A country scale analysis on effectiveness of land use zoning on reducing deforestation in Myanmar

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Kyushu University

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By

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Acronyms and Abbreviations

AAC	Annual Allowable Cut
AIC	Akaike's Information Criterion
Aster GDEM	Advanced spaceborne thermal emission and reflection radiometer (Aster) Global Digital Elevation Map
ATT	Average Treatment effect on the Treated
DoP	Department of Population
FAO	Food and Agriculture Organization of the United Nations
FLEG-T	Forest Law Enforcement, Governance and Trade
FRA	Global Forest Resources Assessment
GADM	Database of Global Administrative Areas
GFCD	Global Forest Change Dataset
GLM	Generalized Linear Model
INDC	Intended National Determined Commitment
MSS	Myanmar Selection System
MIMU	Myanmar Information Management Unit
NDVI	Normalized Different Vegetation Index (NDVI)
OA	Overall Accuracy
PA	Producer's Accuracy
PAs	Protected Areas
PFE	Permanent Forest Estate
PPF	Protected Public Forest
PSM	Propensity Score Matching
RF	Reserved Forest
SEPAL	System for Earth observation, data access, Processing, Analysis for Land monitoring
SMS	Subtropical Mountain System
TDF	Tropical Dry Forest
TMDF	Tropical Moist Deciduous System
TMS	Tropical Mountain System

TRF	Tropical Rain Forest
UA	User’s Accuracy
UNFCCC	United Nations Framework Convention on Climate Change
VFVLM Law	Vacant, Fallow and Virgin Lands Management Law
VIF	Variance Inflation Factor

Summary

Forests providing a variety of ecosystem services are a cost-effective way to mitigate climate change. Therefore, it is important to secure the sustainable management of invaluable forest resources. Around the world, designating permanent forest land is a way to keep the forests in long-term. In Myanmar, forests cover about 42.92% of the country's total areas, and forestry sector plays an essential role in the sustainable development of the country. Permanent Forest Estate (PFE) comprising reserved forest (RF), protected public forest (PPF), and protected areas (PAs) are constituted in Myanmar in order to secure the sustainable forest management. The policy target and the commitment to UNFCCC intended to constitute PFE from 30% in 2019 up to 40% of total country area by 2030. However, because forest areas are decreasing year by year, it is crucial to understand the performances of PFE on reducing deforestation. Thus, the main objectives of this study are to evaluate the forest conservation effectiveness of the PFE compared with non-PFE areas, and also to understand the impacts of each of land-use zoning in the PFE on reducing deforestation.

Remote sensing based forest cover map is a reliable data source for large area monitoring. In this study, I used Global Forest Change Dataset (GFCD) developed by Hansen et al. (2013). However, the accuracy of GFCD is still debate, and it is important to understand whether global land cover product is reliable or not for the specific country. Therefore, firstly, I investigated the accuracy of GFCD using different tree cover thresholds for five ecological zones in Myanmar because an arbitrary choice of a tree cover threshold may yield an overestimation or underestimation of forest cover. The results showed that different tree cover thresholds were required to achieve the highest overall accuracy for different ecological zones. At national scale, the optimal threshold is 40% to achieve the highest accuracy. Therefore, I used 40% tree cover threshold to define forests in further study using GFCD.

In second study, the conservation effectiveness of PFE on reducing deforestation was investigated comparing with non-PFE. This study applied deforestation data from 2006 to 2017 of GFCD and the analysis was conducted using Matching method to control the location bias. The analysis showed that PFE was effective in reducing deforestation, although deforestation occurred inside PFE.

Within PFE, there are different land-use zonings such as reserved forest (RF), protected public forest (PPF), and protected areas (PAs). No surprisingly, PAs are the most effective land use zoning in reducing deforestation among different land use zoning. Although RF and PPF are production forests and extraction of forest resources including logging was conducted inside them, they have a lower deforestation than non-PFE. Thus, policy to constitute PFE up to 40% of the total country areas by 2030 is a good mechanism to control deforestation in Myanmar. However, it should be noted that annual deforestation in both PFE and non-PFE is increasing within the study period, and the efforts to mitigate deforestation should be conducted more effectively and efficiently.

The third study investigated the relationship between deforestation and biophysical factors using the Logistic regression analysis. The most important factor in PFE is slope, followed by distance to road and village. In non-PFE, the most influencing factors are distance to PFE, slope and distance to village. The results showed that deforestation in both PFE and non-PFE is more likely to occur in accessible areas and the areas far from government control. In non-PFE, the probability of being deforestation was increased in the areas far from PFE. It might be related with the presence of government officials near PFEs. The findings can support the policy and decision makers in the implementation of interventions to mitigate deforestation.

In conclusion, GFCD is a powerful tool for large-area monitoring of forest cover changes. However, it is crucial to consider the tree cover threshold in defining forest depending on the dominant ecological zones. The analysis using deforestation data from GFCD showed that PFEs as a whole and each land-use zoning of PFEs are effective in reducing deforestation. Thus, the policy measure to constitute PFE is a good mechanism for sustainable forest management. However, further efforts to mitigate the increased rate of deforestation in PFEs should be conducted more effectively and efficiently. While expanding the areas of PFEs to fulfill the targets, the forests remained in accessible areas should be considered as a priority. It is also crucial to implement the efforts to control deforestation in non-PFE because considerable areas of forests would be remained as non-PFE even after expanding the extent of PFEs up to 40%. In this context, actively participation of local community plays a key role in forest conservation and management. In addition, the government should secure land tenure security in non-PFE and it is also important to strengthen forest law enforcement, governance and trade (FLEG-T) and timber legality assurance system.

Chapter 1

General Introduction

1.1. Background information

Forests provide a number of services represented by climate regulation and habitat restoration and are the most critical renewable resources to the planet. They play a vital role for income, livelihoods and well-being for human, particularly indigenous people living near the forests and relying on forest products for their subsistence as well (FAO. 2018). However, according to the Global Forest Resources Assessment (FRA, 2015), global forest areas decreased about 3% between 1990 and 2015, while the annual rate of net forest loss was falling twice from 7.3 M ha yr^{-1} in the 1990s to 3.3 M ha yr^{-1} between 2010 and 2015 (FAO. 2016a). Tropical regions especially experienced the higher forest cover loss (Hansen et al. 2013a) with annual rate of loss 5.5 M ha yr^{-1} from 2010 to 2015 (Keenan et al. 2015).

Tropical forests occupy approximately 44% of the total world's forest areas (Keenan et al. 2015; Apan et al. 2017), covering only about 7% of the earth's land surface (Estoque et al. 2019). Besides the home to billions of people and wildlife, tropical forests contribute to global carbon balance (Sasaki 2012; Sullivan et al. 2017), becoming both sources and sinks of carbon (Mitchard 2018). However, because of deforestation due to human disturbances such as logging (Ota et al. 2019) and agriculture expansion (Yang et al. 2019), tropical forests are now recognized as the most threatened ecosystems in the earth (Hansen et al. 2013a; FAO. 2016a). Thus, the deforestation of tropical forests has been global concerns (DeFries et al. 2005; Malhi et al. 2014; Heino et al. 2015; Sloan & Sayer 2015), and interventions to combat deforestation in tropical forests became the core of global environmental policy.

Understanding underlying factors of deforestation is a prerequisite to combat deforestation and thus is one of the most critical issues in policy development to curtail deforestation (Hosonuma et al. 2012; Htun et al. 2013; Liu et al. 2015; Morales-Barquero et al. 2015; Lim et al. 2017; Guerra-Martínez et al. 2019). According to the summary of proximate causes and underlying factors of deforestation based on 152 subnational case studies (Geist et al. 2002), tropical deforestation is driven by major three causes, which are agriculture expansion, wood extraction and infrastructure development and five driving forces, which are demographic, economic, technological, policy and institutional and cultural factors. However, factors influencing deforestation vary among nations or regions (e.g. Mon et al. 2012; Vu et al. 2014; Phompila et al. 2017; Lonn et al. 2018), and over time even within a specific study area (Htun et al. 2013). Thus, it is crucial for each country and region to reveal the factor affecting deforestation on their situation.

Besides, it is important to evaluate the effectiveness of conservation approaches for reducing tropical forests. Land-use zoning, which segments the landscape into units with different legal status, is one of the traditional approaches to reduce deforestation. A variety of studies evaluated the performances of land-use zoning, e.g. protected areas (Andam et al. 2008; Andam et al. 2013; Brun et al. 2015; Cuenca et al. 2016; Gray et al. 2016; Miranda et al. 2016; Oldekop et al. 2016; Bowker et al. 2017; Apan et al. 2017; Maharaj et al. 2019) and community forests (Ellis & Porter-Bolland 2008; Porter-Bolland et al. 2012; Lonn et al. 2019; Oldekop et al. 2019)) around the world. However, the results showing the conservation performances vary across nations or landscape, and land-use policies, and thus the effectiveness of land-use zoning should be evaluated in each nation and region.

Permanent Forest Estate (PFE) is designated as permanent land use to keep the forests in long-term (FAO. 2016a). Within PFE, forests are managed by categorizing into different land-use zonings which are allocated for timber production, local supply, nature conservation, recreation, and conservation of wildlife and their habitats (Bruggeman et al. 2015) by assigning different legal status. According to FRA 2015, out of 2.2 billion ha of proposed permanent forest land, about 1.5 billion ha have been designated as PFE and more than half of PFE are found in the tropical regions (FAO. 2016a). While there are considerable portions of PFE, the study evaluating effectiveness of the PFE and the land-use zonings within PFE are few. As a limited study, Bruggeman et al. (2015) evaluated the effectiveness of the PFE and land-use zoning in Cameroon. However, the study only focused on a specific region in Cameroon, which is in African regions. It is still unclear whether PFE effectively reduces deforestation at a national scale in Southeast Asia.

For evaluating conservation performances and analyzing driving factors on deforestation of land-use policy in a large area, a fundamental map for forest cover changes over time is essential (Lim et al. 2017). Remote sensing based forest cover map is reliable data source (Hansen et al. 2000) and one of the powerful tools to study over large areas (e.g. entire country). Recently, several freely available global forest cover maps are developed by using various data sources. However, because global maps are typically not reliable at national or local scales (Sannier et al. 2016), validation of the suitability of global maps for specific regions is important.

1.2. Forestry in Myanmar

Myanmar is geographically located between latitudes 9° 28´ and 28° 29´ N and longitudes 92° 10´ and 101° 10´ E. Owing to long length of land, stretching for 9,236 km from north to south and 2,051 km from east to west, and various topography, the country has several climate zones ranging from temperate region to dry zone. Due to various climate zones, Myanmar is endowed with natural forests comprising with various special composition and stand structure (Htun et al. 2012) and has high forest cover in Southeast Asia (Yang et al. 2019). There are six major forest types in Myanmar, namely mangrove forest (1.12%), tropical evergreen forest (17.30%), mixed deciduous forest (38.20%), dry forest (10.00%), deciduous dipterocarp forest (4.26%), hill and temperate evergreen forest (26.92%), and scrub and grass land (2.20%) (Forest Department. 2020).

In Myanmar, all forests are state-owned forests and classified into Permanent Forest Estate (PFE) and unclassified forests. The PFE comprises with reserved forest (RF), protected public forest (PPF) and protected areas (PAs) in order to ensure sustainable forest management, to restore ecological balance, conserve biodiversity and environment and to strengthen management of wild flora and fauna. Since monarchial times, the first forest policy was started in 18th century with the legislation that the teak tree was royal and no-one was allowed to cut it without permission (Linn & Liang 2015). After the first Anglo-burmese war at 1824, the British conquered Tenasserim region (nowadays Tanintharyi) and teak forests in Tenasserim were managed under a system of *laissez-faire* forestry (1824-1855) (Bryant 1997). After the second Anglo-burmese war at 1852, the British occupied lower Myanmar, and Dr. Brandis was appointed to manage the forests. In 1856, Dr. Brandis founded the Forest department in order to manage the forest scientifically. The scientific forest management had been introduced in Pegu (nowadays Bago) teak forests. Because of the extensive depletion of teak forests in Tenasserim, a new approach had been created with the constitution of reserved forests leading to timber production in long-term (Bryant 1993). Although several reserved forests were selected in the 1860s, the very first reserved forest was legally created in May 1870. Along with the extension of Forest Department, an increase in the creation of reserved forests has been occurred, and by 1900, reserved forest covered about 4.44 Mha (Bryant 1993). The Burma forest act was enacted in 1902 and updated in 1992. In 1883, the elephant preservation act was enforced and the wildlife protection has been implemented within the boundary of reserved forests and some restricted areas. In 1936, the Burma wildlife protection act was enacted and the first wildlife sanctuary was established in 1918. The state timber commission recommended to implement the proposal in 1944 that "the forest estate shall be administered not only for the benefit of the population of today but also for posterity: hence suitable areas shall be reserved on a permanent basis, brought under proper protection and management, and developed with the view to securing sustained annual yields".

According to Myanmar Forest Policy in 1995, one of the policy measures for protection and management is to stipulate 35% of the total country's areas as PFE such as RF, PPF and PAs. The target of PFE is extended to 40% according 30-year National Forestry Master Plan (2001–02 to 2030–31) and the extended target is also one of the commitment of Intended National Determined Commitment of Myanmar (INDC) which was submitted to UNFCCC (The Government of Myanmar 2015). As of December 2019, 31.34% of total country area has been declared as PFE (Forest Department. 2020). The unclassified forests which are located outside of PFE could be managed according to Forest Law, but land covered with unclassified forests is defined as "Virgin Land" according to The Vacant, Fallow and Virgin Land Management Law (2012) under the management of Ministry of Agriculture, Livestock and Irrigation. Therefore, there is overlapping management between government sectors.

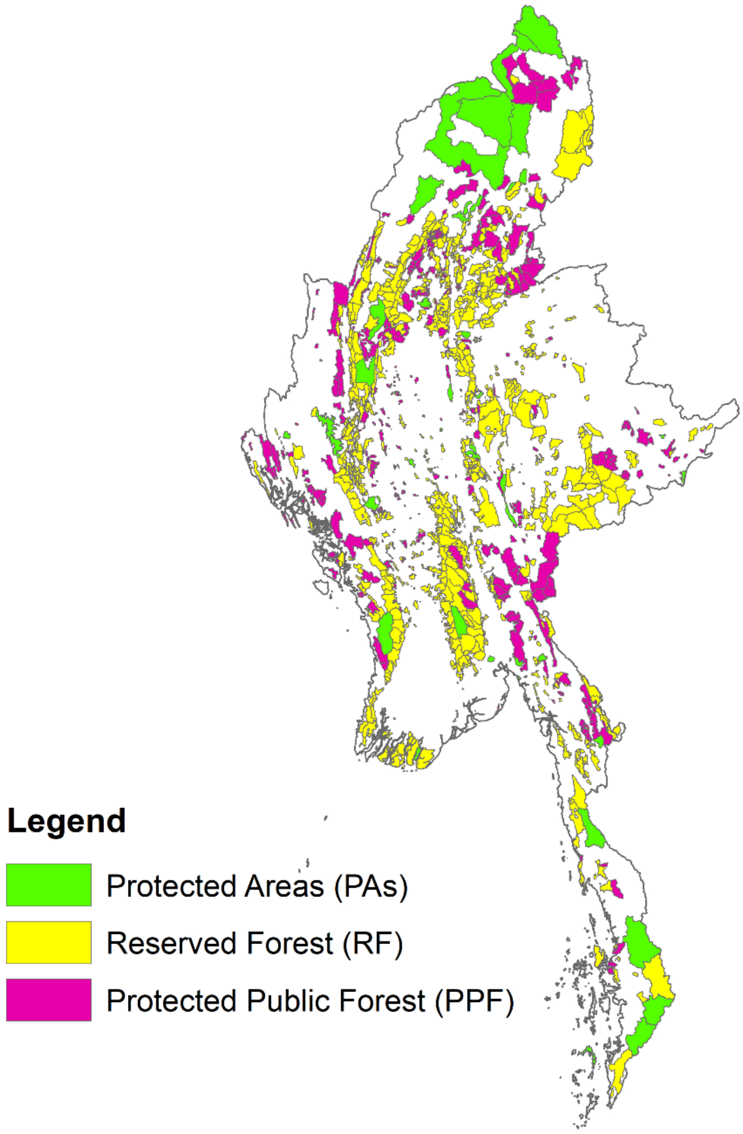


Figure 1.1. Overview location of Permanent Forest Estate (RF, PPF and PA) in Myanmar

In Myanmar, forest cover decreased drastically from about 59% of the total land area of the country in 1990 to about 43% in 2015 due to various factors. According to FRA (2015), Myanmar stands in third place among ten highest deforested countries over the world during 2010-2015 with annual net deforestation rate of 1.7%. Forest cover change in Myanmar has been analyzed by various studies (Leimgruber et al. 2005; Songer et al. 2009; Htun et al. 2010; Mon et al. 2012; Liu et al. 2015; Wang & Myint 2016; Shimizu et al. 2017; Reddy et al. 2019; Yang et al. 2019). In addition, various studies identifying the factors influencing deforestation in specific regions of interest were also conducted in Bago Yoma (Mon et al. 2012), Paung laung watershed (Mon et al. 2009), and Popa mountain national park (Htun et al. 2013). Regarding with evaluating the effectiveness on forest conservation and social sectors, some studies have been conducted in a specific land-use zoning of PFE (Allendorf et al. 2006; Htun et al. 2010; Allendorf et al. 2012; Htun et al. 2012; Allendorf & Allendorf 2013; Biswas et al. 2015; Allendorf et al. 2017). However, no study evaluated the conservation performances of PFE at national level to understand the effectiveness of conservation policy, and factors influencing deforestation inside PFE and unclassified forests at national scale as well.

1.3. The objectives and structure of dissertation

The main objectives of this study are to evaluate the forest conservation effectiveness of the PFE compared with non-PFE areas, and also to understand the impacts of each of land-use zoning of PFE on reducing deforestation.

The dissertation is organized with five chapters and chapter 1 represents general introduction including background of the study, forestry in Myanmar and research objectives.

Chapter 2 evaluated the importance of tree cover thresholds in defining forest and non-forests using remote sensing based global forest cover maps. The study was conducted at national scale and analysis was focused on different ecological zones of Myanmar in order to identify the effect of changing tree cover thresholds on the accuracy of forest cover maps from the Global Forest Change Dataset (GFCD) and to examine the influence of different ecological zones on the optimal threshold of tree cover to achieve the highest overall accuracy.

Chapter 3 studied about the effectiveness of PFE in reducing deforestation. This study was conducted at national scale using deforestation data from GFCD. The conservation performance was evaluated using matching method to control the bias. The objectives of this chapter are to evaluate forest conservation effectiveness of PFE compared with non-PFE areas which are also known as unclassified forests, and to evaluate conservation performances of each land-use zoning of PFE by comparing with non-PFE.

Chapter 4 studied the factors influencing and driving deforestation within PFE and non-PFE using Generalized linear model. The objective of this chapter is to investigate the relationship between driving factors and deforestation and examine the most influencing factor.

Chapter 5 included general discussions and conclusion to cover all the research works.

Chapter 2

Assessing the importance of tree cover threshold for forest cover mapping derived from Global Forest Cover in Myanmar

2.1. Introduction

Deforestation in tropical forests has been of concern for decades (Keenan et al. 2015). Because tropical deforestation negatively impacts the global carbon budget (Houghton 2012; Baccini et al. 2017) and biodiversity (Brooks et al. 2002; Hughes 2017; Giam 2017), forest policy and management need to reverse forest loss. Forest cover maps, which identify forest and non-forest areas, are essential baseline information for tracking forest cover changes; therefore, comprehensive forest cover maps are necessary for policy and management decisions. Remote sensing is one of the tools used to provide complete forest cover maps over extensive land areas, such as entire countries.

Satellite remote sensing is a commonly used to map land cover in a systematic and cost-effective fashion over a variety of spatial extents (Wulder et al. 2008; Gómez et al. 2016). However, creating a forest cover map from raw remote sensing data can be a barrier for users (Turner et al. 2015), because it requires expertise in remote sensing and professional software. An alternative solution is to use existing global datasets for forest cover. Currently, there are several freely available land cover map products, which have been developed from various data sources.

The Global Forest Change Dataset (GFCD) developed by Hansen et al. (Hansen et al. 2013a) is one of these freely available global datasets. This is a Landsat-derived dataset with 30-m resolution and includes three layers, which are: (1) percent tree cover in 2000 (0%–100%) (hereafter tree cover), (2) annual forest cover loss (2000–2016), and (3) forest cover gain (2000–2016). The GFCD is widely used all over the world (e.g., Santika et al. 2017; Johanne. Pelletier et al. 2019; Oldekop et al. 2019). One of the barriers to using the GFCD, however, is that the data do not provide information on forest and non-forest areas. Thus, users must apply knowledge of forest cover from other sources. One practical option is to create a forest cover map from the percent tree cover layer of the GFCD (Davis et al. 2015; Sannier et al. 2016; Peter. Potapov et al. 2017; Lonn et al. 2018; Lonn et al. 2019). In this option, users distinguish forest and non-forest areas by applying a threshold of tree cover. Because the definition of the threshold directly affects the areas of forest and non-forest, setting an appropriate threshold is very important.

Previous studies have used different thresholds while using the GFCD. For example, Davis et al. (Davis et al. 2015) and Lonn et al. (Lonn et al. 2019) used a 30% threshold to distinguish forests and non-forests in Cambodia, but Yang et al. (Yang et al. 2017) used a 10% threshold in China. Lui et al. (Lui & Coomes 2015) used a 50% tree cover threshold in accordance with the definition of forest cover gain in the GFCD, for rainforest cover change analysis of Gola National Park (Sierra Leone, West Africa). A case study in Brazil applied different thresholds to create forest cover maps from the GFCD and suggested that a 95% threshold yielded the highest overall accuracy (McRoberts et al. 2016). The various thresholds defined by previous studies imply that the appropriate threshold of tree cover depends on the region of interest. Thus, it is necessary to pay extra attention to the tree cover threshold to define forest areas, when the GFCD is used for monitoring large areas. To the best of my knowledge, no study has yet evaluated the effect of the tree cover threshold on the accuracy of forest cover detection based on the GFCD for different regions. Although some studies evaluated the accuracy of the GFCD, they have mainly focused on the accuracy of the forest loss or gain layer (Burivalova et al. 2015; Linke et al. 2017; Arjasakusuma et al. 2018). A few studies (Sannier et al. 2016; McRoberts et al. 2016) have investigated the effect of the tree cover threshold on the accuracy of the forest cover map derived from the GFCD. However, they did not consider differences in the effect of tree cover thresholds among different regions. Because it is necessary to understand the accuracies of the GFCD within different forest types and various canopy densities to be appropriate for specific local contexts (Mitchard et al. 2015), here, I investigated the effect of the tree cover thresholds on the accuracy of forest cover detection from the GFCD over different regions.

The Republic of the Union of Myanmar (hereafter Myanmar) used to be one of the most forested countries in mainland Southeast Asia. However, the forest area in Myanmar has decreased rapidly (FAO. 2016a). Monitoring forest cover changes in Myanmar is crucial for action against such deforestation. The GFCD may be an important option for monitoring, despite Myanmar being a long north–south orientated country. The elevation ranges from sea level to more than 5000 m. In some places the annual rainfall reaches 6000 mm but, in other parts of the country, annual rainfall is below 500 mm. Given these diverse topographic and climatic conditions, Myanmar is divided into five ecological zones. Because of these different ecological zones, I may have to use different zonal thresholds to map forest cover using the GFCD.

In this study, I investigated the accuracy of forest cover maps created from the GFCD using different tree cover thresholds across the different ecological zones based on country-scale evaluation of Myanmar. The specific objectives of the study were: (1) to identify the effect of changing tree cover threshold on the accuracy of forest cover maps from the GFCD, and (2) to examine the influence of different ecological zones on the optimal threshold of tree cover to achieve the highest overall accuracy. I evaluated the importance of the tree cover threshold when using the GFCD for monitoring large areas, such as in Myanmar.

