Land Change History of Oil Palm Plantations in Northern Bengkulu Province, Sumatra Island, Reconstructed from Landsat Satellite Archives

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Land change history of oil palm plantations in northern Bengkulu Province, Sumatra Island, reconstructed from Landsat satellite archives

by

Atsushi Tomita

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Abstract

Land change history of oil palm plantations in northern Bengkulu Province, Sumatra Island, reconstructed from Landsat satellite archives

by

Atsushi Tomita

Adviser: Professor Ines Miyares

As of today, in the early twenty-first century, the Earth’s surface has been largely exploited by human activities, which will have long-term effects on land cover and earth systems. However, precise knowledge of changes of the Earth’s surface in many hotspots of land change is lacking. To fill this information gap, a method for monitoring land use changes is developed in this dissertation that uses multi-temporal satellite data to investigate the land conversion of oil palm plantation in tropical Asia, where oil palm plantations play a major role in drastic land changes and deforestation.

The booming oil palm plantation industry in tropical Asia is transforming both preexisting natural landscapes and landscapes affected by human activity into a wide-spread monoculture landscape. This drastic change will cause serious environmental degradation and have long-term impacts on local socioeconomics and land use. To grasp the process of land transformation, it is important to understand the roles of the local factors that are physically, economically and societally embedded at various spatial and temporal scales.
Because most oil palm plantations have developed in tropical Asia, this area is an ideal test site for investigating the outcomes of land use changes, such as the co-evolutionary development of land in favor of oil palm plantations, land use conflicts and environmental concerns. Consequently, a satellite remote sensing method was developed in this study that could provide reliable spatio-temporal knowledge of land use and land cover changes at fine scales.

The selected study area is located in the northern part of Bengkulu Province on Sumatra Island, where natural landscapes and landscapes affected by human activity have widely been transformed to oil palm plantations since the late 1980s, which coincides with the first available regular Landsat satellite observations. Although spectral information of the land surface has been continuously recorded by the Landsat satellites since the 1980s, the availability and quality of the data were reduced by cloud cover and other atmospheric disturbances. A comprehensive, cloud-free Landsat dataset was created from all the available Landsat data from 1988 to 2015. The pixel-based dataset was converted into a polygon-based dataset by applying the multi-temporal image segmentation method. The representation of the spectral information was also reduced to a single index of IB45 (Index derived from Band4 and Band5), the ratio of the near-infrared (Band 4) to mid-infrared (Band 5) bands, which was the most suitable index for detecting and tracking the transformation of land to oil palm plantation.
To extract (or segment) targeted land changes and land uses from a given temporal profile predicted by land change scenarios, an extended concept of segmentation was applied to develop a Land Change Detection Model (LCM). The segmented profiles were then evaluated by using bio-physical metrics in the Land Definition Model (LDM) to define the land uses. The two-tiered LC/LD Model could detect not only large-scale land changes caused by private companies but also small-scale changes caused by smallholders, which is supposedly the most uncertain factor for considering the future development of oil palm development at high spatio-temporal resolutions.

Relationships between local factors and two land change phenomena, the conversion to oil palm plantations and deforestation, have been investigated using quantitative assessments such as Logistic Regression analysis. The results indicated that large sized plantation enterprises were likely to directly convert untouched natural land and are consequently the main contributor to deforestation. In contrast, smallholders mainly converted preexisting farmland to oil palm plantations. The enterprise (private companies) and smallholder plantations had very different spatial and temporal characteristics. The enterprise plantations were densely and homogeneously packed within extensive and regular shaped boundaries. Because all the land conversion occurred during a short period, the plants all had similar ages. Few connections have been detected between local variables and the development of the enterprise plantations. Smallholder developments were very spatially and temporally inhomogeneous. Some local factors that represent the ‘proximity of development’, such as the pre-existence of nearby oil palm plantations and mills, were strongly correlated with smallholder development along with geographical factors.
The results underwrote the assumption that mills were the major local driver of oil palm development. In addition, the results strongly indicated that oil palm development had resulted in the construction of independent mills, whose locations and dates of construction were strongly connected to the profitability resulting from receiving a sufficient supply of fresh oil palm fruit bunches. Regardless of whether plantations were formed by enterprises or independently, most mills were constructed on land previously affected by humans as of the late 1980s, and all the initial development of enterprise plantations occurred in the forest. This result strongly implied that, given the locations of pristine forests, the cultivation of land and infrastructure development, such as mill construction, strongly favored oil palm development in the northern region of Bengkulu Province, which clearly contrasts the underdevelopment in the southern part of the province.
Preface

The idea of studying oil palm plantation development first occurred to me several years ago when I was working for Panthera, one of the world’s leading organizations for wildcat species conservation. I was fortunate to have first-hand experience in applying satellite remote sensing for tackling real environmental issues. From there, I stretched my interests and imagination to find my own research topic. At the same time, however, I was frustrated by the errors incurred by the limitation of single-date-based land classification, the conventional methodology that I had to adopt. First, two critical land uses, oil palm plantations and natural forest, were not well separated from each other because both of them consisted of trees with very similar spectral profiles. Second, specific spectral signatures that represented individual land uses were practically impossible to execute in some cases because their signatures changed according to seasonality, vegetation growth, and human interventions. For rice paddies in tropical Asia change every few months due to cycles of plant growth and harvest. In studying Central American jaguar corridors, I found grasslands in the western part of the Panama Straits oscillated between bare ground and vegetation cover based on the seasonality of precipitation. Oil palm trees take about 10 years to reach maturity, which results in various land cover classifications at different points of their growth. Satellite remote sensing had been plagued with such problems since its inception.

Another issue I encountered was that land use changed at alarming rates where deforestation and reduction of habitat were most serious. Land change in Sumatra Island was so intensive and conspicuous it felt almost impossible to conduct any land studies without considering land changes. Oil palm plantations, one of the primary causes of deforestation and one of the dominant forces for ongoing rural landscape change and economic development, was actually one of the most
appropriate subjects for advancing land change studies. Past deforestation studies had only treated human-side conditions as independent external forces. However, human-side conditions were actually inter-related, and it seemed to be imperative to build a human-domain land change model to better understand the phenomena.

I wished to determine if there was a better methodology that would handle multi-temporal satellite observations altogether rather than analyzing each observation separately? Such a method would naturally lead to comprehensive analysis of both land use and land change simultaneously with much more confidence. The idea was simple in theory but challenging to practice. Past studies seemed to have quite limited success with respect to robustness and universality of methods, spatial and temporal resolutions, overall accuracy, and applicability to real problems. Therefore, I needed to take my own steps forward to create new methodologies. Once the project got started, there was no turning back to old practices. It became endless because every time I made a new step another unique problem emerged. Naturally, I ended up redrawing entire procedures, which were totally redesigned and tuned up for monitoring land development of oil palm plantations. It required several years of solitary work, and being more like an inventor, this reminded me of my junior high school days making a pinhole camera, telescope, enlarger, and photo developing kit.

This research benefited from the most recent technological innovations and infrastructure development of open accessibility to information. All Landsat archives collected by the U.S. Geological Survey became available to the public in 2008 free of charge. Google-Earth and similar platforms had been accumulating increasing numbers of very high resolution satellite images. Vast
amounts of digitalized documents of various kinds, such as statistical data, public and private publications, archived maps and GIS data, social media sites, and international and local newspaper articles, were now available on the Internet. In some sense, this research could also be viewed as a pilot study of how information and knowledge bases can be collected and combined for environmental research.

I would like to express my deepest gratitude to the professors and program officers from the Department of Earth and Environmental Sciences at the Graduate Center-City University of New York and the Department of Geography at Hunter College who have guided and supported me during my doctoral research. I am most grateful to Prof. Ines Miyares for being my supervisor, accommodating the research topic and patiently overseeing the entire process of my doctoral processes. I would like to thank Prof. Sean Ahearn for insightful feedback especially on technical aspects of this research, particularly in data-processing and methodological developments. I am also grateful to Prof. Andrew Maroko for having kindly become a third committee member and for making keen and detailed appraisals on the contents of the research in light of my urgent situation. I am also grateful to Prof. James Biles for his consultation and support as Executive Officer of the program and for facilitating completion processes of my doctoral dissertation. I am also thankful to Swe Swe Htay for coordinating my defense, and to Thomas Walter for his long term help in updating software licenses.

I am also grateful for the people at Panthera: Dr. Hugh Robinson for several years’ supervision of my research and having offered necessary help even after I left Panthera; Dr. Joe Smith for
providing precious field knowledge of Sumatra and oil palm plantations, especially oil palm processing mills; and Dr. Luke Hunter for having allowed me to maintain access to the computer and software even after our contract expired. I was also fortunate that I became acquainted with Dr. Alan Rabinowitz in person and had a glimpse of his life.

I am also grateful to my family, relatives, and friends for their understanding and support through all these years especially since I came to New York and experienced September 11: Miho Fujimori, my wife, for her dedicated support since our marriage; Ayako Tomita, my mother, for her unchanged belief in me; Keiichi Tomita, my late father, for having taught me a sense of wonder; Takashi Tomita, my only brother, for being my older brother; Koaki Harris, my aunt, for watching over our lives in the U.S. from the opposite end of the continent; Dr. Tomonori Nagano, my friend since we studied at New York University, for his countless help, including having introduced the professional editing company for my dissertation; and the classmates of Keio University’s Physics Department for their donation after September 11.
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<td>Badan Informasi Geospasial; Geospatial Information Agency</td>
</tr>
<tr>
<td>BAKO</td>
<td>BAKOSURTANAL</td>
</tr>
<tr>
<td>BAKOSURTANAL</td>
<td>Badan Koordinasi Survei dan Pemetaan Nasional; National Coordinator for Survey and Mapping Agency (former name of BIG)</td>
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<tr>
<td>BPS</td>
<td>Statistics Indonesia (Badan Pusat Statistik Republik Indonesia)</td>
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<tr>
<td>FFB</td>
<td>Fresh Fruit Bunch of Oil Palm</td>
</tr>
<tr>
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<td>GEOgraphic-Object-Based Image Analysis</td>
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<td>IB45</td>
<td>Vegetation Index by ratio of B4 to B5</td>
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<td>IRI</td>
<td>The Infrared Index</td>
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<td>Kerinci-Seblat NP</td>
<td>Kerinci-Seblat National Park</td>
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<tr>
<td>Kerinci-Seblat TCL</td>
<td>Kerinci-Seblat Tiger Conservation Landscape</td>
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<tr>
<td>LCM</td>
<td>Land Change Detection Model</td>
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<tr>
<td>LDM</td>
<td>Land Definition Model</td>
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<tr>
<td>LC/LD Model</td>
<td>Land Change Detection and Land Definition Model</td>
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<tr>
<td>LULC</td>
<td>Land Use/Land Cover</td>
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<tr>
<td>LU-LCC</td>
<td>Land Use Continuation and Land Cover Change</td>
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<tr>
<td>MIR</td>
<td>Mid-infrared</td>
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<tr>
<td>NDVI</td>
<td>Normalized Vegetation Index</td>
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<tr>
<td>NIR</td>
<td>Near-infrared</td>
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<td>SAVI</td>
<td>Soil Adjusted Vegetation Index</td>
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<tr>
<td>TCL</td>
<td>Tiger Conservation Landscape</td>
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<td>TIR</td>
<td>Thermal-infrared</td>
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<tr>
<td>TSP</td>
<td>Temporal Segmentation Procedure</td>
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</table>
Commercial Mill  A mill not tied to any specific large-scale enterprise plantation. Commercial mills are operated purely for profit by buying out oil palm FFBs from smallholders and selling off the extracted palm oil.

Cultivated Area  Planted Area, Agricultural Land, Harvested Area

Forest  Forestlands, Pristine Forests

Independent Mill  Commercial Mill

Land Process  Occurrence of a given land status and changes of land status over time; the occurrence of land processes, including land cover type and phenological development

Large Plantation  Large-scale Oil Palm Plantation; Enterprise Oil Palm Plantation

Oil Palm Development  Expansion of Oil Palm Plantation; Development of Oil Palm Plantation

Other Crops  Other Cropland, Open Land, Land affected by Humans, Land affected by Human Intervention, Cropland

Plantation Mill  A mill tied to (a) specific large-scale enterprise plantation(s)

Productivity  Yield

Small Plantation  Small-scale Oil Palm Plantation; Smallholder Oil Palm Plantation
Chapter 1     Introduction

This study aimed to achieve the two following major goals: 1) to develop a satellite remote sensing method for studying changes in oil palm plantation land, and 2) to test land change hypotheses using an in-depth case study. A conceptual model of oil palm plantation development was schematized at the local to national and global scales (Figure 1.1). Hypotheses were made to investigate the local-scale conditions and interactions that would impact land changes related to oil palm. First, the components of the conceptual model, such as the drivers and modes of oil palm plantation

![Figure 1.1 Correlation diagram of oil palm development from the global to local scales. Local agents and phenomena that were investigated in this study are indicated by thick, solid blue arrows. The letters ‘A’ and ‘R’ indicate that the information was obtained from the literature (ancillary) or this study (remote sensing), respectively.](image-url)
development and the resulting land use changes are discussed. Second, appropriate remote sensing methods and the challenges and development of quantitative land change models are discussed.

Figure 1.2 Tropical Southeast Asia. The North Bengkulu study area is indicated by the red line. The Landsat observation area (path = 126, row = 62) is indicated by four slanted rectangles.
1.1 Research questions and hypotheses

Since land observation satellites began regularly operating in the late 1980s, almost the entire surface of the Earth has been under continuous observation, generating records with a spatial resolution of 30 m for multiple spectral bands. The physical state of the Earth’s surface has been seamlessly measured in time and space for the first time in history, and the resulting data can be utilized for various investigations. However, little progress has been achieved toward establishing general methods for actual applications due to uncertainties and errors that are inherent to conventional land classification methods relying on single-date images. This study aimed to improve the accuracy of land change/land use monitoring by explicitly including multi-temporal elements in the analysis.

Oil palm plantations in tropical Asia, which are responsible for one of the most conspicuous land change phenomena on the Earth’s surface, were chosen as a test case. The proposed method was developed to obtain local-scale information pertinent to understanding the development of oil palm based on the following hypotheses.

1.1.1 Hypotheses:

I. Large-scale oil palm plantation enterprises are major agents responsible for deforestation

II. Smallholders are major agents for the conversion of land from cropland to oil palm

III. Establishment of oil palm plantations is affected by the accessibility of an area to mills; thus, oil palm plantations are distributed near mills
IV. Establishment of large-scale enterprise plantations provides resources and infrastructure for the subsequent development of small-scale plantations by smallholders.

V. Smallholder plantations are more spatially and temporally dispersed than large-scale plantations and vary more in size, shape, location, distribution density, and time of conversion.
1.2 Development of oil palm plantations

1.2.1 Increased demands for foods

Currently, agricultural land occupies approximately 3.38 billion hectares, or 38% of the ice-free land on Earth, making it the most extensive type of land use on the planet, and is a dominant source of environmental degradation (Ramankutty et al. 2008, FAOSTAT 2011, IAASTD 2009). Increased demand for agricultural goods has resulted in intensified pressure on land development, which has resulted in the loss of natural land use and biodiversity in the presence of other environmental threats, such as climate change and the degradation of land and freshwater (Lambin et al. 2011, DeFries et al. 2010, IAASTD 2009). The world population more than doubled from 3.083 billion in 1961 to 6.998 billion in 2011, which is an increase of 127% (FAOSTAT 2014). Both increased productivity and the expansion of cultivated land have been used to meet the increasing demands for food. In addition, agricultural production has drastically increased to keep up with population growth. Total cereal production nearly tripled, from 803 to 2350 million tons (a 194% increase), during the same time period (FAOSTAT 2014), outpacing the population growth rate. Meanwhile, the area of cultivated land expanded from only 648 million ha to 707 million ha, which is a total addition of 59 million ha (an increase of only 9%), while the productivity (yield) drastically increased from 1.24 to 3.32 t/ha (an increase of approximately 168%) (FAOSTAT 2014). This result suggests that the major crop area in this temperate zone has already achieved maximum land development and that not much space is available for agricultural land expansion. Generally, although the area of land cultivated for major crops has remained relatively constant (Kongsager and Reenberg 2012 or GLP 2012), agricultural intensification thanks to technological advancements and improved agricultural practices have accounted for most of the yield increases that occurred in the past half century at the global scale (Foley et al 2011). In other words, agricultural intensification absorbed a
significant portion of land development pressure by increasing the production per unit area. A recent study suggests that production should be doubled in the coming decades to meet future demands, but there is no guarantee that this level of production can be achieved by relying solely on further agricultural intensification because land for agricultural expansion is scarce.

Figure 1.3 Global production of cereals between 1961 and 2011. Yield [t/ha] (upper-left), harvested area [million ha] (upper-right) and a dual plot of total production [million t] and Yield [t/ha] (lower). Source: FAOSTAT (2014).
1.2.2 Agricultural land expansion in tropical Asia

Although global food production has been increased by agricultural intensification without expanding the cultivated area, agricultural intensification has not been successful in some areas of the world or for some agricultural products. One of the most exceptional cases is Southeast Asia. During the past half century, the expansion rate of the agricultural area in Southeast Asia increased by approximately 50%, which exceeded the world average of approximately 10% (FAOSTAT 2014). The main driver of agricultural expansion in this region is globalization rather than conventional subsistence agriculture, which meets local needs (DeFries et al. 2010, Lambin et al. 2011). Market-oriented crops, such as sugar cane, oil palm and soybeans, have driven agricultural land expansion.

Figure 1.4 Trends in agricultural area according to region around the world. The statistics for Asia and Europe were combined because the borders between them might have been redrawn in the 1990s. Data source: FAOSTAT 2014
and have been exported to foreign countries rather than consumed domestically. Among these global agricultural commodities, oil palm has become the most significant boom crop in Southeast Asia (McCarthy 2010).

1.2.3 Global demand for palm oil and concentrated areas of production

Globalization enhances the interconnectedness between locations by mobilizing human and natural resources, information, innovative ideas and capital. Over the last 300 years, globalization has been progressing in terms of spatial separation between locations of production and consumption in search of economic benefits (Lambin et al., 2011). Major expansion of agricultural land and specialization of production already occurred in most temperate areas more than several decades ago where agricultural intensification has become the dominant contributor to production increases to compensate for the stagnation of land expansion. However, some areas in the tropical zone, such as tropical Asia and South and Central America, are currently experiencing major agricultural land expansion and economic optimization (FAOSTAT 2014, Foley et al. 2011). Most of this agricultural land expansion is occurring in forestland (Lambin et al. 2011) and is causing serious environmental damage and threatening the survivals of various endangered and threatened species.

Demands for palm oil have been increasing, with an average growth of 2.2 million tons a year and a global production increase of approximately 5.0 million tons each year over the last decade (USDA/FAS 2009, USDA/FAS 2011). The high demand for palm oil will continue to increase in the future because of its high cost performance, versatility, and potential use as a renewable energy source. Palm oil is currently the most efficient and cost-effective organic oil, with the largest amount
of extracted oil per unit land of any oil plant or seed. Importers of palm oil are spread out worldwide (Figure 1.5), and the top importers are 1. India, 2. China, 3. EU-27, and 4. Pakistan (Table 1.1; IndexMundi, accessed in March, 2014). In spite of the high demands, however, climatic conditions that favor oil palm growth and production are limited to in and around the equatorial zone (between 16°N and 16°S). Currently, major locations of production only exist in tropical Asia, especially on the equatorial islands and on Malay Peninsula (Figure 1.6). Indonesia and Malaysia currently produce 53% and 33%, respectively, of the global palm oil supply, with a combined production of more than 85% of the total global palm oil production in 2013 (Table 1.2; Index Mundi 2014). Although Malaysia was leading in terms of oil palm acreage until the mid-2000s, it had already reached its peak capacity for oil palm development due to limited land and land control policies, which resulted in Indonesia becoming the leader in oil palm acreage (Figure 1.7). Currently, Indonesia leads other countries in palm oil production by a wide margin. Although Indonesia already dominates the palm oil production industry, the country’s production continues to increasing at a high rate of approximately 9% annually and is the largest contributor to meeting the increasing supply needs in response to increasing global demands (Table 1.3).

![Figure 1.5 Palm Oil Imports by Country. (Image was taken from IndexMundi; Year of Estimate: 2013; Source: United States Department of Agriculture).](image)

<table>
<thead>
<tr>
<th>Rank</th>
<th>Country</th>
<th>Imports (1000 MT)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>India</td>
<td>9000</td>
</tr>
<tr>
<td>2</td>
<td>China</td>
<td>6600</td>
</tr>
<tr>
<td>3</td>
<td>EU-27</td>
<td>5800</td>
</tr>
<tr>
<td>4</td>
<td>Pakistan</td>
<td>2450</td>
</tr>
<tr>
<td>5</td>
<td>Other</td>
<td>1775</td>
</tr>
<tr>
<td>6</td>
<td>Malaysia</td>
<td>1675</td>
</tr>
<tr>
<td>7</td>
<td>United States</td>
<td>1225</td>
</tr>
<tr>
<td>8</td>
<td>Egypt</td>
<td>1225</td>
</tr>
<tr>
<td>9</td>
<td>Bangladesh</td>
<td>1100</td>
</tr>
<tr>
<td>10</td>
<td>Singapore</td>
<td>850</td>
</tr>
<tr>
<td>11</td>
<td>Iran, Islamic Republic</td>
<td>740</td>
</tr>
<tr>
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<td>Russian Federation</td>
<td>635</td>
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<tr>
<td>13</td>
<td>Viet Nam</td>
<td>620</td>
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<tr>
<td>14</td>
<td>Japan</td>
<td>570</td>
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<tr>
<td>15</td>
<td>Kenya</td>
<td>550</td>
</tr>
<tr>
<td>16</td>
<td>Myanmar</td>
<td>500</td>
</tr>
<tr>
<td>17</td>
<td>Nigeria</td>
<td>475</td>
</tr>
<tr>
<td>18</td>
<td>Turkey</td>
<td>450</td>
</tr>
<tr>
<td>19</td>
<td>Mexico</td>
<td>450</td>
</tr>
</tbody>
</table>

Table 1.1 Palm Oil Imports by Country (top 20) in 1000 MT. (Year of Estimate: 2013; Source: United States Department of Agriculture).
Table 1.2 Oil palm production by country. (Year of Estimate: 2013; Source: United States Department of Agriculture).

<table>
<thead>
<tr>
<th>Rank</th>
<th>Country</th>
<th>Production (1000 MT)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Indonesia</td>
<td>31,000.00</td>
</tr>
<tr>
<td>2</td>
<td>Malaysia</td>
<td>12,000.00</td>
</tr>
<tr>
<td>3</td>
<td>Thailand</td>
<td>2,100.00</td>
</tr>
<tr>
<td>4</td>
<td>Colombia</td>
<td>1,000.00</td>
</tr>
<tr>
<td>5</td>
<td>Nigeria</td>
<td>930</td>
</tr>
<tr>
<td>6</td>
<td>Papua New Guinea</td>
<td>630</td>
</tr>
<tr>
<td>7</td>
<td>Ecuador</td>
<td>565</td>
</tr>
<tr>
<td>8</td>
<td>Honduras</td>
<td>430</td>
</tr>
<tr>
<td>9</td>
<td>Côte d'Ivoire</td>
<td>400</td>
</tr>
<tr>
<td>10</td>
<td>Brazil</td>
<td>340</td>
</tr>
<tr>
<td>11</td>
<td>Costa Rica</td>
<td>270</td>
</tr>
<tr>
<td>12</td>
<td>Cameroon</td>
<td>270</td>
</tr>
<tr>
<td>13</td>
<td>Guatemala</td>
<td>265</td>
</tr>
<tr>
<td>14</td>
<td>Congo, The Democratic Republic of the</td>
<td>215</td>
</tr>
<tr>
<td>15</td>
<td>Ghana</td>
<td>130</td>
</tr>
<tr>
<td>16</td>
<td>Philippines</td>
<td>120</td>
</tr>
</tbody>
</table>

Figure 1.6 Oil palm production by country (Image was taken from IndexMundi; Year of Estimate: 2013; Source: United States Department of Agriculture).

Table 1.3 Oil palm production growth rate by country (Year of Estimate: 2013; Source: United States Department of Agriculture).

