ABSTRACT

Title of Dissertation: CONTEMPORARY FOREST COVER DYNAMICS IN MYANMAR

Sumalika Biswas, Doctor of Philosophy, 2016

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Understanding forest cover dynamics is important for a nation's environmental, social and political commitments. In the past decade, Myanmar had the highest deforestation rate, in mainland South East Asia (Hansen et al., 2013). Further, in 2009, Myanmar embarked on a landmark political change from military regime to democratic transition which significantly impacted its forest cover. Myanmar also ranks first with respect to forest fires in South/Southeast Asia. In Myanmar, forest cover loss and fire are intrinsically linked through the traditional taungya system of slash and burn. Thus, quantifying factors controlling forest fires in Myanmar is an important topic that needs attention. Although the Myanmar government established protected areas throughout the country to conserve forests, their effectiveness remains unevaluated.

This dissertation aims to understand the current status of forest cover dynamics in Myanmar. The five chapters in this dissertation address the impact of the political transition on forest cover loss and fragmentation, fire disturbance in tropical evergreen and deciduous forests including the factors controlling vegetation fires in the protected and non-protected forests. The dissertation contributes to the existing knowledge in land cover and land use change science (LCLUC), especially the impact of institutional changes on forest cover in the tropics. The analysis of the relationship between forest loss, fire and effectiveness of the protected areas addressed in the study, contributes to regional knowledge on fire and conservation science respectively.

The findings of this dissertation depict that in Myanmar, the political transition to democracy significantly influenced its forest cover. Our analysis showed that during 2001-2014, a total loss of 2,030,101 ha of forest occurred at the rate of 145,007.21 ha/year with a linear increase of 15,359 (±1793) ha/year. The observed increase in variance in between 2008-2011 coincides with political transition period which started with the formation of the new Constitution in 2008 and ended with the military government handing over power to the democratic government in 2011. Analysis of trend and variance patterns of two landscape fragmentation metrics (Number of Patches and Mean Patch Area) at the provincial level show the influence of the political transition on landscape fragmentation. The impact of political transition was more pronounced in provinces associated with plantations and urban areas. Among the rubber producing States, the border States, Shan, Kayah, and Kayin were more impacted compared to inland Mon. Tanintharyi and Bago Regions showed higher variance in residuals of both metrics before the transition occurred due to the military government supported oil palm and teak plantations. Fragmentation and the variance in fragmentation metrics in Kachin increased post 2008. Apart from plantation areas, urban areas like Yangon and Mandalay showed high fragmentation post 2009 period after the new government was formed. We attribute the forest loss and fragmentation to the economic and structural reforms of the democratic government, specifically to the increased granting of agricultural concessions and logging for plantations.

A study of the fire regime from 2003 to 2012 using MODIS satellite data suggested March as the peak of the fire season with 12900 km^2 of Burned Area (BA) and 95000 fire counts. Forests accounted for majority (41.3%) of the total BA and most fires (89.7%) resulted in medium or high vegetation disturbance. A higher negative correlation between BA and Gross Primary Productivity (GPP) was reported for deciduous forests than for evergreen forests ($r=0.49$ vs $r = 0.36$, $p \sim 0$). A maximum decrease in 29% of original GPP (2007-2012) was observed in the evergreen forest patches. The scale-dependent correlation analysis suggested significant BA-GPP correlation at 1×1 degree, as compared to finer resolutions. These results highlight the significance of fires impacting carbon cycle.

An in-depth analysis of fire causative factors in Myanmar was studied. The mean fire density in non-protected areas was found to be two times more than in protected areas.

Fire-land cover partition analysis suggested dominant fire occurrences in the savannas (protected areas) and woody savannas (non-protected areas). The five major fire causative factors in protected areas in descending order were found to be population density, land cover, tree cover percent, travel time from nearest city and temperature. The causative factors in non-protected areas were population density, tree cover percent, travel time from nearest city, temperature and elevation. The fire susceptibility analysis showed distinct spatial patterns with central Myanmar as a hot spot region of vegetation fires. Results from propensity score matching suggested that forests within protected areas have 11% less fires than non-protected areas. These findings provide information to policy makers about the current forest loss, forest fragmentation and forest fire hotspots, status of forest conservation and can be used to inform, update or evaluate policies. These findings are timely and can guide policy makers to arrive at best management strategies as the new government is formulating policies and laws and amending old ones to aid forest conservation.

CONTEMPORARY FOREST COVER DYNAMICS IN MYANMAR

by

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Preface

Chapters 3-4 are journal articles in which Sumalika Biswas is the primary author. Chapter 2 is in preparation for publication. Chapters 3 and 4 have already been published (IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing and PLoS ONE respectively). Data collection, data processing, methods, analysis of the findings and manuscript writing was undertaken by Sumalika Biswas, with contributions from other co-authors, who are named in the footnotes in the corresponding chapters.

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1 Introduction

1.1 Research Objective

This dissertation investigates the contemporary forest cover dynamics in Myanmar. Understanding forest cover dynamics is important for a nation's environmental, social and political commitments. In the past decade (2000-2014), multiple studies (FAO 2015, Hansen et al. 2013) have reported Myanmar as a hotspot of forest loss. A recent FAO study (FAO 2015) ranked Myanmar as having the third worst deforestation rate globally, after Indonesia and Brazil. Another study (Hansen et al. 2013) ranked Myanmar as having the highest forest loss rate in mainland South East Asia. Further, in 2009, Myanmar embarked on a landmark political change from military regime to democratic transition which was expected to significantly impact its forest cover due to rearrangement of institutional structure and uncertainty and the time lag of newly introduced reforms. Consistent information on land cover changes in Myanmar is not available, owing to the country's history of economic and political isolation. Estimates of potential land conversion available from the Myanmar Government sources do not represent the real picture as they do not report information for the 6 self-administered regions in Myanmar. The information on land use that is available from the press and other global/regional institutions is often concentrated in a few regions.

Thus, it is of interest to investigate how the political transition influenced the forest cover dynamics, in a place which already has high forest loss rates. The impact of institutional change on forest cover dynamics is a less studied area and important topic in Geography. Most of the knowledge that exists in this area is from the temperate regions in Eastern Europe, where researchers reported forest regrowth trends in abandoned agricultural areas due to absence of agricultural subsidy after reorganization of the socialist institutional structure following the fall of former Soviet Union (Hostert et al. 2011; Kuemmerle et al. 2011; Prishchepov et al. 2012). Very limited studies exist in the tropics on the institutional factors impacting land/forest cover change (Hecht et al. 2006; Burgess et al. 2011; Meyfroidt & Lambin 2008). The recent political transition in Myanmar, accompanied by opening of its economy to the global market and the recent rapid land cover and land use changes provides an opportunity to study the impact of institutional factors on forest cover change in Myanmar. In addition, a recent forest cover change product has made it possible to monitor spatiotemporal forest cover changes in the past decade at high resolution in a consistent manner. The second chapter in this dissertation addresses this issue.

Given the geographic location of Myanmar, the relation between forest cover loss and fire is very interesting. The majority of Myanmar lies in the subtropics while the southern peninsula lies in tropical belt. In the tropics, fire is used to clear the forest for non-forest (agricultural) purposes through the traditional system of slash and burn (locally called “taungya” in Myanmar). This form of forest clearing fires is practiced both in the hills for shifting cultivation and in the plains to clear forests for commercial plantations and/or development purposes. In this system, land which is no longer considered forest is chosen. However, sometimes fires escape from their intended boundaries and spread through nearby forests. Specifically, in dry subtropical Central Myanmar, the moisture deficient conditions in combination with the deciduous nature of the broadleaf forests result in forest fires with significant forest cover loss (Johnson, L. A., & Dearden 2010). Thus fires play an important role in forest cover change. The third chapter in this dissertation addresses the impact of fire disturbance in the forests of Central Myanmar.

Finally, to help protect the forests from the above two forms of fire related forest cover loss, it is important to study the factors which cause vegetation fires and the effectiveness of the protected areas. Myanmar has the highest number of fires in mainland SE Asia (Vadrevu & Justice 2011). The cause of these fires is not well known. Protected areas have been established throughout the country in order to conserve forests, however, their effectiveness remains unevaluated. The fourth chapter in this dissertation addresses the factors controlling forest fires within, as well as outside the protected areas useful to address forest conservation measures in Myanmar.

1.2 Background

1.2.1 Forest Cover and Forest Cover Dynamics

The term “forest cover” in remote sensing is used as a measure of forest area derived from satellite data. The term is closely related to “tree cover” which is the measure of area of ground covered by trees. Depending on the definition of “forest” used, the area of trees on the ground may or may not qualify as forest (Sexton et al., 2016). The measure of forest cover may be binary (presence or absence of trees in a given grid) or a continuous measure (percent of grid populated by trees). In this dissertation forest cover is defined as tree cover equal or more than 30% as indicated in the Hansen Forest Cover Change product (Hansen et al. 2013).

Forests provide a number of ecosystem services (climate regulation, biogeochemical cycling, nutrient cycling, soil formation and maintenance, biodiversity habitat) and goods (food, fuel, fiber) some of which are essential for human survival. They are affected by both natural factors (drought, floods, cyclones), and human factors (changes in land use or management). The change of forest cover over time is referred to as forest cover dynamics (Kumar et al., 2014). In the past decade, a trend of global forest loss has been observed especially in the tropics Forest loss is detrimental to the overall wellbeing of life on Earth and monitoring forest loss provides important information for forest management (Foley et al. 2005). Forest loss occurs at different rates in different parts of the world (FAO 2015). A recent satellite-based forest cover change product (Hansen et al. 2013) has made it possible to monitor forest cover change at high resolution (30m) in a consistent and continuous manner. In the past decade (2000-2014), multiple studies have reported Myanmar as a hotspot of forest loss (FAO, 2015, Hansen et al., 2013).

1.2.2 Role of institutional factors in driving forest dynamics

Drivers of forest loss may be grouped into proximal and distant factors (Lambin et al. 2003). At the local level, the purpose for which a parcel of land is used is often decided by the land owner, based on the most attractive or beneficial land use option available to him/her. The available land use options are in large part determined by institutional factors such as the economic policies, land use policies, environmental policies, land tenure, provision of price supports, taxes and subsidies for specific types of land use etc (Lambin et al. 2003). Thus, institutional factors play an important role in determining forest cover at the landscape scale (Prishchepov et al. 2012; Lambin et al. 2003). These institutional factors are largely controlled by the ruling government in a manner consistent with their political ideologies (Didia 1997; Dutt & Mitra 2005). Thus, it is commonly seen that in socialist forms of government the economy is regulated by the State with the absence/heavily controlled market forces. In authoritarian forms of government the economy is regulated by the military government with limited market forces, and in democratic forms of government, the economy is largely market oriented with limited regulation from the government. It is through these policies and the extent of control of market forces that national governments influence land use decisions at local levels (Didia 1997; Dutt & Mitra 2005; Lambin et al. 2003). For example, in Soviet Russia, under the communist government, the agricultural sector was subsidized with guaranteed markets, under a centrally planned economy (Prishchepov et al. 2012).

This encouraged land owners to grow crops, even in marginalized lands. However, with the dissolution of Soviet Union, the centrally planned economic system ceased to exist and the incentives to grow crops were much reduced, resulting in significant reforestation in Eastern Europe (Kuemmerle et al. 2011). Among the former Soviet nations, the pattern and extent of reforestation greatly differed and was dependent on the institutional support of the newly created countries (Prishchepov et al. 2012). Under authoritarian governments, the economy is tailored such that it benefits and serves the personal interests of the government officials (Didia 1997). In such forms of government, generally, extractive land uses or crops which earn more foreign exchange are the dominant land use patterns (Woods 2011a). In such countries the deforestation rates is general high. In contrast, in democratic forms of government, economic policies encourage trade liberalization and foreign investments and land uses are largely driven by market conditions and financial investments. In such countries, the rate of forest loss is either stable or conservation measures are adopted to reduce forest loss (Didia 1997). Thus, at the highest level of administration, it is the institutional factors which facilitate or prevent forest loss directly or indirectly by regulating the drivers.

Though institutional factors play an important role in land cover and land use changes, it remains an understudied topic. This is because institutional factors operate at a broad scale, generally at the country or administrative level and undergo change at a much slower rate as compared to rapid changes in the land cover (Prishchepov et al. 2012). This difference in dynamics factors makes it difficult to attribute any land cover to such institutional factors. However, times of drastic changes in institutions (e.g. ideological changes in governments /policies) offer a unique opportunity to study the impacts of institution on land cover change. The recent literature investigating the role of institutional factors in land cover and land use change is concentrated in the East European region focusing on the forest regrowth trends in Eastern Europe after the fall of Soviet Union ((Hostert et al. 2011; Kuemmerle et al. 2011; Baumann et al. 2012; Prishchepov et al. 2012). Limited studies were found to address the impact of change in political and economic institutions on land cover and land use in the tropics (Hecht et al. 2006; Burgess et al. 2011; Meyfroidt & Lambin 2008).

The recent political transition in Myanmar, accompanied by opening of its economy to the global market and the recent rapid land cover and land use changes provides an ideal opportunity to study the impact of institutional factors on forest cover change in Myanmar. Recent advances in forest mapping have enabled the production of high resolution, spatially consistent forest cover maps at a global scale (Hansen et al. 2013). The high spatial resolution of remotely sensed data provides a technique to capture small scale forest losses which was previously unfeasible. Thus, it is now possible to monitor spatiotemporal forest cover changes in the past decade at high resolution, in a consistent manner.

1.2.3 Role of fires in driving forest cover dynamics

Fire is a common land management tool in the tropics (Nepstad et al. 1999; Nepstad et al. 2001; Stolle et al. 2003; Cochrane 2009) where it has traditionally been used for slash and burn agriculture, and is now commonly used to clear forest land for agricultural expansion, logging and to build infrastructure (Nepstad et al. 2001; DeFries et al. 2010). Clearing of forests for agriculture can lead to fragmentation of forests and increased forest edges resulting in greater fire risk (Cochrane 2009). The relationship between fire and land cover and land use change is complex (Eva & Lambin 2000). Anthropogenic fires are used as tools to clear land. LCLUC also effect the fire regime by controlling the spread of fire by limiting the moisture content and amount of fuel available for burning e.g. forests have more biomass available for burning compared to agricultural lands.

Myanmar has the highest number of fires in mainland SE Asia (Vadrevu & Justice 2011). The cause of these fires is presently not known. Specifically, in dry subtropical Central Myanmar, the moisture deficient conditions in combination with the dry deciduous nature of the deciduous broadleaf forests result in forest fires leading to forest cover loss. The mosaicked forested landscape of mainland SE Asia, mostly comprises fire-dependent forests such as tropical broadleaf deciduous forests, though the patches of fire sensitive moist broadleaf forests are often interspersed with fire-dependent dry seasonal broadleaf forests. Fire is a common disturbance agent in the mosaicked landscapes of mainland SE Asia (Johnson, L. A., & Dearden 2010). The region has a distinct dry season during which people traditionally burn forests to clear lands for agriculture, maintain existing agricultural fields and hunt. However in recent times, it has been observed that tracts of former moister closed forests have been converted to more flammable open forests or fields with more frequent fire occurrences (Turner et al. 2006).

To characterize fires in the study, fire occurrence data from the Moderate resolution Imaging Spectroradiometer (MODIS) has been used (Justice et al. 2002; Giglio 2010). MODIS provides continuous, well-calibrated, and relatively long-term global records of daily fire occurrence. The MODIS Active fire data (MCD14ML) provides the location of fires within 24 hours of fire occurrence at a global scale (FIRMS 2011). This global dataset provides geolocation, brightness temperature, scan and track position, date, time, sensor, confidence and version for each fire pixel at 1km resolution. The characteristic spectral and temporal resolution of MODIS make it suitable for fire detection applications (Justice et al. 2002). The 500m MODIS Burned Area product

(MCD64A1) uses MODIS daily surface reflectance data for characterizing fires and associated burnt areas. Under typical conditions, MCD64A1 captures fires larger than 120 ha (Giglio 2010).

1.2.4 Impact of forest loss on biodiversity and the role of protected areas:

Between 2000 and 2012, the tropics experienced the highest amount of forest loss (Hansen et al. 2013). Most of these losses can be attributed to agricultural expansion, urbanization and logging (Laurance et al. 2009; DeFries et al. 2010). The clearing of tropical forests for the aforementioned LCLUC results in loss of habitats. Habitat loss is of greater concern when it occurs in biodiversity hotspots (Sodhi et al. 2004). Biodiversity hotspots contain at least 0.5% or 1,500 species of vascular plants as endemics, and have lost at least 70% of its primary vegetation (Myers et al. 2000). The clearing of forests in biodiversity hotspots may result in extinction of endemic species. Most of biodiversity hotspots are located in SE Asian countries where high rates of forest loss were also reported (Hansen et al. 2013). While a lot of research in forest and biodiversity conservation has been conducted in insular SE Asia, similar studies in mainland SE Asia are limited.

Protected areas are a common means for forest and biodiversity conservation (IUCN and UNEP 2010). However, the effectiveness of protected areas in the tropics has been debated (Bruner et al., 2001). Most researchers agree that at the broader scale, protected forests are better conserved than unprotected forests, though different levels of governance may influence the degree of protection offered (Nepstad et al. 2006; Nelson & Chomitz 2011; Ferraro et al. 2013; Nolte & Agrawal 2013). Myanmar has some of the last large tracts of forest in mainland SE Asia and very rich biodiversity. During 2012-2013, 26 new species have been discovered in the forests of Myanmar (WWF 2014). This discovery highlights the extremely rich biodiversity of this country. Loss of forests for agricultural expansion results in habitat loss and fragmentation of forests threatening the survival of the species and is of grave concern to conservationists (DeFries & Hansen 2005; Songer et al. 2008). Specific to Myanmar, forest loss is occurring at a rapid rate and there is a strong need to protect the forests. It is important to investigate how the land use changes are impacting the forest protected areas and whether legal protection status makes a difference to conservation efforts in this region.

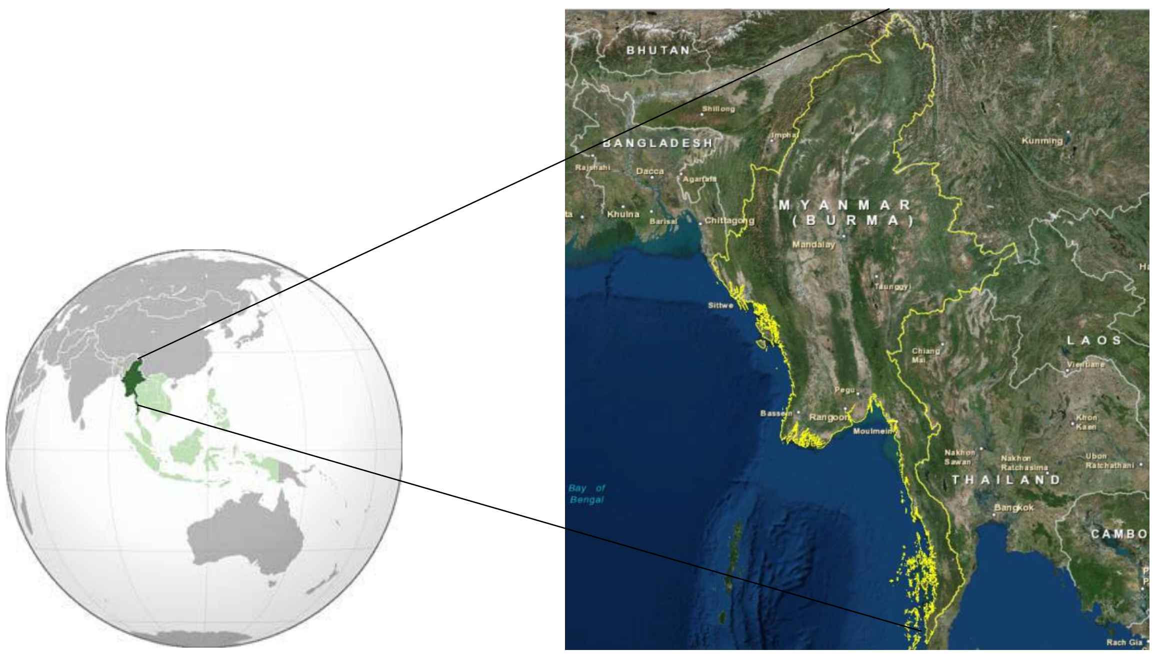


Figure 1.1: Map showing location and topography of the study area.

1.2.5 Significance of study area:

Myanmar is undergoing a political transition from authoritarian military government to democracy. The country was under military rule since 1962. The Constitution for Democratic

Burma was established in 2008 and the first election under the new Constitution was held in 2010. The transition in political landscape in Myanmar is reflected in its biophysical landscape.

In the early 2000s the military government ruled Burma. However, under the military government, there was discontent in the ethnic border states of Burma. These states were dominated by ethnic communities, in contrast to Burmans who dominated the central Burmese regions. Each of the ethnic states had their political groups and there was friction between the Burmese military government and the ethnic political groups. To make peace with the ethnic political groups, the military government signed ceasefire agreements. As a part of these agreements, timber concessions were given to the groups in exchange for territorial control. To finance their organization, the political groups illegally sold most of the timber to Chinese markets across the border ((Woods 2011a; Global Witness 2009a). However, in the mid-2000s, the military government was able to effectively redirect the timber harvested from the border areas to military channels and cut off the source of revenue for the ethnic groups (Woods 2011a; Global Witness 2009b). In addition, a change in the existing Chinese policy in 2006 (Woods 2011b; TNI 2010) resulted in further weakening of the ethnic political group. The new Chinese policy encouraged large scale rubber plantations in the uplands. This lead to displacement of a lot of ethnic people, resulting in loss of ethnic controlled territory (Woods 2011b). Though the military government had been encouraging agricultural plantations by granting large scale agricultural concessions since early 2000s, through its 30-year Agricultural Plan, not much change was observed until 2006. The change in Chinese policy along with liberalization of the agricultural trading policy in the mid-2000s resulted in rapid and uncontrolled expansion of plantations (rubber in north and oil-palm in south) in Myanmar. Civil unrest in response to how the military government dealt with the fuel crisis of 2007 and the Cyclone Nargis in 2008, combined with the economic incentives of attracting foreign investors through democratic government system after the 2008 food & oil crisis, resulted in the military government giving up power to the new quasi-democratic government in 2010. The new government headed by President Thein Sein aimed to develop Myanmar economically. A series of new laws were introduced in 2012, to encourage foreign investment in large-scale agriculture. The change in form of government accompanied by changes in economic structure and policies and law have encouraged agriculture to a great extent. At present, 62% of the agricultural concessions granted by the government are concentrated in two states, Kachin and Tanintharyi. These two states also have the largest remaining forest in the country. The huge agricultural concessions resulted in conversion of forestland to agriculture. In most cases, it is the lowland tropical forest that has been converted. It is more profitable to sell the wood from the cleared forests (called conversion timber) than the actual agricultural export crop (Woods 2015).

1.3 Research Questions

This dissertation investigates contemporary forest cover changes in Myanmar by addressing the following objectives.

Objective 1: Determine the impact of institutional change on forest cover changes in Myanmar

The political transition in Myanmar will be used as a natural experiment to study the impacts of institutional change on forest cover. The above objective will be addressed through the following research questions:

1. How did the recent political transition in Myanmar impact its forest cover?
2. Is the change consistent across different provinces and which of these were most impacted with respect to forest cover change?

Objective 2: Characterize regional fire occurrence and forest disturbance due to fire

Research Questions:

1. What is the spatiotemporal distribution of the fires in Myanmar and what are the typical fire regime characteristics (duration, seasonality, and extent)?
2. Which land cover is most impacted by fires? How much of the vegetation disturbance in Myanmar is due to fires?
3. How does the fire impact the GPP in a forested landscape and how do fire–GPP relationships vary across different ecosystem types (evergreen versus deciduous forests) and across different spatial scales?

Objective 3: Evaluate the dominant causative factors and the effectiveness of protected areas in conserving the forests.

Research Questions:

1. What are the dominant causative factors of fires in protected and non-protected areas?
2. Are protected areas effective in conserving the forests?

To achieve the above objectives, a methodology combining the use of satellite remote sensing data, ancillary GIS data, statistics and reports from government and non-government sources have been used. A schematic diagram of interlinkages between research objectives is given in Figure 1.2.

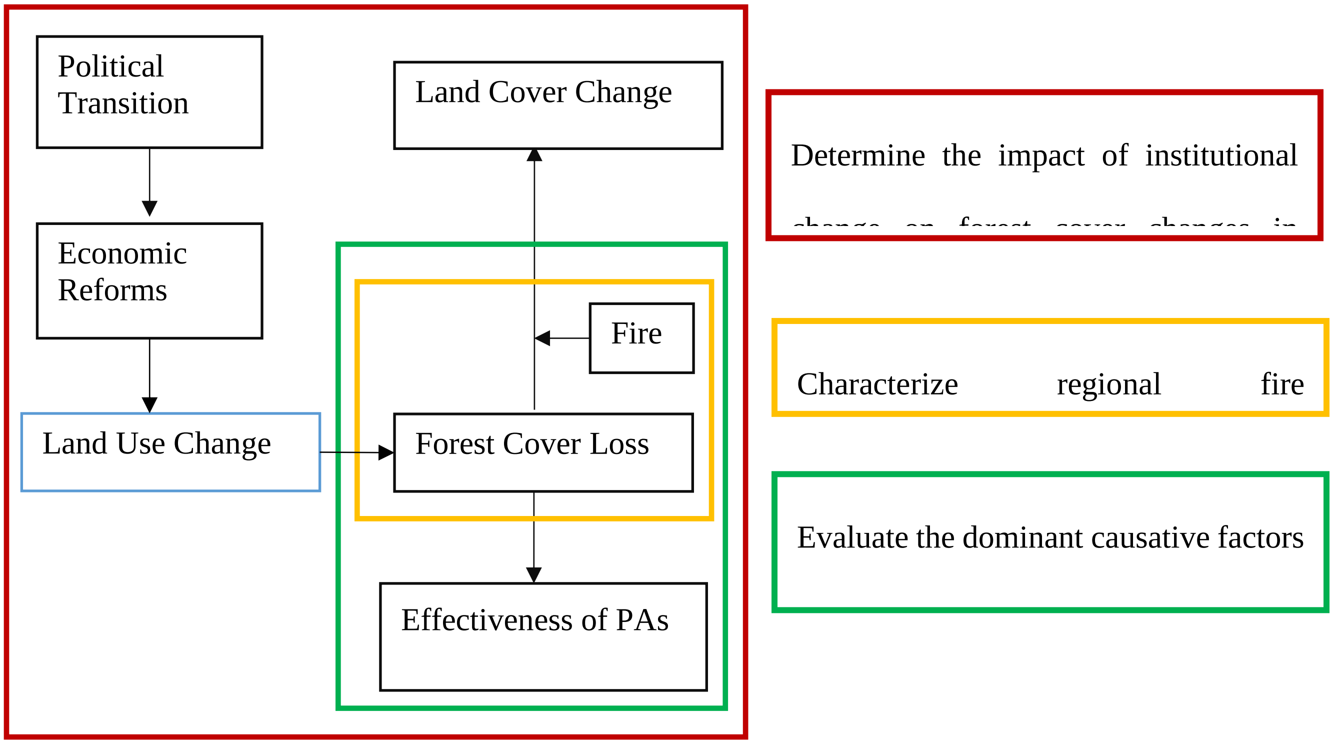


Figure 1.2: Schematic Diagram of the Research Objectives

1.4 Outline of Dissertation

This dissertation is composed of 5 chapters. Chapter 1: Introduction (this chapter), provides a background on the research problem and study area, introduces the research objectives and research questions, and provides an outline of the dissertation. Chapters 2-4 are the three primary chapters and are self-contained and structured in the format of journal articles. Chapter 2 is in preparation for publication. Chapters 3 and 4 have already been published. Each chapter, thus, consists of the relevant literature review and a list of references at the end.

Chapter 2: Regime change and forest fragmentation in Myanmar addresses Objective 1 and estimates forest loss and fragmentation in context of the recent political transition.

Chapter 3: Fire Disturbance in Tropical Forests of Myanmar—Analysis Using MODIS Satellite Datasets addresses objective 2 and analyses fire caused forest disturbance in the tropical evergreen and deciduous forests.

Chapter 4: Factors Controlling Vegetation Fires in Protected and Non-Protected Areas of Myanmar addresses objective 3 and investigates the causative factors of vegetation fires and the effectiveness of protected areas.

