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SPATIOTEMPORAL DYNAMICS OF FOREST
DEGRADATION BY SELECTIVE LOGGING AND FOREST
FIRE IN THE BRAZILIAN AMAZON

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ERALDO A. T. MATRICARDI

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SPATIOTEMPORAL DYNAMICS OF FOREST DEGRADATION BY SELECTIVE LOGGING AND FOREST FIRE IN THE BRAZILIAN AMAZON

By

Eraldo A.T. Matricardi

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ABSTRACT

SPATIOTEMPORAL DYNAMICS OF FOREST DEGRADATION BY SELECTIVE LOGGING AND FOREST FIRE IN THE BRAZILIAN AMAZON

By

Eraldo A T Matricardi

Selective logging and forest fires have increased at a rapid pace in tropical regions in recent decades. Forest disturbances caused by selective logging and forest fires may vary in scale, ranging from local damage to forest canopy, habitats, soils, and biodiversity, to global changes caused by logging-related release of carbon into the atmosphere. This study provides a regional assessment of forest impacts by selective logging and forest fires for 1992, 1996, and 1999. Multivariate statistical models, remote sensing approaches, Geographic Information System (GIS), and remotely sensed imagery combined with field data were applied to verify the scale of environmental changes associated with these processes of forest disturbance. In this regard, the study widens the current knowledge on land use and land cover classifications to include selectively logged and burned forests as additional thematic classes. These classes have not yet been properly accounted for by conventional remote sensing approaches of deforestation assessment, despite their relevance for the understanding of the changes affecting tropical forests. This study is the first multi-temporal and spatial assessment of the selective logging and forest fire impacts in the Brazilian Amazon. The resulting estimates show that at least 11800 km^2, 16500 km^2, and 35600 km^2 of natural forests were selectively logged

and/or burned by 1992, 1996, and 1999, respectively. More than 60% of these forest disturbances observed in the Brazilian Amazon during those years were due to selective logging activities. However, forest fires were responsible for the greatest impacts on natural forests, causing an estimated loss of 18.8% of forest canopy in the study region. I also estimated that approximately 5467 km^2, 7618 km^2, and 17437 km^2 were active areas of selective logging and/or forest fires in 1992, 1996, and 1999, respectively. In addition, approximately 4% of total forest disturbed by selective logging and forest fires was geographically located within protected areas. Areas affected by selective logging and forest fire corresponded to 2.7%, 3.2%, and 6.3% of total deforestation in the Brazilian Amazon by 1992, 1996, and 1999, respectively. Altogether, the present study demonstrated not only the importance of the selective logging and forest fires as important drivers of forest change in the tropics, but improved the existing knowledge of their combined impacts in forested lands in the Brazilian Amazon. Furthermore, the results of this research are expected to support and enhance the scope of global climate change studies associated with environmental changes caused by economic activities based on the exploitation of natural resources available in tropical forests. In terms of its applications to normative efforts, this study could be used to enlighten authorities and staff of environmental agencies working to develop sustainable management programs and environmental policies in Brazil and other tropical countries.

DEDICATION

Dedico esta tese à minha esposa, Cleusa, pelo seu amor incondicional, companherismo e dedicação durante todos estes anos em terras estrangeiras, às minhas filhas, Camila e Marcela, pelo estímulo de fazer e viver sempre mais, aos meus pais, Mauro e Adelina, pela referência de vida pessoal, trabalho incansável, amor e fé, aos meus irmãos, Wagner, Hamilton e Mauro Lúcio, por toda amizade, suporte e apoio incondicional, à Dona Marli, pelo amor, carinho e compreensão, ao Senhor Pedro Inocêncio (*in memoriam*), pela benção e luz sobre toda minha família, aos meus inúmeros amigos no Brasil, Estados Unidos, Índia, Filipinas, Tailândia, Dinamarca, Japão, etc., que me apoiaram e suportaram pacientemente durante meus estudos. Não teria realizado todo este trabalho sem estas pessoas fazendo parte na minha vida.

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TABLE OF CONTENTS

LIST OF FIGURES

"Images in this Dissertation are presented in color".

LIST OF TABLES

LIST OF APPENDICES

CHAPTER I

Problem Statement

The highest rates of tropical deforestation (conversion of natural forests to non-forest uses) have been observed in the Brazilian Amazon in recent decades. In addition to outright deforestation, forest degradation by selective logging and forest fire has become an important issue due to its potential impacts on global environmental processes, natural ecosystems, biodiversity, and economic development. As a result, several studies have been conducted to assess impacts caused by selective logging and forest fire on tropical ecosystems. These studies have provided important direct and indirect estimates of the impacts brought by selective logging and forest fires for particular study sites in which forests have been partially damaged and not removed as in cases of deforestation. However, only a few attempts have been made to measure both the extent of selective logging and forest fires and their impacts on tropical forests using remotely sensed data gathered for the *entire* Brazilian Amazon. Therefore, relevant questions have yet to be addressed to provide a better understanding of selective logging and forest fire dynamics, their impacts on tropical forests, and their interactions with other land use types. For example: Is selective logging and forest fire causing more forest degradation than otherwise would occur? Can we accurately measure these anthropogenic activities in the Brazilian Amazon basin? Where are the most severe selective logging and forest fire events occurring in that region? Why are selective logging and forest fires occurring there and not somewhere else? Is there a particular spatial pattern to these activities in that region? If so, are those patterns changing over time? Is there an interaction between selective logging and fire that may be synergistically causing even more forest disturbances?

1.1. Statement of purpose

The purpose of this study is to investigate the dynamics of selective logging and forest fire processes to better understand the factors that might control these processes at various scales and times, their impacts on natural forests, and their interactions with other factors that may contribute to increase forest degradation in the Brazilian Amazon basin, using field and remotely sensed data, geographic information system, remote sensing techniques, and spatial analysis.

1.2. Hypothesis testing

Hypothesis 1: *Forest impacts by selective logging activities increase over time and severely disturb natural forests in the Brazilian Amazon.*

Natural forests encompass around 3.15 million square kilometers and are the main source of raw material for timber industries in Brazil (Lentini et al., 2003). Amazonian timber production averaged 51 million cubic meters annually from 1990 to 1996, decreasing to an annual average of 17 million cubic meters from 1997 to 2003 (IBGE, 2006). Amazonian timber production and its relative contribution to national markets in Brazil have been quite steady in this period of time (see Figure 1.1). These numbers indicate that most accessible natural forests in the Brazilian Amazon have been under increasing pressure by timber industry in the last decade. Uhl et al. (1997) observed that loggers are advancing into undisturbed forests and are re-logging previously disturbed forests searching for second tier economic species. Matricardi et al. (2007) estimated that the total area of selective logging detected with satellite imagery increased about 436% between 1992 and 1999 in the Amazon. Based on a case study in the state of Mato Grosso, Matricardi et al. (2005) estimated that areas of formerly logged forests that were re-logged increased 1442% between 1993 and 2002. Consequently, it is expected that forest degradation in the Brazilian Amazon has also increased as a consequence of the growth in area and intensity of selective logging activities. If this hypothesis is true, both selective logging impacts on natural forests and degraded forests have significantly increased over time. For the present study, this hypothesis was tested at local and regional scales, focusing on areas where selective logging has been detected using remotely sensed data. At the local scale, a multi-temporal assessment of selective logging impacts was conducted in the Southeastern Amazon using 13 years (1992 to 2004) time-series remotely sensed data and field measurements (i.e. forest regeneration, number of tree species and mortality, and fuel load). This case study sought to contribute to a better understanding of the annual change in degradation rates and the capacity for forest regeneration in areas affected by selectively logging. Additionally, fieldwork activities were carried out to validate remote sensing techniques in different study sites in the Amazon region. At the regional scale, fractional coverage was estimated for areas where selective logging has been detected using Landsat imagery for three different years (1992, 1996, and 1999). These results provided estimates of impacts and temporal changes in canopy degradation and regeneration of selectively logged forests in the Brazilian Amazon. Multiple regression analysis was used to statistically infer the contribution of each land use type on forest disturbances at local and regional scales. Additional statistical tests were applied to assess forest disturbances based on field measurements for different land use types.