<table>
<thead>
<tr>
<th>Rank</th>
<th>Country</th>
<th>Production - Annual Growth Rate [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Philippines</td>
<td>11.1%</td>
</tr>
<tr>
<td>2</td>
<td>Indonesia</td>
<td>8.8%</td>
</tr>
<tr>
<td>3</td>
<td>Thailand</td>
<td>5.0%</td>
</tr>
<tr>
<td>4</td>
<td>Congo, The Democratic Republic Of The</td>
<td>4.9%</td>
</tr>
<tr>
<td>5</td>
<td>Paru</td>
<td>4.7%</td>
</tr>
<tr>
<td>6</td>
<td>Ecuador</td>
<td>4.6%</td>
</tr>
<tr>
<td>7</td>
<td>Benin</td>
<td>4.2%</td>
</tr>
<tr>
<td>8</td>
<td>Ghana</td>
<td>3.9%</td>
</tr>
<tr>
<td>9</td>
<td>Papua New Guinea</td>
<td>3.3%</td>
</tr>
<tr>
<td>10</td>
<td>Colombia</td>
<td>2.7%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-7.2%</td>
</tr>
<tr>
<td>11</td>
<td>Malaysia</td>
<td>-0.6%</td>
</tr>
</tbody>
</table>

Figure 1.7 Oil production in Indonesia and Malaysia. Source: FAS/USDA 2007.
1.2.4 Land consumption by oil palm plantations

Globally, the drastic increase of palm oil production in recent years has been achieved by both increases of productivity and the expansion of oil palm area (USDA/FAS 2009; FAOSTAT 2014). The total production of palm oil in 1961 was only 1.48 million tons, which increased by nearly 34 times to 50.20 million tons in 2011 (Figure 1.8); this rate of increase was ten times the increase of cereal production, which tripled during the same time period (Figure 1.3 Global production of cereals between 1961 and 2011; FAOSTAT 2014). During the same period, the total agricultural area of oil palm plantation expanded from 3.62 to 16.62 million ha (4.5 times), and the average oil palm yield increased from 0.41 to 2.87 t/ha (7 times) (Figure 1.8; FAOSTAT, ibid). When the time frame was narrowed down to the most recent three decades between the mid-1980s and 2011, during which regular satellite observation data were available, the global production increased by more than 5 times. This increase is broken down by yield increase (1.7 times) and the expansion of planted area (3.0 times), where the expansion of planted area played a more significant role than yield increase on productivity. The national production of palm oil in Indonesia was negligible until the mid-1980s (Figure 1.9). In contrast with the global trends, increased production was dominantly achieved in Indonesia by expanding the cultivated area. Production increased from approximately 2 million t to 25 million t, the cultivated area increased from 0.5 million ha to nearly 7 million ha, and the yield fluctuated between 3 and 4 t/ha between the mid-1980s and 2011.
Lastly, the time frame was narrowed down to the post-2000 period, during which visual interpretation of land use became possible thanks to the declassification of very high resolution satellite data for public and commercial use at the turn of the 20th Century. Between 2000 and 2011, both the production and harvested area of oil palm/palm oil tripled. Production increased from 7.0 to 21.45 million t, while the planted area increased from 2.01 to 6.08 million ha. Although yield data were not available, nominal yield was calculated from the ratio of production to planted area and denoted as yield or productivity. The yield remained stagnant during that period, with an increase of merely 1.4% (from 3.48 to 3.53 t/ha). Compared with the global statistics, this result strongly implies that the recent increase of palm oil production was largely achieved by land expansion, in contrast with the globally increasing trend of cereal production, which was mainly achieved by increasing production per unit area. Oil palm’s strong inclination to land expansion is even more enhanced in Indonesia, with statistics showing that approximately 50% of new land has been added for oil palm plantation worldwide in the past decade while 200% of new land has been added for oil palm plantation in Indonesia. Notably, a lag period of several years exists between oil palm planting and

![Figure 1.8 World palm oil production and yield (top) and production and area harvested (bottom) around the world. Source: FAOSTAT (2014).](image)

![Figure 1.9 Palm oil production in Indonesia. Production and yield (top) and production and planted area (bottom). Source: FAOSTAT (2014).](image)
full oil palm productivity. It is possible that a productivity increase would be observed after adjusting for this time factor. However, the general picture that the booming land expansion is sustaining the vast increase in production would hold considering the technical limitations of breeding and intensification.

1.2.5 Oil palm plantations in Indonesia

1.2.5.1 Domination of oil palm plantations and the emergence of stallholders

Though oil palm is the most productive source of biological oil, it exclusively favors tropical climates with hot temperatures and plenty of rainfall; thus, oil palm production is hindered in temperate areas. Preferably, the annual rainfall should be around 2,000 mm and evenly spread throughout the year for oil palm growth, which necessitates irrigation of plantations more than 10° from the equator. The humidity should be approximately 80-90%, and the temperature should be approximately 30°C (Kongsager and Reenberg 2012 or GLP 2012). Because countries in tropical Southeast Asia and Central America have favorable climate and soil conditions, they have become major producers of palm oil. Among these countries, Indonesia currently produced more than half (53%) of the total palm oil produced worldwide in 2013 (Index Mundi 2014).

Until the early 1970’s oil palm was only cultivated by large plantation companies. The areas with soils and climate that were favored for oil palm plantation in Indonesia were also favored for other plantations, such as coconut, rubber, cacao and other species. At that time, small farmers often chose to grow coconut and rubber trees rather than palm because those products were more marketable. However, after exceptionally high prices were recorded for palm oil in the international
market in 1974, the Indonesian government decided to encourage smallholders (small sized independent farmers) to grow oil palm by establishing the Nucleus Estate Scheme (NES), which included granting farmers access to mills. As oil palm has seen exponential growth in planted area and production, the growth and production of all other plantation crops have become relatively minor (Figure 1.10).

Although the private sector initially played major roles in oil palm plantation development, the growth rate of planted area in the smallholder sector has outnumbered that of the private sector since 2000 (Figure 1.11; USDA/FAS 2009). The area planted by smallholders increased by 2.0 million hectares between 2000 and 2009, while the area planted by the private sector increased by 1.1 million (USDA/FAS 2009). As of 2009, approximately 3.5 million hectares were cultivated by smallholders, comprising more than 40% of the total planted area (McCarthy 2010, USDA/FAS 2009). The growing influence of smallholders is one of the most conspicuous phenomena of Indonesian palm oil production, which will also impact future conservation issues and rural development.

Figure 1.10 Plantation crops in Indonesia. (top) Planted area [x 1000 ha], and (bottom) production [x1000 t]. Source: BPTS (2014).
It has been reported that actual smallholder development is highly uneven due to various factors (McCarthy 2010). Oil palm is a labor intensive and costly plantation crop to establish, manage and harvest. Many smallholders do not fulfill all requisite conditions to achieve the highest oil palm yields and quality comparable to large-scale private plantations. The current productivity of smallholders is approximately half of the productivity of the private sector, which indicates that the land use efficiency of smallholder plantations is surprisingly low. This problem could create a higher need for acquiring new land. Considering its growing impacts on land development, oil palm production and rural, smallholder and private sector land development should be considered in any present or future studies of oil palm.

From a socioeconomical viewpoint, Indonesian smallholders can be further broken down to three types: supported, registered independent, and unregistered independent farmers (Sunanti and Burgers 2013). Although information is available for the supported and registered independent smallholders in the form of public statistical data, information is not available for unregistered smallholders. The area cultivated by registered smallholders accounts for approximately 40% of the total palm oil plantation area, which is equal to the private sector nationally. In some areas, such as
the provinces of Riau and Bengkulu on Sumatra Island, smallholders occupy more than half of the total cultivated area.

1.2.5.2 Roles of mills in local scale development

The agrarian changes associated with the expansion of oil palm plantation are highly uneven and affected by various socioeconomic, political, and physical factors (McCarthy 2010), resulting in a highly inhomogeneous and spread-out pattern of smallholder development compared with private development. However, smallholder plantations did not develop at random locations either. A single definitive constraining factor limited oil palm plantation development and prevented oil palm plantations from existing too far from major human development areas. Oil palm plantation sites must be accessible to a mill, which is a modernly equipped palm oil processing plant capable of producing high quality palm oil for the international market. Thus, the plantation site must be located close enough to a mill to transport harvested fresh fruit bunches (FFB) of oil palm as quickly as possible, preferably within 24 hours of harvest, to assure the quality of the extracted crude palm oil (CPO) and to reduce transportation costs.

Sumatra Island has the highest concentration of mills. As of 2007, the IPOC (Indonesian Palm Oil Commission) indicated that 349 mills were located on Sumatra Island, which accounted for 83% of the mills nationally. The construction of a mill is a large investment. According to Indonesia Finance Today (2011), for instance, Cargill would invest 40 million U.S. dollars to build a new palm oil mill in addition to four pre-existing palm oil mills with a total capacity of 320 tons of FFB per hour. These mills are usually located in or near large private estates. However, these mills typically end up
processing FFB of oil palm supplied from both private and smallholder producers (USDA/FAS 2009). Because of the large investment and operation costs of a mill, it is assumed that the companies operating the mills are motivated to spur further oil palm development in the surrounding area until the total FFB supply reaches the maximum capacity of the mills. It was also reported that independent farmers (smallholders) are always willing to start oil palm plantations because oil palm is the most profitable and prospective cash crop in tropical Asia. Once accessibility to the mills is established, the entire surrounding area, including where many smallholders are located, will eventually be converted to oil palm plantations, irreversibly converting the rural landscape to widespread oil palm plantations.

Until 1995, oil palm plantations were developed under the government’s strong commitment model called the PIR-Trans scheme. In an effort to control oil palm expansion, mill construction had to correspond with oil palm plantations, including both estate and smallholder areas. Smallholders were supported by the government-owned estate called ‘the nucleus estate,’ which collected and processed the fruit bunches (McCarthy 2010; Susanti and Burgers 2013). This PIR-Trans scheme, however, was abandoned as the government shifted its policy toward encouraging private sector development in the early 1990s. The new model, called the ‘Primary Cooperative Credit for Members’ (Koperasi Kredit Primer untuk Anggota, or KKPA), assumed a more direct private-community partnership model in which plantation companies were supposed to take over the government’s roles of supporting smallholders. The East Asian economic crisis of 1997-1999, during which the price of oil palm tripled while the price of rubber remained stagnant, established the position of oil palm as the dominant global commodity over any other plantation crops among smallholders and independent growers (McCarthy 2010). These independent growers began
cultivating oil palm without direct assistance from the government or private companies and were not attached to specific mills (Susanti and Burgers 2013). These new comers, either registered or unregistered smallholders, in the oil palm plantation industry have been loosely controlled by the government and private sectors.

1.2.5.3 Agricultural land expansion and forest loss in tropical Asia

Forest loss, or deforestation, is one of the most serious environmental threats imposed by oil palm plantations. The tropical forests within the tropical region of Asia are home to various endangered and threatened animals and other life forms. However, tropical forest habitats are being lost at an alarming pace due to the land development driven by globalization. Between 1980 and 2000, more than three-quarters of new agricultural development in tropical areas occurred in forestland (Lambin et al. 2011). Although habitat loss occurred across all tropical regions worldwide between 1980 and

![Graph showing annual changes of forestland in Indonesia, Brazil, and worldwide (%). Source: FAO/FRA2010.](image)

Figure 1.12 Annual changes of forestland in Indonesia, Brazil, and worldwide (%). Source: FAO/FRA2010.
2000, South and Southeast Asia were the most severely affected (DeFries et al. 2005). According to Hansen et al. 2008, Indonesia accounted for 12.8% of the total loss of humid tropical forests between 2000 and 2005, following Brazil, which accounted for 47.8% of the total loss of humid tropical forests between 2000 and 2005. Indonesia lost approximately 40% of the forest that existed in 1950 by 2000 (Forest Watch Indonesia and Global Forest Watch 2002), which is a decrease from 162 to 98 million ha. Between 2000 and 2005, 3.5 million ha of forestland has been lost, which is an area larger than the country of Belgium (Fact Sheet Indonesia Forest as of May 2010). When comparing deforestation rates, Indonesia is currently losing forestland at a much faster pace than Brazil, which is also experiencing vast deforestation of the Amazonian rainforest (Figure 1.12). Though deforestation dramatically decreased from 2000 to 2005, the deforestation rate in Indonesia surged again from 2005 to 2010.

Possible major drivers of forest loss have been attributed to population growth due to transmigration policy, the development of subsistent agriculture, illegal logging, and the development of plantation agriculture, such as rubber, sugar cane, and oil-palm. Among these types of plantation agriculture, oil palm plantation has become the dominant type of irreversible land conversion on the island due to globalization (McCarthy 2010). As agricultural statistics show, drastic production increases have been achieved by expanding the area of cultivated land (Figure 1.9), mainly by converting pristine forestland into oil palm plantations. It has been proposed that large-scale oil palm plantations are more responsible than smallholders for direct forest loss (Lee et al. 2013, Gutiérrez-Vélez and DeFries 2013). Lee et al. (2013) claimed that nearly 90% of the deforestation that occurred between 2000 and 2010 was performed by private enterprises. On the other hand, some illegal plantation activities by unregistered smallholders in protected areas have
also been reported; however, these data have been omitted from public records and the magnitude of the environmental threat due to these illegal plantation activities remains undetermined. In addition to the direct conversion of pristine forestland to oil palm plantations, pre-existing cropland has been converted to oil palm plantations. The possible significance of the role of farmland conversion in alleviating the pressure for developing forestland has been one focus of conservation efforts. If the majority of forestland conversion is performed by large-scale enterprises, then the growing number of developments by smallholder should have mainly occurred on pre-existing cropland. Considering that the private and smallholder sectors are currently cultivating nearly equal areas of palm land, it is important to understand both land development modes (direct conversion of natural land to oil palm and indirect conversion of land affected by humans to oil palm land) to balance human wellbeing and conservation.
1.3 Remote sensing of land conversion to oil palm plantation

To investigate the key land processes of oil palm development, the use of multi-temporal satellite remote sensing was considered. The immediate goals of land monitoring were to test the land development hypothesis that the land development pathways between large-scale and smallholder oil palm plantations are different to provide crucial information for efficient land use in hot spots of oil palm development. The following key types of land conversion were considered: conversion to large-scale private oil palm plantations, conversion to small-scale smallholder oil palm plantations, the construction of mills, forest loss (deforestation), and the conversion of existing cropland to oil palm plantations.

Compared to large-scale enterprise estates, smallholder developments are more difficult to quantify because of their small size and greater dispersion in space and time. Satellite remote sensing data have only successful been used to detect smallholder plantations where intensive ground-truth data are available. However, investigations of both large-scale and smallholder plantations at high accuracy are indispensable because the most essential questions on how to balance human development and conservation are closely related to both of them.
1.3.1 Land observation by satellites

To investigate the entire process of land conversion to oil palm plantation, the analysis of the satellite image archive is the most effective and arguably the only practical available method for possibly detecting and tracking land uses and land changes seamlessly and accurately over time and space. Continuous land monitoring by satellite observations first became possible in the mid-1980s, corresponding with the launch of Landsat satellites and following the launch of the Landsat 5 satellite in 1984, which enabled data acquisition at a spatial resolution of 30 m for multiple wavelengths with a data acquisition period of approximately two weeks. The successful launch of Landsat 7 in 1999 after the failure of Landsat 6 in 1993 roughly doubled the likelihood of successful data acquisition, but mechanical problems of the sensor began resulting in observation gaps in 2003. After its successful launch, Landsat 8 took the place of Landsat 5 in mid-2014 and began providing seamless and full images again. As of 2016, the period of regular land observations spanned approximately 30 years, with observations divided nearly evenly between the periods before and after 2000. The quality and quantity of accumulated data have drastically improved since the turn of the 20th Century due to the launch of several new earth observation satellites and sensors, such as Terra/ASTER, Terra and Aqua/MODIS, and ALOS, and several new commercial satellites, such as IKONOS and OrbView, which are equipped with very high resolution sensors (less than one meter). These data enrich the pool of accumulated land data by providing more frequent observations with much finer resolutions. For areas like Indonesia, where reliable land use information with sufficient spatial resolution is not available to the public, satellite data are practically the only available source of information that can be used for studying land use changes.
However, several obstacles exist for extracting accurate land information from satellite data. One of the most basic problems encountered when extracting accurate information from satellite data is the spectral similarities of natural land and cropland covered by vegetation (for example, between natural forestland and tree plantations or between natural grasslands and cereal crop fields). These classification errors that result from spectral similarities are problematic for all years of satellite remote sensing data collection and are a major obstacle for practical applications. Although numerous land change studies have used satellite remote sensing, few of them have successfully overcome this problem by using remote sensing alone. Most studies relied on ancillary information, such as intensive ground truth information and personal knowledge of the area, to validate the results. This method has resulted in limited success because the classification results are only valid to the extent of the area covered by the ground-truth data. Thus, it is difficult to acquire any new information from satellite data beyond what has already been obtained through other means. Such circular-reasoning in this type of research has largely been unavoidable, and the wide and continuous spatial and temporal coverage of satellite data, one of the most unique advantageous aspects of satellite observations, has been underutilized for practical applications.

1.3.2 Remote sensing of oil palm development

Although the local drivers for oil palm development and the impacts of oil palm development on deforestation have been widely argued, not many quantitative assessments are available because insufficient amounts of reliable data exist. One major information gap is how the data vary spatially and temporally. Though the events of oil palm plantation development are recorded in the satellite data archive, current methods for extracting these events are underdeveloped and are insufficient for extracting reliable and accurate information from remote sensing data alone. Few remote sensing-
based studies have successfully investigated the development of smallholder oil palm plantations (Gutiérrez-Vélez and DeFries 2013; Lee et al. 2013). To compensate for land classification errors such as those that occur between oil palm plantations and natural vegetation, intensive ground-truth data, certain land conversion rules, and/or ALOS/PALSAR data, which are particularly useful for extracting oil palm plantations, have been used successfully. Although satellite-based observations of smallholder oil palm plantations in Sumatra Island were recently reported (Lee et al. 2013), the spatial resolution of these observations was 250 m (corresponding to an area of 6.25-ha), which was too coarse to properly investigate smallholder plantations, which have an average size of 3-ha, regardless of the use of appropriate classification procedures and accuracy assessments. Though oil palm plantation development and conservation is emerging as one of the most urgent issues in tropical Asia, current assessments (Lee et al. 2013; Koh et al. 2010) are still based on coarse estimates derived from agricultural statistics or unreliable coarse-scale land use maps.

While remote sensing of oil palm development has been hampered by several obstacles, deforestation has been widely investigated at various scales, from local to global scales, for which satellite remote sensing has played a central role. Because deforested areas are relatively easy to detect, various methodologies with various levels of sophistication, from manual to automated, have been developed, and even the most primitive approaches, such as on-screen digitizing or conventional one-shot image classification, have been widely used for delineating deforested areas. Even if the coverage area is limited to Sumatra Island, numerous remote sensing studies have been conducted, such as WWF (2008), Gaveau (2009a), Gaveau (2009b), and Linkie et al. (2008). Relationships between possible drivers and deforestation have also been investigated at various scales. The impacts of globalization and other global and regional effects have been investigated
using macroscopic variables such as urban population growth and agricultural trade (DeFries et al. 2012) and coffee prices in the international market (Gaveau 2009b), and local factors such as topographic features (e.g., slope and elevation, and the locations of rivers, roads, and settlements) and protection status (Gaveau 2009a; Gaveau 2009c; Linkie et al. 2008). However, the possible impacts of oil palm plantation development have not been or have rarely been considered in such analyses, despite the fact that oil palm plantation development has played a major role in deforestation in tropical Asia. Only Gaveau (2009a) regarded large oil palm plantation development as a possible driver of deforestation and found a weak association with deforestation, but this factor was omitted from the final most parsimonious model.

Gaveau (2009a) showed that that satellite image archives can provide local information at fine temporal and spatial scales that are sufficient for performing multivariate regression analysis to investigate local drivers of deforestation. However, land cover/land use changes between 1990 and 2006 were obtained from three forest maps obtained in 1990, 2000, and 2006 that were manually delineated by using on-screen digitization of Landsat images acquired in the three corresponding years. Only large-scale industrial plantations were digitized for oil palm plantations with the help of ancillary information and personal experience. By performing multivariate analysis of deforestation between 1990 and 2006, an oil palm development factor - travel time to the border of the industrial plantation in 1990 – showed a weak but significantly positive effect on deforestation. However, this factor was omitted in the most parsimonious model, which included the most important explanatory variable, combined travel time to roads and the forest edge, followed by protection status and slope. To the best of the author’s knowledge, further investigations of oil palm development have not been conducted previously. Linkie et al. 2008 investigated deforestation between 1995 and 2001/2002 in
the region of Kerinci-Seblat, which includes the North Bengkulu (NB) study area chosen for this study by using the on-screen digitizing method. These authors tested four explanatory factors of villages: logging concession, slope, distance to the border of Kerinci-Seblat National Park, and village area. These authors found that deforestation rates were predominantly related to slope and logging concession.

In this study, a new method was developed to extract land changes and land uses from a long-term, multi-temporal satellite observation dataset. The Land Change Detection and Land Definition (LC/LD) Model was used to obtain necessary outputs with reference to what had been learned from previous remote sensing studies and a wide range of previous results published in oil palm plantation and deforestation literature, such as the inclusion of PALSAR data, the spatio-temporal resolution of the outputs, the selection of local variables, and the format of the regression analysis. The actual procedures and algorithms for the LC/LD Model were, however, devised almost entirely from scratch. To compensate for lacking ground-truth data, a ground-truthing method of using multi-temporal Google Earth and Landsat images was devised.
Chapter 2  Study area

The tropical zone of Southeast Asia lies between approximately 10°N and 10°S of the equator, which is an area with warmth and humidity ideal for oil palm plantation (Figure 1.2). Indonesia became the largest producer of palm oil in 2008, surpassing Malaysia, the longstanding leading producer of palm oil before 2008. In the past, Sumatra Island was mainly covered by tropical forests and mangroves. However, vast agricultural development, mainly the opening up of pristine forestland, occurred on Sumatra Island with the initiation of the trans-migration program since the last quarter of the last century (WWF 2010). It is estimated that approximately half the natural forestland on Sumatra Island has been lost since the 1980s. In addition, Sumatra Island has also seen a long history of oil palm development and is the largest oil palm/palm oil producing island in Indonesia, accounting for approximately 70% of the total planted area in Indonesia. Although Sumatra Island is already the most developed oil palm plantation area in the country, palm plantation development on Sumatra Island has been highly uneven, and the plantation area is still drastically increasing.

To demonstrate the capability of satellite remote sensing for monitoring oil palm development, the study area was selected from the southwestern coastal area of the island, where the extent of land transformation to oil palm plantation has only been observed within the time-frame and spatial coverage of the Landsat observation dataset (Figure 2.1). The exact shape of the area, which spans a length of approximately 240 km and a width of approximately 40 km along the coast, was delineated based on the administrative borders of regencies and protected areas, topographic features, land use and Landsat scene coverage (Figure 2.2; Figure 2.3). The area, which is called the NB study area for convenience, covers a total area of approximately 8,916 km² (891,616 ha). NB is bordered to the
west by the Indian Ocean and to the east by the Barisan Mountains. Most of the area consists of coastal plains, but the steep Barisan Mountains stand on the eastern end of the island (Figure 2.3). The geographic extent of the island is between 101°00’ and 103°00’E and between 3°30’S and 1°00’N. The area is covered by a single Landsat scene with a Path and Row coverage of 126 and 62, respectively. Most of the area (82.8%) is occupied by Bengkulu Province, except for the northern tip of the area, which is occupied by South Pesisir (Pesisir Selatan), a regency of West Sumatra (Sumatera Barat) Province (Figure 2.4). The Mukomuko and NB (Bengkulu Utara) Regencies of Bengkulu Province occupy 356,071 and 369,916 [ha] respectively, which corresponds to 39.9 and 41.5% of the study area. The remaining 1.4% of the study area is occupied by the Tengha Regency of the same province (Table 2.1). Nearly half (45%) of the northern region of Bengkulu Province is included in the study area. A preliminary investigation of multi-temporal Landsat images confirmed that most of the areas in the NB study area have undergone land use changes, such as deforestation and oil palm development, except on the steep, hilly, eastern edge of the area where pristine forest has remained intact.

Most of the Mukomuko and Bengkulu Utara Regencies, except for the steep and high altitude regions of the Barisan Mountains that are not suitable for human development, are included in the study area. Therefore, agricultural statistics for those two regencies can be used to represent the subdivided portions of the study area. Plantation sectors such as coffee, rubber and palm oil form a major portion of the reginal economy in Bengkulu Province, accounting for approximately 40% of the Gross Regional Domestic Product (GRDP) in the area (Hablullah 2013). Among the different types of plantation crops, oil palm is dominant regarding its role in the economy and production and land use. The Mukomuko Regency is the area with the highest oil palm plantation density, with
nearly a quarter of the regency consisting of oil palm plantations (Table 2.2). Large-scale enterprises, which are denoted as large estate and smallholder palm plantations, occupy approximately 40% and 60%, respectively, of the total oil palm plantation area in the regency.

According to the agroclimatic zoning for oil palm cultivation, most of the NB study area is suitable for oil palm plantations, except for the high altitude hillsides at the eastern edge of the region, where the land is protected and consists of pristine forest. According to Adiwiganda et al. (1999), the southern part of Western Sumatra and the northern part of Bengkulu were classified as AS2-h1k1m1, indicating that they are moderately suitable for oil palm plantations, with more than 3,000 mm of rainfall, 1-2 dry months each year and a sunshine duration of 5.5-6.0 h/day (ranked 5th of the 11 agroclimatic zones in terms of suitability). Similar agroclimatic suitability classifications by Siregar et al. (1998) regarded altitudes greater than 200 m as a negative factor due to the lower temperatures found at these altitudes.

The NB study area is also located on the west side of Kerinci-Seblat National Park and shares its eastern portion with the park (Figure 2.5). Kerinci-Seblat National Park is one of three parks that constitute the Tropical Rainforest Heritage of Sumatra and was classified as a UNESCO World Heritage site in 2004. In addition, the Seblat Elephant Conservation Center in the Bengkulu Utara Regency is part of the Tropical Rainforest Heritage of Sumatra. These conservation areas are protected from development, and pristine forestland within the conservation areas is supposed to be kept intact. Kerinci-Seblat National Park is the largest national park in Sumatra, with an area of 13,300 km², and is home to various endangered and threatened flora and fauna, including Sumatran
tigers. However, the Mukomuko Regency was identified as one of the most active sites of illegal oil palm plantations in the park (FFIP 2008).