2.2. Materials and Methods

2.2.1. Study Area

Myanmar is located in Southeast Asia between latitudes 9°32′–28°31′N and longitude 92°10′101°11′E. It is the second largest country in Southeast Asia, with a total area of approximately 0.67 million km^2. According to the Global Forest Resources Assessment (FRA) 2015 (FAO. 2014), forests covered approximately 42.92% of the total land area in Myanmar.

Based on the Global Ecological Zones provided by the Food and Agricultural Organization of the United Nations (FAO) (FAO. 2012), Myanmar is divided into five ecological zones: the subtropical mountain system, tropical dry forest, tropical moist deciduous forest, tropical mountain system, and tropical rainforest (Figure 2.1). An ecological zone is defined as a broad area that has relatively homogeneous natural vegetation formations. The boundaries of ecological zones approximately correspond to the Köppen–Trewartha climatic types, based on temperature and rainfall. Mountain systems are classified as separate ecological zones, characterized by a high variation in both vegetation formations and climatic conditions (Simons 2001).

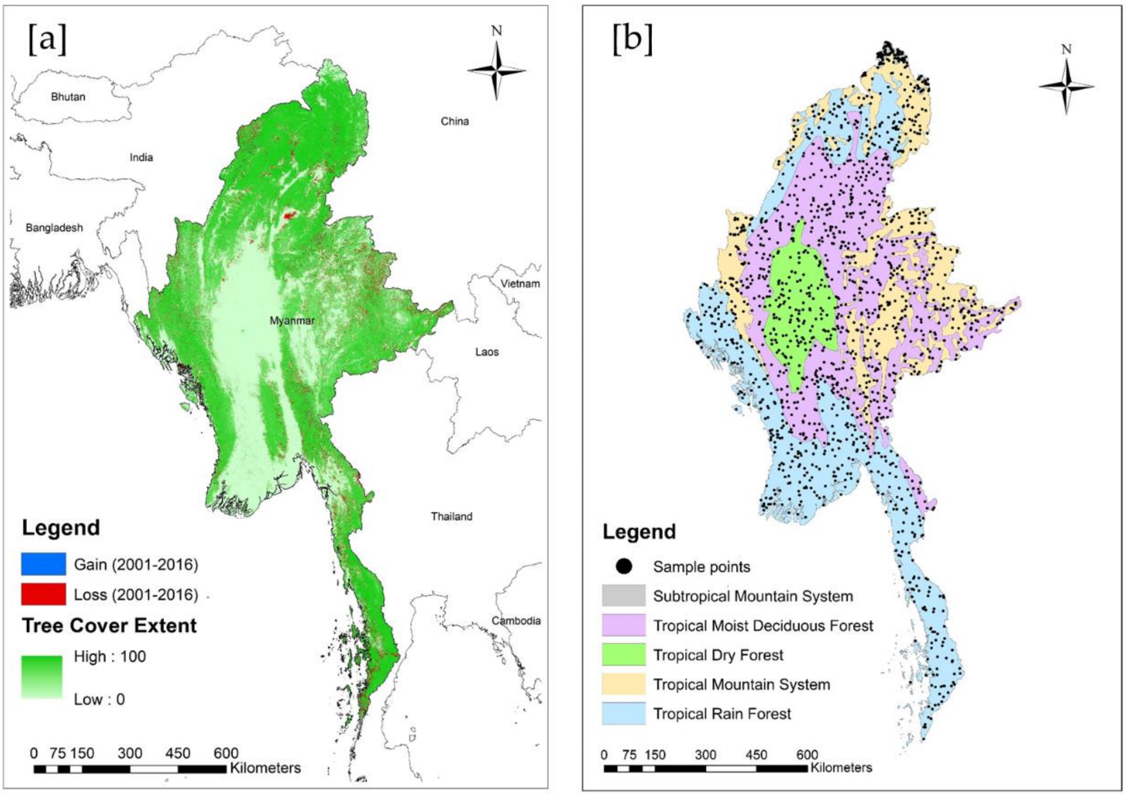


Figure 2.1. (a) Forest Cover Change from 2001-2016, (b) Five ecological zones showing sample points in Myanmar.

The country border data were downloaded from the Database of Global Administrative Areas (GADM) (GADM.), Forest Cover Change Data were from the Global Forest Change website (Hansen et al. 2013b) and the ecological zones were from the Food and Agricultural Organization website (Global Ecological Zone.).

Detailed explanations of the climate, physiography, and vegetation for each ecological zone in the Asian domain are provided in the FAO report by Simons (Simons 2001). Briefly, each ecological zone has different vegetation features. For example, the natural vegetation of the tropical rainforest is mainly dense moist evergreen forest, although semi-deciduous and moist deciduous forests are also distributed in the drier parts of this zone (Simons 2001). In contrast, the natural vegetation of tropical moist deciduous forests comprises mainly deciduous and semi-deciduous species, where teak (Tectona grandis) is found (Simons 2001). In Myanmar, bamboo (Dendrocalamus strictus) is also a common species in tropical moist deciduous forests (Simons 2001). The vegetation of tropical dry forests is complex but dry deciduous dipterocarp forests and mixed deciduous woodlands are common in the tropical dry forests of the Southeast Asian region, including Myanmar

(Simons 2001). The vegetation of the subtropical mountain system and tropical mountain system varies by region.

2.2.2. Global Forest Change Dataset

The GFCD version 1.4, which included: (i) percent tree cover in 2000, (ii) annual loss layer, and (iii) a gain layer, was downloaded from the website (Hansen et al. 2013b). All datasets were first clipped using the Myanmar boundary. Then, I defined forest area in 2000 using a threshold of percent tree cover. Here, I tested nine thresholds from 10% to 90%, with intervals every 10%, and generated nine forest cover maps for 2000. For each forest in the 2000 layer, I created a forest cover map for 2016 by combining the annual loss layer (2001–2016) and gain layer (2001–2016). I defined a pixel as forest in 2016 according to two criteria: (1) when a given pixel was forest in 2000 and was not classified as forest loss between 2001 and 2016, and (2) when a given pixel was classified as forest gain. The pixels satisfying either one of these two criteria were defined as forest. In contrast, I defined the pixels that did not satisfy the above criteria as non-forest in 2016. I assessed the accuracy of these nine different 2016 forest cover maps. When forest cover maps are created using a threshold, the information from neighboring pixels may improve their accuracy. Thus, I tested two different options for percent tree cover in 2000. In the first case, the original percent tree cover in 2000 was used. In the second case, the average value of tree cover in 2000 of a central pixel and its neighborhood was used. In this study, I used the average tree cover of 3 x 3 neighboring pixels.

2.2.3. Methodology

2.2.3.1. Determination of Sample Points

To determine the total number of sample points for the whole study area, the following equations (Olofsson et al. 2014) were used:

$$n \approx \left(\frac{\sum W_i S_i}{S(\hat{o})} \right)^2 \tag{1}$$

$$S_i = \sqrt{U_i(1 - U_i)} \tag{2}$$

where n is the calculated number of total samples, $S(\hat{o})$ is the standard error of the overall accuracy that I would like to achieve, W_i is the mapped proportion of the area of class i, S_i is the standard deviation of class i, and U_i is the expected user accuracy of class i. In this study, there were two classes, forest and non-forest. I assumed the mapped proportions of the areas of the forest class and non-forest class were 0.4 and 0.6, respectively. I also set the U_i of both forest and non-forest classes as 0.8. A total of 1600 sample points were used.

Table 2.1. Number of sample points for the five ecological zones

Ecological Zones	Area (1000 ha)	Sample Points
Subtropical Mountain System	412	100
Tropical Dry Forest	5998	137
Tropical Moist Deciduous Forest	23,080	527
Tropical Mountain System	14,550	334
Tropical Rainforest	22,670	502
Total	66,710	1600

I applied stratified random sampling to allocate the samples to each ecological zone. To calculate the number of allocated samples, I used the Stratified Area Estimator-Design tool on the SEPAL platform (Sepal Platform.). The SEPAL platform is part of the Open Foris suite of tools (FAO. 2016b); it semi-automatically determines the number of samples according to the area of each stratum (an ecological zone) in my case, the total sample size, and the minimum sample size. Because the minimum sample size of each stratum should be at least 20–100 samples (FAO. 2016b), I assigned at least 100 samples to each ecological zone. The respective number of sample points calculated by the tool for the five ecological zones are shown in Table 2.1; sample points were randomly distributed in each ecological zone.

2.2.3.2. Reference Data Collection

There are various approaches to collecting reference data, such as field survey data (Z. Yang et al. 2017; Venkatappa et al. 2019), Google Earth (Potere 2008; Hansen et al. 2013a; Brun et al. 2015; Lui & Coomes 2015; Tilahun & Teferie 2015; Rwanga & Ndambuki 2017; Y. Yang et al. 2017; Dhar et al. 2019; Yang et al. 2019), and very high resolution satellite images, like Aerial photo, GeoEye, and QuickBird (Mahdianpari et al. 2019; Poortinga et al. 2019). In this study, Collect Earth, which is a free open-source software designed to facilitate data collection for land cover monitoring (Bey et al. 2015), was used to interpret forest and non-forest from the samples for the ground situation (Figure 2.2). This software enabled the users to interpret the land cover of the sampled area with plot layout design through imageries with varying spatial and temporal resolutions within Google Earth, Bing Maps, and Google Earth Engine (Bey et al. 2016); it geo-synchronized the views of the ground situation at each sample within different imageries (Figure 2.2 a–c). Previous studies used Collect Earth for various purposes, including ground truth data collection for accuracy assessment, land cover change analysis, and vegetation survey, for analyses at global scale (Bastin et al. 2017) and specific regions of interest (Asrat et al. 2018; Leite et al. 2018; Messina et al. 2018; Muro et al. 2018; Vega Isuhuaylas et al. 2018; Alban et al. 2019; Mitri et al. 2019; Johanne Pelletier et al. 2019).

At the time of reference data collection, I defined forest as an area that was larger than 0.49 ha with tree cover of more than 10%, consistent with the forest definition of the FAO (MacDicken 2012). According to this definition, I set each sample from Section 2.2.3.1 as a 0.49 ha plot (70 m × 70 m) having a systematic grid of 5 × 5 points (i.e., 25 points), as shown in Figure 2.2 d. Within each plot, I identified forest or non-forest areas by counting the number of points covered with trees, based on visualization of the ground situation through geo-synchronized views within Google Earth, Bing Maps, and Google Earth Engine. If the number of points with tree crowns in each plot was equal to or more than three (i.e., > 3/25 = 0.12), I classified the sample as forest. Otherwise, I classified the sample as non-forest.

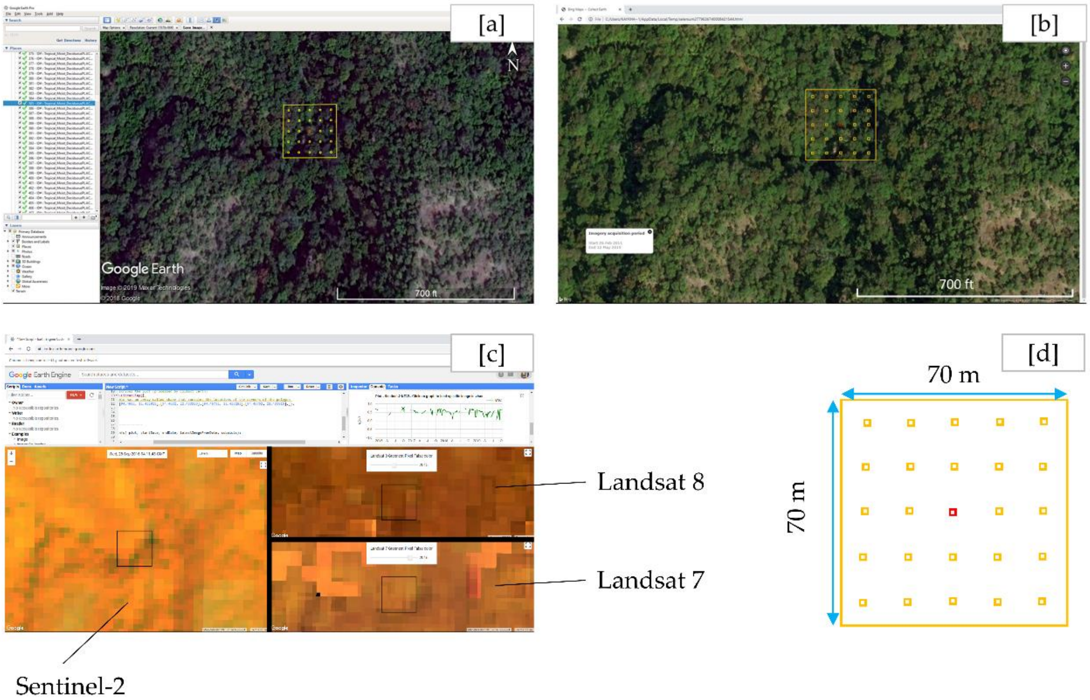


Figure 2.2. Geo-synchronized view of each sample using Collect Earth Software

(a) Google Earth image, (b) Bing Map image, (c) Google Earth Engine showing normalized difference vegetation index (NDVI) values and different satellite images, such as Sentinel-2, Landsat 7, Landsat 8, (d) schematic of a 0.49 ha plot with 25 points. The red point in the center of the plot represents the original sample described in Section 2.2.3.1.

2.2.3.3. Accuracy Assessment

The accuracies for all nine forest cover maps were assessed using overall accuracy (OA), producer's accuracy (PA) and user's accuracy (UA) derived from a confusion matrix between each forest cover map and reference data from Collect Earth. First, I evaluated the effect of the tree cover threshold on the accuracy of each ecological zone using the forest cover maps derived from the nine thresholds from 10% to 90%. Then, the effect of the tree cover threshold at a national scale was evaluated. For the national-scale evaluation, I calculated the national-scale accuracy (1) when the tree cover threshold was uniquely determined over the whole area of the country, and (2) when the tree cover threshold was determined by the optimal thresholds of tree cover from the ecological zones. For the former case, I calculated OA, PA and UA at a national scale from all nine forest cover maps as in the evaluation of each ecological zone. For the latter case, I used the tree cover threshold that received the highest OA for each ecological zone. McNemar's test, which is a non-parametric test to assess the performance of a classification (Foody 2004), was applied to evaluate national scale and ecological zone accuracies.

2.3. Results

2.3.1. Forest Cover Area Estimation

Figures 2.3 a,b show the relationship between the ratio of forest to non-forest and the tree cover threshold. The forest and non-forest areas derived from the two different cases of percent tree cover were similar. Forest area gradually decreased with an increase of the tree cover threshold. However, the gradients depended on ecological zones. Tropical dry forest showed the lowest forest cover and forest areas decreased in a linear fashion. Tropical moist deciduous forest, tropical mountain system, and tropical rainforest showed a similar trend. The forests of these three ecological zones occupied an area of approximately 75% for both cases of percent tree cover, when the tree cover threshold was 10%; it remained at more than 50%, until the tree cover threshold reached 60%. Then, the forest cover ratio decreased sharply, as the tree cover threshold rose from 60% to 90%. The forest cover in the subtropical mountain system was less than 50% in the first case and approximately 52% in the other case, when the tree cover threshold was 10%; it gradually decreased as the threshold increased.

At the national scale, when the tree cover threshold was uniquely determined over the whole country, the trend was similar to that for the tropical moist deciduous forest, tropical mountain system and tropical rainforest in both percent tree cover cases. The forest cover ratio decreased proportionally, as the tree cover threshold rose from 10% to 50%.

[a]

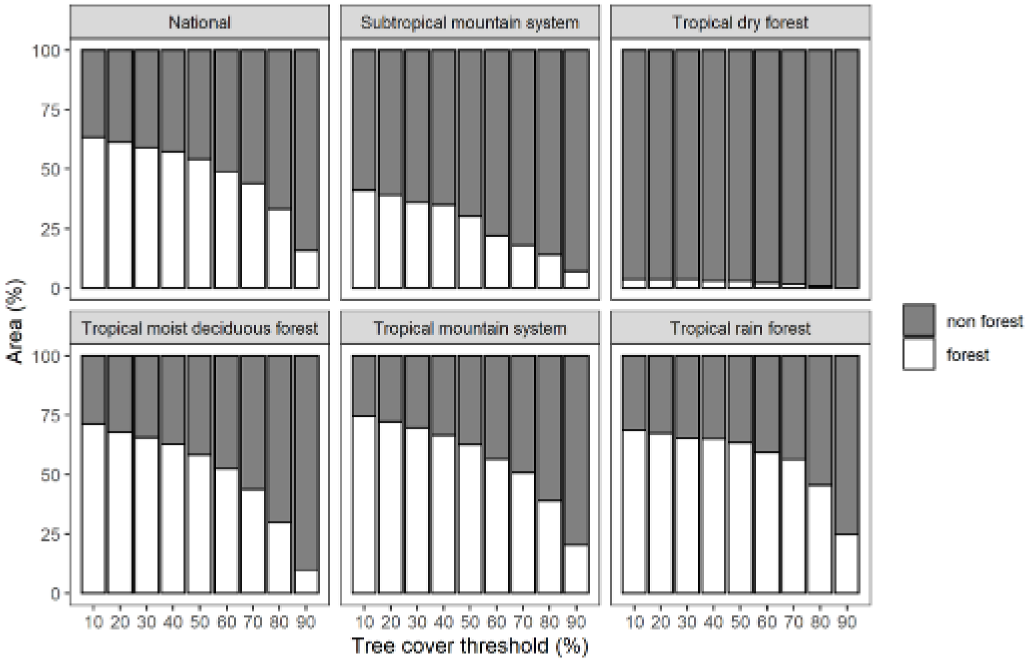


Figure 2.3. Cont.

[b]

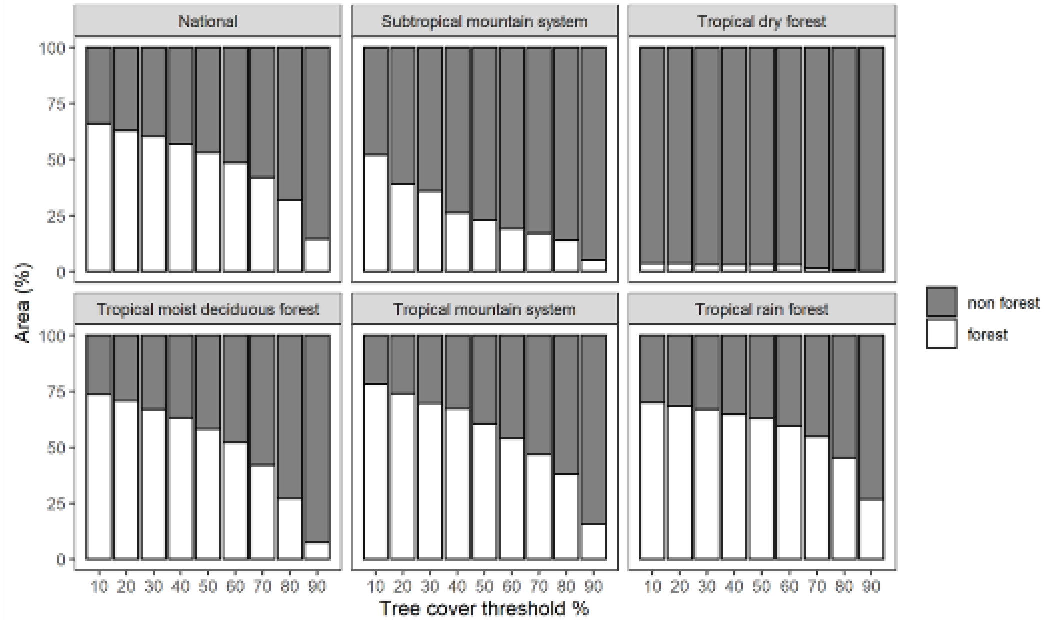


Figure 2.3. Percentage of forest and non-forest in 2016 at the national scale and in the five ecological zones: (a) using original percent tree cover and (b) using average tree cover percent of 3 × 3 neighboring pixels.

2.3.2. Accuracy Assessment

2.3.2.1. Ecological Zones

The OA, UA and PA for each ecological zone using original percent tree cover are shown in Figure 2.4; there are different accuracies for different tree cover thresholds in different ecological zones. In the subtropical mountain system, the OA ranged from 75% to 85% and the highest OA was obtained when the tree cover threshold was 20%. The OA was stable, with a range from 82% to 85% when tree cover threshold changed from 10% to 80%; but it gradually decreased, when the tree cover threshold changed from 80% to 90%. The OA of the tropical dry forest was over 90% for all tree cover thresholds. The highest OA was obtained between tree cover thresholds of 10% and 30%; it also decreased with further increases in tree cover threshold. In the tropical moist deciduous forest, the OA ranged from 58.4% to 74.6% and the highest OA was found at a 40% tree cover threshold. The OA increased, when the tree cover threshold increased from 10% to 40%; but it gradually decreased with an increase in the tree cover threshold from 50% to 90%. The OA of the tropical mountain system showed a similar trend to that of tropical moist deciduous forest and ranged from 60.2% to 78.4%. The OA gradually increased in accordance with the threshold of tree cover, when the threshold was between 10% and 30%. The OA then gradually decreased. Although the OAs of the other ecological zones were highest when the threshold of tree cover was between 10% and 40%, the tropical rainforest zone needed a tree cover threshold of 80% to achieve highest OA. The OA of the tropical rainforest increased from 68.1% at 10% tree cover threshold to 73.7% at 80% threshold and then decreased to 67.5% at 90% tree cover threshold. Therefore, the highest OA was found at various optimal tree cover thresholds, depending on the ecological zone.

The UA and PA of forest and non-forest areas for each ecological zone showed similar trends, except for the tropical dry forest zone. The UA of forest and PA of non-forest areas increased with an increase of tree cover threshold from 10% to 90%, while the PA of forest and UA of non-forest decreased. In the tropical dry forest zone, the UAs of forest and non-forest and PA of non-forest were nearly 100%, indicating they were independent of the tree cover threshold. However, the PA of forest decreased in accordance with increasing tree cover threshold. The PA only reached a maximum of 41.7% and showed lower values than the PA of forest in other ecological zones.

The OA, UA and PA values for each ecological zone using the average of percent tree cover are shown in Figure 2.5. The results were similar to the results for the original percent tree cover. The highest OAs were slightly higher than those using the original percent tree cover in the tropical mountain system, subtropical mountain system, and tropical moist deciduous forest.