Hypothesis 2: *Forest fires mostly occur on fire-prone selectively logged forests and further increase forest degradation in the Brazilian Amazon.*

Selective logging activities can severely impact tropical forests by damaging individual trees and under-story vegetation, compacting and eroding soils (Verissimo et al., 1992, Johns et al., 1996), reducing canopy cover (Uhl and Vieira, 1989, Verissimo et al., 1992), and, potentially, increasing forest fire susceptibility (Holdsworth and Uhl, 1997), especially during years of severe droughts (Uhl and Kauffman, 1990). Uhl and Buschbacher (1985) were the first to observe a synergistic interaction between selective logging and fire-maintained pastures where fire spreads into logged forests. It was then hypothesized that most forest fires were occurring on previously logged forests, and forest fires were spatially associated with logging and deforestation areas; forest degradation would be significantly higher when selective logging was combined with forest fire. This hypothesis was tested at local and regional scales. At the local scale, a study site in Mato Grosso where fire hotspots have been more frequently observed using NOAA and MODIS imagery (INPE, 2007) was studied. First, burned forests were detected using a Landsat time-series imagery (1992 to 2004) and a new remote sensing method based in part on Cochrane and Souza

(1998) was applied. This method involved masking out non-forest areas and applying linear mixture model classification to detect burned forests. Linkage between selective logging and forest fires was demonstrated by juxtaposing selectively logged and burned forests. Moreover, fractional coverage was calculated for both selectively logged only and selectively logged/burned forests. This procedure helped to estimate forest canopy losses and time required for forest regeneration under different land use characteristics (i.e. burned and non-burned forests). Temporal changes were assessed by comparing data from 1992 to 2004. Finally, field measurements (i.e. forest regeneration, number of tree species, trees mortality, and fuel load) were also conducted on disturbed and undisturbed forest sites to provide additional information on forest degradation. At the regional scale, burned forests were detected for three years (1992, 1996, and 1999) using the same methodological approaches applied and validated at the local scale analysis. Fractional coverage was estimated for areas where selective logging has been detected using Landsat imagery. These datasets were mostly derived from remotely sensed data and focused on areas where evidences of selective logging and forest fire had been previously observed in the study region.

Hypothesis 3: *Variables that reflect landscape and land use characteristics (e.g. vegetation type, soil, precipitation, deforestation, forest fragmentation, proximity to road network, etc.) explain spatial distribution and probability of selective logging and forest fire to occur in the Brazilian Amazon.*

Links between selective logging and various socioeconomic and biophysical factors have been studied by many authors. (Uhl and Vieira, 1989) affirmed that access roads left behind by selective logging activities contribute to increase deforestation in new frontiers. Furthermore, fire-maintained agricultural systems may spread out into adjacent logged forests (Uhl and Buschbacher, 1985). More recently, (Cochrane et al., 2004) observed that there are synergistic interactions between different anthropogenic activities (e.g. selective logging and fire, deforestation and forest fragmentation, etc.) potentially increase forest degradation. Particularly, this analysis focused on existing variables derived from remotely sensed data for a sub-region within the Amazon basin where selective logging and forest fire were more evident on satellite imagery, and excluded those areas where this type of activity were improbable. Therefore, it was expected that variables such as forest and soil types, proximity to roads, precipitation regimes, land tenure (private and public lands), proximity to urban areas, and proximity to previous deforestation events could play important roles in explaining the spatial patterns of selective logging and forest fire in the study area. It was also expected that temporal changes in spatial patterns of selective logging and forest fire in the study area could be explained by the use of a multi-temporal dataset (i.e. 1992, 1996, and 1999). Multivariate probit models were applied to assess which factors were influencing the spatial distribution of selective logging and forest fire. This analysis, however, required several attempts and different variables to estimate probability of selective logging and forest fire in the study region. This procedure was intended to select statistically significant variables that represented factors influencing selective logging and forest fire occurrences in the study area. The final statistical models were expected to significantly explain both the selective logging and forest fire probabilities throughout the study region.

1.3. Background

The Brazilian Amazon contains 40% of the Earth's remaining tropical rainforests and plays an important role in sustaining biodiversity, regional hydrological regimes, climatic patterns (Fearnside, 1999), and terrestrial carbon pools (Fearnside, 1999, Houghton et al., 2000).

Consequently, the increasing rates of deforestation in the Brazilian Amazon has become an environmental concern of global dimension (Laurance et al., 2001, Nepstad et al., 2002). Multi-annual estimates of deforestation in the Brazilian Amazon provided by the National Institute for Space Research - INPE, show that total deforestation was 152,200 km^2, 377,500 Km^2, and 551,782 km^2 by 1978, 1988, and 1998, respectively. Such estimates represent an annual increment of 19,979 km^2, an increase of 362% since 20 years ago (the world's highest absolute rate of deforestation). Most recent measurements based on remotely sensed data show that 703,198 Km^2 were deforested by 2005 (Appendix A.1), equivalent to 14.06% of the total legal Brazilian Amazon (INPE, 2007).

Satellite-based remote sensing has been used for several decades to monitor and to evaluate land use and land cover changes in the Amazon, focusing most on deforestation assessments (Fearnside et al., 1990, Skole and

Tucker, 1993). Data from these studies (e.g. rate of deforestation in Brazil's Legal Amazon) are often used to estimate human effects on the global carbon cycle (Fearnside, 1997, Houghton, 1997, Houghton et al. 2000). However, there is evidence that approximately half of the total area of forest damaged or impoverished annually by human activities has not been detected under conventional deforestation classification schemes and, consequently, the total area of disturbed forests has been greatly underestimated. Most of those non-detected areas are related to forest degradation caused by selective logging and forest fires (Cochrane et al., 1999, Nepstad et al., 1999).

Earlier studies (Stone and Lefebvre, 1998, Souza and Barreto, 2000, Asner et al., 2002) in the Brazilian Amazon state of Pará have shown that it is possible, with some limitations, to detect selective logging using remotely sensed data. Matricardi (2003) expanded the scope of these studies by identifying and mapping areas of selective logging in tropical "terra-firme" (high land) forests for the entire Amazon basin for three different years. Matricardi showed that at least 3,689 Km^2, 5,107 Km^2, and 11,638 Km^2 of natural forests had being actively logged in 1992, 1996, and 1999, respectively.

More recently, additional attempts to automatically detect selective logging and its impacts on tropical forests using remote sensing techniques have been conducted in different parts of the Brazilian Amazon. Souza et al. (2003) and Asner et al. (2004) provided valuable information based on different case studies in the state of Pará. Matricardi et al. (2005) also conducted a multi-temporal analysis, from 1992 to 2002, in the state of Mato Grosso. Although these studies have significantly improved detection techniques and current understanding of selective logging for specific sites, its impacts, spatial patterns, and temporal dynamics over the *entire* region have yet to be assessed.

This research sought to enhance the understanding of the spatial patterns and temporal changes of forest degradation associated with selective logging and forest fires, the interactions between selective logging, forest fires, and other land use types, and how forests ecosystems respond to these anthropogenic activities. A final goal was to provide support for prognostics of selective logging and forest fire spatial trends throughout the Brazilian Amazon region.

1.3.1. Forest degradation concepts

The term forest degradation has been defined as a 'temporary or permanent deterioration in the density or structure of vegetation cover or its species composition' (Grainger, 1993). Unlike deforestation, this term has been used to describe disturbances in forest characteristics that do not involve land cover conversion into other land cover types (Grainger, 1999, Lambin, 1999) and that may occur in a short or long-run time-scale (Lambin, 1999). In the Amazon, anthropogenic forest degradation is often related to forest fragmentation (Skole and Tucker, 1993, Cochrane, 2001), selective logging (Pinard and Putz, 1996, Lambin, 1999, Nepstad et al., 1999, Huth and Ditzer, 2001), and forest fires (Uhl and Buschbacher, 1985, Cochrane and Schulze, 1998, Cochrane et al., 1999).

More specifically, forest fragmentation is normally associated to different forms of deforestation or clear-cutting, whether involving conversion of forest for agriculture or infrastructure development, because it increases forest disturbances along the edges of those remaining forests within deforested areas (Skole and Tucker, 1993, Lambin and Ehrlich, 1997, Laurance et al., 1997). Forest disturbances tend to be higher at the edges because of the increased amounts of sunlight and wind that penetrate the forest, causing, among other things, increased tree mortality (Laurance et al., 1997) and increased drying rates of leaves and wood debris on the forest floor (Nascimento and Laurance, 2002). Ultimately, such effects increase forest fire susceptibility. Concomitantly, frequent exposure of fragmented forest edges to agricultural fires increases the risk of forest fires (Laurance et al., 1997).

As a result, forest fire is another important proximate cause of forest degradation. Although tropical forests were until recently deemed as immune to fire (Uhl and Kauffman, 1990, Cochrane and Schulze, 1998), forest fires have been increasing as the deforestation and forest fragmentation increase. Deforested areas display greater risk to fire and often act as ignition sources for fragmented forest sites that have lost their immunity to fire infiltration (Uhl and Kauffman, 1990, Cochrane and Schulze, 1998, Cochrane, 2001, Cochrane et al., 2004).