Chapter 5: Summary of research provides a summary of the findings, conclusion and future directions for the research.

Chapters	Content	Status
Chapter 1	Introduction: Background, Research Objectives and Questions, Research Structure and Logic.	
Chapter 2	Objective 1: Determine the impact of institutional change on forest cover changes in Myanmar. Paper 1- Regime change and forest fragmentation in Myanmar.	In preparation
Chapter 3	Objective 2: Characterize regional fire characteristics and forest disturbance due to fire. Paper 2- Fire Disturbance in Tropical Forests of Myanmar—Analysis Using MODIS Satellite Datasets.	Published (IEEE JSTARS)
Chapter 4	Objective 3: Evaluate the dominant causative factors and the effectiveness of protected areas in conserving the forests. Paper 3- Factors controlling Vegetation fires in Protected and non-protected areas of Myanmar.	Published (PLOS ONE)
Chapter 5	Research Summary, Discussion and Future Directions	

Table 1.1: PhD Dissertation Structure

2 Regime change and forest fragmentation in Myanmar

2.1 Abstract

In 2009 Myanmar embarked on a landmark political change from military regime to democratic transition which significantly influenced its forest cover. In this study, we examine forest loss and fragmentation from 2001 to 2014 in the context of this recent political transition, using Landsat-derived forest change data to estimate forest loss and fragmentation metrics at 2 scales: i) national, and ii) State/Region (in Myanmar States and Regions are geographically exclusive and both refer to level 2 administrative division). Our analysis showed a total loss of 2,030,101 ha of forest at the rate of 145,007.21 ha/year with a linear increase of 15,359 (±1793) ha/year. The observed increase in variance in between 2008-2011 coincides with political transition period which started with the formation of the new Constitution in 2008 and ended with the military government handing over power to the democratic government in 2011. Analysis of trend and variance patterns of two landscape fragmentation metrics (Number of Patches and Mean Patch Area) at the provincial level show the influence of the political transition on landscape fragmentation. The impact of political transition was more pronounced in provinces associated with plantations and urban areas. Among the rubber producing States, the border States, Shan, Kayah, and Kayin were more impacted compared to inland Mon. Tanintharyi and Bago Regions showed higher variance in residuals of both metrics before the transition occurred due to the military government supported oil palm and teak plantations. Fragmentation and the variance in fragmentation metrics in Kachin increased post 2008. Apart from plantations areas, urban areas like Yangon and Mandalay showed high fragmentation post 2009 period after the new government was formed. We attribute the forest loss and fragmentation to the economic and structural reforms of the democratic government,

specifically to the increased granting of agricultural concessions and logging for plantations. Our results highlight hotspots of recent forest fragmentation to aid conservation measures. The challenge for the new government lies in designing win-win policy interventions that not only encourage economic and social development but also ensure environmental protection.

2.2 Introduction

The significant role played by the government in determining national forest cover trends is recognized in forest conservation literature (Deacon 1994; Didia 1997; Mather 2007; Ferreira and Vincent, 2010). Governments influence land use decisions at a local level through policy intervention, institutional and market controls and thus, determine the fate of the available forest resource (Lambin et al. 2001; Hosonuma et al., 2012). From past examples, we can see that the manner in which different forms of governments manage forest resources are different (Didia 1997). Most non-democratic governments are associated with unsustainable forest management activities leading to increased pressure on forest resources, in the absence of appropriate environmental safeguards under autocratic rule (Didia 1997; Barber & Talbott 2003; Larjavaara 2012), while democratic rule with the provision of environmental safeguards has proved beneficial for forest conservation (Deacon 1994; Li & Reuveny 2006; Shandra 2007). However, this trend is not uniform. Not all democratic governments have been able to conserve forests successfully (Midlarsky 1998; Neumayer 2002; McCarthy 2014; Klopp 2012). In a recent study, (Buitenzorgy & Mol 2011) inferred that countries with autocracy and mature democracies have low deforestation rates compared to countries with young, transitional or low democracies and attribute the high deforestation rates in new democracies to the weak State, immature civil society and weak governance.

According to Mather's forest transition theory (Mather 2004; Mather 2007; Rudel et al. 2010) as societies undergo change, initially there is a prolonged decline in the extent of forests followed by partial recovery depending on policy interventions by the government or change in demand for resources due to globalization. The rate of forest loss in the initial period increases due to uncertainties associated with the newly introduced policies, temporarily weakened institutional control and exposure of the local forest communities to global markets. For example, in Borneo, Indonesia, logging rates sky-rocketed during the transition to democracy (Obidzinski 2004). As the transition completes, changes in structure and functions of institutions occurs and based on the policies and implementation rigor, forest resource exploitation might decrease over a period of time in the democratic regime (Barbier & Burgess 1997; Mather & Needle 1999). Rates of forest loss may also depend on the implementation of specific land use reforms including granting of new agricultural or logging concessions (McCarthy & Tacconi 2011; Rudel et al. 2009; Larson 2010; Angelsen 2010), and absence of well-defined property rights or resource regulations that can drive agricultural land expansion at the cost of forest land (Barry et al. 2010).

The issue of forest exploitation associated political transition is most strongly felt by the tropical nations, most of which are undergoing periods of political transition from non-democratic forms of government to democracy. Most of these countries lie in areas of high biodiversity value and have high deforestation rates. Post-democratic integration of these countries into the global economy also faces them with disadvantages associated with resource exploitation. In the Asian region, Myanmar was under the direct military rule until 2011 and has had the longest military government in recent history (Bunte 2012). The transition towards democracy started in September 2008 with the formation of the 3rd Constitution. Since then the military prerogatives have been gradually reduced with increased political liberalization, economic reforms and space for civilian institutions. Historically, forests in Myanmar have been of major importance for both local livelihoods as well as the national economy. Thus, most of the conflicts in Myanmar to-date relate to forest and timber resources (Bryant 1997; Global Witness 2009b). The political transition in Myanmar resulted in opening up of the country to global markets and foreign investments. Considering the recent developments, it is unclear how forest cover changed before and since the beginning of the democratic transition. We address this issue quantitatively by assessing forest cover as well as fragmentation trends spatially and temporally using remote sensing datasets.

Remote sensing data due to its multi-spectral and multi-temporal coverage can aid in successful mapping and monitoring of land use/cover, including forests. High resolution remote sensing data enables better characterization of forest loss patterns and helps in relating to underlying processes of change (Hansen et al. 2013; Congalton et al. 2014). The process of fragmentation is indicated by change in area and configuration of the forest patches resulting in smaller patch area, with increased edges and increase isolation of the patches. Forest fragmentation during different time periods can be determined by using landscape metrics (McGarigal et al. 2002). Some popular compositional and configurational landscape metrics that can be used to characterize fragmentation includes the number of patches, mean patch area, landscape shape index, contiguity and clumpiness index. The number of patches is an important indicator of the extent of landscape fragmentation (Fahrig 2003), whereas the mean area of patch is a compositional landscape metric and is a function of the number of patches (Fahrig 2003). The landscape shape index as well as contiguity captures edge characteristics depicting connectivity of patches. The clumpiness index is a measure of class aggregation independent of the class area (Wang et al. 2010). Forest fragmentation results in habitat fragmentation which has serious biodiversity implications in a biodiversity hotspot like Myanmar.

We address the following questions in the study:

1. How did the recent political transition in Myanmar impact its forest cover?
2. Is the change consistent across different provinces and which of these were most impacted with respect to forest cover change?

2.3 Study Area

The Republic of the Union of Myanmar (previously, Burma) is located between 9°32'N to 28°31'N and 92°10'E and 101°11'E. Geographically, Myanmar is divided into seven *yin* (Regions), seven *pyine* (States), and one union territory. The 7 States are Chin, Kachin, Kayah, Kayin, Mon, Rakhine and Shan while the 7 Regions are Ayeyarwaddy, Bago, Magway, Mandalay, Sagaing, Tanintharyi and Yangon. The capital Naypyidaw is a union territory. Mostly, the States are semi-autonomous areas allocated to specific ethnic groups. For our spatial analysis, we considered 7 States and 7 Regions and included Naypyidaw as a part of Mandalay Region (Figure 2.1).

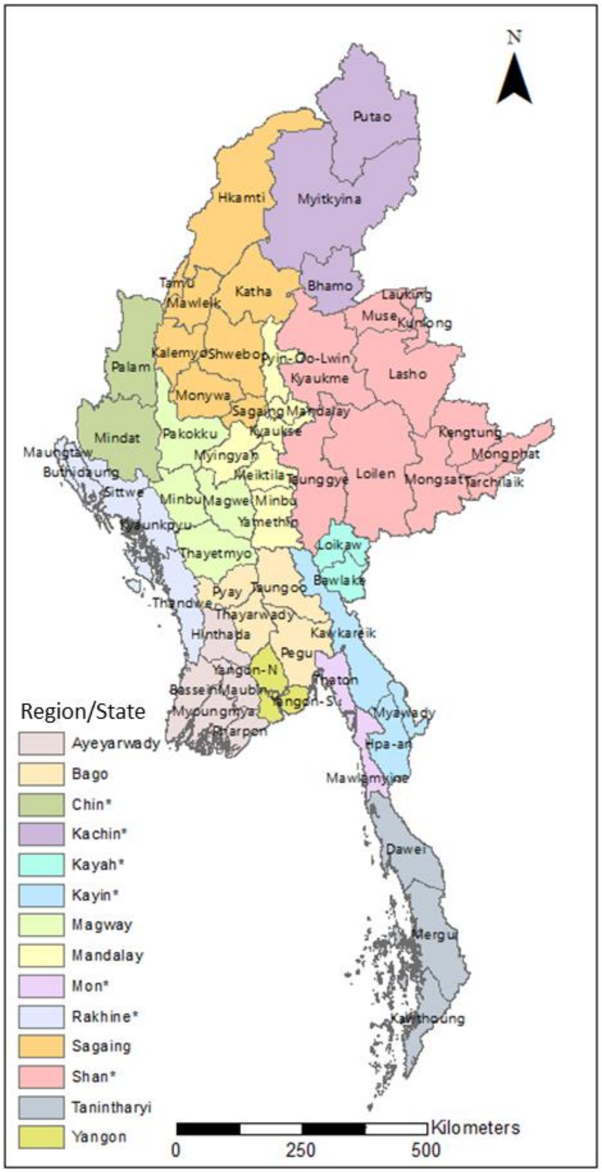


Figure 2.1: Study area location map showing Regions, States and Districts in Myanmar. States are marked with asterisk to differentiate from Regions.

2.4 Data

We downloaded the administrative boundaries of the study area from the Global Administrative Areas (http://www.gadm.org/). To quantify the annual forest loss at various scales, we used the annual forest loss layers for the years 2001-2014 from Global Forest Change data (Hansen et al. 2013). The dataset was downloaded from Google Earth Engine (http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.2.html)and has a resolution of 30m.

2.5 Methods

To determine the changes in forest cover and landscape fragmentation in the context of the political transition, we analyzed the data from 2001-2014. We studied the overall trend and variance in forest loss or forest fragmentation metrics. Forest loss and landscape fragmentation metrics were calculated for individual years (2001-2014). The analysis was performed at two spatial scales, i.e., country level, and province (State or Region) level. To characterize and quantify the spatial pattern of forest loss and fragmentation at the province level, we used landscape metrics. FRAGSTATS (v4.2) software (McGarigal et al. 2002) was used to compute the landscape metrics annually. To describe the forest fragmentation for different years, we used two landscape metrics: Number of Patches (NP), and Mean Patch Area (AREA_MN). A brief explanation and justification of the indices used are in the study are given in Table 2.1.

	Number of Patches (NP)	Mean Patch Area (AREA_MN)
Definition	Number of patches in the landscape.	The area of the patch.
Unit	None	Hectares
Range	NP >1, without limit.	AREA > 0, without limit.

Table 2.1: Landscape metrics used in the study.

For each landscape metric, we fit a linear model to the fragmentation data and analyzed the distribution of the residuals to identify unusual variance patterns.

2.6 Results

During 2001-2014, Myanmar lost 2,030,101 ha of forest at the rate of 145,007.21 ha/year with a linear increase of 15,359 (±1793) ha/year (Figure 2.2). The loss pattern followed a linear trend over time. The increase in variance in between 2008-2011 coincides with political transition period which started with the formation of the new Constitution in 2008 and ended with the military government handing over power to the democratic government in 2011.

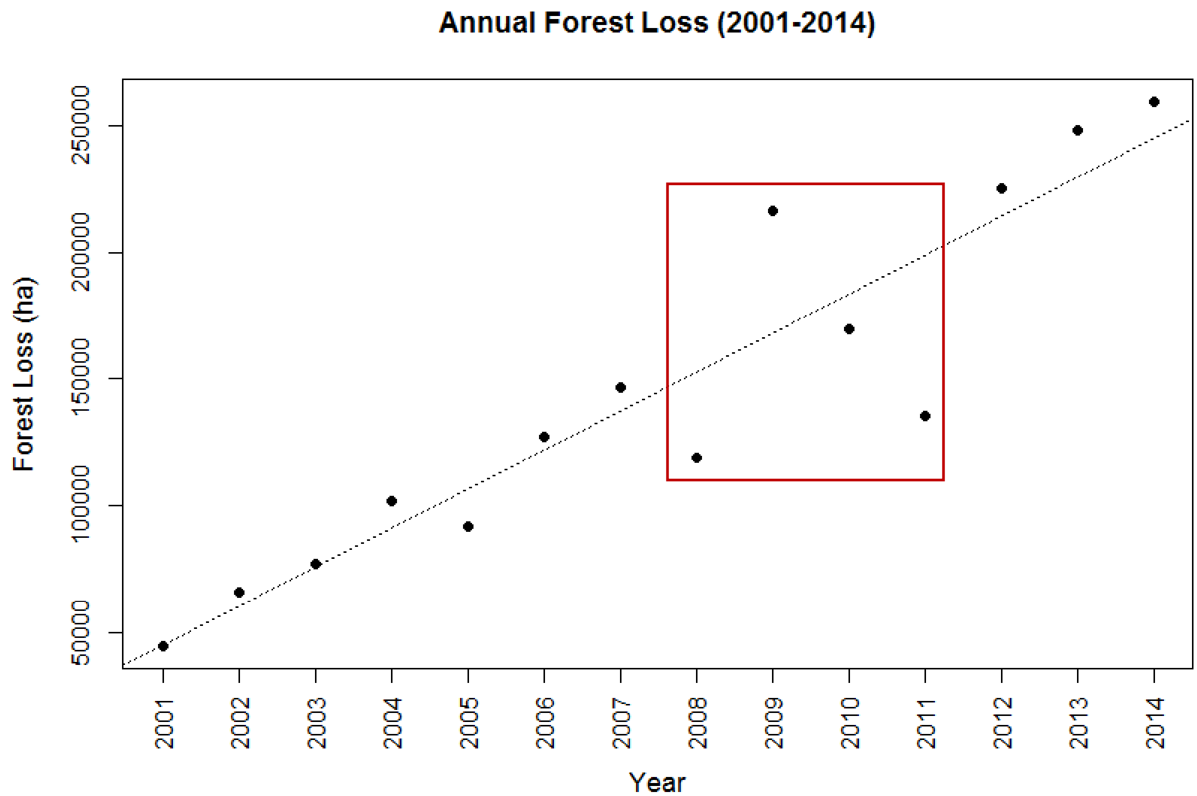
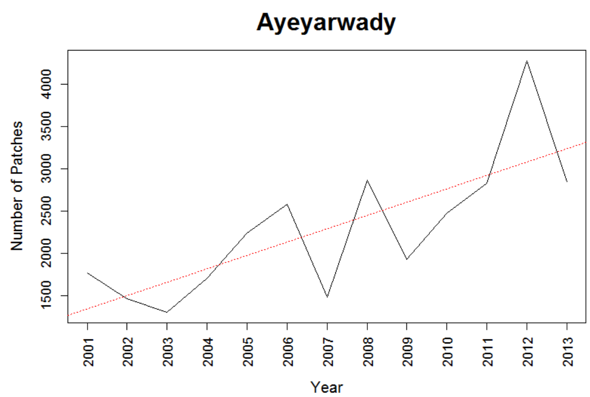
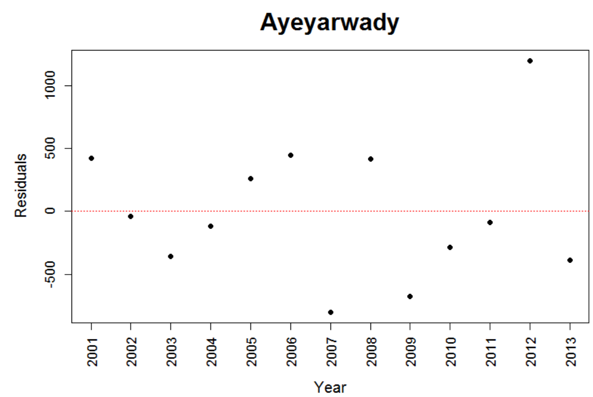
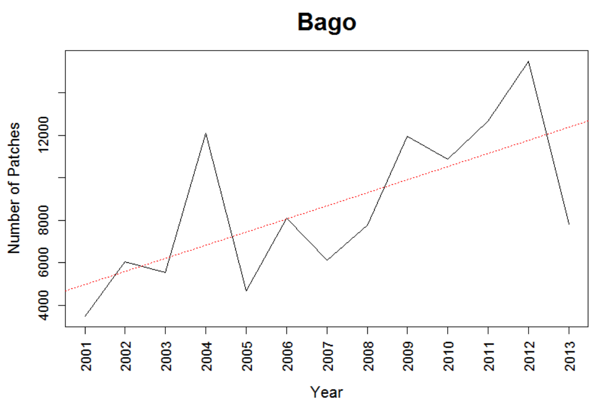


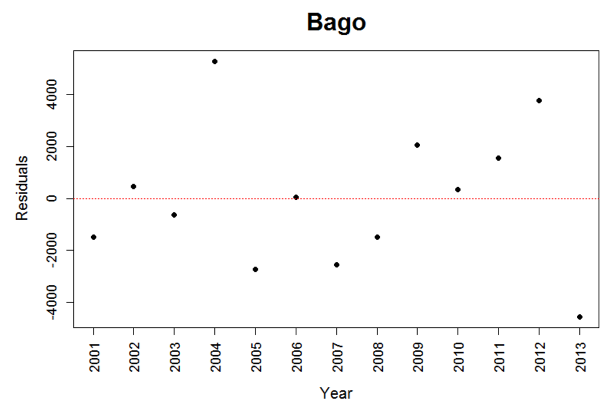
Figure 2.2: Annual Forest Loss in Myanmar (2001-2014).

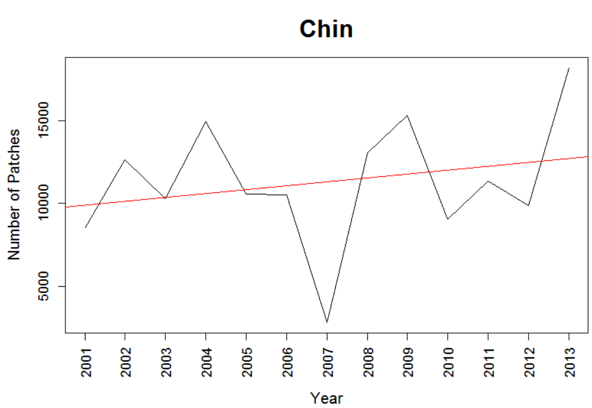
Analysis of trend and variance patterns in Number of Patches and Mean Patch Area metrics at the provincial level show the influence of the political transition on landscape fragmentation at the provincial level (Figure 2.3 and 2.4). Both the metrics (Number of Patches and Mean Patch Area) show an increasing trend over time.

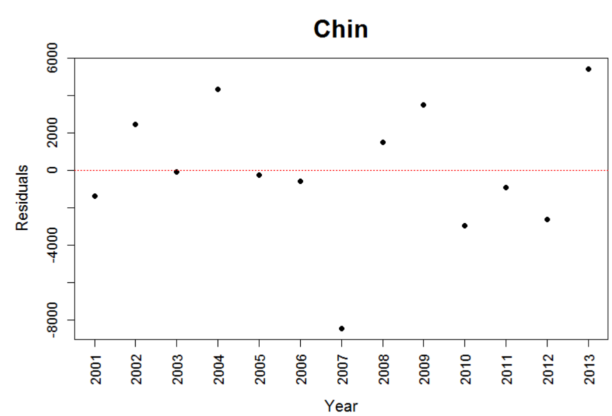

Ayeyarwady
Number of Patches
1500 2000 2500 3000 3500 4000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

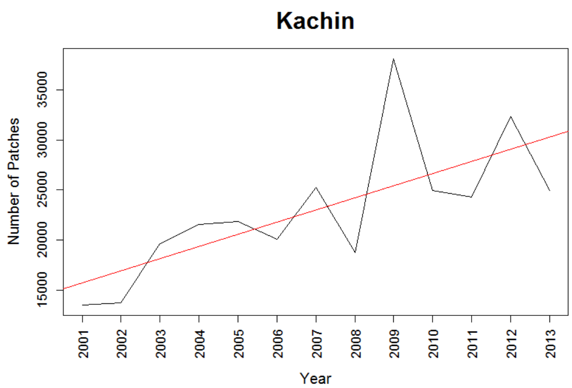

Ayeyarwady
Residuals
-500 0 500 1000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

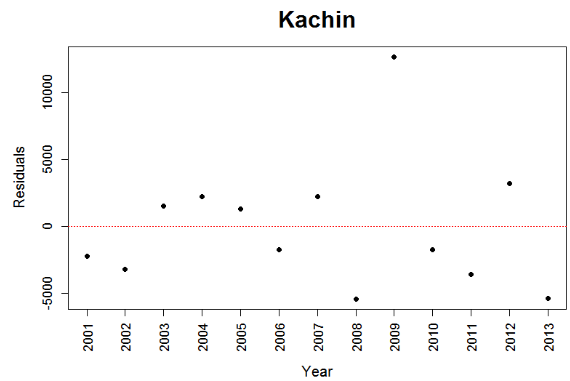

Bago
Number of Patches
4000 6000 8000 12000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

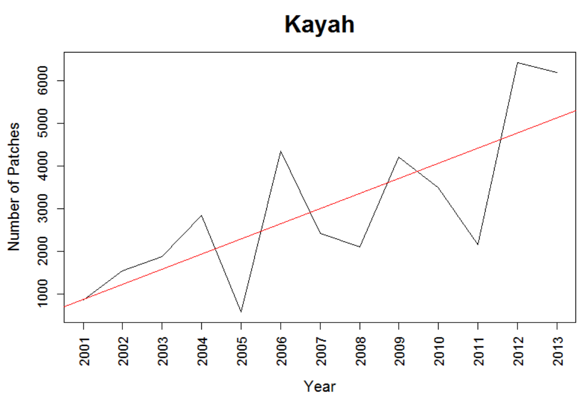

Bago
Residuals
-4000 -2000 0 2000 4000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

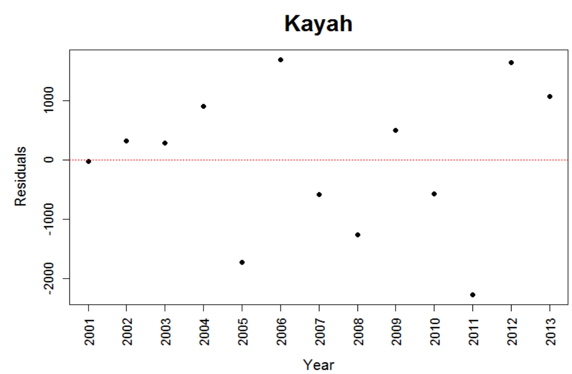

Chin
Number of Patches
5000 10000 15000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

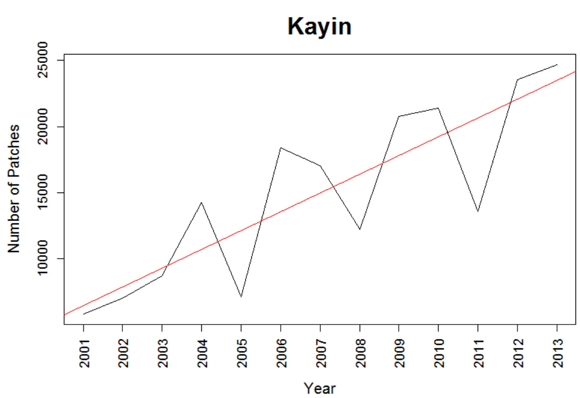

Chin
Residuals
-8000 -4000 0 2000 6000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

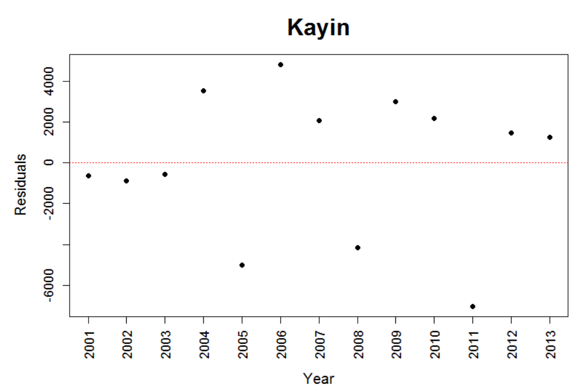

Kachin
Number of Patches
15000
20000
25000
30000
35000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

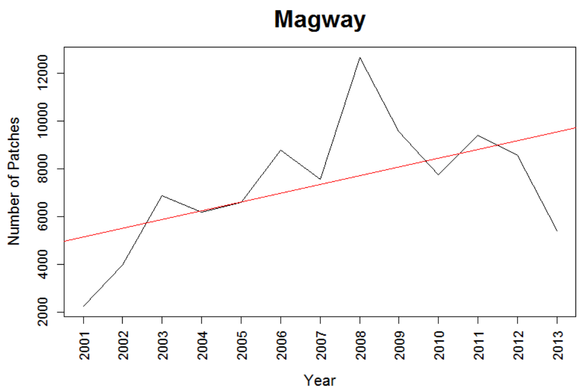

Kachin
Residuals
-5000
0
5000
10000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

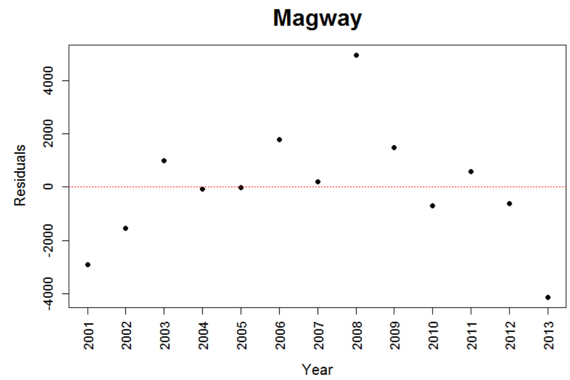

Kayah
Number of Patches
1000
2000
3000
4000
5000
6000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

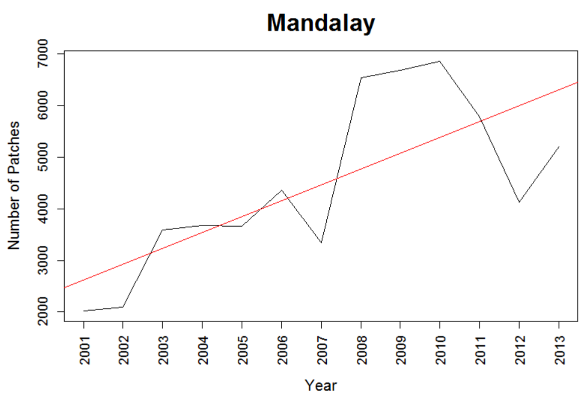

Kayah
Residuals
-2000
-1000
0
1000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

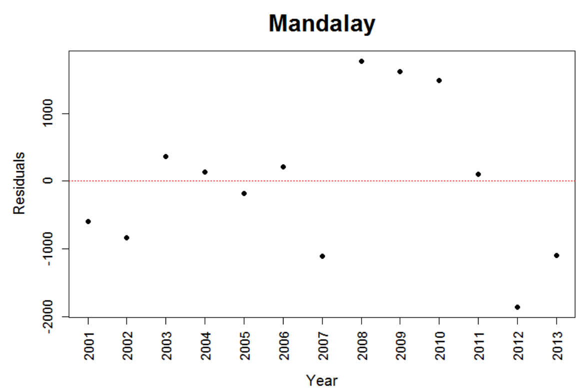

Kayin
Number of Patches
10000
15000
20000
25000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