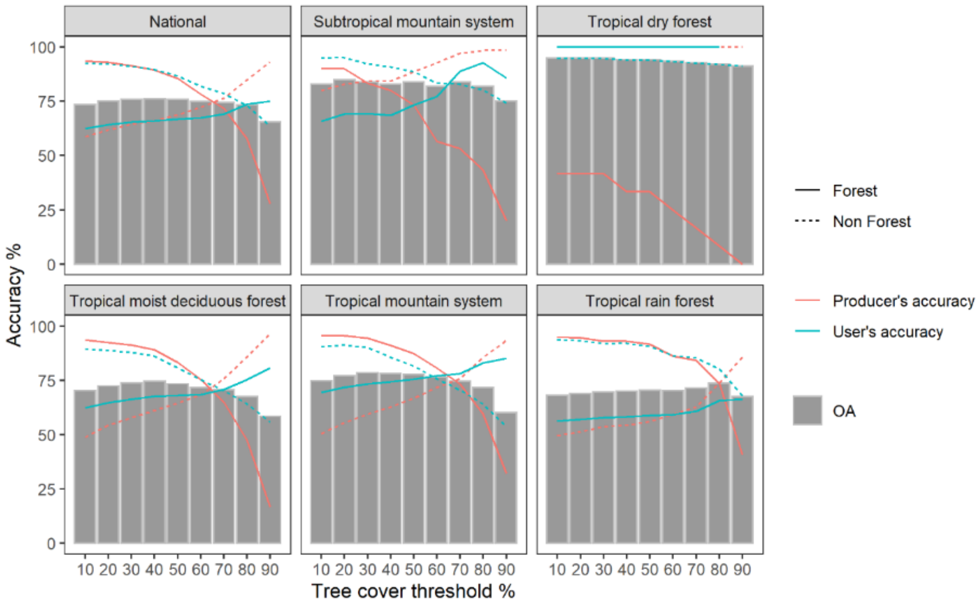


Figure 2.4. Overall accuracy (OA), producer's accuracy, and user's accuracy for forest and non-forest at the national scale and in the five ecological zones using original percent tree cover

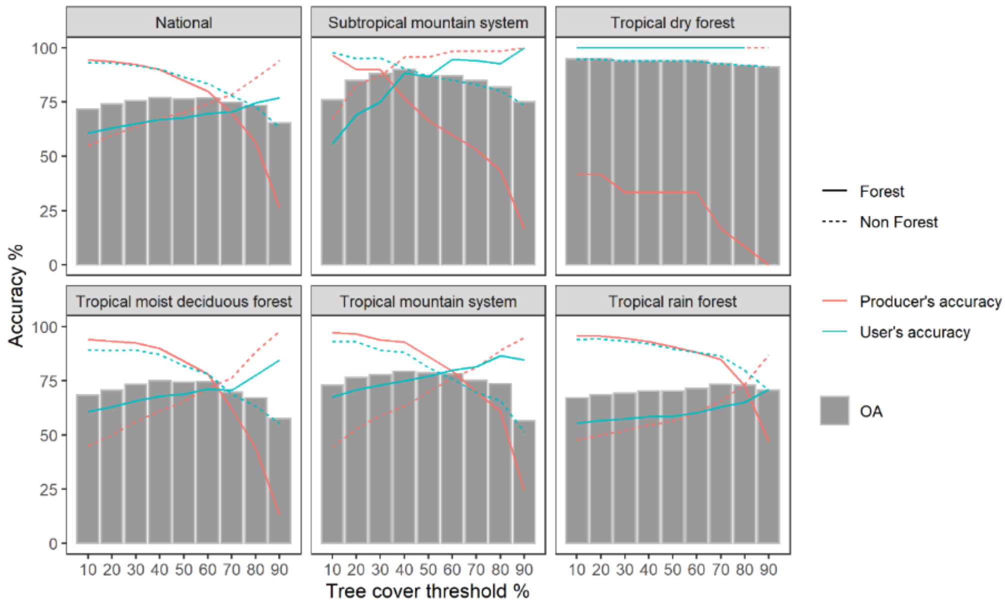


Figure 2.5. Overall accuracy (OA), producer's accuracy, and user's accuracy for forest and non-forest areas at the national scale and in the five ecological zones using the average tree cover percent of nine neighboring pixels

In the tropical dry forest, the highest OAs were same as those using the original percent tree cover. In the tropical rainforest, the highest OAs were lower than those using the original percent tree cover. The highest OAs of the two options were different, with a maximum difference between the two of 7% for the subtropical mountain system. The optimal thresholds using the average of percent tree cover were different from those using the original percent tree cover in the subtropical mountain system, tropical mountain system, and tropical rainforest. The highest OAs were achieved at 40% threshold in the subtropical mountain system and tropical mountain system, and at 70% threshold in the tropical rainforest.

2.3.2.2. National Scale

At a national scale, when the tree cover threshold was uniquely determined for the whole country using original percent tree cover (see Appendix), the OA was almost stable between 10% and 80% tree cover thresholds (Figure 2.4). The OA decreased when the tree cover threshold changed from 80% to 90%. The highest OA was 76.1%, when the tree cover threshold was 40%. Figure 2.6 shows forest cover maps using 40% and 90% tree cover thresholds, which gave the highest and lowest OAs, respectively. The UA of forest increased in accordance with an increase in the tree cover threshold from 10% to 90%. In contrast, the PA of forest continuously decreased from 93.5% to 27.9%, when the tree cover threshold changed from 10% to 90%.

When the tree cover threshold was determined by the optimal thresholds of tree cover from the ecological zones using the original percent tree cover, OA was 77.5%. The PA and UA of forest were 85.1% and 69.0%, respectively. The PA and UA of non-forest were 71.9% and 86.8%, respectively. McNemar's test showed that there was no significant difference at the 0.05 level between the highest OA, when the tree cover threshold was uniquely determined for the whole country (i.e., the OA when the tree cover threshold was 40%) and the OA when the tree cover threshold was determined by the optimal thresholds of tree cover from the ecological zones.

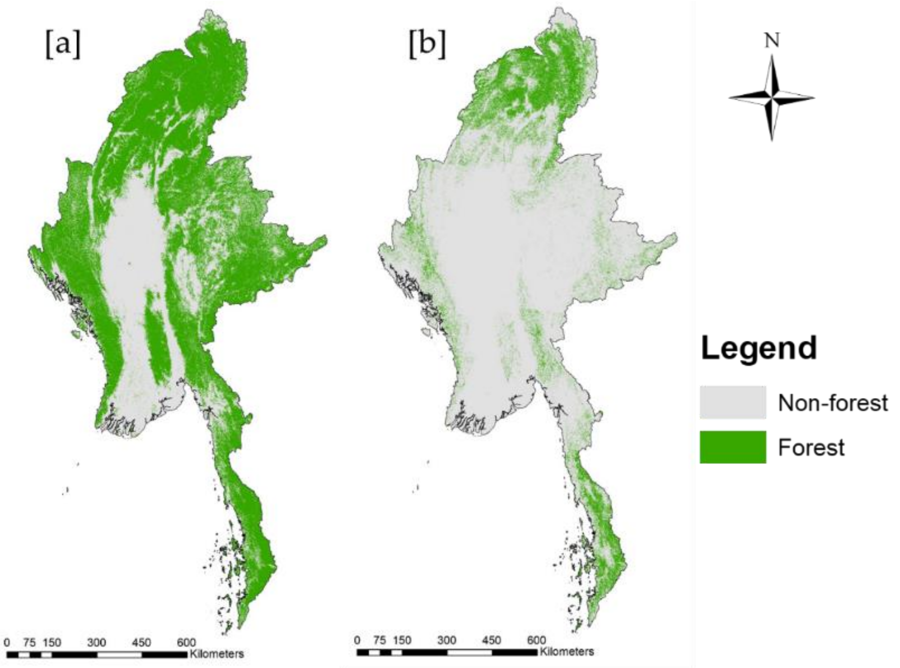


Figure 2.6. Forest cover maps for 2016 developed from the Global Forest Cover Database (GFCD) using original tree cover percent in 2000 [10] and (a) 40% tree cover threshold, or (b) 90% tree cover threshold.

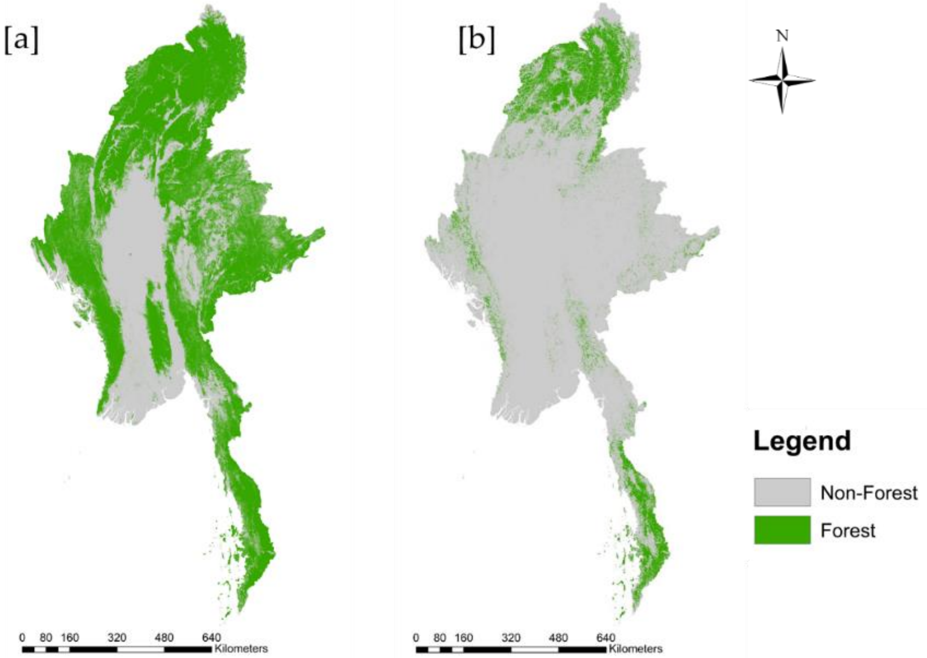


Figure 2.7. Forest cover maps for 2016 developed from the Global Forest Cover Database (GFCD) using average tree cover percent of neighboring pixels in 2000 [10] and (a) 40% tree cover threshold, or (b) 90% tree cover threshold.

When average tree cover percent was used, the results at a national scale showed similar results. When the tree cover threshold was uniquely determined, the highest OA was 77%. This was achieved when the tree cover threshold was 40%, as for the original percent tree cover and the lowest accuracy was found at 90% tree cover threshold. Forest cover maps at 40% and 90% tree cover threshold which have highest and lowest OAs were shown in Figure 2.7. When the tree cover threshold was determined by the optimal thresholds of tree cover from the ecological zones, the highest OA was 78.1%. There was no significant difference at the 0.05 confidence level between the highest OA when the tree cover threshold was uniquely determined and the OA when the tree cover threshold was determined by the optimal thresholds of tree cover from the ecological zones.

2.4. Discussion

The GFCD is a powerful dataset that provides data on tree cover, forest loss, and forest gain. However, to create a forest cover map from the GFCD, it is necessary to choose an appropriate tree cover threshold. Not surprisingly, the tree cover threshold affects the estimated forest cover (Figure 2.3). An arbitrary choice of tree cover threshold may yield an overestimation or underestimation of forest cover. Thus, appropriate determination of the threshold is of practical importance. Here, I investigated the accuracy of the GFCD across different ecological zones based on a country-scale evaluation of Myanmar.

I tested forest cover maps using original tree cover percent downloaded from the website of GFCD and average tree cover percent of neighboring pixels. In both cases, the results of OA, UA and PA showed similar trends in different ecological zones. In addition, the optimal threshold at a national scale was 40% for both cases and the highest OAs showed little difference. Therefore, neighboring pixels were not necessary for accurate forest cover mapping using the GFCD.

The results clearly showed that different tree cover thresholds were required to achieve the highest OA for different ecological zones. The OAs of ecological zones other than the tropical rainforest were highest when the tree cover threshold was less than 50%. However, an 80% tree cover threshold was required to achieve the highest OA in the tropical rainforest. Previous studies that used the GFCD have selected different thresholds. The studies in Cambodia used 30% as the threshold (Davis et al. 2015), while a study in Brazil demonstrated that a 95% threshold yielded the highest OA (McRoberts et al. 2016) and a 70% threshold had the highest OA in Gabon (Sannier et al. 2016). According to the Global Ecological Zones (Simons 2001), Cambodia is dominated by tropical dry forest and tropical moist deciduous forest, but Brazil and Gabon are dominated by tropical rainforest, although tropical moist deciduous forests are sub-dominant in Brazil. Because the results showed that a higher threshold is required for tropical rainforest, the differences in the thresholds among countries may be explained by the differences in their dominant ecological zones. In this study, a 40% tree cover threshold was optimal to get the highest overall accuracy in tropical moist deciduous forest. A case study of Gola National Park in Sierra Leone (Lui & Coomes 2015) used 50% tree cover threshold, where tropical moist deciduous forest is dominant, to achieve an accuracy of more than 90%. Therefore, this study generally confirms that different tree cover thresholds are necessary for different ecological zones, when creating forest cover maps using the GFCD.

While the results indicated that the best threshold to achieve the highest OA depended on the ecological zone, the result also showed that the threshold could be uniquely determined for the whole country. The optimal threshold for each ecological zone, except for tropical rainforest, was concentrated between 10% and 40%. In addition, the variations of the OA for each ecological zone, (except for tropical rainforest), when tree cover threshold was between 10% and 40%, were small. Thus, the effect of changing the threshold on the OA was limited for all ecological zones, except for tropical rainforest. The difference in optimal thresholds and the area ratio between the tropical rainforest and the other zones will substantially affect the optimal threshold at the national scale. In the case of Myanmar, tropical rainforests occupied only approximately 30% of the total area and the remainder was occupied by other ecological zones. Because most of the land was covered by ecological zones other than tropical rainforests, the OA could be uniquely determined over the whole country. However, the threshold may need to be determined by the ecological zone in regions, where tropical rainforests occupy more area than in Myanmar.

According to the FRA 2015 (FAO. 2014), forests covered approximately 42.92% of the total land area in Myanmar. Thus, the GFCD overestimated the forest cover even at a 40% tree cover threshold, which yielded the highest OA at national scale. As shown in Figures 2.4 and 2.5, when the OA was the highest with 76.1% at a 40% tree cover threshold at national scale, the UA of forest with 66.1% had a lower value than the PA of forest with 89.5%. This trend reflects an overestimation of the forest class. The overestimation of forest was observed, when the tree cover threshold was between 10% and 70%. Because a threshold between 10% and 50% is commonly applied (e.g., Davis et al. 2015; Peter Potapov et al. 2017; Lonn et al. 2018; Lonn et al. 2019), the overestimation of forest area when the GFCD is used needs to be considered. The other reason for the overestimation was linked to the definition of forest. In this study, the forest was defined based on a visual interpretation of tree crowns. In the case of the forest cover reported by the FRA 2015 (FAO. 2014), “forest does not include land that is predominantly under agricultural or urban land use” (MacDicken 2012, p. 3). Thus, land covers such as fruit tree plantations and oil palm plantations are not included in the forest cover reported by the FRA 2015 (MacDicken 2012). However, because the tree cover in the GFCD does not take into account the land use of forests, forest areas derived from the GFCD will be overestimated.

In this study, I evaluated the effect of different tree cover thresholds on the accuracy of forest cover maps from the GFCD and the importance of tree cover thresholds in five ecological zones, distributed across Myanmar. The results could be applied to the other regions having the same ecological zones as Myanmar, especially within the tropics. Because Myanmar is located in a tropical region, this study focused on only a limited number of ecological zones. Further study focusing on temperate and boreal regions is also required to refine this method. Clearly, direct comparison among different tropical countries would also be worthwhile.

2.5. Conclusions

Tree cover threshold is one of the important indicators used to create forest cover maps from remote sensing data. This study evaluated the effect of changing tree cover thresholds on the accuracy of forest cover maps derived from the GFCD and the importance of tree cover thresholds for creating forest cover maps from the GFCD for large-area monitoring. It is clearly showed that OA of forest cover maps increased or decreased in accordance with the change of tree cover thresholds for nine different thresholds from 10% to 90% and that the range of effect of changing tree cover threshold on the accuracy was different in five ecological zones. Because the highest OA was found at various thresholds for different ecological zones, different optimal tree cover thresholds should be selected to achieve the highest OA. However, in the unique case of Myanmar, it was able to determine the threshold over the whole country. I concluded that the threshold of tree cover for creating a forest cover map from the GFCD at national scale should be determined according to the areal ratio of ecological zones. The results from this study suggest a need to consider tree cover threshold, when creating forest cover maps from the GFCD, especially in regions where tropical rainforest is dominant. Because this study focused on tropical forest regions, further study is needed in temperate and boreal regions. Clearly, comparative study of different tropical countries is also necessary.

Appendix I

Nine forest cover maps in 2016 and the results of accuracies using (i) tree cover percent in original pixel (later: one pixel) and (ii) average tree cover percent in 3 x 3 neighboring pixels (later: 3 x 3 pixels)

SMS = Subtropical Mountain System

TDF = Tropical Dry Forest

TMDF = Tropical Moist Deciduous Forest

TMS = Tropical Mountain System

TRF = Tropical Rain Forest

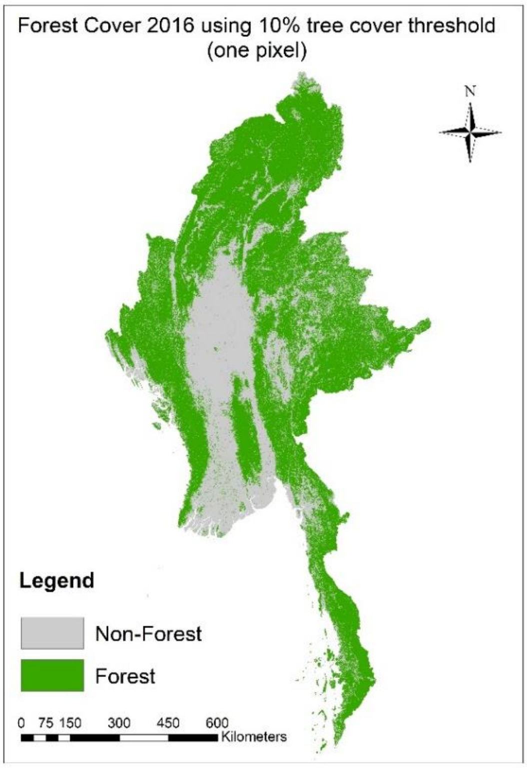
OA = Overall Accuracy

UA (F) = User's Accuracy (Forest)

PA (F) = Producer's Accuracy (Forest)

UA (NF) = User's Accuracy (Non-forest)

PA (NF) = Producer's Accuracy (Non-forest)



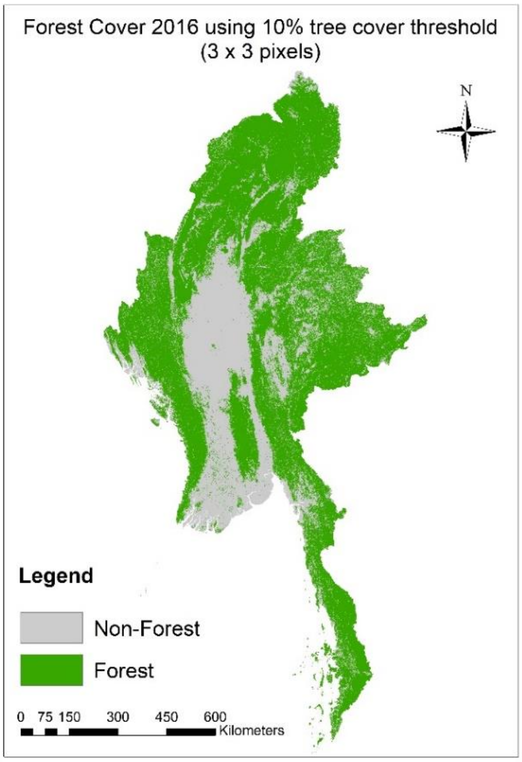
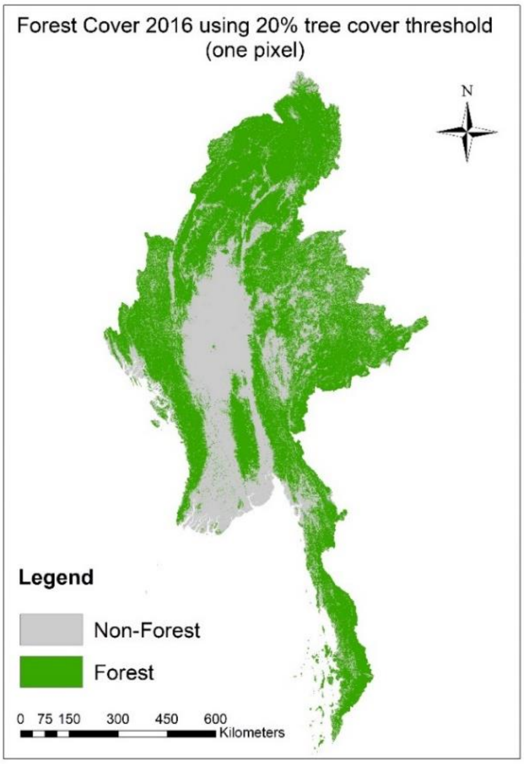


Figure S2.1: Forest cover maps in 2016 using tree cover percent in one pixel and (3x3) pixels at 10% tree cover threshold

Table S2.1: Accuracies of forest cover maps in 2016 using one pixel and (3x3) pixels at 10% tree cover threshold

10% tree cover threshold (one pixel)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	73.4	83.0	94.9	70.2	74.9	68.1
UA(F)	62.5	65.9	100.0	62.5	69.5	56.4
PA(F)	93.5	90.0	41.7	93.6	95.6	95.1
UA(NF)	92.5	94.9	94.7	89.4	90.6	93.7
PA(NF)	58.7	80.0	100.0	48.9	50.3	49.7
10% tree cover threshold (3 x 3 pixels)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	71.7	76.0	94.9	68.3	73.1	67.1
UA(F)	60.6	55.8	100.0	60.8	67.4	55.6
PA(F)	94.5	96.7	41.7	94.0	97.2	95.6
UA(NF)	93.2	97.9	94.7	89.2	93.2	94.0
PA(NF)	54.9	67.1	100.0	44.9	44.4	47.7



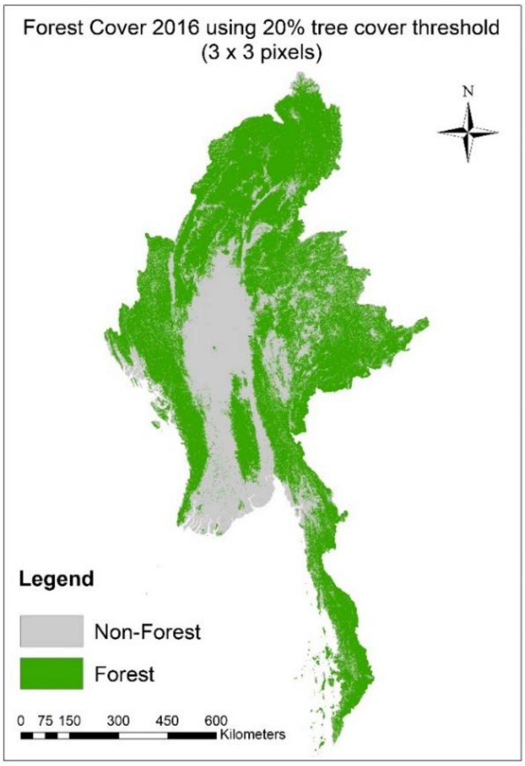


Figure S2.2: Forest cover maps in 2016 using tree cover percent in one pixel and (3x3) pixels at 20% tree cover threshold

Table S2.2: Accuracies of forest cover maps in 2016 using one pixel and (3x3) pixels at 20% tree cover threshold

20% tree cover threshold (one pixel)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	75.1	85.0	94.9	72.5	77.2	68.9
UA(F)	64.2	69.2	100.0	64.8	71.8	57.1
PA(F)	92.9	90.0	41.7	92.4	95.6	94.6
UA(NF)	92.2	95.1	94.7	88.8	91.4	93.3
PA(NF)	61.9	82.9	100.0	54.3	55.6	51.3
20% tree cover threshold (3 x 3 pixels)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	74.2	85.0	94.9	70.6	76.6	68.5
UA(F)	63.2	69.2	100.0	62.9	70.9	56.7
PA(F)	93.8	90.0	41.7	93.2	96.7	95.6
UA(NF)	92.9	95.1	94.7	89.0	93.1	94.3
PA(NF)	59.8	82.9	100.0	50.0	52.9	50.0

