ABSTRACT

Title of Dissertation:	QUANTIFYING VULNERABILITY OF PENINSULAR MALAYSIA'S TIGER LANDSCAPE TO FUTURE FOREST LOSS
	Varada Sanjeev Shevade, Doctor of Philosophy, 2018
Dissertation directed by:	Associate Professor, Tatiana V. Loboda, Department of Geographical Sciences

Agricultural expansion has been the dominant driver of tropical deforestation and increased consumption of commodities and resulting global trade have become distal drivers of land cover change. Habitat loss and fragmentation threaten biodiversity globally. Peninsular Malaysia, particularly, has a long history of land cover land use change and expansion of plantations like those of oil palm (*Elaeis guineensis*). Deforestation and plantation expansion threaten the Malayan tiger (*Panthera tigris jacksonii*), a critically endangered subspecies of the tiger endemic to the Malay Peninsula. Conservation of tigers and their long-term viability requires not only the protection of habitat patches but also maintenance of corridors connecting habitat patches. The goal of this dissertation was to understand patterns of recent forest loss and conversions, determine the drivers of these changes, and model future forest loss and changes to landscape connectivity for tigers. Satellite remote sensing data were used to map and estimate the extent of forest loss and forest conversions to plantations within Peninsular Malaysia. Mapped forest conversions to industrial oil palm plantations were used to model the factors influencing such conversions and the constraints to recent and future conversions. Finally, the mapped forest loss was used to model the deforestation probability for the region and develop scenarios of future forest loss. This study indicates that despite the history of land cover change and an extensive area under plantations, natural forest loss has continued within Peninsular Malaysia with about half of the cleared forests being converted to plantations. Proximity to pre-existing oil palm plantations is the most important determinant of forest conversions to oil palm. Such conversions are increasingly in more marginal lands indicating that biophysical suitability alone cannot determine where future conversions might take place. Forest conversions to oil palm plantations within the region are more constrained by accessibility to infrastructure rather than biophysical suitability for oil palm. The projected patterns of loss indicate lowland forests along the southeastern coast and in the center of the Peninsula are most vulnerable to future loss. This projected loss will likely reduce the connectivity between forest patches further isolating tiger populations in the southern part of the Peninsula. This study demonstrates the continued pressure on Peninsular Malaysia's forests, the potential impact of persistent deforestation on forest connectivity, and draws attention to the need for conservation and restoration of forest linkages to ensure viability of the remaining Malayan tiger population.

QUANTIFYING VULNERABILITY OF PENINSULAR MALAYSIA'S TIGER LANDSCAPE TO FUTURE FOREST LOSS

by

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Dissertation submitted to the Faculty of the Graduate School of the
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Advisory Committee:
Professor Tatiana V. Loboda, Chair
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To my family

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List of Abbreviations

CFS	Central Forest Spine
CIESIN	Center for International Earth Science Information Network
DOSM	Department of Statistics Malaysia
DWNP	Department of Wildlife and National Parks Peninsular Malaysia
EIA	Environmental Investigation Agency
ETM+	Enhanced Thematic Mapper
FAO	Food and Agriculture Organization of the United Nations
FDTCP	Federal Department of Town and Country Planning
GFC	Global Forest Change
GTRP	Global Tiger Recovery Program
HBV	High Biodiversity Value
HCS	High Carbon Stock
HCV	High Conservation Value
IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for the Conservation of Nature
LCP	Least Cost Pathways
LFT	Landscape Fragmentation Tool
MODIS	Moderate Resolution Imaging Spectroradiometer
MOT	Ministry of Transport
MPOB	Malaysian Palm Oil Board

MPOC	Malaysian Palm Oil Council
MPOCC	Malaysian Palm Oil Certification Council
MSPO	Malaysian Sustainable Palm Oil
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NPP	Net Primary Productivity
NTAP	National Tiger Action Plan
NTRP	National Tiger Recovery Program
PA	Protected Areas
PAp	Protected Area Prohibitive
PAr	Protected Area Restrictive
PRF	Permanent Reserved Forest
ROC	Receiver Operating Characteristic
RSPO	Roundtable on Sustainable Palm Oil
SEDAC	Socio-economic Data Acquisition Center
SRTM	Shuttle Radar Topography Mission
TCL	Tiger Conservation Landscape
TM	Thematic Mapper
UNDP	United Nations Development Programme
WDPA	World Database on Protected Areas
WRI	World Resources Institute
WWF	World Wildlife Fund

Chapter 1: Introduction

1.1 Background and Motivation

Anthropogenic impact on the Earth's surface has been extensive and lasting. Humans have been responsible for transforming between one third and one half of the Earth's surface (Vitousek et al. 1997). The impact on the terrestrial biosphere is especially pervasive and more than 75% of the Earth's ice-free land surface is dominated by anthropogenic biomes described as ecosystems with sustained direct human interaction (Ellis and Ramankutty 2008). These transformations are driven by resource consumption for human enterprises like agriculture, industry, trade, etc. Human utilization of land for goods and services results in alteration of structure and functioning of ecosystems, which in turn alters biogeochemical cycles and drives climatic and biotic changes globally (Vitousek et al. 1997). Human impact on the biosphere, when calculated as the proportion of net primary productivity (NPP) appropriated by humans, shows that humans are responsible for directly or indirectly consuming about 40% of the global NPP (Vitousek et al. 1986). However, the human footprint of consumption is uneven globally and there is considerable spatial variation in the human appropriation of NPP with some regions consuming >70% of their regional NPP (Imhoff et al. 2004). Through the 20th century human appropriation of NPP has doubled and with rising human population, consumption, and gross domestic product resulting in greater pressure on the terrestrial biosphere despite increases in land use efficiency (Krausmann et al. 2013).

Humans have an impact on landscapes from local to regional to global scales. Causes of land cover changes can be classified as proximate (or direct) causes – which are direct or immediate alterations of land cover from intended land use decisions that operate at the local level, and underlying (or indirect) causes – which are complex forces driving the proximate causes operating diffusely from regional to global levels (Meyer and Turner II 1992, Geist and Lambin 2002, Lambin et al. 2003). Underlying causes tend to be exogenous to the communities taking land management decisions and result from complex interactions of social, political, economic, cultural, demographic, technological, and biophysical factors (Lambin et al. 2003). These causes can interact with each other within and across levels of organization via feedbacks leading to land use change and synergetic combinations of causes are more common in driving land cover changes (Lambin et al. 2003). Tropical deforestation has been a leading cause of global environmental change and is a phenomenon best explained by synergistic interactions of proximate and underlying causes (Geist and Lambin 2002). Vulnerabilities of people, societies, and ecosystems to global changes are also interconnected through these biophysical linkages and feedbacks, flows of resources, people, or information, and economic market interactions (Adger et al. 2009).

1.1.1 Agricultural Expansion as a driver of deforestation and biodiversity loss in the tropics

Agricultural expansion has been a prominent driver of global deforestation (Geist and Lambin, 2002, Gibbs et al, 2010, Hosonuma et al. 2012). With increased population, greater consumption and demands, enterprise-driven agriculture producing for international markets has become the main driver of deforestation (Rudel et al. 2009, DeFries et al. 2010, Hosonuma et al. 2012). Tropical forest loss has been positively associated with urban population growth and agricultural exports due to the high consumption of processed foods and animal products by urban populations, which is driving commercial production of crops and livestock (DeFries et al. 2010). Globalization, commodity flows and distant causes like remote markets, foreign investments, diffusion of technologies, etc. are increasingly considered to be important drivers of land cover or land use change (Meyfroidt et al. 2013). Displacement of land use resulting from international trade in primary and manufactured products as well as services constituted 24% of the global land footprint in 2004 (Weinzettel et al. 2013).

A shift from state-enabled smallholder-driven deforestation in 1960s-1980s to more enterprise-driven deforestation was very evident in Southeast Asia (Rudel et al. 2009). Southeast Asia has some of the highest rates of deforestation globally (Sodhi et al. 2010). Expanding plantations for commodities like palm oil have been a dominant driver of land cover change within the region. Between 1990 and 2010, industrial oil palm plantations in Malaysia, Indonesia and Papua New Guinea expanded from 3.5 Mha to 13.1 Mha and on average of 32.4% of the new plantations were established on land previously covered with disturbed forests (Gunarso et al. 2013). In 2007, palm oil constituted ~ 30% of global production of vegetable oils while palm oil exports account for ~ 60% of global exports in oils and fats by volume (Carter et al. 2007). Malaysia and Indonesia together produce about 85% of the world’s palm oil (Carter et al. 2007). Malaysia is the second largest producer with 4.3 million ha under oil palm production in 2007 (Wicket et al. 2011). It is also one of the largest exporters of palm oil (Sheil et al. 2009) and its exports of palm oil have more than doubled from 1990 to 2016 (Fig.1). Crude palm oil output increased on an average more than 8% annually between mid 1970s and mid 2000s (Carter et al. 2007) and reached 19.7 million tonnes in 2013 (Johari et al. 2015). The primary reasons for palm oil's popularity are that it is cheaper to produce and is priced lower than most alternative vegetable oils (Carter et al. 2007). Recent growth of palm oil production could also be driven in part by the demand for biofuels (Corley 2009). Oil palm production is highly profitable and the high prices and the increasing demand of palm oil from various industries provide incentives for expanding oil palm production making future land use change highly likely (Wicke et al. 2011).

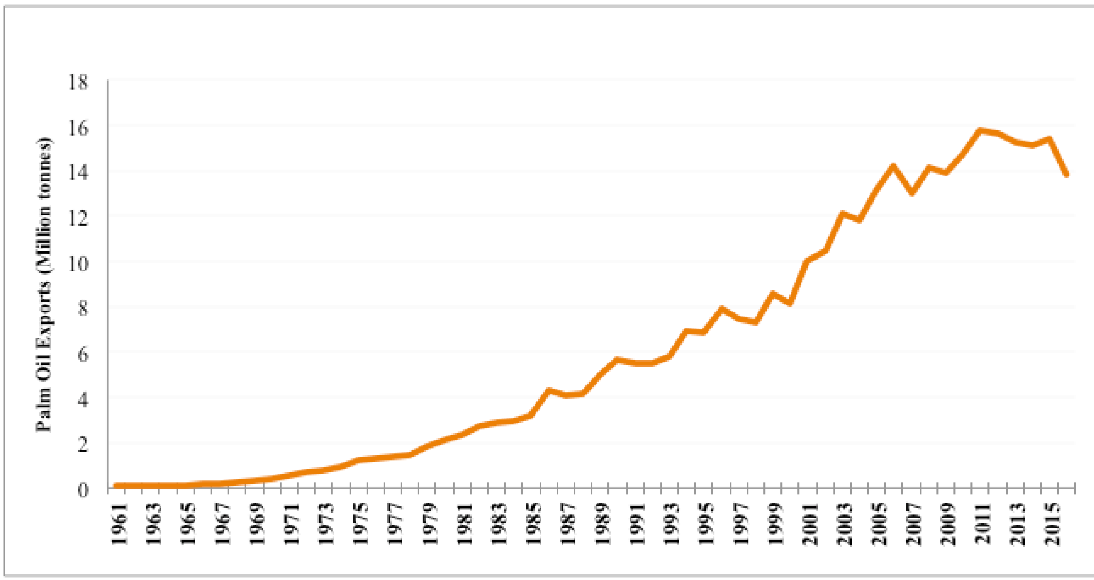

Figure 1.1 Malaysian Palm Oil exports from 1961-2016 (FAOSTAT 2017)

Land transformation has been the primary driver responsible for biodiversity loss globally (Vitousek et al. 1997). As discussed previously, distal drivers of land change can also result in indirect threats to biodiversity. Habitat degradation as a result of globalized economy, consumer demands, and international trade is ever more threatening vulnerable species; ~30% of global species threats are linked to international trade and as many as 135 Malaysian species on the International Union for the Conservation of Nature (IUCN) Red List of Threatened Species and a compatible endangered bird species list from Bird Life International are linked to trade in export-oriented agricultural commodities (Lenzen et al. 2012). Habitat loss and fragmentation are leading causes of biodiversity loss. Habitat destruction not only causes direct species loss but also leads to indirect biodiversity loss through secondary synergistic interactions with processes such as hunting, fires, invasive species, and climate change (Brook et al. 2008). Disturbed tropical forests support fewer species and lower abundance or densities as compared to mature forests (Sodhi et al. 2010). Plantations like those of oil palm and rubber cannot support the biodiversity found in the neighboring tropical forests. Owing to their uniform tree-age composition and low undergrowth oil palm plantations are structurally more homogeneous than natural forests and support only ~ 15% of all the species found in primary forests (Fitzherbert et al. 2008). Oil palm plantations are also found to consistently support fewer vertebrate and bird species found in forests and also fewer species compared to degraded or logged or secondary forests (Fitzherbert et al. 2008, Peh et al. 2006). Koh et al. (2011) estimate that conversion of peatswamp forests to oil palms by the early 2000s is likely to have resulted in a loss of 46 (12.1%) species of forests birds in Peninsular Malaysia. Oil palm plantations are not only very poor habitats for biodiversity in comparison to both primary and degraded forests but also poorer compared to other agricultural areas (Fitzherbert et al. 2008). In non-oil tree plantations, species richness and abundance is found to increase with increasing age of a plantation due to the increased complexity of older plantations (Mang and Brodie 2015). However, as adjacent primary and secondary forests can aid presence of native species within plantations, the mere presence of species within plantations does not imply long-term persistence (Mang and Brodie 2015).

Habitat loss and fragmentation especially impacts large mammals; large carnivores have experienced declining populations and decreasing geographic ranges over the past century (Ripple et al. 2014). Their slow life histories, greater energetic demands, need for larger prey and expansive habitats as well as low population densities make them particularly susceptible to the effects of habitat loss and fragmentation (Ripple et al. 2014). Land cover land use change, agricultural expansion and the resulting habitat fragmentation threatens megafauna like the tiger, the elephant and the rhino in Peninsular Malaysia (Clements et al. 2010). Tigers have been particularly vulnerable because of the impacts such processes have on the dispersal of tigers when establishing territories and for mating (Thapa et al. 2017).

1.1.2 Land Cover and Land Use Change in Malaysia

Malaysia has been a predominantly resource based economy and extraction of resources had led to a loss of ~ 50% of Peninsular Malaysia's original forested area by 1990 (Brookfield and Byron 1990). Forest conversion to oil palm plantations has been considered a major driver of deforestation in Malaysia (Rudel et al. 2009, Wicke et al. 2011). Countrywide estimates of forest conversion to oil palm plantations vary considerably, primarily due to varying data sources used for the analysis. The temporal and regional patterns and extent of deforestation and plantation expansion are very different for Peninsular Malaysia and Malaysian Borneo.

Peninsular Malaysia's plantation history has been influenced by a combination of economic, environmental, technological, cultural, and political factors. While Malaysia had been trading with China, India, and the Middle East for centuries, the real impact on Malaysian forests began with the establishment of a base of the English East India Company at Penang in 1786 (Prakash 1999). The increased spice trade led to plantations of spices and other crops in the region. Although some native crops like coconut, rice, sago palm, sugarcane were cultivated, many crops like cocoa, tapioca, corn, pineapple, guava, etc. were also introduced. The Singapore Botanic Gardens and the University of Malaya in Singapore played an important role in this early introduction of several plantation crops including rubber. With the introduction of rubber in 1895 many of the previous estate crops began to be replaced (Prakash 1999). Production of cash crops represented a sizeable portion of the regional export revenue and was largely a result of economic intrusion associated with western rule (Kaur 1999). Rubber production garnered interest from local and foreign, capitalistic and non-capitalistic producers and rubber production transformed with altered financing, management and production methods to accompany the increased investments of capital, labor from smallholdings to plantations (Kaur 1999). The earliest large-scale oil palm plantation was established in Peninsular Malaysia in 1917. However, rubber continued to be the commodity crop grown extensively on the Peninsula early in the 20th century. Expansion of oil palm plantations did not occur until the 1960s when market rubber prices plummeted. Some of the initial post-colonial agricultural expansion could be attributed to the establishment of Federal Land Development Authority in 1956 that promoted plantations of rubber and oil palm as part of their economic development schemes (Kaur 1999). The long history of plantations and plantation expansion driven deforestation in Peninsular Malaysia make it a unique region within Southeast Asia, where other regions have experienced extensive tropical deforestation and commodity-driven agricultural and plantation expansion only in the recent past.

By 2010 oil palm plantations covered 20% of Peninsular Malaysia (Gunarso et al. 2010). Estimates of Malaysian oil palm plantations established on forest conversions ranged from 38% - 59% over different periods (Koh and Wilcove 2008, Gunarso et al. 2013 and Vijay et al. 2016) while Peninsular Malaysia was estimated to have established 28% of expanding oil palm plantations on converted forests between 1990 and 2010 (Gunarso et al. 2013). In 2015, oil palm contributed 4.17% of Malaysia's Gross National Product (Department of Statistics Malaysia - DOSM 2016) and Peninsular Malaysia contributes to the production of more than half of Malaysia's crude palm oil (MPOB 2018). Malaysia's palm oil product exports in 2016 could be valued at approximately $11 billion, with India, China, Netherlands, Pakistan, and Turkey as the top five importers (Fig.1.2).

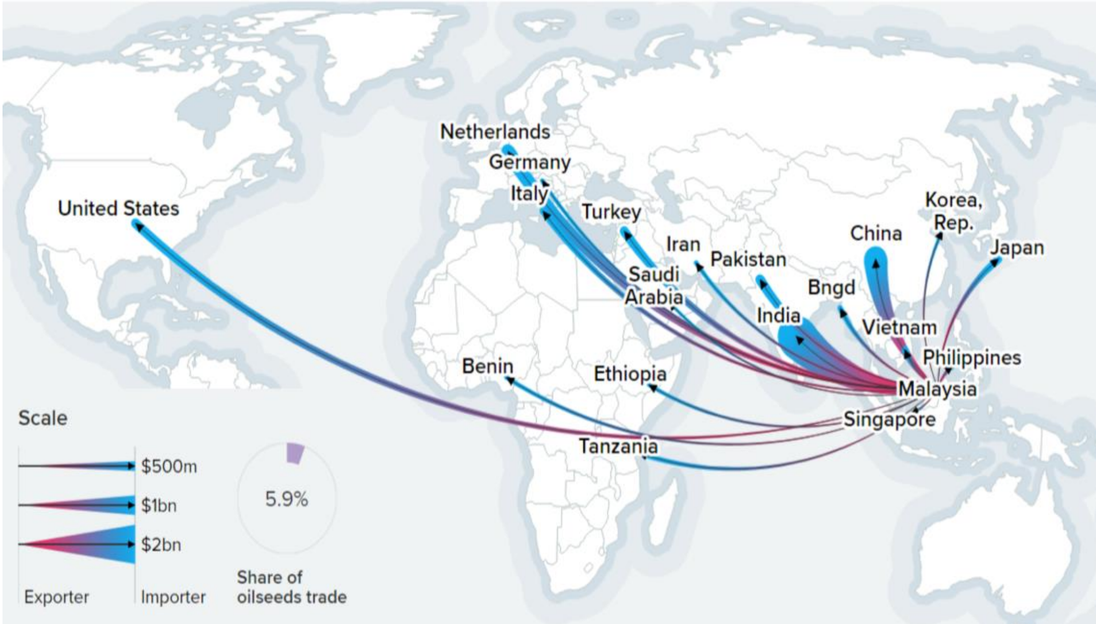

Figure 1.2 Malaysian Palm Product Exports in 2016; blue arrows point to importing countries and the arrow width is relative to the value of the imported products, Source: ResourceTrade.Earth (Chatham House, 2018)

1.1.3 The Malayan Tiger in a Human-Dominated Landscape

The tiger (*Panthera tigris*, Linnaeus 1758) is a charismatic species and Asia's largest predator and has been extirpated from most of its historic range; it is classified as an endangered species by the IUCN (Chundawat et al. 2011). Tigers are threatened across their range; today their range is limited to an estimated 7% of their historic habitat (Dinerstein et al. 2007). The Malayan tiger is a subspecies of the tiger found only on the Malay Peninsula and the southern tip of Thailand.

Maintaining tigers in the wild will depend on conservation efforts requiring protection from killing, ensuring a large prey base and sufficient habitat area (Dinerstein et al. 2007). Tiger Conservation Landscapes (TCLs) are identified as the remaining 76 habitat patches across the tiger range important for tiger conservation – where tigers exist or can be supported (Dinerstein et al. 2006). These areas include protected areas, surrounding habitat and corridors that can provide the ecological requirements for tiger conservation. Some of these are ‘Global Priority Landscapes’ which, as the name suggests are identified as landscapes of global importance for tiger conservation.

Today only 51% of Peninsular Malaysia is considered tiger habitat and only 29% (37,674km^2) constitutes confirmed tiger habitat (Kawanishi et al. 2010). Approximately 90% of Malaysia’s tiger habitat is found in the states of Pahang, Perak, Kelantan, and Terengganu (Department of Wildlife and National Parks Peninsular Malaysia, DWNP 2008). In Peninsular Malaysia, areas around Taman Negara National Park comprise a Global Priority landscape called the Taman Negara – Belum landscape; covering an area of ~ 49,181 km^2 and a habitat area of 26,727 km^2 (Sanderson et al. 2006). Specifically, the DWNP identifies three “Tiger Landscapes” within Malaysia; the Main Range, Greater Taman Negara, and the Southern Forests (DWNP 2008, Fig. 1.3). These are described as follows: the Main Range constitutes the hill and montane forests on the west of the Peninsula including the Royal Belum State Park and the adjacent Temengor Forest Reserve in the north, which form the main tiger areas within the Main Range. The Greater Taman Negara landscape consists of the Taman Negara National Park and adjoining Permanent Reserved Forests (PRFs) and is the largest area of lowland forests (< 300 m above sea level) within the Peninsula. The Southern Forest includes the most fragmented and isolated forest complexes including Endau Rompin National Park, which should serve as a source site for tigers.

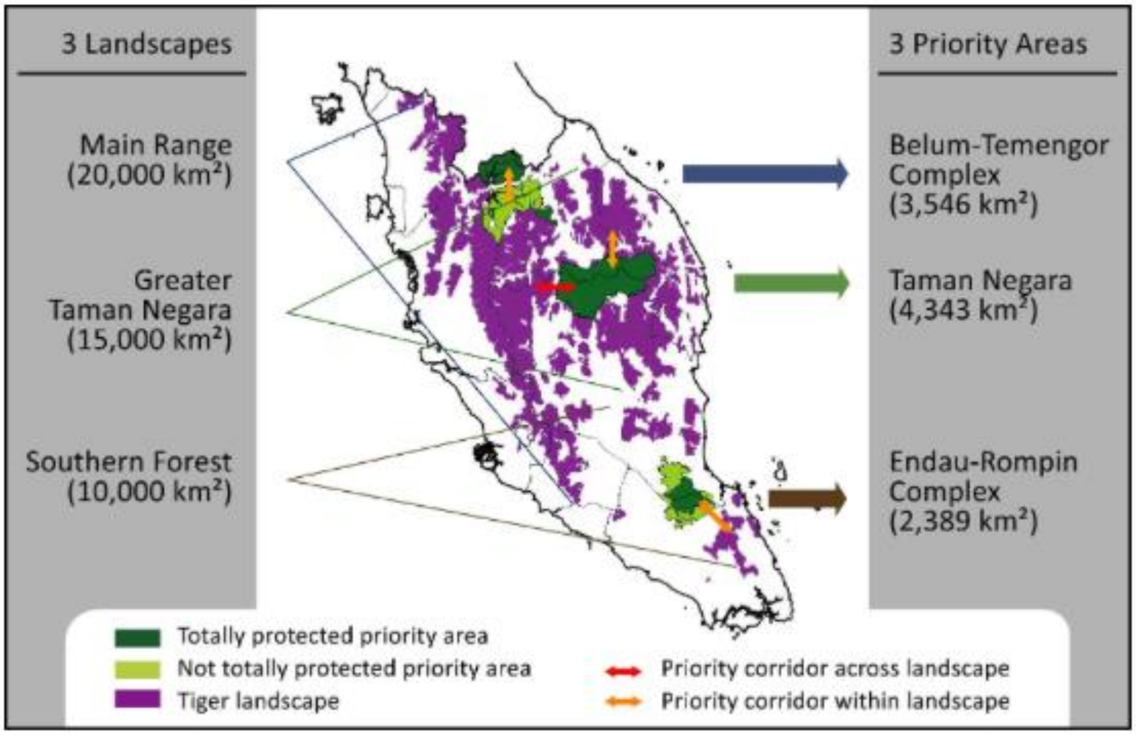

Figure 1.3 Three tiger landscapes and their three priority tiger conservation areas and associated protected areas with a few of the important corridors, Source: National Tiger Action Plan for Malaysia 2008-2020 (DWNP 2008)

The Malayan tiger continues to be threatened by habitat loss and fragmentation in addition to prey depletion, poaching and retaliatory killing despite Malaysia's relatively large area under forest cover (Rayan and Wan Mohamad 2009). The loss of lowland forests over the past century has resulted in a decline in tiger numbers and majority of the remaining forests are now restricted to mountainous areas which support fewer ungulate prey species that can sustain tigers (DWNP 2008). In addition to poaching, human-tiger conflict also threatens tigers through removal of tigers in response to direct encounters where livestock or humans are attacked by tigers and indirectly as humans drive tigers to less productive areas by depleting their prey base (DWNP 2008).

Peninsular Malaysia has been previously estimated to have 500 Malayan tigers (Seidensticker 2010). Comprehensive Peninsula wide surveys of tiger populations do not exist and previous estimates of tiger populations were based on smaller surveys conducted within a few protected areas. Tiger density was estimated to be 0.51 – 1.95 tigers / 100km^2 based on surveys conducted between 1997 – 1999 and supplemented with tiger-human conflict records from 2000 – 2005 Lynam et al. (2007). Based on these surveys at 9 sites across 4 states and assuming the observed densities represented true densities, Lynam et al. (2007) estimated a population of several hundred tigers in Peninsular Malaysia. Kawanishi and Sunquist (2004) estimated between 54-82 tigers (from 1.1 – 1.98 tigers / 100km^2) in Taman Negara National Park. Darmaraj et al. (2007) monitored tigers in Gunung Basor Forest Reserve and estimated a tiger density of 2.59 / 100km^2. Recent evidence suggesting low population of mature individuals (< 250 individuals), declining density estimates, reductions in tiger habitat, depleted prey base and small subpopulations (< 50 mature individuals), has changed the IUCN classification of the Malayan tiger to ‘Critically Endangered’ under Criteria C1+2a(i) (Kawanishi 2015).

The National Tiger Action Plan (NTAP) for Malaysia 2008-2020 was created to achieve the overarching goal of obtaining viable tiger populations in the long-term through a conservation strategy with focused and specific actions (DWNP 2008). As part of the Global Tiger Recovery Program (GTRP), Malaysia’s National Tiger Recovery Program (NTRP) considers enhancing and maintaining linkages between the various forest complexes essential to conserve tiger population (GTRP 2010). As the area required to maintain minimum viable populations for the tiger is very large and only two protected areas (Taman Negara and Belum) are large enough, improving protection for the tiger outside of protected areas like in areas designated as Permanent Reserved Forests (PRFs) will be essential to ensure long-term survival of the tiger (DWNP 2008). Forest corridors are essential to allow dispersal of tigers (DWNP 2008) and the Central Forest Spine (CFS) Master plan has identified several linkages between the various habitat patches to act as corridors. The CFS is planned as a network of forest complexes connected via green linkages to have an expanse of contiguous forest running through the center of the Peninsula. The vision of tiger conservation within Peninsular Malaysia is to manage tiger populations within this interconnected CFS (DWNP 2008).

1.2 Research Questions

This dissertation is developed in this aforementioned context of deforestation and oil palm expansion within Peninsular Malaysia's forests that also serve as the habitat for the critically endangered Malayan tiger. The Malayan tiger is endemic to the Malay Peninsula where land cover and land use dynamics are distinct from Malaysian Borneo. To analyze patterns of forest dynamics, its drivers, and to assess future vulnerability of the tiger landscape to future loss, this research focuses on the following overarching question:

What are the factors driving forest loss and conversion in Peninsular Malaysia and how do they impact the vulnerability of tiger landscape to future forest loss?

This question is further divided into three sub questions with their respective objectives. The mapped forest conversion and forest loss from Question 1 is used to answer Question 2 and Question 3 (Fig. 1.4).

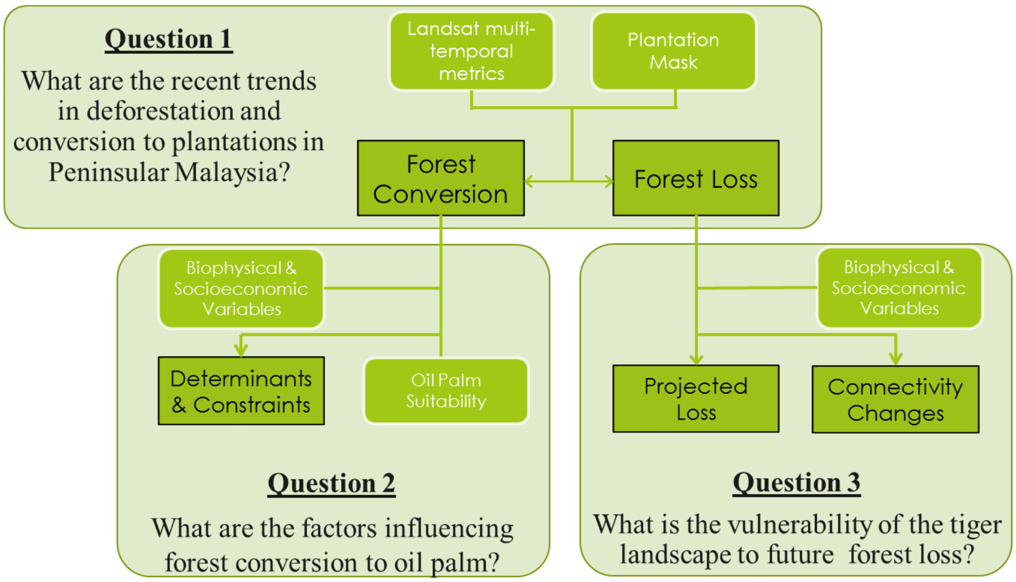

Figure 1.4 Organization of the dissertation

Question 1. What are the recent trends in deforestation and conversion to plantations in Peninsular Malaysia?