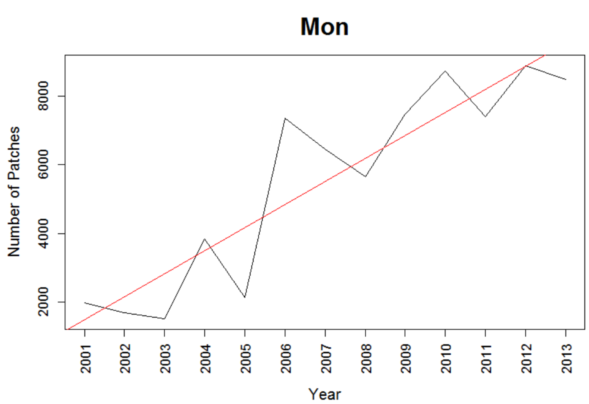

Kayin
Residuals
-6000
-2000
0
2000
4000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

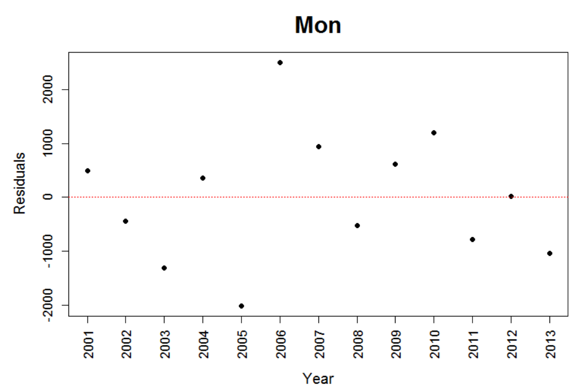

Magway
Number of Patches
2000 4000 6000 8000 10000 12000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

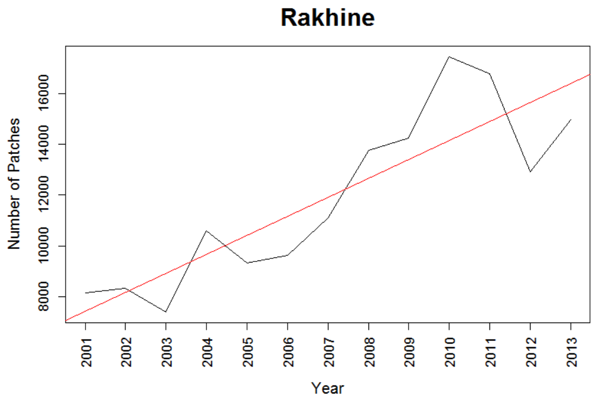

Magway
Residuals
-4000 -2000 0 2000 4000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

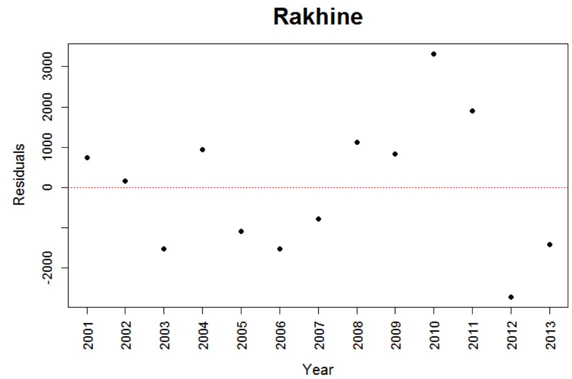

Mandalay
Number of Patches
2000 3000 4000 5000 6000 7000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

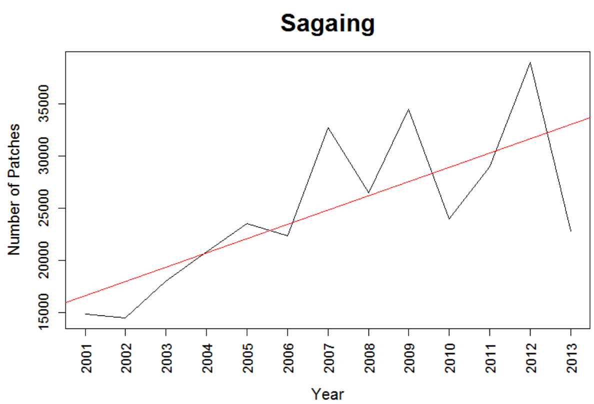

Mandalay
Residuals
-2000 -1000 0 1000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

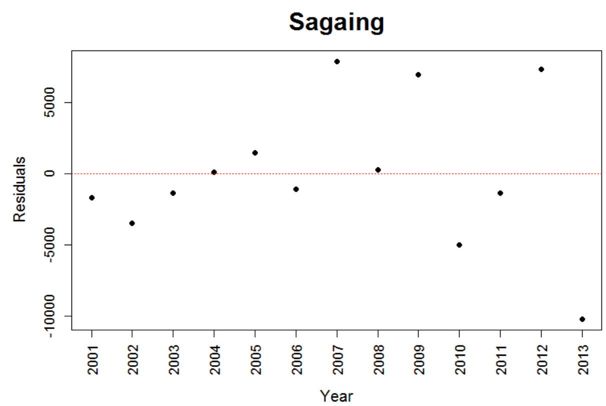

Mon
Number of Patches
2000 4000 6000 8000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

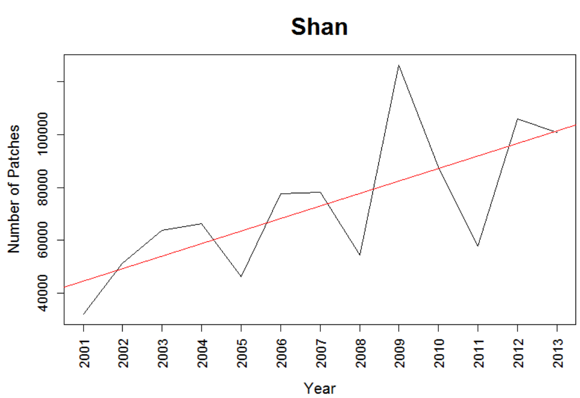

Mon
Residuals
-2000 -1000 0 1000 2000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

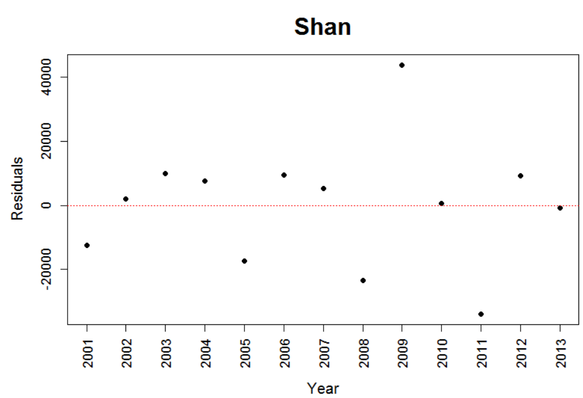

Rakhine
Number of Patches
8000
10000
12000
14000
16000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year


Rakhine
Residuals
-2000
0
1000
2000
3000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year


Sagaing
Number of Patches
15000
20000
25000
30000
35000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year


Sagaing
Residuals
-10000
-5000
0
5000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year


Shan
Number of Patches
40000
60000
80000
100000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year


Shan
Residuals
-20000
0
20000
40000
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

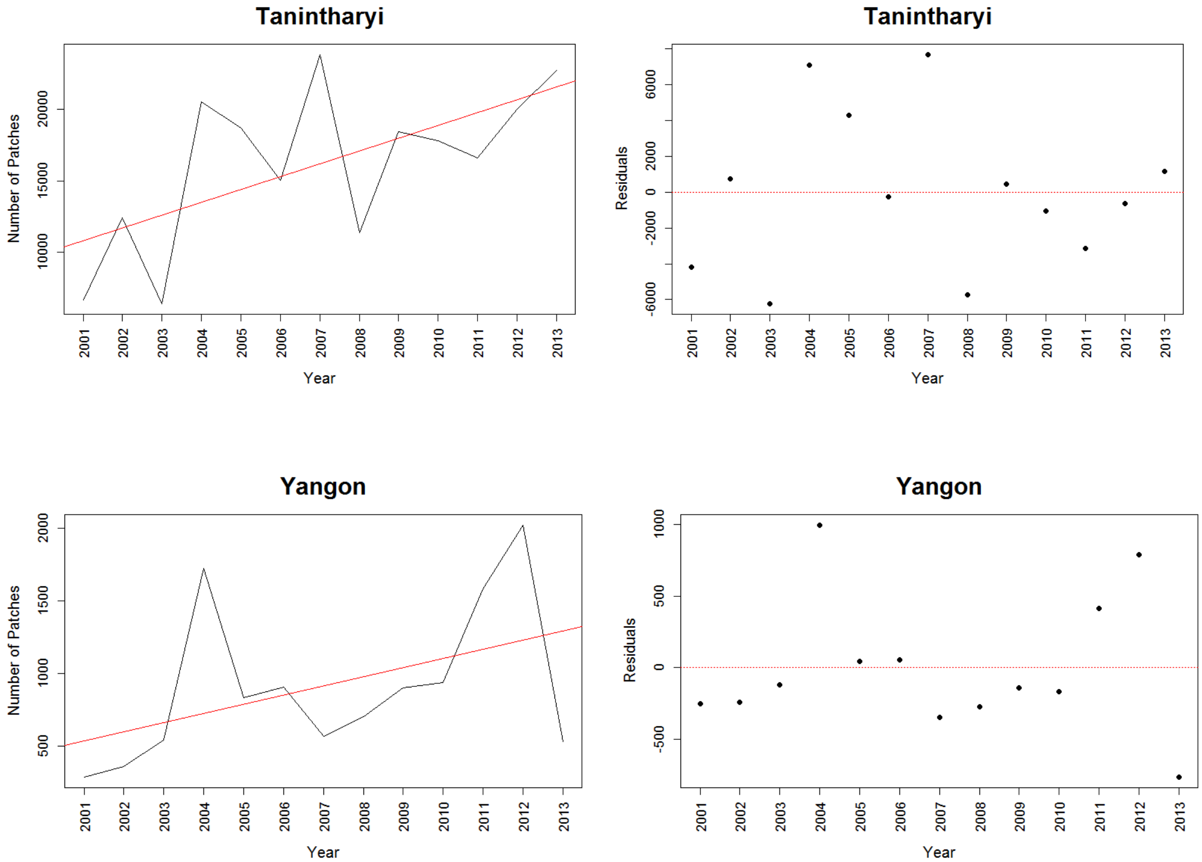
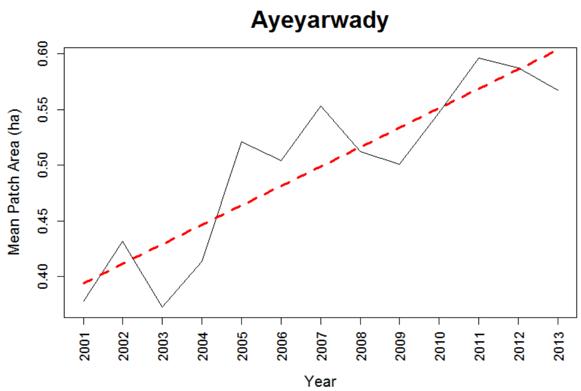
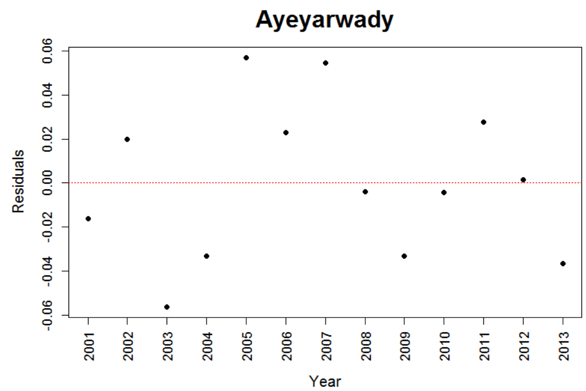
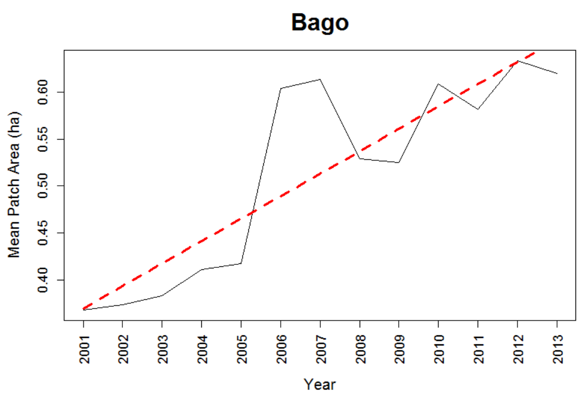
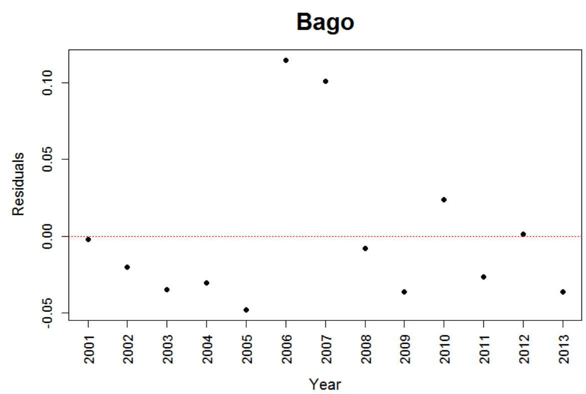


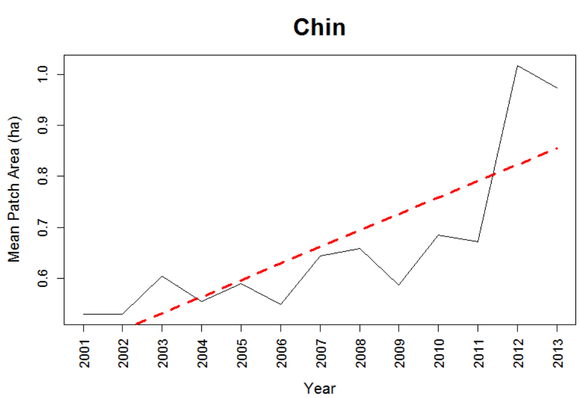
Figure 2.3: Plots showing Number of Patches for every province (left hand) and residuals of linear fit (right hand).

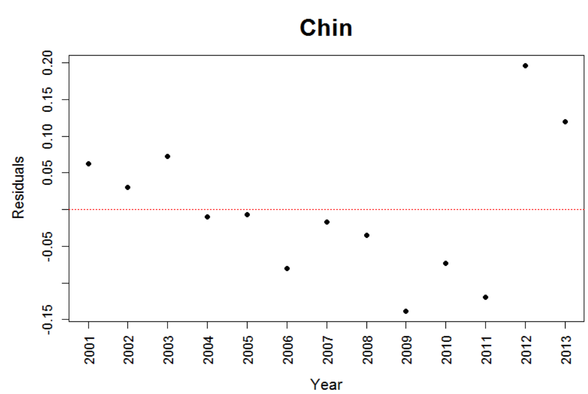

Ayeyarwady
Mean Patch Area (ha)
Year

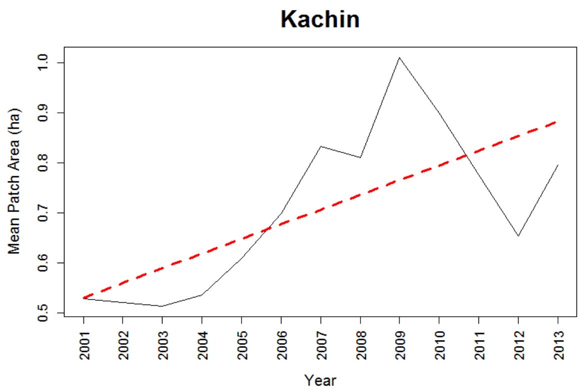

Ayeyarwady
Residuals
Year

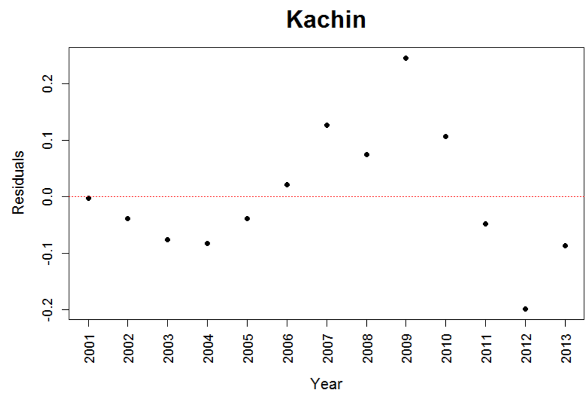

Bago
Mean Patch Area (ha)
Year

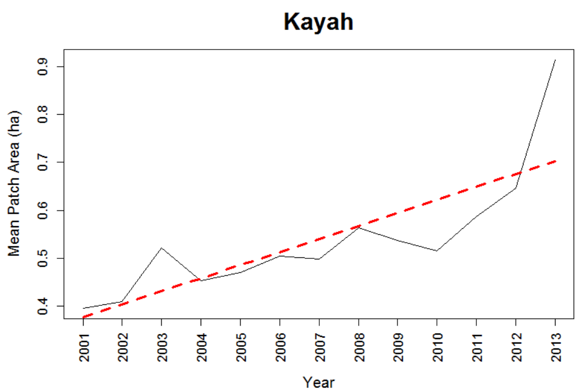

Bago
Residuals
Year

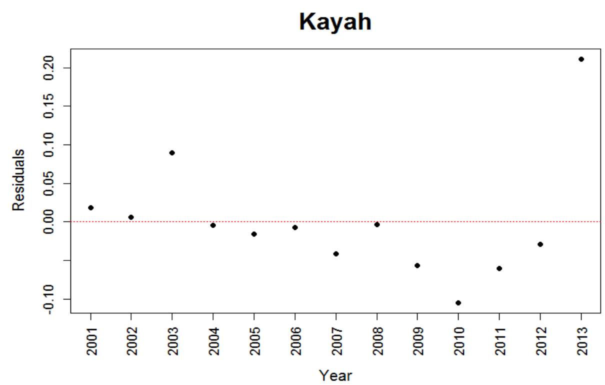

Chin
Mean Patch Area (ha)
Year

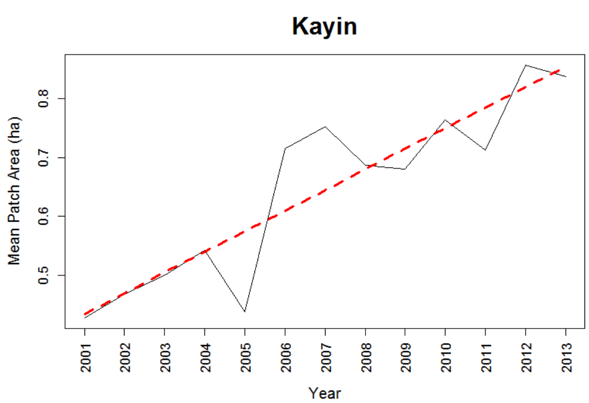

Chin
Residuals
Year

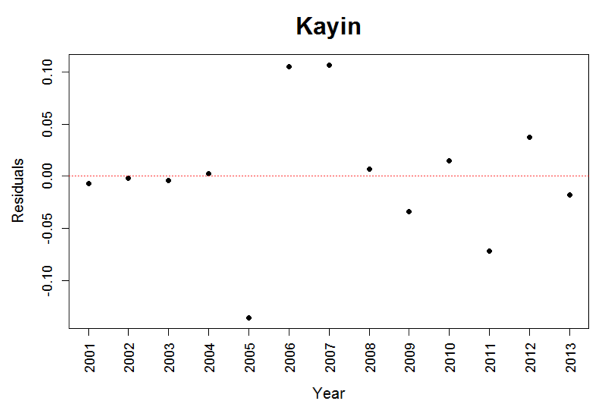

Kachin
Mean Patch Area (ha)
0.5 0.6 0.7 0.8 0.9 1.0
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

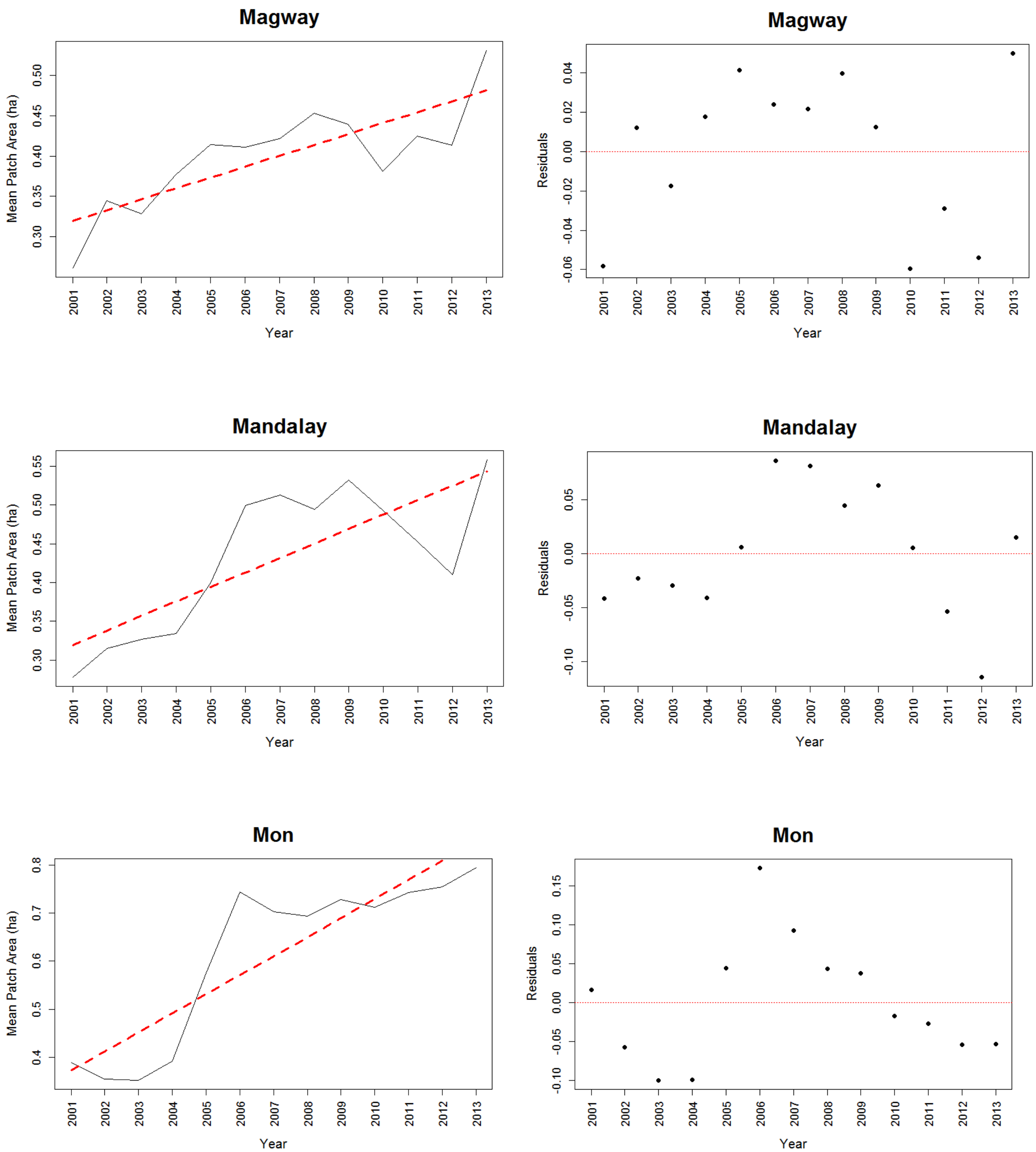

Kachin
Residuals
-0.2 -0.1 0.0 0.1 0.2
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

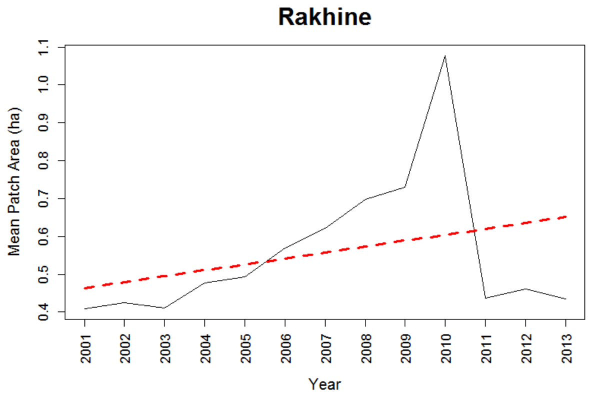

Kayah
Mean Patch Area (ha)
0.4 0.5 0.6 0.7 0.8 0.9
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

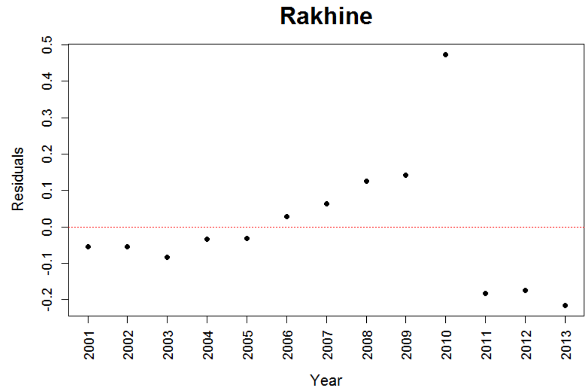

Kayah
Residuals
-0.10 0.00 0.05 0.10 0.15 0.20
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

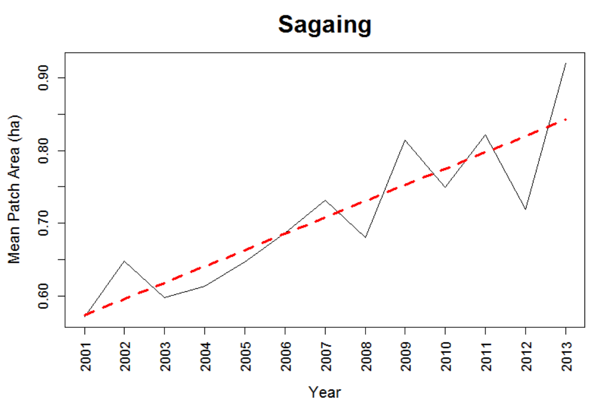

Kayin
Mean Patch Area (ha)
0.5 0.6 0.7 0.8
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

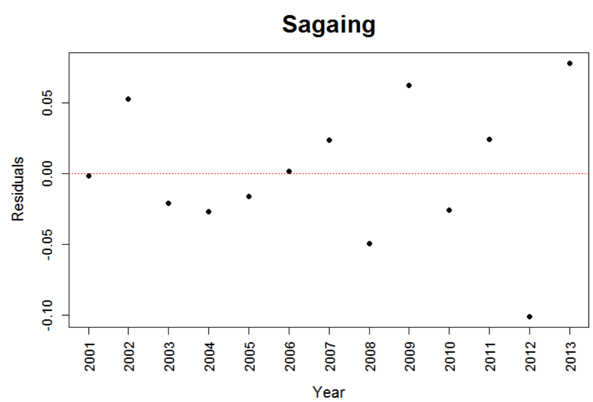

Kayin
Residuals
-0.10 -0.05 0.00 0.05 0.10
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

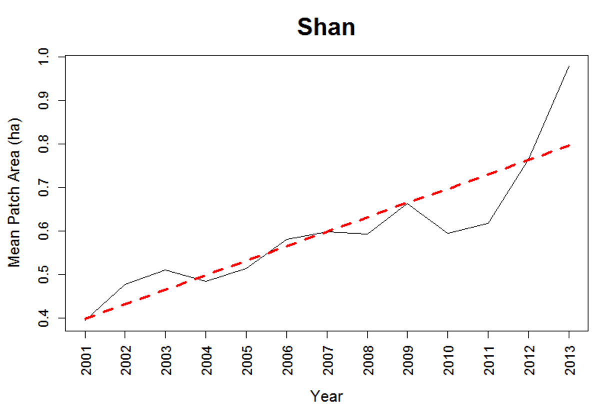

Magway
Mean Patch Area (ha)
0.30 0.35 0.40 0.45 0.50
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year
Magway
Residuals
-0.06 -0.04 -0.02 0.00 0.02 0.04
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year
Mandalay
Mean Patch Area (ha)
0.30 0.35 0.40 0.45 0.50 0.55
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year
Mandalay
Residuals
-0.10 -0.05 0.00 0.05
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year
Mon
Mean Patch Area (ha)
0.4 0.5 0.6 0.7 0.8
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year
Mon
Residuals
-0.10 -0.05 0.00 0.05 0.10 0.15
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

