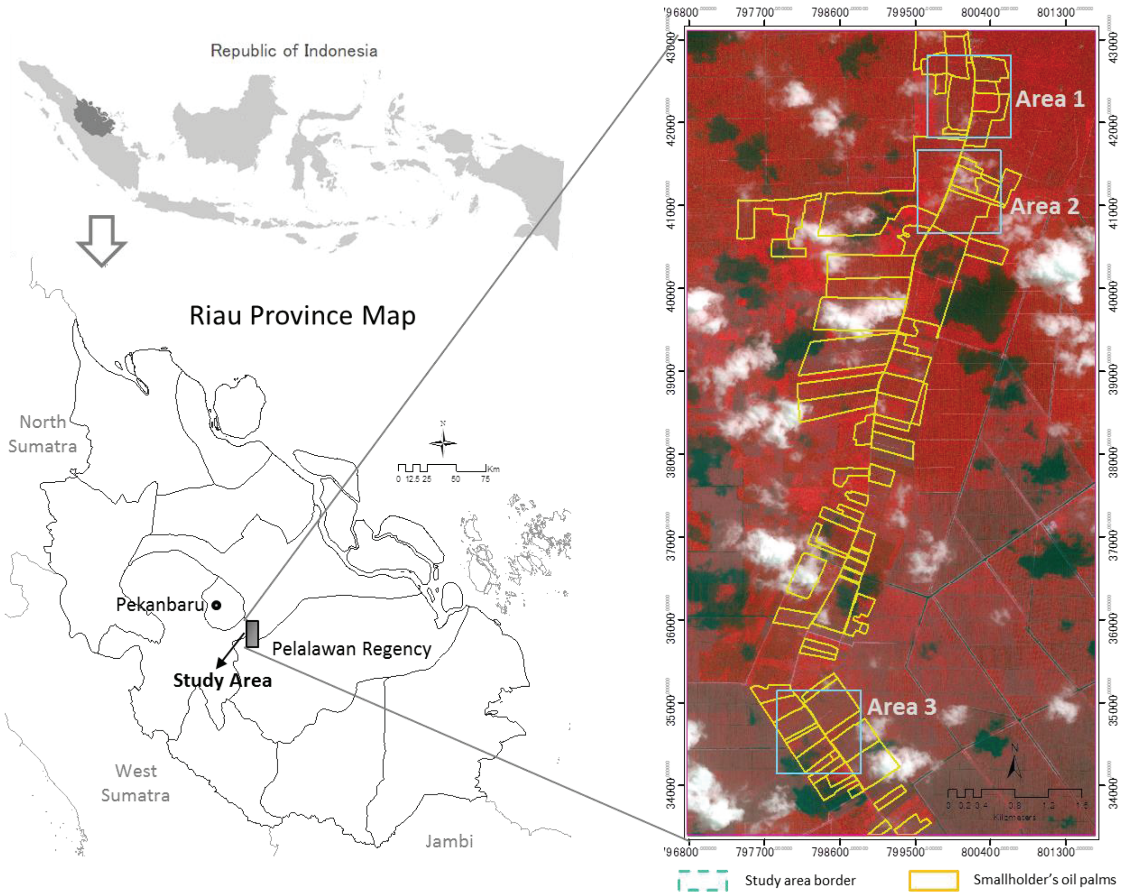

Figure 4.1 Location and false-color composite Pleiades image of study area

palm plantation as shown on Fig.4.1. This area is a part of concession land given to the local citizens for agricultural activities. According to the information gathered from field survey, before the oil palm establishment, acacia plantation and shrubs are mainly occupied the area. In some part, the oil palms even directly developed by converting the natural forest. At the present time, oil palms are mostly planted by the smallholders along the main road, as shown inside the yellow line on Fig. 4.1.

Despite the agroclimatically suitability status for oil palm cultivation, this area is less suitable in term of soil condition, because most of the extent area is occupied by deep peat soil, which is not favorable for oil palm. Unfortunately, proper peat soil managements, such as drainage and compaction, are hardly done by the smallholders. It makes many oil palm trees lean in random direction and early replanted trees are commonly found in this area, especially in mature growing stage.

In order to detect oil palm tree conditions in the study area, the methodology was tested in three representative areas of 1 × 1 km in size (Fig.4.1). The first area is dominated by smallholders' oil palms that are older than 10 years, where leaning trees can be commonly found. In addition, the area also has a small portion of 5-years-olds smallholders' plantations and private company's mature oil palms. The second area consists of both mature and young oil palms, while young trees and newly planted oil palms are dominant in the third

4.2.2 Materials

Data used for analysis of this study consist of fully polarimetric ALOS-2 PALSAR-2 image as the main data, and high resolution peiades image as well as ground truth data as reference.

ALOS-2 or 'Daichi-2' satellite is the new generation of former ALOS satellite, which ended its mission in 2011. The ALOS-2 is especially operated for observation using PALSAR-2 sensor. Comparing to the former sensor, PALSAR-2 provides improvement in various sectors, including higher spatial and temporal resolution. In this study, a level 1.1 PALSAR-2 high-sensitivity image was used as the primary data. The data was acquired on 15 October 2015, which is the end period of dry season in Riau Province and is the closest acquisition time of full polarization data with ground truth activity. The image has four polarization bands, consisting of HH, HV, VH, and VV.

A multispectral Pleiades image, consist of red, green, blue, and Near-Infrared bands were fused with the higher resolution of the panchromatic Pleiades image to produce a 0.5 m resolution pan-sharpened image. This image was used as a reference data to collect training samples for classification and accuracy assessment alongside the ground truth data acquired during field survey in September 2015. In addition, GDEM data acquired by ASTER were used for terrain correction of PALSAR-2 data.