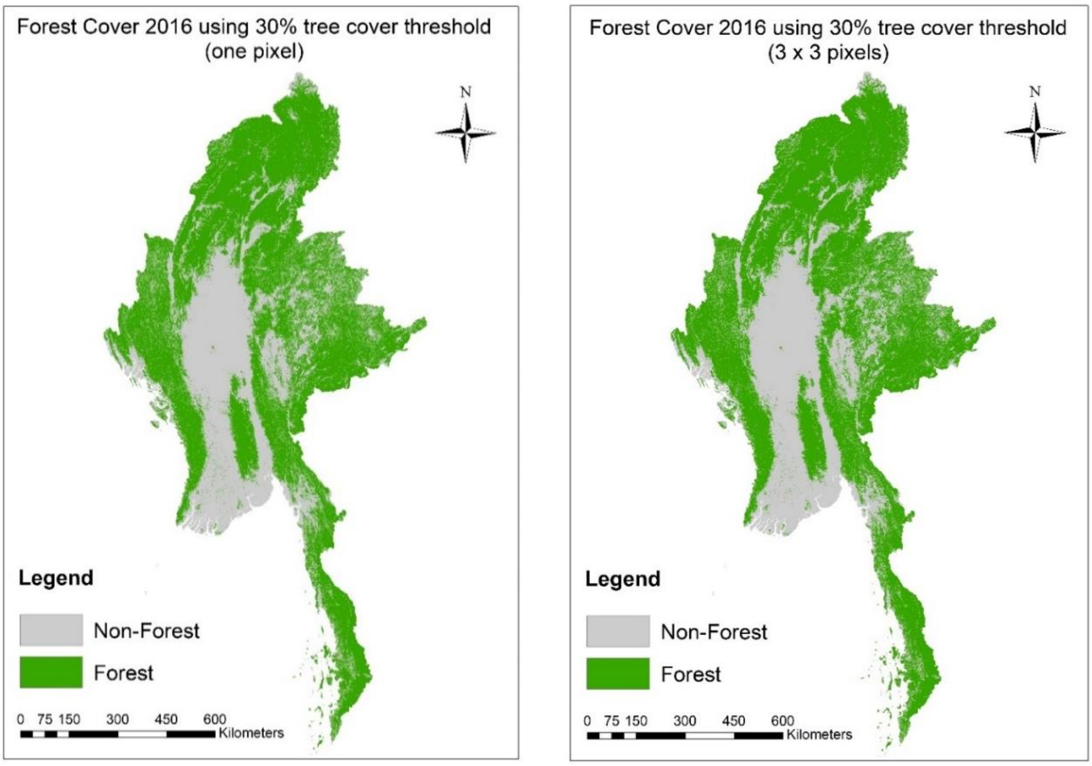


Figure S2.3: Forest cover maps in 2016 using tree cover percent in one pixel and (3x3) pixels at 30% tree cover threshold

Table S2.3: Accuracies of forest cover maps in 2016 using one pixel and (3x3) pixels at 30% tree cover threshold

30% tree cover threshold (one pixel)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	75.9	84.0	94.9	73.8	78.4	70.1
UA(F)	65.5	69.4	100.0	66.4	73.4	58.3
PA(F)	91.4	83.3	41.7	91.2	94.5	93.1
UA(NF)	91.1	92.2	94.7	87.9	90.1	92.0
PA(NF)	64.5	84.3	100.0	58.0	59.5	54.4
30% tree cover threshold (3 x 3 pixels)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	75.8	88.0	94.2	73.4	77.8	69.3
UA(F)	65.1	75.0	100.0	65.7	73.0	57.4
PA(F)	92.3	90.0	33.3	92.4	93.9	94.6
UA(NF)	91.8	95.3	94.0	89.1	89.1	93.4
PA(NF)	63.6	87.1	100.0	56.2	58.8	52.0

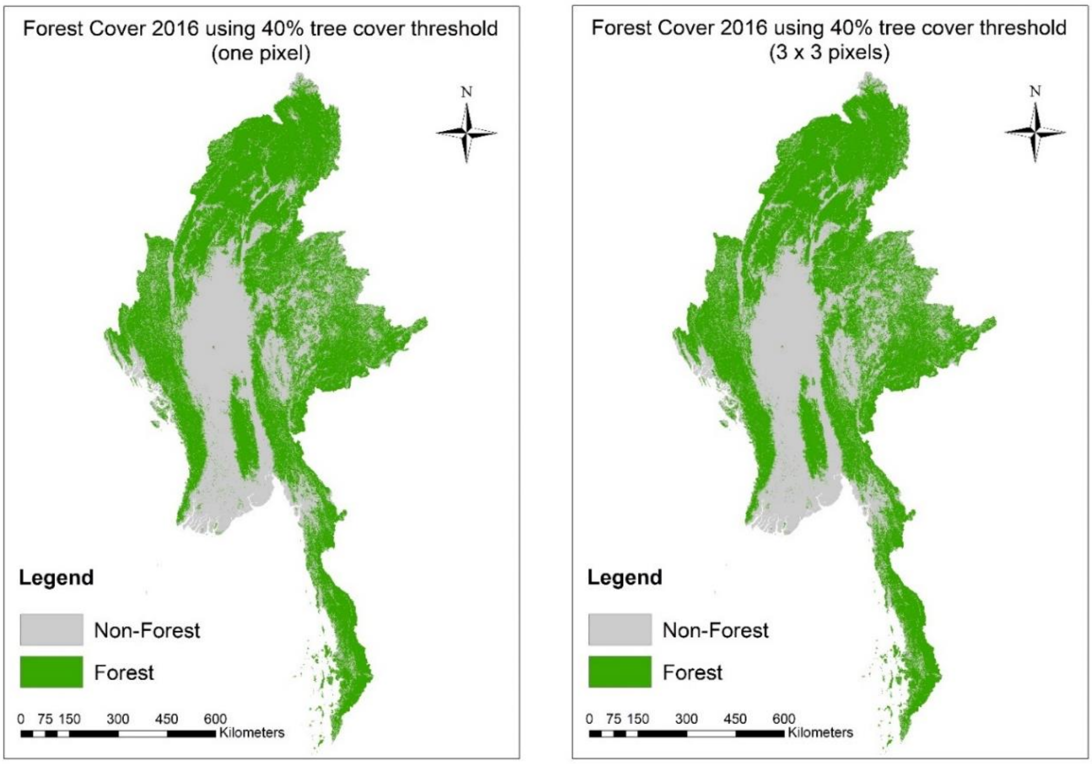
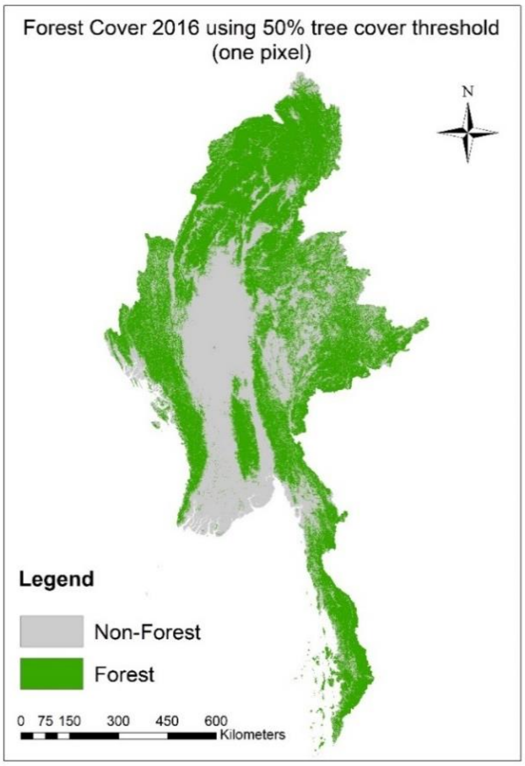


Figure S2.4: Forest cover maps in 2016 using tree cover percent in one pixel and (3x3) pixels at 40% tree cover threshold

Table S2.4: Accuracies of forest cover maps in 2016 using one pixel and (3x3) pixels at 40% tree cover threshold

40% tree cover threshold (one pixel)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	76.1	83.0	94.2	74.6	78.1	70.1
UA(F)	66.1	68.6	100.0	67.7	74.3	58.3
PA(F)	89.5	80.0	33.3	89.2	91.2	93.1
UA(NF)	89.6	90.8	94.0	86.2	85.7	92.0
PA(NF)	66.3	84.3	100.0	61.2	62.7	54.4
40% tree cover threshold (3 x 3 pixel)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	77.0	90.0	94.2	75.0	79.3	70.3
UA(F)	67.0	88.5	100.0	67.9	75.0	58.5
PA(F)	90.1	76.7	33.3	90.0	92.8	93.1
UA(NF)	90.3	90.5	94.0	87.1	88.2	92.1
PA(NF)	67.4	95.7	100.0	61.2	63.4	54.7



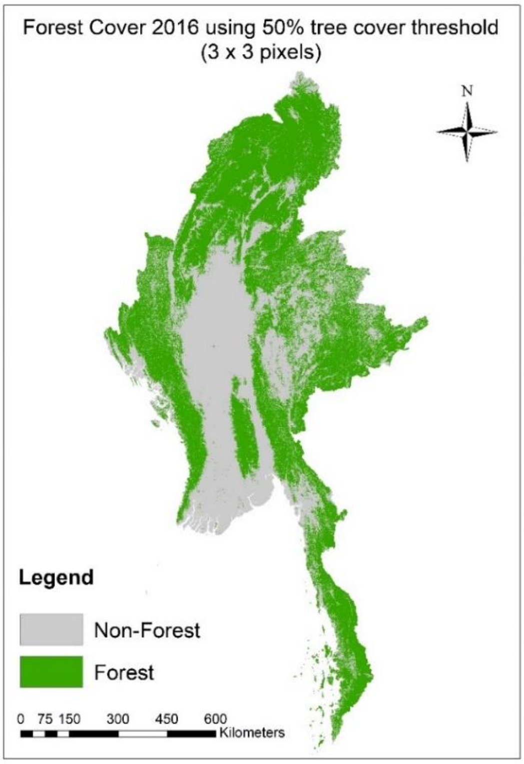
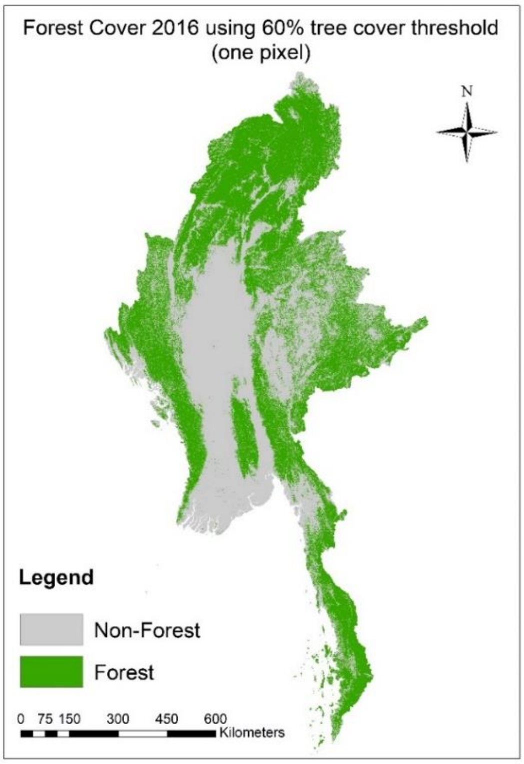


Figure S2.5: Forest cover maps in 2016 using tree cover percent in one pixel and (3x3) pixels at 50% tree cover threshold

Table S2.5: Accuracies of forest cover maps in 2016 using one pixel and (3x3) pixels at 50% tree cover threshold

50% tree cover threshold (one pixel)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	75.9	84.0	94.2	73.4	77.8	70.5
UA(F)	66.8	73.3	100.0	68.1	75.6	58.8
PA(F)	85.5	73.3	33.3	83.3	87.3	91.7
UA(NF)	86.6	88.6	94.0	80.9	81.6	90.8
PA(NF)	68.8	88.6	100.0	64.5	66.7	56.0
50% tree cover threshold (3 x 3 pixels)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	76.5	87.0	94.2	74.4	78.7	70.3
UA(F)	67.8	87.0	100.0	69.0	77.2	58.7
PA(F)	85.0	66.7	33.3	84.1	86.2	90.7
UA(NF)	86.4	87.0	94.0	81.9	81.1	89.8
PA(NF)	70.3	95.7	100.0	65.6	69.9	56.4



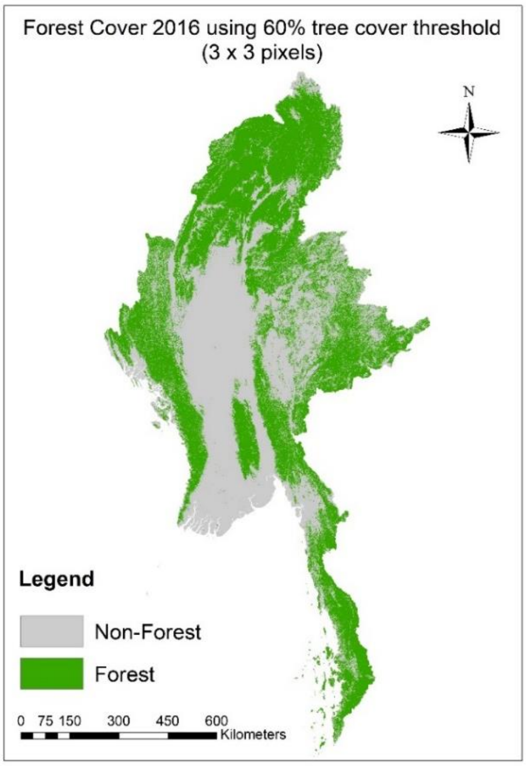


Figure S2.6: Forest cover maps in 2016 using tree cover percent in one pixel and (3x3) pixels at 60% tree cover threshold

Table S2.6: Accuracies of forest cover maps in 2016 using one pixel and (3x3) pixels at 60% tree cover threshold

60% tree cover threshold (one pixel)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	74.8	82.0	93.4	71.7	76.6	70.3
UA(F)	67.5	77.3	100.0	68.5	77.2	59.3
PA(F)	78.3	56.7	25.0	75.3	80.7	86.3
UA(NF)	81.9	83.3	93.3	75.3	75.9	86.3
PA(NF)	72.2	92.9	100.0	68.5	71.9	59.4
60% tree cover threshold (3 x 3 pixels)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	76.8	87.0	94.2	74.6	78.1	71.5
UA(F)	69.8	94.7	100.0	71.3	80.0	60.2
PA(F)	79.9	60.0	33.3	78.1	79.6	88.2
UA(NF)	83.5	85.2	94.0	78.2	76.0	88.2
PA(NF)	74.5	98.6	100.0	71.4	76.5	60.1

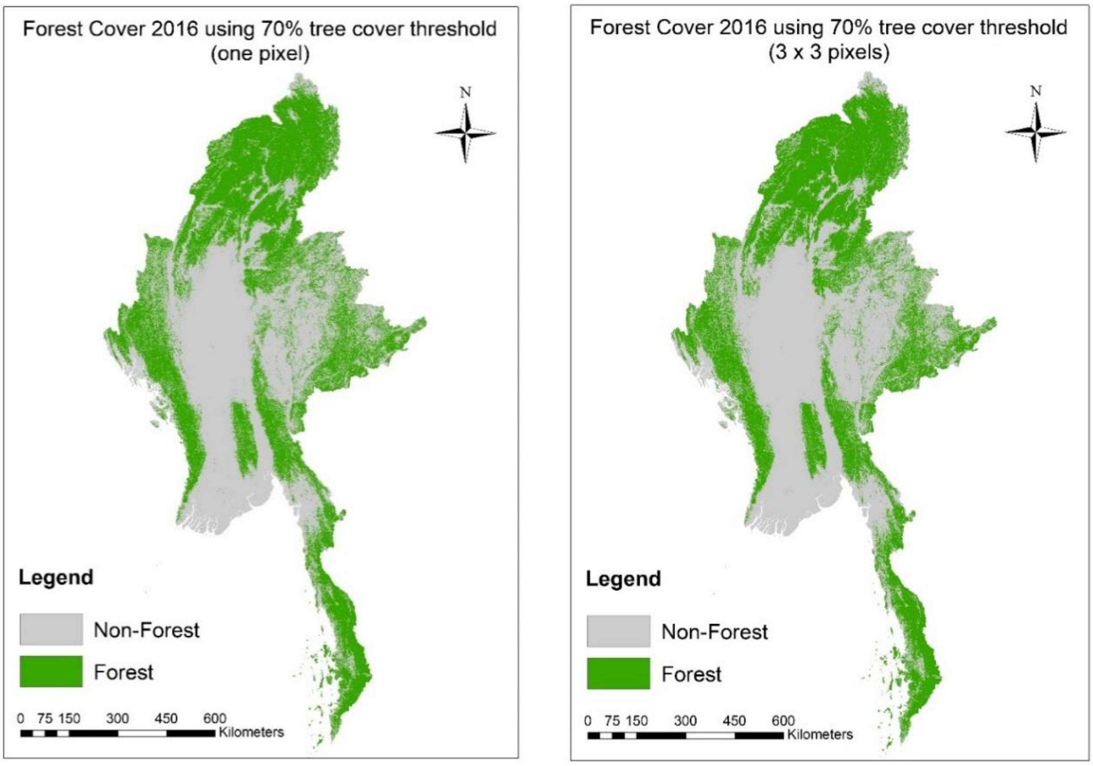


Figure S2.7: Forest cover maps in 2016 using tree cover percent in one pixel and (3x3) pixels at 70% tree cover threshold

Table S2.7: Accuracies of forest cover maps in 2016 using one pixel and (3x3) pixels at 70% tree cover threshold

70% tree cover threshold (one pixel)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	74.4	84.0	92.7	70.6	74.6	71.5
UA(F)	69.1	88.9	100.0	70.9	78.2	60.8
PA(F)	71.7	53.3	16.7	64.9	73.5	84.3
UA(NF)	78.6	82.9	92.6	70.4	70.7	85.4
PA(NF)	76.5	97.1	100.0	75.7	75.8	62.8
70% tree cover threshold (3 x 3 pixels)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	74.9	85.0	92.7	69.6	75.1	73.5
UA(F)	70.6	94.1	100.0	70.6	81.4	62.9
PA(F)	69.9	53.3	16.7	62.2	70.2	84.8
UA(NF)	78.0	83.1	92.6	69.0	69.7	86.3
PA(NF)	78.6	98.6	100.0	76.4	81.0	65.8

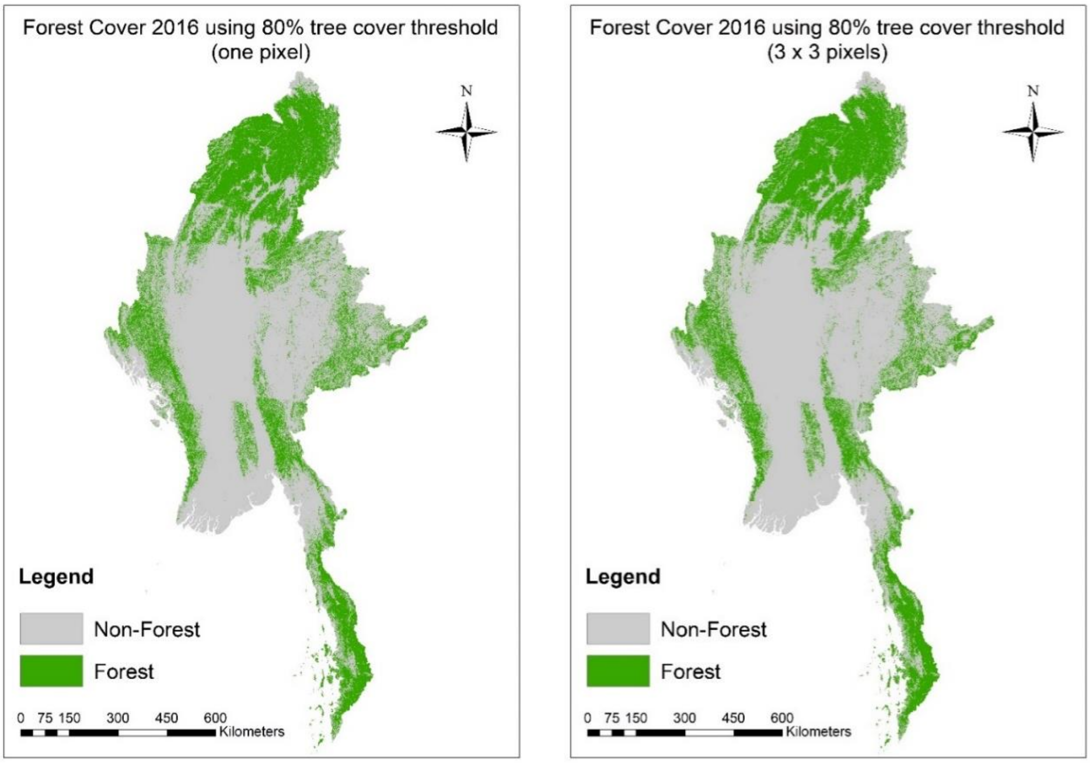
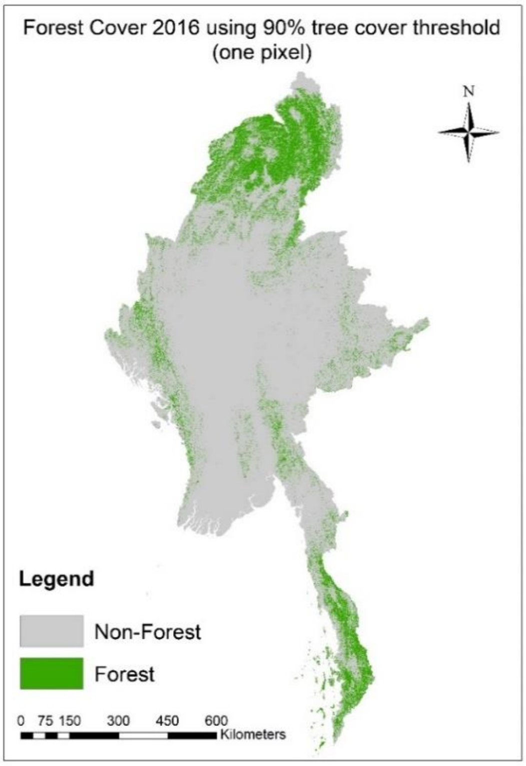


Figure S2.8: Forest cover maps in 2016 using tree cover percent in one pixel and (3x3) pixels at 80% tree cover threshold

Table S2.8: Accuracies of forest cover maps in 2016 using one pixel and (3x3) pixels at 80% tree cover threshold

80% tree cover threshold (one pixel)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	73.3	82.0	92.0	67.6	71.6	73.7
UA(F)	73.6	92.9	100.0	75.3	83.1	65.8
PA(F)	57.7	43.3	8.3	47.4	59.7	73.5
UA(NF)	73.2	80.2	91.9	64.2	64.2	80.3
PA(NF)	84.8	98.6	100.0	85.9	85.6	73.8
80% tree cover threshold (3 x 3 pixels)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	73.4	82.0	92.0	67.2	73.7	73.1
UA(F)	74.8	92.9	100.0	77.5	86.6	65.2
PA(F)	56.3	43.3	8.3	43.8	60.8	72.5
UA(NF)	72.8	80.2	91.9	63.4	65.7	79.6
PA(NF)	86.0	98.6	100.0	88.4	88.9	73.5



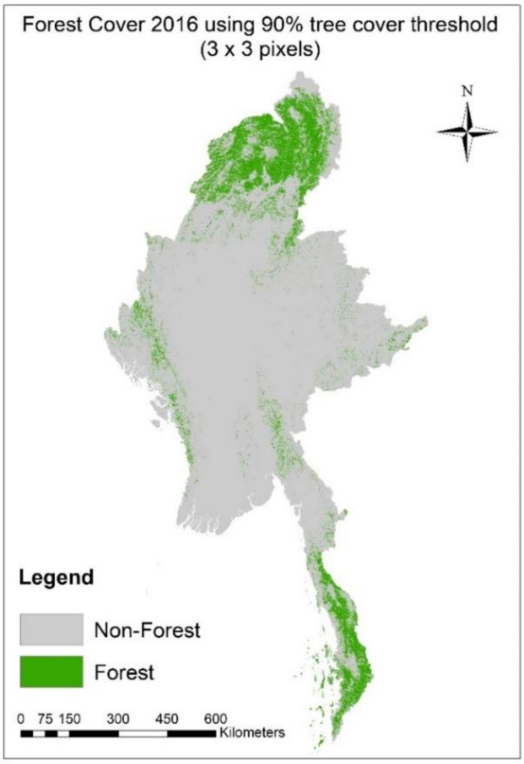


Figure S2.9: Forest cover maps in 2016 using tree cover percent in one pixel and (3x3) pixels at 90% tree cover threshold

Table S2.9: Accuracies of forest cover maps in 2016 using one pixel and (3x3) pixels at 90% tree cover threshold

90% tree cover threshold (one pixel)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	65.5	75.0	91.2	58.4	60.2	67.5
UA(F)	75.0	85.7	0.0	80.8	85.3	66.4
PA(F)	27.9	20.0	0.0	16.7	32.0	40.7
UA(NF)	63.7	74.2	91.2	56.0	53.8	67.9
PA(NF)	93.2	98.6	100.0	96.4	93.5	85.9
90% tree cover threshold (3 x 3 pixels)						
	National	**SMS**	**TDF**	**TMDF**	**TMS**	**TRF**
OA	65.4	75.0	91.2	57.5	56.6	70.7
UA(F)	77.1	100.0	0.0	84.6	84.6	71.1
PA(F)	26.3	16.7	0.0	13.1	24.3	47.1
UA(NF)	63.5	73.7	91.2	55.3	51.4	70.6
PA (NF)	94.3	100.0	100.0	97.8	94.8	86.9

Chapter 3

A country-scale analysis revealed effective land-use zoning affecting forest cover changes in Myanmar

3.1. Introduction

The extent of the world's forest areas continues to decrease (FAO. 2016a). Rapid deforestation in the tropics is of special concern globally (DeFries et al. 2005; Heino et al. 2015; Sloan & Sayer 2015) because it represents one tenth of anthropogenic carbon emissions (Bebber & Butt 2017) and negatively impacts on biodiversity (Brooks et al. 2002; Hughes 2017). Land-use zoning, which segments the landscape into units where different rules and regulations are applied for land use and land management, is a traditionally implemented approach to reduce deforestation.