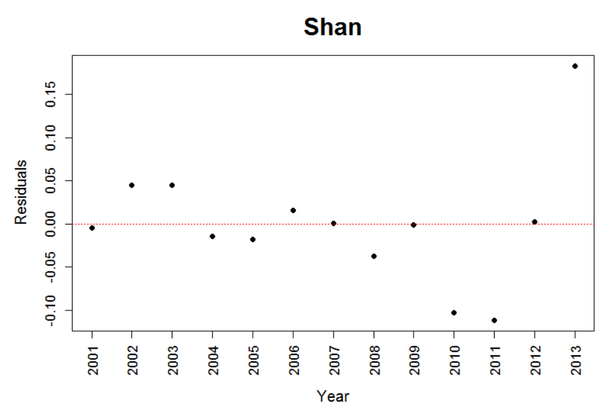

Rakhine
Mean Patch Area (ha)
0.4 0.5 0.6 0.7 0.8 0.9 1.0 1.1
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year


Rakhine
Residuals
-0.2 -0.1 0.0 0.1 0.2 0.3 0.4 0.5
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year


Sagaing
Mean Patch Area (ha)
0.60 0.70 0.80 0.90
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year


Sagaing
Residuals
-0.10 -0.05 0.00 0.05
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year


Shan
Mean Patch Area (ha)
0.4 0.5 0.6 0.7 0.8 0.9 1.0
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year


Shan
Residuals
-0.10 -0.05 0.00 0.05 0.10 0.15
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Year

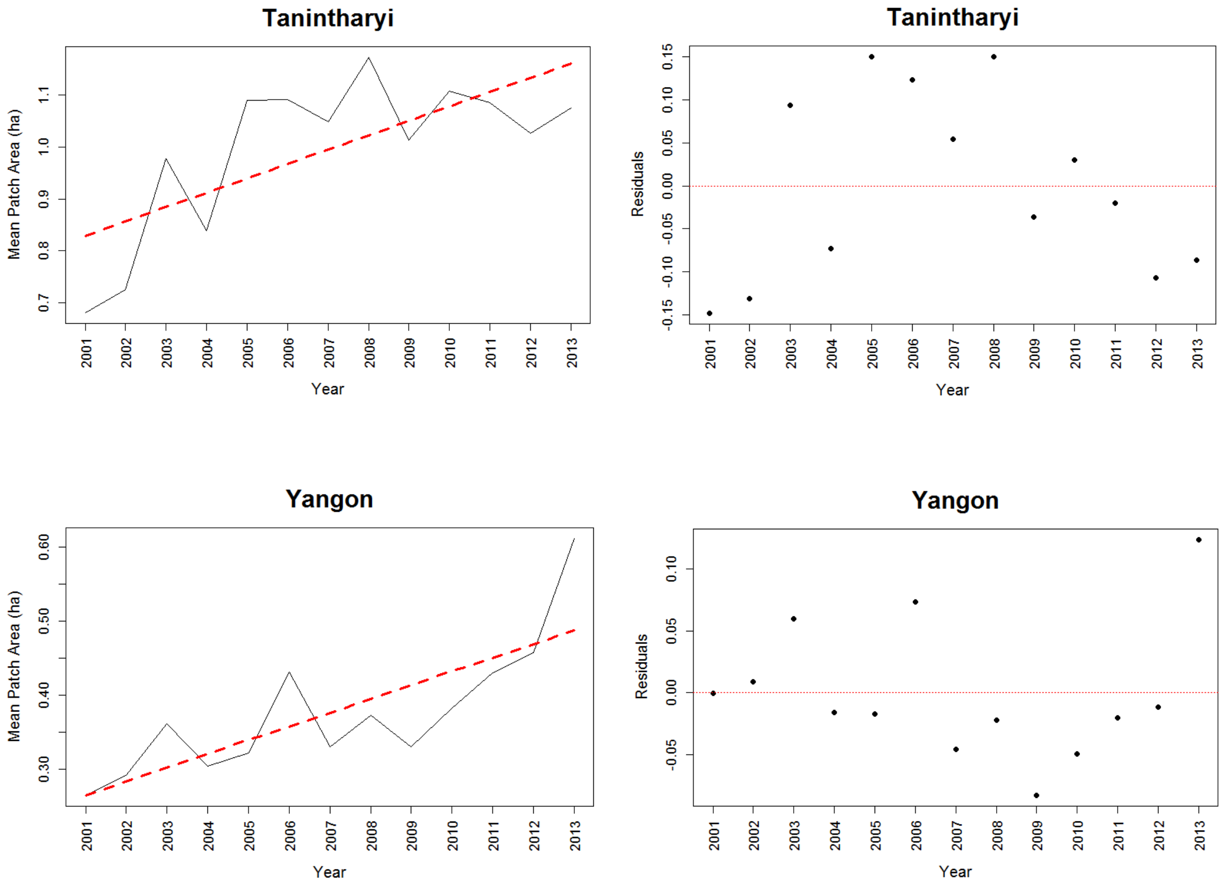


Figure 2.4: Plots showing Mean Patch Area for every province (left hand) and residuals of linear fit (right hand).

2.7 Discussion

Though the amount of forest loss in Myanmar during 2001-2014 (2,030,101 ha) appears to be modest compared to forest loss in other tropical nations (Brazil, Democratic Republic of Congo) and insular South East Asia, nevertheless, it is the highest in mainland South East Asia (Hansen et al. 2013).

It is interesting to see that the trend of forest loss during the above period increased linearly except for brief period of instability coinciding with the political transition in the country (Figure 2.2). The overall linear increase in forest loss trend implies that the previous (military government) drivers of forest loss continue to operate with higher forest losses. The increasing linear trend can be attributed to economic and structural reforms under the democratic government (International Crisis Group 2012; Asian Development Bank 2012; World Bank 2014). The opening of Myanmar's economy to the world facilitated its integration into the global economy and led to huge amounts of foreign investments. To avail the prevailing opportunity and to develop the country economically, the quasi-civilian government within the framework of the existing 30-year Master Plan for the Agriculture Sector (2000-2001 to 2030-2031) increased the number of government approved agricultural concessions, while introducing two new laws during 2012 (the Farmland Law and the Vacant, Fallow, and Virgin Lands Law and Foreign Investment Law) which further encouraged large scale agriculture in Myanmar. While the new reforms have resulted in economic growth and development of the country due to encouragement for the agriculture sector, (Asian Development Bank 2012; World Bank 2014), the forest resources seems to have been significantly affected (Woods 2015). This highlights the need to form sustainable development policies by the democratic government.

The observed variance in the period 2008-2011 coincide with the political transition. In 2008 the new Constitution was formed which led the road to democracy. Under the new Constitution, national elections were held in 2010 and the military backed Union Solidarity and Development Party (USDP) emerged victorious. By 2011, the formal transition to democracy was achieved with the dissolution of military junta and formation of new quasi-civilian government led by President

Thein Sein, a former military commander. We attribute the increased variance during the period 2008-2011 to uncertainty in reforms/policies and weakened institutional control and anticipation of change due to political transition. Similar observations were reported by Obidzinski, (2004) in Borneo when forest loss rates skyrocketed during transition to democracy in Borneo. Overlaying the forest loss polygons on the high resolution Google Earth imagery suggested that most of the loss is due to newly established rubber plantations (Mon, Kayin, Shan (Figure 2.12a-d) and urban expansion in some areas (Yangon, Mandalay). This was confirmed by our field work in Central and Southern Myanmar (see photos in appendix) and by interaction with local rubber farmers and officials from the forest department.

Analysis of fragmentation metrics at provincial level, showed increase in number of patches (Figure 2.3) and mean patch area (Figure 2.4) during this period. Comparison of number of patches and mean patch area metric among the provinces showed interesting results.

i) The traditional rubber plantation States like Kayah, Kayin and Mon show increased number of patches and increased variance in residual distribution of number of patches post 2004. Comparison of mean patch area shows a sudden increase in mean patch area in 2005 for Mon and Kayin, however, the increase in the same metric for Kayah occurred in 2010. These observations coincide with the beginning of the government liberalized rubber export policy in 2004. Our observations confirm earlier published reports that highlight establishment of rubber concessions in Kayin and Mon States (Woods 2011b). The variance of residual distribution of mean patch area show increase for Kayah and Kayin post 2008 but not for Mon. This implies that political transition influenced fragmentation more in the States sharing international borders (Kayah and Kayin) than inland States (Mon). On the other hand, Mon was more impacted by the 2004 government liberalized rubber export policy and showed immediate increase in number of patches, mean patch area and increase in variance in both metrics, as compared to Kayah.

ii) Non-traditional rubber plantation States like Shan showed high increase in number of patches, mean patch area and increased variance in both post 2008. During the military regime, Shan was developed for the production of rubber, followed by the introduction of the Chinese opium substitution program in 2006 (Kramer & Woods 2012) which encouraged Burmese States sharing border with China to plant rubber instead of opium, to meet the dual objectives of increased rubber demand in Chinese markets and restrict drug abuse in China (Kramer and Woods, 2012). The number of patches, mean patch area and associated variance of residuals increased significantly under the quasi-civilian government with more liberal trade policies and increased opportunity of trade with China (Bi 2014). Our results are in agreement with earlier reports of an increase of 40,000 acres of rubber plantation in Shan during 2009-2012 (Woods 2012).

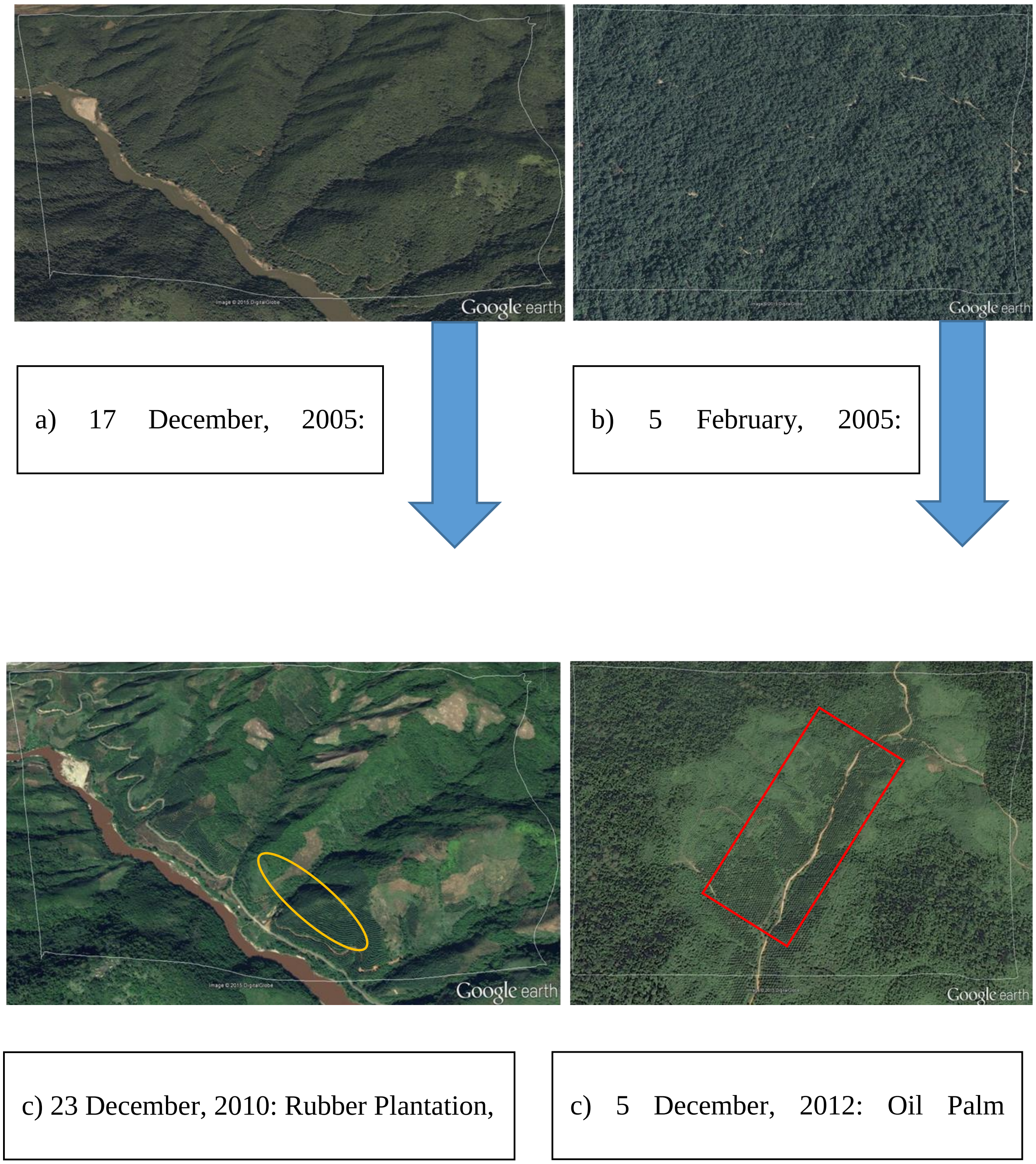


Figure 2.5: a-d. High resolution Google Earth imagery depicting forest (a-b) to (c) rubber conversion in Lashio, Shan and (d) oil palm plantations in Kawthoung, Tanintharyi. Longitude and latitude for Figure 12 (a, c): 21° 23′ 39.86″N, 100° 29′ 07.10″ E and 12(b,d):10° 28′ 58.45″N, 98° 35′ 18.03″ E.

iii) In contrast to the above States which showed higher variance in number of patches and mean patch area in the later part of the time series, Tanintharyi Region showed high variance in both the residual metrics in the period 2003-2008. This is because Tanintharyi was developed as the seat of oil palm plantation under the military government and was accordingly called as the "edible oil palm big pot of the nation." Under the military government in 1999, an industrial oil palm development program was sponsored by the military regime in Tanintharyi, as a part of its national self-sufficiency plan (Woods 2015; Donald et al. 2015). Under the new democratic government, this has not changed and Tanintharyi continues to account for 36% of the country's total agricultural concession area accounting for the linear growth. Tanintharyi has the highest mean patch area which implies the presence of plantations. Similar to Tanintharyi, Bago showed higher variance in number of patches before 2008 period. Bago is the home of the valuable Burmese teak plantations (Bryant 1997) and during the military government period, was heavily exploited for its teak wood.

iv) Other provinces which show increased variance in number of patches post 2008 period include Ayeyarwady, Chin, Kachin, Magway, Mandalay, Rakhine, Sagaing and Yangon. The increase in number of patches and mean patch area in Ayeyarwady and Magway can be attributed to agricultural expansion of crops like rice.

Kachin has high mean patch area, high number of patches and high variance for both metrics post 2008. The fragmentation in Kachin State is mainly attributed to conversion of forests to biofuel and other plantations, logging and infrastructure development (Global Witness 2009; Kachin Development Networking Group 2010; Woods 2011a). In addition, 27% of the total area in Kachin was also under agricultural concessions which might have resulted in the conversion of forests to agricultural lands. Overall, for the States, the availability of forest lands combined with absence of legal land rights and patronage politics in the face of internal conflict seems to have led to rapid forest loss and fragmentation due to logging and/or agricultural concessions (Woods, 2011a).

Sagaing shows high increase and variability in number of patches and mean pact area post 2007 due to expansion of mines in that area.

High increase and variance in number of patches and mean patch area in Mandalay post 2006 is due to urban expansion arising from shifting the capital of Myanmar from Yangon to Nay Pyi Daw officially in 2005.

The recent increase in number of patches, mean patch area and its variance in Yangon post 2009 is due to urban expansion. Though Nay Pyi Daw is the new capital of Myanmar, Yangon the former capital is the largest city in the country and well connected. All international organizations have their country headquarters in Yangon and it is also the business capital accounting for the urbanization, once the new government was formed.

2.8 Conclusion

The above results suggest higher loss of Myanmar forests and greater landscape fragmentation post 2008 period. At national level, the transition period had a brief impact on the forest loss trends. However, the impacts of the transition are more complex and varied at provincial level. During the military regime, economic and political isolation of Myanmar helped to preserve vast tracts of its pristine forests but with the opening of markets under the new quasi-civilian rule, this scenario is rapidly changing. Since the beginning of the democratic transition, highest levels of forest loss and fragmentation were observed in Shan State, Kayin State, Mon State, Kachin State and Tanintharyi Region due to establishment of industrial plantations, encouraged by the increased granting of agricultural concessions under the economic reforms, structural reforms and logging. Post-democracy, granting of resource concessions for economic development of the nation is a common strategy adopted by tropical nations. However, the rapid rate of conversion of forests to non-forest land cover and land use results in loss/or fragmentation of habitats which not only poses greater threat to biodiversity but can also in the long run damage economy (Secretariat of the Convention on Biological Diversity 2010). Similar results were observed after regime change in Indonesia (post-Suharto regime in 1998) and Cambodia (1993) (McCarthy, 2014). These observations are in partial agreement with the Mather's forest transition theory (Mather 1992; Mather & Needle 1998; Rudel et al. 2010) which predicts that the extent of forest cover will continue to decline during the period of transition till the government intervenes (Mather, 2007) or changes in demand due to globalization causes a turnaround in forest cover trends (Rudel et al., 2010). In the context of REDD (UN-REDD, 2011) and the Convention on Biological Diversity (CBD), Myanmar as a signatory has an international obligation to protect its biodiversity and their habitats. Some measures taken by the new government to promote environmental sustainability include: the Environmental Conservation Law, new log export ban since April 2014, draft Land Use Policy, 2014, Forest Law Enforcement Governance and Trade (FLEGT) Action Plan. Further, continuous satellite based monitoring of land cover can provide the decision makers with unbiased and robust, spatial and temporally explicit maps of areas undergoing land cover change. This will enable the decision makers to formulate, implement and possibly enforce new policies and evaluate the impact of previously introduced policies based on regional needs. Satellite-based land cover monitoring has been successful in reducing deforestation in Brazil (Hansen et al. 2013; Assuncao et al. 2014). Future satellite records will confirm whether the above sustainability measures have their intended effects. The challenge for the new Government of Myanmar lies in designing win-win policy interventions that not only encourage economic and social development but also ensures environmental protection.

3 Fire Disturbance in Tropical Forests of Myanmar—Analysis Using MODIS Satellite Datasets*

3.1 Abstract

In this study, we quantified the relationship between fires and vegetation disturbance at varied spatial scales using moderate resolution imaging spectroradiometer (MODIS) datasets for the period 2003-2012. We report satellite-derived fire characteristics (frequency, extent, seasonality, and type of vegetation burnt) in Myanmar, the extent of fire disturbance, and the impact of the fires on gross primary productivity (GPP) at multiple scales. Results suggested March as the peak fire season with burnt areas (BAs) of 12900 km2 and 95000 fire counts. Forests accounted for 41.3% of the total BAs followed by shrub lands (33.6%) and agriculture (24.7%). The "low" vegetation disturbance category accounted for 9.2% of total fires, whereas the medium and high categories accounted for about 89.7%. We found relatively higher negative correlation between BA and GPP for deciduous forests ($r = 0.49$, $p \sim 0$) than for evergreen forests ($r = 0.36$, $p \sim 0$). A maximum decrease in 29% of original GPP (2007-2012) was observed in the evergreen forest patches. The scale-dependent correlation analysis suggested significant BA-GPP correlation at 1×1 degree compared to finer resolutions. Our results highlight the impact of fire disturbance on vegetation greenness and GPP in tropical forests of Myanmar.

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URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7122234&isnumber=7161423

3.2 Introduction

Fire is an important disturbance factor in several regions of the world including South Asia (Thonicke et al. 2008; Vadrevu et al. 2013; Franke et al. 2012). Fires not only affect the structure and function of the vegetation but also contribute to emissions of carbon and other trace gases impacting air quality (Gerwing 2002; van der Werf et al. 2010; Vadrevu et al. 2011). Traditionally, fire has been an important topic of concern in the boreal forests, however, in recent years, increased population, droughts and land use/cover changes have made fire a significant disturbance factor in the tropical forests (Cochrane 2003). In tropical South Asia, fire is commonly used as a land management tool to clear forest land for agriculture and/or plantations (Korontzi et al. 2006). Of the different Asian countries, Myanmar is the least studied. Recent studies suggest that Myanmar ranks first in terms of vegetation fires (Vadrevu et al. 2014). The region was also found to have high tree cover loss from 2000 to 2012 (Hansen et al. 2013). The impact of fires on vegetation disturbance in tropical forests of Myanmar has not been studied so far.

The relationship between disturbance and vegetation dynamics has been studied in other regions. The general concept is that the predisturbed ecosystem fixes carbon at a certain rate and then during disturbance, there is an instantaneous carbon loss. This loss is caused by the death of photosynthesizing vegetation, which in the case of forest fires it is biomass combustion (Prasad 2001). Odum (1969) has shown that vegetation development and decomposition dynamics govern the evolution of carbon flux after an occurrence of disturbance. The normalized difference vegetation index (NDVI) is commonly used to study vegetation disturbance (Buma 2012; Lentile et al. 2006; Peckham et al. 2008). NDVI exploits the spectral signature of vegetation in the near infrared (NIR) and red regions to provide information about the level of greenness of the vegetation. It is correlated to chlorophyll abundance and the fraction of absorbed photosynthetically active radiation (fPAR). NDVI decreases after fire; thus, it is widely used to assess postfire vegetation regrowth (Riano 2002; Abdel Malak & Pausas 2006; Li 2012; Hernández-Clemente et al. 2009; Goetz et al. 2006; Anyamba 2003; Potter et al. 2003; Yool 2008). However, in some cases, NDVI can be underestimated due to low vegetation biomass and can get saturated at high biomass levels (Phillips et al. 2008). Thus, alternate measures of NDVI such as gross primary productivity (GPP) are also used as an indicator of vegetation vigor and carbon cycling (Li et al. 2007). NDVI has a curvilinear relationship with GPP and is used as an input in light use efficiency models to estimate GPP (Wang et al. 2004; Schloss et al. 1999; Yuan et al. 2007).

The dynamics of recovery in the post disturbed ecosystem are controlled by the rate of new growth and in the tropics it can be quite fast. It has been found that post disturbance vegetation recovery is primarily driven by the GPP which is the amount of carbon fixed by vegetation through photosynthesis (Gough et al. 2007; Amiro et al. 2010; Goulden et al. 2011). The GPP is a measure of photosynthesizing biomass and the vegetation recovery after disturbance. Thus, it plays a decisive role in land-surface–atmosphere interactions (Makela et al. 2007). Quantifying disturbance and tracking changes in vegetation gain significance as the magnitude and direction of the GPP after vegetation disturbance can govern ecosystem structure, function, and recovery (Beck & Goetz 2011).

Scale is an important factor in disturbance studies. The occurrence of fire in a given location and its spread is dependent on three factors: ignition source, vegetation type and local weather, all of which are scale dependent (Collins & Smith 2006; Parisien et al. 2011). The GPP is dependent on photosynthesis and plant function types; thus, it is highly scale-dependent (Chasmer et al. 2009; Turner et al. 2004). Although it is known that the impact of fires on any given landscape varies based on spatial and temporal scales of analysis (Romme 2005; Bistinas et al. 2013), it is unclear how each vegetation type responds to fire impacts.

Remote sensing technology with its unique multitemporal, multispectral, synoptic, and repetitive coverage capabilities has made it possible to quantify GPP at different spatial scales (Turner et al. 2006; Running et al. 2004). For example, GPP can be estimated from satellite remote sensing using optical and near-infrared spectral wavelengths. Satellite remote sensing-based observations of GPP provide a quantitative, but indirect, measure of spatial patterns and seasonal to inter-annual variability in vegetation activity. The moderate resolution spectroradiometer (MODIS) sensor has been providing near real-time estimates of GPP since March 2000 (Xiao et al. 2010). Satellite remote sensing can be effectively used to quantify vegetation disturbance. For example, MODIS provides continuous, well-calibrated, and relatively long-term global records of fires, vegetation greenness, and other variables. Thus, they can be integrated to capture abrupt disturbance-related vegetation changes (Beck & Goetz 2011; Xiao et al. 2010; Giglio et al. 2010).

As the vegetation development following fire varies depending on the intensity and history of disturbance, we hypothesized that fire disturbance will be reflected in the vegetation greenness and GPP products at wide spatial and temporal scales. To address the above-mentioned hypothesis, we focused on the following questions. 1) What is the spatio-temporal distribution of the fires in Myanmar and what are the typical fire regime characteristics (duration, seasonality, and extent)? 2) Which land cover is most impacted by fires? 3) How much of the vegetation disturbance in Myanmar is due to fires? 4) How does the fire impact the GPP in a forested landscape and how do fire–GPP relationships vary across different ecosystem types (evergreen versus deciduous forests) and across different spatial scales? We addressed these questions using MODIS satellite products and spatial statistics. The results identify the role of fire in vegetation disturbance in Myanmar landscape. In addition, results on the spatial and temporal dynamics of fire-GPP relationships provide a useful measure of fire disturbance on carbon cycle and aid in a better understanding of the carbon cycle in the region (Zhou et al. 2008; Prentice et al. 2011).

3.3 Data and Method

3.3.1 Study Area

The Union of Myanmar (formerly known as Burma) is located in South-East Asia, between 09°32’N to 28°31’N and 92°10’E to 101°11’E. It covers an area of 676,580 km^2. Myanmar is administratively divided into seven states and seven regions. The landscape is highly heterogeneous in terms of climate, topography as well as land cover. The climate is heavily influenced by the south west Asian Monsoon. Myanmar has two marked seasons, dry season (November to April) and wet season (May to October). The mean annual rainfall varies considerably and is dependent on the local topography. Monthly precipitation of dry season (November to April) is less than 100 mm. Based on the temperature differences, the dry season can be divided into the hot-dry (March to April) and cold-dry (November to February) period. The monthly mean temperature of April, the hottest month exceeds 33°C. March and April correspond to the severe fire months. According to Köppen’s climate classification system, Myanmar covers six climate zones: tropical monsoon (Am), savanna (Aw), humid subtropical (Cwa), temperate highland tropical climate with dry winters (Cwb and Cwc), and alpine climate (ET). Broadly, most of Myanmar can be classified as tropical wet, tropical dry or humid subtropical (National Geographic Society (US) 2011). The coastal regions and islands receiving rainfall most of the year comprise the tropical wet regions, while the central agricultural area is dominated by tropical dry climate, having a distinct wet and dry season.

Most of northern Myanmar, except for the mountains in the extreme north is characterized by humid subtropical climate. The country can be divided into four physiographic regions.

1) Mountains and hills: the hilly regions are found in northern, eastern and western parts of the country. 2) Central highlands: the central region of the country consists of low hills and has been terraced for rice cultivation. 3) Delta: formed from the rich alluvial soil of Irrawaddy and other rivers, draining into the Bay of Bengal. 4) Coastal land: narrow strips of coastal land in between the mountains and the Bay of Bengal. Forests cover an area of 3177,730 km^2 (31773000 ha) accounting for 48% of the total land area (FAO 2011). The major forest type is Mixed Deciduous (38%) followed by Tropical Evergreen forests (16%) (Forest Department 2005). The northern part of Myanmar is dominated by broadleaved evergreen/semideciduous forest, the central region by croplands and the eastern and western regions with shrublands and broadleaved deciduous forests. The study area location map for Myanmar with MERIS-derived land cover map (Bicheron et al. 2008) is shown in Figure. 3.1.