4.3 Methodology

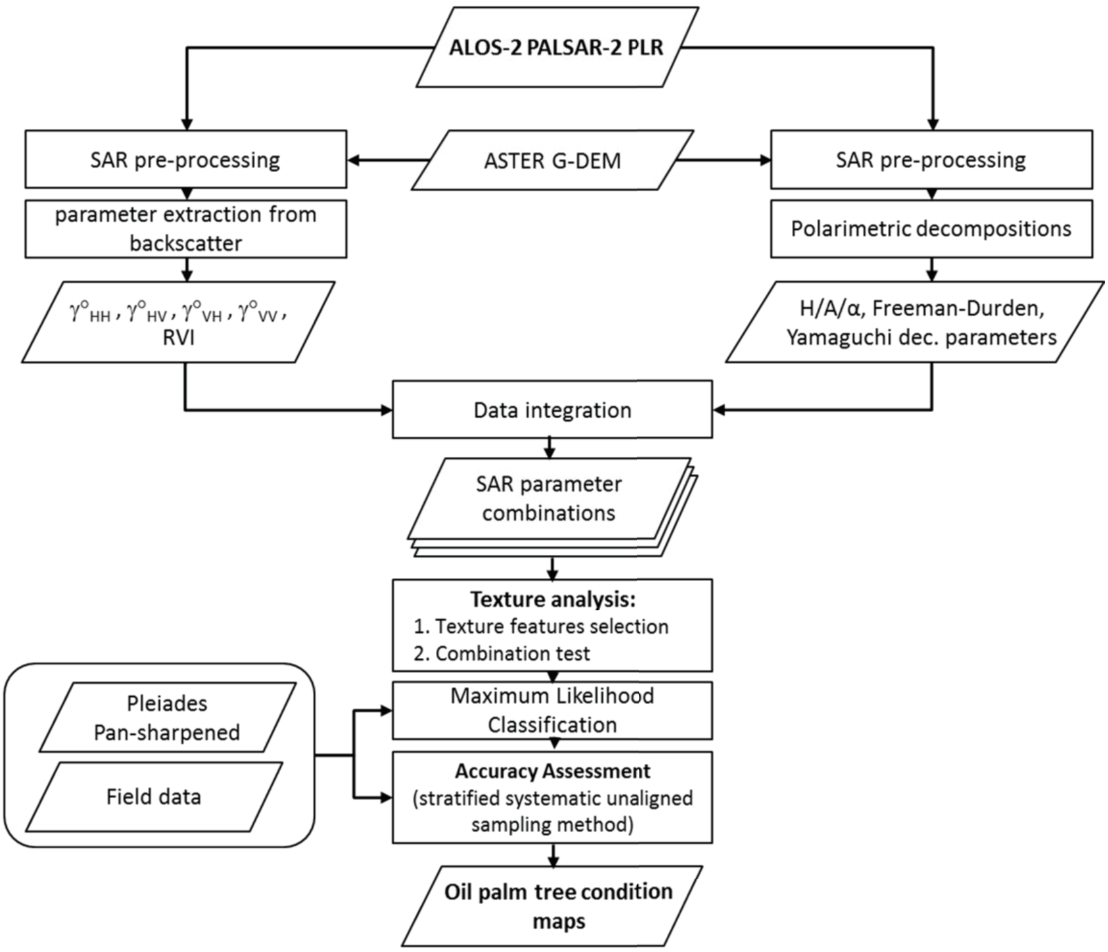

Figure 4.2 Methodology for classifying oil palm tree conditions

Based on the observation about oil palm cultivation in study on Chapter 3, it is known that planting pattern of an oil palm plantation usually becomes the characteristic to differentiate it from other land covers. However, tree conditions on peatland, such as leaning palms and replanted trees might change its three-dimensional characteristic. A plantation with leaning palms is expected to give diverse ground-trunk-ground (double-bounce) and volume scattering in the pixel compare to the one with trees that grow upright. Because the tree trunks of leaning oil palms are partially or mostly close to the ground, more double-bounce scattering is expected to be reflected than in plantation with normal condition. On the other hand, random leaning direction of the trees will cause higher volume scattering in the area with dense leaning trunk and less scattering in wide open space area with less leaning trunk. This situation is different with common oil palm plantation which has uniform spaces between tree trunks. Backscatter intensity and scattering mechanism generated from PD are hypothesized to be effective for differentiating scattering properties of leaning oil palms and detecting the different growing stage of the replanted trees from their surrounding area. Furthermore, texture analysis was applied to identify the spatial pattern change, such as the random ground exposure caused by random canopy closure of leaning palms and scattering difference in an area caused by the replanted trees.

4.3.1 SAR data processing

Backscatter analysis and PD were applied to the PALSAR-2 data using Sentinel Application Platform (SNAP) open source software version 4.0 module Sentinel 1 Toolbox (S1TBX). S1TBX is a toolbox consists of processing tools for SAR data including ALOS PALSAR-2, which can be freely downloaded from http://step.esa.int/main/download/. The data were multi-looked with a 2 × 3 factor in range and azimuth resolution. For backscatter analysis, the image was converted to backscatter coefficient ($\sigma°$) and was corrected using terrain flattening, while in PD analysis, coherency and covariance matrices were extracted. A 5 × 5 window size of two different types of speckle filter was applied based on the data type. Box-car filter was applied to polarimetric data because of its characteristic to preserve the mean value while reducing the speckle noise. This is essential to keep the PD information for discriminating oil palm tree conditions. On the other hand, the Lee filter was applied for backscatter data as the statistical test proved this filter has higher equivalent number of looks (ENL) value, as one of the indicator for noise reduction, compared to other filters.

As the additional data of the four bands polarization, Radar Vegetation Index (RVI) was produced by the following formula (Kim and van Zyl, 2009) :

$$RVI = \frac{8\sigma°_{HV}}{\sigma°_{HH}+\sigma°_{VV}+2\sigma°_{HV}} \quad \text{(Eq. 4.1)}$$

where, $\sigma°_{HH}$, $\sigma°_{HV}$, and $\sigma°_{VV}$ are backscatter of HH, HV, and VV polarizations, respectively. RVI has been implemented for crop monitoring and indicated as an effective technique for estimating forest parameters (Kim and van Zyl, 2001).

Ten polarimetric parameters were generated using the Eigenvalue-Eigenvector (H/A/α), Freeman-Durden, and Yamaguchi - 4 components decomposition methods. Eigenvalue-Eigenvector based decomposition was proposed by (Cloude and Pottier, 1997) for target classification. The Freeman-Durden approach was developed to model three scatterings representing surface, double-bounce, and volume scatterings (Freeman and Durden 1998), while Yamaguchi et al. (2005) improved the decomposition with helix scattering as the fourth component for urban area and modification of volume scattering model.

A total of 15 extracted backscatter and polarimetric parameters were terrain corrected and geocoded to the Universal Transverse Mercator (UTM) projection Zone 47 N of the World Geodetic System (WGS) 1984, using the ASTER Global Digital Elevation Model (GDEM), and resampled to a 9.5 m spatial resolution. Additionally, because the 15-bands of parameters was considered as a large number for classification process, Principal Component Analysis (PCA) was carried out to reduce the dimensionality and maximize the information of the original data into least number of principal components (Estornell et al., 2013, Gupta et al. 2013).

4.3.2 Texture analysis

For the first analysis, eight GLCM texture features, consisting of mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation in singular moving window, 3 × 3, were tested to the 15 SAR parameters. The image extracted from each feature was then classified, and the accuracy was assessed for all classes to obtain the most significant texture feature.

Second, the best feature from the first analysis was used to extract the texture of several SAR parameter combinations, such as backscatter parameter only, the texture from each decomposition method, and 15 bands integrated of all SAR parameters. The texture images were produced using 3 × 3, 5 × 5, and 7 × 7 moving window sizes and were classified. The most suitable methodology to classify tree conditions can be obtained by evaluating the accuracy of each classified image.

4.3.3 Image classification and accuracy assessment

Image classifications performed in the texture analysis were carried out by applying an MLC. The texture images were classified to three oil palm tree conditions classes and other land covers including bare land and shrubs. The tree conditions in this study are defined as normal, replanted, and leaning trees (Fig. 4.3). Normal oil palm is the usual condition of oil palm trees, which grow upright and are planted at the same time as other trees in the plantation. A replanted or dead tree is the condition when a tree has toppled and should be removed; the area remains empty or has been replanted with new an oil palm, which is much younger than the surrounding trees. The leaning oil palm is the tree that could not grow upright and has a curving trunk due to soil conditions. This condition usually occurs in mature oil palms.

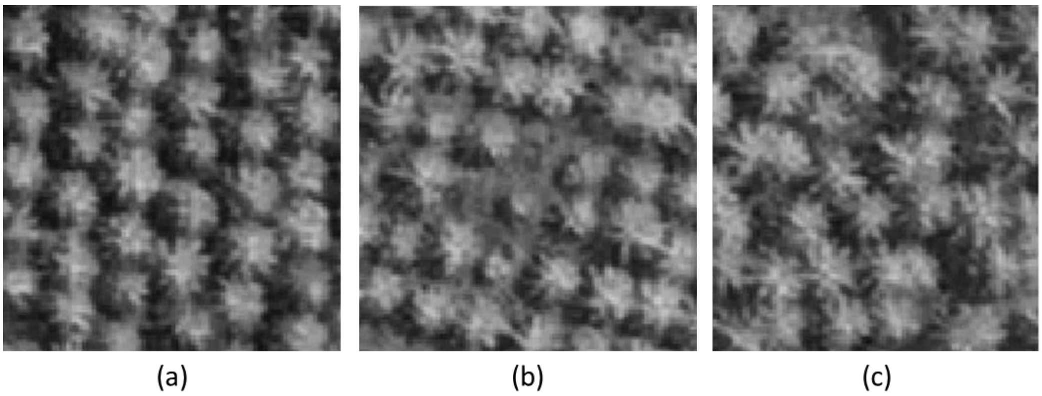

Figure 4.3 Oil palms in (a) normal, (b)replanted, and (c)leaning tree conditions

Ground truth data and Pleiades image were applied for training sampling of classification and accuracy assessment. The ground truth data were used to identify and confirmed the types of tree conditions on Pleiades image (Fig.4.3), while visual interpretation was conducted to the remaining study area on the image to acquire training samples. The stratified systematic unaligned sampling schema was applied to assess the accuracy of each classified image. Different with the sampling method as demonstrated on the previous chapter, this method was carried out by taking several random sampling points from each mesh or grid on the reference image. In other word, this sampling method is more random, but still systematically taken inside each mesh. In this case, this accuracy assessment was performed by taking four random samples for each 100 × 100 m mesh on the Pleiades image.