Permanent forest land is a kind of land-use zonings and is legally recognized around the world as a tool to keep forest areas in the long-term. According to the Global Forest Resources Assessment (FRA) (2015), about 2.2 billion ha of forests are permanent forest land and half of these are found in tropical regions (FAO. 2016a). However, there is little research on the effectiveness of the permanent forest land. As a limited study, Bruggeman et al (2015) evaluated the effectiveness of the permanent forest land in a region in Cameroon (Bruggeman et al. 2015). However, the effectiveness of permanent forest land for forest conservation at a country-scale is still unclear. In addition, within permanent forest land, different forest resource use restrictions can be applied by categorizing the forest lands into different zones based on different purposes such as forest protection and forest production. Thus, forest lands can be allocated to land-use zoning with various levels of forest resource restriction. Since forest conservation performance may differ between land-use zonings, it is crucial to understand the effectiveness of each zoning approach on combating deforestation with empirical evidence. Because forest conservation effectiveness of permanent forest land may vary depending on land-use zoning, it is useful to provide policy makers with evidence regarding which land-use zonings are most effective for forest conservation.

Previous studies evaluating the effectiveness of land-use zoning for forest conservation often focused on protected areas (PAs). The studies showed that PAs are effective for reducing deforestation (Andam et al. 2008; Andam et al. 2013; Brun et al. 2015; Cuenca et al. 2016; Gray et al. 2016; Miranda et al. 2016; Oldekop et al. 2016; Bowker et al. 2017; Apan et al. 2017; Maharaj et al. 2019). However, the effectiveness may vary across landscapes, locations, types, and enforcement (Joppa & Pfaff 2011; Herrera et al. 2019). In addition, PAs sometimes increase deforestation in areas outside PAs boundaries (i.e. leakage), because deforestation is displaced from inside the PAs boundary to outside (Andam et al. 2008; Fuller et al. 2019). Some studies focusing on land-use zonings other than PAs also showed similar results. For example, the studies have shown that community forests (Santika et al. 2017; Lonn et al. 2019; Santika et al. 2019; Oldekop et al. 2019) and production forests (Oliveira et al. 2007; Gaveau et al. 2013; Bruggeman et al. 2015; Bruggeman et al. 2018), which are types of land-use zoning, are effective in reducing deforestation. However, the other studies in Madagascar (Rasolofoson et al. 2015) and Laos (Kukkonen & Tammi 2019) revealed that community forests and production forests, respectively, were ineffective for reducing deforestation. These studies into PAs, community forests, and production forests imply that the effectiveness of land-use zoning may vary across locations, and may have spill-over effects as well. Thus, there is a need to evaluate the effectiveness of land-use zonings in different locations.

Myanmar is a tropical country in Southeast Asia with high forest cover (Yang et al. 2019). However, based on annual net forest cover loss from 2010–2015, Myanmar has the third highest rate of deforestation in the world (FAO. 2016a), although forest conservation efforts have increased over the past 20 years (Wang & Myint 2016). The high deforestation rate in Myanmar is of global concern (Wang & Myint 2016) and challenges the effectiveness of Myanmar's forest conservation policy. The permanent forest estate (PFE), which is state-owned permanent forest land, covered about 30% of Myanmar as of August 2019. The Myanmar government plans to expand the PFE to 40% of the total land area by 2030 according to Myanmar's Intended Nationally Determined Contribution (INDC) (The Government of Myanmar 2015). However, the forest conservation effectiveness of PFE in Myanmar is still unclear, as is the effectiveness of each land-use zoning within the PFE.

In this study, I evaluated the forest conservation effectiveness of the PFE in Myanmar using country-scale datasets. The specific objectives of the study were: (1) to evaluate the forest conservation effectiveness of the PFE compared with non-PFE areas, and (2) to evaluate the forest conservation effectiveness of each of land-use zonings in the PFE compared with non-PFE areas.

3.2. Study area

Myanmar is a country with tropical climate located in Southeast Asia, bordering Thailand, Bangladesh, China, India and Laos. It lies between latitudes 9˚32′–28˚31′N and longitude 92˚10′–101˚11′E. The total area and population are 676,577 km^2 and 54.3 million, respectively (DoP. 2018). The elevation ranges from sea level to more than 5,000 m. It has a typical monsoon climate and the annual average temperature is about 27.4°C (Wang & Myint 2016). The precipitation varies around the country. The annual rainfall reaches 6,000 mm in some places and is less than 500 mm in other parts of the country. Myanmar has unique biodiversity (Reddy et al. 2019) and is third largest forested country in the Greater Mekong Sub-region. In 2015, 42.92% of the country's total land area was covered by forests (FAO. 2014). It has many different forest types ranging from alpine to mangrove (Leimgruber et al. 2005).

In Myanmar, forests are located in areas of PFE and non-PFE. In standard operation procedures of constitution of PFE, while given areas are proposed to be constituted as PFE, such intention has to be declared to the people who are living in or near the proposed areas. Forest settlement officers assigned to constitute PFE are responsible for inquiring and determining the rights of the people who are affected on the proposed PFE land. For example, when there are farmlands within the proposed areas, such areas can continue with farming activities for a 30-year period. Forest department officers usually patrol within the PFE but they sometimes also patrol in non-PFE areas.

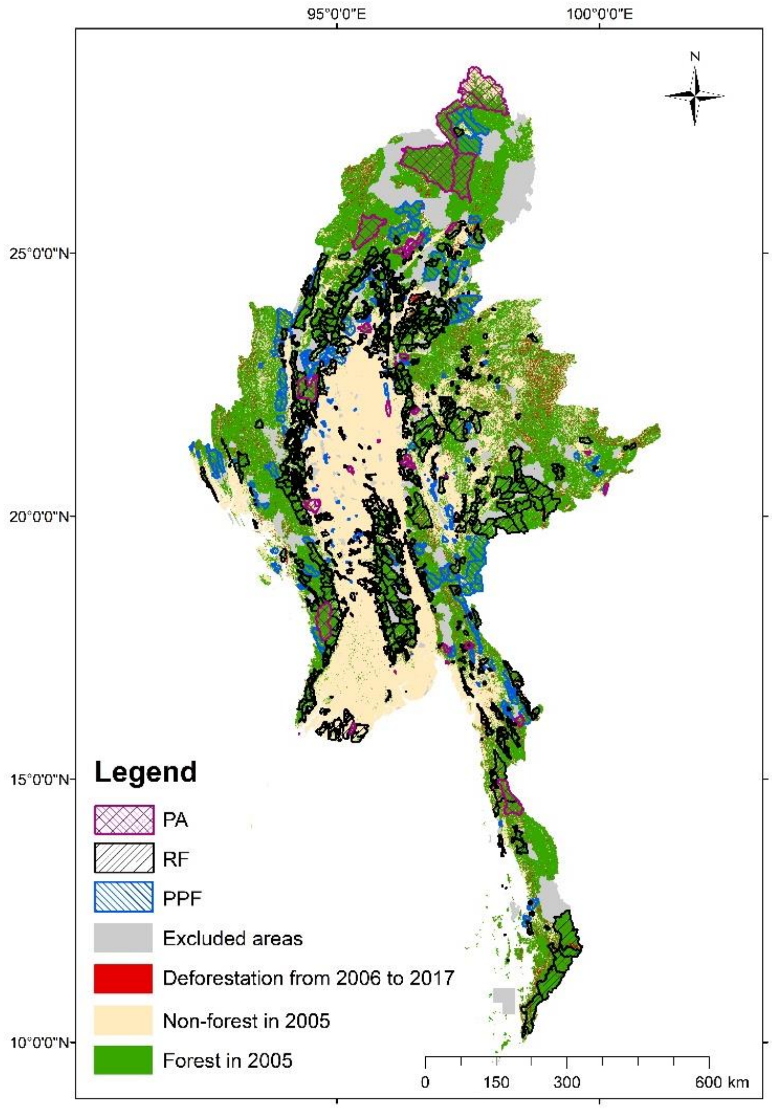


Figure 3.1. Location of reserved forest (RF), protected public forest (PPF), protected areas (PAs), forest cover in 2005 and forest loss between 2001 and 2016. Forest cover extent and loss layer were downloaded from Global Forest Change website (Hansen et al. 2013b).

PFEs are classified into reserved forest (RF), protected public forest (PPF) and protected areas (PAs). RF and PPF aim to conserve environmental values and to maintain a sustainable yield of forest products. They are managed under Forest Law (1992) and have similar legal status. PAs were designated to conserve biodiversity and environment, and are managed under The Protection of Wildlife and Protected Area Law (1994). RF, PPF and PAs are differently managed. Within the RF and PPF, logging activities are being conducted with a 30-year felling cycle under the Myanmar Selection System (MSS). Within RF and PPF, in addition to logging, extraction of forest produce not for commercial scale is allowed in case the extraction amount does not exceed the stipulated amount. While the management of RF and PPF area similar, in general, RF is the priority area for timber production and PPF has lower timber priority and is mainly allocated to local use. In PAs, not only commercial logging but also any extraction of forest products including fuelwood is prohibited. In addition, within PAs, protection of endangered wildlife species is prioritized.

Non-PFEs are the areas outside the PFE and forests in non-PFE are called "unclassified forests". Although forests in non-PFE could be managed by Forest Law (1992), at present they are managed by Ministry of Agriculture, Livestock and Irrigation under the Vacant, Fallow and Virgin Lands Management Law (VFVLM Law) (2012). Non-PFE can be used to establish tree plantations by the government, private companies or organizations including local communities with the permission of the government. According to VFVLM Law, forests in non-PFE come under the category of virgin land and there is potential to conduct other governmental activities such as agriculture, mining, infrastructure development and dam construction, to fulfil government targets.

In this study, I focused on the PFEs established in or before 2005. I used information and boundaries for the PFEs obtained from the Forest Department of Myanmar for selecting the PFEs. Because there was missing information for some PFEs in relation to the year they were established, I excluded these PFEs from the analysis. In addition, there were some PFEs, which were (1) for lake or marine conservation, and (2) not formally authorized. I also excluded those PFEs from the analysis. In total, 996 PFEs, approximately 75% of the total PFEs established before July 2017, were included in final data sets (Figure 3.1).

3.3. Methodology

The areas subject to specific land-use zoning are not randomly distributed but are often distributed in locations with lower or higher deforestation pressure. Because of the non-random distribution of the land use zoning, results may be biased (i.e. over- or under-estimation of the forest conservation effectiveness) if a conventional method is used, which simply compares land-use zoning (Joppa et al. 2008; Andam et al. 2008; Joppa & Pfaff 2009; Joppa & Pfaff 2010; Cuenca et al. 2016). Thus, to reliably assess land-use zonings, propensity score matching (PSM) was used. PSM finds the observed pairs between treated and untreated based on the probability that the observation is assigned to be treated.

3.3.1 Treatment and control variables

First, I evaluated the forest conservation effectiveness of PFE compared with non-PFE, defining PFE and non-PFE as treatment and control, respectively. Then, I evaluated the effectiveness of each of land-use zonings comprising PFE (i.e. RF, PPF, and PAs) compared with non-PFE. In this case, I defined RF, PPF and PAs as separate treatments. Non-PFE was defined as the control. I also measured the spill-over around the PFE. In this case, I defined non-PFEs that were located within 5 km of the boundary of PFE as the treatment. The control group comprised non-PFEs that were located more than 5 km from PFEs. In this study, I didn’t consider spill-over by land-use pressures from non-PFE to inside PFE because a previous study in Myanmar revealed that deforestation due to spill-over from outside to inside PA was much gentler than the deforestation due to spill-over from inside to outside (Htun et al. 2010).

3.3.2 Outcome variables

The impacts of PFEs and each land-use zone on deforestation between 2006 and 2017 were assessed. The Global Forest Change dataset (GFCD) was used to calculate deforestation between 2006 and 2017. The GFCD consists of (i) tree cover extent in 2000 representing 0%–100% tree cover in each pixel, (ii) annual loss layer and (iii) gain layer (Hansen et al. 2013a) at a 30 m spatial resolution. All layers were downloaded from the GFCD website (Hansen et al. 2013b) and clipped to the country boundary of Myanmar.

Myanmar has adopted FAO’s forest definition, “Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ, and it does not include land that is predominantly under agriculture or urban land use” (MacDicken 2012, page No.3). In GFCD, there is no information about forest cover, and tree cover 2000 is defined any vegetation which is taller than 5 m (Hansen et al. 2013a). The practical way is to define forest using tree cover threshold. My previous study investigated the accuracy of GFCD using different tree cover threshold, and the results clearly showed that 40%

tree cover threshold is the optimal threshold to get the highest overall accuracy in defining forest and non-forest (Lwin et al. 2019).

Therefore, I defined forest in 2000 where a pixel had at least 40% tree cover using the tree cover extent of the GFCD (Lwin et al. 2019). Then, “forest in 2005” was defined where the forest pixels in 2000 did not overlap with forest loss between 2001 and 2005. “Deforestation” was defined when the forest pixels in 2005 overlapped with forest loss from 2006 to 2017. “No deforestation” was defined when forest pixels in 2005 did not overlap with forest loss from 2006 to 2017. I ignored forest gain when “forest in 2005”, “deforestation” and “no deforestation” were defined. This is because the forest gain layer was not calculated on an annual basis. I used the “deforestation” and “no deforestation” as outcome variables. Thus, the outcome variable was binary (1 if forest in 2005 was deforested between 2006 and 2017, 0 if forest in 2005 was not deforested between 2006 and 2017). Pixels of 30 m were the unit of the analysis.

3.3.3 Confounding variables

Confounding variables, which might affect both selection of the location of PFEs and likelihood of deforestation, were chosen based on previous studies (Htun et al. 2010; Mon et al. 2012; Lonn et al. 2019) and data availability. The variables included elevation, slope, distance to the nearest road, distance to the nearest river, distance to the nearest railway, distance to the nearest town, and population density. ASTER GDEM, which is a 30-m resolution DEM, obtained from USGS archives (U.S. Geological Survey 2019) was used as elevation data. The slope was also generated from ASTER GDEM. The location of roads, rivers, railways and towns were downloaded from the Myanmar Information Management Unit (MIMU) (United Nations Resident and Humanitarian Coordinator. 2007). Population density at the township level was also used as a confounding variable. The layer for the township boundaries including the data for the population for each township was downloaded from the Department of Population, Myanmar (DoP. 2018). The population density at township level was calculated by dividing population by township area.

3.3.4 Analysis

In this study, I conducted the analysis using a sampling strategy, because an analysis using all pixels may have overestimated the significance of the estimate. In each analysis, I randomly selected one million forest pixels in 2005 (Table 3.1). PSM using the nearest neighbor approach with a caliper was applied. I applied the caliper, which is the distance between matched observations for each land characteristic (Andam et al. 2013), because it reduced the chance of a poor quality of balance in matching without the caliper (Lunt 2014). Based on deforestation in matched observations between the treatment and control group, I estimated the average treatment effect on the treated (ATT), which is the difference of the probability of the treated group being deforested (Kere et al. 2017), using regression. The "MatchIt" package of R version 3.5.1 to conduct PSM was applied (Ho et al. 2011; R Core Team 2018).

Table 3.1. Number of treated and control forest pixels in matching

Analysis	**Treatment**	**Treated pixels**	**Control**	**Control Pixels**	**Matched pairs**
PFE vs Non-PFE	PFEs before 2005	375,474	Non-PFE	624,526	375,474
RF vs Non-PFE	RF before 2005	274,724	Non-PFE	725,276	274,724
PPF vs Non-PFE	PPF before 2005	115,504	Non-PFE	884,496	115,504
PAs vs Non-PFE	PAs before 2005	91,663	Non-PFE	908,337	77,873
Spill-over	Non-PFE near PFE, within 5 km buffer	292,078	Non-PFE beyond 5 km buffer	707,922	273,989

3.4. Results

3.4.1 Deforestation from 2006 to 2017

Table 3.2 represents deforestation calculated from GFCD in the study area, which is the PFEs established in or before 2005, and non-PFE. From 2006 to 2017, there was about 24,389 km^2 of deforestation, which represented 6.58% of total forest area in 2005 (Table 3.2). Deforestation from 2006 to 2017 in PFE and non-PFE was about 5,764 km^2 and 18,625 km^2, respectively, representing 4.12% and 8.08% of the forests in 2005. RF had the highest deforestation rate and PAs had the lowest among land-use zonings in the PFE. Deforestation rates for RF, PPF and PAs were 4.77%, 4.43% and 1.19%, respectively. Before matching, PFE had a 3.95% lower deforestation than non-PFE. RF, PPF and PAs had 3.31%, 3.65% and 6.89% lower deforestation than non-PFE, respectively.

Table 3.2. Deforestation from 2006 to 2017 calculated from the GFCD in the study area

	Total area (km^2)	Forest area in 2005 (km^2)	Forest area in 2017 (km^2)	Deforestation (2006 – 2017)	
				Area (km^2)	(%)
PFE established in or before 2005	174,033	139,822	134,058	5,764	4.12
Non-PFE	439,830	230,621	211,997	18,624	8.08
RF before 2005	111,773	87,493	83,320	4,173	4.77
PPF before 2005	35,406	29,869	28,546	1,323	4.43
PAs before 2005	26,854	22,459	22,191	268	1.19

3.4.2. Effectiveness of PFE after PSM

Covariates and propensity score before and after PSM are shown in Tables S3.1–S3.5 and Figure S3.1–S3.10. Before matching, PFE was located at lower elevations and slopes than non-PFE. Distance to the nearest railway and river for PFE was lower than that for non-PFE. However, PFE was located further from roads and the nearest town, and in higher population density areas than non-PFE. Covariates for PAs showed different trends from those for PFE. PAs was located in higher elevation and slope areas than non-PFE. Distance to the nearest town, the nearest railway and the nearest road for PAs were greater than those of non-PFE. Distance to the nearest river and population density for PAs were lower than those for non-PFE. Covariates for RF and PPF showed similar trends to those of the PFE. However, distance to the nearest road for RF was lower than that for non-PFE, and PPF was located in lower population density areas than non-PFE. The PSM improved the covariate balance of

PFE, PAs, RF and PPF because the difference in mean values of covariates tended towards zero after PSM.

The ATT between PFE and non-PFE showed a negative value, which was statistically significant at the 0.001 level. The PFE reduced deforestation by 3.76% compared with non-PFE. Similarly, the ATTs between PAs and non-PFE, RF and non-PFE, and PPF and non-PFE also showed negative values, which were statistically significant at the 0.001 level. The avoided deforestation rates were 5.42% in PAs, 3.63% in RF and 3.42% in PPF, respectively (Table 3.3). The results of spill-over analysis showed that non-PFE within 5 km from PFE had significantly lower deforestation than non-PFE more than 5 km from PFE.

The annual deforestation rates in the PFE and non-PFE from 2006 to 2017 before and after matching are shown in Figure 3.2. After PSM, annual deforestation rate for non-PFE was approximately 1.5 times higher than that for PFE in 2006. Non-PFE maintained a higher annual deforestation rate than PFE from 2006 to 2017, both before and after PSM. Both PFE and non-PFE showed increases of annual deforestation, but the non-PFE showed a more aggressive increase than PFE. The annual deforestation rate of non-PFE was approximately 2.3 times higher than that of PFE in 2017 after PSM. Similarly, annual deforestation in RF and PPF showed increasing trends while the increases were lower than non-PFE. Annual deforestation in PAs showed different trend from PFE, non-PFE, RF and PPF, and PAs have very little change in deforestation rates over time.