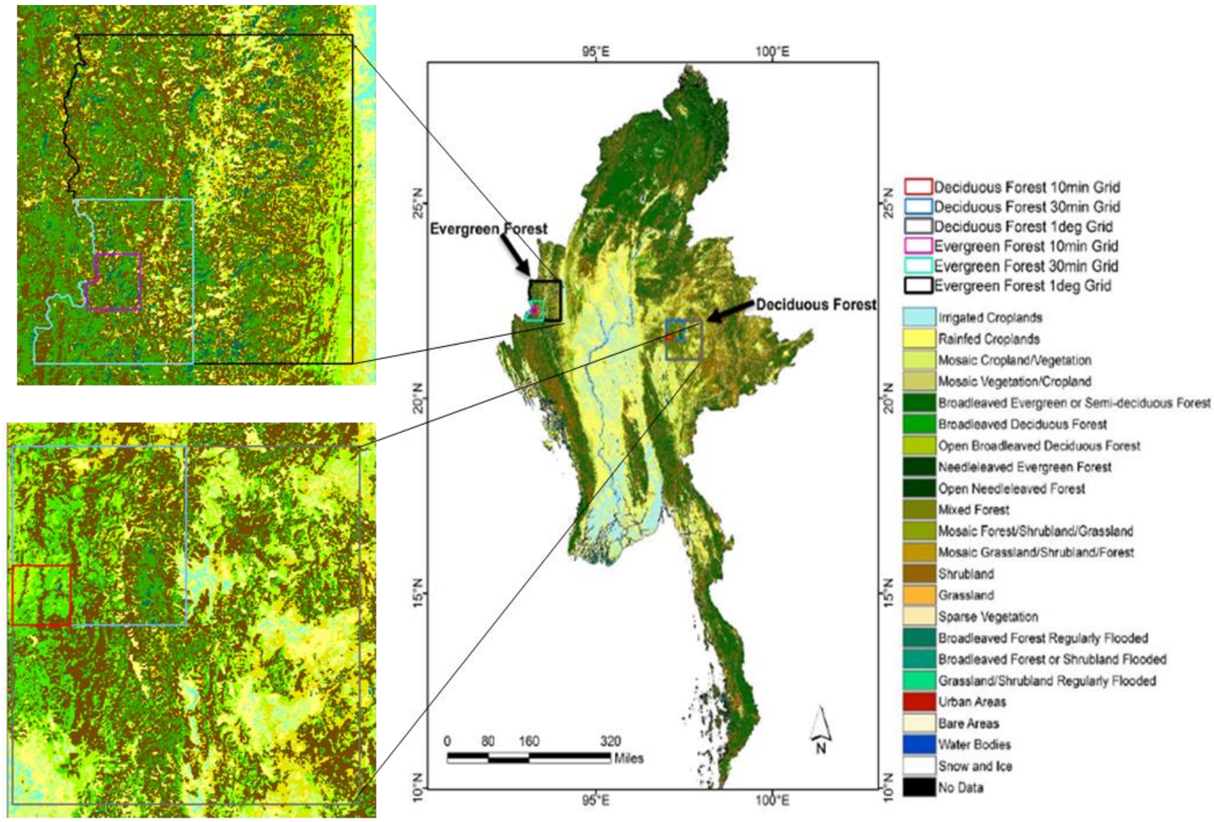

Figure 3.1: Myanmar land cover map derived from MERIS data. The study areas are shown on the left.

To investigate the fire-GPP relationship in evergreen and deciduous broadleaf forests, we chose 6 study sites and three different spatial scales at 1 degree, 30 min, and 10 min. In comparison to tropical dry and humid subtropical zones, we found very little fires in the tropical wet (Tropical monsoon, Am) zone, mainly due to high moisture content. The three nested evergreen broadleaf forest plots, located on the Chin Hills, are shown in Figure. 3.1. Their exact locations are as follows:

1) 1 degree: 22°N to 23°N and 93°E to 94°E;

2) 30 min: 22°N to 22.5°N and 93°E to 93.5°E; and

3) 10 min: 22.17°N to 22.33°N and 93.17°E to 93.33°E.

Most of the study plots except the southeastern regions experience temperate highland tropical climate with dry winters. The southeastern regions are mainly impacted by tropical dry climate. The terrain is steep with the elevation varying from 130 m to 2760 m. The principal vegetation mainly comprises Dipterocarpaceae family with *Dipterocarpus alatus, D. turbinatus, and D. griffithii* including species of *Parashorea stellata, Hopea odorata, Shorea burmanica, Swintonia floribunda, Eugenia grandis, Xylia xylocarpa, Bombax ceiba,* and *Albizia procera* in addition to different bamboo species (FAO 1981; Olson et al. 2001).

The three nested deciduous broadleaf forest plots, located on the Shan Plateau, are shown in Figure 3.1. Their exact locations are as follows:

1) 1 degree: 21°N to 22° N and 97°E to 98°E;

2) 30 min: 21.5°N to 22°N and 97°E to 97.5°E; and

3) 10 min: 21.5°N to 21.67°N and 97°E to 97.17°E.

The plots are located in the humid subtropical zone. Since these plots are located on a plateau, the terrain is less steep compared to the evergreen broadleaf plots. The elevation varies from 540m to 2460 m. The principal vegetation in the deciduous forests includes *Tectona grandis and Accacia catechu*. In addition, the Shan Plateau in Myanmar has well developed montane deciduous forests with families of Theaceae (*Schima spp*.), Magnoliaceae (*Michelia spp., Magnolia spp.*), and Fagaceae (*Quercus spp., Castanopsis spp., Lithocarpus spp*.) (Olson et al. 2001).

3.3.2 Satellite Data

1) Active Fire Data: We used the MODIS Active Fire Product (MCD14ML) for the period 2003–2012. MODIS Active Fire Products are processed through MODIS Adaptive Processing System (MODAPS) using the enhanced contextual fire detection algorithm (Giglio 2010) into the

Collection 5.1 Active fire product. The fire data is at 1 km spatial resolution. Flaming over far less than one tenth of the pixel size can be detected. We used the fire pixels that had more than eighty percent detection confidence.

2) Land Cover Data: To characterize the vegetation cover across the Myanmar landscape, we used GlobCover Land Cover Product 2005, from ENVISAT satellite's medium resolution image spectrometer (MERIS) sensor. The land cover product is derived from an automatic and regionally tuned classification of a time series of MERIS Full Resolution Level 1B data composites covering the period December 2004–June 2006. The spatial resolution of the product is 300 m. It is the highest resolution global land cover product currently available. This product was chosen, as all of its 22 land cover classes are defined within the UN Land Cover Classification System (LCCS) (Bicheron et al. 2008).

3) Burnt Area Data: We used the 500 m Collection 5.1 MODIS direct broadcast (DB) burnt area (BA) product (MCD64A1) for the period 2003–2012. MCD64A1 is based on the MODIS DB BA mapping algorithm(Giglio et al. 2009). The product is more refined than the earlier product as it captures smaller agricultural fires and uses MODIS daily surface reflectance data for characterizing fires and associated BAs under the most pristine, but atypical conditions (Giglio et al. 2013).

4) NDVI Data: We used the MOD13C2 product (2003–2013) which is a monthly composite of cloud free, 16-day gridded MOD13A2 data with 0.05 degree resolution. It is a measure of "greenness" of vegetation and mathematically defined

$$NDVI = (\text{Near Infrared} - \text{Red}) / (\text{Near Infrared} + \text{Red}) \quad (1)$$

5) GPP Data: We used the MOD17A2 product (2003–2012) which is an 8-day composite of GPP data processed through MODAPS, using the radiation-use efficiency concept of Monteith (1972), and the Version 5 GPP product. The GPP data has a spatial resolution of 1 km in sinusoidal projection which we converted to Geographic projection. The data is delivered in a gridded, level 4 format.

3.4 Method

3.4.1 Characterizing the Fire Regimes

In any landscape, spatial variation in vegetation disturbance caused by fires, fire size and frequency may significantly influence the pattern and rate of post disturbance vegetation recovery. The concept of fire regime in landscape ecology is used to describe the regional characteristics of fire for a given landscape. It is defined as the type, size, severity, seasonality, and spatial pattern of fires of a given area (Christensen & Abbott 1989; Agee 1996). In this study, we used both the MODIS active fires and BA datasets (2003–2012) to characterize fire regimes over Myanmar. To characterize the temporal extent of fire regimes, we report the total and mean fire count on a monthly and annual scale for the time period from 2003 to 2012. The spatial extent of fire regimes is characterized by reporting the fire frequency (the number of years each grid cell impacted by fires) at a 25-min grid scale for the entire country for the same time period. The normalized fire frequency values were also used in spatial regression to characterize disturbance.

To study the influence of land cover type on fire regimes, we extracted the dominant land cover class for each BA pixel. We report our results as the percent of burnt pixels belonging to each land cover class using the formula

$$\frac{\textit{Number of burnt pixels in a particular land cover class}}{\textit{Total number of burnt pixels}} \text{ x } 100 \qquad (2)$$

3.4.2 Vegetation and Fire Disturbance

To characterize the vegetation disturbance, we used cloud-free MODIS monthly NDVI datasets (MOD13C2). The datasets for the month of March were stacked across the years (2003–2012). An asymmetric Gaussian function is used as a best fit of time series (Gao et al. 2008). The monthly standardized anomalies for vegetation vigor were calculated for different years, n using the t-distribution as (Potter et al. 2003; Brun & Barros 2013):

$$Z_{ij} = \left(X_{ij} - \bar{X}_{i,n}\right)/\left(SD_{i,n}/\sqrt{N}\right) \tag{3}$$

where X is the NDVI value of a pixel for a specific month (i = March) of a specific year (j = 2003−2012), X-bar is the temporal NDVI average for the specific month (i) over the n years of observation, and SD is the standard deviation for a specific month (i) over the n years of observation. The standardized Zij is calculated for the same monthly calendar period across the years to remove the seasonal cycle. The datasets were gridded to 25-min intervals. The gridded values were then normalized and were used in spatial regression. We also classified the range of values into four disturbance classes, namely, low, medium, high, and very high for easy interpretation.

In our study, we were interested in assessing vegetation disturbance caused by fires. To assess the correspondence between the fires and the vegetation disturbance, MODIS active fires for the month of March were overlaid on the NDVI disturbance product to quantify the relationship between the NDVI-based vegetation disturbance categories and the fires.

In addition to the above approach, we performed spatial regression, also known as locally weighted regression or geographically-weighted regression (Cleveland & Devlin 2012; Fotheringham et al. 2003) with normalized fire frequencies as a predictor of vegetation disturbance at a 25-min grid scale and fire disturbance as response variable. Spatial regression methods take advantage of the spatial aspect of the data and are considered more meaningful than ordinary least square regression, when working with spatial data (Cleveland & Devlin 2012; Fotheringham et al. 2003). The local regression accounts for the spatial heterogeneity in response to variables by estimating separate regression for each sample observation including the location of interest and other spatially weighted observations. The weights represent the adjacency effects for neighboring locations within a specified distance (or bandwidth). Following the assumption that more proximate locations are more alike, the weights decay with distance following a bisquare decay function for an adaptive kernel. When regression points and observation points are the same, one regression is estimated for each observation, allowing parameter estimates to vary across the sample space. The local regression model is specified as

$$y_i = \beta_{i0} + \beta_{i1} x_{i1} + \beta_{i2} x_{i2} + \ldots\ldots + \beta_{ik} x_{ik} + \varepsilon_i ; \varepsilon_i \sim N(0, \sigma^2), i = 1, 2, \ldots\ldots n, \tag{4}$$

where the "i" subscripts on the parameters indicate that there is a separate set of (k + 1) parameters for each of the n-observations (25-min grid cells in our case). The parameter estimates are shown

$$\hat{\beta}_i = (X^{i} W_i X)^{-1} X^{'} W_i Y ; i = 1, 2, \ldots . n \tag{5}$$

where Wi is the n × n weight matrix whose off-diagonal elements are zero land the diagonal elements are the weights of each observation relative to I, i.e., Wi = diagonal (wi1,wi2, . . . ,win). The results obtained from this approach were reported. The identification of patterns in spatial association between two datasets, i.e., fires and vegetation disturbance, is crucial to infer spatial patterns in disturbance.

3.4.3 Effect of Fire Disturbance on GPP:

a) *Correlation analysis:* To infer the relationship between BA and GPP, we performed a spatial correlation at 10 min spatial scale. As March and April were the peak months, we averaged the data from 2007 to 2012 for both BA and GPP and did correlation analysis. This helped us to identify the significant hotspot areas of GPP reduction due to fires. Pearson's correlation coefficient between BA and GPP for each grid cell was calculated in R as (Pearson 1900):

$$r_{xy} = \frac{\sum x_i y_i - n\bar{x}\bar{y}}{(n-1)s_x s_y} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\ \sqrt{n\sum y_i^2 - (\sum y_i)^2}}. \quad (6)$$

b) Spatial scale: Due to the heterogeneous nature of the land cover, spatial scaling was perceived to be an important factor affecting the BA–GPP relationship. To infer the scale dependent nature of the relationship, we investigated BA–GPP relationship at 1 degree, 30-min, and 10-min scales for the tropical evergreen and tropical deciduous forests (Miettinen et al. 2007; Rothermel 1983). A grid was created for each spatial resolution and the variables BA, GPP and land cover were extracted at each respective scale to perform correlations.

c) Time-series plots: In addition to correlation analysis, we also plotted the BA versus GPP relationships as timeseries plots at 1 × 1-degree scale.

3.5 Results

3.5.1 Fires: Monthly and Yearly Variations

Results obtained from MODIS fire data analysis for active fires and BAs are shown in Figures. 3. 2(a)–(d) and 3.3. MODIS-derived fire counts averaged from 2003 to 2012 suggested March as the peak fire season with 32847 fire counts, followed by April. The fire season starts as early as December and lasts until May [Figure. 3.2(a)]. The average annual fire count from 2003 to 2012 is 72987 [Figure. 3.2(c)]. The monthly and annual BA statistics for the entire region are shown in Figure. 3.2(b)and (d)]. The mean values of BAs for a typical fire year range from 0 km^2 in July–August (monsoon season) to 12893 km^2 (1.3 Mha) during March, the peak fire season. 2010 represents a typical fire year with 93,818 fire counts and 2234 km^2 (223.4 Mha) BA, respectively. These figures are modest as some studies have found MODIS underestimates fire counts and BA [49]. Fig. 3.2(e) shows the annual variation in BAs (ha) and precipitation (mm). We found poor correlation (r2 = 0.23) between these variables suggesting anthropogenic nature of fires.

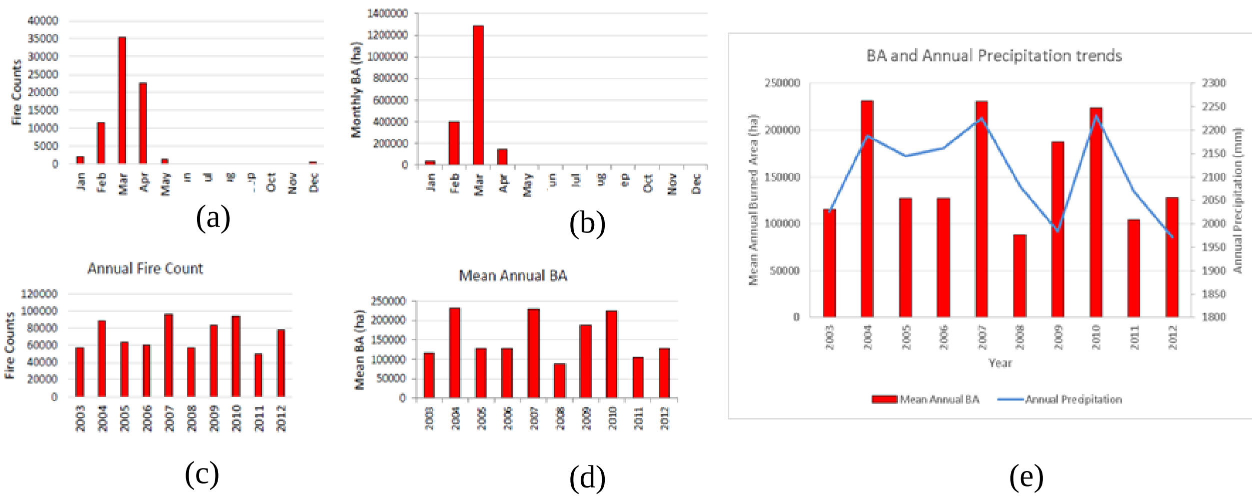

Figure 3.2 a-d. MODIS active fires and burnt areas (BA) analysis for Myanmar. 3.2a). Mean monthly fire counts; 3.2b). Mean monthly BA (ha); 3.2c). Trends in annual fire counts (2003-2012); 3.2d). Trends in mean annual BA (ha) (2003-2012). 2e) Annual variation of fire with trends in annual precipitation.

The fire frequency for each pixel aggregated at 25-min intervals is shown in Fig. 3.3. Results suggest that the western hilly regions in Myanmar experience a number of large fires on average; however, the Eastern highlands of Shan Plateau experience more frequent fires, and hence are more disturbed. This may be partially explained by the steep terrain of the western mountains compared to the flatter terrain of the eastern highlands. Slope is known to influence fire spread

(Olson et al. 2001), thus the steeper western mountains were expected to have more BA compared to flatter eastern highlands. A possible reason for the high number of fires in Shan could be due to slash and burn agriculture locally known as “denshering,” which is common in the remote hilly areas (Myint et al. 2001). The northern mountains, central plains and coastal areas are largely unaffected. Results on fire frequency (Fig. 3.3) suggest that most of the pixels have recurrent fires every year. Of the different land cover classes, forests accounted for 41.3% of the total fires, followed by shrublands (33.6%), and agriculture (24.7%).

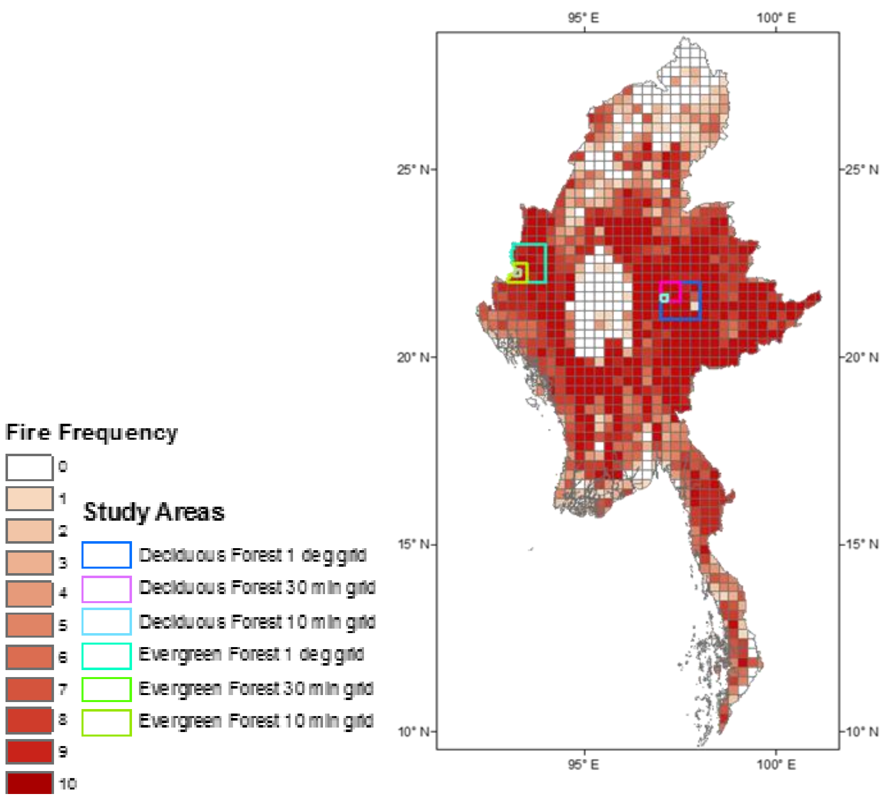

Figure 3.3: Annual fire frequency derived from MODIS active fires at 25-minute grid intervals (the legend indicates the number of years, each grid cell impacted by fires). The numbers on the cells on the zoomed scalar plots show how many times each cell was impacted by fire over the study period.

3.5.2 Fire and Vegetation Disturbance

Results obtained from fire disturbance analysis are shown in Table 3.I, Figs. 3.4 and 3.5. Fig. 3.4 shows the results of the spatial regression between fire frequency and vegetation disturbance, whereas Fig. 5 shows fire disturbance categories corresponding to Table 3.I. As shown in Fig. 3.5, areas of "very high" fire-vegetation disturbance are spatially concentrated in several regions. The general spatial pattern shows that fire vegetation disturbance is most prevalent in the inland areas of Myanmar. In particular, the Kayah state located near the border of Thailand consists entirely of "very high" classification level of fire disturbance cells. This state largely consists of a mosaic of land cover types dominated by croplands, shrublands, and broadleaved-evergreen forests. Shan the largest state in Myanmar is located due north of the Kayah state. We found that approximately 70% of the region in this state was found to be "very highly" disturbed due to fires. In this state, the majority of the land cover is dominated by shrubland followed by broadleaved-evergreen forest, cropland, and broadleaf deciduous forest respectively. A third hotspot of fire disturbance is located in the Bago region.

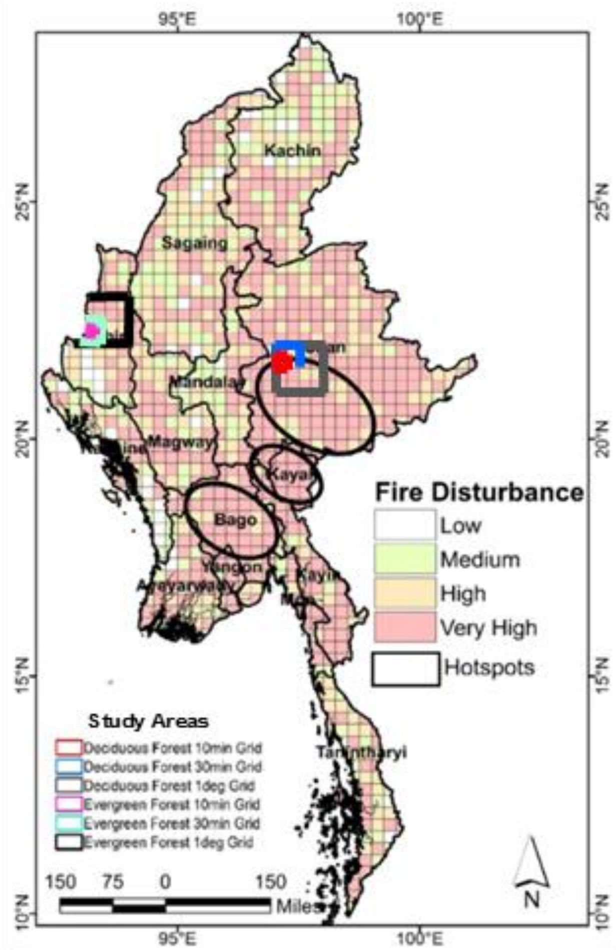

Figure 3.4: Hotspots of fire-vegetation disturbance.

Category	NDVI Disturbance	Percentage of Fires
Low	0 - 0.25	9.2%
Med	0.26 - 0.50	46.4%
High	0.51 - 0.75	43.3%
Very High	0.76 - 1.00	1.1%
Total	-	100.0%

Table 3.1: Percent of fires corresponding with the vegetation disturbance map for March (2003-2012).

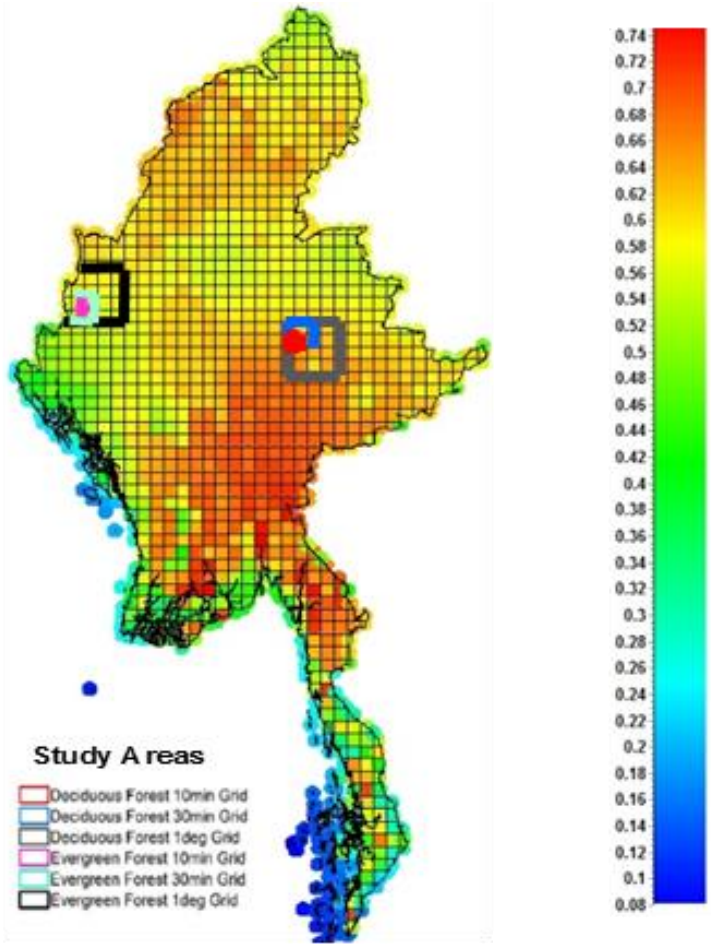

Figure 3.5: Spatial Regression Between Fire Frequency and Vegetation Disturbance in Myanmar for the month of March (averaged from 2003-2012).

Approximately 75% of the region contains "very high" fire disturbance cells interspersed with some "high" and a few "medium" cells. The land cover in the region is characterized largely by cropland followed by shrubland, vegetation mosaic, and broadleaved-evergreen forest respectively. Overall, the three hotspot areas are characterized by cropland, shrubland, mosaic vegetation and broadleaved-evergreen forest. The shrubland areas are often interspersed with broadleaved evergreen forest and cropland areas.

The “low” NDVI disturbance category accounted for 9.2% of total fires, the medium and high categories about 90% and the “very high” category for just over 1% of fires. (Table I). The results suggest “low” NDVI disturbance category impacted by few fires. Additionally, about 43% of fires fall into the “high” NDVI disturbance category. However, we found “very high” category with only 1% of the fires, suggesting that other driving factors than fire contributes to vegetation disturbance in the region. Spatial analysis suggested that most of this category was located in the Bago State and the dominant land cover category is shrub land followed by cropland.

3.5.3 Effect of Fire Disturbance on GPP

Fig. 3.6 shows the spatial correlation analysis between the BA and the GPP at a 10 min ×10 min scale. The results show a significant negative correlation between the BAs and GPP. For the peak fire months of March and April, the western mountains have a stronger negative correlation between BA and GPP than the eastern highlands. This is consistent with our previous observations of high BAs in the western mountains. High negative correlations are observed over shrubs and evergreen forests located in Palam district of Chin, western borders of the state of Magway, Mongsat, and Lasho districts in the state of Shan, as inferred from geolocations.

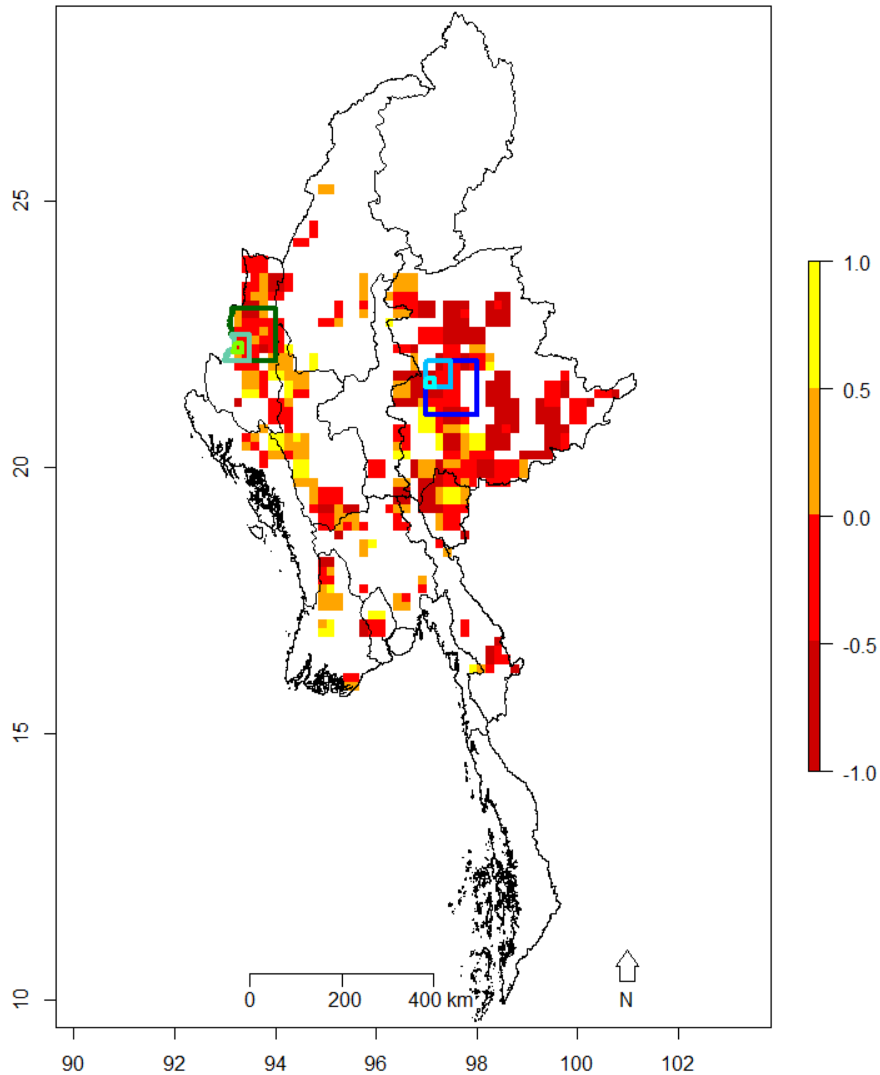

Figure 3.6: Spatial correlation of GPP vs BA for entire fire season (Mar-Apr combined 2007-2012). Negative correlation can be seen in red color for different cells. The scalar plots are shown in colored boxes.