4.4 Result and Discussion

4.4.1 Texture feature selection

Classifications using each texture feature in a single moving window and combination bands were performed to determine the optimal feature for the further combination approach. The summary of overall classification accuracy using the eight texture features for the three areas is displayed in Fig. 4.4.

The graph shows that mean feature steadily outperformed all other texture features in every area, producing 51.52%, 51.45%, and 46.50% overall accuracy for areas 1, 2, and 3, respectively. This is consistent with our previous result, which found the mean to be the most effective feature to classify oil palms. This indicated that different tree conditions also change SAR intensity and polarimetric properties, which by averaging those values within a certain area may generate a particular value for each tree's condition.

Variance, homogeneity, contrast, and dissimilarity features yielded accuracy from about 7% to 18% lower than mean in all areas. Similar accuracies were produced by entropy and second moment in areas 1 and 3, but they decreased rather significantly for area 2, where most confusion mainly occurred from the oil palm classes with bare land. The correlation, however, showed insignificancy, because the extraction using this feature sometimes yields non-value data, which affects the classification.

From this analysis, mean feature is selected as the most significant feature and will be used for the combination approach. In this study, only one optimal texture

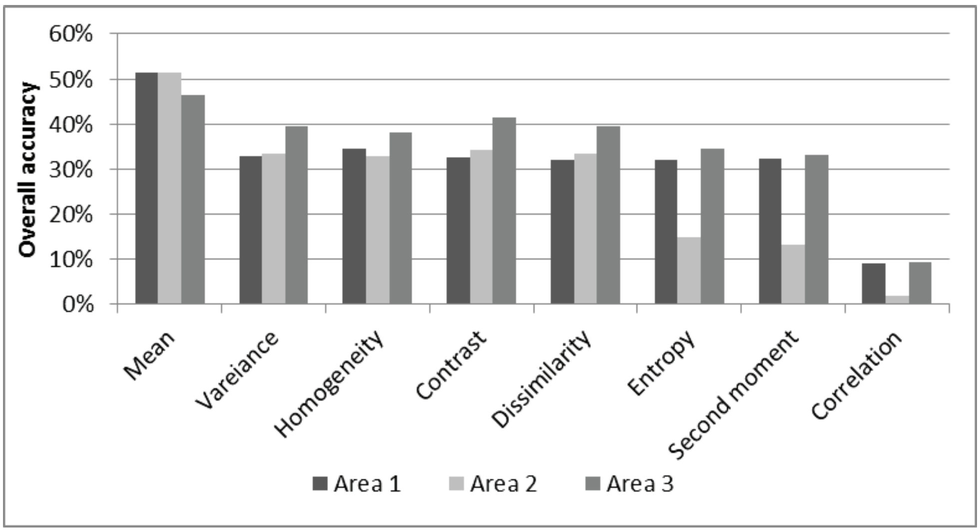

Figure 4.4 Overall accuracy of classification using texture feautre in areas 1, 2, 3

feature was taken, since the main analysis will put more emphasis on the combination of several SAR parameter bands.

4.4.2 Classification using SAR parameter combination

The mean texture feature using 3 × 3, 5 × 5, and 7 × 7 moving window sizes was applied to several combinations of both backscatter and polarimetric parameters. The combinations include four backscatter intensities and RVI (which further will be mentioned as [B] combination), three Freeman- Durden decompositions (FD3), Eigenvalue-Eigenvector parameters (H/A/α), four bands of the Yamaguchi method (Y4), the combination of 15 bands SAR parameter, and PCA. Moreover, to access the effect of each decomposition method to the backscatter, B+FD3 and B+Y4 combinations were examined.

The classification results of a total of 24 combinations are presented in Fig.4.5. The figure shows that a 15-bands combination of all SAR parameters constantly yielded the highest accuracy for the three areas using the same window size. This result indicates that increasing the information of each SAR parameters is essential for improving the accuracy. This combination increased 14.39%, 18.47%, and 12.75% of overall accuracy when compared to the best result from B+Y4 combination in areas 1, 2, and 3, respectively. The result of B+FD3 and B+Y4 also proved that adding the polarimetric parameters is effective in improving the classification, particularly for Y4, which has slightly better accuracy than adding the FD3. On the other hand, the H/A/α parameter produced the lowest accuracies in all areas. This result might be caused by

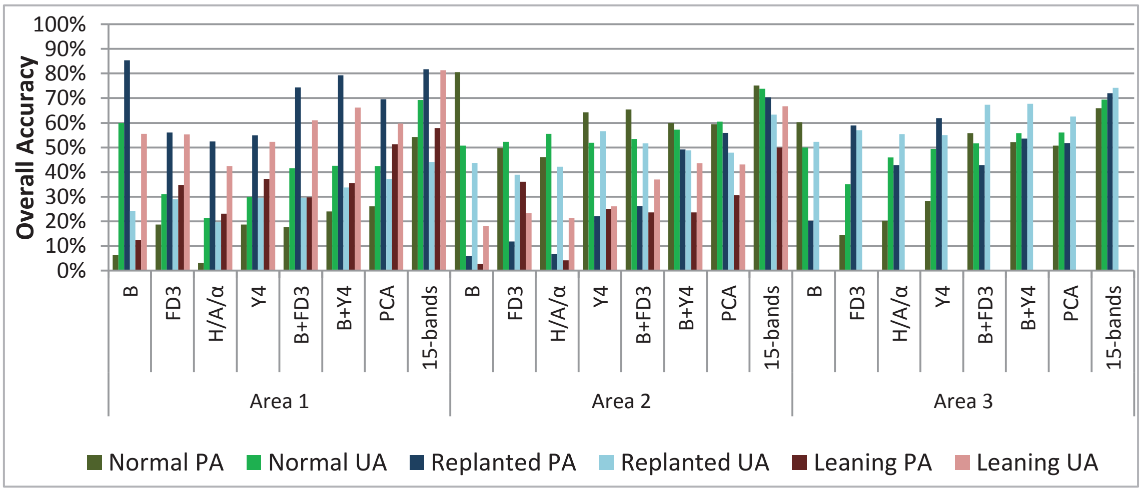

Figure 4.5 Producer’s and user’s accuracy of normal, replanted, and leaning tree conditions in each area

algorithm of this decomposition which derives only eigenvalue of coherency matrix and does not express intensity or power measurement (Alberga et al. 2008).

Ten Principal Components (PCs) with accumulative of 99.83% variance were also extracted from the combination of 15-bands parameter using PCA. The eigenvector of the image shows similar contribution of all bands in the first PC. On the other hand, the contrast of relatively high and positive values of surface scattering from both Freeman-Durden and Yamaguchi decomposition methods were observed in the second PC. This data indicates that the information of surface scattering plays the most important role for discriminating the condition of oil palm, regardless the PD method. Random spatial distribution of surface scattering might be indicating the leaning trees, while homogenous scattering feature could be stated as normal palms. However, the accuracy of the classification using PC bands still behind the total combination of 15-bands which indicating the importance of applying all of the parameters (Fig. 4.5). This result approved that PC process does not always improve the classification, because the structure of the image itself might be too complex and detail that compression into few components by this process may cause significant loss of information instead (Eklundh and Singh 1993).

