MONITORING AND MAPPING OF THE EXTENT OF INDUSTRIAL FORESTS IN MALAYSIA

By

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ABSTRACT

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INDUSTRIAL FORESTS IN MALAYSIA

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There are scattered studies in the international forestry sector that Industrial Forests (IFs) have been expanding as a newly-emerging Land Use and Land Cover Change (LULCC) in the tropics, especially in the Asia-Pacific region. However, these new tree plantations have not yet been well-documented; the area, along with its geography and land use dynamics, are not well known. Additionally, the drivers are not well understood, but it is widely believed that changes in tropical silviculture and increased international demand for wood and fiber are shifting to new demand centers in Asia. These trends have the potential to create global shifts in source producing areas, from long-standing IFs in North America and Europe to newer areas to the tropics. Considerable remote sensing research and product development have been focusing on monitoring closed canopy natural forests, but less work has been done on intensively managed IFs, which involve techniques for remote characterization of the establishment, management, and rotation. Moreover, the studies to date have been geographically limited to some key areas, such as the Amazon and Indonesia, and more work needs to be done outside of these closed natural forest regions. This research is conducted in the tropical Asia-Pacific region with a focus on the new IFs in the Sabah and Sarawak states of Malaysia. This study aims to improve the knowledge base and understanding of the extent and characteristics of new IFs as a new agent of LULCC, and to develop the methods for Landsat data, in particular by using forest fractional cover (*f*C) and vegetation indices (VIs) analyses in time series integrated with textural, spectral, visual, and other analyses to detect and quantify IF LULCC patterns and dynamics in the country.

Results showed that the selected IFs-including acacia, rubber, and other IFs-have expanded quickly from 2000 to 2014 with a net increase of 288,547 ha at the annual mean rate of 20.1% in Sabah, and 459,898 ha at the annual mean rate of 59.9% in Sarawak. The annual mean expansion rate of faster-growing, shorter-rotation acacia IFs at 28.4% in Sabah and 376.5% in Sarawak was much faster than that of slower-growing, longer-rotation rubber IFs at 13.7% in Sabah and 5.8% in Sarawak, as well as other IFs at 10.9 % in Sabah and 78.2% in Sarawak. The development of IFs in both states was primarily dominated by the larger scale holdings; however, the role of the small-scale IFs in developing new IFs in the region grew through an increase of its total area and rate of change in area. The expansion of IFs in Sabah and Sarawak significantly contributed to a LULCC in the regions. Most of these new IFs replaced disturbed natural forests (81-95%), followed by agricultural land (4-18%), and waste land (< 1%). These have caused a significant decline for the aboveground C stock in Sabah (11.5 Tg C) and Sarawak (24.7 Tg C), and resulted in an emission of 42.1 Tg CO_2 in Sabah and 90.5 Tg CO_2 in Sarawak over the period. The expansion of these new IFs had also led to a reduction in biodiversity in Sabah at 2.79-4.98% and in Sarawak at 2.77-4.96%. The results also showed a possibility of developing the *f*C and VIs-based methods in a time series for Landsat datasets that could detect and monitor the extent, pattern, and scale of IFs in the tropics. The accuracy for detecting the IF land using the *f*C-based method (with its producer's accuracy at 83% and Kappa coefficient at 0.46) was higher than that of the VIs-based method. Among VIs, ARVI worked the best with its producer's accuracy at 64% and Kappa coefficient at 0.4, followed by SAVI, SARVI, EVI, $NDVI_{af}$, and $MSAVI_{af}$. For both the *f*C-based method and the VIs-based method, the accuracy of detecting acacia and rubber IFs was better than that of other IFs in the region. In brief, this study successfully developed the *f*C- and VIs-based methods in multi-dated Landsat data to detect and quantify IF LULCC.

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KEY TO ABBREVIATIONS

LULCC:	Land Use and Land Cover Change
LULC:	Land Use and Land Cover
FAO:	Food and Agriculture Organization of the United Nations
ITTO:	International Tropical Timber Organization
NASA:	National Aeronautics and Space Administration
Mha:	Millions of hectares
IF/IFs:	Industrial Forest/Industrial Forests
IF LULCC:	Industrial Forest Land Use and Land Cover Change
*f*C:	Forest/Vegetation Fractional Cover
VI/VIs:	Vegetation Index/Vegetation Indices
ICFRE:	India Council of Forestry Research and Education
MARD:	Ministry of Agriculture and Rural Development of Viet Nam
RS:	Remote Sensing
NDVI:	Normalized Difference Vegetation Index
SAVI:	Soil-Adjusted Vegetation Index
ARVI:	Atmospherically Resistant Vegetation Index
SARVI:	Soil-Adjusted Atmospherically Resistant Vegetation Index
MSAVI2:	Modified Soil Adjusted Vegetation Index 2
EVI:	Enhanced Vegetation Index
AFRI:	Aerosol Free Vegetation Index
MSAVI*af*:	Modified Soil Adjusted Vegetation Index Aerosol Resistant

NDVI*af*: Normalized Difference Vegetation Index Aerosol Resistant

LAI: Leaf Area Index

SWIR: Short-Wave Infrared

EROS: Earth Resources Observation and Science Center

DNs: Digital Numbers

NV/NF: Non Vegetation/Non Forest

V/F: Vegetation/Forest

SR: Short Rotation

LR: Long Rotation

FG: Fast-Growing

SG: Slow-Growing

FGSR: Fast-Growing, Short-Rotation

SGLR: Slow-Growing, Long-Rotation

GLCM: Grey Level Co-occurrence Matrix

MEA: Mean

HOM: Homogeneity

DIS: Dissimilarity

AOI: Area of Interest

PCA: Principal Component Analysis

ICA: Independent Component Analysis

TCA: Tasseled Cap Analysis

UNFCCC: The United Nations Framework Convention on Climate Change

DF: Disturbed Forest

UF: Undisturbed Forest

AL: Agricultural Land

OP: Oil Palm Land

WL: Waste/Degraded Land

RL: Residential Land

Mg C ha^{-1}: Million grams of Carbon per hectare

Tg C or CO_2: Trillion grams of Carbon or Carbon dioxide

tC ha^{-1}: Tonne of Carbon per hectare

MtC or CO_2: Millions of tonnes of Carbon or Carbon dioxide

IPCC: Intergovernmental Panel on Climate Change of the United Nations

CHAPTER 1

OVERVIEW

1.1 Introduction

Forests play an extremely important role in maintaining life on Earth. They contain most terrestrial species on this planet and provide livelihood support to millions of people. Forests provide many precious and important ecological services for billions of people, even those living outside their immediate vicinity.

We also know that today forests, a specific Land Cover (LC) type, have been reduced in area through the activities of humans at the global scale. Forest decline, particularly tropical forests, can affect the global climate system, global carbon cycle, water resource systems, global energy balance, and biodiversity. Tropical forests contain very high carbon stocks and energy, sustain very high biodiversity, and are especially susceptible to significant Land Use and Land Cover Change (LULCC). Currently, the rate of human disturbance of the forests is high compared to other forest biomes. The United Nations Food and Agriculture Organization (FAO, 2000, 2005, & 2010) and the International Tropical Timber Organization (ITTO, 2009) estimated that 16 million hectares (Mha) and 13 Mha of tropical forests have been cleared and degraded annually for the 1990s and 2000s, respectively. As a result, the United Nations Intergovernmental Panel on Climate Change (IPCC, 2007) estimated that tropical forest conversion accounted for nearly 20% of the total anthropogenic global emissions of carbon dioxide to the atmosphere, and was a major driver of climate change.

Current research is now focused on understanding tropical LULCC dynamics, identifying the drivers of tropical deforestation and forest degradation, as well as quantifying their rates, extent, and patterns. Researchers have found that one of the main drivers of deforestation over the last four decades has been the conversion of closed canopy tropical forests to agriculture (Skole & Tucker, 1993; Gibbs *et al*., 2010; Tollefson, 2015); and selective logging has been a main factor for degrading the forests (Matricardi *et al*., 2005; Matricardi *et al*., 2007; Matricardi *et al*., 2010; & Matricardi *et al*., 2013). In response to these challenges, and in recognition of the timber supply shortage from forests, and other benefits of multiple forest uses (ITTO, 2009), government policies in most tropical countries have attempted to address the drivers of deforestation and forest degradation. They also seek to constrain the responsible agents by encouraging and developing solutions such as afforestation, reforestation, and the expansion of plantations.

As a result, FAO (2000, 2006, & 2010) reported that approximately 3.0-4.5 Mha of new tree plantations (equal to the annual average planting rate of 8.6%) have been established worldwide between 1995 and 2005, with the most significant increase occurring in tropical climate zones. ITTO (2009) also indicated that, among the three primary tropical regions over the world - including Asia-Pacific, Latin America and the Caribbean, and Africa - the Asia-Pacific region showed the highest rate of annual growth in land cover devoted to tree plantation area at 9.4%. This is compared to 8.8% in Africa and 4.3% in Latin America and Caribbean during the period. The Asia-Pacific region was also the location of approximately 80% of the world's total tropical plantation area and 80% of its increase in area. Of this quantity, about 90% of the total plantation area in the region was established in a few key countries, including India, Indonesia, Thailand, Malaysia, and Viet Nam. However, unlike deforestation and forest degradation, these tree plantations have not yet been widely studied with respect to the new widespread LULCC. We know little about them in terms of their specific processes, drivers, locations, rates, extent, and patterns (FAO, 2006; ITTO, 2009; Skole *et al*., 2013).

There are a few reports from the international forestry sector suggesting that tree plantations have been expanding in recent years. This portends to be an important emerging Land Use and Land Cover Change (LULCC) in the tropics, especially in the Asia-Pacific region. However, these new tree plantations have not been well documented - the area, geography and land use dynamics are not well known. The drivers are not well understood either, but it is widely believed that advances in tropical silviculture technology and methods, and increased international demand for wood and fiber are shifting industrial wood source areas from North American and European areas closer to new demand centers in Asia (ITTO, 2009; Skole & Simpson, 2010; Skole *et al*., 2013). These trends have the potential to create global shifts in the location of source-producing areas, where long-standing industrial timber plantations in North America and Europe are now moving to the tropics. In spite of this understanding, questions remain: What is the magnitude? What size class are the new forest plantations and their rotations? What are the uses and drivers of these plantations? Are the new plantations replacing natural forests? Furthermore, robust tools to detect, map, and monitor them are also lacking (Skole *et al*., 2013).

Considerable remote-sensing research and product development have been focused on monitoring closed canopy tropical forests, while less work has been done on intensively managed industrial timber plantations. To do so would involve techniques for remote-sensing characterization of the establishment, management, and rotation of even-aged stands of industrial plantations. Moreover, studies done to-date have been geographically limited to some key areas of closed canopy tropical forest, such as the Amazon and Indonesia, and more work needs to be done outside of these closed natural forest regions. Moreover, many institutions (*e.g.*, NASA) and researchers (*e.g.*, Skole *et al*., 2013) have emphasized the plantation phenomenon-along with open forests, woodlands, savanna, and trees outside of forests-as a high-priority topic for the next stage of research on drivers and dynamics of LULCC.

An investigation of the expansion of new tree plantations, including their underlying and proximate LULCC processes and drivers, requires a new and innovative approach that includes development of new remote sensing methods and an analysis of spatial patterns. This approach helps us better understand the extent and dynamics of IFs from perspectives of both driver analysis and monitoring (Skole *et al.*, 2013).

Therefore, the research that supports this dissertation has been aimed at recently-established tree plantations in the tropics, with a focus on the Asia-Pacific region and selection of Malaysia as a case study. Representative plantation species or systems studied consist of *Acacia* spp., *Eucalyptus* spp., *Pinus* spp., *Hevea* spp., and *Tectona* species in terms of both methods development and quantification of their rates, extent, and patterns of establishments. The selection of the above plantation species results from the fact that nearly 90% of tree plantations in the Asia-Pacific region utilize these species (FAO, 2000, 2006; ITTO, 2009). Meanwhile, Malaysia provides a compelling case for the examination of new tree plantations because the annual expansion rate of faster-growing, shorter-rotation industrial timber plantations (such as acacia) is surprisingly high, while the slower-growing, longer-rotation plantation areas (such as rubber) are decreasing remarkably. Additionally, developing and testing new methods for detecting and mapping these new tree plantations are especially challenging in Malaysia due to heavy cloud contamination and haze.

1.2 Industrial Forest: Concepts and Definitions

In this section, the concepts and definitions related to the term "industrial forests" as applied in this study will be developed. The concept and definition of industrial forests are both derived from the concepts and definitions of tree plantations. This study will utilize a widely-accepted and widely-used concept and definition from FAO (2000)[1]: "Plantation forests are forest stands established by planting or/and seeding in the process of afforestation or reforestation. They are either of introduced species (all planted stands), or intensively managed stands of indigenous species, which meet all the following criteria: one or two species at planting, even age class, regular spacing". A plantation could be established on lands which previously did not carry any type of plantations (a new tree plantation) or re-established on already-existing plantation lands.

Plantations are generally divided into two sub-groups: productive plantations and protective plantations (Kanninen, 2010). The productive plantation is a forest plantation mainly established for the provision of wood, fiber (*e.g.*, roundwood, sawnwood, and pulpwood), and non-wood products, while the protective plantation is a forest plantation established chiefly for the provision of such forest ecosystem services as water and soil resource protection. Kanninen (2010) found that most of the world's total plantation area was productive plantation. Specifically, the general ratio of productive and protective plantation forests was 3.6 (equal to the ratio of natural forests allocated for production and protection purposes), but distributed unevenly in different countries, regions, and continents. A plantation could also be classified as hardwoods/broad-leaved (*e.g.*, *Eucalyptus* and *Acacia* spp.) and softwoods/conifers (also known as needle-leaved; *e.g.*, *Pinus* spp.), or for industrial use or non-industrial use (FAO, 2000)[1]. For industrial and non-industrial use, an industrial forest (IF) could be a productive plantation, which is extremely diverse - ranging from horticultural types such as orchards, to fuel oils, to saw logs -

[1] http://www.fao.org/docrep/007/ae347e/ae347e02.htm

and covering many varying worldwide land cover characteristics. It can also be established in a new area or already-existing IF lands. Therefore, this study only focuses on the most important form of new tree plantation LULCC in the tropics, *i.e.,* new tree plantations for timber and biomass feedstock, including the following types of tree systems: timber, saw log, veneer, and pulp in addition to other biomass feedstock plantation systems with the focused species of *Acacia* spp., *Eucalyptus* spp., *Pinus* spp., *Hevea* spp., and *Tectona* spp. These new tree plantation systems involve the replacement of natural forests and other land uses with plantations of commercial trees using forest management and silvicultural rotations. This is a new phenomenon and has not yet been widely studied. This focus also fits with the definition from FAO for the industrial plantations, as those for the production of wood for industry (saw-logs, veneer-log, pulpwood, and mining pillars/pit pros) (FAO, 2003).

In brief, in this study, an industrial forest (IF) is a productive plantation established for the industrial use, as defined here, which involves the planting and harvesting of trees for timber, saw log, veneer, pulp, and other biomaterial feedstock. A new IF could be understood as a new productive plantation created from other land uses and land covers, which do not previously include any types of tree plantations. An industrial forest could come to many different names in different countries in the national forestry statistics. For instance, in Indonesia, industrial forests are called Hutan Tanaman Industri (HTI), meaning industrial plantation forest (Indonesia Forestry Statistics, 2012); in Malaysia they are called plantation forest (Malaysia Timber Council, 2009); and in Vietnam they are called Rừng Trồng Sản Xuất, or productive plantation forest (Vietnamese Ministry of Agriculture & Rural Development [MARD], 2012).They are even simply called a plantation in many cases.

1.3 The Development of Industrial Forests (IFs) in the Asia-Pacific Region

IFs occupy a small percentage of the world's total forest area (FAO, 2010), yet they are heterogeneous in their spatial distribution and cover many different biophysical characteristics. These plantations consist of diverse types, including rubber plantations, saw-log plantations, pulpwood plantations, and more. In spite of their total area being small compared to natural forests, they provide one third of the world's demands for industrial wood (ABARE-Jaakko Pöyry Consulting, 1999). The importance and impact of IFs on humans and LULCC will continue to increase as a result of rapidly increasing their area, especially in the tropics.

The ITTO (2009) and FAO (2000, 2006, & 2010) indicated that the new IFs in the tropics were increasing both in individual size and in total area. In particular, the establishment of new plantations has accelerated significantly since the 1990s and there was a remarkable shift from slow-growing, long-rotation plantations to fast-growing, short-rotation ones. Although the world's total plantation area has been increasing, the main part of these increases has occurred in only a few key areas, dominated by the Asia-Pacific tropical region. Reports by the FAO (2000, 2006, & 2010) indicated that the total world's plantation area increased from 100 Mha in 1990, to 140 Mha in 2005, and to 190 Mha in 2010, resulting in an annual mean increase of approximately 4.5 Mha/year. Out of the 140 Mha of the world's total plantation area in 2005, 67.5 Mha were located in tropical countries, of which the Asia-Pacific tropical region contained 54 Mha (80% of the total tropical plantation area). Of this, India held 33 Mha (60% of the total area of the region), followed by Indonesia (9.9 Mha), Thailand (4.9 Mha), Malaysia (1.8 Mha), and Viet Nam (1.7 Mha). Together, these countries accounted for more than 90% of the regional total. Moreover, the mean annual rate of the increase in this region (9.4% per year) was the highest compared to other tropical regions (Africa 8.8%, Latin America and the Caribbean 4.6%)

(FAO, 2006; ITTO, 2009). This represented a substantial increase from 24 Mha in 1995 to 54 Mha in 2005. India contributed most of the increase, growing from 14.6 Mha to 32.6 Mha in this period.

The ITTO (2009) and FAO (2006, 2010) also showed that most IFs in the tropics were dominated by relatively few genera including *Pinus*, *Eucalyptus*, *Acacia*, *Hevea*, and *Tectona*. Among the tropical IF species, eucalypts (*Eucalyptus* spp.) and acacias (*Acacia* spp.) were important tree species, mainly used for pulp and paper industries. Pines (*Pinus* spp.), rubber (*Hevea brasiliensis*), and teak (*Tectona grandis*) were also widely planted and utilized for the production of saw logs, round wood, and panels (*e.g.*, plywood and veneer) (FAO 2006; ITTO, 2009; Asia-Pacific Forestry Outlook Study, 2010). The ITTO (2009) reported that eucalypts were the most widely planted, with the total area estimated at about 8.5 Mha (24% of the total IF area in the tropics), followed by pines (18%), rubbers (18%), teaks (17%), and acacias (9%).

The Asia-Pacific Forestry Outlook Study (2010) also showed that most of the early IFs in the region were vastly dominated by slow-growing and long-rotation species (such as teak) which were destined to produce saw and veneer logs. Recently, however, the area of short-rotation and fast-growing species such as *Eucalyptus* spp., *Pinus* spp., and *Acacia* spp. has significantly increased, leading a big shift from slow-growing species to fast-growing species. The driving forces for this shift involved changes in wood-processing technologies, which had a primary influence on the selection and widespread planting of the fast-growing IF species. In addition, improvements in silvicultural practices, plantation technology, and management, as well as the high demand for these fast-growing species were also important factors. In India, the most widely planted species were *Tectona grandis, Eucalyptus* spp., *Pinus* spp. (mainly *Pinus roxburghii*), *Acacia* spp. (mainly *Acacia nilotica* and *Acacia mangium)* and *Hevea brasiliensis.*

Tectona grandis, *Acacia* spp., *Pinus* spp. (especially *Pinus merkusii*), and *Hevea brasiliensis* were also the most important IF species in Indonesia. Viet Nam's plantation programs were substantially comprised of *Acacia, Pinus,* and *Eucalyptus* species, while IFs in Thailand and Malaysia were dominated by rubber, followed by other fast-growing species, such as *Eucalyptus* (in Thailand) and *Acacia* (in Malaysia) species (Asia-Pacific Forestry Outlook Study, 2010). IF development has proceeded in the key countries of the Asia-Pacific region in recent decades, including India, Indonesia, Thailand, Viet Nam, and Malaysia.

India is one of the most important players in the establishment of new IFs in the world. Since the 1980s, India has promoted the investment for plantations under different programs, such as agroforestry and social forestry (Ministry of Environment and Forests of India, 2007). The FAO (2000) reported that India had a total of 32.5 Mha of plantations, which accounted for approximately 17% of the globe's total plantation area and was the second largest in the world - only after China - according to the ITTO (2009). Of that, 45% of plantation species were fast-growing species (mostly *Eucalyptus* spp. and *Acacia* spp.) and teak (8%). The ITTO (2009) also estimated the total commercial IF plantation area in India in 2000 at 8.2 Mha, including teak (2.6 Mha), eucalypts (2 Mha), acacias (1.6 Mha), pines (0.6 Mha), rubber (0.6 Mha), and other species (0.8 Mha). The India Council of Forestry Research and Education (ICFRE, 2010) also indicated that most of the annual plantation increase in India was established in conjunction with the Twenty Points Program (TPP) for Afforestation, established in 1970 and restructured in 2006, and the National Afforestation Program (NAP), established in 2000, at the rate of 1-2 Mha annually. The area and rate of plantation establishments were different in different states. The ICFRE (2010, 2011) indicated that the largest area and highest rates of tree plantation establishments were found in some key states, such as Andhra Pradesh, Madhya Pradesh, Gujarat, and Maharashtra. Teak IF area in India was also very significant, with most plantations (2 Mha) planted in some key states, such as Maharashtra, Madhya Pradesh, Andhra Pradesh, and Gujarat (ICFRE, 2010). While the majority of rubber plantations (0.7 Mha) were established in Kerala state (90%), the fast-growing species plantations (such as *Eucalyptus* and *Acacia* spp.) were mainly developed in the key pulp and paper production centers, such as Andhra Pradesh, Karnataka, Maharashtra, Gujarat, and Orissa states.

Indonesia is also one of the most significant plantation forest countries in the world. The ITTO (2009) estimated the total area of plantations in Indonesia at about 10 Mha in 2005. Of that, the total area of Indonesia's commercial IF plantations amounted to about 4.9 Mha, with 1.5 Mha of teak, followed by 1 Mha of rubber, 0.8 Mha of pines, 0.7 Mha of acacias, 0.2 Mha of eucalypts, and 0.9 Mha of other species. The area of fast-growing species plantations in Indonesia increased rapidly from 2.2 to 3.4 Mha between 1990 and 2005 (FAO, 2005). Over the same period, the area of rubber plantations also increased from 1.9 to 2.7 Mha. The Indonesia Forestry Statistical Data showed that the total industrial timber plantation area (HTI) had increased from 5.1 Mha in 2001, to 9.4 Mha in 2009, and to 13.1 Mha in 2012. Most of these plantations were located in the East Kalimantan, West Kalimantan, Riau, and South Sumatra provinces. A study by the FAO (2009) also indicated that these provinces were main material sources for pulp and paper industries. Barr (2007) noted that 80% of pulp industrial plantations were *Acacia* spp., with some *Pinus* and *Eucalyptus* spp., and that sawnwood IFs were mainly teak and other broadleaved species. While most of the state-owned teak IFs (1.7 Mha) were planted on Java island, the teak IFs (1 Mha) owned by private companies were developed primarily on the Sumatra and Kalimantan islands (Indonesia Forestry Outlook Study, 2009). Likewise, the private smallholder-owned rubber plantations (3 Mha) were mostly established on the Sumatra and Kalimantan islands. Indonesia also plans to have 9 Mha more of IFs by the end of 2016. Most of the new IF areas will be established in the Papua (1.7 Mha), East Kalimantan (1.5 Mha), West Kalimantan (1 Mha), Riau (1.2 Mha), and South Sumatra (1 Mha) provinces.

Thailand's total plantation area in 2005 was estimated to be in the range of 4.0-4.9Mha, according to different sources (Blasser *et al.*, 2011; FAO, 2010; ITTO, 2009). The ITTO (2009) estimated that Thailand had a total commercial plantation area of about 4.9 Mha, including rubber (2 Mha), teak (0.8 Mha), pines (0.7 Mha), eucalypts (0.45 Mha), acacias (0.15 Mha), and other species (0.75 Mha). Rubber IFs maintained an important leading position in Thailand's wood-based industries, were mainly owned by smallholders (93%), and were located mostly in southern Thailand (>80%). Data from the FAO (2010) indicated that the area devoted to rubber plantations in Thailand increased from 2 Mha in 2000 to 2.6 Mha in 2010. However, according to the Rubber Statistics of Thailand (2011), in 2011, Thailand had approximately 3 Mha, an increase of 0.2 Mha from 2009. Pulpwood IFs in Thailand (mainly dominated by *Eucalyptus* spp. and some *Acacia* spp.) were principally established by private companies, smallholders, and governmental entities - especially smallholders who held most of the pulpwood plantations in Thailand. Barney (2005a) indicated that most of the *Eucalyptus* plantations were established in the northeastern area of the country (50%). Teak and *Pinus* IFs in Thailand were also significant. However, the information on them was scarce. Teak (0.8 Mha) was reported to be mainly established in agrosystems by governmental entities in the Northeast and North. *Pinus* IFs (0.7 Mha) were predominantly planted in the North, but they tended to be older plantations started in the 1960s (Oberhauser, 1997).

Viet Nam is among a few countries in the world that have significantly accomplished a net gain in forest area since the 2000s. The recovery of Viet Nam's forests mainly resulted from policies on the expansion of new tree plantations and forest rehabilitation. The FAO (2000) estimated the total plantation area of Viet Nam at about 1.7 Mha including eucalypt plantations (0.45 Mha), followed by rubber (0.3 Mha), pines (0.25 Mha), acacias (0.13 Mha), and other species (0.6 Mha). The FAO (2006) also showed the trend that the IF area used for pulpwood/fiber and sawlogs was 0.56 Mha in 1990, 1.2 Mha in 2000, and 1.5 Mha in 2005. Currently, Viet Nam's total area of plantation forest is about 3.4 Mha, which is a significant increase from 1.9 Mha in 2002 (MARD, 2012 a&b). Of that, the total IF productive plantation area was 2.5 Mha. The productive plantations were mainly located in the Northeast, North Central, and South Central Coast/Coastal regions of Viet Nam (Viet Nam Forestry Outlook Study, 2009). These regions are considered the main material suppliers of the pulp, paper, artificial board, and chip production industries in Viet Nam. The report of the Ministry of Agriculture and Rural Development (MARD, 2010) also showed the biggest plantation area in 2009 was found in the Northeast (1 Mha), followed by the North Central Coast (0.7 Mha), and South Central Coast (0.4 Mha). Viet Nam is also a significant natural rubber producer. Luan (2013) reported at the end of 2012 that the total rubber area was 0.91 Mha, an increase from 0.41 Mha in 2000. The average area growth rate in the 2000-2012 period was 6.8%/year. Most of the rubber plantations were distributed in the Southeast region and Central Highlands. Pulpwood IFs including *Eucalyptus, Acacia*, and *Pinus* spp. were about 1 Mha in 2005 (Barney, 2005b). In addition, the Government of Viet Nam plans to establish approximately 1.4 Mha of new plantation area by 2020.

Along with India, Indonesia, Thailand, and Viet Nam, Malaysia is one of the most important countries for tropical plantations. The development of IFs in Malaysia will be presented in the following section.

1.4 The Development of Industrial Forests in Malaysia

Malaysia is one of the key plantation countries in the Asia-Pacific region. The ITTO (2009) estimated Malaysia's total IF area around 1.8 Mha in 2005, including *Hevea* spp. (1.5 Mha), followed by *Acacia* spp. (0.2 Mha), *Pinus* spp. (0.06 Mha), *Eucalyptus* spp. (0.02 Mha), *Tectona* spp. (0.01 Mha), and other species (0.01 Mha) (Figure 1.1). The FAO (2010) reported that while the total rubber area in 2007 was 1.2 Mha - a significant decrease from 1.8 Mha in 1990 - the area of other plantations was 0.5 Mha. This was a remarkable increase from 0.12 Mha in 1990, especially in Sarawak; there was almost no mention of other industrial timber plantations in 2000, and in 2012, the plantations had increased to more than 0.3 Mha, at the mean annual planting rate of 365%. The distribution of IFs of the country is presented in Figure 1.2.

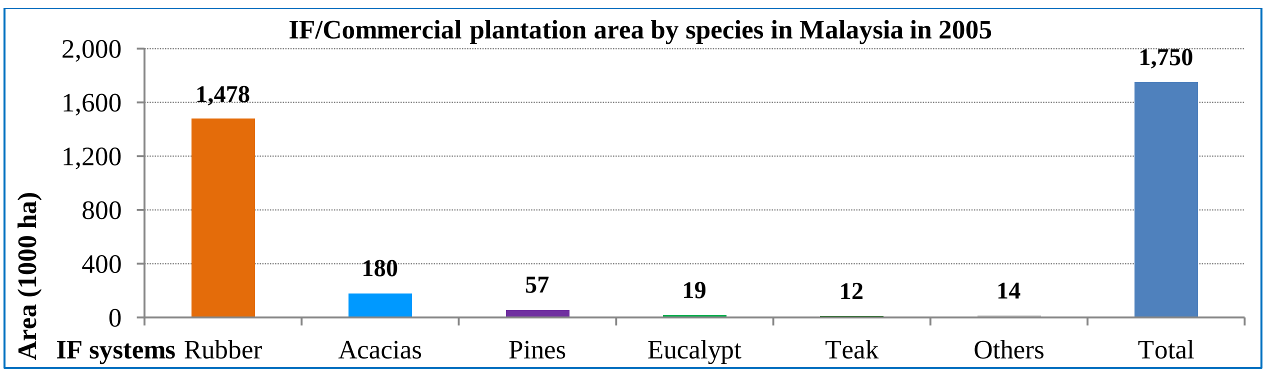


Figure 1.1. The commercial plantation by species in Malaysia in 2005 (ITTO, 2009).

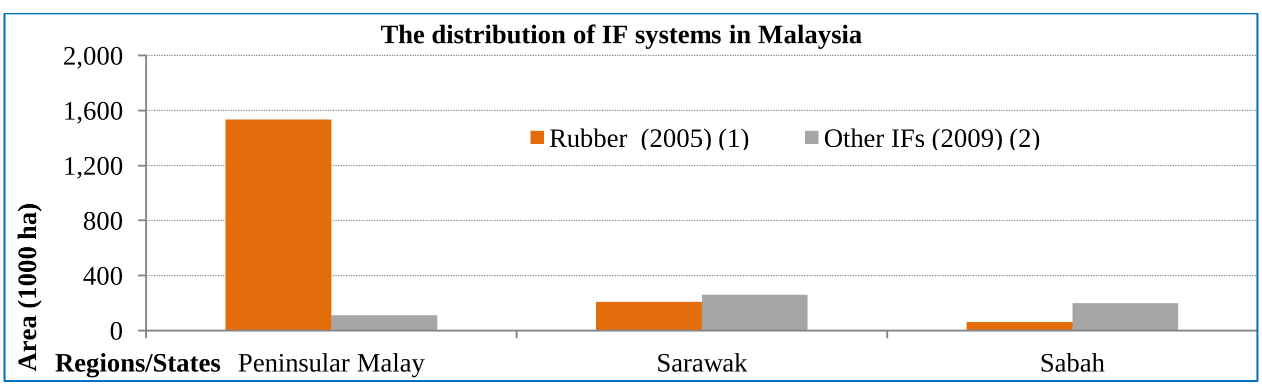


Figure 1.2. The distribution of plantations (rubber in 2005 & other IFs in 2009) in Malaysia (adapted from (1) Malik *et al*., 2013); (2) Malaysia Timber Council, 2009).

In general, Malaysia has extensive rubber plantations and is one of the most important natural rubber producers in the world. The rubber plantations have been established mostly in private lands under smallholders in the Peninsular Malaysia. Rubberwood represents a significant portion of Malaysia's forest industry exports. Currently, the Malaysian Ministry of Plantation Industries and Commodities (MPIC) reports a total rubber area of approximately 1.0 Mha in 2013, significantly decreasing from 1.4 Mha in 2000 and 1.2 Mha in 2005 (MPIC, 2013)[2].

Pulpwood IFs in Malaysia are mainly *Acacia* spp. Although, currently, pulp and paper industries are quite underdeveloped (Roda & Rathi, 2006), the Government of Malaysia has identified that the pulp and paper industry is one of priority areas in the new National Economic Development Plan. The Sabah and Sarawak States are the key pulpwood production centers of the country in this plan. To promote the development of this industry, a number of projects have been proposed and implemented. In addition, big companies have been more involved in planting new IFs. For instance, the most significant project was the Planted Forest Pulp and Paper Project in Sarawak. Under this project, it was planned to establish an IF area of 100,000-150,000 ha to fulfill enough raw materials for the mill (Roda & Rathi, 2006). Besides, Sabah also plans to construct numerous pulp and paper mills and intends to establish significant new pulpwood IF area in the state. As a result, the total timber plantation area (not including rubber) in Sarawak has significantly increased from 7,000 ha in 2000 to 300,000 ha in 2012, with the rate of expansion at 365% or 25,000 ha annually for the period (Figure 1.3). Likewise, Sabah's timber plantation area also increased from 150,000 ha in 2000 to 250,000 in 2012. Meanwhile, the area of other plantations in the Peninsular Malaysia only slightly increased from 74,000 ha in 2000 to 110,000 in 2009. Recently, the Federal Government has launched a new plan to establish

[2] http://www.kppk.gov.my/statistik_komoditi/Data%20Komoditi/general/planted%20071013.pdf

375,000 ha of new forest plantations in the next 15 years, giving priority to rubberwood and *Acacia* spp. (mainly *Acacia mangium* and hybrid). The expected annual planting rate is 25,000 ha. In addition, Sabah has also set a target to establish 0.5 Mha of forest plantations by the year 2020, while Sarawak is expected to have a total of 1.2 Mha by 2020 (Malaysia Forestry Outlook Study, 2009). Additionally, the Government's forest plantation project also covers another 0.5 Mha. In brief, among the key plantation countries in the Asia-Pacific region, the development of IFs in Malaysia shows a very interesting case. While the rubber area is decreasing, the area of other IFs (especially acacias in Sarawak and Sabah) is increasing at the highest rate of area change in percentage, as compared to the rate of increase for IFs in other countries in the region. Moreover, like Indonesia, plantations in Malaysia are principally dominated by oil palms, which are not included in this study. It is indicated that rubber plantations are being outcompeted by these oil palm plantations (Jagatheswaran *et al.*, 2011; Jagatheswaran *et al.*, 2012), but not by other industrial tree plantations, such as the pulpwood IFs as presented above. As a result, this study will be conducted in Malaysia as a case study to investigate and examine this trend.

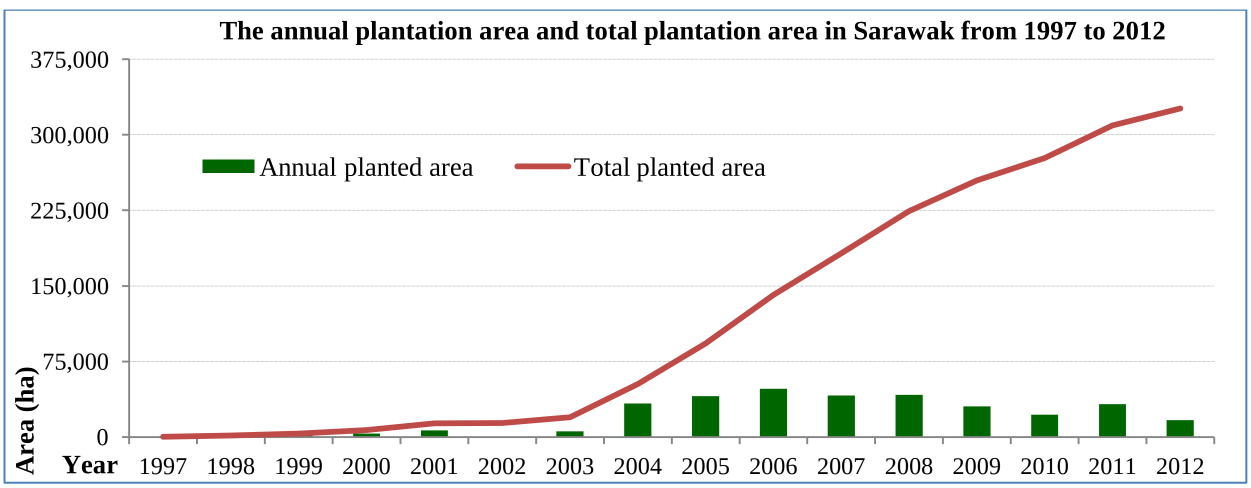


Figure 1.3. Industrial plantation development in Sarawak, 1997-2012 (adapted from Sarawak Forestry Department Statistics, 2012)[3].

[3] http://www.forestry.sarawak.gov.my/modules/web/pages.php?mod=download&id=Annual%20Report&menu_id=0&sub_id=276

1.5 Literature Review of the Studies on Industrial Forests

1.5.1 In the Asia-Pacific Region

The purpose of this section is to examine how industrial forests have been studied in the world and the Asia-Pacific region. By doing a very simple search on the Web of Science with the syntax (1) deforestation and forest degradation, and (2) plantations and industrial forests, in the topic, 1,300 papers were found for "deforestation and forest degradation," and only 8 papers were found for "plantations and industrial forests" from 1990 until present day. This implies that most of the past and current research has been focusing on deforestation and forest degradation, and that there are much fewer concerns and interests on the establishments of new IFs. In general, what we know about IFs now is only from general plantation databases made by international entities such as FAO and ITTO, and national forestry statistics in the region. Thus, the next question is how researchers have studied IFs, especially in the key plantation countries, on the LULCC perspectives in the region.

In India, a few studies have been done in plantation systems - in particular, new tree plantations as a new LULCC phenomenon or process. For instance, several studies have been done on the carbon stocks of plantations (*e.g.,* Semwal *et al.*, 2013; Bohre *et al.*, 2013; Devi *et al.*, 2013; Kanime *et al.,* 2013). Other researchers have studied plantations on their ecology domain (*e.g.,* Dey *et al.*, 2014; Gattoo, 2013; Chaudhuri *et al.,* 2013; Rengan *et al.,* 2010; Mandham *et al.,* 2009) or plantation silvicultural practices, technologies, economics, and management (*e.g.,* Pillai *et al.,* 2013; Prasad *et al.,* 2010). Others still have studied plantation sustainability (*e.g.,* Aggarwal, 2014), pulpwood and paperwood demand from plantations (*e.g.,* Kulkarrni, 2013; Prasad *et al.,* 2009), or constraints to the development of plantations in India (*e.g.,* Palm *et al.,* 2013). The study of Prasad *et al.* (2009) indicated the potential for the development of short-rotation and fast-growing IFs for pulpwood production from arable lands in India. Likewise, Kulkarrni (2013) studied the pulp and paper industry raw material scenarios in India and concluded that India was facing challenges about forest-based raw material source shortages for pulp and paper industries. He advised that the only strategy feasible to solve these challenges was to promote social and farm forestry plantations. Meanwhile, Palm *et al.* (2013) showed that there was a possibility of restoring degraded lands based on plantation activities, and this might bring positive environmental, social and economic benefits to the locals; but, in many cases, these new tree plantation establishments were obstructed by various factors, such as financial constraints, relevant soil unavailability, and water scarcity. In general, there have been very few studies on plantations in India, and in particular on the LULCC perspectives and remote sensing-based IF detection and mapping methods development.

In Indonesia, in addition to the above general statistical data, there is the fact that a few studies also have been conducted on IFs in Indonesia, especially viewing them under the LULCC perspective. Though only some researchers were interested in investigating IF ecosystem properties, such as Wilson and John (1982); Hendrien *et al.* (2007); Erik *et al.* (2010); Tsukomoto and Sabang (2005). Others conducted their research on nutrient flows and other resources factors of IFs (*e.g.,* Bruijnnzee & Wiersum, 1987; Gunadi & Verhoef, 1993; Otsamo, 2000; Ryota *et al.,* 2008; Naoyuki *et al.*, 2008; Ryota *et al.,* 2010). Several studies mentioned the economic and social aspects of IFs. For instance, Nawir and Santoso (2005) found that there was mutual benefit for both communities and companies when they cooperated in plantation development. Likewise, Ahmad *et al.* (2013) recognized and emphasized the role of smallholders in IF development in Indonesia. Obidzinski and Dermawan (2012) studied how global wood demands played its role in expanding the pulp production and timber IFs in Indonesia. They found that the pulp and paper industry continued to depend on natural forests for its material supplies. To deal with this situation, Indonesia needs to promote the use of non-forest land for plantations and engage more smallholders in tree-growing programs. In addition, the conversions of IFs from natural forests in peatland also emitted a large amount of CO_2 in Indonesia (Jauhiainen *et al.*, 2012). In brief, from the studies researchers have conducted on IFs in Indonesia, it is clear that studies on the rates, extent, and patterns of the new IFs in Indonesia is very necessary to identify and fully quantify their roles, contributions, and impacts as a new LULCC phenomenon in the country.

In Thailand, standing on the same mainstream with India and Indonesia, there were also only a few studies *done-to-date* on IFs. Most of these studies have focused on plantation ecosystem properties and characteristics (*e.g.*, Aratraakorn *et al.*, 2006; Narong *et al.*, 2007; Katsunori *et al.*, 2009; Wangluk *et al.*, 2013; Doi & Ranamukkhaarachchi, 2013; Yasunori *et al.*, 2013). While some researchers were interested in IF silvicultural practices and technologies (*e.g.*, Terwongworakul *et al.*, 2005; Kaewkrom *et al.*, 2005), others were concerned over their impacts on climate change - *i.e.*, carbon emissions and sequestrations from plantations (*e.g.*, Warit *et al.*, 2010; Duangrat *et al.*, 2013). They found that a plantation acted either as a sink or source depending on which ecosystems (natural forests *vs.* degraded lands) it replaced. Regarding the use of remote sensing (RS) to study IFs, it was interesting that Doi and Ranamukkhaarachchi (2010) showed a possibility of using a Google Earth Image to evaluate how *Acacia* species helped restore forest land by discriminating canopies of natural forests with *Acacia* plantation plots. Most notably was the effort of Charat and Wasana (2010) in estimating the total rubber area in the Northeast of Thailand by using an integrated satellite and physical data approach. Another RS application to study rubber was from the Rasamee *et al.* study (2012). They used

Thai Earth Observatory Satellite panchromatic images and were able to identify the different rubber plantation ages. In general, studies on IFs in Thailand are still rare, and the field is lacking more comprehensive studies to fully reflect the processes, dynamics, and patterns of new IFs as a new LULCC.

Likewise, published studies on IFs in Viet Nam are also very rare. For instance, Sikor (2012) researched new IFs, focusing on their processions and land grab problems in Vietnam. Mats *et al.* (2010) studied the expansion of farm-based IFs by small holders in Viet Nam and found changes of small holder's incomes as decisive factors for a LULCC from natural forests, followed by deforestation caused by shifting cultivation practices, to a landscape largely controlled by small holder-based IFs. Conversely, Thulstrup (2014) found it was likely that households became more vulnerable, especially to natural disturbances, as a consequence of establishing new fast-growing species IFs, because this action has bolstered existing inequalities in landholding. Therefore, Pultzel *et al.* (2012) discussed and sought opportunities to improve likelihoods of small-scale private IF planters from domestic wood industries. In addition to these social studies, several researchers studied IFs on their ecological properties such as Millet *et al.* (2013); Ermilov and Anichkin (2013); Thinh *et al*. (2011) or silviculture (*e.g.*, Beadle *et al.*, 2013; Amat *et al.*, 2010). It is possible that no studies have been done to date with respect to new IFs as a widespread new LULCC phenomenon in the country, or to remote sensing-based methods development to detect and map these IFs.

1.5.2 In Malaysia

Compared to other key countries in the Asia-Pacific region, the studies on IFs in Malaysia were more numerous. However, similar to them, most of the studies were focused on plantation ecosystem properties and characteristics (*e.g.*, Chey *et al.*, 1997; Malmer, 1992, 1994, 1996) and silviculture (*e.g.*, Majid & Paudyal, 1992; Sahri *et al*., 1993). Several studies on IFs as a LULCC science using remote sensing methods were available (*e.g.*, Aziz *et al.*, 2010; Suratman, 2003, 2007; Suratman *et al.*, 2004). These studies were mainly focused on using Landsat data to quantify rubber area in some areas of interest. Other researchers focused on the production potential of rubberwood in Malaysia on economic perspectives (*e.g.*, Jagatheswaran *et al.*, 2012). They concluded that, although rubberwood was the most important source of wood raw material and has been important for Malaysia's exporting (Akira *et al.*, 2011), the steadily declining rubber cultivation area in the country was raising alarms about the future supply of rubberwood. This resulted from the competition of other land use activities (*e.g.*, oil palm). Thus, the future sustainability of rubberwood in Malaysia will remain debatable unless the profitability of rubber growers is ensured by increasing the net value of the wood resource (Jagatheswaran *et al.*, 2011). This raised a demand for more incentives on plantation establishments (Pinso & Vun, 2000). These researchers also argued that although forest plantations were not comparable with natural forests in terms of supplying ecological goods and services, the natural forest depletion taking place necessitated the establishment of plantations, especially on the degraded lands. Notably, the current investment incentives were not financially attractive enough for big players to come. In addition, these studies also warned of the constraints and challenges for the development of forest plantations/IFs in Malaysia consisting of ecology, land, species selection, inadequate supply of quality planting material, labor, mechanization, finance, and private involvement. These may constrain the efforts of the Government in expanding the area of new forest plantations.

1.6 Literature Review of the Studies on the Methods Development for Detecting and Mapping Industrial Forests

There are a number of studies on the development of remote sensing-based methods to detect and map plantations and industrial forests throughout the world. However, these studies have not yet reached objectives for developing remote sensing-based methods, which can be applied to regional or global detecting and mapping of the expansion of new industrial forests. For instance, Zhai *et al.* (2012, 2014) developed a remote sensing method for Landsat datasets based solely on visual interpretation and ancillary data in combination with supervised classification to map rubber and pulpwood plantation expansions in Hainan, China. The visual interpretation keys the authors used to map these kinds of plantations were textures, landforms, and land terracing for rubber plantations; and spectral color in combination with ancillary data for pulpwood plantations. Likewise, Yi *et al*. (2014) and Xiaona *et al.* (2013) used ancillary data to develop environmental data/variables-based indicators for mapping rubber plantations - including topographical factors - using digital elevation models, climate (precipitation and temperature), and soil conditions. In general, these methods were area-specific and difficult to apply or expand, even regionally.

In addition to creating the Landsat dataset-based methods, Miettinen and Liew (2011) also developed a method using the Advanced Land Observing Satellite with the Phased Array type L-band Synthetic Aperture Radar (ALOS PALSAR) to detect oil palm, rubber, acacia, and coconut plantations on the island of Borneo. They found that the differences between horizontal transmit and horizontal receive (HH) with horizontal transmit and vertical receive (HV) backscatters were able to separate oil palms from others; and that HV backscatters alone could separate acacia and rubber plantations. The authors also argued that separating these plantation types relied not only on spectral reflectance, but also on contextual indicators such as texture, position, slope, association. In addition, they found that, in this area, pulpwood plantations were mainly acacia and were owned by large-scale industries, while rubber plantations were established in both smallholder and industrial scales. Miettinen and Liew (2011) also suggested that combining ALOS PALSAR with Landsat may help better identify these plantations.

As a result of Miettinen and Liew's work, a number of efforts have been made in developing remote sensing-based industrial forest detection methods by combining Synthetic Aperture Radar and Landsat images. For instance, Kou *et al.* (2005) studied and mapped deciduous rubber plantations and their ages by using Synthetic Aperture Radar and Landsat images. They found that rubber plantations could be clearly distinguished from natural forests by color in the leaf-off period. However, they were very similar in the leaf-on, or growth, period. They also used the Normalized Difference Vegetation Index (NDVI) to detect the conversion from natural forests to rubber plantations in the study area. Similarly, Dong *et al.* (2012, 2013) mapped rubber plantations based on both PALSAR and Landsat data. They argued that using Landsat images to map LULCC in general, and rubber plantation in particular, had two constraints: cloud contamination and spectral signal similarity. Moreover, rubber had very similar spectral signals/characteristics with natural secondary forests. These factors presented challenges for mapping rubber plantations. In brief, while these studies suggested that using the combination of Landsat data and ALOS PALSAR to detect and map plantations was a promising method, the data derived from Synthetic Aperture Radar could be spatially and temporally limited.

In another effort to develop an appropriate method to map rubbers, Senf *et al.* (2013) had used multi-spectral phonological metrics for the Moderate Resolution Imaging Spectroradiometer (MODIS) datasets. They also concurrently used TimeSat, a software package for analyzing time-series of satellite sensor data, to extract the phonological metrics from the Enhanced Vegetation Index (EVI) and Shortwave Infrared (SWIR) series. This allowed them to plot time-series vegetation indices data and produce a temporal curve that indicated various stages green vegetation underwent. Li and Fox (2011a, 2011b, & 2012) have developed a method integrating Mahalanobis typicalities with a neural network to map rubber distribution in Southeast Asia by using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data. By combining nine different bands - including Visible and Near Infrared (VNIR) and Short-Wave Infrared (SWIR) – the Normalized Difference Vegetation Index (NDVI), and Mahalanobis typicalities, the authors found an improvement in mapping rubbers in the study area. They argued that the Mahalanobis distance measured the class relative distance to the class mean, scaled by the class covariance; and it was very useful to determine similarity of an unknown sample to a known group of samples.

Overally, a number of methods have been proposed, developed, and tested to detect and map plantations and industrial forests. However, these methods have various constraints in using remote sensing data and broader regional and global applicability. As a result, this research proposes new remote sensing-based methods development approaches, which could work operationally for monitoring the expansion of new IFs in the region and globe.

1.7 The Significance of this Study: Problems and Rationale

Based on the methods review, it is clear that there is a need to develop new remote sensing methods for detecting, mapping, monitoring, and quantifying new IFs as a new LULCC. There is also a need to conduct more comprehensive studies to better understand the extent and dynamics of this phenomenon from both drivers and monitoring perspectives. Some researchers, (*e.g.*, Skole *et al.*, 2013; Li & Fox, 2012), emphasize the fact that less remote sensing (RS) work has been done on plantations and other types of intensively managed industrial forests in the tropics; although there has been considerable RS research and product development for monitoring closed canopy natural forests in the tropics. Moreover, most of the studies to date have been conducted in the Amazon and other closed canopy forest regions, and that more work needs to be done outside of these regions. As a result, this dissertation research is proposed to be conducted in the Asia-Pacific region, with Malaysia as a case study. It will require some methods development and testing, particularly in the feasibility of deploying the developed methods further into the entire region. This study will also bring insights into the processes that drive LULCC in IF dynamics.

In brief, the above rationale for doing this research come from the fact that new IFs are a very important, newly-emerging LULCC in the tropics as a consequence of rapidly increasing their total area and individual patch size in recent years. However, currently, we poorly understand the processes that drive new IF expansion and dynamics. This is because we are currently lacking comprehensive studies with respect to this widespread LULCC process. Moreover, with methods and tools based on RS, we have until now mainly focused on the closed canopy natural forests. Much less work has been done on IFs and other new LULCC, such as open forests and trees outside of forests. Additionally, by detecting, mapping, and monitoring IFs, we are able to quantify the rates, extent, and patterns to understand the underlying processes/causes and proximate drivers of these new IFs. Thus, this research will also contribute to documenting and enriching the understandings of the patterns and processes of the expansion of this new LULCC. We know that the current data on plantations at international, national, and sub-national scales are poorly documented, very unreliable and unlikely to be updated soon (ITTO, 2009). We do not know exactly what is happening to the new IFs - such as their locations, rates, extent, and scale properties - or what kind of ecosystems they have been replacing (*i.e.*, how much the new IFs were converted from natural forests and how much from degraded land, *etc*). Lacking the reliable information on plantations has created difficulties and uncertainties for any policy and management on IFs.

Therefore, this study is focused on documenting and understanding the new IF LULCC trend and phenomenon in the tropics, and will contribute to an international and national need for this kind of information. In brief, this study aims to improve the knowledge base and understanding on the extent, characteristics, and drivers of new IFs as a new agent of LULCC, and to develop the methods to detect and quantify IF LULCC patterns and dynamics. Once appropriate methods have been successfully developed and tested in the pilot study sites, they can be applied for the entire region. In other words, this study will involve the development of a continental-scale monitoring method, using a time series of Landsat data that could operationally monitor and quantitatively report on the rate and scale of IF LULCC on a regular basis. Thus, it will formulate a better understanding of drivers and LULCC dynamics associated with emerging IFs in the tropics.

In addition, there are some contributions to advancing research that could come from this study. This research will not only contribute to developing new RS methods, improve documenting, and enrich the understandings of new IFs as a new LULCC, but will also enable researchers to quantify the IFs impacts or contributions on current climate change, the environment, and biodiversity. A new IF can act as a source or sink, depending on what kind of terrestrial ecosystems it is replacing. As a result, we could use them as a sink to sequester carbon dioxide and mitigate climate change. At the same time, we can also use them as a feasible solution to relieve pressures on natural forests and conserve these forests. The information and data derived from this study could be used to better plan and manage IFs in the country, the region, and the tropical world.

1.8 Selection of the Study Area and Industrial Forest Systems

Generally, it is very challenging to draw a panoramic picture about forest plantations or IFs in the Asia-Pacific region in general, and in Malaysia in particular, because data and information on the targeted IFs in the region and the country are very scarce, unreliable, and outdated. However, by doing a literature review based on what is publicly available, I was initially able to (1) stratify Malaysia for IF sources area and (2) consider and assess forest investment and policy targets for key production areas. As a result, it is possible to select two pilot study sites in this country based on the following selection criteria:

(1) Selected species: the areas should contain most of the selected species or the targeted plantation/IF systems (*i.e., Eucalyptus, Acacia, Pinus, Tectona,* & *Hevea* spp.).

(2) Area: the selected sites should show the largest or very significant new IFs area.

(3) Dynamics: the areas should indicate the highest or a very significant rate of change in new IF area, and;

(4) Policy and investment targets: key production centers and other policy factors should be considered.

The locations selected for this study in Malaysia are the Sarawak and Sabah states (Figure 1.4). This is because these states currently capture the biggest non-rubber selected IFs area and indicate the highest expansion rates, as compared to other states in Malaysia, especially for fast-growing IFs (Table 1.1). Moreover, these regions are also identified as the key production centers for the pulp and paper industry of the country.

Industrial Forest Systems Studied:

Plantations of acacias (*Acacia* spp.), eucalypts (*Eucalyptus* spp.), pines (*Pinus* spp.), teak (*Tectona* spp.), and rubber (*Hevea* spp.) will be chosen for this study. These IFs are mainly used for the production of wood for pulp and paper, saw logs, and other industrial woods. Focusing on these systems and species accounts for more than 90% of all IFs in the Asia-Pacific tropical region in general, and in Malaysia in particular. Moreover, the development and testing of the new RS-based IF detection methods for these systems are more likely to succeed because all types of IFs are very diverse and cover too many varying LULC characteristics and properties.

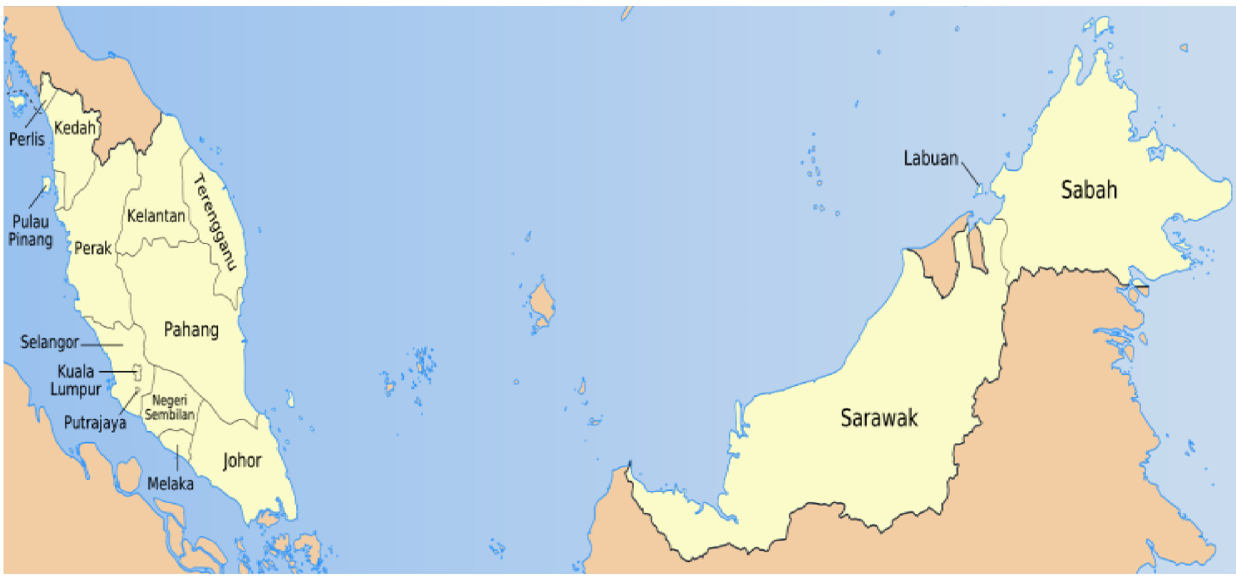


Figure 1.4. Map of Malaysia showing the selected study sites (Sarawak & Sabah States).

In brief, for this study, Sarawak and Sabah were selected because (1) these two states show very impressive IF planting rates over the recent years (since 2000), in particular in Sarawak where the IF area (not including rubber) has annually increased 365% on average from 2000 to 2012; (2) these regions are very notorious for heavy cloud and hazy contamination, therefore it is

Table 1.1. A summary of plantation areas and the rate of their change in Malaysia and by state.

Species	**Region/ State**	**Area (ha)**		**Difference for the period**	**Rate of change**		**Social & Economic Factors**	**Note**	**Source**
		1990 (*or 2000*)	**2005 (*or 2009*)**	**ha**	**%/ year**	**ha/ year**			
Rubber	**Peninsular Malaysia**	2,279,001	1,535,127	-743,874	-2.2	-49,592	Reported as out-competed by oil palms	Most rubbers owned by smallholders (80-96%); Malaysia Rubber Statistics 2011:~ 1,013,000 Mha	Malik *et al.* (2013)
	Sarawak	152,717 *(2000)*	209,918	+ 57,201	0.9	11,440			
	Sabah	78,895 *(2000)*	62,891	-16,004	-4.1	-3,201			
	Total (other statistics)	1,836,700	1,244,600 *(2009)*	-592,100	-1.7	-31,163			Ratnasingam *et al.* (2011)
		Area in year 2000	**Area in year 2012**						
Other selected IF species (mostly *Acacia*, some others)	**Peninsular Malaysia**	74,000	110,000 *(2009)*	+ 36,000	4.1	3,000	Low potentials for IFs		Malaysia Forestry Outlook Study (2009)
	Sarawak	6,830	306,486	+ 299,656	365.6	24,971	Key production centers for pulp & paper industries	<u>*Sarawak*</u> plans to have 1.2 Mha in 2020	<u>*Sarawak*</u> Forestry Statistics (2012)
	Sabah	154,640	244,000	+ 89,360	4.8	7,447		<u>*Sabah*</u> expects to have 0.5 Mha in 2020	<u>*Sabah*</u> Forestry Statistics (2012)

challenging for RS-based methods development. I prefer to choose this area because if my developed methods work in this difficult area, it will be more likely or better work in other regions which have the easier conditions; (3) the area is dominated by oil palm plantations, which are not included in our targeted IF systems but have similar texture and arrangement to them, so that separating these plantations is also very challenging in terms of RS-based methods development; (4) the IF data in Malaysia is quite firm compared to other selected countries, and (5) Malaysia has the most potential among five selected countries to invest and develop industrial forests; it also plans to develop the pulp and paper industries as one of its national priorities.

1.9 Research Questions and Objectives

Research Questions

This study aims to improve understanding of the extent, characteristics, and drivers of new IFs as a new agent of LULCC, and to develop the methods to detect and quantify IF LULCC patterns and dynamics. These methods are prototyped and can be applied for the whole region, and can be worked as operational monitoring methods for this LULCC phenomenon. The fundamental questions posed here guide the research:

1. Can we develop and use methods based on RS datasets (*i.e.,* Landsat) that could detect, map, and monitor the area, expansion rate, patterns, and scale of IFs?
2. Are IFs increasing both in individual patch size and the total area in Malaysia? Can we detect and quantify their total extent, expansion rates, and patterns? Is there any shift from fast-growing, short-rotation (*e.g.,* pulpwood) to slow-growing, long-rotation (*e.g.,* sawnwood) IFs?

3. If IFs are increasing in Malaysia, what types of natural or managed ecosystems are they replacing?

Objectives

From the above research questions, the main objectives for this study are as follows:

1. Develop methods based on vegetation/forest fractional cover (*f*C) and vegetation indices (VIs) analyses for detecting new IFs in a time series of Landsat data.
2. Detect, map, and monitor new IFs in the pilot study sites in Malaysia with more specific aims to measure:
    a. Expansion rates, sizes, extent, and patterns of the newly established IF systems in the study area, and how they have been changed from 2000 to 2014;
    b. How much of these new industrial forests were converted from other LULC types (*e.g.*, natural forests and degraded lands), and their consequences in terms of green house gas emissions and biodiversity losses.

1.10 Research Methods

The initial proposition for this study is that new and needed methods for detecting, mapping, and quantifying IF areas, patterns, and scales in the selected tropical IF systems will be developed. Specifically, I developed methods based on remote sensing (RS) to detect, classify, map, monitor, and analyze changes of Land Use and Land Cover (LULC) for new IFs in the selected tropical country over time. The fundamental principles of these RS-based methods on IFs are that most IFs are monocultures of only a few species, which have similar crown shape, regular spacing, and other typical biophysical characteristics. They greatly differ in form and structure from natural tropical forests and other vegetation covers. This idea exactly fits with the concept of plantation forests of the FAO (2000): that a plantation forest is a forest or a wooded land of introduced species or native species, established through planting or seeding, with a few species at plantation, even age class, and regular spacing. These plantation forests or IFs are typical by their silvicultural rotations or clearing and regrowth cycles, depending on the purpose of using them. For instance, *Acacia* pulpwood plantations can typically last 5-10 years; a rubber plantation can have a rotation of 25 years; a teak plantation used for producing saw logs can take 25-50 years or more. In other words, based on this information - along with the differences in form, structure, texture, spatial, temporal, patterns, tones, crown shape, and other characteristics and properties of IFs from other vegetation covers, such as natural forests in satellite images - by doing RS analysis, I can detect, classify, and map them. By extracting their areas between and among multi-dated images, I can detect and monitor their changes over time.

In brief, in this study, I developed and tested two method approaches for Landsat data to map the IF extents and patterns in the pilot study sites: (1) Forest or Vegetation Fractional Cover (*f*C)-based IF detection method, and (2) Vegetation Indices (VIs) analysis in a Time Series to detect IFs for large coverage area. Skole *et al.* (2013) state that some their recent research results in their lab show strong radiometric signals that can be used in statistical classification methods, as well as other methods, such as forest fractional cover from endmember analysis to detect and map IFs. The approaches and procedures, adapted from Skole *et al.* (2013), for developing the methods of Forest Fractional Cover (*f*C) and Vegetation Indices (VIs) analysis in a time series are generally presented (Figure 1.5).

Regarding the detection of the selected/focused species or specific IF stands/systems - such as acacias, eucalypts, pines, teaks, and rubbers (including pure stands and mixed stands) - it is very challenging to detect and map them separately from other species based on RS methods with medium resolution imagery data, like Landsat datasets. Thus, I will differentiate them by

(1) using extra spectral and textural analyses; and (2) considering ancillary data in combination with visual interpretation, including their biological, physical, and ecological characteristics, as well as other information sources. For instance, rubber IFs will be planted in some certain soil, elevation, and climate conditions. In Malaysia, they are mostly distributed in Peninsular Malaysia. This type of data may be available or reported by owners, organizations or local governments. Likewise, *Acacia* IFs were mainly established in the Sarawak and Sabah states. Their locations and areas may be available in reports of investors, timber companies or maps of state governments or research institutions, *etc*. This kind of information will be combined with information derived from satellite images, such as the silvicultural cycles of clearing and regrowth, textural and spectral analysis, typical green biomass content, and leaf area index, *etc*., enabling us to map focused and unfocused species, and pure or mixed stands.

In brief, the methods developed and tested in this study will use geographic, ancillary, and visual interpretation information in combination with remote sensing analyses to detect and map the expected IFs, and monitor the IF LULCC in Malaysia in particular and enable us to apply to monitor the IFs in the whole tropical Asia-Pacific region in general.

Validation

After the results of the above methods development have been obtained, validation is extremely important to see how these methods work and if they are acceptable. Validation for the developed methods in the Landsat derived pilot area data products was conducted through a stratified random sample design by using the very high-resolution imagery data, such as World View, Quickbird, GeoEye, Ikonos, Pleiades, *etc*. Both study sites in Malaysia (the Sabah and Sarawak states) was validated by using these very high-resolution imagery data, available through the National Geospatial-Intelligence Agency (NGA) Commercial Data agreement with-

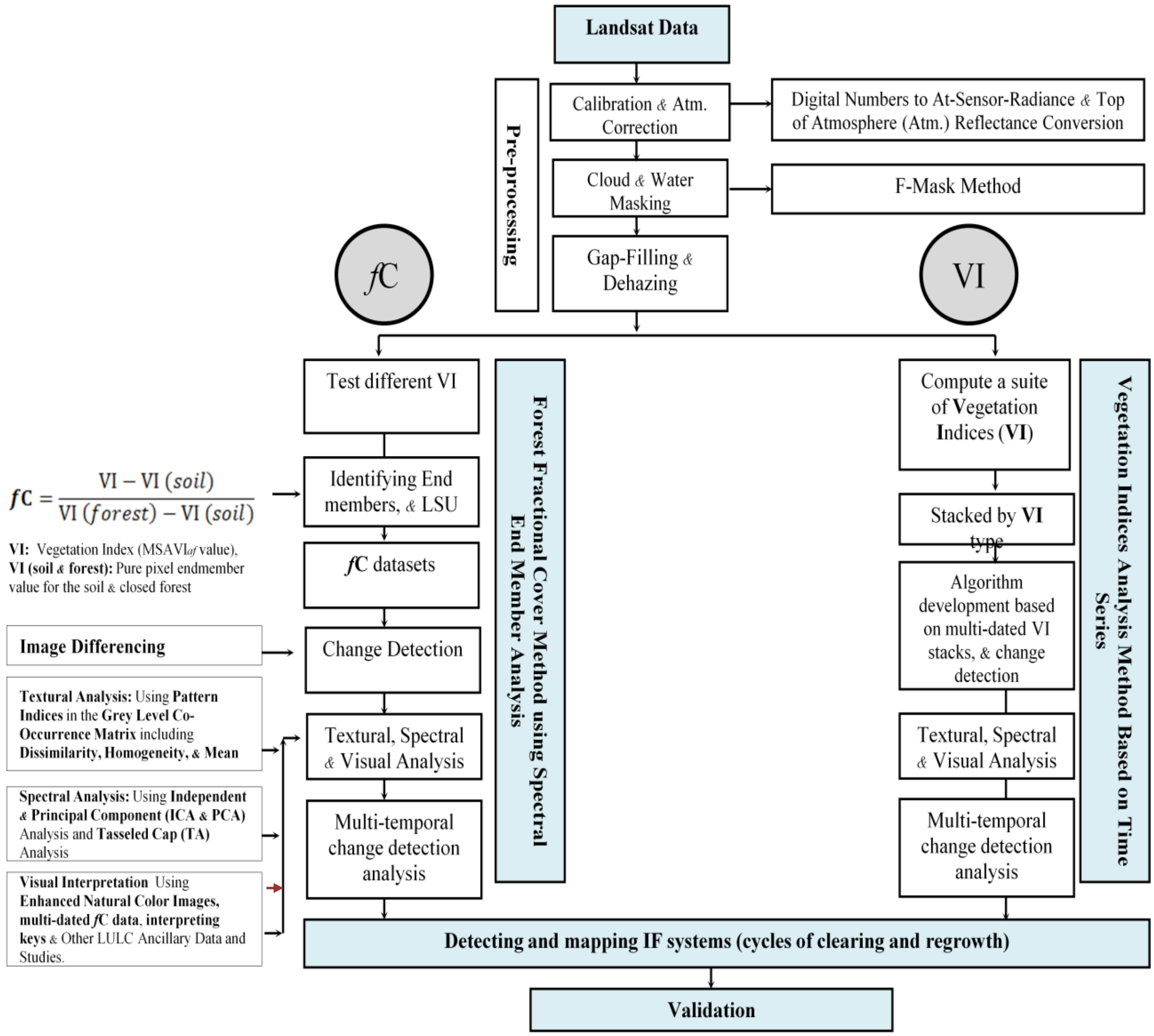


Figure 1.5. The general flowchart for the development of forest fractional cover (*f*C)- and vegetation indices (VIs)-based industrial forest detection methods for Landsat datasets.

-NASA or purchased from commercial suppliers such as Apollo Mapping. The validation targets include the accuracy assessments for (1) IF (in general and specific for the selected species) *vs.* non-IF lands classification and (2) the IF area estimates consisting of individual patch size and total area. The very high-resolution imagery data used to validate the Landsat-derived products was close-to-same date or at least same year data. Error/confusion matrices or contingency tables was computed and reported.

In general, there are three approaches typically used to assess the accuracy of research results based on remote sensed imagery data. For LULCC classification (pixel-based, statistical or hard classification), parameters such as overall accuracy, user's and producer's accuracy, commission and omission errors, or Kappa coefficients deriving from an error matrix (also called confusion matrix or contingency table) are used (*e.g.,* Congalton, 1991; Congalton & Green, 2009; & Olofsson *et al*., 2014). Whereas parameters including the linear regression correlation coefficient (R), the coefficient of determination (R^2), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and System Error (SE) are usually used to evaluate the results obtained from fractional cover methods (*e.g.,* Dennison & Roberts, 2003; Wang *et al.,* 2005; Jimenez-Munoz *et al.*, 2009, Mei *et al.,* 2010; Lu *et al.,* 2011). Conversely, for Geographic-Object-Based Image Analysis (GEOBIA), usually applied for detecting and delineating individual tree crowns (ITC), the two levels of assessment will generally be used to evaluate the accuracy of the method, namely plot and individual accuracy levels for both detection and delineation results. Normally, producer's and user's accuracies or overall accuracy are used for tree crown detection; and mean error, absolute error, root mean square error (RMSE) are used for tree crown delineation (*e.g.,* Lamar *et al.,* 2005; Ke *et al.,* 2010; Ke & Quackenbush, 2011). In addition, some researchers (*e.g.,* Pouliot & King, 2005, Huirschmugl *et al.,* 2007; Ke & Quackenbush, 2011) used Accuracy Index to take both the commission and omission errors to assess the accuracy; consequentially Larsen *et al.* (2011) used a matching score to evaluate the results based on GEOBIA approach derived from very high resolution imagery data.

As clearly stated above, the objectives of this research are to detect, map, and monitor industrial forests in the tropics based on forest/vegetation fractional cover and vegetation indices analysis methods for Landsat datasets. Therefore, IF maps are a type of classification map and the accuracy assessment methods for LULC classification will be used for validating these maps. The principal requirements for the number of samples, their locations, sampling selection methods (random, cluster, systematic, or stratified) is presented in the sampling scheme (Table 1.2), as required for this kind of work.

Table 1.2. The principal requirements for a sampling scheme to validate the developed methods.

Elements of the scheme	**Description**
General requirement	The acceptable accuracy level is 85% at the 90% confident level
Number of samples	50 samples/LU class for the area less than 0.5 Mha, if the area over 0.5 Mha or has more 12 LU categories, 75-100 samples are needed (Congalton, 1991).
Sampling unit	1 or more pixels in field validation or the patch sizes in high-resolution data
Location of samples	Stratified Random Sampling for each land use type/class in the IF thematic maps or direct the high-resolution data to key areas
Reference site/ field survey identification	GPS points (predetermined & checked), photos, data sheet for field surveys (date, time, *etc*), and other data (reports, interviews, *etc*)
Visit plans	Predetermined locations, time, vehicle, tools/equipments, accommodation, and cost, *etc*.

Following that, an error matrix for this validation was produced. In this matrix or table, the classified LULCC types was presented in the rows or column while referenced/verified LULCC types was be located in the columns or rows of the table. As a result, the diagonal line expressed the agreements between the classified and referenced elements/types or classes. The accuracy assessments for three above-stated validation targets include overall accuracy, accuracies of users and producers, Kappa's coefficient (accuracy statistics), or errors of omission and commission for IF maps (Table 1.3).

Table 1.3. The ways for assessing accuracy of IF maps derived from Landsat datasets.

Accuracy	Description	Equation	Note
Overall	The total number of samples in all types classified correctly divided by the total classified samples (the diagonal elements in table/the classified total)	# total correct/total samples	Of all of the reference sites, what proportion is classified correctly
User's	The ratio between the number of correctly classified and the row total	# correct/column total	Map accuracy from the point of view of a map user or how often the type the map presents should be there really there
Producer's	The ratio between the number of correctly classified and the column total	# correct/row total	Map accuracy from the point of view of map makers or how often real features on the ground correctly shown on the map
Kappa's coefficient/ statistics	A measure of how accurate your map is above and beyond the accuracy that would be expected by chance alone	(Observed – Expected) / (1 – Expected) Observed = Overall accuracy Expected = sum of (row total * column total by class in proportion unit)	Taking omission, commission and overall accuracy into account simultaneously
Omission Error	A type on the ground is not that type on the classified image or the real type is omitted from the classified image		The error of exclusion
Commission Error	A type on the classified image is not that type on the ground or the type is committed to the classified image		The error of inclusion

1.11 The Flowchart of the Study

Figures 1.6 and 1.7 present how the study will be developed and conducted.

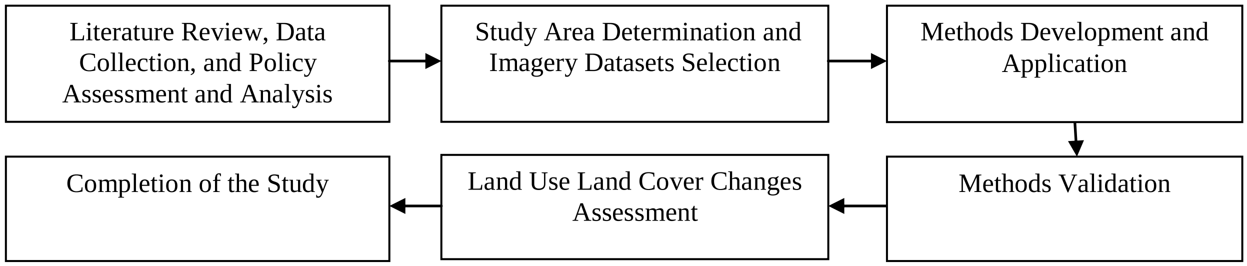


Figure 1.6. The general flowchart of the study.

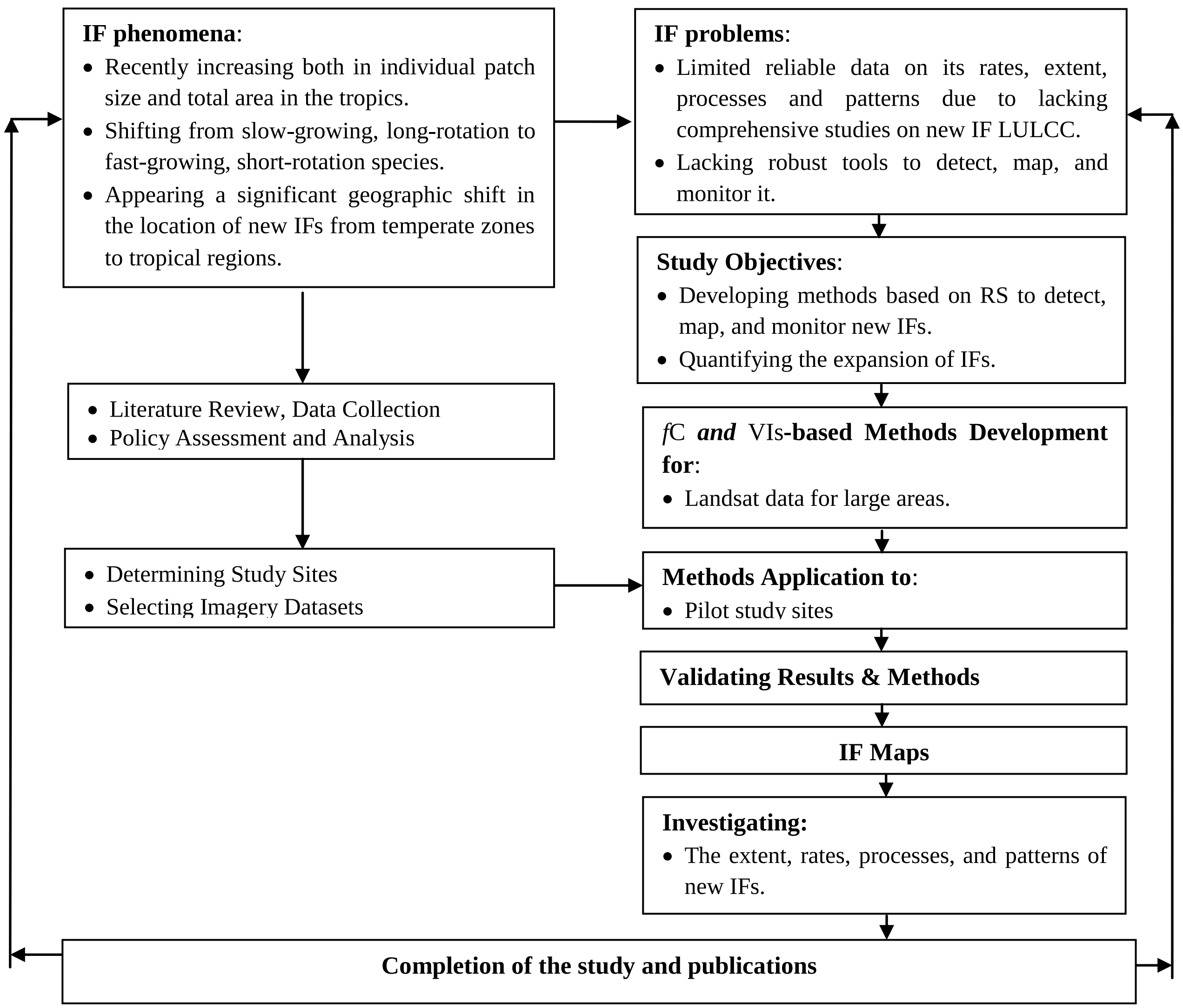


Figure 1.7. The system diagram of the study.

CHAPTER 2

DEVELOPING THE VEGETATION INDICES-BASED INDUSTRIAL FOREST DETECTION METHOD FOR LANDSAT DATASETS

2.1 Introduction

The first approach used in this study to develop a method to detect, map, and monitor new industrial forests in the study area is a vegetation indices change analysis in a time series. Vegetation indices (VIs) analysis is a technique widely used to detect, map, monitor, and analyze vegetation in general, and in forests in particular. The fundamental principles of these VIs-based methods are that vegetation absorbs most of the red band (630-690 nm), while reflecting the near infrared band (760-900 nm). By analyzing the correlations between them, we can obtain information about the status of vegetation or forests necessary for our studies, as well as for other purposes, such as forest management. The vegetation indices-based methods have proven very useful in studying vegetation in a number of cases (*e.g.,* Basso *et al*., 2004; Wu, 2014).

In this study, a suite of Vegetation Indices (VIs) will be computed in a time series: the Normalized Difference Vegetation Index (NDVI; Rouse *et al*., 1974), the Soil-Adjusted Vegetation Index (SAVI; Huete, 1988), the Atmospherically Resistant Vegetation Index (ARVI; Kaufman & Tanre, 1992), the Soil-Adjusted Atmospherically Resistant Vegetation Index (SARVI; Kaufman & Tanre, 1992), the Modified Soil Adjusted Vegetation Index 2 (MSAVI2; Qi *et al.,* 1994), and the Enhanced Vegetation Index (EVI; Huete *et al.,* 2002). NDVI (Rouse *et al*., 1974) is one of the earliest and most widely used vegetation indices and is very useful in studying vegetation and the environment. Among other uses, it is often used to estimate net primary production, identify eco-regions, monitor phenological patterns of the earth and its vegetative surface, and assess the length of the growing season. However, it is affected by interactions with elements such as soil, atmosphere, and sun-target sensor, and will saturate at the Leaf Area Index (LAI) of 3. To reduce these effects, Huete (1988) transformed this NDVI index and developed it into the Soil-Adjusted Vegetation Index (SAVI) to minimize the soil influences. Nevertheless, this index does not solve the additive atmospheric effect problems on satellite images. As a result, Kaufman and Tanre (1992) developed the Atmospherically Resistant Vegetation Index (ARVI) with the purpose of mitigating the effects of the atmosphere by using a self-correction process on the red channel. This transformation uses the difference in radiance between the blue and red band channels to correct the radiance in the red band. Next, they developed the Soil-Adjusted Atmospherically Resistant Vegetation Index (SARVI) to take both soil and atmospheric effects into account. However, although these indices worked well in many cases and specific areas, they still do not completely eliminate the additive effects in many other cases.

In another effort, Qi *et al.* (1994) developed the Modified Soil Adjusted Vegetation Index (MSAVI), a new vegetation index better able to handle the soil effects by considering the soil effects as a variable function instead of a constant, as had been done before. This index proved to work well in tropical environments. In 2002, Huete and his colleagues (Huete *et al.,* 2002) developed a vegetation index with global applicability, called the Enhanced Vegetation Index (EVI). This index deals with both soil and atmospheric effect problems. All of these indices have values from -1 to +1. However, due to the effects of soil and atmospheric conditions mentioned above, specific VIs can perform better than others in the different geographic regions. Therefore, as each index has its own strengths and weaknesses, it is very necessary for us to test and choose the most relevant and best performing indices for the study area.

The idea for using VIs to study IFs is that, with annual Landsat datasets, we can observe their silvicultural clearings and re-growth. These repeated clearings are typical in IFs and could indicate the short or long rotation of IF stands. Moreover, the growth rate of these VI values possibly expresses how fast or slow an IF stand is growing. Therefore, based on this information, we can obtain shorter- versus longer-rotation and faster- versus slower-growing industrial forest stands and are able to analyze both patch size and harvest cycles. Skole *et al.* (2013) state that by stacking annual VI data sets as a single remote sensing data product where clearings (harvests) and re-growth can be observed, analyzed, and reported for area extent, we can observe individual patch sizes, harvest cycle periods of IFs, as well as their changes over time.

2.2 Acquiring and Preprocessing Images

The multi-temporal Landsat scenes used in this study were freely acquired from historical archives at the EROS Data Center, U.S. Geological Survey, U.S. Department of Interior at http://glovis.usgs.gov/ and the Tropical Rain Forest Information Center at Michigan State University, USA over the past 15 years. The scenes were selected for the years 2000, 2003, 2006, 2009, 2012, and 2014. Aldrich (1975, cited in Coppin & Bauer, 1996; Michener & Houhoulis, 1997; Coppin *et al*., 2004) stated that, in most cases, a minimum time interval of three years was required to detect non-forest to forest changes.

In this study, the criteria to select the main scenes were within the time from May to August, cloud cover < 30%, and image quality at least from 7. We know that the study area (Sabah and Sarawak states in Malaysia) is notorious for heavy cloud contamination and haze; therefore, additional scenes were required to fill the gaps created by clouds, cloud shadows, and haze. The criteria to select these extra scenes were as close as possible to the main scenes and at a maximum within one year before and one year after the year of the main scenes chosen. In the case, images close to the date of the main scenes were not available, so better quality images ± one year of the main scenes were selected for the study. Briefly and specifically, details regarding the scenes selected were as follows:

- The main scenes were selected for the years 2000, 2003, 2006, 2009, 2012, and 2014, focusing on images from May to August of those years; if not, the best scene in the year was selected;
- Additional scenes within ± 1 year were considered. For example, the scenes in 1999 and 2001 could be used for filling the scene of 2000. However, more priority was placed on the scenes of 2000 used to fill the gaps for the selected scene (closer to the original data is better);
- The quality of the scenes used to fill the gaps in the selected main scenes was the second priority; and
- All errors or no-data of the Enhanced Mapper Plus Scan Line Corrector off (ETM + SLC off), clouds, and cloud shadows had to be removed and filled until the acceptance level.

Sabah covers 8 Landsat scenes consisting of path 116 with rows 56 and 57; path 117 with rows 55, 56, and 57; path 118 with rows 55, 56, and 57. Likewise, Sarawak covers 9 Landsat scenes including path 118 with rows 57, 58, and 59; path 119 with rows 57, 58, and 59; path 120 with rows 58 and 59; and path 121 with row 59. In total, 563 scenes were selected and processed. The full list, quality, and dates of the Landsat scenes used for this study are provided in the Appendices (Tables A.1, A.2, A.3, and A.4). All the Landsat scenes used for this study were pre-processed following a general procedure (Figure 2.1) or they were downloaded from the free online service in which they were already preprocessed. This online service was freely provided by the Earth Resources Observation and Science Center (EROS), U.S. Geological Survey under the U.S. Department of Interior; namely, the Science Processing Architecture on Demand Interface at https://espa.cr.usgs.gov. This is a new service just developed recently. This service provides calibrated images at surface reflectance and processes cloud and cloud shadow by using the *Fmask* method developed by Zhu and Woodcock (2012); and Zhu *et al.* (2015).

In general, all images were calibrated by converting the processed data digital numbers (DNs) to the at-sensor-radiance values, and then to exoatmospheric top-of-atmosphere reflectance values. This radiometric correction was conducted by using the calibration coefficient provided in the meta data file in each image or calculated from the coefficients given by Chander *et al.* (2009). Then, according to Song *et al.* (2001), and Hadjimitsis *et al.* (2010), for multi-temporal data to monitor LULCC over time, all images would need to be corrected the atmospheric effects. The method widely used to correct the atmospheric effects was extracted from images *i.e.*, applying the darkest pixel (DP) atmospheric correction method (also called the histogram minimization method) to handle the atmospheric effects on the images. The darkest pixel technique was developed based on the assumption that the lowest DN in each band in each pixel would be assigned '0', and thus its radiometric value represented the atmospheric additive effects. The darkest pixels would be selected based on a DN histogram analysis and image examination. The purpose of these works was to maintain consistency in measurement of surface reflectance among multi-dated datasets, which was needed for multi-temporal data to monitor LULCC over time. Then, the *Fmask* method (Zhu & Woodcock, 2012; Zhu *et al.*, 2015) was applied to these images to remove clouds and their shadows. This method was freely available at https://code.google.com/p/fmask/. It was widely applied and proved very effective in masking out clouds and cloud shadows. In addition to using this method to handle cloud contamination in the images, it was also used to remove water bodies, which were not necessary for this study.

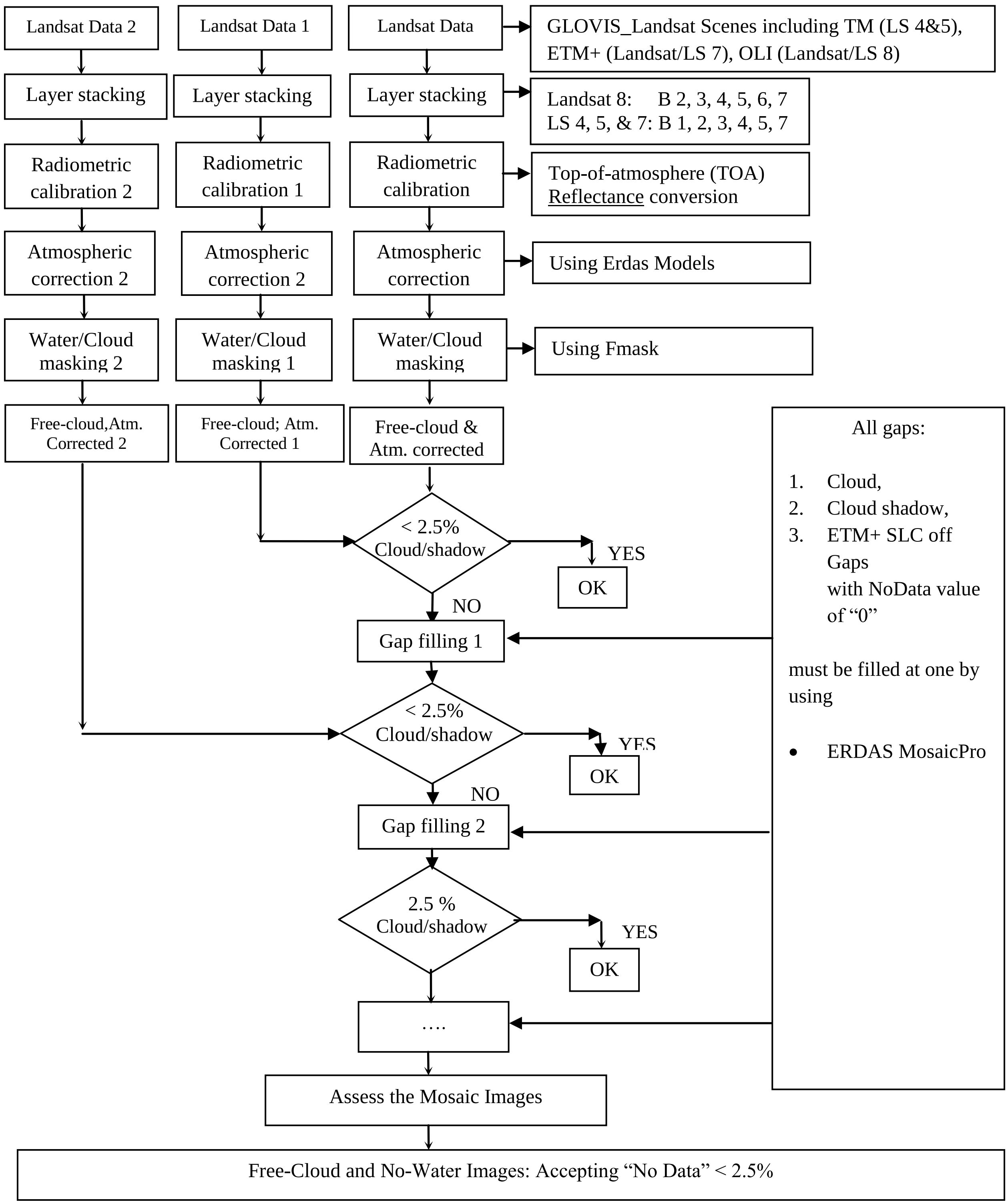


Figure 2.1. The general procedures for preprocessing images.

In the areas well-known for clouds and haze, such as tropical rainforests in Sabah and Sarawak, Malaysia, we had to use many other images to fill the gaps created by clouds and their shadows. In addition, images obtained from Landsat 7 (ETM+ SLC off) were also known for missing values at the scan lines since 2003. To deal with these problems, a gap-filling technique was used. This technique was done in the ERDAS MosaicPro by using the overlay function until it satisfied the requirements with all gaps filled, in which “no data” in the images was ≤ 2.5%.

Regarding the already preprocessed images, they were downloaded from the EROS Data Center at https://espa.cr.usgs.gov. These images were already calibrated by converting the processed data digital numbers (DNs) to the surface reflectance values. At the same time, these scenes were also processed to remove problems created by clouds. First, their individual bands were chronologically stacked by using the stack function in ERDAS Imagine. Second, they were mosaicked by using the ERDAS MosaicPro as described above until they satisfied the requirements.

Then, all the preprocessed images, due to the heavy haze in the study area, were dehazed by using the TM dehazed model. This model was already built up in ERDAS Imagine. Finally, after the images were preprocessed and dehazed, they were ready for further use and analysis.

2.3 Developing the Method

2.3.1 General Principles

The procedure for developing the Landsat-based IF detection method by using vegetation indices to transform the preprocessed images into final IF maps is described in Figure 2.2. The main assumptions used for developing this method were as follows:

- The cycle of increasing and reducing the VI values possibly indicated the silvicultural cycle of clearing and regrowth of vegetation covers, typical for an IF/plantation stand.

- The time span for a silvicultural cycle could indicate shorter (<=7 years) versus longer (> 7 years) rotation IFs.
- The rate of increasing VI values (VI growth rate) may indicate faster-growing versus slower-growing timber plantation species.
- The spectral and textural characteristics of an IF in an image may be different from other vegetation covers (*e.g.,* forests) and might differ among different IF species as well.