At the 1-degree scale, the GPP showed a negative, significant correlation (r = 0.49, p ~ 0) with BA for both the deciduous and evergreen forest types. At the 30-min scale, the GPP showed a moderate negative, significant correlation with BA. The relationship was stronger for the deciduous forest type (r = 0.45, p ~ 0) compared to the evergreen forest types (r = 0.31, p ~ 0). At the 10-min scale, the GPP showed a negative, significant correlation with BA. The relationship was stronger for the deciduous forest type ($r = 0.47$, $p \sim 0$) compared to the evergreen forest types ($r = 0.13$, $p \sim 0$). In summary, the above scale-dependent correlations for evergreen and deciduous forests suggest relatively high negative correlation between BA and GPP for deciduous forests than evergreen forests. The evergreen plots were located on steeper terrain on average compared to the deciduous plots. Hence, the evergreen forests were expected to burn more than deciduous forests; however, we observed more fires in deciduous plots. We attribute higher fires in deciduous plots to low moisture content.

At 1-degree scale, the time series data shows seasonal variation during the fire and nonfire seasons [Fig. 3.7(a) and (b)]. Significant decrease in GPP can be seen during March and April months for both evergreen and deciduous forests. The decrease in GPP varied across months based on the burned area extent. In general, areas which reported a greater extent of burn, had decreased GPP. This trend was expected because increased areal extent of burned area would result in more vegetation extent being disturbed and hence, a lowered GPP. For example, a maximum decrease of 29% of original GPP (2007–2012) was observed in Mongsat district dominated by evergreen forests. Our results on GPP reduction are consistent with earlier studies.

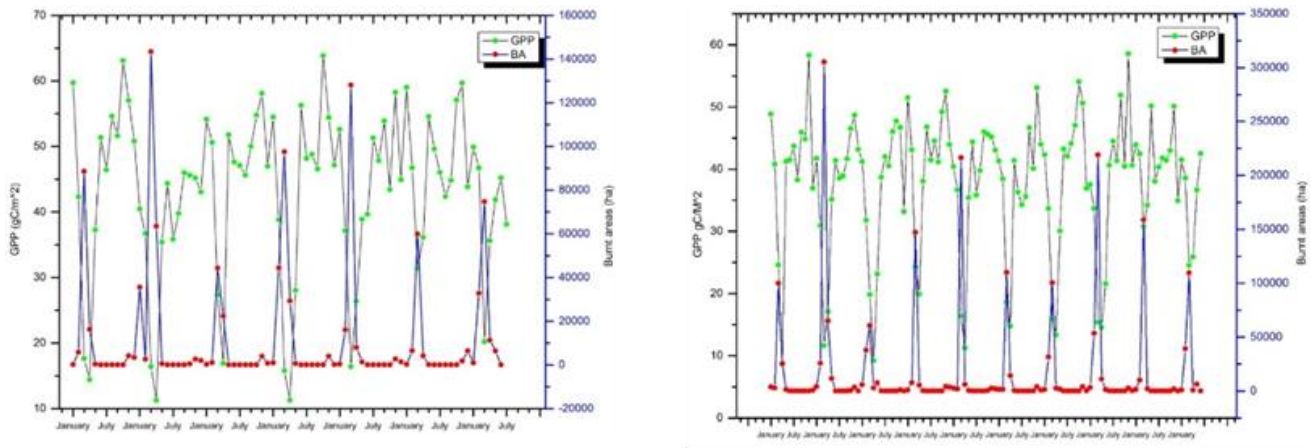

Figure 3.7: a,b. Time series plots of BA-GPP relationships in evergreen and deciduous forests of Myanmar (1x1 degree scale). Significant decrease in GPP corresponding to BA can be seen for different months

For example, Harden et al., (2000) reported that the annual carbon losses resulting from fire disturbance in the Canadian boreal forest are estimated to be 10%–30% of average net primary productivity (NPP). Gough et al., (2007) reported that in temperate forests of Northern US, the maximum annual C storage in stands that were disturbed by harvest and fire twice was 26% less than a reference stand receiving the same disturbance only once. Long term ecosystem dynamics are regulated by processes that control post fire regeneration and by fire frequency. Our results on fire impacts on vegetation disturbance reported on Myanmar are the first of the kind results using remote sensing data. We infer the need for ground-based measurements and verification of burnt-area-GPP relationship for effective carbon management strategies.

3.6 Conclusion

Fires are a common disturbance agent in the tropics, due to their role in land clearance. It is important to understand the nature of these fires and their spatiotemporal distribution to evaluate their environmental impacts. Remote sensing offers a plethora of datasets to study fires. In the current study, we characterized the spatiotemporal distribution of fires in Myanmar and its impact on vegetation disturbance using remote sensing datasets. We included both, the active fires and BAs as a proxy for fire occurrence. Results from satellite data on fire regimes suggested a strong seasonality and annual pattern in Myanmar. The fires occurred mostly during the dry, hot month of March. We studied frequency of fire disturbance in different land cover types and specifically deciduous and evergreen forests. Vegetation disturbance analysis results suggested that most of the fires fell in medium to high vegetation disturbance category.

In addition, we also quantified the impacts of BAs on GPP in evergreen and deciduous forest ecosystems at various spatial and temporal scales. The BAs impacted the GPP of forests negatively to a large extent. The annual change in GPP in the burned patches varied a lot, this was due to the different rate of regrowth in the various pixels. Since regrowth is dependent on factors such as soil type, moisture availability, seed viability and other biotic, and abiotic characteristics, ground-based measurements are needed to precisely understand the role of fire disturbance on GPP at different growth stages. In some of the evergreen forest patches, due to recurring fires, the GPP is reduced by 29% of its original value. The scale-dependent analysis for BA–GPP suggested strong correlations at 1 degree × 1 degree scale compared to the finer spatial resolutions. Overall, our study highlights the role of fires on vegetation disturbance and its impacts on GPP in tropical forests of Myanmar.

Future directions in expanding this research would involve a more detailed spatial examination including ground-based measurements on how the disturbances affect the forest cover structure and function at finer spatial scales including drivers of deforestation.

4 Factors Controlling Vegetation Fires in Protected and Non-Protected Areas of Myanmar*

4.1 Abstract:

Fire is an important disturbance agent in Myanmar impacting several ecosystems. In this study, we quantify the factors impacting vegetation fires in protected and non-protected areas of Myanmar. Satellite datasets in conjunction with biophysical and anthropogenic factors were used in a spatial framework to map the causative factors of fires. Specifically, we used the frequency ratio method to assess the contribution of each causative factor to overall fire susceptibility at a 1km scale. Results suggested the mean fire density in non-protected areas was two times higher than the protected areas. Fire-land cover partition analysis suggested dominant fire occurrences in the savannas (protected areas) and woody savannas (non-protected areas). The five major fire causative factors in protected areas in descending order include population density, land cover, tree cover percent, travel time from nearest city and temperature. In contrast, the causative factors in non-protected areas were population density, tree cover percent, travel time from nearest city, temperature and elevation. The fire susceptibility analysis showed distinct spatial patterns with central Myanmar as a hot spot of vegetation fires. Results from propensity score matching suggested that forests within protected areas have 11% less fires than non-protected areas. Overall,

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our results identify important causative factors of fire useful to address broad scale fire risk concerns at a landscape scale in Myanmar.

4.2 Introduction

Fire is a common land management tool in the tropics (Nepstad et al. 1999; Lambin et al. 2003; Cochrane 2009). Traditionally, fires have been used for slash and burn agriculture in the denser forests and to clear the forest floor in the open forests (Cochrane 2009). However, in recent times, population growth and economic incentives for agriculture have led to widespread clearing of tropical forests to meet food security and urban housing demands (DeFries et al. 2010; Stolle et al. 2003). Clearing of forests for agriculture has led to fragmentation of the forests with increased forest edges resulting in greater fire risk (Cochrane 2001; Cochrane & Laurance 2002). In addition, changing climatic patterns and human land use also alters fire regimes in the tropics (van der Werf et al. 2008; McKenzie et al. 2004; Aldersley et al. 2011).

Specific to Asia, the mosaicked forested landscape of mainland SE Asia harbors a wide range of habitats and is a part of the Indo-Burma biodiversity hotspot (Myers et al. 2000; Sodhi et al. 2004; Sodhi et al. 2010). The region mostly comprises fire sensitive forests like tropical broadleaf deciduous forests. The patches of moist broadleaf forests are often interspersed with fire-dependent dry seasonal broadleaf forests (Baker, P. J., & Bunyavejchewin 2010). Literature review suggests that open canopy forests are more prone to fire than closed forests as the floor in open forests is drier than closed forests due to greater degree of sunlight penetration (Cochrane 1999). Fire susceptibility is also dependent on land cover type. Shrublands are known to be more flammable than evergreen forests (Nunes et al. 2005). Generally, as the agricultural frontier expands at the expense of forest lands, the forest patches near the edges are cleared before the forest interior patches. Also, agricultural fires can spread to nearby forests accidentally. Thus, in cases involving anthropogenic fires, the distance to forest edge is expected to be inversely proportional to fire occurrence (Nepstad et al. 1999; Cochrane 2001; Cochrane 1999).

Apart from vegetation, the topographic factors also play a role in fire susceptibility. Elevation, slope and aspect influence fire behavior (Rothermel 1991; Anderson 1982). Elevation influences fire spread by impacting the wind behavior and precipitation patterns (Bennett et al. 2010). Low elevation areas are more prone to fire due to higher temperature, less precipitation and settlements (Veblen et al. 2000; Harmon 1982). Fire spreads upslope faster as heat rises and preheats the upslope fuel (Rothermel & Forest 1972). The aspect is the compass direction that a slope faces. It determines the amount of insolation, and precipitation received by the surface; the directions which receive more heat and less moisture are more prone to fire. Among climatic factors, temperature is a major factor because it is known that warmer regions are more susceptible to fires than colder regions. Higher air temperatures increases the surface temperature and dry the fuel, increasing the probability of fire (McKenzie et al. 2004; Aldersley et al. 2011; Chuvieco et al. 2004).

Literature review suggests most tropical fires as anthropogenic in nature (DeFries et al. 2010; Cochrane 2001; Trejo 2000; Langner et al. 2007). Distance from road is a measure of accessibility to forest. Forest patches near the road are more prone to disturbance than forest patches deep inside forests which are not easily accessible (Laurance et al. 2009; Nepstad et al. 2001). Roads provide a transportation route for agricultural goods and timber. Since fires are used to clear forests in the tropics, we assumed that distance to roads would be an important anthropogenic causative factor (Nepstad et al. 2001; Arima et al. 2005). Accessibility from cities is a proxy for distance to markets.

Earlier studies have shown that the probability of forest clearing near cities is higher due to easily accessible markets to sell the produce or easy transportation facilities (Armsworth et al. 2006; Lambin & Meyfroidt 2011).

Among the Asian nations, Myanmar is reported to have the highest number of vegetation fires (Vadrevu & Justice 2011); however, the causative factors largely remain uninvestigated. In the past, political isolation and poor data availability has made Myanmar a very difficult region for studying environmental problems. In recent times, the country's changed political system has opened the doors for environmental research. In this study, we focused on causative factors of fires in protected and non-protected areas of Myanmar.

In Myanmar, for the past 20 years, conservation efforts have largely focused on increasing protection in the forested areas (Cochrane 2009). Previously, researchers have documented the role of protected areas, location and strength of management influencing conservation efforts in different countries (Bruner et al. 2001; Nepstad et al. 2006; Nelson & Chomitz 2011; Nolte et al. 2013; Nolte & Agrawal 2013; Andam et al. 2008; Andam et al. 2010). However, no such attempt has been made for Myanmar. Very little is known about the effectiveness of the protected areas in Myanmar. Extending from north to south in Myanmar, the protected areas conserve a wide range of tropical forests harboring rich biodiversity (Fig 4.1). Due to Myanmar's history of economic isolation, large tracts of its forests and associated biodiversity seems to be conserved, as compared to its neighboring countries (Dong et al. 2012). Traditionally, factors posing threats to the forests of Myanmar include hunting and slash and burn agriculture (Rao et al. 2002). However, clearing of forests for large scale industrial agriculture, infrastructure developments, uncontrolled exploitation of natural resources seem to pose a bigger risk in recent times (Woods 2011a; Woods

2011b). A review of country reports suggests that protecting the forests has always been a difficult task given the limited financial and technical resources available to the protected area managers in Myanmar. Nevertheless, the status of conservation of most protected areas seems good though some regions are doing better than others (Instituto Oikos & BANCA 2011).

Rapid developments in computing and information technology including remote sensing have made a wide variety of data sets available to study environmental problems including fires (Chowdhury & Hassan 2014). Specific to fires, MODIS Active Fire data provide the geolocation of fires within 24 hours of fire occurrence at a global scale (FIRMS 2011; Giglio 2010). The characteristic spectral and temporal resolution of MODIS makes it ideal for fire detection (Justice et al. 2002; Akther & Hassan 2011). In addition to fires, recent advances in forest mapping have also enabled the production of high resolution, spatially consistent forest cover maps at a global scale (Hansen et al. 2013). The high spatial resolution has made it possible to capture small-scale forest losses which were previously not possible. The high resolution fire and forest extent data can provide a unique opportunity to study vegetation fire characteristics. Further, geospatial technologies can be effectively used to compute ancillary variables of anthropogenic factors impacting fires such as distance to roads, forests, urban dwellings, etc. In this study, we integrate both biophysical data (satellite data on fires, land cover, elevation, slope, tree percent, etc.) as well as anthropogenic factors (population density, distance travelled to nearest forests, distance to roads) to quantify causative factors of fires in protected and non-protected areas.

In the tropics, the role of protected areas as a tool of conservation is highly debatable (Bruner et al. 2001; Nepstad et al. 2006; Nolte et al. 2013; Andam et al. 2008; Ferraro et al. 2013; Nagendra 2008).

Yet, most researchers agree that at the broader scale, protected forests are better conserved than the unprotected forests though different levels of governance may influence the degree of protection (Bruner et al. 2001; Nepstad et al. 2006; Nelson & Chomitz 2011; Nolte et al. 2013). The question of effectiveness is very relevant to Myanmar because of the 43 protected parks of which 17 are reportedly paper parks (Instituto Oikos & BANCA 2011). As of 2009, 10.1–15.5% of the global land surface is conserved in protected areas (Soutullo 2010). Since fire is a disturbance agent in the tropics, the probability of fires inside protected areas is expected to be less compared to non-protected areas mainly due to fire suppression strategies and legal mechanisms (Bruner et al. 2001).

In this study, we address several questions relevant to vegetation fires in protected and non-protected areas of Myanmar. a) What are the dominant causative factors of fires in protected and non-protected areas? b) Are the causative factors the same or different for different regions? c) How do the causative factors of fires vary spatially in protected and non-protected areas and where are the hotspots? d) What is the relative role of each causative factor in controlling fires? We address the above questions using a probabilistic frequency analysis approach integrating different biophysical and anthropogenic datasets. We hypothesized that protected areas will have fewer fires than non-protected areas. Accordingly, we also tested the relative importance of protected areas compared to non-protected areas in fire prevention and conservation using the propensity score matching technique.

4.3 Data and Method

4.3.1 Study Area

Myanmar (formerly known as Burma) is located in mainland SE Asia, between 9°32'N to 28°31'N and 92°10'E and 101°11'E. It covers an area of 676,580 km^2. The landscape is highly heterogeneous in terms of topography. The mountainous regions are found in northern, western parts of the country while the Shan plateau is located in the east. The central region of the country consists of plains and is the seat of agriculture. The climate is heavily influenced by the south west Asian Monsoon. Myanmar has two marked seasons, dry season (November to April) and wet season (May to October). The mean annual rainfall varies considerably and is dependent on the local topography. Monthly precipitation of dry season (Nov. to Apr.) is less than 100mm. Based on the temperature differences, the dry season can be divided into the hot-dry (March-April) and cold-dry (November to February) period. The monthly mean temperature of April, the hottest month exceeds 33°C. March and April correspond to the severe fire months. Forests cover 48% of mainland Myanmar (United Nations Food and Agriculture Organization 2010). The major forest type is mixed deciduous (38%) followed by tropical evergreen forests (16%) (Forest Department 2005). Broadleaf evergreen forests dominate in northern and southern Myanmar while broadleaf deciduous forests are found mostly in the central, mountainous region. A land cover classification map of Myanmar is shown in Fig 4.1. Fire is an important disturbance agent in the forests of Myanmar. Every year a large area of forests is lost to fires resulting in habitat loss and degradation of forests. The highest number of fires occur in the month of March. In the past decade (2000–2012), 2007 year was found to have highest number of fires. Though the forests of Myanmar is plagued by fires, the causative factors are not clearly documented. Besides the natural factors like climate and fuel characteristics together with increased anthropogenic pressure are expected to contribute to the high numbers of fires in the country. Establishing protected areas have been proposed to be a successful way to conserve forests. Most of the forests are outside protected areas, though efforts are being made by the new government to increase the number of protected areas and extend the boundaries of a few existing protected areas (Instituto Oikos & BANCA 2011). Myanmar has 43 officially recognized protected areas covering 7.3% of the country. The location of protected areas in Myanmar is shown in Fig 4.1. Of the 43 protected areas, 17 are reportedly paper parks. 76 Key Biodiversity Areas (KBAs) have been identified so far, including 54 Important Bird Areas (IBAs) and the Natma Taung National Park as an area of local endemism (Instituto Oikos & BANCA 2011).

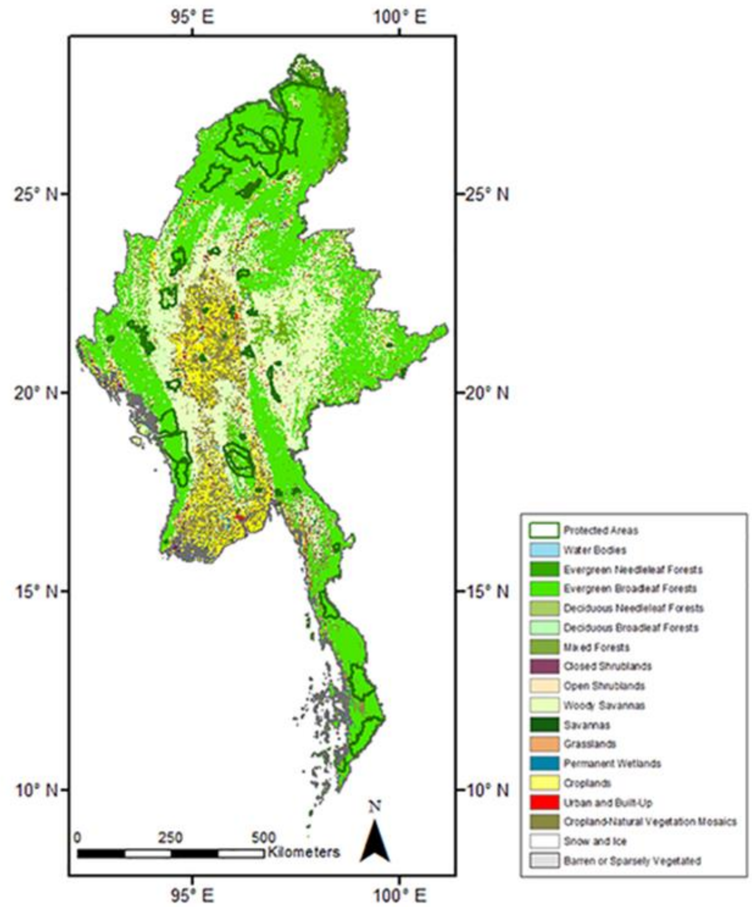


Figure 4.1: A map showing the protected areas in Myanmar with boundaries in dark green color. MODIS land cover map is shown in the background.

4.3.2 Data

We used a variety of datasets for quantifying the major causative factors of fires. The active fire locations were obtained from the MODIS/Aqua & Terra Thermal Anomalies/Fire locations 1km Collection 5.1 dataset (Giglio 2010), also known as MCD14ML. The product is created by the University of Maryland as a monthly fire product and distributed through NASA LANCE-FIRMS website (https://earthdata.nasa.gov/data/near-real-time-data/firms) (FIRMS 2011). The dataset provides geolocation, brightness, scan and track, date, time, sensor, confidence and version for each fire pixel. The resolution of the data is 1km and we used the data from 2000–2012. As cloud and smoke cover reduces the confidence in satellite retrieved fire measurements, we used 95% confidence filter and used high confidence fire detections. We downloaded the country administrative datasets from Global Administrative Areas Database (www.gadm.org). The protected area boundaries were downloaded from World Database of Protected Areas (IUCN and UNEP 2010). The WDPA dataset also includes the IUCN categories to define the conservation status and management objectives of each protected area (Dudley 2008). We used the tree canopy cover percent data from the Landsat-based 30m Global Forest Change 2000–2012 data set (Hansen et al. 2013) available at http://earthenginepartners.appspot.com/science-2013-global-forest. Tree canopy cover percent is defined as canopy closure for all vegetation taller than 5m in height and is expressed as a percentage per output grid cell in the range 0–100. We used the tree cover product to demarcate the extent of forests and calculate the distance to forest edge using Euclidean distance. To determine the land cover type for Myanmar, we used MODIS Land Cover Type Yearly L3 Global 500 m SIN Grid data, also known as MCD12Q1 with the IGBP land cover classification. The data was downloaded for the year 2000 from online Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center (https://lpdaac.usgs.gov/data_access). Elevation was estimated from 30m ASTER data obtained from the Global Land Cover Facility (www.landcover.org). The slope and aspect was derived from the elevation data. The mean temperature for the fire season months (February to April) at 30 arc-seconds (~1 km) resolution was obtained from WorldClim (Hijmans et al. 2005). We used an average of the mean temperature for the three months. Population density estimates were obtained from Socioeconomic Data and Applications Center (SEDAC). We used the Gridded Population of the World (GPW's) v3 dataset for year 2000 at a resolution of 2.5 arcminutes (~5 km) (Center for International Earth Science Information Network - CIESIN - Columbia University 2005). The road dataset was downloaded from Vector Map 0 (VMap0). The VMap0 database provides consistent, continuous global coverage of essential base map features at the largest scale. Travel time estimates were obtained from the "travel time to major cities map" developed by Andrew (2008).

4.3.3 Methods

To analyze the relative contribution of each of the above causative factors and to quantify the fire susceptibility at a pixel level, we gridded the data into 1km resolution. All data were projected to the MODIS sinusoidal equal area projection. Data sets which were not 1km resolution were resampled to 1km using appropriate filters. The land cover classification data was resampled to 1 km grid using majority filter while for the percent tree cover and elevation data we used the cubic convolution filter. Specific to the population datasets, we used proportional allocation, i.e., the 5-km population data has been allocated based on proportions fitting the 1 km scale. Thus for every cell in the study area grid, we retrieved the following information: a). Tree cover percent; b). MODIS Land cover IGBP classification; c). Elevation; d). Slope; e). Aspect; f). Temperature; g). Population estimate; h). Travel time from nearest city; i). Distance to roads; j). Distance to forest edge; k). Protected/non-protected status; and l). Fire presence/absence.

We used the frequency ratio method at a pixel scale to assess the probabilistic value of each causative factor in impacting fires. This method is widely used in risk analysis studies (Manap et al. 2014; Lee & Sambath 2006). The sum of frequency ratios (FR's) is an estimate of the probability of an event occurrence in the total study area for a given range of attribute values. For each grid cell, it is calculated as the ratio of the area where fires occurred in a specific grid cell and also, is the ratio of the probabilities of a fire occurrence to a non-occurrence for a given causative factor. The range of values extracted for each factor was divided into class intervals and the frequency ratio was calculated. The frequency ratio estimate is a quantitative indicator of the strength of the relationship between the risk event occurrence and the specific class values of the causative factor. If the estimate is higher than 1, then the probability of risk event occurrence due to the corresponding class interval values of the causative factor is considered high. If it is lower than 1, then the probability of risk event occurrence considered low. For each of the factors affecting the grid cell, the corresponding frequency ratios were calculated. The frequency ratios (FR's) for all factors affecting a grid cell were then summed to arrive at fire susceptibility index. The fire susceptibility index (FSI) was calculated as:

$$FSI = \sum FR \tag{1}$$

Thus, each cell in our study area grid at 1km scale is associated with a fire susceptibility value which indicates the degree of fire risk in our study area. A higher FSI indicates higher fire risk. Next, we identified the highly susceptible fire pixels by protection status and ranked the factors associated with the pixels in descending order based on their FRs. Factors with higher FRs were considered dominant causative factors and vice versa.

To quantify the relative differences in protected versus non-protected areas with respect to fire incidences, we used propensity score matching technique (Rosenbaum & Rubin 1983). In statistics, matching methods are often used in observational data analysis to measure the average treatment effect on the treated (ATT) group. The essence of the propensity matching method is that it identifies a control group which has similar covariates like the treated group except for the treatment (protected or non-protected). Though matching methods try to closely replicate randomization by pairing treatment and control units having similar covariates, the observational data is quasi-experimental or non-randomized by definition (Stuart 2010). This gives rise to the issue of bias. Propensity score matching is a type of matching method which reduces bias due to confounding variables by using treatment and control units having covariates as similar as possible. This method is especially useful when the dimensionality of the covariates is high as it reduces the large number of matching dimensions to a single propensity score which makes the matching simpler (Dehejia & Wahba 2002). A number of studies from various fields have used this method to evaluate the impact of treatment on target groups (Nelson & Chomitz 2011; Nolte et al. 2013; Andam et al. 2010; Andam et al. 2008).

One of our objectives of the study is to determine if protection by legal status makes a difference to fire occurrence. Thus the treatment in our case has been considered as the protection status and the outcome variable as the presence of fire. The treatment variable (T) is binary and T = 1 when forest is protected and T = 0 when the forest is not protected. Similarly the outcome variable is Y is fire occurrence. Y_1 is the fire occurrence in protected areas and Y_0 is the fire occurrence in unprotected areas. The Average Treatment Effect is difference in the outcome variable (fire occurrence) that can attributed to treatment (protection). Mathematically, the Average Treatment Effect (ATE) represented by Greek letter tau (τ) is calculated by taking an expectation over the population of interest as defined by Eq 2:

$$\tau \equiv E[Y_1 - Y_0] \tag{2}$$

where τ = ATE, Y_1 = outcome when exposed to treatment, Y_0 = outcome in absence of treatment. To estimate the Average effect of Treatment on the Treated (ATT), Eq 3 is modified to reflect the estimate of Average Treatment Effect only for the treated group as shown in Eq 3.

$$\tau \equiv E[Y_1 - Y_0 | \ T = 1] \tag{3}$$

For each unit in the population of interest there will be only one outcome as shown in Eq 4.

$$Y = \begin{cases} Y_0 \ when \ T = 0 \\ Y_1 \ when \ T = 1 \end{cases} \tag{4}$$

The propensity score is defined as a conditional probability of receiving treatment given pre-treatment characteristics (covariates) and is calculated using Eq 5 [62]:

$$p\ (X) = \Pr\ \{T = 1 \mid X\} \tag{5}$$

where T = 1 indicates exposure to treatment and T = 0 indicates not exposed to treatment. X is the vector of pre-treatment covariates. p(X) is the propensity score. The ATT can be derived from the Eqs 2 and 3 if following two conditions are satisfied.