Selective logging also increases forest degradation. Although this economic activity involves cutting down only the few most marketable trees in tropical forests, it can severely impact undisturbed forests during the harvesting operations (Pinard and Putz, 1996, Uhl et al., 1997, Nepstad et al., 1999, Huth and Ditzer, 2001). Thus, the combined effects of selective logging, forest fragmentation, and forest fire can dramatically increase forest degradation rates in tropical regions (Cochrane et al., 2004). A focus on degradation thus expands the previous discussions on deforestation alone. Further details on selective logging impacts on natural forests are presented subsequently.

1.3.2. Forest fires

Previous studies had shown that forest fires rarely occur in intact tropical forests. Fire events should be unexpressive in most of the Brazilian Amazon (Uhl and Kauffman, 1990, Cochrane and Schulze, 1998) because of moist microclimates provided by tropical forests that make it difficult for the propagation of fires, even during dry season periods (Uhl and Kauffman, 1990). In spite of this expected resistance to fire, the spread of forest fire is a growing concern in many tropical countries. Uhl and Buschbacher (1985) suggested that there is a direct relationship between agricultural practices that use fire for land maintenance, such as clearing woody debris and weed control, and increased forest fire susceptibility particularly on logged sites close to agriculture. Accordingly, agricultural plots have been designated as the most common fire triggers in the Brazilian Amazon (Uhl and Buschbacher, 1985, Uhl and Kauffman, 1990, Cochrane, 2001).

In fact, there is a growing probability of fires in tropical forest as the forest become more fragmented by selective logging and the edge formation along forest and deforested areas (Cochrane, 2001). Forest fires are devastating for tropical ecosystems because of their natural low resistance to fire, which allows dominance by thin bark trees (Uhl and Kauffman, 1990). Moreover, once a site is burned for a first time, increase chances for recurring fire and more intense fires because of increased fuel loads and drier microclimate created by the previous fire (Cochrane and Schulze, 1998). Therefore, sequential fires can degrade forests rapidly by drastically destroying their structure and composition and, ultimately, creating a new land cover type whose structural features resembles a secondary regrowth and not an actual pristine tropical forest.

1.3.3. Defining selective logging

The term selective logging is used to define the targeted extraction of a group of tree species in which, usually, the most economically valuable trees are removed from the forest (Verissimo et al., 1995, Uhl et al., 1997).

While deforestation in tropical areas affects directly the carbon cycle and causes massive destruction of plants and animals by clear-cutting and burning natural forests (Skole and Tucker, 1993), selective logging activities do not clear-cut and burn forests, but harvest only a portion of trees. In spite of being a less aggressive form of forest intrusion than clear-cutting, selective logging can damage a large portion of forest and affect many trees during logging operations (Pinard and Putz, 1996, Nepstad et al., 1999, Huth and Ditzer, 2001). For instance, when traditional techniques are used, the harvesting of a single tree alone can directly result in the death of thirteen other trees as result of its fall direction, and, in addition, ordinary logging operations such trail opening, acess road construction, and the establishment of log storage patios also contribute to increase forest degradation (Verissimo et al., 1992).

Meanwhile, selective logging activities have been occurring in Brazil's tropical forests for several decades (Uhl and Kauffman, 1990, Stone and

Lefebvre, 1998, Nepstad et al., 1999, Alvarado and Sandberg, 2001). These activities have been traditionally restricted to flood plains (*várzeas*) due the pre-existent access through the rivers (fluvial transportation). However, the expansion of road networks during 1960s and 1970s in the Brazilian Amazon allowed the expansion of selective logging to the interfluvial (*terra firme*) forest areas (Uhl and Vieira, 1989, Uhl et al., 1997). Moreover, the Avança Brasil[1] program set by the Federal government to strengthen transportation networks in the Brazilian Amazon as a mean to further accelerate economic development (e.g. roads, timber and mining industry) in the region is expected to have major impact on the diffusion of logging operations (Laurance et al., 2001, Fearnside, 2002).

Selective logging can be classified in terms of spatial distribution and severity. Spatially, selective logging can occur in '*várzeas*' and '*terra firme*' in the Brazilian Amazon. Moreover, selective logging varies in terms of impacts (i.e. low, moderate, and high), depending on the volume and number of harvested trees (Uhl et al., 1997). Low impact logging (i.e. highly selective logging) involve the extraction of one or two high valuable tree species, such as Virola (*Virola surinamensis* (Rol.) Warb) (Uhl et al., 1997) and Mahogany (*Swietenia macrophylla*, King) (Verissimo et al., 1995, Uhl et al., 1997). On the other hand,

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[1] "Avança Brasil" (Forward Brazil) is a development program that is being conducted by the Brazilian government in the Brazilian Amazon, involving a total of US$ 43 billion over the 2000-2007 period of which US$20 billion is for infrastructure such as transportation corridor expansion (roads, water ways, and railways) with direct impacts on the (Laurance et al. 2001, Fearnside 2002).

high impact logging encompasses a hundred or more tree species, and requires the use of heavy machinery and the construction of greater infrastructure (i.e. patios, forest roads, etc.) for tree harvesting and transportation. The later form of selective logging is the most common form in the more developed parts of the Brazilian Amazon (Uhl et al., 1997).

Finally, (Uhl et al., 1997) described an additional logging type of logging known as forest 'mining', actually a sequential form of selective logging. Forest mining can completely impoverish a seemingly intact forest tract over a period up to thirty year of successive and ever more intensive selective logging activities that at the end may lead to an acute form of forest degradation or even outright deforestation.

1.3.3.1. Forest impacts by selective logging

Selective logging activities leave behind a mixture of intact forest, treefall gaps, roads, log-loading patios, and damaged forests, increasing amounts of dead slash or dried biomass (fuel) and, consequently, greater risks of forest fire events (Uhl and Buschbacher, 1985, Stone and Lefebvre, 1998, Nepstad et al., 1999, Souza and Barreto, 2000). Estimates of the total of damages arising from logging operations point out that about 40% of the remaining trees in a given forest patch affected by selective logging may end either killed or severely damaged (Uhl et al., 1991). Such impacts can be devastating even when a small volume of timber is harvested (Frumhoff, 1995). The potential impacts of selective logging in tropical forest ecosystem are further discussed bellow.

1.3.3.2. Impacts on carbon cycle

(Skole and Tucker, 1993) have argued that "tropical deforestation is a major component of the carbon cycle and has profound implications for biological diversity". The greatest carbon and biodiversity losses happen when a forested area of high biomass content is converted into a low biomass system such as pasture and agriculture, releasing carbon directly to the atmosphere and destroying natural habitats (Skole and Tucker, 1993).

Nevertheless, Amazonian forests are increasingly being exposed to logging activities (Stone and Lefebvre, 1998, Nepstad et al., 1999, Souza and Barreto, 2000). Although the impacts of selective logging are known to vary according to extraction intensity, their overall impacts are usually substantial on the complex and fragile tropical environments. Meanwhile, selectively logged forests are expected to accumulate carbon over time and return to pre-harvest levels of biomass if left undisturbed. However, many forests are revisited several times by loggers seeking to harvest additional tree species as regional timber markets evolve (Verissimo et al., 1995, Uhl et al., 1997). Re-logged forests become highly degraded and may have 40 – 50% of the canopy cover is destroyed during these re-logging operations (Uhl and Vieira, 1989, Verissimo et al., 1992). In addition, forest heavily impacted by selective logging are expected to face an increase in fire susceptibility (Holdsworth and Uhl, 1997) and, consequently, more emissions of carbon to the atmosphere (Houghton, 1997). Intentionally or not, uncontrolled forest exploitation by loggers also serve to catalyze deforestation by opening roads inside idle public lands and protected areas that are often squandered by large ranchers and small farmers. This process results in increased rates of deforestation and higher carbon emissions to the atmosphere (Verissimo et al., 1995).

1.3.3.3. Impacts on biodiversity

Upper Amazonian forests are considered to be one of the world's richest biomes in terms of plant and animal diversity (Gentry, 1988). Although during selective logging only a few valuable tree species are harvested, high intensity logging can heavily impact a whole forest ecosystem (Frumhoff, 1995) including damage to nearby trees and soils (Uhl and Buschbacher, 1985, Johns et al., 1996) and increased risk of local species extirpation (Martini et al., 1994). Furthermore, hunters gain greater access through the logging road network, which increases both commercial and subsistence hunting, usually aimed at primates and duikers (Frumhoff, 1995).