Fig.4.5 also shows the comparison of the classification result derived by three moving windows. Mostly, an improvement in overall accuracy can be seen by increasing the moving window from 3 × 3 to 5 × 5 in area 1 and area 2, but not likewise in area 3, where the oil palms are mainly still in a young stage. However, a significant effect was shown by using 7 × 7 moving windows with an overall accuracy of 68.69% (Kappa: 0.60) in area 1, 70.18% (0.55) in area 2, and 72.75% (0.60) in area 3. This

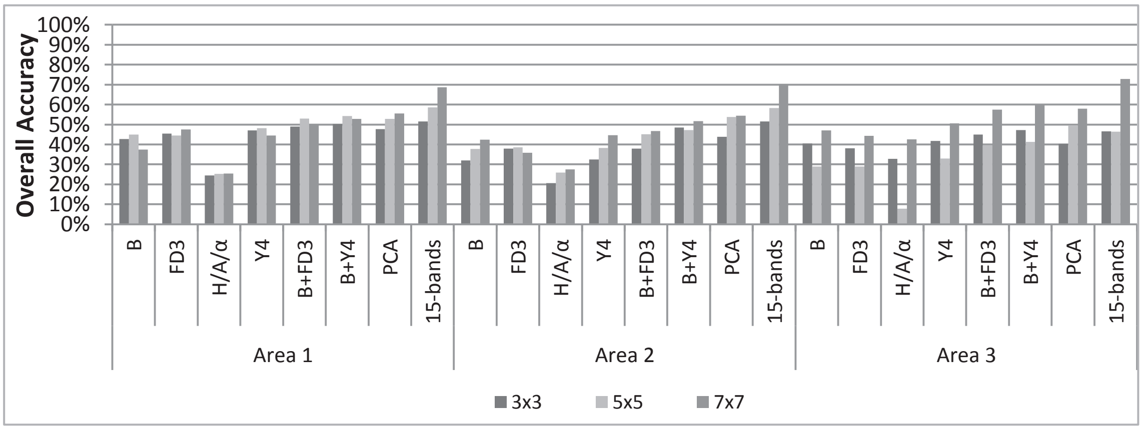

Figure 4.6 Overall accuracy of SAR parameters' combinations using 3 × 3, 5 × 5, and 7 × 7 window sizes in each area

result confirmed the 7 × 7 moving window as the optimum extent of mean feature computation for classifying tree conditions both in mature and young planting stages, as well as other land covers. Nevertheless, larger moving windows were not examined in this study by considering pixel size and the detail analysis of the target objects inside the plantation.

From these results, mean texture extraction of 15-bands SAR parameters in 7 × 7 moving window is determined as the best combination for classifying the land cover in the three study areas. Further analysis of this combination was also carried out by examining the producer's accuracy (PA) and user's accuracy (UA) for tree condition classes of each area. The accuracy result presented in Fig.4.6 shows that backscatter and RVI (B) are more effective in detecting normal plantations than polarimetric parameters. This might be caused by the homogenous condition of normal palms, which reflect a similar intensity without much effect from the condition of the tree stands. However, an inconsistency is shown as it produced high accuracy for normal trees in areas 2 and 3, but not in area 1. The replanted trees in area 1 that mainly cover a large area are considered to be the main reason since they might reflect similar average intensity and cause confusion with normal and leaning palms. Moreover, this confusion also occurred in the classification using PD and combinations of backscatter and single decomposition. However, the significant improvement was obtained by combining all 15 parameters, as it reduced the confusion and increased the UA of replanted trees.

On the contrary, the identification of leaning oil palms increased by applying PD, particularly the FD3 and Y4. This confirmed our expectation that the effect of polarimetric parameters in the pixel is essential for identifying tree stand conditions of leaning palms. The characteristic of volume and double-bounce scattering from FD3 and Y4 might be useful for identifying random leaning tree trunks and canopy cover, while surface scattering may be beneficial for measuring the ground exposure because random canopy coverage makes high surface scatter from one open place but low at other place with dense canopy (Freeman and Durden 1998, Lee and Pottier 2009, Yamaguchi et al. 2005).

4.4.3 Oil palm tree conditions classification map

The tree conditions classification map of smallholders' oil palm plantations was produced by applying the 15-bands combination of SAR parameters using mean texture in 7 × 7 moving windows. Comparisons of the produced map and Pleiades images of each area are presented in Fig.4.7. Area 1 shows the largest number of leaning trees because oil palms have been developed in this area since 1998 and earlier. Some small areas of normal trees were also identified nearby or within the area of leaning palms. Compared to the reference image, the distribution of leaning oil palms has been well generated. Some normal plantations seem to be misclassified as replanted palms, especially in the right top of the area as the result of confusion caused by the large coverage of replanted palms. However, this condition has been much improved by implementing the 15-bands combination.

More random distribution is presented in the tree conditions map of area 2. More normal conditions of mature oil palms exist in this area, while several leaning palms are sparsely identified. On the right-middle side of the map, a newly replanted plantation can be identified. From the Pleiades image, more than half of the trees in this plantation are young with various planting ages, but some mature trees can still be found randomly. Therefore, the whole plantation is classified as a replanted plantation in the tree conditions map. The classification map of area 3 shows that no leaning oil palms exist in this area; this is because most of the plantations are still in the young planting stage. Confusion only occurred in some parts of very young oil palms, where the difference between the replanted and the original tree is difficult to discriminate.

Overall, the results of the three classification maps show more random distribution compared to the usual land cover map; this is because the leaning, replanted and normal trees can randomly exist even in the same plantation. In several cases, single replanted tree surrounded by normal trees are sometimes identified as a large area of replanted palms because of the effect of the large size of the optimum moving window. Therefore, increasing the moving window size more than 7 × 7 is not necessary.

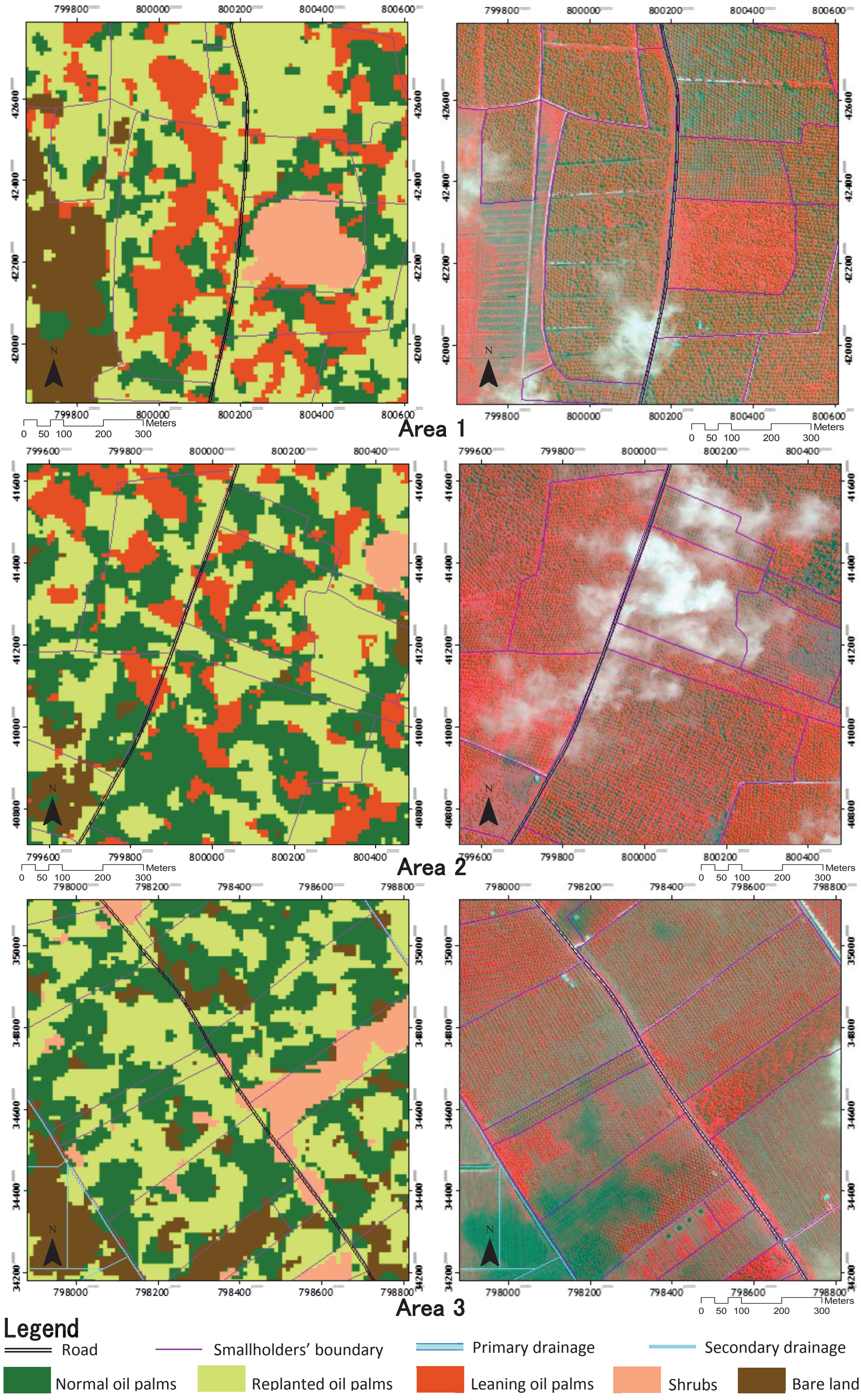

Figure 4.7 Oil palm tree conditions map produced using mean texture of 15-bands SAR parameters' combination in 7×7 moving windows (left) and Pleiades image (right)