2.3.2 Results

In this method, after acquiring the already-preprocessed Landsat datasets, a suite of vegetation indices (*VIs*) was firstly computed: NDVI, EVI, ARVI, SARVI, SAVI, and MSAVI2 as follows:

(1) Normalized Difference Vegetation Index (Rouse *et al.*, 1974)

$$NDVI = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}$$

(2) Soil - Adjusted Vegetation Index (Huete, 1988)

$$SAVI = \frac{(1 + \mathrm{L})(\mathrm{NIR} - \mathrm{RED})}{\mathrm{NIR} + \mathrm{RED} + \mathrm{L}}$$

(3) Atmospherically Resistant Vegetation Index (Kaufman & Tanre, 1992)

$$ARVI = \frac{\mathrm{NIR} - \mathrm{RB}}{\mathrm{NIR} + \mathrm{RB}}$$

$$\mathrm{RB} = \mathrm{RED} - \gamma\,(\mathrm{BLUE} - \mathrm{RED})$$

(4) Soil Adjusted - Atmospherically Resistant Vegetation Index (Kaufman & Tanre, 1992)

$$SARVI = \frac{(1 + \mathrm{L})(\mathrm{NIR} - \mathrm{RB})}{\mathrm{NIR} + \mathrm{RB} + \mathrm{L}}$$

(5) Modified Soil Adjusted Vegetation Index 2 (Qi *et al.*, 1994)

$$\mathrm{MSAVI2} = \frac{2 * \mathrm{NIR} + 1 - \sqrt{(2 * \mathrm{NIR} + 1)^2 - 8 * (\mathrm{NIR} - \mathrm{RED})}}{2}$$

(6) Enhanced Vegetation Index (Huete *et al.*, 2002)

$$EVI = G\,\frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{C1} * \mathrm{RED} - \mathrm{C2} * \mathrm{BLUE} + \mathrm{K}}$$

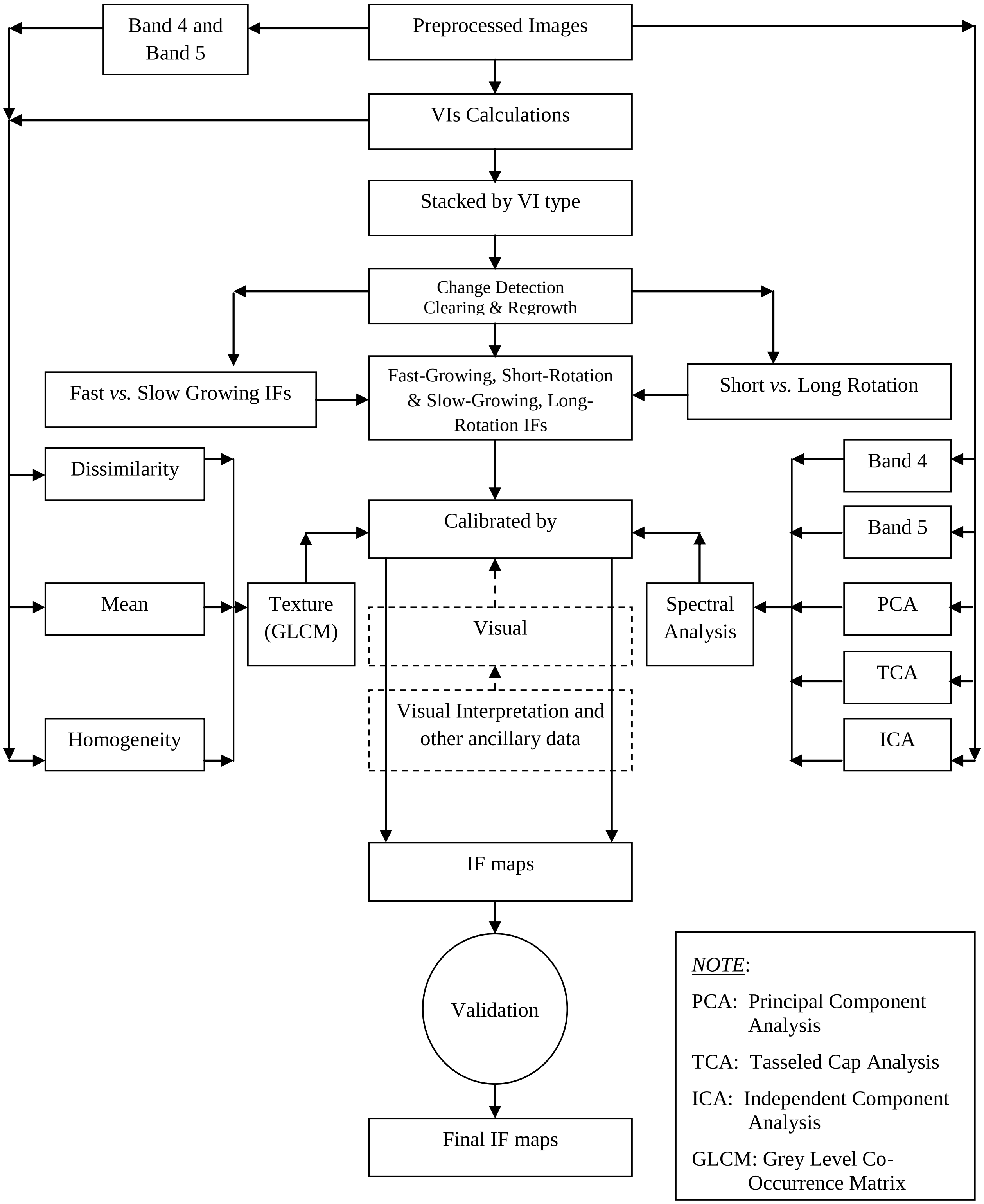


Figure 2.2. The flowchart of development of the VIs-based IF detection method.

Where:

NIR: Landsat Near Infrared Spectrum band (0.76 – 0.90 µm, band 4)

RED: Landsat Visible Red Spectrum band (0.63 – 0.69 µm, band 3)

L: Soil calibration/adjustment factor [0, 1]; its default value is 0.5

RB: Landsat Visible Red (R) and Blue (B) Spectrum bands

γ: The weighting of the Blue band radiance

G: Gain factor, its default value is 2.5

C1&2: Coefficients of the aerosol resistance, the default values for C1 and C2 are 6 and 7.5, respectively.

K: Canopy background adjustment factor, its default value is 1.

For NDVI, to reduce atmospheric effects to this index, Karnieli *et al*. (2001) had modified the original version by replacing the red band in the formula with the shortwave infrared band (SWIR) at 2.1 µm, and renamed it the Aerosol Free Vegetation Index (AFRI), as follows:

$$\boldsymbol{AFRI}\ 2.1 \text{ or } \boldsymbol{NDVI}af = \frac{\text{NIR} - 0.5\ \text{SWIR}}{\text{NIR} + 0.5\ \text{SWIR}}$$

This is because visible bands in vegetation indices in general, and in NDVI in particular, are very sensitive to the atmospheric effects, especially to smoke and other types of aerosols (Karnieli *et al.,* 2001; Huete *et al.,* 2003; Matricardi *et al.,* 2010). In contrast, shortwave infrared (SWIR) and near infrared bands (NIR) are found to be much less sensitive to the atmospheric conditions. Moreover, under aerosol free atmospheric conditions, they have a very high correlation with visible bands. As a result, these bands were used as an alternative to the most sensitive visible band in vegetation indices. The AFRI or NDVI*af* index has been proven to work well (Karnieli *et al.,* 2001; Matricardi *et al.,* 2010). Thus, this modified index was used to obtain vegetation information in the study area instead of using the original NDVI.

Likewise, Matricardi *et al.* (2010) also tested the modified MSAVI under the smoky conditions in the Brazilian Amazon by replacing the red band in the original MSAVI with the shortwave infrared band (SWIR) at 2.1 µm and found improved results compared to the original method. The tropical rainforest conditions in Sabah and Sarawak in Malaysia are very similar to the environmental conditions in the Brazilian Amazon. Therefore, this modified index was also used for the study. This index was named the Modified Soil-Adjusted Vegetation Index Aerosol Resistant (Matricardi *et al.*, 2010) and is presented by the following formulas:

$$\boldsymbol{MSAVI}\ af = \frac{(1 + \mathrm{L})(\mathrm{NIR} - 0.5\ \mathrm{SWIR})}{\mathrm{NIR} + 0.5\ \mathrm{SWIR} + \mathrm{L}}$$

and $\mathbf{L} = [\ (\mathrm{NIR} - 0.5\ \mathrm{SWIR})*s + 1 + \mathrm{NIR} + 0.5\ \mathrm{SWIR}\ ]^2 - 8 *s* (\mathrm{NIR} - 0.5\ \mathrm{SWIR})$

Where s = 1.2 (slope of the soil line)

For other vegetation indices selected for this study, including ARVI, EVI, SARVI**,** and SAVI, the original versions were used to calculate the values. These indices were calculated for the preprocessed images, which have been calibrated and atmospherically corrected. The VIs, calculated for the Landsat scenes, were chronologically stacked for better visual change detection recognition. Specifically, these VI images were stacked in ERDAS Imagine and by type (ARVI, EVI, MSAVI_{af}, NDVI_{af}, SARVI, and SAVI) with the following chronological order rules: the VI image of the year 2000 would be band 1, 2003-band 2, 2006-band 3, 2009-band 4, 2012-band 5, and 2014-band 6. An example of stacking MSAVI_{af} images in Sabah and Sarawak from 2000 to 2014 is presented (Figure 2.3). This provided an illustration of where the values of the MSAVI_{af} have changed over time. For instance, the <u>pink</u> areas showed vegetation cover in those areas that was cleared in 2003 and regrown in 2006-2014; likewise, the <u>yellow</u> areas showed vegetation cover that was cleared in 2006 and regrown in 2009-2014; and the <u>blue</u> areas indicated vegetation cover that was cleared in 2000 and regrown in 2003-2014, *etc*.

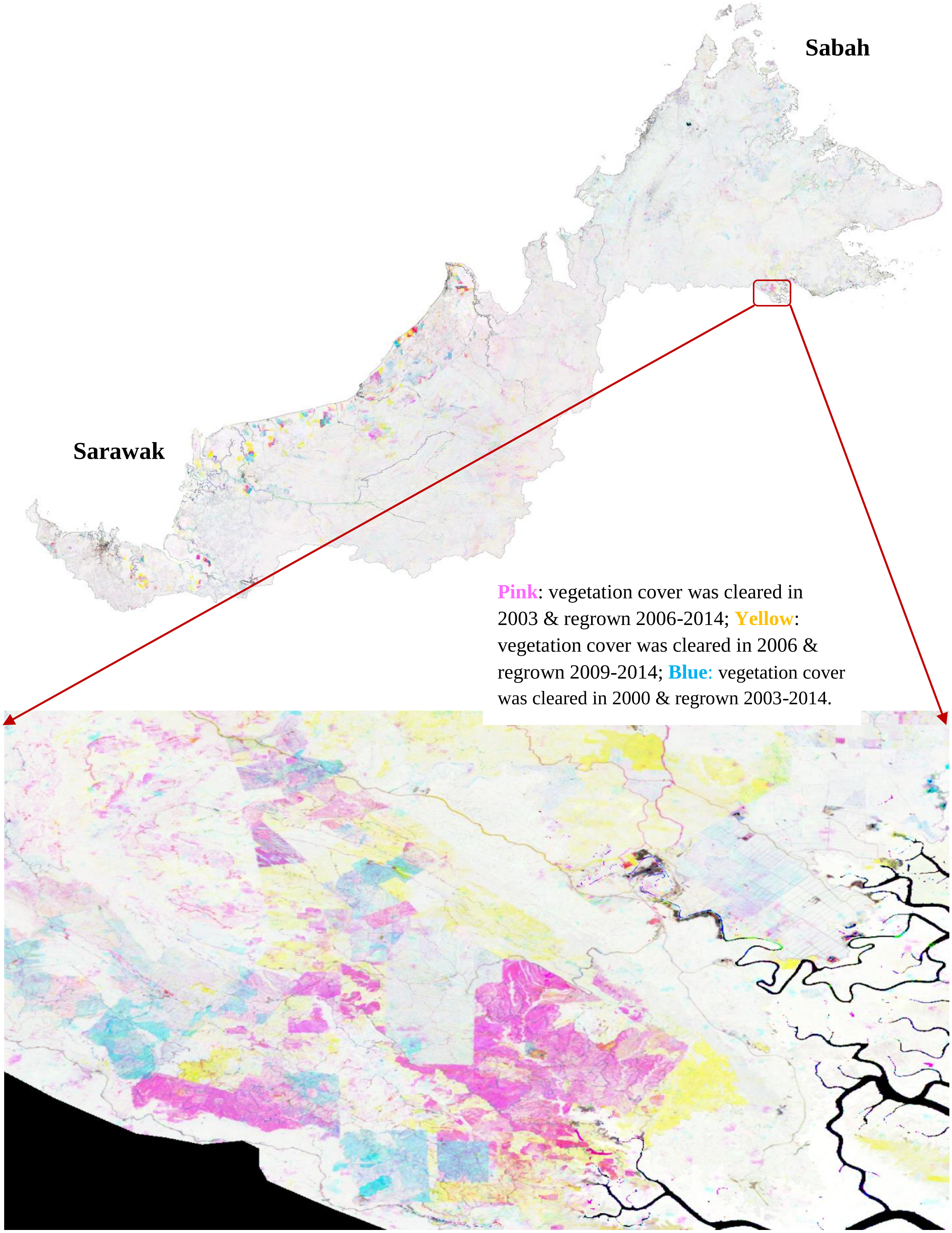


Figure 2.3. The stacked MSAVI$_{af}$ images for Sabah and Sarawak, 2000-2014.

The full VI images stacked from 2000 to 2014 by VI type (ARVI, EVI, $MSAVI_{af}$, $NDVI_{af}$, SARVI, & SAVI) in Sabah and Sarawak are presented in the Appendices (Figures A.1 & A.2). These stacked VI images would be used for further analyses.

Then, the changes of VI values from 2000 to 2014 were detected by using the image differencing method as expressed in the formula [2.1]. The changes were detected for the years 2000-2003, 2003-2006, 2006-2009, 2009-2012, and 2012-2014. The principles for this method, adapted from Cakir *et al.* (2006), are described in Figure 2.4. The VI value of the later year would be deducted from the VI value of the earlier year. A positive result/number (or the value in the right side of the graph) indicated an increase of the VI value from the earlier year (*e.g.*, 2000) to the later year (*e.g.*, 2003), meaning that there was growth of vegetation cover. Whereas, a negative result/number (or the value in the left side of the graph) indicated a decrease of the VI value from the earlier year to the later year, meaning that there was a decline in or clearing of vegetation cover in the later year. The vegetation cover between two years was "not changed" when its value approached 0. Cakir *et al.* (2006) argued that there were 3 regions expressing change or no change in the image differencing method. The first region indicated "absolute change", which was from a chosen certain figure to 100% change or towards the two tails of the graph. The second region was "possibly a change", which was expressed in the given value range in the graph (this region could be affected by atmospheric conditions, image quality, *etc*); and the third region was "absolutely no change", in which the values approached 0 in the graph.

Therefore, in this method, it was very important for us to determine the change point, or threshold of the change. There are a number of ways to do that. One of the most widely used ways is "trial and error" experiments. Based on this method, ±15% was found to be good enough for indicating a change in this study because it could effectively mitigate the additive effects or variability of the atmosphere to the images. Thus, this value was selected as the threshold for the vegetation change detection value in this study. The full changes of VI values for the study area from 2000 to 2014 are presented in the Appendices (Figures A.3, A.4, A.5, A.6, A.7, and A.8).

$$\Delta Change = \mathbf{VI}\ (t_2) - \mathbf{VI}\ (t_1) \qquad \mathbf{[2.1]}$$

Where:
VI is the value of vegetation index.
t_2: the after/later image.
t_1: the before/earlier image.

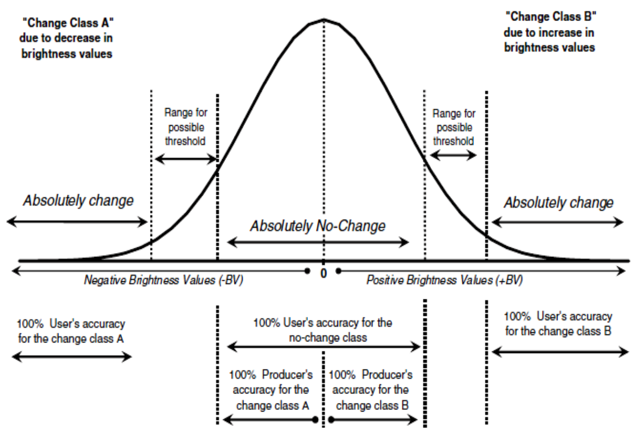


Figure 2.4. The change detection graph (adapted from Cakir *et al.*, 2006).

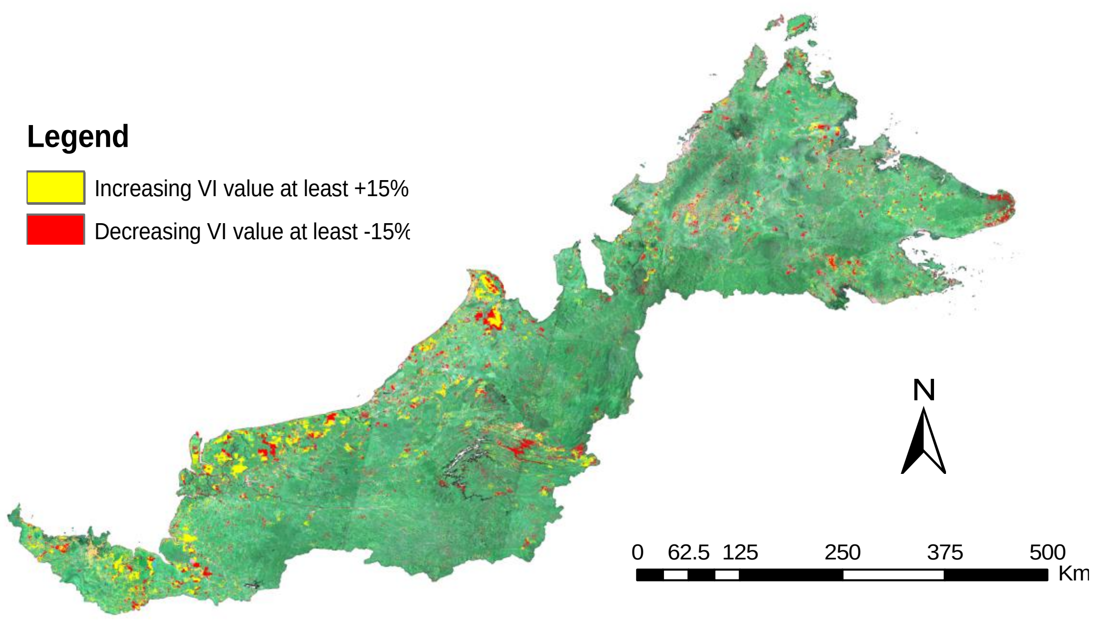
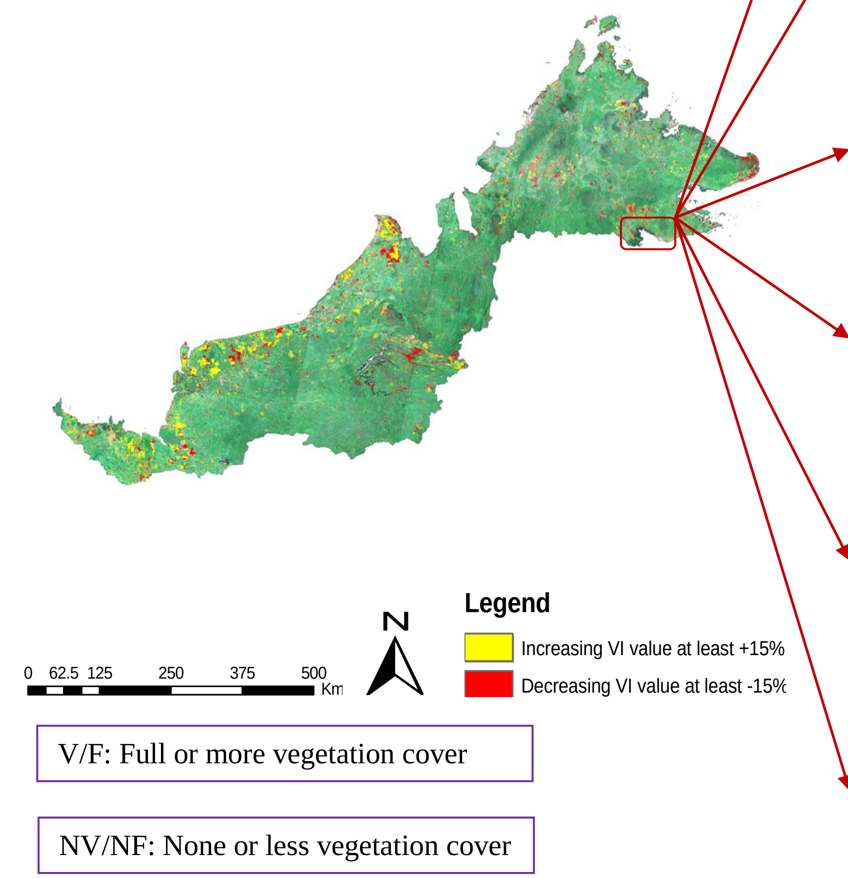


Figure 2.5. The changes of MSAVI$_{af}$ value from 2012 to 2014 in Sabah and Sarawak, Malaysia.

The sequence of change (increasing and declining VI values of at least ±15%) or no change of the VI_MSAVI*af* values at the location 1 as the follows: 2000 - VF, 2003 - VF, 2006 – NV/NF, 2009 - VF, 2012 - VF, and 2014 – NV/NF.



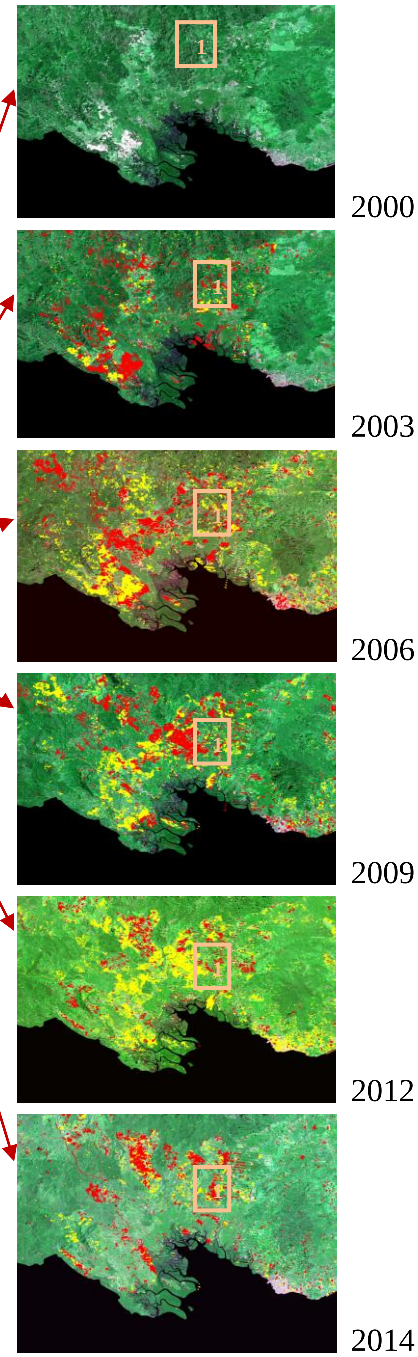
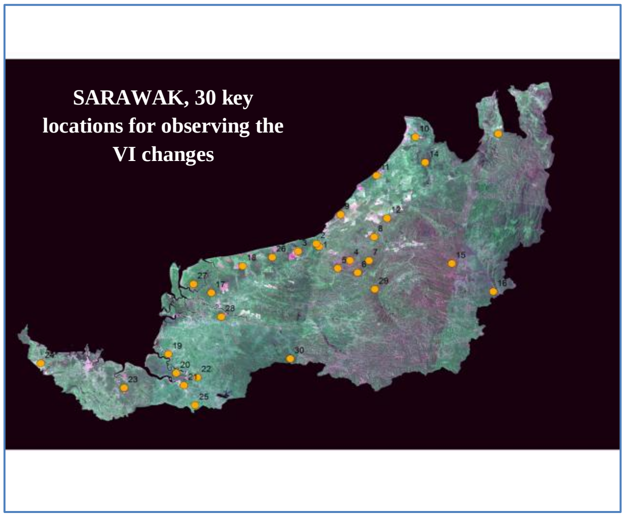


Figure 2.6. The sequence of the VI (MSAVI$_{af}$) value changes, 2000-2014, in the study area.

For instance, Figure 2.5 presents a VI value change in Sabah and Sarawak from 2012 to 2014. The yellow area indicates an increase of the VI value from at least the threshold of +15%. This represents a vegetation regrowth. Conversely, the red area expresses a decrease of the VI value from at least the threshold of -15%. This area indicates a decline in or clearing of vegetation cover.

Next, the sequence of VI value changes in study area from 2000 to 2014 was studied. This sequence shows a cycle of the change. It provided initial clues for detecting industrial forests because it could present a silvicultural rotation, which is typical for an industrial forest stand. For instance, Figure 2.6 presents a sequence of $MSAVI_{af}$ value changes at the threshold of ±15% from 2000 to 2014. The vegetation/forest (V/F) indicates the vegetation cover. It could be the existing vegetation cover as it was or a change from non-vegetation/forest (NV/NF) cover to more or full vegetation cover (regrowth). Conversely, the NV/NF presents none or less vegetation cover (clearing or declining vegetation cover). Additionally, the indication from V/F to NV/NF expresses a reduction in VI values from full or more to none or less vegetation cover (clearing), and the indication from NV/NF to V/F expresses an increase in VI values from none or less to full or more vegetation cover (regrowth). To observe the sequence of the VIs values changes, 30 key locations in each state were chosen to study these VI values changes (Figure 2.7) and the findings of this observation of $MSAVI_{af}$ are presented (Table 2.1) as an example.



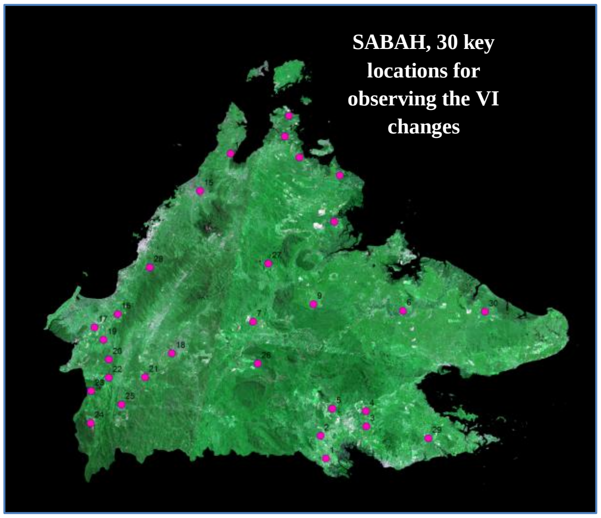


Figure 2.7. The key locations for monitoring the VI value changes in Sabah and Sarawak.

Table 2.1. Sequences of the vegetation cover changes based on the changes of VI values ($MSAVI_{af}$) in 30 key areas chosen to observe in Sabah and Sarawak, 2000-2014.

ID	**SARAWAK**					
	2000	**2003**	**2006**	**2009**	**2012**	**2014**
1	V/F	NV/NF	V/F	V/F	V/F	NV/NF
2	NV/NF	V/F	V/F	V/F	V/F	N/VF
3	V/F	NV/NF	V/F	V/F	NV/NF	V/F
4	NV/NF	V/F	NV/NF	V/F	V/F	V/F
5	V/F	NV/NF	V/F	V/F	V/F	V/F
6	V/F	NV/NF	V/F	V/F	V/F	V/F
7	V/F	V/F	V/F	NV/NF	V/F	V/F
8	V/F	NV/NF	V/F	V/F	V/F	V/F
9	V/F	NV/NF	V/F	V/F	V/F	V/F
10	NV/NF	V/F	V/F	V/F	V/F	V/F
11	V/F	NV/NF	V/F	V/F	V/F	V/F
12	V/F	V/F	V/F	NV/NF	V/F	V/F
13	V/F	V/F	V/F	NV/NF	V/F	V/F
14	V/F	V/F	V/F	V/F	NV/NF	V/F
15	V/F	V/F	NV/NF	V/F	V/F	V/F
16	V/F	V/F	V/F	NV/NF	V/F	V/F
17	V/F	V/F	V/F	V/F	NV/NF	V/F
18	V/F	V/F	V/F	NV/NF	V/F	V/F
19	V/F	V/F	V/F	NV/NF	V/F	V/F
20	V/F	NV/NF	V/F	V/F	V/F	V/F
21	V/F	V/F	V/F	V/F	NV/NF	NV/NF
22	NV/NF	V/F	V/F	V/F	V/F	V/F
23	V/F	V/F	NV/NF	V/F	V/F	V/F
24	V/F	NV/NF	V/F	V/F	V/F	V/F
25	V/F	V/F	V/F	NV/NF	V/F	V/F
26	V/F	V/F	V/F	NV/NF	V/F	V/F
27	V/F	V/F	V/F	NV/NF	V/F	V/F
28	NV/NF	V/F	V/F	V/F	V/F	V/F
29	V/F	V/F	V/F	NV/NF	V/F	V/F
30	V/F	V/F	NV/NF	V/F	V/F	V/F

ID	**SABAH**					
	2000	**2003**	**2006**	**2009**	**2012**	**2014**
1	V/F	NV/NF	V/F	V/F	V/F	V/F
2	V/F	V/F	NV/NF	V/F	V/F	V/F
3	V/F	V/F	NV/NF	V/F	V/F	NV/NF
4	V/F	V/F	NV/NF	V/F	V/F	NV/NF
5	V/F	NV/NF	V/F	V/F	V/F	NV/NF
6	NV/NF	V/F	V/F	V/F	V/F	V/F
7	V/F	NV/NF	V/F	V/F	V/F	V/F
8	NV/NF	V/F	V/F	V/F	V/F	V/F
9	NV/NF	V/F	V/F	V/F	V/F	V/F
10	NV/NF	V/F	V/F	V/F	V/F	V/F
11	V/F	V/F	V/F	V/F	NV/NF	V/F
12	V/F	NV/NF	V/F	V/F	V/F	V/F
13	V/F	NV/NF	V/F	V/F	V/F	V/F
14	V/F	NV/NF	V/F	V/F	V/F	V/F
15	V/F	NV/NF	V/F	V/F	V/F	V/F
16	NV/NF	V/F	V/F	V/F	V/F	V/F
17	V/F	V/F	NV/NF	V/F	V/F	V/F
18	NV/NF	V/F	V/F	V/F	V/F	V/F
19	V/F	V/F	V/F	V/F	NV/NF	V/F
20	V/F	V/F	NV/NF	V/F	V/F	V/F
21	NV/NF	V/F	V/F	V/F	V/F	V/F
22	V/F	NV/NF	V/F	V/F	V/F	NV/NF
23	NV/NF	V/F	V/F	V/F	NV/NF	V/F
24	V/F	NV/NF	V/F	V/F	V/F	V/F
25	V/F	NV/NF	V/F	V/F	NV/NF	V/F
26	V/F	V/F	V/F	V/F	V/F	NV/NF
27	V/F	V/F	V/F	NV/NF	V/F	V/F
28	V/F	V/F	NV/NF	V/F	V/F	V/F
29	V/F	V/F	NV/NF	V/F	V/F	V/F
30	NV/NF	V/F	V/F	V/F	V/F	V/F

Note: *[1] **V/F**: full or more vegetation cover (regrowth); **NV/VF**: none or less vegetation (clearing)*
*[2] From **V/F** to **NV/NF** indicating **a reduction in VI** from full/more to none/less vegetation cover (clearing)*
*[3] From **NV/NF** to **V/F** expressing **an increase in VI** from none/less to full/more vegetation cover (regrowth)*

Considering this table, we can easily realize the changes of vegetation and non-vegetation cover in the observed locations. For instance, for location 1 in Sarawak, two instances of none or less vegetation cover (declining or clearing) at the years of 2003 and 2014 were found, while vegetation cover or its regrowth was observed for 2000, 2006, 2009, and 2012. Based on this information, an algorithm was developed to detect the changes of vegetation cover in the study area from 2000 to 2014 for the VIs datasets (ARVI, EVI, MSAVI*af*, NDVI*af*, SARVI, & SAVI). The full results of this observation are presented in the Appendices (Figure A.9). An example to illustrate how the changes of vegetation cover in Sarawak were detected and monitored based on the changes of MSAVI*af* values is presented (Figure 2.8). In other words, it showed the cycles of clearing and regrowth (rotation) of vegetation cover equal to the increase and decrease of MSAVI*af* values from 2000 to 2014 in Sarawak. To minimize "salt and pepper" noises which may be caused by atmospheric effects, the quality of images, or by other factors, the minimum change detection area of 5 pixels was determined based on the "trial-and-error" experiments.

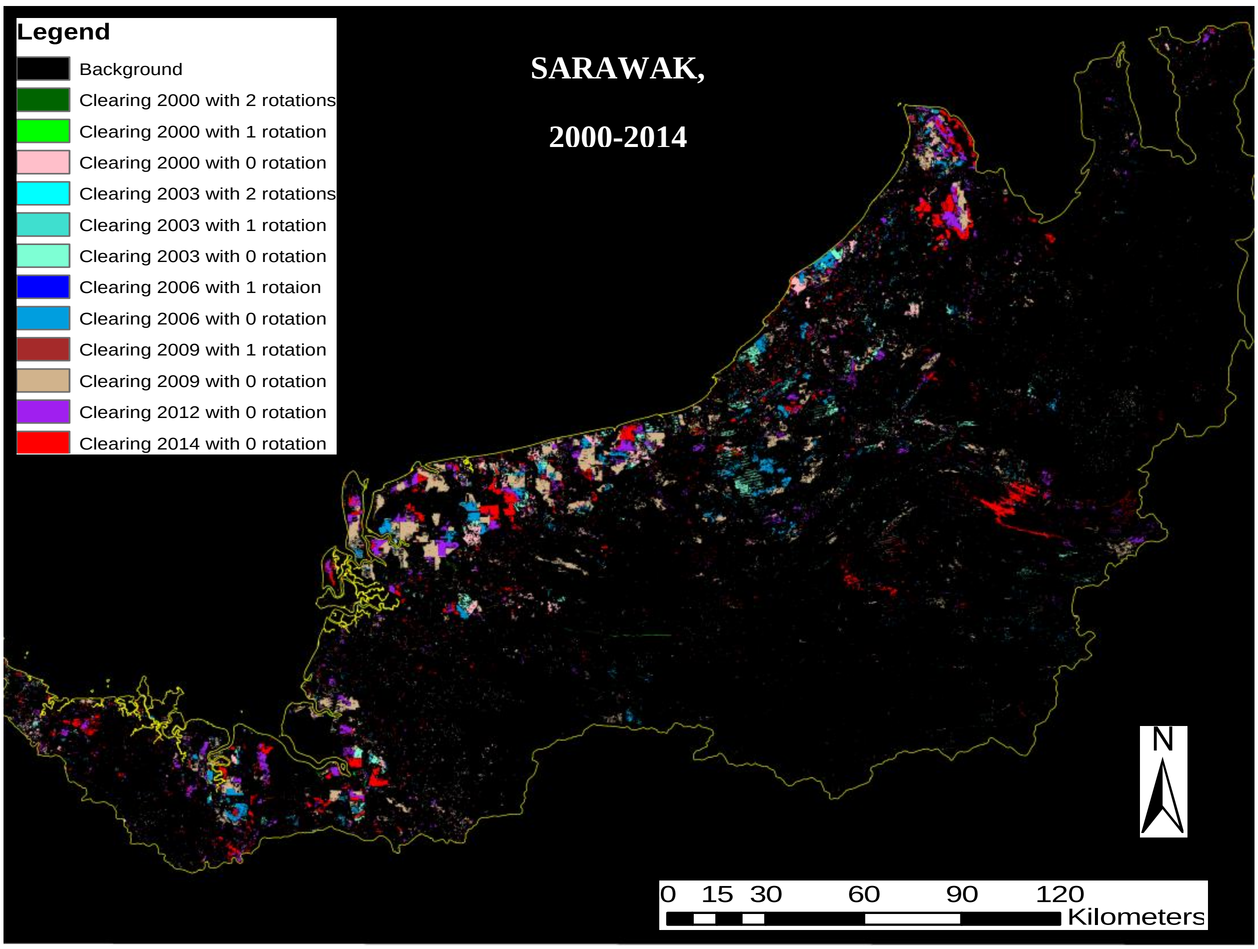


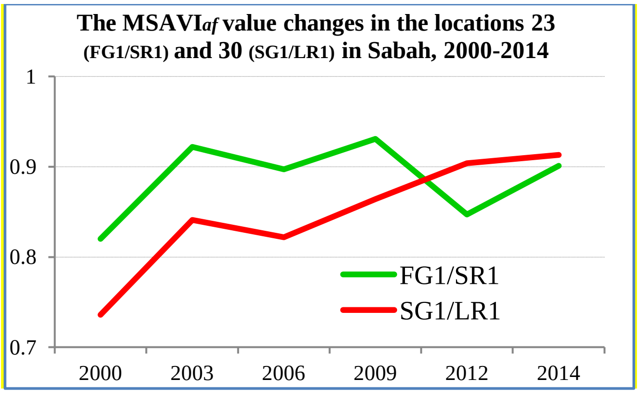
Figure 2.8. The cycle of rotation (clearing and regrowth) of vegetation cover based on the changes of MSAVI*af* values in Sarawak, 2000-2014.

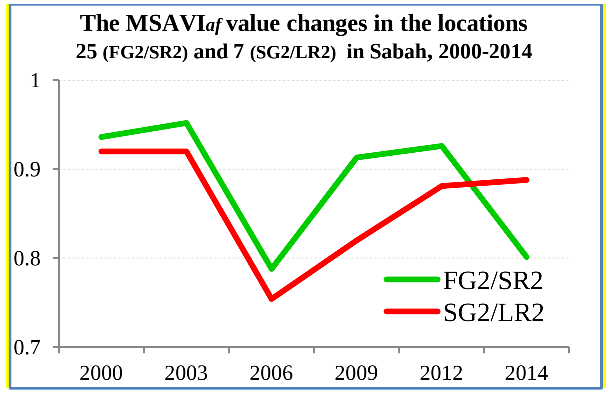
One question that could be posed was what the specific VI values had changed to over time, equaled to the sequence of changes of vegetation cover (*i.e.*, V/F and NV/NF) in the study sites. To answer this question, the values of VIs were observed in 30 key locations in Sabah from 2000 to 2014. The full results are shown in the Appendices (Table A.5). Specifically, an example of how the $MSAVI_{af}$ values changed for location numbers 3, 7, 17, 23, 25, and 30 in Sabah is provided (Table 2.2 and Figure 2.9). These areas/locations were selected as a example because locations 23 and 30 had the VI values decline (or vegetation cover cleared) in 2000, but the vegetation cover in location 23 was cleared again in 2012 while there was no clearing of vegetation cover in location 30 after 2000. Likewise, locations 3 and 25 had two instances of vegetation clearing (2003, 2012; and 2006, 2014, respectively), while locations 17 and 7 had only one clearing in 2003 and 2006, respectively.

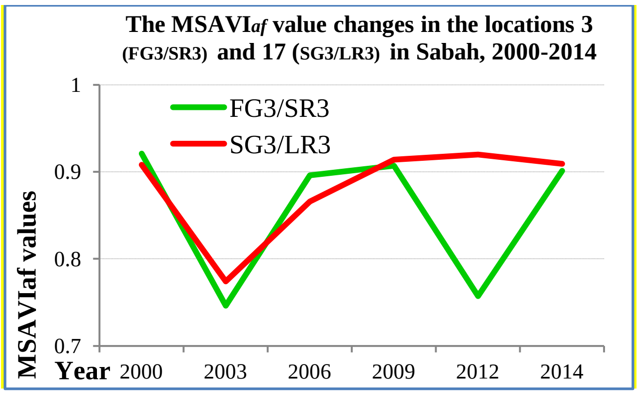
Table 2.2. The changes of $MSAVI_{af}$ values in some key areas in Sabah, 2000-2014.

	2000	2003	2006	2009	2012	2014
Location No.23						
Sequence	NV/NF	V/F	V/F	V/F	NV/NF	V/F
VI value	0.820	0.922	0.897	0.931	0.847	0.901
Location No.30						
Sequence	NV/NF	V/F	V/F	V/F	V/F	V/F
VI value	0.736	0.841	0.822	0.864	0.904	0.913
Location No.3						
Sequence	V/F	NV/NF	V/F	V/F	NV/NF	V/F
VI value	0.921	0.746	0.896	0.907	0.757	0.901
Location No.17						
Sequence	V/F	NV/NF	V/F	V/F	V/F	V/F
VI value	0.908	0.774	0.866	0.914	0.920	0.909
Location No.25						
Sequence	V/F	V/F	NV/NF	V/F	V/F	NV/NF
VI value	0.936	0.952	0.788	0.913	0.926	0.801
Location No.7						
Sequence	V/F	V/F	NV/NF	V/F	V/F	V/F
VI value	0.920	0.920	0.754	0.820	0.881	0.888

Note: *[1]* ***V/F****: full or more vegetation cover (regrowth);* ***NV/VF****: none or less vegetation (clearing)*
[2] From ***V/F*** *to* ***NV/NF*** *indicating* ***a reduction in VI*** *from full/more to none/less vegetation cover (clearing)*
[3] From ***NV/NF*** *to* ***V/F*** *expressing* ***an increase in VI*** *from none/less to full/more vegetation cover (regrowth)*







*NOTE: **SG/LR**: possibly slower-growing/longer rotations. **FG/SR**: possibly faster-growing/shorter rotation.*

Figure 2.9. The changes of the MSAVI*af* values at 6 locations (No. 3, 7, 17, 23, 25, & 30) selected as an example in Sabah.

From the results of monitoring the change sequence, or the cycle of clearing and regrowth, of vegetation cover in the study area, it could indicate shorter- versus longer-rotation plantation stands. The shorter-rotation industrial forests normally last about 7 years. They could be fast-growing species (*e.g.*, *Acacia* or *Eucalyptus* species) and could be destined for producing pulpwood. A longer-rotation timber plantation may last tens of years (*e.g.*, teaks, rubbers, pines) and could be used for producing saw logs, *etc*. Thus, if we have annual monitoring data for a long enough time period, we can observe their full harvesting cycles. However, the time span for this study was only 14 years from 2000 to 2014. As such, it is impossible to observe and monitor the full harvesting cycles of saw-log long-rotation plantation stands. Thus, in this study, an assumption was posed. That is, any change of the VI value at or less than 7 years possibly indicated shorter rotation, and any change of VI value more than 7 years could indicate longer-rotation IFs. The full results of this analysis based on VIs (ARVI, EVI, MSAVI*af*, NDVI*af*, SARVI, and SAVI) are shown in the Appendices (Figures A.10 & A.11). An example showing possibly shorter-rotation (≤ 7 years) and possibly longer-rotation (> 7 years) plantations based on MSAVI*af* value changes from 2000 to 2014 in Sabah is presented (Figure 2.10).

In addition to the time span of the VI changes, which could indicate the silvicultural rotation of an IF stand, another important piece of information that could be drawn from the changes of VIs values was the rate of growth and decline rate of the values. The growth rate of VIs values could indicate how fast or slow a plantation stand grows.

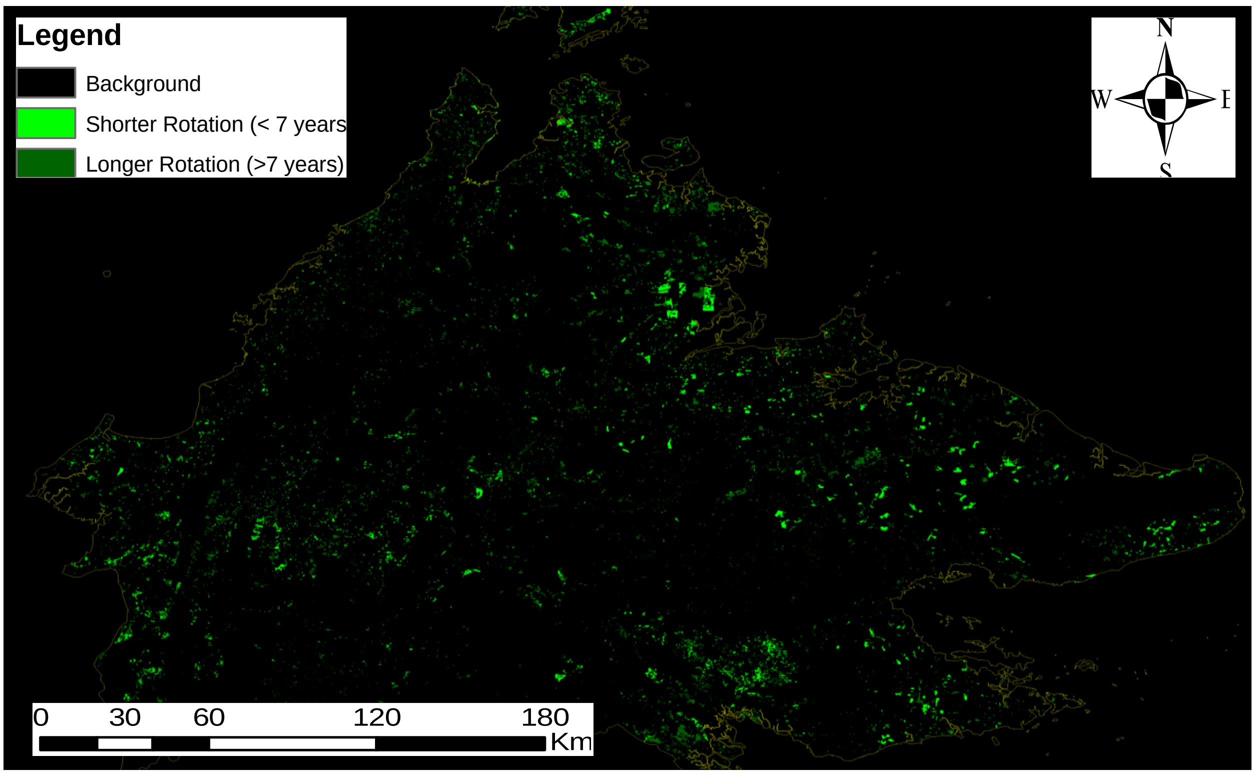
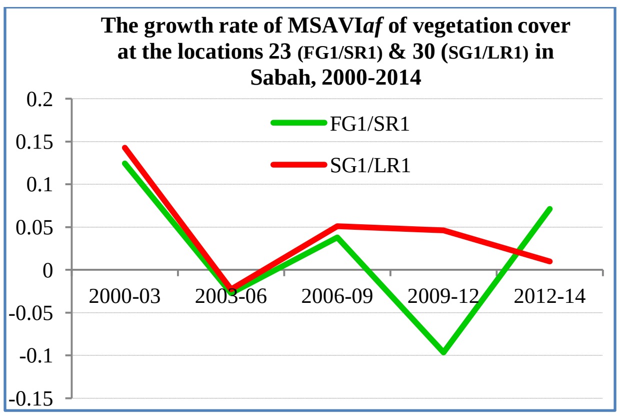


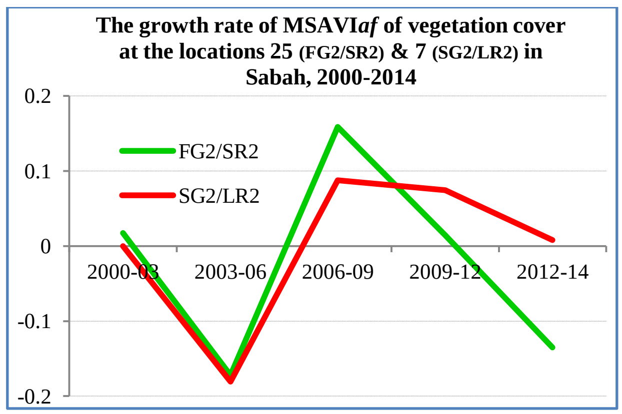
Figure 2.10. Possibly shorter- and longer-rotation plantations based on MSAVI*af*, 2000-2014 in Sabah.

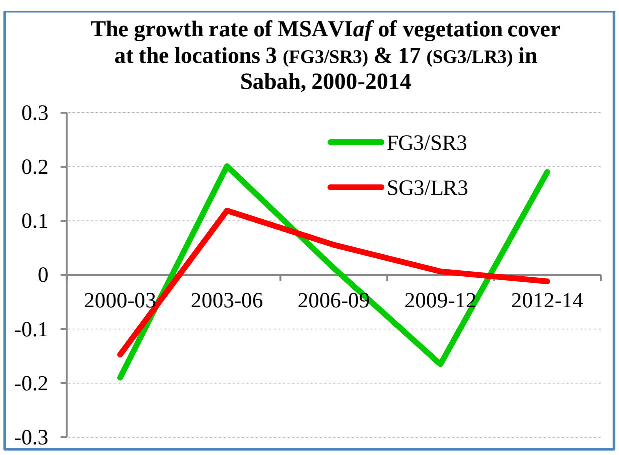
In this study, the growth rate of the VIs values was also interesting because it may relate to the fast-growing and slow-growing timber plantations. The faster-growing industrial forests or timber plantations were supposed to develop or grow their canopy/foliar or biomass faster than the slower-growing industrial forests or timber plantations. The growth rate of the VIs was calculated by the following formula [2.2]:

$$\Delta \textbf{\textit{growth rate}} = (\textbf{\textit{VI}}(t2) - \textbf{\textit{VI}}(t1)) / \textbf{\textit{VI}}(t1) \quad [2.2]$$

Where VI(t1) was the value of VI in the earlier year, or time t1, and VI(t2) was the value of VI in the later year, or time t2. The full results of calculating the growth rates of the VIs in Sabah from 2000 to 2014 are presented in the Appendices (Table A.6). An example to illustrate how the MSAVI*af* values have changed or grown in some selected key areas (location numbers 3, 7, 17, 23, 25, and 30) in Sabah is presented (Figure 2.11).







NOTE: *FG1/SR1 is location 23, SG1/LR1 is location 30; FG2/SR2 is location 25, SG2/LR2 is 7; FG3/SR3 is location 3, & SG3/LR3 is location 17.*

Figure 2.11. The growth rates of the MSAVI*af* values in some locations (location numbers 3, 7, 17, 23, 25, & 30) chosen to monitor their value changes in Sabah, 2000-2014.

Considering Figure 2.11, we could easily realize that, in general, the growth rate of the MSAVI$_{af}$ values in locations 3, 23, and 25 (where there were two clearings of vegetation cover) were faster than the growth rate of the MSAVI$_{af}$ values in locations 7, 17, and 30 (where there was only one clearing of vegetation cover). Based on this information, an assumption was also posed. That is, the faster-growing IFs had the larger VIs growth rates (≥ 0.5) than the slower-growing IFs (< 0.5). The full results of detecting faster-growing and slower-growing IFs in Sabah and Sarawak based on this assumption are presented in the Appendices (Figures A.12 & A.13). An example of the result of possibly faster- versus slower-growing IF detection based on the MSAVI$_{af}$ values in Sabah from 2000 to 2014 is presented (Figure 2.12).

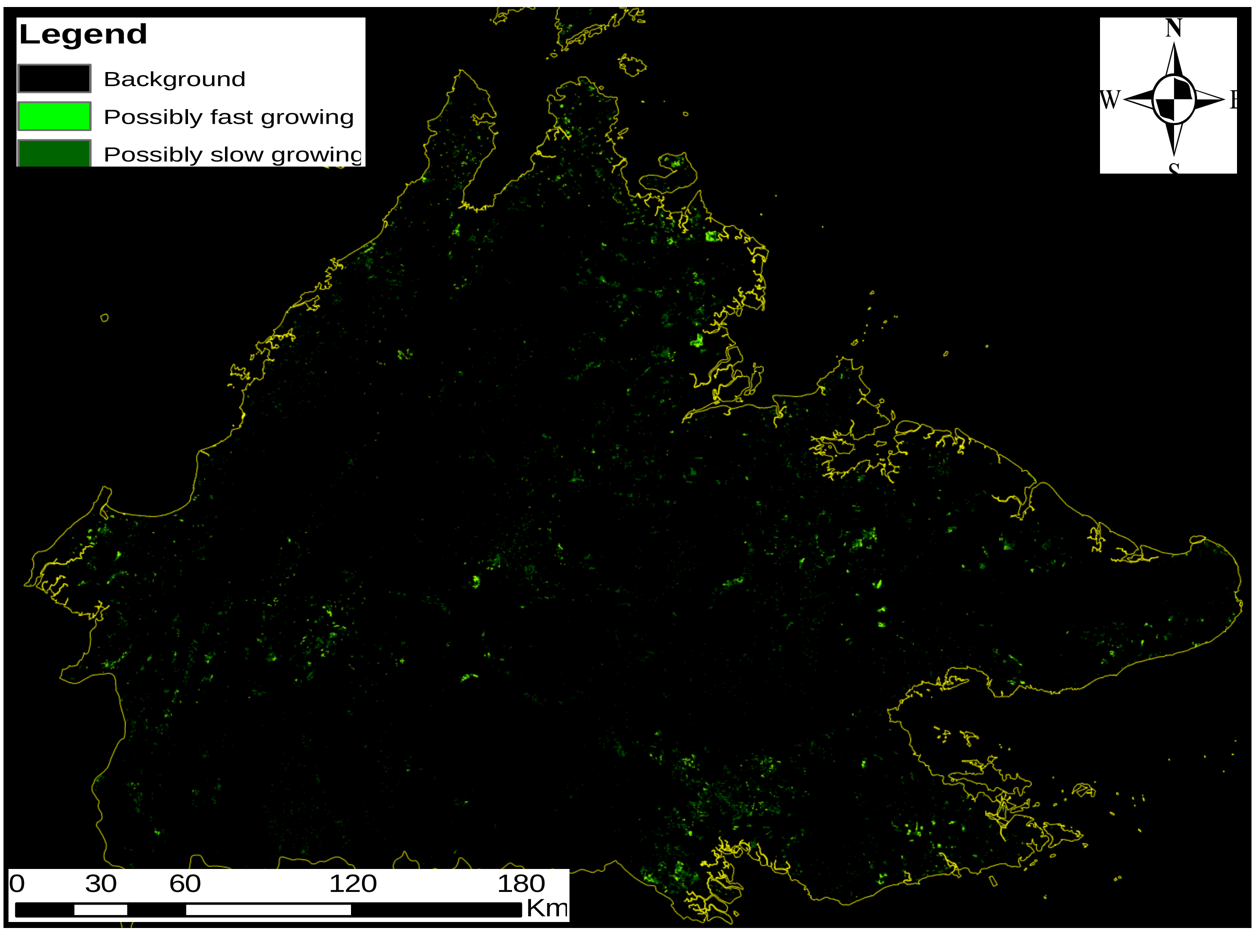


Figure 2.12. The possibly faster-growing and slower-growing plantations based on MSAVI$_{af}$ values in Sabah, 2000-2014.

After obtaining two products of possibly shorter- versus longer-rotation and faster- versus slower-growing plantation stands derived from VIs values changes, an algorithm was developed to detect plantation stands, taking both possibly shorter- versus longer-rotation and faster- versus slower-growing information into account. An example (Figure 2.13) is presented to illustrate this combination (faster-growing, shorter-rotation and slower-growing, longer-rotation plantation stands) in Sabah based on MSAVI$_{af}$ values from 2000 to 2014. The full result of this analysis is presented in the Appendices (Figures A.14 and A.15). This product was used as an input data for detecting and determining industrial forests in the study area.

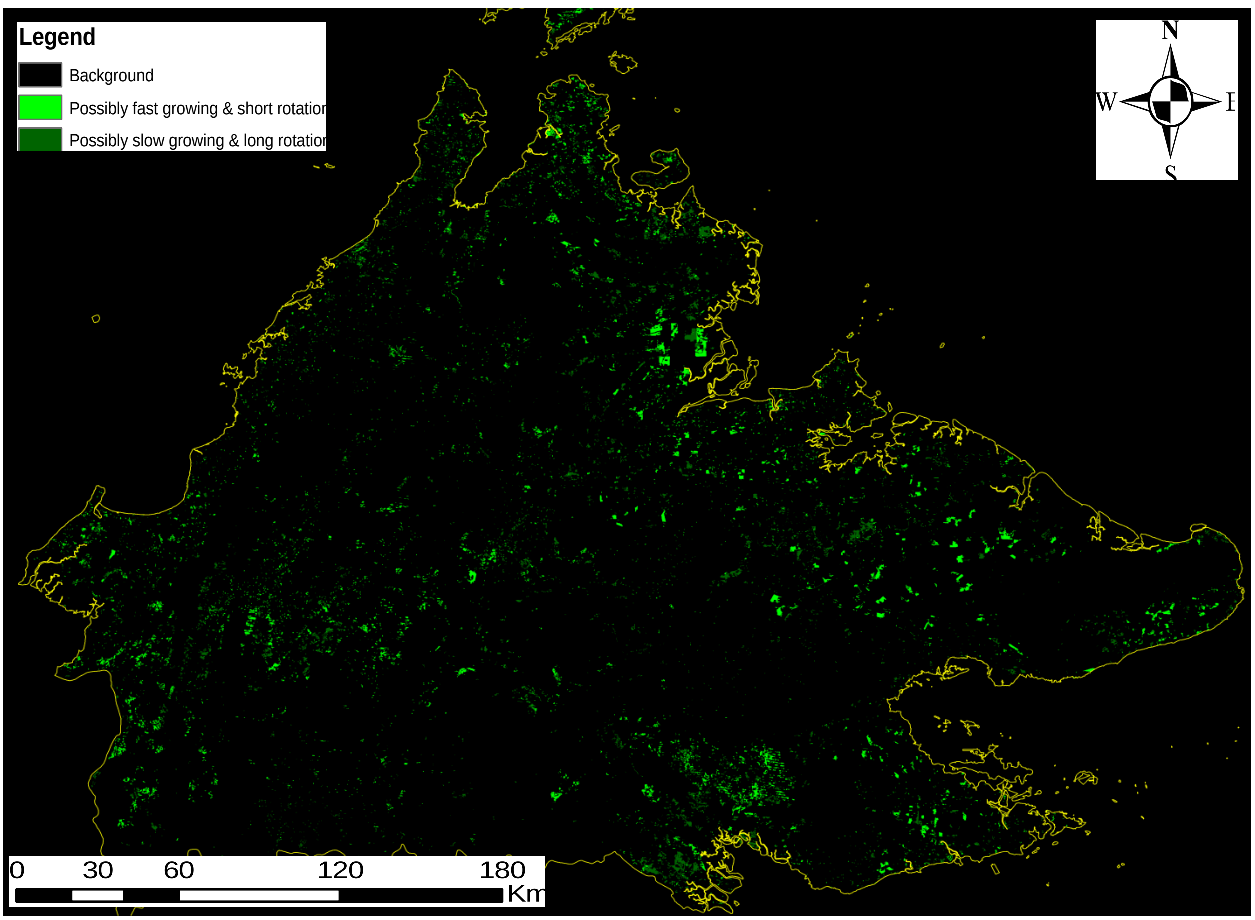


Figure 2.13. Possibly faster-growing, shorter-rotation and slower-growing, longer-rotation plantations based on MSAVI*af*, 2000-2014 in Sabah.

The above analysis provided initial clues for detecting and mapping possibly faster-growing, shorter-rotation and slower-growing, longer-rotation plantations in Sabah and Sarawak from 2000 to 2014. However, this evidence was not enough to know whether they were industrial forests or any specific vegetation covers. Therefore, further analyses were needed to detect and map the targeted IF systems. The additional analyses used to detect industrial forests and calibrate the final results were textural analysis, spectral analysis, and visual interpretation. This task could be simplified by the fact that industrial forests are monoculture of one or a few species. They are usually even-aged and have similar crown shape and regular spacing. Therefore, they will principally differ from other vegetation covers (*e.g.,* natural forests), and these differences can be recognized by using remote sensing methods.

Textural Analysis

One of the promising approaches used to detect IFs in the study area over the study period is textural analysis of vegetation cover. In principal, there are three main ways usually used to analyze texture of an image to identify objects in it *i.e.,* structural, model-based, and frequency-based/feature-based. One of the most-used textural analysis methods is Grey Level Co-Occurrence Matrix (GLCM) consisting of indices: mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation. This method uses variograms and semivariance as a means of classifying images. In this method, it is important for us to determine and design moving window sizes to derive texture variables. In general, using textural analysis to study forests is promising. Thus, many researchers have used it for their studies. For instance, Coburn and Roberts (2004) developed a multiscale texture analysis procedure using variable, variance, mean, mode, and median to improve forest stand classification. They argued that there was only a slight change in the pixel values in relatively homogenous areas. In contrast, coarser texture may contain a lot of abrupt changes. Lu *et al.* (2014) did a study and stressed the roles of using textural images in improving land cover classification in the Brazilian Amazon. They argued that in medium resolution imagery like Landsat, texture had less capability to distinguish land cover types than spectral signature, but combining it with radiometric data could improve this work. By doing so, they found an improvement of the result at 5.2-13.4% depending on the pixel sizes. They also found that the best combinations for Landsat datasets were red band and near infrared band with dissimilarity index at the moving window size of 9*9 pixels. In their study, texture was used as an extra band in the separability analysis.

In this study, the textural analysis was used as a supporting method to detect IFs. This method was developed based on an assumption that the texture of industrial forests and natural forests was different, and that among different timber plantation species their texture was also different. This is because these vegetation covers differ in form and structure. An example showing how a natural forest is different from a plantation is presented (Figure 2.14). This picture was taken in East of Pekanbaru, Indonesia and retrieved from http://news.mongabay.com/2011/0607-greenpeace_vs_barbie.html.

Figure 2.14. The difference between natural forest and plantation.

The Grey Level Co-occurrence Matrix (GLCM) consisting of indices: mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation were used and tested to select the best indices for detecting IFs. The textural computations were done in the VIs products, and on band 4 and 5 images by using ENVI version 4.8 (Exelis Visual Information Solutions, Boulder, Colorado). Additionally, band 4 and 5 were used for calculating textural indices because they could separate different land covers (bare land, forest, and plantation) compared with other bands in the Landsat scenes, as shown in the Spectral Profiles (Figure 2.20) below. A number of tests were completed with the different moving window sizes from 1*1 pixels to 21*21 pixels for all indices (mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation). The following indices: Mean (MEA), Homogeneity (HOM), and Dissimilarity (DIS) worked best with the moving window size at 9*9 pixels for the VIs images, and band 4 and band 5 grey level images. However, for band 5 images, only MEA index was applied. The formulas for calculating MEA, HOM, and DIS, adapted from Lu *et al*. (2014), and Coburn and Roberts (2004), are presented as follows:

$$\text{DIS} = \sum_{i,j=0}^{N-1} P_{i,j}|i-j|$$

$$\text{HOM} = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$$

$$\text{MEA} = \sum_{i,j=0}^{N-1} i(P_{i,j})$$

Where:

N is the number of rows or columns

$\mathbf{V}_{i,j}$ is the value of cell (***i,j***) (row **i** and column **j**) of the moving window.

And

$$P_{i,j} = V_{i,j} \Big/ \sum_{i,j=0}^{N-1} V_{i,j}$$

(Adapted from Lu *et al*., 2014; Coburn & Roberts, 2004)

The values of textural indices of MEA, HOM, and DIS range from 0 to 255. For the DIS index, the lower values express less dissimilarity and the higher values present more dissimilarity among objects or land cover types in the image. Conversely, for the MEA and HOM indices, the higher values indicate more homogenous area, and lower MEA and HOM values will be found in the coarser textural areas, or land cover types which may contain more abrupt changes. An example of how the Mean (MEA) index in GLCM was calculated for an NDVI*af* image in 2014 in Sabah and Sarawak is presented (Figure 2.15).

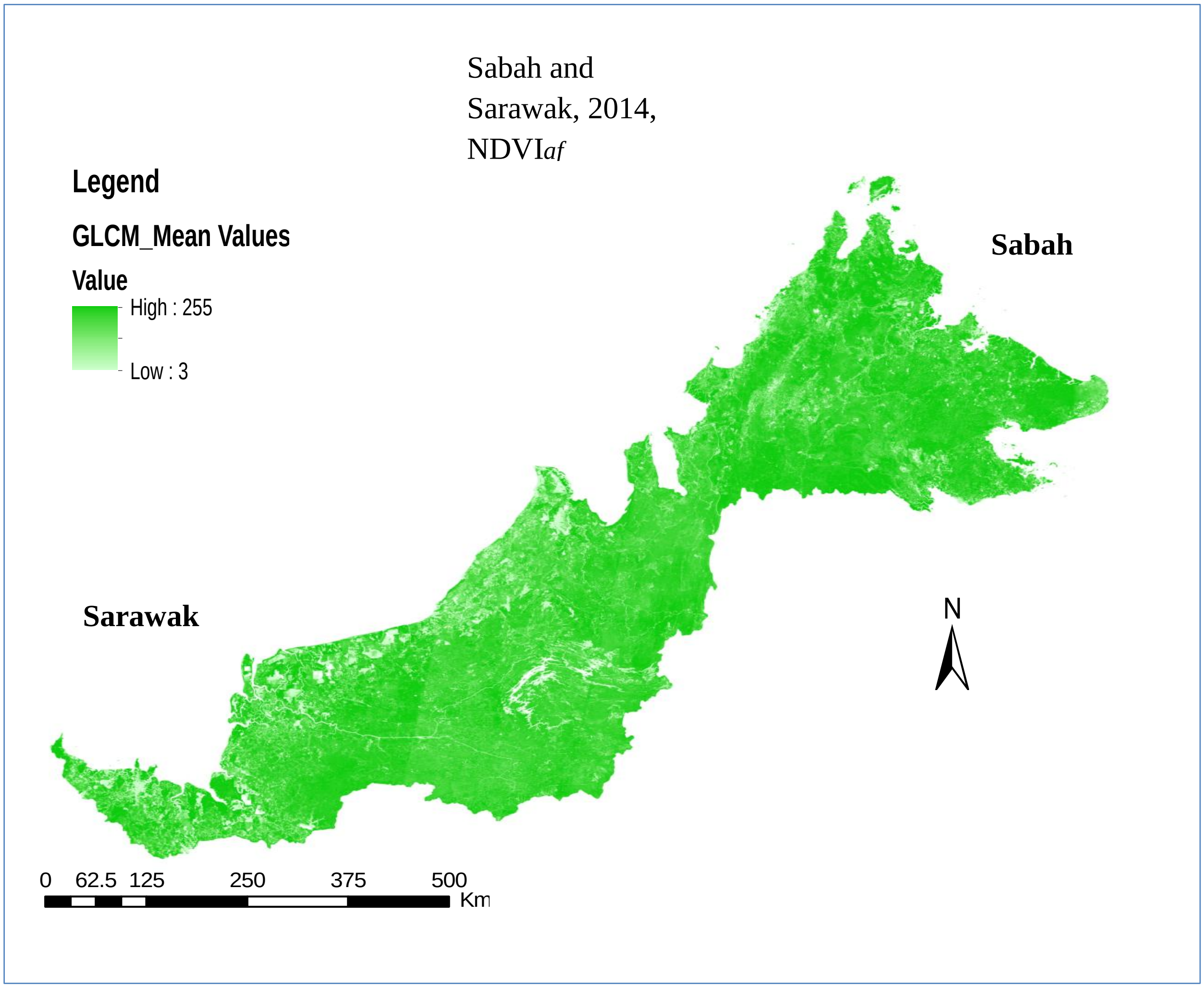


Figure 2.15. The Mean (MEA) index in the GLCM is calculated for an NDVI*af* image in 2014 in Sabah and Sarawak.

To identify the values of the indices of Mean (MEA), Homogeneity (HOM), and Dissimilarity (DIS) in VIs (ARVI, EVI, MSAVI*af*, NDVI*af*, SARVI, and SAVI) and band 4 images and to identify the Mean (MEA) for the band 5 images at the grey level, representing industrial forests or any land use or land cover types, it is necessary for us to know where these land use/land cover types exist and then we will acquire their values by using the *area of interest* (AOI) function in the ERDAS. These are also known as the training areas. The values of MEA, HOM, and DIS for different land use and land cover types were observed for maximum, minimum, mean and mode (the most distributed value range). Then, these values were used in a model to detect the expected land use and land cover types.

To identify texture values typical or representative of the expected land uses/land covers in the study area, different data sources have been used, including other land use and land cover studies, land cover maps of the State Forestry Departments of Sabah and Sarawak, and the reports of timber companies in the study sites. These sources were confirmed by a check using Google Earth. Finally, five expected land use and land cover types were identified, including acacia plantations, natural forests, oil palm plantations, rubber plantations, and other industrial forests (or other timber plantations; for this other IFs type, it was impossible to recognize it in both the Google Earth check and other studies, although other sources indicated it as timber plantations, thus it was classified as other industrial forests/IFs; Figure 2.16).

The full results of observing the values of MEA, HOM, and DIS for different land use and land cover types in different VIs (ARVI, EVI, MSAVI*af*, NDVI*af*, SARVI, and SAVI) and band 4 images, and the Mean (MEA) for band 5 grey level images in Sabah and Sarawak from 2000 to 2014 are shown in the Appendices (Tables A.7 & A.8). An example presenting the mean values of the MEA, HOM, and DIS for five different land uses/land covers (acacia, forest, oil palm, rubber, and other industrial forests) in Sabah from 2000 to 2014 on the NDVI*af* product and band 4 images, and the MEA values for band 5 grey level images is provided (Figure 2.17).

These textural values were used as input data for the texture-based industrial forest detection model (Figure 2.18). An example showing the results of using this model to detect industrial forests through the textural values derived from the NDVI$_{af}$ product, and band 4 and band 5 grey level images in Sabah in 2012 is presented (Figure 2.19).

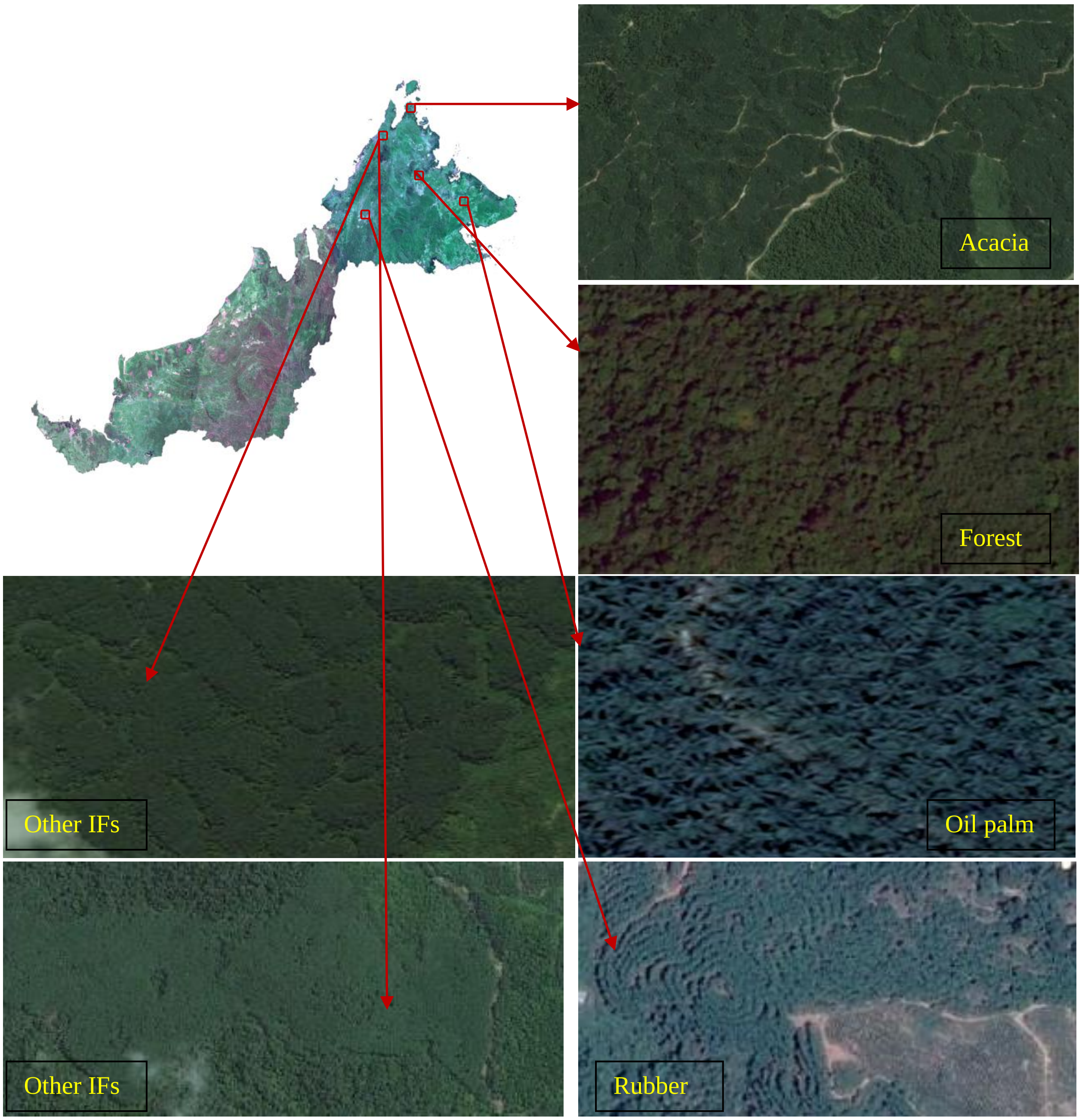


Figure 2.16. The identification of different land uses/land covers used to acquire the textural values in the study sites.

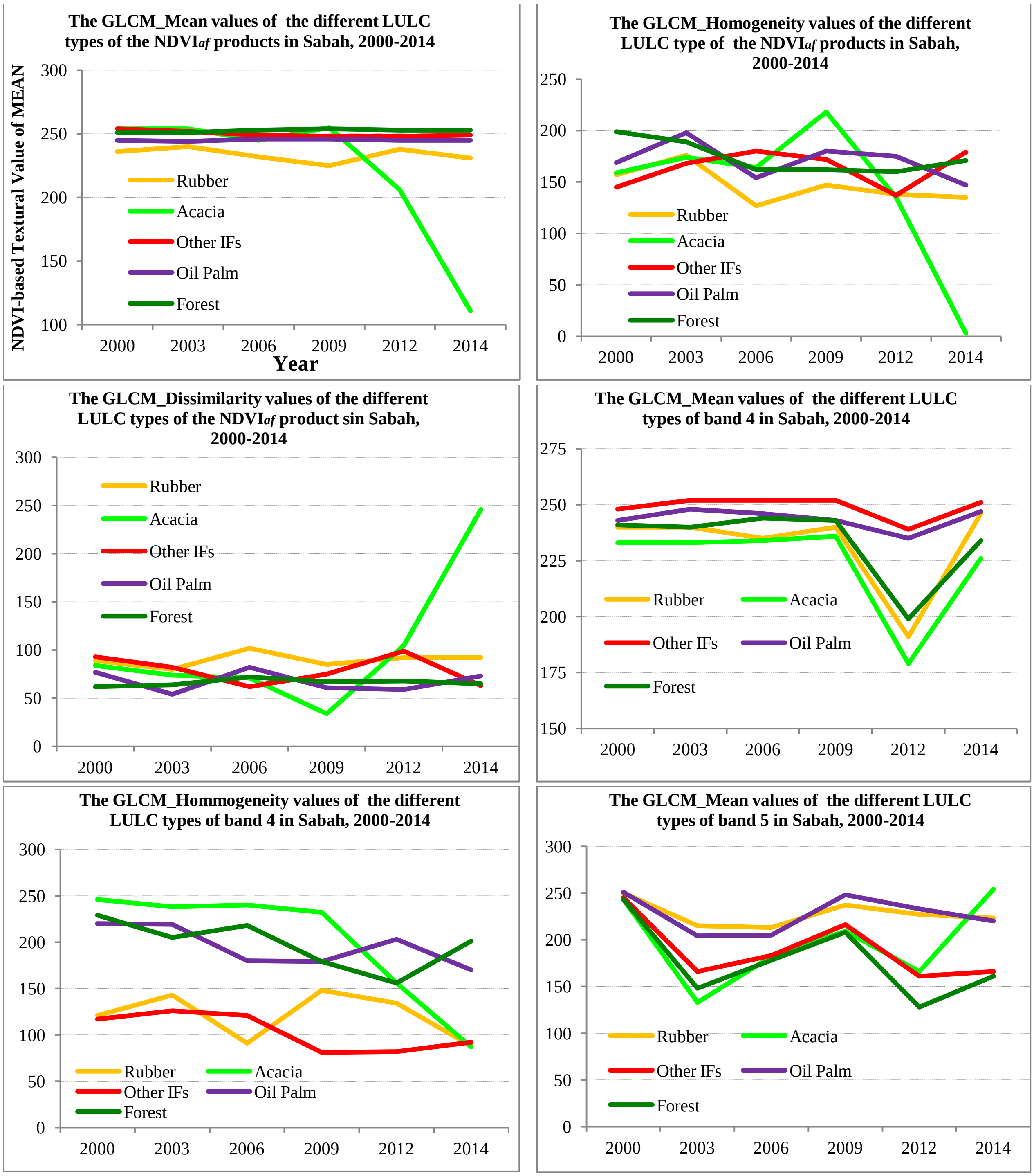


Figure 2.17. The values of GLCM_MEA, HOM, and DIS for different Land Uses/Land Covers in the NDVI*af* product, band 4, and band 5 grey level images in Sabah, 2000-2014.

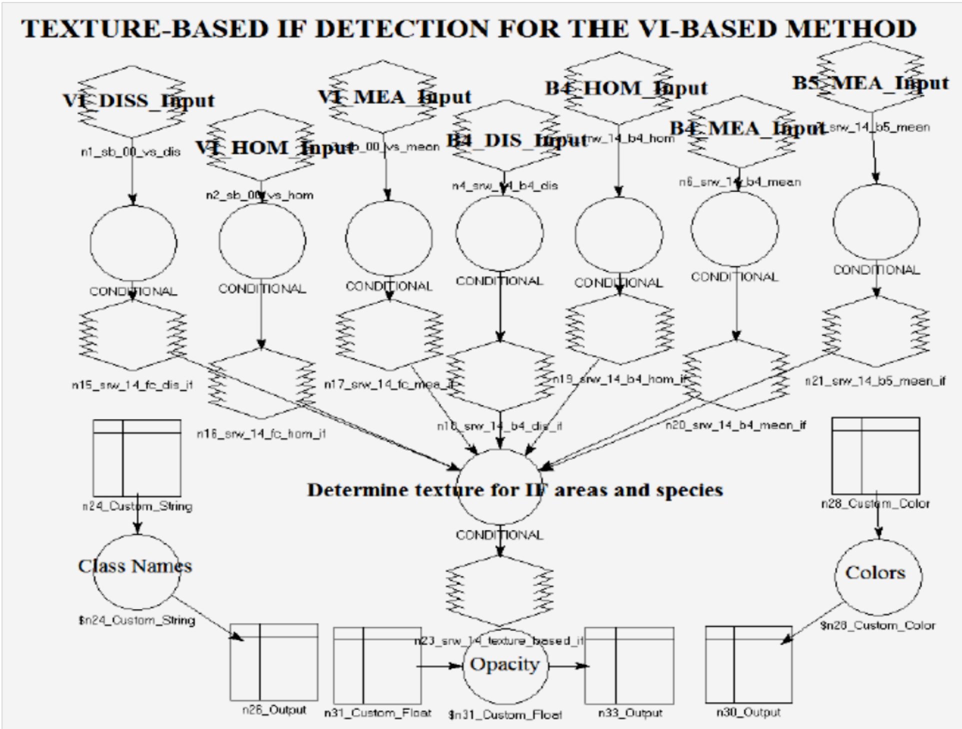


Figure 2.18. The texture-based models for the VI datasets to detect the focused IF systems.

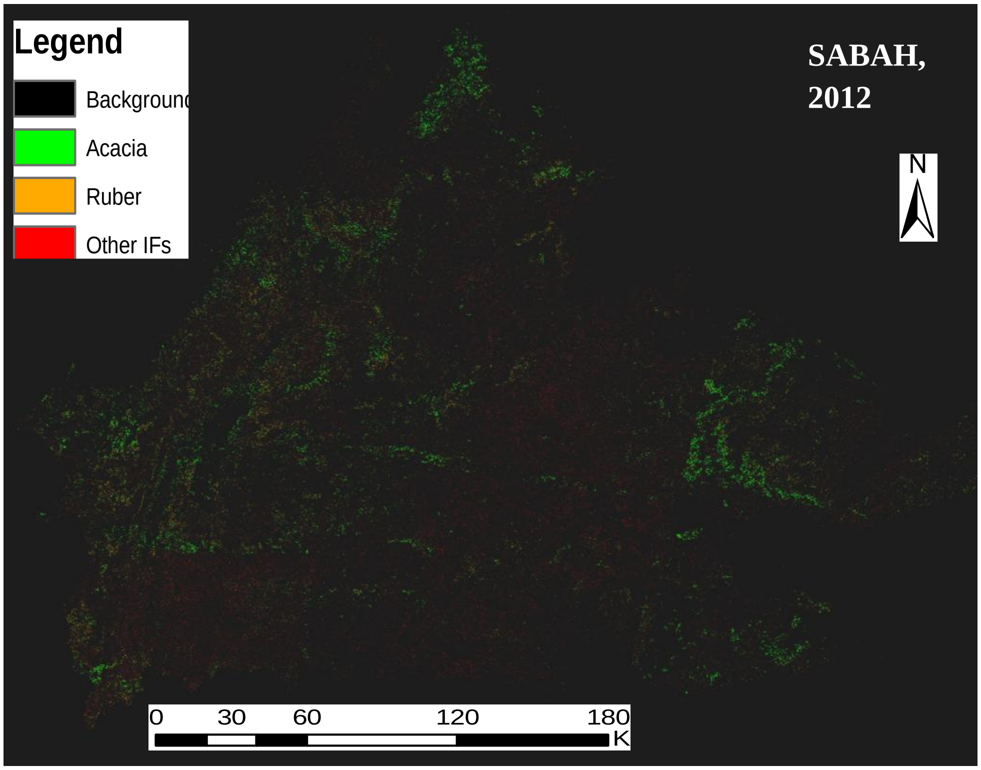


Figure 2.19. Detecting the targeted IF systems based on textural analysis in Sabah, 2012.

Spectral Analysis

Spectral analysis was also used as a necessary supporting step in detecting industrial forests based on vegetation indices analysis, as well as forest fractional cover changes analysis method. The spectral analysis was done by first checking the Spectral Profiles for the expected objects on the preprocessed images. The purpose of this check was to see how the spectra of these objects were different. The objects (areas of interest) in the images chosen for this check were bare lands, natural forests, and plantations in general. These plantations could be oil palm plantations, timber plantations, and other plantations, or even agricultural lands. They were selected because it was easy to visually recognize them in the Landsat images/scenes. In other words, these land use and land cover types could be easily identified visually based on their interpretation keys such as color, texture, and arrangements in an image. The result of this spectral profile check for these chosen land uses/land covers is presented (Figure 2.20). Considering this spectral plot, it was clear that the spectra of bare lands were very different from the spectra of vegetation cover (natural forests and plantations). However, the spectra of natural forests and general plantations were very similar, especially for bands 1, 2, 3, and 6. Only two bands, namely band 4 and 5, were able to somewhat differentiate them. This was why conventional statistical land use and land cover classification methods are not able to recognize and classify these land use/land cover types.

Therefore, in this study, band 4 and band 5 in the Landsat images were selected and used for spectral analysis to detect industrial forests. After checking the spectral profiles for the chosen land uses and land covers to select the bands to be used for the analysis, other spectral analysis methods, including Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Tasseled Cap Analysis (TCA), were also used. These methods are widely applied in anomaly detection, target detection, material mapping and identification, *etc*. In this study, they were used because it was more interpretable to natural forests, plantations, and bare lands in the images derived from these analyses or transformations. Similar to the above textural analysis, the area of interest (AOI) tool in the ERDAS IMAGINE was also used to identify the values for the land uses/land covers of interest (also known as the training areas). Finally, the results of these spectral analyses were used to support the VIs-based industrial forest detection method.

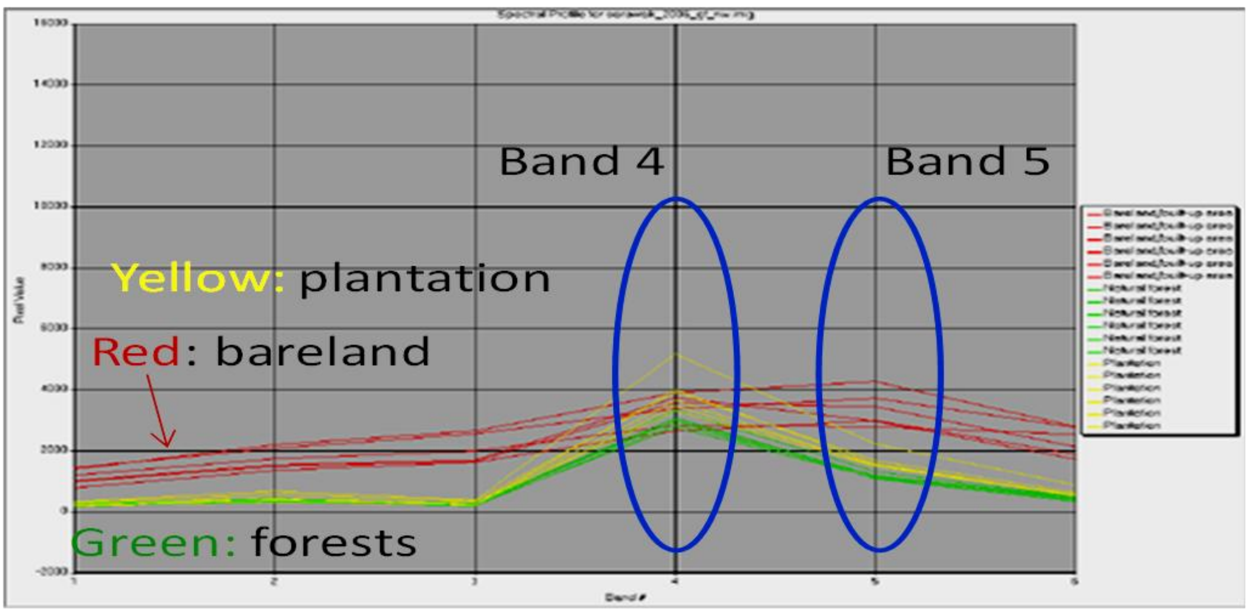


Figure 2.20. Spectral profiles for bare lands, natural forests, and plantations in the study area.

Principal Component Analysis (PCA) is a conventional feature extraction technique which assumes data in images are of normal or Gaussian distribution. It will transform data based on a correlation and be able to recognize statistical patterns in the images (Jia & Richard, 1999). In this study, three main components were selected and applied for the Landsat scenes. The ERDAS worked to group these three main components by itself. The result of this analysis is presented (Figure 2.21) as an example of applying the PCA to the Landsat data in 2000 for Sabah and Sarawak. Considering this PCA product, we can realize that objects in the image were better separable.

Then, like the above textural analysis, five areas of interest consisting of acacias, forests, oil palms, rubbers, and other industrial forests (also known as the training areas) were also identified in Sabah and Sarawak (Figure 2.21). The AOI was created to obtain the values for these land use/land cover types. The full results of this work are presented in the Appendices (Tables A.9 & A.10). These values were used in a model to detect the expected industrial forests. An example of identifying the mean values of acacias, natural forests, oil palms, rubbers and other industrial forests in Sabah from 2000 to 2014 is presented (Figure 2.22).

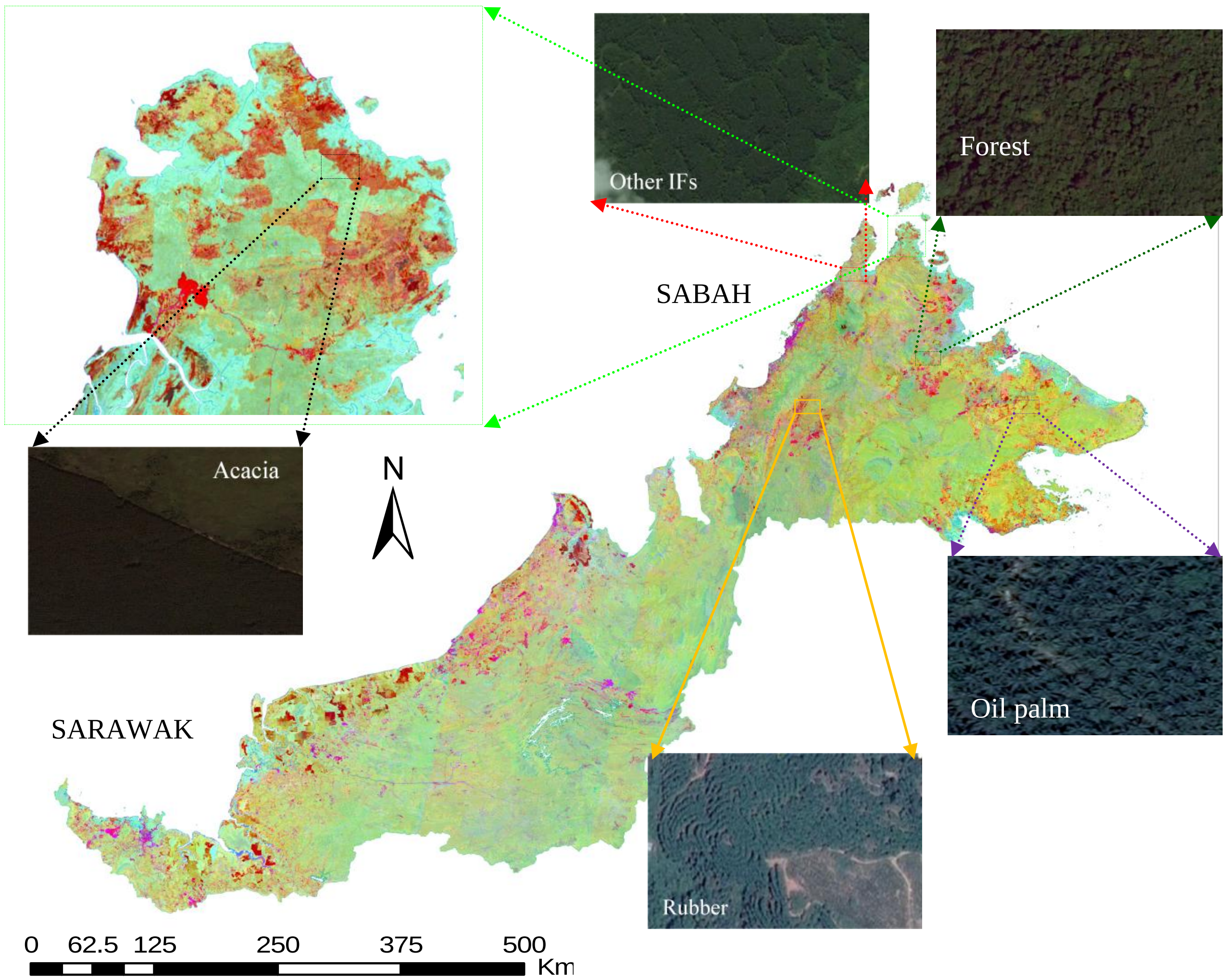


Figure 2.21. The Principal Components Analysis for Sabah and Sarawak in 2000.