Therefore, impacts by selective logging may affect both plant and animal species, especially those associated with the timber species (e.g. mammals and birds that eat timber specie fruits) (Martini et al., 1994). (Frumhoff, 1995) affirmed that the ecosystem changes caused by selective logging result in loss of equilibrium in animal population in terms of number of species and species diversity, with some species tending to become more abundant than others because of hunting. In terms of plant populations, selective logging eliminates the most valuable timber species and, systematically, reduces the number of most fit individuals and, therefore, preclude sustainable species reproduction (Uhl and Vieira, 1989).

Selective logging activities also cause losses in the forest structural integrity and lead to further degradation, especially in open canopy forest patches with presence of vines (Uhl and Buschbacher, 1985). Therefore, although selective logging in the Amazon floodplain concentrates on very few species, it results in profound ecological changes. (Macedo and Anderson, 1993) observed a dramatic transformation in the under-story vegetation as a result of selective logging, with the development of secondary vegetation predominantly formed by vines and herbs. Other environmental changes commonly associated to selective logging include the development of drier conditions within logged patches (Martini et al., 1994) and soil compaction (Pinard and Putz, 1996, Fredericksen and Pariona, 2002). Meanwhile, habitat modifications directly affect the distribution and abundance of amphibians and reptiles, seed dispersion, and forest regeneration (Martini et al., 1994). The extended effects of selective logging, including the decrease in forest yield, can lead to outright forest conversion to other land use types (Pinard and Putz, 1996, Huth and Ditzer, 2001), which implies the complete destruction of a given natural forest patch.

1.3.3.4. Socioeconomic impacts

The Brazilian economy was placed among the 10 largest economies in the world in 2000, with a Gross Domestic Product (GDP) of US$ 596 billion. Alone, the timber sector contributed with approximately 5.5 billion to the Brazilian GDP (ABIMCI, 2002). In the Brazilian Amazon, the timber industries are responsible for approximately 15% of the regional GDP and employ 5% of the regional workforce (World Bank, 1999). It is estimated that 61.1% of the total of effective productive native forests are located in the Brazilian Legal Amazon, placing the region as the main source of raw materials for the Brazilian timber industry (ABIMCI, 2002).

In addition, according to (IBGE, 2006), from the country's reported[2] timber production between 1990 and 2003 a total around of 445 million cubic meters of round wood was extracted in the Brazilian Amazon states, an average around of 34.2 million $m^3 yr^{-1}$. The Brazilian Amazon alone produced approximately 80% of national round wood production in Brazil over this time (Figure 1.1).

Based on the census data provided by IBGE (2006), approximately 74% of the timber production in the Brazilian Amazon from 1990 to 2003 was extracted in the state of Pará, 10% in the state of Amazonas, and 8% in the state of Mato Grosso. Although this overall round wood production results place the State of Amazonas as the second timber producer in the region, the State of Mato Grosso has occupied this place from 1991 to 2003, immediately followed by the states of Rondônia and Amazonas (IBGE, 2006).

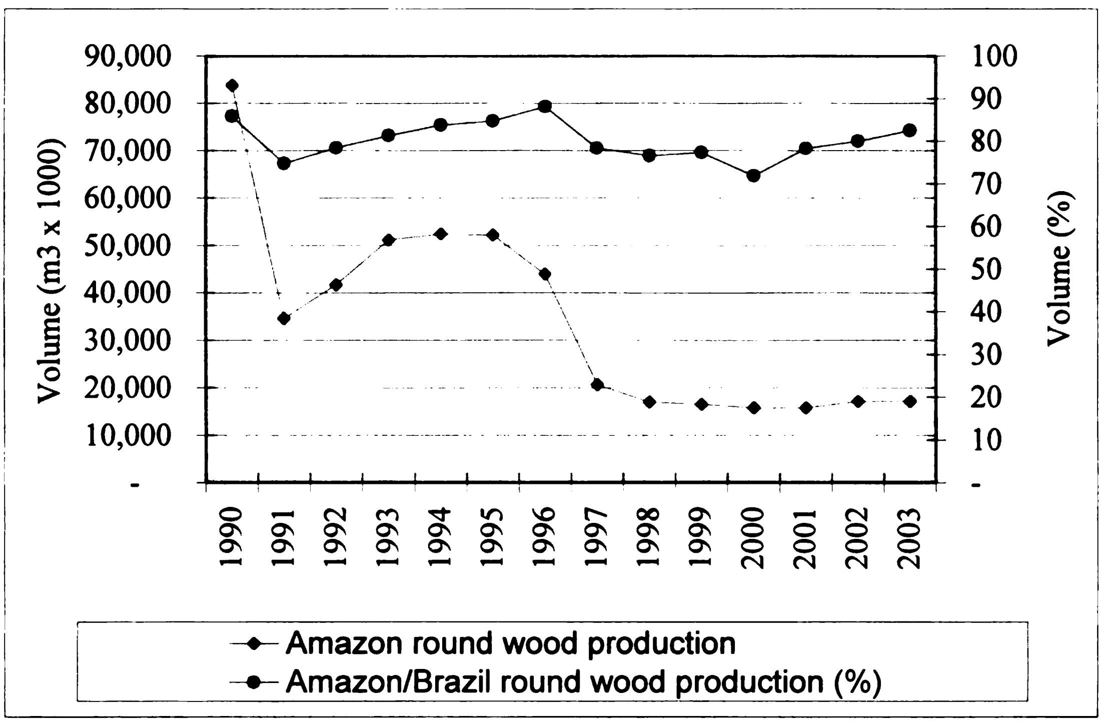
As a result of an abundant timber resource pool, selective logging related activities enhance the local economy. (Verissimo et al., 1992) observed that 112 sawmills in the vicinity of the city of Paragominas in Pará, generated approximately 5,700 jobs, including forestry workers (e.g. forest timber extractors, truck drivers, machinery operators, etc.) and industrial workers.

[2] Total of round wood production reported by timber industries to the Brazilian Institute for Environment and Natural Resources - IBAMA (IBGE, 2005).

Verissimo and collaborators observed that more than 50% of the urban population of Paragominas was directly dependent of the timber industry for income generation. A major indirect impact of the timber industry is the creation of significant tax revenues, which can be used for the benefit of the local and regional population.

Figure 1.1. Forest production (round wood) from 1990 to 2003 in the Brazilian Amazon (adapted from IBGE, 2006)

Timber-based local economies are subject to collapse, however. Pinedo-



Vasquez et al. (2001) conducted a study case in a floodplain forest in the State of Amazonas, following a logging “boom” . In this case, the local timber industry collapsed after the high value timber species were exhausted, leading industries and individuals to migrate to other regions seeking new sources of raw material and job opportunities, respectively.

Uhl and Vieira (1989) observed some indirect socio-economical impacts of selective logging. Uhl and Vieira suggested that forest access roads left behind after selective logging activities lead to the occupation of new areas by landless peasants, increasing deforestation and threatening indigenous communities. Furthermore, Uhl and Buschbacher (1985) observed that fire used by farmers in the Amazon region to manage crops and pastures often spread into adjacent forests. In contrast to non-logged forest, fire spreads readily in exploited forest causing extensive damage.

1.4. General comments

A great number of articles available in the literature have been used to support analyzes regarding the impacts by selective logging and forest fires in the Brazilian Amazon. This body of literature has contributed to create a conventional wisdom that characterizes these anthropogenic activities as major drivers of forest degradation in tropical regions. For example, Fearnside (1997) and Uhl and Vieira (1997) affirmed that logging often leads to significant losses in canopy and biomass content. Furthermore, Holdsworth and Uhl et al. (1997), Cochrane (1999), and Cochrane and Schulze (1999) observed that selective logging leads to a significant increase in the number of forest fires in tropical ever green forests. Meanwhile, Nepstad et al. (1999) have estimated areas impacted by logging based on records of sawmills' production because they believed that logging was cryptic and, therefore, could not be adequately resolved by the usage of remotely sensed data. In addition, these authors had never directly measured the extent of selective logging at the regional scale. Nonetheless, Nepstad et al. (1999) combined these studies and concluded that selective logging is highly significant, equal or more than deforestation to explain forest degradation in tropical countries. Another major conclusion of Nepstad and his colleagues was the lack of reliable measurements of the combined impacts of selective logging and forest fires in the Brazilian Amazon.