Table 3.3. Average treatment effect on treated (ATT) for deforestation

	ATT				
	PFEs	**RF**	**PPF**	**PAs**	**Spill-over**
Estimate	-0.0376 ***	-0.0363***	-0.0342***	-0.0542***	-0.0144***
Standard error	0.0005	0.0006	0.0009	0.0009	0.0007

Notes: *** indicate $p < 0.001$

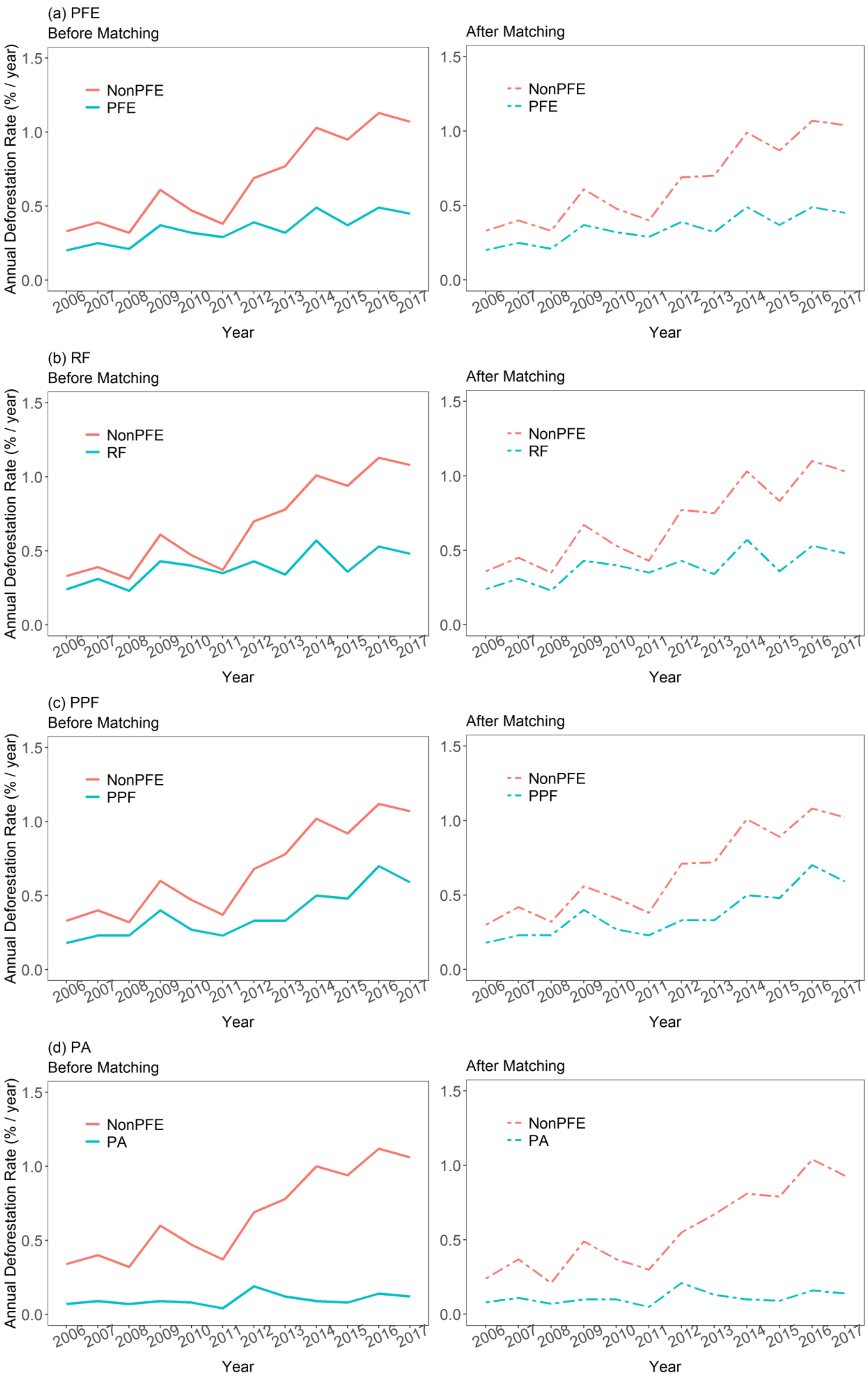


Figure 3.2. Annual deforestation rate between PFE and non-PFE before and after matching

3.5. Discussion

Evaluating the effectiveness of land-use zonings is crucial to understand their performance in achieving their conservation goals. Here, I investigated the effectiveness of PFE and three land-use zonings of PFE on reducing deforestation at the country-scale by controlling for land characteristics between PFE and non-PFE. The results clearly showed that PFE was effective in reducing deforestation by 3.76% compared to non-PFE. The results were similar to the case study in Cameroon (Bruggeman et al. 2015). In Myanmar, land in non-PFE is managed by the Ministry of Agriculture, Livestock and Irrigation (MOALI) according to VFVLM Law (2012), although the forests in non-PFE could be managed by the Forest Department according to Forest Law (1992). Thus, forests in non-PFE are facing deforestation not only because of illegal logging but also because of attempts to meet the targets of different government sectors such as agricultural expansion, mining, hydropower development and infrastructure development (Lim et al. 2017).

In addition to the forest conservation effectiveness of PFE, this study also showed that the PFE decreased deforestation in forests around the PFE. The result implies that the PFE in Myanmar does not lead to leakage of deforestation. One possible reason why the PFE did not lead to leakage may be related to standard operational procedure for the constitution of PFE. As described above, forest settlement officers are responsible for inquiring and determining the rights of the people who are affected on the proposed PFE. Thus, the people can continue farming activities in their farmlands for a 30-year period. In addition, within RF and PPF, the extraction of forest products is allowed for self-consumption within a stipulated amount, but extraction for commercial use is not allowed. Because of these reasons, local people do not need to shift to non-PFE to clear and use the forests. However, although these reasons may explain the lack of leakage around the PFE, they do not fully explain why there is decreased deforestation around the PFE. The reduced deforestation around the PFE may be because of patrols. Forest department officers usually patrol within the PFE but they sometimes also patrol in non-PFE areas. The presence of the officers and patrol efforts in non-PFE areas close to PFE areas may reduce forest clearing in those areas.

Among the land-use zonings in the PFE, PAs showed the highest avoided deforestation rates compared with non-PFE. Previous studies around the world have indicated PAs are effective for forest conservation (Andam et al. 2008; Agarwal et al. 2016; Miranda et al. 2016; Bowker et al. 2017). Thus, the result is not surprising at a global level. Previous studies in Myanmar have also shown the forest conservation effectiveness of PAs (Songer et al. 2009; Htun et al. 2010; Liu et al. 2015; Connette et al. 2017), but these studies have simply compared PAs and non-PAs. This study confirmed that PAs in Myanmar were still effective for forest conservation after minimizing the effect of confounding variables.

This study showed that production forests in Myanmar (i.e. RF and PPF) reduced deforestation compared to non-PFE. Research in Cameroon (Bruggeman et al. 2015) and Bhutan (Bruggeman et al. 2018) has shown that land-use zoning for timber production was effective for forest conservation, but another study in Laos (Kukkonen & Tammi 2019) found that production forests increased deforestation. Because research focusing on the forest conservation effectiveness of production forests is still limited, it is unclear whether there are common points that lead to success or failure of forest conservation in production forests between countries. In the case of Myanmar, one major factor that may help explain forest conservation effectiveness may be the timber extraction system in production forests. In Myanmar, since 1856, timber extraction in production forests has been conducted based on the MSS. Under the MSS, economically important trees larger than a predefined minimum size are selectively felled with a 30-year felling cycle (Win et al. 2018a). The number of felling trees does not exceed the Annual Allowable Cut (AAC), which is determined in each district and varies depending on the composition of trees across the districts. Moreover, AAC is separately calculated for Teak and non-teak hardwood trees. In addition to AAC, disturbance due to skidding is quite low under MSS, because MSS tends to use elephants rather than heavy machinery for skidding (Khai et al. 2016a). From these reasons, a previous study in Myanmar also confirmed that logging is not related with deforestation (Mon et al. 2012). Thus, timber extraction in production forests may not cause deforestation. It is also worth noting that there is a less difference between RF and PPF. It might be related with the similar law-enforced status in RF and PPF. Based on their purposes, both RF and PPF might encounter forest cover loss due to extraction of timber including illegal logging and other forest products.

The results from this study support the need for policy and decision makers or conservationists from the forestry sector to consider the extension of PFE areas in other forests (i.e. non-PFE) for forest conservation. According to Myanmar Forest Policy (1995), it is mandatory for RF and PPF to cover at least 30% and for PAs to cover 5% of the country area. As a policy target and a commitment to UNFCCC from the forestry sector, the Myanmar government plans to expand PFEs to cover up to 40% of the country by 2030. Among PFEs, production forests such as RF and PPF are targeted to increase to 30% of country's total area and the extent of PAs is targeted to increase to 10%. As of August 2019, approximately 25.46% of the total land area was constituted as production forest. Approximately 5.85% of total land area was allocated as PAs. Thus, the areas of production forest and PAs will be expanded by 4.54% and 4.15% of total land area by 2030. Because this study showed that both production forest and PAs reduce deforestation, and showed that around the PFE, there is no negative spill-over effect, the intention to extend PFEs would be a good mechanism to control deforestation in Myanmar. While constituting PFEs, it is vital to take into account both forest conservation and the needs of local communities who are living near or in the forests because they heavily rely on forest resources for their livelihoods, and participatory forest management is an important way to achieve sustainable forest management (Santika et al. 2019). For example, creating ecotourism sites within PAs might be fruitful for Myanmar's economy and environmental conservation, but also for local communities in terms of job opportunities and income generation. Thus, extension of the PFE may be an efficient way to achieve forest conservation as well as enhance local livelihoods.

However, it should be noted that both PFE, especially in production forests (both RF and PPF), and non-PFE showed an increasing trend of annual deforestation from 2006 to 2017. It is unclear why both non-PFE and production forests showed this increasing trend. Though lands in production forests and non-PFE are under the management of different ministries, one possible reason causing the increasing trend of deforestation might be agriculture expansion (Enters 2017). With an increasing human population and land-tenure insecurity, agriculture expansion is becoming the significant driver of deforestation (Prescott et al. 2017). The deforestation due to agricultural expansion happens both in PFE and non-PFE (Enters 2017).

I also suggest that perhaps the difference in the forest conservation effectiveness between production forests and PAs is increasing because of stable deforestation in PAs and increasing deforestation in production forests within the study period. Thus, the expansion of production forests may not make a significant contribution to forest conservation if the trend of increasing annual deforestation continues. Further efforts to mitigate the increase of deforestation in production forest (e.g. patrols, formulation of stronger rules and policies) should be conducted in parallel with the expansion of production forests. In addition, efforts to reduce deforestation in non-PFE should be made. This is because considerable areas of forests would be remained as non-PFE even if the PFE expand to 40%. Forests in non-PFE have the potential to be allocated to land uses other than forests, such as agriculture. Minimizing the impact due to land use reallocation should be considered.

It should be also noted that this study did not evaluate the difference of conservation effectiveness with different administrative district, because this is out of the scope of this study. In additions to PFE and non-PFE, administrative district may affect the degree of deforestation. For example, insecurity district due to civil war may be more susceptible to deforestation due to the difficulty in law enforcement. The study that evaluates conservation effectiveness of different administrative district may provide further evidence to reduce deforestation.

3.6. Conclusion

In Myanmar, PFE is constituted to fulfil different purposes for long-term maintenance of forest areas. It is categorized into RF, PPF and PAs. Though many studies have evaluated forest cover changes in Myanmar, few have investigated the effectiveness of the PFE in reducing deforestation at the national scale. In this study, I evaluated the impacts of the PFE as a whole and of different land-use zonings in the PFE such as RF, PPF and PAs in reducing deforestation at national level compared with non-PFE using a matching method. The results showed that not only PFE as a whole but also all the land-use zonings of PFE reduced deforestation compared to non-PFE. Matching showed that the PFE in Myanmar was effective in reducing deforestation due to protection and not due to land characteristics. However, the PFE and non-PFE showed an increasing trend of annual deforestation between 2006 and 2017. Thus, further efforts to mitigate deforestation in production forest should be conducted. In addition, ways to reduce deforestation in non-PFE should be investigated.

Appendix II

Table S3.1: Covariate Balance before and after propensity score matching using PFEs as treatment and non-PFEs as control

	Before Matching			After Matching		
	Means Treated (n=375474)	**Means Control (n=624526)**	**Mean Difference**	**Means Treated (n=375474)**	**Means Control (n=375474)**	**Mean Difference**
Elevation (m)	573.96	748.47	-174.51	573.96	579.72	-5.76
Slope (˚)	16.20	17.45	-1.25	16.20	16.33	-0.13
Distance to nearest Town (m)	27011.40	22994.99	4016.41	27011.40	25959.20	1052.20
Distance to nearest Railway (m)	87194.40	100730.38	-13535.98	87194.40	88818.30	-1623.90
Distance to nearest Road (m)	12783.06	12250.84	532.22	12783.06	12712.99	70.07
Distance to nearest river (m)	28297.54	35366.67	-7069.13	28297.54	27920.94	376.60
Population density (per km^2)	40.88	34.60	6.28	40.88	39.50	1.38

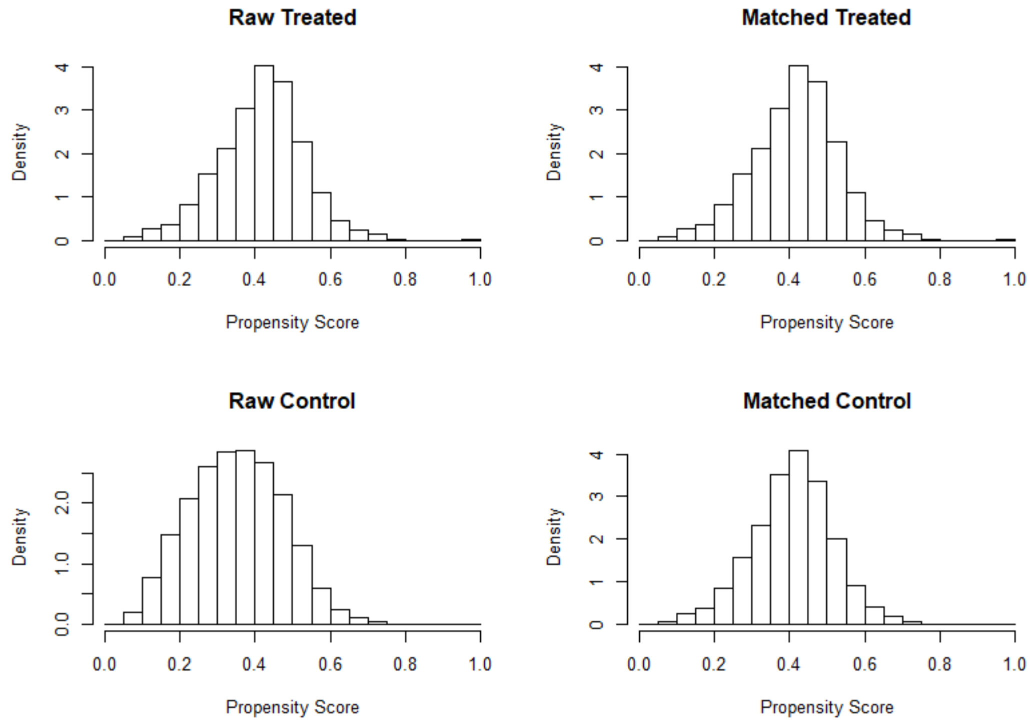


Figure S3.1: Propensity Score before and after matching using PFEs as treatment and non-PFEs as control

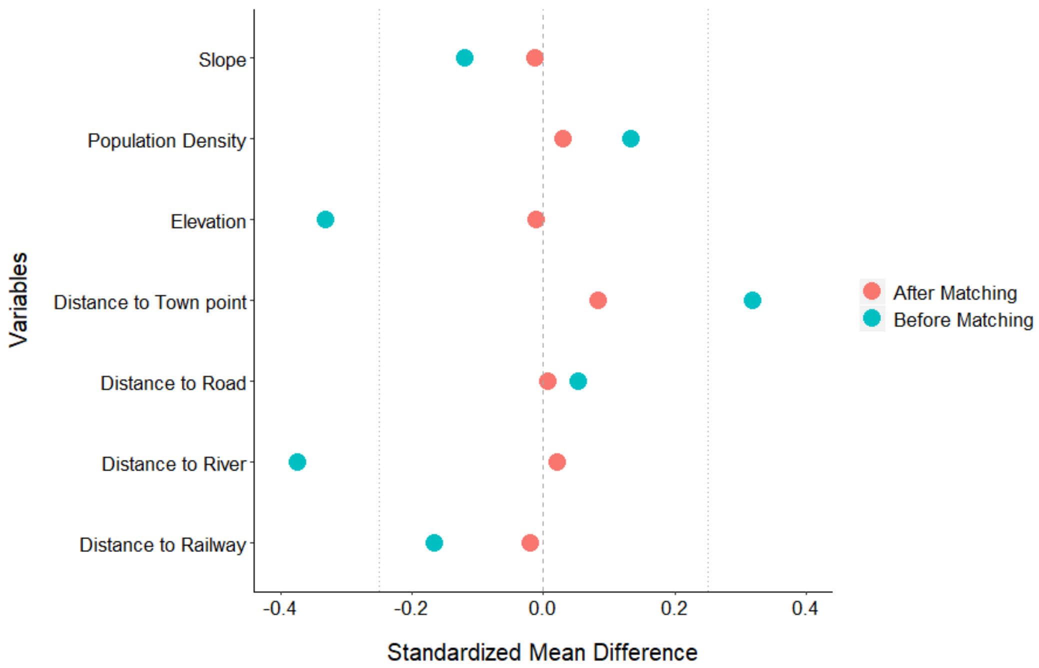


Figure S3.2: Covariate balances before and after matching using PFEs as treatment and non-PFEs as control

Table S3.2: Covariate Balance before and after propensity score matching using PAs as treatment and non-PFEs as control

	Before Matching			After Matching		
	Means Treated (n=91663)	**Means Control (n=908337)**	**Mean Difference**	**Means Treated (n=77873)**	**Means Control (n=77873)**	**Mean Difference**
Elevation (m)	979.48	749.33	230.15	836.39	870.92	-34.53
Slope (˚)	20.95	17.44	3.51	19.30	19.76	-0.46
Distance to nearest Town (m)	34937.24	22977.09	11960.15	31766.70	32472.93	-706.23
Distance to nearest Railway (m)	130731.71	100819.18	29912.53	121940.01	117600.52	4339.49
Distance to nearest Road (m)	20998.05	12274.22	8723.84	17668.65	18561.74	-893.09
Distance to nearest river (m)	32340.04	35390.24	-3050.20	32497.88	32577.30	-79.42
Population density (per km^2)	15.36	34.61	17.08	17.32	20.02	4.50

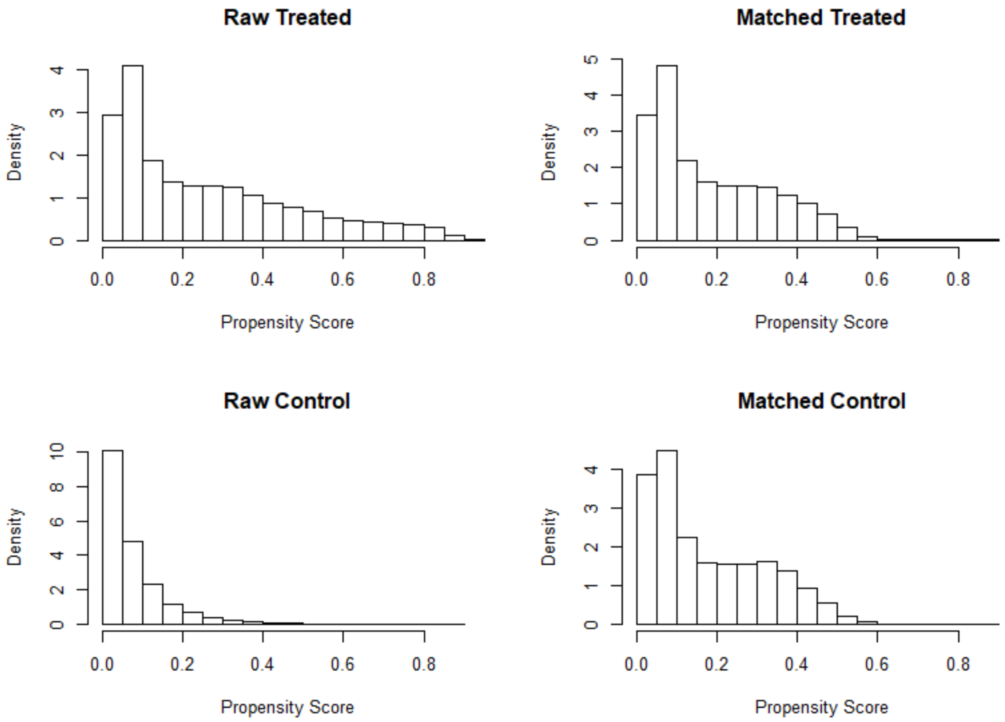


Figure S3.3: Propensity score before and after matching using PAs as treatment and non-PFEs as control

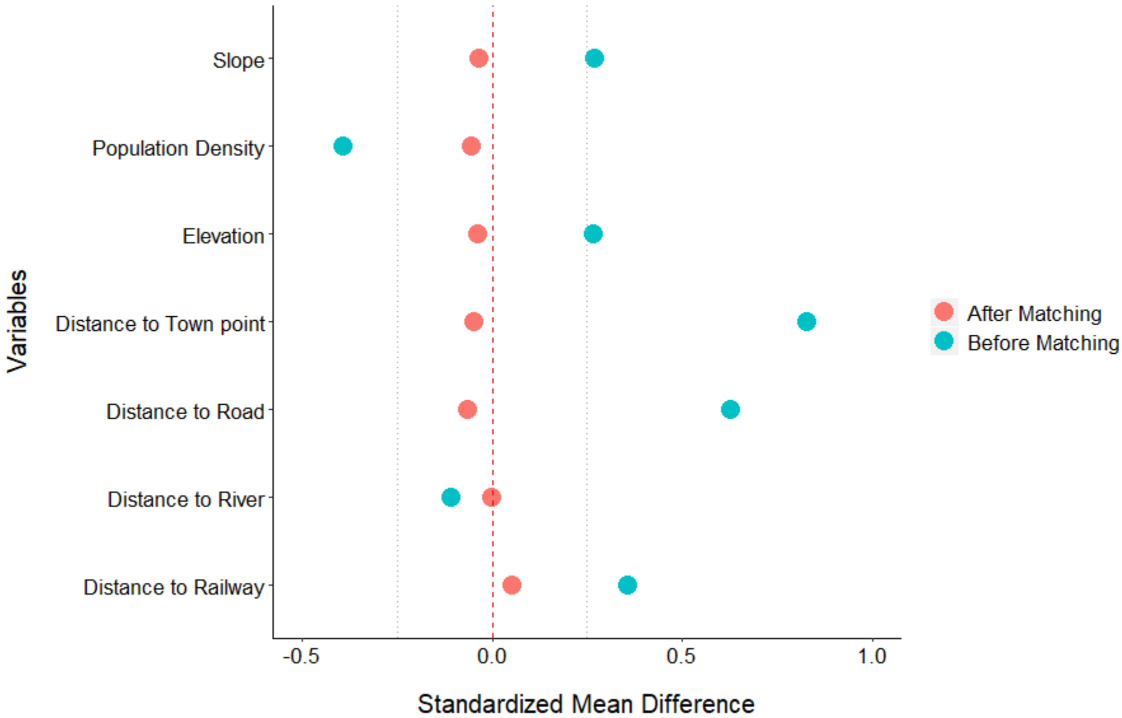


Figure S3.4: Covariate balances before and after matching using PAs as treatment and non-PFEs as control

Table S3.3: Covariate Balance before and after propensity score matching using RF as treatment and non-PFEs as control

	Before Matching			After Matching		
	Means Treated (n=274724)	**Means Control (n=725276)**	**Mean Difference**	**Means Treated (n=274724)**	**Means Control (n=274724)**	**Mean Difference**
Elevation (m)	462.13	750.02	-287.89	462.13	455.23	6.90
Slope (˚)	14.84	17.45	-2.61	14.84	14.86	-0.02
Distance to nearest Town (m)	26314.11	23006.03	3308.08	26314.11	25673.78	640.33
Distance to nearest Railway (m)	74049.65	100907.79	-26858.13	74049.65	76863.04	-2813.39
Distance to nearest Road (m)	10742.98	12300.05	-1557.07	10742.98	10746.84	-3.86
Distance to nearest river (m)	27918.48	35419.47	-7500.99	27918.48	26836.06	1082.42
Population density (per km^2)	50.78	34.68	16.10	50.78	45.38	5.40