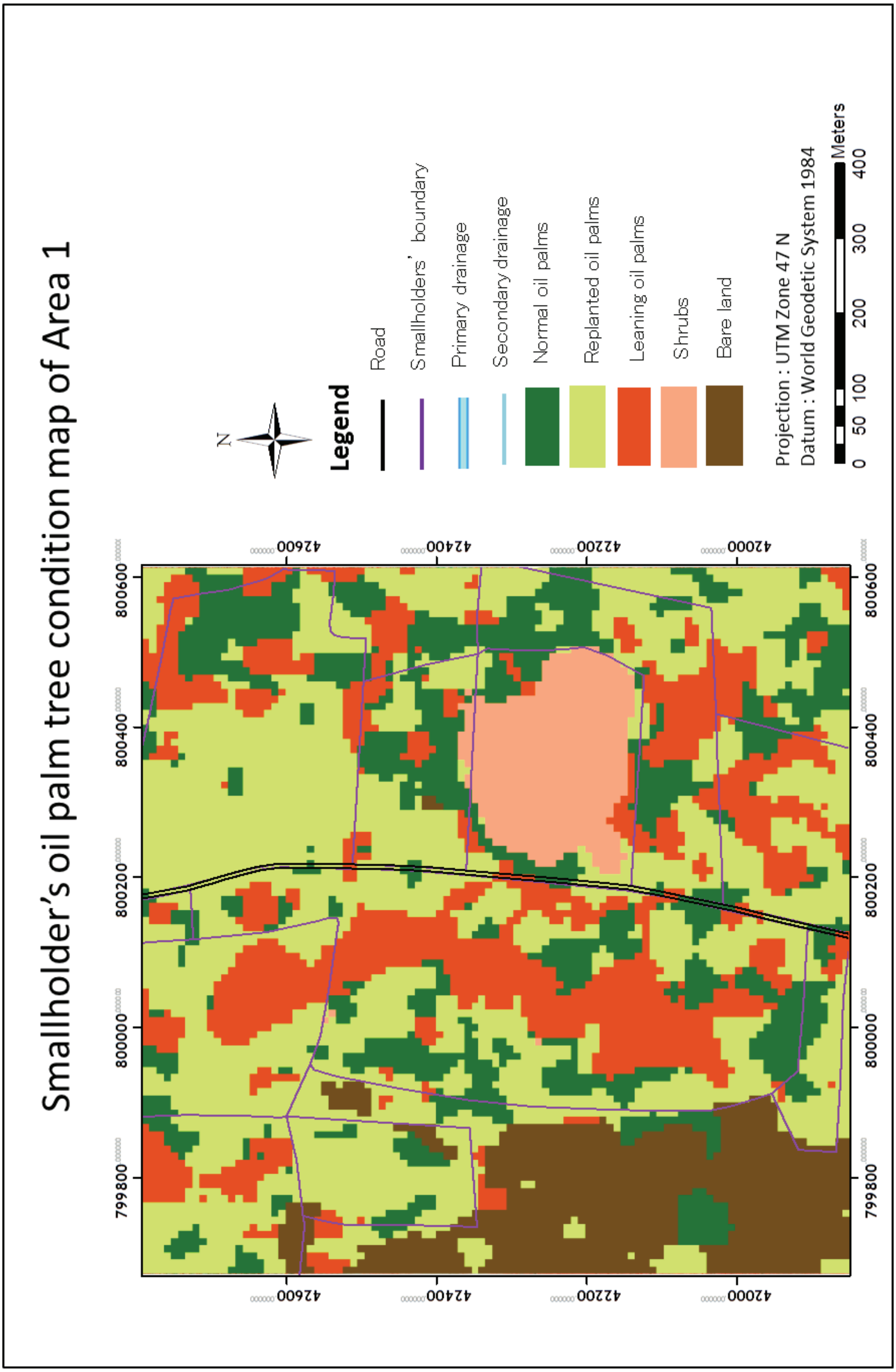

Figure 4.8 Smallholder’s oil palm tree condition map of area 1

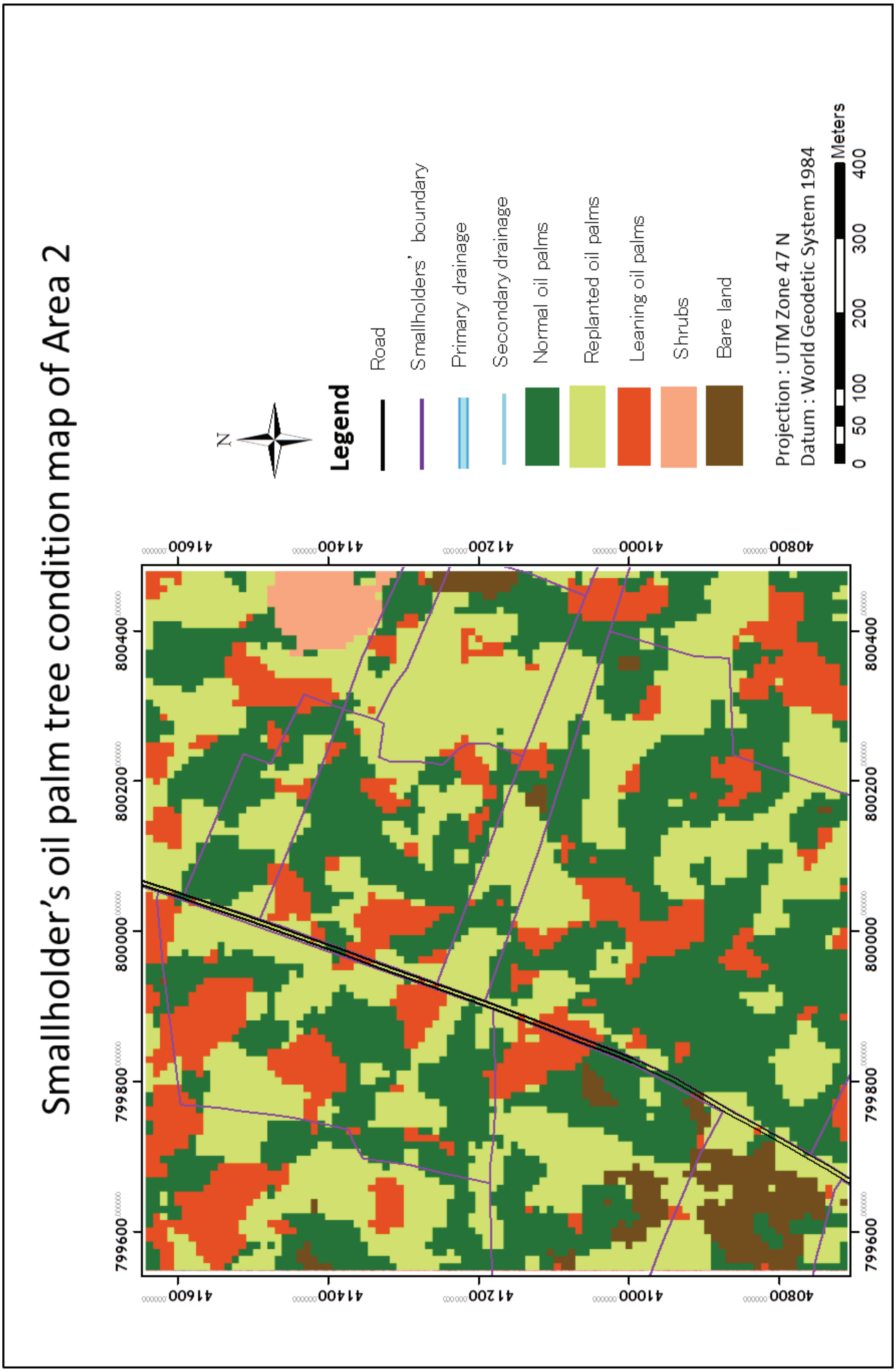

Figure 4.9 Smallholder's oil palm tree condition map of area 2

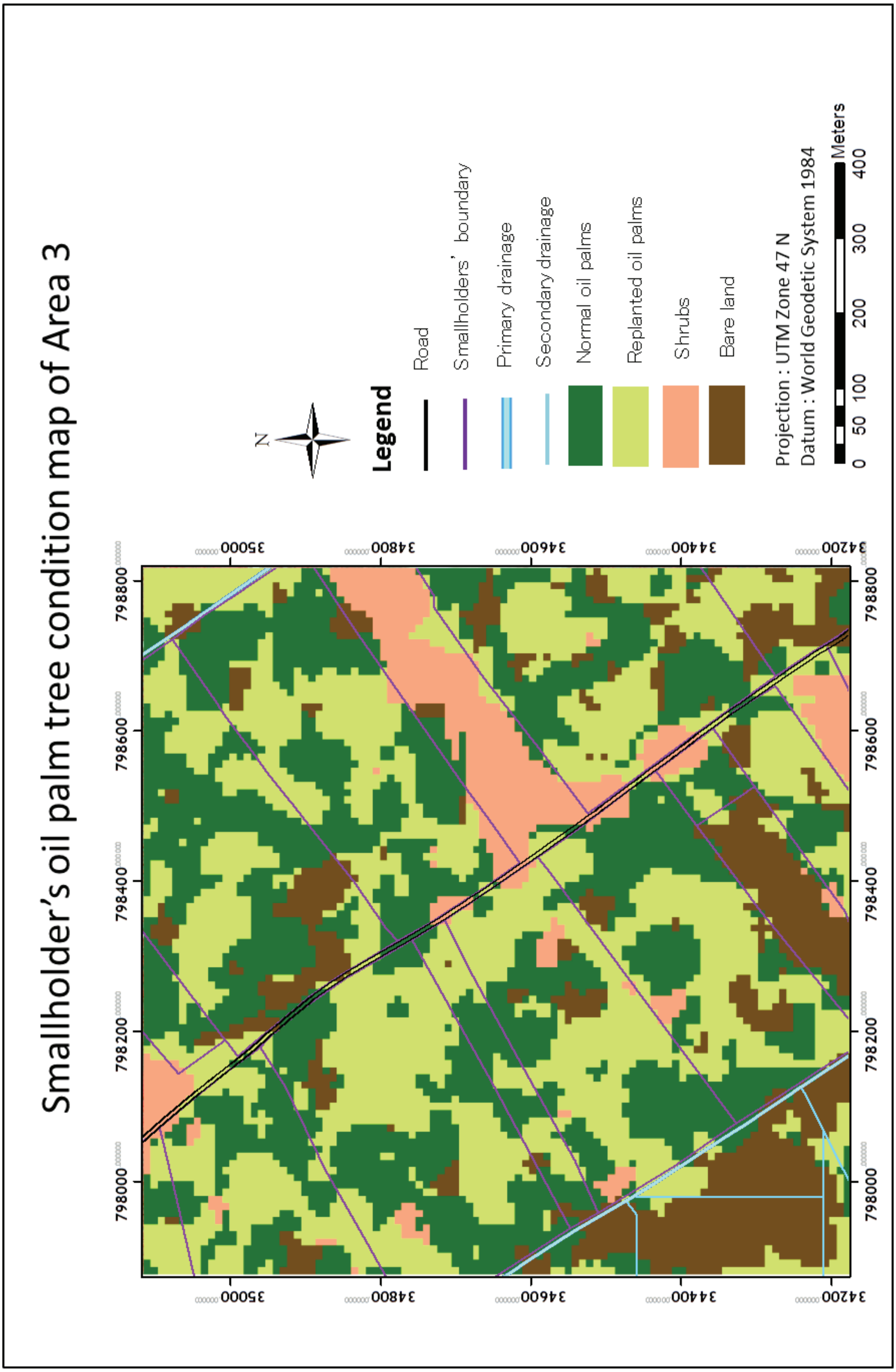

Figure 4.10 Smallholder's oil palm tree condition map of area 3

4.5 Conclusion

Texture analysis of SAR parameters combination from ALOS-2 PALSAR-2 fully polarimetric data was examined to classify tree conditions of smallholders' oil palm plantations on peatland area. The normal, replanted, and leaning oil palm tree conditions were attempted to be identified in three representative study areas. The mean feature of texture analysis was discovered as the most effective feature for identifying tree conditions, while 7 × 7 is the optimum moving window size.

The backscatter intensities are particularly effective to identify the normal oil palm trees. However, polarimetric parameters derived after decomposition are confirmed to be useful for identifying the standing condition of leaning oil palms, while combining backscatter and polarimetric parameters can improve the classification of all tree conditions. Finally, the mean texture analysis of 15-bands SAR parameter in a 7 × 7 window size was determined as the most effective combination. This combination obtained the highest overall accuracy, with as much as 68.69% (Kappa statistic: 0.60), 70.18% (0.55), and 72.75% (0.60) in areas 1, 2, and 3, respectively.

This study also revealed that detail target in the same species, such as tree conditions of smallholders' oil palms, can be identified by using the data of a single SAR sensor, PALSAR-2, which will be useful for application in tropical countries. Lastly, we suggest further analysis regarding the classification approach suitable for the target and the application for other tree species for the future studies

Chapter 5

General Discussion and Recommendation

5.1 Discussion and conclusion

This study aimed to conduct remote sensing analysis for the smallholder's oil palm plantations management purpose. The research tried to design the best methodology for detecting the distribution of smallholder's oil palm plantations as well as the detail analysis of oil palm tree condition on peatland area.

Before conducting the first study regarding to the detection of smallholder's oil palms, the biggest constraint in use of remote sensing should be found out. In this study, we figure out the characteristic of the smallholder's oil palm plantation as the main problems. Firstly, the scale of the area usually planted by the smallholder's makes the utilization of medium to high resolution of satellite image become necessary. Secondly, the random distribution of the plantations occupying