Objective 1: Map forest loss and characterize conversion to plantations from 1988-2012

This part of the study uses satellite remote sensing data to map, estimate extent of and understand spatio-temporal patterns of forest loss and conversion within Peninsular Malaysia.

Question 2. What are the factors influencing forest conversion to oil palm?

Objective 2: Identify determinants and constraints to oil palm expansion

As oil palm expansion is a major driver of deforestation within the region, mapped forest loss and conversion information from Objective 1 is then used to specifically model forest conversions to industrial oil palm plantations and assess factors influencing such conversions.

Question 3. What is the vulnerability of the tiger landscape to future forest loss?

Objective 3: Quantify the potential of future forest loss in remaining forests and impacts on connectivity within the tiger landscape

Vulnerability of the tiger landscape is assessed via projected loss and changes to landscape connectivity. The observed forest loss from Objective 1 is used to develop a model of forest loss probability, which is used to project future forest loss. These projections of forest loss are finally used to assess potential changes to landscape connectivity for tigers.

1.3 Structure of the Dissertation

Chapter 1 of the dissertation provides a background to the research question and introduces the research questions and the structure of the dissertation.

Chapter 2 of the dissertation answers Question 1 and focuses on achieving the associated Objective 1. This chapter develops a natural forest mask for Peninsular Malaysia to identify the extent of natural forest in 1988. This mask is then used to then map forest loss occurring within the identified natural forest areas between 1988 and 2012, and using an existing plantation map (Petersen et al. 2016) the fraction of that forest loss that is converted to plantations of different types is identified. This chapter was published in Remote Sensing (Shevade et al. 2017).

Chapter 3 of the dissertation answers Question 2 and is related to the associated Objective 2. This chapter focuses on forest conversions to industrial oil palm plantations between 1988 and 2012. It explores the biophysical and socioeconomic factors that are associated with forest conversions to industrial oil palm plantations using the mapped forest conversions from Chapter 2. It also characterizes the biophysical suitability and accessibility of these forest conversions to oil palm plantations to identify the possible constraints to such conversions. This chapter is under revision in PLOS One (Shevade and Loboda 2018).

Chapter 4 of the dissertation answers the Question 3 and is related to the Objective 3. This chapter builds on the results from Chapters 2 and 3 to develop a model of deforestation probability for Peninsular Malaysia. This is then used to model and project forest loss post-2016 for five years until 2021 using two different scenarios for future loss. This helps quantify the potential of future forest loss within Peninsular Malaysia. These projected forest loss scenarios are used to the assess connectivity and changes to connectivity within the landscape for tigers. Finally, the chapter helps in understanding forest areas vulnerable to future forest loss and the resulting loss of connectivity within the landscape. This chapter is currently being prepared for publication.

Chapter 5 is the concluding chapter of the dissertation providing a summary of the results of each of the chapters. This chapter then discusses the broader context of this research, its limitations and policy implications for tiger conservation in Peninsular Malaysia.

Chapter 2: Forest Loss and Conversion to Plantations in Peninsular Malaysia from 1988 to 2012[1]

2.1 Summary

Southeast Asia has some of the highest deforestation rates globally, with Malaysia being identified as a deforestation hotspot. The Malayan tiger, a critically endangered subspecies of the tiger endemic to Peninsular Malaysia, is threatened by habitat loss and fragmentation. In this study, we estimate the natural forest loss and conversion to plantations in Peninsular Malaysia and specifically in its tiger habitat between 1988 and 2012 using the Landsat data archive. We estimate a total loss of 1.35 Mha of natural forest area within Peninsular Malaysia over the entire study period, with 0.83 Mha lost within the tiger habitat. Nearly half (48%) of the natural forest loss area represents conversion to tree plantations. The annual area of new plantation establishment from natural forest conversion increased from 20 thousand ha year^{-1} during 1988–2000 to 34 thousand ha year^{-1} during 2001–2012. Large-scale industrial plantations, primarily those of oil palm, as well as recently cleared land, constitute 80% of forest converted to plantations since 1988. We conclude that industrial plantation expansion has been a persistent threat to natural forests within the Malayan tiger habitat. Expanding oil palm plantations dominate forest conversions while those for rubber are an emerging threat.

[1]This chapter has been published in Remote Sensing as Shevade VS, Potapov P V., Harris NL, Loboda T V. 2017. Expansion of Industrial Plantations Continues to Threaten Malayan Tiger Habitat. Remote Sensing, 9(7):747.

2.2 Introduction

Malaysia is a megadiverse country (CBD 2015) and is a part of the Southeast Asian biodiversity hotspot (Myers et al. 2000). The Malayan tiger, *Panthera tigris jacksoni*, is endemic to Peninsular Malaysia and is threatened by habitat loss, in addition to poaching and the illegal trade of tiger parts, hunting of tiger prey, and retaliatory killings arising from human-wildlife conflicts (Kawanishi 2015). Following recent reports of a decline in Peninsular Malaysia's tiger population, the Malayan tiger is now classified by the International Union for Conservation of Nature (IUCN) as a critically endangered species, i.e., a species facing an extremely high risk of extinction in the wild (Kawanishi 2015). Current estimates suggest a likely population of 250–340 adult tigers and an effective breeding population of 80–120 tigers, indicating a greater than 25% decline in one generation (equivalent to seven years). Additionally, repeated population studies at a couple of sites indicate a 50 and 90% decline in tiger density estimates (Kawanishi 2015).

Increasing human population, in addition to agricultural and infrastructure development, have resulted in the reduction of wildland extent, forcing tigers to survive in human-dominated landscapes (Seidensticker 2010). Asian countries have the highest population densities in forested areas and a long history of agricultural development (Gibbs et al. 2010). Southeast Asia has some of the highest deforestation rates globally (Sodhi et al. 2010) and has a large proportion of cultivated/agricultural land under tree plantations (Gibbs et al. 2010). Peninsular Malaysia has a long history of land cover and land use change. Expanding agriculture, especially rubber (*Hevea brasiliensis*) and oil palm (*Elaeis guineensis*) plantations, has been historically responsible for forest reduction in the region (Kummer and Turner 1994, Abdullah and Nakagoshi 2007, Abdullah and Hezri 2008, Koh and Wilcove 2008). Rubber plantations in Peninsular Malaysia first appeared in the 1880s (FAO 2002) and expanded rapidly after a surge in rubber prices during 1905–1910 (Byerlee 2014). Oil palm plantations appeared in Malaysia as early as 1917 (Fitzherbert et al. 2008) and with a drop in rubber prices in the 1960s, commercial oil palm plantations started replacing those of rubber (Byerlee 2014). By the 1940s, Peninsular Malaysia's west coastal region was already heavily deforested. It had lost half of its original forest area by the late 1980s, while agricultural land had expanded from an estimated 21 to 35% of the land area between 1966 and 1982 (Brookfield and Byron 1990). Agricultural expansion and oil palm production are considered significant threats to biodiversity and tiger habitat in Peninsular Malaysia (Sodhi et al. 2010, Clements et al. 2010).

Historically, tigers inhabited all forest areas of Peninsular Malaysia (Kawanishi et al. 2003). Currently, most breeding tiger populations are restricted to protected areas due to intensive human pressure (Joshi et al. 2016). Rapidly growing economies and expanding markets have put greater pressure on the remaining tiger habitats (Seidensticker 2010). As a commitment to doubling wild tiger numbers by 2022, tiger-range countries adopted the Global Tiger Recovery Program (GTRP) (World Bank 2011). Under the GTRP, Malaysia's National Tiger Recovery Program (NTRP) will focus on its National Tiger Recovery Priorities and the tiger recovery strategy described in its National Tiger Action Plan (NTAP) (GTRP 2010), which has identified the 'net loss and gain of forests' as an indicator for monitoring conservation actions, along with other indicators like tiger occupancy (presence or absence of species at sites within the study area), prey and tiger densities, and the use of corridors by tigers (DWNP 2008). While collecting data for most of these indicators is costly and time consuming, monitoring habitats using remotely sensed data may be achieved with minimal investments. Remote sensing is an effective tool for change assessment and the repeatable monitoring of large and remote tracts of land. Various remotely sensed datasets have been specifically generated to estimate the spatial extent of forest cover and forest loss from regional to global scales (Hansen et al. 2008, Hansen et al. 2010, Miettinen et al. 2011, Hansen et al. 2013, Kim et al. 2015). Landsat's 30 m spatial resolution allows mapping at a scale congruent with most human activity (Kim et al. 2015). The Landsat program also features the longest data archive suitable for multi-decadal regional change assessments (Cohen and Goward 2004). Remotely sensed forest and forest change products often use a biophysical forest definition, which includes forestry dynamics and plantation cycles in the quantification of forest and forest loss area (Hansen et al. 2013, Margono et al. 2014). Natural forests and tree plantations offer a different suitability as tiger habitats. Plantations, like those of oil palm, have a uniform tree-age structure (Fitzherbert et al. 2008), support fewer species than primary, logged, or disturbed forests (Fitzherbert et al. 2008, Srinivas and Koh 2016), or even degraded forests (Peh et al. 2006), and provide poor habitat for tigers (Maddox 2007). Additionally, agricultural expansion also impacts tigers through access for poaching, disruption of connectivity for movement and dispersal, and by increasing human-tiger conflicts (Clements et al. 2010). Hence, it is important to separate natural forests from plantations when assessing forest dynamics in the context of tiger habitat.

Some studies providing forest loss estimates for Malaysia (Koh and Wilcove 2008, Wicke et al. 2011) use national land use data compiled by the Food and Agriculture Organization of the United Nations (FAO) or other sources and do not distinguish between Peninsular Malaysia and Malaysian Borneo, which have very different land cover and land use change dynamics. This is partly due to the autonomy of states to make land and forest resource decisions (Clements et al. 2010, McMorrow and Talip 2001). Previous studies providing forest loss estimates for Peninsular Malaysia (Miettinen et al. 2011, Gunarso et al. 2013) do not focus on tiger habitat and only a recent study by (Joshi et al. 2016) assessed forest loss within the global priority tiger conservation landscapes (TCLs) across all tiger-range countries, identifying Malaysia's Taman-Negara-Belum as a TCL with some of the highest forest loss during 2001–2014.

Given the history of land cover changes in Peninsular Malaysia and the role of plantations in land use conversion, it is important to assess the drivers of forest loss in the region and to quantify the role of plantation expansion. In this study, we assess recent forest dynamics in Peninsular Malaysia and considering the Malayan tiger as an example of Malaysia's endangered and threatened megafauna, we specifically focus on forest dynamics within Malaysia's tiger landscapes. The overarching goal for this study was to quantify the area of natural forest loss and conversion to plantations between 1988 and 2012 within Malaysia's tiger habitat. The specific objectives of this study were: (1) to map Peninsular Malaysia's natural forest in 1988 as a proxy for potential tiger habitat; (2) map and quantify natural forest loss between 1988 and 2012 in Peninsular Malaysia and its tiger habitat; and (3) quantify the proportion of the total forest and tiger habitat loss converted to plantations.

2.3 Materials and Methods

2.3.1 Study Area

Peninsular Malaysia lies on the Malay Peninsula and is bordered by Thailand in the North and Singapore in the South. It occupies an area of 13.2 million ha (Figure 1). The region is equatorial with influences of the southwest monsoon from May to September and the northeast monsoon from October to March. Average day temperatures are around 32 °C and average precipitation is around 2550 mm with a maximum rainfall of more than 5000 mm on exposed mountains [34]. Coastal plains and lowlands dominate regional topography below a 300 m elevation (FAO 2012), which are covered with mangroves and peat swamp forests along the coast and lowland dipterocarp forests further inland (FDPM 2016). Mountain ranges dominate the northern and central-western parts of the country (FAO 2012). Hill and upper dipterocarp forests are found between 300–750 m and 750–1200 m above sea level, respectively, while montane-oak forests are found between 1200–1500 m (FDPM 2016). About 51% of Peninsular Malaysia has a suitable habitat for tigers; however, only 29% of its area is considered to have good conservation value based on evidence of tiger presence (DWNP 2008). Protected areas represent only 15% of the tiger habitat area (DWNP 2008). Tiger habitat for the purpose of this study is restricted to Peninsular

Malaysia's Tiger Conservation Landscapes (TCLs) (Fig. 2.1), which include areas with a potential effective habitat and confirmed tiger occurrence during the preceding years and no knowledge of tiger extirpation (Sanderson et al. 2006).

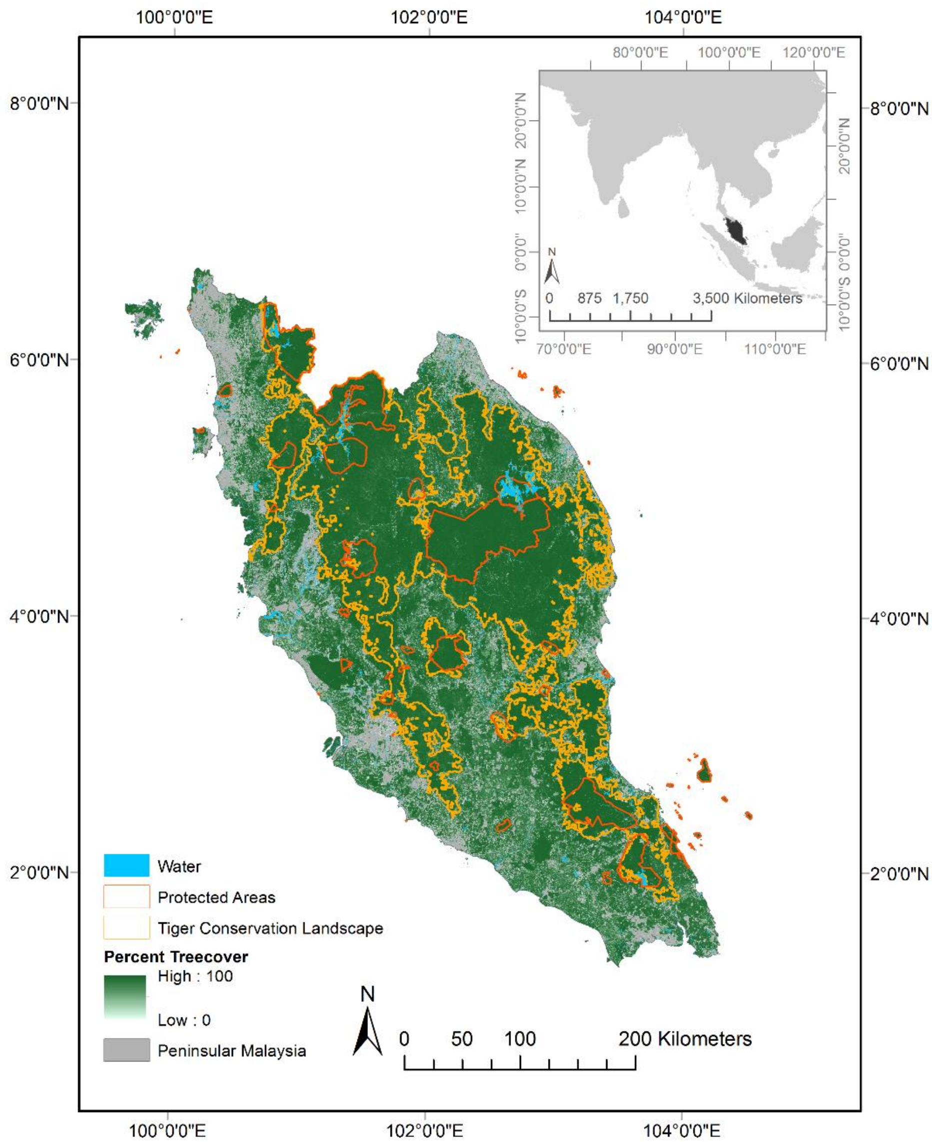

Figure 1.1 Study Area in Peninsular Malaysia showing the Tiger Conservation Landscapes (TCL) (Sanderson et al. 2006), percent tree cover for year 2000 (Hansen et al. 2013), and protected areas from the World Database on Protected Areas (WDPA, UNEP-WCMC 2016)

2.3.2 Overview

Natural forests are defined as mature naturally regenerated forests that have a minimum area of 5 ha, and have not been completely cleared or replanted in recent history, although some signs of disturbance like selective logging might be present (Margono et al. 2014). Natural forest loss includes tree removal due to logging, as well as land use conversion (from agriculture and plantation expansion, infrastructure development, etc.). To quantify natural forest loss, we: (1) mapped the natural forest extent for the year 1988; (2) applied a change detection model to map forest loss between 1988 and 2000; and (3) aggregated the pre-year 2000 forest loss with the existing published Landsat-based Global Forest Change (GFC) tree cover loss product for 2001–2012 (Hansen et al. 2013) and assessed the loss within mapped natural forests (Fig. 2.2). We then overlaid the plantation map obtained from (Petersen et al. 2016) with the 1988–2012 natural forest loss map to estimate the role of plantations in the overall forest loss. PCI Geomatica software was used for generating training samples for natural forest and forest loss mapping, while ArcGIS was used for the analysis of forest loss and conversion to plantations.

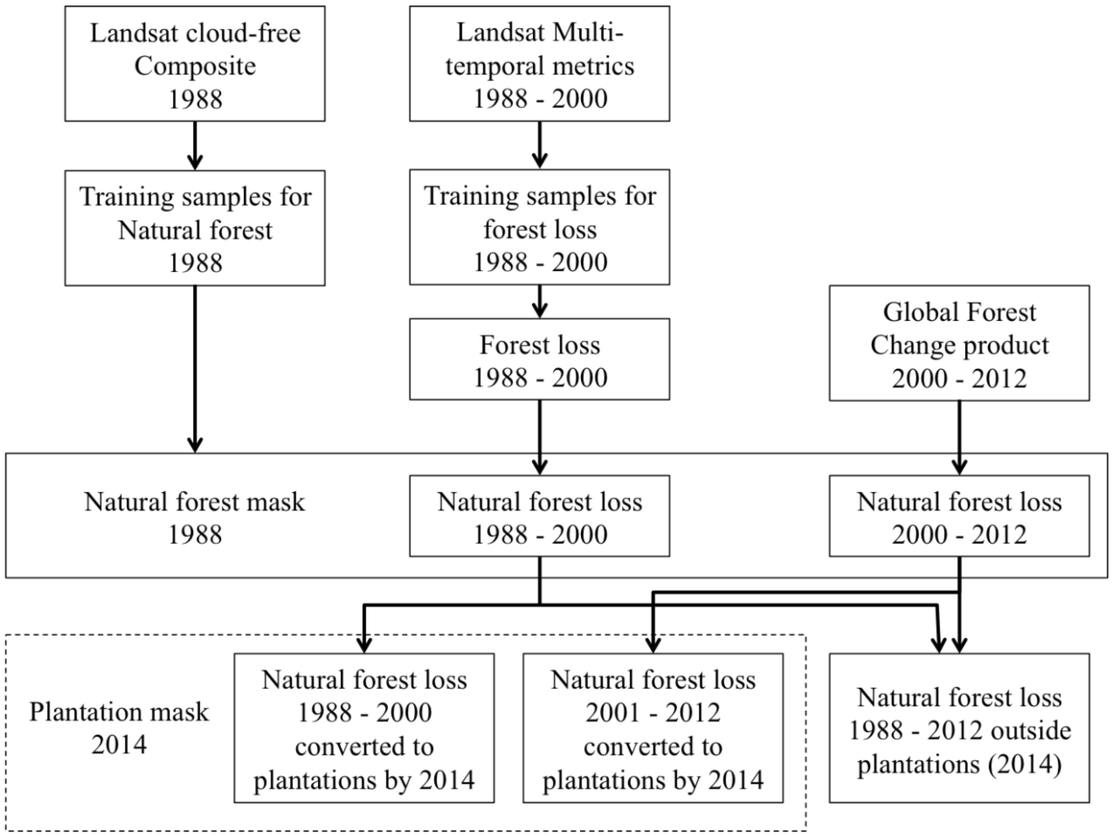

Figure 1.2 Methodology used to map natural forest, natural forest loss, and plantation expansion

2.3.3 Data

We analyzed the entire archive of Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper (ETM+) images available for the region from 1988 to 2002. The region is covered by 20 WRS-2 footprints. The entire archive of available imagery, consisting of 1110 processing Level 1 terrain corrected (L1T) images was employed. The number of images used from the different Landsat sensors is listed in Table S1. Landsat imagery processing followed the methodology of (Hansen et al. 2013) and is described in detail in (Potapov et al. 2012), where per-pixel raw digital numbers were converted to top of atmosphere reflectance, screened for cloud/shadow/haze/water, and following quality assessment, were radiometrically normalized and composited into a single clear-surface layer. Screening and quality assessment involved using decision tree models to predict the presence of cloud, shadow, and water to obtain the per-pixel probability of contamination by these features (Hansen et al. 2013, Potapov et al. 2012). The observation quality of pixels was recorded and pixels with a high probability of contamination were then excluded from processing (Hansen et al. 2013, Potapov et al. 2012). Normalization was carried out using Moderate Resolution Imaging Spectroradiometer (MODIS) derived surface reflectance products as normalization targets in order to reduce the variations in reflectance resulting from differences in image dates, atmospheric conditions, and surface anisotropy (Potapov et al. 2012). As Peninsular Malaysia is a part of the humid tropics, images from the entire year were used for multi-date image compositing in order to generate start or end date (1988 or 2000) cloud-free image mosaics using only pixels with the highest quality observations (Potapov et al. 2012). Due to limited image availability and the very high incidence of cloud cover in this region, clear surface observations from adjacent years were used to fill the gaps in both the image composites. For the “circa 1988” composite, 71% of the pixels used were from the 1988–1990 interval and for the “circa 2000” composite, 99% of the pixels used were from the 1999–2001 interval.

All processed per-pixel cloud-free observations between the earliest observation for the start year (1988) and the latest observation for the last year (2000) were used to create a set of multi-temporal metrics that was used for natural forest mapping and forest loss detection (Table 2.1). This multi-temporal metric set was developed following the methods described in (Hansen et al. 2013, Potapov et al. 2012, Potapov et al. 2015) using two approaches: 1) time-sequential reflectance observations by date; and 2) ranked (low to high) band reflectance values, or ranked observations corresponding to the ranked normalized difference vegetation index (NDVI) (Tucker 1979), normalized difference water index (NDWI) (Xiao et al. 2004) values, and thermal/infrared band values. In addition to the start/end date cloud-free image mosaics, the means and medians of the first three observations and last three observations, the maximal values of time-sequential reflectance gain and loss, and the slope of linear regression of reflectance/index values and observation date (Hansen et al. 2013, Potapov et al. 2015) were generated. For the rank-based metrics, a set of percentile values and symmetrical and asymmetrical averages for various percentile range intervals were used (Hansen et al. 2013, Potapov et al. 2015). On average, about 16 cloud-free observations were available per-pixel for the calculation of metrics. The first (circa 1988) and last (circa 2000) cloud-free image composites, along with the medians/means of the first three and last three observations, were used for visual interpretation to generate training samples for mapping.

Table 2.1 Overview of the different multi-temporal metrics used for classification and mapping

Types of Metrics	Multi-Temporal Metrics
Image Composites	1. First and last cloud-free observations
	2. Mean and Median of first 3 observations
	3. Mean and Median of last 3 observations
Rank-based Metrics	1. Percentiles representing minimum, 10%, 25%, 50%, 75%, 90% and maximum for band reflectance or index (NDVI, NDWI) values,
	2. Symmetrical averages for various intervals: minimum–maximum, 10–90%, 25–75%,
	3. Asymmetrical averages for various intervals: minimum–10%, 10–25%, 25–50%, 50–75%, 75–90%, 90%-maximum
Trend Analysis Metrics	1. Slope of linear regression of band reflectance versus image date,
	2. Standard deviation of band reflectance 1988–2000,
	3. Maximum loss/gain of reflectance/index value between consecutive observations

We used the GFC tree cover loss product (Hansen et al. 2013) for the years 2001–2012 to extend our 1988–2000 forest loss map. This product maps the loss of tree cover taller than 5 m at a resolution equivalent to Landsat data. To estimate forest loss converted to plantations, we used a plantation map generated for Peninsular Malaysia by the World Resources Institute (WRI) (Petersen et al. 2016). This product maps plantation areas in 2014, categorized into large industrial-sized plantations, medium-sized and small-sized mosaic plantations, and recently cleared or young plantation classes. Large industrial plantations are monocultures with species information associated with plantation areas, while mosaic plantations include some non-plantation areas like other agriculture, forest patches, and settlements interspersed with plantations.

2.3.4 Natural Forest Mapping

The 1988 Landsat image mosaic was visually interpreted to determine the training samples for natural forest (dependent variable) versus all other land cover types. The natural forest classification training sample consisted of more than 450,000 training pixels. Multi-temporal metrics (Table 2.1) were used as independent variables to build a bagged decision tree model to map natural forest areas (Hansen et al. 2013). While using “bagging” or bootstrap aggregation, the data are divided into a test set, which is a random sample drawn from the training population, and a learning set, which is the remaining portion of the training population (Breiman 1996). We used a test set of 20% of the training data and developed output maps based on the median class likelihood from the outputs of several trees.

Natural forest patch size was restricted to 5 ha (Margono et al. 2014) and manual editing of the classification results was performed (Margono et al. 2014) to correct for obvious errors, like removing older plantations and including some omitted water-logged forest areas along the coast. For this study, tiger habitat for Peninsular Malaysia is defined as natural forest area within the TCL. Tiger habitat and habitat are used interchangeably in the rest of the paper.

2.3.5 Forest Loss Mapping

Forest loss is defined as a temporal or permanent reduction in tree cover density (Hansen et al. 2013, Margono et al. 2014, Giree et al. 2013), resulting in a complete or almost complete removal of trees within a 30 m Landsat pixel (Potapov et al. 2015). It could result from conversion to agriculture/plantations, intensive logging, or natural disturbances. Training samples for ‘forest loss’ and ‘no loss’ between 1988 and 2000 were created after the visual interpretation of 1988 and 2000 image mosaics and maximum reflectance composites (Potapov et al. 2015). In total, more than 510,000 pixels were used to train the forest loss classification. Forest loss during 1988–2000 (pre-2000) was mapped in one time-step using a decision tree classifier and multi-temporal metrics. Forest loss during 2001–2012 (post-2000) within mapped natural forest areas was extracted from the GFC product. Owing to the increased image availability after the year 2000, as opposed to that in the 1980s and 1990s, we can estimate post-2000 loss at an annual time-step using the GFC product. All forest loss within the mapped 1988 natural forest mask was considered as natural forest loss (Fig. 2.2). As the pre-2000 and post-2000 forest loss is mapped separately, in cases of overlap between the two, the loss year (interval) was attributed to the first detected loss event (pre-2000). However, as imagery from years 2001 and 2002 had been used to gap-fill the 2000 mosaic, in instances of overlap between mapped pre-2000 loss and the GFC product loss from either year 2001 or 2002, we attributed loss to the respective post-2000 year. Tiger habitat loss was quantified by assessing forest loss within the tiger habitat area.

2.3.6 Sample-Based Adjustment of the Area Estimation

Separate sample-based assessments were performed for the newly developed pre-2000 forest loss and the post-2000 forest loss subset from the GFC product following the methodology used by (Potapov et al. 2015). In this approach, the strata for sampling were based on ‘natural forest loss’ and ‘no loss’ classes for both the pre-2000 and post-

2000 periods. For each forest loss period, sample pixels were drawn using a stratified random sampling design. Following the "good practices" suggested by (Olofsson et al. 2014), in order to balance the area estimates and all accuracies, we used a sampling design slightly away from proportional such that rare strata have a sample size slightly greater than proportional allocation. We used Landsat imagery mosaics for 1988 and 2000 along with composites for 1990 and 1995 for visual assessment of the pre-2000 loss validation samples. Landsat images, where available (Appendix I, Table S2), the minimum annual NDVI, and Google Earth imagery were used, in addition to the 2000 and 2012 Landsat mosaics for an assessment of the 2001–2012 validation samples. Following the visual assessment of all samples, an accuracy assessment of the map and sample-based area estimation of mapped classes was conducted following the method for the land area change estimation described in (Olofsson et al. 2013). Additionally, we followed the same procedure to estimate the forest loss area within the tiger habitat separately using only validation samples within the TCL. The accuracy of the plantation map is reported in (Petersen et al. 2016). The overall accuracy of the plantation map is 86.7%, while the producer's and user's accuracies were 96.8% and 78.8%, respectively.