In my research, one of my main goals was to investigate the validity of the existent conventional wisdom about the extent and impacts of selective logging and forest fires in the Amazon region. To achieve this goal I created a methodological framework to quantify forest degradation at local and regional scales by examining the spatial characteristics and the temporal changes of selective logging and forest fires. I also investigated the factors controlling the processes of forest degradation at various geographical and temporal scales in the Amazon basin.

1.5. Overview of the study

This manuscript was divided into five chapters to address the previously stated research purposes. Chapter I presents the research design and describes the general scientific development of the study. Chapter II focuses on the development of remote sensing and statistical analysis approaches used to assess extent and impacts by selective logging and forest fires in a case study in the southwestern Amazonian state of Mato Grosso. Chapter III shows the application of the scientific approaches developed in Chapter II to a basin wide assessment of both the extent of selective logging and forest fires and their impacts on Amazonian forests. Chapter IV shows the development and implementation of spatiotemporal analyzes of selective logging and forest fires using probabilistic probit models at the regional scale in the Brazilian Amazon. Finally, Chapter V summarized analyses presented in the previous chapters by revisiting all research questions and hypotheses, and by connecting all research findings to the global change context. Finally, I concluded by presenting the potentials raised by this study for further inquiries on the processes controlling the pace of environmental changes in the Brazilian Amazon.

CHAPTER II

Methods for Assessment of Impacts by Selective Logging and Forest Fire: A Case Study in Mato Grosso, Brazil

2.1. Abstract research

Many studies have been conducted to assess the process of forest degradation in the Brazilian Amazon. Several of those researches relied on remote sensing approaches to estimate the extent and impact by selective logging and forest fires on tropical rain forest. However, only a few studies assessed the combined impacts of those anthropogenic activities. I conducted a detailed analysis of selective logging and forest fire impacts on natural forests in the Southern Amazon State of Mato Grosso, Brazil, one of the key logging centers in Brazil. I used a 13-year series of annual Landsat images (1992-2004) to test different remote sensing techniques for measuring the extent of selective logging and forest fires and their impacts and interactions with other land use types in the study region. I also assessed forest canopy regeneration following these disturbances. Field measurements and observations were conducted to validate remote sensing approaches. The results indicated that the Modified Soil Adjusted Vegetation Index aerosol free ($MSAVI_{af}$) is a reliable estimator of fractional coverage under both clear sky and smoke conditions in this study region. Multi-temporal analysis of land use and land cover change from 1992 to 2004 indicated that around of 29% of the study area had been converted into agricultural land by 2004. In terms of extent, selective logging activity was the most important forest disturbance factor, impacting more than 31% of the total

study area by 2004. Approximately 28%, 5%, and 3% of the study area was impacted by deforestation, selective logging and forest fire combined, and forest fire only, respectively. Although selective logging impacted the largest extent of natural forest in the period of analysis, more than 35% and 28% of the observed forest canopy losses were due to forest fire and selective logging combined and to forest fire only, respectively. These study results also indicated that approximately 70% of total area of forest disturbed by logging and fire had sufficiently recovered to become undetectable on satellite imagery in 2004, which implies that selectively logged and burned forests may transition from a carbon sources to carbon sinks in the subsequent years due to strong forest regeneration. This type of forest degradation is an addition to outright deforestation analysis and has yet to be accounted for. Finally, the results of this research could be useful to global climate change analysis, sustainable forest management programs, and environmental policy development in Brazil.

2.2. Introduction

Selective logging activities have been occurring in Brazil's tropical forests for several decades (Stone and Lefebvre, 1998, Nepstad et al., 1999, Alvarado and Sandberg, 2001). Logging activities were restricted to flood plains (*várzeas*) until the 1960s due to the pre-existent access though rivers (fluvial transportation) in areas flooded annually, but the widespread construction of roads during the 1960s and 1970s allowed the expansion of selective logging into the inter-fluvial (*terra-firme*) forest in the Brazilian Amazon (Uhl and Vieira, 1989, Uhl et al., 1997).

As a result of increased access provided by roads, selective logging has become a major environmental concern in the Brazilian Amazon due to its potential negative effects on natural forests. Selective logging is a form of timber extraction of a select group of tree species where only the most valuable tree species are removed from the forest (Verissimo et al., 1995, Uhl et al., 1997). Selective logging activities leave behind a complex landscape comprised of intact forest, treefall gaps, roads, log-loading patios, and damaged forest. These activities increase the amount of dead slash or dried biomass (fuel) and, consequently, forest fire susceptibility is substantially increased (Uhl and Buschbacher, 1985, Stone and Lefebvre, 1998, Nepstad et al., 1999, Souza and Barreto, 2000).

The impacts caused by logging in tropical forests are significant in terms of forest degradation and fire susceptibility (Uhl and Buschbacher, 1985, Stone and Lefebvre, 1998, Nepstad et al., 1999, Souza and Barreto, 2000). Selectively logged forests become highly degraded and usually have 40 – 50% of the canopy cover destroyed during logging operations (Uhl and Vieira, 1989, Verissimo et al., 1992). Forests heavily impacted by selective logging will have a significant increase in the level of forest degradation and fire susceptibility (Holdsworth and Uhl, 1997, Stone and Lefebvre, 1998, Cochrane, 2001). Not surprisingly, forest fires have been increasing in the Brazilian Amazon, and are more common in fragmented forests located next to deforested areas, which serve as ignition sources of forest fire (Uhl and Kauffman, 1990, Cochrane and Schulze, 1998, Cochrane, 2001, Cochrane et al., 2004).

Most studies on the impacts of selective logging that relied on remotely sensed data quantified forests affected by selective logging were conducted for study sites in Eastern Pará, Brazil, using Landsat images and visual interpretation. For example, Souza and Barreto (2000) conducted an investigation using a linear mixture model and Landsat imagery to detect logging patios within selectively logged forests in a study site in the State of Pará, Brazil. Cochrane and Souza Jr (1998) developed a remote sensing technique to detect and classify burned forests using non-photosynthetic vegetation derived from Linear Mixture Analysis for a study site in Tailândia, Amazon State of Pará. Cochrane and Sousa Jr (1998) and Cochrane et al. (1999) conducted field studies and a multi-temporal analysis of remotely sensed imagery to understand forest fire dynamics in a study site in the Amazon state of Para, Brazil. Souza et al. (2003) developed a methodology to map classes of degraded forest for a study case in the State of Pará using fraction images (vegetation, non-photosynthetic vegetation, soil, and shade) derived from spectral mixture models.

More recently, Souza et al. (2005) conducted an evaluation of different vegetation and infrared indices and fraction images derived from spectral mixture analysis in assessing multi-temporal forest degradation within nineteen transects in the eastern Amazon. Matricardi et al. (2005) estimated areas of selectively logged forests throughout an entire Landsat scene in the State of Mato Grosso, Brazil, by combining fieldwork and remote sensing approaches.

Although these previous studies significantly improved remote sensing approaches to assess both extent and impacts caused by selectively logging and forest fires using remotely sensed data in tropical forests, they have focused on particular study sites, a more comprehensive assessment of forest disturbances by forest fire and selective logging and their interactions with other land use and land cover processes have yet to be conducted. Moreover, atmospheric changes caused by smoke derived from deforested and forested areas have limited multi-temporal analysis using remotely sensed data (Karnieli et al., 2001, De Moura and Galvão, 2003).

To address these scientific gaps, I conducted field observations and tested performance of different vegetation indices and a green vegetation fraction (GV) derived from Spectral Mixture Analysis (SMA) to assess forest canopy degradation in the presence of smoke. I also improved the Modified Soil-Adjusted Vegetation Index (MSAVI) to MSAVI_af (MSAVI aerosol-free). In addition, I developed an automated remote sensing approach to map burned forest using non-photosynthetic vegetation (NPV) fraction derived from SMA. Finally, I conducted a multi-annual analysis of forest canopy degradation in the study area that provided useful information to assess forest impact and forest regeneration for years following selective logging and forest fire events. Spatial interactions between burned and selectively logged forests were also examined.

2.3. Methodology

2.3.1. Study site

This research was conducted using one Landsat scene (path 226 and row 068) that encompassed approximately 30,000 km^2 in the State of Mato Grosso, Southern Brazilian Amazon (see Appendix B.1). The study area includes the *municípios* of Santa Carmem and União do Sul and parts of the *municípios* of Colider, Feliz Natal, Itaúba, Marcelândia, Nova Ubiratã, Paranatinga, Sinop, Sorriso, and Vera, which form a territory known as the Sinop region.