Figure 2.1 Location of the North Bengkulu study area on Sumatra Island. A single Landsat scene (path, row = 126, 62) covers the entire study area. The base map was provided by ESRI.
Figure 2.2 North Bengkulu study area. The protected area is indicated in dark green and bordered by white lines. The base map was provided by ESRI.
Figure 2.3 3D view of the NB study area from the north. The study area is bordered by white lines. The base image was obtained from a pseudo-color representation of a Landsat/TM image acquired in 2009, with (RGB) = (B5, B4, B3). Elevation data were obtained from ASTER GDEM data with a height enhancement of x5. Forest and thick vegetation are indicated in green. Bare and urban surfaces are indicated in red. Oil palm plantations are represented by bright green.
Figure 2.4 Subdivision of the North Bengkulu study area using administrative borders.
### Table 2.1 Subdivisions of the North Bengkulu study area by regency.

<table>
<thead>
<tr>
<th>ID</th>
<th>Regency name</th>
<th>Province</th>
<th>Area in the study area [ha]</th>
<th>Area in the study area [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Pesisir Selatan</td>
<td>Sumatera Barat</td>
<td>152,992</td>
<td>17.2</td>
</tr>
<tr>
<td>2</td>
<td>Mukomuko</td>
<td>Bengkulu</td>
<td>356,071</td>
<td>39.9</td>
</tr>
<tr>
<td>3</td>
<td>Bengkulu Utara</td>
<td>Bengkulu</td>
<td>369,916</td>
<td>41.5</td>
</tr>
<tr>
<td>4</td>
<td>Bengkulu Tengah</td>
<td>Bengkulu</td>
<td>12,638</td>
<td>1.4</td>
</tr>
<tr>
<td>1+2+3+4</td>
<td></td>
<td></td>
<td>891,616</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Table 2.2 Areas planted in oil palm in 2013 [ha]. Source: BPS

<table>
<thead>
<tr>
<th>Regency</th>
<th>Large Estate Crop [ha]</th>
<th>Smallholders [ha]</th>
<th>Total [ha]</th>
<th>smallholders [%]</th>
<th>Density [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mukomuko</td>
<td>40,431</td>
<td>56,216</td>
<td>96,647</td>
<td>58.2</td>
<td>23.9</td>
</tr>
<tr>
<td>Bengkulu Utara</td>
<td>20,878</td>
<td>35,235</td>
<td>56,113</td>
<td>62.8</td>
<td>13.0</td>
</tr>
<tr>
<td>Bengkulu Province</td>
<td>90,859</td>
<td>157,409</td>
<td>248,268</td>
<td>63.4</td>
<td>12.5</td>
</tr>
</tbody>
</table>
Figure 2.5 Kerinci-Seblat National Park and the North Bengkulu study area.
Chapter 3  Methods

Oil palm is currently the most productive crop, resulting in the highest oil yields per hectar of all known crops. Palm fruit consist of a central hard-shelled nut surrounded by an outer layer of pulp called the mesocarp, which contains normal palm oil. A palm kernel is located inside the nut and contains kernel oil. To obtain high quality oil for the international market, ripe fruits must be collected at the correct time and transported to a nearby plantation mill as soon as possible, preferably within 24 hours after harvest. The mills use modern equipment to extract both normal and kernel palm oil, which are referred to as crude palm oil (CPO) and kernel palm oil (KPO). Once CPO and KPO are obtained, they can be stored in tanks and then transported by truck and/or shipped by sea to refinery plants where value-added products can be produced from the crude oils. These refinery plants are not necessarily located near mills. Therefore, any post-mill processes are regarded as external factors that are outside the local-level analysis, which is the focus of this study. The local-level activities are practically equivalent to the agricultural phase of oil palm and palm oil production. Demand for oil palm is also external. These external factors were outside the scope of this study and omitted from the analysis (Figure 1.1 and Figure 3.1).

The primary goal of this study was to establish a method to obtain spatio-temporal information for oil palm development. Satellite data with a long-term observation period is the only first-hand data from which such information can be extracted. Landsat satellites have achieved long-term continuous coverage since the late 1980s, with a high observation frequency, wide spatial coverage, fine spatial resolution and spectral bands are suitable for land cover studies. An equally or more important aspect of these data is that they are open for public use. The Landsat data stored in the USGS data-archive can be accessed online by searching and can be download free of charge.
Computer algorithms for undermining changes in land and land information from the multi-temporal spectral data obtained from the Landsat data collection were developed from scratch. The LC/LD model was designed to detect key land changes and land uses that are essential for studying oil palm (Figure 3.1). The locations of mills were also detected in time and space by using a combination of Google Earth and the Landsat data collection. The plantation type (large enterprise or smallholder) was clarified by using a combination of ancillary information and satellite data.

Topography is another local factor that usually has a significant impact on agricultural development. Other local factors, such as neighborhood oil palm development and prior land use, were obtained from the results of the LC/LD Model. Elevation data were obtained from the Digital Elevation Model (DEM) data provided by public agencies, including the Space Shuttle’s Shuttle Radar Topography Mission (SRTM) and ASTER GDEM projects. To test the impacts of those local factors on oil palm development and deforestation, logistic regression analyses were performed.

![Conceptual model of the development of oil palm plantations at the local scale.](image)

**Figure 3.1** Conceptual model of the development of oil palm plantations at the local scale. Thick arrows indicate investigations conducted in this study using either ancillary information collection (AN) or satellite remote sensing (RS) data.
3.1 Monitoring the Earth’s surface by using satellite remote sensing

Since the invention of a prototype camera in the early 1800s, air-borne remote sensing, which aimed to take aerial photos, has been developed for use on various platforms, such as hot-air balloons, airships, kites, airplanes and helicopters and, most recently, remotely controlled drones. Space-borne remote sensing began in the late 1950s as soon as earth-orbiting artificial satellites became available. The first land observation satellite, Landsat 1, was launched by an agency affiliated with the U.S. government in 1972. The satellite was equipped with a digitized multi-spectral sensor system called a Multi-Spectral Scanner (MSS), which provided observations of Earth’s land surface in the visible and near-infrared (NIR) bands with a spatial resolution of less than 100 m. Next, a new era arrived in the mid-1980s with the launch of new Landsat satellites with highly capable Thematic Mapper (TM) sensors with finer spatial resolutions (30 m for visible-mid-infrared bands; 120 m for thermal-infrared bands) and more spectral bands (4 visible and NIR bands, 2 mid-infrared (MIR) bands, 1 thermal-infrared band, and 1 panchromatic visible band) with a data-acquisition period of 16 days (Table 3.1). Since the launch of Landsat 4 and 5, continual temporal and spatial coverage of the Earth at fine spatial and spectral resolutions has made space-borne Earth monitoring practical.

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Launch</th>
<th>End of service</th>
<th>Sensors</th>
<th>Resolution</th>
<th>Altitude [km]</th>
<th>Revisit interval [days]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat1</td>
<td>7/23/1972</td>
<td>1/6/1978</td>
<td>RBV/MSS</td>
<td>80/80</td>
<td>917</td>
<td>18</td>
</tr>
<tr>
<td>Landsat2</td>
<td>1/22/1975</td>
<td>2/25/1982</td>
<td>RBV/MSS</td>
<td>80/80</td>
<td>917</td>
<td>18</td>
</tr>
<tr>
<td>Landsat4</td>
<td>7/16/1982</td>
<td>12/14/1993</td>
<td>MSS/TM</td>
<td>80/30</td>
<td>705</td>
<td>16</td>
</tr>
<tr>
<td>Landsat5</td>
<td>5/1/1984</td>
<td>6/5/2013</td>
<td>MSS/TM</td>
<td>80/30</td>
<td>705</td>
<td>16</td>
</tr>
<tr>
<td>Landsat6</td>
<td>10/5/1993</td>
<td>10/5/1993</td>
<td>ETM</td>
<td>15(pan)/30(m)</td>
<td>705</td>
<td>16</td>
</tr>
<tr>
<td>Landsat7</td>
<td>4/15/1999</td>
<td></td>
<td>ETM+</td>
<td>15(pan)/30(m)</td>
<td>705</td>
<td>16</td>
</tr>
<tr>
<td>Landsat8</td>
<td>2/11/2013</td>
<td></td>
<td>OLI</td>
<td>15(pan)/30(m)</td>
<td>705</td>
<td>16</td>
</tr>
</tbody>
</table>

3.1.1 Landsat satellites and sensors

Two Landsat Thematic Mapper sensor systems were launched in 1982 and 1984 on Landsat 4 and 5, respectively. The TM/ETM+ sensor system was designed to obtain information from the Earth’s surface by using a set of a few spectral bands. TM sensors measure electromagnetic radiation at spectral bands ranging from the visible (VIS; Band 1, 2, 3 for blue, green, red, respectively; 0.45 – 0.69 µm) to NIR (Band 4; 0.76 – 0.90 µm), MIR (Band 5, 7; 1.55 – 1.75, 2.08 – 2.35 µm) and thermal infrared bands (TIR; Band 6; 10.40 – 12.50 µm) (Table 3.2). All Landsat sensors are passive sensors that do not project probe beams, such as active radar sensors. Visible and near- and MIR sensors are designed to observe reflected light from the Earth’s surface that is illuminated by solar irradiance, while thermal-infrared sensors measure thermal radiation that is emitted by the heat of the Earth’s surface.

The original form of solar radiation is electromagnetic radiation with wavelengths of 0.28 to 3.0 µm (Figure 3.2). Approximately half (49%) of this energy is converted by visible light, which has wavelengths ranging from 0.38 to 0.78 µm. In addition, an equal portion (49%)
of the energy is conveyed by infrared radiation, which has longer wavelengths of 0.78 to 3.0 μm. Approximately one two-billionth of the energy created by the sun reaches the top of Earth’s atmosphere, and only 47% of the top of the atmosphere radiation directly reaches the Earth’s surface due to atmospheric disturbances, such as reflection, scattering and absorption. The Earth’s

Figure 3.3 Spectral radiation and satellite sensors. (top) Blackbody radiation from the sun and earth. (middle) Categories of electromagnetic radiation. (bottom) Solar irradiation (%) on the Earth’s surface after atmospheric absorption. Landsat TM bands are indicated by red lines with band numbers. The ALOS PALSAR sensor in the microwave range is indicated by the dotted light blue line.
atmosphere has certain absorption regions in the spectrum due to various atmospheric components, such as H$_2$O, O$_2$, CO$_2$ and O$_3$ (Figure 3.2). The heated earth emits radiation with longer wavelengths and lower energy levels. The bandpass wavelengths of the sensors were chosen to avoid these atmospheric absorption regions (Table 3.2; Figure 3.3). Various objects and conditions, such as vegetation type and vigor, plant and soil moisture content, rock types, and cloud, snow and ice cover, can be monitored using the given TM spectral bands. A spatial resolution of 30 m is not fine enough to distinguish between individual crops or plants but is generally adequate for monitoring individual agricultural plots. In most oil palm plots in the study area, plants are grown in a regular 9-m equilateral triangular lattice pattern (Figure 3.4). The space around each plant is equivalent to two triangles or 70.146 m$^2$. Thus, each Landsat pixel observed in an oil palm plot includes $30 \times 30 = 900$ m$^2$/70.146 m$^2 = 12.83$ plants.

Figure 3.4 True-color image of oil palm from Google Earth showing the planting pattern of oil palm. Square areas are indicated by white lines and are equivalent to the size of a Landsat pixel of 30 m. Each side of the triangle has a width of 9 m, which is the distance between nearby oil palm plants. Each plant is given an individual area of 70.146 m$^2$. One Landsat pixel, which has an area of $30 \times 30 = 900$ m$^2$, includes $900/70.146 = 12.83$ oil palm plants.
3.1.2 Landsat data archive

A single Landsat scene, with path and row numbers of 126 and 62, respectively, from a Landsat global coverage system, covers the entire NB study area (Figure 2.1). All available Landsat scenes with path and row numbers of 126 and 62 from the mid-1980s to present (as of 2015) were searched for in the Historical Landsat Archive through the GLOVIS and ESPA websites (USGS Global Visualization Viewer 2016; Landsat Surface Reflectance High Level Data Products 2016) and downloaded from those websites for free. Though the 16-day revisit period of the Landsat satellites assures 22 to 23 image acquisitions each year, only a few clear images were found among the total 500+ images accumulated during the observation period. Another obstacle for image acquisition is the failure of Landsat 7’s ETM+ sensor, which occurred on May 31, 2003. Since the launch of Landsat 7 in 1999, most images under the Landsat mission were obtained by using Landsat 7. However, the Scan Line Corrector (SLC), which compensated for the forward motion of the Landsat 7, failed. This failure was permanent, and the ETM+ has never been restored to its fully functional state again. Without the operation of the SLC, which is called the ‘SLC-off’ state, the scanning line follows a zig-zag pattern as it moves forward against the Earth’s surface. Consequently, image gap strips are created that become thicker toward the edges of the scene.

![With SLC and Without SLC](http://landsat.usgs.gov/products_slcoffbackground.php)
From the preliminary investigation of the multi-temporal Landsat dataset and from the literature review, the land clearing and/or transplantation phase of oil palm is the most conspicuous and deterministic phenomenon for detecting oil palm plantations. To detect the initial stage of an oil palm plantation with no or little vegetation before the land is vegetated again with oil palm, a sufficient frequency of satellite observation is required. To maximize the chance of obtaining observations despite prevalent cloud cover and in the SLC-off state, the clearest images and the ‘cloud covered but partially observable and reasonably clear’ images were collected. Because the ESPA website provides value-added satellite data products with atmospheric correction and cloud-masks automatically generated for each image, the satellite data initially collected through GLOVIS were omitted from the final study. After pre-screening potentially useful data from the ESPA website, 99 Landsat scenes from 1988 through 2015 were selected and downloaded. After further screening for image quality and cloud elimination efficiency, 60 scenes were considered useful.

Figure 3.6 Prerequisites for land observations of oil palm plantations. According to the oil palm plantation planning chart and spectral changes observed from satellite observations, the required frequency of satellite observations and periods for the satellite data collection were determined.
3.1.3 Image pre-processing

Although the spectral bandwidths of Landsat’s optical sensors have been selected to avoid the major absorption wavelengths of gaseous particles in the atmosphere, such as O$_2$ and CO$_2$, the light reflected from the land can still be obscured by clouds and hazes in the atmosphere before it reaches the satellite sensor. The shaded area on the land that is created by a cloud shadow also irregularly disturbs the spectral information detected by the satellite sensors. To meet the severe prerequisites required to perform multi-temporal analysis of oil palm development using a limited number of observations, these disturbing factors must be avoided. The inclusion of noise signals in the input data could easily lead to the misinterpretation of land change phenomena and would make the multi-temporal approach impractical. Thus, it is imperative to thoroughly eliminate disturbed areas marred by clouds and cloud shadows while obtaining as much intact area as possible from all the images. The intact areas free of clouds and cloud shadows are still affected by the atmospheric conditions, which vary with the time of satellite data acquisition. The ESPS-USGS website is equipped with the LEDAPS software, which corrects for the effects on the satellite sensor counts (Masek et al., 2006). The Landsat Ecosystem Disturbance Adaptive Processing System software applies the Moderate Resolution Imaging Spectroradiometer (MODIS) atmospheric correction routine to the Landsat Level-1 data products. Atmospheric correction is performed by using the Second Simulation of a Satellite Signal in the Solar Spectrum (6S) radiative transfer model, which generates outputs such as surface reflectance and masks for clouds and cloud shadows. Corrections and mask generation are made based on the atmospheric conditions derived from the Landsat scene itself that is being processed (Huang et al. 2010). However, the mask files automatically generated by the LEDAPS
were not sufficiently accurate. Thus, an additional masking procedure to manually delineate the masked areas based on visual interpretations of the image had to be performed for almost all cloud-affected images (Figure 3.7).

Figure 3.7 Data processing flow chart: Distinguishing clouds and cloud shadows from Landsat data.
3.1.4 Advanced data pre-processing

3.1.4.1 Creating segmented polygons

Image segmentation by using multi-spectral data, which converts pixel-based raster images into polygon-based vector datasets by grouping the neighboring pixels that have similar spectral values, has served as a powerful remote sensing method since it was introduced. When properly segmented, the image becomes more intuitively recognizable than the original pixels. Within the segmented polygons, the spectra are homogenous and most likely represent a certain type of land cover that can be associated with a certain type of land use or degree of land development. Segmentation-based analysis generally reduces data size and simplifies the arduous land classification and post-classification processes, often improving the overall data-process efficiency compared to pixel-based approaches.

In this study, segmented polygons rather than pixels were used as the unit area for multi-temporal analysis. Several major reasons exist for adopting segmented polygons, including the following: 1) improving the readability of the data and the analysis results (Gao et al. 2006), 2) avoiding and/or mitigating classification errors due to half-pixel geo-referencing errors, 3) saving the consumption of computer memory and computation time, and 4) associating Landsat spectral information with thematic information, such as land use and year of land change. The most dire need for image segmentation arises from the third reason. The computer resource limitations and the set of software that was available in this study required the data size to be reduced by at least one tenth to be executable, and a desired reduction of one one-hundredth was needed to obtain results within a reasonable computation times. In this study, however, single-date image segmentation was not applicable because the land considered in the study had already gone through various land changes.
during the observation period and because any single-date image segmentation could properly delineate all the areas of those changes that occurred in time and space. Therefore, a method for combining all the conspicuous land phenomena observed during the observation period is needed. Theoretically, the most straightforward and desirable approach would be to simply combine all of the segmented polygons generated by single-date images (Figure 3.8). However, this approach is

Figure 3.8 Image segmentation for multi-temporal changes of land use. The conceptual pseudo-color multispectral images represent land use/land cover types such as forest (green), cleared/bare land (red), crops (thin green), growing oil palm (thin yellow), and mature oil palm (thick yellow). The number of dates is arbitrary.
impractical. The lines created for the same borders from different dates generally did not line up well each other and created numerous minute polygons due to this dislocation. These errors accumulated as more single-date segmentation layers were combined. Therefore, an alternative approach was taken. Using a single multi-temporal dataset generated by combining all the single-date images as an input for one-time image segmentation was observed to greatly mitigate the problem. Therefore, one-time image segmentation was performed for the multi-dates spectral layer (Figure 3.9).

Figure 3.9 Working procedure for image segmentation of multi-temporal data. The number of dates is arbitrary.
3.1.4.2 Selecting the vegetation index

Earth-observation satellites equipped with multispectral sensors can be used to observe target objects using different spectral bands. Various indices with combinations of two or more multispectral bands had been used to investigate various objects, such as vegetation, rocks, water and buildings. Landsat/TM and ETM+ sensors are equipped with sensors that cover a wide range of wavelengths, from visible to NIR to MIR, with the same spatial resolution of 30 m, which allows for choosing the most appropriate band combination for oil palm plantations rather than a general band combination. Among the available bands, three were considered: bands 3 and 4, which are the most widely used bands for vegetation, and band 5, which is regarded as the most essential band based on the literature and from preliminary investigations of the satellite dataset. The combinations of the considered bands were also limited to three normalized indices and one band ratio, namely NDVI, SAVI, IRI, and B4/B5, which had been regarded as the prospect candidate. These formulae are shown below.

\[
\begin{align*}
\text{NDVI} &= \frac{(\text{B}_4 - \text{B}_3)}{(\text{B}_4 + \text{B}_3)} \quad (3.1.1) \\
\text{SAVI} &= \frac{(1.0 + \rho) \times (\text{B}_4 - \text{B}_3)}{(\rho + \text{B}_4 + \text{B}_3)} , \\
&= \frac{(\text{B}_4 - \text{B}_3)}{(\text{B}_4 + \text{B}_3)}, \quad (3.1.2) \\
\text{where } \rho &= 0.5. \\
\text{IRI} &= \frac{(\text{B}_4 - \text{B}_5)}{(\text{B}_4 + \text{B}_5)} \quad (3.1.3) \\
\text{IB}_{45} &= \frac{\text{B}_4}{\text{B}_5} \quad (3.1.4)
\end{align*}
\]

B3: Red, B4: Near-infrared, B5: Mid-infrared
The Normalized Difference Vegetation Index (NDVI) is the most widely used vegetation index for general purposes, and the Soil Adjusted Vegetation Index (SAVI) is used to adjust for the effects of partial vegetation coverage. These conventional indices use two characteristic properties of vegetation, chlorophyll absorption in the red band and high reflection in the NIR band, and are thus generally considered appropriate for vegetation monitoring. On the other hand, from the preliminary investigation of the Landsat dataset, it was implied that the MIR band (Band 5 for TM/ETM+, Band 10 for Le8) would be more effective than a combination of the red and NIR bands for oil palm monitoring. The same implication was obtained by McMorrow (2001), who examined the association of various Landsat bands and their combinations with oil palm age. These authors found that an MIR band (TM/Band 5) and an infrared index (IRI) derived from MIR and NIR (TM/Band 4) had the highest correlation with palm age among the other bands and indices, such as the NDVI. IB45, and the ratio of Band 4 to Band 5 was devised in this study as a more convenient equivalent for IRI and adopted as a vegetation index for oil palm monitoring.

3.1.5 Building a land change detection and land change model

The conventional single-image land classification approach was abandoned for oil palm plantation because its inherent error was too large for the land change/land use investigations intended in this study. A better alternative that could analyze the total land processes, including all the previous and current land uses and their changes, was previously searched for. The new method was developed based on the land process scenarios that had been modeled from the literature and satellite observations themselves.
To facilitate the feed-back process between the satellite observations and land process scenario, the original pixel-based raster dataset was converted to a ‘pseudo-thematic’ polygon-based dataset by performing multi-temporal image segmentation.

3.1.5.1 Conceptual models of land uses

The conceptual model of the IB45 temporal profile for oil palm development was built based on observations of the spectral temporal profiles extracted from the segmented polygons and the literature regarding the land management of oil palm plantations (Corley et al. 2008) and oil palm plant growth stages (McMorrow 2001). The exposure of the bare surface due to clearing land and following the transplanting stage was assumed to continue for approximately 2 years (Malaysia Department of Irrigation 1986; McMorrow 2001), followed by the growth stage for approximately 8 to 10 years, and the mature stage approximately 10 years after transplantation, which lasted approximately 10 years. The senescent stage occurs approximately 20 years after transplantation. The changes of the IB45 value over time were associated with the growth stages of oil palm by using the literature knowledge mentioned above and the observed IB45 profiles, with the lowest IB45 values occurring at the land clearing and transplanting stage. As the oil palm plants grew, the IB45 value steadily increased during plant growth and remains relatively constant when the plants reached the maturity stage and then slowly decreases due to the degradation of the vegetation at the senescent stage.
Figure 3.10. The correspondence between the growth stages of oil palm and the IB45 values was further confirmed by the multi-temporal Google Earth images, from which the growth stage of each oil palm plant can be visually determined.

Other major types of land, such as pristine forest, natural regrowth, rice paddies, urban, water and bare land, were also modeled based on a preliminary investigation of the satellite data (Figure 3.11). Because pristine forest is constantly covered with fully grown vegetation, IB45 should maintain a constantly high values over time. In contrast, the urban surface, which is covered with artificial materials such as asphalt, concrete, pebbles, building and roof-top materials, should maintain low values. Natural regrowth shows a steep increase in the very low IB45 values after land clearing. Ordinary annual crops, such as rice, are observed one or more times a year in a repetitive zig-zag

Figure 3.11 Conceptual models of the IB45 profiles of the major types of land use: oil palm, forest, regrowth, seasonal/annual rice paddy, and urban/water body/bare (top to bottom). Oil palm and regrowth start from the initial stage after land clearing.
pattern that resembles rapid vegetation growth and a sudden decrease of the IB45 values due to harvest.

Two major land change patterns were assumed for oil palm plantations: direct conversion from pristine forest and direct conversion from cropland/human-affected land. The latter change was also assumed to originate from pristine-forest or some other natural land. Thus, the second conversion can also be regarded as ‘indirect’ conversion from natural land/pristine forest to oil palm plantation. When the initial conversion from natural land to cropland/human-affected land occurs during the satellite observation period, the third land transition path, which consisted of three land use phases, should be considered.
3.1.5.2 Building a computer model

The conceptual models of land use and land changes built from the literature and from preliminary investigations of the satellite data were interpreted using a computer algorithm to build a working computer model to process the time-series Landsat data. Based on the conceptual model structure, the computer model consisted of two sub-models, the Land Change Detection (LC) Model and the Land Definition (LD) Model.