Our total natural forest loss and habitat loss area estimates were obtained from the sample-based area estimation for pre-2000 and post-2000. The error-adjusted area for natural forest and habitat loss within plantations was estimated by using the proportion of mapped loss within plantations. The error-adjusted estimates for the annual area of natural forest and habitat loss between 2001 and 2012 were obtained by disaggregating the post-2000 sample-based area estimate into annual time scales using the yearly proportion of post-2000 natural forest and habitat loss. All areas reported in the paper are based on error-adjusted area estimates unless categorically noted as “mapped area” or “mapped loss”.

2.4 Results

2.4.1 Natural Forest Extent and Change from 1988-2012

The total natural forest area within Peninsular Malaysia in 1988 was estimated as 7.16 Mha. Roughly, 65% of the 1988 natural forest area was within the TCL and is considered as tiger habitat for the remaining analysis. The error-adjusted areas for total forest loss and habitat loss, along with their error estimates, are reported in Table 2. Standard errors for pre-2000 and post-2000 sample-based area estimates were obtained following (Olofsson et al. 2013), while the total error for the sample-based area estimate was obtained following the method for propagation of error suggested by the Intergovernmental Panel on Climate Change (IPCC) Guidelines (IPCC 2006). Our map (Figure 3) underestimates the area of loss and the sample-based area estimates (Table 2) are higher than the mapped loss for both periods (579,568 ha for pre-2000 and 565,881 ha for post-2000).

By 2012, the total gross forest loss area in Peninsular Malaysia was estimated to be 1.35 Mha, or 19% of its 1988 natural forest area (Fig. 2.3, Table 2.2). The annual rate of loss has increased between the two periods from an average of 49,281 ha year^{-1} pre-

2000 to 63,422 ha year^{-1} post-2000 (Fig. 2.4). Using the GFC product, we estimated loss at an annual time step for the post-2000 period. This annual loss has been increasing since 2001 and reached a peak at 122,167 ha in 2012 (Fig. 2.4).

Plantation expansion is responsible for 651,757 ha or 48% of the total natural forest loss. The mean annual rate of natural forest converted to plantations has increased from 19,970 ha year^{-1} pre-2000 to 34,344 ha year^{-1} post-2000 (Figure 4). The majority of the forest loss converted to plantations (57% loss within plantations) was due to the large industrial plantation expansion. Recently cleared land constitutes 17% and 30% of all pre-2000 and post-2000 forest loss within plantations, respectively. Based on the species information associated with large industrial plantations, we estimate that oil palm dominated plantations constitute about 80% of the total forest loss (1988-2000) converted to this category, while the proportion of forest loss converted to large rubber plantations has increased from 15% pre-2000 to 25% post-2000.

Table 2.2 Sample-based area (Mha) estimates with 95%confidence intervals for pre-2000 and post-2000 total natural forest and habitat loss and loss within plantations by 2014

Study Period	Total Loss	Total Loss within Plantations	Habitat Loss	Habitat Loss within Plantations
Pre-2000	0.59 ± 0.11	0.24 ± 0.05	0.42 ± 0.11	0.15 ± 0.04
Post-2000	0.76 ± 0.13	0.41 ± 0.07	0.41 ± 0.10	0.23 ± 0.06
Total	1.35 ± 0.17	0.65 ± 0.08	0.83 ± 0.15	0.38 ± 0.07

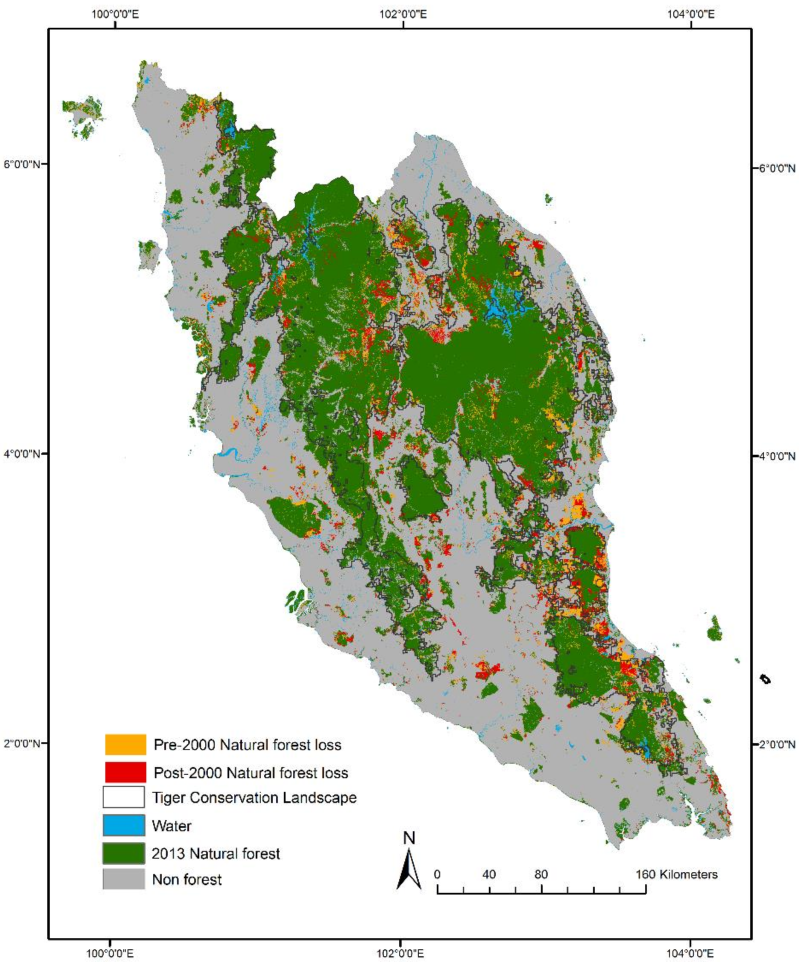

Figure 1.3 Mapped natural forest remaining in 2013, Tiger Conservation Landscape (TCL), and natural forest loss between 1988-2000 (pre-200) and 2001-2012 (post-2000)

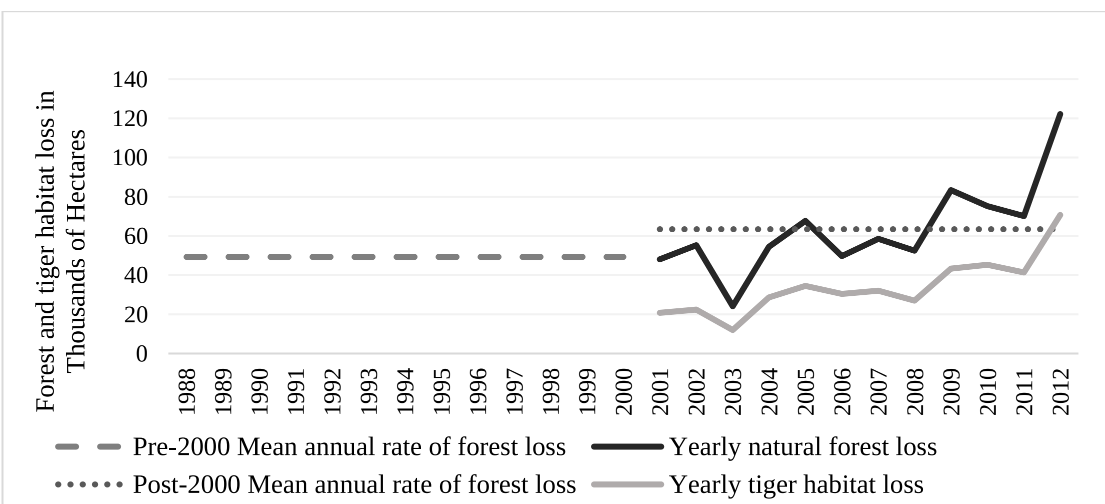

Figure 1.4 Sample based area (thousand ha) estimates for yearly natural forest and habitat loss and annual rates of total natural forest loss for pre-2000 and post-2000 periods. Yearly losses are depicted as solid lines, while mean annual rates of loss for the pre-2000 and post-2000 periods are average rates of loss for the respective periods, depicted as constant dashed lines

2.4.2 Tiger Habitat Loss and Change from 1988-2012

A total of 831,571 hectares of tiger habitat (18% of 1988 habitat area) have been lost over the entire study period. The average annual habitat loss pre-2000 and post-2000 has remained nearly the same (34,060 ha and 35,237 ha, respectively). However, the annual habitat area lost has been increasing from 2001 to 2012, with an estimated 70,692 ha lost in the year 2012 (Fig 2.4).

Approximately 46% of the total habitat loss has been converted to plantations, adding 381,808 ha to Peninsular Malaysia's land under plantations by 2014. The rate of habitat conversion to plantations has increased from 12,309 ha year^{-1} pre-2000 to 19,508 ha year^{-1} post-2000 (Table 2.2). Large industrial plantations constitute the largest fraction (61% of pre-2000 loss and 49% of post-2000 loss) of the converted habitat area, followed by cleared land (23% of pre-2000 loss and 37% of post-2000 loss), while the remaining converted habitat is within mosaic plantations (Fig. 2.5a). The habitat loss area from more recent years has a greater proportion within the recently cleared plantation class (Fig. 2.5b). Large industrial monoculture plantations established within the tiger habitat are dominated by oil palm; 65% of all habitat loss converted to large plantations is now under oil palm, while the remaining (35%) habitat loss converted to large plantations is under rubber cultivation. However, the proportional area of large industrial plantations under rubber cultivation that has been established from habitat loss has increased between pre-2000 and post-2000 from 29 to 41%.

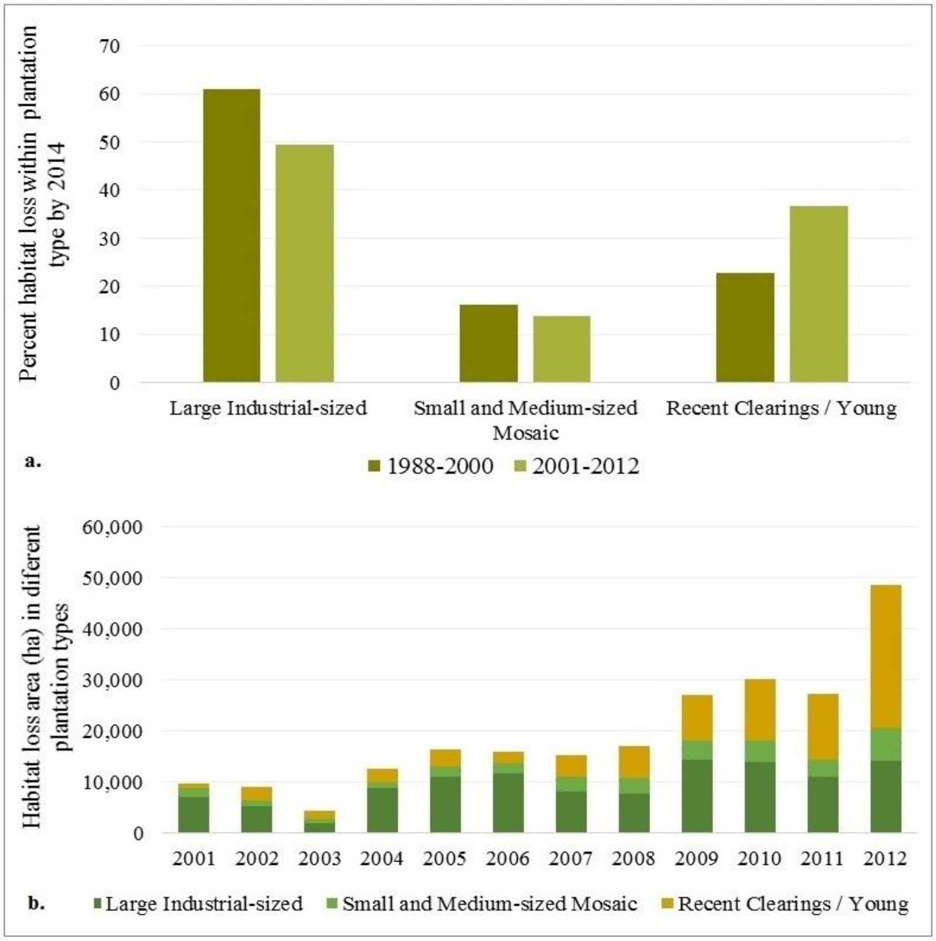

Figure 1.5 a) Percent of total tiger habitat loss pre-2000 (1988-2000) and post-2000 (2001-2012) within different plantation types by 2014, and b) Sample-based area estimates of habitat loss between 2001 and 2012 within plantations (in 2014) by plantation type

2.4.3 Accuracy Assessment of 1988-2000 and 2001-2012 Forest Loss

We performed separate accuracy assessments for natural forest loss and tiger habitat loss for the 1988–2000 interval mapped in this research and 2001–2012 loss obtained from the GFC product (Table 2.3). The overall accuracy for both products exceeds 95%; however, specific user's and producer's accuracies for each class vary. The lowest producer's accuracies are reported for forest loss classes within the TCL (below 60%). User's accuracies are consistently higher, with the lowest value (75%) reported for the forest loss class in the pre-2000 mapping period.

Table 2.3 Error Matrices for pre-2000 (1988-2000) and post-2000 (2001-2012) natural forest and habitat loss / no loss maps with cell entries depicting the estimated area proportions. N is the number of total sample points used for the assessment.

	Reference					
	Loss	**No Loss**	**Total**	**User's**	**Producer's**	**Overall**
Pre-2000 Forest	N = 475					
Map						
Loss	0.06	0.02	0.08	0.75	0.75	0.96
No Loss	0.02	0.9	0.92	0.98	0.98	
Total	0.08	0.92	1			
Post-2000 Forest	N = 489					
Map						
Loss	0.07	0.01	0.08	0.88	0.63	0.95
No Loss	0.04	0.88	0.92	0.96	0.99	
Total	0.12	0.88	1			
Pre-2000 Habitat	N = 314					
Map						
Loss	0.05	0.01	0.06	0.90	0.55	0.95
No Loss	0.04	0.90	0.94	0.96	0.99	
Total	0.09	0.91	1.00			
Post-2000 Habitat	N = 358					
Map						
Loss	0.06	0.005	0.06	0.92	0.57	0.95
No Loss	0.04	0.90	0.94	0.96	0.99	
Total	0.096	0.904	1.00			

2.5 Discussion

Sample-based area estimates provide a better estimation of loss area than simple map-based estimates (Olofsson et al. 2013) and have been used to correct for the underestimation of forest loss (Tyukavina et al. 2013, Potapov et al. 2014). Error-adjustment increased the estimated areas of natural forest loss and tiger habitat loss for both pre-2000 and post-2000 periods. User's and producer's accuracies are not distributed uniformly, although the omission error is consistently high for both periods for natural forest and tiger habitat loss.

Based on our total estimated gross natural forest loss of 1.35 Mha, it is evident that deforestation continues to be a problem for Peninsular Malaysia's forest. Our estimated forest loss area from 2000–2010 of 0.49 Mha is higher compared to the 0.44 Mha value reported by (Miettinen et al. 2011). This difference can be attributed to the improved spatial resolution of data used (250 m vs. 30 m in this study), and the implementation of the sample-based unbiased area estimation method. We observe an acceleration in forest loss from pre-2000 to post-2000, similar to previous reports across the humid tropics and in Asia (Kim et al. 2015). Our study adds to a recent study of global tiger habitat (Joshi et al. 2016) and provides a more extensive assessment of habitat loss within Peninsular Malaysia and the contribution of expanding plantations. However, we have only mapped forest loss within habitat and have not assessed the quality of the remaining habitat, which can be further affected by the fragmentation or creation of greater edge and increased access. Furthermore, the estimated conversion of natural forests and habitat to plantations in our study is limited by the plantation dataset used. Any undetected or cryptic plantations will result in an underestimation of the forest area converted to plantations over the study period. While any forest conversion to cryptic plantations is a concern for tiger habitat loss, the forest area converted to these plantations is of relatively low importance when compared with forest conversions to large industrial plantations like those of oil palm and rubber.

With 48% of all the natural forest lost during 1988–2012 converted to plantations by 2014, plantation expansion can be considered a major contributor to forest loss in Peninsular Malaysia. Large industrial plantations constitute more than half of the forest converted to plantations in both study periods. Contrary to claims by the Malaysian palm oil industry (Sheil et al. 2009, Gaveau et al. 2016), our results show that oil palm plantations have continued to expand at the expense of natural forest areas. Our analysis shows that approximately 242,000 ha of mapped forest loss between 1988 and 2012 were converted to industrial oil palm plantations by 2014. Additionally, we observe an increased conversion of both forest and habitat loss to plantations post-2000, primarily due to the observed increase of annual loss after 2006, especially within tiger habitat. The proportion of total loss converted to plantations has increased from 40 to 54% between the two periods, while the proportion of habitat loss converted to plantations has increased from 35 to 57%.

Although the conversion of forest and habitat to oil palm plantations has dominated throughout the study period, the proportion of conversions to large-scale rubber plantations has increased significantly post-2000. Mapped habitat loss converted to rubber plantations has increased by 96% between pre-2000 and post-2000, while conversions to oil palm plantations have only increased by about 14%, suggesting that rubber cultivation could be a developing threat for the forests and tiger habitat. Other reports also indicate substantial increases in the forest reserve area converted to rubber plantations between 2005 and 2012 (Kawanishi 2015). Latex-timber clones, rubber trees that can be used for both rubber and timber, are being propagated across the landscape as a means to expand timber plantations (Clements et al. 2010). Policies that allow for selectively logged forests under state jurisdiction to be converted to rubber tree plantations (Clements et al. 2010) and aggressive plantation schemes by the government (Kawanishi 2015) continue to endanger Malaysia's forests and tiger habitat.

The observed increase in habitat loss under the cleared plantation class could probably be explained by delays in plantation establishment after forest clearing and that recently established plantations could look very similar to land cleared for other land-uses (Koh et al. 2011). It is important to note that our analysis focuses on forest loss area that is under plantation in the year 2014 and other intermediary land uses could exist before plantation establishment. Forest conversion has been shown to follow initial logging disturbance in Indonesia (Margono et al. 2014). In Peninsular Malaysia, oil palm plantations are usually established on degraded, previously logged forest or other existing plantations (Wicke et al. 2011, Gunarso et al. 2013). Moreover, about 85% of the Malaysian tiger population inhabits forest reserves that have been predominantly assigned for selective logging (Rayan and Linkie 2015). It is essential that the role of logging in deforestation and habitat loss in the region be further investigated.

2.6 Conclusions

The Malayan tiger continues to be threatened by habitat loss and fragmentation despite Malaysia's relatively large area under forest cover (Rayan and Mohamad 2009). Our study maps the natural forest for Peninsular Malaysia for circa 1988 and the forest loss between 1988 and 2000, and aggregates our forest loss with the GFC global forest loss product to produce a consistent forest loss dataset from 1988 to 2012 for the region. We find that natural forest loss continues within Peninsular Malaysia, specifically within its tiger habitat. The conversion of forests to plantations within the region is responsible for about half of all the deforestation. Furthermore, we find that the contribution of plantations to the total area of natural forest loss has increased from pre-2000 to post-2000. Large industrial plantations and recently cleared land are the major contributors of land-use conversion. While large industrial plantations continue to be dominated by oil palm, conversion to rubber plantations has been on the rise. In this work, we have quantified the total loss of habitat but have not assessed more subtle changes in habitat quality that result from natural forest conversion. Our map product enables studying the spatial distribution and patterns of natural forest loss within Peninsular Malaysia and its tiger habitat.

Chapter 3: Factors Influencing Oil Palm Plantation Expansion in Peninsular Malaysia

3.1 Summary

Agricultural expansion is one of the leading causes of deforestation in the tropics and in Southeast Asia it is predominantly driven by large-scale production for international trade. Peninsular Malaysia has a long history of plantation agriculture and has been a predominantly resource-based economy where expanding plantations like those of oil palm continue to replace natural forests. Habitat loss from deforestation and expanding plantations threatens Malaysian biodiversity. Expanding industrial plantations have also been responsible for drainage and conversions of peatland forests resulting in release of large amounts of carbon dioxide. The demand for palm oil is expected to increase further and result in greater pressures on tropical forests. Given Malaysia's high biophysical suitability for oil palm cultivation, it is important to understand patterns of oil palm expansion to better predict forest areas that are vulnerable to future expansion. We study natural forest conversion to industrial oil palm in Peninsular Malaysia between 1988 and 2012 to identify determinants of and constraints on recent oil palm expansion. We find that accessibility to previously existing plantations is the strongest determinant of oil palm expansion and is significant throughout the study period. Almost all (> 99%) of the forest loss between 1988 and 2012 that has been converted to industrial oil palm plantations is within 1 km from oil palm plantations that have been established earlier. Although most forest conversions to industrial oil

palm have been in areas of high biophysical suitability, there has been an increase in converted area in regions with low oil palm suitability since 2006. We find that reduced suitability does not necessarily restrict conversions to industrial oil palm in the region; however, lack of access to established plantations does.

3.2 Introduction

Agricultural expansion is one of the primary causes of deforestation globally (Geist and Lambin 2002, Gibbs et al. 2010, Hosonuma et al. 2012). Between 1980 and 2000 about 83% of agricultural expansion in the tropics occurred on previously forested land (Gibbs et al. 2010). With increasing urban populations and greater consumption of agricultural products (Rudel et al. 2009, DeFries et al. 2010), over time, the primary agents of deforestation resulting from agricultural expansion have changed from state-enabled smallholders in the 1980s to large enterprises producing for international markets in the 1990s, particularly in the Amazon and Southeast Asia (Rudel et al. 2009). The amplified global trade of commodities has linked distant areas of consumption and production and has lead to local environmental impacts at sites producing goods for meeting international demand (Henders et al. 2015); for instance road building and forest clearing has also become enterprise-driven (Rudel et al. 2009) and trade of agricultural commodities has been linked specifically to high rates of forest loss in the humid tropics (DeFries et al. 2010). Commercial actors producing for international markets are now globally the most important drivers of deforestation in developing countries and contribute to approximately 35% of the deforestation in Asia (Hosonuma et al. 2012).

Between 2000 and 2012 Malaysia had the highest percent of tree cover loss relative to its land area (Hansen et al. 2013). Deforestation and expanding plantations, especially those of oil palm, are a threat to biodiversity in Malaysia, which had the highest number of threatened species per square kilometer in relation to palm oil production in 2005 (Turner et al. 2008). Habitat loss from expanding plantations particularly threatens megafauna like the tiger, the rhino and the elephant in Peninsular Malaysia (Clements et al. 2010), where expanding plantations continue to replace natural forests and an estimated 651,757 ha of forest loss between 1988 and 2012 has been converted to plantations by 2014 (Shevade et al. 2017). Owing to their uniform tree-age structure and homogeneity compared to forests, oil palm plantations support fewer species (Peh et al. 2006, Fitzherbert et al. 2008). Conversion of peatswamp forests to oil palm in Peninsular Malaysia by early 2000s is estimated to have caused a loss of 46 species of forest birds (Koh et al. 2011).

In Peninsular Malaysia, agricultural expansion and extension of permanently cultivated land has always been the major cause of deforestation or forest conversion (Brookfield and Byron 1990). Malaysia has been a predominantly resource-based economy with its exports dependent on minerals, timber, and other tree crops such as rubber and oil palm (Brookfield and Byron 1990). While major drivers of deforestation switched from logging for export (1950 – 1980) to plantation expansion during the 1980-1990s (Kummer and Turner 1994), large industrial plantations are not a newly emerging driver. First large industrial plantations appeared in the region during the early 1900s and have since expanded with the increased demand for commodities. In the early phase of industrial plantations, rubber plantations spread with increasing rubber prices early in the 20th century. Following a drop in rubber prices during the 1960s, an increased demand for palm oil eventually led to the growth of oil palm plantations; including both development of new plantations on previously forested land and those replacing old rubber plantations. By 1990, oil palm plantations accounted for the largest area under industrial tree crops in Malaysia (Hai 2000) and by 2010 oil palm plantations covered 20% of Peninsular Malaysia (Gunarso et al. 2013). A significant portion of the expanding plantations have been established by converting natural forests, estimates for oil palm expansion originating from deforestation, however, vary drastically. Countrywide estimates for the proportion of expanding oil palm replacing forests in Malaysia range from 38-39% between late 1980s or 1990 and 2010 (Gunarso et al. 2013, Vijay et al. 2016) to 55-59% during 1990 – 2005 (Koh and Wilcove 2008). The patterns and extent of plantation expansion driven deforestation vary regionally and temporally. In Malaysia, the proportion of new oil palm plantations established by converting forests reduced from ~56% during 1990-2000 to ~33% during 2006-2010 (Gunarso et al. 2013). Direct conversion of forests to plantations has been more common in Sabah and Sarawak (Malaysian Borneo) (Gunarso et al. 2013, Gaveau et al. 2016). Forest conversions during 1990-2000 accounted for 62% and 48% of new oil palm plantations in Sabah and Sarawak respectively, while in Peninsular Malaysia, an estimated 28% of oil palm expansion during 1990-2010 originated from forest conversion and the proportional contribution of forest conversions has reduced from ~38% in 1990-2000 to ~ 6% during 2006-2010 (Gunarso et al. 2013).

The global importance of palm oil has risen to new levels since the beginning of the 21st century; by 2007, palm oil constituted 30% of global production of vegetable oils while palm oil exports accounted for 60% of global exports in oils and fats by volume (Carter et al. 2007). Malaysia is currently the second largest producer (Wicke et al. 2011) and one of the largest exporters of palm oil products accounting for 44% of global palm oil exports (Malaysian Palm Oil Council - MPOC, 2017). The Malaysian palm oil industry plays a significant role in the Malaysian economy and in 2015 oil palm contributed to 4.17% of Malaysia's Gross Domestic Product (Department of Statistics Malaysia - DOSM, 2016). Oil palm plantations covered 5.2 Mha in Malaysia in 2010 with 2.7 Mha in Peninsular Malaysia and the remaining in Malaysian Borneo (Gunarso et al. 2013). Additionally, between 48-56% of all deforestation in Peninsular Malaysia has been converted to oil palm plantations in the 1990s and 2000s (Shevade et al. 2017, Gunarso et al. 2013). Peninsular Malaysia has also continued to produce a large fraction of Malaysia's total palm oil products; around 52% of Malaysia's crude palm oil was produced by Peninsular Malaysia in 2017 (Malaysian Palm Oil Board – MPOB, 2018). As the demand for palm oil is expected to grow (Corley 2009), up to 5 Mha of additional land would be required to meet Malaysia's production projections for 2020 (Wicke et al. 2011). Given this anticipated demand (Corley 2009) and the recent trends of forest conversion (Shevade et al. 2017, Gunarso et al. 2013), Malaysia's remaining forests continue to be threatened by expanding oil palm plantations. Thus, understanding factors that influence expanding plantations is important to identify where future plantations might be established.

Commodity crop expansion pathways are controlled by availability of suitable forestland versus other land areas, relative economic and technical characteristics of different land uses, differences in constraints and opportunities for small and large-scale actors, and factors affecting costs versus benefits of forest clearing (Meyfroidt et al. 2014). Typically, land cover and land use changes are modeled following land rent theories that use factors determining costs and returns to vary with potential profitability from that conversion (Mertens and Lambin 2000, Gaveau et al. 2009, Wheeler et al. 2013), i.e. conversion of forest to agriculture is based on potential agricultural revenues exceeding costs of production and clearing the forest (Chomitz and Thomas 2003). Several biophysical, socioeconomic and institutional factors may influence the costs or returns of converting forested land to agriculture. Forest clearing has been linked to several economic factors like expected prices and demands for commodities like palm oil (Wheeler et al. 2013), higher commodity prices and potential agricultural revenue (Busch and Ferretti-Gallon 2017). Transportation costs are also expected to impact deforestation probabilities (Wheeler et al. 2013) and proximity to built infrastructure has been linked to greater deforestation (Busch and Ferretti-Gallon 2017), however, changes in transport costs have been shown to influence deforestation differently based on prior land use and extent of development (Weinhold and Reis 2008) – they are typically represented using proxies like distances to roads, cities, markets, etc. Oil palm expansion, specifically, has been linked to elevation, slope, precipitation, soil type, distance to existing palm oil areas as well as distance to palm oil extraction centers, roads, ports, population centers and settlements (Castiblanco et al. 2013, Sumarga and Hein 2016, Austin et al. 2015). Other accessibility and infrastructure measures like distance to forest edges, communications cost, presence of protected areas and other land use designations or zoning criteria have also been shown to influence deforestation dynamics (Gaveau et al. 2009, Wheeler et al. 2013).

Most economic or infrastructure variables influencing expansion of oil palm plantations change with time as market prices, road networks, area under plantation, etc. change. Other variables like land use designations, protected areas, and other institutional factors also might potentially change, although, they are usually considered to be static due to their nature of being constant over long time periods. As the demands for commodities, land use dynamics, availability of suitable land change; it is likely that drivers of oil palm expansion also change with time. With its long history of forest conversions and plantation cultivation, Peninsular Malaysia has seen changes in agents and drivers of deforestation and is now limited by its available land outside forests for expanding plantations. Due to this history and distinct forest dynamics trends as compared to Sabah and Sarawak in Malaysian Borneo, we are interested in the determinants of oil palm expansion specifically in Peninsular Malaysia and changes in these determinants over time.

Determinants and constraints are essentially two sides of the same coin and identifying determinants of land use change has been used to recognize and explore constraints to related land use changes (Meyfroidt et al. 2016). Previous global studies have used suitability for oil palm to determine potential areas for oil palm expansion (Pirker et al.