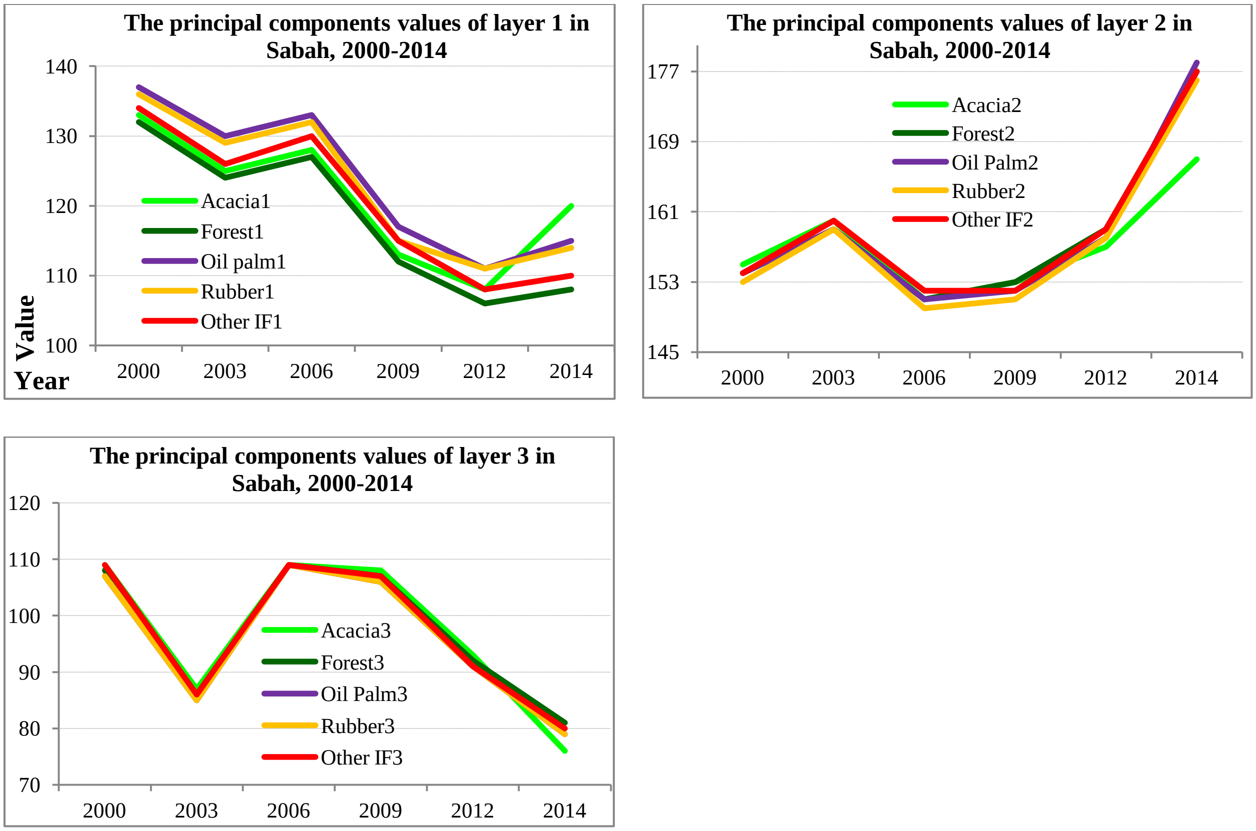


Figure 2.22. The mean values of acacias, natural forests, oil palms, rubbers, and other industrial forests of layer 1, 2, and 3 in the PCA product in Sabah, 2000-2014.

Independent Component Analysis (ICA) is also a feature extraction technique which was just developed recently. The purpose of this technique is to de-correlate the spectral bands to recover the original features in the images. It performs a linear transformation of the spectral bands, such that the resulting components are de-correlated (Shah *et al.*, 2007a; Shah *et al.*, 2007b). Each component will contain information corresponding to a specific feature in the original images. The ICA is used not only to de-correlate the features, but also to make them independent of each other for spectral bands. It can work both in normal distribution data, and skewness or kurtosis data (Comon, 1994). Thus, it is a higher order feature extraction technique compared with the PCA. The ICA is applied in the visual image interpretation because it can improve the recognition of the objects through component color coding. It can be also used in the spectral unmixing model, shadow detection, and especially for land use and land cover classification. In LULCC studies, the ICA can further analyze changes and improve land use and land cover classification based on their spectral, textural, and contextual features/information. The ICA is well-suited for the analysis of multi-temporal data because feature-based change detection techniques necessitate extraction of feature with high accuracy. An example of applying the ICA to the Landsat data in 2000 for Sabah and Sarawak is presented (Figure 2.23). Considering this figure, we could also realize that the objects in the image were better separable.

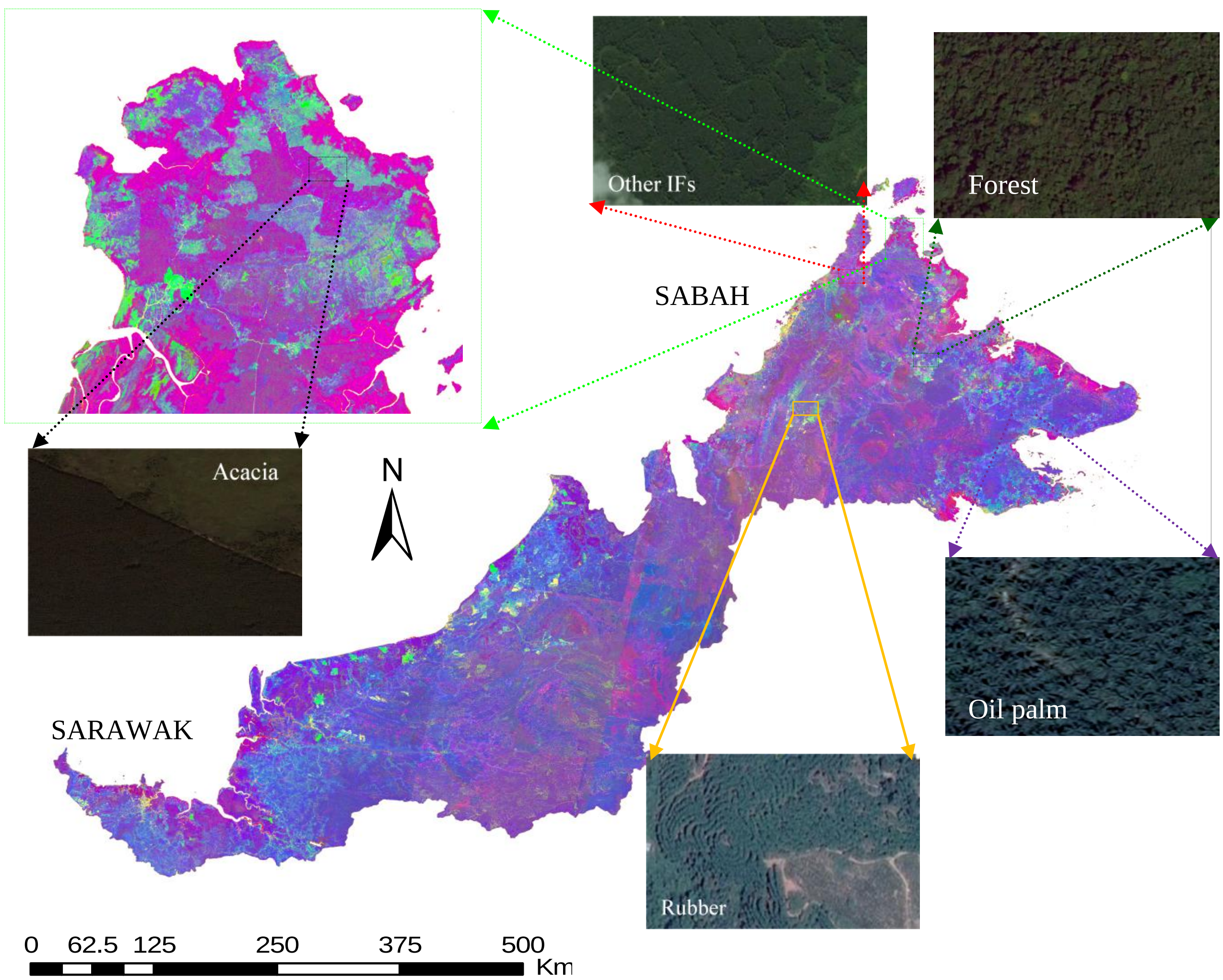


Figure 2.23. The Independent Components Analysis for Landsat data in the study area in 2000.

Then, similar to the PCA above, five areas of interest consisting of acacias, forests, oil palms, rubbers, and other industrial forests were also identified in Sabah and Sarawak. The areas located for these land use/land cover types were the same as the areas identified in the PCA above. The full results of obtaining the mean and range values for these land use/land cover types are expressed in the Appendices (Tables A.9 and A.10). These values were used in a model to detect the expected industrial forests. Figure 2.24 presents an example of the mean values of acacias, natural forests, oil palms, rubbers, and other industrial forests in Sabah from 2000 to 2014.

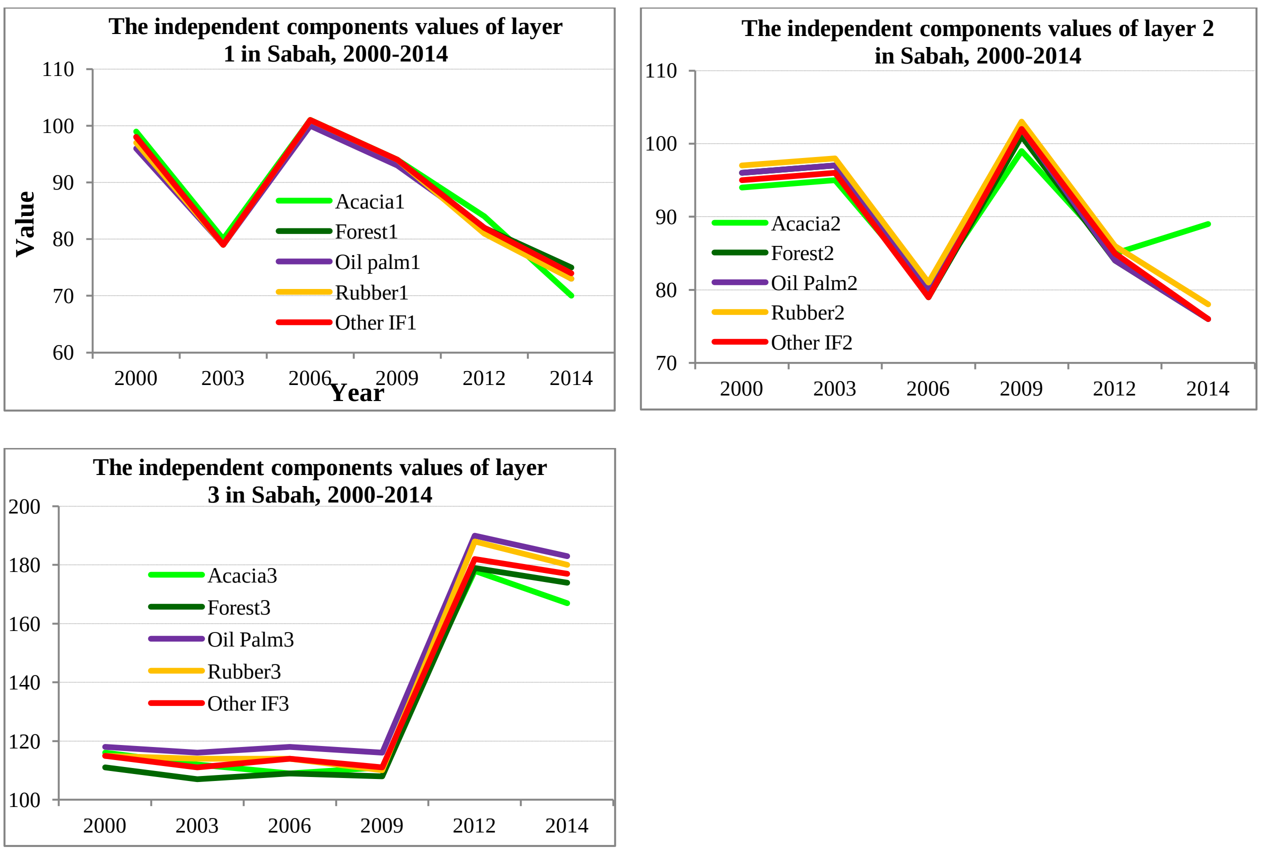


Figure 2.24. The Independent Components mean values (acacias, natural forests, oil palms, rubbers, and other industrial forests) of layer 1, 2, and 3 in Sabah, 2000-2014.

Tasseled Cap Analysis/Transformation (TCA) is often used to study vegetation content in an image through scene brightness, greenness, and wetness and is calculated by using different coefficients for Landsat datasets (Crist & Cicone, 1984; Crist, 1985; Crist &Kauth, 1986; Jensen, 2015). The TCA offers a way to optimize data to study vegetation. This may be helpful in detecting industrial forests. In the TCA, three data structure axes are viewed as a degree of brightness, greenness, and wetness. In that, the brightness component indicates areas of low vegetation and high reflectors, such as bare lands; the greenness component indicates vegetation; and the wetness component reveals water and moisture. In this study, each IF type was supposed to be planted in certain soil, elevation, and climate conditions. Therefore, by using this analysis, IFs in the study area could be detected.

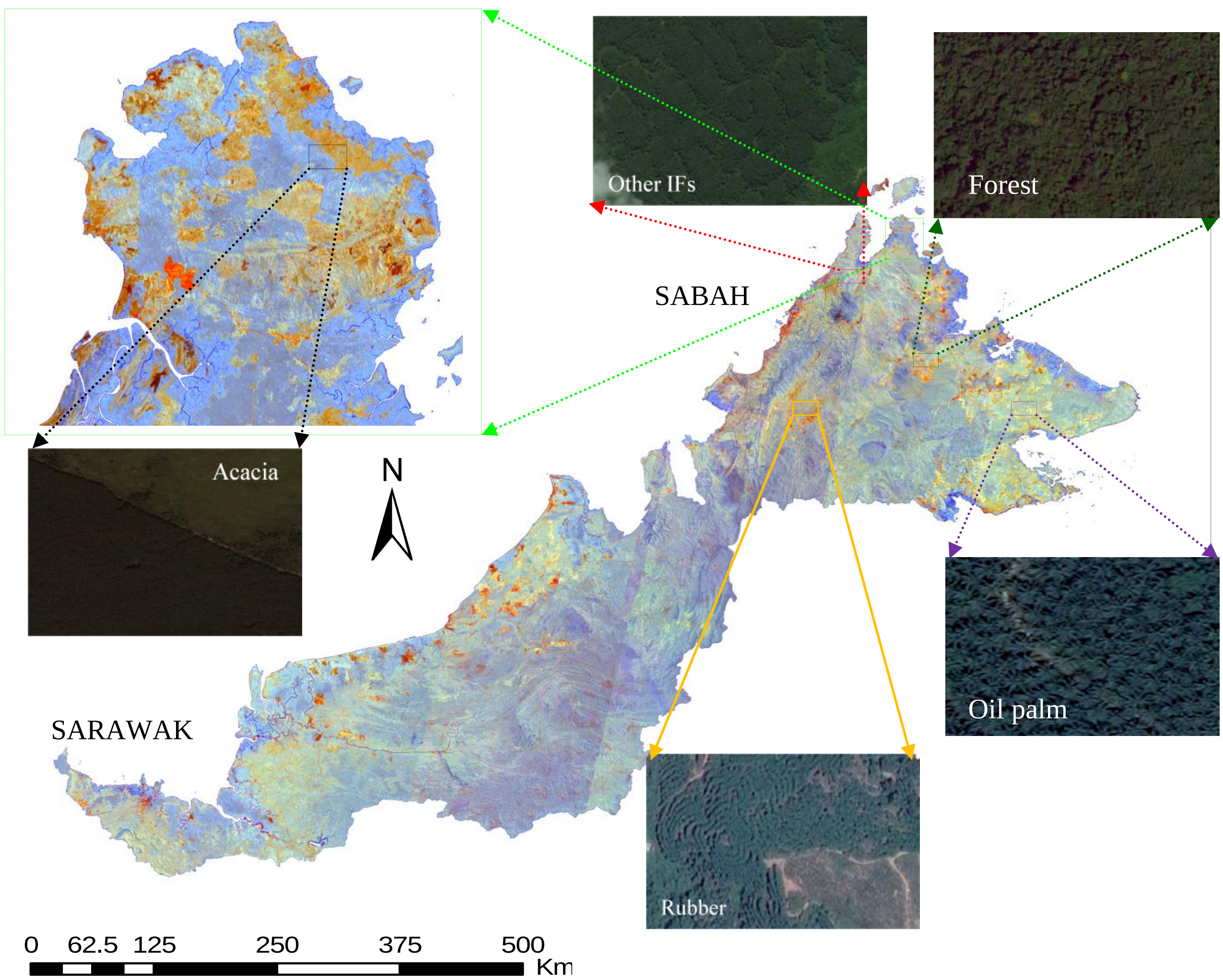


Figure 2.25. The Tasseled Cap Analysis for Landsat data in the study area in 2000.

An example showing the result of applying the TCA to the Landsat data in 2000 is presented (Figure 2.25). Then, similar to the PCA and ICA above, five areas of interest consisting of acacias, forests, oil palms, rubbers, and other industrial forests were also identified in Sabah and Sarawak. The full results of obtaining the mean and range values for these land use/land cover types are expressed in the Appendices (Tables A.9 and A.10). These values were also used in a model to detect the expected industrial forests. An example (Figure 2.26) presents the mean Tasseled Cap values of acacias, natural forests, oil palms, rubbers, and other industrial forests in Sabah from 2000 to 2014.

Next, in the spectral analysis, as stated above, only band 4 and band 5 could somewhat separate natural forests from plantations in general. The Band 4 is Near Infrared (NIR) in the Landsat 4-5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) with the wavelength range of 0.77–0.9 µm. In Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS), the Near Infrared (NIR) is band 5 with the wavelength of 0.85-0.88 µm.

However, in this study, only the following individual bands (bands 2, 3, 4, 5, 6, and 7) for Landsat 8 (OLI TIRS) were used and stacked. Thus, its band 5 (NIR) would be chronologically stacked and renamed to band 4 to be consistent with data of Landsat 4-5 TM and Landsat 7 ETM+. The NIR (band 4) is well-known and frequently used to study green biomass content of vegetation cover. In addition, band 5 (Short Wave Infrared) in Landsat 4-5 TM and 7 ETM+ with the wavelength of 1.55-1.75 µm; and band 6 in Landsat 8 OLI TIRS, which was renamed to band 5 with 1.57-1.65 µm wavelength, were often used to discriminate moisture content of soil and vegetation. In this step, this study further examined how the mean values of band 4 and band 5 were different among five chosen land use and land cover types (*i.e.*, acacias, natural forests, oil palms, rubbers, and other industrial forests) in the study area. These chosen areas for this examination were the same as the areas selected for textural and spectral analyses above.

Figure 2.26. The Tasseled Cap values (acacias, natural forests, oil palms, rubbers, and other industrial forests) of layer 1, 2, 3, 4, 5, and 6 in Sabah, 2000-2014.

The full results of this examination are presented in the Appendices (Tables A.9 & A.10). The results (Figure 2.27) indicated that they could be used as supporting information in the models to detect industrial forests.

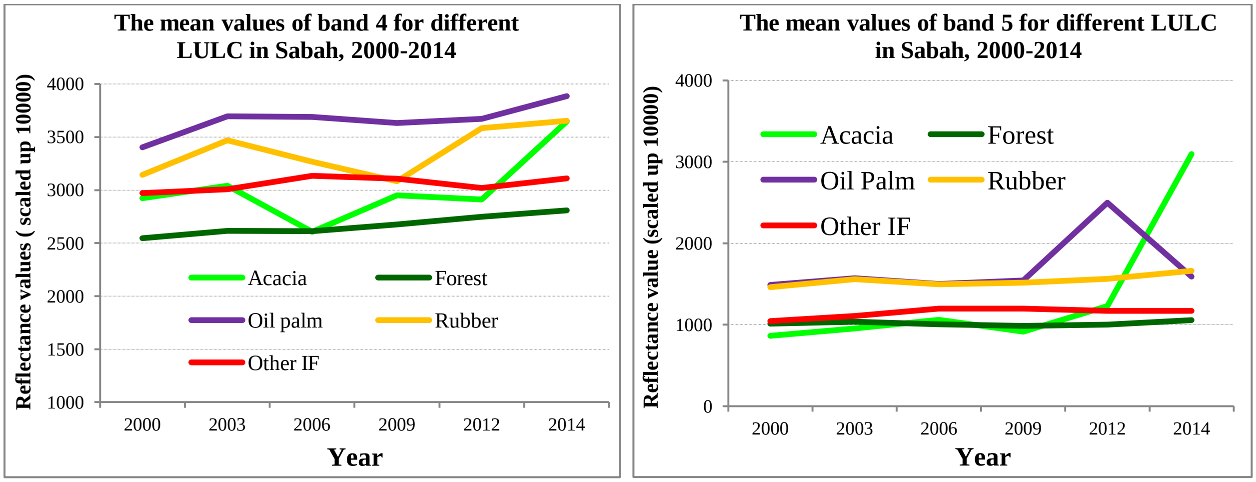


Figure 2.27. The mean values of band 4 and band 5 for the different land use/land cover areas of interest in Sabah, 2000-2014.

After doing spectral analyses including Principal Component Analysis, Independent Component Analysis, Tasseled Cap Analysis, and Band 4 and 5 analyses as described above, the results were used in the spectral analysis-based model to detect industrial forests (Figure 2.28). The results are shown in Figure 2.29 as an example of how to detect industrial forests based on the spectral analysis in Sabah in 2012.

Visual Interpretation and Using Other Data

To calibrate the final results for detecting industrial forests, visual interpretation and other data were also used. In addition to the silvicultural rotation, spectral, and textural datasets, a number of land use and land cover studies have been conducted in Sabah and Sarawak. These studies mentioned industrial forests or timber plantations in Malaysia in general, and Sabah and Sarawak in particular, to some degree. A review was done for these studies in combination with visual interpretation to calibrate the final results of detecting industrial forests in the study area.

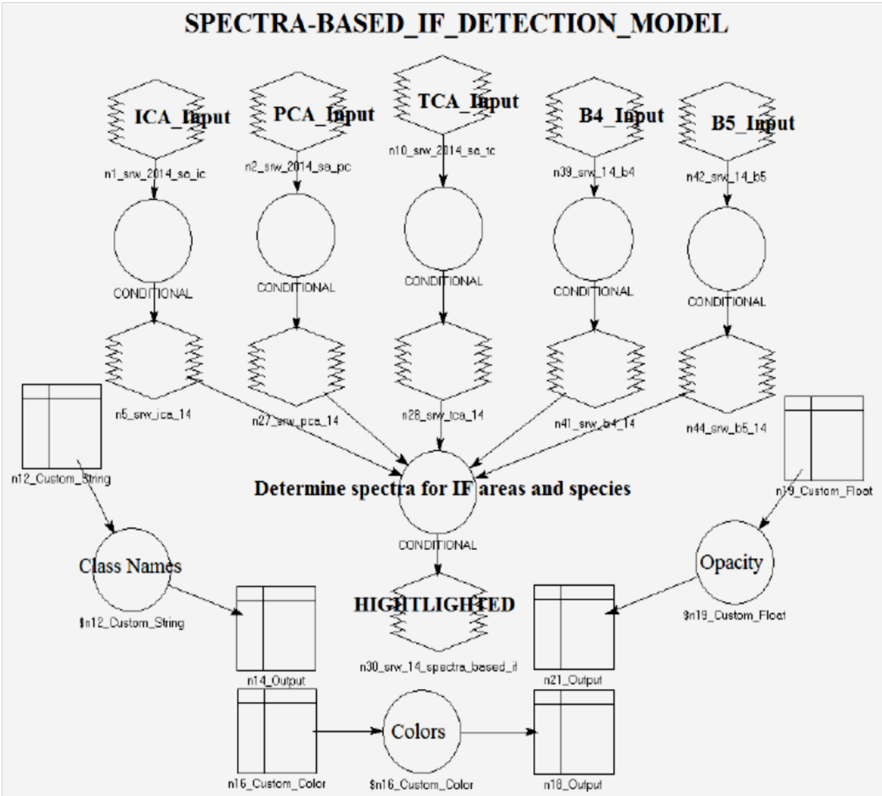


Figure 2.28. The spectra-based models for the VI datasets to detect the focused IF systems.

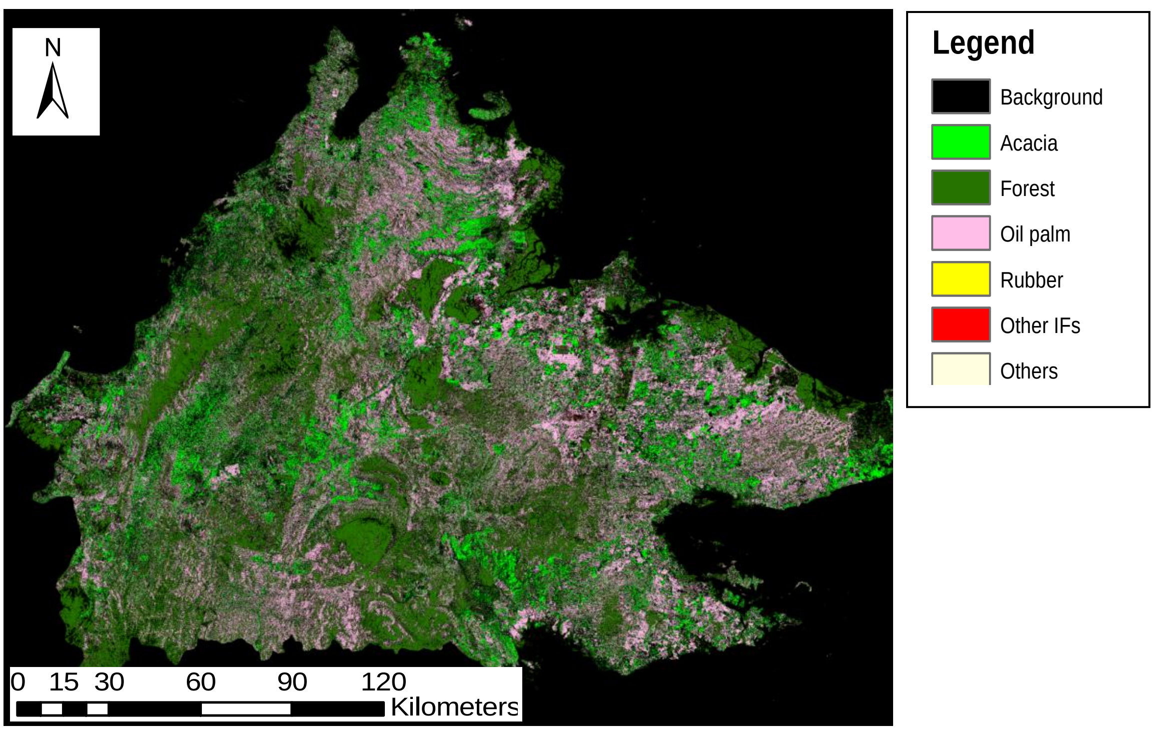


Figure 2.29. The spectral analysis-based industrial forest detection in Sabah, 2012.

In addition, the final calibration for the industrial forest maps also used data, reports and documents from the Forestry Departments of Sabah and Sarawak states and local timber companies, such as statistical data and land use/land cover maps.

For Sabah, the following data sources were used (1) Forest Reserves and Other Forest Lands Maps (Sabah Forestry Department, 2012); (2) Forest Resource Management (Sabah Forestry Department 2006, 2009, 2012, 2013); (3) Roda and Rathi (2006); (4) Raynold *et al.* (2011); (5) Malik *et al.* (2013); (6) McMorrow and Talip, (2001); (7) Malaysian Timber Council (2009); and (8) maps, reports, and documents from companies: Sabah Softwoods Berhad[3], Sabah Forest Industries[4], and other smaller timber companies. For Sarawak, the following data sources were used to identify industrial forests in the area: (1) Roda and Rathi (2006); (2) Malik *et al.* (2013); (3) Annual reports (Sarawak Forestry Department, 2009, 2011, 2012); (4) Ta Ann Plantation Company's maps[5]; (5) Wyn (2011); (6) Bryan *et al.* (2013), (7) Gunarso *et al.* (2013), and (8) SarVision (2011). These documents provided a firm foundation for identifying the industrial forests in the study area.

Then, based on visual interpretation keys, the areas and types of industrial forests in Sabah and Sarawak from 2000 to 2014 could be identified. The visual interpretation keys include texture (fractional dimension), position, slope, associations, contextual (spatial dependence), and other environmental factors. For instance, rubber plantations have typical textures, land forms, and landscape terracing, and they were planted both in the smallholder and industrial scale. On the contrary, pulp or acacia plantations also have special color, and they were normally established at the large scale by industries. Oil palm plantations also have special texture. The following figure (Figure 2.30) provides an example of how the different land uses/land covers

[3] http://www.softwoods.com.my/;
[4] http://www.avanthagroup.com/downloads/Sabah-Forest-Industries-Sdn-Bhd.pdf
[5] http://www.taann.com.my/reforestation/

were interpreted. However, in general, because the quality and type of Landsat scenes were very different, it was not easy to interpret the expected land uses and land covers in the study area.

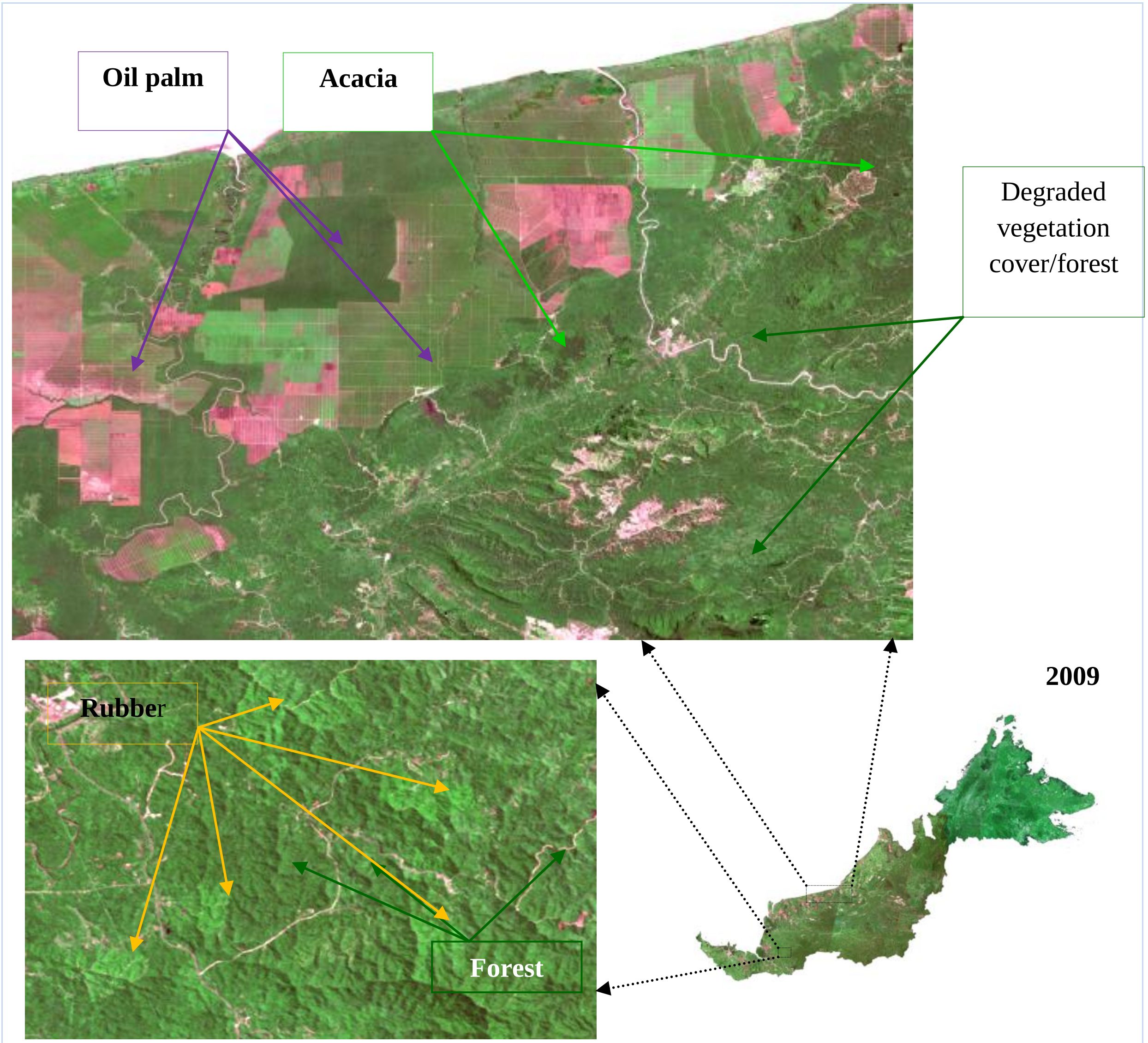


Figure 2.30. An example of how to interpret the different land uses/land covers based on their interpretation keys in Sarawak in 2009.

The visual interpretation for Landsat datasets from 2000 to 2014 was done in the ArcGIS 10.2.2, and then this vector data was converted into raster to be used in the ERDAS for further analysis. The results of visual interpretation and using other data to identify industrial forests in Sabah and Sarawak are presented (Figure 2.31) as an example.

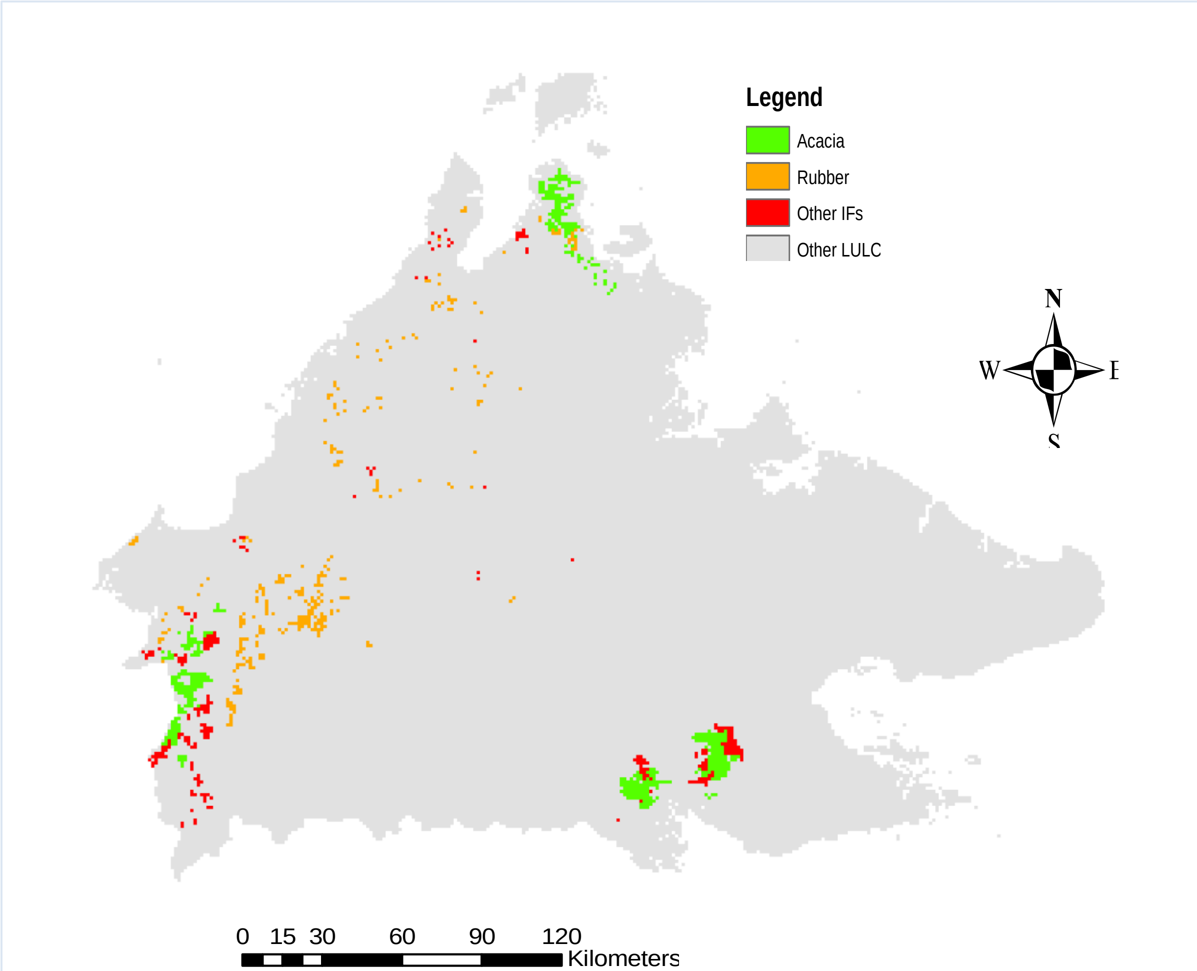


Figure 2.31. The visual interpretation-based industrial forest map in Sabah, 2000.

Making IF Maps

Then, finally, an algorithm based on rules for the shorter- versus longer-rotation (SR *vs.* LR), faster-growing versus slower-growing (FG *vs.* SG) IFs, textural analysis, spectral analysis, and visual interpretation as mentioned above was developed.

The algorithm is described in Figure 2.32. In other words, the algorithms could be presented as follows: $f_{(IFs)} = \sum([\textbf{Texture}_{(IFs)} \cap \textbf{Spectra}_{(IFs)} \cap \textbf{FGSR-SGLR}_{(IFs)} \cap \textbf{Visual}_{(IFs)}] + [\textbf{FGSR-SGLR}_{(IFs)} \cap (\textbf{Texture}_{(IFs)} \text{ OR/AND } \textbf{Spectra}_{(IFs)} \text{ OR/AND } \textbf{Visual}_{(IFs)})] + [\textbf{Visual}_{(IFs)} \cap (\textbf{Texture}_{(IFs)} \text{ OR } \textbf{Spectra}_{(IFs)})])$.

The final results were clumped and the areas smaller than 2 ha were eliminated. The purpose of this work was to reduce the “salt and pepper” noises that were caused by the atmospheric effects and image quality. This was also due to the fact that the smaller IF patches were more difficult to detect; and because Fox and Castella (2013) indicated smallholders in Southeast Asia commonly owned a land size around 1-4 ha of plantations. Therefore, the minimum land size selected in detecting and mapping new IFs in the study area was 2 ha. The results of detecting industrial forests in Sabah and Sarawak from 2000 to 2014 based on the vegetation indices analysis including ARVI, EVI, MSAVI*af*, NDVI*af*, SARVI, and SAVI are presented (Figures 2.33, 2.34, 2.35, 2.36, 2.37, and 2.38).

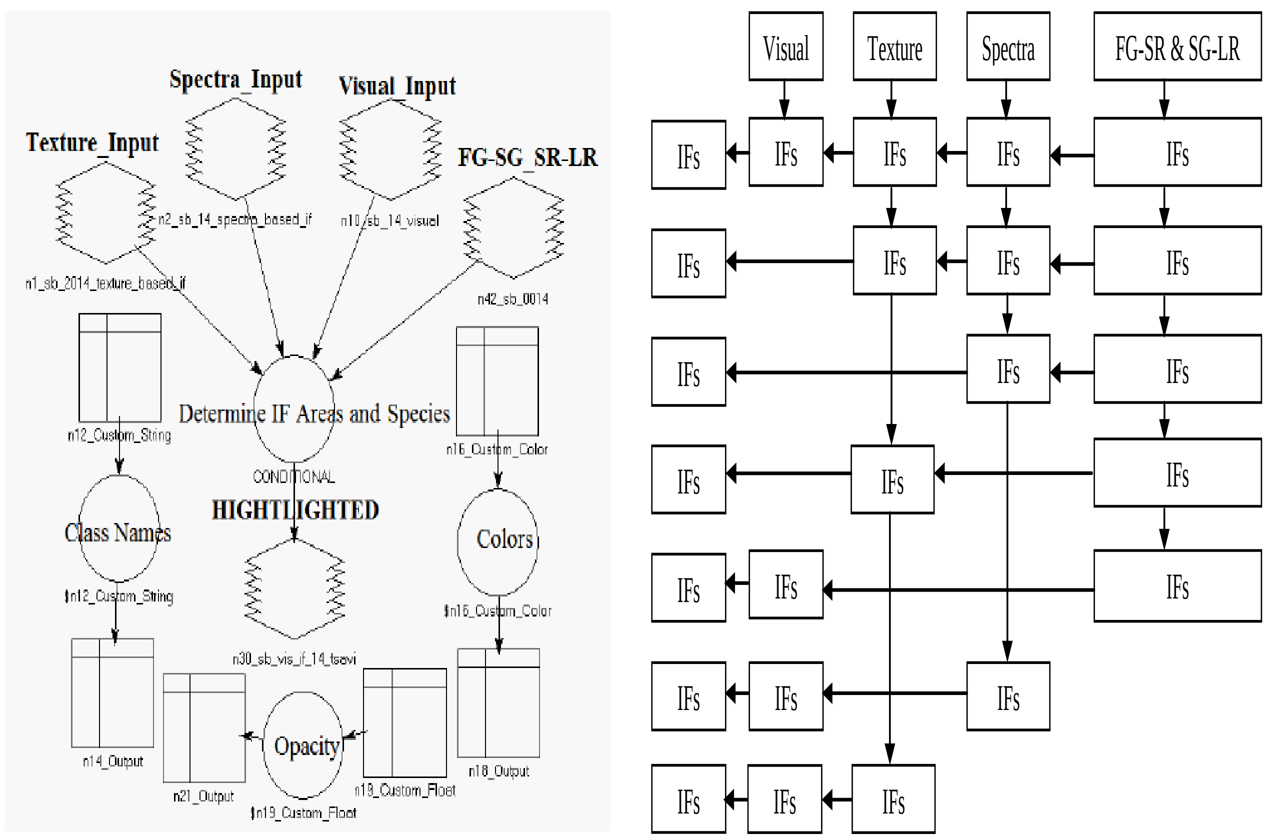


Figure 2.32. The final algorithm to identify industrial forest areas and species based on textural analysis, spectral analysis, visual interpretation, and faster-growing, shorter-rotation (FGSR) and slower-growing, longer-rotation (SGLR) IF products.

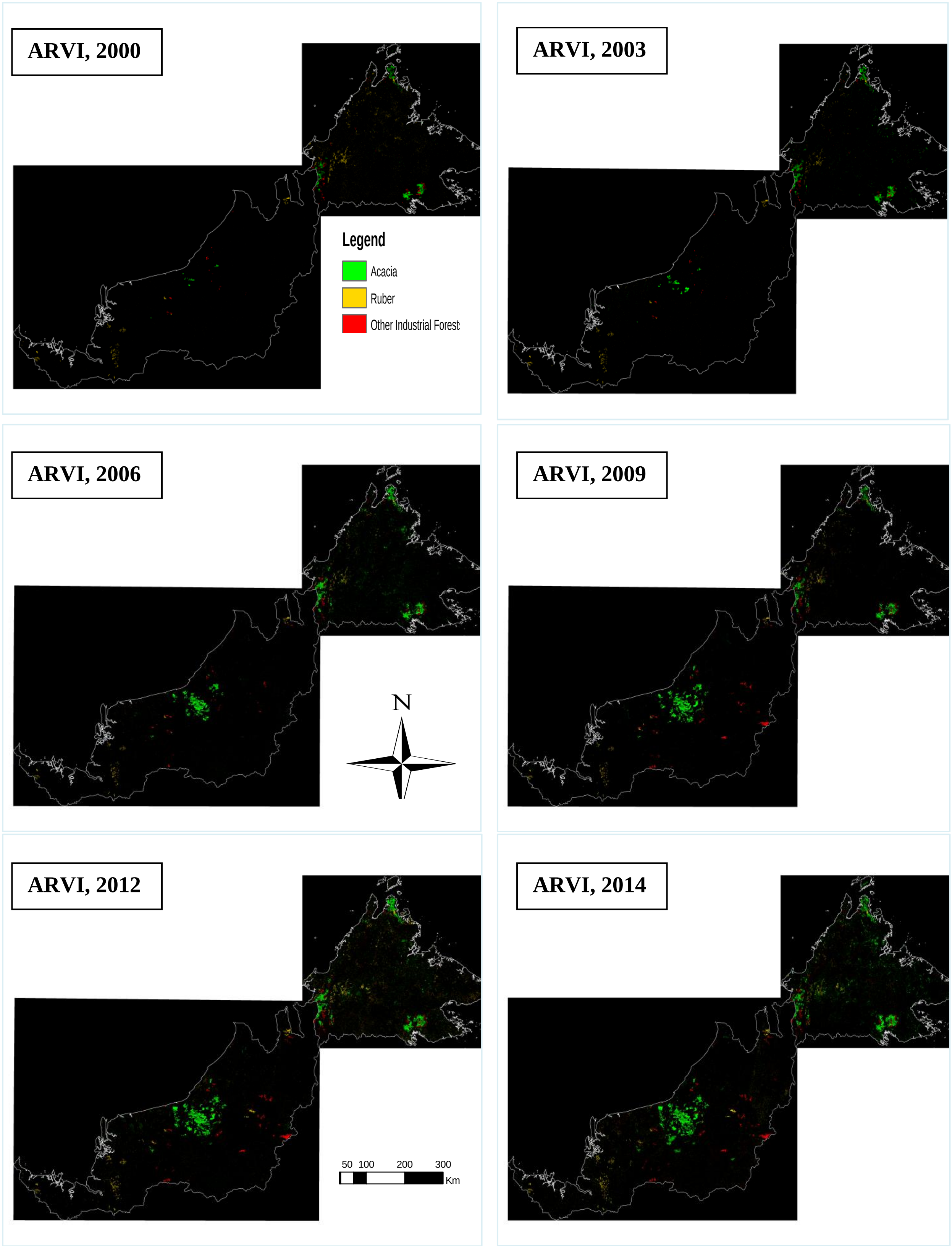


Figure 2.33. The ARVI-based industrial forest maps in Sabah and Sarawak, 2000-2014.

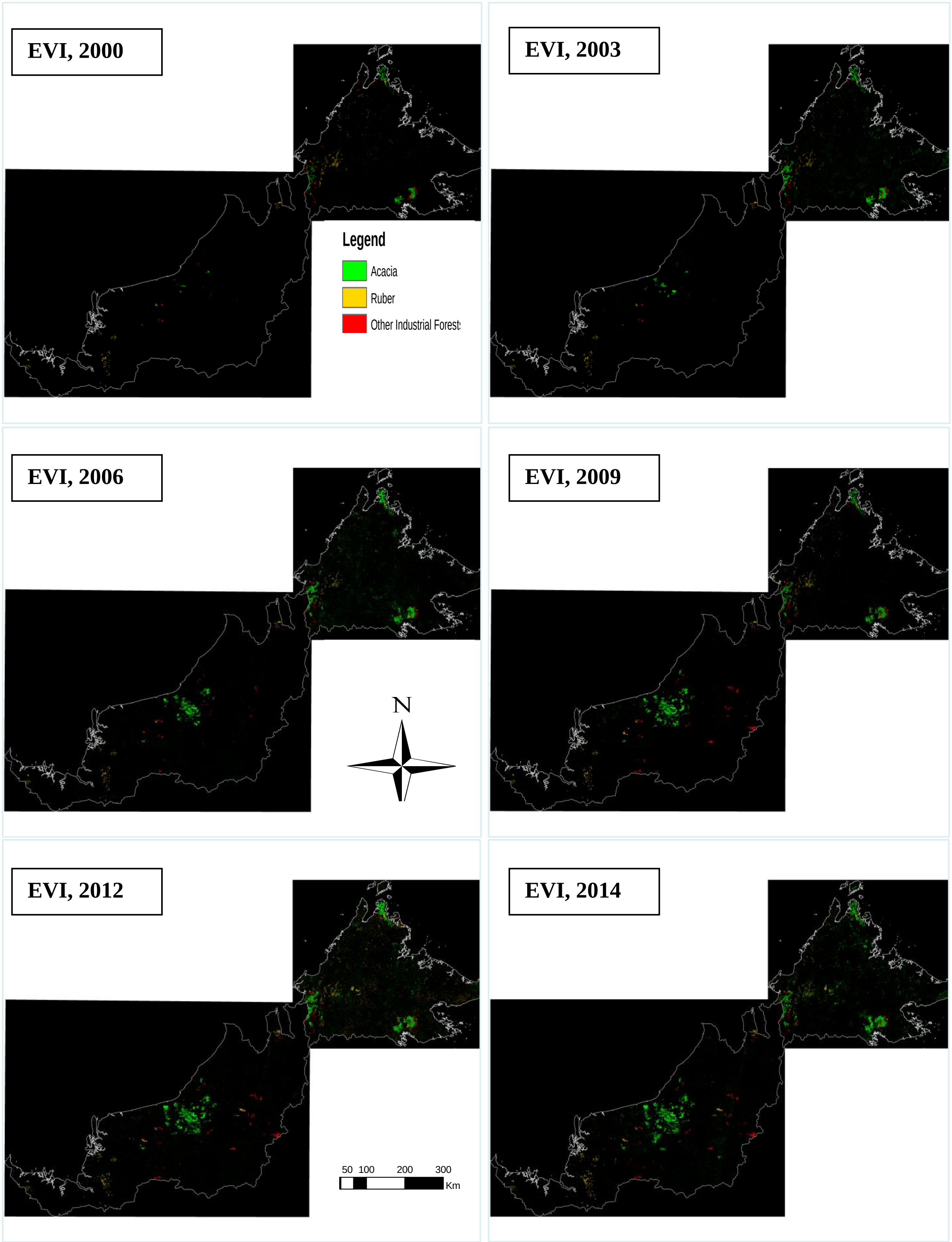


Figure 2.34. The EVI-based industrial forest maps in Sabah and Sarawak, 2000-2014.

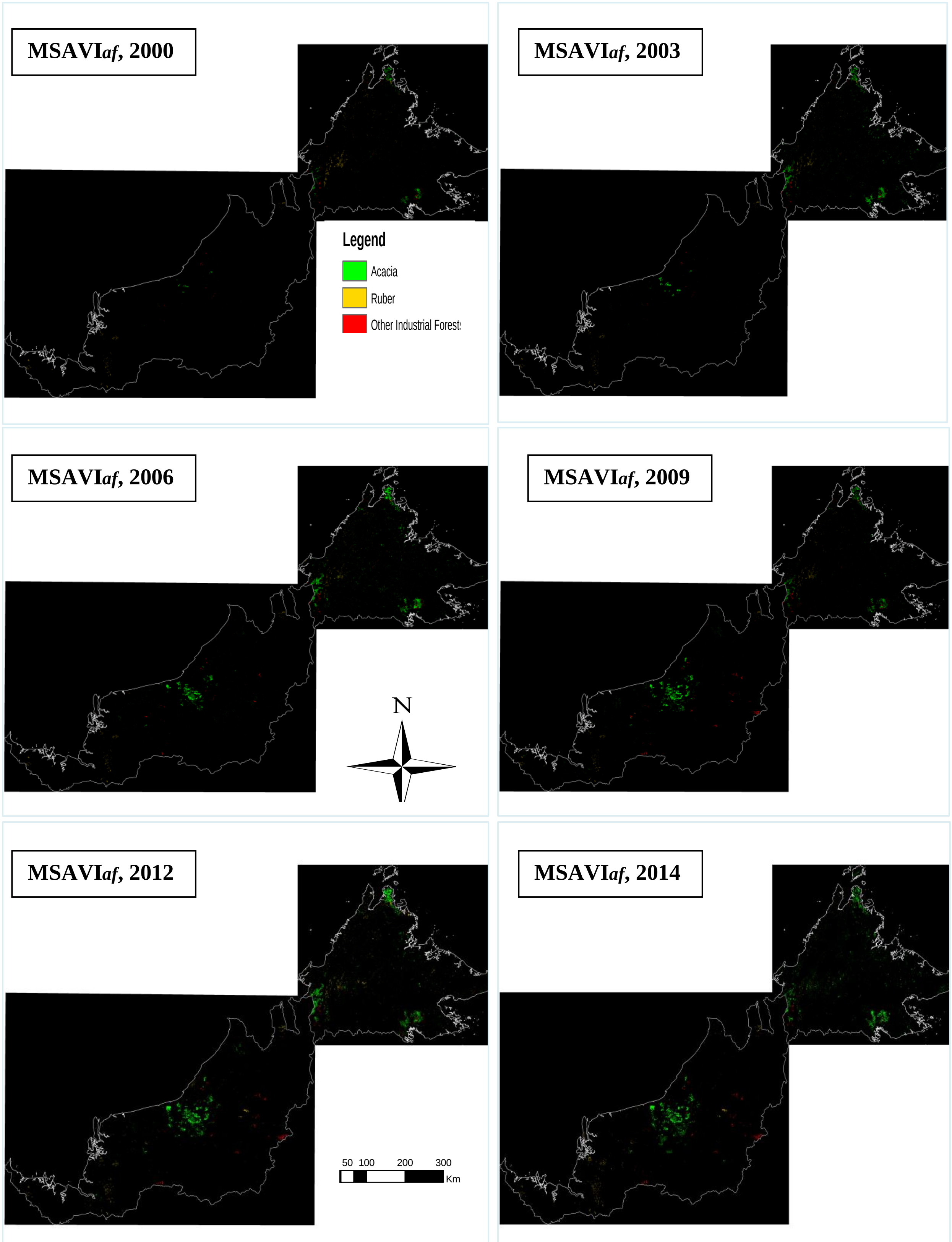


Figure 2.35. The MSAVI*af*-based industrial forest maps in Sabah and Sarawak, 2000-2014.

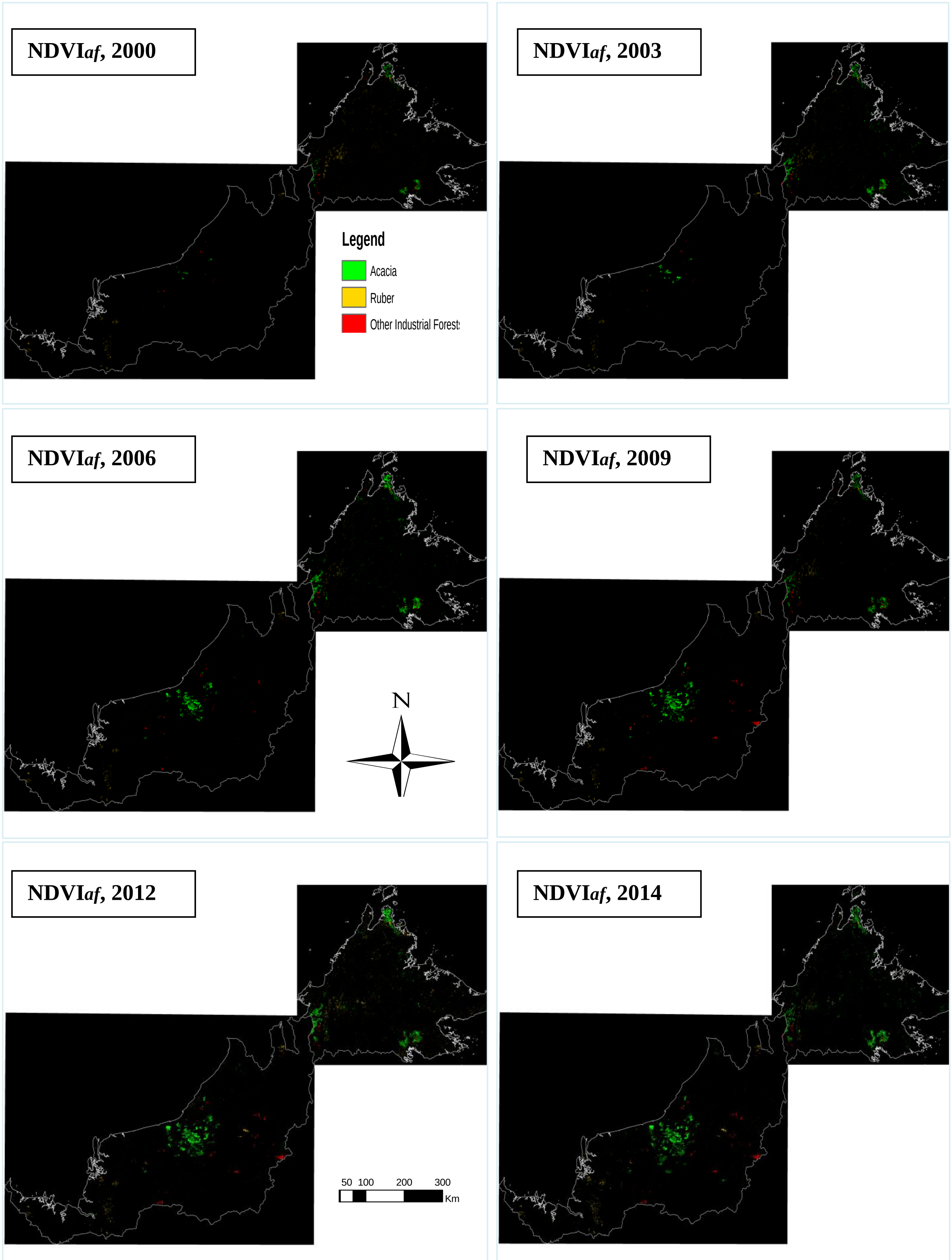


Figure 2.36. The NDVI*af*-based industrial forest maps in Sabah and Sarawak, 2000-2014.

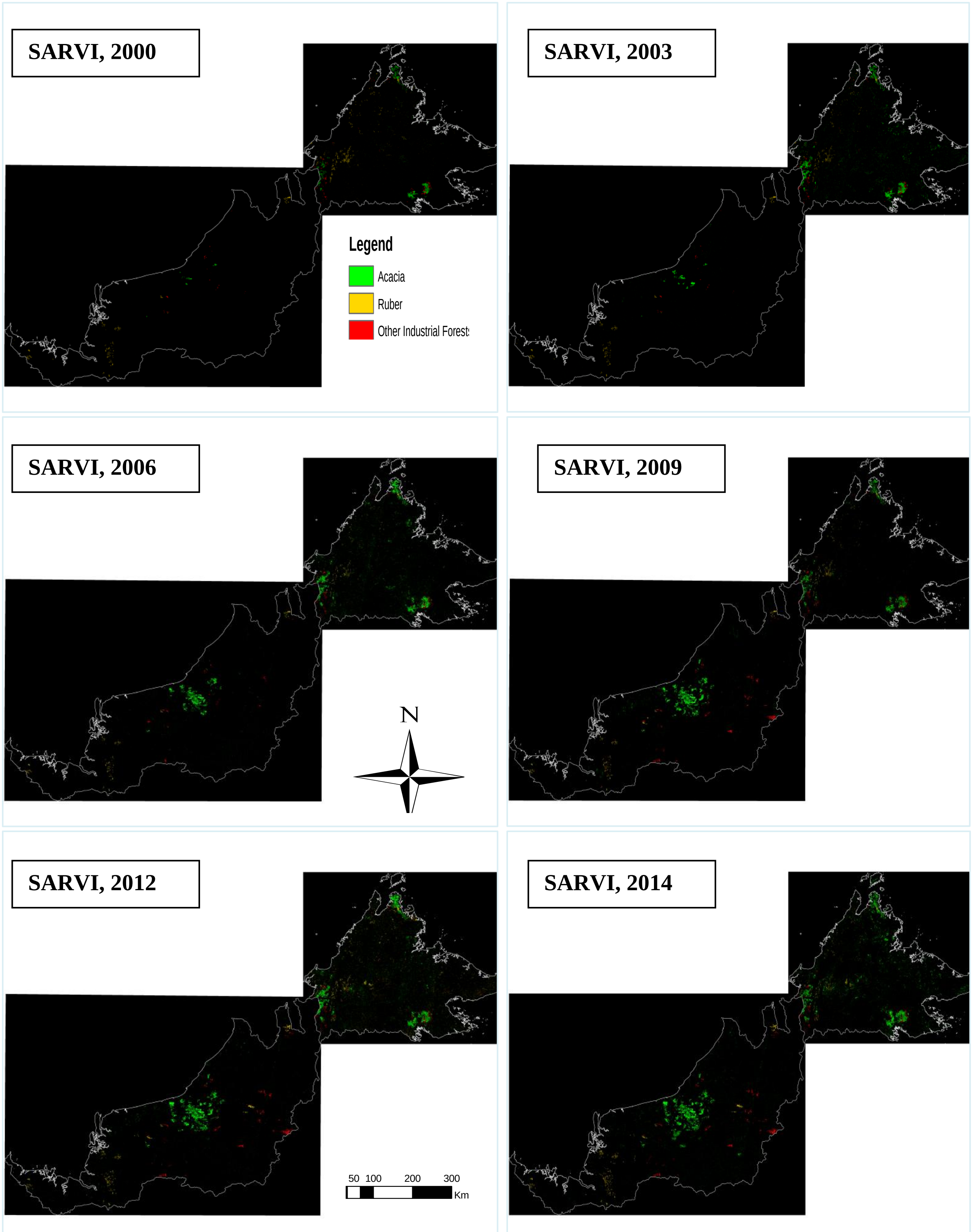


Figure 2.37. The SARVI-based industrial forest maps in Sabah and Sarawak, 2000-2014.

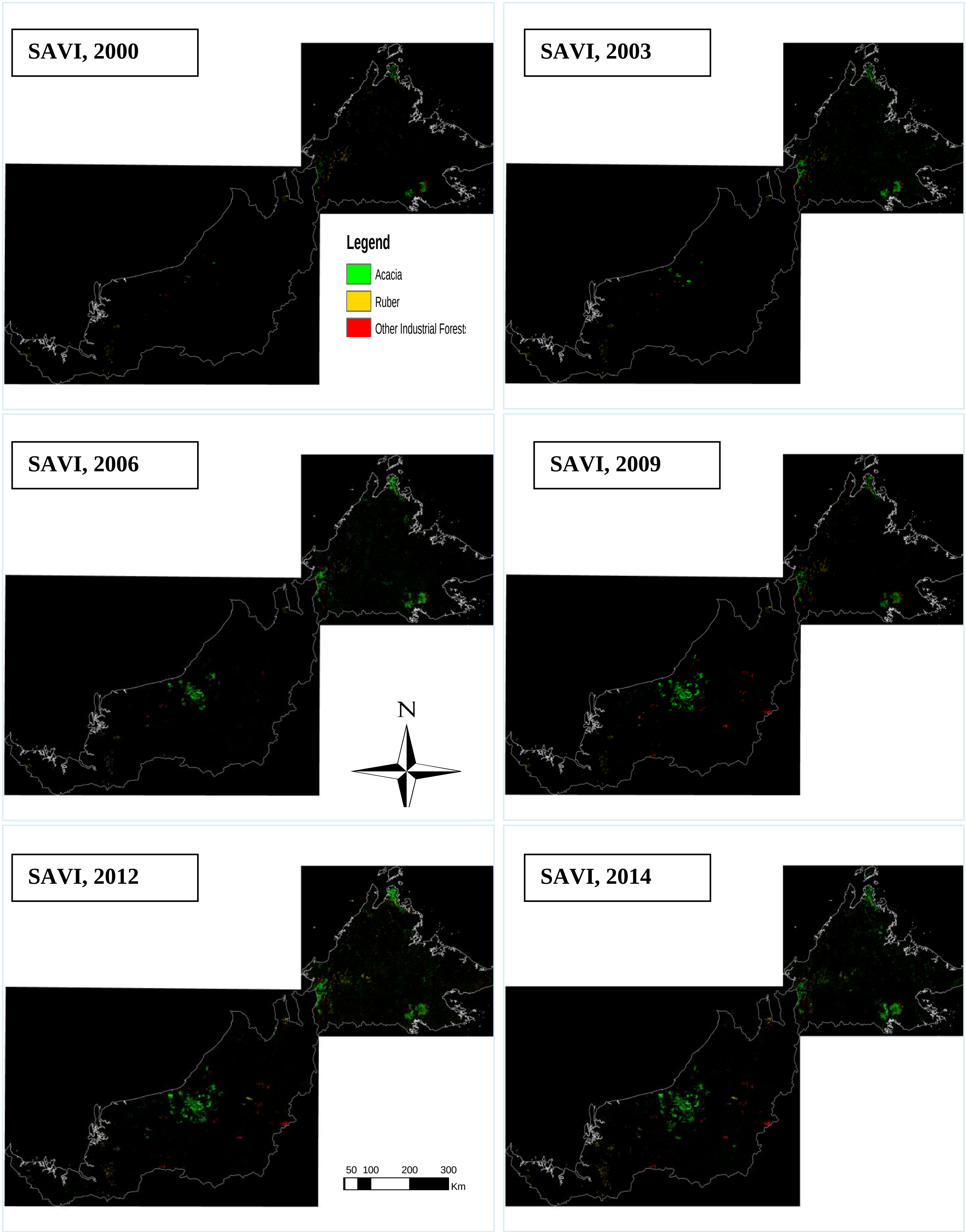


Figure 2.38. The SAVI-based industrial forest maps in Sabah and Sarawak, 2000-2014.

2.4 Validation

The validation work for the VIs-based IF detection method in the Landsat datasets was conducted through the use of very high resolution imagery data. Specifically, two high resolution imagery scenes in each state were randomly selected based on the following conditions: (1) the location must contain the significant IF area and various LULC types, (2) the availability of the scenes close to the date or at least in the same year to the Landsat-derived IF maps, (3) the quality of the scene including cloud coverage less than 20% and off-nadir less than 25^0. Finally, the two scenes in each state were selected (Figure 2.39). The details of the selected scenes are presented in the Appendices (Tables A.12 & A.13). Then, a procedure for the validation was developed as follows:

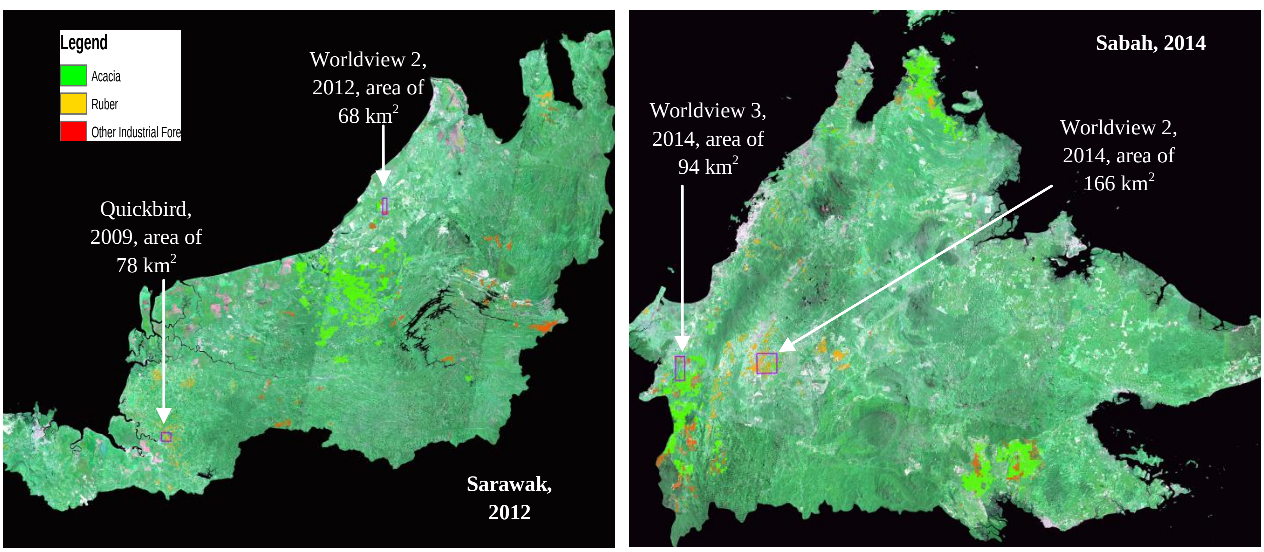


Figure 2.39. The locations, areas, years, and sensors of the high resolution imagery scenes used to validate the Landsat-derived IF maps in Sabah and Sarawak.

- Clipping the Landsat-derived IF maps at the same locations and years as the high resolution imagery data (called the classified IF maps).
- Calculating the number of samples based on the area proportion of the IF land versus non IF land. Congalton (1991) recommended taking 50 samples for each LU class for the area

less than 0.5 Mha. In this study, the Landsat-derived IF maps were classified into the IF land (including acacia, rubber, and other IFs) and non IF land. Therefore, totally, 200 samples were taken.

- Creating the point shapefiles and randomly locating the samples in each class (randomly stratified sampling) in the clipped Landsat-derived IF maps. The sample locations had to be relatively evenly distributed in the class, as presented in the Appendices (Figures A.20, A.21, A.23, A.24, & A.25).
- Classifying the high resolution imagery data into the IF maps (called the referenced IF maps) based on the visual interpretation approach.
- Converting both the classified and referenced IF maps from vector data into raster data.
- Using the combine tool in the ArcGIS software to acquire the accuracy of two maps.
- Exporting the data into excel to compute and report the accuracy in the confusion matrices, including overall accuracy, user's and producer's accuracy or omission and commission errors, map accuracy, and Kappa coefficient.

The accuracy assessment was first conducted for the IF land versus non IF land to see how the developed method and algorithms could separate the lands. Then, it was scaled down to the finer IF classes specific for acacia, rubber, and other IFs. The results of assessing accuracy at the coarser scale indicated that the ARVI-based IF map best separated the IF land versus non IF land, generally followed by the SAVI, SARVI, EVI, $NDVI_{af}$ and $MSAVI_{af}$-based IF maps (Table 2.3). In other words, ARVI worked the best in detecting the IF land in the regions, followed by SAVI, SARVI, EVI, $NDVI_{af}$ and $MSAVI_{af}$. Specifically, the user's accuracy for IFs of the ARVI-based product was 44%, slightly different, compared to 44% for EVI, 41% for SAVI, 39% for SARVI, and 36% for $NDVI_{af}$ and 34% for $MSAVI_{af}$. Consistently, the ARVI's commission error was least (56%), followed by EVI (56%), SAVI (59%), SARVI (61%), NDVI$_{af}$ (64) and MSAVI$_{af}$ (66%).

Table 2.3. The accuracy assessment results for ARVI, EVI, MSAVI$_{af}$, NDVI$_{af}$, SARVI, and SAVI-based IF land detection methods for Landsat data.

ARVI

Classified	Referenced LULC		
	IFs	Non IFs	Total
IF land	21	27	48
Non IF land	12	140	152
Total	33	167	200
Overall Accuracy			81%
User's Accuracy	44%	92%	
Producer's Accuracy	64%	84%	
Omission Error	36%	16%	
Commission Error	56%	8%	
Map Accuracy	35%	78%	
Kappa Coefficient	(moderate agreement)		0.40

EVI

Classified	Referenced LULC		
	IFs	Non IFs	Total
IF land	17	22	39
Non IF land	21	140	161
Total	38	162	100
Overall Accuracy			79%
User's Accuracy	44%	87%	
Producer's Accuracy	45%	86%	
Omission Error	55%	14%	
Commission Error	56%	13%	
Map Accuracy	28%	77%	
Kappa Coefficient	(fair agreement)		0.31

MSAVI$_{af}$

Classified	Referenced LULC		
	IF s	Non IFs	Total
IF land	10	19	29
Non IF land	20	151	171
Total	30	170	200
Overall Accuracy			81%
User's Accuracy	34%	88%	
Producer's Accuracy	33%	89%	
Omission Error	67%	11%	
Commission Error	66%	12%	
Map Accuracy	20%	76%	
Kappa Coefficient	(fair agreement)		0.22

NDVI$_{af}$

Classified	Referenced LULC (ha)		
	IF s	Non IFs	Total
IF land	9	16	25
Non IF land	19	156	175
Total	28	172	200
Overall Accuracy			83%
User's Accuracy	36%	89%	
Producer's Accuracy	32%	91%	
Omission Error	68%	9%	
Commission Error	64%	11%	
Map Accuracy	20%	82%	
Kappa Coefficient	(fair agreement)		0.24

SARVI

Classified	Referenced LULC		
	IF s	Non IFs	Total
IF land	14	22	36
Non IF land	16	148	164
Total	30	170	200
Overall Accuracy			81%
User's Accuracy	39%	90%	
Producer's Accuracy	47%	87%	
Omission Error	53%	13%	
Commission Error	61%	10%	
Map Accuracy	27%	80%	
Kappa Coefficient	(fair agreement)		0.31

SAVI

Classified	Referenced LULC		
	IF s	Non IFs	Total
IF land	13	19	32
Non IF land	16	152	168
Total	29	171	200
Overall Accuracy			83%
User's Accuracy	41%	90%	
Producer's Accuracy	45%	89%	
Omission Error	55%	11%	
Commission Error	59%	10%	
Map Accuracy	27%	81%	
Kappa Coefficient	(fair agreement)		0.32

For the IF land producer's accuracy, it also showed the highest in the ARVI-based product (64%), followed by SARVI (47%), EVI (45%), SAVI (45%), MSAVI$_{af}$ (33%) and NDVI$_{af}$ (32%) to the same was found for the omission error for ARVI (36%), SARVI (53%), EVI (55%), SAVI (55%), MSAVI$_{af}$ (67%) and NDVI$_{af}$ (68%). For the map accuracy of IF land and Kappa coefficient - which were more reliable and useful in comparing the accuracy of maps - their values indicated the highest at 35% and 0.4, respectively, in the ARVI-based product, followed by SAVI (27% & 0.32), EVI (28% & 0.31), SARVI (27% & 0.31), NDVI$_{af}$ (20% & 0.24), and MSAVI$_{af}$ (20% & 0.22), respectively (Table 2.3). In other words, the value of Kappa coefficient of ARVI (0.4) showed a moderate agreement (0.4-0.6) by chance of the IF land between the classified and referenced IF maps, while the values of this statistic index in the SAVI (0.32), SARVI and EVI (0.31), and NDVI$_{af}$ (0.24) and MSAVI$_{af}$ (0.22) indicated a fair agreement (0.2-0.4). For the overall accuracy index, which took both the IF land and non IF land into account and was probably least used in the accuracy assessment, it showed a slight difference between the VIs-based products from 79% for EVI, 81% for ARVI, SARVI, and MSAVI$_{af}$ to 83% for NDVI$_{af}$ and SAVI.

Next, considered the accuracy scaled down to the specific IF systems to see how and which VI worked the best in detecting the IF systems in the region. In general, similar to that described above for the detection of the IF land versus non IF land, ARVI continued to work the best, followed by SAVI, SARVI, EVI, NDVI$_{af}$ and MSAVI$_{af}$ (Table 2.4). The assessment results showed that the accuracy for each VI index (ARVI, EVI, SARVI, SAVI, NDVI$_{af}$ and MSAVI$_{af}$) in detecting the selected IF systems was different. In general, the accuracy for detecting acacia IFs was larger than that for rubber and other IFs in ARVI, while the accuracy for detecting rubber IFs was larger than that for acacia and other IFs in the remaining VIs. In particular, in all

Table 2.4. The accuracy assessment results specific for acacia, rubber, and other IFs for ARVI, EVI, $MSAVI_{af}$, $NDVI_{af}$, SARVI, and SAVI-based IF detection methods for Landsat data.

ARVI

Classified	Referenced LULC				
	Acacia	Other IFs	Rubber	Non IFs	Total
Acacia	8	0	0	8	16
Other IFs	0	2	0	4	6
Rubber	0	0	11	15	26
Non IFs	3	2	7	140	152
Total	11	4	18	167	200
Overall Accuracy					81%
User's Accuracy	50%	33%	42%	92%	
Producer's Accuracy	73%	50%	61%	84%	
Omission Error	27%	50%	39%	16%	
Commission Error	50%	67%	58%	8%	
Map Accuracy	42%	25%	33%	78%	
Kappa Coefficient	(moderate agreement)				0.44

EVI

Classified	Referenced LULC				
	Acacia	Other IFs	Rubber	Non IFs	Total
Acacia	6	0	0	9	15
Other IFs	0	1	1	4	6
Rubber	0	0	9	13	22
Non IFs	4	2	11	140	157
Total	10	3	21	166	200
Overall Accuracy					78%
User's Accuracy	40%	17%	41%	89%	
Producer's Accuracy	60%	33%	43%	84%	
Omission Error	40%	67%	57%	16%	
Commission Error	60%	83%	59%	11%	
Map Accuracy	32%	13%	27%	77%	
Kappa Coefficient	(fair agreement)				0.34

$MSAVI_{af}$

Classified	Referenced LULC				
	Acacia	Other IFs	Rubber	Non IFs	Total
Acacia	3	0	0	7	10
Other IFs	0	1	0	3	4
Rubber	0	0	6	9	15
Non_IFs	9	2	9	151	171
Total	12	3	15	170	200
Overall Accuracy					81%
User's Accuracy	30%	25%	40%	88%	
Producer's Accuracy	25%	33%	40%	89%	
Omission Error	75%	67%	60%	11%	
Commission Error	70%	75%	60%	12%	
Map Accuracy	16%	17%	25%	79%	
Kappa Coeficient	(fair agreement)				0.26

$NDVI_{af}$

Classified	Referenced LULC (ha)				
	Acacia	Other IFs	Rubber	Non IFs	Total
Acacia	3	0	0	6	9
Other IFs	0	1	0	3	4
Rubber	0	0	5	7	12
Non_IFs	8	3	8	156	175
Total	11	4	13	172	200
Overall Accuracy					83%
User's Accuracy	33%	25%	42%	89%	
Producer's Accuracy	27%	25%	38%	91%	
Omission Error	73%	75%	62%	9%	
Commission Error	67%	75%	58%	11%	
Map Accuracy	18%	14%	25%	82%	
Kappa Coeficient	(fair agreement)				0.27

SARVI

Classified	Referenced LULC				
	Acacia	Other IFs	Rubber	Non_IFs	Total
Acacia	5	0	0	9	14
Other IFs	0	1	0	5	6
Rubber	0	0	8	8	16
Non_IFs	6	0	10	148	164
Total	11	1	18	170	200
Overall Accuracy					81%
User's Accuracy	36%	17%	50%	90%	
Producer's Accuracy	45%	100%	44%	87%	
Omission Error	55%	0%	56%	13%	
Commission Error	64%	83%	50%	10%	
Map Accuracy	25%	17%	31%	80%	
Kappa Coeficient	(fair agreement)				0.35

SAVI

Classified	Referenced LULC				
	Acacia	Other IFs	Rubber	Non IFs	Total
Acacia	6	0	0	8	14
Other IFs	0	1	0	3	4
Rubber	0	0	6	8	14
Non_IFs	5	0	11	152	168
Total	11	1	17	171	100
Overall Accuracy					83%
User's Accuracy	43%	25%	43%	90%	
Producer's Accuracy	55%	100%	35%	89%	
Omission Error	45%	0%	65%	11%	
Commission Error	57%	75%	57%	10%	
Map Accuracy	32%	25%	24%	81%	
Kappa Coeficient	(fair agreement)				0.36

VIs-based products, the accuracy for predicting, detecting, and mapping other IFs was least. For acacia IFs, ARVI showed that it worked the best with the user's and producer's accuracy at 50% and 73%, followed by SAVI at 43% and 55%, EVI at 40% and 60%, SARVI at 36% and 45%, $NDVI_{af}$ at 33% and 27%, and $MSAVI_{af}$ at 30% and 25%, respectively. Whereas, for rubber IFs, the user's and producer's accuracy was found the highest in SARVI product at 50% and 44%, followed by 43% and 35% for SAVI, ARVI (42% & 61%), $NDVI_{af}$ (42% & 38%), EVI (41% and 43%), and $MSAVI_{af}$ (40% and 40%, respectively; Table 2.4). Consistent with the user's and producer's accuracy was the commission and omission error. For instance, the commission and omission error for acacia IFs was lowest in the ARVI-based product at 50% and 27%, followed by SAVI (57% & 45%), EVI (60% & 40%), SARVI (64% & 55%), $NDVI_{af}$ (67% & 73%), and $MSAVI_{af}$ (70% & 75%, repectively; Table 2.4).

For the map accuracy, it also showed that the accuracy of acacia IFs was better than that of rubber IFs in the ARVI, EVI, and SAVI-based products, and the highest accuracy for acacia was found in the ARVI (42%), followed by EVI and SAVI (32%), SARVI (25%), $NDVI_{af}$ (18%) and $MSAVI_{af}$ (16%). The accuracy in detecting and mapping rubber IFs was slightly different: it showed the highest accuracy in ARVI (33%), followed by SARVI (31%), EVI (27%), $MSAVI_{af}$ and $NDVI_{af}$ (25%), and SAVI (24%). Meanwhile, for other IFs detection, it reached the highest accuracy for ARVI and SAVI-based products at 25%, followed by SARVI and $MSAVI_{af}$ at 17%, $NDVI_{af}$ at 14%, and EVI at 13% (Table 2.4).

Lastly, the Kappa statistical coefficient general for detecting and mapping the specific IF systems was found the highest in the moderate agreement in ARVI (0.44); then SAVI (0.36), SARVI (0.35) and EVI (0.34), and the least was in $NDVI_{af}$ and $MSAVI_{af}$ at 0.27 and 0.26, respectively, at the fair agreement (Table 2.4).

2.5 Discussions and Conclusions

The above study results showed a possibility of using the vegetation indices (specifically ARVI, EVI, $MSAVI_{af}$, $NDVI_{af}$, SARVI, & SAVI) analysis in a time series to detect and map industrial forests in the tropics, and that the index that worked the best in the region was ARVI. In other words, the most accurate index for detecting the industrial forests in Sabah and Sarawak, Malaysia in this study was ARVI, followed by SAVI, SARVI, EVI, $NDVI_{af}$, and $MSAVI_{af}$. However, the accuracy assessment results of this method found that their accuracies by using different VIs were at the fair and moderate level. The accuracy of detecting of acacia IFs was the best in ARVI, followed by rubber and other IFs in this index; while the other VIs including SAVI, SARVI, EVI, $NDVI_{af}$, and $MSAVI_{af}$ showed that their ability in detecting rubber plantations was higher than that for detecting acacia and other IFs. For detecting the other IFs, it showed the least accuracy in all VIs. This could be because this kind of IFs was very diverse, including all other types of IFs in the region, such as teak, pine, eucalypt, and other timber species. Therefore, detecting this kind of IFs was extremely challenging and much more difficult than the homogenous acacia and rubber plantations in the regions. Besides, the lower accuracy of the VIs-based method probably came from the following facts, difficulties, and challenges.

The first challenging issue in developing the VIs-based method to detect industrial forests came from the Landsat data itself. The Landsat scenes were very notorious for the effects of cloud contaminations, their shadows, haze, and missing values in the Landsat 7 (ETM+ SLC off). In other words, the quality of the Landsat scenes greatly influenced the ability to detect an IF. The mosaics - or use of a large amount of Landsat scenes to fill the gaps created by cloud problems and the missing values in Landsat 7 in the different times, different sensors, and different quality - may have also resulted in the changes of LULC, rather than the LULCC themselves in reality. This definitely caused difficulties and challenges in detecting IFs in particular and classifying LULC types in general.

The second challenging issue this study faced came from the ideas used to develop the method to detect IFs. As described above, the first assumption used in this study to detect IFs was based on their silvicultural rotations. However, there was the fact that it was impossible to monitor the full cycles of sawlog long-rotation IFs such as teak, rubber, and pine. The rotation of these sawlog IF systems could take tens of years, and we could not take annual Landsat datasets long enough to observe them. Also, clearing was possibly not based on silviculture. Moreover, the silvicultural rotation of an IF system or species also varied greatly depending on the purpose of using it. Even for the same purpose of using it, its rotation might also vary depending on the intention and economic considerations of the owners, as well as the market's availability and other factors. For instance, in Thailand, a pulpwood eucalyptus stand could last as short as five years or as long as ten years. In the case that the eucalyptus stand is destined for producing saw logs, it could last tens of years. The same thing was also found for the acacia IFs in the study area: they could last 7 years to more than 10 years for pulpwood production. Therefore, using the silvicultural rotation to detect the specific IFs in these cases was challenging. Besides, almost all of the IFs would have been subjected to the silvicultural practices, including thinning and pruning activities. It was possible that we could misclassify these IF stands as a new rotation as well.

For the use of the growth rates of VI values to detect IFs, the fact was that we could detect the faster- versus slower-growing IF species or systems. However, the growth rate of an IF system might also depend on the soil and climate conditions, and silvicultural practices. It was possible that a slower-growing IF species planted in a good soil (good site-species matching) and exposed to proper silvicultural practices could grow the stand faster than a fast-growing IF species established in a poor condition.

In regard to using the textural analysis as a support step in detecting IFs, although the textures of an IF stand was principally different from other natural vegetations, we could easily realize them in a fine scale image. However, in the medium-resolution satellite imagery data like Landsat, it was also very challenging. How well this analysis worked may be dependent on how well we chose the training areas to be used as the references in classifying IFs in images. In addition, for spectral analysis, the fact was that the spectra were also very similar among different vegetation cover types and different IF systems. Therefore, it was also very challenging to work on this analysis. For example, oil palm - which was one of the most dominating plantations in the region - had very similar spectra and texture to the selected IFs. Consequently, separating them was very difficult. One of the best possible ways we had was to select the training area well enough to represent the typical values for the expected land use and land cover in the region. This may involve dividing the region into the smaller areas and for different kinds of Landsat scenes such as Landsat 4-5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). Our best option was to build a good spectral library well representative of the different IF systems in the different times, different types of images, and different stages of an IF stand.

Lastly, visual interpretation was a very subjective method, and it was dependent on the knowledge and experience of interpreters. It also relied on the quality of the other LULC sources that we would use to identify the IFs in the images. All of these things in combination created difficulties and challenges in detecting IFs in Landsat datasets.

In brief, it was possible for us to develop and use a vegetation indices analysis-based method for Landsat datasets that could detect, map, and monitor the area, expansion rate, patterns, and scale of IFs in the tropics. The study results showed that ARVI worked the best in the region, followed by SAVI, SARVI, EVI, $NDVI_{af}$, and $MSAVI_{af}$. The accuracy of detecting the acacia IFs was the best, followed by rubber plantations, while the other IFs showed the least accuracy in the method. Although there is still much that can be done to improve the accuracy of this method, it opened a new, innovative, and promising approach in methods development to detect and map new industrial forests in the tropical regions.

The development of the VIs-based IF detection method for Landsat data in Sabah and Sarawak was very challenging because these areas are very notorious for cloud contamination and haze. As a result, this method had to process as many as 600 images for 6 points in time from 2000 to 2014 to handle problems created by clouds, their shadows, and haze.

Moreover, the most challenging issue this method had to face and deal with was the spectral and textural similarity among different land use and land cover types, as well as the spectral and textural variability in the same land use and land cover class. Additionally, there was the added variable of the rotation and growth rate of an IF normally involved the silvicultural practice activities such as thinning and pruning, and soil condition. These activities and conditions may result in challenges in developing a VIs-based method to detect and map IFs.

CHAPTER 3

DEVELOPING THE VEGETATION/FOREST FRACTIONAL COVER-BASED INDUSTRIAL FOREST DETECTION METHOD FOR LANDSAT DATASETS

3.1 Introduction

The second approach used in this study to develop a method to detect, map, and monitor new industrial forests in the study area is a vegetation/forest fractional cover changes analysis in a time series. In forestry, remote sensing (RS) tools are most well-known for their applications for studying, quantifying, and monitoring deforestation, and other changes in forest land uses and land covers over a long period of time (*e.g.*, Skole & Tucker, 1993).

Recently, many researchers (*e.g.,* Bateson *et al.,* 2000; Sousa *et al.,* 2005) have successfully developed and applied RS methods in identifying and quantifying forest degradation. These methods, mainly developed based on the continuous-field analysis (also called spectral mixture analysis or spectral endmembers analysis), are very different from the conventional RS methods, in which each pixel of images is assigned one and only one value of a land cover or land use type (*e.g.,* forest or water). Among RS studies on forest degradation, the most remarkable is the Global Observatory Center for Ecosystem Services (the GOES lab/center) at Michigan State University in the USA, which has very successfully developed and published methods for the detection and quantification of selective logging and forest degradation in Amazon tropical forests based on Landsat datasets (*e.g.,* Matricardi *et al*., 2013; Matricardi *et al*., 2010; Matricardi *et al.,* 2007; Matricardi *et al.,* 2005; Wang *et al.,* 2005; Skole *et al.,* 2004). These methods were also developed based on a spectral mixture analysis in combination with visual interpretation to quantify the forest fractional cover. In other words, these authors had used spectral endmembers analysis that produced a forest fractional cover dataset. This, in turn, could be used to identify where in forests there has been logging and degrading (Skole *et al.*, 2013). The basic principles of this method are that each pixel can contain one or more land use/land cover types, and that we can extract, analyze, and estimate the proportion and composition of each land cover type in that pixel based on its spectral composition analysis.

This study would also take the same approach as the above-mentioned studies. That is, it would use spectral mixture analysis to estimate the proportion of vegetation fractional cover in each pixel based on its spectral endmembers characteristics. A spectral endmember is a pure spectrum representing a land cover type (*e.g.*, forest) and used as a reference to determine the spectral composition of mixed pixels. As explained by Skole *et al.* (2013), Landsat data would be processed to present forest fractional cover, *f*C, a continuous-field algorithm. A threshold value of *f*C was used to define forest (upper threshold, high *f*C) and non-forested areas (lower threshold, low *f*C). Values in *f*C in the interval between the upper and lower thresholds would be used to detect IFs. This initial detection would be calibrated by using textural analysis, spectral analysis, visual interpretation, and other analyses based on typical characteristics and properties of IFs, as well as ancillary data.

3.2. Acquiring and Preprocessing Images

Similar to the above VIs-based IF detection method, this method would also use the same preprocessed Landsat dataset. That is, the Landsat scenes have been already converted from DN to top-of-atmosphere reflectance, calibrated for the atmospheric effects to present surface reflectance, processed clouds and their shadows, filled the gaps of no data, and dehazed. More details on how this Landsat dataset was selected, acquired, and preprocessed were presented in the Section 2.2, Chapter 2 above.

3.3. Developing the Method

3.3.1 General Principles

In general, the approach for this method is similar to the above VIs-based IF detection method. However, it is developed based on the changes of vegetation fractional cover or the silvicultural cycles of clearing and regrowth of vegetation cover, as opposed to being based on the VIs value changes. In other words, it further examines the planting and harvesting cycles of a tree plantation - which are typical for an industrial forest stand - based on how its fractional cover has been changed over time. This vegetation fractional cover analysis method would be generally called the forest fractional cover (*f*C) method, and it was built based on the following assumptions:

- The cycle of increasing and reducing the vegetation coverage fraction (*f*C) possibly indicates the silvicultural cycle of clearing and regrowth, or the harvesting and planting cycle, which is typical for an IF stand.
- The time span for the planting and harvesting cycle of a tree plantation could indicate the shorter (≤ 7 years) *vs.* longer rotation (> 7 years).
- The rate of increasing the coverage (*f*C value) of an industrial forest stand may be an indicator for faster growing *vs.* slower growing species.
- The different vegetation cover types, in general, and industrial forests in particular, can get the same coverage (or the same *f*C value), but their green biomass content and leaf area index may be different (*e.g.*, closed forest *vs.* timber plantation *vs.* oil palm *vs.* agricultural land).
- The different vegetation covers may have different image texture and spectra.

The procedure for developing the Landsat-based IF detection method by using vegetation/forest factional cover analysis to transform the preprocessed images into final IF maps is described (Figure 3.1).