The LD Model was developed as a semi-empirical model and assumes physical processes of land use and land surface changes and parameter values that should be determined using the trial-and-error approach. First, it was assumed that the timing of when land was converted to oil palm can be identified from the last observation of the bare surface. Thus, at the end of the land clearing/transplanting stage, the bare surface is not completely exposed. The threshold value that
was used to detect the bare surface was initially determined to be 1.0 by cross-referencing with the imageries and temporal dataset. The threshold value was later modified to accommodate scene-specific variable factors that would shift the optimum threshold value. The third lowest value in the given time series was adopted as a threshold value for that time series. Second, after the last bare surface was identified in the given time series, all neighboring observations that were also indicated as bare surface were grouped together. Then, all the observations below another threshold value, which was set to 2.0 to represent the upper value for the growing stage of oil palms and is supposed to last approximately 5 to 10 years following planting, were grouped together and combined with the bare surface observations to represent the entire growth stage (Figure 3.12). This grouping process is called ‘temporal segmentation,’ and the entire growth stage is represented by a growth stage segment. All the remaining observations after the growth period were also segmented as a mature stage segment.
To allow for an interactive and flexible model construction process, the computer model was coded using Microsoft Excel and the Visual Basic Application (VBA) script. The model was developed brick-by-brick and step-by-step by cross-referring with Google Earth fine images, Landsat temporal change images, and IB45 temporal profiles extracted from segmented polygons and by considering the feedback from test results. The current LCM consists of eight classes: 1. Oil Palm, 2. Forest, 3. Regrowth, 4. Urbanization, 5. Paddy, 6. Crops, 7. Others, and 8. Most Recent Change. Of these 8 classes, 6 are specific and 2 are not specific (7: Others and 8: Most Recent Change). The LULC-8 class is land that recently underwent a land surface change but the observation period is too short to define the resulting LULC.

In this analysis, a time series that showed land use/land cover changes within the two most recent years (between 2011 and 2013) was excluded from land classification and labeled as ‘Most Recent Change’ because it was considered to have an observation period that was too short for determining land uses/land changes from temporal trends. The ‘Others’ category includes everything that was not classified as a specific land category.

Figure 3.15 Temporal segmentation model (3). Multiple land conversions from forest to other intermediate land uses and to oil palm.
3.1.6 ALOS-2 and ALOS-PALSAR data for separating natural and human-affected vegetation

Advanced Land Observing Satellite (ALOS)’s Phased Array type L-band Synthetic Aperture Radar (PALSAR) data, which have been used in previous oil palm studies (Gutiérrez-Vélez and DeFries 2013; Lee et al. 2013), were used for cross-validation and to improve classification accuracy.

After the land uses of the segmented temporal profiles were defined by referencing them to the modelled biophysical metrics in the LCM, the ALOS-2 and ALOS/PALSAR data were used to improve the separation between the natural and human-affected vegetation. Global 25-m resolution PALSAR-2/PALSAR mosaic data provided by the Japanese agency Jaxa were available free of charge for 2007, 2008, 2009 and 2010. The original HH and HV modes were converted to a HH/HV ratio. The original digital counts (DN) of 25-m pixels were averaged by using segmented polygons and the ERDAS/IMAGINE’s Zonal Statistics tool. The threshold value for HH/HV to separate oil palm plantations from other LULCs was defined using a sensitivity analysis and the sample land use/land cover sites.

3.2 Obtaining information of possible local drivers

3.2.1 Mills

As previously pointed out by many authors, “Oil palms are cultivated in the regions where they grow well and where there are oil mills (UN/FAO 1977).” Thus, the existence of oil palm plant mills was regarded as an integral element for the development of oil palm plantations. All fresh oil palm fruit bunches which intended for the international market should be carried to an existing mill for
processing as soon as possible and ideally within 24 hours. The palm oil processing plants (mills) in the area have impact the transformation of the surrounding areas to oil palm plantations. In many urbanization studies, of the centrality of the business district has been assumed as a possible driver (Amin 2010; Huang et al. 2010). In palm oil production, fresh fruit bunches must be collected and transported to the mills as soon as possible. Therefore, it is plausible to assume that a strong centrality effect of mills on oil palm development exists, similar to the effect of CBDs (Central Business Districts) on urbanization.

Statistical reports such as the Directorate General of Estate Crops (2008), which reported the presence of 12 mills in Bengkulu Province, provided the number of facilities in the area but did not provide any further temporal or spatial information, which was crucial for testing our hypothesis. To obtain information regarding the locations and years of construction of the mills, visual investigations were performed by using Google Earth and Landsat satellite images. Exhaustive investigations of the mills were conducted using Google Earth fine images for the entire Sumatra Island to directly locate the mills on the computer display. The years of mill construction were determined by examining Landsat images over the study period. We visually compared the land use/land cover of the mill facilities between two neighboring observation times and successfully detected the land cover change from agricultural use to an artificial surface where the main plant and other peripheral facilities were built and the surrounding fields to the water bodies used as waste treatment ponds (Figure 4.47 to Figure 4.50).
3.2.2 Ancillary data collection

Most ancillary data were collected over the internet, including the BPS agricultural statistics, historical maps (such as topographical maps in the early 1950s), vegetation cover maps (as of early the 1980s), Bengkulu provincial government’s report of oil palm plantation and mills as of 200x, websites of oil palm estates or mills, RSPO environmental assessment report for Mukomuko oil palm plantations, and other qualitative and quantitative literature and data written in English, Indonesian, and Japanese. One digital data source, however, was obtained by contacting BAKOSURTANAL (Badan Koordinasi Survei dan Pemetaan Nasional: Coordinating Agency for Surveys and Mapping), an Indonesian government agency. The data request was made using the name Panthera. BAKOSURTANAL digital maps were directly used as a part of the constituents used for Logistic regression analysis. Topographic information was obtained from SRTM (Shuttle Radar Topography Mission) and ASTER’s GDEM websites. Ancillary information was also helping for making a list of mills and for delineating large enterprise plantations.

3.2.3 Land conversion to oil palm

Logistic regression models were constructed to determine the occurrence of oil palm plantations, which was denoted as DPP. Two models, one with and one without using BAKO data as independent variables, were constructed for each time period of the 7 periods from 1998 to 2012. The spatial coverage of this model is indicated in Figure 4.52, which covers the entire Area 1 and most of Area 2. The independent variables commonly adopted for all of the models are the density of the palm plantation (PDEN), distance to the nearest mill (ML), distance to the protected area (PA), and the topographic factors elevation (ELE) and slope (SLP). The variables included in the BAKO data were the distance to settlement (VIL), the distance to major roads (RDS), and the
distance to a river (RIV). The first term, PDEN, was adopted to represent ‘neighborhood effects,’ which are new oil palm development tends that are more likely to occur near the areas where oil palm plantations already exist. This term was included in the model because some circumstantial evidence existed that made this assumption plausible. Independent farmers or smallholders near large enterprise estates learned how to manage oil palm plantations by working as an employee at these estates (Hablullah 2013). Thus, the proximity and/or accessibility of areas with existing oil palm plantations is a crucial factor for new development. In many urbanization studies, neighborhood effects were assumed to occur and variables such as the distance to a built-up area (Amin 2010) and the density of the surrounding built-up cells were adopted (Huang et al. 2010). Density measures were considered more appropriate than distance in this study to better represent the total degree of development in the area.
Chapter 4    Results

4.1 Multi-temporal Landsat satellite dataset

All the Landsat satellites considered in this study (Landsat 4, 5, 7 and 8) observed the Earth’s surface with a repeat interval of 16 days, which is equivalent to approximately 365/16 = 22.8 scenes/year. However, the presence of cloud cover in the atmosphere limits where and when or how often the surface is observable. Other than natural phenomena, anthropogenic factors and mechanical failures, such as the failure of Landsat 7’s SLC and possibly inadequate and dispersed data acquisition and data storage systems, have also negatively impacted the efficiency of image collection, resulting in fewer observable areas in the image and a smaller number of pre-screened satellite images. All the Landsat data used in this study were acquired from the USGS Earth Resources Observation and Science (EROS) Center using an online search and download services tools, such as GLOVIS, EarthExplorer and ESPA (Science Processing Architecture). The EROS Center holds the single most geographically and temporally comprehensive collection of Landsat data in the world, with more than 6 million Landsat scenes (as of December 2015; LGAC 2016). These Landsat data were originally acquired and held locally at numerous International Ground Stations (IGS) around the world without duplication in the USGS archive until the Landsat Global Archive Consolidation (LGAC) effort began in 2010. According to the USGS-LGAC website, the number of Landsat 4-5 TM and MSS scenes available for the NB study area has reached between 500 and 800 (as of December 2015; Figure 4.1). However, the actual number of scenes accessible through these search and download service tools is much lower: (0 (MSS) + 2 (LND4/TM) + 259 (LND5/TM) = 268 scenes) (Table 4.1). Because MSS sensor systems lack MIR bands, only the TM sensor series (TM, ETM+ and OLI) is considered useful. It is apparent that the process of data consolidation has been underway because some Landsat 4–5/TM scenes have been recently added to the data list provided
by the search tools since the last search attempts. It is not clear how many, if any, Landsat 4–5/TM scenes will eventually become available through the USGS-LGAC archive. If data have been acquired by any international ground stations and are recoverable, the observation period can be extended back to as early as 1982/1983 by using Landsat 4/TM or to 1984/1985 by using Landsat 5/TM, which would enable the investigation of preexisting land use/land cover before oil palm plantations were introduced in the late 1980s. Only two Landsat 4/TM scenes are listed and they were not used because they contained heavy cloud cover. The original Landsat 5 scenes that were obtained previously (as of June 2015) were also incomplete and several years of data were missing. For example no observations were listed for the periods of 1984/1985- mid-1987, 1992-1993, 1995, 1998-1999, 2001-2005, and 2005-mid-2007. Consequently, no scenes could have been selected from Landsat 5/TM for those years (Figure 4.2 top). However, the most recent search for Landsat data (as of April 2016) produced 8 Landsat 5/TM, 2 Landsat 7/ETM+, and 7 Landsat 8/OLI scenes that were added to the selected scenes list. Although these scenes were not included in any further analyses of this study, the identification of these scenes indicates that amendments can include all years, except 2003, when the failure of Landsat 7’s SLC resulted in a period with no data acquisition. All Landsat 7 scenes collected since the failure in 2003 included only 78% of their pixels and had a data gap of 22% (http://landsat.usgs.gov/products_slcoffbackground.php). The observable area of each SLC-off scene was 65.4%, which was lower than SLC-on (76.8) and Landsat 5/TM (87.8) scenes by approximately 11 to 22%; however, the observable area for each scene varied widely between 40 and 100% (Table 4.1; Figure 4.2-top).

The number of available observations varied by site in the NB study area (Figure 4.3-top). The middle part of the scene, where SLC-off had the least effect on data acquisition, generally had more observations and decreased toward both ends. Other than the marginal areas of the study area where
clouds persisted due to high altitude and some over-masking areas, such as water bodies, more than or equal to 35 observations (approximately \( \frac{35}{28} \) years = 1.25 observations per year) were available for most (approximately 95%) of the study area. Overall, the average number of observations was 45.8, with approximately 1.64 observations per year.
Figure 4.1 Number of Landsat 4-5 Thematic Mapper (TM) and Multispectral Scanner (MSS) scenes received from International Ground Stations. Archived through the Landsat Global Archive Consolidation (LGAC) as of December, 2015. (Reprinted from http://landsat.usgs.gov/Landsat_Global_Archive_Consolidation.php: Accessed on 6/24/2016)

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Observation period</td>
<td>(July) 1972 – (January) 2013</td>
<td>(July) 1982 – December 1993 (10.5 years)</td>
<td>(March) 1984 – Nov. 2012 (28.4 years)</td>
<td>(April) 1999 – May 2003 (4.1 years)</td>
<td>(Late) 2003 – Present (as of June 2016)</td>
<td>(Late) 2003 – Present (as of June 2016)</td>
</tr>
<tr>
<td>Number of selected scenes</td>
<td>0</td>
<td>0</td>
<td>24 (+8)</td>
<td>10</td>
<td>26 (+2)</td>
<td>(+7)</td>
</tr>
<tr>
<td>%Average available area per scene</td>
<td>N/A</td>
<td>N/A</td>
<td>87.8%</td>
<td>76.8%</td>
<td>65.4%</td>
<td>N/A</td>
</tr>
<tr>
<td>Listed scenes /Potentially maximum scenes</td>
<td>7/ (more than 1 k +)</td>
<td>2/240 (0.8%)</td>
<td>259/648 (40.0%)</td>
<td>61/93 (65.3%)</td>
<td>206/285 (72.2%)</td>
<td>72/72 (100.0%)</td>
</tr>
<tr>
<td>Selected scenes/Listed scenes</td>
<td>N/A</td>
<td>0/2 (0%)</td>
<td>(24 + 8)/259 (12.4%)</td>
<td>10/61 (16.4%)</td>
<td>(26 + 2)/206 (13.6%)</td>
<td>7/72 (9.7%)</td>
</tr>
<tr>
<td>Average number of selected scenes per year</td>
<td>N/A</td>
<td>N/A</td>
<td>1.1 scenes/year</td>
<td>2.4 scenes/year</td>
<td>2.2 scenes/year</td>
<td>2.2 scenes/year</td>
</tr>
<tr>
<td>%Average area/Year</td>
<td>N/A</td>
<td>N/A</td>
<td>99%</td>
<td>187%</td>
<td>147%</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 4.1 Availability of Landsat scenes. The numbers in the parentheses in the row containing the %Average available area per scene indicate the number of scenes recently added to the selected scenes list (as of April 2016) since the last search was performed in June 2015. These new scenes were not included in further data analysis.
Figure 4.2 Availabilities of Landsat scenes. Acquisition dates and observable areas (top) and yearly histograms of satellite data acquisitions. Observation areas by year (middle) and the listed observations by year obtained using GLOVIS (bottom). The maximum observable areas in the middle figure show the maximum possible observable areas after combining the newly added scenes assuming that 100 % of the area would be available for those scenes.
Figure 4.3 The number of observations in the North Bengkulu study area (top) and its histogram (bottom). The red line indicates the average value of 45.8.
4.2 Sample sites

All the land-related validation data, such as land use/land cover, land change and land change years, were collected by visual interpretations of Google Earth images and spectral profiles extracted from multi-temporal Landsat data. This method was used for the following reasons. 1) On-site ground truth data collection was not available for this study. 2) Any comprehensive and quantitative data collection for the past land-related phenomena can only be performed using the satellite data. Since the second problem was actually innate to the nature of land changes in the study, it was inevitable that the sample data collection method should have been developed. Several conditions and restrictions were needed to obtain land cover and land change information. 1) Individual land use types were not evenly distributed in the study area. Actually, most types of land use were highly concentrated in specific areas. 2) Google Earth image(s) with very high spatial resolution of less than several tens of centimeters would be needed to recognize the spatial features that can be used to determine specific types of land use. 3) Regarding the collection of land change information, multiple Google Earth images should be available over the land change period. The most valid cases involve images that show the moment when a land change occurs, such as bare land right after land has been cleared. Consequently, the possible spatial-temporal windows for each type of land use become highly uneven. Thus, the conventional stratified random sampling method that has been widely adopted for ordinary land use/land cover studies was abandoned. These conditions and the restrictions for sample data collection varied among the target land uses/land covers. The uneven distribution of land use clearly restricts the locations of sample collection; for instance, pristine forests only existed in the protected mountains, and most rice paddies were found in the alluvial areas at the edge of the mountains. Regarding the detection of phenomena related to changes in land use by Google Earth, more frequent and longer observations are more likely to provide direct observations, from which the comprehensive information of land use/land cover, land change, and
year of change can be retrieved. Of the 891,606 [ha] of the studied area, 95% was covered by Google Earth fine images at least once as of April 2016, and the entire covered area was observed as recently as 2011 or later (Figure 4.5; Figure 4.6), which ensured that all the collected land use/land cover information were obtained within the past 5 years. Moreover, 52% of the entire study area was covered in 2015 or 2016 (as of April 2016), which means that approximately half of the area was observed within the past 1.5 years. The total observation area covered 424% of the NB study area, which means that one arbitrary location could expect to appear in an average of 4 Google Earth fine images. This number varied from 0 to 10 with location (Figure 4.6 - left figure). The chances of detecting land change phenomena would increase when the higher frequency of observations, the longer observation period (Figure 4.6 - both figures), and the right timing of land change occurrence are combined. The best location that satisfies these conditions for detecting land changes in oil palm plantations was the north-western part of the NB study area; thus, the sampling sites for oil palm were concentrated in this area. One other aspect of the methodological limitations of Google Earth sampling was that it could only cover for commercial satellites that were equipped with optical sensors with resolutions of tens of centimeters, which became available in 2000. The actual first year of observation varied by location, but no images were available before 2003 (Figure 4.7 - left). However, 45% (approximately half of the entire study area) had not been observed before 2011, and 5% of the study area had not been observed until April 2016. Therefore, for half of the study area, Google Earth image could not go back to more than 5 years or back beyond 2011. Thus, multi-temporal Landsat datasets are more capable of tracking targeted land-related phenomena thanks to the depth of the temporal component. Partly because of this limitation, the sample collection procedures used for oil palm were two-tiered: 1) finding areas with current land use and areas undergoing a change to oil palm production could be observed and 2) collecting other samples with more variations, especially older oil palm plants, for which the times of plantation establishment
could not be determined by Google Earth images. For other land uses, which also involved land changes, except for forest and paddy land uses, sample collection could not be performed as extensively as for oil palm because these types of land use exist in much smaller and confined areas. To compensate for their small collection sizes, the timing of land changes was confirmed by Google Earth and Landsat data. Because the Forest class only included pristine forest by definition, no land change was assumed. The paddy class was also assumed to have undergone no changes during the Landsat observation period according to the U.S. army’s geographical map produced in the mid-1940s. This map confirmed that the current major paddy areas had already existed in the mid-1940s. In total, approximately 300 sites with land change information, except for Forest and Paddy land change information, were obtained. These sites were referenced in several phases of this study, including the temporal spectral signatures collection for the bands and the vegetation index selection, model building and accuracy assessment of the model.
Table 4.2 Conditions and restrictions of the target land uses for sample data collection over time and space.

<table>
<thead>
<tr>
<th>No</th>
<th>Land use</th>
<th>Spatial distribution</th>
<th>Google-Earth spatial-temporal cover</th>
<th>Landuse data had to be used?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Oil Palm</td>
<td>Void area in the south-east of the plain</td>
<td>2 core collection areas; individual oil palm plants and their spatial arrangement patterns were distinguishable</td>
<td>No.</td>
</tr>
<tr>
<td>2</td>
<td>Forest</td>
<td>Primarily forest only remained in the protected mountains</td>
<td>Persistent clouds at the tops of the mountains; Some might be regrowth</td>
<td>No. Could be used to exclude regrowth &amp; most recent deforestation</td>
</tr>
<tr>
<td>3</td>
<td>Regrowth</td>
<td>Only confirmed on the land change sites</td>
<td>One single area too much variations</td>
<td>No.</td>
</tr>
<tr>
<td>4</td>
<td>Paddy</td>
<td>Concentrated in the alluvial areas at the edge of mountains</td>
<td>Circumstantial evidences such as plot shapes and harvest pattern are used; no direct evidences</td>
<td>Yes. Spectral signature of paddy was checked</td>
</tr>
<tr>
<td>5</td>
<td>Urban/Infra structure</td>
<td>No large site urban development; mills spread out in the study area</td>
<td>Unfinished; Some land changes into residence &amp; mills could be observed</td>
<td>Yes. Complete list of mills and their built years (1585 – Present)</td>
</tr>
<tr>
<td>6</td>
<td>Water Body (WTP)</td>
<td>Waste treatment ponds (WTP)</td>
<td>Unfinished/not enough samples</td>
<td>Yes. Same as Mills</td>
</tr>
<tr>
<td>7</td>
<td>Others</td>
<td>N/A</td>
<td>Vague criteria; any land covers that did not fall one of the specified land uses</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Figure 4.4 Sample sites restricted by the uneven distribution of land use/land cover. Landsat/TM acquired on 1989/151 (left) and 2015/127 (right) in pseudo-color: (R, G, B) = (B5, B4, B3).
Figure 4.5 Google Earth fine images of the observation areas by year. Percentages of the total area of the North Bengkulu study area. The observed study areas consist of all observations, including possible overlapping data for the same locations during the same year. The dotted line represents the two-period average moving window.

Figure 4.6 Sample sites and number of Google Earth observations in very high spatial resolution (left) figures and the years between the earliest and latest observations (right).
Figure 4.7 Sample sites and years of earliest (left) and most recent (right) Google Earth observations (left).

<table>
<thead>
<tr>
<th>Land Use Name</th>
<th>Number of Samples</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Land Use (LU)</td>
<td>LU only</td>
<td>LU &amp; Year of Land change</td>
</tr>
<tr>
<td>1 Oil Palm</td>
<td>228</td>
<td>149</td>
<td>79</td>
</tr>
<tr>
<td>2 Forest</td>
<td>93(b)</td>
<td>93</td>
<td>N/A</td>
</tr>
<tr>
<td>3 Regrowth</td>
<td>50</td>
<td>(16)</td>
<td>44</td>
</tr>
<tr>
<td>4 Paddy</td>
<td>61(c)</td>
<td>61</td>
<td>N/A</td>
</tr>
<tr>
<td>5 Urban/Infrastructure</td>
<td>15</td>
<td>(1)</td>
<td>14</td>
</tr>
<tr>
<td>6 Water Body</td>
<td>8</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>7 Others</td>
<td>101</td>
<td>(101)</td>
<td>0</td>
</tr>
<tr>
<td>Total (#7 excluded)</td>
<td>465(a)</td>
<td>220</td>
<td>145(o)</td>
</tr>
<tr>
<td>Total (#7 included)</td>
<td>566(f)</td>
<td>321</td>
<td>N/A</td>
</tr>
<tr>
<td>Most effective set of samples: (a)+(b)+(c)</td>
<td>299(d)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.3 Numbers of sample sites for target land uses.
4.3 Advanced data pre-processing

4.3.1 Advanced data pre-processing: multi-temporal segmentation

The segmentation tool equipped in ERDAS/IMAGINE 10 was used for multi-temporal image segmentation. The region growing algorithm, which has been widely used in major segmentation software, was also used in this tool. The tool requires the specification of several parameters and options, including edge detection (Yes/No), the minimum length of the edge, the minimal value difference between the neighboring segments, the variance factors within the same segment, the identification of narrow strips of one or two pixel widths (Yes/No), and the minimum size of the segments.

Ideally, the inclusion of more observation dates results in better segmentation results. However, most of the collected satellite images were significantly covered by clouds that could not be ignored during segmentation. To minimize the segmentation errors due to cloud cover, only the clearest images were used. Another limitation regarding the total number of images used for image segmentation occurred from the computation capacity for the tool, which limited the maximum amount of data performed. The best combination of the observation dates, multi-spectral inputs and the adjustment of segmentation parameters were sought out through a trial and error process. To maintain the traces of the land changes, satellite observations should be dated closely with each other before the traces become too blurred or lost. Another consideration for image selection is that the finest scale land change phenomena would have occurred during the most recent years. The land in the study area generally developed from primitive stages such as forest to more advanced phases such as agricultural fields, oil palm plantations and urban infrastructure over time. Taking these considerations into account, four clear and SLC-on images acquired in 2000, 2002, 2009, and 2013
were selected for segmentation. Four spectral inputs (Table 4.4) and two segmentation procedures were tested to obtain the best delineation results. The two segmentation procedures include the following: 1. Segmentations of single date images and merging all the segmentations on different observation dates. 2. One-time segmentation of multi-date stacked dataset. Segmentation procedure #1 was not immediately practical because the boundaries from different segmentations did not line up well with each other. An unavoidable half-pixel registration error between the images resulted in fluctuations of the boundaries and in numerous polygons created by the boundary fluctuations in the merged vector layer. Therefore, procedure #2, involving the one-time segmentation of the stack of the multi-temporal multispectral raster layers, was adopted, which generally resulted in the observation of a single line between the fluctuating boundaries.

The segmentation results from the inputs of the two vegetation indices were also good. However, the wide variation of the polygon size tended to be very large for monotonous areas of land cover, such as large enterprise oil palm plantations. This result would be desirable for land use classification purposes but not for the intra-land use analysis considered in this study. Good results were the

<table>
<thead>
<tr>
<th></th>
<th>Input data</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Original Band 5, 4, 3</td>
<td>Segmentation parameters needed to be adjusted. Segmentation results were not as good as the enhanced image input (#2).</td>
</tr>
<tr>
<td>2</td>
<td>Enhanced Band 5, 4, 3</td>
<td>Delineation was good by default. No further adjustment was needed.</td>
</tr>
<tr>
<td>3</td>
<td>Vegetation index (SAVI, NDVI)</td>
<td>Polygon size tend to be larger than multi-bands inputs. Segmented recognizable boundaries well. No adjustment was needed</td>
</tr>
</tbody>
</table>

Table 4.4 Spectral inputs for segmentation.
hardest to obtain from the Band 5, 4, and 3 (MIR, NIR, and RED) inputs because the number of control variables for segmentation was too large and no clear guidance was given for finding optimal values. Besides, more inherent problems potentially existed that prevented proper segmentation. It was difficult to improve segmentation performance by only focusing on relevant land processes. Certain statistics existed that were used for the parameter values at the beginning of segmentation. However, these statistical parameters were unavoidably affected by some irrelevant land and atmospheric conditions, such as clouds, and were consequently not useful. Among the four types of multi-spectral inputs, enhanced images of Band 5, 4, and 3 (MIR, NIR, and RED) gave the most appropriate and cost-effective results. The original (Band5, 4, 3) = (R, G, B) pseudo-color image was

![Figure 4.8 Creating multi-temporal segmented boundaries. Four Landsat images were acquired between 2000 and 2013.](image)

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converted by commercial image-processing software to only emphasize the land processes of interest. This conversion was conducted by combining multiple image modifications of image intensities and color saturation. The greatest merit of this approach was that it could substitute for an arduous and counter-intuitive trial and error search for an optimal parameter set for segmentation with image enhancement, which could be readily available and intuitively assessed. Because only the land processes of interest were magnified and because other factors, such as clouds, were suppressed in the output values, no additional adjustments were needed for segmentation. The segmented polygons covered an average area of 2.6 ha and a median area of 1.2 ha. Thus, half of the polygons have an area of 1.2 ha or less or consist of 1.2 ha/0.09 ha = 13.3 or more pixels, which significantly reduced the total executable computation load while maintaining the spatial resolution at a sufficiently low level to detect stallholder oil palm plantations, which have an average area of 3 ha. The delineation performance was also considered satisfactory or better.
4.3.2 Advanced data pre-processing: pseudo-color and partial pseudo-color representations of time-series spectral data collection

Both the conceptual and computer model building processes included much consultation with the time-series Landsat data itself. A preliminary land change assessment was performed by visually interpreting the pseudo-color Landsat images displayed on screen and flipped over time, which provided an intuitive grasp of land change phenomena over a long period, such as the recession of pristine forest and the emergence of oil palm plantation.