2016, Vijay et al. 2016). Malaysia has very high climate suitability for oil palm (Paterson et al. 2017) and 88% of its land area is biophysically suitable for oil palm cultivation (Pirker et al. 2015). However, due to extensive land use change in the past, there is limited land available in Malaysia for future oil palm expansion (MPOC 2017). With low land availability, other competing land uses, and various government designated land uses it is understandable that agro-environmental suitability alone cannot determine areas of oil palm expansion. Protected areas and other existing land uses have been considered to limit areas available for future expansion of oil palm (Pirker et al. 2016, Vijay et al. 2016). High carbon stocks or areas of high conservation value have also been explored as possible constraints for future expansion when taking implementation of sustainability criteria into consideration (Pirker et al. 2016). Accounting for biophysical suitability, land already under use or protection and different sustainability criteria leaves very little of the biophysically suitable area available for expansion; only 17% of global palm oil suitable area would be available upon considering all the restricting criteria (Pirker et al. 2016). Sparing high carbon stock or high conservation value land from conversion is currently proposed as part of the sustainability commitment of the palm oil sector (Pirker et al. 2016) and high conservation value areas are currently protected under the Roundtable on Sustainable Palm Oil (RSPO) regulations that apply to certified palm oil plantations producing 21% of the global palm oil (Vijay et al. 2016). However, they are either suggested sustainability criteria as a part of a proposed methodology (Raison et al. 2015) or criteria that aren't applicable to majority of the forests and are not prohibitive and thus do not limit oil palm expansion by their very nature. Another constraint considered is the market accessibility of suitable areas and only 18% of the global suitable land is within 2 hours transportation to large cities (Pirker et al. 2016). Unlike high carbon or conservation value areas, infrastructure accessibility of a location on the can be restrictive for future expansion as it might potentially influence the profits generated by plantations in that location.

In order to better understand where future oil palm expansion can threaten forests and biodiversity habitat characterizing patterns of expansion and factors associated with expanding oil palm plantations is essential. An understanding of the determinants of recent plantation expansion and the environmental suitability of those areas is essential for better land use planning and policy making. The objectives of this study are to (a) identify primary determinants of forest conversion to oil palm plantations and their temporal shifts between 1988-2000 (pre-2000) and 2001-2014 (post-2000), (b) spatially characterize patterns of agro-environmental suitability and socio-economic variables including market and infrastructure accessibility for recent areas of oil palm expansion, and (c) characterize constraints on converting remaining forest to oil palm plantations.

3.3 Materials and Methods

3.3.1 Study Area

Our study focuses on Peninsular Malaysia. It is an equatorial region experiencing the southwest monsoon from May to September and the northeast monsoon from October to March. The average temperatures are between 25 and 35 °C and average annual precipitation ranges between 1500 – 5000 mm. It thus has ideal climatic conditions for growing oil palm, which requires annual precipitation between 1000 – 5000 mm/m^2, average annual temperature between 18 and 38 °C, and four or fewer months with rainfall lower than 100 mm/m^2 (Pirker et al. 2016). Forested areas of Malaysia have a high potential for agriculture and an estimated 146,000 square kilometers of Malaysia's forests in 2001 were estimated to be suitable for oil palm cultivation (Stickler et al. 2007).

Peninsular Malaysia's area under oil palm plantations increased from 1.7 Mha in 1990 to 2.7 Mha in 2010 (Gunarso et al. 2013). Industrial plantations in peatlands continue to expand in the region with 276,000 ha of peatlands under industrial oil palm plantation in 2015 (Miettinen et al. 2016). A recently generated plantation map (Petersen et al. 2016) estimates Peninsular Malaysia had 5.5 Mha under plantations in 2014 and large industrial-sized plantations covered 2,631,070 ha with 89% (2,335,260 ha) under oil palm cultivation (Fig 3.1).

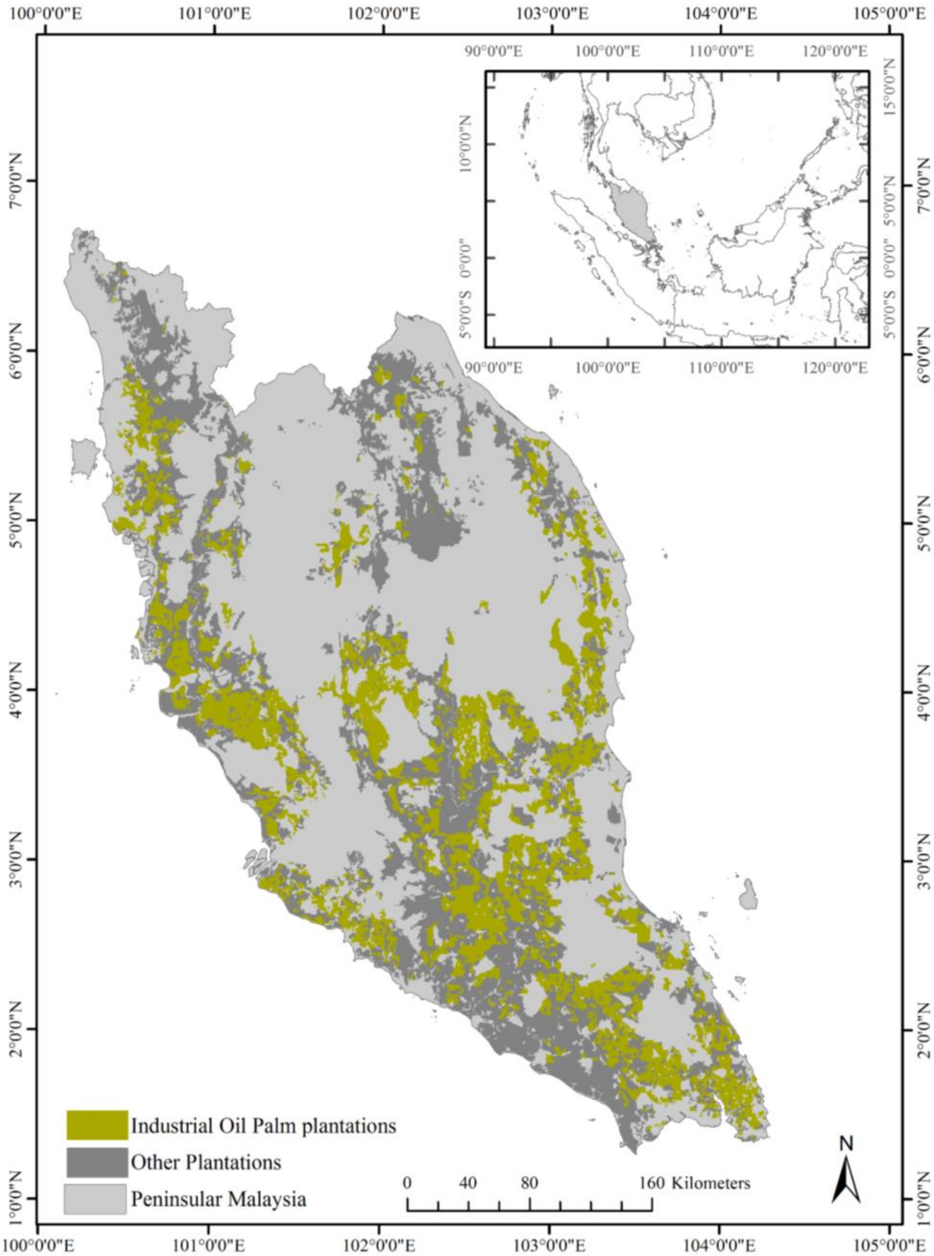

Figure 3.1 Peninsular Malaysia with industrial oil palm plantations and other plantations from World Resources Institute (WRI, Petersen et al. 2016)

3.3.2 Methodology

To achieve our primary objective of identifying the determinants of oil palm expansion, we built several statistical models to assess the combined impact of various potential drivers defined in the scientific literature within a spatially explicit modeling framework. To identify possible constraints on future conversion of forests we characterized agro-environmental suitability and accessibility of recently converted areas. The overall methodological flow is described in Fig 3.2. This approach was applied to two time periods – pre-2000 (1988-2000) and post-2000 (2001-2015) to compare the impact of various determinants and constraints over time.

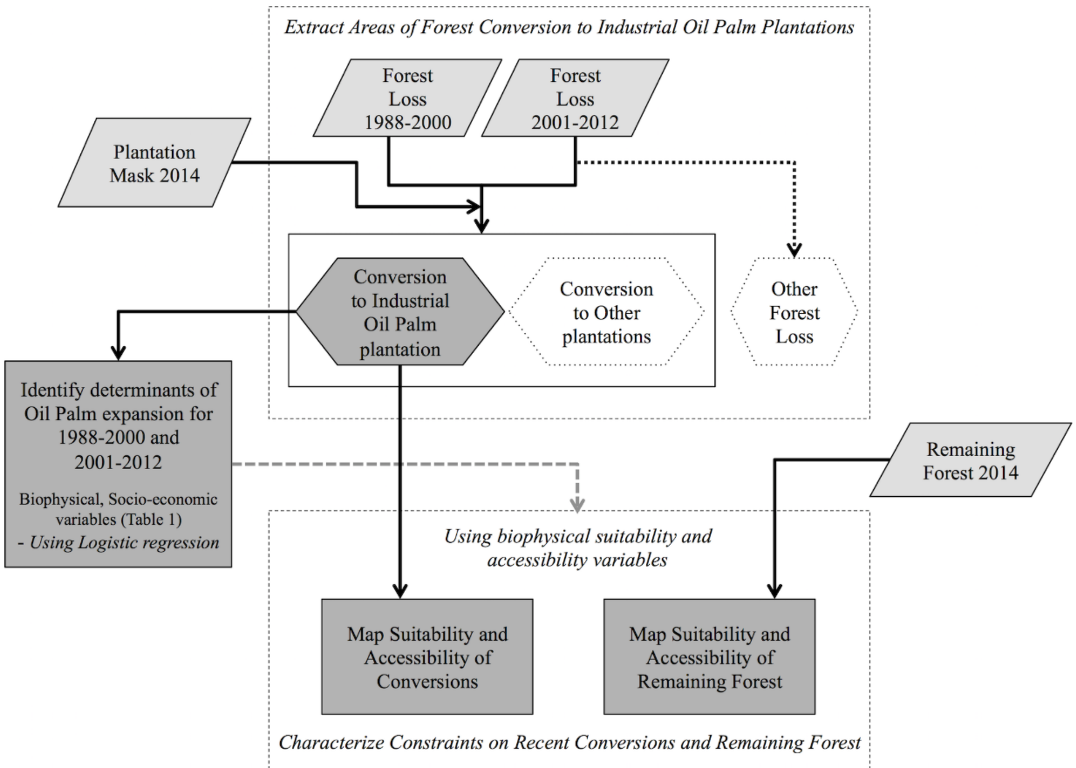

Figure 3.2 Overview of the methodology

3.3.3 Data and Variables

We use the tree plantation dataset from WRI (available from www.globalforestwatch.com) (Petersen et al. 2014) for the region that delineates four types of plantations in the year 2014; large industrial-sized plantations, small-sized mosaic plantations, medium-sized mosaic plantations and recently cleared or young plantations. The large plantations tend to be monocultures and the species information associated with them was used to identify large single-species plantations of oil palm. Mosaic plantations also have species information associated with them and are dominated by oil palm and rubber but these tend to be a mix of a variety of species. As mosaic plantations are a mix of several species interspersed with croplands and settlements these can pose difficulties to identifying determinants and constraints to expanding plantations of specific species and recently cleared / young plantations don't have species information associated with them. Hence, we focus only on industrial oil palm plantations.

Natural forest loss is defined strictly as complete or nearly complete tree cover loss within a 30 m Landsat pixel occurring within a natural forest mask of 1988 developed by Shevade et al. (2017). The natural forest mask obtained from (Shevade et al. 2017) delineates mature naturally regenerated forests with a minimum area of 5 ha and was developed using a bagged decision tree model applied to multi-temporal metrics derived from a1988 Landsat image mosaic to develop (see (Shevade et al. 2017) for further details). Tree cover loss for 1988 – 2000 (pre-2000), obtained from Shevade et al.(2017), was mapped in a one time-step (due to the limited availability of Landsat imagery before 2000) while 2001 – 2012 (post-2000) loss mapped annually was obtained from the Global Forest Change (GFC) product (Hansen et al. 2013). The tree cover losses for pre-2000 and post-2000 use similar methods providing a consistent forest loss dataset for the region. Using the natural forest mask for Peninsular Malaysia to identify loss within the existing natural forest overcomes the limitations of the GFC tree cover loss dataset, which does not distinguish between natural forests and plantations. Forest conversion is defined as all the natural forest loss (1988 – 2012) that is within plantation areas (Petersen et al. 2016) and conversion to oil palm refers to forest loss converted to large industrial plantations of oil palm.

Factors Influencing Conversion to Plantations

Several variables were evaluated as factors influencing deforestation and conversion to plantations. Variables chosen have been shown to influence deforestation, conversion to plantations or environmental suitability of oil palm and are listed in Table 3.1 below.

(i) Agro-environmental factors: Environmental variables that determine suitability for oil palm or influence forest conversion to these plantations were used in the model. Topographic variables like elevation and slope not only determine agricultural suitability for oil palm (Pirker et al. 2016) but also determine accessibility for deforestation and conversion (Mertens and Lambin 2000). Other environmental variables used in the model that determine suitability for oil palm include annual precipitation, and mean temperature (Pirker et al. 2016). Additionally, minimum precipitation (average yearly minimum precipitation obtained from WorldClim, Fick and Hijmans 2016) was also used for the analysis.

(ii) Access to markets: Access to large cities is related to the accessibility of areas to markets and costs of transportation and has been used to model deforestation (Wheeler et al. 2013) or to assess the economic appeal of areas available for conversion (Pirker et al. 2016). Proximity to urban areas has been also associated with higher deforestation (Busch and Ferretti-Gallon 2017). Given palm oil is traded internationally, distance to major ports is expected to influence forest clearing (Wheeler et al. 2013) and has been

shown to negatively influence oil palm expansion in Indonesia (Austin et al. 2015). We use the following major Federal ports - Johor Port Pasir Gudang, Kemaman Port, Kuantan Port, Penang Port, Port Klang, and Port Tanjung Pelepas for our analysis (Ministry of Transport, Malaysia – MOT, 2016).

(iii) Access to infrastructure: a) Distance to previously established oil palm plantations: Previously established plantations have been shown to heavily influence newer areas of conversion to plantations (Gaveau et al. 2009, Sumarga and Hein 2016). Old deforestation / plantations and areas around them will have established infrastructure like cleared areas, access roads, and settlements for workers, making it easier to develop newer plantations adjacent to those lands and reducing costs of conversion. "Old" plantations are assumed to be plantations existing before the study period in question. We used the WRI plantation mask for industrial oil palm plantations and removed all plantation areas converted from forests between 2000 and 2012 to get plantations existing before year 2000 and removed all plantation areas converted from forests between 1988 and 2012 to obtain plantations existing before 1988. As detailed trajectories of land use change are not available for the region, we assumed that all areas deforested prior to 1988 and that are currently under oil palm cultivation, were converted to oil palm plantations immediately following clearing. Euclidian distances to these "old" plantations – plantations that were already established by the time period under consideration - are then calculated. b) Distance to palm oil-processing facilities: Access to palm oil-processing mills has been shown to explain presence of oil palm plantations (Castiblanco et al. 2013). Palm oil mills within Peninsular Malaysia obtained from WRI. c) Distance to settlements: Proximity to

settlements has been shown to be preferred for expansion of oil palm plantations (Sumarga and Hein 2016). Settlements within the region were obtained from the NASA - Socio Economic Data Acquisition Center (SEDAC) (Center for International Earth Science Information Network –CIESIN, 2011).

(iii) Socioeconomic Factors: Population has been linked with greater deforestation in several studies (Busch and Ferretti-Gallon 2017).

Table 3.1Explanatory Variables Used in the Model

	Variable	**Source**	
Climatic variables	Total Precipitation (mm)	WorldClim (30 arc seconds) http://worldclim.org/version2 (Fick and Hijmans 2016)	
	Minimum Precipitation (mm)		
	Mean Temperature (Celsius)		
Topographic variables	Elevation (m)	NASA Shuttle Radar Topography Mission (SRTM) (90m)	
	Slope (degrees)		
Accessibility variables *	Distance to Old Plantations (km)	WRI www.globalforestwatch.com	Calculated Euclidean distance to source
	Distance to Palm Oil Mills (km)		
	Distance to Forest Edge (km)	Shevade et al. 2017	
	Distance to Settlements (km)	NASA-SEDAC (CIESIN 2011) http://sedac.ciesin.columbia.edu/	
	Distance to Major ports (km)	Google Earth	
	Accessibility to large cities (population >50,000) (travel time in min)	Joint Research Centre of the European Commission (Nelson 2008) http://forobs.jrc.ec.europa.eu/products/gam/download.php (30 arc seconds)	
Socioeconomic	Population (density per km^2) in 2000 / 2010	NASA-SEDAC (CIESIN 2016) http://sedac.ciesin.columbia.edu/ (1km)	

* We used logs of all the accessibility variables in our model.

3.3.4 Identifying Determinants of Oil Palm Expansion

To identify determinants of oil palm expansion, we modeled forest conversion to oil palm plantations for pre-2000 and post-2000 separately. We used pre-2000 and post-2000 forest conversion to oil palm plantations separately to generate our presence (forest conversion to oil palm) and absence (persistent forest) samples for forest conversion for each of the models using an equalized stratified random sample of a total 500 points. We used logistic regression models as these are well-suited for binary dependent variables and have been used successfully for predicting land cover change (Mertens and Lambin 2000, Busch and Ferretti-Gallon 2017, Austin et al. 2015, Etter et al. 2006). We related the presence or absence of conversion to oil palm (binary dependent variable) with the explanatory variables (Table 3.1) extracted at the sample points, using logistic regressions for the two study periods separately. To avoid the effect of multi-collinearity, we selected independent variables after testing for pairwise correlations and selected only one variable from a pair when the Pearson's correlation coefficient was greater than 0.7 for any pair of variables. As mean temperature and elevation were highly correlated (Pearson's correlation coefficient -0.97) we decided to retain only elevation for the logistic regression.

Logistic regression analysis (using the GLM package in R) was followed by hierarchical partitioning (using the hier.part package in R) to assess the contribution of individual variables to the model by calculating the percentage of total variance explained by the independent variables (Prishchepov et al. 2013). We classified the pre-2000 model predicted probabilities into two classes of 'predicted oil palm' and 'predicted forest' using a probability threshold of 0.9. We used this map of predicted oil palm / forest to assess model accuracy using forest loss converted to oil palm plantations between 2001 and 2012.

3.3.5 Characterizing Patterns of Recent Oil Palm Expansion

Agro-environmental suitability for a crop is considered an important factor for its cultivation in any particular area. We used biophysical suitability classification for oil palm production by Pirker et al. (2016) (Available for download from: http://www.iiasa.ac.at/web/home/about/news/160722-Palm_Oil.html) to determine the biophysical suitability of the pre-existing plantations (pre-1988) and recently converted (1988-2012) oil palm plantations within the region. We also used the suitability classes to determine the biophysical suitability of recently converted oil palm plantations.

We used accessibility to large cities, accessibility to palm oil processing, and accessibility to existing oil palm plantations (per study period) to determine market and infrastructure accessibility for all pre-existing plantations (pre-1988) and recently converted (1988 – 2012) oil palm plantation areas. Accessibility of recent conversions to large cities in travel time (Nelson 2008) was used as a proxy to determine their accessibility to markets and transportation costs. Lower travel time represented greater accessibility to markets. We classified accessibility to cities into 6 categories; < 1hr, 1-3 hrs, 3-6 hrs, 6-12 hrs, 12-24 hrs, and >24 hrs. Accessibility to palm oil mills for processing is an important factor influencing the establishment of oil palm plantations and distance to palm oil mills was used as a proxy for accessibility. Distance to palm oil mills was classified into 5 categories; < 5km, 5-10 km, 10-20 km, 20-40km and > 40km. Distance to previously existing plantations was used to determine accessibility to old plantations. Accessibility to old plantations was classified into 5 categories; < 1 km, 1-2 km, 2-4 km, 4-8 km, > 8 km.

To understand the characteristics of areas with low agro-environmental suitability for oil palm that might lend to establishment of oil palm plantations, we determined the market and infrastructure accessibility of all areas of forest loss (pre-2000 and post-2000) converted to oil palm plantations. We used the marginal suitability and moderate suitability for oil palm from Pirker et al. (2016) to define low suitability for oil palm.

3.3.6 Characterizing Constraints on Future Conversion to Oil Palm Plantations

We characterized agro-environmental suitability and accessibility constraints to future forest conversion to oil palm plantations. The remaining natural forest in 2014 for Peninsular Malaysia was determined using the natural forest mask for circa 1988 and subtracting all the areas of mapped forest loss between 1988 and 2000 (from Shevade et al. 2017) and 2000 – 2014 (from Hansen et al. 2013 updated for year 2014). To map the constraints onto the natural forest (2014) we used the classification for suitability as described by Pirker et al. (2017) and classifications for accessibility as described in the previous section. Additionally, restrictions on conversions due to the protection status, land ownership, presence of peat soils, etc. will also impact where future conversions take place and have been considered as constraints in other studies (Vijay et al. 2016, Pirker et al. 2016). We considered remaining forest within protected areas and the presence of peat soils as possible constraints. We used the following protected areas for our assessment, Taman Negara National Park (434,300 ha), which is the largest and oldest National Park in the region, Endau Rompin National Park, Royal Belum State Park, and Krau Wildlife Sanctuary (Ratnayeke et al. 2018).

3.4 Results

3.4.1 Determinants of Plantation Expansion

Our logistic regression models for forest conversion to industrial oil palm plantations identify a combination of environmental variables and socio-economic variables as significant (Table 3.2). Distance to old oil palm plantations is an extremely significant variable ($p < 0.001$) having a negative effect on forest conversions to oil palm plantations during both time periods (pre-2000 and post-2000) and could be considered the most important determinant of forest conversion to oil palm plantations.

Table 3.2 Logistic regression results for the pre-2000 and the post-2000 model

	Pre-2000 model			**Post-2000 model**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
(Intercept)	-7.785	5.254	0.138	-3.625	3.390	0.285
Elevation	-0.007	0.006	0.289	-0.001	0.003	0.775
Slope	-0.233	0.095	0.014*	-0.118	0.061	0.054
Total Precipitation	-0.002	0.001	0.180	0.001	0.001	0.475 .
Minimum Precipitation	0.080	0.026	0.002**	-0.044	0.018	0.015**
Population	-0.009	0.005	0.096 .	-0.001	0.004	0.743
Accessibility to Large Cities	0.901	1.082	0.405	-0.340	0.614	0.580
Distance to Major Ports	0.139	0.403	0.730	0.409	0.207	0.048
Distance to Palm Oil Mills	-0.117	0.534	0.827	0.784	0.473	0.098
Distance to old Oil Palm Plantations	-3.000	0.463	0.000***	-3.012	0.334	0.000***
Distance to Settlements	-0.317	0.877	0.718	-0.069	0.551	0.900*

Notes: Significance levels of raw coefficients are shown as: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

For the pre-2000 model, slope and population density have a significant negative effect while minimum precipitation has a significant positive effect on forest conversions to oil palm. For the post-2000 model, minimum precipitation and distance to settlements have significant negative effects on forest conversions to oil palm. Minimum precipitation changes from being positively significant for pre-2000 conversions to being negatively significant for post-2000 conversions. Additionally, population has a small significant ($p < 0.1$) negative effect for pre-2000 conversions and total precipitation has a small significant ($p < 0.1$) positive effect for post-2000 conversions. The independent contributions of the variables are shown in Fig 3.3; distance to previous plantations had the greatest contribution for both pre-2000 (79.9%) and post-2000 (96.6%) models.

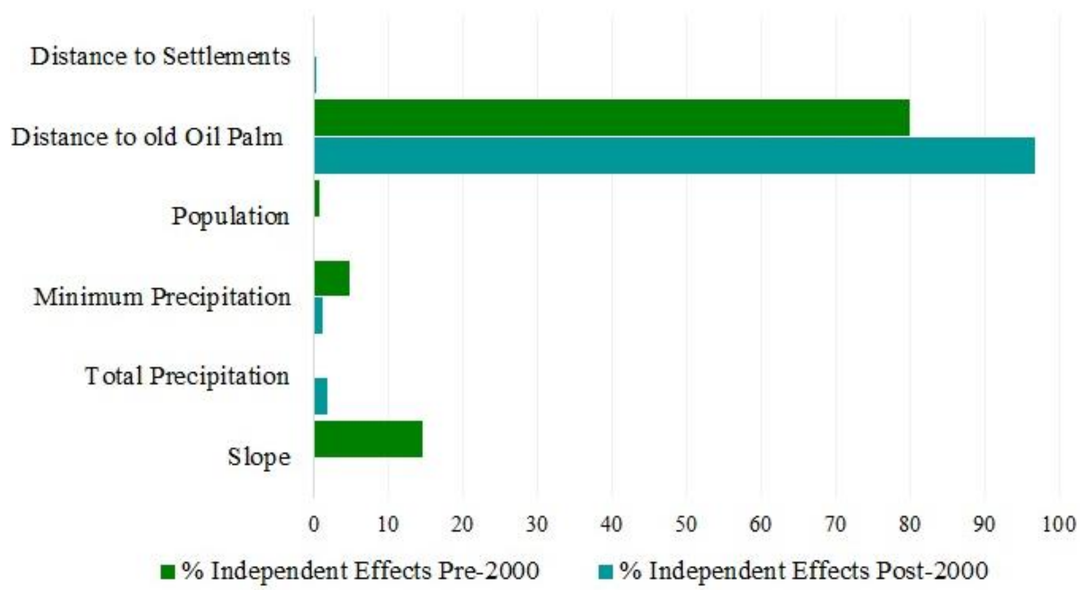

Figure 3.3 Independent contributions of significant variables for pre-2000 and post-2000 using hierarchical partitioning

The overall accuracy of the pre-2000 model is 98.25%. The producer's accuracy for 'predicted oil palm' class is 77.22% while the user's accuracy is 59.17%. The lower user's accuracy corresponds to a higher commission error, which is expected when predicting forest conversions to plantations without a suggested timeline for the predicted changes (Mertens and Lambi 2000). In addition, the lack of information on land tenure and the possibility or legality of forest conversions in the model also affect predictions of where forest conversion to oil palm will occur in the future.

3.4.2 Suitability and Accessibility Characterization of Recent Conversions

Pirker et al. (2016) define 5 classes of biophysical suitability for oil palm cultivation primarily determined by low slopes and elevations and moderate to high rainfall; marginal, moderate, suitable, high and perfect. We used their biophysical suitability classification to assess the suitability of forest conversions to oil palm since 1988. Majority (76%) of Peninsular Malaysia is within high suitability classes (suitable, high, perfect) for oil palm. A large area portion of Peninsular Malaysia was already under plantations by 1988 and almost all (93%) of the pre-1988 plantations that are under oil palm (in 2014) have predominantly been established in areas within high biophysical suitability for the species. Thus, by 1988 only 56% of the natural forests were within high biophysical suitability for oil palm cultivation.

Of all the forest area converted to oil plantations between 1988 and 2014, most (> 80%) conversions have taken place within areas with high suitability for oil palm cultivation (Fig 3.4). There has been an increase in the proportional forest conversions to oil palm plantations in the low suitability classes (marginal and moderate). There is also a small increase in the absolute area and percent area of available forest conversions to oil palm within low suitability classes from pre – 2000 to post – 2000. This is evident when considering the yearly (between 2001 and 2012) forest conversions to oil palm plantations (Fig 3.5). Although the total area of conversions has fluctuated throughout the period, we find that both the absolute and proportional area of forest converted within marginal and moderate suitability classes has been increasing throughout the decade (especially since 2006, Figs 3.5a and 3.5b) while that in the higher suitability classes has been reducing.