The climate in the study area is humid tropical with very distinct dry and wet seasons that extend from June through September and from December through March, respectively. The average annual precipitation and temperature is 2000 mm and 26° C, respectively (RADAMBRASIL, 1980). Prior to modern colonization the study area was mostly covered by transitional forests, a semi-deciduous forest type, with emergent canopy. However, by 2004 approximately 8,500 km^2 of native forest had been converted into extensive soybean plantations and pasture. Nonetheless, the Sinop region remains a major timber center in the Amazon in spite of prevailing high deforestation rates.

2.3.2. Dataset

2.3.2.1. Land use and land cover dataset

Multi-annual land use and land cover GIS (Geographic Information System) layers for 1992 through 2004, produced at GOES for the Landsat path 226 and row 068, were used in this analysis. These layers were generated via standard unsupervised classification of Landsat TM and ETM+ imagery and subsequent manual editing using GIS. Each layer included seven classes of land use (forest, deforestation, secondary regrowth, savannah, cloud, shadow, and water body) (see Table 2.1). Multiple non-forest land use and land cover classes were lumped together to create a forest and non-forest mask. This masking procedure was performed to separate forest only, degraded or not, on each

Landsat image. Forest masked images were used to detect selectively logged and burned forests.

Table 2.1. Land Use and Land Cover dataset characteristics

Dataset	Features	Format	Spatial resolution	Period of Analysis	Projection
Land use and land cover GIS layers	Forest, deforestation, secondary regrowth, cerrado, clouds, and shadows.	Arc/Info grid	30m x 30 m	1992 to 2004	UTM, Zone 21, Datum and Spheroid WGS84

Moreover, cumulative cloud and shadow layers for the period of analysis also were masked out of all Landsat images, which provided a common area of analysis. However, forested areas affected by smoke, visible on bands 4, 5, and 7, were not masked out.

2.3.2.3. Selective logging dataset

Selective logging GIS layers prepared by Matricardi et al. (2005) were used. Matricardi et al. (2005) used semi-automated (texture algorithm) analysis of Landsat band 5 to detect log landings (log storage patios). Subsequently, Matricardi et al. (2005) applied variable buffer zones (180 and 450 meters) around patios to estimate areas affected by selective logging. In addition, selective logged forests showing obvious forest canopy degradation on Landsat images were mapped by digitally circumscribing them on a computer screen. The combination of these techniques allowed the detection of selective logging with 92.9%, 91.2%, and 92.9% of user, producer, and overall accuracy, respectively.

Common areas between these two techniques were around 50% without double counting. Areas eventually missed by using automatic analysis were added later by visual interpretation.

In this study, the dataset created by Matricardi et al. (2005) was used. This dataset involves multi-annual measurements (1992 to 2002) of selective logging in the study area (path 226 and row 068), located in State of Mato Grosso (Table 2.2).

Table 2.2. Selective Logging dataset characteristics

Dataset	Features	Format	Spatial resolution	Period of Analysis	Projection
Selectively logged forest GIS layers	Binary classes (1 = logging, 0 = no data)	Arc/Info grid	30m x 30 m	1992 to 2002	UTM, Zone 21, Datum and Spheroid WGS84

Selective logging layers for two additional years (2003 and 2004) were prepared for this study area using the same methodological approach developed by (Matricardi et al., 2005). Subsequently, selective logging layers were incorporated as part of the land use and land cover change dataset the present analytical effort.

2.3.2.4. Satellite imagery

The satellite imagery used in this study was drawn from the archive maintained by the Tropical Rain Forest Information Center (http://www.trfic.msu.edu/) at the Global Observatory for Ecosystem Services (GOES), Michigan State University, and by the Brazilian National Institute for

Space Research (http://www.inpe.br). The archive holds Landsat TM and ETM+ images from 1992 to 2004, bands 1 to 5, and 7. The Appendix B.2 shows further details of the Landsat imagery used in this analysis.

2.3.2.4.1. Radiometric and atmospheric corrections of Landsat imagery

Radiometric and atmospheric corrections can significantly improve image quality by reducing atmospheric effects of the absorption by atmospheric gases and the atmospheric scattering processes (Vermote et al., 1997). In this study, radiometric correction was performed to normalize satellite images for factors such as sensor degradation, earth-sun distance variation, incidence angle, view angle, and time of data gathering. This correction involved converting digital number (DN) into radiance and, subsequently, radiance into reflectance using different calibration coefficients provided by the metadata files that accompanied the image files. Coefficients provided by Chamder and Makham (2003) were used for those Landsat TM images in which coefficients were not provided.

According to Chamder and Markham (2003), radiometric corrections of Landsat imagery can be performed, first, by converting digital numbers (DN) to radiance:

$$L\lambda = \left(\frac{LMAX\lambda - LMIN\lambda}{Qcal\max}\right)Qcal + LMIN\lambda\,, \qquad (1)$$

where $L\lambda$ = spectral radiance at the sensor's aperture in W/(m^2 . sr .µ) and *Qcal* = Quantized calibrated pixel value in units of digital numbers (DNs).

Then, by converting radiance values to top of atmosphere reflectance using the following equation:

$$\rho P = \left(\frac{\prod . L\lambda . d^2}{ESUN\lambda . \cos \vartheta s} \right) Qcal + LMIN\lambda \text{ ,} \quad (2)$$

where ρP = unit less planetary reflectance, $L\lambda$ = spectral radiance at the sensor's aperture, d = earth-sun distance in astronomical units, $ESUN\lambda$ = mean solar exoatmospheric irradiances, and θs = solar zenith angle in degrees.

The resultant at satellite apparent reflectance was then corrected for atmospheric effects providing at-ground surface reflectance. For converting apparent into surface reflectance the 5S (Simulation of the Satellite Signal in the Solar Spectrum) model was used. It required, however, the input of different parameters from the site and sensor as input such as site elevation, sensor altitude, visibility, date of image acquisition, and solar and sensor zenith and azimuth angles. Landsat images are provided with sensor parameters available in a corresponding metadata file for each Landsat image. The site altitude (340 meters) at the center of the Landsat path 226 row 068, and visibility of 20 Kilometers were applied. Based on these parameters, this atmospheric correction model provided linear equation coefficients (Appendix B.3.) for each Landsat scene. Figure 2.1 shows the procedure for performing these image corrections.

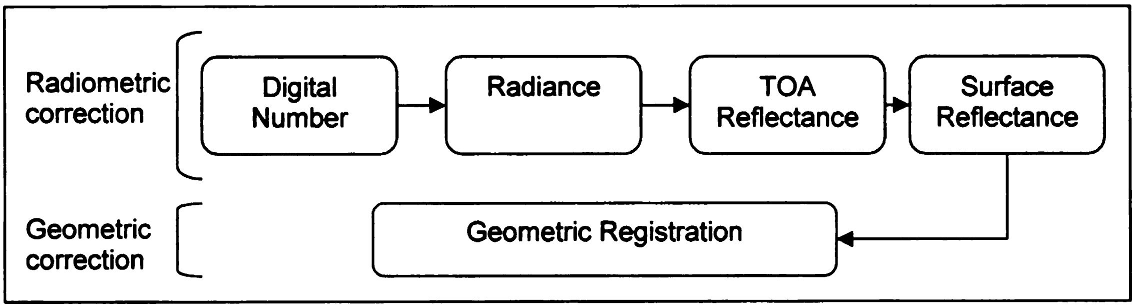


Figure 2.1. Stepwise procedure for radiometric and geometric corrections of Landsat imagery

Finally, the atmospherically corrected Landsat images were geometrically corrected. The entire procedure for geometric registration is described bellow.

2.3.2.4.2. Normalization of seasonality effect of Landsat imagery

Seasonality effects on soil moisture, vegetation phenology, sun angle, etc. occur due to different date of acquisition of remotely sensed data. These effects may affect performance of remote sensing procedures on multi-temporal analysis (Mas, 1999). Therefore, in order to minimize these effects in this study, most images were acquired between May and August. Additionally, normalization of seasonality effects was applied to enable inter-comparison of fourteen Landsat images from different dates in this analysis. Normalization also may minimize atmospheric and other sensor and image variation Elvidge et al. (1995) due to the study area characteristics during the image acquisition period.

Normalization was carried out on each Landsat scene. First, a Landsat scene acquired in 2001 was selected as the reference image (a good quality image) after a careful spectral and visual examination of all Landsat scenes included in this study. Then, the brightest and darkest pixels were selected on the reference image and every other image used in the analysis (Elvidge et al., 1995). These sampled pixel values consisted of areas covered by undisturbed forests, soil exposure (brightest pixels), and deep water (darkest pixels). A linear regression model was calculated using surface reflectance values from the reference (dependent variable) and every other Landsat image (independent variable), which produced the normalization coefficients (slope and intercept) for each band and Landsat scene. Based on these coefficients (Appendix B.4), each band and Landsat image was normalized accordingly.