After major land changes and land uses were identified by visual interpretation of both time-series Landsat data and Google Earth superfine images, sample sites were selected and time-series of spectral data were extracted from those sites. The pseudo-colored representation of the spectral information from the sampling sites were also very useful for understanding and modeling key land processes. After various representations were tried, an image enhancement technique aimed at maximizing the recognition capability of chromatic differences was used. This method maximizes the displayed brightness while the color ratio of Red:Green:Blue = B5:B4:B3 is held constant by linearly increasing the RGB values (Figure 4.9).
Another pseudo-color representation using only the combination of Red and Green (R-G) colors was also devised to obtain an intuitive understanding of IB45 temporal profiles. One of the merits of using IB45 values over other vegetation indices is that the progress of development for oil palm plantations should be traceable as the value increases (from bare land to the plant seedling, growth and mature stages).

The combination of R-G color was adjusted to represent the land development similarly to the pseudo-color B543 representation, beginning with red for bare land and changing to yellow and then green with vegetation growth (Figure 4.10 to Figure 4.13). Color enhancement by maximizing the display brightness (Figure 4.12), which is the same technique used for pseudo-color B543 and was applied to better represent

\[ Y = \beta \cdot IB45 + \gamma \]
\[ \beta = -0.47 \]
\[ \gamma = 1.2 \]
\[ G = 1 - Y \]
\[ \text{If } Y < 0 \text{ then } Y = 0 \]
\[ \text{If } Y > 1 \text{ then } Y = 1 \]

Figure 4.10 Characteristic function of the R-G color representation.

\[
R = Y \cdot 255 \\
G = (1 - Y) \cdot 255
\]

Figure 4.11 R-G color representation of IB45.

If \( R \geq G \) then 
\[ a = 255/R \]
\[ R = 255; G = a \cdot G \]

If \( R < G \) then 
\[ a = 255/G \]
\[ R = a \cdot R; G = 255 \]

Figure 4.12 Enhanced R-G color representation of IB45.

If \( Y = 0 \) then
\[ nG = 255 \cdot (1 - (IB45 - 2.8) / IB45) \]

Figure 4.13 Shading for high IB45.
intermediate stages. Shading effects were also added to the higher values, which were supposed to indicate mature trees, including fully grown oil palm or natural forests, for better visual interpretation (Figure 4.13).

<table>
<thead>
<tr>
<th>LU#</th>
<th>Land use name</th>
<th>Number of samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Oil Palm</td>
<td>79</td>
</tr>
<tr>
<td>2</td>
<td>Forest</td>
<td>61</td>
</tr>
<tr>
<td>3</td>
<td>Regrowth</td>
<td>44</td>
</tr>
<tr>
<td>4</td>
<td>Urban (Mill)</td>
<td>14</td>
</tr>
<tr>
<td>5</td>
<td>Paddy</td>
<td>61</td>
</tr>
<tr>
<td>6</td>
<td>Water body (Waste Treatment Pond)</td>
<td>8</td>
</tr>
</tbody>
</table>

Table 4.5 Sample sites used for pseudo-color spectral-temporal representations.
Figure 4.14 Enhanced pseudo-color spectral-temporal representation of oil palm land history. Column: year from 1988 to 2015, Rows: sample sites (79). (RGB) = (B5, B4, B3). The years when conversion to oil palm occurred are noted by black-outlined rectangles.
Figure 4.15 Enhanced pseudo-color spectral-temporal representation of forest land history. Column: year from 1988 to 2015, Rows: sample sites (93). (RGB) = (B5, B4, B3).

Figure 4.16 Enhanced pseudo-color spectral-temporal representation of regrowth land history. Column: years from 1988 to 2015, Rows: sample sites (44). (RGB) = (B5, B4, B3). The years when land clearing occurred are indicated by black-outlined rectangles.
Figure 4.17 Enhanced pseudo-color spectral-temporal representation of waste treatment pond history. Column: years from 1988 to 2015, Rows: sample sites (8). (RGB) = (B5, B4, B3). Conversion years are indicated by black-outlined rectangles.

Figure 4.18 Enhanced pseudo-color spectral-temporal representation of the history of mill land. Column: years from 1988 to 2015, Rows: sample sites (14). (RGB) = (B5, B4, B3). Conversion years are indicated by black-outlined rectangles.

Figure 4.19 Enhanced pseudo-color spectral-temporal representations of paddy land history. Column: years from 1988 to 2015, Rows: sample sites (61). (RGB) = (B5, B4, B3).
Figure 4.20 Oil palm land history by IB45 enhanced R-G color representation. Column: years from 1988 to 2015, Rows: sample sites (79). The years of conversion to oil palm are indicated by black-outlined rectangles.
Figure 4.21 Forest land history by IB45 enhanced R-G color representation. Column: years from 1988 to 2015, Rows: sample sites (93).

Figure 4.22 Regrowth land history by IB45 enhanced R-G color representation. Column: years from 1988 to 2015, Rows: sample sites (44). Conversion to oil palm years are indicated by black-outlined rectangles.
Figure 4.23 Urban land history by IB45 enhanced R-G color representation. Column: years from 1988 to 2015, Rows: sample sites (14).

Figure 4.24 Waterbody land history by IB45 enhanced R-G color representation. Column: years from 1988 to 2015, Rows: sample sites (8).

Figure 4.25 Paddy land history by IB45 enhanced R-G color representation. Column: years from 1988 to 2015, Rows: sample sites (61).
4.3.3 Determining the vegetation index

The principal criteria for choosing appropriate vegetation indexes is the ability to detect oil palm land processes such as land clearing and the phenological development of oil palm plants. From this aspect, the NDVI is the least effective index among the four candidates, the NDVI, SAVI, IRI, and IB45; however, the NDVI is generally the most widely used vegetation index in remote sensing. The SAVI is generally as good as the IRI and IB45, except for one point, the values of the SAVI for the forest class are significantly lower than those for mature oil palm and natural regrowth, which make the SAVI less favorable than the other two indices. The remaining two indices, the IRI and SAVI, which used NIR and MIR bands, were practically equally effective for detecting oil palm land processes. However, IB45 was selected because the simple band ratio was better for understanding the relationships between the original band values and land processes.

4.3.3.1 Assessment of multispectral reflectance

This study focused on investigating the land processes of oil palm plantations, which include any possible types of land cover that exist where oil palm plantations occur. A desirable vegetation index should be capable of detecting these types of land cover, such as bare land and growing and mature oil palm and should separate pre-plantation periods from the entire observation period by temporal profile analysis. Several major land uses other than oil palm, such as forestland, other cropland and paddy land, also require land process scenarios for the Land Change Detection Model (LCM) and should be used to investigate land use transitions based on LCM & Land Definition Model (LDM) results. The multispectral spectra of oil palm and some other vegetation and land surface types were collected from the literature (Figure 4.26). The real values obtained from the multi-temporal Landsat/TM/ETM+ dataset on sample sites showed overall agreement with the spectra from the
literature (Figure 4.27). To test the effectiveness of candidate indices for detecting oil palm phenological development, simulated values were plotted against the percent of oil palm plant coverage (% Oil Palm Coverage), which was calculated by using linear-combination fitting of the bare surface and mature oil palm spectra (Table 4.6; Figure 4.28, Figure 4.29). The theoretical maximum range of the NDVI, SAVI and IRI is between -1 and +1. The range of IB45 is theoretically between indefinites. The simulation was assumed to model the land clearing/initial stage, intermediate growth stage and mature stage of oil palm. The NDVI ranged from 0.63 to 0.89, the SAVI ranged from 0.24 to 0.60, and the IRI ranged from -0.27 to 0.41. When comparing the indices, including the red and NIR bands, the SAVI (0.36) had a larger range than the NDVI (0.26), with a middle range of 0 to 1, which was supposed to be the possible range for vegetation, and it showed better linearity all through the simulated oil palm development (Figure 4.28). Therefore, the SAVI, or Soil Adjusted Vegetation Index, was considered a much better indicator. When comparing the two indices, which included the MIR and NIR bands, both showed nonlinearities against increases in oil palm coverage (Figure 4.29). It was unclear which index was better than the other from the simulation results. However, there was some advantage of choosing IB45 over IRI from the user’s viewpoint. The value of IB45 is the ratio of the Red to Green in the Red-Green-Blue space used by Bands 5, 4, and 3 in the pseudo-color representation of the satellite image. This simple relationship between satellite images and IB45 helps to intuitively interpret the outputs, and this advantage was used to visualize IB45 time-series data in the spreadsheet (Figure 4.20 to Figure 4.25) by simulating the pseudo-color representation.

Lastly, by comparing IB45 and the SAVI, the SAVI was dropped from the candidate list because it gave average values for the major types of vegetation in an undesirable order; the SAVI proved an
average value that was significantly lower for the Forest class than for the Mature Oil Palm and Natural Regrowth classes (SAVI: Bare << Forest < Mature Oil Palm ≈ Regrowth), and the Forest class in IB45 gave the highest average value among the different types of vegetation (IB45: Bare << Regrowth ≤ Mature Oil Palm < Forest; Figure 4.30). With the relative magnitude of this relationship, the land information that could be drawn from the SAVI temporal profiles became much more ambiguous than the IB45 profiles. For instance, when the land changed from forest to oil palm, which is one of the most representative land changes in this study, all land processes from forest to land clearing/bare, and the initial to full-growth/mature stages were well distinguished in the IB45 profile with high contrast between the land cover transitions and developments while the overall shape of the SAVI profile became blurred because of the effects of land transitions and developments were canceling each other out (Figure 4.33). The relative magnitude of the relationships of IB45 increased as follows: Bare << Regrowth (≈ Growth Stage Oil Palm) ≤ Mature Oil Palm < Forest. This relationship generally resulted in well-shaped temporal profiles that clearly indicated individual land processes. The main reason for this result could be attributed to its coincidence with the natural course of human or natural land transitions, for example, starting from bare land.
Figure 4.26 Vegetation, soil and water spectra that were regarded as references for major types of land use in the NB study area (Source: USGS spectral library; Shafri et al. 2009). The oil palm spectrum was recreated from Shafri et al. 2009. Spectral bands of Landsat/TM and ETM+ sensors are indicated by dotted lines with band widths and the band numbers are indicated in the circles.

Figure 4.27 Multi-spectral reflectance of Landsat/TM/ETM+ Bands 3, 4, and 5. Band widths are represented in blue, green, and red for Bands 3, 4, and 5 in accordance with the pseudo-color representation. Sample observations were collected as a time-series of the sample sites. Standard deviations are presented as ±σ ranges as solid lines forming rectangles around the average values.
Table 4.6 Vegetation index values of the bare surface and mature oil palm calculated from the measured values from the sample sites.

<table>
<thead>
<tr>
<th>Index</th>
<th>Bare</th>
<th>Oil Palm (Mature: 10 yrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>0.63</td>
<td>0.89</td>
</tr>
<tr>
<td>SAVI</td>
<td>0.24</td>
<td>0.60</td>
</tr>
<tr>
<td>B4/B5</td>
<td>0.58</td>
<td>2.40</td>
</tr>
<tr>
<td>IRI</td>
<td>-0.27</td>
<td>0.41</td>
</tr>
</tbody>
</table>

Figure 4.28 The SAVI and NDVI plotted against the percent oil palm coverage over bare land.

Figure 4.29 IB45 and IRI plotted against the percent oil palm coverage over bare land.
Figure 4.30 The IB45 and SAVI for the major types of land cover. Sample observations were collected from time-series data obtained for the sample sites. Standard deviations represented as ±σ are shown by empty rectangles around the average values.
Figure 4.31 Investigation of the temporal spectral behaviors at the sample sites (1) Oil Palm. There are multi-temporal Google Earth images (upper left & middle), multi-temporal pseudo-color Band 5-4-3 Landsat images (upper 2nd left & right), time-series IB45 data in the RYG tri-color scale assignment (R: 0.5, Y: 2.0, G: 4.0; middle), and its graphical representation (temporal profile; bottom).

Figure 4.32 Investigation of the temporal behaviors of spectra at sample sites (2) with more Oil Palm. Data sources and representations are the same as those shown in Figure 4.31.
Figure 4.33 Land processes of oil palm plantations at a sample site (#1009). Google Earth images from the bare/initial stage to the growth & full-growth/mature stages (upper-left to right; years 2005, 2009, 2011 and 2015). Landsat images in B5-4-3 pseudo-color from forest to bare/initial, growth and full-growth/mature stages (upper middle-upper left to right, middle-lower left to right; forest: years 1988 - 2002, bare: 2004 – 2005; growth stage: 2007 – 2015, full growth/mature: 2015), Colored time-series data (lower-middle) of B5-4-3 pseudo-color (first row), SAVI (second row), and IB45 (third row), and temporal profiles (bottom) of SAVI (first plot) and IB45 (second plot). The timing/year of land conversion to oil palm is indicated by the empty black boxes in the colored time-series data and by the solid vertical line with short bars at both ends in the temporal profiles. The timing of the Google image acquisition also is also indicated in the temporal profiles by dotted vertical lines. Though the timing of land conversion was defined in 2005 when the first Google Earth image was available, land clearing/land preparation for oil palm plantations seems to have begun sometime in the previous year of 2004.
4.3.4 Integrating site-specific land information

4.3.4.1 Land use/land cover, land change and spectral-temporal profiles

Both qualitative and quantitative information regarding major land use/land cover was obtained from Google Earth fine images and the multi-temporal Landsat dataset. The Google Earth fine images had the highest spatial resolutions among the available data sources and could identify key shapes, such as individual oil palm trees, natural forest plants and other types of trees, such as rubber, as well as the felling of trees to clear land, the sizes and shapes of agricultural plots and the development of urban and infrastructure developments, such as residences and mills. Multi-temporal Google Earth fine images could also detect key land changes, such as clearing forestland, oil palm plant growth, and the conversion of crop fields to oil palm plantations or to urban land or infrastructure. The land information obtained through Google Earth investigations was linked with the corresponding temporal-spectral profiles derived from the multi-temporal Landsat dataset, which was going to be used as input data in the computer model (Figure 4.36 to Figure 4.46). The computer model was built based on the temporal-spectral land information obtained through these visual interpretations of Google Earth and Landsat data, color-table representations of the temporal-spectral profiles, and statistical analyses (Figure 4.34). When the initial model was built in the spring of 2013, fewer Google Earth images were available than are currently listed, and the rectangular area in Pasarsebelah (Pasarsebelah test site) was practically the only area where the land-processes of oil palm plantations could be investigated by using the multi-temporal Google Earth images.
Figure 4.34 Procedures used for land information acquisition for building the Land Change Detection and Land Definition Model.

Figure 4.35 Total observation areas in percent per year for Landsat (yellow) and Google Earth (green) images.
The Google Earth fine images had the highest spatial resolution of several tens of centimeters, while the Landsat/TM/ETM+ sensors had a moderate (30 m) spatial resolution (For instance, see Figure 4.36). However, Landsat sensors obtained multi-spectral information in the infrared region that was suitable for monitoring vegetation and had a much wider temporal coverage in terms of observation period and frequency (Figure 4.36). Therefore, both data sources were used to enable the feedback process of model building, calibration and validation.

Figure 4.36 Land information for the sampled oil palm plantation site at the Pasarsebalah test site (1): PT07. The bare/transplantation stage in 2005 (upper-left: Google Earth; upper-2nd left: Landsat/TM (RGB = B543)) and growth stage in 2011 (upper-2nd right: Google Earth; upper-right: Landsat (same as 2005)). A color table representation of the IB45 multi-temporal Landsat data between 2005 and 2011 (middle) and its graphical representation (bottom).
Figure 4.37 Sample site (2): PT113, 114, and 116. Google Earth images acquired in 2006 (upper-left), 2008 (upper-right), 2011 (lower-left), and 2015 (lower-right). All sites were initially used for oil palm plantations. PT113 was converted to urban land use between 2008 and 2011.
Figure 4.38 Sample site (2): PT113, 114, and 116. Google Earth images acquired in 2006 (upper-left), 2008 (upper-right), 2011 (lower-left), and 2015 (lower-right). All sites were initially used for oil palm plantations. PT113 was converted to urban land use between 2008 and 2011. Landsat/TM (RGB = B543) images before Google Earth images became available (top). Google Earth and Landsat images after Google Earth images became available (2nd top). Color table representation of the IB45 multi-temporal Landsat data between 1988 and 2015 (middle) and the corresponding graphical representation of the three sites (bottom). The dotted vertical lines indicate the acquisition dates of the Google Earth images.
Figure 4.39 Sample site (3): PT123 and 131. Google Earth images acquired in 2006 (upper-left), 2008 (upper-right), 2011 (lower-left), and 2015 (lower-right). Both sites were initially covered with forest. PT123 was converted to oil palm between 2008 and 2011. The forest at the PT131 site was cut down before 2006, which was only confirmed by the Landsat data (Figure 4.40) This site was converted back to natural regrowth as of 2015.
Figure 4.40 Sample site (3): PT123 and 131. Both sites were initially covered with forest. PT123 was converted to oil palm plantation between 2008 and 2011. The forest at the PT131 site was cut down before 2006, which was only confirmed by the Landsat data (next figure). This site was converted back to natural regrowth as of 2015. Landsat/TM (RGB = B543) images before Google Earth images became available (top). Google Earth and Landsat images after Google Earth images became available (2nd top). Color table representation of the IB45 multi-temporal Landsat data between 1988 and 2015 (middle) and a graphical representation of the three sites (bottom). The dotted vertical lines indicate the acquisition dates of the Google Earth images.
Figure 4.41 Sample site (4): Natural regrowth. Google Earth images (top). Landsat/TM (RGB = B543) images (2nd-top). Color table representation of the IB45 multi-temporal Landsat data between 1988 and 2015 (middle) and the graphical representation of site #17 (bottom).
Figure 4.42 Sample site (5): Google Earth images of paddy fields at different stages of the crop. Bare (top) and thin vegetation cover (bottom). The bio-physical information of the sites was extracted from the segmented polygons indicated by white lines.
Figure 4.43 Sample site (5): Paddy fields. Google Earth images (top). Landsat/TM (RGB = B543) images (2nd-top). The color table representation of the IB45 multi-temporal Landsat data between 1988 and 2015 (middle) and the graphical representation of site #17 (bottom).
Figure 4.44 Construction of mill and land conversions: Google Earth images before construction (2006/9/1) and after construction (2013/9/25) of Mill-X.
Figure 4.45 Integrated land use information at the mill construction site: Satellite images (top), temporal pseudo-color table representations of Band-543 (upper-middle) and IB45 (lower-middle), and graphical representation of the IB45 profiles of Palm1 and Urban1 sites (bottom) derived from multi-temporal Landsat data. The times of land changes confirmed by Google Earth images are indicated by rectangles in red in the pseudo-color tables and by a thick blue line in the graphical representations. The land use before and after land changes were also confirmed by multi-temporal Google Earth images.
Figure 4.46 Integrated pristine forest information (Forest): Satellite images (top), temporal pseudo-color table representations of Band-543 (middle) and a graphical representation of IB45 (bottom) derived from multi-temporal Landsat data.
4.3.4.2 Obtaining information of the local drivers

4.3.4.2.1 Mills

In contrast with collecting land use information from the sample sites, all the existing mills in the study area needed to be listed with their construction years to perform multi-temporal logistic regressions. Although this process is labor intensive, the most reliable methods were as follows: 1. Search for mills using Google Earth. 2. Determine construction years for the identified mills by using multi-temporal Google Earth and/or Landsat images. 3. Match the images with the ancillary information of the mills in the study area (Figure 4.47). In the Google Earth images, the mills were observed to consist of an elongated main building complex with chimney(s), reserve tanks, and several waste treatment ponds surrounding the building, and were surrounded by areas dominated by oil palm plantations. (Figure 4.48 - left). For some newly constructed mills, the years of construction could be determined based on older Google Earth images, which showed the previous land use on the construction site (Figure 4.49 - top). However, older images did not exist for most of the construction sites. In this case, once a mill was identified using Google Earth images, Landsat images (Figure 4.50 - right) were used to investigate the changes in land cover by looking at older images of the mill site. The identified mills were also matched with the corresponding mills that were indicated in the literature (Bengkulu 2008). Overall, 15 mills were identified in the study area as of April 2014 (Figure 4.51).
Figure 4.47 Identifying mills using Google Earth and Landsat images.

Figure 4.48 Close-up satellite images of Mill-7 by Google Earth in true-color (left) and by Landsat/TM in pseudo-color (RGB = B543) (right).
Figure 4.50 Identifying mills and construction years. Mill-7 (top) and Mill-8 (bottom). Google Earth images (left) were used to identify the mills and Landsat images (right) were used to determine the construction years.
Figure 4.51 List of mills in the North Bengkulu study area (left) and their locations (right) as of April 1 2014. Two new mills were constructed after April 2014 and are indicated by #0 and #00 in the figure but are not listed in the table.
4.3.4.2.2 Ancillary data collection

4.3.4.2.2.1 BAKOSURTANAL digital map

The digital map was obtained through BAKOSURTANAL (Badan Koordinasi Survei dan Pemetaan Nasional: Coordinating Agency for Surveys and Mapping), which included information about natural and human features, such as rivers, major roads, settlements, and land use with limited details and spatial coverage. Because the map covered the entire Area 1 and most of Area 2, independent variables derived from the digital map were included in the logistic regression models for Areas 1 and 2 but not for Area 3 or the combined area of Areas 1, 2, and 3, called Area123.

Figure 4.52 BAKOSURTANAL digital map coverage. Settlements are indicated in pink, major roads are indicated by black and yellow lines, and rivers/water lines shown in blue.
4.3.4.2.2 Delineation of large plantation estates

Knowing the types of oil palm plantation operations is important for understanding the development of oil palm plantations. Although definitive and comprehensive information was not available for this study, large plantations were delineated by several information sources. The first and most reliable information source of information was the public report of oil palm plantations provided by P.T. Agro Muko. The boundaries of all affiliated plantations were digitized onscreen from the figure provided in the report and manually geo-corrected (Figure 4.53). Other large plantations were selected and digitized by referring to several less definitive but informative sources, such as the spatio-temporal continuum extracted from satellite data (Figure 4.54) and a sectorial map introduced by Lee et al. 2013 (Figure 4.55). Overall, 15 large plantation areas were delineated that occupied a total of approximately 65,000 [ha], or 7.4% of the entire study area (Figure 4.56). Large plantations also account for approximately one-third of the total area of oil palm plantations as of 2012, which was obtained through this study (Table 4.7).
Figure 4.55 Sectorial boundaries of entrepreneur (red), smallholder (black) and government (blue) plantations. Numbers indicates areas 1, 2, 3, and 4, respectively.
Table 4.7 Areas of small and large oil palm plantations obtained in this study.

<table>
<thead>
<tr>
<th></th>
<th>Area [ha]</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small Plantations as of 2012</td>
<td>130,057</td>
<td>14.8</td>
</tr>
<tr>
<td>Delineated Large Plantation Areas</td>
<td>64,620</td>
<td>7.4</td>
</tr>
<tr>
<td>Total Plantations as of 2012</td>
<td>194,677</td>
<td>22.1</td>
</tr>
<tr>
<td>Total Area of A1234</td>
<td>878,968</td>
<td>100</td>
</tr>
</tbody>
</table>

Figure 4.56 Delineated boundaries of the large-scale oil palm plantations. Numbers are arbitrary for convenience. The blue numbers indicate areas 1, 2, 3, and 4.
4.4 Model building

The core idea of the LC/LD computer model was to analyze all available satellite observations together to include all temporal elements that would be lost if the individual observations were classified separately in a conventional manner. The model is fed the multi-temporal satellite observations dataset as input data and the land changes and land uses are determined from the temporal profiles by modeling the assumed land use and land change (LU-LCC) scenarios. The LU-LCC scenarios were built from the literature and from the ground-truth sampling data of the multi-temporal satellite dataset. A temporal segmentation algorithm was developed to break down the entire profile into essential land change elements and built into the LC/LD model. ALOS Phased Array type L-band Synthetic Aperture Radar (PALSAR) data, which were previously used in oil palm studies (Gutiérrez-Vélez and DeFries 2013; Lee et al. 2013), were also used for cross-validation and to improve classification accuracy.
4.4.1 Building the LC/LD Model

The LC/LD Model was first conceptualized from the literature of oil palm plantations and the investigation of satellite data (Figure 3.10 to Figure 3.15). The conceptual model was then interpreted as a computer model that can analyze the temporal-spectral profiles extracted from the multi-temporal Landsat dataset. The computer model consists of two sub-models: the LDM (Figure 4.57 - top) and the LCM (Figure 4.57 - bottom).