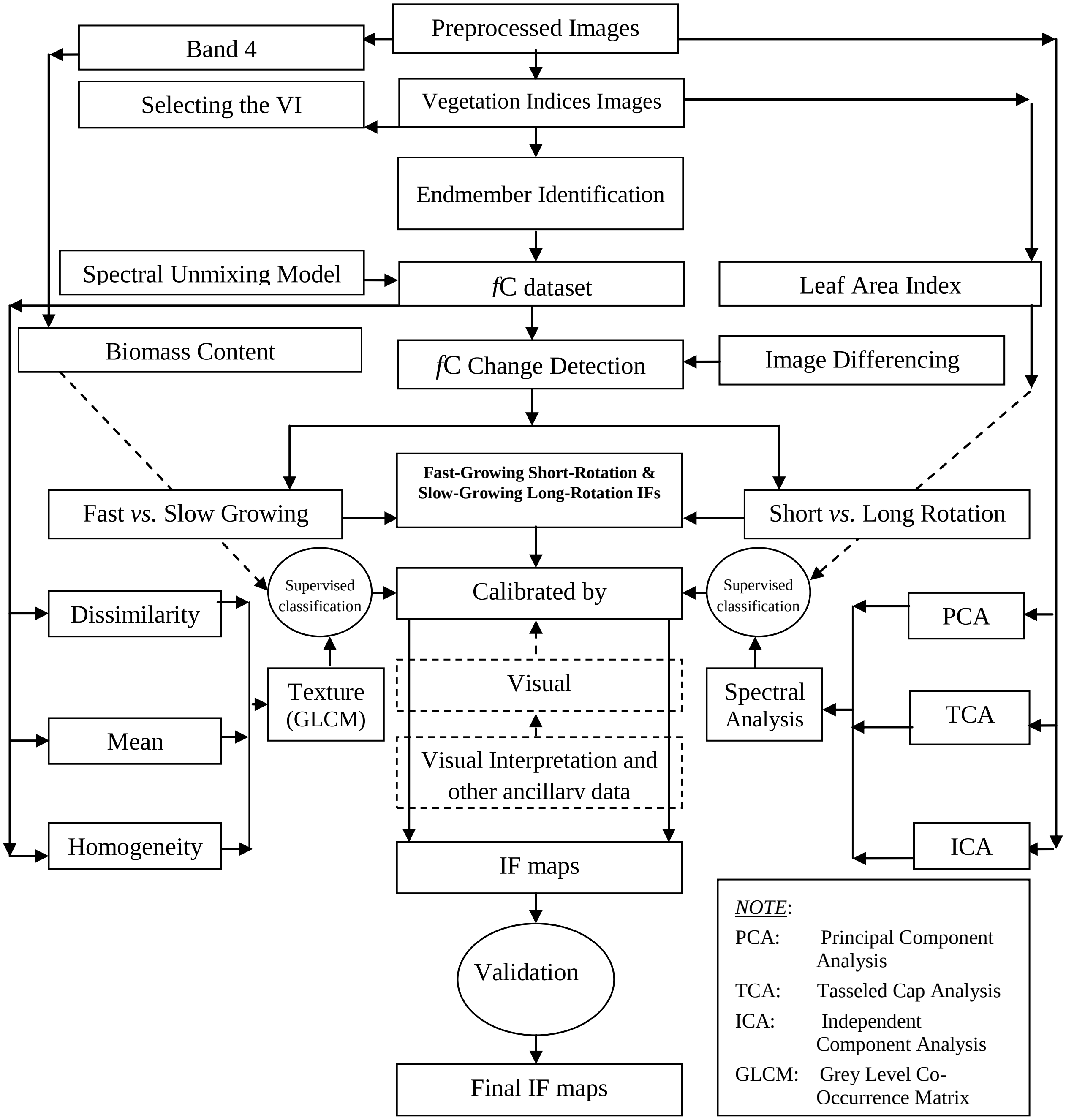


Figure 3.1. The flowchart of development for the forest factional cover (*f*C)-based IF detection method.

3.3.2 Results

First, a test was completed for vegetation indices consisting of ARVI, EVI, MSAVI*af*, NDVI*af*, SARVI, and SAVI to see which index was the best for further *f*C analysis. The results of this test showed that the MSAVI*af* performed the best in terms of reducing the atmospheric and soil effects (Figure 3.2). Thus, this MSAVI*af* index would be used for producing *f*C datasets. Moreover, some *f*C studies (*e.g.*, Matricadi *et al.*, 2010) also found this index worked well in the humid tropic environment and recommended using it. This MSAVI*af* index, adapted from Matricadi *et al.* (2010), would be calculated for all preprocessed Landsat images.

$$\boldsymbol{MSAVI}\ af = \frac{(1 + \mathrm{L})(\mathrm{NIR} - 0.5\ \mathrm{SWIR})}{\mathrm{NIR} + 0.5\ \mathrm{SWIR} + \mathrm{L}}$$

and $\mathbf{L} = [\ (\mathrm{NIR} - 0.5\ \mathrm{SWIR})*s + 1 + \mathrm{NIR} + 0.5\ \mathrm{SWIR}\ ]^2 - 8*s*(\mathrm{NIR} - 0.5\ \mathrm{SWIR})$

Where s = 1.2 (slope of the soil line)

From the MSAVI*af* products, two spectral endmembers - namely, bare soil/land and closed canopy forest - would be created and extracted from the images based on image examinations using the AOI (*area of interest*) tool in the ERDAS (Figure 3.3) and histogram analysis (Somer *et al.*, 2011). The identification of bare soils/lands and closed canopy forests in the images was quite easy based on their texture, color, position, association, *etc*. For instance, in the dehazed natural color images, closed forests appeared dark green in the large area, normally associated with mountains. While the white and bright areas indicated bare lands or soils. In addition to these visual interpretation keys, other LULC sources were also used to confirm this identification. To calculate the representative value of bare land and fully forested endmembers in the study area, five and six AOIs were created in Sabah and Sarawak respectively for closed forest and bare land to obtain their endmember values. The value of bare land and fully forested endmembers for the areas were mean values of these AOIs.

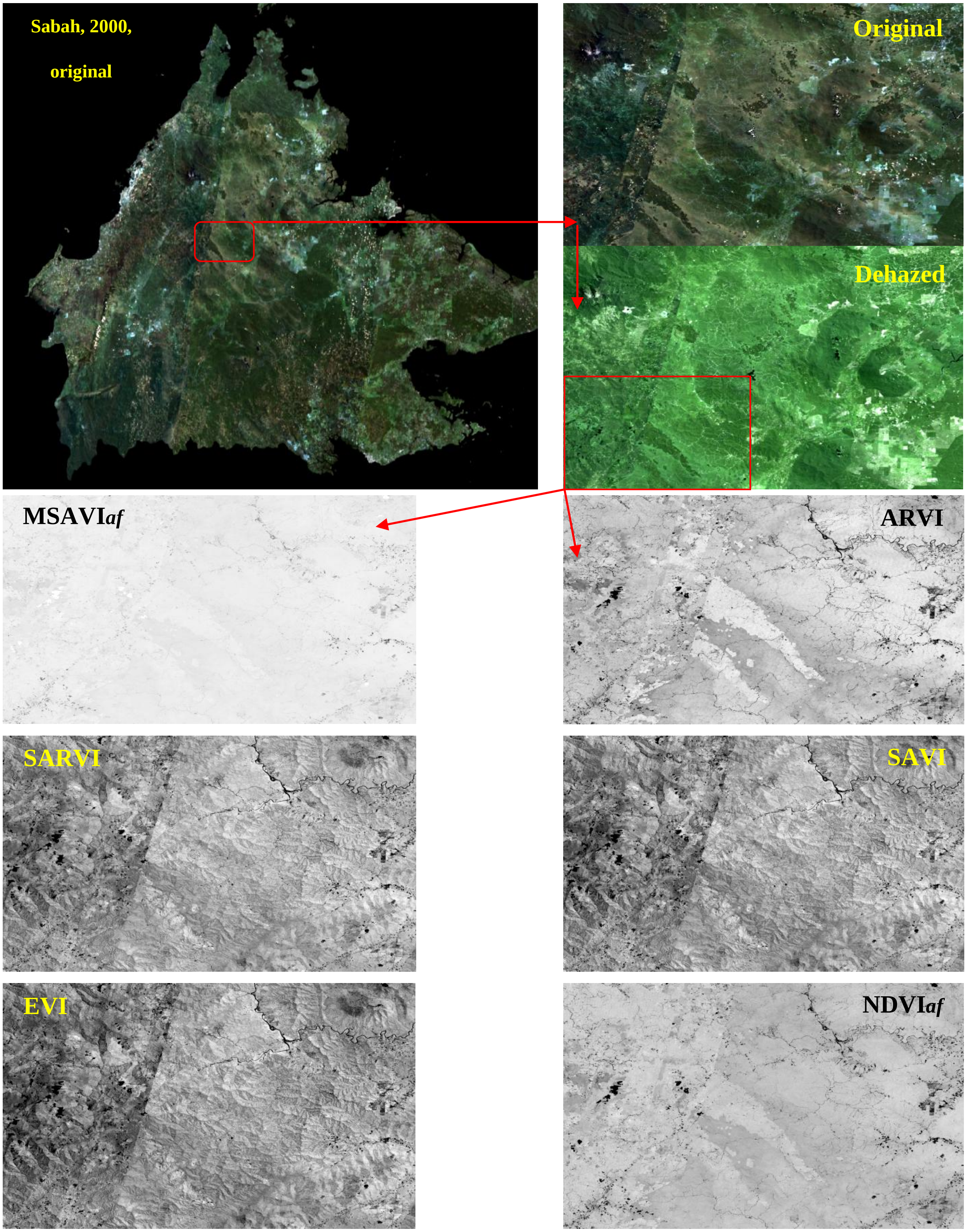


Figure 3.2. A test for different VIs to choose the best index applied to the *f*C method.

Figure 3.3. An example of choosing the areas for closed forest and bare land endmembers.

The values for closed canopy forest and bare land end-members identified for Sabah and Sarawak from 2000 to 2014 on the MSAVI*af* products are presented (Figure 3.4).

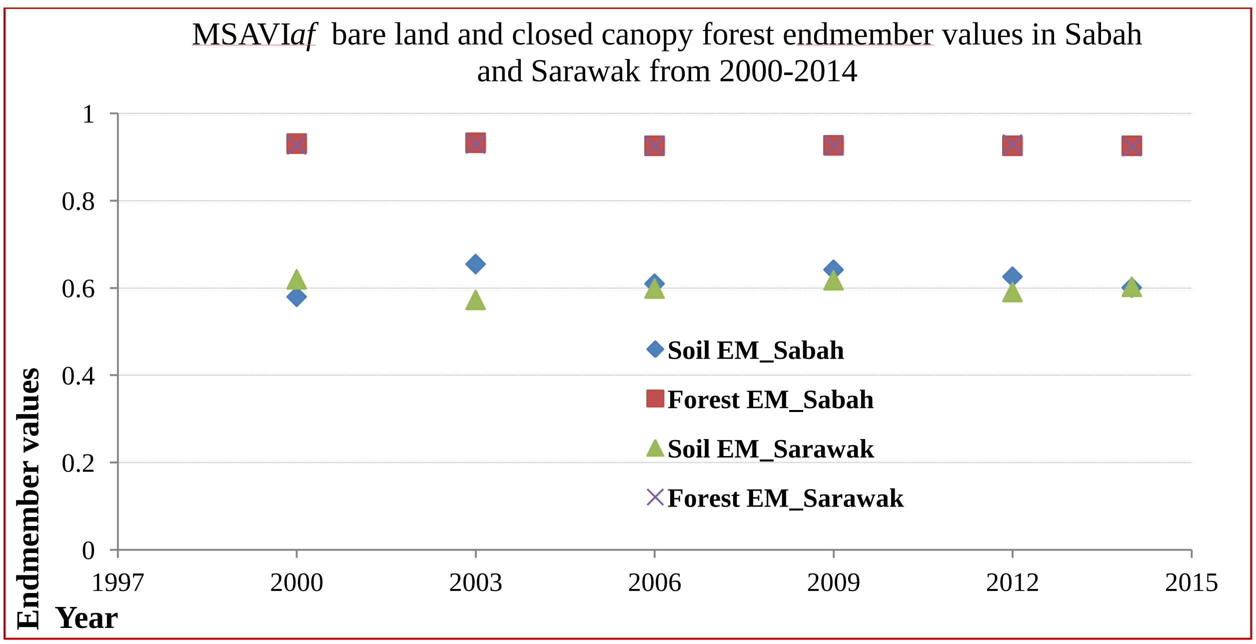


Figure 3.4. The endmember values of closed canopy forest and bare soil/land in Sarawak and Sabah, 2000-2014.

Considering this figure, we could easily realize that the values for closed canopy forest and bare land endmembers in Sarawak and Sabah were very similar and stable from 2000 to 2014. This indicates that these values are highly representative of the areas and have a very high consistency. Then, these two spectral endmembers were used to “un-mix” each pixel into a ratio of the two components in the linear spectral un-mixing model.

$$\boldsymbol{f}\mathbf{C} = \frac{\mathrm{VI} - \mathrm{VI}\ (soil)}{\mathrm{VI}\ (forest) - \mathrm{VI}\ (soil)}$$

Where:

VI: Vegetation index (MSAVI*af* value [0-1])

VI *(soil)*: Pure pixel endmember for soil value

VI *(forest)*: Pure pixel endmember for closed canopy forest value

The results of un-mixing two spectral endmembers in each pixel as described above would produce forest/vegetation fractional cover datasets, which were a vegetation continuous field ranging from 0 to 1, or equally from 0 to 100% coverage of vegetation, for Sabah and Sarawak from 2000 to 2014. The full results of this work are presented in the Appendices (Figure A.16). An example (Figure 3.5) presents the vegetation/forest fractional cover map in Sabah and Sawarak in 2014. Considering this figure, we easily realized that the darkest green areas indicated the areas with full coverage or 100% vegetation cover. Conversely, the darkest red areas presented the areas of totally bare land/soil or no vegetation cover.

As illustrated in the above VIs-based industrial forest detection method, the changes of vegetation fractional cover (*f*C) in the study area would also be detected and analyzed by using the image differencing method (Cakir *et al.*, 2006). The harvesting and planting cycles of an IF stand would indicate the clearing and regrowth of vegetation cover. This cycle would be expressed through an increase and declining of the *f*C value or the vegetation coverage fraction.

Skole *et al.* (2013) argued that, by doing so, a threshold for forest/non-forest would be identified using a level slice and visual interpretation. Multi-temporal change detection analysis would be done on 1) the full *f*C datasets, 2) the forest/non-forest datasets, and 3) the *f*C forest only datasets. Therefore, by using this multi-temporal change analysis, it was possible for us to identify the cycles of clearing and re-growth consistent with IF systems in the study areas.

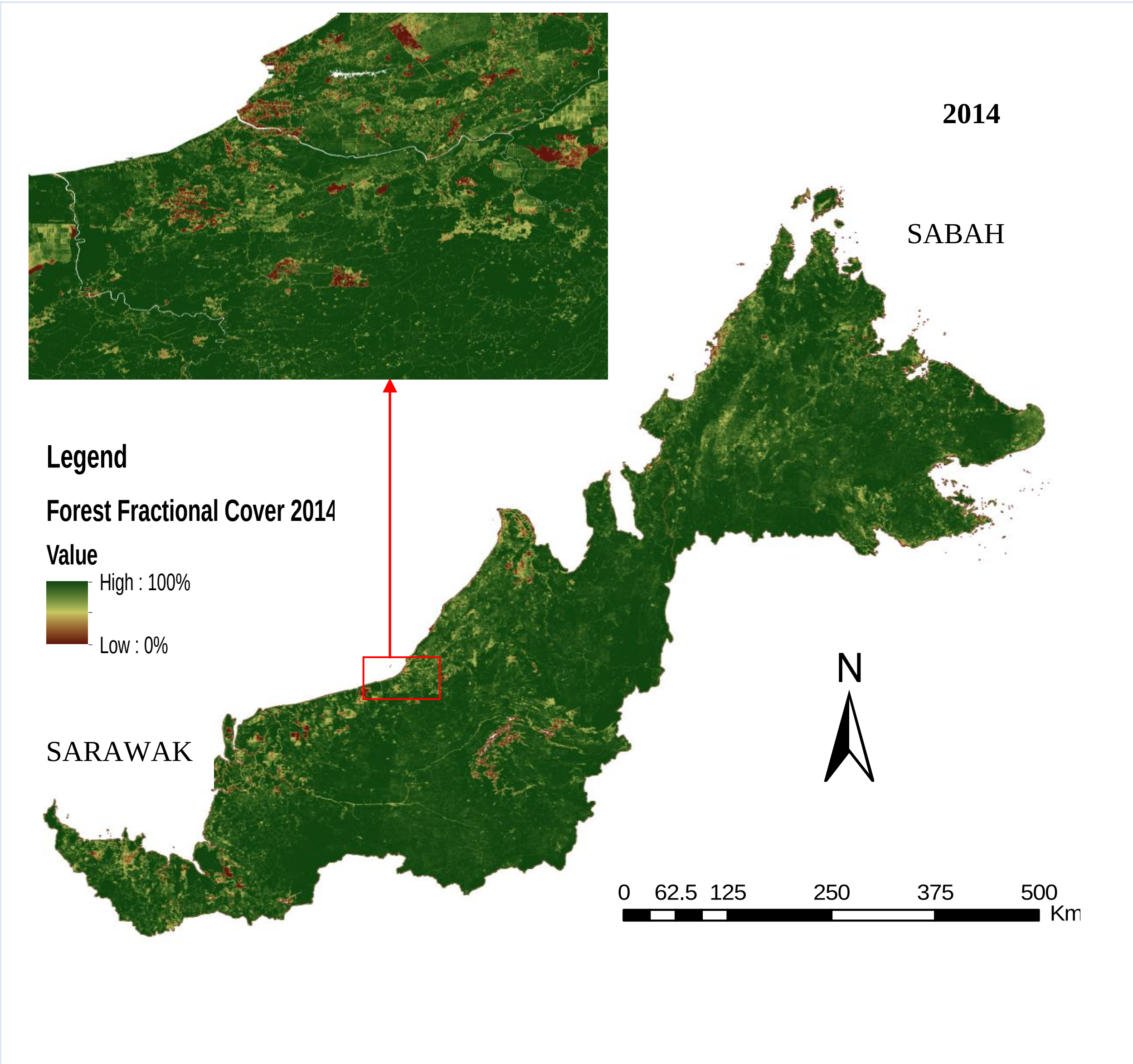


Figure 3.5. The forest/vegetation fractional cover (*f*C) map produced from the MSAVI*af* products in 2014 for Sarawak and Sabah.

According to Cakir *et al.* (2006), the image differencing resulted in three possibilities for an *f*C change *i.e.*, absolute no change, some possible change, and absolute change. To determine the values for these possibilities, a threshold for *f*C changes must be identified. Similar to the VIs-based method above, by doing the "trial-and-error" experiments, a threshold of ± 15% or 0.15 was chosen for identifying an *f*C change. The value of differencing two dated images was "0", meaning absolute no change; from > 0 to < +15% or < 0 to > -15%, indicating some possible changes; or > + 15% or < -15%, meaning absolute change. The *f*C change detection analysis was done for the years 2000-2003, 2003-2006, 2006-2009, 2009-2012, and 2012-2014 (Figure A.17 in the Appendices). An example of fractional cover image differencing to detect the *f*C change for the years of 2012 and 2014 in Sarawak and Sabah is presented (Figure 3.6). It clearly indicates the areas of absolute change, some possible change, and absolute no change.

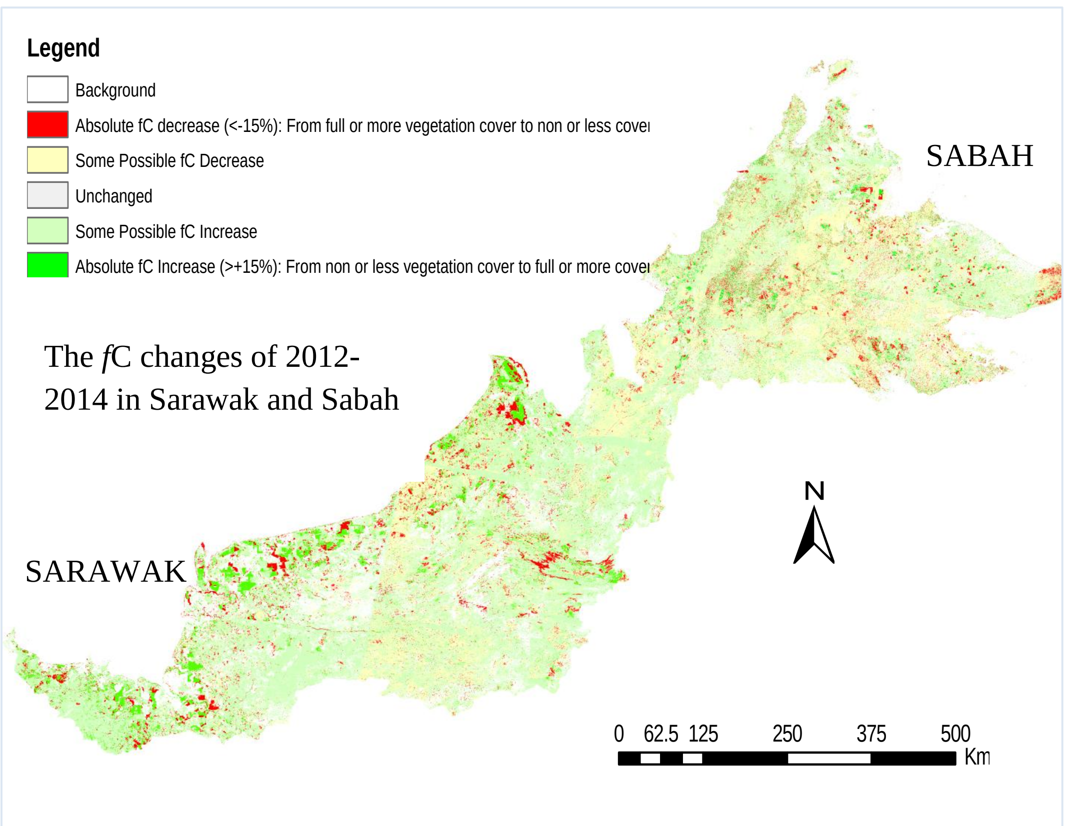


Figure 3.6. The *f*C changes detection for 2012-2014 in Sarawak and Sabah.

To observe how the *f*C has been changed in the study area over time, 30 key locations for each state (Sarawak and Sabah) were created to monitor the *f*C changes (Figure 3.7). These locations were the same locations created in the VIs-based IF detection method. The results of monitoring of the *f*C changes and the sequences of increasing and reducing the *f*C values at the threshold of ± 15% for 30 monitored key locations in Sabah from 2000 to 2014 are presented (Table 3.1). The same result for Sarawak is shown in the Appendices (Table A.11). These *f*C value increasing and declining sequences could indicate or provide initial clues for the silvicultural cycle of planting and harvesting (or clearing and regrowth) of an IF stand.

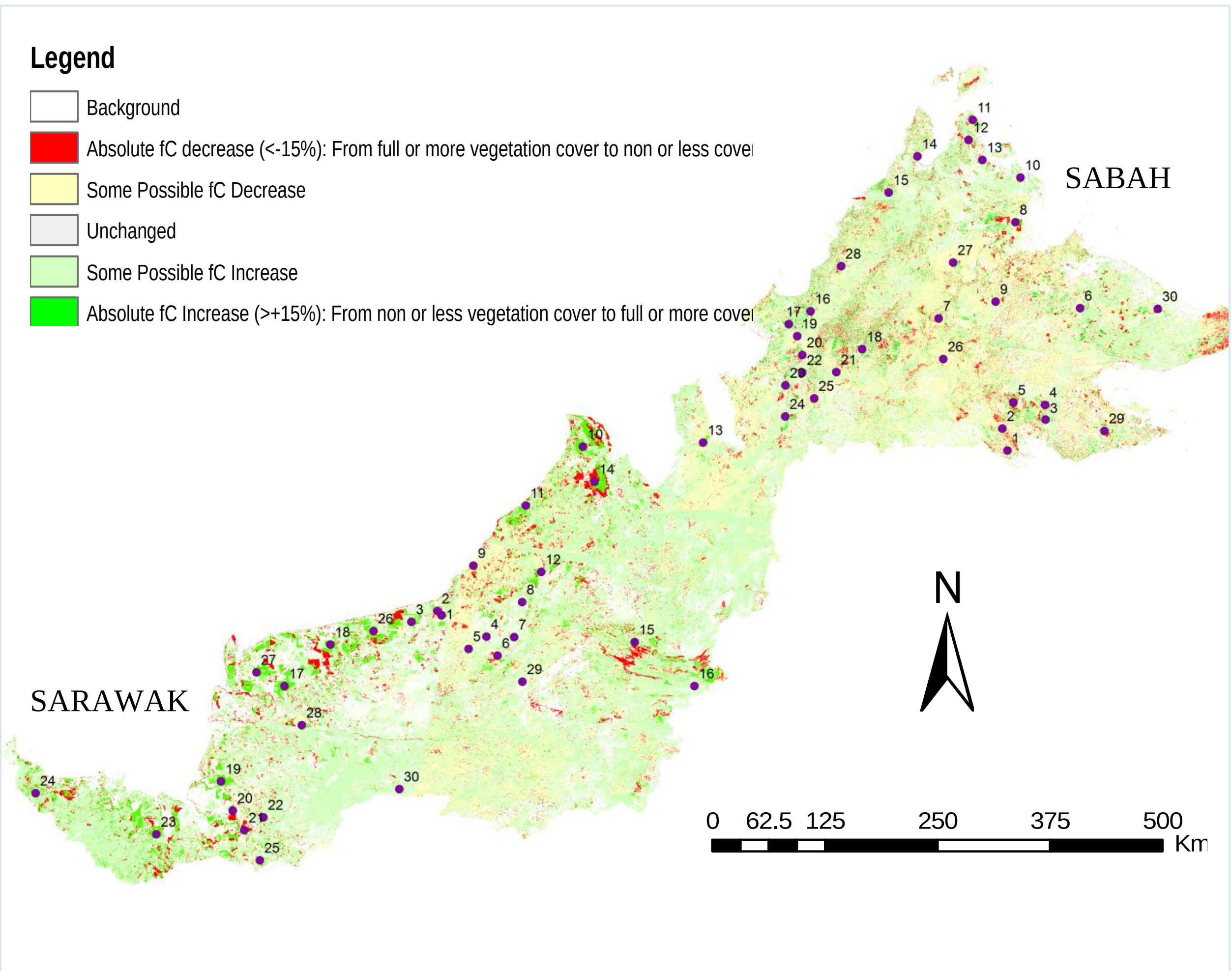


Figure 3.7. The key locations for monitoring the *f*C changes in Sabah and Sarawak, 2000-2014.

Table 3.1. The *f*C value changes in 30 monitored key locations in Sabah, 2000-2014.

ID	**SEQUENCES IN INCREASING & REDUCING *fC* IN KEY AREAS/LOCATIONS IN SABAH, 2000-2014**						**THEVALUE OF *fC* IN KEY AREAS/LOCATIONS IN SABAH, 2000-2014**					
	2000	**2003**	**2006**	**2009**	**2012**	**2014**	**2000**	**2003**	**2006**	**2009**	**2012**	**2014**
1	V/F	NV/NF	V/F	V/F	V/F	V/F	0.987	0.024	0.815	0.755	0.975	0.916
2	V/F	V/F	NV/NF	V/F	V/F	V/F	0.991	0.974	0.828	0.924	0.974	0.859
3	V/F	V/F	NV/NF	V/F	V/F	NV/NF	0.990	0.990	0.562	0.945	0.985	0.616
4	V/F	V/F	NV/NF	V/F	V/F	NV/NF	9.800	0.889	0.423	0.983	0.988	0.742
5	V/F	NV/NF	V/F	V/F	V/F	NV/NF	0.971	0.448	0.980	0.938	0.961	0.447
6	NV/NF	V/F	V/F	V/F	V/F	V/F	0.248	0.842	0.909	0.890	0.937	0.930
7	V/F	NV/NF	V/F	V/F	V/F	V/F	0.935	0.427	0.810	0.951	0.972	0.946
8	NV/NF	V/F	V/F	V/F	V/F	V/F	0.067	0.727	0.861	0.953	0.945	0.918
9	NV/NF	V/F	V/F	V/F	V/F	V/F	0.548	0.867	0.868	0.951	0.984	0.974
10	NV/NF	V/F	V/F	V/F	V/F	V/F	0.088	0.801	0.943	0.943	0.963	0.977
11	V/F	V/F	V/F	V/F	NV/NF	V/F	1.000	0.990	0.971	0.997	0.598	0.853
12	V/F	NV/NF	V/F	V/F	V/F	V/F	0.998	0.624	0.974	0.853	0.890	0.887
13	V/F	NV/NF	V/F	V/F	V/F	V/F	0.992	0.561	0.956	0.918	0.965	0.948
14	V/F	NV/NF	V/F	V/F	V/F	V/F	0.561	0.309	0.754	0.893	0.953	0.906
15	V/F	NV/NF	V/F	V/F	NV/NF	V/F	0.690	0.001	0.490	0.431	0.219	0.703
16	NV/NF	V/F	V/F	V/F	V/F	V/F	0.509	0.722	0.911	0.811	0.852	0.901
17	V/F	V/F	NV/NF	V/F	V/F	V/F	0.965	0.945	0.458	0.625	0.850	0.885
18	NV/NF	V/F	V/F	V/F	V/F	V/F	0.181	0.346	0.808	0.891	0.967	0.978
19	V/F	V/F	V/F	V/F	NV/NF	V/F	0.877	0.925	0.983	0.957	0.620	0.998
20	V/F	V/F	NV/NF	V/F	V/F	V/F	0.901	0.835	0.237	0.960	0.970	0.970
21	NV/NF	V/F	V/F	V/F	V/F	V/F	0.317	0.846	0.980	0.929	0.981	0.987
22	V/F	NV/NF	V/F	V/F	V/F	NV/NF	0.960	0.392	0.984	0.969	0.973	0.434
23	NV/NF	V/F	V/F	V/F	NV/NF	V/F	0.683	0.958	0.890	0.988	0.738	0.922
24	V/F	NV/NF	V/F	V/F	V/F	V/F	0.967	0.623	0.987	0.996	0.986	0.990
25	V/F	NV/NF	V/F	V/F	NV/NF	V/F	0.970	0.335	0.904	0.931	0.454	0.922
26	V/F	V/F	V/F	V/F	V/F	NV/NF	0.988	0.984	0.904	0.945	0.971	0.697
27	V/F	V/F	V/F	NV/NF	V/F	V/F	0.951	0.943	0.995	0.026	0.696	0.883
28	V/F	V/F	NV/NF	V/F	V/F	V/F	0.955	0.972	0.560	0.775	0.859	0.941
29	V/F	V/F	NV/NF	V/F	V/F	V/F	0.986	0.976	0.210	0.897	0.981	0.970
30	NV/NF	V/F	V/F	V/F	V/F	V/F	0.444	0.671	0.671	0.780	0.926	0.959

Note: *[1]* ***V/F****: full or more vegetation cover (regrowth);* ***NV/VF****: non or less vegetation (clearing)*
[2] From ***V/F*** *to* ***NV/NF*** *indicating* ***a reduction in VI*** *from full/more to none/less vegetation cover (clearing)*
[3] From ***NV/NF*** *to* ***V/F*** *expressing* ***an increase in VI*** *from none/less to full/more vegetation cover (regrowth)*

In other words, the silvicultural cycle of planting and harvesting an IF stand indicated its time span, which could help us detect shorter *vs.* longer rotation plantation stands. In fact, there is no global standard for how long a shorter *vs.* longer rotation plantation stand is. The short or long rotation stand is dependent on the purpose of using that plantation stand. In common practice, the short rotation industrial forests last a few years to around 10 years, while a long rotation timber plantation may last tens of years. Thus, in this study, like the above VIs-based method, any change of the *f*C value at or less than 7 years was assumed to be shorter rotation IFs, and any change of *f*C value more than 7 years was assumed to be longer rotation IFs. The results of detecting shorter *vs.* longer rotation plantation stands are presented (Figure 3.8) as an example.

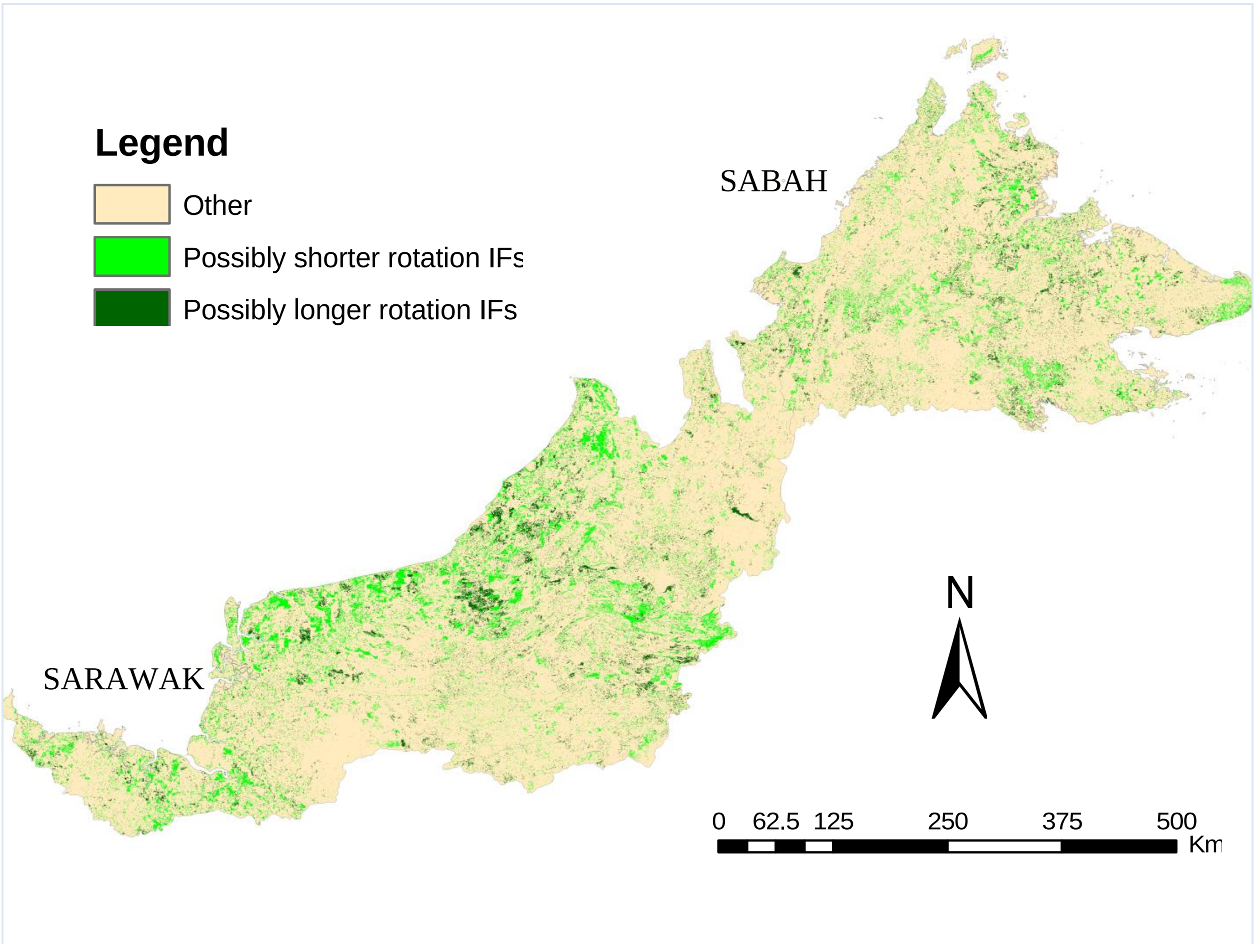


Figure 3.8. The possibly shorter- and longer-rotation industrial forests in Sabah and Sarawak, 2000-2014.

In addition to acquiring the initial clues for detecting industrial forests (*i.e.*, rotation data for plantations derived from analyses of the clearing/harvesting and regrowth/planting cycles of industrial forests based on the increasing and declining *f*C values, as presented above), the next analysis for the growth rate of the vegetation cover (*f*C value) would also provide an important clue for detecting industrial forests, because the growth rate of the vegetation cover (*f*C value) may indicate the faster-growing and slower-growing timber plantations.

In this *f*C method, the faster-growing industrial forests or timber plantations, such as *Acacia* spp., were hypothesized to have the higher *f*C growth rate as compared to the slower-growing species, such as teaks or rubbers. The growth rate of the *f*C was calculated as follows:

$$\Delta \textit{growth rate} = (fC_{(t2)} - fC_{(t1)}) / fC_{(t1)}$$

where $fC_{(t1)}$ was the value of vegetation/forest fractional cover (*f*C values) in the earlier year, or time t_1, and $fC_{(t2)}$ was the value of vegetation/forest fractional cover (*f*C values) in the later year, or time t_2.

The threshold chosen for identifying the faster-growing industrial forest species and the slower-growing species was 0.5 for both species. This value, like the VIs-based method, was determined based on assumption and the “trial-and-error” experiments. The growth rate with *f*C value larger than 0.5 possibly indicated the faster-growing species, while the growth rate with *f*C value lower than 0.5 possibly indicated the slower-growing species. The *f*C growth rate was calculated for the study period. The preliminary results of calculating this *f*C growth rate in Sarawak and Sabah for the period of 2000-2014 are presented (Figure 3.9).

Then, these two datasets (shorter *vs*. longer rotation IFs and faster-growing *vs.* slower-growing IF species) would be combined to create a faster-growing, shorter-rotation and slower-growing, longer-rotation industrial forest dataset (Figure 3.10). This dataset would be used as an input data in the final model to determine the area and species of industrial forests in Sarawak and Sabah.

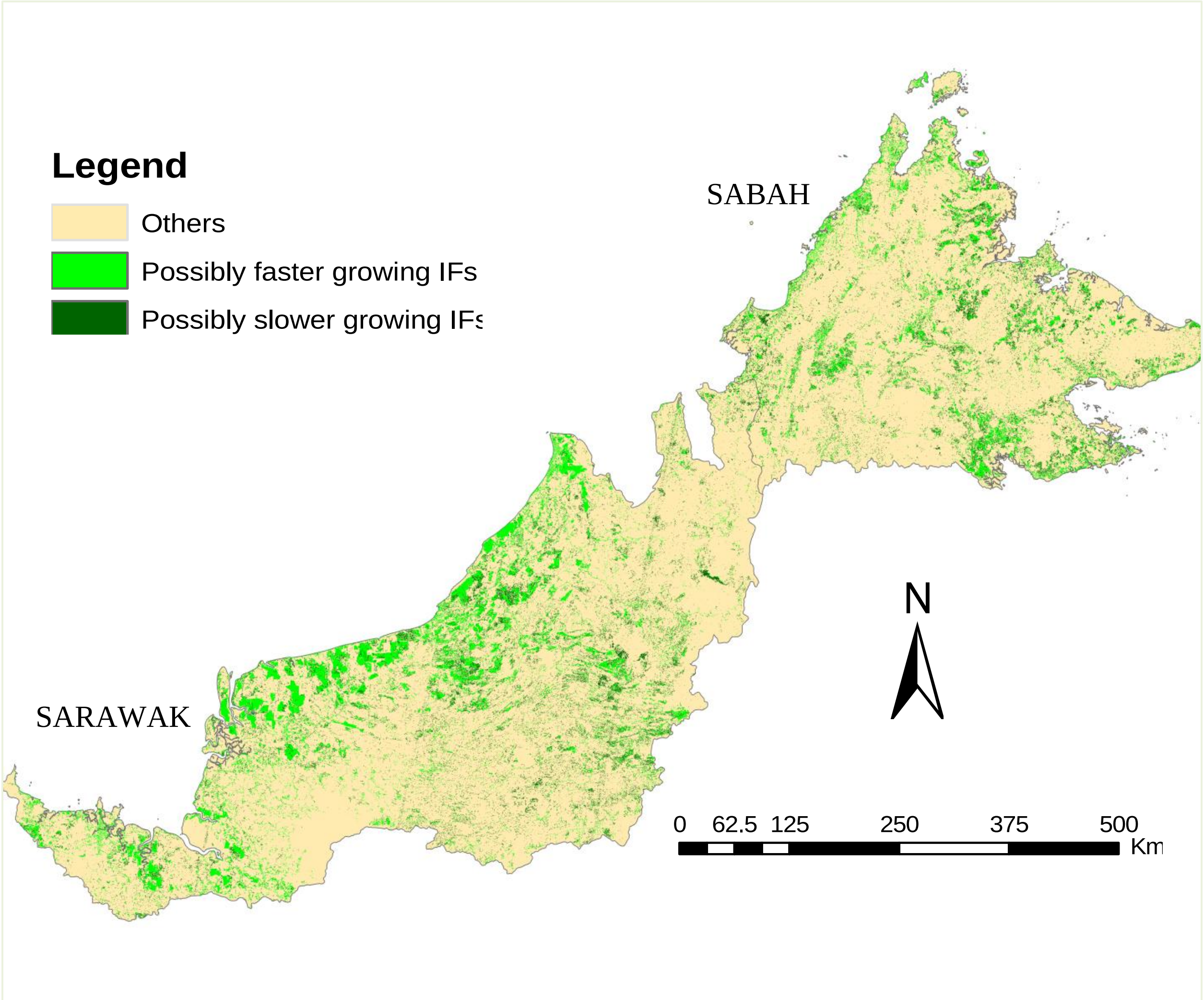


Figure 3.9. The possibly faster-growing and slower-growing industrial forests in Sabah and Sarawak, 2000-2014.

Another important assumption used to develop the *f*C-based IF detection method was that the different vegetation cover types (*e.g.*, closed forest *vs.* timber plantation *vs.* oil palm *vs.* agricultural land) in general, and industrial forests (*e.g.*, acacias *vs.* rubbers *vs.* teaks) in particular, can score the same coverage (or the same *f*C value), but their green biomass contents may be different. In remote sensing application studies, band 4 (Near Infrared (NIR) in the Landsat 4-5 TM and Landsat 7 ETM+ with the wavelength range of 0.77–0.9 μm, and band 5 with the wavelength of 0.85-0.88 μm in Landsat 8 OLI & TIRS) is used to study the green biomass content in vegetation.

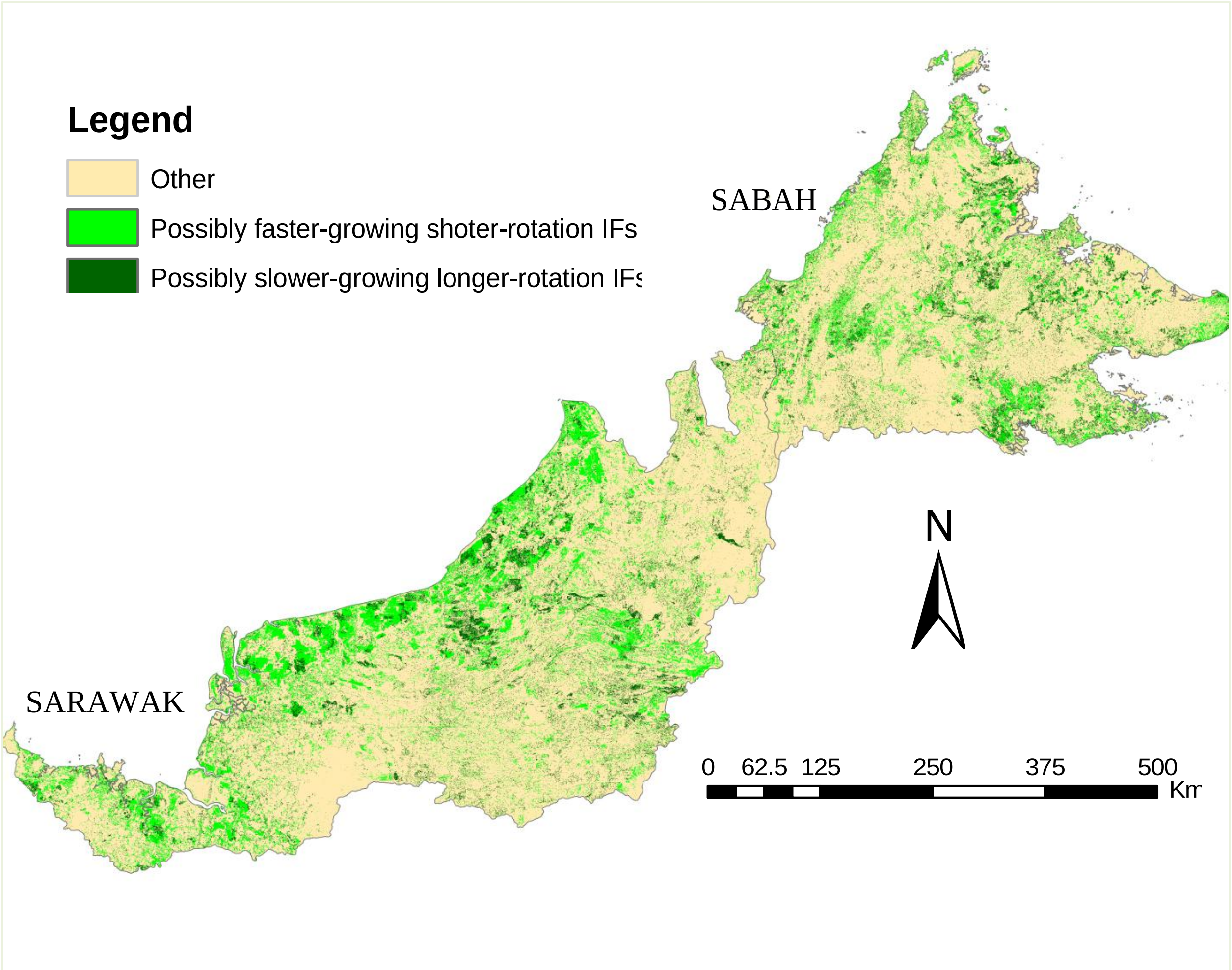


Figure 3.10. The possibly faster-growing, shorter-rotation and slower-growing, longer-rotation industrial forests in Sabah and Sarawak.

Thus, this study would also use this band to study green biomass content for different IF systems. Firstly, the values of band 4 were obtained in the same *f*C areas to examine any difference among them. Its results showed that there were some differences in the band 4 values in the same *f*C area (Figure 3.11). Then, five different vegetation types including acacia, natural forest, oil palm, rubber, and other industrial forests were also identified as presented in the above

VIs-based IF detection method. An AOI was created to obtain the band 4 values in these areas and the results are shown (Figure 3.12). Considering this figure, we could realize that the band 4 values for these land use/land cover types were also different.

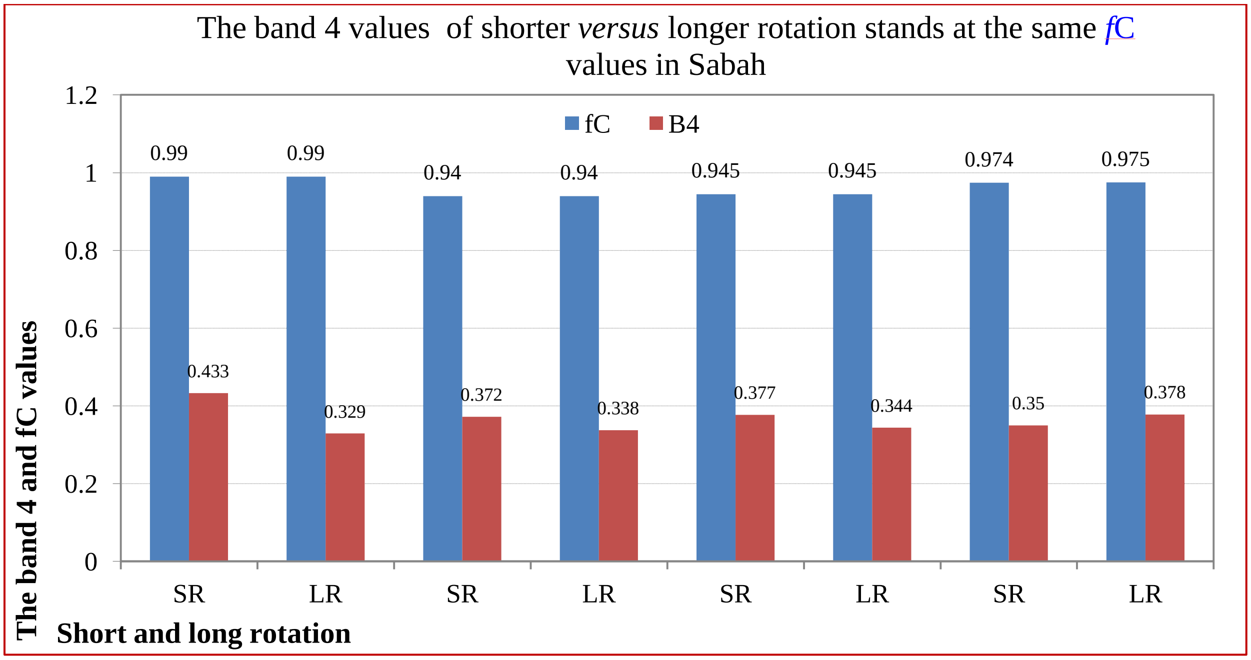


Figure 3.11. The band 4 values in the same vegetation cover in Sabah.

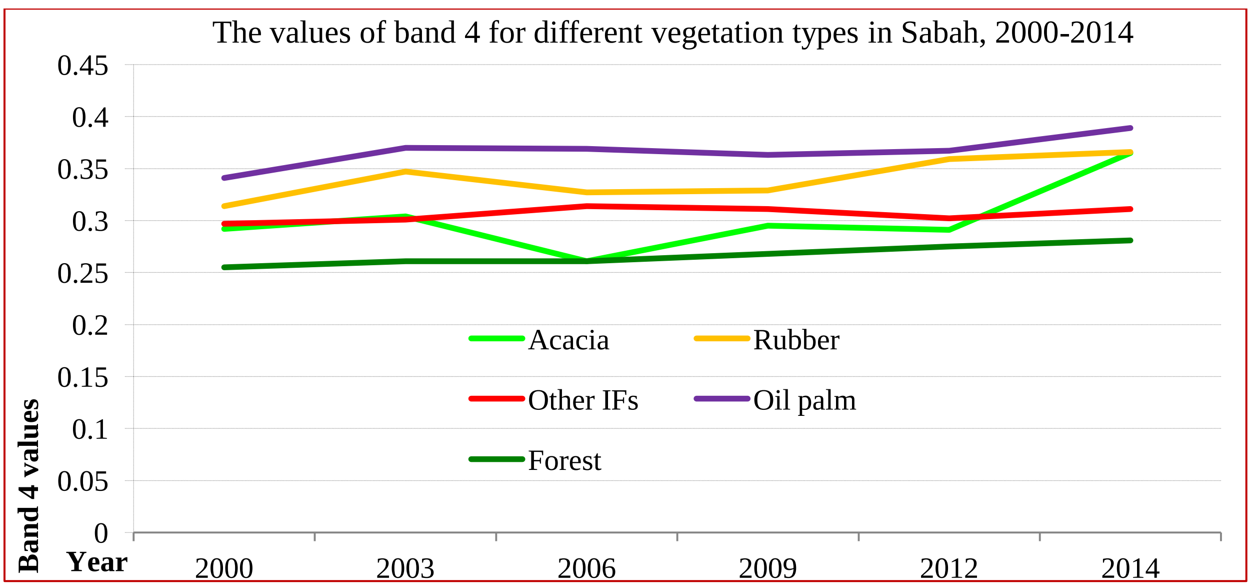


Figure 3.12. The band 4 values for different vegetation cover types in Sabah, 2000-2014.

To further examine this assumption, a statistical test was conducted by using non-parametric two-related-samples test (Wilcoxon Signed Ranks Test) for 30 key locations in Sabah and another 30 locations in Sarawak from 2000 to 2014. The results indicated the same *f*C values and band 4 values were significantly different at $p<.0001$. This meant that we could use this information for further analysis for detecting industrial forests in the study area.

In addition, among different vegetation cover types in general, and industrial forests in particular, although their fractional cover (or their *f*C values) are the same, their leaf area index (LAI) may be different. In the other word, this study examines whether the LAI among different IF types in particular, and vegetation types in general, that have the same *f*C values are different. A number of studies were conducted to investigate the relationship between LAI with the vegetation indices. For instance, Broge and Leblanc (2000), and Haboudane *et al.* (2004) published studies using hyperspectral vegetation indices to predict green LAI and suggested we should use the following predictive equation based on MSAVI to estimate LAI:

$$\mathrm{LAI} = 0.1663\exp(4.2731*\mathrm{MSAVI})$$

$$\mathrm{MSAVI} = 0.5 * [2 * \mathrm{NIR} + 1 - \sqrt{(2 * \mathrm{NIR} + 1)^2 - 8 * (\mathrm{NIR} - \mathrm{RED})}$$

Another study by Boegh *et al.* (2002) used multispectral data to quantify LAI and found that LAI had a very high correlation with the EVI (Enhanced Vegetation Index), and thus the authors proposed the following formula: LAI = (3.618 * EVI – 0.118) > 0 to estimate the leaf area index of vegetation cover. This index is also used in the ENVI (Exelis Visual Information Solutions, Boulder, Colorado) as a reference. Later, Potirthep *et al.* (2010) also investigated the relationship between NDVI and EVI with LAI for a deciduous broadleaf forest and found that the LAI-EVI had a better correlation compared with the LAI-NDVI. Likewise, Hassan and Bourque (2010) also found a strong linear correlation between LAI and EVI in the boreal forest region. However, while reviewing this predictive equation for LAI by using EVI, I realized that LAI in this formula/predictive equation was never larger than 4 because of the value range of EVI [-1, 1], while Leigh Jr (1999) showed that the typical LAI for lowland tropical forests normally ranged from 7 to 8 in Pasoh, Malaysia, or even higher. Therefore, using EVI to estimate LAI in the tropical environment may not work. As a result, in this study, MSAVI would be used to investigate LAI of different vegetation cover types in the study area over the study period. However, as presented in the previous section, the modified version (MSAVI*af*) was used in this study instead of using the original MSAVI. Thus, to be consistent with the dataset, the MSAVI*af* product was used to estimate LAI for different vegetation cover types in the study area. The preliminary results of estimating LAI based on MSAVI*af* in Sabah and Sarawak are presented (Figure 3.13).

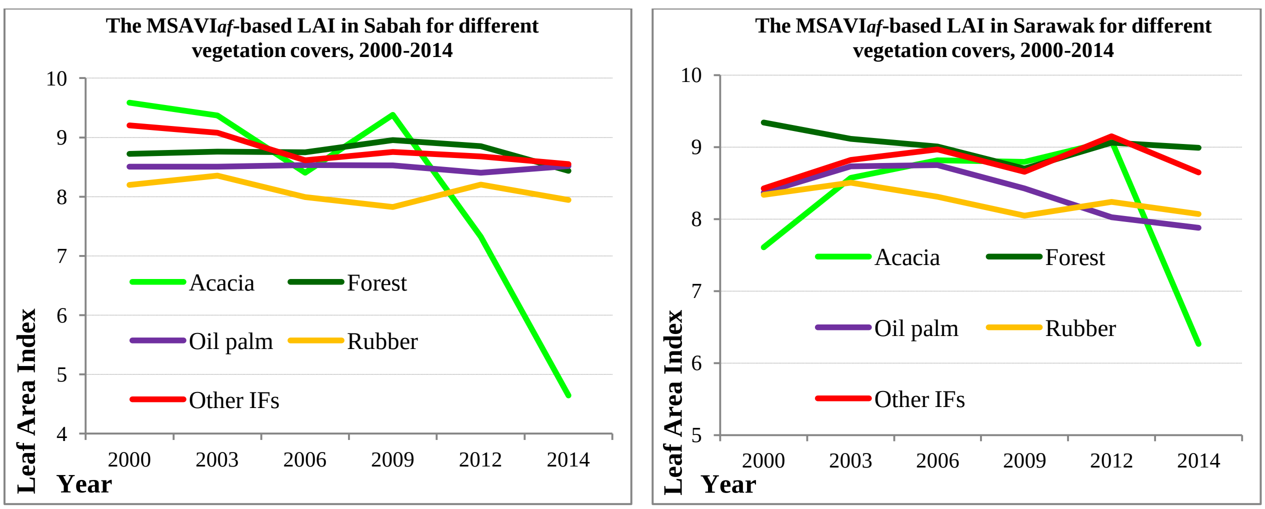


Figure 3.13. The MSAVI*af*-based LAI for different vegetation cover types in Sabah and Sarawak, 2000-2014.

For IF detection based on LAI and band 4, the supervised classification in the ERDAS was used to classify six LULC types, including acacia, rubber, other IFs, oil palm, forest, and other

LU/LC types. The locations for the AOI were the same locations identified in the textural analysis and spectral analysis in the VIs-based IF detection method and in this method.

Spectral Analysis

Similar to the VIs-based IF detection method described above, this *f*C-based method also used the spectral analysis consisting of Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Tasseled Cap Analysis (TCA) to support and calibrate the results of using multi-temporal *f*C dataset analysis, green biomass content, and leaf area index (LAI) analysis to detect industrial forests in the study area (Sabah and Sarawak in Malaysia) over the period of 2000-2014. The datasets used for the spectral analysis in this method were the same datasets used in the VIs-based method. However, there was only one difference; instead of manually identifying the typical values for the expected IFs or other land uses/land covers by examining histograms, the supervised classification function available in the ERDAS IMAGINE was used to statistically classify the expected land uses/land covers. Then, three datasets of the PCA, ICA, and TCA were used to identify and classify the expected land use and land cover types. The full results of this spectral analysis are shown in the Appendices (Figure A.18). An example of classifying land uses/land covers (acacias, forests, oil palms, rubbers, other IFs, and other land uses and land covers/other LULCs) based on the ERDAS' supervised classification function for Sabah and Sarawak in 2003 is presented (Figure 3.14).

Textural Analysis

This method also used textural analysis, along with spectral analysis, green biomass content, and leaf area index (LAI) analysis as mentioned above, as a supporting method to calibrate the results of detecting industrial forests (IFs) based on multi-temporal forest fractional cover datasets analysis. This method took the same approach with the textural analysis method in the

VIs-based IF detection method, but they were different in how they used specific steps and datasets. Specifically, the textural analysis in the VIs-based method applied the Grey Level Co-occurrence Matrix (GLCM) for VIs image datasets including ARVI, EVI, MSAVI*af*, NDVI*af*, SARVI, and SAVI; band 4 and band 5 images. Of that, in the GLCM, the image textural indices consisting of Mean (MEA), Dissimilarity (DIS), and Homogeneity (HOM) were calculated for the VIs images and band 4 datasets, while only the index MEA was applied for band 5 grey level

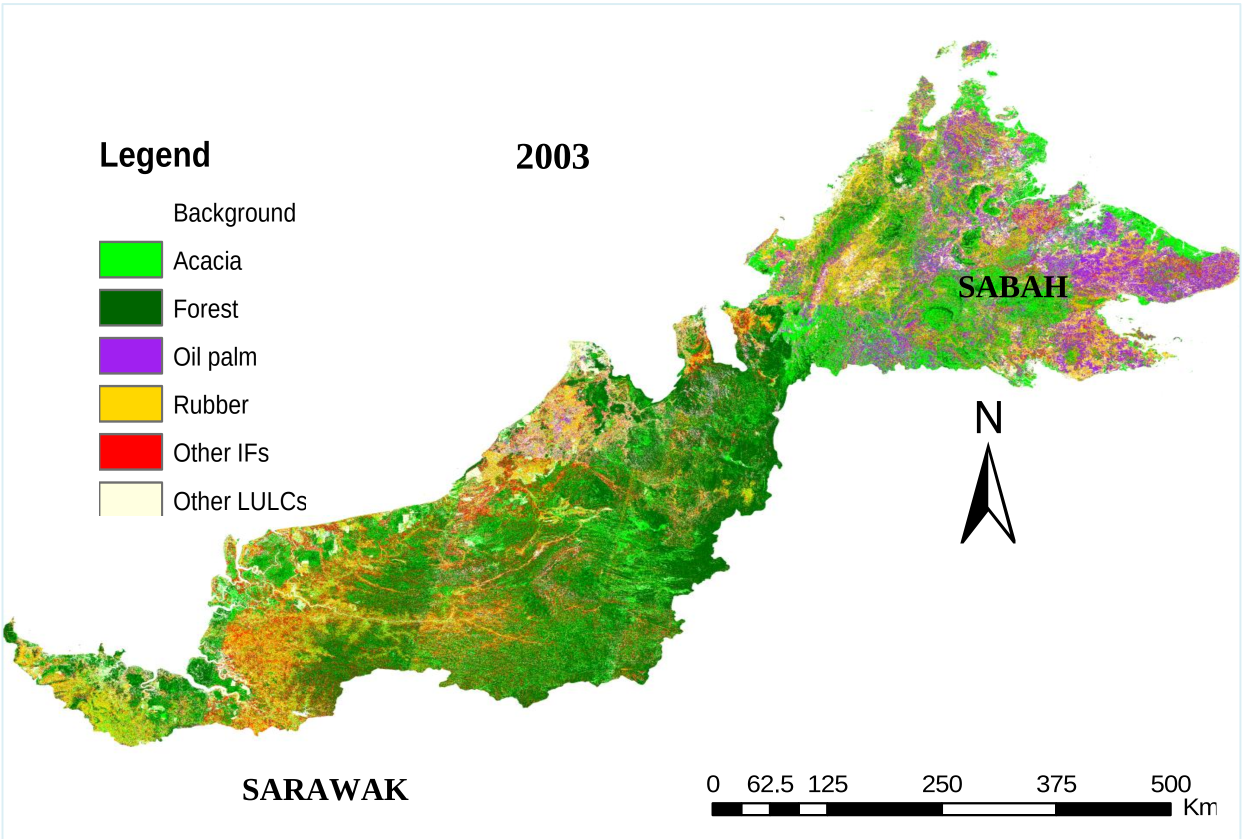


Figure 3.14. The spectral analysis-based land use/land cover map in Sabah and Sarawak, 2003.

images. In this method, the indices in the GLCM comprised of Mean (MEA), Dissimilarity (DIS), and Homogeneity (HOM) would be applied for the *f*C datasets only. Then, similar to the implementation of the spectral analysis for this method, the supervised classification function in the ERDAS would also be used to classify the expected land use and land cover types for the resulting datasets. The expected land use/land cover types classified for the study area (Sabah and Sarawak in Malaysia) from 2000 to 2014 were acacia plantations, natural forests, oil palm plantations, rubber plantations, other industrial forest types, and other land uses and land cover types, such as residential areas, agricultural, and degraded lands. Then, these datasets were used in a textural analysis-based model to determine the area and type of the expected land uses/land covers in Sabah and Sarawak from 2000 to 2014. The full results of this textural analysis method are expressed in the Appendices (Figure A.19). An example of classifying land uses/land covers types based on textural analysis in Sabah and Sarawak in 2000 is presented (Figure 3.15).

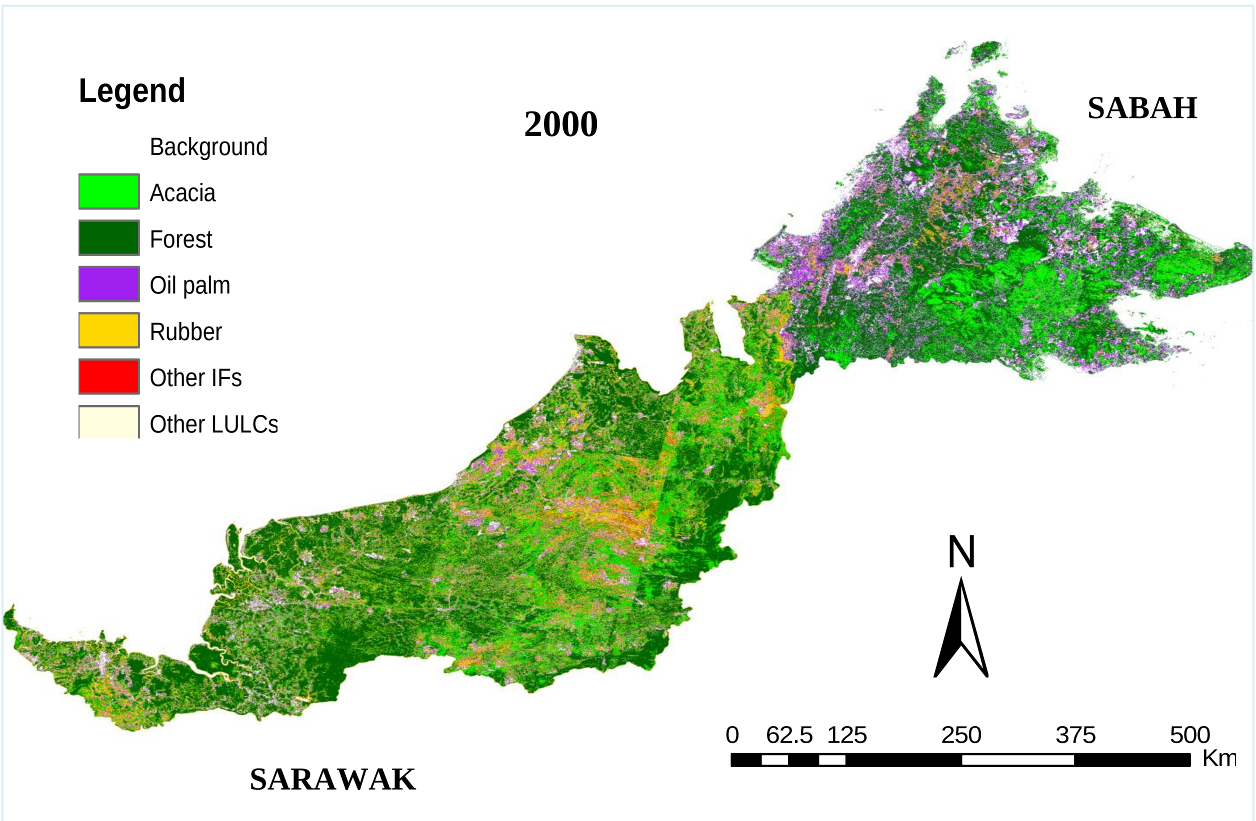


Figure 3.15. The textural analysis-based land use/land cover map in Sabah and Sarawak, 2000.

Visual Interpretation and Using Other Data

After obtaining the multi-temporal *f*C dataset analysis results, LAI, green biomass content, textural analysis, and spectral analysis, visual interpretation - along with other LULCC and ancillary data - were used to calibrate the final results for detecting industrial forests. The results of using visual interpretation and other ancillary data were described and acquired from the above VIs-based IF detection method.

Making IF Maps

Then, an algorithm was developed based on rules for the faster-growing, shorter-rotation (FGSR) and slower-growing, longer-rotation (SGLR) datasets, leaf area index, green biomass content, textural analysis, spectral analysis, and visual interpretation. The algorithm is described in Figure 3.16. In other words, the algorithms could be presented as follows:

$\boldsymbol{f}_{\boldsymbol{(IFs)}} = \sum([\text{Texture}_{\mathbf{(IFs)}} \cap \text{Spectra}_{\mathbf{(IFs)}} \cap \text{FGSR-SGLR}_{\mathbf{(IFs)}} \cap \text{Visual}_{\mathbf{(IFs)}} \cap \text{Biomass}_{\mathbf{(IFs)}} \cap \text{LAI}_{\mathbf{(IFs)}}] + [\text{Texture}_{\mathbf{(IFs)}} \cap \text{Spectra}_{\mathbf{(IFs)}} \cap \text{FGSR-SGLR}_{\mathbf{(IFs)}} \cap \text{Biomass}_{\mathbf{(IFs)}} \cap \text{LAI}_{\mathbf{(IFs)}}] + [\text{Visual}_{\mathbf{(IFs)}} \cap (\text{Texture}_{\mathbf{(IFs)}} \text{ OR/AND } \text{Spectra}_{\mathbf{(IFs)}} \text{ OR/AND } \text{FGSR-SGLR}_{\mathbf{(IFs)}} \text{ OR/AND } \text{Biomass}_{\mathbf{(IFs)}} \text{ OR/AND } \text{LAI}_{\mathbf{(IFs)}})] + [\text{FGSR-SGLR}_{\mathbf{(IFs)}} \cap (\text{Texture}_{\mathbf{(IFs)}} \text{ OR/AND } \text{Spectra}_{\mathbf{(IFs)}} \text{ OR/AND } \text{Biomass}_{\mathbf{(IFs)}} \text{ OR/AND } \text{LAI}_{\mathbf{(IFs)}})])$.

Similar to the above VIs-based IF map product, the final results were also clumped and any area smaller than 2 ha would be eliminated to reduce the “salt and pepper” noises caused by the atmospheric effects and image quality, as well as to adapt with the fact that the smaller IF patches were more difficult to detect and that smallholders in Southeast Asia commonly owned a land size around 1-4 ha of plantations (Fox & Castella, 2013).

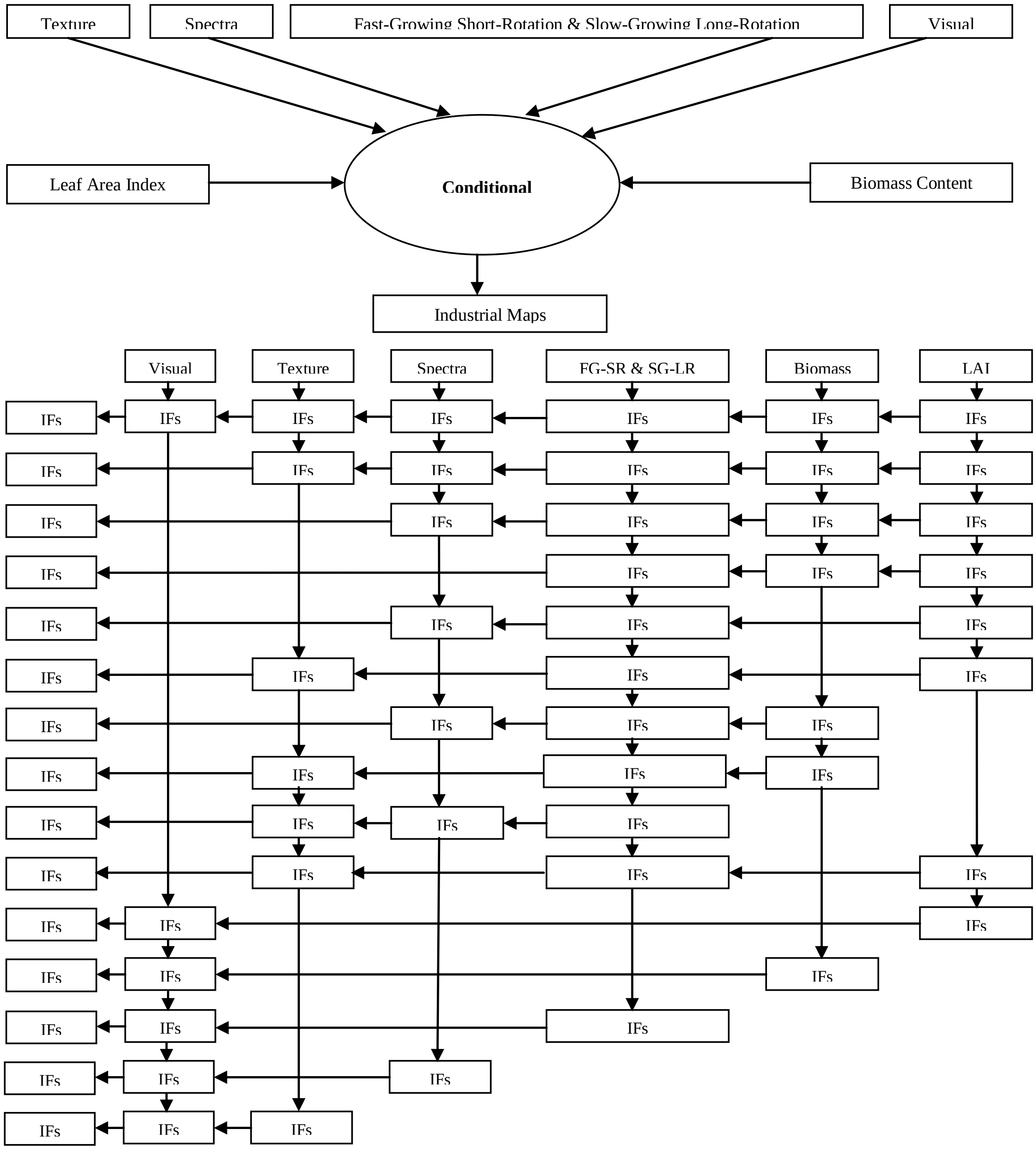


Figure 3.16. The simple diagram for developing the final algorithm to detect and map industrial forest areas and species based on the *f*C dataset analysis.

The results of detecting industrial forests in Sarawak and Sabah for the years 2000, 2003, 2006, 2009, 2012, and 2014 based on the multi-temporal *f*C dataset analysis are presented (Figures 3.17, 3.18, 3.19, 3.20, 3.21, and 3.22).

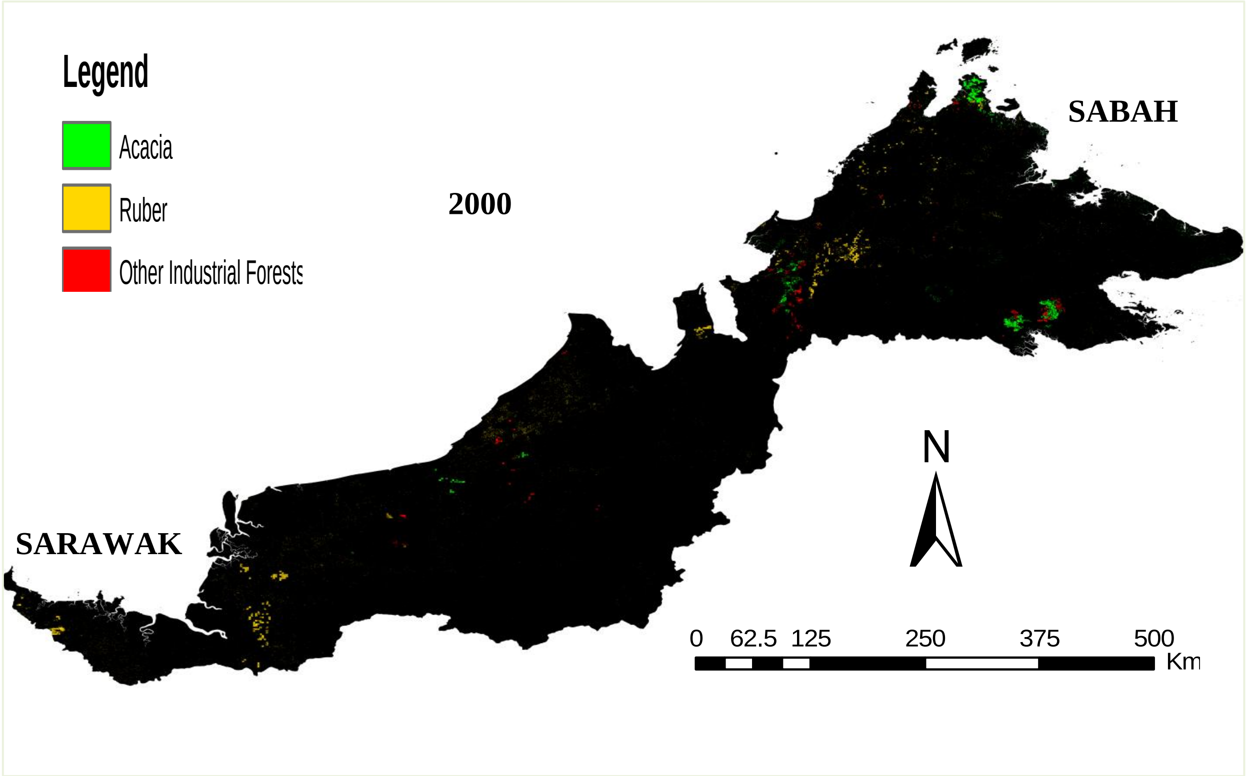


Figure 3.17. The *f*C-based IF map for Sabah and Sarawak in 2000.

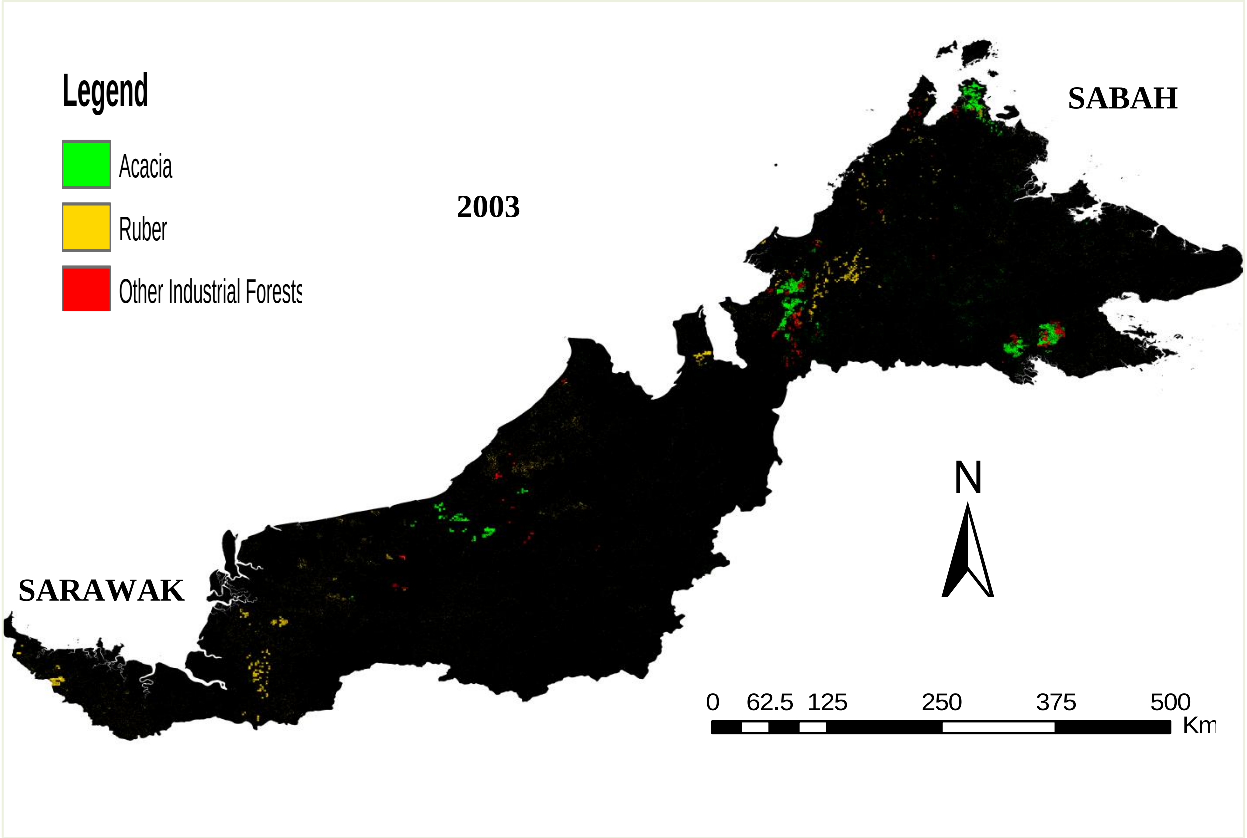


Figure 3.18. The *f*C-based IF map for Sabah and Sarawak in 2003.

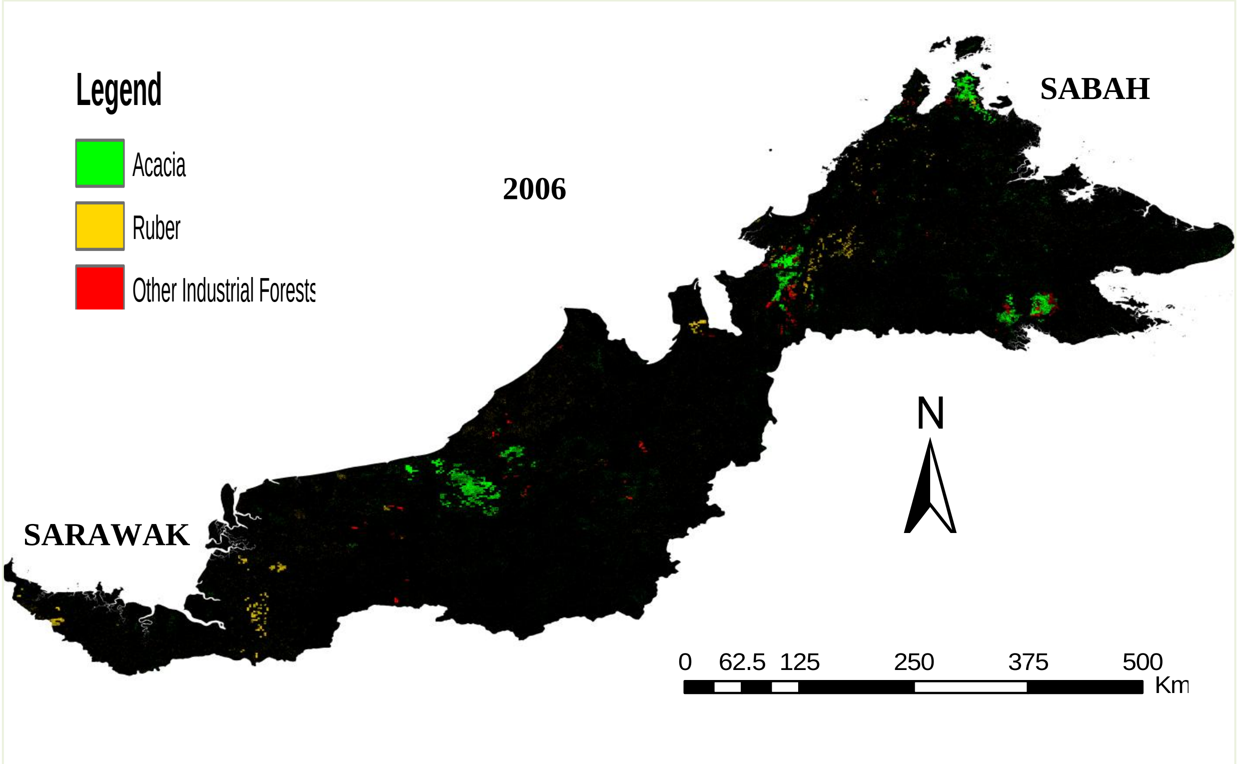


Figure 3.19. The *f*C-based IF map for Sabah and Sarawak in 2006.

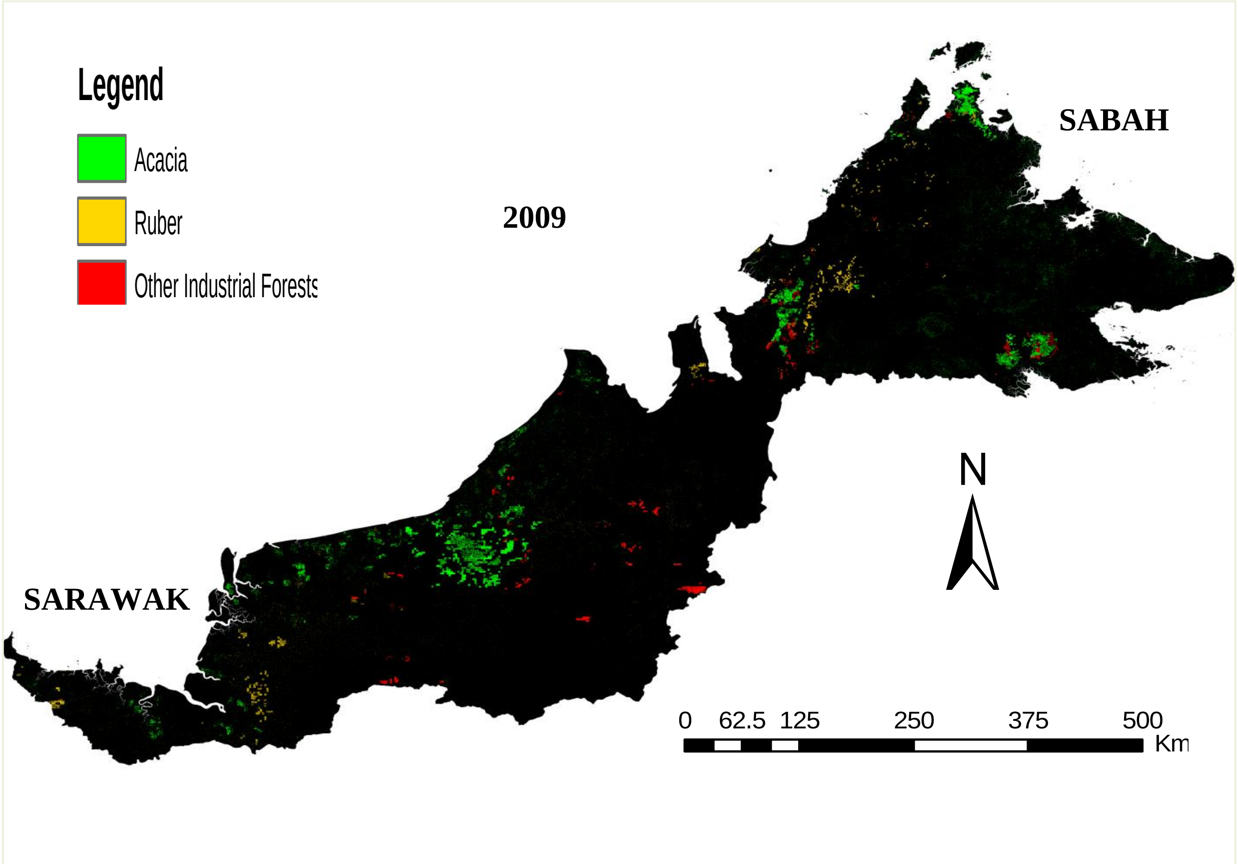


Figure 3.20. The *f*C-based IF map for Sabah and Sarawak in 2009.

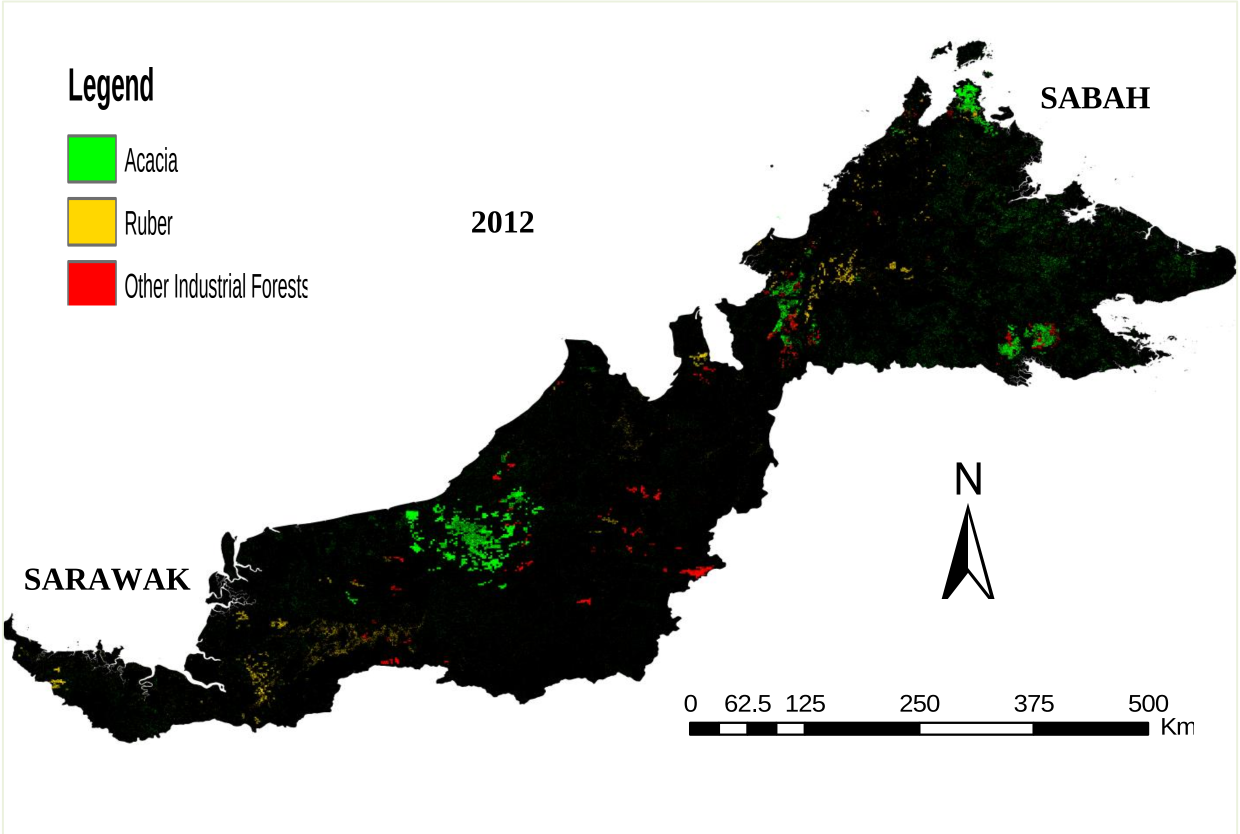


Figure 3.21. The *f*C-based IF map for Sabah and Sarawak in 2012.

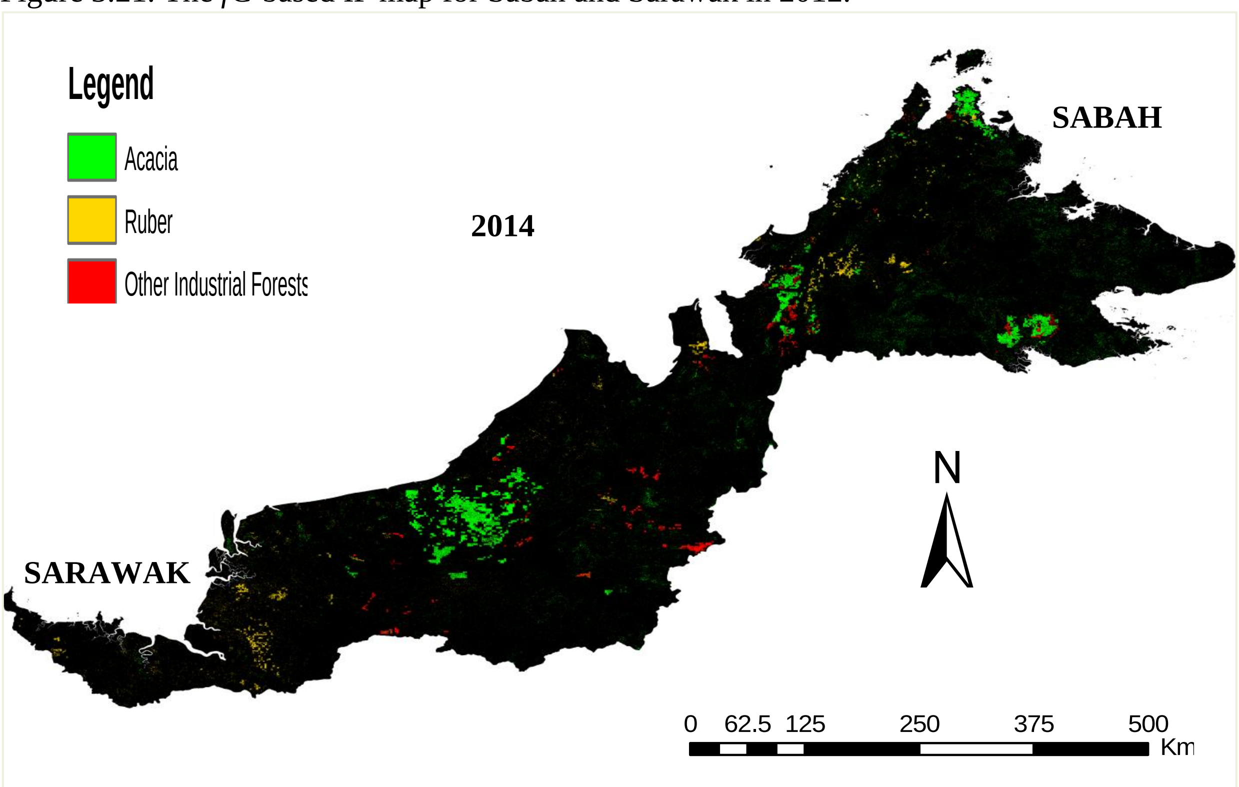


Figure 3.22. The *f*C-based IF map for Sabah and Sarawak in 2014.

3.4 Validation

The validation work for the *f*C-based IF detection method in the Landsat datasets would also be conducted through the use of very high resolution imagery data. The same high resolution imagery data and the procedure to assess the accuracy of the method were used as in the VIs-based IF detection method. The sample locations were randomly located in each class in the *f*C-based IF maps and had to be relatively evenly distributed in the class, as presented in the Appendices (Figure A.26). Similar to the VIs-based IF detection method, the accuracy assessment was also first conducted for the IF land versus non IF land to see how the method and algorithms could separate the lands. Then, it would be scaled down to the finer IF classes, specifically for acacia, rubber, and other IFs.

The results of the IF land versus non-IF land accuracy assessment showed that the user's and producer's accuracy for the IF land was 47% and 83% (Table 3.2). The commission and omission error was 53% and 17%, respectively. The map accuracy achieved by the *f*C-based IF detection method for Landsat data was 43%. At the same time, the Kappa coefficient for detecting and mapping the IF land in this method was 0.46 at the moderate agreement.

Table 3.2. The accuracy assessment results for the *f*C-based IF land detection method.

fC				
		Referenced LULC		
Classified		IF land	Non IF land	Total
	IF land	34	38	72
	Non IF land	7	121	128
	Total	41	159	200
Overall Accuracy				78%
User's Accuracy		47%	95%	
Producer's Accuracy		83%	76%	
Omission Error		17%	24%	
Commission Error		53%	5%	
Map Accuracy		43%	73%	
Kappa Coefficient		(moderate agreement)		0.46

Next we would further examine how this method worked for detecting specific IF systems in the regions. The findings of this study showed that it could detect and map acacia plantations better than rubber and other IFs (Table 3.3). For acacia IF detection, the user's accuracy and commission error were 50% and 50%, compared to those for the rubber IFs at 47% and 53%, and other IFs at 43% and 57%, respectively. For the producer's accuracy, the method also presented its detection for acacia (82%) higher than that for rubber (81%) but less than that for other IFs (100%). This was also consistent with the omission error for acacia of 18%, rubber of 19%, and other IFs of 0%. The acacia IF detection and mapping also acquired the higher map accuracy (45%) than other IFs (43%) and rubber (42%). The Kappa statistics for detecting the specific IF systems at 0.50 was slightly higher than for detecting the IFs in general at 0.46. This also showed a moderate agreement by chance between the classified and referenced IF maps.