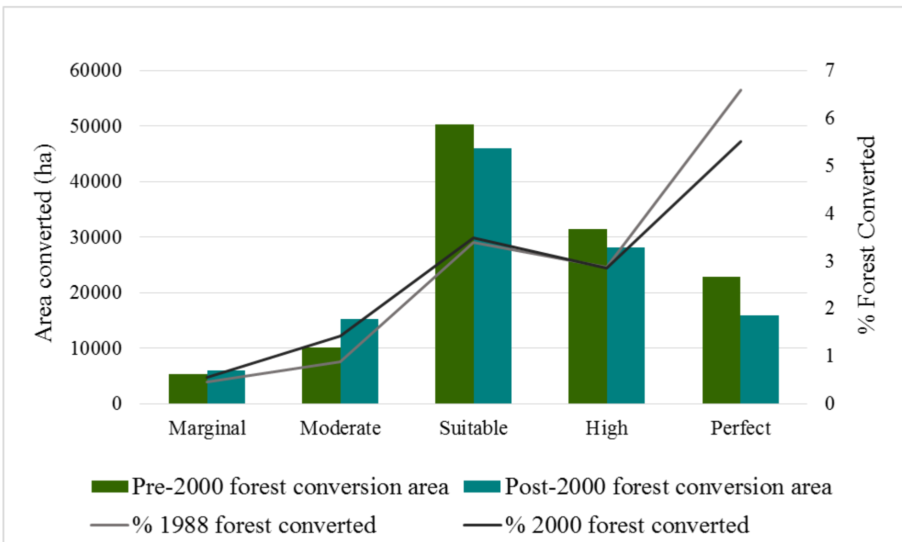

Figure 3.4 Pre-2000 and post-2000 area and percent area of natural forest converted to oil palm plantations by suitability class

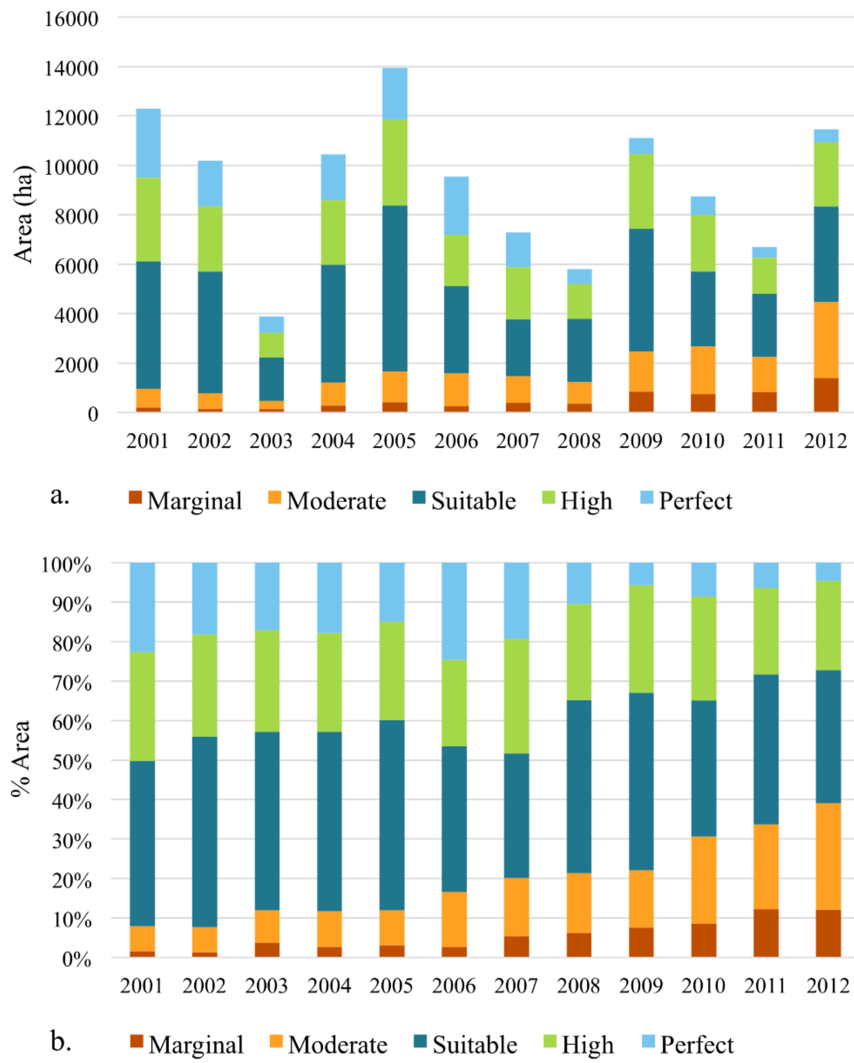

Figure 3.5 a) Yearly (2001-2012) area of forest converted to oil palm by suitability class, and b) Yearly proportional forest conversion by oil palm suitability class

Forest conversions to oil palm have been in regions with very high accessibility to infrastructure. All pre-2000 and post-2000 forest loss that was converted to oil palm plantations was in regions with very high accessibility to old oil palm plantations. Almost all (99.85% of pre-2000 forest loss and all of the post-2000 forest loss) that is now under oil palm cultivation was within 1km from pre-existing oil palm. Pre-2000 and post-2000 absolute and percent area of forest conversion to oil palm was greatest in regions with moderate accessibility to cities and reducing with decreasing accessibility to cities (Fig 3.6). Areas within 1 hour of cities also had low forest conversion to oil palm. Percent forest area converted is greatest at moderate travel times to large cities and reduces beyond that where forest converted is reduced drastically at travel times greater than 12 hours and becomes negligible at travel times greater than a day.

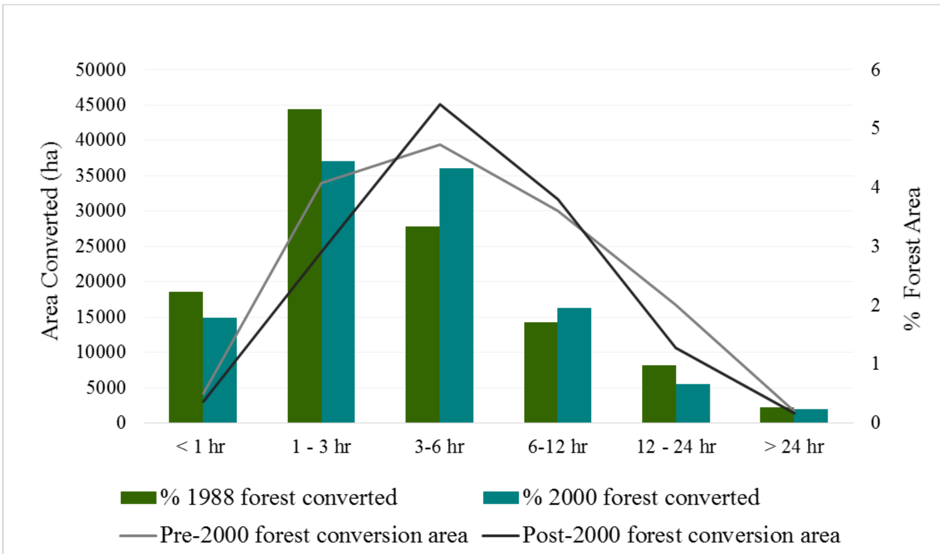

Figure 3.6 Pre-2000 and post-2000 forest area and percent forest converted to oil palm plantations by accessibility to large cities (travel time in hours)

Area of forest converted to oil palm is lowest in areas closest (< 5km) to palm oil procssing mills, peaks at moderate distances between 5km and 10km of the mills before reducing with greater distances (Fig 3.7). The percent forest area converted to oil palm reduces with decreasing accessibility to oil palm processing facilities. These patterns are similar for both pre-2000 and post-2000 forest conversions.

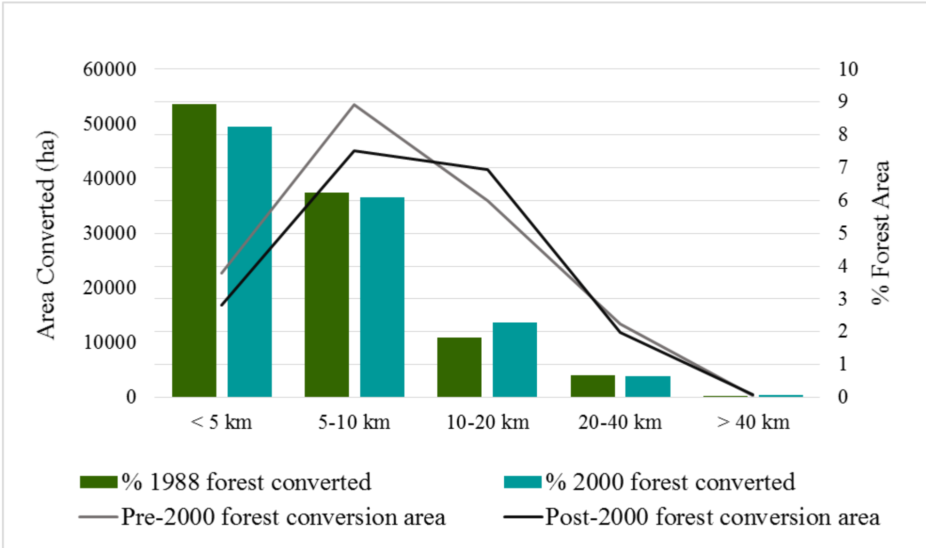

Figure 3.7 Pre-2000 and post-2000 forest area and percent forest area converted to oil palm plantations by proximity to palm oil processing centers

Furthermore, 50% of the increase in conversions within low suitability classes between pre-2000 and post-2000 is a result of increased conversion in areas with high accessibility to palm oil mills. Conversion within areas of low suitability was predominantly in areas with high infrastructure accessibility. About 74% of pre-2000 forest conversions and at least 78% of post-2000 conversions were within areas moderate to very high accessibility to cities, had moderate to high proximity to palm oil processing mills and were all also within 2 km from previously existing oil palm plantations.

3.4.3 Constraints on Remaining Natural Forest Areas for Oil Palm Expansion

Approximately half (~52%) of the remaining natural forest in 2014 is well suited (suitability class – suitable, high or perfect) for oil palm cultivation and about 57% has moderate to high market accessibility. Of the remaining forest only 31% has moderate to very high accessibility to old oil palm plantations and only 22.5% is within 5 hours travel time of large cities (Figs 3.8a and c) while about 48% of the remaining forests have moderate to very high accessibility to palm oil processing (Fig 3.8b). About 31% of remaining natural forest with low suitability and 40% of the forest with high suitability for oil palm cultivation is within the four protected areas and 7% of the total remaining natural forest under high / perfect suitability is in peat swamps (Fig 3.9).

Figure 3.8 Remaining natural forest (2014) in biophysical suitability classes for oil palm separated by a) proportional accessibility to old palm plantations, b) proportional accessibility to palm oil mills, and c) proportional accessibility to large cities

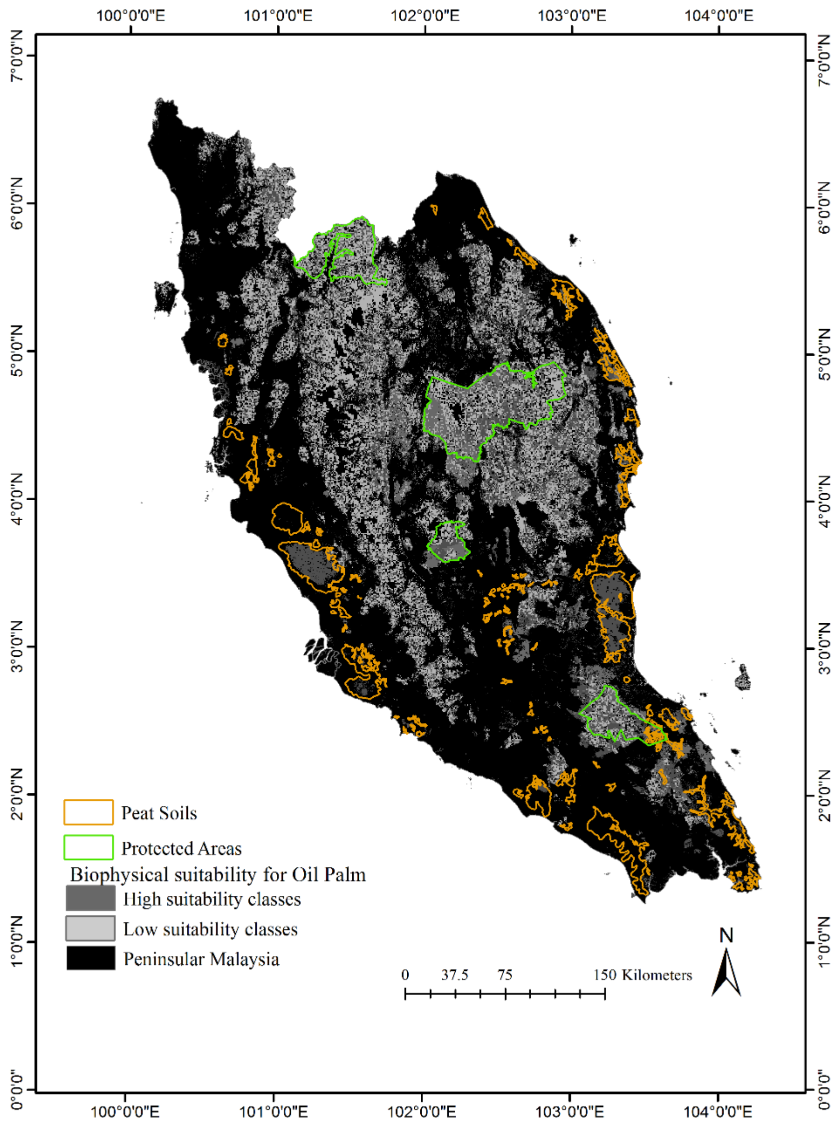

Figure 3.9 Remaining natural forest (2014) within high and low suitability classes for oil palm, selected protected areas based on Ratnayeke et al. (2018) obtained from the World Database on Protected Areas (WDPA, UNEP-WCMC and IUCN 2016), and peat soils (World Resources Institute, WRI 2017)

3.5 Discussion

Peninsular Malaysia's oil palm plantations have been primarily established in coastal and low-lying areas, which are biophysically highly suitable for oil palm production. As a result, most high suitability areas within the region have already been converted. However, conversions within marginal and moderate oil palm suitability classes have been increasing and about 30% of all conversions in 2012 were in areas with low oil palm suitability. The increased conversions in low suitability areas might be driven by the limited land availability in areas with high suitability for oil palm and has been observed in Sumatra (Guillaume et al. 2016). With low land availability, competing land uses and continued increase in the global palm oil demand, this recent expansion of oil palm plantations in low suitability areas might indicate economic and infrastructure factors are driving the establishment of oil palm rather than strictly biophysical factors as has been discussed by Sayer et al. (2012).

Indeed, our regression analysis and characterization of forest conversions from 1988-2012 also indicate that accessibility of a location to existing infrastructure, especially pre-existing plantations is more important than its biophysical characteristics for oil palm cultivation and that lack of accessibility has constrained forest conversions to industrial oil palm plantations. Slope and minimum precipitation are the biophysical factors that are associated with oil palm establishment. Slope, however, does not have a significant effect on post-2000 conversions. Minimum precipitation changes from having a significant positive effect on conversions before 2000 to having a negative effect on conversions after 2000. This would indicate that older conversions were in areas with more rainfall while more recent conversions have been in areas with lower rainfall. As the best available land had already been converted, this suggests expansion is moving into more marginal lands as has been observed since 2006.

The importance of connectivity and infrastructure with respect to expansion of oil palm plantations has been observed previously in Indonesia (Gaveau et al. 2016. Austin et al. 2015), where oil palm plantations are located in areas with easy access and lack of proximity to existing infrastructure like roads, concessions, plantations, and ports reduces the likelihood of oil palm expansion (Austin et al. 2015). In Colombia and Latin America too oil palm plantation expansion is often clustered and is most likely in areas closest to existing plantations (Castiblanco et al. 2013, Furumo and Aide 2017). The importance of proximity to old plantations for conversions might indicate that economic incentives play a greater role than and at times override the influence of agro-environmental suitability of a region for oil palm establishment such that profits generated despite low suitability are greater than costs. Farmer perception surveys in Indonesia have informed that planting of oil palm is constrained by lack of accessibility of villages, which is eventually overcome with road development and changes in the landscape (Feintrenie et al.2010) rather than rejection of the crop. The relatively lower importance of biophysical characteristics for oil palm establishment could also be a result of highly intensive plantation management, use of irrigation, or use of improved cultivars that could overcome poor biophysical suitability for oil palm crops. Additionally, the generalized nature of the input datasets used for generating the biophysical suitability map, like the climatic information, which has a lower quality in tropical areas and the soil data, which has a lower reliability in South Asia, limit the reliability of the biophysical suitability map (Pirker et al. 2016) and might result in misclassification of some areas.

Although oil palm has been planted successfully in regions with elevation of up to 1500m and slopes up to 16 degrees (Pirker et al. 2016), Harris et al. (2013) have observed that 96% of oil palm existing in parts of southeast Asia by 2010 were established at elevations below 200m and that 65% of these plantations were on slopes below 3% rise. The suitability classification (Pirker et al. 2016) uses very broad topographic criteria allowing elevations up to 1500m and slopes up to 25 degrees in suitability classes, which might not be very realistic for the region. It is important to understand this limitation of the analysis. Most of the remaining forest area within marginal or moderate suitability classes (~77%) either is at higher elevations (>300m) or has steeper slopes (>16 degrees) making it less accessible and less likely to be converted. Changes to the biophysical characteristics like the loss of soil fertility can also influence future conversions. Soils in oil palm plantations in Sumatra have been extensively degraded as a result of management, erosion, compaction over time and lack of carbon inputs (Guillaume et al. 2016). This was observed especially in older plantations, which have been typically planted on land previously used for plantations like rubber or in marginal areas due to land scarcity (Guillaume et al. 2016). The long history of plantation cultivation in Peninsular Malaysia and the more recent expansions into marginal lands can also result in soil degradation in the region.

Although the presence of peat has been considered a constraint, it is not necessarily a deterrent to forest conversion Peatlands have been drained and converted in the past and an estimated 27% of peatland forests in Peninsular Malaysia had been converted to large oil palm monocultures by the early 2000s (Koh et al. 2011). By 2015, about 31% of peatland area in Peninsular Malaysia was converted to industrial plantations with a majority of these under oil palm plantations (98.7%, 275,680 ha) (Miettinen et al. 2016). Similarly, all protected areas are also not necessarily effective in preventing forest loss and conversions and protected area effectiveness does vary with the protection status (Nelson and Chomitz 2011). In the four protected areas considered, we observed forest loss of 12258 ha from 2001-2016, mostly concentrated in the southern part of Endau Rompin. This suggests that presence of protected areas as a constraint for conversion might depend on its protection status. Additional constraints on conversion to oil palm plantations could include local land tenure and ownership of land, state and federal policies for development, market demand and commodity prices, and other competing land uses, for example about 80% of Peninsular Malaysia's forests under Permanent Reserved Forests (PRFs) are designated for logging (Rayan and Linie 2015).

It is important to note that not all factors associated with oil palm cultivation are static in nature. Proximity to palm oil processing, existing plantation infrastructure, and markets are all potentially highly dynamic variables. The accessibility of a location to infrastructure will change with new roads, processing mills or new plantations or as new trade centers emerge. Thus, any of these dynamic variables constraining oil palm cultivation at a location in the present might not continue to be constraints in the future or there could be new constraints in the future, for example suitability for oil palm in Malaysia is expected to change drastically with the climate; studies project large reductions in areas with highly suitable climate but increases in suitable and marginal climate area by 2100 (Paterson et al. 2017, Paterson et al. 2015). Finally, the assessment of determinants and constraints is limited by the quality of the datasets used for this analysis. Errors in the forest / forest loss datasets, plantation boundaries or missed plantation areas will impact the estimates of conversion and possibly the estimation of determinants and constraints.

As has been suggested previously (Vijay et al. 2016, Austin et al. 2015, Pirker et al. 2016), forest conservation incentives should be designed to take into consideration the areas of potential oil palm expansion. Protected areas tend to be in areas with lower pressures and are less likely than average to be deforested (Joppa and Pfaff 2011). Our results show that biophysical suitability alone is not sufficient to determine where future expansion can take place and accessibility to infrastructure should be considered. Accessibility to old oil palm plantations is strongly associated with conversion, ~8% of the remaining natural forest in 2014 within all suitability classes that is within 1 km of existing oil palm plantations could be vulnerable to conversion in the near future. Areas of high suitability and high accessibility are of greatest concern with regards to potential conversion to industrial oil palm. Areas of low suitability but high accessibility will have the next greatest vulnerability to conversion. Such areas with high biodiversity or conservation value or aboveground carbon / peat content should be prioritized for protection over other high conservation value areas with low accessibility. As previously shown, protected areas have a greater impact when they are established in areas closer to roads, cities and on lower slopes (Joppa and Pfaff 2011).

3.6 Conclusions

Our study identifies proximity of previously existing oil palm plantations has been the strongest determinant of forest conversion from 1988 to 2012. Expansion of industrial oil palm plantations replacing forests between 1988 and 2012 has predominantly (> 99%) been within 1 km from oil palm plantations that have been established earlier. Given the perfect environmental conditions for growing oil palm in Malaysia and a large proportion of its land area having high biophysical suitability for the crop, most previously established plantations have been in regions of high biophysical suitability. With extensive land already under plantation cultivation and limited land availability, only 5% of forest “perfectly suitable” for oil palm remains. However, greater conversions in regions with low oil palm suitability since 2006 suggests that low suitability is not necessarily a limiting factor for recent forest conversions to industrial oil palm in the region. As most of the expansion of plantations has been in areas adjoining existing oil palm plantations, we determine that poor accessibility to infrastructure is the most important constraint to future forest conversions to oil palm plantations in Peninsular Malaysia.

Chapter 4: Vulnerability of Peninsular Malaysia's Tiger Landscape to Future Forest Loss and Impacts on Connectivity

4.1 Introduction

Tigers (*Panthera tigris*) are threatened across their entire range and today are limited to only an estimated 7% of their historic habitat (Dinerstein et al. 2007). As with most endangered species, tigers now exist within small protected areas surrounded by a matrix of human dominated landscape. It is known that the effectiveness of protected areas for conservation is reduced as they become increasingly isolated. Through the 1980s and 1990s 69% of protected areas in moist tropical forests experienced some degree of deforestation within 50km of their boundaries reducing the effective size of the protected area and impacting the ecological processes dependent on interactions between the protected areas and their surroundings (DeFries et al 2005). While conservation of all biodiversity is impacted by the observed loss and fragmentation of the habitat, large predators like tigers, which require extensive area to support individuals, are at the greatest disadvantage. In these highly fragmented landscapes, tigers exist across their range as a metapopulation. A metapopulation represents a network of disconnected subpopulations of individuals with restricted movement between the subpopulations (Seidensticker 2010). The subpopulations are concentrated in patches of habitat that are surrounded by a matrix of unsuitable environment through which individuals can travel but where they cannot breed. As individual subpopulations are too small to maintain the genetic diversity required for long-term wellbeing of the tiger species, the persistence of the metapopulation is dependent on processes of colonization and extinction between the sub-populations (Elmhagen, and Angerbjö̈rn 2001). Tiger dispersal thus plays a key role in population dynamics and survival within this metapopulation structure (Seidensticker 2010). Hence, metapopulation management is promoted to conserve large mammals as most protected areas are too small and incapable of supporting viable populations in the long-term and such isolated populations have an increased risk of local extinctions (Wikramanayake et al. 2004). Consequently, maintaining tigers in the wild depends not only on protection of individuals from killing, ensuring a large prey base, and a sufficient habitat area (Dinerstein et al. 2007) but also on full protection of core breeding sites and protection of population sink areas that might serve as dispersal corridors (Seidensticker 2010). Metapopulation management therefore promotes protection of breeding populations and the linking of habitat patches to provide dispersal opportunities through the matrix landscape (Wikramanayake et al. 2004).

Peninsular Malaysia – the only known range of the endemic Malayan tiger (*P. tigris jacksonii*) - has experienced extensive land cover and land use change during last century. Expanding agriculture and permanently cultivated land has been a major driver of forest loss and conversion in Peninsular Malaysia (Brookfield and Byron 1990). Although the primary drivers of deforestation varied over the decades (Kummer and Turner II 1994), economic dependency on resource extraction resulted in conversion of half of Peninsular Malaysia's natural forests by late 1980s (Brookfield and Byron 1990). More recently, as shown in Chapter 2, forest loss and conversions to plantations have continued to negatively impact tiger habitat in Peninsular Malaysia. An estimated 1.35 Mha of forest were lost between 1988 and 2012 where 48% of the loss was converted to tree plantations (Shevade et al 2017). Approximately 61% of that forest loss was within Malaysia's Tiger Conservation Landscape (TCL) as defined by Sanderson et al. (2006) (Shevade et al. 2017) and the Taman-Negara-Belum TCL has experienced some of the highest forest loss across all global TCLs during 2001-2014 (Joshi et al. 2016).

Like numerous other species, Malayan tigers too are threatened by loss of habitat especially from agricultural expansion (Clements et al 2010). Recent reports suggest drastic declines in the Malayan tiger population over few generations (Kawanishi 2015). Forests converted to other land cover types degrade or eliminate suitable tiger habitat. Although tigers are habitat generalists (Seidensticker 2010) they are known to strongly prefer forests to plantations like those of acacia and oil palm (Sunarto et al. 2012). While tigers are encountered in oil palm concessions, they tend to avoid oil palm crops and keep to fringe areas (Maddox 2007). Overall, areas of oil palm have been shown to be unable to support long-term persistence of tigers and the decline in tiger use of plantation concessions is primarily linked to activities associated with human encroachment of the habitat (ibid). In addition to the creation of unsuitable habitat, forest conversions to other land uses brings humans and tigers in close proximity increasing the incidence of human-tiger conflict, including tiger attacks on livestock or humans or the perceived fear of an attack. All Malaysian states with tiger populations have experienced human-tiger conflict and an average of 160 cases per year have been reported between 1991 and 2006 resulting in tiger capture and relocation or retaliatory killing by farmers (DWNP 2008). Tiger attacks on livestock increased beginning in the 1970s with increased conversion of forests and large-scale livestock farming resulting in farmers or land managers killing tigers (DWNP 2008). Reports also suggest that most incidents of tiger attacks on humans are around plantations (United Nations Development Programme - UNDP 2014) and around 31 attacks on humans were reported between 1979 and 2006, with rubber tappers most frequently attacked (DWNP 2008). In addition to habitat loss and fragmentation, human hunting and poaching for meat also impact tiger prey species and have an indirect negative impact on tigers. The abundance of tiger prey is the most important determinant of tiger densities and reductions in prey densities have strong impacts on tiger populations (DWNP 2008). The sambar, a key tiger prey species, has lost 50% of its habitat in Peninsular Malaysia and is restricted to only some protected areas and permanent reserved forests (Kawanishi et al. 2014). Subsequently, the number of individual tigers that can be supported by the landscape is declining as well (DWNP 2008).

The combined impact of increased human-wildlife conflict and reduced prey densities create massive challenges for continued existence of the Malayan tiger. These are further exacerbated by the fragmentation and reduction in connectivity of the remaining habitat which further reduces the viability of a species by impacting animal dispersal and movement necessary to maintain metapopulations for species like the tiger. Carnivores of conservation concern in Peninsular Malaysia are believed to be less likely to survive in fragmented habitats (Ratnayeke et al 2018). Modeling studies also show that higher forest loss can result in greater reduction in genetic diversity of tiger metapopulation (Thatte et al. 2018). Being a solitary and long- ranging animal, factors impeding tiger movement have long-term consequences for reproductive fitness and population survival (Reddy et al. 2017). Thus maintaining habitat connectivity between the various tiger subpopulations in Malaysia is essential to conserve the Malayan tiger and is indeed part of Malaysia's tiger conservation plan. A successful approach of landscape-scale conservation with the inclusion of habitat corridors on the India/Nepal border has been shown to improve tiger population recovery in the Terai Arc landscape. In this case, the use of trans-boundary corridors by tigers has facilitated tiger population recovery within the region (Thapa et al. 2017). Forest corridors in central India have also been reported to maintain high gene flow in tiger sub-populations (Sharma et al. 2013). The documented success of maintaining tiger metapopulations within India's fragmented tiger landscape through the preservation of corridors between the high quality habitat components highlights the importance of continued monitoring and assessment of habitat connectivity to ensure the long-term survival and even possible growth of Malayan tiger metapopulation. Belum-Temengor Forest Complex within the Main Range, Taman Negara in the Greater Taman Negara Forest Complex, and Endau Rompin Forest Complex within the Southern Forests are considered the three priority areas for Malayan tiger conservation (DWNP 2008, Clements et al. 2010). Malaysia's NTAP 2008-2020 was created to achieve the overarching goal of obtaining viable tiger populations in the long-term (DWNP 2008). Enhancing and maintaining linkages between the three forest complexes is one of the priorities of Malaysia's National Tiger Recovery Program (NTRP) to allow long-term viability of tiger populations (NTRP, 2010). Malaysia's Central Forest Spine (CFS) is envisioned as a contiguous expanse of forest complexes connected via green linkages running through the center of the Peninsula (DWNP 2008). The goal of NTAP for 2020 is to actively manage tiger populations in the three priority landscapes within the CFS (DWNP 2008).

Given the continued forest loss and fragmentation in Peninsular Malaysia threatening Malayan tigers, the decline in Malayan tiger population in response to these pressures, and the importance of maintaining connectivity within the landscape to achieve the vision of CFS and tiger conservation in the region, it is crucial to understand the vulnerability of the landscape to future forest loss and impacts on connectivity within the landscape. The objective of this study was to 1) quantify the potential future forest loss in Peninsular Malaysia's forests for five years post-2016, and 2) to assess changes to connectivity within the tiger landscape between 2016 and 2021.

4.2 Methods

To support the study objectives, the overall conceptual framework includes development of probability-based scenarios of forest loss between 2017 and 2021 at an annual time step, quantifying cumulative potential loss over the 5-year period averaged over five independent model runs, and an assessment of potential changes in habitat connectivity between 2016 and 2021 (Fig. 4.1). Within this framework, the satellite-derived estimate of forest cover loss up to the year of 2016 creates the basis for assessing spatially-explicit forest loss probability using a suite of spatial datasets within a Random Forest model. The forest loss probability layer is then used to develop scenarios of potential forest loss based on known characteristics of forest loss derived from satellite data products. These are in turn used to update the forest loss probability for the next iteration of the modeling run for the subsequent year. The iterative process continues for 5 years producing a single scenario of forest loss by 2021. Within the scope of this study, ten separate model runs were completed under two scenarios of restrictions for forest loss described in detail below. Finally, forest connectivity for the observed conditions in 2016 and projected scenarios for 2021 were assessed independently using Circuitscape, Linkage Mapper and Pinch point Mapper software and analyzed to evaluate the potential changes over the 5-year period.