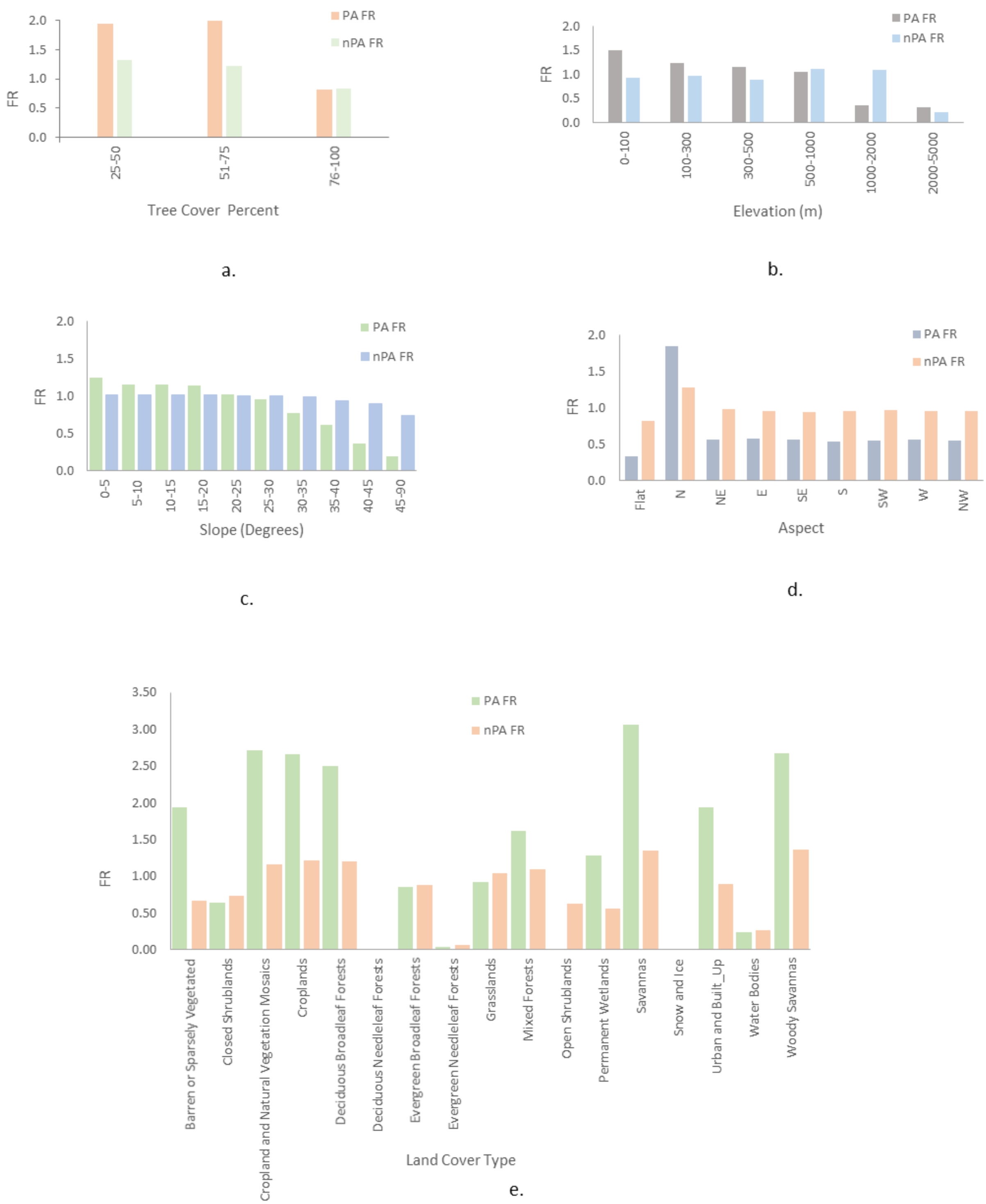
Condition I:$T \perp X \mid p(X)$: Balancing pre-treatment covariates given propensity score

Condition II:$Y_1, Y_0 \perp\!\!\!\perp T \mid p(X)$: Unconfoundedness given propensity score

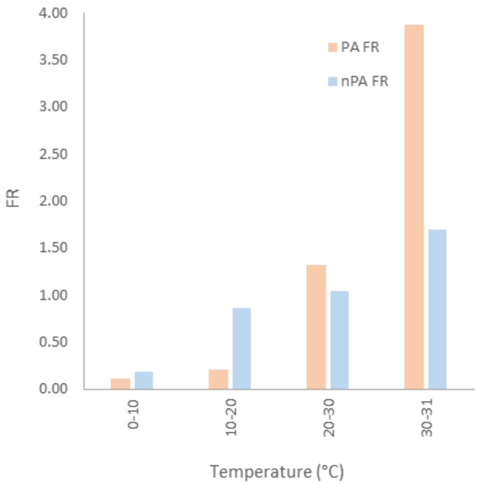
Propensity score matching was particularly suitable for our study because it measures ‘conservation’ as an observable characteristic with as few parametric assumptions as possible about the model on protection effectiveness and fire occurrences. The matching package was run in R (Sekhon 2011). We used the Mahalanobis distance method to identify the similar matches. Matching was done with replacement and a caliper of 1 standard deviation (Sekhon 2011).

4.4 Results

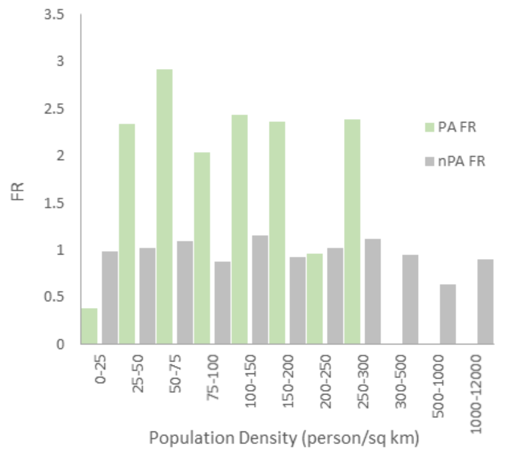
The range of percent tree cover values in the forests of the study region varied from 25–100. 84% of protected areas are covered by the 75–100% tree cover category in contrast to 60% in unprotected forests. Only 13% of protected areas are covered by the 51–75% tree cover category as compared to 30% in unprotected forests. The lowest percent tree cover category (25–50%) covered an area of only 3% in protected forests compared to 10% in unprotected forests. As shown in Fig 4.2a, protected areas in the tree cover category ranging from 51–75% are most susceptible to fire as indicated by their high frequency ratios as compared to the protected areas in the lowest tree cover category (25–50%). However this trend is not seen in the non-protected areas, where we observed a decrease in frequency ratio with decrease in tree cover percent. In both cases, i.e., protected and non-protected areas, the highest tree cover percent category has the lowest frequency ratio indicating that forests with highest tree cover percent has least fire occurrences.



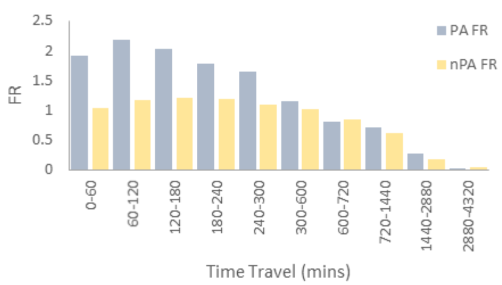
PA FR
nPA FR
FR
Tree Cover Percent
25-50
51-75
76-100
a.
Elevation (m)
0-100
100-300
300-500
500-1000
1000-2000
2000-5000
b.
Slope (Degrees)
0-5
5-10
10-15
15-20
20-25
25-30
30-35
35-40
40-45
45-90
c.
Aspect
Flat
N
NE
E
SE
S
SW
W
NW
d.
Land Cover Type
Barren or Sparsely Vegetated
Closed Shrublands
Cropland and Natural Vegetation Mosaics
Croplands
Deciduous Broadleaf Forests
Deciduous Needleleaf Forests
Evergreen Broadleaf Forests
Evergreen Needleleaf Forests
Grasslands
Mixed Forests
Open Shrublands
Permanent Wetlands
Savannas
Snow and Ice
Urban and Built_Up
Water Bodies
Woody Savannas
e.



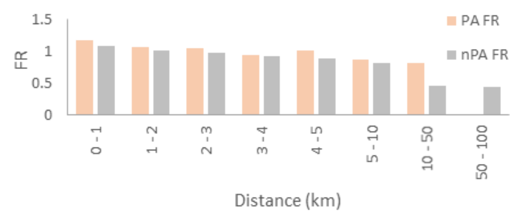
f.



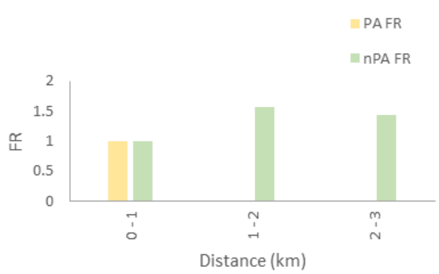
g.



h.



i.



j.

Figure 4.2: Histograms of Frequency Ratios for each causative factors in protected and non-protected forests.

Analysis from the MODIS land cover data suggested significant variability in forest type as one moves from north/south towards center. In the north and southern regions, Myanmar is characterized by broadleaf evergreen forests, whereas the central region contain deciduous forests, shrublands and mixed forests. Protected areas are mainly dominated by broadleaf evergreen forests (79%), but include mixed forests (6%) and deciduous broadleaf forests (4%). Protected areas in the extreme north of Myanmar are mainly dominated by evergreen needleleaf forests. Outside protected areas, forests are composed of evergreen broadleaf forests (59%), woody savannas (15%), cropland and vegetation-mosaics (4%). Fig 4.2e reveals that protected areas on average are more prone to fire occurrences than non-protected areas as shown by their high frequency ratio values. Within protected areas, most fire occurrences were found in savannas, followed by woody savannas, cropland-natural vegetation mosaics, cropland and deciduous broadleaf forests. In non-protected areas, most fires were found in woody savannas, savannas, croplands, deciduous broadleaf forests, and cropland-vegetation mosaics.

In general, protected forests in the north and central region have higher elevation than their southern counterparts. With respect to elevation, the majority of the protected forests lie in the elevation range of 100–1000m while most of the non-protected forests lie in the elevation range of 500–2000m. As shown in Fig 4.2b, the probability of occurrence of fire decreases with increase in elevation in protected areas. However the same does not hold true for non-protected areas. Elevation in the range of 500–2000m show highest probability of fire occurrences in non-protected areas while lower elevation ranges i.e., 0–500m show moderate probability of fire occurrences in non-protected areas. Beyond 2000m elevation, both areas show least fire probability of fire occurrence.

The majority of the protected and non-protected forests lie in the slope range of 5–25 degrees as shown in Fig 4.2c. Protected areas within slope range of 0–20 degrees show high probability of fire occurrence while declines sharply as the slope increases beyond 20 degrees. The trend though similar, is not as clear for non-protected areas. Non-protected areas have a high probability of fire occurrence between 0–35 degrees and a gradual drop in fire occurrence probability was observed beyond 35 degrees slope.

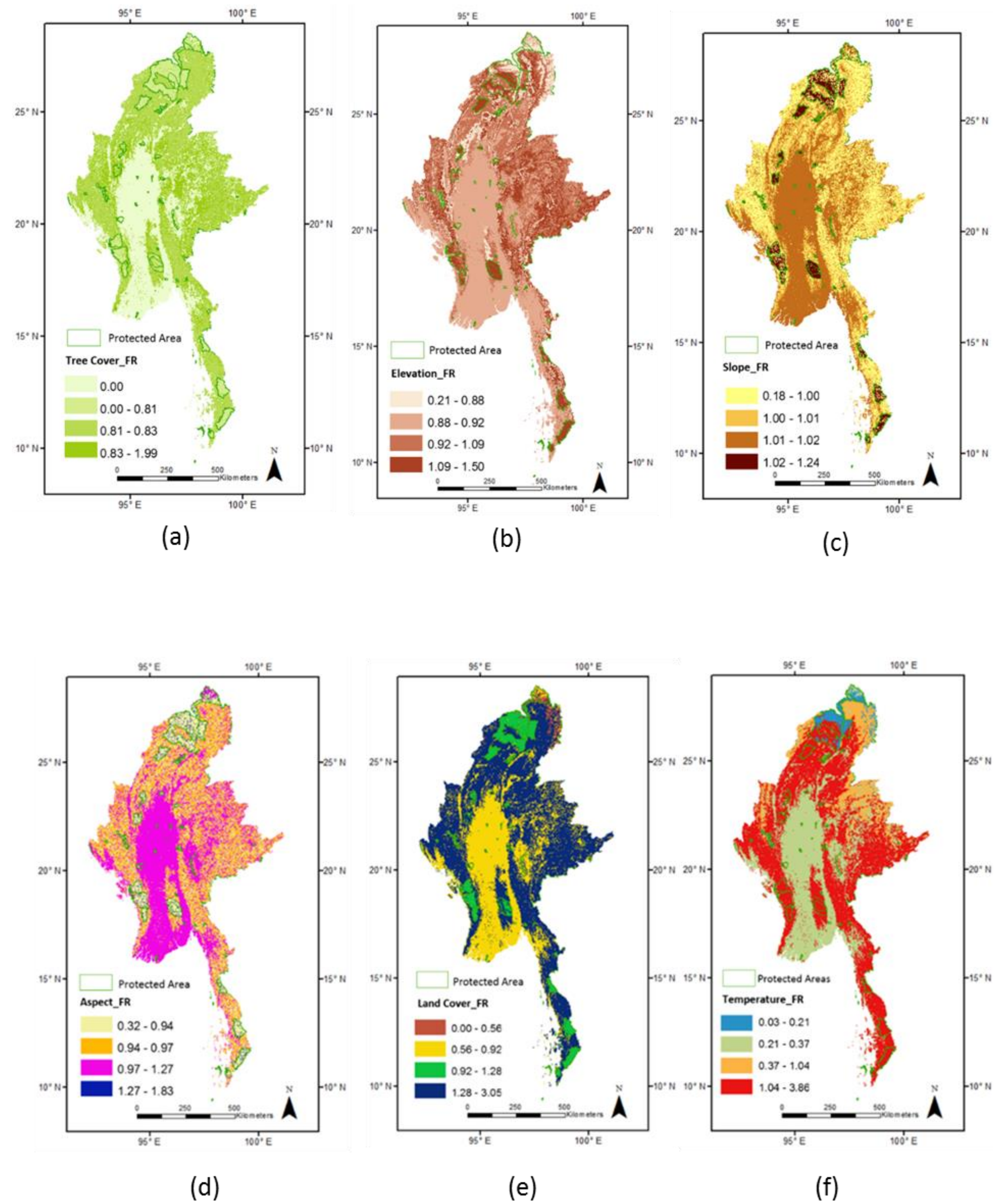
Most protected areas have a northern aspect compared to unprotected forests, which dominantly had southwestern or north-eastern aspect. As shown in Fig 4.2d, the highest probability of fire occurrence is seen in northern aspect for both protected and non-protected areas.

The majority of protected (71%) and unprotected (81%) forests had a temperature range of 20–40°C. As expected, both protected and non-protected areas showed an increase in probability of fire occurrences with increase in temperature as seen in Fig 4.2f. However, compared to non-protected areas, within the temperature range of 20–30°C protected areas were more impacted by fires. This is in contrast to the lower temperature category range (0–20°C) where non-protected areas showed higher probability of fire occurrence.

In general, protected areas in north and south Myanmar have very low population density (0–25 person/ km^2) compared to protected forests in central Myanmar where higher population densities of 75–150 persons/ km^2 were observed. Within the range of population density of 0–300 persons/ km^2, protected areas showed higher probability of fire occurrences than their non-protected counterparts as shown in Fig 4.2g.

The majority (31%) of the protected forests are at a distance of 12–24 hours from the nearest city while the majority (40%) of the unprotected forests are located at a distance of 5–10 hours from the nearest city. Further, we observed protected areas in central Myanmar being much closer to the cities than in north or south. As seen in Fig 4.2h, the probability of fire occurrence decreases with increase in time required to travel to the nearest cities. However, the impact of travel time on fire occurrence is more prominent in protected areas than in non-protected areas.

Our analysis revealed that only 36% of the protected forests are at a distance of 0–1km from roads compared to 61% of unprotected forests. The majority (40%) of the protected forests are at a distance of 5–50km from the road while only 14% of the unprotected forests are at the same distance from the road. Fig 4.2i, shows that with increase in distance from roads, the probability of fire occurrence decreases for both protected and non-protected areas. Though the frequency values of both groups are close for each category, the frequency ratio of the protected areas are consistently higher than the non-protected areas.


(a)
Protected Area
Tree Cover_FR
0.00
0.00 - 0.81
0.81 - 0.83
0.83 - 1.99
(b)
Protected Area
Elevation_FR
0.21 - 0.88
0.88 - 0.92
0.92 - 1.09
1.09 - 1.50
(c)
Protected Area
Slope_FR
0.18 - 1.00
1.00 - 1.01
1.01 - 1.02
1.02 - 1.24
(d)
Protected Area
Aspect_FR
0.32 - 0.94
0.94 - 0.97
0.97 - 1.27
1.27 - 1.83
(e)
Protected Area
Land Cover_FR
0.00 - 0.56
0.56 - 0.92
0.92 - 1.28
1.28 - 3.05
(f)
Protected Areas
Temperature_FR
0.03 - 0.21
0.21 - 0.37
0.37 - 1.04
1.04 - 3.86

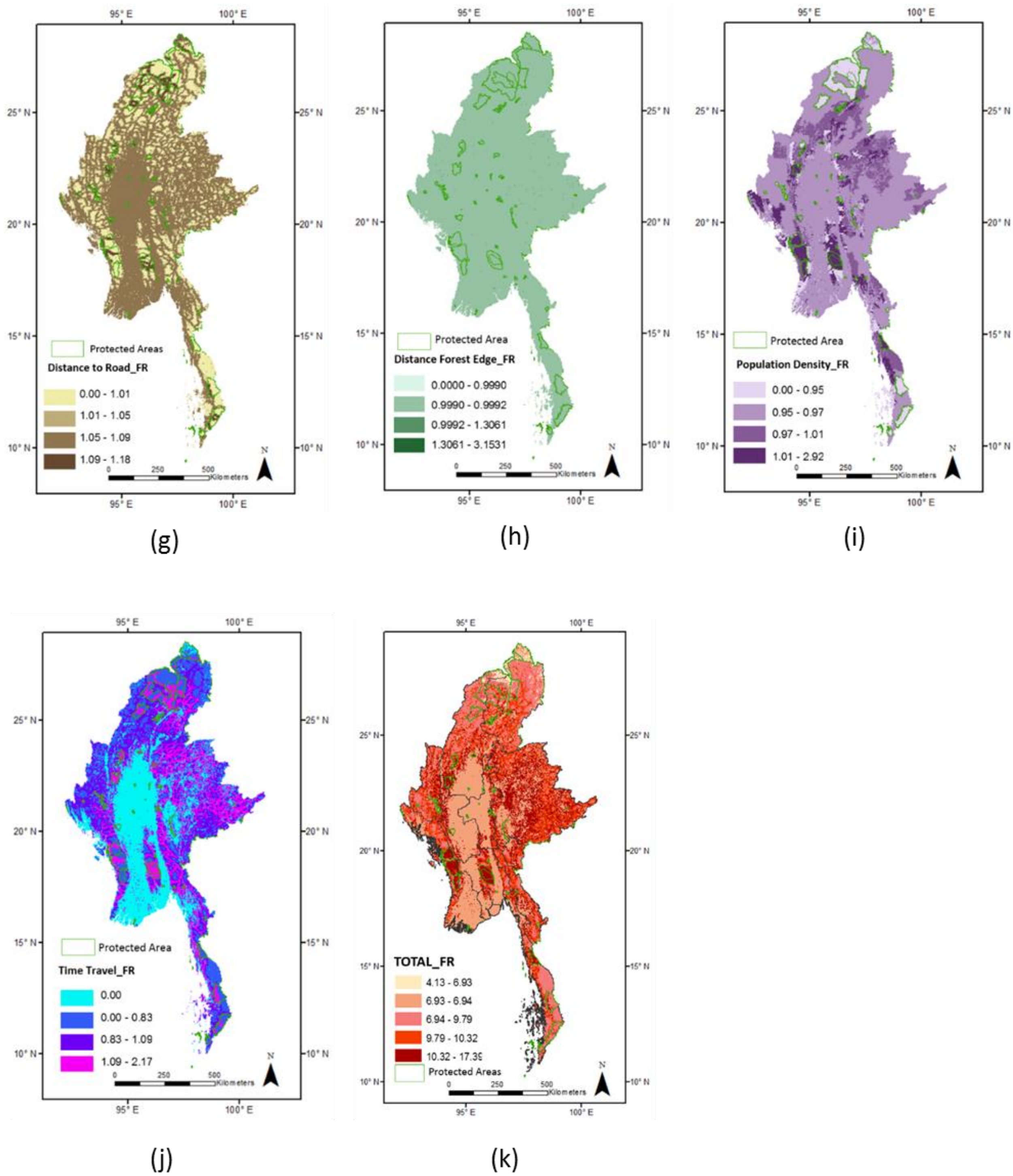


Figure 4.3: Spatial distribution of the frequency ratios (FR's) for causative factors of fire in Myanmar.

Fig 4.3a shows the spatial distribution of the frequency ratios of tree cover percent. High frequency ratio values for percent tree cover were found in non-protected forests of Shan, Kayah, southern Kayin, Mon, Chin, southwestern Sagaing,and western border of Magway state. A small patch is seen in north Bago, and along the eastern borders of Magway and south Mandalay. In protected forests, high frequency ratio values for percent tree cover were found in Chatthin Wildlife Sanctuary, Alaungdaw Kathapa National Park, Maharmyaing Wildlife Sanctuary and Panlaung-Pyadalin Cave Wildlife Sanctuary.

Among the non-protected forests, high frequency ratio values for elevation follows the terrain of Myanmar as shown in Fig 4.3b. High frequency ratio values for elevation is found in higher elevation areas like the mountains in northern Myanmar, Chin hills, Shan plateau, Arakan Yoma, and eastern Tanintharyi while in the protected forests, it is seen in Hukuang Valley, Bumhpabum Wildlife Sanctuary, Pidaung Wildlife Sanctuary, Indawgyi Lake Wildlife Sanctuary, Chatthin Wildlife Sanctuary, Maharmyaing Wildlife Sanctuary, Panlaung-Pyadalin Cave Wildlife Sanctuary, Tanlwe-ma-e-chaung, Thandwe-chaung, Rakhine Yoma elephant range, Pegu and Bago Yoma National Parks, Kahilu Wildlife Sanctuary, Tanintharyi National Park, Lenya National Park, Pakchan Nature Reserve, and portions of Tanintharyi Nature Reserve.

Protected areas had distinctly high frequency ratio values of slope compared to the non-protected areas (Fig 4.3c). The highest frequency ratio of aspect was mostly found in protected areas (Fig 4.3d). As shown in Fig 4.3e, the frequency ratio of land cover was predominantly higher for non-protected forests. A few protected areas showing high frequency ratio values for land cover are Chatthin Wildlife Sanctuary, Alaungdaw Kathapa National Park, and Panlaung-Pyadalin Cave Wildlife Sanctuary. In general, protected areas had higher frequency ratio of temperature compared to non-protected areas as shown in Fig 4.3f. A notable exception to this trend include Hponkanrazi Wildlife Sanctuary, Khakhaborazi National Park in northern Myanmar, Natma Taung National Park in central Myanmar and portions of Hukuang Valley, portions of Bumhpabum Wildlife Sanctuary and portions of Shwe-U-Daung Wildlife Sanctuary.

The frequency ratio of distance to roads was on average less for protected areas than their non-protected counterparts. Most protected areas are located in remote regions with limited road access. Protected areas in the north and south of Myanmar and those located on the hills of central Myanmar had mostly low frequency ratio value for roads (Fig 4.3g). Large portions of Hukuang Valley had high frequency ratio value for roads reflecting incidents when fire was used to clear forests to build roads for infrastructure development. Similar trend reflecting anthropogenic interference is seen in the protected areas of Htamanthi Wildlife Sanctuary, Indawgyi Lake Wildlife Sanctuary, Chatthin Wildlife Sanctuary, Alaungdaw Kathapa National Park, Bago and Pegu Yoma, Kahilu Wildlife Sanctuary, foothills of Tanintharyi National Park, edges of Lenya National Park and Maharmyaing Wildlife Sanctuary. The frequency ratio of population density is shown in Fig 4.3h. High frequency ratio for non-protected forests occur in central Myanmar and in the state of Rakhine. Similar trend is observed in the protected forests of central Myanmar. The frequency ratio for travel time from nearest cities was an important causative factor of fire occurrrence for some protected areas like Hukuang Valley, Bago and Pegu Yoma National Parks, foothills of Tnaintharyi National Park and Tanintharyi Nature Reserve, Panlaung-Pyadalin Cave Wildlife Sanctuary, Natma Taung National Park, Chatthin Wildlife Sanctuary, Alaungdaw Kathapa National Park, Maharmyaing Wildlife Sanctuary, Shwe-U-Daung Wildlife Sanctuary.

Non-protected forests along roads in south Kachin, around Huluang Valley, in state of Shan and in Tanintharyi coast were most impacted (Fig 4.3i).

4.4.1 Protected areas and causative factors of fire

In protected areas of Myanmar, four important causative factors of fires were identified from the frequency analysis. They include population density, land cover type, tree cover percent and travelled time from the nearest city. Highest fire frequencies were observed for population density range of 50–75 persons/ km^2 in protected areas. Protected areas of Chatthin Wildlife Sanctuary, Alaungdaw Kathapa National Park, parts of Maharmyaing Wildlife Sanctuary, Tanlwe-ma-e-chaung, Thandwe-chaung, Rakhine Yoma elephant range, Pegu and Bago Yoma National Parks and Tanintharyi Nature Reserve show high frequency ratio for population density. Specific to the land cover type in the protected areas, fire frequency was highest in savannas followed by woody savannas, croplands and deciduous forests. Chatthin Wildlife Sanctuary, Alaungdaw Kathapa National Park, and Panlaung-Pyadalin Cave Wildlife Sanctuary being composed of mainly of the fire susceptible land cover types showed high frequency of fire occurrences. Also, the fire frequency was highest in tree cover percent range of 51–75. Chatthin Wildlife Sanctuary and Alaungdaw Kathapa National Park showed highest frequency ratio for tree cover percent. Fig 4.2i shows that in protected areas, most fires occur near roads. This is in agreement with the map in Fig 4.3g which shows the protected areas of Hukuang Valley, Chatthin Wildlife Sanctuary and Alaungdaw Kathapa National Park most impacted by fires. Apart from the aforementioned factors, fires showed a decreasing trend with increase in elevation i.e. the highest fire frequencies were found in low elevation (0–100m) areas. In addition, highest fire frequency was found in the lower slope range (0–5 degrees). North facing slopes showed the highest fire frequencies. Further, fire frequencies increased with increasing temperature. The fire frequencies decreased with an increase in distance to roads (Fig 4.3i). The relative contribution of other factors is shown in (Fig 4.3a–4.3j).

4.4.2 Non-protected areas and causative factors

Outside the protected areas, the causative factors included population density, tree cover percent and travel time from the nearest city. Non protected forests supported a higher range of population density (100–150 person/km^2) compared to protected areas. Most of these areas are located in the valleys of central Myanmar and northern coast of Tanintharyi. We found a higher probability of fires in the tree cover range of 25–50%. Most of the high frequency ratio pixels were located in the states of Shan and Chin Hills. Compared to protected areas, the high frequency ratio of the fires in non-protected forests is concentrated in lower percent tree cover ranges of 25–50% tree cover. This indicates the impact of edge effects in the non-protected forests. Most non-protected forests were located within 2–3hrs from nearest cities, implying that accessibility to market impacts the non-protected forests. As shown in Fig 4.3g, forests in south Kachin and Shan are more accessible by roads show high probabilities of fire occurrence. The highest number of fires were found in 500–2000m elevation. Similar to the protected areas, the highest fire frequency was found for slope ranges from 0–5 degrees however, fire frequency was relatively high in higher slope categories (30–90 degrees slope range) than in protected areas. Similar to the protected areas, non-protected areas showed highest fire frequencies in northern slopes and increase in fire frequency with increasing temperature. The highest fire frequencies were observed for population density range of 100–150 persons/ km^2, which is much higher than the protected areas. The fire contribution potential for each factor is shown in Fig (4.3a–4.3j).