2.3.2.4.3. Geometric correction

The Landsat images were previously system-corrected at the TRFIC using the sensor calibration data. Geometric correction accuracy was calculated by comparing common points on system-corrected images to ground collected using GPS from several locations within the study area. Image rectification using 3 to 10 point coordinates and nearest neighbor re-sampling technique was applied. Individual geometric correction was deemed acceptable only if the root-mean-square (RMS) was less than 0.5 pixels.

2.4. Methods

This research was based on remote sensing approaches and fieldwork measurements and observations to investigate the processes of forest degradation due to selective logging and forest fire and their temporal changes in the study area in the Mato Grosso state.

2.4.1. Field measurements of forest canopy

Field measurements intended to support the assessment of remote sensing approaches and analysis of forest disturbances were conducted from

June 20 to July 10, 2004. Different types of selective logging (e.g. ongoing logging and previously logged forests), logged and burned forests, and undisturbed forests were sampled within the study area. Eight transects of 500 meter length were set in these sites. Each transect was appropriately located using Geographic Positioning System (GPS) with *x* and *y* coordinates at the start and finish locations (see Appendix B.5 for further details). Hemispherical photos were acquired for each transect. Canopy openness was measured for both disturbed and undisturbed forests using hemispherical photos (further details are described below). Various types of forest disturbances and intensities were also observed.

Hemispherical photos acquired with "fish eye" lens and digital camera (3.2 mega pixels resolution) beneath undisturbed and disturbed forest canopies were used to estimate canopy openness. The photo-shots were taken at 10-meter intervals along each transect. Canopy openness measurement for each individual location was calculated using the Gap Light Analyzer (GLA) software. Fraction canopy openness was estimated using a semi-automated technique because each individual photo requires a threshold empirically defined by the photo interpreter (Appendix B.6). Subsequently, the canopy fraction was obtained by calculating the difference between 100% and canopy openness (%).

In addition, 120 sampling points randomly distributed over forested areas within the study site were visited. Sampling points located too far from the road network were re-located to a closer distance, within a similar forest pattern visually observed on Landsat image. Based on visual evidences of forest fires observed in the field, each sampling point was classified either as burned or not burned forest and appropriately located with x and y coordinates using GPS.

2.4.2. Remote sensing approaches

As previously indicated, changes in forest attributes (degradation) are usually too subtle to be accurately assessed using conventional remote sensing approaches and land use classification schemes (Lambin, 1999, Nepstad et al., 1999). Lambin (1999) suggested that biophysical attributes derived from remotely sensed data (e.g. vegetation indices and land surface temperature) at fine spatial resolution should be used to assess changes in forest canopy and identify process of forest degradation throughout a study region. Landscape attributes such as type, size, distribution, and shape, may reveal important spatial components and their interactions that may help to explain process of land cover modification. And, finally, the multi-temporal information can explain processes of land cover changes over time by detecting natural, anthropogenic, seasonal or permanent modifications on the landscape.

Analysis forest degradation due to selective logging and forest fire impacts were assessed in this study at local and multi-annual scales, using information from the previously described field measurements, remotely sensed data, and statistical analysis. Moreover, as suggested by Lambin (1999), spectral, spatial, and temporal indicators of forest degradation and regeneration associated with selective logging and forest fire were assessed. Firstly, vegetation indices retrieved from Landsat imagery were tested against canopy cover measurements derived from hemispherical photos acquired in the field, which helped to select an optimum vegetation index, which was used to estimate fractional cover using Landsat imagery. Secondly, time-scale variation of these forest attributes was assessed through multi-temporal analysis of canopy degradation derived from remotely sensed data. Finally, spatial pattern of forest degradation due to selective logging and forest fire and their relationship with other land uses and land cover was analyzed.

Further details on remote sensing approaches to assess forest canopy degradation are described as following.

2.4.2.1. Vegetation Indices

Different vegetation indices have been developed and used to better understand the vegetation dynamics in different regions (Qi et al., 1994, Karnieli et al., 2001, Huete et al., 2003). Vegetation Indices (VIs) are mathematical transformations of multiple spectral reflectances employed to estimate the amount of photosynthetically active vegetation at the land surface (Huete et al., 2003) and may be used as indicators of vegetation growth (Wiegand et al., 1991) and forest disturbances (Qi et al., 2002). VI's principles are based on the variation of reflected near infrared and red energies by vegetation, and takes advantage of contrasts between soil and vegetation reflectances. Consequently, near infrared and red are the most commonly used spectral bands to calculate vegetation index (Qi et al., 1995).

Distance and slope based are the two most important vegetation index developing approaches. Differential between near infrared and red reflectances and the ratio of these two spectral bands are used by the distance and slope based approaches, respectively (Qi et al., 1995, Qi, 2001). Both approaches aim to be more sensitive to the vegetation component, while minimizing external effects due to reflectance of red and near infrared variation at the sensor caused by solar irradiance, atmospheric conditions, canopy background, and vegetation canopy structure and composition (Qi, 2001).

MSAVI (Modified Soil Adjusted Vegetation Index), NDVI (Normalized Difference Vegetation Index), and GEMI (Global Environmental Monitoring Index) were tested against canopy cover derived from hemispherical photos to support the selection of the optimum vegetation index. NDVI is one of the earliest and widely used indexes in environmental studies using remotely sensed data. Meanwhile, MSAVI and GEMI are newer approaches aiming to adjust to soil factor and to minimize atmospheric effects, respectively (Qi, 2001).

MSAVI is a ratio-based vegetation index developed by (Qi et al., 1994).The basic idea of MSAVI is to provide a variable correction factor "L". This adjustment factor "L" depends on the level of vegetation cover being observed and on the product of NDVI and WDVI (Weighted Difference Vegetation Index). In this case, the isovegetation lines do not converge to a single point, leading to a circular problem because vegetation covers must be known before calculating the vegetation index, which will generate the vegetation cover. The soil line has arbitrary slope and passes through origin, ranging from –1 to +1.

$$MSAVI = \frac{\rho NIR - \rho red}{\rho NIR + \rho red + L}(1 + L), \qquad (3)$$

where ρ_{NIR} = reflectance at near infrared band, ρ_{red} = reflectance at red band,

$$L = [(\rho_{NIR} - \rho_{red}) * s + 1 + \rho_{NIR} + \rho_{red}]^2 - 8.0 * s * (\rho_{NIR} - \rho_{red}), \tag{4}$$

where s = 1.2 (slope of the soil line calculated from surface reflectance at non-forested areas in the study site).

The NDVI, developed by Tucker (1979), is the most applied index in vegetation studies. NDVI is a ratio-based vegetation index calculated from the difference divided by the sum of two spectral bands yielding a normalized (-1 to +1) difference. NDVI preceded and offered theoretical basis for many other vegetation indices and it still is widely used in remote sensing applications (Qi, 2001). It is defined as follows:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}, \tag{5}$$

where ρ_{NIR} = reflectance at near infrared band and ρ_{red} = reflectance at red band.

The GEMI was developed by (Pinty and Verstraete, 1992). It is a distance-based approach and non-linear vegetation index developed to be less sensitive to atmospheric effects. Although GEMI was initially intended to minimize atmospheric effects, it also is more sensitive index to soil background (Qi et al., 1994).

$$GEMI = \frac{\eta(1 - 0.25\eta) - (\rho_{red} - 0.125)}{(1 - \rho_{red})}, \quad (6)$$

where ρ_{NIR} = reflectance at near infrared band and ρ_{red} = reflectance at red band, and,

$$\eta = \frac{2(\rho^2_{NIR} - \rho^2_{red}) + 1.5\rho_{NIR} + 0.5\rho_{red}}{\rho_{NIR} + \rho_{red} + 0.5} \quad (7)$$

Vegetation index applications, however, have been limited by their sensitivity to atmospheric effects, especially on visible bands which are strongly affected by aerosols such as smoke and other types of aerosols (Karnieli et al., 2001, Huete et al., 2003, Moura and Galvão, 2003). Shortwave bands are insensitive to atmospheric effects and are also highly correlated with visible bands under aerosol-free atmospheric conditions. Therefore, shortwave bands have been favored as an alternative approach to replace the most sensitive bands when atmospheric effects thwart multi-temporal analysis (Karnieli et al., 2001, Moura and Galvão, 2003).