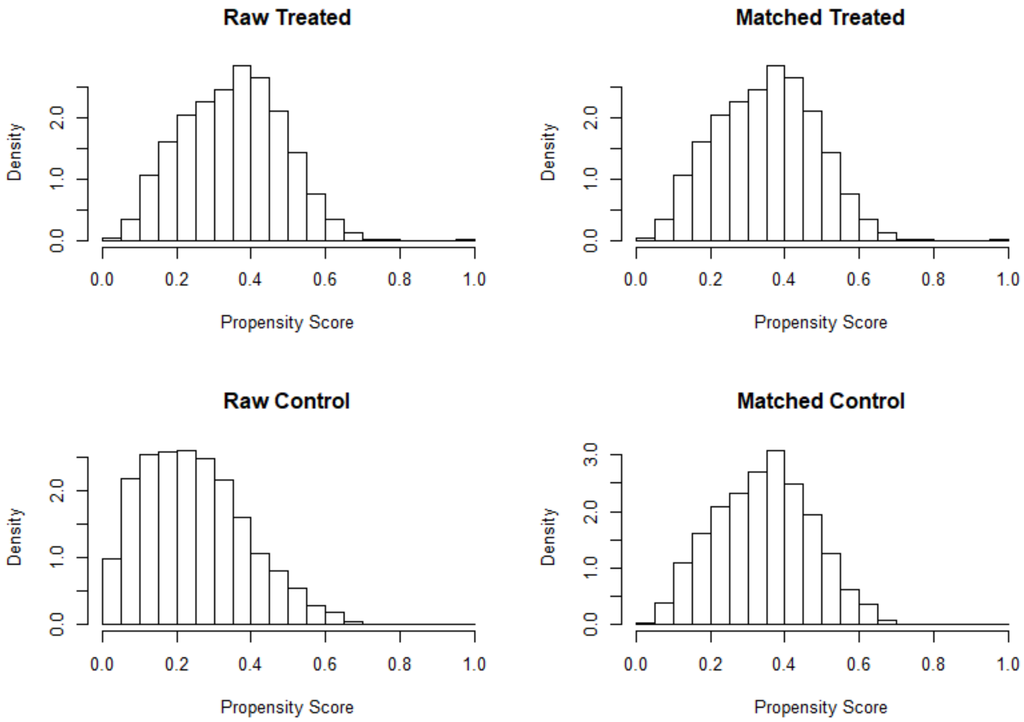


Figure S3.5: Propensity Score before and after matching using RF as treatment and non-PFEs as control

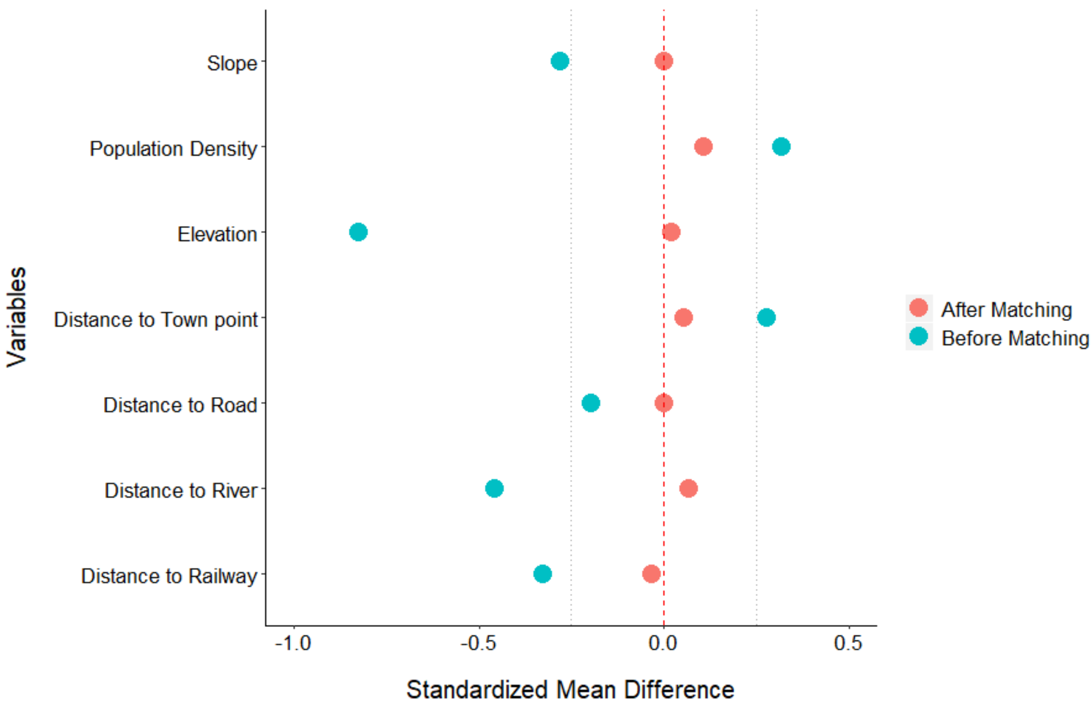


Figure S3.6: Covariate balance before and after matching using RF as a treatment and non-PFEs as control

Table S3.4: Covariate Balance before and after propensity score matching using PPF as treatment and non-PFEs as control

	Before Matching			**After Matching**		
	Means Treated (n=115504)	**Means Control (n=884496)**	**Mean Difference**	**Means Treated (n=115504)**	**Means Control (n=115504)**	**Mean Difference**
Elevation (m)	583.90	749.37	-165.47	583.90	585.23	-1.33
Slope (˚)	16.56	17.45	-0.89	16.56	16.53	0.03
Distance to nearest Town (m)	23243.50	23005.61	237.89	23243.50	23453.67	-210.17
Distance to nearest Railway (m)	87076.21	100817.71	-13741.50	87076.21	86636.84	439.37
Distance to nearest Road (m)	12367.70	12282.77	84.93	12367.70	12313.83	53.87
Distance to nearest river (m)	26377.63	35430.26	-9052.63	26377.63	26386.10	-8.47
Population density (per km^2)	30.48	34.68	-4.20	30.48	31.40	-0.92

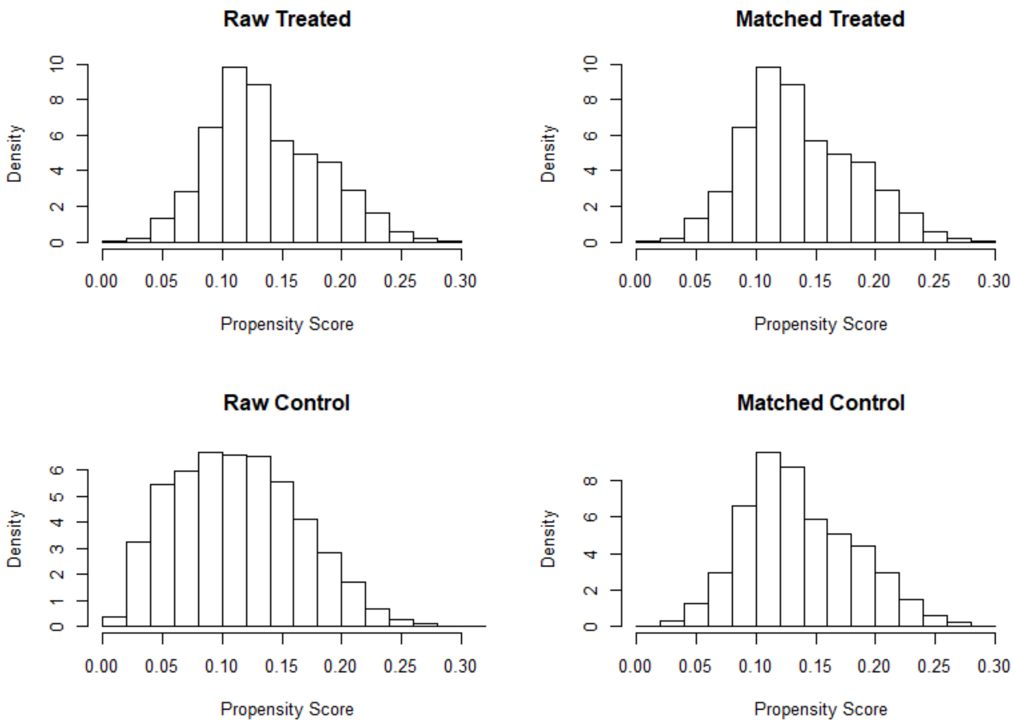


Figure S3.7: Propensity Score before and after matching using PPF as treatment and non-PFEs as control

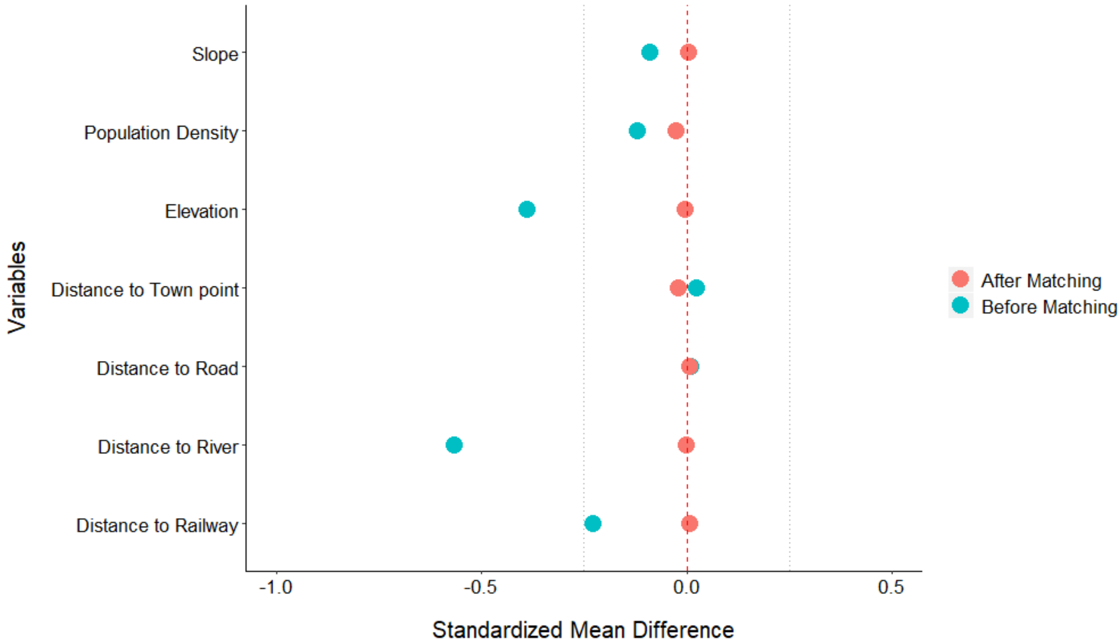


Figure S3.8: Covariate balance before and after matching using PPF as treatment and non-PFEs as control

Table S3.5: Covariate Balance before and after propensity score matching using non-PFEs within 5 km buffer as treatment and other remaining non-PFEs to check spillover

	Before Matching			**After Matching**		
	Means Treated (n=292078)	**Means Control (n=707922)**	**Mean Difference**	**Means Treated (n=273989)**	**Means Control (n=273989)**	**Mean Difference**
Elevation (m)	509.41	848.82	-339.41	532.25	552.86	-20.61
Slope (˚)	14.69	18.58	-3.89	14.98	15.18	-0.20
Distance to nearest Town (m)	21742.84	23510.88	-1768.04	21823.61	22125.53	-301.92
Distance to nearest Railway (m)	74611.40	111622.10	-37010.70	77479.71	82691.11	-5211.40
Distance to nearest Road (m)	8777.88	13707.38	-4929.50	9079.01	9238.28	-159.27
Distance to nearest river (m)	27123.30	38866.10	-11742.80	27752.44	28132.05	-379.61
Population density (per km^2)	45.85	30.02	15.83	44.40	39.80	4.60

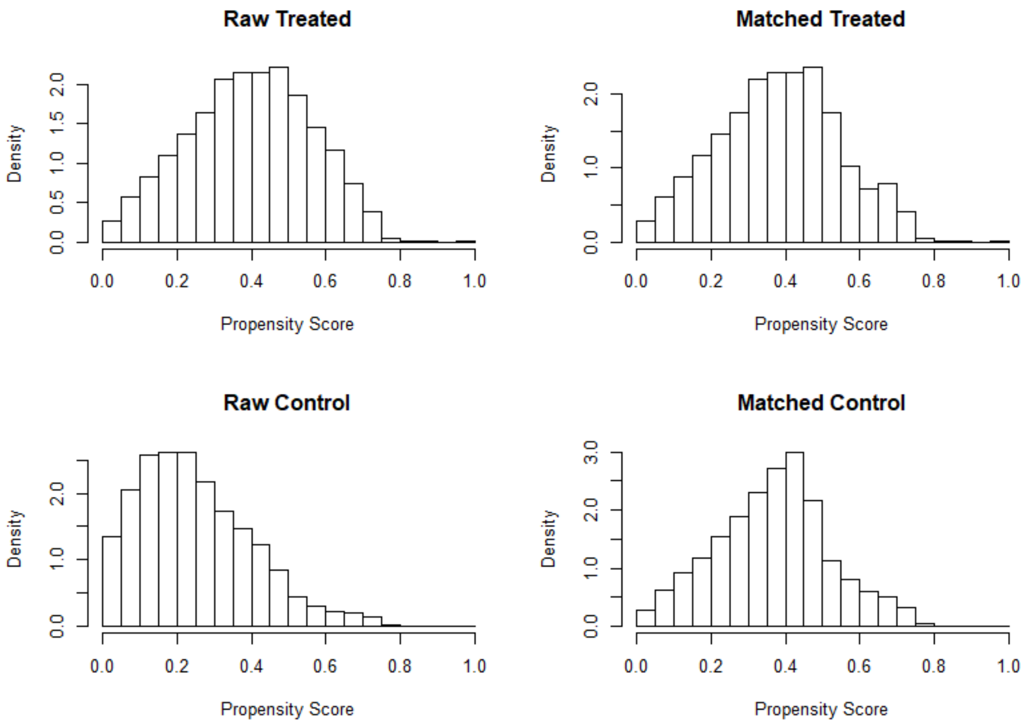


Figure S3.9: Propensity Score before and after matching using non-PFEs within 5 km buffer as treatment and non-PFEs as control

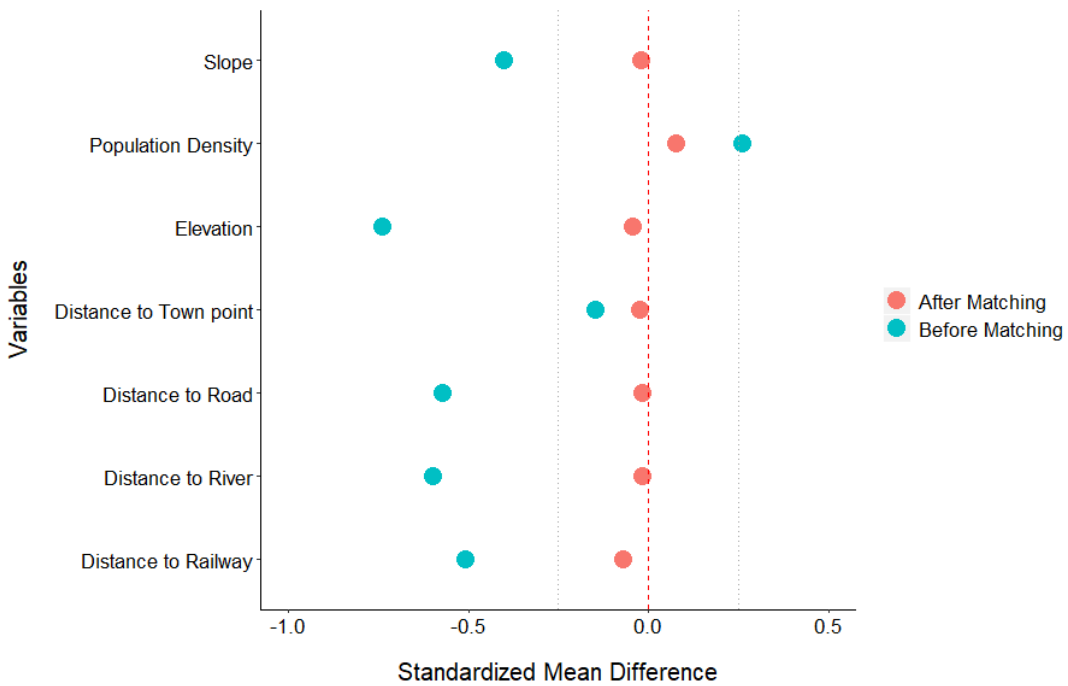


Figure S3.10: Covariate balance before and after matching using non-PFEs within 5 km buffer as treatment and non-PFEs as control

Chapter 4

Factors affecting deforestation inside and outside PFE in Myanmar

4.1. Introduction

Myanmar is rich in forest resources ranging from tropical rainforests to alpine forests (Wang & Myint 2016), and has high forest cover in Southeast Asia (Lim et al. 2017; Prescott et al. 2017; Reddy et al. 2019). Myanmar's forests have a significant contribution to not only carbon sequestration, and biodiversity conservation as well (Myers et al. 2000). In addition, they are also important to fulfill country's economy, and provide basic needs for local livelihoods. However, deforestation became a critical issue in Myanmar, and according to FRA 2015, forest cover is gradually decreasing from 39 Mha in 1990 to 29 Mha in 2015. Myanmar ranked third greatest annual forest cover loss around the world between 2010 and 2015 (FAO. 2016a). Thus, mechanisms and interventions to control accelerating deforestation became one of the major priorities for sustainable use of forest resources. For the development of the policy to formulate deforestation controlled mechanisms and to implement the interventions, identifying the drivers of deforestation and examining the factors facilitating the drivers of deforestation are important (Hosonuma et al. 2012; Htun et al. 2013; Liu et al. 2015; Morales-Barquero et al. 2015; Lim et al. 2017; Guerra-Martínez et al. 2019). It is dealing with sustainable management of forest resources (Mon et al. 2012), and future land cover changes (Mon et al. 2009).

Numerous studies investigated the influencing factors on forest cover changes in different parts of the world (Vu et al. 2014; Morales-Barquero et al. 2015; Bowker et al. 2017; Kleemann et al. 2017; Phompila et al. 2017; Imai et al. 2018; Lonn et al. 2018; Guerra-Martínez et al. 2019; Xu et al. 2019). These studies revealed that biophysical (e.g. elevation and soil) and socioeconomic (e.g. market accessibility) factors affecting forest cover change (Vu et al. 2014; Phompila et al. 2017; Lonn et al. 2018). However, the factors driving forest cover change varies across the countries or regions. For example, the risks of being deforestation are likely to increase in flat land in Nigeria (Bowker et al. 2017), but higher deforestation was found in high elevation mountainous areas in Laos (Phompila et al. 2017). The driving factors are site and scale specific (Geist, Helmut J. & Lambin 2002), and change over time, even within a specific region (Htun et al. 2013). Therefore, it is important to understand the factors driving deforestation according to the situation of a country or region, instead of following the results from other countries or regions.

Around the world, permanent forest lands are legally designated to keep the forests in perpetuity (FAO. 2016a). Previous studies demonstrated that permanent forest lands reduced deforestation and forest degradation (e.g reserved forests (Bruggeman et al. 2015; Bruggeman et al. 2018), protected areas (Andam et al. 2008; Miranda et al. 2016), community forest (Lonn et al. 2019; Oldekop et al. 2019)). On the other hand, higher deforestation was found in non-permanent forest lands. Therefore, one possible way to reduce deforestation is designation non-permanent forest land as permanent forest land. It is important to understand the factors influencing deforestation in non-permanent forest land in order to place the priority to assign as permanent forest land. However, previous studies that investigated the factors affecting deforestation mainly focused on permanent forest land, such as protected area (e.g. Htun et al. 2013; Bowker et al. 2017; Phompila et al. 2017; Imai et al. 2018), reserved forest (e.g. Mon et al. 2012), and community forest (e.g. Lonn et al. 2018). Therefore, it is crucial to examine factors driving deforestation not only inside permanent forest land, and outside as well. Studies that analyzed a country-wide using large dataset are particularly essential, because they will provide useful results for decision makers for a given country.

Myanmar's forests are classified into permanent forest estate (PFE) comprising reserved forest (RF), protected public forest (PPF) and protected areas (PAs), and unclassified forests located outside PFE (hereafter non-PFE). In order to control deforestation and manage the forests sustainably, the government of Myanmar plans to expand the PFE up to 40% of country area by 2030 according to Myanmar's Intended Nationally Determined Contribution (The Government of Myanmar 2015). In Myanmar, several case studies on factors driving deforestation and forest degradation have been conducted across country (Mon et al. 2009; Mon et al. 2012; Htun et al. 2013; Liu et al. 2015; Lim et al. 2017; Yang et al. 2019). However, such studies mainly focused on permanent forest land in specific regions, and there is a lack of study emphasizing on non-PFE. Therefore, this study would be an ideal case study for evaluating the influencing factors of deforestation in non-PFE.

In this research, factors affecting deforestation were investigated in PFE and non-PFE separately using country dataset between 2006 and 2017. The logistic regression analysis for samples randomly selected in PFE and non-PFE were developed and both biophysical and socioeconomic factors were evaluated as potentially influential factors for deforestation.

4.2. Materials and Methods

4.2.1. Study Area

This study was conducted in PFE and non-PFE across the country. PFE is comprised with RF, PPF and PAs, and is under the management of Forest Department. Within PFE, no one is allowed to conduct any activities without permission. The unclassified forests are the forests located in non-PFE. Though all forests could be managed by Forest Department under Forest Law (1992), land covered with forests in non-PFE is under the management of Ministry of Agriculture, Livestock and Irrigation according to the Vacant, Fallow and Virgin Land Management Law (2012). Therefore, there is a complex management system in non-PFE between different government sectors. In this study, PFEs which were constituted after 2005 and intended to conserve water or lake were excluded from the analysis, and the study was focused in both PFE and non-PFE.

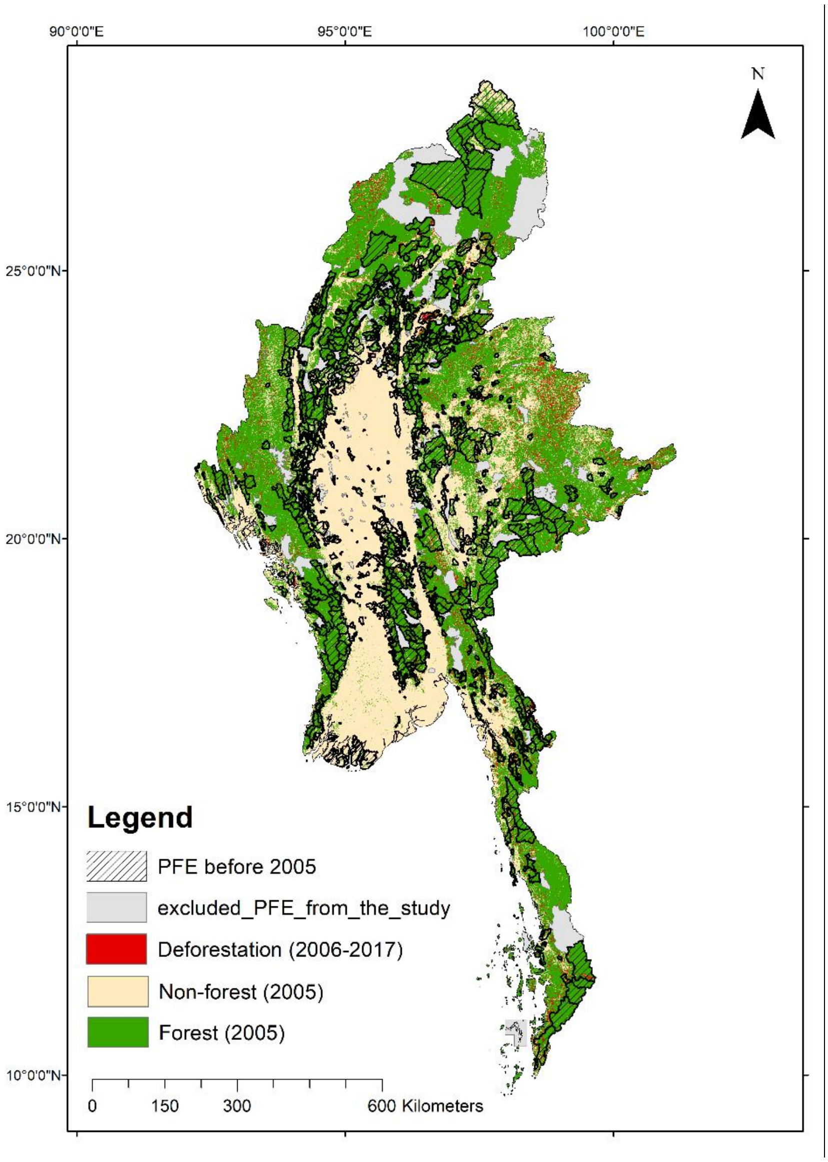


Figure 4.1 The location of Permanent Forest Estate with forest cover changes

4.2.2. Data

Data of deforestation was extracted from Global Forest Change Dataset (GFCD) developed by Hansen et.al (Hansen et al. 2013a). GFCD includes tree cover percent 2000, annual forest loss layer (2001-2017), and cumulative forest gain layer (2001-2017). Because PFEs which are constituted before 2005 are selected in this study, deforestation between 2006 and 2017 was analyzed. Using tree cover percent 2000 layer, forest pixel was defined while a pixel has at least 40% tree cover according to my previous study (Lwin et al. 2019). Forest pixel in 2005 was defined when a forest pixel in 2000 was not overlapped with loss between 2001 and 2005. In this study, gain data was ignored because there is no information of annual gain data.