remote area that surrounded by other vegetation problem lead to the requirement of remote sensing data and methodology that has the ability to distinguish the type of vegetation, as well as the need of specific characteristic of oil palm plantation that can differentiate its feature from other land cover types. Thirdly, location of study area itself, which is situated in tropical country where the cloud cover almost all of the time.

By considering these problems, we broke down the main objectives to solve each limitation. The first objective, *to explore the characteristic of oil palm plantation that can be identified by remote sensing data*. By learning the procedure of oil palm cultivation, it was found out that the oil palm trees are always planted in regular interval between each tree in order to make sure that all of tree could receive sufficient nutrient, sunshine, and water supply. We also confirmed this fact from the field survey activity to the study area where the most effective triangular planting pattern is used. We therefore used this unique characteristic to as the main feature of oil palm and the methodology to extract this pattern on satellite image. In this case, GLCM of texture analysis was used because of its ability to measure the grey tone pattern in the image. The result of the first study that confirmed that mean and variance texture features in 11 x 11 window size are efficient to discriminating oil palms from other land cover.

The second objective is *to examine the ability of dual and full polarization of*

ALOS PALSAR data in discriminating oil palms from other land cover types. According to the third problem about the cloud cover problem in Indonesia, this objective become necessary to be conducted, because of the ability of ALOS PALSAR data in penetrating the cloud cover. In this study, we tried to carry out the classification using both of FBD and PLR data. FBD has the limitation of only consist of two linear polarizations. Therefore, in this study, we tried to make synthetic band to add more information for the classification. Based on the solution of the first problem, the classification of FBD data was conducted by extracting the texture feature. Based on the classification, the ALOS PALSAR FBD data alone also can be used for the detection.

On the other hand, fully polarimetric ALOS PALSAR data has the advantages of having four polarization bands. This fact was utilized to produce more parameters from decomposition. This study then tried to examine the ability of this data by using SVM classifier. It has been proven that the combination of intensity bands and H/A/α parameters can produced the highest accuracy. The data also yielded higher accuracy than the analysis of ALOS PALSAR FBD only.