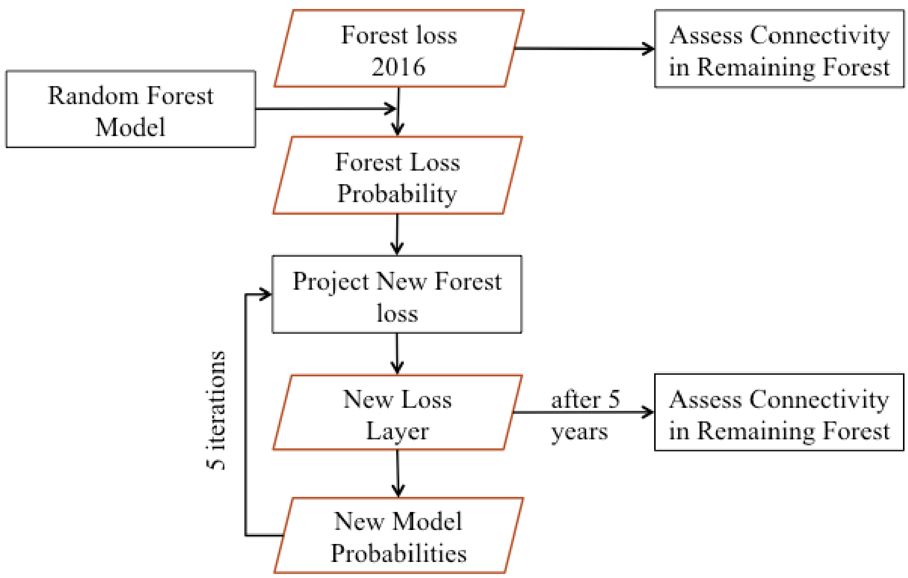

Figure 4.1 Overview of the modeling framework

4.2.1 Modeling Forest Loss Probability

Global Forest Change (GFC) dataset (Hansen et al. 2013) provides annual spatially explicit estimates of tree loss at the 30 m resolution between 2001 and 2016. In this study, forest loss was defined as GFC-mapped tree cover loss within the natural forest mask for 1988 developed in Chapter 2 (Shevade et al. 2017) and was used as training (2001-2011) and validation (2012-2016) samples within a Random Forest model to assess forest loss probability. Forest loss data were resampled using the nearest neighbor method to a 90m X 90m grid. The independent variables within the model were represented by a suite of biophysical and socio-economic variables. These independent variables and the data sources from which they were extracted are summarized in Table 4.1.

Table 4.1 Variables used for modeling forest loss probability

<table>
<tr><th></th><th>Variable</th><th colspan="2">Source</th></tr>
<tr><td rowspan="3">Climatic variables</td><td>Total Precipitation (mm)</td><td rowspan="3" colspan="2">WorldClim (30 arc seconds)
http://worldclim.org/version2</td></tr>
<tr><td>Minimum Precipitation (mm)</td></tr>
<tr><td>Mean Temperature (°C)</td></tr>
<tr><td rowspan="2">Topographic variables</td><td>Elevation (m)</td><td rowspan="2" colspan="2">NASA Shuttle Radar Topography Mission (SRTM) (90m)</td></tr>
<tr><td>Slope (degrees)</td></tr>
<tr><td rowspan="5">Accessibility variables</td><td>Distance to Old Plantations (km)</td><td rowspan="2">WRI www.globalforestwatch.com</td><td rowspan="4">Calculated Euclidean distance to source</td></tr>
<tr><td>Distance to Palm Oil Mills (km)</td></tr>
<tr><td>Distance to Forest Edge (km)</td><td>Shevade et al (2017)</td></tr>
<tr><td>Distance to settlements (km)</td><td>SEDAC
http://sedac.ciesin.columbia.edu/</td></tr>
<tr><td>Accessibility to large cities (population >50,000) (travel time in min)</td><td colspan="2">Joint Research Centre of the European Commission
http://forobs.jrc.ec.europa.eu/products/gam/download.php (30 arc seconds)</td></tr>
<tr><td>Population</td><td>Population (density per km^2) in 2000 / 2010</td><td colspan="2">SEDAC http://sedac.ciesin.columbia.edu/ (1km)</td></tr>
</table>

Previous studies have identified a number of parameters linked to forest loss or oil palm expansion in Malaysia, which are included in this study. Numerous biophysical and socio-economic factors influence decisions of converting forest land to other land uses like agriculture, pasture, mining areas, or developed areas. The socio-economic factors represent market demands for commodities, which impact the revenue that can be gained by the conversion, infrastructure which affects transportation costs, a variety of social, demographic and cultural factors, and finally a combination of land ownership, violence, and corruption which interact in complex ways to influence decisions on forest loss and conversions (Busch and Feretti-Gallon 2017). Within tropical regions, proximity to forest/non-forest edge is related to the accessibility of a location and has been linked to forest loss (Mertens and Lambin 2000, Gaveau et al 2009). Similarly, proximity to towns or markets (Mertens and Lambin 2000, Muller et al. 2011), previous clearing (Muller et al. 2011), and roads (Mertens and Lambin 2000, Gaveau et al 2009) enhance the likelihood of deforestation. Biophysical factors generally include topography, soil quality, and climate. Chomitz and Thomas (2003), Muller et al. (2011) have shown that increasing rainfall reduced the rate of agricultural conversion and the probability that land was used for agriculture or stocking of cattle. Topographic factors – specifically slope and elevation - influence the area accessibility and suitability for specific land management operations and have been linked directly to forest loss and oil palm expansion (Gaveau et al 2009, Muller et al. 2011). Temperature and precipitation also serve as indicators for area suitability for plantation and agricultural land management operations and are generally included in assessment of land suitability for conversion. In this study, however, mean temperaature was dropped from the selected variables because of its high correlation (Pearson's correlation coefficient > 0.7) with elevation. All the chosen variables were resampled to generate a 90m x 90m resolution raster to match the resolution of the SRTM dataset for modeling forest loss probability.

The design of this modeling approach stems from the challenges in assessing the reliability of modeled probabilities for future forest loss. In general, a reserved sample of validation points from the same time period as the training sample can be used to assess accuracy of the resultant map. However, the goal of this study is to assess how representative the modeled probabilities are for subsequent rather than contemporary forest loss. Therefore, the approach used in this study to model forest loss includes three components that involved temporally non-overlapping subsets of forest loss observations. First, a Random Forest model is developed based on a temporal subset of forest loss data covering the period between 2001 and 2011. Second, the resultant forest loss probability is validated against the observed patterns of forest loss between 2012 and 2016. Once it is established that this modeling approach produces reasonable projections of forest loss probability, a second Random Forest model is built based on the 2012-2016 forest cover loss samples to capture the dynamics of most recent forest cover loss in Peninsular Malaysia.

In the first component, 2001-2011 forest loss and persistent forest at the end of 2011 were used to draw a random sample of 2500 points each for the loss and no-loss classes for which spatially corresponding values for all independent variables were extracted. A Random Forest model was run in a classification mode with two primary classes to be identified – "forest loss" and "no-loss" as the dependent variable. Similarly, in the third component a random sample of 2500 points was chosen for "forest loss" and "no-loss" classes for the period 2012-2016 to then create a random forest model for predicting forest loss beyond the year 2016. Within the second component, the resultant forest loss probability for 2001-2011 model was validated using observed forest loss information for the period 2012-2016. The Receiver Operating Characteristic (ROC), which plots the true positive rate against the false positive rate, area under the curve was used to assess the model's performance. The predicted probabilities of forest loss were converted to expected "loss" and "no-loss" classes using increasing probability thresholds from 0.1 – 1.0 with a 0.1 step. These expected forest loss rasters were then compared with actual forest loss occurring between 2012-2016 to generate a classification matrix and get an accuracy assessment for the 2001-2011 model. The percent of total available forest within model predicted probability class that was observed to be lost (2012-2016) was also assessed.

4.2.2 Developing Scenarios of Future Forest Loss

The primary assumption of this modeling component is that the characteristics of forest loss over the 2017-2021 period will be similar to that observed during the preceding years. These characteristics will include the total amount of forest loss as well as the overall number and size of individual patches of forest loss. Projecting forward, a number of random seeds corresponding to the total number of expected patches within each of the six size categories (see the detailed description in the text below) were placed in areas of high suitability for forest loss and were subsequently allowed to grow to a specified patch size following the spatial constraints summarized within the "suitability" layer.

GFC forest loss estimates between 2010 and 2014 were used to quantify the total number of patches cleared within a year and the size of each clearing. A region group analysis was first performed in ArcMap to identify contiguous areas of forest loss for each year and thus define individual forest loss patches. Once area of each contiguous patch was calculated, patches were grouped based on their area into classes of <1ha, 1-

10ha, 10-50ha, 50-100ha, 100-200ha, 200-500ha and above 500ha. The average number of patches per class and the average area per patch was then calculated. The average area per patch was converted to average number of pixels per patch based on a pixel size of 90m x 90m or 0.81ha (Table 4.2). These values were used were then used to grow the clearing patches.

Table 4.2 Average number of patches and average number of pixels per patch used per patch size class for projecting forest loss

Patch Class	< 1 ha	1-10 ha	10-50 ha	50-100 ha	100-200 ha	200-500 ha	> 500 ha
Average number of patches	9308	4962	588	80	35	21	5
Average number of pixels per patch	1	4	26	86	167	344	996

The suitability layer was created by combining variables that influence the feasibility for forest clearing. In this approach, the suitability for forest loss was assessed as a function of natural forest availability, suitable terrain, conversion probability, and resource protection restrictions imposed by establishment of Protected Areas (PAs). The influence of each variable was quantified by rescaling the variable's values between 0 (poor suitability) and 1 (perfect suitability) and subsequently combining the influence of individual variables into a single suitability value ranging between 0 and 1 using equations and weighting schemes described below. The Natural Forest presence was quantified as a binary [0,1] value, which essentially serves as a masking component since forest conversion can occur only within areas where natural forests are present. Slopes of 0-4° are ideal for growing oil palm but oil palms can be grown on slopes up to 16° (Pirker et al. 2016) and thus slopes <16° are most likely for forest conversions. My analysis of previous forest loss from 2001-2016 showed that 88% of forest loss was limited to slopes less than 16° and 85% of forest loss was restricted to elevations below 300m above sea level. The slope value was first classified into slopes 0-4°, 4-16°, and above 16° and then rescaled such that lower slopes had a high suitability of 1.0 and slopes above 16° had the lowest suitability. Similarly, a linear rescaling scheme was applied to elevation values such that lower elevations had the highest suitability of 1.0 and elevations above 1000m above sea level had a suitability of 0. Forest loss probability layer required no additional rescaling. Finally, PAs were added as a binary [0,1] variable to simulate the impact of protective policies on resource conservation. Considering challenges with obtaining precise boundaries of the existing PAs in Peninsular Malaysia, and the inability to distinguish any clear patterns of loss associated with the protection level, the chosen variables were combined in two restrictive scenarios, where: 1) PAs were restrictive but not prohibitive for forest loss, and 2) PAs were completely prohibitive for forest loss.

Under the first scenario, referred to as PA-restrictive (PAr), presence /absence of PAs was weighted equally with probability of loss, elevation and slope (0.25 each) following:

$$\text{LossSuitability(PAr)} = \text{NaturalForest} * (0.25 * \text{Slope} + 0.25 * \text{Elevation} + 0.25 * \text{ForestLossProbability} + 0.25 * \text{PA})$$

Under the second scenario, referred to as PA-prohibitive (PAp), presence of PAs was considered a full limiting factor (i.e. no loss could occur within established PAs) while the remaining three parameters were equally weighted following:

$$LossSuitability(PAp) = NaturalForest * PA * (0.3 * Slope + 0.3 * Elevation + 0.4 * ForestLossProbability)$$

Forest clearings were grown iteratively by patch size categories starting with the largest size group (Fig. 4.2). At each iteration, a single random seed is selected within areas of high forest loss probability (ForestLossProbability > 0.7). A forest loss patch was then allowed to grow within LossSuitability areas > 0.25 until it reached a target patch size ± 5%. If the total amount of LossSuitability area > 0.25 surrounding the random seed is less than the expected patch size, the seed is abandoned and the model moves to the next iteration. The area of a successfully grown forest loss patch is immediately removed with the remaining NaturalForest layer available for the next iteration. The process continues until the total number of forest loss patches for a given size category is met after which the model repeats the forest loss growth patches for the next group size. The model continues iterations to generate projected loss with a distribution of patches ranging from <1ha (equivalent to 1 pixel) to > 500ha in area annually.

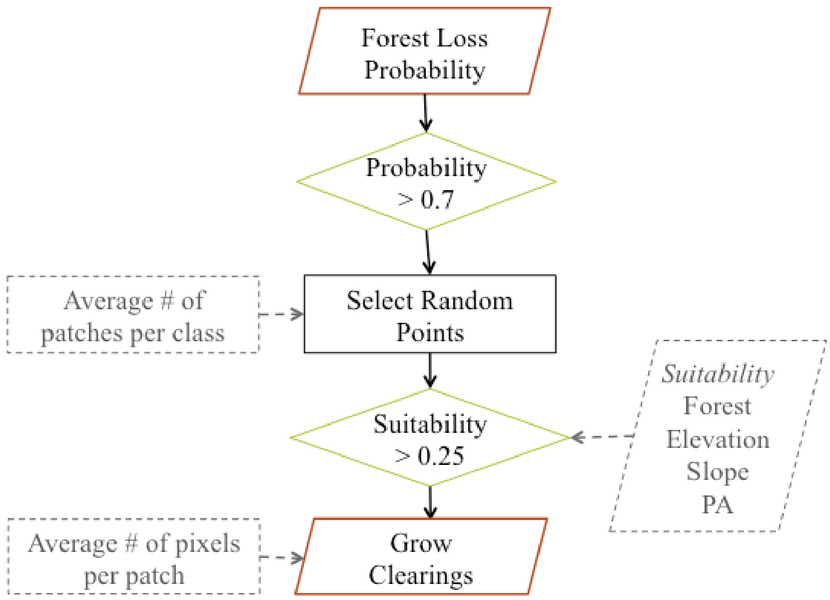

Figure 4.2 Forest loss projection

At the end of each year of projected forest loss, modification to a suite of variables is required and subsequently, ForestLossProbability and LossSuitability layers are recalculated. Projected forest loss is used to update distance variables for the Random Forest model and the NaturalForest mask. For example, the projected forest loss for the end of 2017 is subtracted from NaturalForest in 2016 to obtain new extent of NaturalForest for the next year (2018) of model iteration. This new NaturalForest is then used to update the "distance to forest edge" variable within the Random Forest model. Similarly, the projected loss itself is combined with the previous forest loss from 2001-2016 to update the "distance to previous loss" variable. All other variables including climatic, topographic, other accessibility variables and population density remain unchanged for the period between 2016 and 2021.The updated variables along with all the other variables are ingested in a new run of the Random Forest model to generate a ForestLossProbability for the next time step – in this example year 2018.

The process of updating input variables and NaturalForest extent is repeated annually to generate forest loss for five years after 2016.

Because the seeds for the projected forest loss patches are selected randomly and the total area available and suitable for deforestation exceeds by far the amount of projected loss over the five-year modeling period, the individual model runs can potentially produce a wide range of spatial patterns of deforestation. Therefore, ten model runs (five runs of PAr and PAp scenarios each) were performed to replicate the results and assess the congruence between the various model runs. The results of the individual runs were summarized for each of the PAr and PAp scenarios independently to identify areas with highest congruence of model runs. In addition, to compare broader spatial patterns average projected forest loss was computed for each of the five runs of the PAr and PAp scenarios within a 9km x 9km grid (a direct multiplicative of the model's native 90 m resolution) to identify general areas vulnerable to future loss and to compare the two scenarios.

4.2.3 Assessing Potential Changes to Connectivity

Forest connectivity was assessed for the year 2016 and for forests remaining in 2021 for each projected forest loss scenario. Connectivity within a landscape can be predicted using a variety of methods (McRae et al 2008). I use a method based on circuit theory principles to model connectivity for this landscape. In this method developed by McRae et al. (2008), circuit theory is related to movement ecology through random-walk theory and applied to the landscape in the form of networks or raster grids. To do this, when using landscape raster grids connectivity is analyzed by assigning different resistances to different habitat types or land covers. The resistance values of the landscape are used to represent the opposition the land covers offer to movement of organisms, similar to the resistance offered by resistors to the flow of electrical current. Current passed through a circuit from a source location to a destination location passing through a set of resistors is used to predict net movement probabilities of random-walkers and areas with higher current densities are used to identify corridors (McRae et al. 2008). This method is used to highlight critical habitat linkages. A cumulative current map between all pairs of habitat patches or protected areas indicates the overall connectivity between the habitat patches. The current map can also be used to highlight "pinch points" on the landscape that are bottlenecks for movement within the identified corridors. Least cost pathways, on the other hand, identify the path through the landscape connecting the selected habitat patches that has the lowest resistance.

I combined information on landcover, human population density and presence of roads and railways to generate a landscape resistance surface based on previous studies that have shown these factors to be important. Tigers strongly prefer forested areas with prey abundance and lack of human disturbance (Dutta et al. 2015). Dense human settlements and population density (Joshi et al. 2013, Thatte et al. 2018) as well as roads with high traffic (Thatte et al. 2018) negatively impact tiger movement and dispersal. Low human footprint, high forest cover and topography have been used to determine low cost, low risk dispersal routes of tigers although they might not sustain tiger populations (Reddy et al. 2017). To incorporate the effect of forest fragmentation and forest edges, total forest edge has also been used as an input for the resistance surface (Rathore et al. 2012).). Due to the lack of information on specific tiger habitat preferences for the region, the specific landscape resistance values used in this analysis were derived using previously published studies. Different studies have scaled data layers differently (1-25, 1-10, 0-100). We follow Dutta et al. (2015), who have used previous studies to estimate their landscape resistance values, to inform and scale the resistance values from 0-100. The landscape resistance layer was then resampled to reduce computing time and connectivity was assessed at a resolution of 270m.

The Landscape Fragmentation Tool (LFT) (Vogt et al. 2007) was first applied to existing forest cover data for years 2016 and projected remaining NaturalForest for 2021 to classify forest into patches, edges, perforated areas and core areas. Fragmentation analysis classes were used as proxies for tiger habitat quality for the region and incorporate the effect of edges following Rathore et al. (2012). We then combined these forest classes with the plantation data available until 2014 (Petersen et al. 2016) and classified all the remaining land area as non-forest. Clearings or non-forest areas include recently cleared plantations and urban areas and all other non-forest areas. These are estimated to have the highest resistance. Large plantations are treated similar to agricultural areas in Dutta et al. (2015) for estimating resistance values and mosaic plantations being a mix of croplands, plantations and settlements are estimated to have a higher resistance between that of agriculture and urban or cleared areas. All forest loss areas for years 2015 and 2016 were considered as 'non-forest' habitat and were assigned the highest resistance. Similarly, all the projected forest loss was also assigned the highest resistance considering it was recently cleared (within 5 years). Table 4.3 lists the landscape resistance values for each class and the weightage used for each layer to generate the combined landscape resistance surface.

Table 4.3 Landscape resistance values and weightage for the data layers

Data Layers	Classes	Weightage	Resistance value
LANDCOVER	Non-forest	0.44	100
	Forest patch		15
	Forest edge		20
	Forest perforated		10
	Forest core <250acres		6
	Forest core 250-500		2
	Forest core >500acres		1
	Large plantation		40
	Other plantations		70
	Clearings / Other non-forest		100
POPULATION DENSITY	Absent	0.32	0
	Low		30
	Medium		60
	High		100
ROADS	Present	0.12	100
	Absent		0
RAILWAYS	Present	0.12	100
	Absent		0

The resultant resistance to movement surface was ingested into the Circuitscape v4.0.5 (McRae et al 2013) to perform connectivity analysis for Peninsular Malaysia. Specifically, I sought to assess connectivity and linkages between the forest patches remaining in 2016 when considering the network of four well-established protected areas – Taman Negara National Park, Royal Belum State Park, Endau Rompin National Park and Krau Wildlife Sanctuary. All of these protected areas have been shown to have source populations of tigers or have had tiger sightings (DWNP 2008). Additionally, connectivity analysis was also performed on the forest remaining after the five year projected loss for each model run of both the forest loss scenarios. To assess the changes in connectivity from the projected five-year loss, a difference image was generated by subtracting the connectivity analysis output - cumulative current map for year 2016 form the cumulative current map for remaining forest in 2021 for each model run.

The Linkage Mapper toolkit (McRae and Kavanagh 2011) was subsequently applied to identify and map corridors and least cost pathways in 2016 as well as in 2021 for each model run of both the forest loss scenarios. Following mapping of individual corridors, Pinch point Mapper (McRae 2012) was used to identify areas where movement is funneled or constricted to generate bottlenecks. Pinch point analysis was performed for year 2016 and 2021 for all model runs. The least cost pathways for the various model runs in 2021 were mapped and compared to that for 2016.

4.3 Results

4.3.1 Forest Loss Probability

The internal statistics of the Random Forest-modeled forest loss probability post-2011 show a strong potential for modeling of forest loss using the suite of the environmental and socio-economic variables applied in this study. The random forest model was built using 500 trees and had an out-of-bag estimate of error rate of 20.38%. The variable importance ranking indicated that biophysical and accessibility variables were both important in predicting forest loss. Elevation was the most important variable followed by accessibility to large cities, minimum precipitation and distance to the forest edge.

As expected, the assessment of the resultant probabilities against the subsequent observed forest loss during 2012-2016 shows that, the amount of observed forest loss as a fraction of the total area available within that probability bracket increases sharply with increasing probability (Fig. 4.3a). The ROC area under the curve was 0.79 for the deforestation model, which indicates that this model performs reasonably well at predicting forest loss in the region (recognizing that a ROC value of 0.5 is equivalent to a random model and that of 1.0 indicates a perfect model). When considering the model accuracies by the forest loss probability thresholds the user's accuracy increases with increasing probability threshold while the producer's accuracy decreases (Fig. 4.3b).

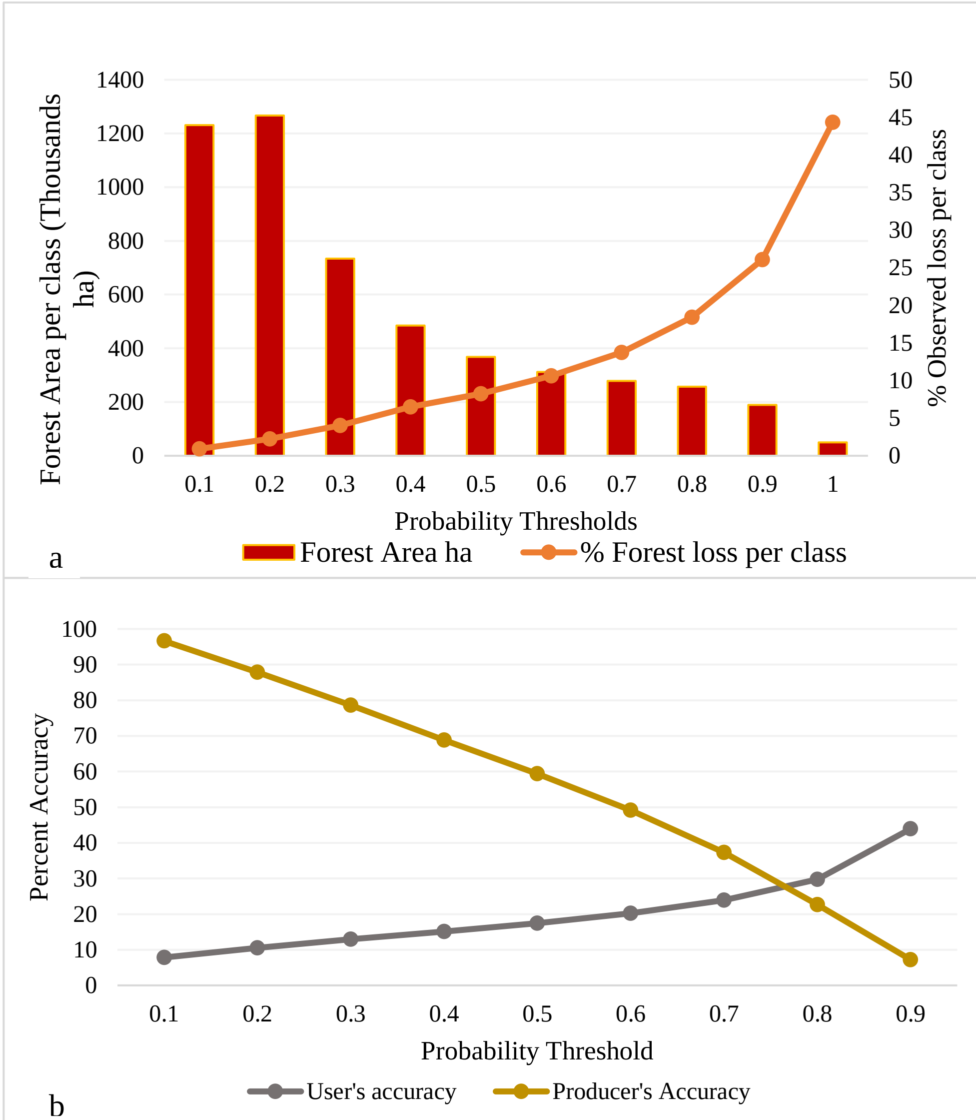

Figure 4.3 a) Proportion of 2011 forest within the predicted forest loss probability classes observed to be converted between 2012 and 2016, and b) Producer's and User's accuracy for predicted forest loss per forest loss probability threshold

For the 2012-2016 deforestation model, the random forest model was built using 500 trees and had an out-of-bag estimate of error rate of 22.2%. The variable importance ranking again included a mix of both biophysical and accessibility variables. Elevation continued to be the most important variable followed by minimum precipitation and then by distance to previous clearings. The accessibility variables important for predicting deforestation have changed from accessibility to large cities and distance to forest edge before 2012 to distance to previous clearings post-2016. The post-2016 deforestation model predicted loss probability is shown in Fig. 4.4. The influence of elevation and distance to previous loss is clear from the predicted probability of deforestation. Coastal and low-lying areas especially in the southeast tend to have the highest probability of loss. Lowland forests in the center of the Peninsula between the Main range on the West and the Greater Taman Negara forests on the East also have high probability of loss as do most areas close to the forest edge.

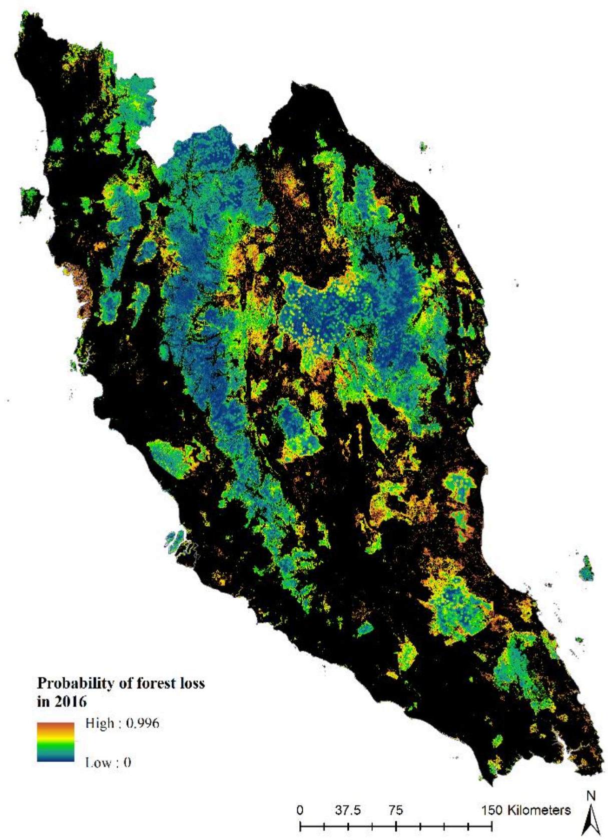

Figure 4.4 Predicted forest loss probability for 2016 forest

4.3.2 Patterns of Future Forest Loss

The five year scenarios of forest loss were projected to continue at the rate resembling that observed in Peninsular Malaysia in the recent past, which resulted in an average loss of 290,798 ha of natural forest by 2021 (with a standard deviation of 2,533 ha, which arises from allowing clearings to be within ± 5% of observed forest loss). Across all model runs, future forest loss is predicted to concentrate in the low-lying areas along the southeast coast and in the central part of the Peninsula between the Main Range and the Greater Taman Negara forest areas of the CFS (Figs. 4.5 and S1). The five separate model runs for the PAp scenario had similar broad patterns and the consensus amongst the five year total forest loss is shown in Fig. 4.5a. Given protected areas in this case are considered completely prohibitive for any forest loss, all the loss is concentrated in forests outside of protected areas. Some areas bordering protected areas seem to have a high consensus amongst the model runs. This indicates that if the protection status is lost or diminished these forest areas are very likely to be cleared. There are a few states that are projected to experience a very high proportion of the projected loss (Table 4.4). The forests in the states of Pahang, Kelantan, Johor, Terengganu, and Perak are the most vulnerable to future loss. These were also the states with the largest fractions of forests remaining in 2016. The state of Pahang is projected to experience most of the loss with an average of 56% of the total future forest loss. This isn't surprising as Pahang had the largest fraction of forest remaining in 2016 and specifically forests within low-lying areas. The states of Pahang, Kelantan, and Johor are also projected to lose a large fraction of their 2016 remaining forest (Table 4.4) with Pahang projected to lose ~9.7% of its forests in 2016. States with high vulnerability of future forest loss are the same states that have experienced high loss in the recent past, however, the proportional loss by state was different and probably varied over the time period. Between 2001 and 2016, Pahang was leading with 42.7% of the loss, followed by Kelantan (18.5%), Perak (11.4 % of the loss), Johor (8.74% of the loss), and

Terengganu (8.5% of the loss). The reduction in proportion of projected deforestation in states of Kelantan, Perak, and Terengganu results from the increased projected loss in the states of Pahang and Johor. The state of Perak continues to have a large fraction of the forest area in 2016, yet the projected loss is only 7.14% of the total loss and lower than the observed loss between 2001 and 2016. The drop in projected deforestation rates by the year 2021 might reflect the low availability of lowland forests within the state.