Deforestation between 2006 and 2017 was defined when a forest pixel in 2005 was overlapped with forest loss between 2006 and 2017.

Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model (ASTER GDEM), which is a 30-m resolution DEM, was used as elevation. The slope was also calculated from ASTER GDEM. The location of road, river, town, and village were downloaded from the Myanmar Information Management Unit (MIMU) (United Nations Resident and Humanitarian Coordinator. 2007). The township boundary and population for each township was downloaded from the Department of Population, Myanmar (DoP. 2018). I calculated the population density at township level by dividing population by township area. The boundary of PFE is obtained from Forest Department, Myanmar. Country boundary is also downloaded from Database of Global Administrative Areas. The map of soil types for Myanmar was extracted from FAO's world soil map (FAO. 2007) and the level of suitability for agriculture was coded based on previous studies in Myanmar (Mon et al. 2009; IFDC. International Fertilizer Development Center. 2018). There are nine different soil types, and the lowest code represents the most suitability for agriculture and the largest code is not good for agriculture.

Table 4.1. Characteristics of the variables used in GLM

Variables	**Unit**	**Source**
Dependent variable		
Deforestation (2001-2017)	Yes = 1, No = 0	GFCD
Independent variable		
Elevation	m	Aster GDEM
Slope	degree	Aster GDEM
Distance to town	m	MIMU
Distance to road	m	MIMU
Distance to river	m	MIMU
Population Density	per km^2	MIMU
Distance to village	m	MIMU
Distance to country border	m	GADM
Distance to PFE boundary	m	FD
Soil Type	1 – 9	FAO

Notes: GFCD = Global Forest Change Dataset, Aster GDEM = Advanced spaceborne thermal emission and reflection radiometer (Aster) Global Digital Elevation Map, MIMU = Myanmar Information Management Unit, GADM = Database of Global Administrative Areas, DoP = Department of Population in Myanmar, FAO = Food and Agriculture Organization of the United Nations

4.2.3 Data analysis

Two separate regression models for deforestation in PFE and non-PFE were developed using Generalized Linear Model (GLM) with binomial error distribution and a logit link function in R statistical software (version 3.5.1) (R Core Team 2018). For both regressions, the response variable was whether a pixel which is forest in 2005 was deforested (1) or not deforestation (0) within 2006 and 2017. The independent variables included in this study were selected based on previous studies (Crk et al. 2009; Mon et al. 2009; Mon et al. 2012; Htun et al. 2013; Lonn et al. 2018; Guerra-Martínez et al. 2019) and data availability (Table 1). For logistic regression, 1% of total forest pixels in 2005 of PFE and non-PFE were randomly selected. There are 1,920,115 forest pixels in PFE and 3,207,778 in non-PFE.

Because there might be a statistical problem due to high collinearity among independent variables (Mon et al. 2012), the presence of absence of collinearity among independent variables was checked using Variance Inflation Factor (VIF). When VIF is greater than 5 (Defries et al. 2010; Vu et al. 2014; Lonn et al. 2018), there will be high collinearity. I confirmed that there is no collinearity with VIF value lower than 2 in all variables. To examine the importance of independent variables, Akaike's information criterion (AIC), and the delta AIC (ΔAIC) which is the difference between the best model and the model excluding a variable from the best model (Lonn et al. 2018) were calculated. By following the previous study in Cambodia by Lonn et al. (2018), the variables which have higher ΔAIC value were determined as more influencing variables in deforestation.

4.3. Results

4.3.1. Factors affecting deforestation inside PFE

The statistical results showed that all explanatory variables except distance of PFE boundary are significantly correlated with deforestation inside PFE.

Table 4.2. Results of regression analysis for deforestation inside PFE

	Estimate	**Standard Error**	
(Intercept)	-9.459×10^{-1}	1.372×10^{-2}	***
Elevation	-5.411×10^{-4}	1.334×10^{-5}	***
Slope	-4.337×10^{-2}	5.240×10^{-4}	***
Distance to town	-9.859×10^{-6}	3.756×10^{-7}	***
Distance to road	-4.409×10^{-5}	6.275×10^{-7}	***
Distance to river	3.118×10^{-6}	2.367×10^{-7}	***
Population density	1.386×10^{-3}	7.265×10^{-5}	***
Distance to village	-5.020×10^{-5}	8.530×10^{-7}	***
Distance to country border	-3.350×10^{-6}	7.142×10^{-8}	***
Soil type	-7.627×10^{-2}	2.251×10^{-3}	***
Distance to PFE boundary	-2.895×10^{-6}	$1.697 \times 10^{-}6$	.

Notes: *** indicate $p < 0.001$

The logistic regression analysis showed that elevation and slope is negatively correlated with the likelihood of being deforestation in PFE. This revealed that the risks of being deforestation in PFE were likely to occur in flat lands. There was negative correlation between deforestation and the variables such as distance to town, road, village, and country border. The areas close to human settlements are more vulnerable to human disturbances, and forests located near human settlements are more susceptible to deforestation. In addition, positive correlation between deforestation and the distance to river and population density showed that the probability of deforestation within PFE is more likely to occur in the areas far from river and denser populated areas. Forests located on suitable soil type for agriculture are more likely to be disturbed. According to ΔAIC values shown in Table 4.3, the variables representing accessibility such as slope, distance to road and distance to village are the most important variables for being deforestation inside PFE. In this context, accessibility plays a key role in deforestation inside PFE.

Table 4.3. The estimated delta Akaike's information criterion (ΔAIC) values for deforestation in PFE

Models										**AIC**	**ΔAIC**
Elevation	Slope	D-Town	D-Road	D-River	PP-density	D-village	D-border	Soil	D-PFE	597,425	0
	Slope	D-Town	D-Road	D-River	PP-density	D-village	D-border	Soil	D-PFE	599,203	1,778
Elevation		D-Town	D-Road	D-River	PP-density	D-village	D-border	Soil	D-PFE	604,926	7,501
Elevation	Slope		D-Road	D-River	PP-density	D-village	D-border	Soil	D-PFE	598,128	703
Elevation	Slope	D-Town		D-River	PP-density	D-village	D-border	Soil	D-PFE	602,869	5,444
Elevation	Slope	D-Town	D-Road		PP-density	D-village	D-border	Soil	D-PFE	597,595	170
Elevation	Slope	D-Town	D-Road	D-River		D-village	D-border	Soil	D-PFE	597,832	407
Elevation	Slope	D-Town	D-Road	D-River	PP-density		D-border	Soil	D-PFE	601,334	3,909
Elevation	Slope	D-Town	D-Road	D-River	PP-density	D-village		Soil	D-PFE	599,707	2,282
Elevation	Slope	D-Town	D-Road	D-River	PP-density	D-village	D-border		D-PFE	598,608	1,183
Elevation	Slope	D-Town	D-Road	D-River	PP-density	D-village	D-border	Soil		597,426	1

D-Town = Distance to town, D-Road = Distance to road, D-River = Distance to river, PP-density = Population density, D-village = Distance to village, D-border = Distance to country border, Soil = Soil type, D-PFE = Distance to PFE boundary

4.3.2. Factors affecting deforestation in non-PFE

Regarding with deforestation in non-PFE, the GLM results showed that all of the explanatory variables have a significant correlation with deforestation. Flat lands are more susceptible to deforestation in non-PFE than mountainous areas. The risks of being deforestation were likely to increase with the shorter distance to town, road, river, village, and country border. The more suitable soil for agriculture, the higher the probability of being deforestation. However, the negative correlation between population density showed that deforestation in non-PFE is more likely to occur in township with lesser population density. Because of positive correlation with distance to PFE boundary, forests located far from PFE have more risks of deforestation.

Table 4.4. Results of regression analysis for deforestation in non-PFE

	Estimate	**Standard Error**	
(Intercept)	-1.520	7.865×10^{-3}	***
Elevation	-2.358×10^{-4}	5.144×10^{-6}	***
Slope	-2.633×10^{-2}	2.472×10^{-4}	***
Distance to town	-1.775×10^{-6}	2.086×10^{-7}	***
Distance to road	-1.763×10^{-5}	2.430×10^{-7}	***
Distance to river	-2.879×10^{-7}	1.050×10^{-7}	**
Population density	-5.069×10^{-4}	4.768×10^{-5}	***
Distance to village	-4.065×10^{-5}	5.090×10^{-7}	***
Distance to country border	-1.837×10^{-6}	4.968×10^{-8}	***
Soil type	-1.631×10^{-2}	1.359×10^{-3}	***
Distance to PFE boundary	2.200×10^{-5}	1.577×10^{-7}	***

Notes: *** indicate $p < 0.001$, ** indicate $p<0.01$

The results of ΔAIC showed that the distance to PFE boundary, followed by slope and distance to village were the three most influencing factors on deforestation in non-PFE.

Table 4.5.The estimated delta Akaike's information criterion (ΔAIC) values for deforestation in non-PFE

Models										AIC	ΔAIC
Elevation	Slope	D-Town	D-Road	D-River	PP-density	D-village	D-border	Soil	D-PFE	1,724,174	0
	Slope	D-Town	D-Road	D-River	PP-density	D-village	D-border	Soil	D-PFE	1,726,332	2,158
Elevation		D-Town	D-Road	D-River	PP-density	D-village	D-border	Soil	D-PFE	1,736,043	11,869
Elevation	Slope		D-Road	D-River	PP-density	D-village	D-border	Soil	D-PFE	1,724,245	71
Elevation	Slope	D-Town		D-River	PP-density	D-village	D-border	Soil	D-PFE	1,729,783	5,609
Elevation	Slope	D-Town	D-Road		PP-density	D-village	D-border	Soil	D-PFE	1,724,180	6
Elevation	Slope	D-Town	D-Road	D-River		D-village	D-border	Soil	D-PFE	1,724,303	129
Elevation	Slope	D-Town	D-Road	D-River	PP-density		D-border	Soil	D-PFE	1,731,869	7,695
Elevation	Slope	D-Town	D-Road	D-River	PP-density	D-village		Soil	D-PFE	1,725,569	1,395
Elevation	Slope	D-Town	D-Road	D-River	PP-density	D-village	D-border		D-PFE	1,724,317	143
Elevation	Slope	D-Town	D-Road	D-River	PP-density	D-village	D-border	Soil		1,742,427	18,253

D-Town = distance to town, D-Road = distance to road, D-River = distance to river, PP-density = population density, D-village = distance to village, D-border = distance to country border, Soil = soil type, D-PFE = distance to PFE

4.4. Discussion

In this chapter, I investigated the factors affecting deforestation in PFE and non-PFE using two separate logistic regression models. Both models showed that the likelihood of being deforestation is likely to occur in accessible areas. Several previous studies in different parts of the world also highlighted the importance of accessibility on deforestation. For instance, the risks of being deforestation are likely to increase in flat land in Nigeria (Bowker et al. 2017). In Thailand, forest cover decrease was associated with the closer distance to villages (Popradit et al. 2015). Phompila et al (2017) suggested that the probability of deforestation in Laos is more likely to occur with the shorter distance to roads (Phompila et al. 2017).

This study suggested that slope and distance to village are the important factors on deforestation in both PFE and non-PFE. Forests located at gentle slope areas are more susceptible to deforestation because steep slope is a barrier to access forests for the people in extracting forest resources or converting land into agriculture areas. In addition to accessibility, there are a larger number of human settlements compared to steep slope areas. Due to close to human settlements, demand on forest resources makes a pressure on the nearest natural forests. In Myanmar, rural people living in the vicinity of forests heavily rely on forest resources for their subsistence livelihood. They extract fuelwood, charcoal, timber for household use and farm, and non-timber forest products. Forests in the proximity of villages could be cleared to expand the cultivated areas or permanent agriculture land because of accessibility. Moreover, because of accessibility, there might be illegal logging which is one of the causes of deforestation though government officials patrol within PFE and surrounding PFEs.

Within PFE, roads are also one of the important factors on deforestation within 2006 and 2017. Roads also create the ease of accessibility to forests to extract timber, and to markets, and could allow new land uses which cause deforestation along the road. For example, there was an encroachment of farmland areas to the surrounding forest areas along the new constructed road in Tachileik, Myanmar (Liu et al. 2015). Previous studies in other tropical forests suggested that road systems have negative impacts on forest cover change (Nepstad et al. 2001; Fearnside 2007; Phompila et al. 2017). Similar with this study, a case study in Brazilian Atlantic forest also highlighted the importance of roads and topography on forest cover changes (Freitas et al. 2010). The result is similar to the studies in Ghana (Kleemann et al. 2017) and Oxaca, Mexico (Guerra-Martínez et al. 2019), but it is quite different in Cambodia where deforestation is likely to increase far from the road (Lonn et al. 2018).

In non-PFE, distance to PFE boundary was the most influencing factors among various variables. The positive correlation with the distance to PFE boundary revealed that deforestation in non-PFE was less likely to occur in the surrounding areas of PFE and forests located far from PFE have more risks to cause deforestation. The distance from PFE could be a proxy for the presence of governmental officials. Within PFEs and non-PFE around PFEs, the officials from Forest Department conduct monitoring activities such as a patrol in order to control illegal activities such as illegal timber extraction. Therefore, the likelihood of deforestation in non-PFE is less likely to occur near the PFE boundary.

This study showed that deforestation is more likely to occur in the accessible areas, in the vicinity of human settlements and the areas out of government control. First of all, role of local communities should be considered in conservation program not only within PFE, and non-PFE as well. For example, in the vicinity of the villages, implementation of community forestry which is managed by local community is an important way of sustainable forest management. Because forests in non-PFE which are near PFE are less likely to occur deforestation and forests in accessible areas are more susceptible to deforestation, the remaining forests in non-PFE which are located in accessible areas should be considered as priority to constitute new PFE. However, because deforestation within PFE is more likely to occur in accessible areas, monitoring activities (e.g. patrol) and law enforcement should be more effective and sufficient. Moreover, in order to control illegal logging and illegal timber trade, government should secure policies and legislations and strengthen forest law enforcement, governance and trade (FLEG-T) and timber legality assurance system.

4.5. Conclusion

In this study, I investigated the factors influencing forest cover changes from 2006 to 2017 in PFE and non-PFE using logistic regression separately. In both PFE and non-PFE, GLM showed that the risks of being deforestation are higher in the areas with ease accessibility and out of government controls. This study might be useful for policy and decision makers to design the necessary management interventions to curtail deforestation and enhance reforestation activities in the future. To curtail deforestation in PFE, monitoring and patrols should be increased with effective law enforcement. In non-PFE, because forests near PFE are less likely to occur deforestation, government should consider remaining forests of non-PFE in flat land and accessible areas as priority to constitute as new PFE. However, because the probability of being deforestation in both PFE and non-PFE is likely to happen in accessible areas, monitoring activities such as patrols should be conducted with more effective and stronger law and regulations. In both cases, participation of local community in forest conservation and management is important, and the government should also strengthen timber legality system to control illegal logging and illegal timber trade to neighboring countries.

Chapter 5

General Discussion and Conclusion

Global forest areas have been decreasing due to economic and population growth leading to overexploitation of forest resources. Changes in forest cover have negative impacts on important ecosystem services, including climate change, carbon storage and biodiversity. Therefore, monitoring forest cover changes is crucial in environmental conservation policy (Milodowski et al. 2017). In order to monitor and control forest cover changes, several measures have been initiating around the world. One of the critical measures is the designation of forest lands into permanent forest estate in order to achieve sustainable forest management. In this context, understanding the performances of permanent forest estate also became the important issue.

5.1. Global Forest Change Dataset (GFCD)

The reliable and updated spatial information about forest cover changes over time is essential to manage the forests sustainably. In addition, remote-sensing based forest cover data is cost-effective for large area monitoring. Among existing and freely available land cover products, GFCD which was developed by Hansen et al (2013a) using Landsat satellite images with 30 m resolution has been widely used around the world. However, the accuracy of GFCD is still debating.

In this study, the importance of tree cover thresholds in defining forest cover using GFCD was analyzed for different ecological zones. According to the results, different tree cover thresholds were required for different ecological zones to get the highest overall accuracy. The tropical rain forests required 80% tree cover threshold to achieve the highest accuracy, while the optimal thresholds for other ecological zones such as tropical moist deciduous forests, tropical dry forest, tropical mountain system and subtropical mountain system ranged between 10% and 40%.

In the previous studies that used GFCD, different thresholds were selected. For example, the studies in Cambodia used 30% as threshold (Davis et al. 2015), while the optimal threshold to get highest overall accuracy was 95% in Brazil

(McRoberts et al. 2016) and 70% in Gabon (Sannier et al. 2016). According to Global ecological zones, Cambodia is dominated by tropical dry forest and tropical moist deciduous forest, but Brazil and Gabon are dominated by tropical rainforest, although tropical moist deciduous forests are sub-dominant in Brazil. In addition, a case study of Gola National Park in Sierra Leone (Lui & Coomes 2015) where tropical moist deciduous forest is dominated used 50% tree cover threshold to get the accuracy of more than 90%.

In addition, the optimal threshold at national scale could be determined by the areal ratio of ecological zones in a country. This study showed that the highest overall accuracy was achieved at 40% tree cover threshold at the national scale, because approximately 30% of the total area is occupied by tropical rainforests and the remainder was occupied by other ecological zones in which the optimal tree cover thresholds ranged from 10% to 40%. Therefore, it is necessary to consider tree cover thresholds in defining forest cover using GFCD according to the dominant ecological zones in study area.

5.2. Effectiveness of Permanent Forest Estate

In Myanmar, forests which are state-owned are classified into Permanent Forest Estate (PFE) comprising with reserved forest (RF), protected public forest (PPF) and protected areas (PAs), and unclassified forests (non-PFE). RF and PPF are also known as production forests, and PAs are strictly protected areas for biodiversity conservation. The government of Myanmar has committed to biodiversity conservation, climate change mitigation and restoration of degraded forests. The commitment to UNFCCC from forestry sector is to constitute Permanent Forest estate (PFE) up to 40% of total country areas by 2030. This study investigated the effectiveness of PFE on reducing deforestation from 2006 to 2017 as a proxy to understand the conservation performances of PFE. The result clearly showed that PFE was effective in reducing deforestation by 3.76% compared to non-PFE, and PFE did not cause any leakage to non-PFE near PFE. Moreover, each of land use zonings of PFE such as RF, PPF and PAs can also reduce deforestation than non-PFE. Among three land use zonings, PAs is the most effective land use, and RF and PPF have similar rates of reducing deforestation.

Based on the results, it might be concluded that government policy, constituting PFE up to 40% of country areas, is a good mechanism to control deforestation in Myanmar and supports the policy and decision makers or conservationists from the forestry sector to consider the extension of PFE areas in other forests (i.e. non-PFE) for forest conservation. However, it is important to take into account the roles of local people, who are living in and near the intended areas to constitute PFE, especially PAs, in the conservation and utilization of forests. While the conservationists support to create PAs in land outside government control (especially in some parts of Kachin and Tanintharyi), the local people thought that government tried to control over their land (Prescott et al. 2017). Although the forest settlement officers consider the rights and privileges of local people in the affected areas, it is important to conduct extension program to understand the purposes of the constitution of PFEs, and the important role of forests in the well-being and socio-economic development of the nation. Along with the increasing public awareness, the possible conflict might be reduced in the process of the constitution of PFEs.

Moreover, the important thing to concern is the increasing trend of annual deforestation in both PFE, especially RF and PPF, and non-PFE during 2006 and 2017. Thus, if the trend of increasing annual deforestation continues, the expansion of RF and PPF might not contribute to forest conservation. To control deforestation in RF and PPF, more efforts such as frequent patrols, formulation of stronger rules and policies and law enforcement should be implemented in parallel with the extension of PFE. In addition, because selective logging has been conducting within production forests such as RF and PPF, it is important to harvest the timber in sustainable manner following the rules of MSS. There is also illegal logging causing deforestation within production forests (Win et al. 2018a), particularly during one or two years after legal logging because logging road might cause the accessibility for illegal loggers (Khai et al. 2016b; Win et al. 2018b).

Due to complex management system in non-PFE, forests located in non-PFE are more vulnerable to deforestation than PFE. An increasing deforestation in non-PFE might be related with agricultural expansion, mining, infrastructure development, hydropower development and unsustainable extraction of forest resources including illegal logging. Further efforts to mitigate the increase of deforestation in non-PFE should be focused because considerable areas of forests would be remained as non-PFE even after the expansion of the extent of PFE up to 40% of the country area.

5.3. Factors affecting deforestation

The evidence to reveal the important factors driving forest cover changes is important in sustainable forest management. Understanding the relationship between biophysical factors and deforestation would support the information to the policies, plans and strategies for preventing deforestation (Vu et al. 2014). This study examined the factors influencing deforestation in PFE and non-PFE. The results showed that deforestation in both PFE and non-PFE is more likely to occur in accessible areas, in the vicinity of human settlements, and the areas out of government control. The most important factor affecting deforestation in non-PFE was distance to PFE boundary, and the positive correlation with distance to PFE boundary showed that the probability of deforestation in non-PFE was less likely to occur nearby PFE. It might be related with the presence of forest department officials within PFE and near PFE by patrolling. Therefore, the remaining forests in non-PFE which are located in accessible areas should be considered as priority to constitute new PFE. However, because deforestation within PFE is more likely to occur in accessible areas, monitoring activities (e.g. patrol) and law enforcement should be more effective and sufficient. Moreover, in order to control illegal logging and illegal timber trade, government should secure policies and legislations and strengthen forest law enforcement, governance and trade (FLEG-T) and timber legality assurance system. Moreover, higher probability of being deforestation in both PFE and non-PFE was found in the vicinity of the villages. Therefore, public awareness about the important role of the forests is crucial and the participation local communities should be taken into account in conservation programs.

5.4. Conclusion

Based on the evidence from this study, it can be concluded that the government plan to expand the extent of PFE up to 40% of the country area by 2030 is a good system to control deforestation in Myanmar. While constituting PFEs, it is vital to take into account both forest conservation and livelihoods of local communities because participatory forest management plays a key role in sustainable forest management. Moreover, especially in production forests, it is important to conduct logging operation within the frame of Myanmar Selection System, and monitoring efforts to control deforestation caused by illegal activities should be focused in accessible areas of PFE. Thus, extension of the PFE may be an efficient way to achieve forest conservation as well as enhance local livelihoods. In order to control deforestation in non-PFE, it is crucial to secure land use policy and cooperate within different government sectors. In addition, strengthening forest law enforcement, governance and trade (FLEG-T) and timber legality assurance system is essential to control illegal timber trade.

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