Table 3.3. The accuracy assessment results specific for acacia, rubber, and other IFs for the *f*C-based IF detection method for Landsat data.

fC						
		Referenced LULC				
		Acacia	Other IFs	Rubber	Non IF land	Total
Classified	Acacia	9	0	0	9	18
	Other IFs	0	3	0	4	7
	Rubber	0	0	22	25	47
	Non IF land	2	0	5	121	128
	Total	11	3	27	159	200
Overall Accuracy						78%
User's Accuracy		50%	43%	47%	95%	
Producer's Accuracy		82%	100%	81%	76%	
Omission Error		18%	0%	19%	24%	
Commission Error		50%	57%	53%	5%	
Map Accuracy		45%	43%	42%	73%	
Kappa Coefficient		(moderate agreement)				0.50

3.5 Discussions and Conclusions

The above study results showed a high possibility of using the vegetation fractional cover (*f*C) changes analysis method for Landsat datasets in a time series to detect and map industrial forests in the tropics. The accuracy assessment results of this method for both IF land in general, and specific IF systems in particular, were found to be at the acceptable level. The accuracy of detecting and mapping acacia IFs was better than that of rubber and other IFs. Similar to the VIs-based IF detection method, this method least worked in detecting and predicting other IFs. This proved that detecting this kind of IFs was very challenging because of its diversity. In brief, similar to the aforementioned VIs-based IF detection method, the ability of this method to detect and map IFs in the region was confounded by some challenges and difficulties including, the quality and disadvantages of the Landsat data, as well as the rotation and growth rate assumptions used to develop the method, and other textural, spectral, and visual interpretation issues.

For the quality of Landsat scenes, this method used the same data as the VIs-based method. However, instead of directly computing the VI values in the images, this method analyzed the spectral composition and proportion for soil and forest in each pixel based on their spectral endmembers to produce a forest/vegetation fractional cover (*f*C) dataset. This approach would help reduce the additive effects of image quality to the method. However, it also faced the problem of spectral similarity among different endmembers and spectral variability in an endmember.

The second challenging issue this study faced also came from the ideas used to develop the method to detect IFs. That is, the uses of the information about the silvicultural rotation and growth rates of the forest/vegetation covers based on their changes analysis over time also inherited the outstanding issues, which were similar to and argued in the VIs-based method above.

Regarding the use of the textural and spectral analysis as a supportive step in detecting and mapping IFs, this method took the same approach as the above VIs-based method. However, instead of subjectively identifying the spectral and textural values for the expected LULC classes and using them in the built models, this method used the supervised classification function in the ERDAS software to classify the expected LULC classes. Therefore, it could help reduce the subjectivity in identifying the selected IF systems. Besides, this method and the VIs-based method used the same visual interpretation data. Therefore, they would have the same issues.

For other analyses including band 4 value-based green biomass content and $MSAVI_{af}$-derived leaf area index that were added to the method to detect and map IFs, the values of band 4 might only represent the green biomass of vegetation canopy instead of representing the whole biomass of the stands. Therefore, using it for biomass content analysis should be carefully considered. Besides, using $MSAVI_{af}$-derived leaf area index to identify the IF systems should be also additionally tested in the fields.

In brief, it was possible for us to develop and use a forest/vegetation fractional cover changes analysis-based method for Landsat datasets that could detect, map, and monitor the area, expansion rate, patterns, and scale of IFs in the tropics. The study results showed the accuracy of this method in detecting IFs in the region was better than that of the VIs-based method. Detecting and mapping acacia IFs in this method was better accurate than detecting and mapping rubber plantations, while the other IFs showed the least accuracy in this method. Consequently, like the VIs-based method, there is still much to be done to improve the accuracy of this method in detecting and mapping IFs in tropical regions like Sabah and Sarawak, Malaysia. It also opened a new, innovative, and promising approach in methods development for detecting and mapping new industrial forests in the tropics.

CHAPTER 4

ASSESSING THE INDUSTRIAL FOREST LAND USE AND LAND COVER CHANGES, AND THEIR CONSEQUENCES

4.1 Industrial Forest Land Use and Land Cover Changes

4.1.1. The fC-based LULCC

The results of the *f*C-based IF detection method showed that the total IF area (acacia, rubber, and other IFs) in Sabah increased from 102,667 ha in 2000 to 391,214 ha in 2014 at the annual mean rate of 20.1%; in Sarawak, it increased from 54,840 ha to 514,738 ha in the same period at the annual mean rate of 59.9% (Figures 4.1, 4.2a&b).

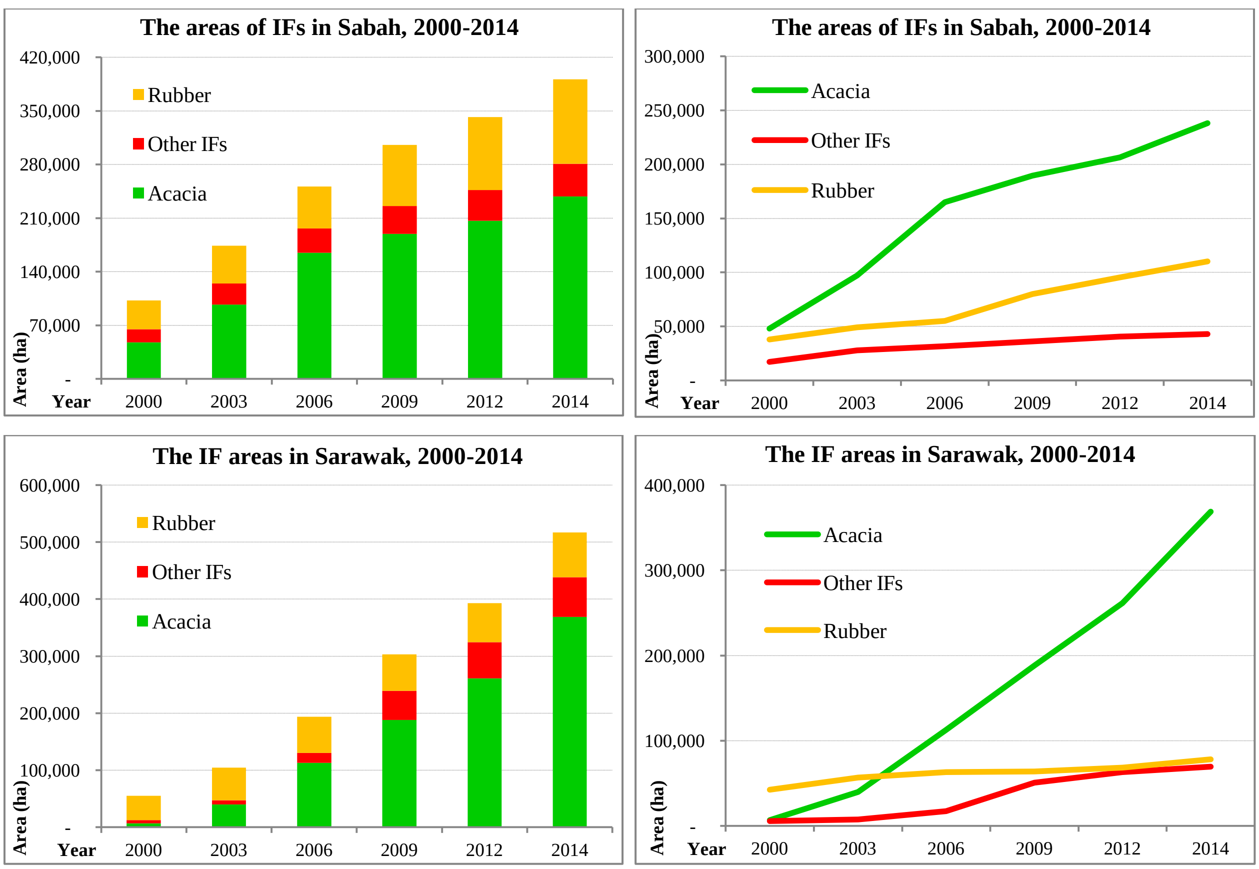


Figure 4.1. The IF areas in 2000, 2003, 2006, 2009, 2012 and 2014 in Sabah and Sarawak.

The total IF area newly established for the period of 2000-2014 was 288,547 ha in Sabah, and 459,898 ha in Sarawak (Tables 4.1 & 4.2). Specifically, the acacia IF area in Sabah increased 190,353 ha from 47,868 ha in 2000 to 238,221 ha in 2014, with the yearly mean expansion rate for the whole study period at 28.4%, much higher compared to the annual mean increasing rate of rubber plantations (13.7%) and other IFs (10.9%). In the same period, the rubber area increased 72,274 ha from 37,788 ha in 2000 to 110,062 ha in 2014. Likewise, the area of other IFs in Sabah also slightly increased 25,920 ha from 17,011 ha in 2000 to 42,931 ha in 2014 (Table 4.1 & Figure 4.2a). Compared to the expansion rate of IFs in Sabah, the expansion rate of IFs in Sarawak in the period was much higher and very impressive. Specifically, the total area of acacia IFs has increased from almost nothing (6,864 ha in 2000) to 368,640 ha in 2014 with a net increase of 361,776 ha for 2000-2014 at the annual rate of 376.5% (Table 4.2 & Figure 4.2b). Likewise, the yearly expansion of other IFs in Sarawak was also very impressive, with the annual mean rate of 78.2% in the period, representing a net increase of the area of 63,808 ha from 5,829 ha in 2000 to 69,637 ha in 2014. In contrast, the development of rubber plantations was much lower compared with the development of acacia and other IFs; it only increased at the annual mean rate of 5.8% over the study period. The rubber area had increased 34,314 ha from 42,147 ha in 2000 to 76,461 ha in 2014. The development trend for rubber plantations in Sarawak was similar to the trend of development for rubber plantations in Sabah over the period of 2000-2014 (Table 4.2 & Figure 4.2b).

Breaking the IF expansion area and its rate in Sabah and Sarawak down into the intervals, we realize that the largest newly-expanded IF area (77,538 ha) was found in the period of 2003-2006 in Sabah, followed by 2000-2003 (71,318 ha); after that, the growth slowed down for 2006-2009 (54,089 ha) and 2009-2012 (36,423 ha), and increased again for the period of 2012-2014 (49,179 ha) (Table 4.1). A similar trend was also found for the expansion rate of total IFs. The highest rate of change in IF area was also found in 2000-2003 at 23.2% (specific to acacia at 34.3% and other IFs at 21.2%, the highest compared to other periods); then, the IF expansion rate slowed down for 2003-2012, and increased again for 2012-2014 (Figure 4.2a). In Sarawak, the largest new expansion IF area was found in 2012-2014 with an area of 123,572 ha and a growth rate of 15.8%. However, the highest rate of change in IF area was found for 2000-2003 at 29.1%, followed by 2003-2006 (28.9%), 2006-2009 (19.3%), and 2009-2012 (9.7%) (Figure 4.2b).

Table 4.1. The IF area expansion in Sabah, 2000-2014.

	Newly expanded IF area in Sabah (ha)					
Species	*2000-2003*	*2003-2006*	*2006-2009*	*2009-2012*	*2012-2014*	*2000-2014*
Acacia	49,206	67,944	24,536	16,917	31,750	190,353
Other IFs	10,814	3,800	4,574	4,177	2,555	25,920
Rubber	11,298	5,794	24,979	15,329	14,874	72,274
Total	**71,318**	**77,538**	**54,089**	**36,423**	**49,179**	**288,547**

Table 4.2. The IF area expansion in Sarawak, 2000-2014.

	Newly expanded IF area in Sarawak (ha)					
Species	*2000-2003*	*2003-2006*	*2006-2009*	*2009-2012*	*2012-2014*	*2000-2014*
Acacia	32,967	73,072	75,452	72,880	107,405	361,776
Other IFs	1,862	9,779	33,440	12,303	6,424	63,808
Rubber	13,026	6,300	2,108	3,137	9,743	34,314
Total	**47,855**	**89,151**	**111,000**	**88,320**	**123,572**	**459,898**

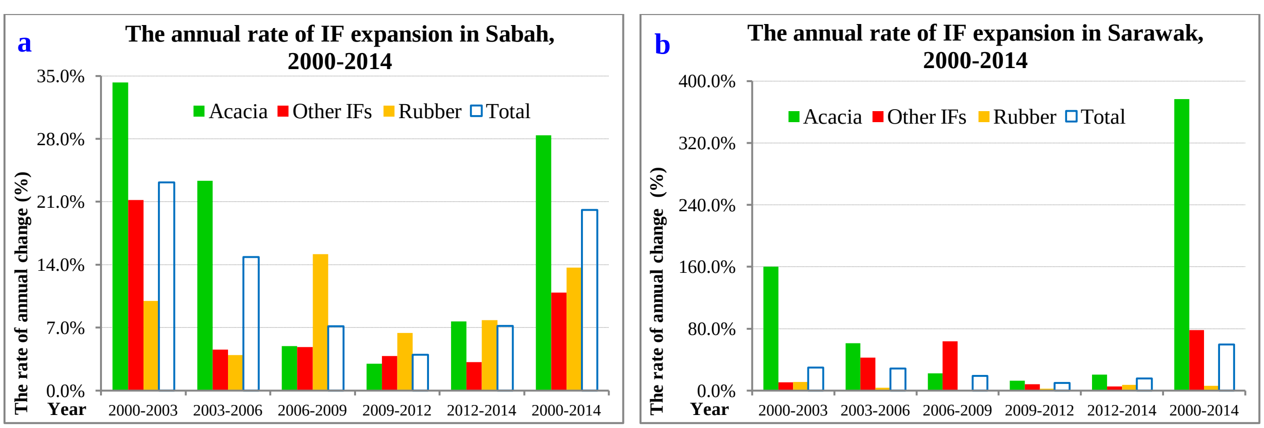


Figure 4.2. The annual rate of change in area in Sabah (a) and Sarawak (b), 2000-2014.

To further understand the dynamics and processes of the expansion of new IFs in Malaysia, we should consider how IFs at the small- versus large-scale plantations had been expanded. In fact, for the satellite images only-derived LULC map products, it is very challenging or even impossible for us to know which patch is owned by industries or smallholders without any further ownership investigation in the field. However, based on the individual patch size, it is possible for us to assume which patch may belong to smallholders (small-scale) or industries (large-scale). For instance, Bissonnette and De Koninck (2015) find that most countries divide the small-scale and large-scale IFs/plantations based on the land size ranging from 20-40 ha. Lintangah *et al.* (2010) investigated tree plantation activities among smallholders in Ranau, Sabah and found that, in addition to other tree plantation species, rubbers and acacias were main species, followed by teaks, pines, and eucalypts. For rubber plantations, the average patch size owned by smallholders was about 1.3-1.4 ha. Most of other tree plantations had a size of 0.4 to 2 ha, while some reached 2 to 6.5 ha, and very few were larger than 6.5 ha. This is very likely a common practice in Southeast Asia, where smallholders own a land size around 1-4 ha for perennial cash crops (Fox & Castella, 2013). Therefore, for this reason and conservativeness, the land size used to divide the small-scale versus large-scale IFs in Malaysia in this study was assumed at 40 ha.

In general, based on this assumption, in both states, the total area of small-scale IFs (~30-40%) was found to be much less than the area of large-scale IFs (~60-70%; Figure 4.3; Tables 4.3a&b, & 4.4a&b). Specifically, in Sabah, the large-scale IF area in 2000 was 77,927 ha (76%), while the small-scale area owned by smallholders was only 24,740 ha (24%) for the same year. This increased to 215,910 ha (55%) in 2014 compared to 175,304 ha (45%) under the same ownership (Tables 4.3a&b). The study also found that the percentage of the large-scale IF area in the state declined from 76% in 2000, to 73% in 2003, to 61% in 2006, to 56% in 2009, to 57% in 2012, and to 55 % in 2014. Likewise, in Sarawak, the total large-scale IF area in 2000 was 44,194 ha (81%), compared to 10,646 ha (19%) of smallholdings (small-scale IFs). The large-scale IF area had increased to 348,350 ha (68%) in 2014 compared with an increase to 166,388 ha (32%) for small-scale IFs (Tables 4.4a&b). The trend of change for IF scales in Sarawak over the study period was similar to the trend in Sabah. Specifically, the percentage of small-scale IF area slightly increased from 19% in 2000, to 25 % in 2009, and to 32% in 2014 (Table 4.4b).

In general, most of the absolute expansion of new IFs in the study area was in the large-scale IFs. However, the percentage of total large- versus small-scale IFs also slightly declined over 2000-2014. The percentage specific for different IFs under the large-versus small-scale IFs in different years indicated some differences. For instance, in Sabah, the percentage of rubber IFs

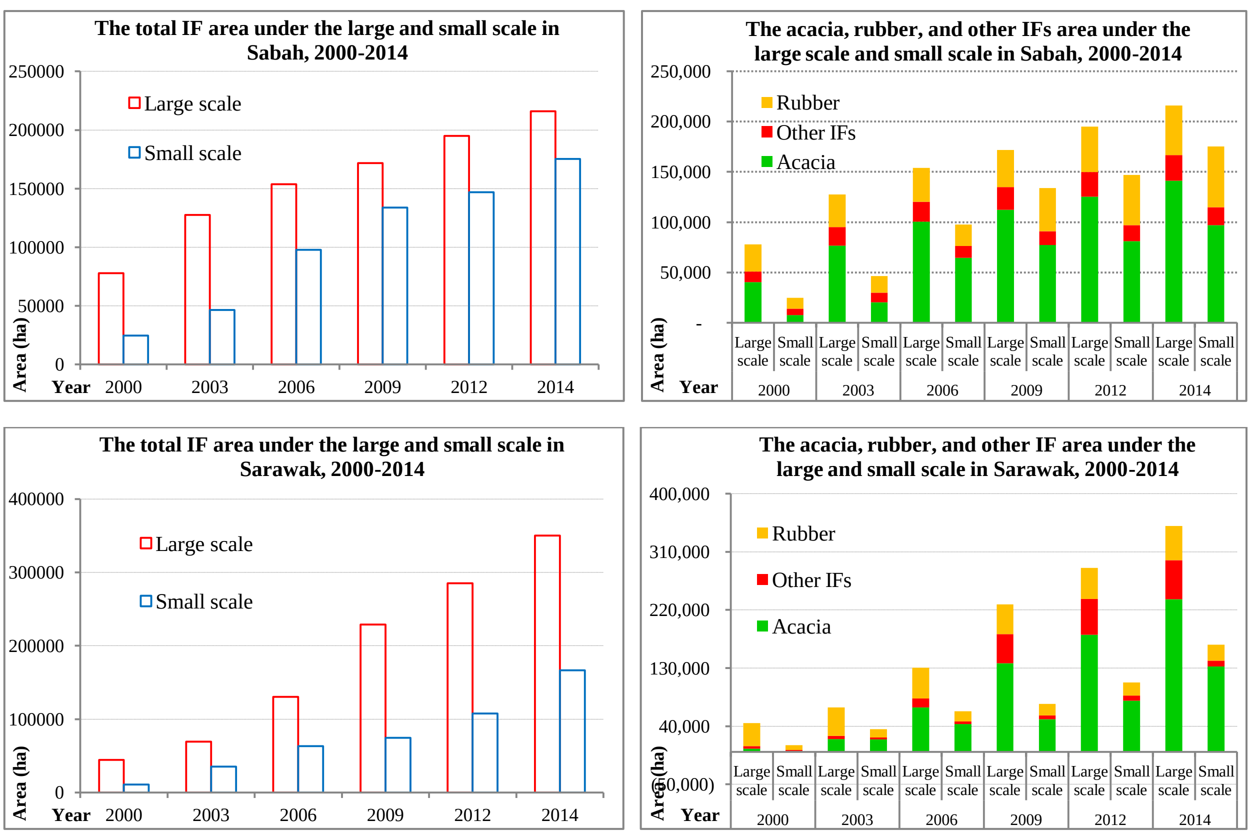


Figure 4.3. The total large-scale and small-scale IF area in Sabah and Sarawak, 2000-2014.

Table 4.3a. The area (in ha) of large-scale and small-scale IFs in Sabah, 2000-2014.

Species	2000		2003		2006		2009		2012		2014	
	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale
Acacia	40,311	7,557	76,645	20,429	100,433	64,585	112,272	77,282	125,236	81,235	141,160	97,061
Other IFs	10,699	6,312	18,322	9,503	19,897	11,728	22,683	13,516	24,480	15,896	25,344	17,587
Rubber	26,917	10,871	32,524	16,562	33,451	21,429	36,893	42,966	45,319	49,869	49,406	60,656
Total	**77,927**	**24,740**	**127,491**	**46,494**	**153,781**	**97,742**	**171,848**	**133,764**	**195,035**	**147,000**	**215,910**	**175,304**

Table 4.3b. The percentage of large-scale and small-scale IFs in Sabah, 2000-2014.

Species	2000		2003		2006		2009		2012		2014	
	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale
Acacia	84%	16%	79%	21%	61%	39%	59%	41%	61%	39%	59%	41%
Other IFs	63%	37%	66%	34%	63%	37%	63%	37%	61%	39%	59%	41%
Rubber	71%	29%	66%	34%	61%	39%	46%	54%	48%	52%	45%	55%
Total	76%	24%	73%	27%	61%	39%	56%	44%	57%	43%	55%	45%

Table 4.4a. The area (in ha) of large-scale and small-scale IFs in Sarawak, 2000-2014.

Species	2000		2003		2006		2009		2012		2014	
	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale
Acacia	5,053	1,811	20,247	19,584	69,328	43,575	137,392	50,963	181,784	79,451	236,320	132,320
Other IFs	4,243	1,586	4,867	2,824	13,718	3,752	45,336	5,574	55,376	7,837	60,642	8,995
Rubber	34,898	7,249	42,243	12,930	45,485	15,988	45,667	17,914	46,151	20,567	51,388	25,073
Total	**44,194**	**10,646**	**67,357**	**35,338**	**128,531**	**63,315**	**228,395**	**74,451**	**283,311**	**107,855**	**348,350**	**166,388**

Table 4.4b. The percentage of large-scale and small-scale IFs in Sarawak, 2000-2014.

Species	2000		2003		2006		2009		2012		2014	
	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale	Large scale	Small scale
Acacia	74%	26%	51%	49%	61%	39%	73%	27%	70%	30%	64%	36%
Other IFs	73%	27%	63%	37%	79%	21%	89%	11%	88%	12%	87%	13%
Rubber	83%	17%	77%	23%	74%	26%	72%	28%	69%	31%	67%	33%
Total	81%	19%	66%	34%	67%	33%	75%	25%	72%	28%	68%	32%

under smallholdings (patch size < 40ha) was generally slightly larger than that for acacia and other IFs (Table 4.3b). Conversely, in Sarawak, the percentage of acacia and other small-scale IFs was larger than that for rubber, except for other IFs after 2006. For instance, 74% (2000), 51% (2003), 61% (2006), and 64% (2014) of acacia plantations were large-scale IFs, compared with 83% (2000), 77% (2003), 74% (2006), and 67% (2014) of the large-scale rubber plantations. Likewise, 73% (2000) and 63% (2003) of other IFs were large-scale IFs, compared with 83% and 77% of rubber plantations under the same scale in 2000 and 2003, respectively. More detailed information on the area and percentage of small- and large-scale IFs specific for acacia, rubber, and other IFs from 2000 to 2014 in Sabah and Sarawak are presented (Tables 4.3a&b & 4.4a&b; Figure 4.4).

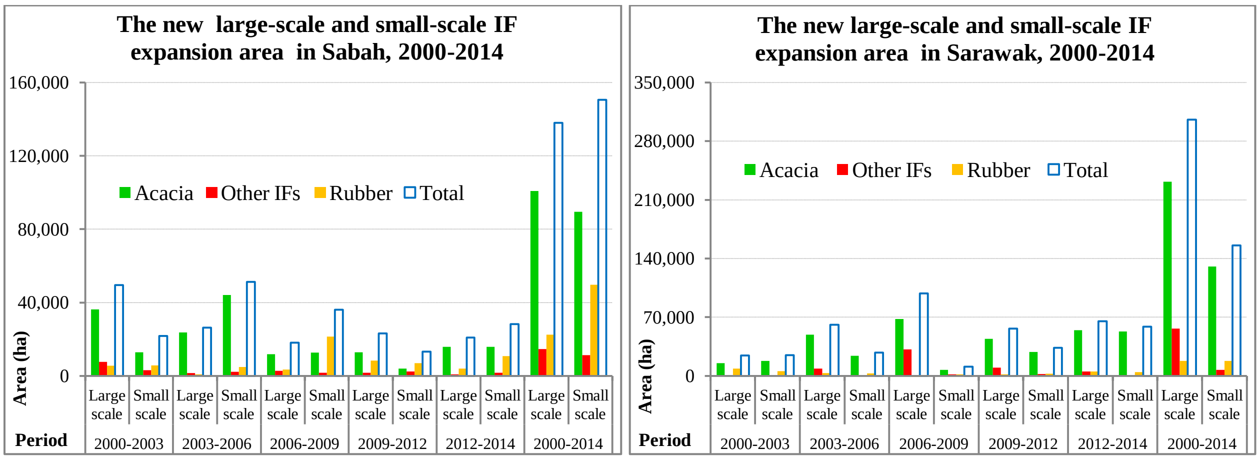


Figure 4.4. The expansion of the large- and-small-scale IFs in Sabah and Sarawak, 2000-2014.

Likewise, when considering the rate of change in large- and small-scale IF areas for the different periods of 2000-2003, 2003-2006, 2006-2009, 2009-2012, 2012-2014, and 2000-2014 in Sabah and Sarawak, it also presented the same stories. That is, while the total IF area in both states were dominated by large-scale IFs over the study period, the expansion rates for small-scale IFs were also very significant and much higher than that of the large-scale IFs. Specifically, the expansion rate for the total small-scale IF area in Sabah for 2000-2014 (43%) was much higher than the expansion rate for the large-scale IF area (13%; Figure 4.5). It was also similar for the expansion rates of the small-scale acacia (85%), other IFs (13%), and rubber (33%) versus the large-scale acacia (18%), other IFs (10%), and rubber (6%). Similarly, in Sarawak, the rate of small-scale acacia IF area expansion over the period of 2000-2014 (515%) was higher than the rate of large-scale acacia IF area expansion (327%). The same trend was also found for rubber plantations: the expansion rate of the small-scale rubber plantations was 18%, compared to an expansion rate of 3% for the large-scale rubber plantations (Figure 4.5). Further data on the large- and small-scale expansion rates specific for acacia, rubber, and other IFs in the different periods in both states are presented (Figure 4.5).

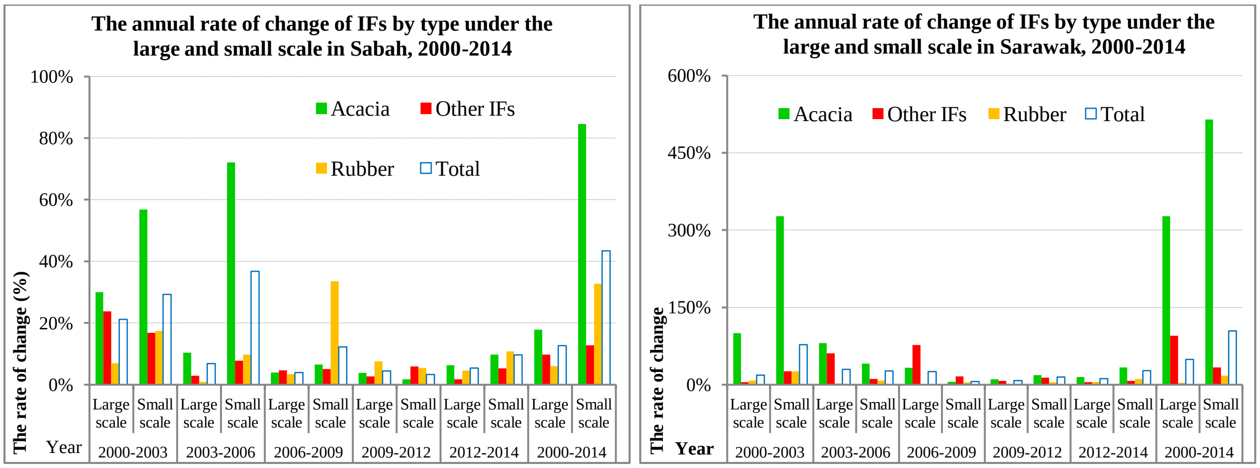


Figure 4.5. The annual rate of change in large- and small-scale IF area by type in Sabah and Sarawak, 2000-2014.

The Pattern Indices for IF LULC Changes

Along with the increase of the total IF area in both Sarawak and Sabah as described above, the number of IF patches and the largest IF patch size also increased (Figure 4.6). Specifically, in Sabah, the total number of IF patches increased from 4,382 in 2000 to 39,327 in 2014. At the same time, the size of the largest patch also increased from 5,475 ha to 9,721 ha. Likewise, in Sarawak, the total number of patches increased from 2,496 in 2000 to 30,413 in 2014. Along with this increase, the largest patch size also increased from 3,759 ha to 15,624 ha (Figure 4.6). In Sabah, the largest IF patch size was found for acacia plantations, with 5,475 ha in 2000 and 9,721 ha in 2014, while the largest patch size for other IFs slightly increased from 948 ha (2000) to 1,280 ha (2014). The largest patch size for rubber was 2,741 ha, and it did not change over the study period (Figure 4.7). Conversely, in Sarawak, the largest patch size found for 2000 was of rubber IFs with 3,759 ha. Then, the largest patch size of acacia increased from 1,224 ha (2000) to

15,624 ha (2014), while other IFs increased from 1,063 ha (2000) to 11,609 ha (2014; Figure 4.7).

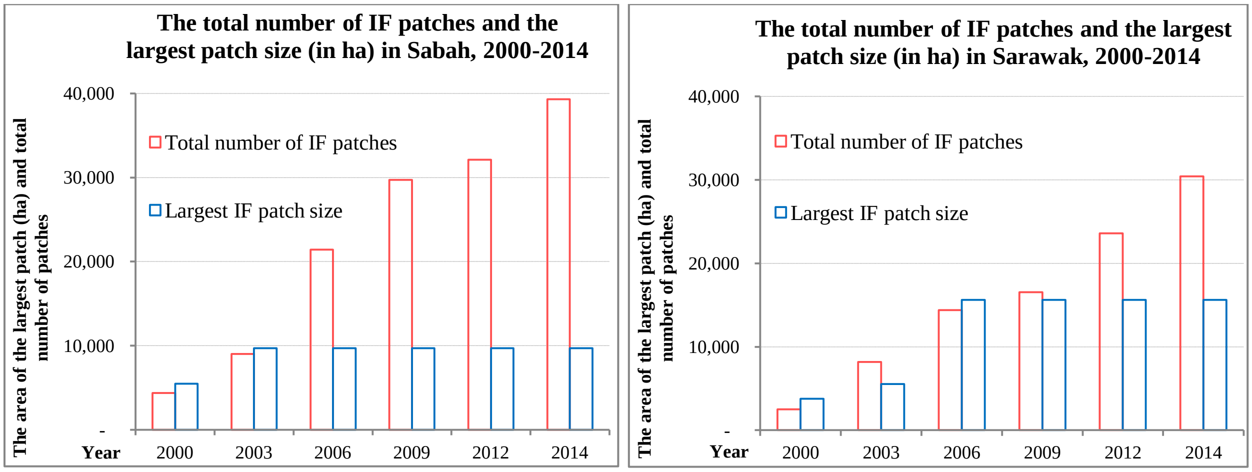


Figure 4.6. The total number of patches and the largest IF patch area (in ha) in Sabah and Sarawak, 2000-2014.

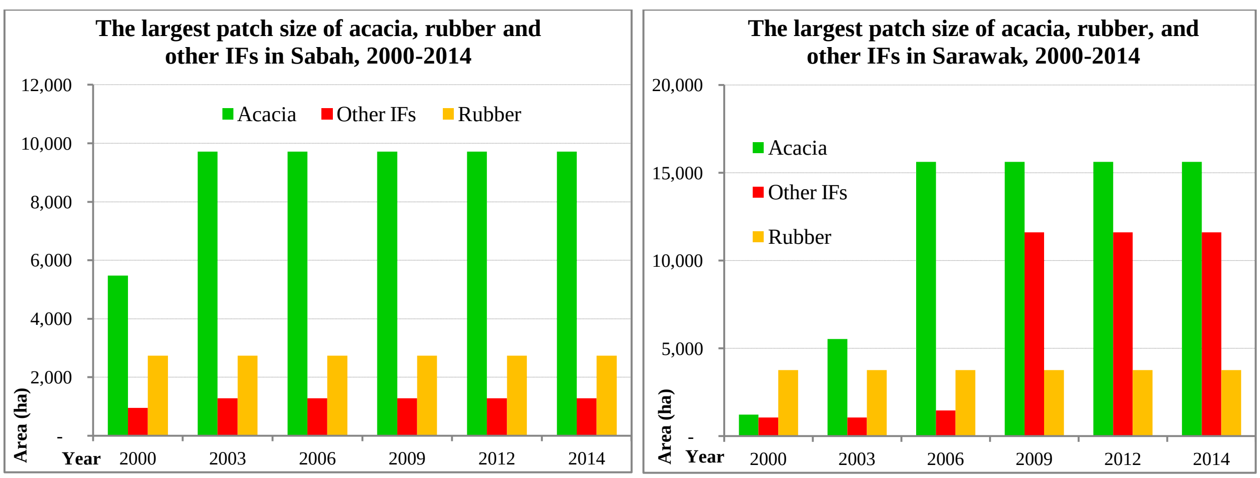


Figure 4.7. The largest patch size of acacia, rubber and other IFs in Sabah and Sarawak, 2000-2014.

Another necessary pattern index for assessing IF LULCC in Sabah and Sarawak is the mean patch size index. Generally, in Sabah, the mean patch size decreased, while the mean IF patch size in Sarawak increased (Figure 4.8). In Sabah, the mean size for all IFs declined from 23 ha in 2000 to 10 ha in 2014. Of which, the acacia mean patch size decreased from 32 ha (2000) to 10 ha (2014). For rubber and other IFs, their mean patch size also decreased from 20 to 8 ha, and from 18 to 15 ha, respectively, in the same period (Figure 4.8). Conversely, in Sarawak, the mean IF patch size for all IFs first declined from 22 ha (2000) to 13 ha (2003 & 2006), and then increased again to 18 ha (2009) and 17 ha (2012 & 2014). Of which, other IF mean patch size increased from 23 ha (2000) to 52 ha (2014), while the rubber mean patch size declined from 24 ha (2000) to 14 ha (2014). For acacia IFs, the mean patch size declined from 14 ha (2000) to 9 ha (2003) and increased again to 11 ha (2006), 15 ha (2012), and 16 ha (2014; Figure 4.8).

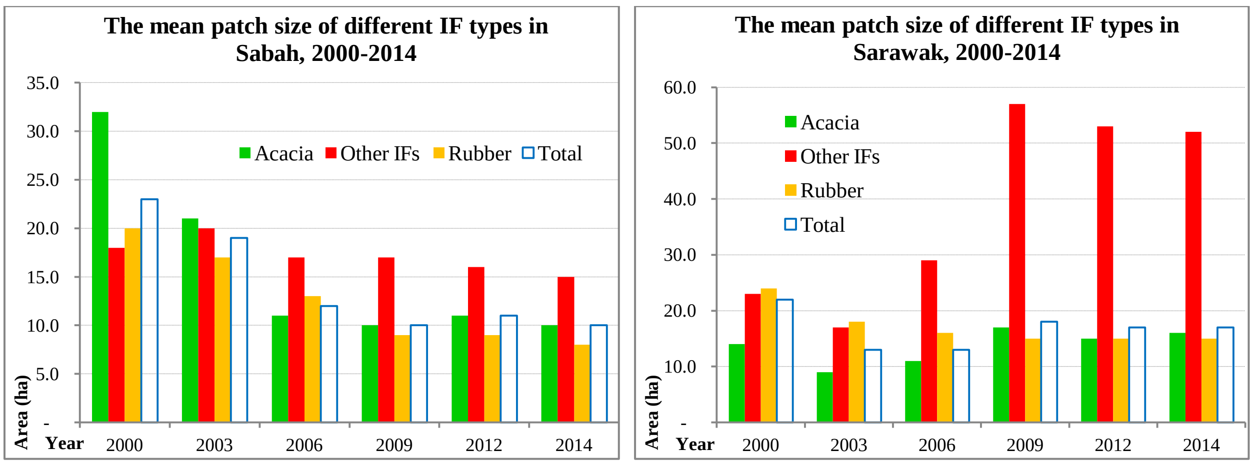


Figure 4.8. The mean patch size index of acacia, rubber and other IFs in Sabah and Sarawak, 2000-2014.

To formulate a better understanding of drivers and LULCC dynamics associated with emerging IFs in Malaysia, we should consider how IFs had been developed at the different scales over time. The scales of IFs were divided into six patch size classes including ≤ 5 ha, 5-20 ha, 20-40 ha, 40-100 ha, 100-200 ha, and ≥ 200 ha. In general, in Sabah, most of IF areas were distributed in the IF patch size class over 200 ha, followed by IF patch size class smaller than 5 ha. In other words, the distribution of area classes based on the patch size classes in general was as follows: $A_{\geq 200ha}$ (the total area of the 200-ha-larger-patches class) > $A_{\leq 5ha}$ > $A_{5\text{-}20ha}$ > $A_{40\text{-}100ha}$ > $A_{100\text{-}200ha}$ > $A_{20\text{-}40ha}$ (Figure 4.9). Specifically, for instance, in 2014, the distribution of the total IF area into class size was as follows: 159,640 ha ($A_{\geq 200ha}$) > 88,044 ha ($A_{\leq 5ha}$) > 65,309 ha ($A_{5\text{-}20ha}$) > 30,017 ha ($A_{40\text{-}100ha}$) > 26,211 ha ($A_{100\text{-}200ha}$) > 22,051 ha ($A_{20\text{-}40ha}$). A similar trend was also found for the remaining years (2000, 2003, 2006, 2009, & 2012), and also for acacia, rubber, and other IFs. Likewise, in Sarawak, the patch size class over 200 ha occupied most of the total IF area in the state, followed by the patch size class smaller 5 ha; the IF area of the patch size class of 20-40 ha was the smallest (Figure 4.10). This trend was similar for all years selected for the study (except for 2014 when $A_{\leq 5ha} < A_{5\text{-}20ha}$), and for all IF types in the state (Figure 4.10).

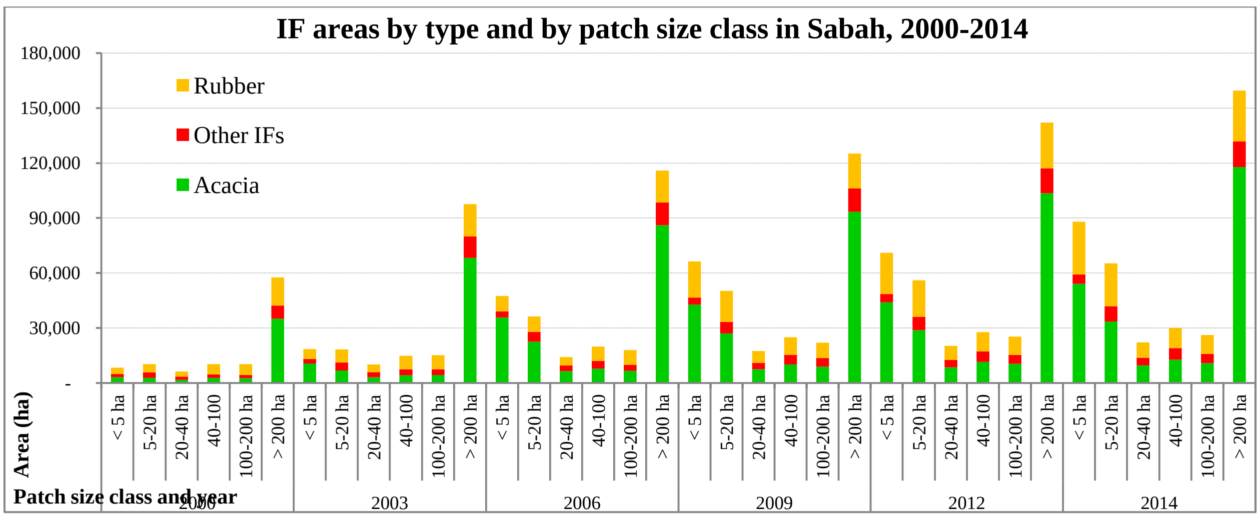


Figure 4.9. IF areas by type and by patch size class in Sabah, 2000-2014.

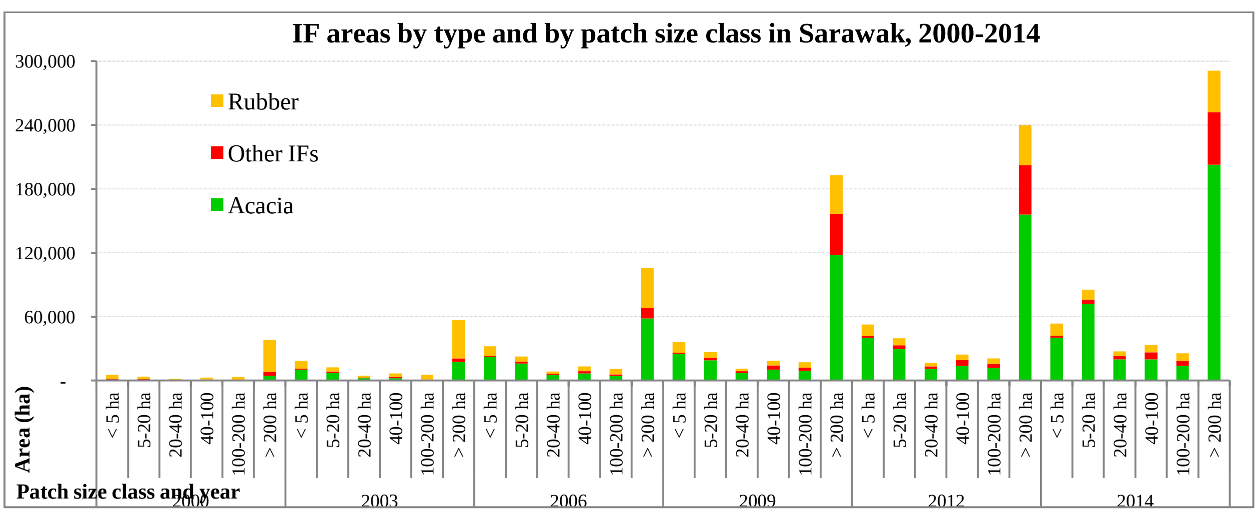


Figure 4.10. IF areas by type and by patch size class in Sarawak, 2000-2014.

Next, we would further examine the total number of the large-scale patches (≥ 40 ha,) as classified above and their mean patch size indices in the study area over the period of 2000-2014. The result of studying the pattern indices for the large-scale plantations (industries) showed an increase of the total number of the large-scale IF patches in both Sarawak and Sabah. Specifically, in 2000, Sabah had 308 large-scale patches, which increased to 881 patches in 2014 (Figure 4.11). The acacia IFs contributed to most of this increase. The number of the large-scale acacia patches increased from 90 patches in 2000 to 397 patches in 2014, while the number of the large-scale patches of other IFs and rubber only increased from 61 to 177, and from 157 to 307, respectively, over the same period. Contrary to the increase in the total number of large-scale patches, the mean size of these patches in the state slightly declined from 253 ha in 2000 to 245 ha in 2014 (Figure 4.11). In particular, while the mean patch size for rubber and other IFs under this scale remained stable or slightly increased over the study period, the large-scale mean patch size of acacia IFs remarkably declined from 448 ha in 2000 to 356 ha in 2014 (Figure 4.11). Likewise, in Sarawak, the number of the large-scale IFs patches in the state also noticeably increased (Figure 4.12). Specifically, the total number of large-scale IF patches increased very impressively from 114 in 2000 to 1,006 in 2014. The large-scale acacia IFs substantially contributed to this increase with 583 patches. For rubber and other IFs, each contributed a net increase of 127 and 182 patches, respectively, over the period of 2000-2014. In particular, while the mean size for acacia and other IFs increased, the mean size for rubber in the state decreased (Figure 4.12). The mean large-scale patch size for acacia IFs increased from 337 ha in 2000 to 395 ha in 2014, and the mean size for large-scale other IFs patches also increased from 223 ha to 302 ha in the same period. Conversely, the mean patch size of the large-scale rubber plantations significantly declined from 436 ha in 2000 to 248 ha in 2014 (Figure 4.12).

The details of the changes to the mean large-scale patch size and the number of these patches specific for acacia, rubber, and other IFs in the different periods in both Sabah and Sarawak states are presented (Figures 4.11 & 4.12).

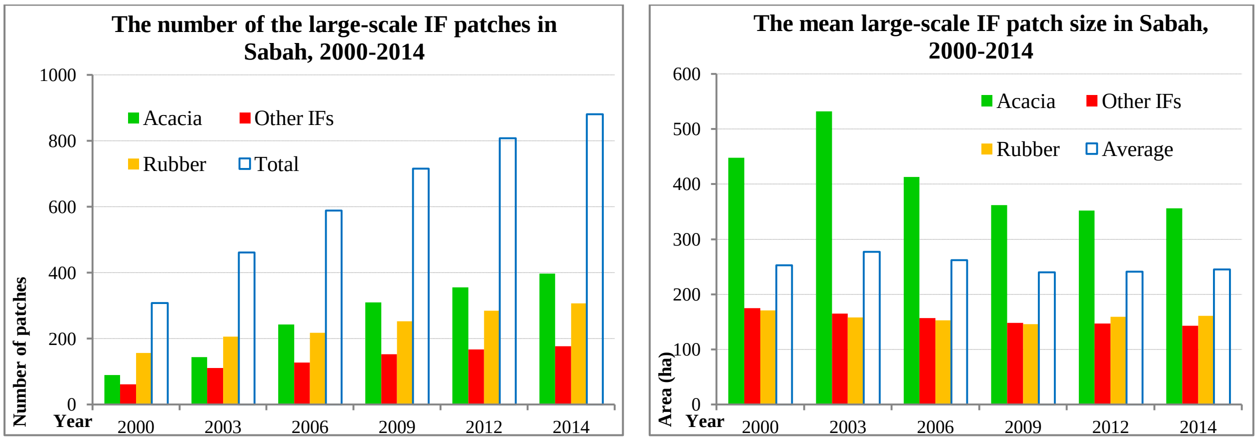


Figure 4.11. The total large-scale patch number and the mean patch size of IFs in Sabah, 2000-2014.

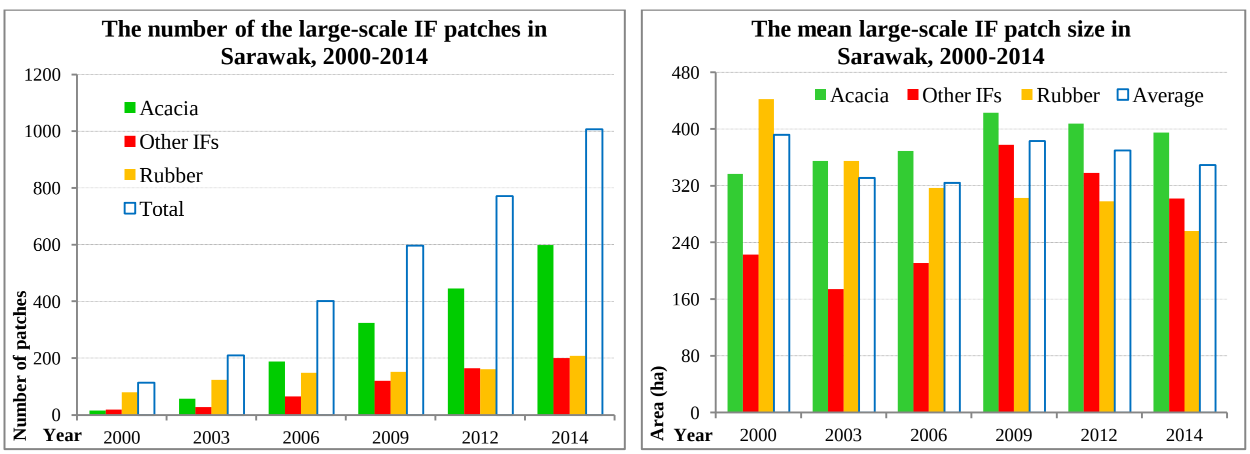


Figure 4.12. The total large-scale patch number and the mean patch size of IFs in Sarawak, 2000-2014.

4.1.2. The Vegetation Indices-based LULCC

As described above, this method used vegetation indices (VIs) including ARVI, EVI, $MSAVI_{af}$, $NDVI_{af}$, SARVI, and SAVI to detect, map, and monitor the IF expansion in Sabah and

Sarawak from 2000 to 2014. We also know that due to the additive effects of soil and atmospheric conditions as mentioned above, specific VI can perform better than others in the different geographic regions and each index has its own strength and weakness. Therefore, this study would consider and assess how IF area has changed over time in the study area by using the different vegetation indices, as well as which index worked the best in the study area.

The total IF areas that were detected in Sabah and Sarawak by using the different VIs were extremely variable. In general, the IF areas detected in both states were as follows: MSAVI*af* < NDVI*af* < SAVI < SARVI < EVI < ARVI. Specifically, the total IF area detected in 2000 in Sabah was 32,160 ha (by using MSAVI*af*), 42,149 ha (NDVI*af*), 46,917 ha (SAVI), 56,268 ha (SARVI), 71,475 ha (EVI) to 85,167 ha (ARVI), increasing to 219,743 ha (MSAVI*af*), 209,235 ha (NDVI*af*), 284,524 ha (SAVI), 309,190 ha (SARVI), 379,428 ha (EVI), and 386,523 ha (ARVI) in 2014, respectively (Figure 4.13). Likewise, in Sarawak, the total IF area in this state had increased from 9,791 ha in 2000 to 148,996 ha in 2014 by using MSAVI$_{af}$, 13,804 ha to 184,848 ha (NDVI$_{af}$), 13,417 ha to 206,716 ha (SAVI), 18,988 ha to 240,363 ha (SARVI), 22,207 ha to 266,623 ha (EVI), and 28,382 ha in 2000 to 340,816 ha in 2014 by using ARVI.

Not only was the detected total IFs area different by using the different vegetation indices, the IF areas specific for the different species or systems - including acacia, rubber, and other IFs - also varied greatly (Figure 4.13). Specifically, the acacia area detected in Sabah in 2000 had a range from 19,286 ha (MSAVI$_{af}$) to 44,683 ha (ARVI), increasing to a range from 163,026 ha (NDVI$_{af}$) to 288,583 ha (EVI) in 2014. The rubber area also increased from 8,980-27,380 ha in 2000 to 32,617-88,347 ha in 2014 by using MSAVI$_{af}$ (smallest) and ARVI (biggest), respectively. For other IFs, the smallest area was also found in the MSAVI$_{af}$ product with 3,912 ha in 2000, increasing to 12,264 ha in 2014, while the biggest area was found in the ARVI product with 13,104 ha in 2000, expanding to 32,601 ha in 2014 (Figure 4.13). The same findings were also found in Sarawak. The acacia area increased from almost nothing in 2000 - about 3,298 ha ($MSAVI_{af}$)-5,806 ha (ARVI) - to 107,298 ha ($MSAVI_{af}$)-222,295 ha (ARVI) in 2014 (Figure 4.13). Likewise, the rubber area was also detected in 2000 ranging 4,844-17,682 ha, increasing to 18,334-54,891 ha in 2014 in the $MSAVI_{af}$ and ARVI products, respectively. For other IFs, it presented a net area increase from 21,716 ha ($MSAVI_{af}$) to 58,918 ha (ARVI) over the study period of 2000-2014. The areas specific for the different IF systems over the period of 2000-2014 in Sabah and Sarawak are indicated (Figure 4.13).

Because the detected total IF areas and specific areas for acacia, rubber, and other IFs were different using the different VIs the rates of change in their area were also different and quite variable in the study area over 2000-2014. Specifically, in Sabah, the annual rates of change in total IF area specific for the different VIs from 2000 to 2014 were 25% (ARVI), 28% ($NDVI_{af}$), 31% (EVI), 32% (SARVI), 36% (SAVI), and 42% ($MSAVI_{af}$; Figure 4.14). Of these, the highest annual IF area change rates were found for the period of 2000-2003 with a range of 23% (ARVI)-41% ($MSAVI_{af}$), while the lowest annual rates of change in IF area were 2006-2009 from 2% (EVI, $NDVI_{af}$, SARVI, & SAVI) - 3% (ARVI & $MSAVI_{af}$). For the different IF species/systems, we found that the annual rates of change in their area also varied among the different VIs usages. Specifically, the annual rates of change in acacia area over 2000-2014 were 36% (ARVI), 40% ($NDVI_{af}$), 45% (EVI), 48% (SARVI), 53% (SAVI), and 58% ($MSAVI_{af}$). These rates were much higher compared with those for rubber plantations [13% (SARVI), 14% (ARVI & $NDVI_{af}$), 15% (SAVI), 16% (EVI), & 19% ($MSAVI_{af}$)], and other IFs [8% (EVI, $NDVI_{af}$, & SARVI), 9% (SAVI), 11% (ARVI), & 15% ($MSAVI_{af}$)]. In particular, acacia and other IFs showed the highest rate of change in its area for 2000-2003 at the range from 40%

(ARVI)-61% ($MSAVI_{af}$), and from 9% (EVI, SARVI, & SAVI) to 11% (ARVI & $MSAVI_{af}$), respectively; meanwhile, rubber plantations were most expanded in 2009-2012 at the range of the expansion rate of 25% ($MSAVI_{af}$)-54% (EVI). More details of the annual rates of change in area specific for the different IF systems, years or intervals, and by using the different VIs in the state are presented (Figure 4.14).

Likewise, in Sarawak, the annual rates of change in IF area specific for the different years, IF species/systems, and VIs also varied greatly and were much higher than those in Sabah. The yearly expansion rates in the total IF area ranged from 79% to 103% over the 2000-2014 period (Figure 4.14). The highest rate was found in the SAVI-based IF map product (103%), followed by $MSAVI_{af}$ (102%), $NDVI_{af}$ (89%), and SARVI (82%); the lowest rates were found in the ARVI and EVI-based products (79%). This total annual expansion rate over the period of 2000-2014 in this state was most contributed to by the acacia expansion rate. Specifically, the expansion rate of acacia IFs was 225% ($MSAVI_{af}$), 239% ($NDVI_{af}$), 266% (ARVI), 299% (SARVI), 319% (EVI), and 355% (SAVI). Likewise, the expansion rates for other IFs were found in the range of 76% (lowest by using EVI) to 110% (highest by using SARVI); and for rubber plantations, the area expanded at the annual rate with a range from 10% (EVI & SARVI) to 20% ($MSAVI_{af}$; Figure 4.14). Breaking the expansion rates down to the intervals, we found that the acacia IF development rate was highest for the period of 2000-2003 (74%-95%) and 2003-2006, with more than 100%. While the highest rate of rubber was found in 2009-2012 with a range of 11-28%, the highest rate for other IFs (74%-104%) was also over the period of 2003-2006 (Figure 4.14). More details of the annual rates of change in area specific for the different IF systems, years, and by using the different VIs in both states are presented (Figure 4.14).

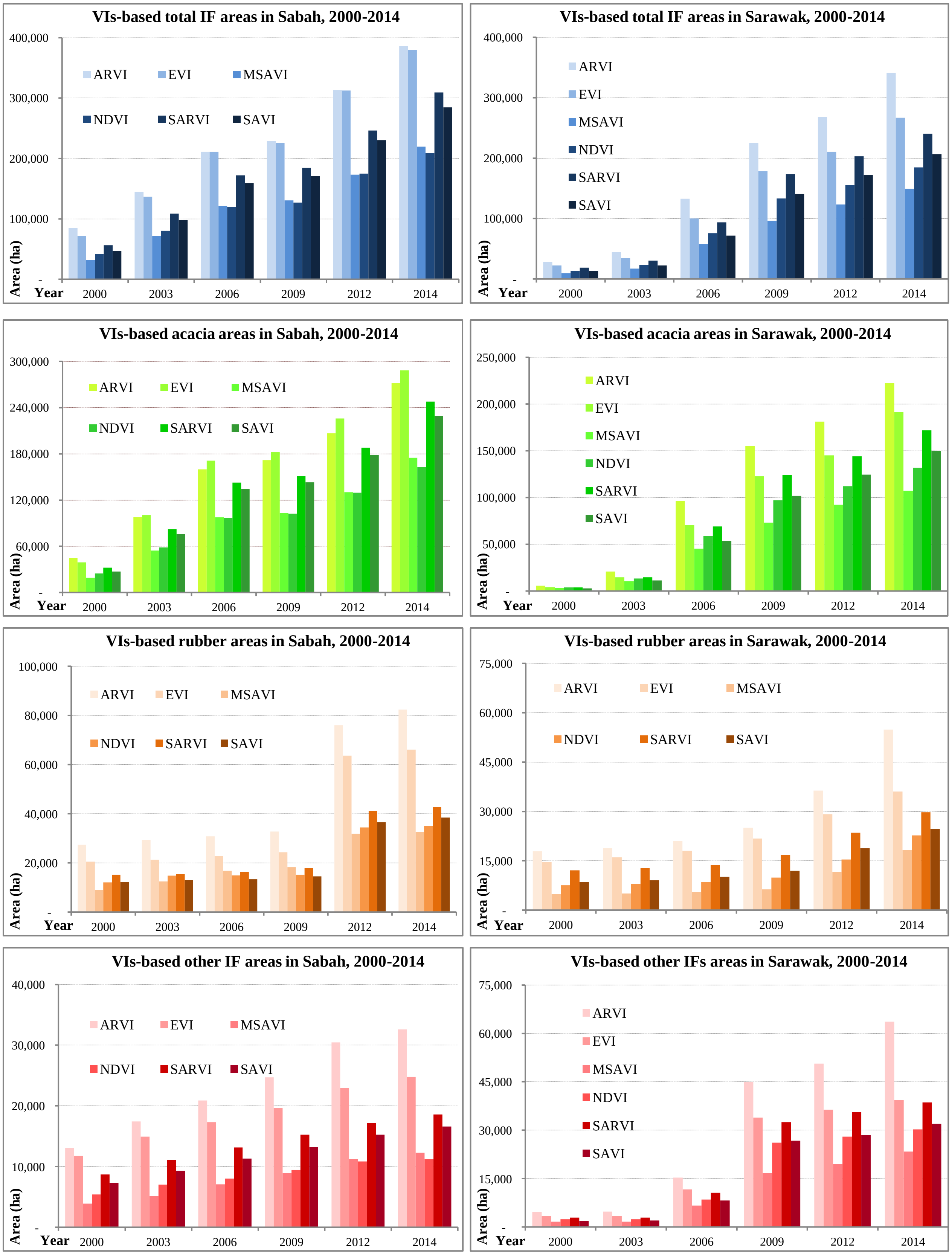


Figure 4.13. The VIs-based IF areas in Sabah and Sarawak, 2000-2014.

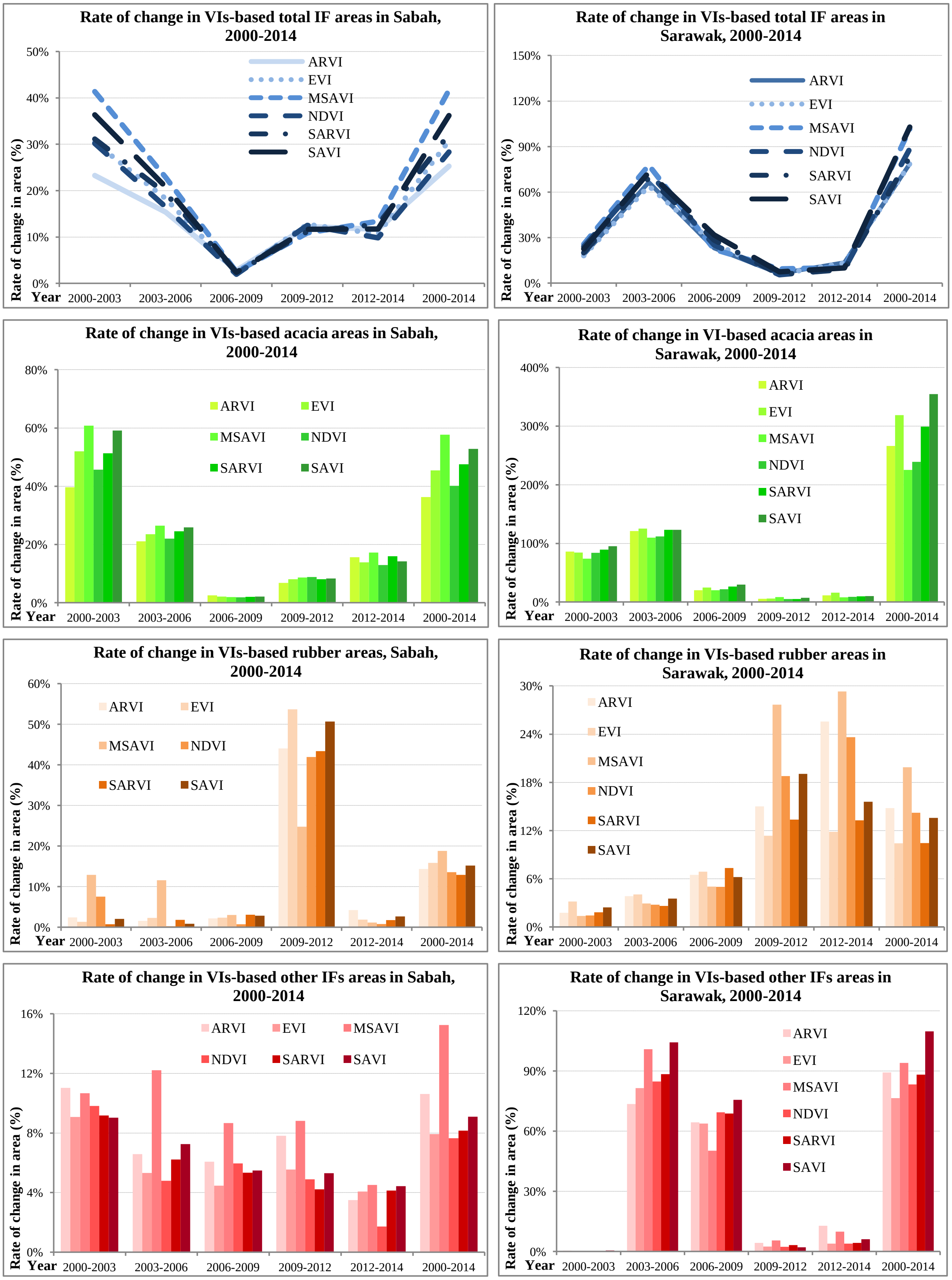


Figure. 4.14. The VIs-based rates of change in IF areas in Sabah and Sarawak, 2000-2014.

Similar to the above *f*C-based LULCC discussions, the VIs-based IF area and its annual rates specific for IF species, time intervals, and the small-scale versus large-scale IF areas were also studied. In general, in Sabah, the total area under smallholdings in all VIs-based IF map products was larger than or almost equal to that of large-scale IFs, while the large-scale IF area in Sarawak was remarkably larger than that of small-scale IFs (Figure 4.15). For instance, in 2014, the total small-scale IF area (patch size < 40 ha) in Sabah that was detected by using VIs was 213,337 ha (ARVI), 227,447 ha (EVI), 139,890 ha ($MSAVI_{af}$), 118,557 ha ($NDVI_{af}$), 182,210 ha (SARVI), and 181,170 ha (SAVI) - much higher compared with 173,186 ha (ARVI), 151,981 ha (EVI), 79,853 ha ($MSAVI_{af}$), 90,678 ha ($NDVI_{af}$), 126,980 ha (SARVI), and 102,814 ha (SAVI) for the large-scale IF area (patch size ≥ 40 ha). The same trends were also found for other years and specific IF species, especially for rubber plantations (Figure 4.15). Conversely, in Sarawak, the total large-scale IF area was significantly larger than the small-scale IF area. For instance, the total large-scale IF area in 2014 was 249,787 ha (ARVI), 161,704 ha (EVI), 83,373 ha ($MSAVI_{af}$), 117,275 ($NDVI_{af}$), 154,499 ha (SARVI), and 109,665 ha (SAVI), compared to 91,031 ha (ARVI), 104,919 ha (EVI), 65,623 ha ($MSAVI_{af}$), 67,573 ha ($NDVI_{af}$), 85,864 ha (SARVI), and 97,051 ha (SAVI) for the small-scale IF area. This trend was also the same for acacia and other IFs, while the small-scale rubber area was bigger than the large-scale rubber area (Figure 4.15). The VIs-based study findings for the rates of change in the total IF area - and specifically for acacia, rubber, and other IF areas - in both Sabah and Sarawak over 2000-2014 also showed that their expansion rates for small-scale IFs was higher compared to those for the large-scale IFs, except the expansion rate for the total IF area in Sarawak, in which the expansion rates for the small-scale IFs was lower than those for the large-scale IFs over the period of 2000-2009 (Figure 4.16). More information on the expansion rates is presented (Figure 4.16).

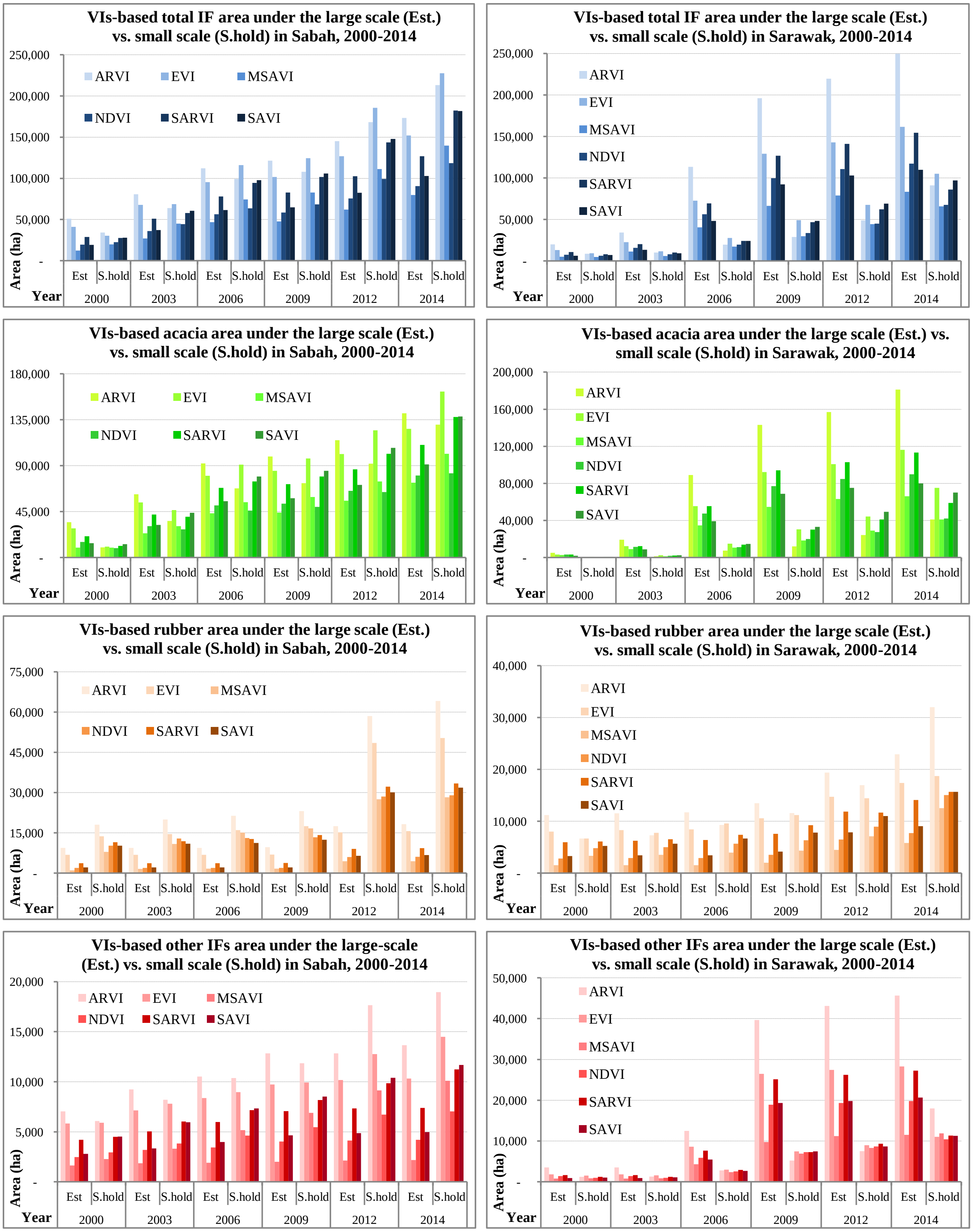


Figure 4.15. The VIs-based large- and small-scale IF areas in Sabah and Sarawak, 2000-2014.

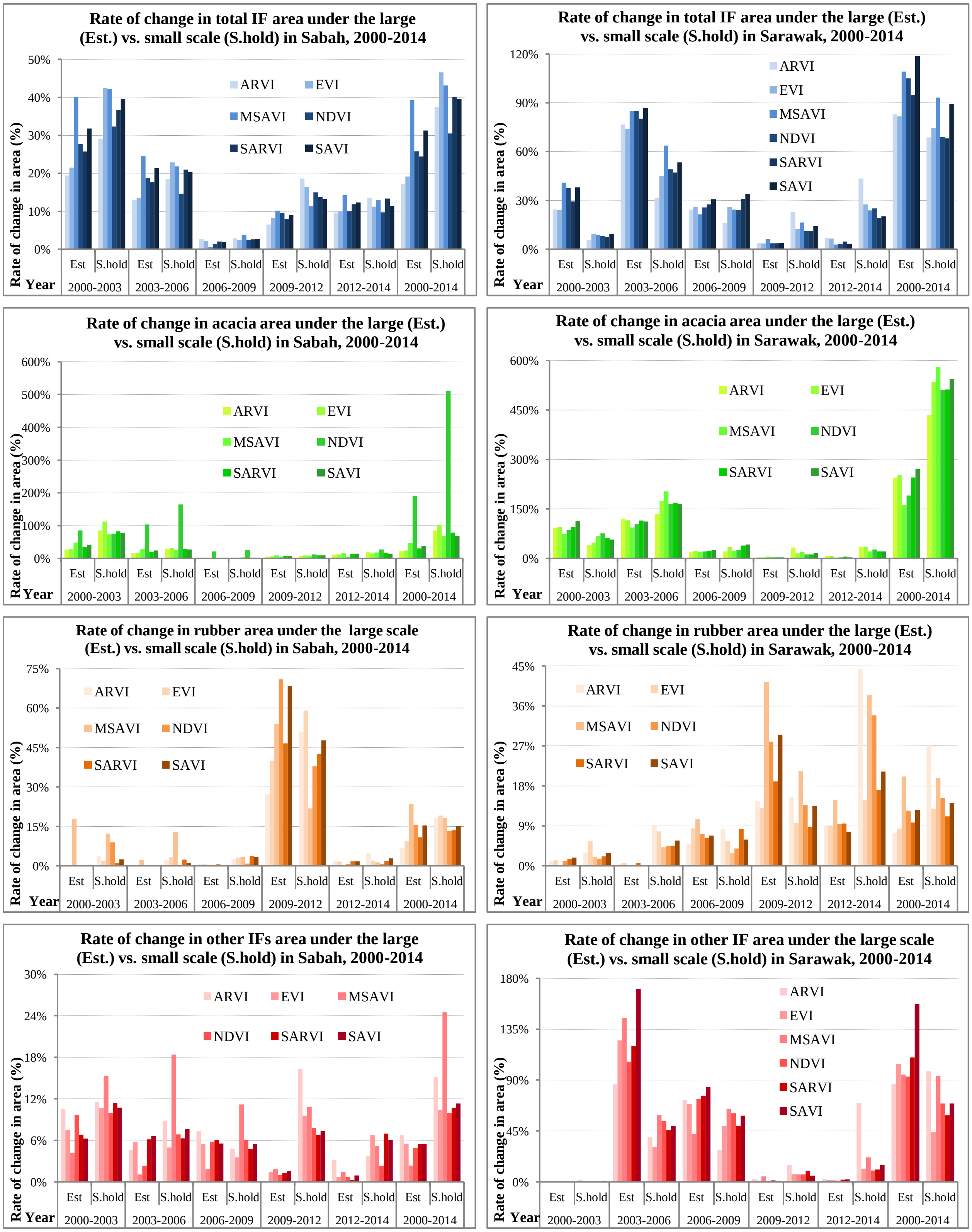


Figure 4.16. The VIs-based rate of changes in large- and small-scale IF areas in Sabah and Sarawak, 2000-2014.

4.2 Assessments of the IF LULC Changes and their Consequences

The above findings clearly indicate that the IFs have been increasing in Sabah and Sarawak, Malaysia, both in the individual patch size and the total area, over the study period. The next questions this study clarified were what types and how much area of natural or managed ecosystems these new IFs had replaced. To answer these questions, a procedure to assess the IF LULCC was developed (Figure 4.17).

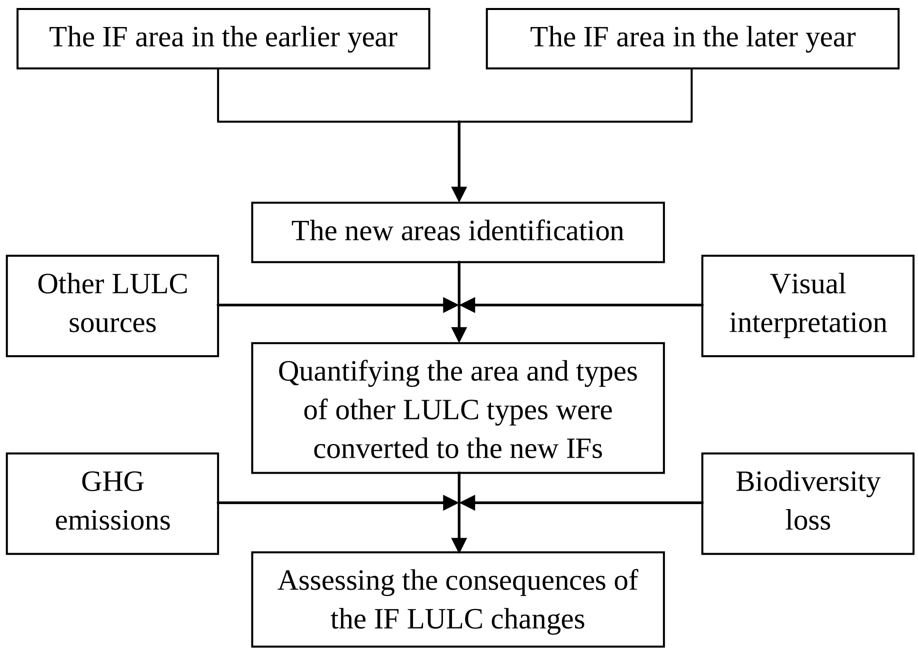


Figure 4.17. The procedure to assess the IF LULC changes in Sabah and Sarawak, Malaysia.

To identify the new IF areas, two IF maps in the consecutive years were first overlaid. Then, the IF areas in the earlier year (*e.g.*, 2000) were used to erase the pre-existing IF areas in the later year (*e.g.*, 2003) by using the ArcGIS analysis tool. The remaining IF areas in the later year (2003) would be the new IF areas, which were expanded between the earlier year (2000) and the later year (2003). Another way to acquire these new areas was to select the attributes by using the following formula: [(“year_2”=‘the later year, *e.g., 2003*’) and (“year_1” <> ‘the earlier year, *e.g.*, 2000’)], and export the new areas into the new shapefiles. To know what kinds of natural or managed ecosystems these new IFs had replaced, other LULC sources and visual interpretation would be used to identify what kind and how much area of other LULC types were converted to these new IF areas.

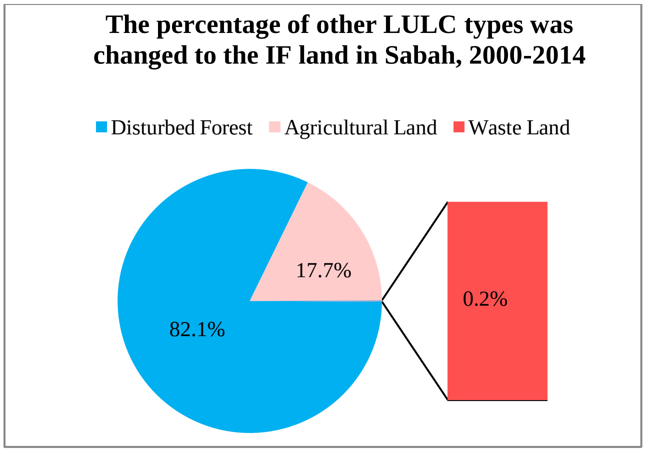
The other LULC sources used in this study were obtained from the Roundtable on Sustainable Palm Oil (RSPO) Organization (Gunarso *et al.,* 2013) for the years of 2000, 2005, and 2010. The LULC was classified into 6 different types, including Undisturbed Forest (UF), Disturbed Forest (DF), Agricultural Land (AL), Oil Palm Land (OP), Waste/Degraded Land (WL), and Residential Land (RL). At the same time, visual interpretation analysis and editing would be also used to identify, include or exclude, and quantify the new IF areas and other LULC types based on the following arguments and assumptions. The study first eliminated the IF areas smaller than 2 ha. This was due to the fact that the smaller IF patches were more difficult to detect; and Fox and Castella (2013) indicated smallholders in Southeast Asia commonly own a land size around 1-4 ha of plantations. Therefore, the minimum land size selected in detecting and mapping new IFs in the study area was 2 ha. It was also very unlikely that people destroyed their buildings to establish new IFs. Therefore, the new IFs appearing in the built-up or residential area would be eliminated. In addition, various studies (*e.g.*, Jagatheswaran *et al.*, 2012; Jagatheswaran *et al.,* 2011; Akira *et al.,* 2011; Pinso & Vun, 2000) indicated that oil palm plantations were much more profitable than other plantations, so that they outcompeted and replaced other plantations. Therefore, it was impractical to claim that oil palms were converted into the new IFs. Lastly, it was also unlikely that the new IFs would be directly converted from undisturbed forests. This was because much research (*e.g.,* Lawson *et al.*, 2014; Miyamoto *et al.,* 2014; Aziz *et al.,* 2010; Wicke *et al.* 2008; Suratman, 2007; Grieg-Gran *et al.,*

2007) has shown that the deforestation pathway in the region was that primary forests were first converted into disturbed forests and then to other LULC types.

By doing so, the study findings showed that, from 2000 to 2014, the total new IF area in Sabah was 288,551 ha including 190,354 ha of acacia, 25,920 ha of other IFs, and 72,277 ha of rubber (Table 4.5). These new IF areas have replaced 237,039 ha (82.1%) of disturbed forest (DF), 51,011 ha (17.7%) of agricultural land (AL), and only 501 ha (0.2%) of degraded/wasteland (WL; Table 4.5 & Figure 4.18). Specifically, 87.5% of new acacia IFs were expanded in DF, 12.47% in AL, and 0.03% in the degraded/waste land (Figure 4.19). Likewise, most new rubber plantations (63.1%) were converted from DF, followed by AL (36.3%), and WL (0.6%). Following the same pattern as new acacia and rubber IFs, 95.9% of new other IFs had replaced DF, and only 4.1% of these IFs were established in AL. There were no new other IFs established in WL. The new IF areas in Sabah specific for the selected IFs, and their replacements for other LULC types are presented (Table 4.5; Figures 4.18 & 4.19).

Table 4.5. The new IF areas and their LULC replacements in Sabah, 2000-2014.

IF Species	LULC Type	Newly Expanded Area (ha)					Total
		2000-03	2003-06	2006-09	2009-12	2012-14	
Acacia	Disturbed Forest	42,440	62,682	20,132	12,938	28,362	166,554
	Agricultural Land	6,729	5,262	4,402	3,980	3,369	23,742
	Waste Land	37	0	3	0	18	58
	Total	**49,026**	**67,944**	**24,537**	**16,918**	**31,749**	**190,354**
Other IFs	Disturbed Forest	10,216	3,659	4,532	3,973	2,483	24,863
	Agricultural Land	559	140	42	204	72	1,057
	Waste Land	0	0	0	0	0	0
	Total	**10,815**	**3,799**	**4,574**	**4,177**	**2,555**	**25,920**
Rubber	Disturbed Forest	6,503	3,382	14,055	10,935	10,747	45,622
	Agricultural Land	4,782	2,399	10,834	4,278	3,919	26,212
	Waste Land	13	13	90	119	208	443
	Total	**11,298**	**5,794**	**24,979**	**15,332**	**14,874**	**72,277**
Total	Disturbed Forest	59,159	69,723	38,719	27,846	41,592	237,039
	Agricultural Land	12,110	7,801	15,278	8,462	7,360	51,011
	Waste Land	50	13	93	119	226	501
	Total	**71,319**	**77,537**	**54,090**	**36,427**	**49,178**	**288,551**



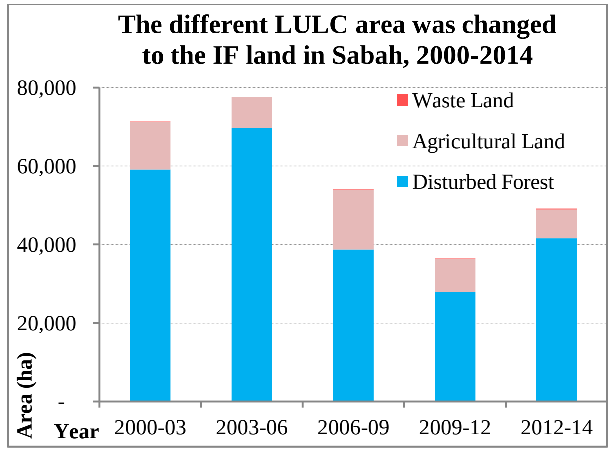
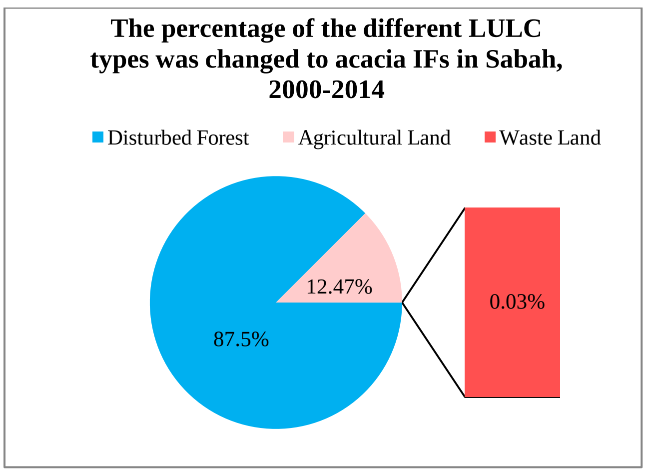
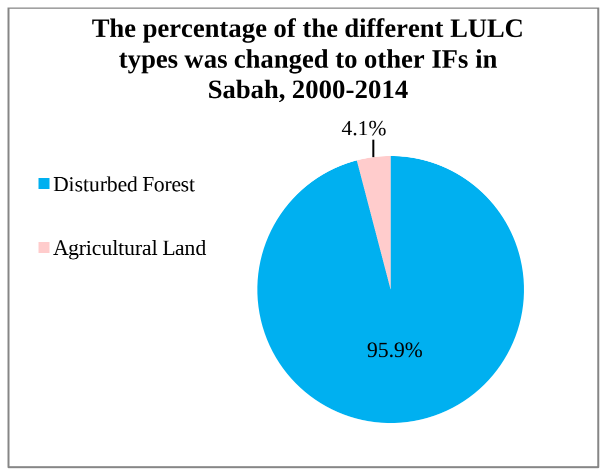


Figure 4.18. The new IF areas and their other-LULC-types-replacements percentage and area in Sabah, 2000-2014.





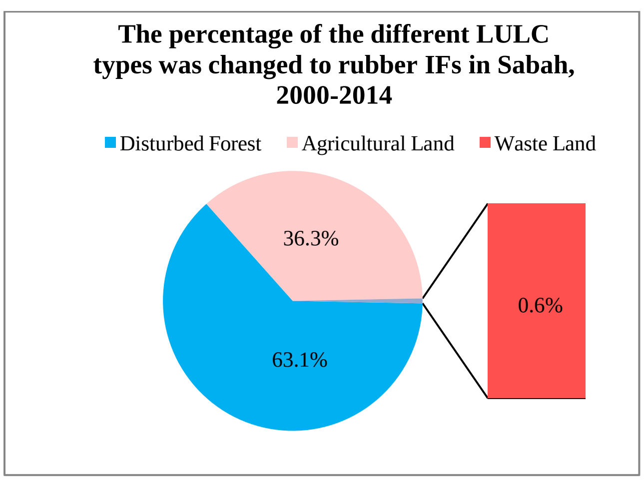


Figure 4.19. The percentage of the different LULC types converted to new acacia, rubber, and other IFs in Sabah, 2000-2014.

In other words, 70% of the conversion of DF to the new IFs was accounted for by new acacia plantations (166,554 ha), 19% by new rubber plantations (45,622 ha), and 11% by new other IFs (24,863 ha; Figure 4.20). Conversely, the largest part of AL was lost by new rubber IFs (51%; 26, 212 ha), followed by new acacia IFs (47%; 23,742 ha), and new other IFs (2%; 1,057ha). For WL, the total conversion area was 501 ha. Of that, new rubber IFs took 88.4% (443 ha) and acacia IFs 10% (58 ha); there was no conversion to new other IFs (Figure 4.20).

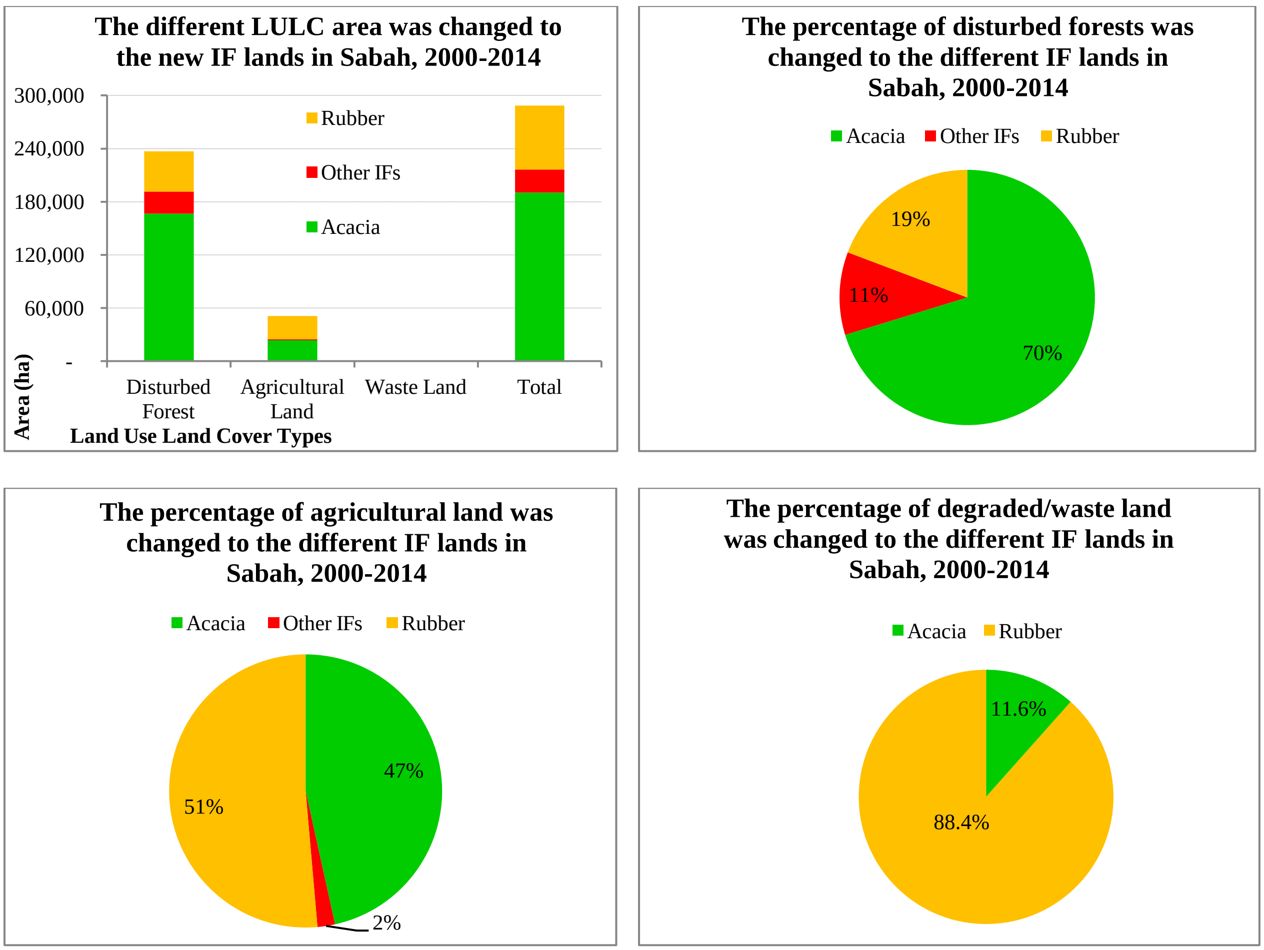
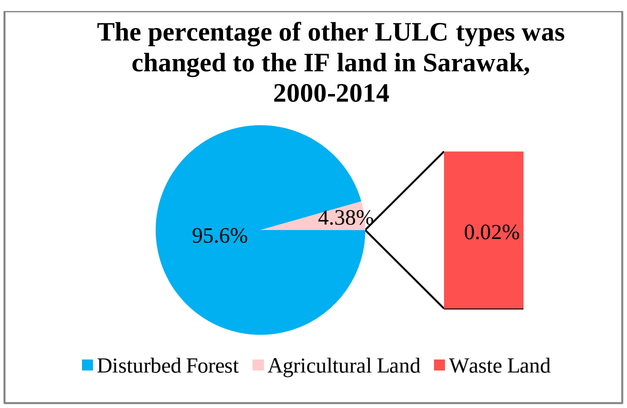


Figure 4.20. The different LULC types area and their percentage converted to new acacia, rubber, and other IFs in Sabah, 2000-2014.

Similar to the IF LULC changes in Sabah, the total new IF area in Sarawak established from 2000 to 2014 was 459,896 ha, including 361,775 ha of acacia, 63,808 ha of other IFs, and 34,313 ha of rubber (Table 4.6). Most of these new IF areas (95.6%; 439,610 ha) were established in the disturbed forest land (DF), 4.38% (20,192 ha) in agricultural land (AL), and only 0.02% (94 ha) in degraded/wasteland (WL) (Table 4.6 & Figure 4.21). Specifically, 96.4% of new acacia IFs were expanded in DF, 3.5% in AL, and only 0.1% in WL (Figure 4.22). Likewise, most new rubber IFs (81%) were converted from DF, followed by AL (19%), and no new establishments in degraded land. For new other IFs, 98.6% were established in DF and only 1.4 % in AL.

Table 4.6. The new IF areas and their LULC replacements in Sarawak, 2000-2014.