Table 4.4 Percent observed total forest loss, five model mean and standard deviation of percent projected total forest loss, and Mean percent of available 2016 forest projected to be lost

State	Percent of Total Forest in 2016	Mean Percent of Total Projected Forest Loss	Standard deviation	Mean Percent of Forest in 2016 Projected to be Lost
Johor	7.72	9.13	0.20	7.06
Kedah	5.31	0.76	0.08	0.85
Kelantan	11.56	15.28	0.35	7.89
Melaka	0.08	0.01	0.01	0.82
Negeri Sembilan	2.85	0.93	0.07	1.95
Pahang	34.48	56.01	0.72	9.69
Perak	20.69	7.14	0.16	2.06
Perlis	0.09	0.00	0.00	0.17
Pulau Pinang	0.19	0.04	0.01	1.40
Selangor	4.64	2.99	0.24	3.85
Terengganu	12.40	7.70	0.76	3.70

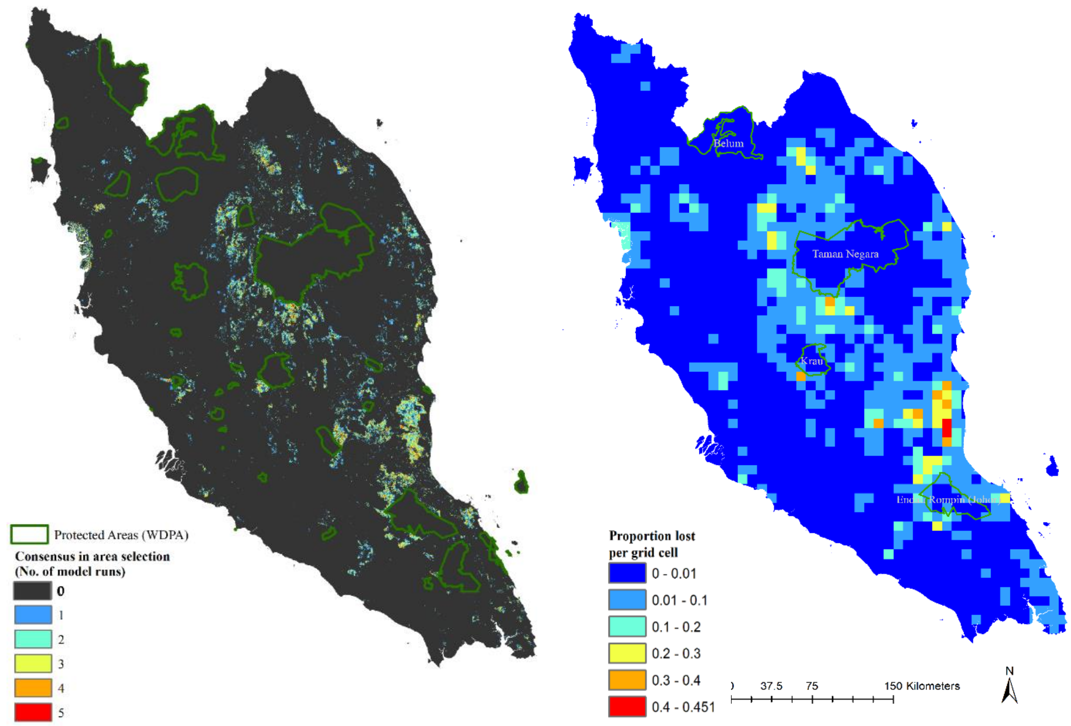

Figure 4.5 a) Consensus amongst five model runs of the PA prohibitive (PAp) scenario, b) Five model average proportional forest loss per 9km grid cell for the PA prohibitive scenario

Broad spatial patterns of projected deforestation, assessed through aggregating the five year cumulative loss for every model run to 9km grid cells, show strong consistency across all model runs and the two scenarios PAp and PAr (Figs. 4.5b and S2 – Appendix II respectively). These patterns indicate that the southeastern coastal forest patches have the highest projected proportional loss per grid cell as well as areas to the north and west of Taman Negara National Park. Patterns of projected forest loss for the of the PAr scenario are also consistent across the five model runs and similar to those of the PAp scenario (Fig. S1 – Appendix II). The most important difference between the two scenarios is that within the PAr scenario some loss is projected within the boundaries of some protected areas viz. Taman Negara, Endau Rompin, and Krau. While the projected loss is relatively low, when considering the broad spatial patterns using the 9km x 9km aggregated cumulative forest loss, the PAr scenario does result in higher proportional loss within the protected area boundaries (Fig. S2 – Appendix II) when compared with the PAp scenario (Fig. 4.5b).

4.3.3 Changes in Forest Connectivity under the Projected Scenarios of Forest Loss

Forest connectivity was first assessed for year 2016 using a cumulative current flow map. Broad routes linking the selected protected areas are highlighted in areas of high current density in forested areas of the Main Range in the west and the fragmented forest patches in the east (Fig. 4.6a). Areas with higher current densities (areas in blue) indicate areas through which random walkers pass at higher probabilities while areas with lower current densities can provide redundancy for movement through the landscape. High current densities indicate critical habitat connections between the selected protected areas. These are most important to maintain overall connectivity within the landscape. Areas to the north of Endau Rompin and Krau and areas to the south of Taman Negara and Belum have high current flow densities. Additionally, areas close to the coast and northeast of Endau Rompin and small regions to the west of Taman Negara are highlighted as critical habitat linkages. Although most of the projected connectivity pattern for 2021 is similar to that of the current flow in 2016, a reduction in current flow density emerges in the southeastern coastal areas and areas to the north of Endau Rompin as well as in the areas between the forests of the Main Range to the West and Greater Taman Negara to the East.

Changes in landscape connectivity between 2016 and in 2021, assessed through differencing of average projected current flow in 2021 and the current flow 2016, identify the southeastern portion of the Peninsula and areas to the north of Endau Rompin as the areas likely to experience the highest reduction in connectivity (shown in red in Fig. 4.6b). Other areas to the southwest and northwest of Taman Negara, which are important for connectivity between Taman Negara and other protected areas exhibit reduced current flow densities. Areas with an increase in current flow density (shown in blue) between 2016 and the projection for 2021 indicate areas which could provide possible alternate connections between selected protected areas. The different model runs of projected forest loss result in generally similar general patterns of connectivity in 2021 and loss of connectivity when compared with that in 2016 although the specific current flow routes and magnitudes at the landscape scale vary somewhat based on the projected forest loss.

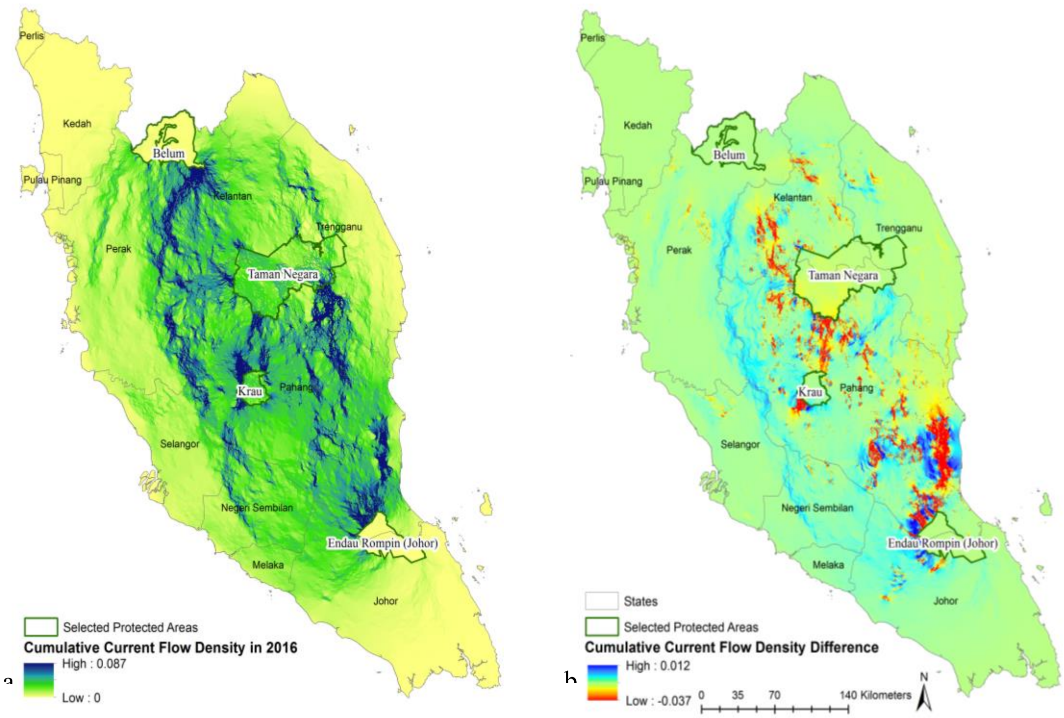

Figure 4.6 a) Cumulative current flow through the landscape in 2016. Regions in dark blue indicate areas with high current flow density, and b) Difference in cumulative current flow in 2016 and 2021. Regions in red indicate areas of reduced current flow between 2021

Similarly, although individual model runs produce slight landscape-scale differences in least cost pathways, the broad patterns of connectivity are similar across all model runs under both PAr and PAp scenarios. Least cost pathways identify the routes with the lowest cumulative cost and thus the most efficient routes connecting the chosen protected areas. Fig. 4.7 shows the different least cost pathways for five PA prohibitive scenario model runs where there is some overlap and some unique pathways selected as least cost pathways depending on where future loss is projected. The most obvious differences are again within the southern part of the Peninsula where the least cost pathways in 2021 for the five PAp forest loss projections identify three alternate routes between Endau Rompin, Krau and Taman Negara. Similarly, two alternate least cost pathways are identified between Krau and Belum. As expected, the corridors between Endau Rompin and Krau and Taman Negara are highly constricted and have several pinch points (areas in purple) where the cumulative current flow density is very high and movement is restricted (Fig. 4.8). Any small loss of area within these pinch points can greatly restrict connectivity and obstruct the flow of the tigers across the landscape. Several additional pinch points are detected between Krau, Taman Negara and Belum, especially at the western boundary of Taman Negara, which is an extremely important area for maintaining connectivity between the Main Range forest complex to the West and the Greater Taman Negara forest complex on the East.

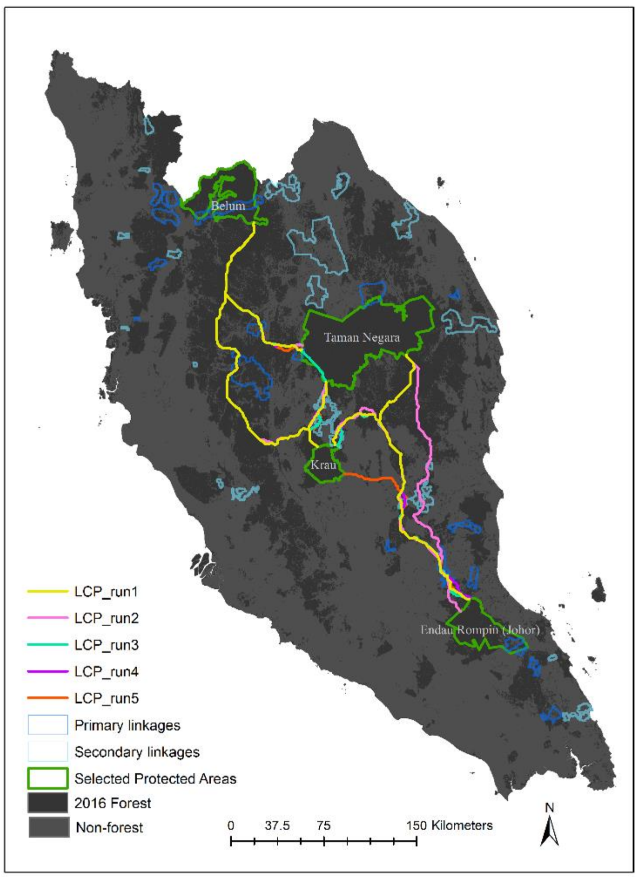

Figure 4.7 Least cost pathways (LCP) for five model runs of the PA prohibitive scenario (PAp) and planned primary and secondary linkages

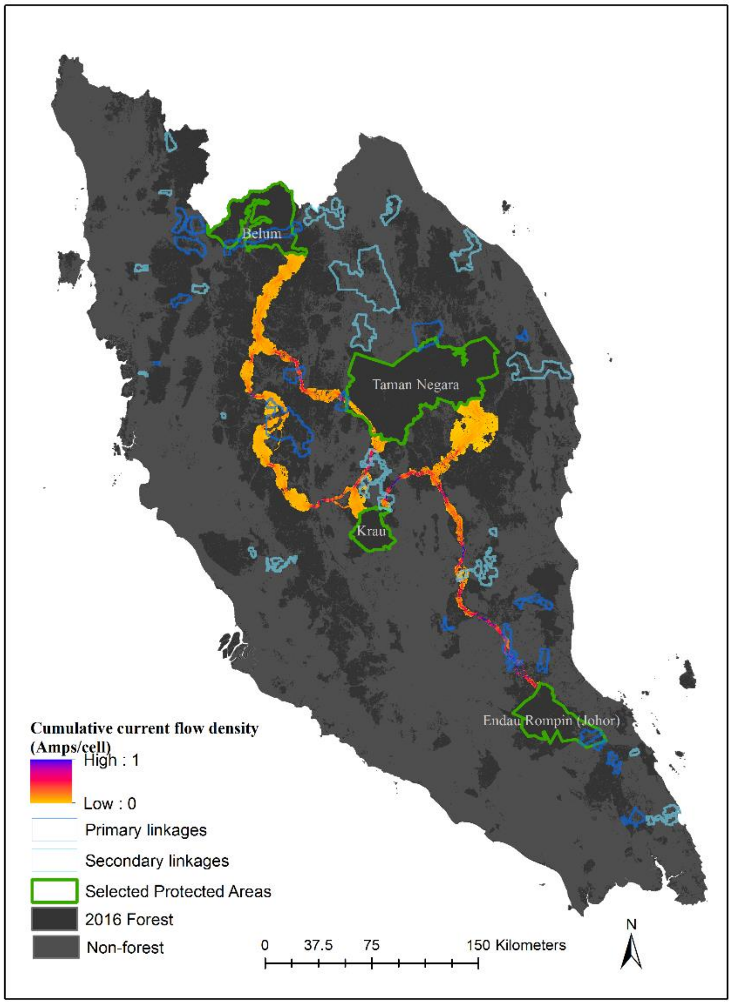

Figure 4.8 Pinch points for 2021 in corridors between selected protected areas for a PA prohibitive (PAp) model run and the primary and secondary linkages between the forest complexes - planned as a part of the Central Forest Spine Master Plan

4.4 Discussion

4.4.1 Patterns of Future Forest Loss and Connectivity

The projected patterns of post-2016 forest loss within various states of Peninsular Malaysia appear to differ from the historic trends. Although the states expected to be experiencing loss are the same as those in the recent past, the projected distribution across the states varies from the historic trends. The proportional loss for Pahang is projected to increase substantially to ~56% while that during 2001-2016 was 42.7%.

This difference could be because the projections are based on the deforestation model built using forest loss occurring between 2012 and 2016. Some variables influencing forest loss have changed from 2001-2011 and 2012-2016. The random forest model is driven by elevation and distance to previous loss and the state of Pahang has both a large area of lowland forest still available and experienced a high proportion (46.6%) of the total 2012-2016 forest loss. It is important to note that four (Pahang, Perak, Kelantan, and Terengganu) out of the top five states with highest historic forest loss and highest projected forest loss are the four states with 90% of the tiger habitat remaining (DWNP 2008).

The results of projected forest loss for the PAr and PAp scenarios are largely very similar. As expected, in the PAr restrictive scenario some loss is projected to encroach into protected areas including Taman Negara and Endau Rompin. This indicates that if the protection for such regions is not strictly enforced, forest loss is likely to occur in the near-future as evidenced by the development of large areas of clearing along the existing park boundaries.

Cumulative current maps for the landscape in 2016 highlight several areas of high current density, which serve as critical linkages between the selected habitat patches. These areas are important for maintaining connectivity across the landscape and maintaining genetic diversity of the tiger metapopulation. Projected forest loss by 2021 results in reduced current flow in areas that are essential to maintain connectivity within the different sections of the CFS. Most importantly, the reduction in current flow to the north of Endau Rompin and the southeastern coastal forest patches will result in further isolating the Endau Rompin forest complex from the remaining tiger habitat patches in Taman Negara and the Main Range. Similarly, the reductions in current flow density near the western and southwestern borders of Taman Negara can restrict movement between Taman Negara and Krau or the Main Range, which is absolutely essential to achieve a structurally and functionally connected CFS. The consequence of these current reductions is increased fragmentation and increased costs for movement. While there is also some relative increase in current flow elsewhere that can allow redundancy for connectivity, the projected forest loss along the southeastern coastal area results in altering the projected future corridors and least cost pathways. The projected loss also impacts pinch points within the southeastern coastal corridor between Endau Rompin and Taman Negara through the fragmented forest patches as shown by the current flow through least cost corridors for one model run of the PAp scenario (Fig. 4.8) and results in altering the corridor and least cost pathway for all the PAp forest loss projections (see Figs. 4.7 and 4.8) as compared with those for 2016 (Fig. S3 in Appendix II).

4.4.2 Policy Implications

Peninsular Malaysia has a very detailed plan for connecting the various forest complexes within the Peninsula to create a CFS. The objectives of the CFS Master Plan are to restore and maintain connectivity, propose viable land use and management guidelines to eventually have an unbroken link of forests from Johor in southern Peninsular Malaysia to the Thai border in the north (FDTCP 2009a and FDTCP 2009b). The CFS Master Plan identifies primary and secondary linkages to support tiger movement across all available sections of habitat between South and North of the

Peninsular Malaysia. Primary forest linkages are crucial for re-establishing connectivity within the CFS and normally allow movement of large mammals. Secondary linkages are envisioned in areas where primary linkages are unfeasible but some degree of connectivity is still required and are usually designed to serve as stepping-stones for use by smaller animals (FDTCP 2009a and FDTCP 2009b). The management plan includes establishment of corridors prioritized as primary and secondary linkages within the landscape. The modeling results indicate that some amount of forest loss is likely to occur within the planned CFS linkages; on average about 2% area of the primary linkages and about 5% area of the secondary linkages are projected to be converted to non-forest by 2021.

Projected forest loss within the planned linkages is not the only threat to maintaining connectivity within the landscape. If forest patches that the linkages are connecting experience loss, the linkages lose their function as seen in the southeastern coastal area. The Linkage Mapper analysis indicates that least cost pathways do pass through some of these identified primary and secondary linkages even after the projected loss indicating that they can continue to be useful for tiger connectivity (Fig. 4.7). This analysis shows that primary linkages 1 and 3 (PL1 and PL3) are essential to maintain connectivity within Taman Negara and Belum while primary linkage 4 in the southern forests (PL4 in CSFII) is essential for connectivity between Endau Rompin and both Krau and Taman Negara (Figs. 4.9 a, c). However, it is also important to note that both Krau and Endau Rompin, which are already fairly isolated from the rest of the tiger habitats, can retain connectivity with the remaining landscape only with the support of planned secondary linkages (SL2 in CFSI and SL2 in CFSII, fig. 4.9 b). Although secondary linkages are planned for the use of smaller animals, in some of the highly fragmented areas they might also serve to be vital for connecting subpopulations of larger mammals. The results also draw our attention to the possible loss of functionality of some of the planned linkages. As discussed earlier, the projected loss of forest in the southeastern coastal areas might make the primary linkages PL2 and PL5 in CFSII, which are important for connecting Endau Rompin to the rest of the landscape in 2016, obsolete in 2021 as evidenced by the fact that none of the least cost pathways pass through it in 2021. The very high current density in the southern fragmented forests in the projected forest loss scenario is indicative of very few connectivity options in that region and of increased isolation of Endau Rompin. However, the projections of future loss can also result in pinch points outside of the planned linkages (Fig. 4.8), suggesting it will be increasingly important to take into consideration current patterns of forest loss and implications of policies that will impact future forest loss in order to ensure planned linkages will continue to be of use in the future. The CFS Master plan has identified threats to the planned linkages and a linkage strategy with policy and land use management initiatives. The CFS Master Plan for Ecological linkages was expected to take about 15 years for completion after it was approval in 2010 (UNDP 2014). Development projects like the building of highways and railways that cut through the landscape are expected to impact the connectivity greatly. It is crucial to manage land cover and land use in and around protected areas and the planned linkages if they are to function as planned.

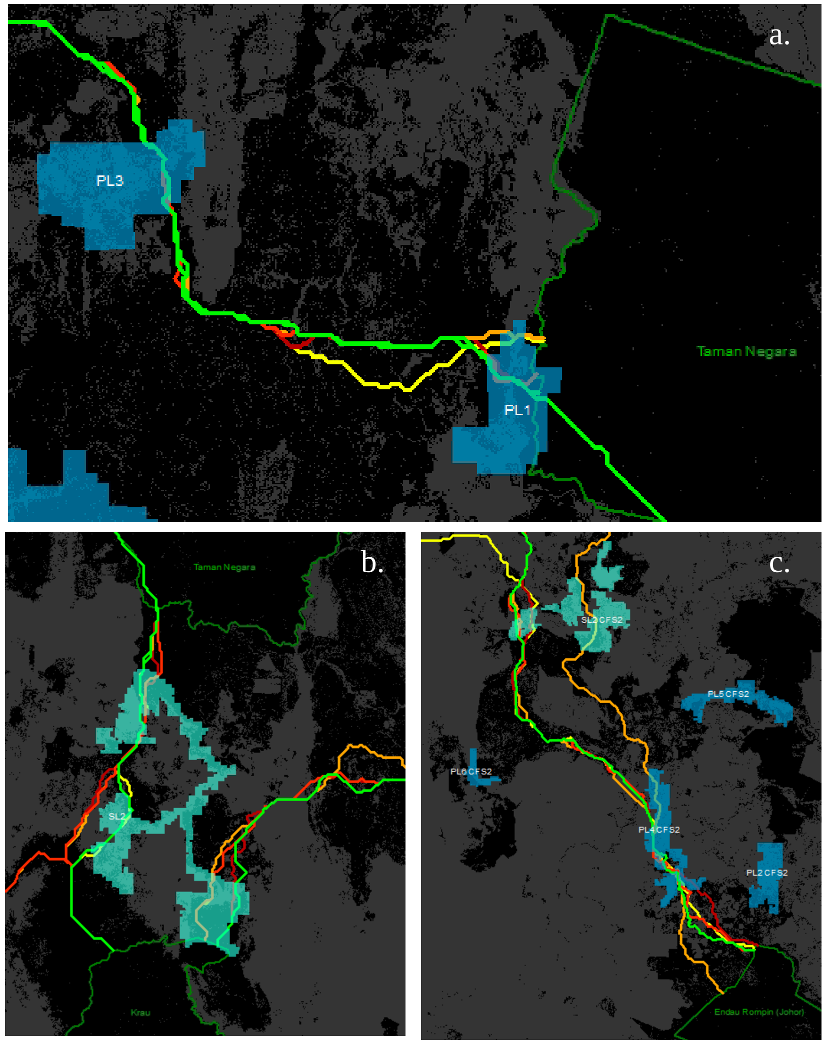

Figure 4.9 Important primary and secondary Linkages between the selected protected areas and least cost pathways of 5 model runs (colored lines) passing through them a) PL1 and PL3 linkages between Taman Negara and Belum, b) SL2 secondary linkage between Taman Negara and Krau, and c) PL4 and SL2 in the southern forest (Central Forest Spine (CFS) II) between Endau Rompin and the rest of the landscape

4.4.3 Limitations of the Study

As a complex modeling environment, this study is based on a considerable number of assumptions and is subject to limitations. Specifically, although the Random Forest model performs well, it is not able to explain ~ 20% of the forest loss occurring within the study period. There are several other variables that can influence where forest clearing takes place that are not included within he model, e.g. information on land ownership, forest designation or local infrastructure to access forested areas which affect the deforestation probability. In addition, the predicted probabilities are only projections of future deforestation and indicate where future forest clearing is most likely but not when it is going to occur (Mertens and Lambin 2000). Thus the probability map only indicates where future loss will occur but it isn't necessary that the forest loss should have occurred in the time period used for validation (2012-2016), resulting in a lower model user's and producer's accuracies.

Future forest loss projections developed assume that future (post-2016) drivers of forest loss will stay the same as the recent past (2012-2016). These projections also assume the extent of forest loss will be the same as the average rates from 2010-2014 to project loss. They do not take into consideration any other information for building future scenarios including regional and federal policies that can impact forest conservation or the logging industries as well as market demand for timber or other competing land uses. Similarly, the sizes and numbers of forest loss patches are based on historic information but are very simplified. The total area of forest loss is limited to the average historical rate of loss observed in the region and the acceleration observed in forest loss rates as shown in Chapter 2 is not taken into consideration. Thus these estimates of projected forest loss are fairly conservative.

With regards to connectivity modeling, uncertainties are primarily associated with developing the resistance surface used. Selection of resistance values for different land covers and landscape components is based on previous studies and relies on some reports about general tiger use of such landscapes. However, there is no specific evidence about tiger habitat usage and movement within the region, nor is there any possibility of proper quantification of weighting and resistance values to parameters for tigers. Therefore, assignment of relative movement resistances to the different land cover types within a landscape is largely subjective and is based on the interpretation of qualitative indicators. It presents the most challenging step of applying circuit theory for modeling connectivity (McRae et al 2008). The major limitations for connectivity modeling thus arise from these assumptions about landscape resistance, lack of data on tiger habitat quality e.g. prey species densities and distributions, and lack of tiger population and movement data. Finally, animals can be expected to modify their behavior and activity patterns while moving through less suitable landscapes and outside protected areas (Dutta et al 2015) adding to the uncertainties of developing a resistance surface.

4.5 Conclusions

The Malayan tiger continues to be threatened by habitat loss, degradation, and fragmentation. The results of this study show that if the drivers and rates of forest loss remain consistent with those observed since 2010, approximately 290,451 ha of forest will be lost in 5 years. Forest loss will continue to affect lowland forests and forests along the southeastern coast and in the center of the Peninsula appear to be most vulnerable. Achieving viable tiger populations, as part of the NTAP for Malaysia, requires both habitat conservation and maintenance of linkages between the various habitat patches. Future of tiger conservation thus depends on ensuring enforcement of laws prohibiting forest loss within protected areas and the planned corridors. Modeling results from this study indicate that diminished enforcement within protected areas (PAr modeling scenario) is likely to result in forest loss and encroachment of Taman Negara and Endau Rompin, key Malayan tiger landscapes with breeding populations.

The results of the study indicate that just five years of sustained forest loss can result in impacting the connectivity between the different habitat patches within the landscape. Patterns of connectivity and loss of connectivity in 2021 when compared to the 2016 landscape are similar for both the forest loss scenarios. The small differences within the projected forest loss areas, however, result in different least cost pathways between the various protected areas suggesting that the best pathways or linkages between the habitat patches can vary based on where future loss occurs. Furthermore, the analysis identifies CFS Master Plan linkages that might be affected by forest loss in the future and also highlights linkages that might need to be strengthened to maintain any connectivity between the already isolated protected areas of Krau and Endau Rompin and the remaining tiger landscape. Pinch points are identified along corridors where movement could be restricted and these need to be considered while planning interventions for maintaining landscape connectivity. Finally, maintaining forest patches and restricting land cover and land use within and around planned linkages is absolutely essential to maintain connectivity within Peninsular Malaysia's CFS.

Chapter 5: Conclusions

Land cover and land use change is occurring all across the globe. It is one of the primary causes of habitat loss and fragmentation that results in biodiversity loss. Agricultural expansion to meet the growing demands is one of biggest drivers of this land cover and land use change. Peninsular Malaysia has been experiencing agricultural expansion driven forest loss for more than a century. It has also witnessed biodiversity loss and drastic reductions in the populations of many of its endemic species and specifically the Malayan tiger. Given the conflicting information on the contribution of oil palm plantation expansion to deforestation in the region, the expectations of further growth in the palm oil industry to meet growing demands globally and the critically endangered status of the Malayan tiger, this dissertation sought to answer the following overarching question –

What are the factors driving forest loss and conversion in Peninsular Malaysia and how do they impact the vulnerability of tiger landscape to future forest loss?

Towards this end I have developed new datasets mapping the extent of natural forests and natural forest loss in Peninsular Malaysia, identified the spatial patterns of forest loss driven by oil palm expansion, and developed scenarios of likely future forest loss patterns and consequences for tiger habitat connectivity. This chapter summarizes the major findings of this dissertation, considers the policy implications of these findings, and discusses avenues for future research stemming from this work.