4.4.3 Spatial patterns of cumulative fire frequency ratio

The final fire susceptibility map is shown in Fig 4.4. The fire susceptibility analysis at the national level showed distinct spatial patterns. We found Central Myanmar to be more susceptible to fires than the northern or southern regions due to unique land cover characteristics. Central Myanmar is mostly dominated by shrublands followed by deciduous broadleaf forests and cropland-natural vegetation mosaics. At the state level, highest fire susceptibility is observed for Shan, Kayah, Kayin, Mon, central Bago, southern Rakhine, southern Kachin, southwestern Sagaing, the borders of Chin, Magway and Sagaing, northern and central Tanintharyi. Distinct clusters of fires with highest frequencies were observed in the following districts; a). Thandwein in Rakhine; b). Pegu, Taungoo and Thayarwady in Bago; c). Lashio, Kyaukme, Loiken and d). Taunggye in Shan. Fire pattern is more dispersed in the states of Kayah, Kayin, Mon, and Shan. In Tanintharyi, high fire susceptible pixels occurred mainly along the coast.

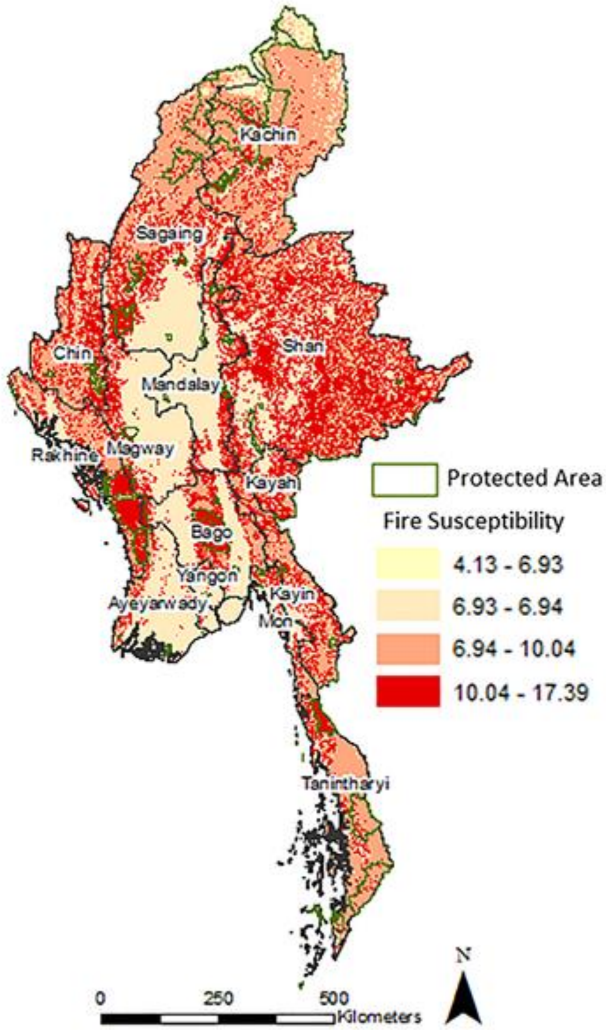


Figure 4.4: Fire Susceptibility Map of Myanmar.

The following protected areas were highly susceptible to fire: Tanlwe-ma-e-chaung, Thandwe-chaung, Rakhine Yoma elephant range, Tanintharyi Nature Reserve, Alaungdaw Kathapa National Park, Maharmyaing Wildlife Sanctuary, Chatthin Wildlife Sanctuary, Indawgyi Wildlife Sanctuary and Pidaung Wildlife Sanctuary.

Further, in Shan most of the fires in central Loiken district occurred in the mixed forest patches of evergreen and deciduous broadleaf forests. In Kayin and Mon districts, most of the fires occurred in shrublands, woody savanna and cropland-natural vegetation mosaic classes. The fires in central Bago regions occurred primarily over Bago and Pegu Yoma districts that are mainly composed of deciduous broadleaf forests and mixed forests interspersed with evergreen broadleaf patches. Fires in the district of Thandwein, Tanlwe-ma-e-chaung, Thandwe-chaung and Rakhine Yoma elephant range occurred in evergreen broadleaf forests. Fires in north and south Myanmar were less prevalent. In Kachin, Sagaing and Tanintharyi fires mostly occurred in cropland-vegetation mosaics and evergreen broadleaf forest classes.

4.4.4 Comparison of protected versus non-protected areas for fire occurrences

A correlation analysis was done amongst different causative factors as a part of the propensity score estimation. The resultant correlograms for forest analysis are shown in Fig 4.5. Elevation was strongly correlated to temperature (-0.80). Since the correlations were not greater than 0.95, no collinearity was assumed. The resultant propensity score estimate is -0.1149 with standard error of 0.0024. The result is significant at 99% confidence level (t- val = -46.26, p val~0). The degree of balance achieved in the covariates while estimating the propensity score is shown in Table 4.1. The table shows the mean values of the treatment and control variable before and after matching. The variance ratio is a measure of the degree of balance between the treatment and control variable. Perfect balance is achieved when the variance ratio is equal to 1. In our study, after matching, the variables of tree cover percent (1.07), travel time (1.04), slope (1.09), aspect (0.97), and fire season temperature (1.04) were very well balanced with variance ratio values approaching 1. The remaining variables of elevation (1.29), distance to forest edge (0.87), distance to road (0.68) and population density (1.12) were also well balanced. The matching process greatly improved the balance of tree cover percent (from 0.59 to 1.07), travel time (from 3.65 to 1.04) and average fire season temperature (from 1.59 to 1.04). Moderate improvement was observed in the cases of elevation, slope and distance to forest edge. In summary, the propensity score analysis revealed that protected forests have 11% lower probability of fire occurrence compared to unprotected forests.

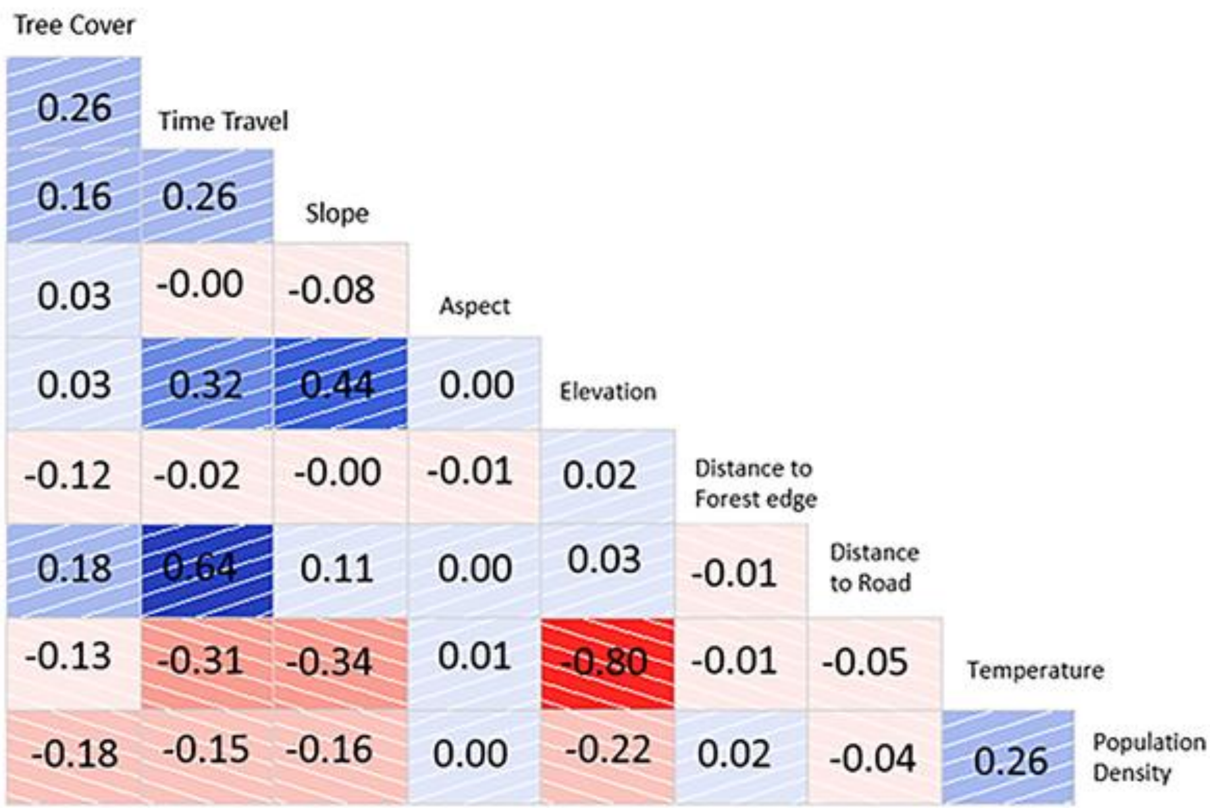


Figure 4.5: Correlogram of covariates used in propensity matching analysis.

Variables	Before Matching			After Matching		
	Mean Treatment	Mean Control	Variance Ratio	Mean Treatment	Mean Control	Variance Ratio
Tree Cover Percent	85.54	75.61	0.59	85.54	85.68	1.07
Travel Time	804.66	426.58	3.65	804.66	803.42	1.04
Elevation	715.14	691.93	1.56	715.14	704.76	1.29
Slope	19.85	17.61	1.23	19.85	19.71	1.09
Aspect	163.36	165.39	0.98	163.36	162.56	0.98
Distance to Forest Edge	0.53	2.71	0.15	0.53	0.65	0.87
Distance to Road	5846.30	2531.00	1.68	5846.30	6075.60	0.68
Average Fire Season Temperature	223.39	233.80	1.59	223.39	224.02	1.04
Population Density	23.20	35.13	0.31	23.20	24.61	1.12

The variance ratio is an indicator of the degree of balance achieved in the matching process. Variance ratio closer to 1 indicates better balance and robustness of the resultant propensity estimate.

doi:10.1371/journal.pone.0124346.t001

Table 4.1: Mean treatment, mean control and the variance ratio before and after matching for fire-causative factors.

4.5 Discussion

The results of our study suggest the anthropogenic nature of fires in Myanmar. Our results are in agreement with similar studies in the region (Pyne 1998; Saha 2002; Prasad et al. 2008). Moreover, analysis of the fire probabilities for the individual causative factors provides further evidence. Earlier studies (Aldersley et al. 2011) reported drier areas and locations with tree cover less than 60% being more prone to fires in tropical areas. We observed a similar trend in non-protected areas. However, in protected areas, fires occurred in areas of moderate tree cover. Among the land cover types, both protected and non-protected areas showed higher probability of fires in savannas and woody savannas respectively, suggesting more natural fires. Woody savannas in continental SE Asia are thought to have resulted from degradation of open forests where repeated vegetation disturbance has led to dominance of woody vegetation (Baker, P. J., & Bunyavejchewin 2010; Kellman et al. 1998; Giri et al. 2003). The difference of trends in fire probabilities over the elevation ranges is another major sign of anthropogenic interference. In protected areas, higher fire probability is associated with lower elevations, but in non-protected areas, higher fire probabilities were associated with mid-elevation range of 500–2000m. Further, most low elevation fires are associated with clearings near settlements while high elevation fires were associated with slash and burn agriculture (called taungya in Myanmar) practiced by the indigenous populations in the mountains (Fox et al. 2009; Fox 2000) or associated with clearing of forests for rubber plantations in recent times (Woods 2011b; Fox & Castella 2013). Fires from the shifting cultivation and/or rubber plantations were found in areas outside the protected areas while such fires were totally absent in the protected areas. The fire probability in protected areas suddenly dropped after the slope varied from 25–30 degrees while the drop was more gradual for non-protected areas that occurred on higher slope ranges (30–35 degrees).

We also observed a clear influence of climate, i.e., the northern slopes were more fire prone in both protected and non-protected areas than those of the south. We attribute the climate differences to the Asian monsoon. Myanmar is mostly impacted by monsoonal climate in the south. Thus, the southern region receives more moisture than northern areas. Higher fire probability was also associated with higher temperature and population densities. This is as expected because higher air temperatures are conducive for ignition and spread of fires. Studies by Aldersley et al., (2011) reported highest mean monthly burned area percent for tropical regions with a mean monthly temperature of 30°C. The same study reported an increase in burned area with an increase in population density up to 30 inhabitants per km^2 at a global level. This value is close to the population density estimates in the protected areas, but far lower than our population density estimate outside the protected areas in Myanmar. The population density was lower in protected areas compared to non-protected areas, thus fewer fires were observed in protected areas than non-protected areas.

Accessibility from the nearest cities is a proxy for distance from markets. It was expected that areas closer to cities will have more fires than areas that are far from cities (Armsworth et al. 2006). We observed a similar trend in this study, i.e., decrease in fires with increasing travel time from the nearest cities. For protected areas, most fires occurred in areas within 1–2 hours from cities, whereas in non-protected areas most fires occurred within 2–3hours from cities. The higher travel time range for non-protected areas indicate the increased anthropogenic pressure on the forest lands. Distance from roads has been found to be a major cause for forest loss (Laurance et al. 2009). For example, Wyman & Stein (2010) reported a decrease in deforestation by 50% with an increase in distance to roads up to 2.5km and Stolle et al.,(2003) reported a 2.5 times increase in fire occurrence within a distance of 1–5km from roads. In our study, we found most fires occurring within 1km of roads in both protected and non-protected areas suggesting the anthropogenic nature of these fires. Proximity to forest edges is another indicator of the nature of 'encroachment' into forests. In protected areas, we found areas within 1km of the forest edge being most susceptible to fire while in non-protected areas, areas within 1–2km from forest edges were fire prone. Our results are in agreement with a similar study in the Amazon (Cochrane 2001) where the authors found that most fires occur within 2.5 km from forest edges, while in rare events it can be as far as 5.5 km from the forest edge. The above results from frequency analysis were quite effective in delineating factors controlling vegetation fires in protected and non-protected areas of Myanmar.

Our results from propensity matching analysis show the effectiveness of protected areas in controlling vegetation fires. The protected areas had 11% less fires than the non-protected areas. Our results are comparable to a similar study conducted in Costa Rica (Andam et al. 2008) where the authors found that 10% of deforestation was avoided due to protected areas. Similar studies conducted at a regional level reported a reduction in fire incidences of 2–4% in the protected areas in Asia (Nelson & Chomitz 2011). Overall, our results highlight spatial controls of vegetation fires in protected and non-protected areas of Myanmar. To arrive at our conclusion, we used the best available datasets at the time of publication. However in spite of our best efforts, the authors recognize the limitations of data availability and any implications it could have on our results.

4.6 Conclusion

We investigated the biophysical and anthropogenic controls of vegetation fires in Myanmar. We used a probabilistic frequency ratio analysis to map the causative factors of fires. To analyze the effectiveness of protected areas in preventing forest fires, we used propensity matching methods. Our results suggest population density and travel time as two important anthropogenic factors impacting vegetation fires. We also mapped different biophysical fire causative factors at a 1km scale for the entire Myanmar useful for fire management. Results suggested central Myanmar being more fire prone than the southern and northern regions. Results also suggested 11% less fires in protected areas than the non-protected areas. Our study results highlight important causative factors of fires useful for understanding fire ecology and management in Myanmar.

5 Summary of research

5.1 Summary

This dissertation investigates and seeks to understand the contemporary forest cover dynamics in Myanmar using coarse, high and fine resolution satellite data in conjunction with GIS and ancillary datasets in a statistical framework. It specifically provides quantitative information on magnitude, trends and spatial patterns of recent forest loss. It also provides in-depth analysis of causative factors of forest fires in addition to the role of protected areas in conserving forests. Detailed summaries for each research objective identified in section 1.3, are provided in the subsequent sections.

5.1.1 Determining the impact of institutional change on forest cover in Myanmar

Chapter 2: "Regime change and forest fragmentation" addresses this objective. In this chapter, I examined forest loss and fragmentation from 2001 to 2014 in the context of recent political transition, using Landsat data to estimate forest loss and fragmentation metrics at two different scales: i) national, and ii) State/Region (in Myanmar States and Regions are geographically exclusive and both refer to level 2 administrative division). The above objective was addressed by answering two different research questions

1. How did the recent political transition in Myanmar impact its forest cover?

   Our analysis showed a total forest loss of 2,030,101 ha at the rate of 145,007.21 ha/year with a linear increase of 15,359 (±1793) ha/year. The observed increase in variance in forest loss during 2008-2011 coincides with political transition, period which started with the formation of the new Constitution in 2008 and ended with the military government handing over power to the democratic government in 2011.

2 *Is the change consistent across different provinces and which of these were most impacted with respect to forest cover change?*

The political transition impacted different provinces differently. Provinces known for plantation agriculture and urban areas were more impacted than others. Pre 2008 increase in variance in residual distribution for both fragmentation metrics (mean patch area and number of patches) were observed for Tanintharyi and Bago Regions while post 2008 increase for the same parameter was observed for Shan, Kayah and Kayin. Border States like Shan, Kayah and Kayin were more impacted by the political transition than inland Mon State. Urban areas like Yangon and Nay Pyi Daw show high fragmentation due to the political transition.

5.1.2 Characterizing regional fire characteristics and forest disturbance due to fire.

Chapter 3: **"**Fire Disturbance in Tropical Forests of Myanmar—Analysis Using MODIS Satellite Datasets" addressed the above objective. In this chapter, the relationship between fires and vegetation disturbance was quantified at various spatial scales using MODIS datasets from 2003-2012. The research questions addressed along with the results obtained are given below:

1. *What is the spatiotemporal distribution of the fires in Myanmar and what are the typical fire regime characteristics (duration, seasonality, and extent)?*

Results suggested March as the peak fire season with burnt areas (BAs) of 12900 km^2 and 95000 fire counts.

2. *Which land cover is most impacted by fires? How much of the vegetation disturbance in Myanmar is due to fires?*

   Forests accounted for 41.3% of the total BAs followed by shrub lands (33.6%) and agriculture (24.7%). The "low" vegetation disturbance category accounted for 9.2% of total fires, whereas the medium and high categories accounted for about 89.7%.

3. *How does the fire impact the GPP in a forested landscape and how do fire–GPP relationship vary across different ecosystem types (evergreen versus deciduous forests) and across different spatial scales?*

   Results indicated relatively higher negative correlation between BA and GPP for deciduous forests ($r = 0.49$, $p \sim 0$) than for evergreen forests ($r = 0.36$, $p \sim 0$). A maximum decrease (29%) in GPP (2007-2012) was observed in the evergreen forest patches. The scale-dependent correlation analysis suggested significant BA-GPP correlation at 1×1 degree compared to finer resolutions.

5.1.3 Evaluating the dominant causative factors and the effectiveness of protected areas in conserving the forests.

Chapter 4: **"**Factors Controlling Vegetation Fires in Protected and Non-Protected Areas of Myanmar" addressed the above objective. Satellite data in conjunction with biophysical and anthropogenic factors were used in a spatial framework to map the causative factors of fires. The frequency ratio method was used to assess the contribution of each causative factor to overall fire susceptibility at a 1km scale. The propensity score analysis was conducted to evaluate the effectiveness of the protected areas. Specific questions addressed and the results obtained are summarized below:

1. *What are the dominant causative factors of fires in protected and non-protected areas?*

   The five major fire causative factors in protected areas in descending order include population density, land cover, tree cover percent, travel time from nearest city and temperature. The causative factors in non-protected areas were population density, tree cover percent, travel time from nearest city, temperature and elevation. The fire susceptibility analysis showed distinct spatial patterns with central Myanmar as a hot spot of vegetation fires.

2. *Are protected areas effective in conserving the forests?*

   Results from propensity score matching suggested that forests within protected areas have 11% less fires than non-protected areas in Myanmar.

5.2 Future Research Directions

Research avenues: There is very little current information available on Myanmar, mostly due its history of political and economic isolation. From my perspective, additional research is needed on characterizing forest cover loss due to rubber and palm oil plantations. Thus, plantation mapping in forested lands might provide useful results. Such studies are hampered due to limited access to field data. Country specific land cover and forest maps are available, however, they need to be validated on the ground to provide a reliable estimate of land/forest cover changes. As inferred in the dissertation, operational monitoring of forest loss and fires will contribute to regional conservation efforts. Most of the fires are related to slash and burn, thus alternate methods of subsistence agriculture should be promoted. For addressing the natural fires, research on fire forecasting and fire spread models may help in arriving at fire mitigation measures. Habitat conservation and land use planning are also important issues to address LCLUC in Myanmar.

Future research avenues for land use science in Myanmar include telecoupling studies linking large scale agriculture to demands for palm-oil /rubber in China and other countries; annual mapping of slash and burn areas and assessing their contribution to national carbon accounting; developing spatially gridded emissions inventory from land use/forestry sector; forest biomass mapping integrating optical, radar and LIDAR data for REDD+ reporting at Tier 3 level, etc.

Practical use of remote sensing and geospatial technologies in Myanmar is hampered by a lack of technical expertise. Though there is a lot of interest in using remote sensing data for policy applications, practical logistic issues such as slow internet connections inhibit downloading of data and accessing platforms like Google Earth Engine for analysis of data etc. Other challenges include difficulties in procuring cloud-free images, procuring high resolution images, application and development of automated methods for large area mapping and funding constraints. With the recent democratic transition, the Myanmar Government is showing immense interest on capacity building activities in remote sensing and GIS technologies. International organizations such as FAO and USAID are helping Myanmar in various capacity building activities.

Need for country-specific maps and monitoring: The datasets used in this analysis (forest loss and fire) were derived by clipping global datasets. There is an urgent need to involve local experts in generating some of the country-level products. The landscape in Myanmar is heterogeneous so high resolution data and ground information are necessary to derive highly accurate land cover maps. There is an urgent need for Myanmar to harness the available satellite systems (Landsat, Sentinel) and establish national satellite-based monitoring of forest loss and fires using well-developed techniques, that were applied in this dissertation and as is being implemented in other countries of South and Southeast Asia.

Reliable statistics/data from the Myanmar Government: As of now very limited data are available from the Government on the status of forest, fire and wildlife. The fact that Myanmar is located in the Indo-Burma biodiversity hotspot, warrants regular reporting on the status of its forests and wildlife. At this point of time, most of the information comes from non-government organizations like Biodiversity and Nature Conservation Association (BANCA), Economically Progressive Environmental Development (EcoDev), Fauna and Flora International (FFI), World Wildlife Fund (WWF), and Wildlife Conservation Society (WCS). Given the high rates of forest loss and fragmentation reported for the country, it is time that the government puts in place the necessary data collection systems and releases an annual or bi-annual reports on the status of its forests and wildlife.

5.3 Conclusion

The transition to democracy in Myanmar has been welcomed internationally by lifting previously imposed sanctions by pro-democracy nations. The lifting of economic sanctions provided a much needed opportunity to the Myanmar Government to “develop” the country after decades of political and economic isolation. Myanmar is rich in natural resources and exporting of it’s natural products contributes to the economy. The economic and structural reforms, specifically the increased granting of agricultural concessions and logging for plantations led to rapid forest loss and fragmentation. The rapid rate of forest loss and fragmentation is of concern to environmentalists due to important role forests play in maintaining ecosystem structure and function, especially in a biodiversity hotspot like Myanmar. The new democratic government has shown interest in environmental conservation issues. The need to conserve forest, woodlands and wildlife and amend old laws and enact new laws for environmental conservation by recently formed government is well received by the local people.

The results presented in this dissertation come at an opportune moment as the new government is still under inception. It furthers the present understanding of contemporary forest cover dynamics and fires in Myanmar in context of the recent political transition. Understanding the dynamics and drivers of forest loss and fragmentation is necessary to formulate forest conservation policies. Throughout this dissertation, remotely sensed data has been combined with GIS in a statistical and spatial framework to arrive at the results and explain the findings. Specifically, they provide information on magnitude, trends and spatial patterns of recent forest loss, fragmentation, fire hotspots, the status of protected areas and investigates the causative factors of forest loss, fragmentation and fires.

The challenge for the new government lies in designing sustainable development policy interventions that not only encourage economic and social development but also ensures environmental protection. The formative years of the new government is of great importance for the country's future. How the country manages its natural resource management now will decide its long term economic future.

6 Appendix: Photos taken during field work for this thesis

New rubber plantation with very young rubber saplings.

New planted rubber saplings.

Close look at a single rubber sapling.

Collecting rubber sample data.

Private rubber plantation.

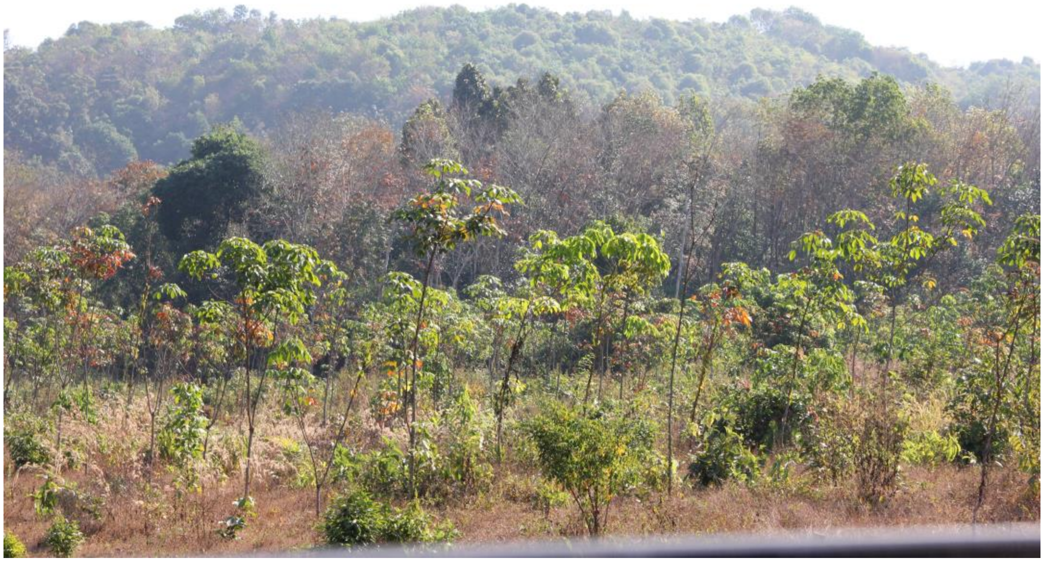
Mature rubber trees.

Young rubber plants in defoliation stage during the dry season.

Young rubber plants with foliage.

Young (sapling stage) rubber plantation (front) and mature defoliated rubber (back).

Young (sapling stage, older than previous photo) rubber plantation in (front) and mature defoliated rubber (back).



Age stratified rubber plantations.

Clear felling of existing plantation to make space for new plantation.

Interaction with rubber farmer.

Interaction with local people to gain knowledge about rubber plantations and policies.

Interaction with Burmese forester from Forest Department.

Mature teak plantation in Central Myanmar.

Young teak plantation.

Young teak plantation in a drier region.

Oil palm in southern Myanmar.

Oil palm under rubber canopy. Mixed plantation.

Oil palm (front) and rubber plantation (back).

Mixed plantation with oil palm under rubber canopy.

Rice paddy in Central Myanmar.

Flooded rice paddy.

Bullock cart. Agricultural practices in Myanmar are mostly traditional and non-mechanized.

Ploughing field by plough drawn by bulls.

Interaction with farmers.

Agricultural burn.

Burning degraded forest.

Burning to prepare land for next rubber crop.

Field work team in the rubber belt.

Road sign (to Wingan) in remote village.

Crossing state borders in the rubber belt.

Downtown Kyaikto.

Tapping mature rubber. The white latex is nicknamed white gold.

Rubber sheet making kit.

Flattening rubber sheets.

Drying rubber sheets in a small factory.

Drying rubber sheets in private backyard.

Earthen cups to collect latex.

Transporting rubber sheets.

Logged timber for sale in timber yard.

Logged timber lying on roadside.

Transporting logged timber.

Timber stacked in private house for domestic use.

Domestic Timber stacked for private use.

Wetland in Central Myanmar. Drainage of wetlands for agriculture or urban development is increasing.

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