Figure 4.57 Data processing flows of the Land Change Detection and Land Definition (LC/LD) model, parameter optimization and accuracy assessment.
4.4.2 Land Change Detection Model (LCM)

The core of the LDM is the detection of the conversion of land to oil palm plantations. Assuming that the IB45 values increase after land is cleared and following the transplanting stage (Figure 3.10), the last bare period should indicate the onset of oil palm plantation (Figure 4.58). A threshold IB45 value (Vth_2) was used to extract observations that were under the specified threshold. The last cluster of the extracted bare stage observations was grouped (segmented) together and defined as the last bare stage. The onset of the last bare stage, which was also a candidate for the onset of oil palm plantations, was then identified as the oldest observation in the segment (Figure 3.13; Figure

![IB45 temporal profile of oil palm and the land change detection procedure using the Land Change Detection Model (LCM): A Sample profile (PT01; top) and two threshold values (Vth_1, Vth_2) of the LCM. The year of land change was derived by segmenting the observations encircled by the dashed line.](image)
To further investigate the history of the land, another threshold value (Vth_1) was used to detect pristine forestlands if they had existed. The observations with values above the threshold were grouped together beginning with the oldest observations until certain observations became lower than the threshold value (Figure 3.13 to Figure 3.15; Figure 4.58). The period between the Forest and Oil Palm periods was defined as the Intermediate Period. At this stage of analysis, the last land change included all types of land, including oil palm, natural regrowth, other cropland, and urban land. Thus, the detection capability of the model for land changes was evaluated by including the major types of land changes identified by Google Earth observations, which included oil palm, regrowth, WTP, and urban/mill land. The ability to detect unchanged land was also evaluated by using the Forest sample sites. The accuracy of the year of land change was also evaluated by comparing the calculated (ChY_m) and observed (ChY_a). The optimum values for Vth_1 and Vth_2 were obtained through iterations of the LCM with varied (Vth_1, Vth_2) inputs and the three evaluation outputs (Figure 4.57). The results showed that approximately 98% of the Change Land category were correct and that approximately 95% of the Unchanged Land category was correct. The following interactions existed between the changed and unchanged lands: Error1 - Changed

<table>
<thead>
<tr>
<th>Ave. of</th>
<th>1.78</th>
<th>1.42</th>
<th>3.16</th>
<th>5.87</th>
<th>2.11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ave. of</td>
<td>1.01</td>
<td>-0.76</td>
<td>2.53</td>
<td>5.64</td>
<td>1.02</td>
</tr>
</tbody>
</table>

Table 4.9 Differences between the calculated (ChY_m) and observed (ChY_a) years of major land changes.

| Table 4.8 Detection rates of changed/unchanged land (%) | 97.93 | 96.47 | 1.38 | 0.00 | 97.93 | 95.09 |

Table 4.8 Detection rates of changed/unchanged land (%).
land classified as unchanged land, and Error2 - Unchanged land classified as changed land. The final detection rates of land change/no land change were obtained by subtracting the errors from the diagonal elements of land change/land unchanged (Table 4.8). Another accuracy measure was calculated as the difference between the estimated year of land change obtained by the LCM (ChY_m) and the observed year of land change confirmed by multi-temporal Google Earth images (ChY_a). The average values of the major land changes of Oil Palm, Regrowth, Water, and Urban were 1.78, 1.42, 3.16 and 5.87, respectively, and the overall average value was 2.11 years (Table 4.9).

The accuracy of the year of conversion to oil palm was 1.78, which was better than the overall accuracy of 2.11 (Table 4.9; Figure 4.60). The average and median values of ChY_m – ChY_a were 0.91 and 0.3 years, respectively, which suggested that systematic estimation errors existed and that the detected year of land change was slightly delayed relative to the actual year of land change. Approximately 65% of all the samples fell within the estimation error range of ±1.5 years. A secondary peak existed between 2.5 and 3. years, which accounted for approximately 22% of all samples.

![Figure 4.59 Histogram of difference between calculated (ChY_m) and observed (ChY_a) year of land change of Oil Palm sample sites. The numbers above the bars indicated number of observations and the numbers in parentheses indicate % to total number of samples.](image)

| ChY_m - ChY_a | |ChY_m - ChY_a| |
|---------------|---------------|
| **AVE**       | 0.91          | 1.69         |
| **MEDIAN**    | 0.30          | 1.39         |
| **STDEV**     | 1.94          | 1.31         |
| **N**         | 78            | 78           |

Table 4.10 Accuracy assessment of Year of Land Change (ChY) for Oil Palm sample sites.
The most probable interpretation of the second peak would be the existence of early peaks (within a few years after the land clearing/transplantation period), which were observed in some IB45 profiles of Oil Palm. When the peak value exceeded the threshold Vth_2, the segmentation process was stopped at this early peak period and consequently never reached the time of land change (Figure 4.60 - bottom).

The average \( |\text{ChY}_m - \text{ChY}_a| \) and \( (\text{ChY}_m - \text{ChY}_a) \) values of Regrowth were 1.42 and -0.76 years, respectively, which were the smallest values observed among all the land uses (Table 4.9). These low values were observed because Regrowth showed the most distinctive change in the IB45 profiles (Figure 4.61).
Compared to oil palm plantations or other human-controlled types of land use, vegetation cover and growth by natural regrowth occurred very quickly after clearing land. The quick recovery curve from land clearing within the first few years and the stable high value following the recovery phase indicated that the LC/LD Model was accurate. The systematic bias of \((\text{ChY}_m - \text{ChY}_a)\) toward negative values also resulted from the high accuracy of land change detection by the LCM. The accuracy of the model estimation \(\text{ChY}_m\) was higher than that of the Google Earth observation \(\text{ChY}_a\), which involved ambiguity when deciding the precise time of land change. The Regrowth sample sites were selected from the areas that represented land clearing from certain Google Earth images and then showed natural regrowth in later image(s). Because the frequency of Google Earth observations was not sufficient for detecting the precise moment of land change, it was inevitable that the dates of observation, which showed land clearing stages, were used as proxies.
The remaining two types of land use, Water (Waste Treatment Pond) and Urban (Urbanization or Mill), showed low estimation accuracies for $|Ch_{Ym} – Ch_{Ya}|$ of 3.16 and 5.87, respectively. The decreases of these estimates likely resulted from the much lower quality of the input data at and after the occurrence of the land changes rather than the LCM itself. The QF mask files that accompanied the Landsat data had over-masked certain types of land cover, such as Urban and Water, which had similar or overlapping spectral signatures as clouds or cloud shadows. Consequently, many observations after converting land to those uses were eliminated in the data pre-processing phase, which resulted in much broader data gaps (Figure 4.45; Figure 4.62, Figure 4.63) and lower accuracy when detecting land use changes (Figure 4.63) and defining land use type.

### 4.4.3 The Land Definition Model (LDM)

After the LCM was used to detect the occurrence of land changes and the
calculated bio-physical metrics for segmented IB45 sub-profiles, the results were passed on to the LDM, and another computer model was used to determine the land uses of the segmented sub-profiles and to reconstruct the land use history (Figure 4.57). The main concept adopted for defining land use was ‘land development scenarios,’ in which certain land uses were assumed as follows. ‘Land development’ assumed land cover transitions or development, which means that certain land use would evolve with temporal factors, such as the land clearance, transplantation, growth, mature, and senescent stages of oil palm plantations, or remain with certain land conditions or land cover patterns, such as pristine forest and paddy fields. These land transitions or phenological developments were modelled for the target land use, oil palm, and other considered land uses, such as regrowth, pristine forest, and rice paddy. These scenarios were then interpreted as the temporal behaviors of the vegetation index IB45 (Figure 3.10 for oil palm plantation). The actual behaviors of IB45 on certain sites would be compared with the templates of land development scenarios to determine land use. The justification for this spectral-temporal approach was based on the assumption that the inclusion of spectral-temporal information would improve the chances of accurately discriminating between different types of land cover/land use with spectral signatures that appear very similar and are thus inseparable when relying on spectral analysis alone. Therefore, the spectral and temporal components were combined and investigated to search for appropriate parameters for identifying the land uses of given segmented temporal profiles with reference to land development scenarios. These parameters should represent certain vegetation conditions or land at certain temporal stages and have conventionally been called ‘biophysical metrics (DeFires 1995).’
4.4.3.1 Selection of biophysical metrics from real data

An appropriate set of biophysical metrics should be able to efficiently represent vegetation conditions at certain temporal or growth stages. For periodic or nearly periodic land cover phenomena, such as filed crops and rice paddies, the temporal or growth stage could be identified by detecting the periodic or semi-periodic repetition of similar patterns. In addition, the temporal or growth stages of annual crops could be identified based on the day of the year or other measures, such as accumulative temperature, which could be reset to the initial stage for all the sites in the region once the year is renewed. However, the conversion of land to oil palm plantation is an asynchronous and relatively persistent phenomena, and these methods were not previously available.

The temporal profiles that began during the year of land conversion were extracted for the sample sites for which both the year of land change and land use information were available (Table 4.3). Then, the average IB45 profiles collected over the sample sites for individual types of land use.

![Average IB45 values of oil Palm, regrowth and mill land uses plotted against time from land change. Sample sites with the year of land change (ChY_a) were used. The plotted points indicate the averages and the error bars indicate the standard deviation, ±σ, which were calculated for the samples that fell within the [Years - 1, Year] period.](image-url)
against the number of years since the
land use change (ChY) were obtained
(Figure 4.64). Mills had a much longer
temporal coverage because the
construction of mills had been
thoroughly investigated in space and
time by using both Google Earth and
Landsat images. Other land uses were
investigated using Google Earth
images alone and thus could
potentially have temporal coverages
of up to 16 years (as of year 2016).
However, the temporal coverage was
often shorter due to the limitation of
the Google Earth coverage, especially
the first 10 years (2000 to 2010)
(Figure 4.5).

To evaluate temporal curves, some
basic measures, such as the average,
slope or higher order derivatives of
the curves, and the deviations around
the least square regression line were
used. These measures could be obtained for various periods. In this study, statistics were obtained

![Figure 4.65 Average IB45 profiles since the year of land change (ChY_a) and for the [0-1]- to [9-10]-year periods. Oil Palm, Regrowth and Mill (top), Oil Palm (upper-middle), Regrowth (lower-middle) and Mill (bottom) land uses. The detailed representations of the figures are the same as those in Figure 4.64. Three time periods, [1-2], [3-5] and [6-10], are separated by vertical lines.](image)
for the first 2 years and the averages of the 3rd, 4th, and 5th years. These periods were considered appropriate for separating oil palm plantations from other types of land uses (Figure 4.65; Figure 4.66). It was confirmed that the conversion of land to land uses related to urbanization and artificial surfaces, such as settlement, urban infrastructure, and industrial facilities, remained low and had relatively constant IB45 values throughout the period after land conversion, in contrast with the oil palm plantation and natural regrowth land uses. The profiles of Oil Palm and Regrowth showed distinctive differences during the [0-2]- and [3-5]-year periods.

Although both types of land use showed increased IB45 values since the year of land change, the speeds of the increases were different. Regrowth quickly resulted in the maximum range of IB45 values (greater than 2.0), which was considered as equivalent to full vegetation, during the [0-2]-year period and then remained stable. In contrast, Oil Palm showed a slower but steady increase during

![Figure 4.65](image1.png)

![Figure 4.66](image2.png)

Figure 4.65 The separation abilities of the IB45 temporal profiles between land uses. Between the Oil Palm, Regrowth and Mill (top) and Oil Palm and Regrowth (bottom) land uses. The averages and standard deviations of the IB45 profiles were calculated for three periods and are represented using long dashed (Ave12, Ave345, Ave6_10) and short dashed (SD+ and SD-) lines. The overlapping ranges between the types of land are represented by diagonal gray stripes. Ranges only occupied by Oil Palm, regrowth, and mills are represented in yellow, green, and blue, respectively.
longer time periods. This difference could be effectively detected by using certain biophysical metrics, such as the average and slope for the [1-2]- and [3-5]-year periods (Figure 4.66 - bottom; Figure 4.68). Time periods longer than 5 years were not considered for biophysical metrics calculations and the land definition process because it was important to develop a land definition methodology with wide applicability for the most recent land changes. Another biophysical metric to consider is the standard error of estimate (σ_{est}), which is a measure of the accuracy of the least-squared regression line and is defined as follows:

\[ \sigma_{est} = \sqrt{\frac{\sum(Y - Y')^2}{N}} \]

where \( \sigma_{est} \) is the standard error of the estimate, \( Y \) is an actual value, \( Y' \) is a predicted value, and \( N \) is the number of pairs between the actual and predicted values. The \( \sigma_{est} \) of Oil Palm showed relatively stable values over time for up to 9 years, indicating that oil palm grew steadily during the growth stage (Figure 4.67). Among the biophysical metrics, such as the average, slope and standard error of estimates, the plotted points for the years [0-2] varied widely, which resulted in large standard deviations (SD+ and SD−) around the average (denoted as Ave12) (Figure 4.65). The most probable
cause of this error was actually
the error of the land change
years obtained through the
Google Earth investigation.
Before and after land changes
occurred, the IB45 values
changed drastically and the
negative effects from the errors
of the year of land change were
magnified. This negative impact
had a greater slope because the
first derivatives with time was
affected more by signal noise or
the errors of the input data.
Because these apparently large errors were extrinsic to the quality of the model itself, these
biophysical metrics calculated for short periods could still be candidates for the land use definition.
The actual selection of candidates, parameterization and optimization were performed later by using
sensitivity analysis tied with an accuracy assessment (Figure 4.57).

Another biophysical metric, the Spike value, was devised to detect paddy fields. The Spike value has
distinctly different specifications and uses relative to the other metrics considered in this study.
While all other metrics that were used for the extracted profiles were segmented by land change

Figure 4.68 Slopes of linear regression lines drawn for the [0, Years from Land Change] period.
occurrences, the Spike value measures a certain arbitrary period of the entire profile and consists of the following two thresholds: Th_below and Th_above. The Spike value is obtained by counting the number of ‘spikes’ that exceed the thresholds. To obtain individual spike values, the observations next to each other, below Th_below and above Th_above are segmented. The Spike value is obtained by counting the total number of segments during a certain period (Figure 4.69). The periods for calculations were set to the last 5 years from the most recent observation to coincide with the maximum time range chosen for another Biophysical metric.

One of the main rationales for adopting this metric was that the IB45 profiles of paddy fields drastically changes many times between low and very high values during a short period (Figure 4.69). This distinctive pattern was expected for ordinary field crops and rice paddies with short growth periods of less than or equal to one year. Among these areas, however, rice paddies were considered even more distinctive than the other types of upland field crops because of the presence of water during the transplantation stage, which results in greater spikes than ordinary vegetation when using a combination of Band 3 (Red) and Band4 (Near Infrared). The multiple scattering of solar
irradiance in wastewater is more effective at shorter wavelengths and has a higher spectral reflectance than the shorter waveband, which results in a large IB45 value for water. The spectral data provided by the USGS Digital Spectral Library (USGS 2016) provides an IB45 value of 1.07 for Sea Water (B3:B4: B5 = 3.82: 1.98: 1.85%) and 0.51 for Gray Silty Loam (B3:B4: B5 = 13.3: 20.8: 40.5%). The actual spectral data of Landsat/TM/ETM+ were more extreme toward the enhancement of IB45 for water. The average Spike values (Th_above = 3.0, Th_below = 2.0) were calculated for individual land uses using the sample sites (Table 4.11). The paddy fields had a much larger value (4.8) than any other type of land use, which ranged from 0.4 to 1.2. Therefore, the Spike value was assumed to be a very effective metric for detecting rice paddy fields.

<table>
<thead>
<tr>
<th>Land Use</th>
<th>Threshold values (Th_above, Th_below)</th>
<th>Number of samples</th>
<th>Average counts of spikes</th>
<th>Spike</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: oil palm</td>
<td>&gt;= 3.0, &lt; 2.0</td>
<td>124, 124</td>
<td>0.00, 1.04</td>
<td>1.0</td>
</tr>
<tr>
<td>2: Forest</td>
<td>&gt;= 3.0, &lt; 2.0</td>
<td>10, 10</td>
<td>0.30, 0.90</td>
<td>1.2</td>
</tr>
<tr>
<td>3: Regrowth</td>
<td>&gt;= 3.0, &lt; 2.0</td>
<td>78, 78</td>
<td>0.00, 0.37</td>
<td>0.4</td>
</tr>
<tr>
<td>8: WTP</td>
<td>&gt;= 3.0, &lt; 2.0</td>
<td>8, 8</td>
<td>0.13, 0.75</td>
<td>0.9</td>
</tr>
<tr>
<td>12: Paddy</td>
<td>&gt;= 3.0, &lt; 2.0</td>
<td>106, 106</td>
<td>1.56, 3.25</td>
<td>4.8</td>
</tr>
<tr>
<td>15: Mill</td>
<td>&gt;= 3.0, &lt; 2.0</td>
<td>22, 22</td>
<td>0.05, 0.55</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Table 4.11 Average number of Spike for each type of land use.
4.4.3.2 Incorporating PALSAR data

Aside from the development of methods for the definition of land by using biophysical metrics obtained from optical sensors, radar sensors and ALOS/PALSAR were used to verify the results evaluated by using biophysical metrics. The ratio of HH and HV bands was used to obtain the average for each type of land use (Figure 4.70). The HH/HV ratio was a good indicator of the separation between natural types of vegetation, such as forest and regrowth, and human-intervened land uses, such as Oil Palm, Mill and Paddy land use classes. The length and accuracy of the temporal profiles for individual land uses were not sufficient for evaluating any temporal behaviors. Therefore, only fixed threshold values were used for validating individual land uses without considering temporal factors. The proper threshold values for individual types of land use all converged around 200.

Figure 4.70 Averaged PALSAR HH/HV for each type of land use and for each year from the occurrence of a land change. The values for Forest and paddy areas were simply averaged over all available sample sites, and the average and standard deviations are denoted by horizontal lines. The lower figure shows the ranges of natural vegetation (forest and regrowth) in green and human land uses (Oil Palm, Mill and Paddy) in yellow. The overlapping region is shown by red diagonal stripes.
4.4.4 Parameterization, calibration and validation of the LDM

The core of the LD Model consists of sets of biophysical metrics and conditional expressions (Table 4.12). The optimal parameters were obtained by using a sensitivity analysis of the model, which was an iterative process that was performed by varying the input parameter values and evaluating the accuracies of the land uses obtained by the LD model (Figure 4.71). The threshold value for PALSAR data was obtained independently from another sensitivity analysis. Half of the total sample sites (272 samples) were used for this calibration phase of the model. The results of land definition were evaluated by using several accuracy measures, such as the Producer’s and Users’ accuracies of Oil Palm, the overall accuracy of all the land uses and the Kappa coefficient. The Producer’s

Figure 4.71 Data processing flows of the Land Change Detection and Land Definition Model (LC/LD Model), parameter optimization and accuracy assessment: Calibration of LDM.
accuracy was expressed as the portion of the correct land use defined by the LDM for given sample sites, while the User’s accuracy was expressed as the portion of the correct sample points for the land use defined by the LDM. The optimal parameter values were selected for the set that provided the highest overall accuracy and Kappa coefficient and balanced for the Producer’s and User’s accuracies for Oil Palm. Once the parameter values were decided, the LDM was used again to obtain real accuracy assessment results with parameter values decided by the calibration phase and by using the other half of the sample sites, which were reserved for the model validation phase (Figure 4.72). The results of the accuracy assessment were considered successful for both detecting land use and for discriminating between different types of land use (Table 4.13). The model had seven land use classes, including five identified and two unidentified land use classes (1. Oil Palm, 2. Forest, 3. Regrowth, 4. Urban, 5. Paddy, 7. Others, and 8. Most Recent Change). The parameter value set is shown in Table 4.12. An accuracy assessment was also performed using the following reconciled categories: 1. Oil Palm, 2. Forest, and 3. Others. These categories were actually used for all land use and land change analyses in this study. Oil palm had Producer’s and User’s accuracies of 92% and 85%, respectively. Forest had the highest Producer’s and User’s accuracies of 97% and 86%, respectively. Paddy land also had high Producer’s and User’s accuracies of 100 and 81%, respectively. Regrowth land had moderate Producer’s and User’s accuracies of 68 and 70%, respectively, and urban land had Producer’s and User’s accuracies of 75 and 75%, respectively. Some over-classification tendencies existed that
resulted in the classification of most other samples into one of five specific types of land use, with a Producer’s accuracy of only 5%. In addition, 42.3% of the total sample sites showed land changes within 5 years of the last available observation and were classified as Most Recent. The overall accuracy after excluding the Most Recent land was 81.4%, and the Kappa coefficient was 0.75. When the accuracy was assessed for the 3 reconciled land use categories, both the overall accuracy and Kappa coefficient increased by 87.1% and 0.80, respectively. The reconciled Others class had Producer’s and User’s accuracies of 78 and 90%, respectively, which were comparable to those of Oil Palm and Forest. Thus, the land use model with 3 categories could be considered successful for discriminating between different types of land use. The Producer’s accuracy for Oil Palm was 92%, indicating that more than 9 out of 10 sample sites confirmed as oil palm were also classified as Oil Palm by the LD model. In addition, 1 out of every 10 sites were omitted or underestimated by the model. This method is a natural method for evaluating the classification accuracy of the map producer based on ground-truth data. On the other hand, a User’s accuracy of approximately 85% means that approximately 8 to 9 out of 10 sites classified as Oil Palm by the model were classified correctly. In addition, approximately 1 to 2 sites should have been classified as a type of land use other than oil palm; thus, oil palm was overestimated by the model.

The LDM was considered successful according to the accuracy assessment. In this study, however, an older version of the model that has a simpler parameter set without the Spike metric was used due to the lack of resources for rerunning the full-scale LC/LD Model and for performing the necessary land use/land change analysis. The older version of the LDM considered biophysical measurements for the entire period (more than 2 years) of the segmented IB45 profiles (Table 4.14) instead of the measurements for specific time periods. This condition was also applied to Paddy
instead of using the Spike metric. The threshold value of PALSAR was set to 200, which is the same as the current LDM. The Producer’s and User’s accuracies for Oil Palm were 66 and 79%, respectively, which means that approximately 2 out of 3 ground-truth sites were correctly identified and that approximately 4 out of the 5 sites were correctly classified as Oil Palm by the model. The overall accuracy and Kappa coefficient for the 3 land category models were 75.6% and 0.62, respectively. Although these accuracies were significantly lower than those of the current model, they were still considered successful and available for land use/land change analyses. Because the older model can accommodate sample sites with segmented IB45 profiles longer than 2 years, the portion of Recent Change was drastically reduced to 13.2%. Thus most of the sample sites (86.8%) were evaluated by the model. Because the last observations of the Landsat data were obtained sometime between 2014 and early 2015, the results of the LC/LD model run were analyzed up to 2012.
Table 4.12 Selected biophysical parameter set and conditions for the 5-year evaluation model. The parameter values were obtained through a sensitivity analysis that used the sample sites for calibration (iselect = 0).

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Ave</td>
<td>β</td>
<td>α</td>
<td>Ave</td>
<td>β</td>
</tr>
<tr>
<td>1</td>
<td>Oil palm</td>
<td>≥ 0.00 &amp; &lt; 0.20</td>
<td>&lt; 0.10</td>
<td>≥ 1.5 &amp; &lt; 1.2</td>
<td>≥ 0.05 &amp; &lt; 0.30</td>
<td>≥ 0.005 &amp; &lt; 0.08</td>
</tr>
<tr>
<td>2</td>
<td>Forest</td>
<td>≥ 1.85</td>
<td></td>
<td></td>
<td>&lt; 200</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Regrowth</td>
<td>≥ 1.60</td>
<td>≥ 0.20 &amp; &lt; 0.08</td>
<td>≥ 2.1</td>
<td>≥ 0.10</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Urban</td>
<td>&lt; 1.5</td>
<td>&lt; 0.03 &amp; &lt; 0.03</td>
<td>&lt; 1.5</td>
<td>&lt; 0.03</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Paddy</td>
<td></td>
<td></td>
<td></td>
<td>≥ 6.0</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Others</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Land change after 2010</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Table 4.13 Accuracy assessments of the 5-year model using the sample sites reserved for validation (iselect = 1).