Finally, on the third objective*, to identify the best integration methodology of ALOS-Sensor data to detect smallholders' oil palm plantations*, we tried to design more comprehensive analysis for detecting oil palms. The integration of both SAR and optical data was hypothesized to be effective for classification, because of the multispectral information owned by the AVNIR-2data may enrich the information. The result shows that even though low accuracy was obtained by using ALOS AVNIR-2 data only, when this data were integrated with ALOS PALSAR texture data, it indeed improved the accuracy. This is particularly caused by the fact that AVNIR-2 data increase the separability of vegetation and man-made land cover. Finally, the methodology of mean and variance texture feature extracted from the ALOS PALSAR data in 11 x 11 moving window combined with all band of ALOS AVNIR-2 data, the best accuracy was achieved as much as 72.48% of overall accuracy with 0.63 kappa statistics.

As for the last objective, *to investigate the most effective backscatter and polarimetric parameter for identifying oil palm tree conditions on peatland area*, the analysis was carried out in different area with the first study. By considering the detail target to be analyzed, which is the oil palm tree condition, the ALOS-2 PALSAR-2 data that offers higher spatial resolution were used. By this study, we found out that the backscatter data and polarimetric decomposition parameters produced from the data is useful to detect the normal, replanted, and leaning oil palm. This study also revealed that the combination of backscatter, with Freeman-Durden, Yamaguchi, and eigenvalue-eigenvector parameters is the best methodology by yielding the best accuracy when they are extracted using mean texture feature by resulting by resulting 68.69% overall accuracy in area 1, 70.18%, and 72.75% for area 2 and 3, respectively.

By the result of this study, detail monitoring of oil palm expansion, especially by the smallholder farmers is hopefully can be carried out in order to avoid more problem for the environment. Moreover, we also hope this study will be useful for rehabilitation process of un-productive and less-productive oil palm trees planted on the peatland. Finally, we wish the study will be helpful for improvement of the management of smallholder oil palm farmer, and so that the sustainable oil palm cultivation can be accomplished.

5.2 Recommendation

This study provides the methodological analysis for the issue related to mapping of smallholder’s oil palm plantation and their tree condition. However, there are still some limitations on this study that should be improved for the future study. Firstly, better methodology for selecting the parameter should be improved. This study conducted pre-classification using the MLC for selecting the effective texture feature and analyzed the effectiveness from the accuracy result. Another method that can be used for determining the separability of each parameter should be employed to improve the effectivity of analysis.

Second, the dimensionality reduction using PCA in this study is proven to be not useful for improving the classification. However, big amount of data because of many parameter used for identification is not effective either. Therefore, examination of effective parameter for detecting smallholder’s oil palm plantations and the tree conditions should be explored.

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List of Publications

CHAPTER 3

Author : Lissa Fajri Yayusman, Ryota Nagasawa

Title : ALOS-Sensor data integration for the detection of smallholder's oil palm plantation in Southern Sumatra, Indonesia

Journal : Journal of The Japanese Agricultural Systems Society, 2015, Vol.31, No.2, pp.27-40.

CHAPTER 4

Author : Lissa Fajri Yayusman, Ryota Nagasawa

Title : Classifying the smallholders' oil palm tree condition on peatland area - A case study in Riau Province, Indonesia -

Journal : Journal of The Japanese Agricultural Systems Society (to be published on the journal Vol. 33, No.3)

APPENDIX A

Photograph of each land cover type in Simpang Pematang, Mesuji, Lampung

a. Agricultural land
b. Bare land
c. Mature oil palm
d. Young oil palm
e. Other woody vegetation
f. Settlement
g. Waterbody

APPENDIX B

Photograph of smallholder's oil palm tree condition in Riau

1. Normal oil palm tree

Oil palms grow straight up in normal condition, similar as common oil palms planted on mineral soil

2. Replanted oil palms

Fallen oil palm tree since young stage

Contrast condition (height and canopy cover) of replanted oil palm with other surrounding mature trees

3. Leaning oil palms

Oil palm tree trunk lean close or up to the ground when it grow higher

Oil palms lean to similar direction, leaving exposed-ground in one place (center) and densely-covered area in other place (left side of picture)

Oil palms lean to random direction, causing uneven sunshine penetration to the ground

Summary

Expansion of oil palm plantation on low-land tropics has rapidly increased in response of high global demand for palm oil. Indonesia has become a major location of oil palm cultivation as it possess favorable conditions supporting this activity. While it plays role as a vital economic strategy for the country, massive expansion in recent years has drawn criticisms for its potential of environmental damage and land use management problems. The involvement of independent smallholders in oil palm cultivation has caused even more uncontrollable expansion and land fragmentation since the cultivation is usually carried out in small patches area in random location. Moreover, decreasing availability of mineral soils has driven the expansion to the rich-carbon peatland area, which is principally less suitable for oil palms. Proper peat soil management, however, is still hardly applied by the smallholders that lead to decrease in production. Addressing the problem regarding the uncontrolled oil palm expansion by independent smallholders, and the urgency of improvement and recovery for existed plantations on peatland, comprehensive study on the detection of distribution and tree conditions of smallholders' oil palm plantations are necessary for detail monitoring of small-scale plantation, as well as to support rehabilitation process, control, and implementation of best management practice. Synthetic Aperture Radar (SAR) data, which is notably favorable to overcome the cloud cover in tropics, is mainly explored.

The main purpose of this study is to explore the methodology of ALOS PALSAR and ALOS PALSAR-2 application for identification and mapping of areal distribution and tree conditions of smallholders' oil palm plantations. In order to achieve this purpose, this study focused on the following specific objectives: (1) to explore the characteristic of oil palm plantation that can be identified by remote sensing data, (2) to examine the ability of dual and full polarization of ALOS PALSAR data in discriminating oil palms from other land cover types, (3) to identify the best integration methodology of ALOS-Sensor data to detect smallholders' oil palm plantations, (4) to investigate the most effective backscatter and polarimetric parameter for identifying oil palm tree conditions on peatland area.

Texture analysis is mainly applied as the methodology for classifying oil palm plantations and their tree conditions. Total of eight texture features of Gray Level Co-occurrence Matrix (GLCM) in 6 window sizes are tested and the most effective

features and window size are selected to generate best combination for identifying oil palms. Land cover classification, as the general part to detect both area distribution and oil palm trees conditions, is performed using Maximum Likelihood Classifier (MLC). Support Vector Machine method was also used as alternative and comparison for detecting smallholders' oil palms using full polarization of ALOS PALSAR data.

The study on the detection of smallholders' oil palm plantations was carried out in Mesuji District of Lampung Province in Southern Sumatra, Indonesia, which is known as the development area of independent smallholders' oil palm. The smallholders in this area mainly cultivate the oil palm covering small area in random locations, which are surrounded by other land cover types. The result of this study revealed that the triangular planting pattern of oil palm plantation is the unique characteristic that can be interpreted in satellite image as distinct texture. Combination of mean and texture feature from dual polarization ALOS PALSAR data was discovered as the most effective features to distinguish oil palms from other land covers. This is proved the ability of PALSAR data only for detecting oil palms. However, significant improvement in accuracy was achieved by integrating those data with multispectral AVNIR-2 image. The mean and variance extracted from HH, HV and HH-HV bands combined with all AVNIR-2 bands yielded in the best classification of mature oil palm with 92.45% of producer's accuracy and 66.67% of user's accuracy. While for the young oil palms, the producer's accuracy was 64.44% and the user's accuracy was 63.04%. The analysis for detecting smallholder' oil palms was also carried out using full polarization of ALOS PALSAR data which showed that the combination of four backscatter bands and 11 eigenvalue-eigenvector decomposition parameters resulted the best accuracy. It is also proved that classification using SVM yields slightly better accuracy than using MLC method. Overall, detection using full polarization image might produce higher accuracy comparing to result of detection using dual polarization of PALSAR data only, however, it is still lower than the result achieved by using data integration of both PALSAR and AVNIR-2 image, which remarks the important of multispectral information for the classification.