IF Species	LULC Type	Newly Expanded Area (ha)					Total
		2003	2006	2009	2012	2014	
Acacia	Disturbed Forest	30,588	72,157	74,466	67,551	104,157	348,919
	Agricultural Land	2,363	914	979	5,258	3,248	12,762
	Waste Land	17	0	7	70	0	94
	Total	**32,968**	**73,071**	**75,452**	**72,879**	**107,405**	**361,775**
Other IFs	Disturbed Forest	1,643	9,506	33,241	12,153	6,344	62,887
	Agricultural Land	220	273	198	150	80	921
	Waste Land	0	0	0	0	0	0
	Total	**1,863**	**9,779**	**33,439**	**12,303**	**6,424**	**63,808**
Rubber	Disturbed Forest	10,149	5,339	1,830	2,871	7,615	27,804
	Agricultural Land	2,876	961	278	266	2,128	6,509
	Waste Land	0	0	0	0	0	0
	Total	**13,025**	**6,300**	**2,108**	**3,137**	**9,743**	**34,313**
Total	Disturbed Forest	42,380	87,002	109,537	82,575	118,116	439,610
	Agricultural Land	5,459	2,148	1,455	5,674	5,456	20,192
	Waste Land	17	0	7	70	0	94
	Total	**47,856**	**89,150**	**110,999**	**88,319**	**123,572**	**459,896**



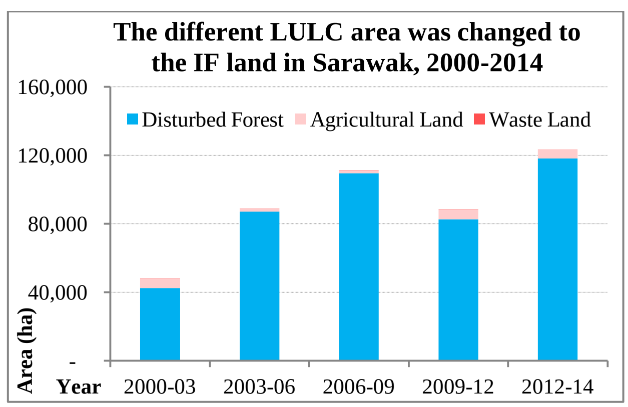


Figure 4.21. The new IF areas and their other-LULC-types-replacements percentage and area in Sarawak, 2000-2014.

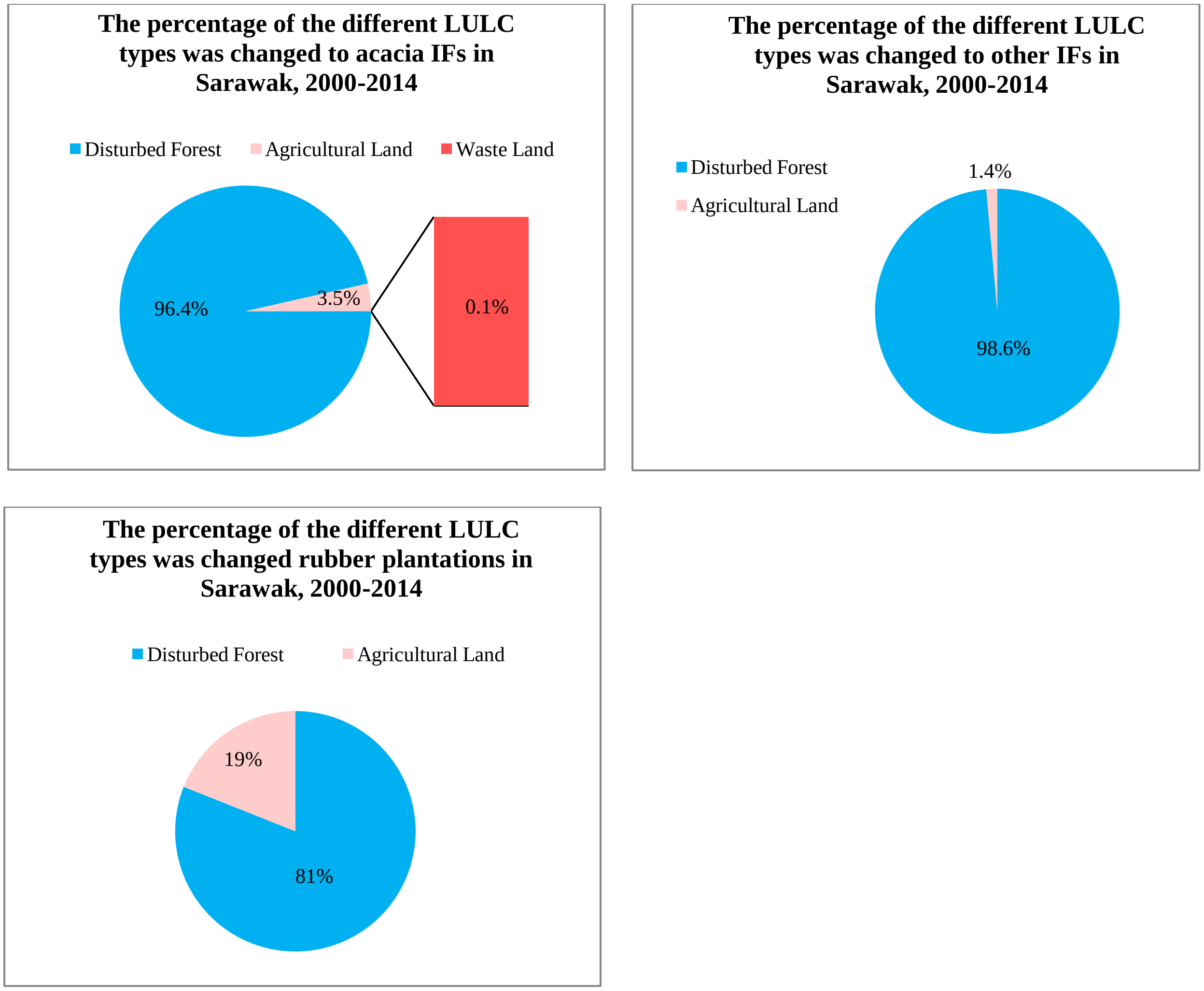


Figure 4.22. The percentage of the different LULC types converted to new acacia, rubber, and other IFs in Sarawak, 2000-2014.

In other words, 80% of the loss of disturbed forests were caused by the new acacia IFs (348,919 ha), 14% by the new other IFs (62,887 ha), and 6% by the new rubber plantations (27,804 ha; Figure 4.23). Likewise, the largest part of agricultural land was also lost by the new acacia IFs (63%; 12,762 ha), followed by the new rubber plantations (32%; 6,509 ha), and the new other IFs (5%; 921 ha). Finally, 100% of the degraded land (94 ha) was converted to the new acacia IFs, and no new rubber and other IFs were established in this kind of land (Figure 4.23).

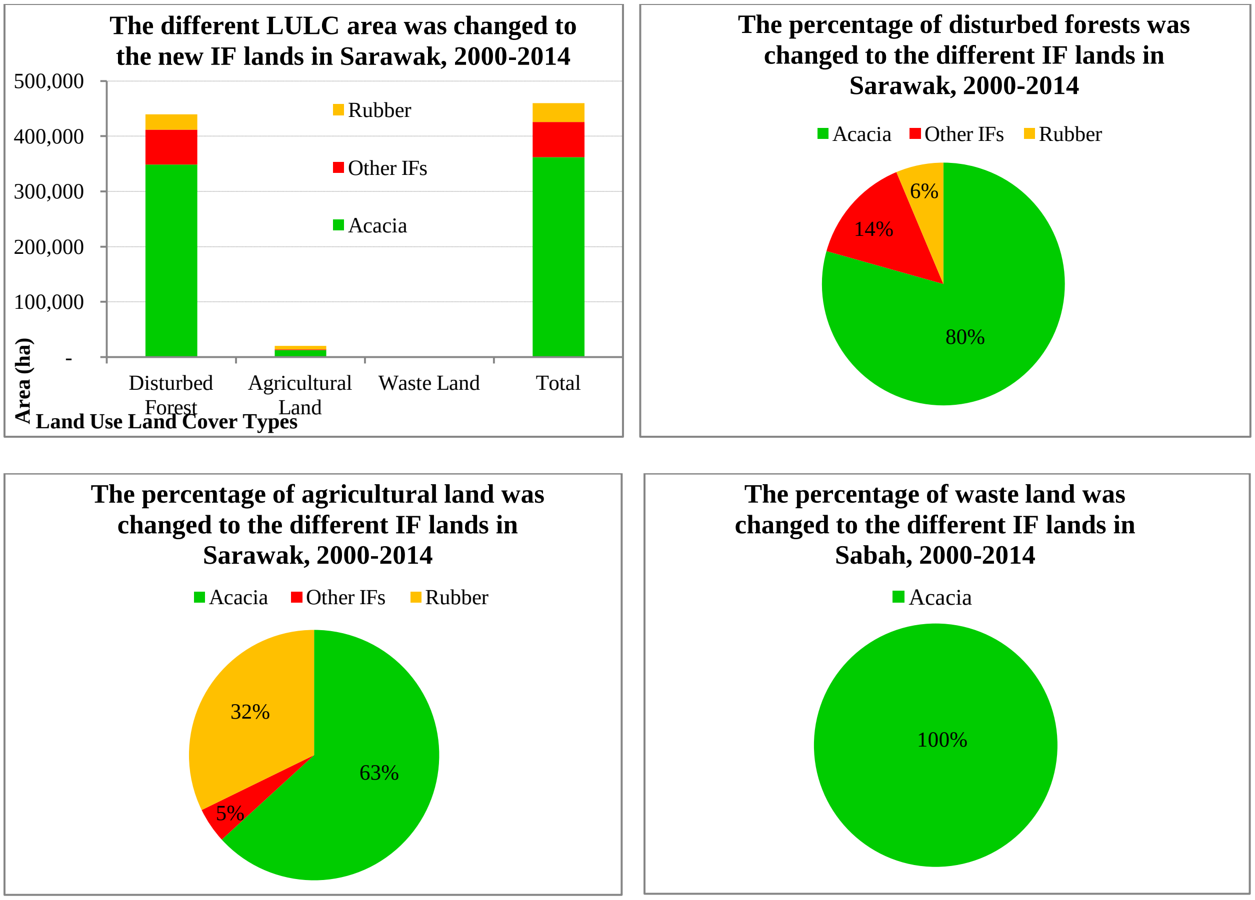


Figure 4.23. The different LULC area and percentage converted to new acacia, rubber and other IFs in Sarawak, 2000-2014.

The Consequences of the IF LULC Changes

In LULCC studies, quantifying the consequences of a LULCC is very important in understanding and assessing its contributions and impacts to humans and nature. As we know, LULCC influences the global climate, the carbon cycle, water, energy balance, biodiversity, and other environmental and resource factors. However, the comprehensive, adequate, and accurate quantification of these impacts are very challenging. Therefore, this study would only grossly estimate the contributions and impacts of changes from managed and natural ecosystems to the new IF land, in terms of carbon emissions and biodiversity loss, based on literature review and general approaches.

CO_2 Emissions: To estimate the net carbon emissions caused by the IF LULCC in the study area over the period of 2000-2014, the approach of the United Nations Intergovernmental Panel on Climate Change (IPCC, 2006) would be used as follows:

$$Emission = Activity\ Data * Emission\ Factor$$

Where activity data is the area of specific LULC changes, and emission factor is the changes in carbon stock of a LULC type. In the previous part, the IF LULCC quantitative assessments specific for acacia, rubber, and other IFs over the period of 2000-2014 have been conducted.

For the emission factors, Agus *et al.* (2013a), and Agus *et al.* (2013b) did a comprehensive literature review for C stocks for the different LULC types in Malaysia, Indonesia, and Papua New Guinea including Sabah and Sarawak, and found that the above ground biomass (AGB) or C stocks (in tonne of carbon per ha, tC ha^{-1} or Mg C ha^{-1}) for the different LULC types in the study area were the following: (1) undisturbed forests/UF (189 ± 87 tC ha^{-1} for upland, 162 ± 51 tC ha^{-1} for swamp, & 148 ± 43 tC ha^{-1} for mangrove), (2) disturbed forest/DF (104 ± 59 tC ha^{-1} for upland, 84 ± 42 tC ha^{-1} for swamp, & 101 ± 15 tC ha^{-1} for mangrove), (3) 58 tC ha^{-1} for rubber plantation, (4) 36 ± 11 tC ha^{-1} for oil palm plantation/OP, (5) 44 ± 14 tC ha^{-1} for timber plantation, (6) 54 ± 24 tC ha^{-1} for mixed tree crop, (7) 7 ± 3 tC ha^{-1} for settlement/residential land/RL, (8) 36 tC ha^{-1} for bare soil and 3-30 tC ha^{-1} for degraded non-forest land/WL, (9) 8-12.5 tC ha^{-1} for agricultural land/AL, and (10) 0-36 tC ha^{-1} for other LULC types. The Roundtable for Sustainable Palm Oil (RSPO, 2014) also recommends using the following default AGB carbon stock values: 268 Mg C ha^{-1} for undisturbed forest, 128 Mg C ha^{-1} for disturbed forest, 46 Mg C ha^{-1} for shrub land, 75 Mg C ha^{-1} for tree crops, 50 Mg C ha^{-1} for oil palm, and 8.5 Mg C ha^{-1} for annual/food crop or agricultural land for Sabah and Sarawak. As a result, this study would take those values to quantify C stocks and their changes in the classified LULC types (Table 4.7).

Table 4.7. The above ground carbon stock values (tC ha^{-1}/MgC ha^{-1}) for the classified LULC types in Sabah and Sarawak (adapted from Agus *et al.*, 2013a; Agus *et al.*, 2013b; RSPO, 2014).

LULC Type	Mean AGB Mg C ha^{-1}	Range (Mg C ha^{-1}) for above ground c stock (AGB)	
		Lowest	Highest
Disturbed Forest (DF)	104	33	250
Undisturbed Forest (UF)	189	66	399
Agricultural Land (AL)	11	8	12.5
Oil Palm Land (OP)	36	22	60
Waste Land (WL)	19	3	36
Residential Land (RL)	7	4	10
Acacia	44	29	70
Rubber	55	31	89
Other IFs	54	33	77

The results of the study found that the total AGB stock in Sabah has declined -11,472,205 Mg C (tC) from 2000 to 2014 as a consequence of the LULCC caused by the expansion of new IFs (Figure 4.24 & Table 4.8). This change is equal to a total release of about 42,064,752 Mg of CO_2 into the atmosphere over the period. Of that, the new acacia IFs contributed most of the C stock change and emissions (81%), and other IF systems (rubber and other IFs) contributed the remaining part (19%; Figure 4.24). The majority of the carbon stock change caused by the IF LULCC over 2000-2014 in Sabah had mainly occurred in the disturbed forests/DF (98%); only 2% occurred in the other LULC types (AL & WL; Figure 4.24). The C stocks in the new IFs, their replacements, and estimates of CO_2 emissions for specific years are presented (Table 4.8).

Table 4.8. Comparisons of AGB stocks (Mg) of new IFs and their LULC replacements in Sabah.

LU/LC type (Mg C)	**2000-03**	**2003-06**	**2006-09**	**2009-12**	**2012-14**	**Total**
Disturbed Forest	6,152,536	7,251,192	4,026,776	2,895,984	4,325,568	24,652,056
Agricultural Land	133,210	85,811	168,058	93,082	80,960	561,121
Waste Land	950	247	1,767	2,261	4,294	9,519
Total other LULC types	6,286,696	7,337,250	4,196,601	2,991,327	4,410,822	25,222,696
Total new IFs	3,370,464	3,507,558	2,700,469	1,813,210	2,352,996	13,750,491
Difference	-2,916,232	-3,829,692	-1,496,132	-1,178,117	-2,057,826	-11,472,205
CO_2 Emissions (Mg)	**10,692,851**	**14,042,204**	**5,485,817**	**4,319,762**	**7,545,362**	**42,064,752**

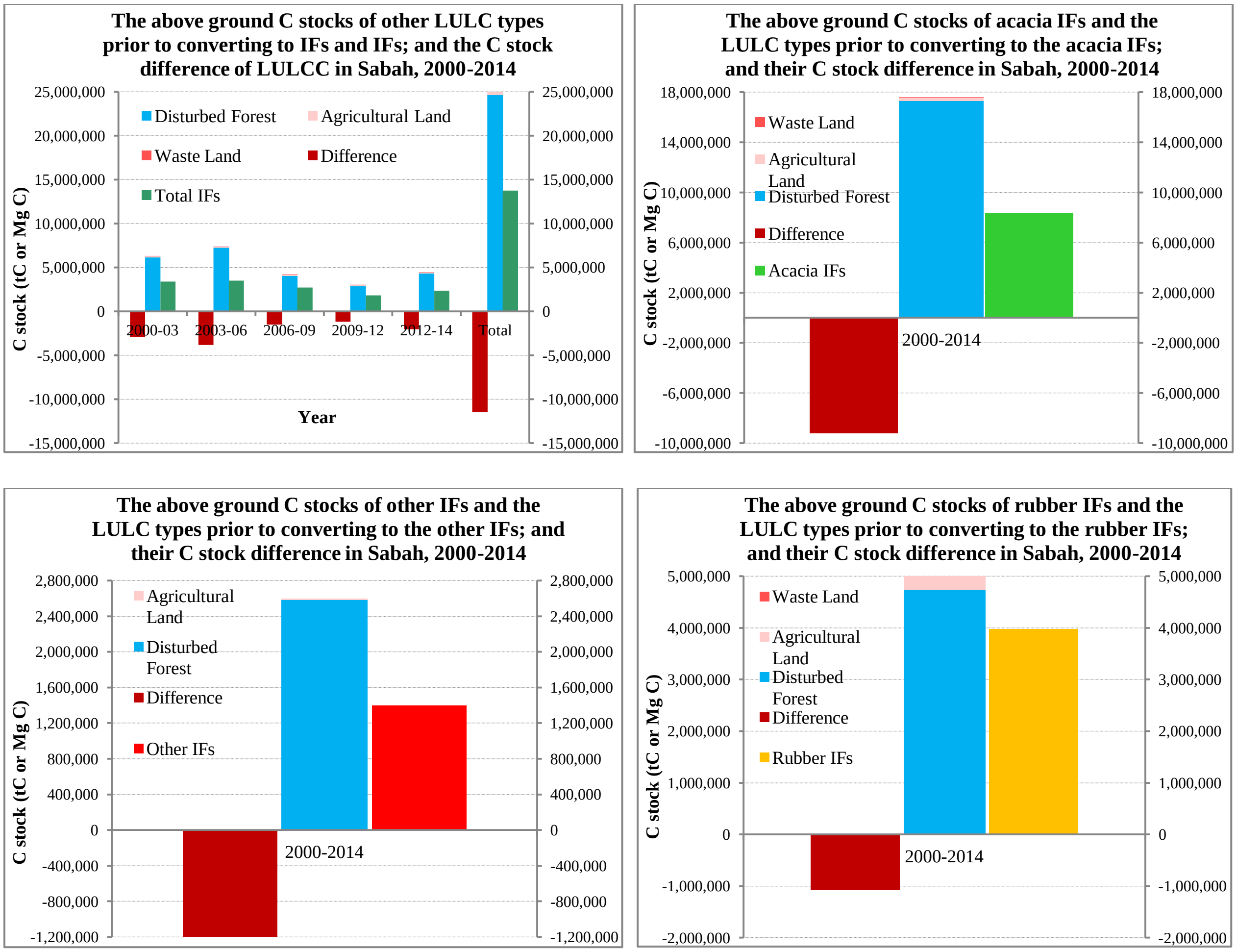


Figure 4.24. The AGB stock changes as a consequence of the IF LULCC in Sabah, 2000-2014.

Likewise, the total AGB stock in Sarawak over the study period of 2000-2014 also declined 24,692,391 MgC/tC as a consequence of IF LULCC (Figure 4.25 & Table 4.9). This change contributed an emission of 90,538,767 tCO_2 into the atmosphere over the study period. Most of

Table 4.9. Comparisons of C stocks (Mg) of new IFs and their LULC replacements in Sarawak.

LU/LC type	2000-03	2003-06	2006-09	2009-12	2012-14	Total
Disturbed Forest	4,407,520	9,048,208	11,391,848	8,587,800	12,284,064	45,719,440
Agricultural Land	60,049	23,628	16,005	62,414	60,016	222,112
Waste Land	323	0	133	1,330	0	1,786
Total other LULC	4,467,892	9,071,836	11,407,986	8,651,544	12,344,080	45,943,338
Total IFs	2,267,569	4,089,690	5,241,534	4,043,573	5,608,581	21,250,947
Difference	-2,200,323	-4,982,146	-6,166,452	-4,607,971	-6,735,499	-24,692,391
CO_2 Emissions	**8,067,851**	**18,267,869**	**22,610,324**	**16,895894**	**24,696,830**	**90,538,767**

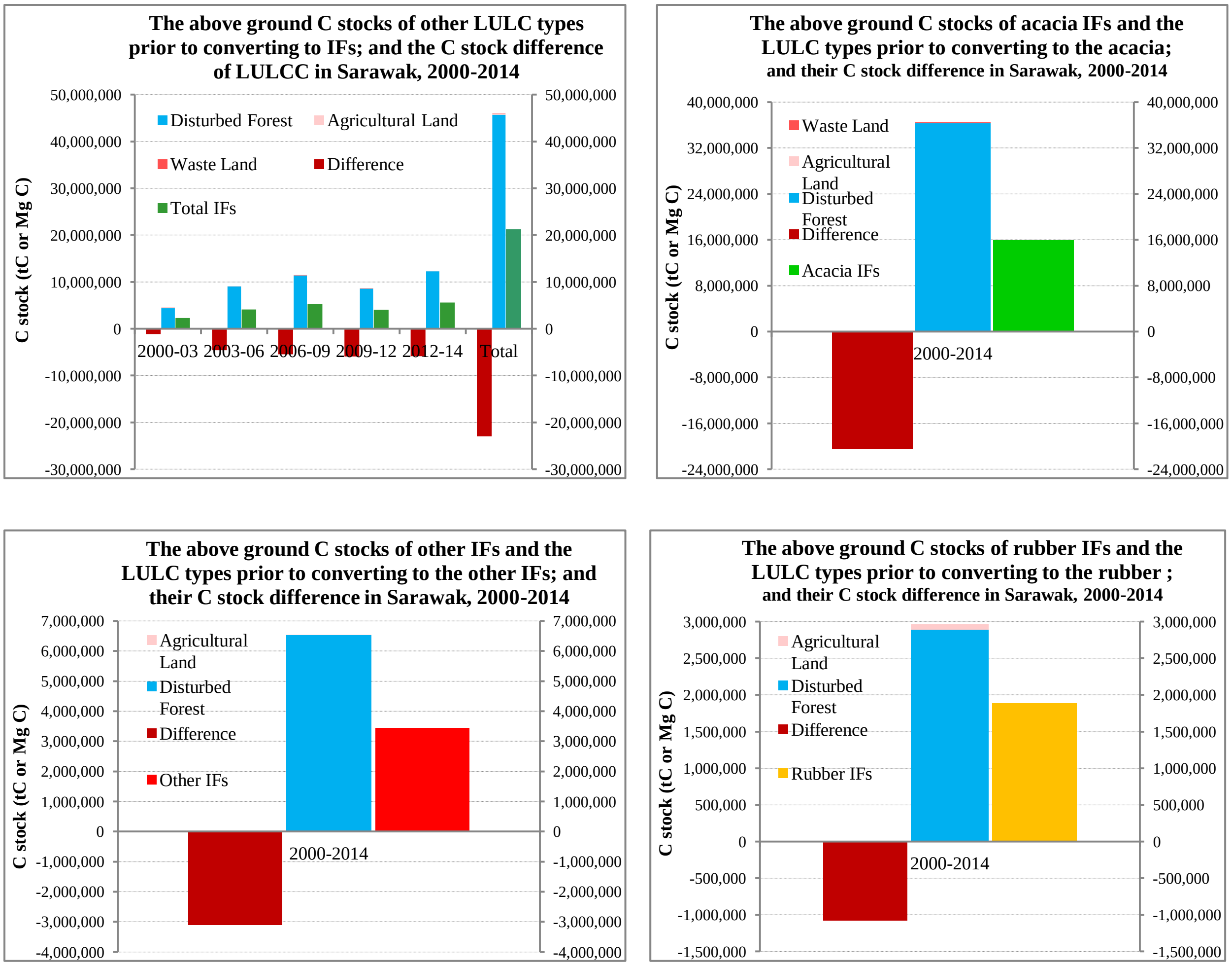


Figure 4.25. The C stock changes as a consequence of the IF LULCC in Sarawak, 2000-2014.

the above ground C stock changes and CO_2 emissions also occurred in the disturbed forests (99.5%) and was accounted for by the new acacia IFs (~83%), followed by new other IFs (13%), and new rubber plantations (4%). The above ground C stock changes in agricultural land and degraded land negligibly contributed to the total C budget change in the region over the period of 2000-2014. The above ground C stocks in the new IFs, their replacements, and estimates of CO_2 emissions caused by the IF LULCC specific for years are presented (Table 4.9 & Figure 4.25).

In summary, the changes of LULC in Sabah and Sarawak caused by the expansion of new IFs from 2000 to 2014 released a significant amount of CO_2 into the atmosphere (Figures 4.24, 4.25 & 4.26; Tables 4.8 & 4.9).

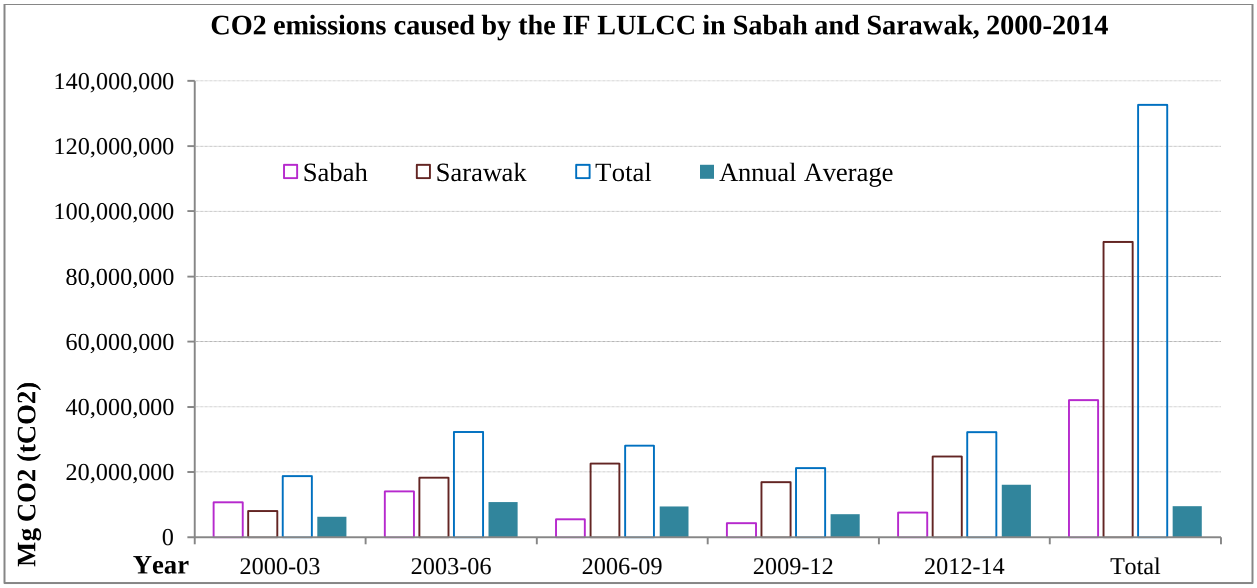


Figure 4.26. CO_2 emissions caused by the IF LULCC in Sabah and Sarawak, 2000-2014.

Biodiversity loss: In addition to concerns over carbon stock changes and carbon emissions in the IF LULCC, another issue that also received much concern in this LULCC was biodiversity loss. In general, adequately and accurately quantifying biodiversity loss in a LULCC is notoriously difficult because of the lack of reliable data. One of the most widely-accepted models used to quantify the biodiversity loss or impacts by a LULCC is the species-area relationship model (Brook *et al.*, 2003; Desmet & Cowling, 2004; Triantis *et al.*, 2008; Sodhi, 2009; Koh & Ghazoul, 2009; Koh *et al.*, 2010; He & Hubbell, 2011; He & Hubbell, 2013; Matthews *et al.*, 2014; Chaudhary *et al.*, 2015).

A literature review was also conducted for biodiversity for the different LULC types in the study area and other tropical regions. Various studies have been done on the quantification and comparison of biodiversity in the different land use and land cover types in Malaysia in particular, and, in general, in other tropical regions that have environmental conditions similar to Sabah and Sarawak (*e.g.*, Chung *et al.*, 2000; Hammer *et al.*, 2003; Dumbrell & Hill, 2005; Peh *et al.*, 2005; Peh *et al.*, 2006; Gardner *et al.*, 2007; Barlow *et al.*, 2007a; Barlow *et al.*, 2007b;

Barlow *et al.*, 2007c; Koh, 2007; Fitzherbert *et al.*, 2008; Koh, 2008; Koh & Wilcove, 2008; Wilcove & Koh, 2010; Yule, 2010; Koh *et al.*, 2011). Most of these studies focused on biodiversity quantification in primary (or undisturbed) forest, secondary (or disturbed) forest, plantation forests (rubber, acacia, eucalyptus plantations; here they were generally called IFs), and oil palm plantations, while very few studies were conducted on biodiversity for other LULC types, such as agricultural land, residential land or degraded land.

A summary for these studies was synthesized and is presented (Table 4.10 & Figure 4.27). It indicated that, in general, for forest birds, forest butterflies, beetles, trees and lianas, amphibians, reptiles, and mammals, primary/undisturbed forests were found the most diverse, followed by disturbed forests, IFs, and oil palm plantations. Conversely, there was little difference among UF, DF and IFs for fruit flies; and between DF and IFs for bat species. In particular, for orchid bees, moths, and grasshoppers, the number of species in IFs was higher than those in forestland, including UF and DF (Table 4.10; Figure 4.27). Briefly, biodiversity in IF land was more diverse compared with oil palm plantations, but less diverse than forestlands.

Table 4.10. The number of species in the different LULC types in the study area.

Number of Species	**Undisturbed Forest**	**Disturbed Forest**	**IFs**	**Oil Palm**
Forest Birds	159	127	43	37
Forest Butterflies	68	58	N/A	11
Beetles	79	66	24	18
Trees and Lianas	200	80	1	1
Amphibians	96	61	22	N/A
Reptiles	81	48	45	N/A
Mammals	49	43	15	N/A
Bats	45	32	30	N/A
Fruit Flies	28	28	25	N/A
Orchid Bees	15	18	16	N/A
Moths	145	140	200	N/A
Grasshoppers	25	20	27	N/A

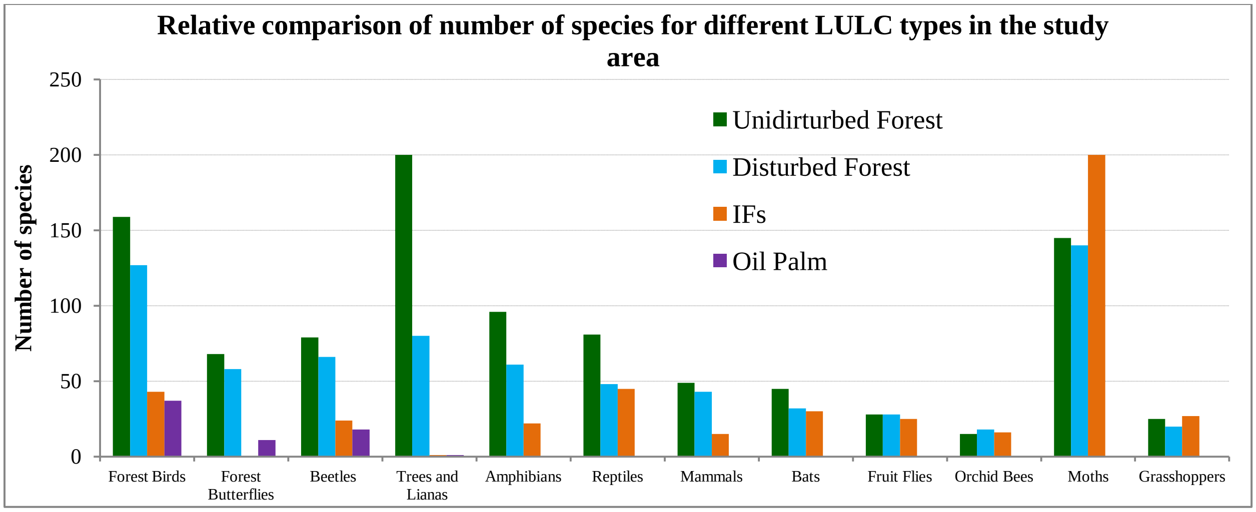


Figure 4.27. A number of species for different ecosystems (UF, DF, IF, and OP) in the study area.

Considering the above literature review on biodiversity for different LULC types, we could conclude that the conversion of forestlands into IF lands would lead to a reduction of biodiversity for most species in the region (Table 4.11; Figure 4.28). For instance, forest bird species in the UF and DF would reduce 73% and 66%, respectively. A monoculture IF with one or a few tree species would replace forestlands with hundreds of tree species (Figure 4.28).

Table 4.11. The percentage of declining or increasing number of species if UF, DF and OP lands were converted into IF land.

Number of Species	**Undisturbed Forest/UF**	**Disturbed Forest/DF(**)**	**Oil Palm/OP**
Forest Birds	-73%	-66%	16%
Forest Butterflies	N/A	N/A	N/A
Beetles	-70%	-64%	33%
Trees and Lianas	-100%	-99%	0%
Amphibians	-77%	-64%	N/A
Reptiles	-44%	-6%	N/A
Mammals	-69%	-65%	N/A
Bats	-33%	-6%	N/A
Fruit Flies	-11%	-11%	N/A
Orchid Bees	7%	-11%	N/A
Moths	38%	43%	N/A
Grasshoppers	8%	35%	N/A

(**) Note that in this study, only disturbed forests were converted into new industrial forestlands

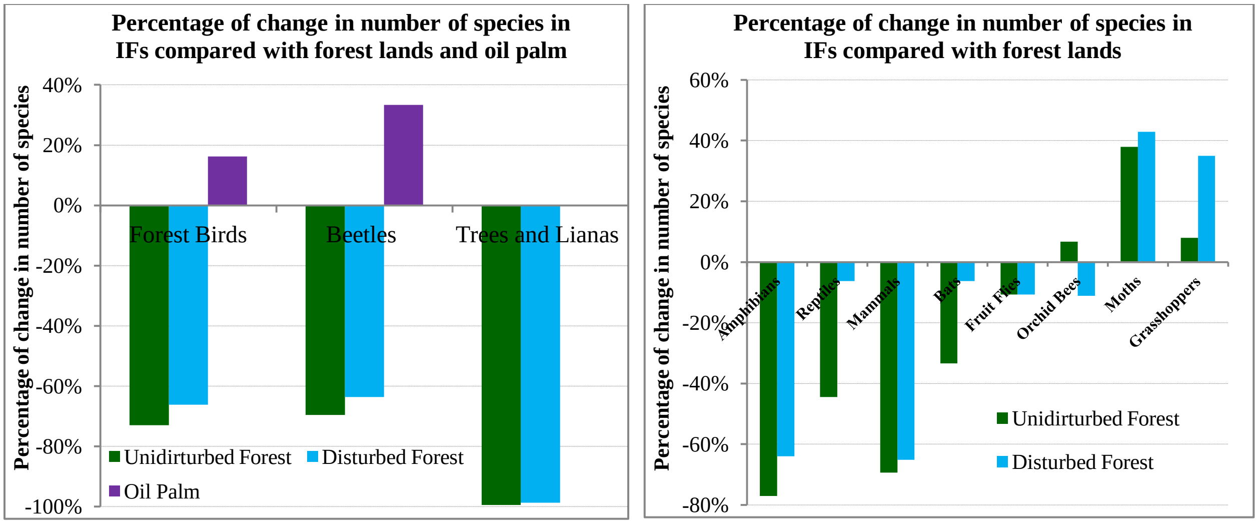


Figure 4.28. The percentage of change in number of species in IFs compared with other LULC types in the study area.

Conversely, the conversion of oil palm lands to IF lands could increase biodiversity in the region (*e.g.*, increasing 16% for forest birds and 33% for beetle species). In addition, for some species, such as moths and grasshoppers, the conversion of forestlands to IF lands could increase their richness and abundance. For instance, the number of species of moths and grasshoppers would increase 43% and 35%, respectively, if disturbed forests were changed to IF lands (Table 4.11; Figure 4.28).

It is clear that, in general, the conversion of forestlands to IF lands indicated a reduction of biodiversity (number of species) for most species. The next question was how much biodiversity had been lost as a consequence of the expansion of new IFs in Sarawak and Sabah over the study period from 2000 to 2014. To answer this question, the species-area relationship model was used. The model was expressed as follows: $S = k(A)^z$, where S was species, A was area, and k and z were constants. The model could be written $S = k(A_{new}/A_{original})^z$. The value of z = 0.25 was usually used as a default value for Southeast Asia (Brook *et al.*, 1999; May & Stumpf, 2000).

However, later, Brook *et al.* (2003) proposed new *z* values for the different species in Southeast Asia (Table 4.12).

Table 4.12. Estimating the biodiversity loss caused by the expansion of the new IFs in the study area from 2000 to 2014 (adapted from Brook *et al.*, 2003).

Study area	Species	Forest area		*z* value	Biodiversity loss (%)
		Total in 2000 (1000 ha)	Total area lost by new IFs (1000 ha)		
Sabah	*Average*	*5034*	*237*	*0.11*	*0.71*
	Trees	5034	237	0.1	0.74
	Butterflies	5034	237	0.15	0.63
	Amphibians	5034	237	0.02	0.94
	Reptiles	5034	237	0.02	0.94
	Birds	5034	237	0.13	0.67
	Mammals	5034	237	0.17	0.59
	Average (other studies*)	5034	237	0.25	0.47
Sarawak	*Average*	*9719*	*440*	*0.11*	*0.71*
	Trees	9719	440	0.1	0.73
	Butterflies	9719	440	0.15	0.63
	Amphibians	9719	440	0.02	0.94
	Reptiles	9719	440	0.02	0.94
	Birds	9719	440	0.13	0.67
	Mammals	9719	440	0.17	0.59
	Average (other studies*)	9719	440	0.25	0.46

* the value $z = 0.25$ was derived from (Brook *et al.*, 1999; May & Stumpf, 2000).

The results of this study showed that the expansion of new IFs could cause a biodiversity loss. In other words, biodiversity in the region most likely faced a probability of extinction due to the expansion of new IFs between 2.79% and 4.98% in Sabah and between 2.77% and 4.96% in Sarawak. Specifically, amphibians and reptiles in both Sabah and Sarawak faced the highest loss at 0.94%, followed by tree species at 0.74% and 0.73% in Sabah and Sarawak, respectively. Birds, butterflies, and mammals also faced a loss ranging from 0.59% to 0.67% in these areas as a consequence of the expansion of new IFs in the area (Table 4.12).

4.3 Discussions and Conclusions

The above findings clearly indicate that the selected IFs (acacia, rubber, and other IFs) were increasing in Sarawak and Sabah over the study period of 2000-2014. In other words, the selected IFs have been expanding in these areas. However, the extent of expansion, the expansion rate, and expansion pattern specific for the different selected IF systems and years in Sabah and Sarawak were different. In general, this study found that the total extent and expansion rate of fast-growing, short-rotation IFs, such as acacia plantations, were much higher than those of slow-growing, long-rotation IF systems, such as rubber and other IFs. For the development of IFs in Sabah, which is known as an old area for IFs because the IFs were established there a very long time ago, the new IFs continued to expand significantly in this area, although their expansion rates were much lower than those in Sarawak, where new IFs just emerged as a new LULCC recently.

The IF area detected in this study was consistent and inconsistent with various other research results and data, depending on the sources. Specifically, in Sabah, the total IF area, including acacia and other IFs, that was detected in 2000 was 64,879 ha lower than the IF statistical data from the Sabah Forestry Statistics in 2000 (154,640 ha) and from FAO (2002), with 117,000 ha detected in 2001. This detected IF area increased to 225,753 ha in 2009 and 246,874 ha in 2012, with the annual mean expansion rate of 23.8%, compared with 244,000 ha in 2012 from Sabah Forestry Statistics, with the annual expansion rate of 4.8%. This number was also relatively consistent with the plantation forest data reported by Malaysian Timber Council (2009) in 2009, with 200,000 ha, and the study of Reynolds *et al*. (2011), with the total timber plantation area of 122,000 ha in 1990 and 244,700 ha in 2010. The Malaysia Forestry Outlook Study (2009) also reported that in Sabah, over a 20-year period from 1985 to 2005, the area of forest plantations had increased from a low of 50,000 ha to 200,000 ha - an increase of 150,000ha at an average annual rate of 14.9%. In addition, this study also presented relatively consistent IF area data compared with FAO (2010), which found that Sabah had 90,000 ha of plantation forests (including 56,000 ha of acacia and 34,000 ha of other species, not including rubber) in 2001, increasing to 244,000 ha in 2010.

In Sarawak, the development of IFs, including acacia and other IFs, showed a different trajectory from Sabah. These IFs were a relatively new LULC in the area. FAO (2010) indicated that in 2001, Sarawak had merely 4,000 ha of acacia and 9,000 ha of other IFs. These areas increased to 221,000 ha of acacia and 82,000 of other IFs in 2010. The IF statistical data from Sarawak Forestry Department also presented that the total IF area (acacia and other IFs, not including rubber) in this state had increased impressively from 6,830 ha in 2000 to 141,050 ha in 2006 and 306,486 ha in 2012. However, some studies did not find the same results as the statistical figures mentioned previously. For instance, Miettienen *et al.* (2010) reported there were no pulp and other industrial plantations in Sarawak in 2010. In general, the data from FAO (2010) and Sarawak Forestry Department (2012) were relatively consistent with the findings in this study. This study found that the IF area (not including rubber) in 2000 was 12,693 ha (including 6,864 ha of acacia and 5,829 ha of other IFs), increasing to 130,373 ha (112,903 ha of acacia, and 17,470 ha of other IFs) in 2006 and 438,277 ha (368,640 ha of acacia, and 69,637 ha of other IFs) in 2014.

In contrast, the development of rubber plantations from 2000-2014 presented some differences between this study and various data sources. For instance, in Sabah, the detected rubber area in this study in 2000 was 37,788 ha, increasing to 110,062 ha in 2014, with the annual expansion rate of 13.7%. This was significantly different from the findings of Malik *et al.*

(2013), in which the total rubber area reported in 2000 was 78,895 ha, declining to 62,891 ha in 2005 at the annual reduction rate of 4.1%. The statistical data from Malaysia Rubber Board (2010) also reported that, in 2000, Sabah had a total of 87,400 ha (including 2,400 ha under estates and 85,000 ha under smallholdings), shrinking to 64,400 ha in 2003 and increasing again to 71,100 ha in 2009. Likewise, the development of rubber plantations in Sarawak that were detected in this study also revealed different pathways than other data sources. For instance, Malik *et al.* (2013) indicated the rubber plantation area in Sarawak increased at the rate of 7.49% *per annum* from 153,000 ha in 2000 to 210,000 ha in 2005. Meanwhile, the statistical data from Malaysia Rubber Board (2010) reported that, in 2000, Sarawak had a total of 160,100 ha, shrinking to 155,610 ha in 2006 and slightly increasing again to 157,160 ha in 2009. The rubber plantation area detected in this study was inconsistent with the data mentioned previously. The total detected rubber area in 2000 was 42,147 ha, increasing to 61,473 ha in 2006 and 63,581 ha in 2009.

One of the important findings in this study is that the development of IFs in both states was largely dominated and promoted by the large-scale IFs, as opposed to the small-scale IFs. The smallholders in Sabah captured about 24-45% of the total IF area, and those in Sarawak captured from 19-34%. This ratio gradually increased over time from 2000 to 2014. FAO (2010) also showed that, of 90,000 ha of forest plantations in Sabah in 2000, 62% belonged to private companies and 38% belonged to state government agencies. However, it was possible that the elimination of IF areas smaller than 2 ha in this study would underestimate the area of small-scale IFs. For instance, Lintangah *et al.* (2010) investigated tree plantation activities among smallholders in Ranau, Sabah and found that the average rubber patch size owned by smallholders was about 1.3-1.4 ha. Besides, quantifying the small- *vs.* large-scale areas by using remote sensing (RS) tools may not truly reflect the reality. A large IF patch in the RS-based product may be created by many smaller patches gathering together, or it is also possible that a large patch could be divided into many smaller patches due to the harvesting and planting activities on the ground.

However, this study found that the increase in percentage of the small-scale IFs over time proved that the small-scale IFs played a more and more important role in developing the IFs in the regions. In other words, the dynamics and processes of LULCC in the regions associated with the emerging new IFs were dominated by both the large-scale and small-scale. The increasing roles of the small-scale IFs in the regions were also indicated by an increase of the number of IF patches and a decrease of the mean IF patch size index in both states. Moreover, the study findings from investigating the IF area distribution based on the IF patch size classes presented that the IF areas were mainly distributed in the IF patch size classes over 200 ha and less than 5 ha. This was consistent with the study finding of Lintangah *et al.* (2010) that most smallholders owned a plantation area less than 6.5 ha. An investigation into the scales of rubber plantations in this study showed that most rubber plantations (~45%-71%) were large-scale plantations (with the patch size > 40 ha), and this figure gradually reduced from 2000 to 2014 in both states, whereas Malaysia Rubber Board (2010) reported that almost all rubber plantations in Sabah and Sarawak were under smallholdings. This difference may derive from the difference between this study and the source in defining the small- and large-scale areas. Besides, this study also found that the increase in the number of large-scale IF patches presented a consistency with the increase of the large-scale IF area in both states. However, the mean patch size for all selected IF systems in Sabah was declining. This could also indicate a reduction in establishing large-scale IFs. Conversely, in Sarawak, both the number of large-scale IF patches and their mean size was increasing. This likely revealed a more dynamic IF development in this state as opposed to Sabah because the IF land use just emerged recently in the state, while the IFs in Sabah had been established a long time ago.

For the VIs-based IF detection, VIs were well-known for additive effects caused by soil and atmospheric conditions. Therefore, using them to detect IFs varied greatly depending on the atmospheric and soil conditions at the time the satellite images were taken. Generally, ARVI worked the best in the regions, followed by SAVI, SARVI, EVI, $NDVI_{af}$, and $MSAVI_{af}$. In Sabah, the IF area detection results by using VIs showed that the small-scale IF area was larger than the large-scale IF area. This differed from the results of the *f*C-based IF detection method presented above. In contrast, the large-scale and small-scale IF area detected using these vegetation indices in Sarawak were consistent with the results of the *f*C-based method.

In general, the expansion of new IFs in Sabah and Sarawak over the study period of 2000-2014 significantly contributed to LULC change in the regions. Most of new IFs in Sarawak and Sabah replaced disturbed forest (81-95%), followed by agricultural land (4-18%), and waste land (less than 0.5%). This finding was also consistent with other study findings. For instance, Malaysian Timber Council (2009) also indicated that plantations in Sarawak were mostly located inside permanent reserved forests. Grieg-Gran *et al.* (2007), Koh and Wilcove (2008), and Wicke *et al.* (2008) argued that pulpwood plantations in Malaysia accounted for 17% of the forest loss. In particular, since 2000, the conversion of forests to industrial timber plantations in Sabah and Sarawak has been an important driver of deforestation. Other analyses by SarVision (2011) and Lawson *et al.* (2014) indicated that, from 2006-2010, Sarawak lost 0.9 Mha of forests and that 43% of this loss was accounted for by the expansion of oil palm, while new timber plantations contributed 21%. Malik *et al.* (2013) also found that, from 2000-2005, 29,000 ha of rubber plantations displaced natural forests in Sarawak. In brief, this study found that new IFs were a significant deforestation driver, possibly only after oil palm plantations, in Sabah and Sarawak over the period of 2000-2014.

The conversion of forestland into industrial forestland has led a significant reduction of the above ground C stock in the regions. This change released a remarkable amount of CO_2 into the atmosphere over the 2000-2014 period in Sabah and Sarawak. However, this CO_2 emission only accounted for the balance of the above ground C stocks in the area; it did not include the C stocks regarding how much this IF wood helped reduce the wood extraction from natural forests for the industries in the regions. Moreover, the C stocks that were taken into account in this study were only for above living biomass by using the default values. This did not include below ground C stock, soil C stock and nonliving biomass in the area. Therefore, the calculations of C stocks and CO_2 emissions did not truly reflect the all of reality; it only provided a gross estimate about the living C stocks partially captured and lost by new IFs in the area.

This significant forestland conversion into new IFs also noticeably reduced biodiversity in the area. The biodiversity faced a loss or reduction of 2-5%. However, the biodiversity loss in this study only accounted for forest birds, butterflies, beetles, trees and lianas, amphibians, reptiles, mammals, bats, fruit flies, orchid bees, moths, and grasshoppers. Thus, this did not fully reflect biodiversity loss or impacts caused by the expansion of new IFs in the areas; it can only provide us a general quantitative estimate of how much the expansion of new IFs would influence the biodiversity. Besides, the quantification of the impact of new IFs in this study did not include assessments of their impacts on natural resources, such as water, soil and energy balance.

In brief, the following conclusions could be drawn from this study: The total IF area in both Sabah and Sarawak increased over the study period. This increase was accounted for by all of the selected IF species/systems (acacia, rubber, and other IFs). The increase of acacia IFs, both in the total area and in its rate of change in area, were larger than that of rubber and other IFs. Additionally, the increase of the total IF area and the rate of change in area in Sarawak (known as a newly emerging IF area) was larger than that in Sabah (known as an old IF area).

The development of IFs in Sabah and Sarawak were generally dominated by the large-scale IFs with a patch size larger than 40 ha, and the percentage of large-scale IF area in Sarawak (68-81%) was larger than that in Sabah (55-76%). However, in both states, the percentage of large-scale IFs decreased, while the percentage of small-scale IFs increased over the study period. The same trend was also found for all selected IF systems (acacia, rubber, and other IFs). This fact was proven through evidence that the expansion rate of the small-scale IFs was much higher than that of the large-scale IFs. This indicated that small-scale IFs played a more and more important role in developing new IFs in the regions.

Along with the increase of the total IF area, the number of IF patches and the largest patch size in both Sabah and Sarawak also increased. The increase in the number of acacia IF patches and the largest acacia IF patch size were both larger than those for rubber and other IFs. However, the mean IF patch size index generally decreased, especially in Sabah, except in Sarawak, where the mean patch size index of acacia and other IFs increased. The study results of the IF area class distribution based on the IF patch size classes showed that most of the IF area was distributed in the 200-ha-or-larger-patch-size class (industrial scale), followed by the-5-ha-or-smaller-patch-size class (smallholdings), with the least in the transitional patch size class of 20-40 ha.

Likewise, along with the increase of the large-scale IF area in both states, the number of the large-scale IF patches also increased. This increase was accounted for by both the total IFs and by the specifically selected IF systems. However, the increase in the number of large-scale acacia patches was larger than that of rubber and other IFs. Besides, the study findings indicated that while the mean large-scale patch size in Sarawak - particularly for acacia and other IFs - increased, the mean large-scale patch size in Sabah decreased.

The VIs-based IF detection study results also presented the same trend as the *f*C-based study findings. That is, the total IF area and the area for the specifically selected IF systems increased in both states over the study period of 2000-2014. Of that, most of this increase was contributed to acacia IFs. However, the detected IF area and the rate of change in area using different VIs were different and variable. In general, the IF area detected by using ARVI was the largest, followed by EVI, SARVI, SAVI, $NDVI_{af}$, and $MSAVI_{af}$. Conversely, the rates of change in the VIs-based IF areas were generally highest using SAVI, followed by $MSAVI_{af}$, $NDVI_{af}$, SARVI, EVI, and ARVI, depending on specific areas, years, and IF systems. The study results for the large-scale versus small-scale IF area showed that the small-scale IF area in Sabah was larger than the large-scale IF area, while the opposite was true in Sarawak, where the large-scale IF area was larger than the small-scale IF area.

The emerging and expansion of new IFs in Sabah and Sarawak over the study period of 2000-2014 made a significant land use and land cover change in the regions. Specifically, most of these new IF expansions have replaced disturbed forests (82.1% in Sabah, 95.5% in Sarawak), followed by agricultural land (17.7% in Sabah and 3.5% in Sarawak). Only a very insignificant amount of degraded or waste land (0.2% in Sabah and 0.02% in Sarawak) was converted into IF land. Acacia IFs contributed most of this change. Specifically, they contributed to the conversion of forestland into IF land at a rate of 70% in Sabah and 80% in Sarawak. This was followed by other IFs at 11 % in Sabah and 14% in Sarawak. Rubber IFs contributed to only 4% of forest loss in Sarawak, but to 19% in Sabah. Most of the agricultural land was converted into rubber plantations (51% in Sabah and 32 % in Sarawak), followed by acacia IFs (47% in Sabah and 63% in Sarawak).

The changes of land use and land cover caused by the expansion of new IFs in Sabah and Sarawak from 2000 to 2014 have significantly decreased the living C stock in the regions. Specifically, in total, Sabah lost 11.5 Tg C and Sarawak lost 24.7 Tg C over the study period. This contributed remarkably to an emission of 42.1 Tg CO_2 in Sabah and 90.5 Tg CO_2 in Sarawak into the atmosphere. Most of this C stock change happened in the disturbed forests (98% in Sabah and 99.5% in Sarawak) and was mainly caused by new acacia IFs (81% in Sabah and 83% in Sarawak), followed by other IFs (10% in Sabah and 13% in Sarawak), and new rubber plantations (9% in Sabah and 4% in Sarawak).

The expansion of new IFs in Sabah and Sarawak also placed a threat to biodiversity in the regions. It led to a reduction of biodiversity estimated in Sabah at 2.79-4.98% and in Sarawak at 2.77-4.96%. Of that, amphibians and reptiles faced the highest loss at 0.94%, followed by other species (tree, forest birds, butterflies, and mammals) from a loss of 0.59% to 0.74%.

CHAPTER 5

SYTHESIS

5.1 Introduction

This chapter will explain and discuss the shortcoming and applicability of this study. How the developed methods in this research should be improved for the future works and how the methods are possibly applied to other parts of the works will also be discussed.

5.2 Shortcoming

In the process of the new remote-sensing method development for Landsat datasets based on vegetation/forest fractional cover (*f*C) and vegetation indices (VIs) analyses in time series to detect, map, and monitor new IFs in the tropic with the selection of Sarawak and Sabah states of Malaysia as a case study, this study faced with some facts, difficulties, and challenges, which led to the shortcomings of the developed methods. These shortcomings have resulted in the moderate and fair accuracy in detecting IF land and specific for acacia, rubber, and other IFs in both methods.

The first shortcoming in developing the VIs- and *f*C-based methods to detect industrial forests came from the quality of the Landsat scenes, which was notoriously affected by cloud contaminations, their shadows, haze, and missing values in the Landsat 7 (ETM+ SLC off). To deal with these problems, gap filling techniques were used by the mosaics or use of a large amount of other Landsat scenes to fill the gaps created by cloud problems and the missing values in Landsat 7 in the selected scenes. The use of many Landsat scenes in the different times, different sensors, and different quality definitely greatly influenced the ability of the developed algorithms in the VIs- and *f*C-based methods to detect an IF because it may result in the changes of LULC due to the scene quality rather than the LULC changes by themselves in reality. In other words, this could lead to the interpretation and detection in the changes of LULC due to the differences between and among Landsat scenes as the clearing and regrowth of a predicted IF stand. Moreover, to reduce the influences of seasonal factors, this study selected the Landsat datasets from May to August. However, the scenes in this time period were not always available. Consequently, the scenes in other times were also selected. This possibly also led to the changes of vegetation covers due to seasonal influences in the reality in the study sites rather than the changes by the silvicultural cycles. Therefore, it will be definitely easier for developing the Landsat data-based IF detection methods by using *f*C and VIs analyses in time series in the places where less cloud contamination.

The second shortcoming came from the ideas using the silvicultural rotation and growth rate of IFs to develop the methods to detect them. As described above, it was impossible to annually monitor the full cycles of sawlog long-rotation IFs such as teak, rubber, and pine destined for producing saw logs because their rotations can last tens of years. It is impractical for us take annual Landsat datasets long enough to observe them. Also, many clearing activities were possibly not based on silviculture. Moreover, the silvicultural rotation of an IF system or species also varied greatly depending on the purpose of using it. Even for the same purpose of using it, its rotation might also vary depending on the intention and economic considerations of the owners, as well as the market's availability and other factors. Therefore, using the silvicultural rotation to detect the specific IFs in these cases was challenging. Besides, almost all of the IFs would have been subjected to the silvicultural practices, including thinning and pruning activities. It was possible that we could misclassify these IF stands as a new rotation as well. In this study, choosing the threshold detect the changes of VIs and *f*C at ± 15% was only based on the "trial-and-error" experiment but not based on any the field surveys or silvicultural observations due to the lacks of this kind of data to check the validity of these threshold values. For the use of the growth rates of VI or *f*C values to detect IFs, the fact was that we could detect the faster- versus slower-growing IF species or systems. However, the growth rate of an IF system might also depend on the soil and climate conditions, and silvicultural practices. It was possible that a slower-growing IF species planted in a good soil (good site-species matching) and exposed to proper silvicultural practices could grow the stand faster than a fast-growing IF species established in a poor condition. Therefore, it is important for the next studies in detecting IFs based on their silvicultural cycles that investigators need to acquire the adequate and reliable silvicultural data in their study sites.

In regard to using the textural and spectral analysis as a support step in detecting IFs in both the VIs- and *f*C-based methods, although, in fact, their textures were principally different from other natural vegetations; and these differences were easily recognized in the very high resolution imagery data, it was very difficult to realize them in the coarser or medium-resolution satellite imagery data like Landsat, especially in the small patches. The fact is that the smaller patch size is more difficult to detect. To identify their typical textural values in the Grey Level Co-occurrence Matrix, how well this analysis worked may be dependent on how well we chose the training areas to be used as the references in classifying IFs in images. The textural values must represent for the different development periods or ages of a given IF system in different types of Landsat scenes.

In addition, for spectral analysis, the fact was that the spectra were also very similar among different vegetation cover types and different IF systems in the Landsat datasets. Therefore, it was also very challenging to work on this analysis. For example, oil palm - which was one of the most dominating plantations in the region - had very similar spectra and texture to the selected IFs. Consequently, separating them was very difficult. One of the best possible ways we had was to select the training area well enough to represent the typical values for the expected land use and land cover in the region. This may involve dividing the region into the smaller areas and for different kinds of Landsat scenes such as Landsat 4-5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). Our best option was to build a good spectral library well representative of the different IF systems in the different times, different types of images, and different stages of an IF stand.

In other words, the most challenging issue leading to the biggest shortcoming of the study was the spectral and textural similarity among different land use and land cover types including IF systems, as well as the spectral and textural variability in the same land use and land cover class comprising of IF systems. The future studies must handle this challenge to better detect, map, and monitor the IFs in the tropic.

For other analyses used in the *f*C-based IF detection method development including band 4 value-based green biomass content and $MSAVI_{af}$-derived leaf area index that were added to the method to detect and map IFs, the values of band 4 might only represent the green biomass of vegetation canopy instead of representing the whole biomass of the stands. Therefore, using it for biomass content analysis should be carefully considered, specific for IF systems and their stand ages in the different Landsat types. Besides, using $MSAVI_{af}$-derived leaf area index to identify the IF systems should be also additionally tested in the fields specific for the selected IF systems or species at the different stages of an IF stand or system.

Lastly, visual interpretation was a very subjective method, and it was dependent on the knowledge and experience of interpreters. It also relied on the quality of the other LULC sources that we would use to identify the IFs in the images.

In brief, for both *f*C- and VIs-based IF detection methods, their ability in detecting and map IFs in the region was confounded by some challenges and difficulties including, the quality and disadvantages of the Landsat data, as well as the rotation and growth rate assumptions used to develop the method, and other textural, spectral, and visual interpretation issues.

5.3 Applicability

The developed methods have a potential to apply in areas, where have similar conditions as in the study sites (Sarawak and Sabah of Malaysia). They could be in the island of Borneo. For other regions in the tropics which have different environmental conditions or IF systems, the algorithms must be modified to better reflect the reality in those regions. For instance, if they are applied in Thailand, the sivilcultural cycles, textural and spectral values, and others (*e.g.,* green biomass content and leaf area index) for eucalypts, teak, and pines (these IF systems/species are prevalent or dominated in the country) must be considered and identified while acacia IFs were more dominated in the study sites of this research. Likewise, production plantations (or IFs) in Vietnam are usually mixed of some IF species (e.g., acacia with eucalypt), it must be also considered carefully.

In addition, these methods need to be radically modified to work in the temperate zones providing that we have enough data on the silvicultural cycles, textural and spectral data, and other typical characteristics for the IFs in the regions.

APPENDIX

Table A.1. The full list of Landsat scenes used for the study in Sarawak, Malaysia, 2000-2014.

2000	118-57	LT51180572000190DKI00	LE71180572001056SGS00	LE71180571999355EDC00	LE71180572001248SGS00	LE71180572001296SGS01	LT51180571998328DKI00		
	118-58	LT51180582000190DKI00	LE71180582001056SGS00	LE71180582001232EDC00	LE71180581999355EDC00	LT51180581998328DKI00	LT51180581998024DKI00		
	118-59	LE71180592000246SGS00	LE71180592000198EDC00	LT51180591997213DKI00					
	119-57	LT51190572000069DKI00	LT51190572000101DKI00	LT51190572000117DKI00	LE71190572001191SGS00	LE71190572001095SGS00	LE71190571999330SGS00		
	119-58	LT51190582000101DKI00	LT51190582000197DKI00	LE71190582001191SGS00	E71190582001095SGS00				
	119-59	LT51190592000197DKI00	LT51190592000101DKI00	LE71190592001175EDC00	LE71190592001143SGS00	LE71190592001191SGS00	LE71190592001351EDC00		
	120-58	LE71200582000132SGS00	LE71200582001166SGS02	LE71200582000244EDC01	LE71200582000052EDC00	LT51200582000092DKI00	LT51200581999233DKI00	LE71200582001182SGS00	
	120-59	LE71200592000244EDC01	LE71200592000132SGS00	LE71200592001006SGS00	LE71200592001182SGS00				
	121-59	LE71210592000139SGS00	LT51210592000131DKI00	LT51210592000163DKI00	LE71210591999312SGS00	LE71210592001189SGS00	LE71210592001077SGS00		
2003	118-57	LE71180572003142EDC00	LE71180572002139SGS00	LE71180572002235EDC00	LT51180572004169BKT01	LT51180572004185BKT01	LE71180572004193SGS01	LE71180572004081EDC02	LE71180572002091SGS00
	118-58	LE71180582003142EDC00	LT51180582004185BKT01	LT51180582004137BKT02	LE71180582004145EDC01	LE71180582002139SGS00	LE71180582002347EDC00		
	118-59	LE71180592003142EDC00	LE71180592003110EDC00	LE71180592002347EDC00	LE71180592002187SGS00				
	119-57	LE71190572003213EDC03	LE71190572002178SGS00	LE71190572002098EDC00	LE71190572004248EDC02	LT51190572004224BKT00	LT51190572004080BKT00		
	119-58	LE71190582003213EDC03	LE71190582002098EDC00	LE71190582003101ASN00	LT51190582004224BKT00	LE71190582004248EDC02	LE71190582001191SGS00		
	119-59	LE71190592003149EDC00	LE71200592003316ASN01	LE71190592004232EDC02	LE71190592004104EDC01	LE71190592002098EDC00	LT51190592004256BKT00	LT51190592005162BKT01	
	120-58	LE71200582003316ASN01	LE71200582003108ASN00	LE71200582002217DKI00	LE71200582002153SGS00	LE71200582004239DKI01	LE71200582004223EDC01	LE71200582004143EDC03	
	120-59	LE71200592003268ASN01	LE71200592002233SGS00	LE71200592002201SGS00	LE71200592002153SGS00	LE71200592002217DKI00	LE71200592004143EDC03	LE71200592004223EDC01	
	121-59	LT51210592003315BKT00	LE71210592003051DKI00	LE71210592002176SGS00	LT51210592004174BKT01	LT51210592004094BKT00	LE71210592004182DKI00		
2006	118-57	LE71180572006070EDC00	LT51180572006190BKT00	LT51180572006158BKT01	LT51180572006094BKT00	LT51180572007177BKT00	LE71180572005211EDC00	LE71180572005259EDC00	
	118-58	LT51180582006094BKT00	LT51180582006110BKT00	LE71180582006214EDC00	LT51180582007177BKT00	LE71180582007185EDC00	LE71180582005211EDC00		
	118-59	LE71180592006278EDC00	LE71180592005211EDC00	LT51180592007177BKT00	LE71180592007217EDC00	LE71180592007185EDC00			
	119-57	LE71190572006237EDC00	LE71190572006157EDC00	LT51190572005210BKT00	LT51190572005162BKT01	LE71190572007240EDC00	LT51190572007184BKT00		
	119-58	LE71190582006157EDC00	LT51190582006165BKT00	LT51190582005226BKT01	LT51190582005258BKT00	LT51190582007200BKT00	LT51190582007184BKT00	LE71190582007240EDC00	
	119-59	LE71190592006189EDC00	LT51190592005226BKT01	LT51190592005162BKT01	LT51190592005258BKT00	LT51190592007216BKT00	LT51190592007184BKT00	LE71190592007128EDC00	
	120-58	LE71200582006164EDC00	LE71200582006068EDC00	LE71200582006116DKI00	LT51200582006044BKT00	LT51200582006140BKT00	LT51200582005249BKT00	LE71200582007231EDC00	LE71200582007103EDC00
	120-59	LE71200592006228EDC00	LE71200592006164EDC00	LE71200592006180EDC00	LT51200592006268BKT01	LE71200592005017EDC00	LE71200592005065EDC00		
	121-59	LE71210592006155EDC00	LT51210592006099BKT00	LT51210592006179BKT00	LT51210592005224BKT01	LE71210592005216EDC00	LE71210592007174EDC00		
2009	118-57	LE71180572009062EDC00	LT51180572008148BKT00	LT51180572009230BKT00	LT51180572009166BKT01	LT51180572009246BKT00	LE71180572009174EDC00	LE71180572008268EDC00	
	118-58	LT51180582009310BKT00	LT51180582009246BKT00	LE71180582009062EDC00	LE71180582010241EDC00	LE71180582010225EDC00	LE71180582008268EDC00		
	118-59	LE71180592009062EDC00	LE71180592009222EDC00	LE71180592008140EDC00	LT51180592010041BKT00				
	119-57	LE71190572009117EDC00	LT51190572009157BKT00	LE71190572008163EDC00	LE71190572008179EDC00	LT51190572008315BKT00	LT51190572008331BKT00		
	119-58	LE71190582009213EDC01	LT51190582009221BKT00	LT51190582009157BKT00	LE71190582009357EDC00	LT51190582009253BKT00	LT51190582010224BKT00		
	119-59	LE71190592009357EDC00	LT51190592009253BKT00	LE71190592009213EDC01	LE71190592010040EDC01	LE71190592008163EDC00	LT51190592008123BKT00	LT51190592008283BKT00	LT51190592010224BKT00
	120-58	LE71200582009332EDC00	LE71200582009204EDC00	LT51200582009212BKT00	LT51200582009164BKT00	LE71200582010287EDC00	LE71200582010239EDC00		
	120-59	LE71200592009220EDC00	LE71200592009284EDC00	LT51200592009212BKT00	LT51200592008146BKT00				
	121-59	LE71210592009291EDC00	LE71210592009211SGS00	LT51210592009235BKT00	LE71210592008017EDC01	LE71210592008305EDC00	LE71210592010134EDC00		
2012	118-57	LE71180572012167EDC01	LT51180572011220BKT00	LE71180572012215PFS00	LC81180572013241LGN00	LE71180572012087EDC00	LE71180572011196EDC00	LT51180572011172BKT00	
	118-58	LE71180582012215PFS00	LE71180582012167EDC01	LE71180582012055EDC00					
	118-59	LE71180592012055EDC00	LE71180592012215PFS00	LE71180592012167EDC01					
	119-57	LE71190572012014EDC00	LE71190572012126EDC00	LE71190572012222EDC00	LE71190572011171EDC00	LT51190572011227BKT00	LC81190572013168LGN00		
	119-58	LE71190582012222EDC00	LC81190582013328LGN00	LC81190582013168LGN00	LE71190582012126EDC00	LT51190582011227BKT00	LE71190582011251EDC00	LE71190582011171EDC00	
	119-59	LE71190592012222EDC00	LE71190592012126EDC00	LE71190592013288EDC00	LC81190592013216LGN00	LE71190592011219EDC00	LE71190592011171EDC00	LE71190592013160EDC00	
	120-58	LE71200582012277EDC00	LC81200582013159LGN00	LE71200582012245EDC00	LE71200582012165EDC00				

Table A.1. (cont'd)

	120-59	LE71200592012229EDC00	LE71200592012277EDC00	LE71200592012341EDC00	LT51200592011170BKT00	LE71200592011322EDC00	LE71200592013167EDC00	
	121-59	LT51210592011273BKT00	LE71210592011313EDC00	LE71210592013142DKI00	LE71210592013110EDC00			
2014	118-57	LC81180572014260LGN00	LC81180572014100LGN00	LC81180572014292LGN00	LE71180572014124EDC00	LE71180572014028EDC00	LC81180572014116LGN00	
	118-58	LE71180582014252EDC00	LC81180582014292LGN00	LC81180582014036LGN00	LC81180582014116LGN00	LC81180582014260LGN00		
	118-59	LC81180592014036LGN00	LC81180592014116LGN00	LC81180592014260LGN00				
	119-57	LE71190572014035EDC00	LC81190572014187LGN00	LC81190572014075LGN00	LC81190572014123LGN00	LC81190572014347LGN00	LC81190572013328LGN00	
	119-58	LC81190582014075LGN00	LE71190582013160EDC00	LC81190582014347LGN00	LC81190582014235LGN00	LC81190582014267LGN00	LC81190582014347LGN00	LC81190582014075LGN00
	119-59	LC81190592014075LGN00	LC81190592014219LGN00	LC81190592013168LGN00	LC81190592013152LGN00	LC81190592014075LGN00	LC81190592013168LGN00	
	120-58	LC81200582014178LGN00	LC81200582014146LGN00	LC81200582014130LGN00	LC81200582014114LGN00	LE71200582014122EDC00	LE71200582013167EDC00	LC81200582013287LGN00
	120-59	LC81200592014338LGN00	LC81200592014114LGN00	LC81200592014178LGN00	LE71200592014282EDC00	LE71200592013167EDC00	LC81200592013175LGN00	
	121-59	LE71210592014257EDC00	LE71210592014273EDC00	LC81210592014233LGN00	LC81210592014201LGN00	LC81210592014089LGN00	LC81210592014217LGN00	

Table A.2. The date, type, and cloud coverage of Landsat scenes used for the study in Sarawak, Malaysia, 2000-2014.

2000	118-57	7/8/00,TM,10%	12/21/00,ETM+,14%	2/25/01,ETM+,13%	9/5/01,ETM+,18%	10/23/01,ETM+,21%	11/24/98,TM,15%		
	118-58	7/8/00,TM,19%	2/25/01,ETM,22%	8/20/01,ETM+,29%	12/21/99,ETM,29%	11/24/98,TM,30%	1/24/98,TM,14%		
	118-59	7/16/00,ETM+,16%	9/2/00,ETM+,27%	8/1/97,TM,24%					
	119-57	4/26/00,TM,19%	4/5/01,EMT+,2%	4/10/00,TM, 13%	3/9/00,TM,11%	11/26/99,ETM+,7%	7/10/01,ETM+,0%		
	119-58	4/10/00,TM,9%	7/10/01,ETM+,0%	7/15/00,TM,21%	4/5/01,ETM+,20%				
	119-59	7/15/00,TM,14%	4/10/00,TM,19%	5/23/01,ETM+,14%	6/24/01,ETM+,11%	7/10/01,ETM+,8%	4/8/02,ETM+,17%	12/17/01,ETM+,30%	
	120-58	5/11/00,ETM+,7%	6/15/01,ETM+,11%	8/31/00,ETM+,7%	2/21/00,ETM+,14%	8/21/99,tm,25%	7/1/01,ETM+,6%	4/1/00,TM,27%	
	120-59	8/31/00,ETM+,13%	5/11/00,ETM+,19%	1/6/01,ETM+,17%	7/1/01,ETM+,12%	6/2/02,ETM+,7%			
	121-59	6/11/00,TM,2%	3/18/01,ETM+,11%	7/8/01,ETM+,8%	5/18/00,ETM+,0%	5/10/00,TM,11%	11/8/99,ETM+,7%		
2003	118-57	5/22/03,ETM+,13%	6/17/04,TM,9%	5/19/02,ETM+,8%	8/23/02,ETM+,28%	3/7/04,TM,22%	3/21/04,ETM+,28%	4/1/04,ETM+,ETM+,20%	5/22/03,ETM+,13%
	118-58	5/22/03/ETM+,25%	5/19/02,ETM+,21%	12/13/ETM+,24%	5/16/04,TM,16%	7/3/04,TM,25%	5/25/04,ETM,28%		
	118-59	5/22/03,ETM+,28%	4/20/03/ETM+,27%	12/13/02,ETM+,24%	7/6/02,ETM+,26%				
	119-57	8/1/03,ETM+,13%	3/20/04,TM,13%	8/11/04,TM,23%	9/4/04,ETM+,1%	6/7/02,ETM+,1%	4/8/02,ETM+,5%		
	119-58	8/1/03,ETM-off,8%	4/8/02,ETM+,9%	8/11/04,TM,18%	4/11/03,ETM+,30%	9/4/04,ETM-off,27%	7/10/01,ETM-off,0%		
	119-59	5/29/03,ETM+,29%	5/26/02,ETM+,19%	4/13/04,ETM+,26%	8/19/04,ETM+,3%	4/8/02,ETM+,17%	9/12/01,TM,27%	6/11/05,TM,10%	
	120-58	11/12/03,ETM-off,4%	4/18/03,ETM+,13%	8/5/02,ETM+,6%	6/2/02,ETM+,5%	5/22/04,ETM+,7%	8/10/04,ETM+,0%	8/26/04,ETM+,5%	
	120-59	9/25/03,ETM-off,17%	11/12/03,ETM-off,23%	8/21/02,ETM+,15%	7/20/02,ETM+,12%	8/5/02,ETM+,26%	5/22/04,ETM+,16%	8/10/04,ETM+,5%	
	121-59	11/11/03,TM,20%	4/3/04,TM,8%	6/22/04,TM,1%	6/25/02,ETM+,15%	2/20/03,ETM+,25%	6/30/04,ETM+,4%		
2006	118-57	3/11/06,ETM+,19%	4/4/06,TM,16%	6/7/06,TM,12%	7.9.06,TM,22%	9/16/05,ETM-off,15%	7/30/05,ETM-off,9%	6/26/07,TM,7%	
	118-58	4/20/06,TM,24%	4/4/06,TM,15%	8/2/06,ETM-off,27%	7/30/05,ETM,18%	6/26/07,TM,11%	7/4/07,ETM,8%		
	118-59	10/5/06,ETM-off,5%	7/20/05,ETM+,30%	6/20/07,TM,28%	7/4/07,ETM,24%	8/5/07,ETM-off,30%			
	119-57	6/6/06, ETM+,5%	8/25/06/ETM-off,12%	7/3/07,TM,0%	8/28/07,ETM+,7%	7/29/05,TM,0%	6/11/05/TM,0%		
	119-58	6/6/06,ETM-off,21%	9/15/05,TM,105	8/14/05,TM,15%	6/14/06,TM,19%	7/3/07,TM,9%	8/28/07,ETM-off,15%	7/19/07,TM,18%	
	119-59	7/8/06,ETM+,19%	9/15/05,TM,9%	8/14/05,TM,8%	6/11/05,TM,10%	7/3/07,TM,8%	8/4/07,TM,11%	5/8/07,ETM+,30%	
	120-58	6/13/06,ETM-off,6%	12/13/06,TM,19%	3/9/06,ETM-off,15%	4/26/06,ETM-off,27%	5/20/06,TM,19%	6/9/05,TM,18%	4/13/07,ETM+,6%	8/19/07,ETM-off,9%
	120-59	8/16/06,ETM+,2%	6/13/06,ETM-off,13%	6/5/06,TM,21%	6/29/06,ETM-off,27%	3/6/05,ETM+,18%	1/17/05,ETM+,8%	9/25/06,TM,1%	
	121-59	6/4/06, ETM+,12%	6/28/06,TM,5%	6/23/07,ETM+,2%	4/9/06,TM,7%	8/12/05,TM,4%	8/4/05,ETM+,22%		
2009	118-57	3/3/09,ETM-off,16%	6/15/09,TM,12%	8/18/09,TM,23%	5/27/08,TM,14%	9/24/08,ETM-off,14%	9/3/09,TM,13%	6/23/09,ETM-off,19%	
	118-58	9/3/09,TM,9%	3/3/09,ETM-off,10%	9/24/08,ETM,15%	11/6/09,TM,26%	6/26/07,TM,11%	8/29/10,ETM,18%		

Table A.2. (cont'd)

	118-59	8/10/09,ETM+,26%	3/3/09,ETM+,30%	5/19/08,ETM+,9%	10/30/10,TM,30%				
	119-57	6/609,TM,10%	4/27/09,ETM-off,9%	11/26/08,TM,14%	11/10,08,TM,15%	6/27/08/ETM+,0%	6/11/00,ETM+,4%		
	119-58	8/1/09,ETM-off,1%	6/6/09,TM,14%	8/9/09,TM,14%	12/23/09,ETM-off,14%	9/10/09,TM,6%	8/12/09,TM,9%		
	119-59	12/23/09,ETM+,11%	8/1/09,ETM+,8%	9/10/09,TM,18%	2/9/10,ETM+,15%	5/2/08,TM,20%	6/11/08,ETM+,19%	10/9/08,TM,24%	8/12/10,TM,17%
	120-58	11/28/09,ETM+,10%	7/31/09,TM,15%	7/23/09,ETM-off,15%	6/13/09,TM,15%	8/27/10,ETM+,20%	10/14/10,ETM+,15%		
	120-59	8/8/09,ETM+,6%	7/31/09,TM,3%	5/20/09,ETM_off,13%	10/11/09,ETM-off,27%	5/25/08,TM,17%			
	121-59	7/30/09,ETM+,21%	10/18/09,ETM+,14%	5/14/10,ETM+,8%	1/17/08,ETM+,13%	10/31/08,TM,14%	8/23/09,TM,17%		
2012	118-57	6/15/12,ETM-off,8%	8/2/12,ETM-off,11%	8/8/11,TM,17%	8/29/13,OLI,24%	6/21/11,TM,13%	3/27/12,ETM-off,21%	7/15/11,ETM-off,23%	6/15/12,ETM-off,8%
	118-58	8/2/12,ETM,10%	6/15/12/ETM,9%	2/24/12,ETM,23%					
	118-59	6/15/12,ETM+,18%	8/2/12,ETM+,23%	2/24/12,ETM,19%					
	119-57	8/9/12,ETM,9%	8/15/2011,TM,0%	6/20/11,ETM+,5%	5/5/12,ETM+,18%	1/14/12,ETM+,13%	6/17/13,OLI,14%		
	119-58	8/9/12,ETM-off,8%	6/9/13,ETM-off,6%	6/17/13,OLI,16%	5/5/12,ETM-off,20%	6/20/11,ETM+,8%	8/9/11,ETM+,24%	8/15/11,TM,29%	
	119-59	8/9/12,ETM-off,11%	6/1/13,OLI,15%	5/5/12,ETM-off,15%	6/17/13,OLI,19%	7/8/11,ETM+,24%	6/20/11,ETM+,22%	6/9/13/ETM+,17%	
	120-58	10/3/12,ETM+,0%	9/1/12,ETM-off,13%	6/13/12,ETM-off,16%	6/6/13,OLI,17%				
	120-59	8/16/12,ETM-off,13%	6/19/11,TM,14%	10/3/12,ETM-off,23%	12/6/12,ETM-off,24%	11/18/11,ETM+,19%	6/16/13,ETM+,8%		
	121-59	5/19/12,ETM+,26%	4/20/13,ETM+,1%	11/9/11,ETM+,22%	9/30/11,TM,5%	5/22/12,ETM+,9%	6/15/13,ETM+,5%		
2014	118-57	9/17/14,OLI,9%	1/23/15/OLI,16%	10/19/14,OLI,19%	4/10/14,OLI,20%	1/28/14,ETM-off,15%	4/26/14,OLI,24%		
	118-58	9/17/14,OLI,12%	9/9/14,ETM+,28%	4/26/14,OLI,22%	2/5/14,OLI,24%	1/23/15,OLI,24%	10/19/14,OLI,30%		
	118-59	9/17/14,OLI,12%	4/26/14,OLI,14%	2/5/14,OLI,14%					
	119-57	5/3/14,OLI,7%	12/13/14,OLI,8%	2/4/14,OLI,11%	11/24/13,OLI,14%	3/16/14,OLI,15%	7/6/14,OLI,18%		
	119-58	3/16/14,OLI,12%	11/24/13,OLI,13%	8/23/14,OLI,27%	12/13/14,OLI,25%	3/16/14,OLI,12%	13/12/14,OLI,25%	9/24/14,OLI,25%	
	119-59	3/16/14,OLI,17%	8/4/13,OLI,18%	8/7/14,OLI,29%	10/15/13,ETM-off,30%	3/16/14,OLI,17%	6/9/13,ETM,17%	6/17/13,OLI,17%	
	120-58	6/27/14,OLI,16%	5/26/14,OLI,17%	5/10/14,OLI,17%	4/24/14,OLI,12%	10/14/13,OLI,14%	5/2/14,OLI,25%	6/16/13,ETM+,8%	
	120-59	12/4/14,OLI,16%	4/24/14,OLI,15%	6/27/14,OLI,26%	10/9/14,OLI,23%	6/24/13,OLI,16%	6/16/13,ETM+,8%		
	121-59	5/8/14,OLI,10%	30/9/14,ETM+,11%	7/20/14,OLI,13%	3/30/14,OLI,17%	8/21/14,OLI,21%	9/14/14,ETM-off,14%		

Table A.3. The full list of Landsat scenes used for the study in Sabah, Malaysia, 2000-2014.

2000	116-56	LT51160562000128DKI00	LE71160562000312SGS00	LE71160562000344EDC00	LT51160561999317DKI00				
	116-57	LE71160572000312SGS00	LE71160572001266AGS00	LE71160572001250DKI00	LE71160572001138DKI01	LE71160571999261SGS00	LE71160572001106DKI01	LE71160572000312SGS00	
	117-55	LT51170552000199DKI00	LT51170552000119DKI00	LT51170552000071DKI00	LT51170551999196DKI00	LE71170552000127SGS00	LE71170551999252SGS00		
	117-56	LE71170562000191EDC00	LE71170562000127SGS00	LE71170561999252SGS00	LT51170562000135DKI00	LE71170562001241DKI00	LE71170562001177EDC00		
	117-57	LE71170572000191EDC00	LE71170572000127SGS00	LE71170572001177EDC00	LE71170571999252SGS00	LT51170572000199DKI00	LE71170572001353EDC00	LE71170571999364EDC00	
	118-55	LT51180552000158DKI00	LT51180551999235DKI00	LE71180552000118EDC00	LE71180552001104SGS00				
	118-56	LT51180562000190DKI00	LT51180562000014DKI00	LT51180562000158DKI00	LE71180561999275SGS00	LE71180562001248SGS00	LE71180562001152DKI01	LE71180562001200SGS00	LT51180561999251DKI00
	118-57	LT51180572000190DKI00	LE71180572001056SGS00	LE71180571999355EDC00	LE71180572001248SGS00	LE71180572001296SGS01	LT51180571998328DKI00		
2003	116-56	LE71160562003112BKT01	LE71160562002205BKT00	LE71160562002237EDC00	LE71160562004099EDC02				
	116-57	LE71160572003112BKT01	LE71160572002365BKT00	LE71160572004099EDC02	LE71160572004051EDC02	LE71160572002269SGS00	LE71160572002205EDC00		
	117-55	LT51170552003319BKT00	LE71170552003119BKT00	LT51170552004098BKT00	LE71170552003279EDC01	LE71170552004058EDC02	LE71170552003103EDC00		
	117-56	LE71170562003279EDC01	LE71170562002148EDC00	LT51170562003319BKT00	LT51170562004082BKT00	LT51170562004146BKT00	LT51170562004098BKT00		
	117-57	LE71170572003023EDC00	LE71170572004010EDC01	LT51170572004146BKT00	LT51170572004178BKT00	LT51170572004306BKT00	LE71170572004218PFS01	LE71170572002340EDC00	
	118-55	LE71180552003126BKT00	LE71180552002203EDC00	LE71180552002235EDC00					

Table A.3. (cont'd)

	118-56	LE71180562003318DKI00	LE71180562003046SGS00	LE71180562003126DKI00	LE71180562003014EDC00	LE71180562004081EDC02	LE71180562002091DKI00	LE71180562002139SGS00	
	118-57	LE71180572003142EDC00	LE71180572002139SGS00	LE71180572002235EDC00	LT51180572004169BKT01	LT51180572004185BKT01	LE71180572004193SGS01	LE71180572004081EDC02	LE71180572002091SGS00
2006	116-56	LT51160562006208BKT01	LE71160562006296EDC00	LT51160562005221BKT00	LT51160562005141BKT00				
	116-57	LT51160572006064BKT01	LE71160572006328EDC	LE71160572006296EDC00	LT51160572005221BKT00	LT51160572005141BKT00	LT51160572005061BKT00	LT51160572006064BKT01	LE71160572006296EDC00 LE71160572006328EDC00
	117-55	LT51170552006215BKT01	LE71170552006287EDC00	LE71170552006255EDC00	LT51170552007106BKT00	LT51170552007138BKT00	LT51170552007074BKT00		
	117-56	LT51170562006231BKT00	LT51170562006167BKT00	LT51170562006215BKT01	LE71170562006159EDC00	LT51170562005212BKT00	LT51170562007074BKT00		
	117-57	LE71170572006159EDC00	LT51170572005260BKT01	LE71170572006319EDC00	LE71170572007066EDC00	LT51170572005164BKT00	LT51170572005020BKT00	LT51170572007074BKT00	
	118-55	LT51180552006286BKT00	LT51180552006158BKT01	LT51180552006126BKT00					
	118-56	LT51180562006158BKT01	LT51180562006350BKT00	LT51180562006318BKT00	LT51180562006286BKT00	LT51180562007065BKT00	LE71180562005211EDC00	LE71180562005259EDC00	
	118-57	LE71180572006070EDC00	LT51180572006190BKT00	LT51180572006158BKT01	LT51180572006094BKT00	LT51180572007177BKT00	LE71180572005211EDC00	LE71180572005259EDC00	
2009	116-56	LT51160562009216BKT01	LT51160562009200BKT01	LT51160562009232BKT00					
	116-57	LT51160572009344BKT00	LT51160572009008BKT00	LT51160572009216BKT01	LE71160572009128EDC00	LE71160572008142EDC00	LT51160572008278BKT00		
	117-55	LT51170552009255BKT00	LE71170552009087EDC00	LE71170552009327EDC00	LE71170552009295EDC00	LE71170552009231EDC00	LT51170552008285BKT00		
	117-56	LE71170562009231EDC00	LE71170562009087EDC00	LT51170562009255BKT00	LT51170562009223BKT01	LT51170562010242BKT00	LE71170562009295EDC00		
	117-57	LE71170572009215EDC00	LT51170572009303BKT00	LT51170572009223BKT01	LE71170572009295EDC00	LT51170572010034BKT00	LT51170572010242BKT00	LE71170572008213EDC00	
	118-55	LT51180552009134BKT00	LT51180552009310BKT00	LE71180552009222EDC00					
	118-56	LT51180562009118BKT01	LT51180562009310BKT00	LT51180562009134BKT00	LE71180562009222EDC00	LT51180562009230BKT00	LE71180562009078EDC00	LT51180562008292BKT00	
	118-57	LE71180572009062EDC00	LT51180572008148BKT00	LT51180572009230BKT00	LT51180572009166BKT01	LT51180572009246BKT00	LE71180572009174EDC00	LE71180572008268EDC00	
2012	116-56	LE71160562012265EDC00	LE71160562012233EDC00	LE71160562011246EDC00	LC81160562013115LGN01				
	116-57	LE71160572012233EDC00	LE71160572011246EDC00	LE71160572012121EDC00	LE71160572012361DKI00	LC81160572013115LGN01	LE71160572011246EDC00	LE71160572012121EDC00	LC81160572013179LGN01 LC81160572013147LG N00
	117-55	LE71170552012240EDC00	LE71170552012224EDC00	LE71170552011173EDC00	LE71170552013178EDC00	LE71170552013146EDC00	LC81170552013154LGN00		
	117-56	LE71170562012240EDC00	LE71170562012224EDC00	LC81170562013170LGN00	LC81170562013154LGN00	LE71170562013178EDC00	LE71170562011173EDC00		
	117-57	LE71170572012240EDC00	LE71170572011221EDC00	LC81170572013154LGN00	LC81170572013170LGN00	LE71170572011349EDC00	LC81170572013314LGN00	LC81170572013122LGN01	
	118-55	LE71180552012343EDC00	LE71180552012055EDC00	LE71180552011292EDC00					
	118-56	LE71180562012215PFS00	LE71180562012055EDC00	LC81180562013113LGN01	LE71180562012359EDC00	LC81180562013241LGN00	LE71180562013057EDC00		
	118-57	LE71180572012167EDC01	LT51180572011220BKT00	LE71180572012215PFS00	LC81180572013241LGN00	LE71180572012087EDC00	LE71180572011196EDC00	LT51180572011172BKT00	
2014	116-56	LE71160562014174EDC00	LE71160562014206EDC00	LC81160562014246LGN00	LC81160562014294LGN00				
	116-57	LE71160572014110EDC01	LC81160572014342LGN00	LC81160572014262LGN00	LC81160572014182LGN00	LC81160572014134LGN00	LC81160572014102LGN00		
	117-55	LE71170552014037EDC00	LE71170552014053EDC00	LC81170552014061LGN00	LC81170552014109LGN00	LC81170552014157LGN00	LC81170552014221LGN00	LC81170552014237LGN00	
	117-56	LC81170562014237LGN00	LC81170562014157LGN00	LC81170562014221LGN00	LE71170562014149EDC00	LC81170562014125LGN00	LC81170562014061LGN00	LC81170562014029LGN00	
	117-57	LE71170572014069EDC00	LE71170572014053EDC00	LC81170572014029LGN00	LC81170572014253LGN00	LE71170572014293EDC00	LC81170572014157LGN00	LC81170572014365LGN00	
	118-55	LC81180552014116LGN00	LC81180552014180LGN00	LC81180552014292LGN00					
	118-56	LC81180562014260LGN00	LC81180562014180LGN00	LC81180562014292LGN00	LC81180562014116LGN00	LC81180562014052LGN00	LC81180562014068LGN00	LC81180562014100LGN00	
	118-57	LC81180572014260LGN00	LC81180572014100LGN00	LC81180572014292LGN00	LE71180572014124EDC00	LE71180572014028EDC00	LC81180572014116LGN00		

Table A.4. The date, type, and cloud coverage of Landsat scenes used for the study in Sabah, Malaysia, 2000-2014.