<table>
<thead>
<tr>
<th>No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>LU</td>
<td>Oil Palm</td>
<td>Forest</td>
<td>Others</td>
</tr>
<tr>
<td>P's A</td>
<td>92%</td>
<td>97%</td>
<td>78%</td>
</tr>
<tr>
<td>U's A</td>
<td>85%</td>
<td>85%</td>
<td>90%</td>
</tr>
</tbody>
</table>

Too Recent = 42.3%

Overall Accuracy = 87.1%

Kappa’s = 0.80

<table>
<thead>
<tr>
<th>No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>LU</td>
<td>Oil Palm</td>
<td>Forest</td>
<td>Regrowth</td>
<td>Paddy</td>
<td>Urban</td>
<td>Others</td>
<td></td>
</tr>
<tr>
<td>P's A</td>
<td>92%</td>
<td>97%</td>
<td>68%</td>
<td>100%</td>
<td>75%</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td>U's A</td>
<td>85%</td>
<td>80%</td>
<td>70%</td>
<td>81%</td>
<td>75%</td>
<td>33%</td>
<td></td>
</tr>
</tbody>
</table>

Too Recent = 42.3%

Overall Accuracy (excl. most recent change) = 81.4%

Kappa’s = 0.75
Table 4.14 Selected biophysical parameter set and conditions for the 2-year evaluation model. The parameter values were obtained using a sensitivity analysis by using the sample sites for calibration (iselect= 0).

<table>
<thead>
<tr>
<th>LU No.</th>
<th>Class Name</th>
<th>Ave</th>
<th>β</th>
<th>α</th>
<th>Ave</th>
<th>β</th>
<th>α</th>
<th>SSpike1</th>
<th>SSpike2</th>
<th>PALSAR mb/bu 2010</th>
<th>Other factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Oil palm</td>
<td>≥ 0.00 &amp; &lt; 0.30</td>
<td>&lt; 0.10</td>
<td>≥ 1.5 &amp; &lt; 2.2</td>
<td>≥ 0.05 &amp; &lt; 0.30</td>
<td>≥ 0.005 &amp; &lt; 0.03</td>
<td>≥ 200</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Forest</td>
<td>≥ 2.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Regrowth</td>
<td>≥ 1.00</td>
<td>≥ 0.20</td>
<td>≥ 0.08</td>
<td>≥ 2.1</td>
<td>≥ 0.10</td>
<td></td>
<td>&lt; 200</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Urban</td>
<td>&lt; 1.5</td>
<td>&lt; 0.03</td>
<td>&lt; 0.03</td>
<td>&lt; 1.5</td>
<td>&lt; 0.03</td>
<td>&lt; 0.03</td>
<td>≥ 200</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Paddy</td>
<td>≥ 2.00</td>
<td>&lt; 0.02</td>
<td>≥ 0.18</td>
<td></td>
<td></td>
<td>&gt;= 6.0</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Others</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Too recent change</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>9</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.15 Accuracy assessment for the 2-year model using the sample sites reserved for validation (iselect = 1).

No. 1 2 3
LU Oil Palm Forest Others
P’s A 66% 100% 76%
U’s A 79% 84% 68%

Too Recent Too Recent 13.2 %

Overall Accuracy = 75.6 %
Kappa’s = 0.52

No. 1 2 3 5 4 7
LU Oil Palm Forest Regrowth Paddy Urban Others
P’s A 66% 100% 53% 67% 43% 25%
U’s A 79% 84% 32% 56% 100% 26%

Too Recent = 13.2 %

Overall Accuracy (excl. most recent change) = 64.1 %
Kappa’s = 0.52

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4.5 Land use and land changes

The outputs of the LC/LD Model provide comprehensive land use and land change information from 1988 to 2015 at any site, or for any segmented polygon in the NB study area. Considering certain gaps of Landsat data availability (Figure 4.35), the model results were summarized into 7 periods separated by 3 years, except the first period, which spans for 6 years: (P1: 1988 – 1994, P2: 1994 – 1997, P3: 1997 – 2000, P4: 2000 – 2003, P5: 2003 – 2006, P6: 2006 – 2009, P7: 2009 – 2012). The results were also summarized into 2 periods that equally spanned 12 years before and after 2000: (P1: 1988 – 2000, P2: 2000 – 2012). The land uses were reconciled into three different types of land use, Oil Palm, Forest, and Others, as well as Unclassified, because the most recent land change had occurred within 2 years. The land use/land change results with spatial-temporal information were plotted as needed in thematic maps.

4.5.1 Overall assessments

4.5.1.1 Overview of the land use/land cover changes between 1988 and 2012

Land use maps for different periods were created by extracting the temporal land information obtained from the LC/LD model (Figure 4.73; Figure 4.74). These maps revealed drastic forest loss between 1988 and 2000 and oil palm expansion from 2000 to 2012. Statistics of land use areas were collected during 7 periods (Figure 4.76) and 2 periods (Table 4.16).
Figure 4.73 Land use types of Oil Palm, Forest and Others as of 2012 obtained by using the LC/LD model. The boundaries of the protected area are indicated by dashed lines, while the boundaries of the study sub areas are indicated by dashed and white lines. The North Bengkulu study area is divided into 4 sub-study areas: Areas 1, 2, 3 and 4, which are indicated by dashed and gray lines.
Figure 4.74 Historical land uses as of 1988 (top-left) through 2012 (lower-right). The Oil Palm, Forest, and Others land uses are indicated in red, green, and yellow respectively. The protected area is indicated by dotted lines. Area123 is the total area (Areas 1, 2, and 3) except for the south-eastern tip (Area 4) of the image.
Figure 4.75 Year of conversion to oil palm plantation in the study area. The period of occurrence is indicated by color. Large plantations are bordered by red lines. The numbers correspond with the plantations indicated in Figure 4.56.
Throughout the study area of approximately 879,000 ha, the dominant land use in 1988 was Forest, covering approximately 600,000 ha and accounting for 68% of the total land. However, approximately one-third of the land had already been converted for human use. Oil palm plantations existed on only 2% of the land, and more than 300,000 ha, or half the remaining forest, had been lost during the entire period of 1988 to 2012. Two-thirds of the total lost forestland was lost during the first 12 years of the observation period, indicating the deceleration of forest loss during the last 12-year period. On the other hand, expansion of oil palm plantations has greatly accelerated during the last 12 years, accounting for more than 75% of all oil palm plantations. As of 2012, forest accounted for 34%, or just half of the value of 68% observed in 1988. Both oil palm and other types of human-intervened lands (Others; human-lands) have increased (from 2% to 22% and from 27 to 40%, respectively). However, the net expansion of other types of human-land stopped and actually decreased during the latter period of 12 years, which strongly infers that a significant portion of the recent oil palm development occurred on land that had already been developed by humans.

<table>
<thead>
<tr>
<th>Land area or converted area [ha]</th>
<th>% of total area</th>
<th>Unclassifie</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil Palm</td>
<td>Forest</td>
<td>Open Land Oil Palm</td>
</tr>
<tr>
<td>as of 1988</td>
<td>16,253</td>
<td>598,553</td>
</tr>
<tr>
<td>P2: 2000 - 2012</td>
<td>148,238</td>
<td>-101,513</td>
</tr>
<tr>
<td>as of 2012</td>
<td>194,677</td>
<td>298,197</td>
</tr>
</tbody>
</table>

Table 4.16 Land use and land changes of Area123 between 1988 and 2012.
Breaking down land change further into 7 periods clearly showed land change trends (Table 4.17; Figure 4.77). The pace of forest loss has been decelerated since the mid-1990s, while the pace of oil palm expansion has been increasing since 2000, with the conversion of more than 1% of the total study area to oil palm annually. Based on this calculation, the remaining forestland will be completely lost in two to three decades if all oil palm development occurs on forestland. However, recent oil palm developments have occurred on both forestland and land altered for human use.

<table>
<thead>
<tr>
<th>Period</th>
<th>Oil Palm</th>
<th>Forest</th>
<th>Open Land Oil Palm</th>
<th>Forest</th>
<th>Open Land</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1: 1988 - 1994</td>
<td>2,012</td>
<td>-12,470</td>
<td>10,406</td>
<td>0.2</td>
<td>-1.4</td>
</tr>
<tr>
<td>P2: 1994 - 1997</td>
<td>3,347</td>
<td>-25,498</td>
<td>14,666</td>
<td>0.4</td>
<td>-2.9</td>
</tr>
<tr>
<td>P3: 1997 - 2000</td>
<td>2,691</td>
<td>-15,844</td>
<td>14,038</td>
<td>0.3</td>
<td>-1.8</td>
</tr>
<tr>
<td>P4: 2000 - 2003</td>
<td>16,565</td>
<td>-13,853</td>
<td>-828</td>
<td>1.9</td>
<td>-1.6</td>
</tr>
<tr>
<td>P5: 2003 - 2006</td>
<td>12,562</td>
<td>-6,886</td>
<td>-5,190</td>
<td>1.4</td>
<td>-0.8</td>
</tr>
<tr>
<td>P6: 2006 - 2009</td>
<td>8,611</td>
<td>-6,889</td>
<td>-1,211</td>
<td>1.0</td>
<td>-0.8</td>
</tr>
<tr>
<td>P7: 2009 - 2012</td>
<td>11,675</td>
<td>-6,211</td>
<td>-4,984</td>
<td>1.3</td>
<td>-0.7</td>
</tr>
</tbody>
</table>

Table 4.17 Annually converted area and the percent of the total area converted in Area123.

Figure 4.77 Percent of the total area converted annually in Area123.
4.5.1.2 Development of oil palm plantations by small and large plantations

The development of oil palm plantations was further investigated by separating small and large plantations, which had been delineated in previous literature, and the results of the LC/LD model (Figure 4.56). The conversion rates of both small and large plantations drastically increased since the P4: 2000 – 2003 period (Figure 4.78; Figure 4.79). Particularly, small developments became dominant following P4 (2000 – 2003 through the most recent period) and P7 (2009 – 2012), while the total area of large developments had been continuously declining since P4 (2000 – 2003).

4.5.1.3 Spatial characteristic: distance to protected area

The average distance from an oil palm plantation to the protected area of the Kerinci-Seblat National Park (Figure 2.2, Figure 2.5) in 2012 was 20.7 km, with a range of 0 km to 50 km (Figure 4.80). Areas 2 and 3 showed that large plantations were generally located closer to protected areas than smaller plantations. In contrast, Area 1 showed the opposite trend, with large plantation located farther from protected areas than small plantations. However, a large-scale oil palm development occurred in the isolated lowland forest area that was not included in the montane forest in the protected area. In this case, isolated forest was actually designated as ‘dense low swamp forest of the
Indrapure plain’ in the vegetation map of 1983 (Figure 4.81; Laumonier 1983). The large-scale plantation in Area 1 was created by opening that forest. Therefore, the results support one hypothesis of this study, which is that large-scale oil palm plantations are more responsible for forest loss than the creation of plantations by smallholders (Hypothesis I). However, small-scale developments are more disperse than large-scale developments. Some small-scale oil palm plantations were identified very near or even beyond the border of the protected area in all three areas, which raises the possibility that small plantations could have already imposed certain impacts of environmental degradation deep in the forest.

![Figure 4.80 Mean distance of oil palm plantations to protected areas as of 2012. The error bars indicate the data range.](image1)

![Figure 4.81 Evidence of direct conversion from forest to large-scale oil palm plantations in Area 1.](image2)
4.5.1.4  Deforestation, intermediate land use, and conversion to oil palm plantation

The most essential questions that resulted in this study are when, where, and how (direct or indirect) is pristine forestland converted to oil palm plantations. Distinction between direct and indirect conversion were defined by measuring the temporal gap (Figure 4.82 - right) between the occurrence of deforestation (Figure 4.82 - left) and the onset of oil palm plantations (Figure 4.82 - middle):

\[(\text{Intermediate period}) = (\text{Start year of oil palm plantation}) - (\text{Year of deforestation}).\]

Figure 4.82 Occurrence maps of deforestation (left), conversion to oil palm plantation (middle), and the intermediate period between deforestation and conversion to oil palm plantation (right).

The histograms of the intermediate periods for large and small plantations indicated that most of the oil palm sites in large plantation areas were created within a few years after deforestation (Figure 4.84). In contrast, most of the small plantations were created after a certain period and several years since deforestation. Most small plantations were not a direct outcome of deforestation. Rather, the land had already been used by humans for other purposes, such as crops, and initial deforestation was likely not conducted with the aim of creating oil palm plantations.
Small and large plantations were further divided into two categories according to the length of the intermediate period (threshold value = 10 years), which resulted in $2 \times 2 = 4$ sub-categories: Small PL/0 to 10 years, Small PL/10 to 25.5 years, Large PL/0 to 10 years, and Large PL/10 to 25.5 years. The temporal plots of these four categories revealed that most new oil palm plantations after 2000 were small and were converted from land that had existed as intermediate land for more than 10 years (Figure 4.83).

Figure 4.83 Histograms of the intermediate period between deforestation and the conversion to oil palm plantation.

Figure 4.84 Land conversion to oil palm plantation broken down by years (0 – 10 and 10 – 25.5) of intermediate land use and plantation category (Small/Large PL).
4.5.1.5 Locations of direct and indirect conversions: distances to the protected area

Another essential analysis is to determine when and where direct and indirect conversion have occurred. Direct and indirect conversion were defined by the intermediate years between the occurrence of deforestation and oil palm plantation, with a threshold value of 2.0 years. The mean distances of the direct and indirect conversion to the protected area were calculated over the study area and summarized into 7 periods (Figure 4.85). At the beginning of the monitoring period (P1), the mean distances of both direct and indirect conversions (24 and 23 km, respectively) were in the middle of the flatland. Then, the mean center of direct conversion proceeded toward the protected area much faster than that for indirect conversion.

Figure 4.85 Temporal changes of the mean distance between oil palm plantations and the protected area plotted by direct/indirect conversion.
Figure 4.86 Deforestation in the study area. The occurrence period is indicated by color.
Figure 4.87 Conversion to oil palm plantations in the study area. The period of occurrence is indicated using the same color scheme as that used in Figure 4.56.
Figure 4.88 Intermediate periods between deforestation and conversion to oil palm plantation in the study area. The lengths of the periods are indicated by color.
4.5.1.6 Expansion of land used by humans

A mirror image of deforestation is the expansion of human land use, or human land, which includes all types of land use by humans, including oil palm plantations. Approximately 256,000 [ha] of human land existed in 1988, which increased to approximately 546,000 [ha] in 2012. This increase indicates that the area of human land doubled during this period (Figure 4.76, Table 4.16; note that ‘human-land’ in this section consists of oil palm, or Oil Palm, and the land uses denoted as Others in the other sections). A connected area or continuum of human land is defined as an area that exclusively consists of human lands that are spatially located next to each other. Thirteen continuums existed as of 1988 (Figure 4.90, Figure 4.89 - left) that were already large in size but separated from each other in Areas 1, 2 and 3. These major continuums had merged together by 2000, forming a single dominant continuum (Figure 4.89 - middle). The remaining forest on the coastal side had mostly disappeared by then, except in the northern part of the study area. Between 2000 and 2012, the progress of human land toward montane pristine forest occurred, infilling the flat plain and taking from the coastal forest in the northern part of the study area (Figure 4.89 - right).

![Figure 4.89 Areas and connectivity of human land in 1988 (left), 2000 (middle), and 2012 (right). Each color specifies certain connected area. The color schemes are arbitrary.](image-url)
Notably, all the mills that were nonexistent in 1988 were located within human land continuums that existed in 1988 (Figure 4.90). On the other hand, almost all of the large plantations, most of which did not exist in 1988, were located outside those continuums. This arrangement may partially explain why large plantations were concentrated in Area 2; the intricate shape of the human land in the area set the conditions that allowed for the construction of many mills near pristine forestland, where large plantations could be built.

Figure 4.90 Continuums of human land as of 1988. The colors indicate individual continuums. Arbitrary numbering for the continuums is shown in the legend. The boarders of the large plantations are indicated by red lines with numbers. The locations of the mills are indicated by small circles with colors that indicate the years of construction.
4.5.1.7  Density of oil palm plantations

The spatial density of oil palm plantations was obtained by taking the focal mean of the nearest neighbors in a 1 km x 1 km (33 x 33 pixels) square moving window (Figure 4.91). This value was used as a measure of oil palm development at the local scale and was used as an independent variable in the logistic regression analysis. The areas within large plantations showed a high density of oil palm. Area 2 showed the highest concentration of oil palm development, including large plantations, small plantations and mills. In contrast, Area 3 showed distinctive under-development, with large and small plantations and mills sparsely distributed in the area.

4.5.1.8  Continuums of oil palm plantations

The continuum of oil palm plantations was delineated by grouping the oil palm plantations that were located next to each other (Figure 4.92). This measure provides a certain measure of spatial
connectivity of the oil palm plantations, which could be interpreted as the dominance of oil palm plantations at the landscape level.

The temporal development of oil palm continuums provides a clear picture of the transformation of rural areas to oil palm (Figure 4.93). The first 12 years of the observation period have only seen patchy development of small continuums inside of large plantations. The actual development of continuums occurred during the latter half of the observation period (Figure 4.93). Notably, high concentrations of small plantations only occurred during this period. Several continuums were also merged into larger ones. Area 2 and the contiguous areas in Areas 1 and 3 showed the accumulation of oil palm plantations. Those continuums will

Figure 4.92 Oil palm plantation continuums as of 2012. The colors indicate the sizes of the continuums from small (blue) to large (red). The locations of mills are indicated by small circles. The boundaries of large plantations are indicated by blue lines. Four study areas are indicated by grey lines, and the protected area is indicated by black dashed lines.
merge together as the immediate future if the pace of development continues. The occurrence of small plantations is disperse, and the small plantations do not form continuums of significant size until the latter half of the observation period (Figure 4.94). Large continuums that included significant portions of small plantations began to emerge after 2003. Individual continuums began to merge and form very large continuums that included both large and small plantations. It remains to
be seen if the pace of oil palm development will continue to form one very large continuum in the immediate future.


**Figure 4.94** Oil palm continuums at 7 years: 88 (upper-left), 94, 97, 00 (upper-right), 03, 06, 09, and 12 (lower-right). *x*-axis: Size of palm plantation continuum, *y*-axis: % area

### 4.5.1.9 Inhomogeneity of land conversion to oil palm plantations

From the viewpoint of efficiency, the inhomogeneity of oil palm plantations would become a major obstacle for the future intensification of oil palm. In this respect, the inhomogeneity of planting year is possibly one of the most important factors. The negative impacts due to inhomogeneous years of planting between nearby plantations would linger for years and make it difficult to synchronize the timing of replanting. As one of the possible indices that is associated with certain aspects of land use efficiency, the Temporal-Spatial Inhomogeneity Index (TSIH Index) was devised, which is the standard deviation of planting years within a 1 km x 1 km square window and was computed on the rasterized map resampled at a resolution of 30 m pixels (**Figure 4.95**). Result showed that small
plantation neighborhoods were more inhomogeneous regarding the timing of planting than large plantations (Figure 4.96). There were also differences between areas. Regardless of whether a plantation was large or small, Area 3 showed the largest inhomogeneity among the three sub areas, followed by Areas 2, 4 and 1.

Figure 4.95 Inhomogeneity of the conversion year to oil palm: TSIH Index = Standard deviation of the conversion year within a 1 km x 1 km moving window. Values are scaled by 10. Calculations were based on the data used for the map of conversion year (Figure 4.75).

Figure 4.96 Temporal-Spatial Inhomogeneity Index (TSIH Index) for small and large plantations. Calculations were based on the data used for the map of conversion year (Figure 4.75). Error bars represent the standard deviation (±σ).
4.5.1.10 Emergence of mills and oil palm plantations

To determine the impacts of mills on oil palm development, which was indicated in Hypothesis-III, the relationships between the construction year of a mill and the conversion years of the surrounding oil palm plantations were analyzed. Statistics were obtained from the oil palm plantations within 0, 2, 5, 10 and 15 km of the individual mills (Figure 4.97 to Figure 4.102). The emergence of mills, large plantations and small plantations are shown. Overall, 5 of every 15 mills (M-3, 6, 9, 11, and 15) were constructed prior to the emergence of small-scale oil palm plantations. On the other hand, 7 out of 15 mills (M-2, 4, 5, 7, 12, 13, and 14) were constructed after the emergence of small plantations. The remaining 3 mills, M-1, 8, and 10, were not definitive.

To illustrate the emergences of a mill and the oil palm surrounding the mill, Mill-3, which is identified as the Mukomuko Estate Mill of PT, was considered. Agro-Muko and its surrounding area is shown in Figure 4.98. Mill-3 was constructed in 1992, which coincided with the emergence of a large plantation. Much of the conversion to small plantations occurred up to 15 years later (between 1994 and 2007) (Figure 4.98 - bottom). Mill-4 was

![Figure 4.97 Concentric rings around individual mills. Ring radiiuses are 2, 5, 10 and 15 [km]. Colors indicate periods of mill construction and the conversion to oil palm plantations (from blue (oldest) to red (most recent)).](image-url)
constructed in 2005, after the majority of oil palms had already emerged (Figure 4.99). Several reports exist that might be useful for interpreting these results (Ref-1, 2, 3, 4). Ref-1 reported all the mills that belonged to PT. The Agro-Muko group only accepted fresh fruit bunches of oil palm from its own estates; Ref-2 reported that employees of PT. Agro-Muko eventually started their own oil palm plantations once they learned how to manage them to their economic advantage. Ref-3 describes how smallholders find mills, and Ref-4 confirms that private mills that do not own any plantations provide services for ‘local growers,’ which should target local smallholders. To produce these reports, a land development scenario can be hypothesized detailing the construction of PT. The Agro-Muko Mukomuko Estate and Estate Mill spurred smallholders started their own plantations after a certain lag time and brought their fresh fruit bunches to either the Mukomuko Estate Mill or next closest
available mill. Then, due to the need for a processing facility, mills M-4 and M-5 were constructed, which mainly serve local smallholders in the area.

Figure 4.99 (top) Mill-4: PT. Agri Mitra Karya and its vicinity. The color schemes of the mills and their conversion to oil palm plantations are the same as those shown in Figure 4.75. (bottom) The construction year of Mill-4 is shown by a red dotted line, to the years of the conversion of large plantations are shown by red lines, and to the years of the conversions to small plantations are shown in black against the distance from Mill-4. The error boxes and bars represent the standard deviations.
Figure 4.100 Spatio-temporal relationships between the emergence of mills and oil palm plantations. The x-axis denotes the distance from a mill to oil palm. The y-axis denotes the mean year of land conversion to oil palm plantation calculated over concentric rings with one-sigma standard deviation (STD). Ranges of STD for small/free plantations are indicated with error bars and those for large plantation are indicated by boxes. The dotted red line s indicates the year of mill construction.
Figure 4.101 Continuation of Figure 4.100 for Mills 6 to 10.
Figure 4.102 Continuation of Figure 4.100 for Mills 11 to 15
4.5.2 Logistic regressions

4.5.2.1 Logistic regression analysis of the conversion to oil palm plantations

Logistic regressions were performed for the conversion of oil palm plantations by using the binary variable denoted as DPP (0: did not occur, 1: occurred) as a dependent variable. Logistic regressions were performed on two independent variable sets, with or without BAKO data, for 7 periods between 1998 and 2012. The spatial coverage of this model is indicated in Figure 4.52, which covers all of Area 1 and most of Area 2. The independent variables that were included in all the models were the PDEN, ML, PA, and the two topographic factors ELE and SLP. The variables included in the BAKO data were the VIL, RDS, and RIV.

Pseudo R², one of the measures that corresponds with the fitness of the model ranges between 0 and 1 from non-significant to perfect fit, were obtained for each period (Figure 4.103), which ranged from 0.09 to 0.24. Notably, the inclusion of BAKO data did little to improve the results. The relatively low R² was also expected because it was assumed that various factors existed that would have an affected on the starting oil palm plantation other than those included in this study. The absence of other factors would make those models ineffective for predictions. Nevertheless, the obtained models were still considered useful for evaluating the individual factors included in the model. The contributions from the individual factors included in the model. The contributions from the individual
factors to the model were estimated by z-values (Figure 4.105). Collinearities, or interactions between the independent variables, were obtained by conducting a pairwise correlation analysis (Figure 4.104). Some pairs showed high correlations above 0.5, including the correlations between the distances from settlements and major roads (0.8), the distance to protected areas and elevation (0.7), and the distance to settlements and elevation (0.6). Further modifications or omissions have not been performed because the impacts of these factors on the model were minimal.

The PDEN showed the largest impact among the variables in all the models, followed by the ML, ELE and SLP. This finding strongly implies that oil palm development in the neighborhood would have initiated further development in nearby areas. The presence of a mill also increased the chance of an area of land of becoming a palm plantation. Two topographic

Figure 4.104 Correlation matrices between independent variables. Conversion to oil palm plantation with BAKO data (left) and without BAKO data (right) for Period-7.

Figure 4.105 z-values for independent variables. Logistic model of oil palm plantation with BAKO data (top) and without BAKO (bottom). PDEN: density of oil palm plantation, ML: distance to nearest mill, PA: distance to the protected area, ELE: elevation, SLP: slope, and three variables from BAKO: the distances to settlement (VIL), major roads (RDS), and rivers (RIV). Negative signs were given to the original values of ML, VIL, RDS, ELE and SLP to obtain positive values.
factors, elevation and slope, negatively impacted on occurrence of oil palm plantation, which indicate flat and low altitude land favored oil palm plantation than steep and high altitude land. PA, RDS, RIV had mixed or negligible results. In other words, no evidence existed that indicated that the presence of protected area, major roads, or rivers had any definitive roles on the development of oil palm plantations outside the protected area. The VIL, or distance to settlements, barely showed a positive impact on oil palm development.