The second study related to classification of smallholders' oil palm tree conditions was conducted in Pelalawan Regency of Riau Province, where the expansion of oil palm has been expanded to peatland area. In spite of the smallholders in this area generally own only slightly larger land than the first study area, the plantations in this area are located close to each other. The methodology in this study was tested in 3 representative areas. Oil palm tree was classified in to three conditions, namely normal, replanted, and leaning trees. The classification using single texture feature in this study showed similar pattern with the previous one, which proved that mean feature has the greatest ability in detecting tree conditions, while 7 × 7 was the optimum window size. On the other hand, the analysis using PALSAR-2 parameters showed that even though the backscatter intensities are already effective to identify the normal palm trees, the other polarimetric parameters derived after decompositions are useful for identifying the standing condition of leaning oil palm trees. It is found that the 15 bands SAR parameter in 7 × 7 moving windows are the most combination for identifying tree conditions, by resulting 68.69% overall accuracy in area 1, 70.18%, and 72.75% for area 2 and 3, respectively.

The findings of the current study emphasize that the regular feature of oil palm planting patterns are the main characteristic and reason why the textural analysis become suitable for identification process. In this analysis, mean feature was constantly showed as the most significant GLCM feature, and can be directly applied for any further analysis related to oil palm classification. This study also proved that data integration derived from SAR and optical sensor will enrich the information and improve the classification accuracy. However, it is also revealed that whenever cloud-free image is not available, the identification of smallholders' oil palms and their tree conditions are still can be conducted using SAR data only. In this case, various polarimetric decompositions produced from the full polarization data are useful to provide more information of three-dimensional condition of tree standings, and therefore, detail analysis of identification of tree conditions are also possible. Finally, the distribution of smallholders' oil palm plantations map produced in this study, are hopefully can be useful for analyzing and predicting the expansion pattern by the smallholders, so that detail monitoring and policy making regarding to land management can be conducted to avoid more fragmented area. On the other hand, the tree condition maps on peatland area are hopefully will be useful as the guide for rehabilitation process to increase the yield and to encourage the application of best management practice by smallholders.

Keywords : Oil palm, smallholder, ALOS, PALSAR, PALSAR-2, polarimetric decomposition, texture analysis

Japanese Summary

近年，オイルパーム油に対する高い需要は世界各地でオイルパーム園の拡大を引き起こしている。その傾向はインドネシアでも顕著であり，同国の国民所得の増大，代替エネルギーの開発に大きく貢献した一方，さまざまな生態環境や土地管理上の諸問題をもたらしている。近年，特に小規模農家による経営規模の小さいオイルパーム園が各地で分散的に拡大し，現象を一層複雑にしている。従来の栽培地から泥炭地へのオイルパーム園の拡大も著しく，立地環境上深刻な問題も抱えている。小規模農家によるオイルパーム園の場合，資本不足や営農管理技術の欠如から適切な周辺環境への配慮が十分に行われていないのが現状である。こうした諸問題の改善のためには，まず小規模農家のオイルパーム園の分布や栽培状況の実態をモニタリングし，営農改善のための適切な情報を整備することが早急に求められている。ここにおいて，全天候型電波センサーであるSAR (Synthetic Aperture Radar)の有用性を提示しようと試みたのが本研究である。

本研究の主たる目的は，日本の陸域観測技術衛星（ALOS）に搭載されたALOS PALSAR及びその後継センサーであるALOS PALSAR-2を用いて小規模農家のオイルパーム園の空間的分布とオイルパーム樹の生育状況を把握する手法を確立することにある。この目的のために，次のような項目に焦点を当てた検討を進めた。１）リモートセンシングの手法に有用なオイルパーム園の特性（形状・スペクトル等）を把握する，２）オイルパームを他の土地利用型から差別化（分類）するための ALOS PALSAR の 2 偏波及び全偏波データの利用可能性を評価する，３）小規模農家のオイルパーム園を抽出するためのALOS PALSARデータの統合化手法を確立する，４）泥炭地に立地するオイルパーム樹の生育状況を把握するために必要な後方散乱特性やポラリメトリック（偏波）指標を明らかにする。

まず，オイルパーム園やオイルパーム樹の状態を分類抽出する手法としてテクスチュア分析を試みた。ここでは，Gray Level Co-occurrence Matrix (GLCM)手法を用いて8つのテクスチュア指標を6種類のウィンドウ（画素）サイズで試み，オイルパーム抽出のための最適な組み合わせを検討した。その後，ALOS PALSARの全偏波データを用いて最尤法分類を実行した。その際，Support Vector Machine手法を採用した。

解析の対象地域は，インドネシアの南スマトラ州に位置する Mesuji 郡である。この地域は小規模オイルパーム園が急速且つスプロール的に拡大しており，周辺の土地利用，

土地管理に対する影響が危惧されている。解析の結果として，ALOS PALSAR 画像に表されたオイルパーム園の特徴的な形状をテクスチュア解析によって的確に抽出できることがわかった。すなわち，ALOS PALSAR 画像の HH，HV and HH-HV 偏波を 11 x 11 ピクセルの moving window サイズで統計値 mean-variance のテクスチュア特性を抽出し，さらに ALOS AVINIR-2 の全バンドのマルチスペクトル特性をデータ統合することにより，小規模オイルパーム園を最も良い精度で抽出できた。精度評価の結果，成熟したパームオイルの場合，プロデューサー精度で 92.45%，ユーザー精度で 66.75%の値，また成長段階にある若いオイルパームではプロデューサー精度で 64.44%，ユーザー精度で 63.04%の分類精度を得ることができた。

もう一つの課題は，小規模オイルパーム園に分布するオイルパーム樹の生育状況に関する情報を SAR の手法を通じて得ることにある。泥炭地におけるオイルパーム栽培には、地下水位の管理や樹木の変形を最小限にするために泥炭土壌の圧密、排水管理に関する特殊な対処法が必要とされる。しかしながら、零細な小規模農家のオイルパーム園では往々にしてその適用が困難であり、結果として樹木の変形や転倒が多発している。そこで、本研究では ALOS-2 PALSAR-2 の全偏波画像データを用いてインドネシア、リアウ州の Pelalawan 郡に発達する泥炭地に立地する小規模農家によるオイルパーム園を対象とし樹木の生育形状を標準、変形、再植樹の３つのタイプに区分・分類する手法の開発を試みた。テクスチュア解析を適用して、SAR 画像の後方散乱量、レーダ植生指標（RVI）、ポラリメトリック（偏波）合成から得られたパラメータ値の個々およびその組み合わせを検討した。その結果、すべてのテクスチュアー特性において MEAN 値を用いることで最適な分類ができ、なかでも偏波パラメータ値はオイルパーム樹の変形を捉えるのに有効であることが分かった。最適な組み合わせは、７ x ７のウィンドウサイズを用いた 15 バンドの SAR パラメータの MEAN 値であり、3 つのケーススタディエリアでそれぞれ総合分類精度 68.69%、70.18% 、 72.75% の精度評価値が得られた。これにより、単時期の PALSAR-2 を用いることでオイルパーム樹の生育形状を把握、分類図化する手法が提示できた。

本研究の包括的な結論として，オイルパーム園の幾何学的な形状特性からリモートセンシングにおけるテクスチュア分析がその分類抽出に有効であることがまず示された。特に，GLCM 手法の mean-variance テクスチュア特性が有意な値を持つことがわかった。さらに，SAR と光学センサーを併用するとその分類抽出精度は一層改善されることも明

らかになった。熱帯地域では雲の被覆率が高いため，光学センサーの活用は必ずしも常時期待されるものではないが，その際はSARの全偏波を最大限に活用しさまざまなポラリメトリック合成を試みることで，2次元のみならず3次元的なオイルパーム樹の特徴抽出を図ることが重要である。最後に，本研究で提示された小規模農家のオイルパーム園のマッピング手法が今後のオイルパーム園拡大のモニタリングや土地管理，環境管理に関わる政策決定意思支援に貢献できるものであることを期待する。一方，泥炭地におけるオイルパーム樹の生育状況把握の手法は農園の樹木管理手法の改善や収量管理に貢献するものと考えている。

キーワード：オイルパーム，小規模農家，ALOS，PALSAR，ポラリメトリック（偏波）合成，テクスチュア分析