2000	116-56	5/7/2000, TM, 29%	11/7/2000, ETM+, 14%	12/7/2000, ETM+, 2%	11/13/1999, TM, 6%		
	116-57	7/11/00, ETM+,5%	9/18/99, ETM+, 4%	4/16/01, ETM+, 13%	5/18/01, ETM+, 12%	9/7/01, ETM+, 15%	9/23/01, ETM, 13%
	117-55	5/6/00, ETM,4%	3/11/00,TM,12%	9/9/99,ETM,6%	7/15/99,TM, 7%	4/28/00,TM, 16%	7/17/00,TM,4%

Table A.4. (cont’d)

	117-56	7/9/00,ETM+,15%	9/9/99,ETM+,8%	5/14/00,TM,23%	5/6/00,ETM+,18%	6/26/01,ETM+,12%	8/29/01,ETM+,11%		
	117-57	9/7/00,ETM+,23%	9/9/99,ETM+, 14%	6/26/01,ETM+,10%	5/6/00,ETM,21%	12/30/99,ETM+,15%	12/19/01,ETM+,22%	7/17/00,TM,23%	
	118-55	6/6/00,TM,15%	4/22/00,ETM+,18%	8/23/99,TM,17%	4/14/01,ETM+,9%				
	118-56	7/8/00,TM,15%	6/6/00,TM,15%	1/14/00,TM,13%	10/2/99,ETM+, 14%	9/5/01,ETM+,18%	7/19/01,ETM+,24%	6/1/01,ETM+,25%,	9/8/99,TM,21%
	118-57	7/8/00,TM,10%	12/21/00,ETM+,14%	2/25/01,ETM+,13%	9/5/01,ETM+,18%	10/23/01,ETM+,21%	11/24/98,TM,15%		
2003	116-56	4/22/2003, ETM+, 10%	8/25/2002,ETM+, 9%,	7/24/2002, ETM+, 29%	4/8/2004, ETM+, 10%				
	116-57	4/22/03, ETM, 25%	7/24/02, ETM+, 27%	9/26/02, ETM+,11%	12/31/02, ETM, 15%	2/20/04, ETM-off,8%	4/8/04,ETM-off,9%		
	117-55	4/13/03,ETM,8%	4/29/03,ETM,11%	10/6/03,ETM,15%	2/27/04,ETM,0%	4/7/02,TM,4%	11/15/03,TM,22%		
	117-56	10/6/03,ETM-off,19%	5/28/02,ETM+,12%	11/1503,TM,30%	3/22/04,TM,17%	4/7/04,TM,16%	5/25/01,TM,14%		
	117-57	1/23/03,ETM+,26%	1/10/04,ETM-off,25%	5/25/04,TM,21%	6/26/04,TM,27%	12/6/02,ETM+,29%	8/5/04,ETM-off,25%	11/1/04,TM,26%	
	118-55	5/6/03,ETM+, 13%	8/23/02,ETM+,1%	7/22/02,ETM+,2%					
	118-56	11/14/03,ETM-off,16%	1/14/03,ETM+,15%	5/6/03,ETM+,20%	2/15/03,ETM+,24%	10/26/02,ETM+,13%	5/19/02,ETM+,5%	4/1/02,ETM+,8%	3/21/04,ETM-off,5%
	118-57	5/22/03,ETM+,13%	6/17/04,TM,9%	5/19/02,ETM+,8%	8/23/02,ETM+,28%	3/7/04,TM,22%	3/21/04,ETM+,28%	4/1/04,ETM+,ETM+,20%	7/11/04,ETM-off,22%
2006	116-56	7/27/06, ETM+, 29%	10/23/06, ETM+, 9%	8/9/05,TM, 24%	5/21/05,TM,3%				
	116-57	5/3/06, TM, 3%	10/23/06,ETM-off,5%	11/24/06, ETM-off,11%	3/2/05,TM,8%	5/21/05,TM,5%	8/9/05,TM,8%		
	117-55	8/3/06,TM,7%	9/12/06,ETM+,14%	3/15/07,TM,7%	5/18/07,TM,5%	4/16/07,TM,3%	10/14/06, ETM+,28%		
	117-56	8/19/06,TM,10%	8/3/06,TM,18%	6/16/06,TM,27%	6/8/06,ETM+,24%	5/31/05,TM,9%	3/15/07,TM,10%		
	117-57	6/8/06,ETM-off,19%	3/7/07,ETM+,17%	9/17/05,TM,26%	11/15/06,ETM+,23%	3/15/07,TM,15%	1/20/05,TM,21%	6/13/05,TM,22%	
	118-55	5/6/06,TM,8%	6/7/06,TM,0%	10/13/06,TM,7%					
	118-56	6/7/06,TM,5%	10/13/06,TM,15%	11/14/06,TM,11%	12/16/06,TM,12%	5/16/05,ETM-off,5%	7/30/05,ETM-off,7%	6/3/07,TM,8%	
	118-57	3/11/06,ETM+,19%	4/4/06,TM,16%	6/7/06,TM,12%	7.9.06,TM,22%	9/16/05,ETM-off,15%	7/30/05,ETM-off,9%	6/26/07,TM,7%	
2009	116-56	8/20/09,TM,9%	7/19/09, TM,9%	8/4/09, TM, 8%					
	116-57	5/8/09,ETM-off,4%	8/4/09,TM,10%	1/8/09,TM,17%	10/4/08,TM,10%	8/21/09,ETM-off,4%	12/10/09/TM,4%		
	117-55	8/19/09,ETM-off,5%	9/12/09,TM,27%	10/22/09,ETM-off,7%	11/23/09,ETM-off,3%	3/28/09,ETM-off,3%	10/11/08,TM,4%		
	117-56	8/19/09,ETM-off,8%	8/11/09,TM,6%	9/12/09,TM,11%	3/28/09,ETM+,16%	10/22/09,ETM-off,9%	8/30/10,TM,7%		
	117-57	8/3/09,ETM-off,8%	8/11/09,TM,21%	10/22/09,ETM-off,22%	10/30/09,TM,29%	8/30/10,TM,19%	2/3/10,TM,26%	7/3/08,ETM-off,26%	
	118-55	8/10/09,ETM-off,0%	11/6/09,TM,2%	5/14/09,TM,21%					
	118-56	4/28/09,TM,2%	5/14/09,TM,9%	8/10/09,ETM-off,4%	11/6/09,TM,7%	3/19/09,ETM-off,13%	8/10/08,TM,12%	8/18/09,TM,12%	
	118-57	3/3/09,ETM-off,16%	6/15/09,TM,12%	8/18/09,TM,23%	5/27/08,TM,14%	9/24/08,ETM-off,14%	9/3/09,TM,13%	6/23/09,ETM-off,19%	
2012	116-56	8/20/12, ETM-off, 19%	21/9/12, ETM+, 20%	9/3/11, ETM+, 13%	5/24/13/OLI, 15%				
	116-57	8/20/12,ETM-off,23%	12/26/12,ETM-off,27%	4/30/12,ETM-off,10%	9/3/12,etm-OFF,12%	4/25/13, oli,13%	4/30/12,etm-OFF,16%		
	117-55	8/11/12,ETM-off,7%	6/22/11,ETM-off,16%	8/27/12,ETM,18%	3/6/13,OLI,18%	5/26/13, ETM,22%	6/27/13,ETM+,30%		
	117-56	8/27/12,ETM-off,9%	6/3/13,OLI,9%	8/11/12,ETM+,11%	6/19/13,OLI,11%	6/26/11,ETM-off,9%	6/27/13,ETM-off,5%		
	117-57	8/27/12,ETM-off,23%	8/9/11,ETM,15%	6/3/13,OLI,20%	6/19/13,OLI,20%	12/15/11,ETM-off,22%	5/2/12/OLI,29%	11/10/13,OLI,24%	
	118-55	2/24/12,ETM+,13%	10/19/11,ETM+,8%	12/8/12,ETM+,4%					
	118-56	8/2/12,ETM-off,9%	7/1/12,ETM-off,12%	4/23/13,OLI,12%	2/24/12,ETM-off,7%	12/24/12,ETM-off,20%	2/26/13,ETM-off,18%	9/29/13,OLI,18%	
	118-57	6/15/12,ETM-off,8%	8/2/12,ETM-off,11%	8/8/11,TM,17%	8/29/13,OLI,24%	6/21/11,TM,13%	3/27/12,ETM-off,21%	7/15/11,ETM-off,23%	
2014	116-56	6/23/14, ETM-off,0%	7/25/2014, ETM-off,6%	9/3/14, OLI, 20%	10/21/14, OLI, 9%				
	116-57	4/20/14,ETM,5%	4/12/14,OLI,14%	5/14/14,OLI,12%	7/1/14,OLI,12%	9/19/14,OLI,14%	12/8/14,OLI,17%		
	117-55	8/25/15,OLI,3%	8/9/14,OLI,7%	6/6/14, OLI,9%	4/19/14, OLI,11%	3/2/14,OLI,9%	2/22/14,ETM+,8%	2/6/14,ETM-off,12%	
	117-56	8/25/14,OLI,5%	11/29/14,OLI,16%	8/9/14,OLI,11%	6/6/14,OLI,14%	5/29/14,ETM-off,11%	1/29/14,OLI,19%	2/3/14,OLI,19%	5/5/14,OLI,13%

Table A.4. (cont'd)

117-57	3/10/14,ETM-off,9%	1/29/14,OLI,9%	2/22/14,ETM-off,11%	9/10/14,OLI,17%	6/6/14,OLI,18%	10/20/14,ETM+,17%	12/31/14,OLI,22%
118-55	6/29/14,OLI,5%	10/19/14,OLI,5%	4/26/14,OLI,5%				
118-56	9/17/14,OLI,6%	10/19/14,OLI,10%	6/29/14,OLI,12%	4/26/14,OLI,9%	2/21/14,OLI,12%	4/10/14,OLI,11%	3/9/14,12%
118-57	9/17/14,OLI,9%	1/23/15/OLI,16%	10/19/14,OLI,19%	4/10/14,OLI,20%	1/28/14,ETM-off,15%	4/26/14,OLI,24%	5/4/14,ETM-off,27%

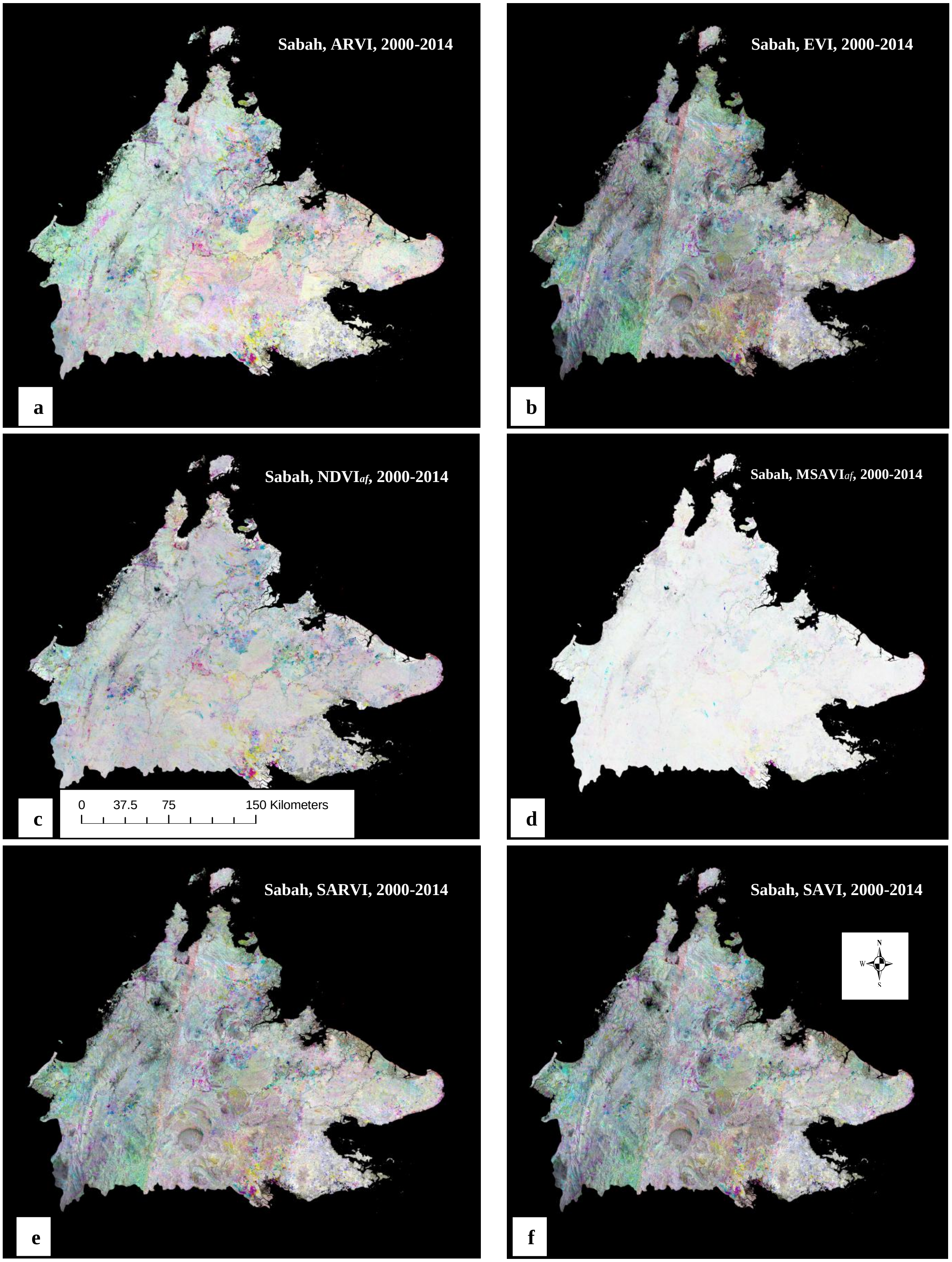


Figure A.1. The stacked VI images by type for Sabah, 2000-2014.

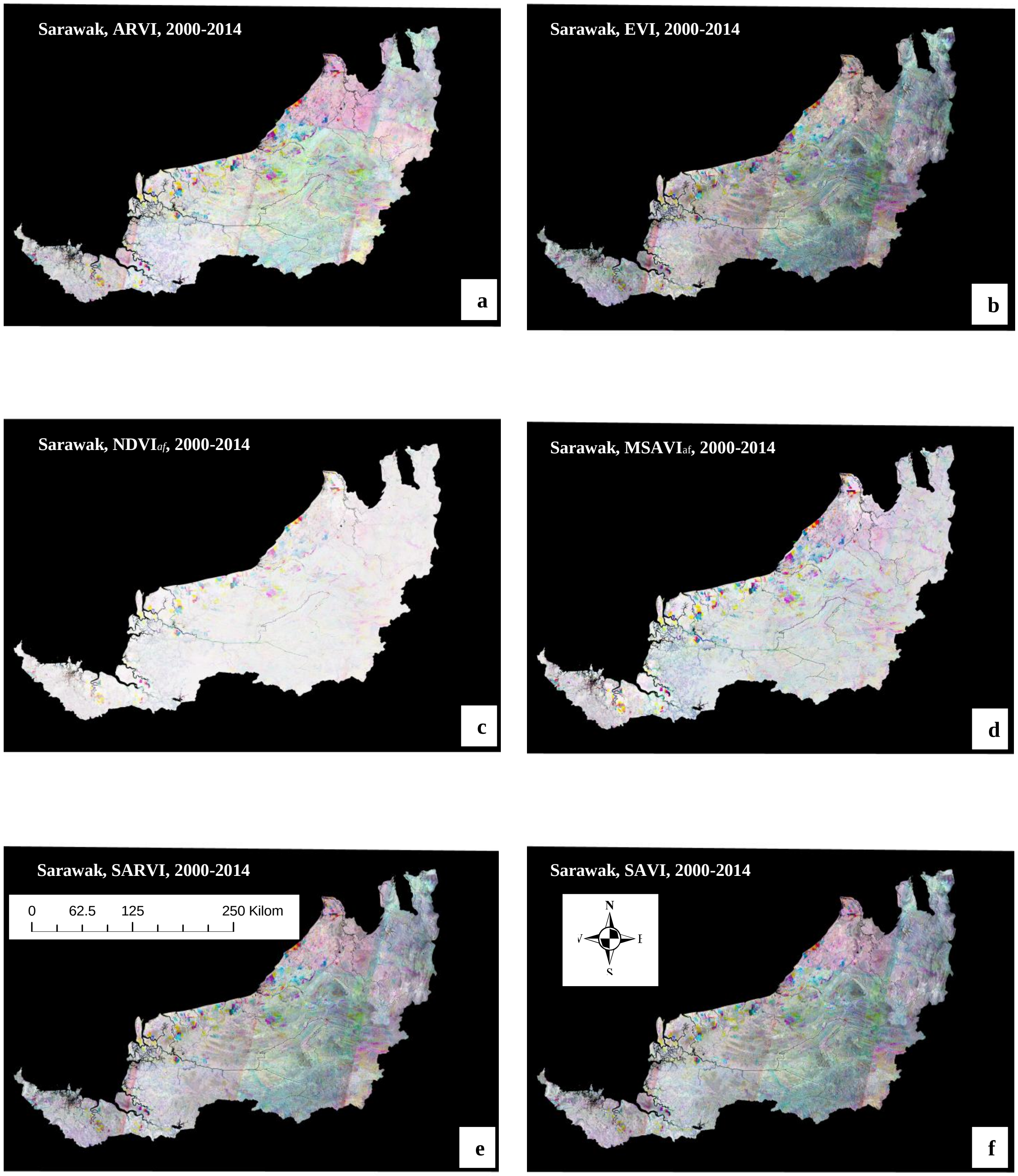


Figure A.2. The stacked VI images by type for Sarawak, 2000-2014.

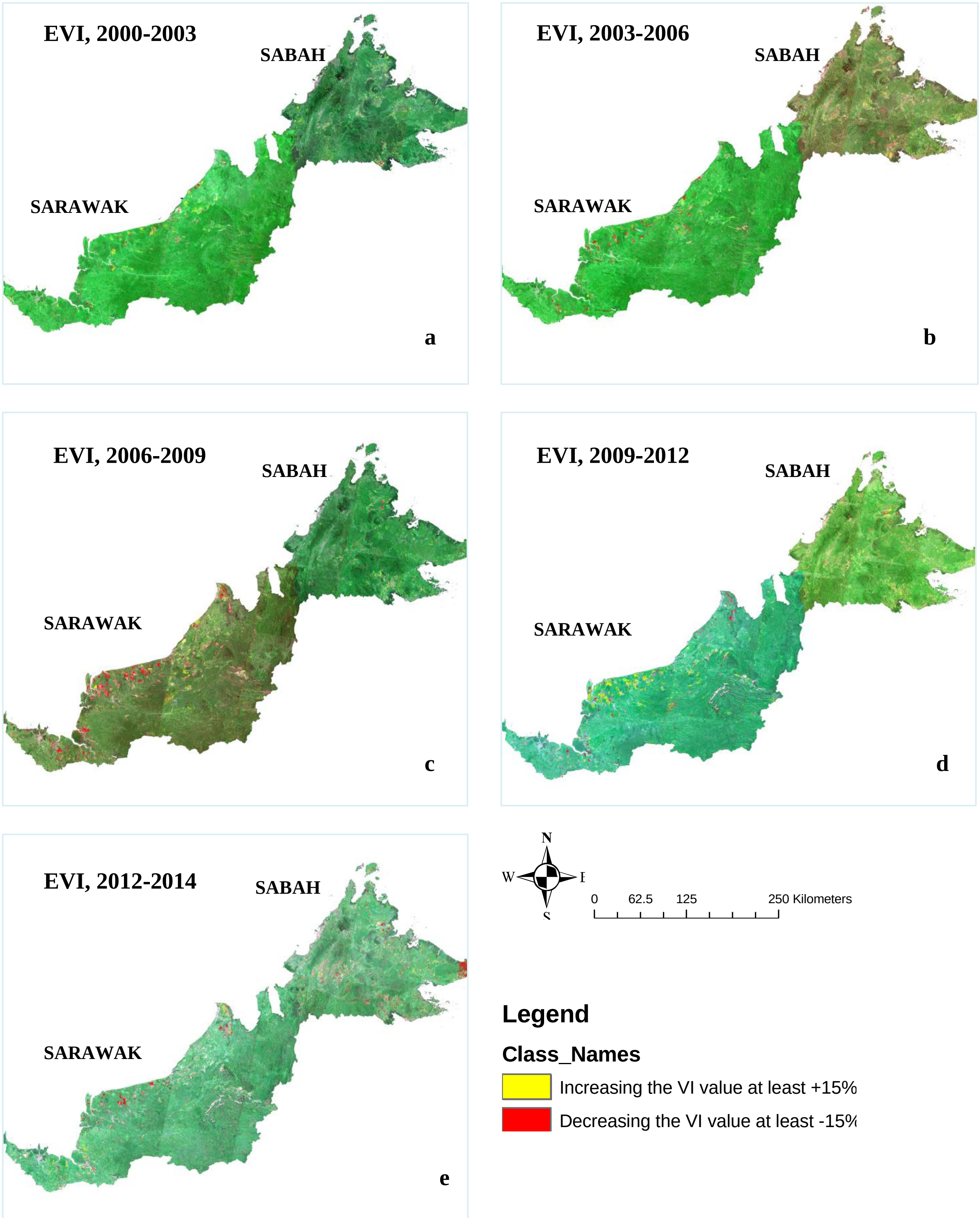


Figure A.3. The changes of EVI values from 2000 to 2014 in Sabah and Sarawak, Malaysia.

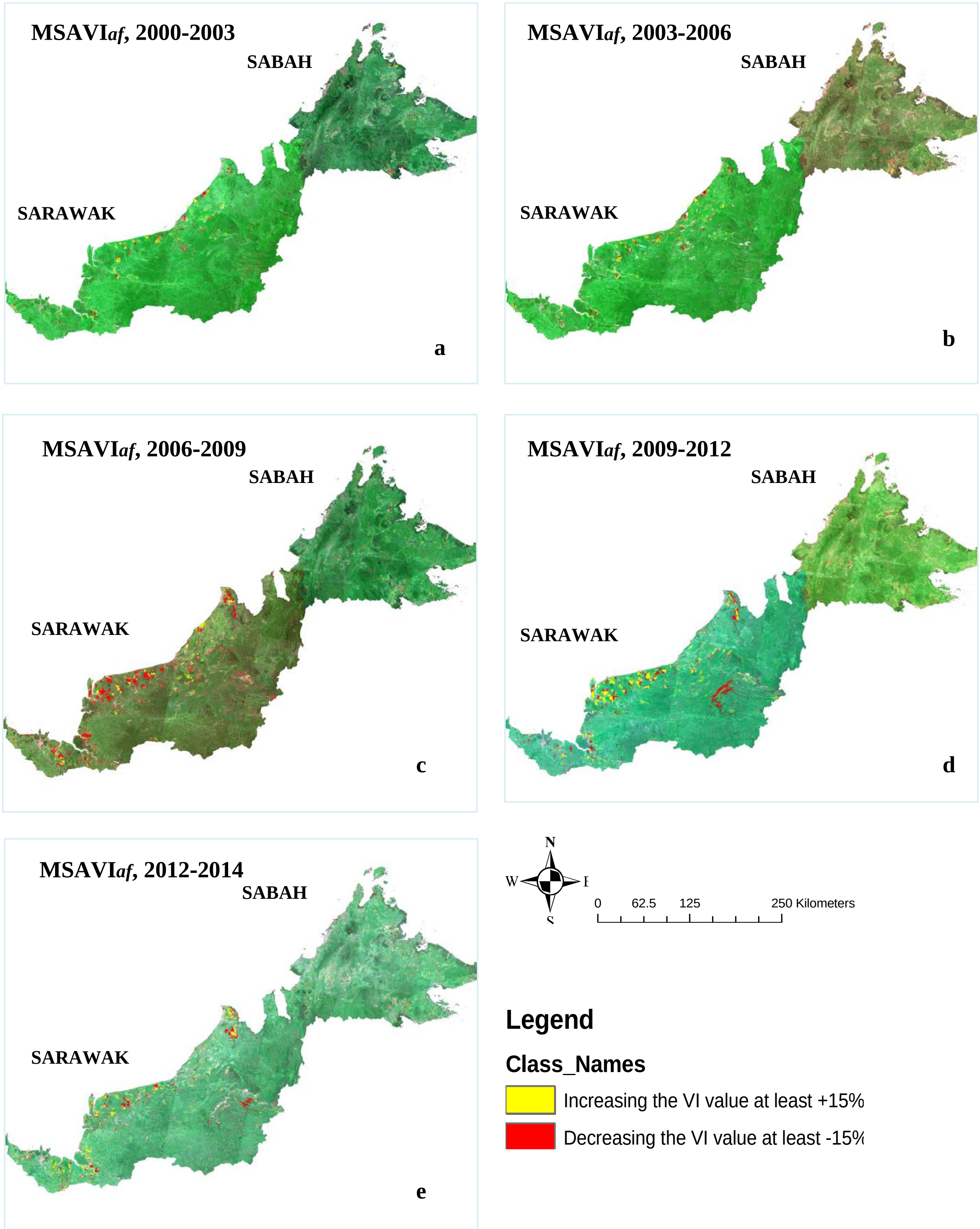


Figure A.4. The changes of MSAVI*af* values from 2000 to 2014 in Sabah and Sarawak, Malaysia.

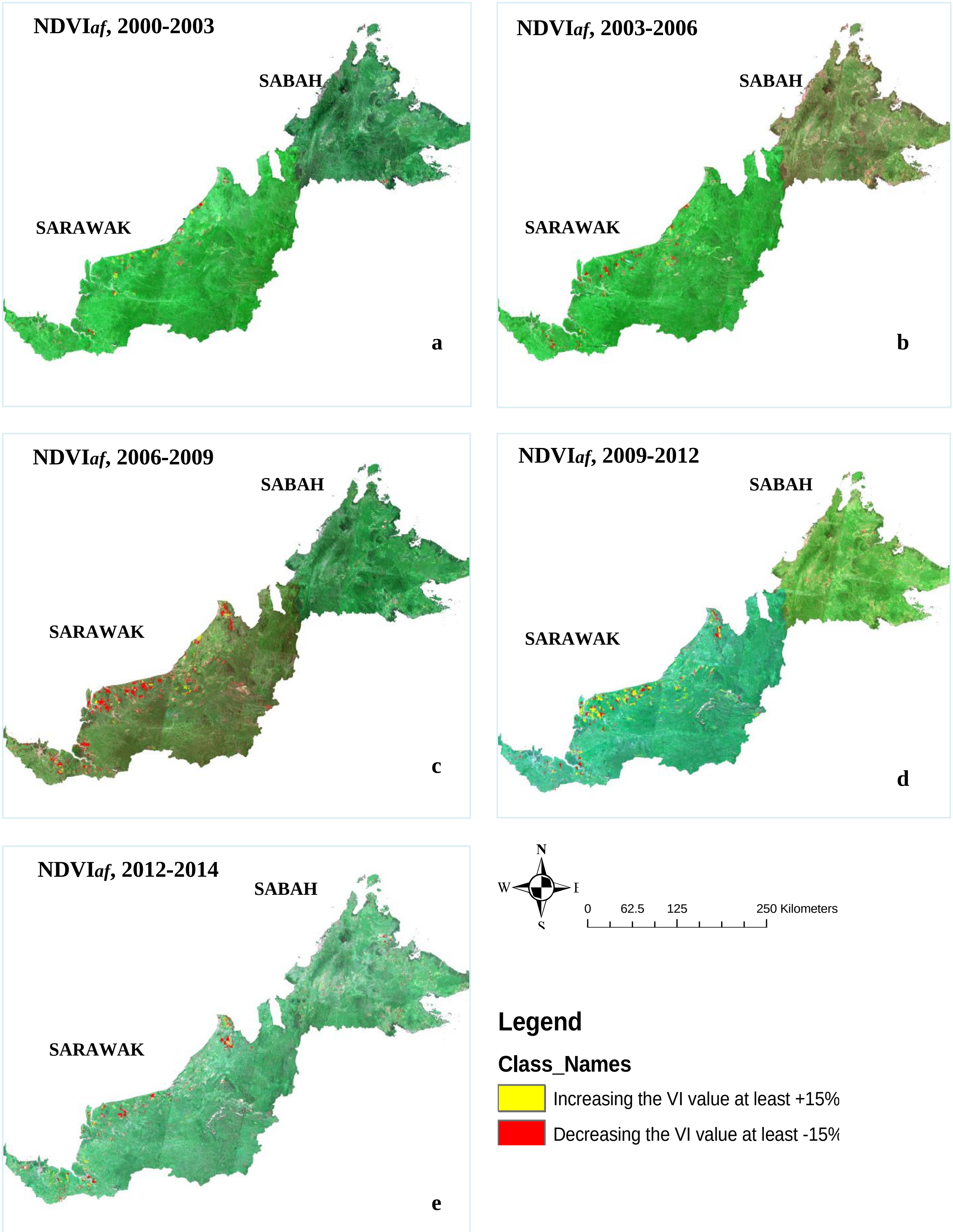


Figure A.5. The changes of NDVI*af* values from 2000 to 2014 in Sabah and Sarawak, Malaysia.

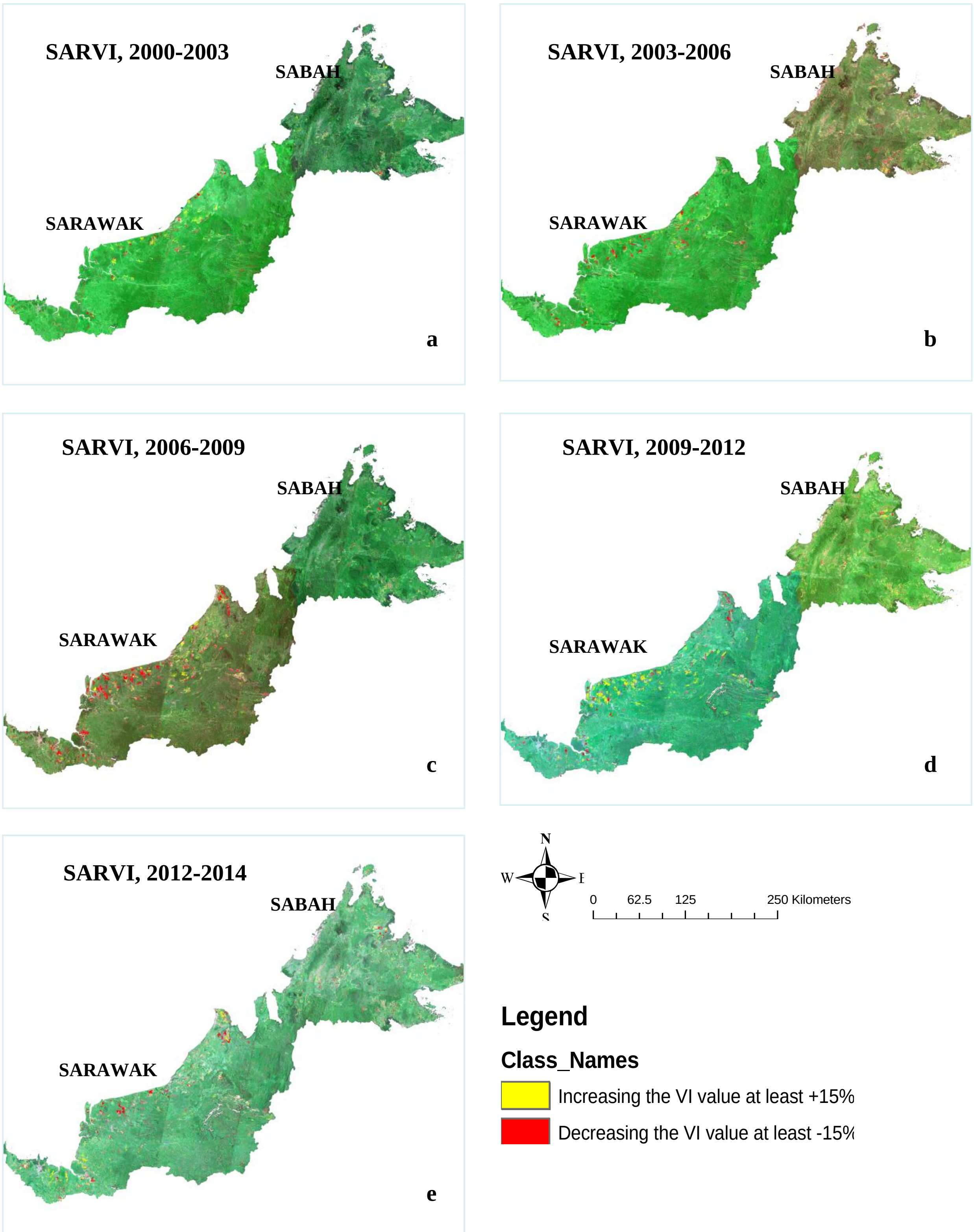


Figure A.6. The changes of SARVI values from 2000 to 2014 in Sabah and Sarawak, Malaysia.

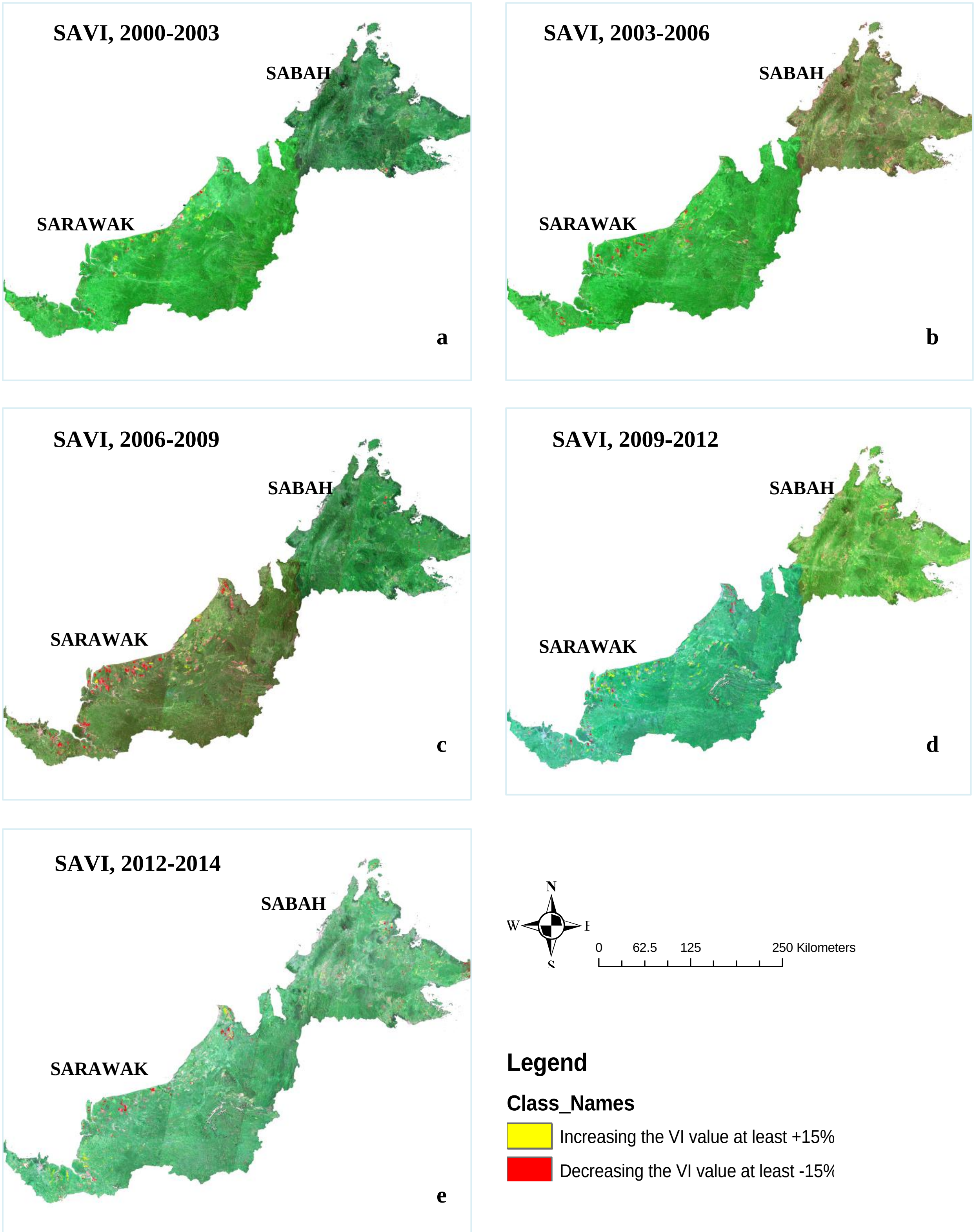


Figure A.7. The changes of SAVI values from 2000 to 2014 in Sabah and Sarawak, Malaysia.

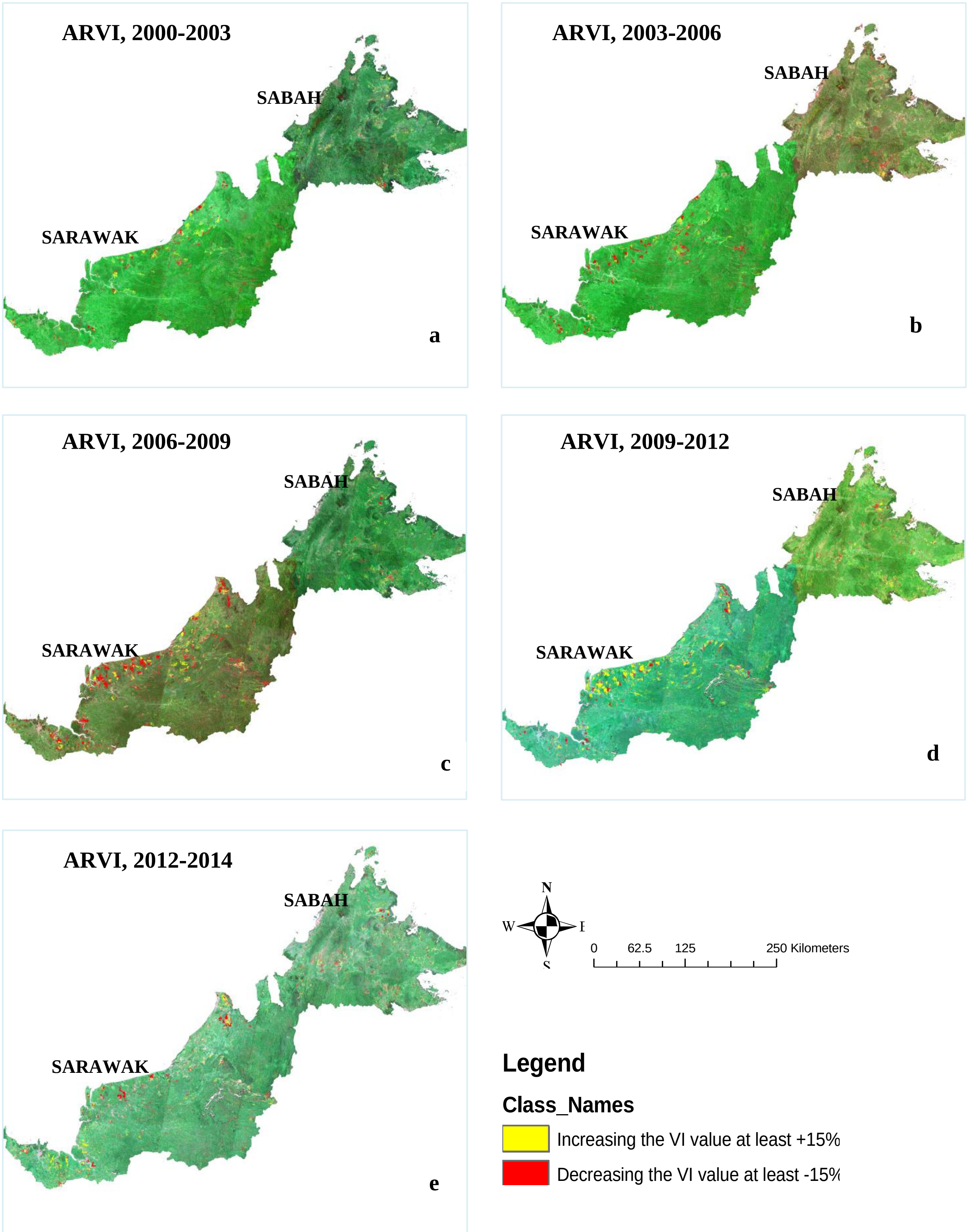


Figure A.8. The changes of ARVI values from 2000 to 2014 in Sabah and Sarawak, Malaysia.

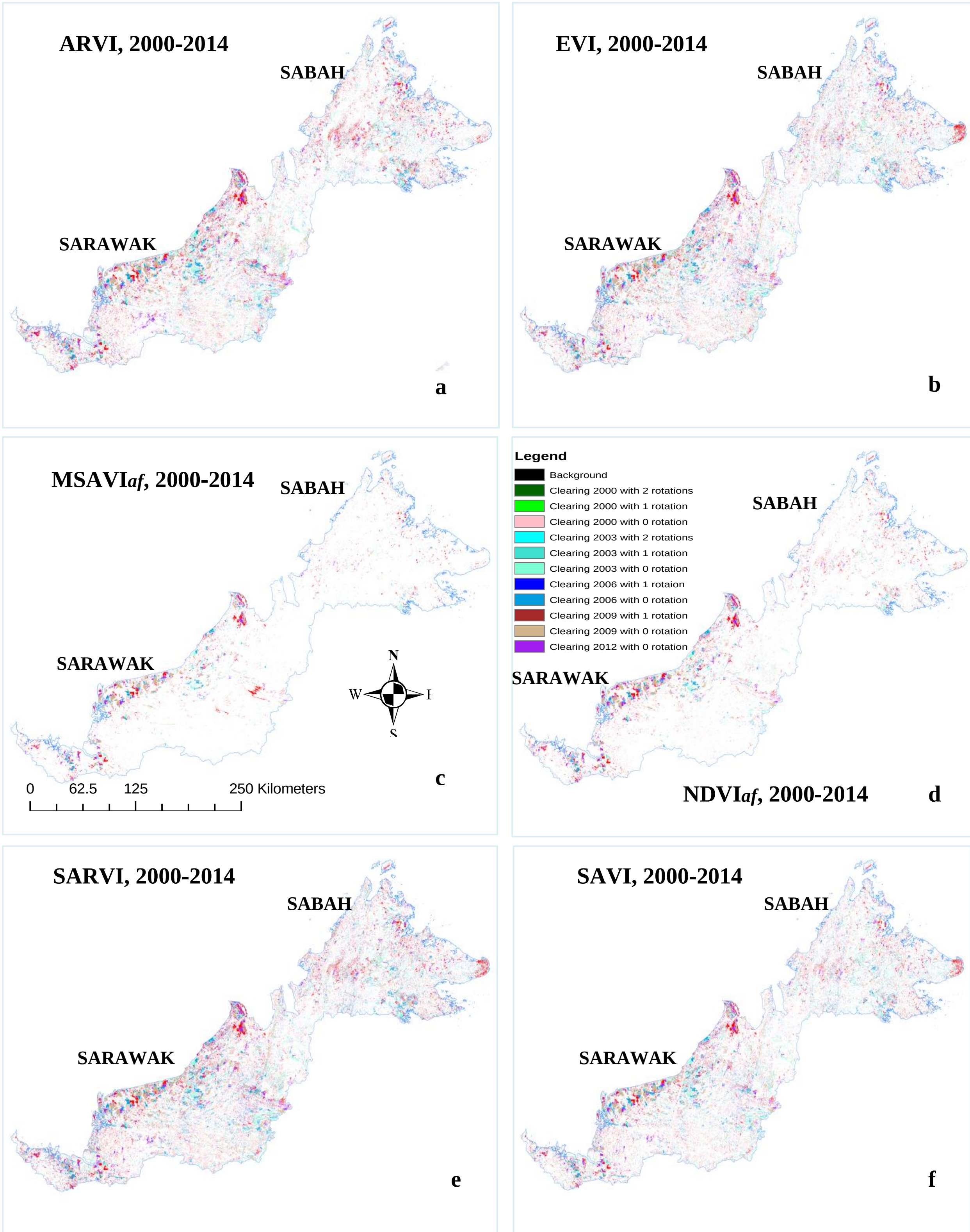


Figure A.9. The clearing and regrowth cycle (rotation) of vegetation cover based on the changes of ARVI, EVI, MSAVI*af*, NDVI*af*, SARVI, and SAVI values in Sabah and Sarawak, 2000-2014.

Table A.5. The changes of ARVI, EVI, $MSAVI_{af}$, $NDVI_{af}$, SARVI, and SAVI values in 30 key areas in Sabah, 2000-2014.

SABAH		THE VI VALUES IN KEY AREAS/LOCATIONS IN SABAH, 2000-2014					
ID	**VI**	2000	2003	2006	2009	2012	2014
1	ARVI	0.887	0.359	0.711	0.799	0.821	0.764
	EVI	0.603	0.19	0.575	0.601	0.622	0.61
	$MSAVI_{af}$	0.929	0.587	0.868	0.857	0.92	0.899
	$NDVI_{af}$	0.868	0.418	0.768	0.752	0.852	0.817
	SAVI	0.538	0.185	0.527	0.497	0.517	0.561
	SARVI	0.545	0.039	0.491	0.481	0.554	0.539
2	ARVI	0.858	0.85	0.729	0.844	0.797	0.752
	EVI	0.572	0.511	0.488	0.611	0.615	0.483
	$MSAVI_{af}$	0.931	0.927	0.872	0.906	0.919	0.88
	$NDVI_{af}$	0.871	0.864	0.776	0.829	0.85	0.788
	SAVI	0.526	0.482	0.46	0.533	0.568	0.456
	SARVI	0.533	0.487	0.44	0.538	0.563	0.441
3	ARVI	0.873	0.908	0.536	0.926	0.831	0.569
	EVI	0.716	0.57	0.38	0.646	0.583	0.476
	$MSAVI_{af}$	0.936	0.952	0.788	0.913	0.926	0.801
	$NDVI_{af}$	0.881	0.908	0.652	0.841	0.862	0.763
	SAVI	0.63	0.532	0.378	0.535	0.541	0.45
	SARVI	0.625	0.535	0.327	0.539	0.537	0.409
4	ARVI	0.816	0.826	0.464	0.905	0.83	0.643
	EVI	0.585	0.609	0.348	0.624	0.564	0.599
	$MSAVI_{af}$	0.924	0.902	0.734	0.929	0.927	0.842
	$NDVI_{af}$	0.859	0.824	0.587	0.868	0.864	0.732
	SAVI	0.545	0.538	0.348	0.545	0.529	0.546
	SARVI	0.543	0.533	0.272	0.555	0.526	0.503
5	ARVI	0.835	0.542	0.852	0.856	0.809	0.479
	EVI	0.475	0.407	0.508	0.54	0.524	0.404
	$MSAVI_{af}$	0.912	0.779	0.926	0.915	0.916	0.746
	$NDVI_{af}$	0.838	0.642	0.863	0.844	0.846	0.6
	SAVI	0.449	0.397	0.485	0.495	0.497	0.39
	SARVI	0.445	0.328	0.468	0.49	0.488	0.327
6	ARVI	0.373	0.796	0.791	0.764	0.824	0.817
	EVI	0.338	0.673	0.614	0.601	0.679	0.618
	$MSAVI_{af}$	0.65	0.889	0.897	0.896	0.908	0.903
	$NDVI\_{af}$	0.489	0.801	0.815	0.813	0.832	0.825
	SAVI	0.314	0.574	0.549	0.551	0.586	0.546
	SARVI	0.275	0.564	0.537	0.532	0.587	0.544
7	ARVI	0.871	0.583	0.812	0.831	0.856	0.85
	EVI	0.621	0.363	0.666	0.668	0.662	0.626
	$MSAVI_{af}$	0.908	0.774	0.866	0.914	0.92	0.909
	$NDVI_{af}$	0.832	0.633	0.768	0.842	0.853	0.833
	SAVI	0.535	0.357	0.541	0.585	0.58	0.548

Table A.5. (cont’d)

	SARVI	0.536	0.239	0.524	0.583	0.578	0.539
8	ARVI	0.273	0.732	0.768	0.81	0.793	0.823
	EVI	0.201	0.506	0.56	0.643	0.632	0.606
	MSAVI$_{af}$	0.566	0.857	0.882	0.914	0.91	0.899
	NDVI$_{af}$	0.398	0.752	0.791	0.842	0.835	0.818
	SAVI	0.205	0.466	0.512	0.584	0.577	0.539
	SARVI	0.071	0.42	0.476	0.559	0.556	0.516
9	ARVI	0.536	0.783	0.872	0.837	0.838	0.826
	EVI	0.408	0.575	0.556	0.631	0.637	0.631
	MSAVI$_{af}$	0.772	0.896	0.884	0.915	0.927	0.92
	NDVI$_{af}$	0.63	0.812	0.793	0.844	0.865	0.852
	SAVI	0.393	0.528	0.473	0.563	0.579	0.574
	SARVI	0.327	0.499	0.459	0.554	0.572	0.559
10	ARVI	0.27	0.779	0.807	0.819	0.841	0.849
	EVI	0.244	0.635	0.595	0.633	0.67	0.636
	MSAVI$_{af}$	0.574	0.878	0.908	0.914	0.919	0.922
	NDVI$_{af}$	0.408	0.784	0.833	0.844	0.852	0.856
	SAVI	0.244	0.546	0.546	0.571	0.594	0.571
	SARVI	0.127	0.53	0.525	0.558	0.581	0.561
11	ARVI	0.955	0.948	0.853	0.9	0.709	0.741
	EVI	0.549	0.586	0.463	0.503	0.466	0.645
	MSAVI$_{af}$	0.951	0.945	0.918	0.934	0.805	0.88
	NDVI$_{af}$	0.908	0.897	0.849	0.877	0.68	0.789
	SAVI	0.508	0.525	0.443	0.474	0.403	0.573
	SARVI	0.506	0.534	0.432	0.467	0.367	0.548
12	ARVI	0.911	0.652	0.826	0.74	0.841	0.725
	EVI	0.505	0.562	0.618	0.537	0.613	0.599
	MSAVI$_{af}$	0.937	0.826	0.919	0.871	0.893	0.889
	NDVI$_{af}$	0.882	0.711	0.85	0.788	0.809	0.803
	SAVI	0.476	0.503	0.563	0.5	0.527	0.559
	SARVI	0.468	0.46	0.553	0.482	0.516	0.534
13	ARVI	0.827	0.621	0.814	0.772	0.863	0.786
	EVI	0.624	0.532	0.623	0.605	0.672	0.631
	MSAVI$_{af}$	0.932	0.811	0.914	0.905	0.916	0.909
	NDVI$_{af}$	0.873	0.684	0.843	0.827	0.846	0.834
	SAVI	0.565	0.478	0.566	0.559	0.578	0.574
	SARVI	0.558	0.432	0.553	0.543	0.578	0.565
14	ARVI	0.658	0.482	0.687	0.77	0.796	0.782
	EVI	0.347	0.365	0.529	0.533	0.61	0.571
	MSAVI$_{af}$	0.777	0.734	0.848	0.897	0.915	0.895
	NDVI$_{af}$	0.64	0.586	0.738	0.813	0.843	0.811
	SAVI	0.321	0.354	0.481	0.502	0.563	0.525
	SARVI	0.264	0.288	0.459	0.48	0.551	0.501
15	ARVI	0.628	0.256	0.496	0.496	0.375	0.671
	EVI	0.371	0.201	0.353	0.353	0.276	0.388
	MSAVI$_{af}$	0.822	0.577	0.765	0.765	0.681	0.83
	NDVI$_{af}$	0.7	0.407	0.622	0.622	0.524	0.711

Table A.5. (cont'd)

	SAVI	0.368	0.208	0.356	0.356	0.283	0.374
	SARVI	0.321	0.131	0.296	0.296	0.224	0.339
16	ARVI	0.617	0.701	0.81	0.752	0.802	0.829
	EVI	0.276	0.52	0.546	0.521	0.58	0.55
	MSAVI*af*	0.759	0.856	0.898	0.873	0.882	0.894
	NDVI*af*	0.613	0.75	0.816	0.777	0.79	0.81
	SAVI	0.275	0.483	0.504	0.482	0.507	0.495
	SARVI	0.153	0.441	0.469	0.445	0.495	0.47
17	ARVI	0.895	0.838	0.503	0.627	0.801	0.845
	EVI	0.514	0.578	0.372	0.452	0.562	0.588
	MSAVI*af*	0.92	0.92	0.754	0.82	0.881	0.888
	NDVI*af*	0.852	0.854	0.609	0.697	0.789	0.8
	SAVI	0.47	0.53	0.367	0.432	0.497	0.508
	SARVI	0.466	0.529	0.289	0.374	0.479	0.486
18	ARVI	0.422	0.566	0.757	0.777	0.838	0.837
	EVI	0.178	0.385	0.484	0.553	0.651	0.643
	MSAVI*af*	0.642	0.75	0.865	0.896	0.921	0.924
	NDVI*af*	0.475	0.604	0.765	0.813	0.854	0.86
	SAVI	0.181	0.354	0.443	0.514	0.581	0.583
	SARVI	0.089	0.282	0.418	0.494	0.578	0.57
19	ARVI	0.791	0.797	0.808	0.813	0.655	0.876
	EVI	0.497	0.599	0.582	0.606	0.451	0.694
	MSAVI*af*	0.888	0.912	0.921	0.915	0.812	0.937
	NDVI*af*	0.799	0.838	0.854	0.843	0.693	0.881
	SAVI	0.463	0.552	0.548	0.556	0.414	0.618
	SARVI	0.44	0.539	0.528	0.54	0.383	0.608
20	ARVI	0.924	0.752	0.362	0.83	0.85	0.819
	EVI	0.436	0.476	0.265	0.538	0.581	0.583
	MSAVI*af*	0.896	0.887	0.645	0.917	0.918	0.917
	NDVI*af*	0.812	0.799	0.495	0.847	0.848	0.847
	SAVI	0.392	0.456	0.264	0.505	0.525	0.539
	SARVI	0.393	0.438	0.215	0.49	0.525	0.53
21	ARVI	0.418	0.738	0.831	0.788	0.836	0.901
	EVI	0.235	0.632	0.634	0.581	0.655	0.679
	MSAVI*af*	0.691	0.89	0.922	0.907	0.923	0.924
	NDVI*af*	0.531	0.804	0.856	0.83	0.857	0.858
	SAVI	0.253	0.578	0.581	0.543	0.59	0.58
	SARVI	0.104	0.549	0.554	0.512	0.576	0.575
22	ARVI	0.819	0.529	0.862	0.902	0.902	0.546
	EVI	0.531	0.424	0.642	0.582	0.582	0.381
	MSAVI*af*	0.917	0.752	0.931	0.919	0.919	0.739
	NDVI*af*	0.847	0.615	0.872	0.851	0.851	0.602
	SAVI	0.5	0.394	0.581	0.512	0.512	0.353
	SARVI	0.492	0.339	0.57	0.515	0.515	0.286
23	ARVI	0.621	0.849	0.827	0.853	0.685	0.758

Table A.5. (cont'd)

	EVI	0.453	0.615	0.597	0.687	0.559	0.609
	MSAVI*af*	0.82	0.922	0.897	0.931	0.841	0.901
	NDVI*af*	0.695	0.856	0.804	0.87	0.737	0.819
	SAVI	0.431	0.559	0.521	0.544	0.506	0.565
	SARVI	0.383	0.543	0.504	0.537	0.469	0.54
24	ARVI	0.81	0.733	0.836	0.865	0.839	0.809
	EVI	0.491	0.447	0.579	0.612	0.6	0.522
	MSAVI*af*	0.92	0.828	0.925	0.933	0.925	0.928
	NDVI_swir	0.851	0.71	0.86	0.874	0.861	0.866
	SAVI	0.482	0.402	0.543	0.561	0.555	0.51
	SARVI	0.451	0.36	0.517	0.551	0.537	0.491
25	ARVI	0.845	0.507	0.815	0.805	0.533	0.728
	EVI	0.455	0.286	0.597	0.558	0.375	0.603
	MSAVI*af*	0.921	0.746	0.896	0.907	0.757	0.901
	NDVI*af*	0.854	0.599	0.812	0.831	0.623	0.821
	SAVI	0.441	0.292	0.529	0.516	0.365	0.573
	SARVI	0.428	0.22	0.513	0.504	0.289	0.543
26	ARVI	0.84	0.898	0.858	0.814	0.848	0.678
	EVI	0.559	0.566	0.581	0.62	0.665	0.504
	MSAVI*af*	0.928	0.93	0.896	0.911	0.918	0.828
	NDVI*af*	0.866	0.87	0.813	0.837	0.848	0.708
	SAVI	0.521	0.506	0.5	0.554	0.579	0.454
	SARVI	0.525	0.529	0.501	0.559	0.583	0.413
27	ARVI	0.9	0.885	0.899	0.331	0.647	0.804
	EVI	0.538	0.549	0.532	0.158	0.491	0.648
	MSAVI*af*	0.914	0.918	0.929	0.622	0.835	0.888
	NDVI*af*	0.841	0.849	0.867	0.453	0.719	0.799
	SAVI	0.479	0.492	0.488	0.173	0.46	0.554
	SARVI	0.48	0.497	0.49	0.04	0.417	0.545
28	ARVI	0.842	0.838	0.535	0.698	0.766	0.77
	EVI	0.511	0.502	0.257	0.507	0.561	0.587
	MSAVI*af*	0.916	0.927	0.787	0.863	0.884	0.907
	NDVI*af*	0.846	0.863	0.654	0.762	0.793	0.83
	SAVI	0.479	0.477	0.267	0.48	0.508	0.549
	SARVI	0.467	0.48	0.225	0.444	0.494	0.531
29	ARVI	0.867	0.867	0.379	0.83	0.794	0.782
	EVI	0.637	0.637	0.319	0.699	0.633	0.673
	MSAVI*af*	0.927	0.927	0.674	0.898	0.921	0.916
	NDVI*af*	0.864	0.864	0.51	0.815	0.853	0.846
	SAVI	0.564	0.564	0.317	0.585	0.586	0.615
	SARVI	0.527	0.572	0.222	0.582	0.576	0.601
30	ARVI	0.555	0.721	0.649	0.713	0.818	0.799
	EVI	0.262	0.47	0.444	0.495	0.574	0.604
	MSAVI*af*	0.736	0.841	0.822	0.864	0.904	0.913
	NDVI*af*	0.586	0.729	0.701	0.763	0.826	0.84
	SAVI	0.259	0.427	0.418	0.466	0.519	0.558
	SARVI	0.185	0.402	0.378	0.436	0.508	0.541

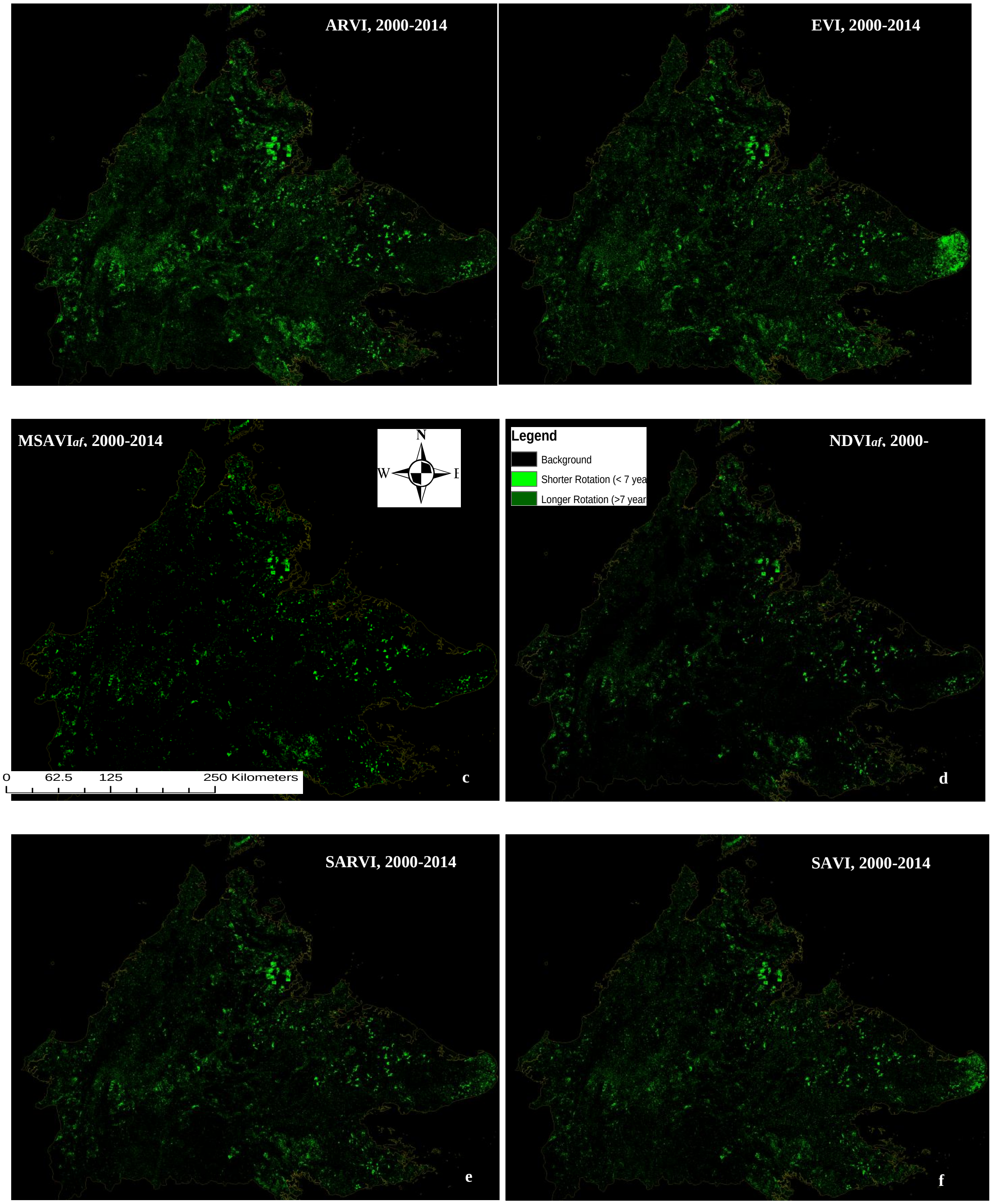


Figure A.10. Possibly shorter- and longer-rotation plantations based on ARVI, EVI, MSAVI*af,* NDVI*af*, SARVI, and SAVI in Sabah, 2000-2014.

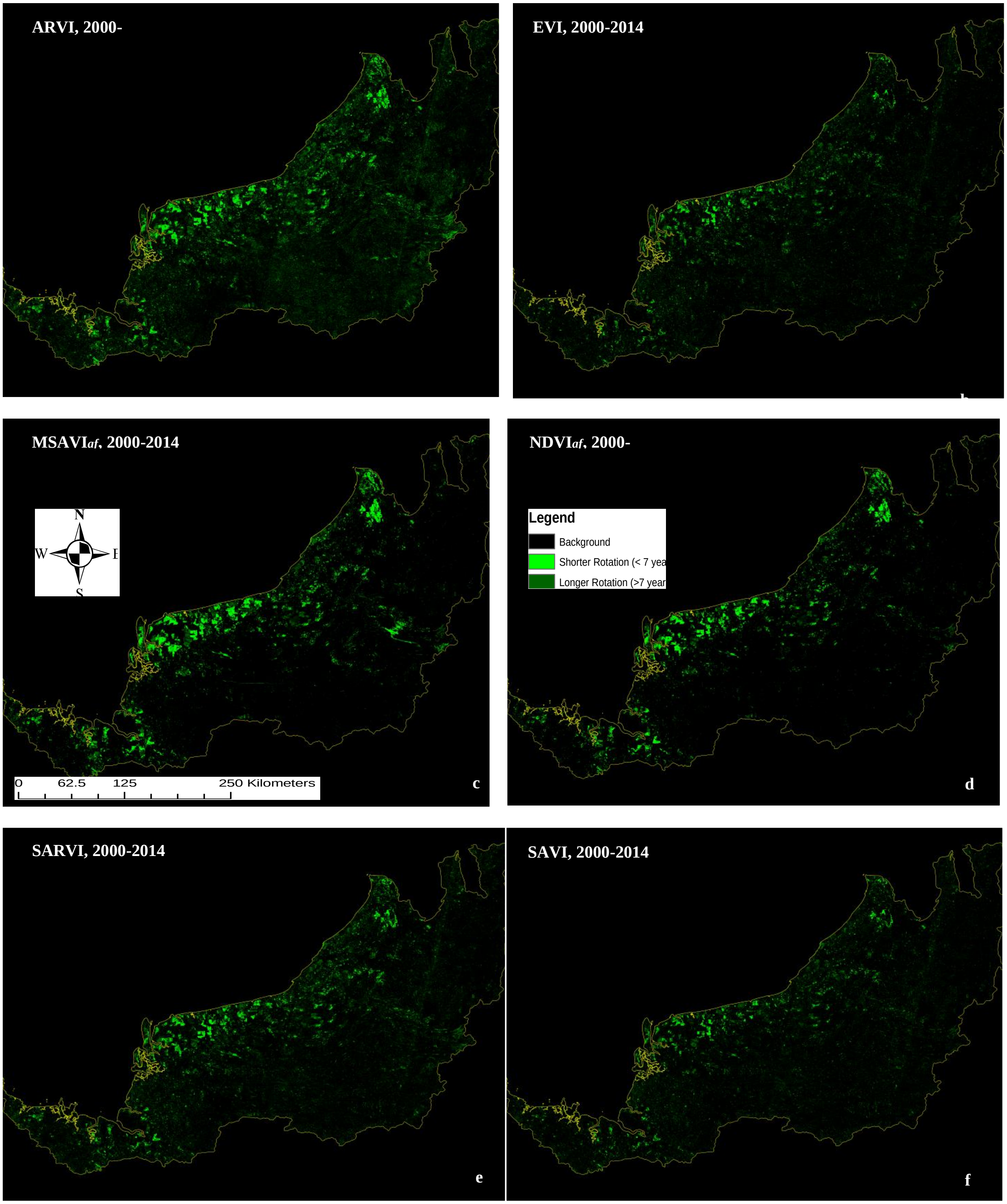


Figure A.11. Possibly shorter- and longer-rotation plantations based on ARVI, EVI, MSAVI*af*, NDVI*af*, SARVI, and SAVI in Sarawak, 2000-2014.

Table A.6. The result for calculating the growth rate of VIs in Sabah, 2000-2014.

ID	VI	2000-03	2003-06	2006-09	2009-12	2012-14	ID	VI	2000-03	2003-06	2006-09	2009-12	2012-14
		The growth rate of different vegetation represented though the rate of VI changes							The growth rate of different vegetation represented though the rate of VI changes				
1	ARVI	-0.60	0.98	0.12	0.03	-0.07	16	ARVI	0.14	0.16	-0.07	0.07	0.03
	EVI	-0.68	2.03	0.05	0.03	-0.02		EVI	0.88	0.05	-0.05	0.11	-0.05
	MSAVIaf	-0.37	0.48	-0.01	0.07	-0.02		MSAVIaf	0.13	0.05	-0.03	0.01	0.01
	NDVIaf	-0.52	0.84	-0.02	0.13	-0.04		NDVIaf	0.22	0.09	-0.05	0.02	0.03
	SAVI	-0.66	1.85	-0.06	0.04	0.09		SAVI	0.76	0.04	-0.04	0.05	-0.02
	SARVI	-0.93	11.59	-0.02	0.15	-0.03		SARVI	1.88	0.06	-0.05	0.11	-0.05
2	ARVI	-0.01	-0.14	0.16	-0.06	-0.06	17	ARVI	-0.06	-0.40	0.25	0.28	0.05
	EVI	-0.11	-0.05	0.25	0.01	-0.21		EVI	0.12	-0.36	0.22	0.24	0.05
	MSAVIaf	0.00	-0.06	0.04	0.01	-0.04		MSAVIaf	0.00	-0.18	0.09	0.07	0.01
	NDVIaf	-0.01	-0.10	0.07	0.03	-0.07		NDVIaf	0.00	-0.29	0.14	0.13	0.01
	SAVI	-0.08	-0.05	0.16	0.07	-0.20		SAVI	0.13	-0.31	0.18	0.15	0.02
	SARVI	-0.09	-0.10	0.22	0.05	-0.22		SARVI	0.14	-0.45	0.29	0.28	0.01
3	ARVI	0.04	-0.41	0.73	-0.10	-0.32	18	ARVI	0.34	0.34	0.03	0.08	0.00
	EVI	-0.20	-0.33	0.70	-0.10	-0.18		EVI	1.16	0.26	0.14	0.18	-0.01
	MSAVIaf	0.02	-0.17	0.16	0.01	-0.13		MSAVIaf	0.17	0.15	0.04	0.03	0.00
	NDVIaf	0.03	-0.28	0.29	0.02	-0.11		NDVIaf	0.27	0.27	0.06	0.05	0.01
	SAVI	-0.16	-0.29	0.42	0.01	-0.17		SAVI	0.96	0.25	0.16	0.13	0.00
	SARVI	-0.14	-0.39	0.65	0.00	-0.24		SARVI	2.17	0.48	0.18	0.17	-0.01
4	ARVI	0.01	-0.44	0.95	-0.08	-0.23	19	ARVI	0.01	0.01	0.01	-0.19	0.34
	EVI	0.04	-0.43	0.79	-0.10	0.06		EVI	0.21	-0.03	0.04	-0.26	0.54
	MSAVIaf	-0.02	-0.19	0.27	0.00	-0.09		MSAVIaf	0.03	0.01	-0.01	-0.11	0.15
	NDVIaf	-0.04	-0.29	0.48	0.00	-0.15		NDVIaf	0.05	0.02	-0.01	-0.18	0.27
	SAVI	-0.01	-0.35	0.57	-0.03	0.03		SAVI	0.19	-0.01	0.01	-0.26	0.49
	SARVI	-0.02	-0.49	1.04	-0.05	-0.04		SARVI	0.23	-0.02	0.02	-0.29	0.59
5	ARVI	-0.35	0.57	0.00	-0.05	-0.41	20	ARVI	-0.19	-0.52	1.29	0.02	-0.04
	EVI	-0.14	0.25	0.06	-0.03	-0.23		EVI	0.09	-0.44	1.03	0.08	0.00
	MSAVIaf	-0.15	0.19	-0.01	0.00	-0.19		MSAVIaf	-0.01	-0.27	0.42	0.00	0.00
	NDVIaf	-0.23	0.34	-0.02	0.00	-0.29		NDVIaf	-0.02	-0.38	0.71	0.00	0.00
	SAVI	-0.12	0.22	0.02	0.00	-0.22		SAVI	0.16	-0.42	0.91	0.04	0.03
	SARVI	-0.26	0.43	0.05	0.00	-0.33		SARVI	0.11	-0.51	1.28	0.07	0.01
6	ARVI	1.13	-0.01	-0.03	0.08	-0.01	21	ARVI	0.77	0.13	-0.05	0.06	0.08
	EVI	0.99	-0.09	-0.02	0.13	-0.09		EVI	1.69	0.00	-0.08	0.13	0.04
	MSAVIaf	0.37	0.01	0.00	0.01	-0.01		MSAVIaf	0.29	0.04	-0.02	0.02	0.00
	NDVIaf	0.64	0.02	0.00	0.02	-0.01		NDVIaf	0.51	0.06	-0.03	0.03	0.00
	SAVI	0.83	-0.04	0.00	0.06	-0.07		SAVI	1.28	0.01	-0.07	0.09	-0.02
	SARVI	1.05	-0.05	-0.01	0.10	-0.07		SARVI	4.28	0.01	-0.08	0.13	0.00
7	ARVI	-0.33	0.39	0.02	0.03	-0.01	22	ARVI	-0.35	0.63	0.05	0.00	-0.39
	EVI	-0.42	0.83	0.00	-0.01	-0.05		EVI	-0.20	0.51	-0.09	0.00	-0.35
	MSAVIaf	-0.15	0.12	0.06	0.01	-0.01		MSAVIaf	-0.18	0.24	-0.01	0.00	-0.20
	NDVIaf	-0.24	0.21	0.10	0.01	-0.02		NDVIaf	-0.27	0.42	-0.02	0.00	-0.29
	SAVI	-0.33	0.52	0.08	-0.01	-0.06		SAVI	-0.21	0.47	-0.12	0.00	-0.31
	SARVI	-0.55	1.19	0.11	-0.01	-0.07		SARVI	-0.31	0.68	-0.10	0.00	-0.44
8	ARVI	1.68	0.05	0.05	-0.02	0.04	23	ARVI	0.37	-0.03	0.03	-0.20	0.11
	EVI	1.52	0.11	0.15	-0.02	-0.04		EVI	0.36	-0.03	0.15	-0.19	0.09
	MSAVIaf	0.51	0.03	0.04	0.00	-0.01		MSAVIaf	0.12	-0.03	0.04	-0.10	0.07
	NDVIaf	0.89	0.05	0.06	-0.01	-0.02		NDVIaf	0.23	-0.06	0.08	-0.15	0.11

Table A.6. (cont'd)

	SAVI	1.27	0.10	0.14	-0.01	-0.07		SAVI	0.30	-0.07	0.04	-0.07	0.12
	SARVI	4.92	0.13	0.17	-0.01	-0.07		SARVI	0.42	-0.07	0.07	-0.13	0.15
9	ARVI	0.46	0.11	-0.04	0.00	-0.01	**24**	ARVI	-0.10	0.14	0.03	-0.03	-0.04
	EVI	0.41	-0.03	0.13	0.01	-0.01		EVI	-0.09	0.30	0.06	-0.02	-0.13
	MSAVIaf	0.16	-0.01	0.04	0.01	-0.01		MSAVIaf	-0.10	0.12	0.01	-0.01	0.00
	NDVIaf	0.29	-0.02	0.06	0.02	-0.02		NDVIaf	-0.17	0.21	0.02	-0.01	0.01
	SAVI	0.34	-0.10	0.19	0.03	-0.01		SAVI	-0.17	0.35	0.03	-0.01	-0.08
	SARVI	0.53	-0.08	0.21	0.03	-0.02		SARVI	-0.20	0.44	0.07	-0.03	-0.09
10	ARVI	1.89	0.04	0.01	0.03	0.01	**25**	ARVI	-0.40	0.61	-0.01	-0.34	0.37
	EVI	1.60	-0.06	0.06	0.06	-0.05		EVI	-0.37	1.09	-0.07	-0.33	0.61
	MSAVIaf	0.53	0.03	0.01	0.01	0.00		MSAVIaf	-0.19	0.20	0.01	-0.17	0.19
	NDVIaf	0.92	0.06	0.01	0.01	0.00		NDVIaf	-0.30	0.36	0.02	-0.25	0.32
	SAVI	1.24	0.00	0.05	0.04	-0.04		SAVI	-0.34	0.81	-0.02	-0.29	0.57
	SARVI	3.17	-0.01	0.06	0.04	-0.03		SARVI	-0.49	1.33	-0.02	-0.43	0.88
11	ARVI	-0.01	-0.10	0.06	-0.21	0.05	**26**	ARVI	0.07	-0.04	-0.05	0.04	-0.20
	EVI	0.07	-0.21	0.09	-0.07	0.38		EVI	0.01	0.03	0.07	0.07	-0.24
	MSAVIaf	-0.01	-0.03	0.02	-0.14	0.09		MSAVIaf	0.00	-0.04	0.02	0.01	-0.10
	NDVIaf	-0.01	-0.05	0.03	-0.22	0.16		NDVIaf	0.00	-0.07	0.03	0.01	-0.17
	SAVI	0.03	-0.16	0.07	-0.15	0.42		SAVI	-0.03	-0.01	0.11	0.05	-0.22
	SARVI	0.06	-0.19	0.08	-0.21	0.49		SARVI	0.01	-0.05	0.12	0.04	-0.29
12	ARVI	-0.28	0.27	-0.10	0.14	-0.14	**27**	ARVI	-0.02	0.02	-0.63	0.95	0.24
	EVI	0.11	0.10	-0.13	0.14	-0.02		EVI	0.02	-0.03	-0.70	2.11	0.32
	MSAVIaf	-0.12	0.11	-0.05	0.03	0.00		MSAVIaf	0.00	0.01	-0.33	0.34	0.06
	NDVIaf	-0.19	0.20	-0.07	0.03	-0.01		NDVIaf	0.01	0.02	-0.48	0.59	0.11
	SAVI	0.06	0.12	-0.11	0.05	0.06		SAVI	0.03	-0.01	-0.65	1.66	0.20
	SARVI	-0.02	0.20	-0.13	0.07	0.03		SARVI	0.04	-0.01	-0.92	9.43	0.31
13	ARVI	-0.25	0.31	-0.05	0.12	-0.09	**28**	ARVI	0.00	-0.36	0.30	0.10	0.01
	EVI	-0.15	0.17	-0.03	0.11	-0.06		EVI	-0.02	-0.49	0.97	0.11	0.05
	MSAVIaf	-0.13	0.13	-0.01	0.01	-0.01		MSAVIaf	0.01	-0.15	0.10	0.02	0.03
	NDVIaf	-0.22	0.23	-0.02	0.02	-0.01		NDVIaf	0.02	-0.24	0.17	0.04	0.05
	SAVI	-0.15	0.18	-0.01	0.03	-0.01		SAVI	0.00	-0.44	0.80	0.06	0.08
	SARVI	-0.23	0.28	-0.02	0.06	-0.02		SARVI	0.03	-0.53	0.97	0.11	0.07
14	ARVI	-0.27	0.43	0.12	0.03	-0.02	**29**	ARVI	0.00	-0.56	1.19	-0.04	-0.02
	EVI	0.05	0.45	0.01	0.14	-0.06		EVI	0.00	-0.50	1.19	-0.09	0.06
	MSAVIaf	-0.06	0.16	0.06	0.02	-0.02		MSAVIaf	0.00	-0.27	0.33	0.03	-0.01
	NDVIaf	-0.08	0.26	0.10	0.04	-0.04		NDVIaf	0.00	-0.41	0.60	0.05	-0.01
	SAVI	0.10	0.36	0.04	0.12	-0.07		SAVI	0.00	-0.44	0.85	0.00	0.05
	SARVI	0.09	0.59	0.05	0.15	-0.09		SARVI	0.09	-0.61	1.62	-0.01	0.04
15	ARVI	-0.59	0.94	0.00	-0.24	0.79	**30**	ARVI	0.30	-0.10	0.10	0.15	-0.02
	EVI	-0.46	0.76	0.00	-0.22	0.41		EVI	0.79	-0.06	0.11	0.16	0.05
	MSAVIaf	-0.30	0.33	0.00	-0.11	0.22		MSAVIaf	0.14	-0.02	0.05	0.05	0.01
	NDVIaf	-0.42	0.53	0.00	-0.16	0.36		NDVIaf	0.24	-0.04	0.09	0.08	0.02
	SAVI	-0.43	0.71	0.00	-0.21	0.32		SAVI	0.65	-0.02	0.11	0.11	0.08
	SARVI	-0.59	1.26	0.00	-0.24	0.51		SARVI	1.17	-0.06	0.15	0.17	0.06

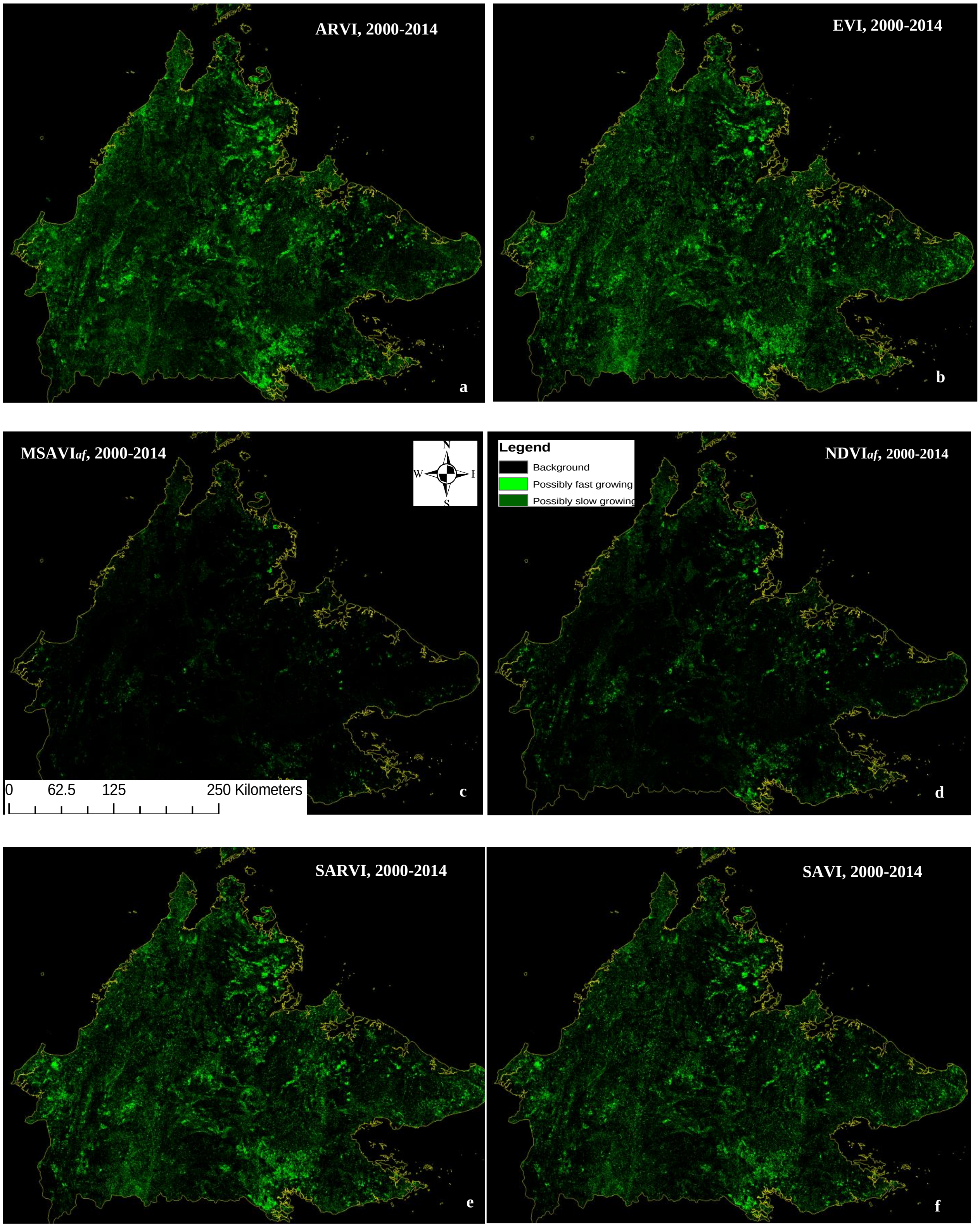


Figure A.12. The possibly faster-growing and slower-growing plantations based on ARVI, EVI, MSAVI*af*, NDVI*af*, SARVI, and SAVI values in Sabah, 2000-2014.

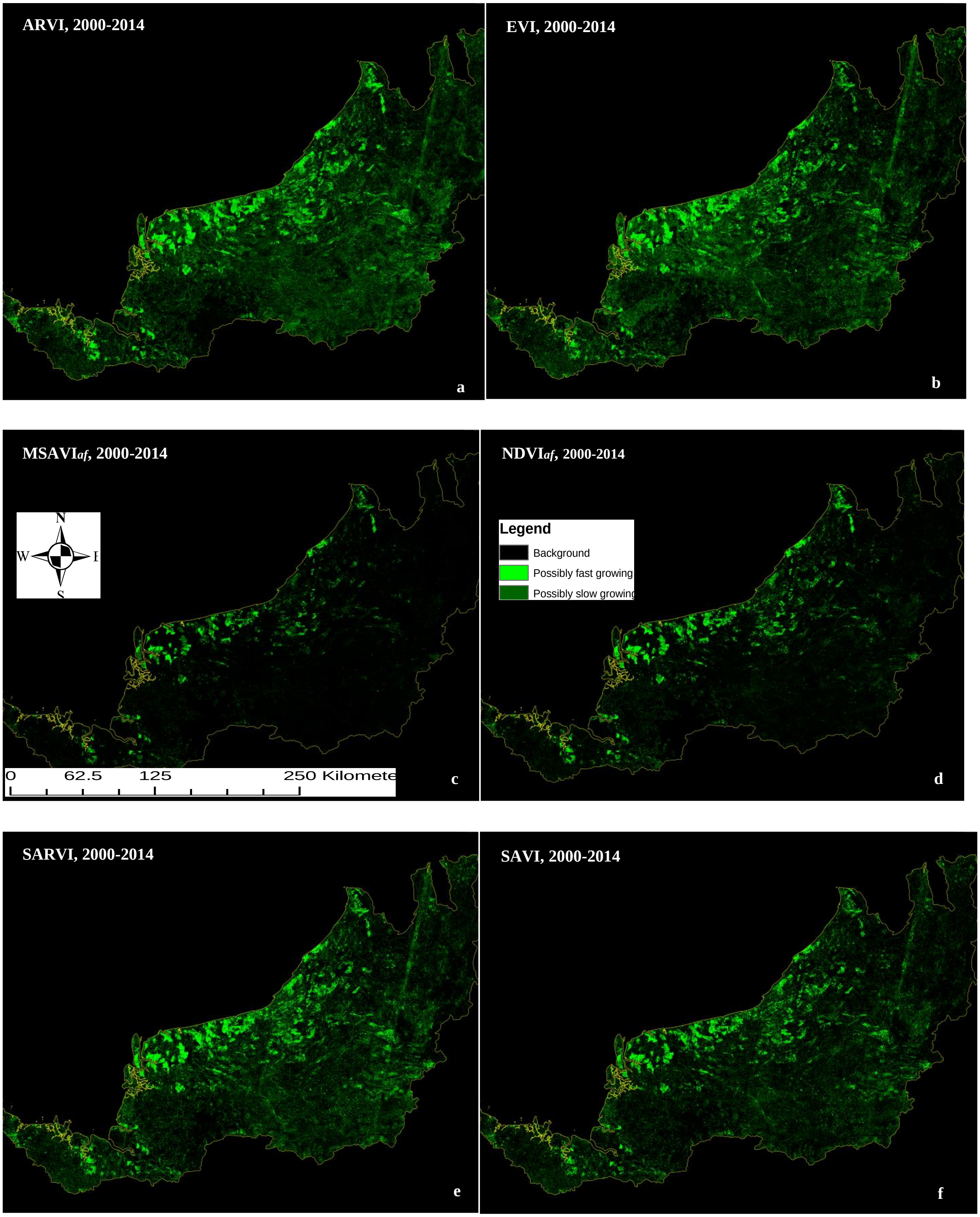


Figure A.13. The possibly faster-growing and slower-growing plantations based on ARVI, EVI, MSAVI$_{af}$, NDVI$_{af}$, SARVI, and SAVI values in Sarawak, 2000- 2014.

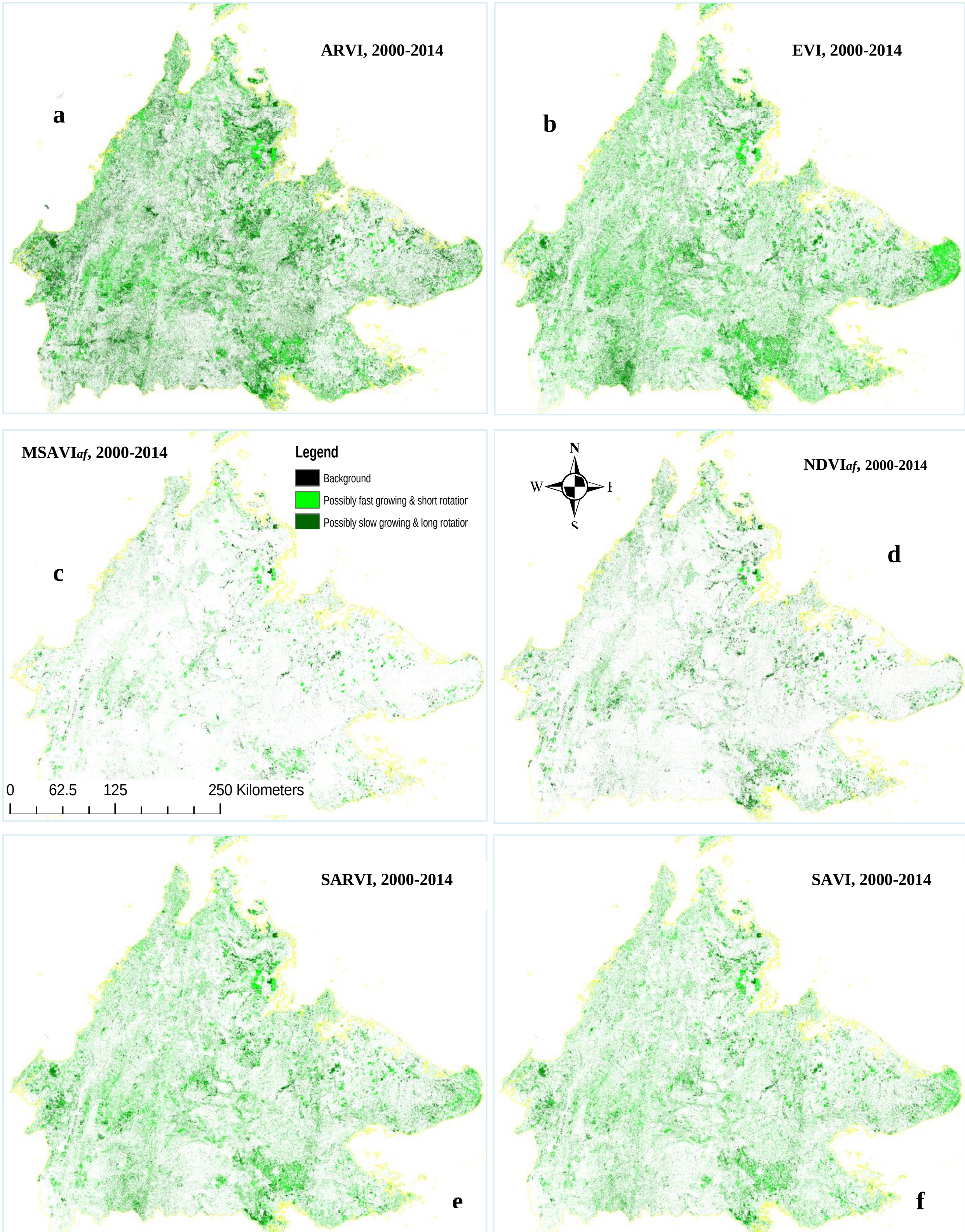


Figure A.14. Possibly faster-growing, shorter-rotation and slower-growing, longer-rotation plantations based on VIs values in Sabah, 2000-2014.

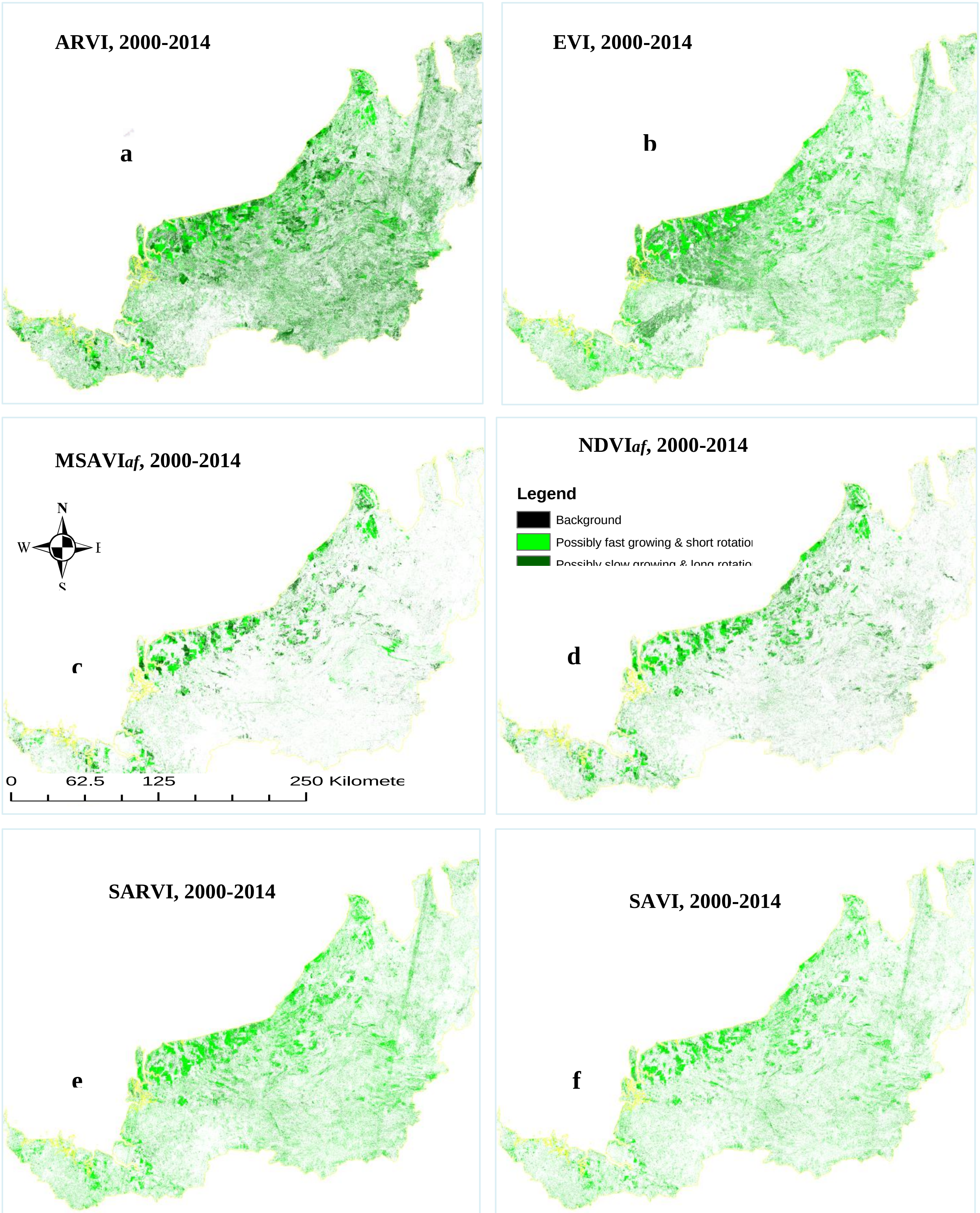


Figure A.15. Possibly faster-growing, shorter-rotation and slower-growing, longer-rotation plantations based on VIs values in Sarawak, 2000-2014.