5.1 Summary of the Findings

5.1.1 Recent Trends in Deforestation and Forest Conversions in Peninsular Malaysia

To understand the role of oil palm expansion in the deforestation in Peninsular Malaysia, it was essential to determine the extent of natural forest within the region and separate tree cover loss resulting from tree plantation harvest cycles from natural forest loss. In Chapter 2 I developed a natural forest mask for the year 1988 using Landsat composites and mapped loss occurring within natural forests between 1988 and 2012. The results showed that in 1988 natural forests covered an estimated ~ 7Mha within Peninsular Malaysia. However, between 1988 and 2012 a total of 1.35 Mha of these natural forests were lost. The average annual rate of forest loss has increased from 49,281 ha $year^{-1}$ before the year 2000 to 63,422 ha $year^{-1}$ after 2000. Approximately 65% of the total forest loss occurred within the tiger habit as defined by the forests within Peninsular Malaysia’s tiger conservation landscape. About 48% of this loss was eventually converted to tree plantations where 80% of these conversions were to large-scale plantations dominated by those of oil palm or recently cleared land, suggesting that large-scale industrial plantations were an important driver of deforestation within the region over the entire study period.

5.1.2 Factors Influencing and Constraining Oil Palm Expansion in Peninsular Malaysia

Having identified in Chapter 2 that a significant proportion of deforestation was driven by conversions to tree plantations dominated by those of oil palm, Chapter 3 explored the factors influencing forest conversion to oil palm. I identified determinants of forest conversions to oil palm, characterized agro-environmental suitability and infrastructure accessibility of recent conversions as well as constraints on these recent conversions. Almost all of Peninsular Malaysia's pre-1988 established industrial oil palm plantations are within areas of high biophysical suitability for oil palm. Similarly, more than 80% of forest conversions to oil palm have been in areas of high biophysically suitability for the crop. However, forest conversion within lower biophysical suitability classes has been increasing since 2000 with an acceleration of conversion after 2006. The analysis revealed that accessibility to infrastructure is the strongest determinant of forest conversion to oil palm plantations by far exceeding the influence of biophysical suitability. Characterization of forest conversions to industrial oil palm plantations between 1988 and 2012 also show that almost all new plantations (more than 99%) are established within 1km of existing oil palm plantations. In contrast, reduced biophysical suitability hasn't necessarily restricted conversions within the region.

5.1.3 Vulnerability of Peninsular Malaysia's Tiger Landscape to Future Forest Loss

After mapping and estimating the extent of Peninsular Malaysia's forests, forest loss, and conversions to tree plantations from 1988-2012 (in Chapter 2), and the specific factors associated with forest conversions for oil palm expansion within the region (Chapter 3), I modeled future potential for deforestation in the region to assess the vulnerability of the forests to future loss and the impacts on forest connectivity by 2021 in Chapter 4. I first developed a model for determining the probability of forest loss based on the observed spatial patterns of forest loss. Using the forest loss probability surface I then developed scenarios to project forest loss for five years between 2017 and 2021 and then assessed the changes to landscape connectivity based on projected loss. Within this modeling exercise, I tested the impact of the magnitude of protected area status enforcement for major source-areas of the tiger population. The results of this study indicate that the remaining lowland forests along the southeastern coast and in the center of the country are most vulnerable to future loss. Additionally, although both scenarios for different protection enforcement level resulted in similar broad patterns, the lower protection (PAr) scenario exposed the vulnerability of protected areas like Taman Negara and Endau Rompin, which are considered to be tiger strongholds with breeding populations, to future forest loss. This projected loss subsequently reduces connectivity within the different tiger habitat areas especially in the southern part of the landscape where Endau Rompin and Krau are already fairly isolated. This analysis also highlights which of the Central Forest Spine (CFS) Master Plan planned linkages would be essential for maintaining the connectivity for tigers. Overall, this study demonstrates the consequences of unchecked forest loss within Peninsular Malaysia and its implications for forest connectivity in the context of tiger conservation. It draws attention to the need for conservation and restoration of planned linkages and the need for policies that will restrict forest loss within and around corridors if Malaysia is to maintain a functionally connected CFS landscape for tigers.

5.2 Significance and Policy Implications of the Research

5.2.1 Historical and Future Role of the Palm Oil Industry in Peninsular Malaysia's Land Cover and Land Use Change

There have been extensive discussions on the role of the palm oil industry in deforestation within Malaysia and Indonesia. Koh and Wilcove (2008) estimated that within Malaysia 55-59 % of oil palm expansions occurred on previously existing forests and Gunarso et al. (2013) estimated that 42 % of all new oil palm plantations between 1990 and 2010 were established on disturbed forests. The differences in the estimates arise from differences in methodologies, temporal periods, data sources, land cover definitions, classification processes, as well as the intermediate land cover types within the dynamic landscapes (Gunarso et al. 2013). The palm oil industry, however, has maintained that they do not engage in converting forests for expanding oil palm plantations. Industry and government representatives, the Malaysian Palm Oil Council have also stated that oil palms were not the cause of deforestation but were planted on already deforested and degraded land (Gaveau et al. 2016). There are regional differences in the land cover and land use change patterns and especially in the forest conversions for establishment of oil palm (Wicke et al. 2011, Gunarso et al. 2013). The proportional contribution of forests for establishment of oil palm is even smaller when considering Peninsular Malaysia alone; even after considering the proportion of bare soil originating from forests, only 28% of expanding oil palm in the region was established on previously forested land (Gunarso et al. 2013). While the rates of forest conversion for oil palm expansion within Peninsular Malaysia have slowed and the use of other land uses like previously existing plantations of rubber have been more common (44% of expanding oil palm) in the recent past, the contribution of oil palm expansion towards total deforestation is important to understand to determine the role of the palm oil industry in deforestation within the region. This dissertation has shown that about half of the deforestation occurring within the region was converted to tree plantations and large industrial plantations of oil palm and new clearings dominated these forest conversions indicating that the palm oil industry continued to play a significant role in the deforestation of the region despite their claims and the fact that a relatively small proportion of expanding plantations are established on converted forests.

The palm oil industry promises commitment to conservation and sustainability. The Roundtable on Sustainable Palm Oil (RSPO) was formed by Malaysian and Indonesian companies in 2004 in response to a call for sustainably produced palm oil products (Sheil et al. 2009). As of July 31st 2018, 3.52 Mha were certified by RSPO producing 19% of global palm oil and ~1.37 Mha were certified in Malaysia alone (RSPO 2018). The Malaysian Palm Oil Board (MPOB) is a government agency established in 1998 responsible for implementing the Malaysian Sustainable Palm Oil (MSPO) standard, a national voluntary certification scheme (Pacheco et al. 2017). MSPO standards were launched in 2013 and the implementation of the voluntary MSPO Certification Scheme began in January 2015. However, MSPO certification has now been made mandatory by the government and all implementation is expected to be completed by December 2019 (MPOCC 2018a). The MSPO standards require that new oil palm plantations cannot be established in Environmentally Sensitive Areas (ESAs) like primary forest, land designated for protection of nature or ecosystem services / cultural values as required under the National Physical Plan of Peninsular Malaysia or on areas with high biodiversity values (HBV) unless it is in compliance with the National Biodiversity Policy or State Biodiversity Legislation. However, MSPO standards do not exclude high aboveground carbon stock areas or peat land where new planting and replanting may be developed as per MPOB guidelines and best practices for development of peat land (MPOCC 2018b, World Wildlife Fund (WWF) 2018). MSPO is hence considered a starting point to achieve basic sustainability in the Malaysian Palm Oil Industry but there is a need to strengthen and improve MSPO standards and a need for greater robustness and accountability (WWF 2018). RSPO is the most adopted certification scheme and has several provisions for sustainable production of oil palm including bans on use of fire for land clearing and 'No Deforestation' on new plantations established beginning November 2005. While RSPO does notify members about fire detections on their plantations, it does not monitor deforestation within plantations and deforestation has continued within the boundaries of certified plantations through large forest clearing events (>10 ha), especially within Malaysia (Noojipady et al 2017). RSPO is currently restructuring its Principles and Criteria used for certification as well as proposing changes to the 'No Deforestation' requirement by identifying forests with high conservation values and high carbon stock which should be maintained and enhanced (RSPO 2018), although there are concerns about loopholes in the new proposal that might allow deforestation in some forests within high forest countries (EIA 2018). Going forward, it is important that these certification schemes remove loopholes by modifying their certification criteria and ensuring implementation through monitoring of plantation expansion.

5.2.2 Protecting Forests and Maintaining Connectivity in the Context of Tiger Conservation

Tigers exist in an increasingly human-dominated landscape and with over 93 % of its original habitat lost, they are restricted to a few protected areas (Joshi et al 2016). However, the protected areas are too small to maintain long-term tiger populations by themselves and hence a landscape approach to conserving tigers is crucial for the species survival. In 2010, the 13 tiger range countries agreed to a goal of doubling the wild tiger population (Tx2) by 2022 (World Bank 2011). As a part of the Tx2 goal, maintaining habitat extent and connectivity is required. Joshi et al. (2016) estimate 7.7% of the tiger range habitat was lost to conversions and that the Taman Negara landscape in Peninsular Malaysia was had some of the largest observed forest loss within the global tiger conservation landscapes. They estimate the forest loss resulted in a loss of about 400 tigers based on the associated fragmentation and impacts to prey densities, which is a very substantial number for such a brief time period. Tigers can recover from population loss if their habitat and prey populations are maintained (Sunquist et al. 1999). However, recovery won't be possible without active efforts to restrict any further loss of habitat and connectivity between the breeding populations within various protected areas. A recent study from Sumatra has shown that conservation efforts resulted in population recovery from extensive poaching in the previous decades and an increase in tiger densities within the protected areas and yet the tiger population across the island had reduced and become more fragmented between 2001 and 2012 (Luskin et al. 2017). Conservation of Malayan tigers similarly requires protection of its habitat and maintenance of connectivity. The Malaysian National Physical Plan calls for restoration of forest connectivity to have a contiguous stretch of forests from the southern tip of the Peninsula to the boundary with Thailand in the north (Federal Department of Town and Country Planning - FDTCP 2010). The CFS Master Plan has a detailed plan to materialize this vision. This dissertation shows that not only has previous loss affected the planned linkages in Peninsular Malaysia but future loss is also expected to continue to degrade the existing connectivity. Maintaining landscape connectivity via corridors has been shown to allow tiger dispersal between protected areas in India and Nepal allowing tiger population recovery (Thapa et al 2017). This has been achieved after restoration of corridors identified as important for ecological connectivity between the protected areas. It is extremely crucial to maintain and restore the linkages within Peninsular Malaysia's CFS to maintain structural and functional connectivity between the components of the tiger metapopulation. This will require making the necessary policy changes and implementing the plan that has been proposed.

5.3 Future Research Directions

This dissertation addresses several questions related to land cover land use change dynamics within Peninsular Malaysia and the potential implications for Malayan tiger conservation. Specifically, I analyzed the spatial and temporal patterns of natural forest loss, its drivers, and modeled likely short-term future patterns of forest loss and impacts on connectivity for the tiger landscape. The findings from this dissertation contribute to a better understanding of the nuances of land cover and land use changes and consequences to Malayan tigers. However, several gaps remain in the knowledge in relation to detailed trajectories of land cover and land use change, local knowledge regarding forest designations, land tenure, plantation or timber concessions, distribution of biodiversity and population distribution of highly endangered species like the tiger.

5.3.1 Trajectories of Land Cover Change

Land cover land use change trajectories are difficult to track in dynamic landscapes. This study mapped forest loss and utilized a static plantation map from 2014 to identify forest loss converted to plantations. However, it does not track when the forest conversions took place and the plantations established nor does it identify any other intermediate land covers or proximate drivers of loss. Peninsular Malaysia's forests have been extensively logged for timber (Brookfield and Byron 1990). Logged forests are often considered degraded and tend to be followed by clearing (Margono et al. 2014) or conversions to other land uses like oil palm plantations (Wicke et al. 2011, Gunarso et al. 2013). Understanding the intermediate land cover will not only help ascertain the trajectories of land cover change better but will also help identify the intentions behind forest clearing and thus the immediate causes of deforestation. New plantations established on already cleared or degraded forest is considered desirable and such plantations are considered sustainable and even certified by certification schemes endorsing zero-deforestation pledges (Gaveau et al. 2016). Temporal analysis of forest clearing, intermediate "cleared" or "degraded" land cover type and the delay in planting has been used to parse out intentional clearing for plantations from planting on previously cleared land (Gaveau et al. 2016). Such an analysis in the region can help better identify immediate drivers of deforestation, help bring attention to loopholes in certification schemes for sustainable commodity production and help inform policy decisions regarding forest resources. Furthermore, selectively logged forests have been shown to be rich in biodiversity although not as biodiverse as primary or undisturbed forests (Sodhi et al. 2010). Despite being disturbed in nature, due to the possibility of better understory and increased prey species, selectively logged forests have shown the potential to support tigers (Rayan and Wan Mohamad 2009). Finally, 80% of Malaysia's forests are within Permanent Reserved Forests (PRFs) and ~56% of PRFs were within production forests – designated for producing wood and non-wood forest products – in 2010 (FAO 2010). Identifying logged forests can be useful for biodiversity conservation and maintaining connectivity via corridors instead of labeling them degraded and converting to plantations.

5.3.2 Improved Tiger Presence and Biodiversity Data Availability

Malaysia lacks comprehensive data on biodiversity and endangered species including the Malayan tiger. Current policy decisions for conservation are being made based on very old and or limited biodiversity surveys conducted within the country. Data on the Malayan tiger are especially lacking. The NTAP for Malaysia also states that very little information is available about the Malayan tiger's ecology, its feeding ecology, and dynamics of its prey population (DWNP 2008). Current estimates of 250-340 adult Malayan tigers and 80-120 breeding adults are inferred from only seven population studies conducted across the three tiger landscapes between 2004 and 2013 (Kawanishi

2015). A better understanding of tiger populations, their distribution and responses to human disturbances is vital to develop, execute, and monitor realistic conservation plans. At present, Malaysia not only has limited data about tiger occurrence but also lacks information about tiger movement through the landscape and usage of corridors between subpopulations or the genetic structure of the population. As the NTAP aims to achieve viable tiger population in Peninsular Malaysia and the success of the plan hinges upon not just maintaining but improving tiger numbers across the region, collecting baseline data of tigers and continued monitoring should be a priority. Moreover, information on actual use of habitat corridors by tigers is critical for improving assessments of connectivity across the landscape to adapt the CFS Master Plan to existing conditions. Additionally, information of tiger prey population and their distribution as well as human-tiger conflicts will be useful in determining habitats that might allow tiger persistence as well as help identify areas that tigers frequent or pass through, which can be useful in determining actual tiger movement, estimate resistances of land covers, and tiger utilization of corridors between habitats.

Accurate biodiversity information like updated species distribution or forest biomass maps can also be valuable for evaluating sustainability approaches for oil palm expansion. Such data have been essential to assess environmental impacts, plan conservation strategies and land use to safeguard ecosystem services especially while implementing High Carbon Stock (HCS) or High Conservation Value (HCV) approaches for sustainable oil palm production (Austin et al. 2017). Improved data collection and data availability will improve the accuracy of the assessments of forest loss impacts on biodiversity, reduce the number of assumptions in developing conservation strategies, and make policy decisions more relevant.

In addition to biodiversity-related observations, improved access to spatially explicit land use and management data is needed to improve the modeling capability for assessing tiger habitat loss, degradation, and fragmentation. Data on land tenure and forest designations can improve the understanding of land cover and land use change patterns and increase the modeling accuracy. Currently, information on Malaysia's government designated forest areas like Permanent Reserved Forests reserved for logging or land tenure like timber or plantations concessions is not publicly available. As described in Chapters 3 and 4 of this dissertation, deforestation or plantation expansion models currently rely only on biophysical, topographic, and other socioeconomic datasets to understand drivers or determinants of land cover change, develop scenarios of future change and predict future patterns of land cover. Studies in Indonesia have shown that a significant proportion of primary forest loss occurred within government designated forest lands that restrict, limit, or prohibit clearing (Margono et al. 2014). Such data are critical for evaluating policy implementation and making land cover change dynamics much more transparent.

5.4 Conclusions

"*Wild tigers are at a tipping point and action, or inaction, in the coming decade will decide the tiger's fate*" – Global Tiger Recovery Program (GTRP, World Bank, 2011).

Tiger conservation is at a critical juncture. Globally, the Tiger's range has reduced by more than 50% in about 3 generations (3x 7 years), most tiger populations are on a decline, and two source populations have been lost leaving breeding populations only in 8 remaining tiger countries (India, Nepal, Bhutan, Bangladesh, Malaysia, Indonesia, Thailand and Russia) (Goodrich et al. 2015). In 2010, tiger range countries adopted the GTRP in St. Petersburg in Russia and pledged to double wild tiger populations by 2022 (World Bank, 2011). As a part of the GTRP, tiger range countries developed their own National Tiger Recovery Program (NTRP). Malaysia's NTRP focuses on the tiger recovery strategy outlined in its National Tiger Action Plan (NTAP). Tigers are a conservation dependent species that require landscape-scale management with protection from threats of habitat loss and fragmentation, poaching and illegal trade, engagement of local communities, community-based conservation, and financial support (World Bank 2011). Malaysia's NTAP has been incorporated within Malaysia's development plan. Malaysia's National Physical Plan has created a spatial framework for sustainable development and identified areas for conservation (DWNP 2008). The aim of the NTAP is to have a holistic strategy for conservation and will require the collaboration of several agencies including federal and state governments, non-governmental organizations, and other stakeholders (DWNP 2008). It is clear that tiger conservation and implementation of landscape-scale management is very complex and requires consistent efforts. A plan for conservation is only as good as its implementation. The NTAP is a comprehensive plan, however, for Malayan tiger conservation to be successful it requires strong policy, appropriate implementation and monitoring, and adaptive management framework.

Appendices

Appendix I: Supplementary Materials Chapter 2

Table S1 Image numbers per year and per Landsat sensor used for mapping

Year	TM	ETM+
1988	19	
1989	65	
1990	19	
1991	4	
1992	7	
1993	5	
1994	56	
1995	57	
1996	37	
1997	107	
1998	32	
1999	32	46
2000	84	120
2001		187
2002		233

Table S2 Landsat images used for validation

Path	Row	Number of Images
125	58	4
125	59	7
126	56	6
126	57	10
126	58	16
126	59	2
127	56	11
127	57	14
127	58	20
128	56	16
128	57	11

Appendix II: Supplementary Materials Chapter 4

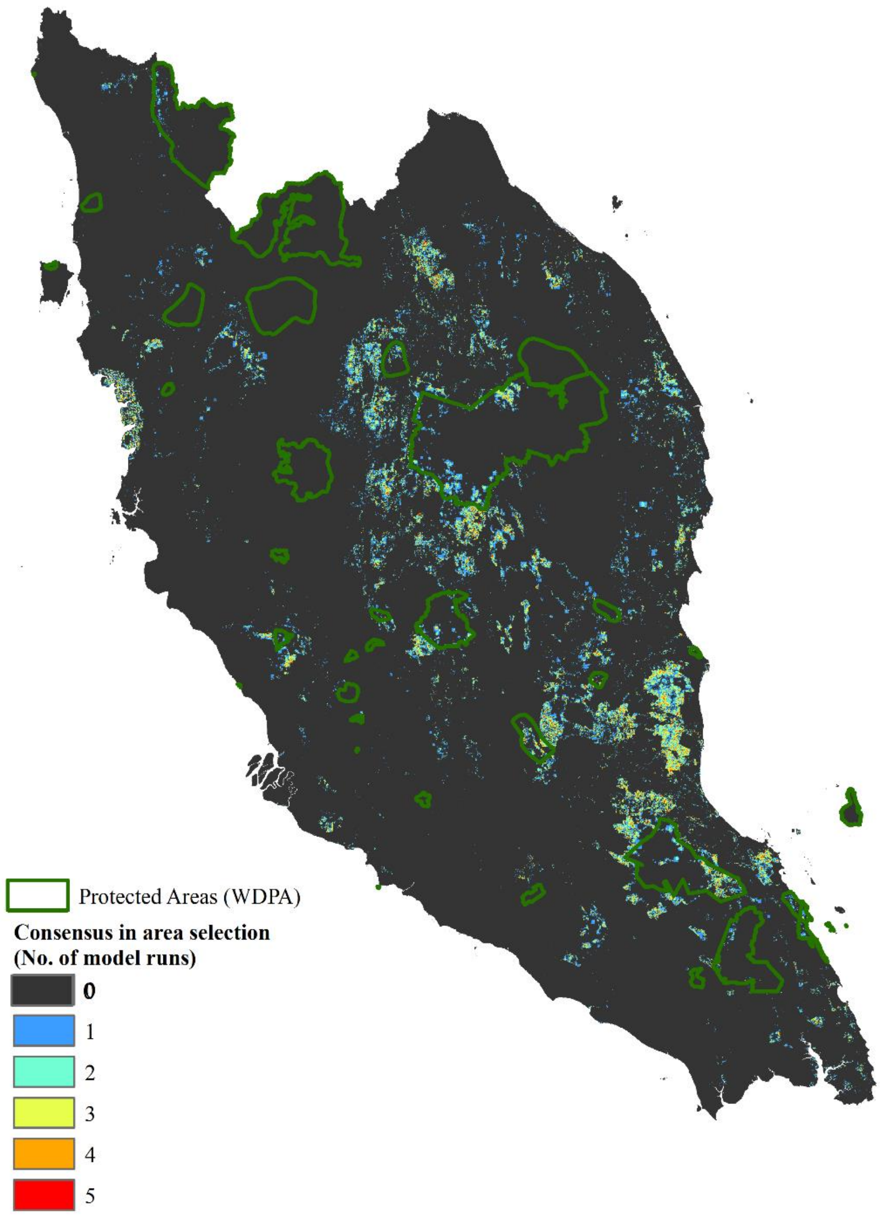

Figure S1 Consensus amongst five model runs for the PA restrictive (PAr) scenario

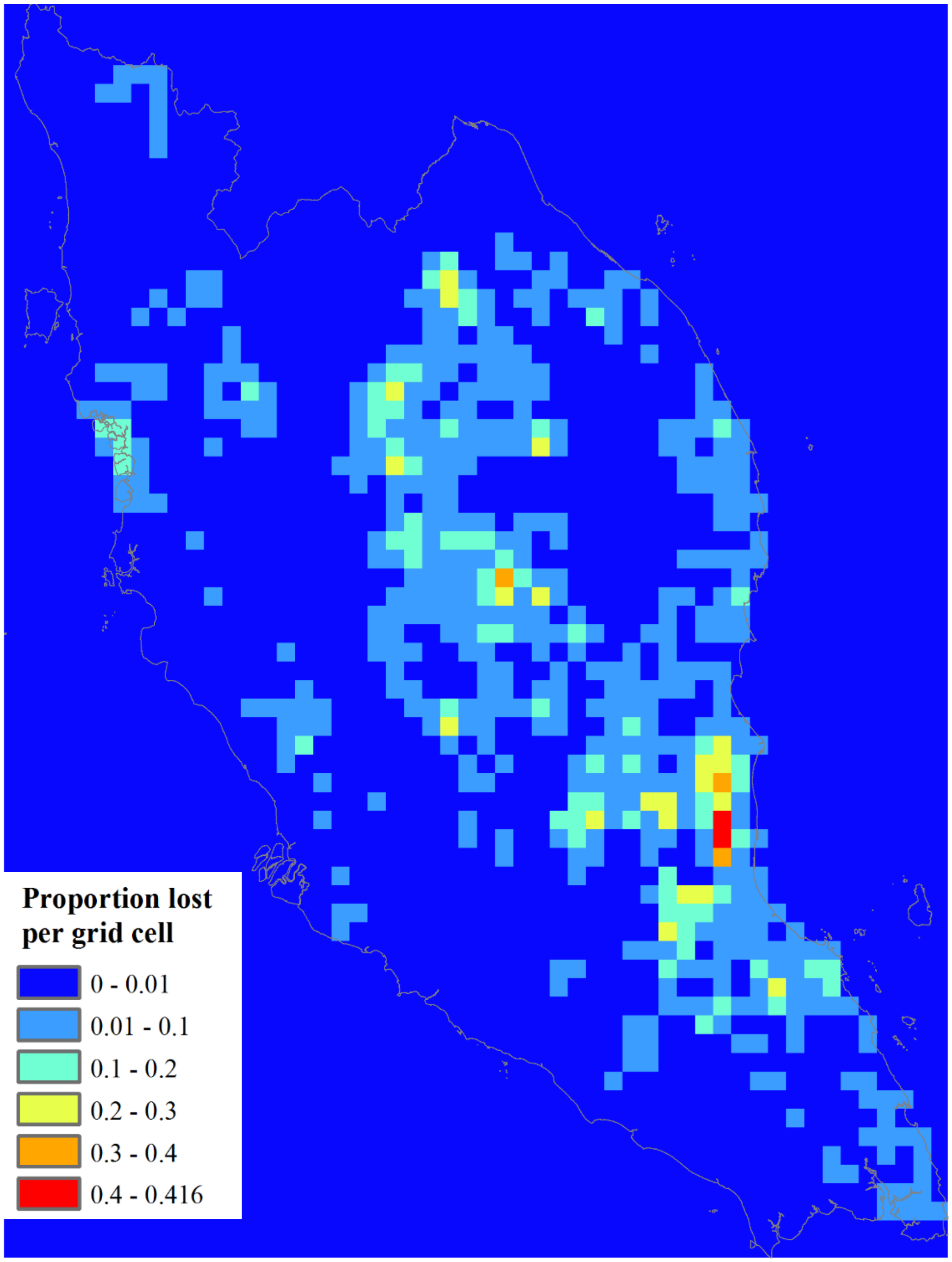

Figure S2 Five model average proportional forest loss per 9km grid cell for the PA restrictive (PAr) scenario

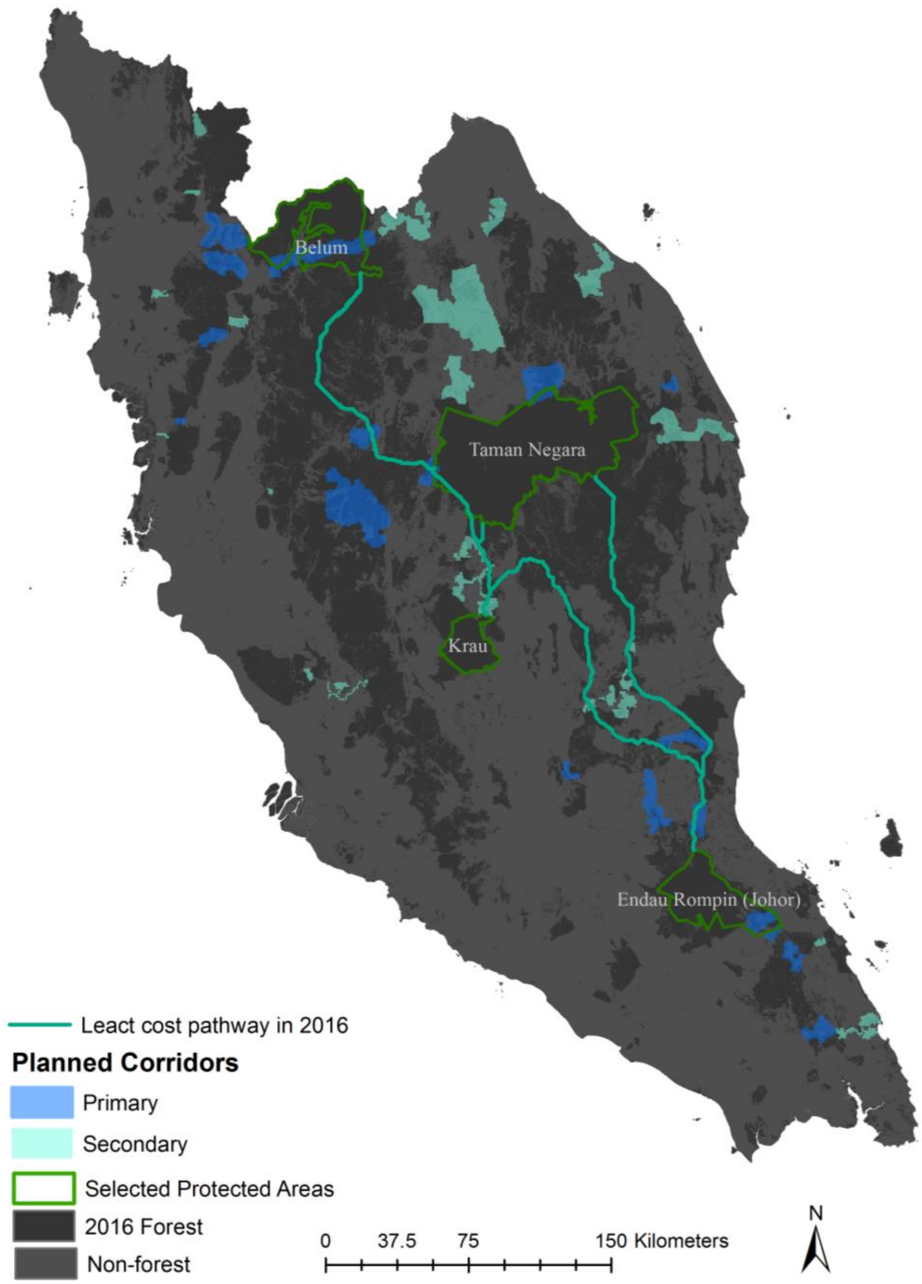

Figure S3 Least cost pathway connecting the selected protected areas in 2016 and the primary and secondary planned linkages from the Central Forest Spine Master Plan for Linkages

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