Next, logistic regression models were prepared separately for small and large plantations. The pseudo $R^2$ and Z-values obtained from the models are shown in Figure 4.106 and Figure 4.107, respectively. Models for small plantations indicated better model fits than those for large plantations overall, except for Period-1 (P1). The distances to protected areas, settlements, and rivers had the largest 3 z-values for the large plantation P1 model, which could indicate that the first large plantations built during P1 were located far from the protected area and near settlements and rivers. After P1, the contributions of the individual variables to the large plantation models were not consistent, except for the PDEN and SLP. This result implies that some powerful external factor(s) existed, such as the economy of scale, corporate decisions and land permissions, that had driven large plantation development and overridden other favored conditions.
The results for small plantation showed better model fits. The Z-values for PDEN, MIL, ELE, VIL, and SLP were consistently positive over the studied periods, with the relative Z-values increasing in the presented order. This finding implies that the occurrence of small plantations that were not confined in the large sized developments were affected by the development of oil palm plantations in the neighborhood, of mills and settlements and on land with specific elevations and slopes.

Figure 4.107 Z-Values for the independent variables. Logistic model of small plantations (top) and large plantations (bottom). The independent variables are the same as those shown in Figure 4.105.
4.5.2.2 Logistic regression analysis of deforestation

Logistic regression models were made for the occurrence of forest loss or deforestation using the binary variable denoted as DDF (0: Not occurred; 1: Occurred) because dependent variable Logistic regressions were performed on two independent variable sets, with or without BAKO data, for 7 periods between 1998 and 2012. Spatial coverage of this model is indicated in Figure 4.52, which covers the entire Area 1 and most of Area 2. The independent variables that were included in all the models were the density of previous deforestation (DFN), distance to forest edge (OL), ML, LP, PA, and two topographic factors: ELE and SLP. The variables included in the BAKO data were: VIL, RDS, and RIV.

Pseudo R^2 values were obtained for each period (Figure 4.108), which ranged from 0.11 to 0.29. As for oil palm, the inclusion of BAKO data contributed little to improving the results. The fineness of the models was significantly better than the fineness of the oil palm models. The impacts from the independent
variables on the model were estimated by z-values (Figure 4.110). Collinearities were obtained in a correlation matrices (Figure 4.109). Although some pairs showed high correlations above 0.5, no variables were modified or omitted. DFN and OL showed the largest positive impacts among all the variables in all the models, followed by ML, ELE and SLP. This result strongly implies that deforestation occurred at or near the forest edge and that once deforestation occurred it initiated further deforestation of the nearby or newly shaped forest edge. The presence of mills also enhanced deforestation. Two topographic factors, elevation and slope, negatively impacted the occurrence of deforestation, which indicate that deforestation also favored lower, flatter areas. PA, VIL, RDS, RIV had mixed or negligible results. In other words, no evidence indicated that the existence of protected areas, settlements, major roads, or rivers had any definitive impact on deforestation outside of the protected area.
Chapter 5  Discussion

5.1 Verification of hypotheses

The logistic regression results explicitly showed the positive impacts of mills and/or large plantations on the occurrence of small oil palm plantations (Figure 4.107), which have underwritten hypothesis IV, which was that mill and large enterprise development of oil palm spurred the development of smallholder developments in their surrounding neighborhood (Figure 4.105). Because the distances to nearby mills and large plantation are highly correlated ($R^2$ values of 0.7 to 0.9), only one of these distances (the one that showed a higher z-value) was included in the final models. The results from the logistic regression models also confirmed Hypothesis V, which was that smallholders were spatially and temporally inhomogeneous and more dispersed than large enterprise plantations (Figure 4.95 and Figure 4.96). Small plantations were more inhomogeneous and dispersed in space and time. In addition, the plantations located nearest the protected were always small (Figure 4.80). However, the mean distance of the large plantations from the protected area was smaller than the mean distance of the small plantations from the protected area. Most of the direct conversion from forestland had also occurred for large plantation rather than small plantations, which supports hypothesis I. These results imply that large plantations are more invasive or destructive against forest and biological conservation, at least quantitatively. Although large plantations are recognized as major responsible agents for deforestation, it should be noted that some small plantations were also located on the border of the protected area. Even the total area of the small plantations was minimal, and the impacts on the environment could be fatal because they could disrupt the continuity of the environmental services and result in extensive degradation of the conservation area. However, this detrimental effect is beyond the scope of this study. Hypothesis II, which was that smallholders are mainly responsible for the indirect conversion of land to oil palm
plantations, was also confirmed because most small plantation sites were established for intermediate land use between deforestation and oil palm plantation (Figure 4.84).

Furthermore, drastic shifts in the conversion mode of oil palm development occurred since 2000, with small plantations becoming more responsible for new development than large plantations and the location of development shifting from forest to human land, such as cropland, which has made indirect conversion the major mode of land change (Figure 4.83). This trend shifts after 2000 and is reflected by the decreased pace of deforestation and the decrease in other types of human lands, which are denoted as Others or Openland Figure 4.76 and Figure 4.77). The total area of forest, which initially occupied 68% of total study area in 1988, decreased by 50% by 2012 (34%; Table 4.16), with the first half of the entire period accounting for two-thirds of the decrease (23%) and the latter half accounting for the final third (12%). Oil palm increased from 2% to 22%, which was an increase of 20% during the entire period. The former half of the period accounted for an increase of 3% and latter half accounted for an increase of 16%, respectively. Of the 16% expansion of oil palm plantation area between 2000 and 2012, 82% (14/ (2 + 14 ) = 0.82 from Table 5.1) occurred on human land and only 18% occurred on forestland. In addition, 3% of the expansion occurred between 1988 and 2000, 40% occurred in human land and 60% occurred in the forest. Therefore,
most of the oil palm development after 2000 occurred on human land, which should have reduced deforestation pressure and contributed to decreasing the pace of deforestation.

Hypothesis III is that the accessibility of an area to a mill limits the number of small plantations that develop. This hypothesis was examined using a concentric ring analysis around the mills (Figure 4.97 to Figure 4.102). The timing of mill construction and the formation of small plantations in the neighborhood satisfied the hypothesis that the mills were built for large plantations. Regression analysis also showed a significant impact of the distance to a nearby mill on the development of small plantations (Figure 4.107 - top). Although the impacts of mills on the development of small plantation were indicated statistically, the land change and land use patterns observed in this case study had limitations for further investigating the direct relationships between the mills, large plantations and small plantations. The method of land analysis for Hypothesis III initially assumed that the centrality of the mills would be explicitly represented by the concentric land development beginning around the mills, which was predicted by general land-rent theory. However, the land change patterns were more disperse and irregular than initially assumed. Also, the ability to carry FFBs for long distances by using modern transportation, such as trucks, enabled dispersion of the plantation sites rather the formation of dense, concentric ring around the mills that was predicted by land-rent theory. Smallholders generally seek to maximize profit by selling their FFBs to a mill that pays a higher rate than other nearby mills. Smallholders sometimes bring their FFBs to a mill that pays a higher rate than other nearby mills.

<table>
<thead>
<tr>
<th>Period</th>
<th>Area [ha]</th>
<th>[%] to total Oil Palm</th>
<th>[%] to total study area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direct</td>
<td>Indirect</td>
<td>Total</td>
</tr>
<tr>
<td>2000 - 2012</td>
<td>14,828</td>
<td>126,702</td>
<td>141,530</td>
</tr>
<tr>
<td>Total</td>
<td>43,688</td>
<td>142,529</td>
<td>186,218</td>
</tr>
</tbody>
</table>

Table 5.1 Mode of land change: Direct or indirect conversion from forest to oil palm plantations for the former 12-year and latter 12-year periods. Recreated from the same data used for Figure 5.1.
km from the plantation site to obtain a good price; however, transportation costs also limited that the transport of FFBs beyond this distance (Skalanews 2012). The possibility of distant transportation could not be explicitly investigated by the interferences of other mills and the plantations in-between the mills. It will be indispensable to conduct investigations to discover the temporal-spatial development of how small plantations begin feeding FFB to specific mills.

In the course of this investigation, another factor that could be added to the land change scenarios emerged. Like oil palm plantations, two types of mills exist, those with their own large plantations (plantation mills) and commercial (or private) or ‘free mills’ that do not have their own large plantations. The commercial mills had not been built to serve any specific plantations. Rather, the mills were buying FFB from all customers, supposedly free smallholders in pursuit of profit. It was strongly implied that these two types of mills play significantly different roles in oil palm development at the local scale. When the hypotheses of mill and oil palm development relationships were made, only plantation mills were considered. The investigation of plantation mills resulted in some planation development, as typically shown for Mill-3 (Figure 4.98). On the other hand, most free mills were constructed after small plantations had become well-developed nearby, as shown for mill 4 (Figure 4.99). This finding strongly indicates that free mills were built only after the development of smallholder plantations, and the potential customers for them progressed to the level that investors of the free mills began seeing that they could make sufficient profits. Therefore, the oil palm development scenario can be rewritten as follows: plantation mills spur the development of small plantations in the area, which create a need for more oil processing capacity and induces the construction of free mills, enhancing the oil processing capacity and further facilitating the conversion of land to oil palm plantations. Quantitative analyses according to mill
type have not been performed in this study but will be performed in the next steps toward comprehensively understanding oil palm development.

5.2 Impacts of historical infrastructure development and human land

The long-term satellite dataset has also made it possible to understand oil palm development in a larger context. It should be noted that more than half (approximately 54%) of the total land that had been converted to oil palm as of 2012 had been used for other land uses for more than 10 years since deforestation (Figure 4.84). In other words, about a lag period of approximately 10 years occurred between deforestation and the establishment of oil palm plantations. At the beginning of the observation period in 1988, approximately half of the original human-intervened land (human land) that was observed in 2012 existed. Notably, the human land in 1988 already suggested that increases in land development would occur (Figure 4.90). All the large oil palm plantations were located outside that human land as of 1988, while all the constructed mills were concentrated within that human land and covered much narrower strips of land. This finding underwrote the claim that large enterprise plantations avoided locations with human land and would rather establish on forestland to avoid dealing with land right issues (Koh and Ghazoul 2010, Gutierrez 2013 and Lee et al. 2013). The long-term satellite data imply that oil palm first emerged as a large enterprise plantation just outside of the human land where plantation mills processed the harvested FFB. Next, small plantations began developing on the human land, where free mills had been added to keep up with the heightened demand for FFB processing capacity. It is unclear why the mills lined up in the oldest open land strips, but it is strongly implied that infrastructural developments, such as the construction of arterial roads, could have made the core human development area favorable for mill construction.
The impacts of roads on deforestation and oil palm development were only significantly positive during the early period. This finding seemed to contradict the widely accepted idea that road construction was the single most powerful local driver of deforestation. It was likely that the road data only represented major areas that had been constructed several years ago. The effects of those roads had already been imposed on land development back in 1988. New developments after 1988 had been facilitated by new road construction, which was not included in the BAKO road data.

Topographical maps that were published around the end of World War II revealed that the core parts of the roads and settlements had already been laid out by that time (Figure 5.2). During that time, the land was dominated by forest and not much land was used for subsistence agriculture which consisted of rice fields that remained the same until today. Another historical map, a vegetation map from 1983, indicated open land development, which was limited for subsistent
agriculture and/or the mosaic of subsistence agriculture and some plantations, such as rubber and coconut, and no large-scale oil palm plantations were recorded (Figure 5.3). Based on the knowledge acquired from these historical maps, the infrastructure and land development seemed to have predated the oil palm development that began in the late 1980s, whose effects on oil palm development had lingered throughout the period, including its effects on determining the locations of large plantations and mills and for determining where small plantations could have emerged. Any quantitative studies of the relationships between historical land uses and oil palm development are beyond the scope of this study and should be considered in future studies. The same methods that have been developed for oil palm would also be applicable for extracting spatio-temporal infrastructure developments, such as new roads and their construction years and new settlements, which will further compensate for missing ancillary information.
Figure 5.3 Vegetation map of 1983 and the Bakosurtanal digital map of major roads (yellow and black lines) and settlements (pink). The study area is indicated by gray lines with black dots.
5.3 Summaries of the methodological developments

One of the major goals of this study was to extract human-affected land change information at fine scales to enable the analysis of land change at the local scale. This goal was accomplished by utilizing the Landsat satellite data that accumulated over more than two and one-half decades. The LC/LD Model was designed to extract the major land changes of interests, deforestation and conversion to oil palm plantation, from the long-term measurements of land surface spectral information. The specifications of land use change detection and determination procedures were newly modeled by referring to the Landsat long-term data, multi-temporal Google Earth images, and ancillary information of the growth stages, land practice, effective spectral bands and spectral signatures of oil palm plantations. Instead of using conventional vegetation indices such as the NDVI and SAVI, which had been commonly adopted for satellite data analysis, the much less popular band combination, the ratio of NIR to MIR bands (IB45 = Band4/Band5), was used to represent the temporal profiles of the land and land change from the long-term Landsat dataset. To detect two major land changes, deforestation and conversion to oil palm plantations and distinguish these changes from other types of land use and land changes, two-tiered computer models were developed. The first model, the LC model detects and the second model, the LDM and determines land changes. Both models were designed using various biophysical metrics based on the modeled temporal profiles that had been assumed from land development scenarios regarding the transitions of land surfaces due to land use changes and phonological development. The parameter values for the LC/LD model were calibrated to minimize the prediction errors of the half of the sample sites that had been collected from multi-temporal Google Earth images and the long-term Landsat dataset. In addition, the model was validated by running the model again using the other half of the sampling sites. The ALOS-PALSAR annual data from 2010 were used as supplementary data to distinguish between oil palm and other types of plants, especially natural vegetation and other tree
species, such as rubber. The highest part of the montane area where clouds persisted throughout the observation period was excluded from analysis. An accuracy assessment was performed by comparing the Google Earth fine imageries for the sample sites with the land uses derived from the results of the LC/LD model, which resulted in accuracies of approximately 88.5% and 91.5% for oil palm and forest, respectively.

The spatial unit for all data analysis was the polygon, which was delineated from multi-temporal spectral data using the multi-temporal segmentation method. One of the main objectives of adopting irregular polygons rather than pixels or regular polygons is to enable a visibly intuitive approach in the model building process by enhancing the temporal-spectral characteristics of the data. Adopting segmented polygons rather than pixels played a critical role in building the conceptual land use model from scratch. The continuous pixels of the segmentation algorithm groups have similar spectral patterns. By incorporating temporal factors, segmentation could account for both the spectral features of land cover and the spectral changes corresponding to land cover changes. This procedure was successful for reducing the redundancy of temporal-spectral information, which also reduced the amount of data so that all applications could be handled without execution errors or within the practically acceptable computing time. It was also expected that adopting segmented polygons would reduce the specific type of error inherent to the pixel-based approach plagued by unavoidable half-pixel displacement errors and also increase the chance of observation. To fully use the observable areas, the observed pixels in the polygon were regarded as representatives of the entire polygon. This procedure increased the chance of obtaining values from cloud-covered or/and SLC-off images (Figure 5.4). Briefly, the temporal-spectral features of land cover and land changes could have been agglutinated by multi-temporal spectral segmentation.
in the two-dimensional space, which played an essential role in the model building process in the course of the heuristic approach. Although qualitative assessments of segmentation results and extracted temporal profiles have been made when proper segmentation was chosen, quantitative assessments on the efficiency of segmentation on how good polygons exactly delineate changes and if they improved the accuracy of land change/land use determinations were not performed in this study. Thus the need for quantitative assessment is left open for future studies.

To begin model construction, conceptualized ideas of how values and shapes of temporal-spectral profiles for key land uses and land changes should be used existed, which were deduced from expert knowledge of the oil palm growth stages and land practices found in the literature and analogized based on plant phenology. These conceptual models, which assumed land uses and land cover transitions such as pristine forest and land clearing, show scarce vegetation during the initial stages of oil palm, and plant growth to maturity and senescence and replantation were confirmed by visually interpreting the multi-temporal Google Earth fine images and their temporal-spectral profiles obtained from the long-term Landsat dataset. The effectivities of spectral indices derived from two band combinations of six Landsat/TM or ETM+ multispectral bands were examined and IB45 = B4/B5 was found to be the most effective for both qualitative and quantitative analyses.

Figure 5.4 Conceptual image of data acquisition from the segmented polygon. The observation value is obtained by taking the average of the observable pixels.
IB45 allowed the sue of an intuitive approach for relating the values with the pseudo-color representation of (Band 3,4,5) = (blue, green, red) on screen to investigate land changes over time. The comprehensive investigation consisted of the visual interpretation of Google Earth images acquired on multiple dates, plotting and coloring the IB45 temporal profiles derived from the segmented Landsat dataset, and visual interpretation of land cover and land change by flipping through the long-term Landsat dataset. This cross-referencing between land changes, land cover transitions and spectral signature changes was crystallized to a conceptual model that provided insights for determining the basic structures of the following computer model.

To extract the land use and land changes of interest from the IB45 temporal profiles, the temporal factor was ‘segmented’ and separated into different land use/land cover periods. This segmentation, named the Temporal Segmentation Procedure (TSP), was performed by detecting points of spectral changes that could indicate the times of deforestation or conversion to oil palm plantation: two focal land changes in this study. The algorithm of TSP was developed in this study from scratch and implemented in the LCM. The results of the LCM and the segmented IB45 temporal sub-profiles were passed onto another computer model called the LDM. These sub-profiles were evaluated separately by using the statistical values called biophysical metrics that would provide certain measures of given profiles that determined their land cover/land uses, such as forest, oil palm, other corps, and other land uses. This segmentation and land definition process was crucial not only for detecting land changes but also for obtaining good land cover/land use classification results with higher accuracy and more robust methods than the conventional LULC classification of one-shot images, which is inherently plagued with the spectral overlapping between major types of land cover/land use. Segmentation procedures were designed to only detect key land changes, such as
deforestation and the conversion to oil palm, and ignore minor changes, such as annual crop growth and harvest. These repetitive types of land cover change, which does not include land use changes, was beyond the scope of this study and classified as other land uses denoted as Others or Openland. The results from the combined LC/LD Model provide comprehensive information regarding land use/land cover changes with specific focus on forest and oil palm plantations, deforestation, and the direct and indirect conversion of land to oil palm plantations.

Another heuristic approach was also taken to search for oil palm processing plants (denoted as mills for short). The inclusion of mills in the land change analysis make this study unique and distinctive from other previous studies. All fine-scale Google Earth images that covered the study area were exhaustively investigated in search of mills. Once a potential mill site was spotted, its visual features were appraised to determine if they satisfied conditions of a mill, such as elongated buildings with chimneys, storage tanks and waste treatment ponds. For the mills determined by using Google Earth images, the year of construction was determined by referring to the long-term Landsat dataset. The technique of flipping through pseudo-color Landsat images over time allowed us to visually determine the timing of mill construction. Overall, 15 mills were identified with their locations and years of construction. This information was used in land change analysis to determine the significant impacts of mills on the development of small plantations.
6.1 Future improvement and extensions of the LC/LD models

Land change is considered a major environmental problem. Deforestation is one of the most serious global issues that could greatly impact nature and the well-being of humans. Tropical Asia is one of the two main hotspots for deforestation, along with the Amazon in South America. The creation of oil palm plantations is identified as one of the most dominant causes of deforestation in tropical Asia, where the richness of biodiversity and endangered and threatened species are under serious threat of extinction. Like urbanization, the conversion of land to oil palm plantations is considered a permanent land change, which would result in long-term local socioeconomic effects in the areas around the oil palm plantations. However, the future prospects of palm oil are unclear, even though palm oil is currently the most efficient and consequently cheapest edible oil in the world. The breeding process of oil plants requires too many years to efficiently improve the production efficiencies of other oil plants. Local economic prosperity, which is being built around oil palm plantations and palm oil production, could be hampered by the emergence of more efficient oil crops. Therefore, rampant development should be controlled under the guidance of land use policies to mitigate the negative impacts of oil crops on nature and on the well-being of humans. This study introduces quantitative methods that can be used to search for local factors that drive oil palm plantation development. To achieve this goal, however, a total framework of data collection and analysis was established. Satellite images were regarded as the most complete and the only available practical source of information for this purpose. The study area, most of which was located in the Mukomuko and NB Regencies in the northern half of Bengkulu Province, was chosen partly because of its significant location for conservation. The study area was located in the western part and near Kerinci-Seblat National Park, which is one of the major constituents of the Natural World
Heritage site designated as the Tropical Rainforest Heritage of Sumatra. Because oil palm plantations were started in this area in the late-1980s according to the literature, using all available satellite data from that period to the most recent period was essential for building and applying a land change model for the entire study area. The land change model also required continual acquisition of satellite imageries with sufficient frequently to track the temporal behaviors of the spectra. Under such conditions, the first critical phase of this study was to obtain a sufficient number of temporal spectral signatures. To accomplish this task, an exhaustive search of satellite images was performed of the free Landsat archive using relaxed image quality criteria to obtain any signatures of pixels that could be saved after masking out clouds, cloud shadows and any other atmospherically disturbed pixels. The use of masking was important to eliminate disturbed pixels to avoid misinterpreting land changes. Applying cloud masks, which had been automatically obtained through spectral information extracted from the image itself, was not sufficient to meet the severe criteria of this study. Thus, to remove the remaining disturbed pixels, another masking layer was created by manually delineating areas from all available images. Using this combination of automatic and manual filters decreased the total required working time, because over-masking only occurred for specific types of land cover that showed spectral signatures similar to clouds or cloud shadows. These types of land cover included water bodies and certain urban surfaces and degraded the accuracy of the LC/LD Model results. However, it is unclear if any improved automatic masking procedures will become available for public use in the near future, which has already occurred for image rectification, freeing the users of satellite data from that labor-intensive work. Successful launch and operation of Landsat 8 in 2014 will assure continuation of land change monitoring seamlessly over space and time. Although more satellites are being put into space, the prospects of accessibility to other earth-observation satellites, which are operated by private firms or government agencies other than the U.S. government, are uncertain under the shaky climate of international
cooperation and confidentiality or the disclosure and enclosure of information and the business aspects of data distribution. Study areas can and will be extended to wider areas, other locations in Sumatra, or other places in tropical Asia, South America, and Africa, where oil palm plantations are resulting in major land use changes. In future studies, the inclusion of more case studies will be investigate to corroborate the current results or add new discoveries for understanding oil palm development. Another direction of the next study phase will be to build a more comprehensive land change model that includes more factors, especially socioeconomic and other ‘soft’-factors, such as ethnicity and the accessibility to financial sources, information and technology from the local to areal, national and global scales that could be affecting oil palm development. One such factors, the operation type of plantation (large-scale enterprise or small-scale smallholder) was explicitly included in the current model, which has shown great potential for socioeconomic applications and other soft-factors in the land change analysis. Another critical ‘soft’-factor, the type of mil (plantation or independent) was discussed when interpreting the results. These results have shown that the inclusion of soft-factors can dramatically clear the haze of data outputs and enhance our deeper understandings of the problem. To augment ‘hard’-factors, upgrading the LC/LD Model to investigate more land uses and land changes with higher accuracy will be a more immediate and achievable goal. Actually, the prototypes of the models for extracting other crops, such as rice paddy fields, and infrastructure developments, such as the constructions of roads and settlements, was already built into current land change models. However, the model must be improved for practical use. The current study area and satellite dataset will remain an ideal location and source of information for more comprehensive investigations in the next phase of study. of the variety of land uses and land changes have been showcased in this area throughout the satellite observation period, which will enable in-depth investigations that consider various local conditions and factors.
6.2 Utilizing open-access resources

The following two major goals of this study have been accomplished: building practical methodologies for land use/land change monitoring using multi-temporal satellite datasets and performing a quantitative analysis of the factors impacting the development of oil palm plantations. It has been demonstrated that as far back as the late 1980s, the history of land uses and land changes can be traced by utilizing Landsat data archives with high accuracy, which could also be used for the general purpose of environmental or socio-economic studies.

In the current era of information, the potential of the Internet and the use of open-access knowledge for earth and environmental studies have been explored for various uses. For example, the internet can be used for searching satellite data, observing land and collecting samples through Google Earth. Other digital spatial data sources, such as GIS data and digital maps, and different types of literature collections, such as government or private reports, research publications and statistical data, are stored and can be found online. Social types of media, including the official websites of the plantations, and mass media, such as local and international newspaper articles can also be found. Thus, the physical addresses of these plantations have been dispersed around the world, including university libraries in the U.S., chemical firms of the Japanese conglomerate investigation department, and Ph.D. theses archives at local universities in Southeastern Asia. The robustness of this study has been enhanced by the richness of such open-access information, which can be used to compensate for lacking ground-truth data. One of the main focuses and unique aspects of this study is the separate investigation of large-scale enterprise plantations and small-scale smallholder plantations. Therefore, the delineation of large-scale enterprise plantations was an essential step for further understanding oil palm development. After a significant amount of effort has been paid to automatic/computational delineation without results, the manual delineation
procedure of on-screen digitization was adopted. This procedure was partially supplemented by estate maps acquired through the internet. Supporting materials that included information such as estate names, establishment years, and estate sizes were also found for most large-scale plantations. Supporting materials for mills were also extensively collected over the internet. All except 2 of the 15 mills identified by satellite image interpretation were confirmed by primary documents such as government publications, private reports, and local newspaper articles or by social media or websites hosted by the owners of the mills. The completed list of mills was also cross-validated with local governments reports that provided the names, locations and processing capacities of the mills.
Bibliography