Table A.7. The GLCM_MEA, DIS, and HOM values for different LULC types in VIs, band 4 and 5 images in Sarawak, 2000-2014.

TYPE	Value	SARAWAK_GLCM_MEAN_ARVI						SARAWAK_GLCM_HOM_ARVI						SARAWAK_GLCM_DIS_ARVI					
		2000	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***
Rubber	Mean	240	235	238	233	214	236	152	138	142	171	140	122	61	82	89	51	70	96
	Mode	249-251	248-252	250-255	247-250	227-233	253-255	188-195	149-167	179-189	190-219	179-207	199-221	26-32	33-49	35-42	17-38	21-38	20-40
Acacia	Mean	166	195	220	219	245	140	29	66	110	173	88	43	205	156	97	47	134	177
	Mode	177-181	197-228	220-233	221-231	249-255	210-242	0-27	0-63	113-136	180-198	100-119	0-109	197-201	79-112	50-75	22-41	51-128	151-218
Other IFs	Mean	223	246	241	233	248	239	222	187	211	157	117	180	99	41	29	69	81	45
	Mode	223-228	253-255	243-246	241-245	252-255	244-249	232-237	217-223	200-213	200-219	113-143	201-223	16-21	23-27	30-39	25-38	41-52	14-26
Oil Palm	Mean	223	248	243	234	223	215	201	160	179	159	100	112	30	55	39	58	94	83
	Mode	215-239	230-255	239-249	227-225	220-255	241-245	168-255	106-221	167-255	114-246	22-186	50-189	0-61	18-94	10-75	9-126	34-116	57-63
Forest	Mean	250	216	231	224	221	234	174	169	193	160	167	201	40	43	37	55	37	26
	Mode	247-255	210-227	222-239	199-249	214-230	235-238	129-227	116-236	146-252	109-241	125-216	160-255	6--72	24-66	15-62	10-109	22-61	16-28

TYPE	Value	SARAWAK_GLCM_MEAN_EVI						SARAWAK_GLCM_HOM_EVI						SARAWAK_GLCM_DIS_EVI					
		2000	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***
Rubber	Mean	249	243	239	240	229	238	148	106	117	133	113	87	86	129	114	90	112	126
	Mode	253-255	253-255	247-254	241-248	232-247	250-252	181-189	101-133	135-169	131-166	113-149	89-109	51-58	68-93	50-85	58-79	55-93	77-88
Acacia	Mean	141	189	169	173	204	124	74	67	112	171	140	106	166	163	118	63	93	128
	Mode	143-157	167-183	155-183	163-203	215-237	150-179	76-83	51-81	88-109	161-198	130-157	80-133	106-111	147-159	111-133	33-59	61-93	83-128
Other IFs	Mean	218	242	237	242	208	202	139	167	156	112	123	111	82	62	72	107	100	95
	Mode	211-213	247-251	223-231	244-252	201-216	202-209	167-171	171-199	162-178	121-149	140-169	104-121	57-61	48-70	51-66	73-99	73-97	74-96
Oil Palm	Mean	247	254	254	250	225	200	198	206	200	165	159	183	45	41	45	67	85	54
	Mode	228-255	241-255	249-255	224-255	222-255	160-255	150-255	186-255	164-244	99-247	130-225		6--80	6--76	7--86	21-117	34-91	6--68
Forest	Mean	184	189	176	189	169	186	160	166	141	98	152	155	67	64	83	121	73	59
	Mode	166-207	161-221	155-211	156-233	155-187	154-212	80-239	105-234	80-218	16-179	92-234	95-223	24-117	19-121	37-132	63-192	39-117	27-90

TYPE	Value	SARAWAK_GLCM_MEAN_MSAVI*af*						SARAWAK_GLCM_HOM_MSAVI*af*						SARAWAK_GLCM_DIS_MSAVI*af*					
		2000	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***
Rubber	Mean	228	234	232	239	238	231	146	144	149	155	143	119	88	82	91	69	83	91
	Mode	241-247	245-250	247-251	253-254	253-255	247-251	173-189	137-177	203-211	201-208	191-198	142-175	25-36	21-51	45-49	27-33	35-39	31-54
Acacia	Mean	197	233	246	252	251	164	189	109	135	178	148	55	184	106	88	47	73	175
	Mode	221-227	229-243	241-244	253-255	253-255	247-254	0-47	59-131	121-163	188-195	164-186	0-149	119-123	21-73	62-78	31-41	44-53	49-89
Other IFs	Mean	234	246	253	250	254	246	208	212	214	163	148	162	34	33	42	63	62	52
	Mode	233-235	245-247	251-153	254-255	252-254	250-253	197-202	200-205	223-233	208-213	152-169	168-199	34-37	35-41	31-37	19-27	47-58	30-47
Oil Palm	Mean	232	243	248	248	230	222	208	196	194	184	135	147	35	43	52	42	85	68
	Mode	218-250	239-252	244-255	242-255	239-251	231-255	188-244	162-255	184-236	138-251	97-213	107-229	16-52	16-75	30-72	11-71	30-110	46-53
Forest	Mean	254	253	253	250	254	253	207	188	195	180	193	209	35	43	49	45	39	27
	Mode	250-255	250-255	248-255	246-255	253-255	251-255	169-255	148-236	157-243	144-237	149-236	167-255	12--63	27-62	35-66	17-62	26-56	2-56

Table A.7. (cont'd)

TYPE	Value	SARAWAK_GLCM_MEAN_NDVI*af*						SARAWAK_GLCM_HOM_NDVI*af*						SARAWAK_GLCM_DIS_NDVI*af*					
		2000	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***
Rubber	Mean	223	237	235	236	238	235	153	142	144	149	139	123	86	92	106	84	97	97
	Mode	240-242	250-253	251-254	251-253	249-252	247-250	227-232	203-210	182-191	199-209	179-189	139-184	26-38	41-49	63-75	39-47	54-63	30-67
Acacia	Mean	197	237	244	250	246	164	39	102	123	180	166	62	182	120	114	59	79	174
	Mode	211-217	221-241	246-249	248-252	248-253	241-251	0-38	73-131	158-188	178-204	195-213	26-147	161-165	53-87	72-80	45-51	46-58	93-148
Other IFs	Mean	234	249	252	246	252	247	189	201	200	165	150	168	48	46	60	74	77	55
	Mode	233-235	252-254	252-254	251-252	253-254	251-254	187-192	197-211	210-219	210-227	157-178	179-191	43-46	39-51	46-62	28-38	51-67	37-45
Oil Palm	Mean	233	247	248	238	229	232	201	164	199	183	136	116	42	68	219	55	98	94
	Mode	218-251	235-255	244-253	233-250	235-251	220-255	146-254	130-221	144-255	143-255	99-213	81-178	12--73	39-92	35-97	19-83	46-120	34-129
Forest	Mean	254	250	254	248	254	253	200	188	180	172	183	199	43	53	70	64	57	36
	Mode	248-255	242-255	248-255	225-255	247-255	246-255	132-255	132-246	136-238	126-244	133-241	165-255	16-78	27-80	47-95	29-83	32-84	10-56

TYPE	Value	SARAWAK_GLCM_MEAN_SARVI						SARAWAK_GLCM_HOM_SARVI						SARAWAK_GLCM_DIS_SARVI					
		2000	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***
Rubber	Mean	249	244	241	242	232	242	171	121	134	152	137	99	70	110	103	77	97	114
	Mode	254-255	254-255	241-248	249-254	241-249	250-253	204-211	151-161	140-159	160-227	171-196	68-179	36 -39	59-79	59-84	40-88	48-74	32-89
Acacia	Mean	154	199	188	192	217	131	54	66	125	175	157	86	181	162	102	60	80	147
	Mode	147-153	187-209	187-205	182-219	218-239	170-225	47-62	47-112	125-150	191-215	194-219	80-129	136-141	171-196	79-93	30-52	40-62	103-132
Other IFs	Mean	230	247	241	241	225	217	173	184	184	134	150	128	58	54	55	93	81	80
	Mode	223-226	252-254	244-249	245-252	230-240	211-229	183-190	170-212	190-219	131-178	169-190	117-135	41-45	53-87	37-50	22-67	52-81	57-76
Oil Palm	Mean	249	254	254	247	230	208	206	199	215	175	149	167	41	47	40	61	91	65
	Mode	233-255	249-255	251-255	233-255	230-255	186-255	158-255	142-255	180-255	133-250	189-240	114-250	9--68	11--83	6--73	11-103	32-119	10-101
Forest	Mean	209	199	199	205	233	205	176	180	160	108	169	170	55	55	69	105	63	48
	Mode	185-244	180-223	117-229	169-245	172-213	179-224	124-243	124-240	94-222	37-189	117-237	118-235	22-103	27-94	41-101	40-163	31-96	20-84

TYPE	Value	SARAWAK_GLCM_MEAN_SAVI						SARAWAK_GLCM_HOM_SAVI						SARAWAK_GLCM_DIS_SAVI					
		2000	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***
Rubber	Mean	247	243	241	242	241	243	177	113	131	147	120	97	74	132	112	87	103	122
	Mode	248-250	254-255	250-254	251-254	253-255	253-255	183-195	161-171	141-179	134-205	118-145	110-149	42-49	69-88	61-107	45-94	73-94	82-114
Acacia	Mean	153	201	176	181	201	125	69	69	113	169	160	108	177	168	122	70	72	132
	Mode	165-171	199-207	188-200	169-201	190-214	161-193	66-86	50-81	73-103	150-181	142-189	72-129	105-130	159-187	110-136	52-86	56-78	91-128
Other IFs	Mean	232	244	231	232	219	212	152	172	174	135	127	117	83	76	64	94	97	97
	Mode	211-239	231-237	231-239	237-241	220-233	212-229	73-138	161-197	168-193	144-175	139-158	105-133	45-89	67-93	41-62	60-88	66-89	69-111
Oil Palm	Mean	252	254	250	237	236	208	209	208	223	184	160	180	47	51	35	63		62
	Mode	241-255	246-255	244-255	230-255	236-255	178-255	165-255	155-255	186-255	150-255	113-241	145-255	21-62	20-76	5--71	21-91	23-96	9-101
Forest	Mean	198	186	191	198	195	199	165	171	141	88	138	159	75	72	87	132	80	64
	Mode	172-238	163-214	163-223	157-245	172-218	172-221	95-233	124-227	75-212	21-179	76-201	93-224	36-123	36-115	42-133	62-212	42-118	32-102

Table A.7. (cont'd)

TYPE	Value	GLCM_MEAN_Band 4						GLCM_HOM_Band 4						GLCM_DIS_Band 4						GLCM_MEAN_Band 5					
		2000	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*
Rubber	Mean	253.4	253	252.6	252.6	254	252	167.7	92	120.6	127	109	92	83	164	132	113	135	149	254	230	221	219	251	221
	Mode	249-255	245-255	249-255	249-255	251-255	249-255	96-255	0-173	45-223	63-200	66-174	36-169	22-154	83-234	57-210	62-160	85-175	62-222	251-255	203-255	197-242	195-227	248-255	195-255
Acacia	Mean	239.8	245	240	239	240	233	98.5	88.5	124	161.6	173	154	152	166	130	84	79	92	251	171	166	140	243	197
	Mode	237-245	241-255	233-252	235-242	235-244	219-239	39-187	0-208	38-235	128-234	144-255	88-222	70-202	82-213	38-130	35-150	13-135	26-138	247-255	135-216	137-207	128-132	240-247	110-222
Other IFs	Mean	249.8	251	250	250	244	242	119	164.7	166	129	108	101	126.7	88	85.5	111	138	135	253	200	195	191	246	159
	Mode	246-255	248-255	246-255	248-255	242-251	239-248	38-218	111-242	109-235	61-196	68-176	36-160	58-206	46-124	43-134	69-170	80-166	79-181	252-255	161-236	194-201	170-218	244-250	128-191
Oil palm	Mean	254.8	254.3	254.5	252.6	253	249	216	232	235	184	197	212	39	26	23	67	58	39	254	244	201	208	250	192
	Mode	252-255	253-255	253-255	243-255	251-255	231-255		181-255	196-255	141-255	150-255	158	0-76	0-89	0-74	18-97	0-91	0-70	253-255		174-206	212-225	249-253	110-121, 190-222
Forest	Mean	240.7	243	241	242	241	239	170	172	140	79	141	158	82	81	106.6	162	104	80	245	138	173	135	244	129
	Mode	237-248	238-249	239-247	237-250	238-247	235-245	139-245	122-236	83-216	22-170	108-192	115-216	38-122	42-129	53-152	96-220	68-132	43-120	245-248	136-139	157-194	128-137	240-247	110-152

Table A.8. The GLCM_MEA, DIS, and HOM values for different LULC types in VIs, band 4 and 5 images in Sabah, 2000-2014.

TYPE	Value	SABAH_GLCM_MEAN_MSAVI*af*						SABAH_GLCM_HOM_MSAVI*af*						SABAH_GLCM_DIS_MSAVI*af*					
		2000	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*
Rubber	Mean	237	241	232	227	238	230	162	178	127	127	149	138	79	65	93	78	80	82
	Mode	237-243	240-249	230-253	230-238	237-242	231-255	164-188	168-235	129-193	129-153	162-186	139-206	52-85	29-65	44-81	36-107	40-85	18-108
Acacia	Mean	254	254	245	255	254	113	178	190	153	228	132	2	67	50	63	26	106	248
	Mode	242-244	248-255	248-253	255	250-255	93-170	162-206	212-252	136-183	226-255	157-231	0-71	43-73	21-61	45-81	12--44	27-75	109-255
Other IFs	Mean	254	254	250	250	246	247	165	186	183	187	152	190	73	53	53	59	82	46
	Mode	251-255	217-255	248-255	252-255	249-255	143-255	150-197	158-246	170-239	181-246	159-185	178-255	58-76	23-93	34-50	21-58	35-70	3-48
Oil palm	Mean	245	245	248	246	245	247	172	183	165	184	150	158	69	52	64	52	65	58
	Mode	244-254	246-252	240-255	247-255	239-254	139-255	138-243	146-243	173-255	163-255	113-188	96-231	40-85	31-76	4-90	17-77	38-94	Jan-95
Forest	Mean	250	252	253	254	254	245	186	209	176	192	178	182	61	40	55	47	53	47
	Mode	250-255	251-255	251-255	252-255	250-255	247-255	160-218	187-245	152-225	161-227	146-226	215-255	51-72	20-60	19-50	26-74	29-77	1-42

Table A.8. (cont'd)

TYPE	Value	SABAH_GLCM_MEAN_NDVI*af*						SABAH_GLCM_HOM_NDVI*af*						SABAH_GLCM_DIS_NDVI*af*					
		2000	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*
Rubber	Mean	236	240	232	225	238	231	157	176	127	147	138	135	89	80	102	85	92	92
	Mode	237-242	249-250	234	228-235	238-241	240-244	159-179	200-226	158-168	158-171	133-163	176-186	71-93	46-68	78-80	64-75	68-77	49-65
Acacia	Mean	254	254	245	255	206	111	159	174	164	218	135	3	84	74	71	34	105	246
	Mode	251-254	254-255	248--250	255	221-232	120-160	171-185	167-176	188-203	205-215	204-231	1--4	70-91	66-77	50-63	23-47	29-51	240-250
Other IFs	Mean	254	252	249	248	248	249	145	168	180	172	137	179	93	82	62	75	99	63
	Mode	253-255	249-250	251-253	247-255	254-255	253-254	160-181	186-209	214-230	190-208	147-165	188-196	74-90	55-72	32-46	46-59	67-77	41-49
Oil palm	Mean	245	244	246	246	245	245	169	198	154	180	175	147	77	54	82	61	59	73
	Mode	248-252	245-250	254-255	250-255	247-251	247-251	139-215	234-253	163-206	193-209	148-166	135-185	43-98	32-59	51-72	39-59	48-80	52-79
Forest	Mean	251	251	253	254	253	253	199	189	162	162	160	171	62	64	72	67	68	65
	Mode	252-255	251-254	254-255	252-255	253-255	253-255	192-224	181-215	158-197	155-179	132-156	193-244	48-74	50-72	55-78	59-78	62-86	20-52

TYPE	Value	SABAH_GLCM_MEAN_ARVI						SABAH_GLCM_HOM_ARVI						SABAH_GLCM_DIS_ARVI					
		2000	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*
Acacia	Mean	236	248	228	238	165	106	184	182	166	199	164	8	37	35	46	30	67	220
	Mode	238-242	252-255	225-236	233-243	160-241	110-205	222-228	203-215	145-170	181-213	225-254	1--106	21-36	15-40	35-55	11--35	7--49	190-235
Forest	Mean	238	243	237	240	237	222	157	169	145	134	123	190	48	33	61	66	74	51
	Mode	235-247	236-255	236-247	231-251	237-255	228-240	125-202	129-202	145-192	70-194	103-123	186-255	27-64	15-55	39-50	32-112	59-81	2--52
Oil palm	Mean	248	246	244	240	232	244	129	170	157	159	142	120	91	33	64	56	65	84
	Mode	248-255	245-253	245-255	245-254	228-242	245-255	104-180	140-218	188-211	158-189	109-171	88-167	25-108	20-43	27-45	25-61	38-82	46-98
Rubber	Mean	221	241	229	214	239	227	178	188	139	162	115	144	43	33	82	60	81	84
	Mode	221-224	235-251	241-247	212-227	235-245	240-252	181-204	201-222	195-212	161-183	118-137	161-189	29-39	10--15	27-41	31-43	60-73	18-49
Other IFs	Mean	234	248	246	229	242	233	165	166	207	186	111	187	49	36	33	51	94	53
	Mode	240-243	245-253	246-252	231-241	241-249	227-248	156-172	165-185	215-235	201-229	131-146	215-239	33-44	20-35	17-39	24-33	51-75	22-46

Table A.8. (cont'd)

TYPE	Value	SABAH_GLCM_MEAN_EVI						SABAH_GLCM_HOM_EVI						SABAH_GLCM_DIS_EVI					
		2000	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*	*2000*	*2003*	*2006*	*2009*	*2012*	*2014*
Acacia	Mean	199	208	167	196	170	142	221	224	200	235	219	36	25	37	33	19	34	185
	Mode	191-195	205-245	150-195	181-227	196-237	173-200	243-255	200-234	170-277	204-238	119-255	0-82	9-15	0-34	15-39	4--39	0-30	126-161
Forest	Mean	171	173	173	178	183	193	231	212	216	199	183	189	25	40	26	44	58	36
	Mode	165-181	155-197	162-182	169-192	174-196	149-190	222-255	184-250	229-253	162-255	133-248	137-255	6--41	5--80	0-46	9--80	15-77	5--72
Oil palm	Mean	238	246	245	241	238	244	184	213	163	184	172	140	56	35	76	55	59	81
	Mode	226-251	236-255	229-255	227-255	231-251	216-255	163-241	173-255	149-249	159-240	124-229	88-210	21-90	10-56	Oct-65	9--85	29-86	15-129
Rubber	Mean	201	225	213	189	235	226	128	152	99	158	129	97	93	83	126	66	95	112
	Mode	196-206	215-235	210-240	173-207	231-246	231-248	102-139	155-177	80-125	129-168	141-159	101-127	83-91	59-101	60-87	49-67	51-69	61-89
Other IFs	Mean	196	200	215	199	200	190	114	131	128	101	87	90	106	87	80	117	124	105
	Mode	190-198	185-200	215-235	201-227	195-225	178-229	139-153	86-111	100-133	72-96	71-98	52-99	61-80	92-124	70-92	93-118	91-113	61-99

TYPE	Value	SABAH_GLCM_MEAN_SARVI						SABAH_GLCM_HOM_SARVI						SABAH_GLCM_DIS_SARVI					
		2000	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***
Acacia	Mean	215	226	188	214	165	144	224	233	200	238	213	22	30	30	43	20	43	208
	Mode	205-225	218-242	175-206	188-229	161-205	127-205	217-241	182-240	190-225	221-249	177-255	0-68	9--51	0-37	15-61	0-45	0-36	175-208
Forest	Mean	195	198	193	200	198	191	231	217	214	191	186	196	28	36	36	48	58	43
	Mode	191-204	185-218	180-202	192-217	177-216	180-214	216-255	169-255	165-253	158-236	148-239	163-255	14-42	0-73	4--80	9--82	14-88	Jun-57
Oil palm	Mean	246	251	246	245	239	247	181	206	169	184	165	137	61	40	80	57	67	88
	Mode	236-255	242-255	223-255	241-255	233-252	230-255	139-255	177-253	199-254	159-250	144-200	99-224	20-92	14-61	7-142	17-67	29-116	25-120
Rubber	Mean	213	238	219	203	239	232	148	166	105	161	153	113	84	73	125	68	83	106
	Mode	210-220	205-248	215-240	194-217	229-245	240-253	116-178	160-195	87-125	174-199	141-175	127-162	50-75	10--48	67-99	34-53	30-61	65-79
Other IFs	Mean	213	221	227	215	216	213	131	141	159	124	108	120	95	77	69	98	111	93
	Mode	195-214	219-235	230--242	207-231	213-232	211-231	154-184	107-135	169-180	108-127	111-130	130-153	40-66	80-94	50-69	76-98	79-102	52-77

TYPE	Value	SABAH_GLCM_MEAN_SAVI						SABAH_GLCM_HOM_SAVI						SABAH_GLCM_DIS_SAVI					
		2000	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***
Acacia	Mean	210	223	186	210	159	158	225	229	207	235	221	28	24	34	37	28	35	195
	Mode	200-235	222-242	173-205	197-231	150-203	159-181	230-255	184-221	175-215	221-255	132-255	0-83	0-42	0-72	11--59	0-52	0-35	123-203
Forest	Mean	187	191	186	193	188	174	222	207	209	193	180	181	28	47	37	57	68	50
	Mode	174-197	178-212	174-200	173-218	164-207	161-200	184-255	175-246	158-255	123-255	122-245	144-255	1--60	15-81	0-104	6-112	12-164	11--59
Oil palm	Mean	240	251	244	246	239	244	195	226	172	189	157	139	51	33	79	63	73	87
	Mode	231-254	242-255	224-255	238-255	227-252	221-255	175-255	202-255	126-255	176-255	108-205	88-241	12--86	10--53	0-107	10-104	41-111	26-101
Rubber	Mean	214	241	217	207	237	227	137	157	93	156	153	103	92	84	137	78	86	113
	Mode	205-220	218-241	192-248	203-219	231-242	241-251	120-134	140-170	77-119	161-183	175-199	123-158	80-97	45-75	67-98	52-74	41-61	60-98
Other IFs	Mean	212	220	221	217	211	207	118	130	140	98	92	93	106	92	81	127	125	108
	Mode	190-214	212-238	221-239	211-239	201-223	201-225	140-165	82-121	102-139	78-99	71-107	84-112	50-75	75-107	63-89	110-129	101-119	89-109

Table A.8. (cont'd)

TYPE	Value	GLCM_MEAN_Band 4						GLCM_HOM_Band 4						GLCM_DIS_Band 4						GLCM_MEAN_Band 5					
		2000	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***	***2000***	***2003***	***2006***	***2009***	***2012***	***2014***
Acacia	Mean	240	240	235	240	191	246	246	238	240	232	156	87	9	20	18	26	91	152	243	133	182	209	166	254
	Mode	239-241	241-243	234-236	240-242	188-191	247-251	247-248	249-250	245-246	234-237	155-167	144-157	0-19	0-21	0-18	0-34	107-119	77-115	243-246	125-127	182-184	209	130-135	
Forest	Mean	233	233	234	236	179	226	229	205	218	179	156	201	26	50	39	75	93	42	243	148	178	208	128	161
	Mode	232-235	231-237	232-238	234-239	174-187		223-249	194-240	228-230	136-196	132-223	174-246	0-46	0-86	0-75	27-123	39-138	13-72	243-246	135-145	177-184		127-137	154-166
Oil palm	Mean	248	252	252	252	239	251	220	219	180	179	203	170	34	36	80	77	51	79	251	204	205	248	233	220
	Mode	246-250	250-252	249-255	250-255	233-245	242-255	213-249	190-240	215-240	144-238	198-255	173-221	1--55	0-50	0-63	50-109	0-90	38-62	251-254	203-205	192-196	253-255	233-235	200-234
Rubber	Mean	243	248	246	243	235	247	121	143	91	148	134	88	119	108	160	102	116	146	250	215	213	237	227	223
	Mode	243-246	247-249	246-247	242-244	234-237	249-252	80-103	143-150	93-101	149-141	160-172	106-109	100-120	101-107	140-143	108-110	68-113	122-136	251-253	203-206	204-212	230-232	231-236	222-234
Other IFs	Mean	241	240	244	243	199	234	117	126	121	81	82	92	127	120	121	165	159	128	245	166	183	216	161	166
	Mode	240-242	239-241	246-249	246-248	205-211	234-237	210-225	124-131	115-125	53-66	104-107	76-89	157-169	138-141	114-130	172-181	166-169	106-155	244-246	164-167	182-183	209-211	130-133	157-167

Table A.9. The PCA, ICA, TCA, band 4 and band 5 values for different Land Use Land Cover (LULC) types in Sabah, 2000-2014.

YEAR		ICA_ VALUES			PCA_VALUES			TCA_VALUES						B4	B5
	LU	L1	L2	L3	L1	L2	L3	L1	L2	L3	L4	L5	L6		
2000	**Acacia**														
	mean	99	94	116	133	155	109	121	153	164	222	192	120	2923	864
	range	**98-99**	**94-97**	**114-120**	**133-134**	**155-157**	**109-111**	**123-124**	**156-157**	**164-167**	**222-224**	**192-196**	**120-123**	**2699-3192**	**755-953**
	Forest														
	mean	98	96	111	132	154	108	121	150	161	223	193	119	2547	1015
	range	**97-100**	**96-99**	**110-115**	**131-135**	**153-158**	**108-111**	**121-124**	**149-154**	**161-164**	**222-226**	**193-197**	**119-122**	**2236-2906**	**862-1167**
	Oil Palms														
	mean	96	96	118	137	154	107	124	157	161	223	192	120	3405	1490
	range	**96-98**	**96-98**	**116-123**	**136-141**	**154-159**	**106-110**	**123-128**	**155-162**	**160-165**	**223-226**	**191-196**	**119-123**	**2927-4011**	**1307-1845**
	Rubber														
	mean	97	97	115	136	153	107	123	154	160	223	192	119	3144	1460
	range	**97-99**	**93-99**	**112-122**	**133-141**	**153-156**	**107-111**	**121-129**	**149-162**	**160-164**	**223-226**	**191-196**	**119-123**	**2616-3674**	**972-1996**
	Other IFs														
	mean	98	95	115	134	154	109	122	153	163	222	192	120	2973	1047
	range	**98-101**	**94-98**	**110-124**	**132-139**	**154-158**	**106-112**	**121-127**	**149-161**	**161-167**	**222-226**	**191-197**	**120-123**	**2344-3634**	**712-1481**
2003	**Acacia**														
	mean	80	95	112	125	160	87	115	160	143	220	190	161	3042	956
	range	**79-84**	**94-99**	**111-117**	**124-129**	**159-165**	**86-91**	**115-118**	**160-165**	**142-147**	**219-224**	**190-194**	**161-164**	**2879-3285**	**844-1108**
	Forest														
	mean	79	97	107	124	159	86	114	157	142	220	191	161	2615	1036
	range	**79-84**	**96-100**	**104-113**	**122-129**	**158-163**	**86-89**	**114-118**	**154-163**	**141-146**	**219-224**	**191-195**	**160-165**	**2144-2993**	**887-1209**
	Oil palms														
	mean	79	97	116	130	159	85	118	164	142	220	189	161	3698	1571
	range	**79-82**	**97-101**	**114-122**	**129-133**	**158-163**	**85-88**	**117-121**	**162-169**	**141-145**	**220-224**	**189-192**	**160-164**	**3419-3988**	**1437-1703**
	Rubber														
	mean	79	98	114	129	159	85	117	162	141	221	189	161	3471	1560
	range	**78-82**	**97-101**	**110-122**	**126-134**	**158-162**	**85-89**	**116-122**	**159-169**	**140-145**	**221-224**	**188-194**	**160-164**	**2795-4126**	**1124-2061**
	Other IFs														
	mean	79	96	111	126	160	86	115	160	142	220	190	161	3009	1108
	range	**79-83**	**95-100**	**106-121**	**86-89**	**158-163**	**86-89**	**114-120**	**157-168**	**142-146**	**220-224**	**189-194**	**160-165**	**2503-2756**	**751-1626**
2006	**Acacia**														
	mean	101	80	109	128	151	109	119	150	183	213	194	113	2606	1060
	range	**100-105**	**79-84**	**107-114**	**127-132**	**150-154**	**108-112**	**119-122**	**149-155**	**182-187**	**212-217**	**193-197**	**112-117**	**2344-2812**	**926-1250**
	Forest														
	mean	101	79	109	127	151	109	119	151	184	212	194	112	2614	1004
	range	**101-104**	**79-83**	**107-114**	**126-132**	**151-156**	**109-113**	**118-122**	**149-155**	**184-187**	**212-216**	**194-198**	**112-115**	**2273-2912**	**839-1165**
	Oil palms														
	mean	100	80	118	133	151	109	122	158	184	213	191	113	3691	1501
	range	**100-104**	**79-84**	**115-126**	**132-138**	**151-155**	**108-113**	**122-126**	**156-164**	**183-188**	**212-216**	**191-195**	**112-116**	**3334-4276**	**1330-1814**
	Rubber														
	mean	101	81	114	132	150	109	121	154	183	212	192	112	3269	1497
	range	**100-104**	**79-87**	**109-124**	**129-139**	**149-154**	**107-113**	**120-127**	**151-162**	**181-187**	**212-217**	**191-196**	**111-116**	**2854-4009**	**1016-2107**
	Other IFs														
	mean	101	79	114	130	152	109	120	154	184	213	192	112	3136	1199
	range	**100-104**	**79-84**	**107-124**	**127-137**	**151-155**	**108-113**	**119-125**	**149-163**	**184-189**	**212-216**	**191-197**	**112-116**	**2388-4082**	**756-1682**
2009	**Acacia**														
	mean	94	99	111	113	153	108	112	154	168	222	193	113	2951	915
	range	**94-99**	**99-103**	**109-116**	**113-117**	**153-158**	**108-111**	**111-116**	**153-158**	**168-171**	**222-226**	**192-196**	**113-116**	**2708-3213**	**823-1021**
	Forest														
	mean	94	101	108	112	153	107	111	152	166	222	194	113	2675	987
	range	**93-97**	**100-104**	**105-114**	**111-117**	**152-156**	**107-110**	**111-115**	**150-158**	**166-170**	**222-225**	**193-197**	**112-116**	**2317-3110**	**861-1194**
	Oil palms														
	mean	93	102	116	117	152	106	114	159	166	223	192	113	3632	1544
	range	**93-96**	**102-105**	**112-122**	**116-121**	**151-156**	**106-109**	**111-118**	**156-164**	**165-169**	**222-226**	**191-195**	**113-117**	**3261-4067**	
	Rubber														
	mean	94	103	110	115	151	106	114	154	164	223	193	112	3085	1516
	range	**93-98**	**102-106**	**106-117**	**113-121**	**150-155**	**106-108**	**113-117**	**152-159**	**163-168**	**223-226**	**192-196**	**112-116**	**2554-3636**	
	Other IFs														
	mean	94	101	111	115	152	107	113	155	166	223	192	113	3108	1199
	range	**93-97**	**100-105**	**105-124**	**112-122**	**151-156**	**106-110**	**111-118**	**151-164**	**166-170**	**222-226**	**191-196**	**113-116**	**2325-4184**	**821-1724**

Table A.9. (cont'd)

2012	**Acacia**														
	mean	84	85	178	108	157	93	106	177	162	216	184	163	2911	1231
	range	**83-87**	**83-87**	**177-184**	**107-109**	**153-161**	**89-97**	**105-116**	**176-181**	**163-167**	**216-219**	**184-187**	**162-167**	**2706-3114**	**902-1381**
	Forest														
	mean	82	84	179	106	159	92	104	178	163	219	186	164	2749	1003
	range	**82-86**	**83-88**	**176-187**	**105-112**	**158-162**	**91-96**	**104-108**	**177-184**	**162-167**	**217-223**	**186-190**	**163-167**	**2405-3167**	**814-1256**
	Oil palms														
	mean	82	86	190	111	158	91	107	185	162	219	184	163	3671	2497
	range	**82-84**	**85-90**	**184-197**	**110-114**	**157-162**	**91-94**	**107-111**	**183-190**	**161-166**	**219-223**	**184-187**	**163-167**	**3290-4015**	**1468-1704**
	Rubber														
	mean	81	86	188	111	158	91	107	185	161	220	184	164	3586	1564
	range	**80-85**	**85-89**	**182-203**	**108-117**	**158-162**	**90-94**	**106-112**	**182-193**	**161-165**	**220-223**	**183-188**	**164-167**	**2931-4373**	**1150-2025**
	Other IFs														
	mean	82	85	182	108	159	91	105	181	162	220	185	164	3019	1171
	range	**81-85**	**83-88**	**173-201**	**105-114**	**159-162**	**91-95**	**104-110**	**176-191**	**162-166**	**219-223**	**184-190**	**164-167**	**2207-4248**	**744-1682**
2014	**Acacia**														
	mean	70	89	167	120	167	76	105	200	126	227	186	106	3647	3097
	range	**65-76**	**77-108**	**146-190**	**117-128**	**156-179**	**70-83**	**102-113**	**185-221**	**112-140**	**224-231**	**184-190**	**104-110**	**2700-4486**	
	Forest														
	mean	75	76	174	108	177	81	95	201	137	226	191	107	2810	1056
	range	**74-76**	**75-78**	**170-180**	**105-113**	**171-181**	**81-83**	**94-97**	**198-207**	**136-141**	**214-229**	**191-195**	**101-111**	**2312-3268**	**870-1130**
	Oil palms														
	mean	73	76	183	115	178	79	99	212	137	227	189	108	3887	1591
	range	**72-75**	**75-79**	**178-192**	**111-121**	**177-182**	**79-81**	**98-104**	**207-221**	**136-141**	**226-231**	**188-193**	**108-112**	**3205-4517**	
	Rubber														
	mean	73	78	180	114	176	79	99	209	136	227	189	107	3655	1661
	range	**71-76**	**76-80**	**175-189**	**111-121**	**176-181**	**78-85**	**97-105**	**205-219**	**135-140**	**227-231**	**188-193**	**106-111**	**2929-4560**	
	Other IFs														
	mean	74	76	177	110	177	80	96	205	137	227	190	108	3112	1171
	range	**73-77**	**75-78**	**172-186**	**106-117**	**177-181**	**80-84**	**95-101**	**200-215**	**137-141**	**227-230**	**189-194**	**108-111**	**2551-4008**	**820-1586**

Table A.10. The PCA, ICA, TCA, band 4 and band 5 values for different Land Use Land Cover (LULC) types in Sarawak, 2000-2014.

YEAR		**ICA_ VALUES**			**PCA_VALUES**			**TC_VALUES**						**B4**	**B5**
	LU	**L1**	**L2**	**L3**	**L1**	**L2**	**L3**	**L1**	**L2**	**L3**	**L4**	**L5**	**L6**		
2000	**Acacia**														
	mean	97	86	105	120	156	106	111	149	164	216	167	160	2756	1426
	range	**97-98**	**86-87**	**102-110**	**119-120**	**159-160**	**107-108**	**111-112**	**150-151**	**165-166**	**217-218**	**169-170**	**160-161**	**2035-3513**	**696-2080**
	Forest														
	mean	97	83	107	118	159	106	109	152	167	216	168	160	2723	939
	range	**96-99**	**82-85**	**104-114**	**115-124**	**159-162**	**106-108**	**109-114**	**149-156**	**166-170**	**216-220**	**167-171**	**159-163**	**2093-3432**	**629-1310**
	Oil palms														
	mean	96	85	114	123	152	105	113	157	165	217	166	161	3612	1582
	range	**95-98**	**84-88**	**112-118**	**123-126**	**158-161**	**105-107**	**113-116**	**156-161**	**164-169**	**217-222**	**165-169**	**161-164**	**3270-3950**	**1410-1773**
	Rubber														
	mean	95	85	113	123	158	105	113	156	165	217	166	160	3503	1586
	range	**94-97**	**84-89**	**111-119**	**121-127**	**157-162**	**104-106**	**111-117**	**152-163**	**163-169**	**215-219**	**166-170**	**160-163**	**2982-4153**	**1073-2126**
	Other IFs														
	mean	96	85	111	121	158	106	112	154	165	217	167	160	3253	1401
	range	**96 -100**	**84-88**	**105-120**	**118-128**	**158-161**	**105-109**	**110-118**	**150-162**	**162-169**	**216-221**	**164-170**	**160-165**	**2581-3920**	**1058-1714**

Table A.10. (cont'd)

2003	**Acacia**														
	mean	78	97	113	125	158	97	114	156	164	215	166	128	3039	1197
	range	**78-79**	**97-98**	**110-112**	**125-126**	**158-159**	**98-99**	**114-115**	**154-156**	**164-165**	**217-218**	**167-168**	**129-130**	**2278-4182**	**734-1863**
	Forest														
	mean	78	96	112	123	159	97	113	155	165	214	167	128	2784	949
	range	**77-84**	**94-101**	**107-119**	**122-128**	**158-162**	**97-100**	**112-117**	**153-161**	**164-169**	**214-218**	**166-170**	**128-131**	**2161-3434**	**694-1249**
	Oil palms														
	mean	77	98	118	127	159	95	115	161	164	216	166	128	3513	1449
	range	**76-81**	**97-102**	**116-123**	**127-131**	**157-163**	**95-99**	**115-119**	**160-165**	**162-168**	**214-220**	**165-169**	**127-132**	**3216-3844**	**1302-1628**
	Rubber														
	mean	77	98	118	128	158	95	116	161	163	216	165	128	3603	1562
	range	**75-81**	**97-103**	**109-125**	**121-132**	**156-162**	**94-100**	**113-117**	**152-170**	**161-170**	**213-220**	**164-171**	**126-133**	**2777-4644**	**927-2308**
	Other IFs														
	mean	77	98	116	126	159	96	115	159	164	216	166	128	3292	1308
	range	**77-85**	**96-104**	**108-126**	**122-133**	**157-160**	**93-99**	**113-120**	**155-166**	**163-172**	**213-221**	**165-172**	**125-131**	**2750-4149**	**987-1655**
2006	**Acacia**														
	mean	83	102	106	124	158	99	114	153	162	217	163	123	2619	935
	range	**83-84**	**102-103**	**105-107**	**125-126**	**158-159**	**100-101**	**115-116**	**153-154**	**163-164**	**218-219**	**164-165**	**124-125**	**1703-3621**	**544-1317**
	Forest														
	mean	83	102	106	124	158	99	114	153	162	218	164	124	2680	974
	range	**83-86**	**102-105**	**104-111**	**123-128**	**158-161**	**99-102**	**115-118**	**151-159**	**162-166**	**218-222**	**163-168**	**114-119**	**1933-3959**	**678-1301**
	Oil palms														
	mean	82	103	114	129	158	98	117	159	162	218	163	123	3495	1436
	range	**82-85**	**103-106**	**112-117**	**128-131**	**157-161**	**98-101**	**116-120**	**158-163**	**161-163**	**217-219**	**162-164**	**123-127**	**3220-3858**	**1268-1631**
	Rubber														
	mean	82	104	113	129	157	97	117	158	161	219	162	123	3445	1552
	range	**81-86**	**102-108**	**110-120**	**131-132**	**160-162**	**97-101**	**120-126**	**147-153**	**158-161**	**216-219**	**161-163**	**120-121**	**2668-4266**	**1004-1989**
	Other IFs														
	mean	82	103	111	127	158	98	116	157	162	218	163	123	3210	1252
	range	**82-87**	**102-107**	**103-121**	**130-133**	**156-160**	**97-100**	**114-120**	**162-165**	**165-167**	**217-221**	**162-167**	**122-125**	**2704-3774**	**1009-1532**
2009	**Acacia**														
	mean	84	109	112	122	159	91	113	154	157	212	162	154	2599	962
	range	**84-85**	**109-110**	**112-113**	**122-123**	**160-161**	**92-93**	**113-114**	**154-155**	**157-158**	**213-214**	**163-164**	**154-155**	**2013-3050**	**627-1267**
	Forest														
	mean	84	109	113	123	159	91	114	155	157	212	162	154	2785	1028
	range	**85-86**	**108-111**	**110-119**	**120-127**	**158-162**	**91-94**	**114-118**	**153-158**	**158-160**	**214-216**	**161-165**	**155-156**	**1994-3719**	**696-1398**
	Oil palms														
	mean	84	110	118	126	159	91	116	159	156	212	161	153	3412	1445
	range	**87-88**	**110-113**	**116-123**	**125-130**	**157-163**	**90-96**	**118-121**	**159-163**	**155-158**	**212-213**	**160-162**	**153-154**	**2982-3947**	**1153-1729**
	Rubber														
	mean	83	111	118	126	158	90	116	158	155	213	161	154	3371	1553
	range	**83-84**	**115-117**	**109-124**	**132-133**	**156-163**	**88-89**	**120-123**	**163-165**	**153-156**	**215-217**	**159-161**	**152-153**	**2712-4729**	**1032-1934**
	Other IFs														
	mean	84	109	117	125	159	91	115	158	157	212	161	153	3235	2755
	range	**82-89**	**108-114**	**120-125**	**122-131**	**154-163**	**90-91**	**112-113**	**152-164**	**151-154**	**211-214**	**159-166**	**156-157**	**2748-3840**	**2206-3307**
2012	**Acacia**														
	mean	72	118	161	122	160	81	110	166	144	219	163	133	2755	981
	range	**73-74**	**118-119**	**160-162**	**122-123**	**160-161**	**81-82**	**110-111**	**166-167**	**145-146**	**218-219**	**163-164**	**133-134**	**2206-3334**	**596-1403**
	Forest														
	mean	73	117	160	122	159	81	110	165	144	220	163	133	2723	1002
	range	**73-76**	**117-120**	**157-165**	**121-126**	**159-162**	**81-85**	**109-112**	**164-168**	**144-147**	**220-223**	**163-167**	**133-136**	**2063-3389**	**720-1323**
	Oil palms														
	mean	72	120	169	127	158	80	133	170	142	220	161	133	3517	1713
	range	**72-74**	**119-123**	**166-172**	**126-129**	**158-163**	**80-86**	**112-115**	**168-172**	**142-144**	**221-224**	**161-163**	**132-137**	**3197-3923**	**1372-1864**
	Rubber														
	mean	73	119	172	128	158	81	114	171	143	220	161	132	3688	1646
	range	**77-78**	**123-125**	**172-176**	**130-132**	**154-158**	**83-87**	**116-117**	**173-174**	**149-150**	**217-220**	**160-162**	**131-133**	**2987-403**	**1008-2242**
	Other IFs														
	mean	72	118	164	123	160	81	110	167	144	220	163	133	2937	1085
	range	**72-76**	**117-122**	**153-157**	**116-123**	**158-163**	**80-86**	**105-109**	**159-164**	**147-148**	**215-218**	**167-168**	**132-136**	**2417-3600**	**677-1589**

Table A.10. (cont'd)

2014	**Acacia**														
	mean	95	109	178	137	148	85	126	171	146	223	188	159	2546	1614
	range	**95-96**	**105-106**	**161-181**	**136-138**	**149-152**	**86-87**	**126-127**	**162-170**	**151-153**	**223-225**	**189-190**	**160-161**	**1458-3721**	**648-1533**
	Forest														
	mean	94	104	190	136	152	85	125	178	151	224	189	160	2857	1069
	range	**94-97**	**104-108**	**185-195**	**134-141**	**152-155**	**85-89**	**124-128**	**175-182**	**150-154**	**224-228**	**188-192**	**159-162**	**2209-3615**	**808-1363**
	Oil palms														
	mean	94	107	191	140	150	84	127	179	148	225	187	160	3249	1611
	range	**93-98**	**106-109**	**195-200**	**139-145**	**151-156**	**84-88**	**124-131**	**174-184**	**148-153**	**222-229**	**183-192**	**158-163**	**2357-4209**	**922-1988**
	Rubber														
	mean	93	107	198	142	151	83	129	184	149	226	186	160	3717	1750
	range	**92-99**	**105-111**	**200-205**	**145-148**	**147-149**	**82-84**	**129-133**	**185-190**	**144-149**	**225-230**	**182-193**	**158-164**	**2799-4678**	**1065-2655**
	Other IFs														
	mean	94	105	191	137	152	85	126	179	150	225	188	160	3042	1225
	range	**91-98**	**103-109**	**181-186**	**132-147**	**149-157**	**84-91**	**123-126**	**171-177**	**148-154**	**223-228**	**186-193**	**159-163**	**2460-3831**	**827-1807**

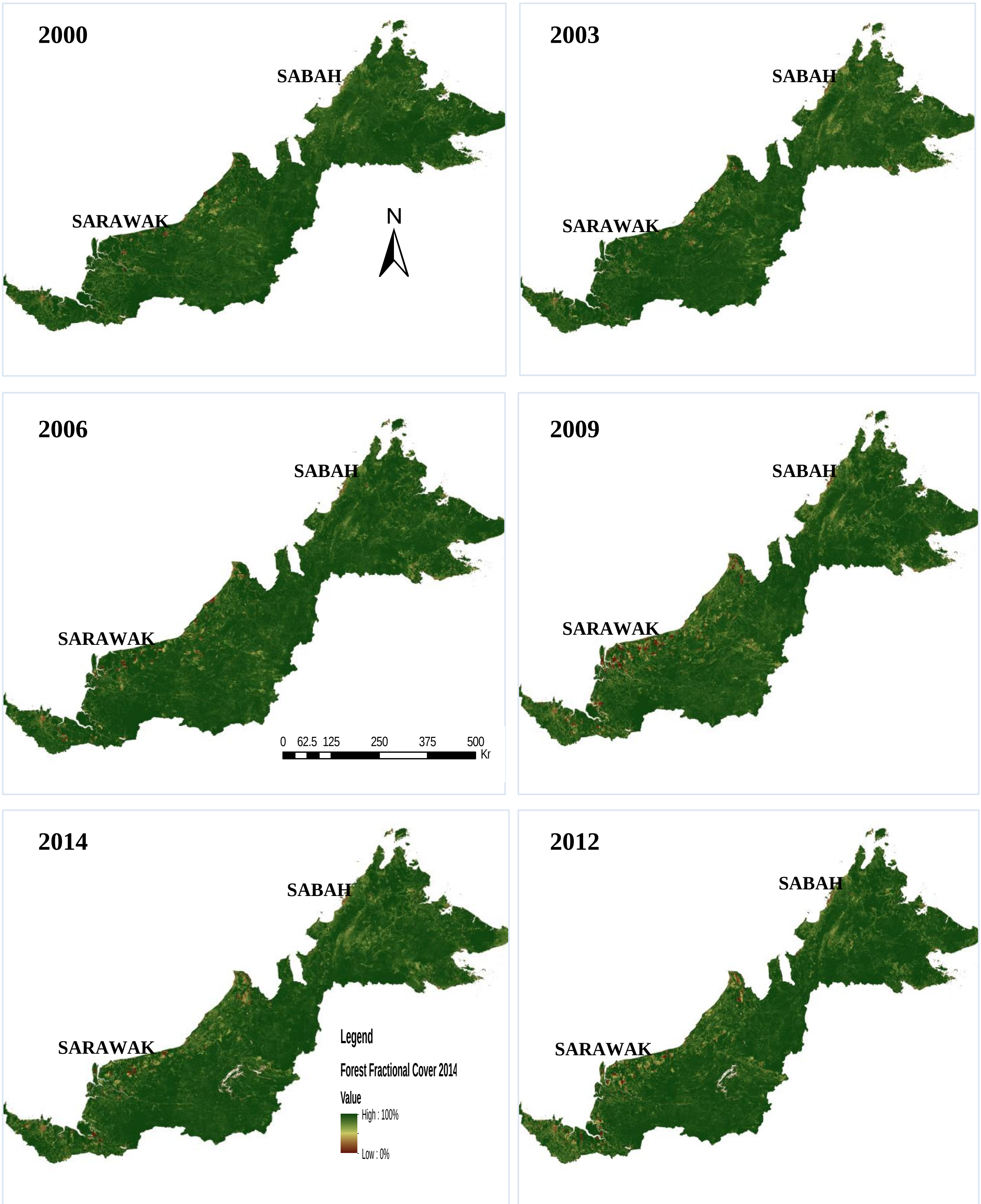


Figure A.16. Vegetation/forest fractional cover maps of 2000, 2003, 2006, 2009, 2012, and 2014 in Sarawak and Sabah.

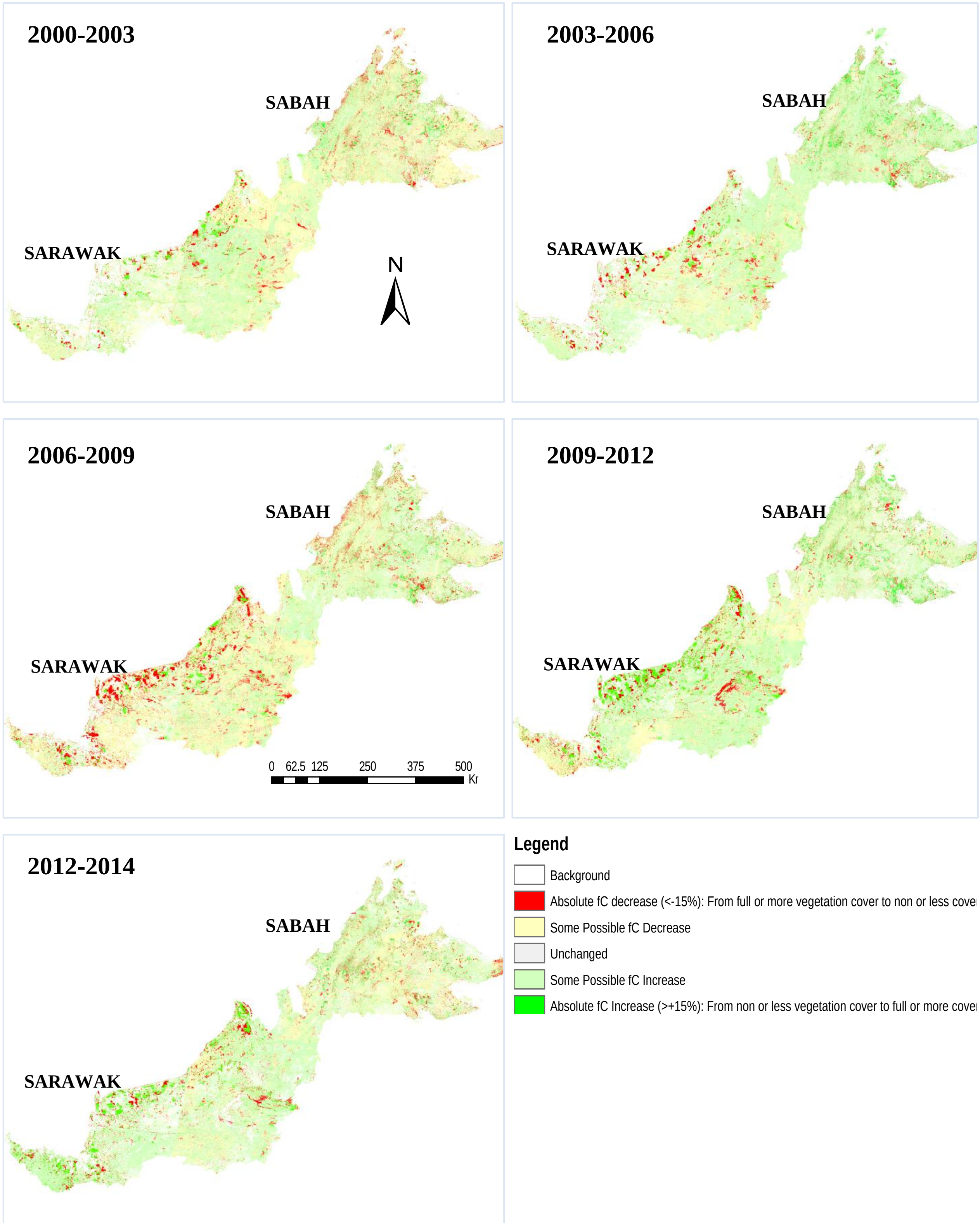


Figure A.17. Vegetation/forest cover change detection for 2000-2014 in Sarawak and Sabah.

Table A.11. The *f*C value changes and its change sequence in 30 monitored key locations in Sarawak, 2000-2014.

ID	SEQUENCES IN INCREASING & REDUCING *f*C IN KEY AREAS/LOCATIONS IN SARAWAK, 2000-2014						THE VALUES OF *f*C IN KEY AREAS/LOCATIONS IN SARAWAK, 2000-2014					
	2000	**2003**	**2006**	**2009**	**2012**	**2014**	**2000**	**2003**	**2006**	**2009**	**2012**	**2014**
1	V/F	NV/NF	V/F	V/F	V/F	NV/NF	1	0.45	0.96	1	1	0.1
2	NV/NF	V/F	V/F	V/F	V/F	NV/VF	0	1	1	0.98	0.99	0
3	V/F	NV/NF	V/F	V/F	NV/NF	V/F	1	0.52	1	0.94	0	0.68
4	NV/NF	V/F	NV/NF	V/F	V/F	V/F	0.55	0.97	0.39	0.97	0.93	0.96
5	V/F	NV/NF	V/F	V/F	V/F	V/F	0.98	0	0.95	1	1	0.99
6	V/F	NV/NF	V/F	V/F	V/F	V/F	1	0.73	1	0.97	1	1
7	V/F	V/F	V/F	NV/NF	V/F	V/F	1	1	1	0.34	1	1
8	V/F	NV/NF	V/F	V/F	V/F	V/F	0.97	0.5	1	0.99	1	0.99
9	V/F	NV/NF	V/F	V/F	V/F	V/F	0.77	0.28	0.76	0.89	1	0.97
10	NV/NF	V/F	V/F	V/F	V/F	V/F	0	0.26	0.46	0.89	0.93	1
11	V/F	NV/NF	V/F	V/F	V/F	V/F	1	0	0.44	0.54	0.86	0.83
12	V/F	V/F	V/F	NV/NF	V/F	V/F	0.97	0.92	0.97	0	0.76	0.91
13	V/F	V/F	V/F	NV/NF	V/F	V/F	0.98	1	1	0.18	0.83	0.81
14	V/F	V/F	V/F	V/F	NV/NF	V/F	1	1	1	1	0	0.6
15	V/F	V/F	NV/NF	V/F	V/F	V/F	0.92	0.95	0.15	0.78	0.96	1
16	V/F	V/F	V/F	NV/NF	V/F	V/F	1	1	1	0.3	0.96	1
17	V/F	V/F	V/F	V/F	NV/NF	V/F	1	1	1	1	0	0.3
18	V/F	V/F	V/F	NV/NF	V/F	V/F	0.97	1	1	0.33	0.68	0.97
19	V/F	V/F	V/F	NV/NF	V/F	V/F	1	0.98	1	0.59	0.65	0.93
20	V/F	NV/NF	V/F	V/F	V/F	V/F	1	0	0.37	0.83	0.88	0.93
21	V/F	V/F	V/F	V/F	NV/NF	NV/NF	1	1	1	1	0.79	0
22	NV/NF	V/F	V/F	V/F	V/F	V/F	0.4	0.77	0.85	0.96	0.89	0.94
23	V/F	V/F	NV/NF	V/F	V/F	V/F	0.97	1	0	0.36	0.71	0.9
24	V/F	NV/NF	V/F	V/F	V/F	V/F	1	0	0.53	0.69	0.74	0.92
25	V/F	V/F	V/F	NV/NF	V/F	V/F	1	1	1	0	0.71	0.92
26	V/F	V/F	V/F	NV/NF	V/F	V/F	1	1	1	0	0.8	0.94
27	V/F	V/F	V/F	NV/NF	V/F	V/F	1	1	1	0	0.84	0.68
28	NV/NF	V/F	V/F	V/F	V/F	V/F	0	0.54	0.8	0.93	0.95	0.87
29	V/F	V/F	V/F	NV/NF	V/F	V/F	1	1	1	0.58	1	1
30	V/F	V/F	NV/NF	V/F	V/F	V/F	1	1	0	0.97	0.98	1

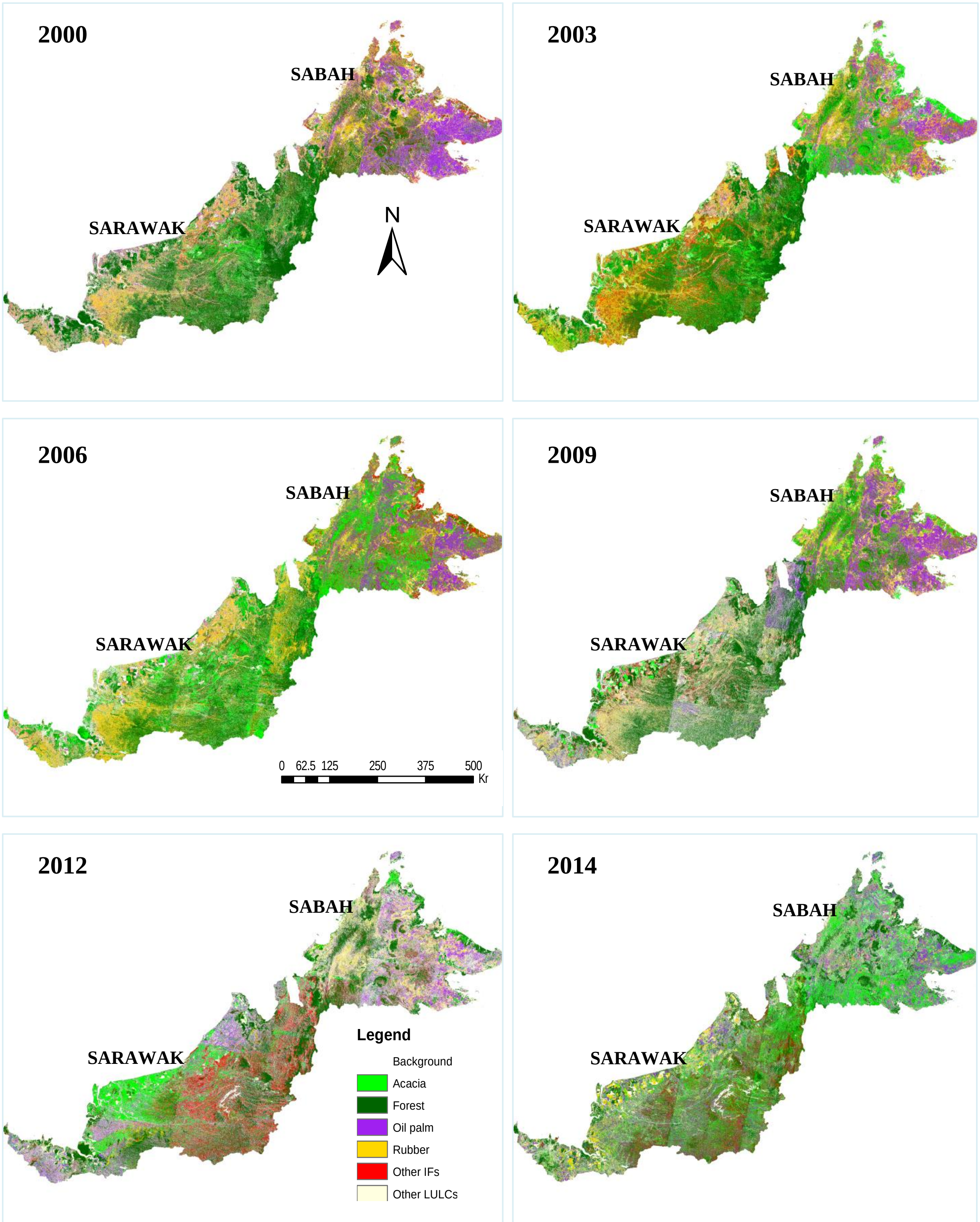


Figure A.18. The spectral analysis-based LULC maps in Sabah and Sarawak, 2000-2014.

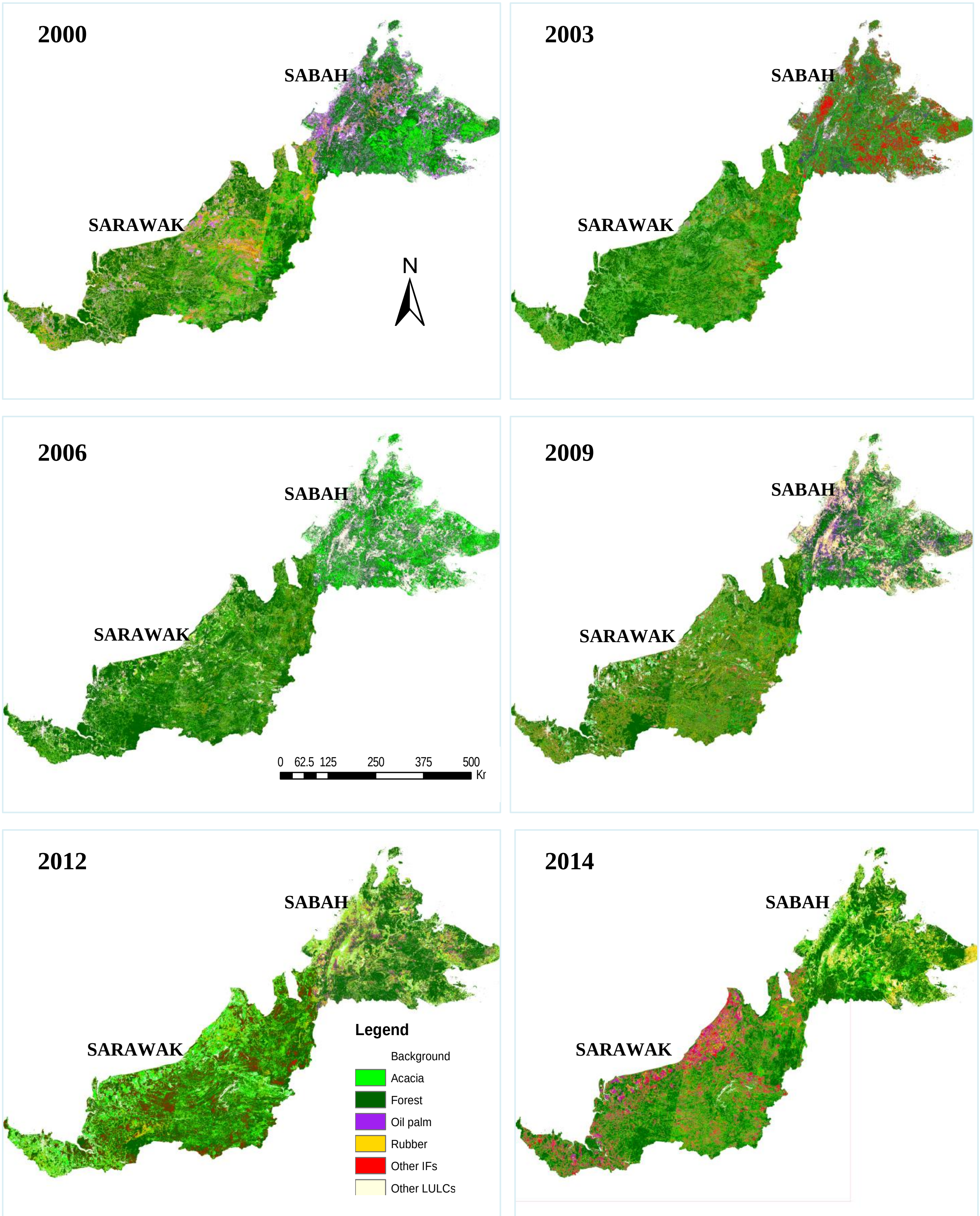


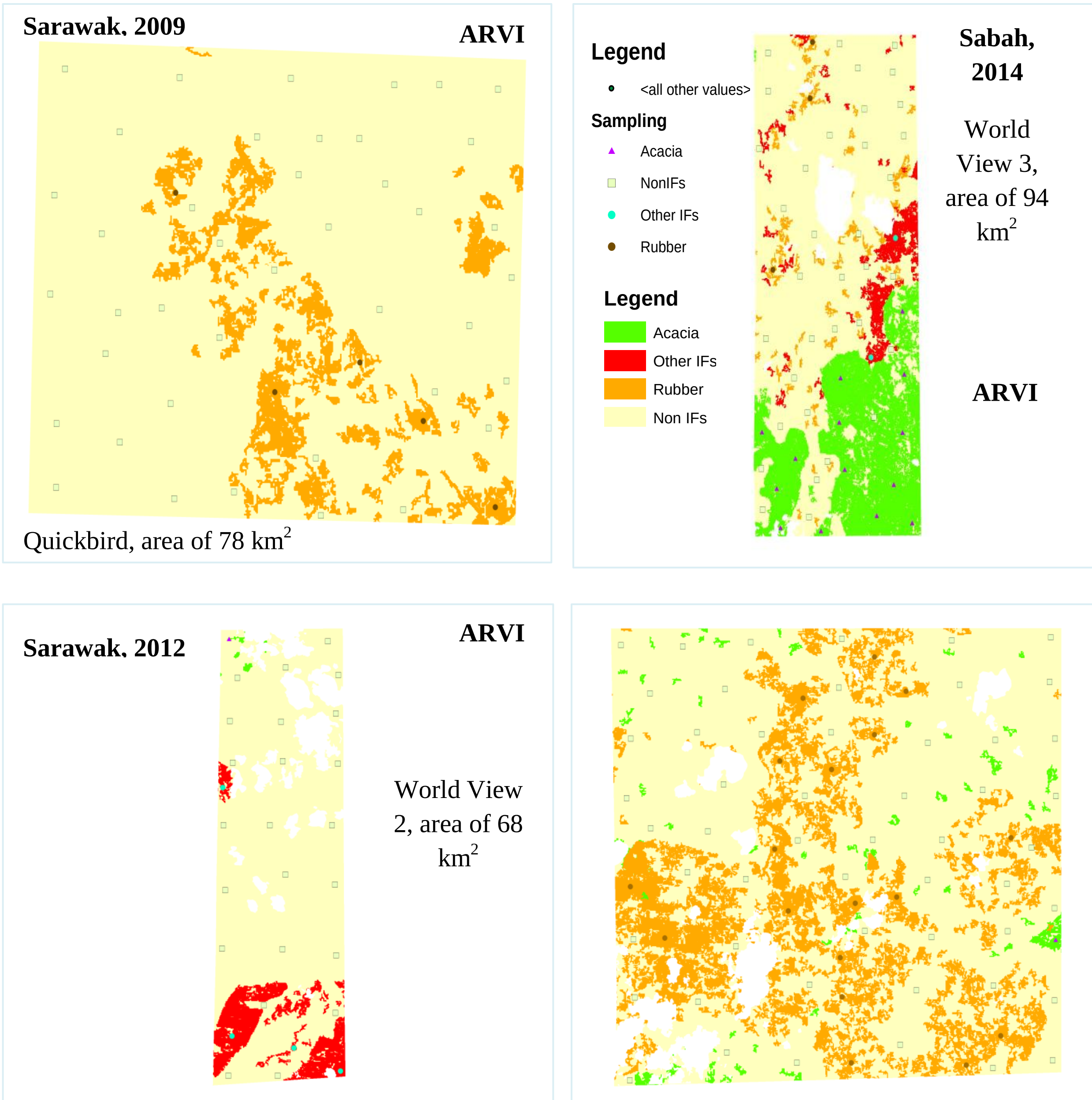
Figure A.19. The textural analysis-based LULC maps in Sabah and Sarawak, 2000-2014.

Table A.12. Details of the high resolution imagery data used for the validation in Sabah.

LULC Types	**#ID**	**Sensor**	**Resolution**	**Acquisition Date**	**Off-Nadir**	**Sun Azimuth**	**Sun Elevation**	**Cloud (%)**	**Cost /km2**	**Area (km^2)**
Acacia, Rubber, Other IFs, Non IFs	1040010004CF5900	World View 3 (WV3)	31 cm	11.29.2014	12	143.1	56.4	1	23	94
Rubber, Acacia, Non IFs	1030010033109F00	World View 2 (WV2)	50 cm	07.26.2014	23	330	68.6	1.2	12.25	166

Table A.13. Details of the high resolution imagery data used for the validation in Sarawak.

LULC Types	**#ID**	**Sensor**	**Resolution**	**Acquisition Date**	**Off-Nadir**	**Sun Azimuth**	**Sun Elevation**	**Cloud (%)**	**Cost /km^2**	**Area (km^2)**
Acacia, Other IFs, Non IFs	103001001A506000	World View 2 (WV2)	50 cm	08.13.2012	24	51.9	71.6	5	12.25	68
Rubber, Non IFs	1010010009B8F700	Quickbird (QB)	60 cm	06.05.2009	8	40.6	61.6	0	12.25	78



Sabah, 2014, Worldview 2, area of 166 km^2

Figure A.20. The location and distribution of the samples in the ARVI-based IF maps in Sarawak and Sabah.

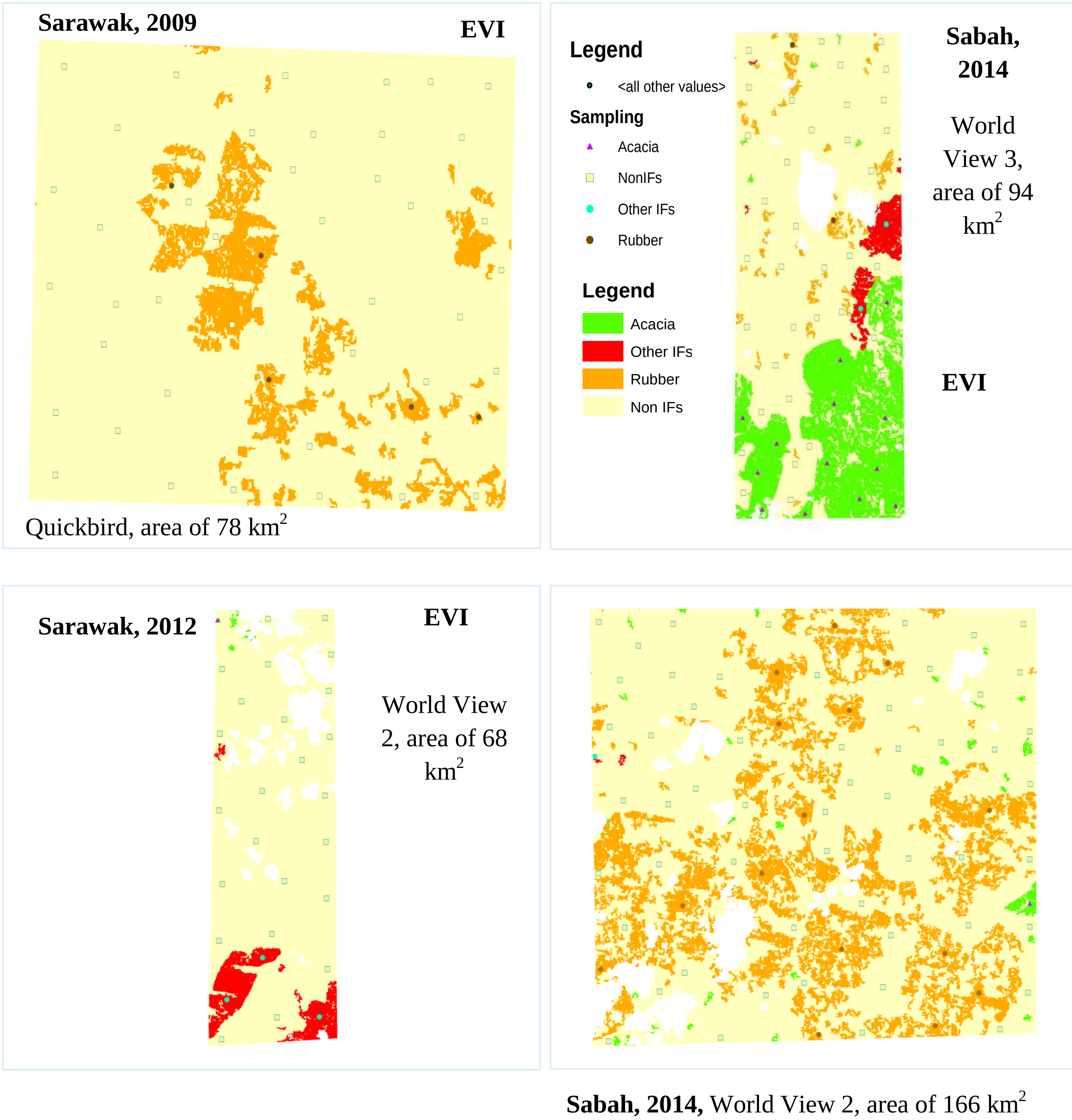
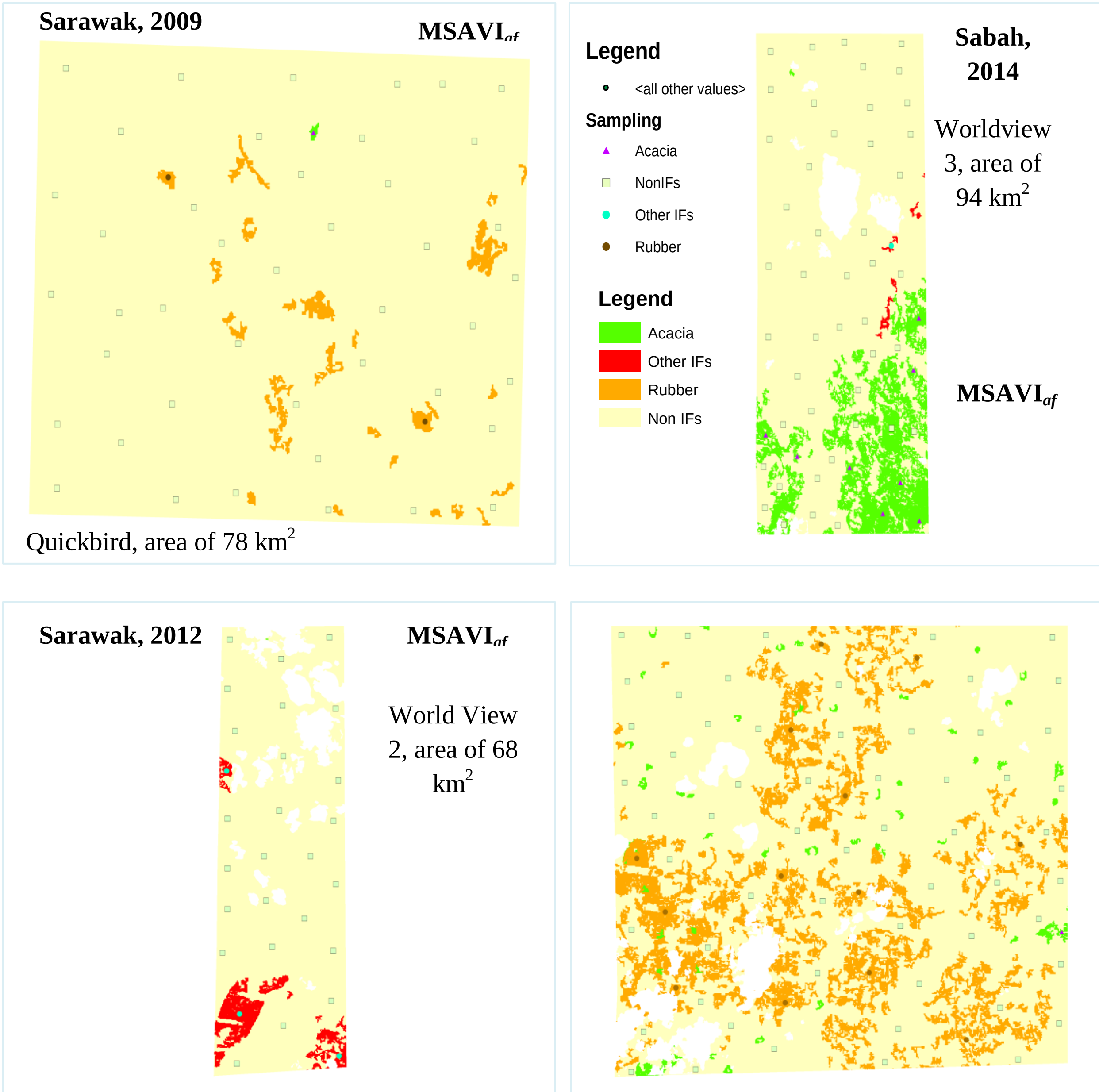
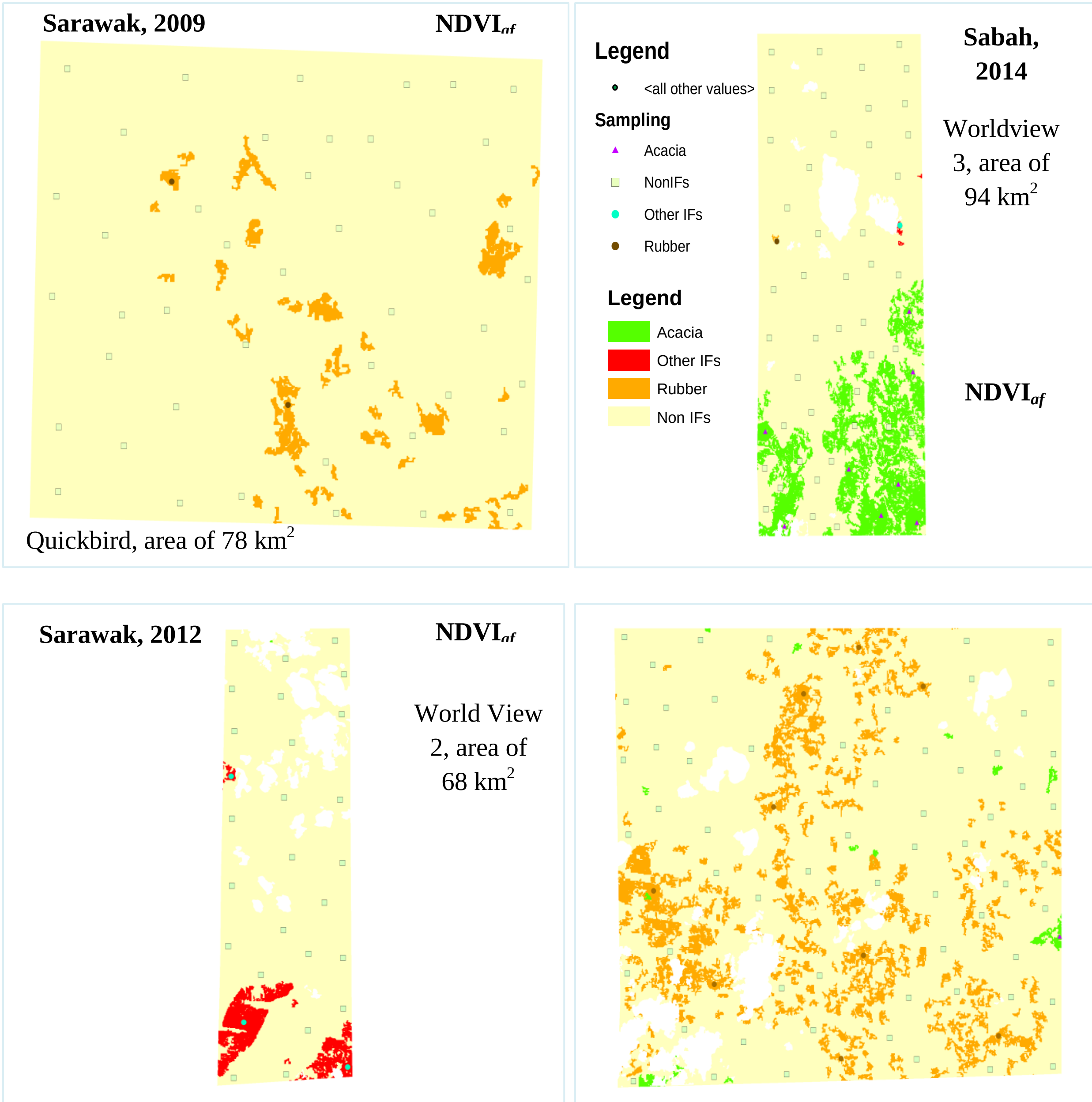


Figure A.21. The location and distribution of the samples in the EVI-based IF maps in Sarawak and Sabah.



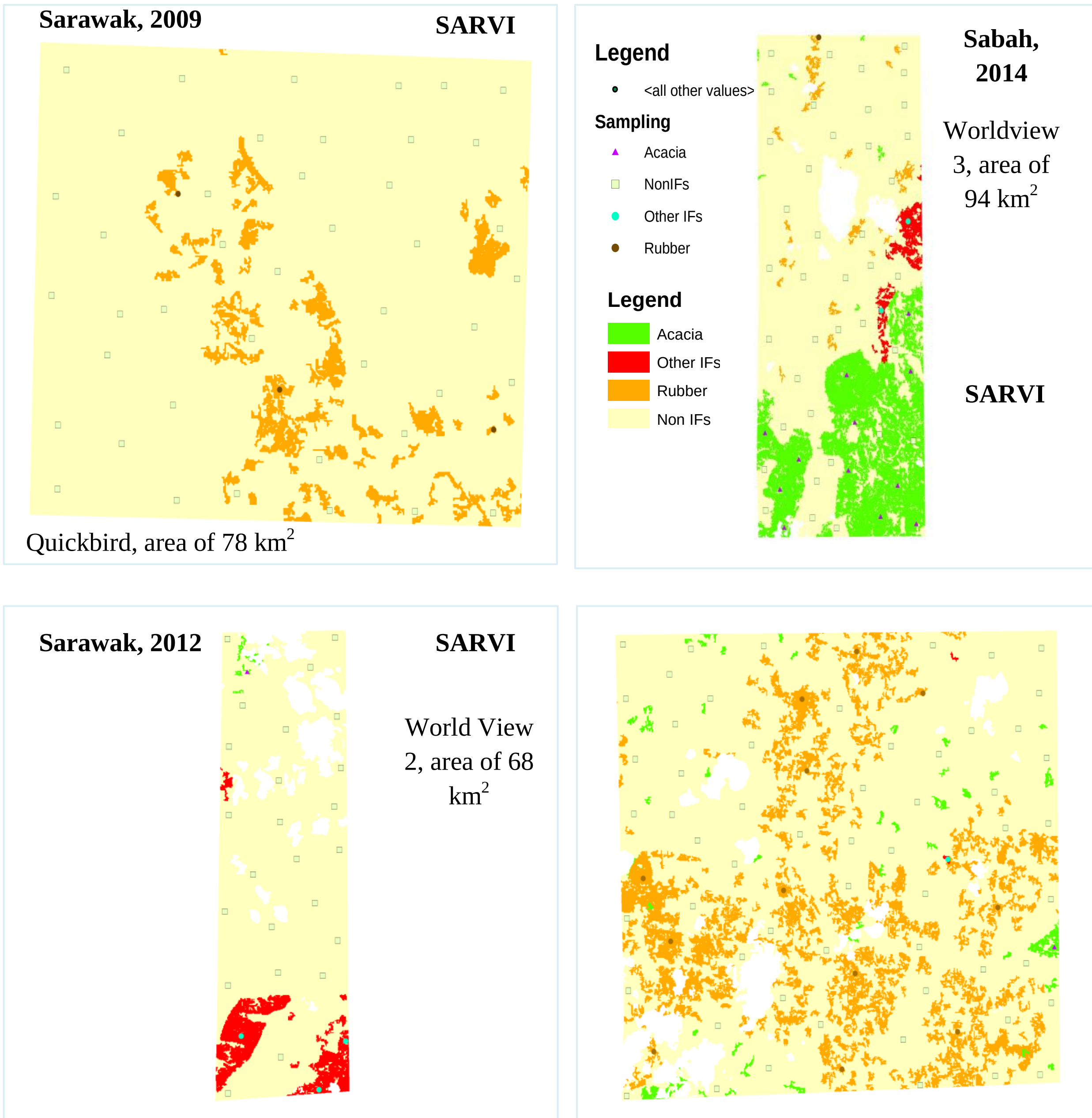
Sabah, 2014, World View 2, area of 166 km^2

Figure A.22. The location and distribution of the samples in the MSAVI$_{af}$-based IF maps in Sarawak and Sabah.



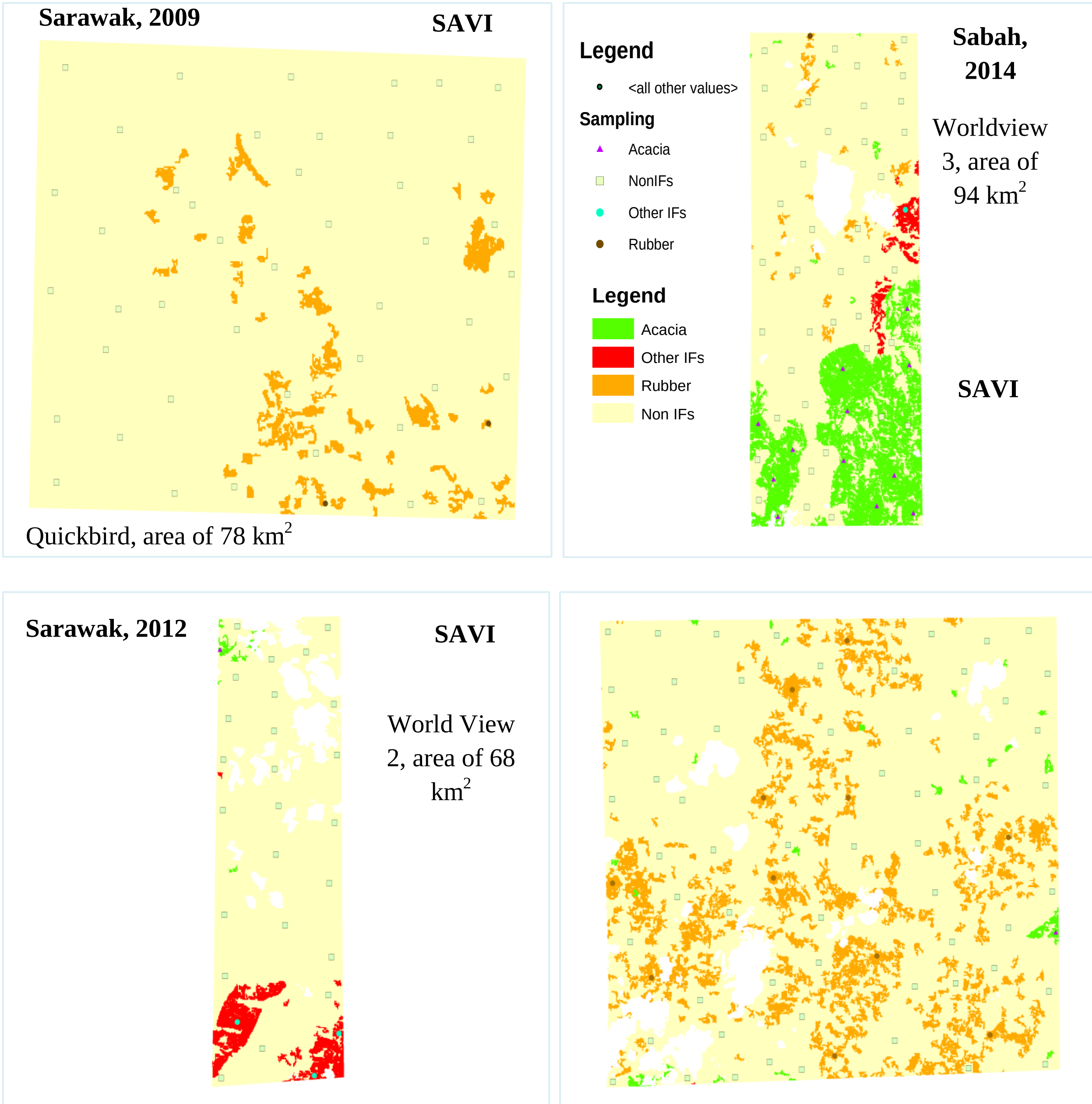
Sabah, 2014, World View 2, area of 166 km^2

Figure A.23. The location and distribution of the samples in the NDVI$_{af}$-based IF maps in Sarawak and Sabah.



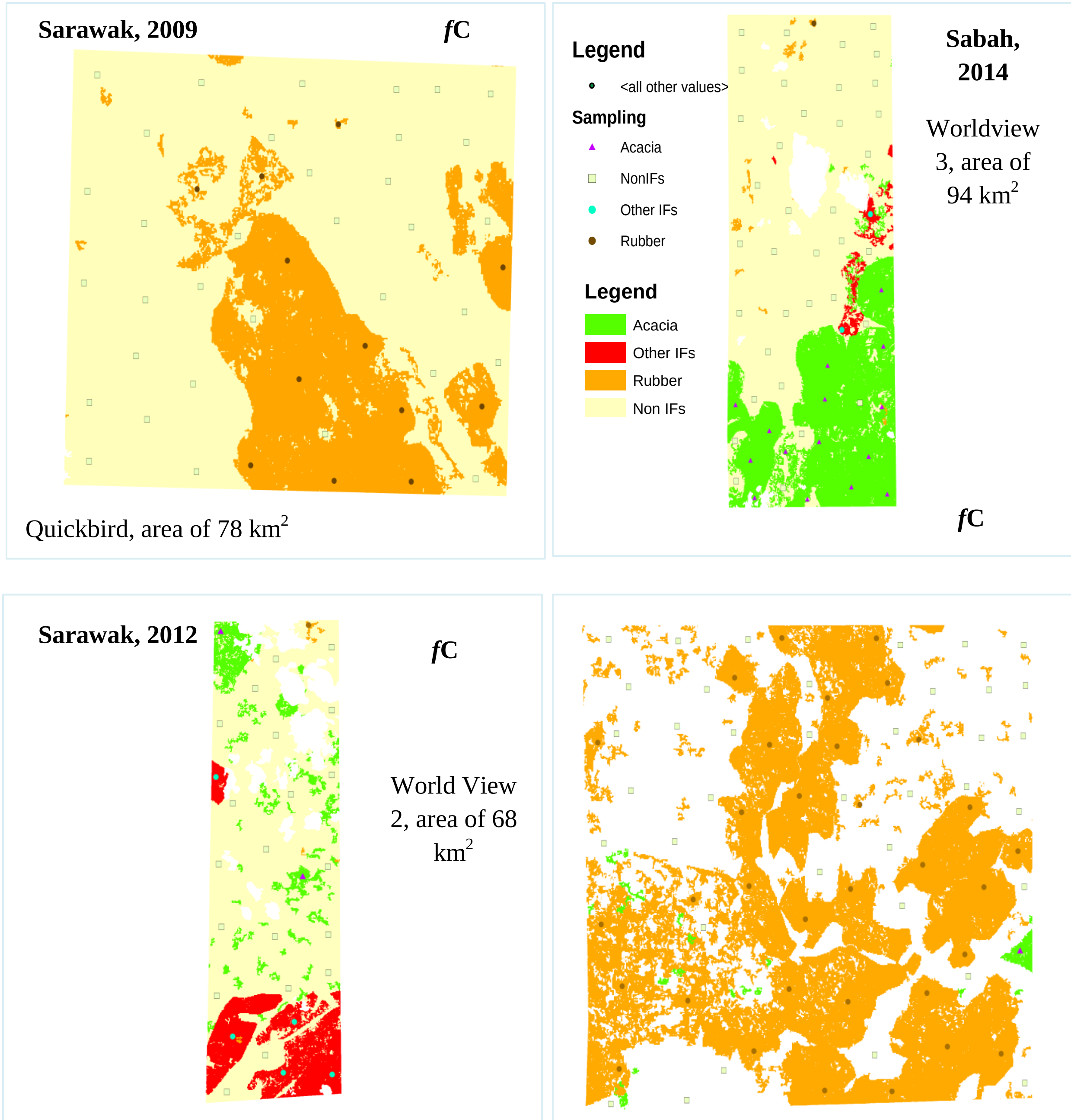
Sabah, 2014, World View 2, area of 166 km^2

Figure A.24. The location and distribution of the samples in the SARVI-based IF maps in Sarawak and Sabah



Sabah, 2014, World View 2, area of 166 km^2

Figure A.25. The location and distribution of the samples in the SAVI-based IF maps in Sarawak and Sabah



Sabah, 2014, Worldview 2, area of 166 km^2

Figure A.26. The location and distribution of the samples in the *f*C-based IF maps in Sarawak and Sabah.

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