Based on these characteristics of the shortwave bands, Karnieli et al.(2001) tested four modified vegetation indices (NDVI, Soil-Adjusted Vegetation Index – SAVI; Atmospheric Resistant Vegetation Index - ARVI; Soil-Adjusted Atmospheric Resistant Vegetation Index – SARVI) for a study site in the Amazon State of Mato Grosso, Brazil. Karnieli and his colleagues developed a modified NDVI, named the Aerosol Free Vegetation Index (AFRI), which uses an empirical relationship to estimate red band reflectance from shortwave infrared band at 2.1 µm. Equation 8 defines this vegetation index:

$$AFRI_{2.1} = \frac{\rho_{NIR} - 0.5\rho_{SWIR}}{\rho_{NIR} + 0.5\rho_{SWIR}}, \quad (8)$$

where ρ_{NIR} = reflectance at near infrared and ρ_{SWIR} = reflectance at 2.1 µm (Shortwave infrared).

This vegetation index has proven to be useful to estimate biomass burned in the presence of smoke and other atmospheric pollutants. However, AFRI may not produce good results if atmospheric particles are of equal or larger sizes than the wavelength at 2.1 µm (Karnieli et al. 2001).

2.4.2.2. Modified Vegetation Index approaches

The acquisition of remotely sensed data affected by smoke and other aerosols was unavoidable due to the prevailing land use practices in the study region. Consequently, I had to assess performance of various vegetation indices to estimate forest canopy degradation under adverse atmospheric conditions. I tested four vegetation indices (AFRI, NDVI, MSAVI, and GEMI) and the Green Vegetation (GV) derived from SMA to estimate fractional coverage in the study site under smoke conditions. Additionally, I also tested a modified GEMI and MSAVI using the same empirical linear relationship estimated by Karnieli et al.(2001) to predict red band reflectance based on shortwave infrared at 2.1 µm. The equations 9 and 10 define the $GEMI_{2.1}$ model.

$$GEMI_{2.1} = \frac{\eta(1 - 0.25\eta) - (0.5\rho_{SWIR} - 0.125)}{(1 - 0.5\rho_{SWIR})}, \quad (9)$$

where ρ_{NIR} = reflectance at near infrared band and ρ_{SWIR} = reflectance at shortwave infrared band (2.1 µm), and,

$$\eta = \frac{2(\rho^2_{NIR} - 0.5\rho^2_{SWIR}) + 1.5\rho_{NIR} + 0.5(0.5\rho_{SWIR})}{\rho_{NIR} + 05\rho_{SWIR} + 0.5}, \qquad (10)$$

The MSAVI using wavelength at 2.1 µm was named $MSAVI_{af}$ (Modified Soil-Adjusted Vegetation Index aerosol resistant). The equations '11' and '12' describe the $MSAVI_{af}$ model.

$$MSAVI_{af} = \frac{\rho_{NIR} - 0.5\rho_{SWIR}}{\rho_{NIR} + 0.5\rho_{SWIR} + L}(1 + L), \qquad (11)$$

where ρ_{NIR} = reflectance at near infrared band, ρ_{SWIR} = reflectance at Shortwave infrared band (2.1 µm).

$$L = [(\rho_{NIR} - 0.5\rho_{SWIR}) * s + 1 + \rho_{NIR} + 0.5\rho_{SWIR}]^2 - 8.0 * s * (\rho_{NIR} - 0.5\rho_{SWIR}), \qquad (12)$$

where s = 1.2 (slope of the soil line calculated from surface reflectance at deforestation areas in the study site).

2.4.2.3. Spectral Mixture Analysis

Multi-spectral categories may be represented by each pixel, and mixing proportions (class fractions or abundances) change from pixel to pixel. Furthermore, real world scenes always have spatial details with smaller dimension than any Ground Instantaneous Field of View (GIFOV) which ultimately represent the spatial resolution of a given sensor or satellite image. Moreover, spatial mixing can be also derived from a image resampling process (Rencz, 1999).

The number of spectral bands available in the dataset plus 1 defines the total of possible end members. In practice, the number of end members ranges from three to seven, depending on the number of bands of the data set and the spectral variability of the scene components (Rencz, 1999).

The selected endmembers are used to solve the following mixture modeling equation:

$$DN_b = \sum_{i=1}^{N} F_i DN_{ib} + \varepsilon_b \qquad \text{or} \qquad DN_b = \sum_{i=1}^{N} F_i R_{ib} + \varepsilon_b \,, \tag{13}$$

where DN_b = intensity of a given pixel in bandpass '*b*', DN_{ib} = intensity of image endmember '*i*' at wavelength '*b*', R_{ib} = reflectance of end member '*i*' in bandpass '*b*' (if an image is calibrated to reflectance, R_{ib} must be used instead), N = number of endmembers, and ε_b = error of the fit for bandpass '*b*'.

A second equation may be used to constrain the sum of fractions to 1:

$$\sum_{i=1}^{N} F_i = 1.0 \,, \tag{14}$$

where F_i= fractional abundance of endmember '*i*'

Since spectral endmembers may be the result of mixing with different materials, fractional abundance of endmember '*i*' may be less than 0 and greater than 1, although the overall fraction will be 1. It indicates that two materials may be combined, which will result a negative or greater than 1 fraction. It does not necessarily mean that there are method errors (Rencz, 1999).

2.4.2.3.1. Endmember selection

Spectral mixture analysis approach relies on endmember selection and, therefore, accuracy depends on their accurate selection of endmembers. Spectral signatures or spectral endmembers correspond to the physical endmembers that show maximum abundance. Spectral endmember identification for each piece of terrain is the first stage Rencz (1999) and main objective in mixture modeling (Adams et al., 1995, Bateson and Curtiss, 1996, Rencz, 1999). Theoretically, the data dimension and constraints of the mixture inversion define the number of end members. Consequently, the number of spectral bands in the dataset plus 1 defines the total of possible end members. However, empirically, the number of end members ranges from three to seven, depending on the number of bands of the data set and the spectral variability of the scene components (Rencz, 1999).

As previously indicated, the available dataset (spatial and spectral resolution, bands, etc.) and classes of surface materials (soil, shade, green vegetation, non-photosynthetic vegetation, etc.) of a given area affect the definition of endmembers in SMA. Thus, image endmembers can be identified based on some criteria (spectral library acquired from a specific site) or using other techniques (Rencz, 1999).

The end members are idealized pure signature for a class of a particular location and are the extreme pixels of the scatter plot when spectral libraries are used. Endmembers do not actually exist in the dataset, but their convex hull will enclose all data in the scattered plot. Endmembers represent 100% pure pixels in their respective classes. For example, the shade endmember is a result of both shade and shading highly affected by the local topography, vegetation, and seasonal and daily solar variation. Therefore, shade endmember may compose with other endmembers in a given satellite scene and proportionally vary with these illumination characteristics (Rencz, 1999).

The Pixel Purity Index (PPI) also is presented as an option to select end members. This technique was based upon the principle that spectral signature of a specific material is 'pure' (not compounded) Adams et al. (1995) and, therefore, PPI was designed to identify the most spectrally extreme, different, or 'pure' pixels, which commonly correspond to mixing endmembers (Adams et al., 1995, Boardman et al., 1995). The PPI is calculated by repeatedly projecting n-dimensional scatterplots onto a random unit vector. To find the PPI value, the extreme pixels in each projection are identified and their frequencies as extreme are determined. A PPI image is generated accordingly with the resultant histogram of the frequency of each pixel value as extreme, and thus making evident the purest pixels with extremity-scores (Boardman et al., 1995).

For the present study, a four-endmember mixing model was constructed to generate fraction images of shade, soil, non-photosynthetic vegetation, and green vegetation. The end-member candidates were selected by using the previously describe PPI technique. Six image subsets of 502 x 502 pixels representing the variety of land use and land cover types within the study site were used as input for the PPI algorithm for each year of analysis. Purest pixel candidates were identified based on the PPI results and located on the original

Landsat imagery within the study area. A final visual and spectral examination of spectral shape and image context was conducted accordingly to select the final endmembers for the SMA.

2.4.2.4. Fractional cover

Fractional cover or green fractional percentage can be estimated by using a simple linear mixture model (LMM) and two spectral end members (plant canopy and bare soil) as following (Maas, 2000, Qi et al., 2000):

$$fc = \frac{VI - VIopen}{VIcanopy - VIopen} * 100 \quad , \qquad (15)$$

where *fc* = green fractional percentage, *VI* = vegetation index value, *VI canopy* = vegetation index value of the tree green canopy, and *VI open* = vegetation index value of senescent open areas (Figure 2.2).

Figure 6 shows the procedure to calculate fractional cover.

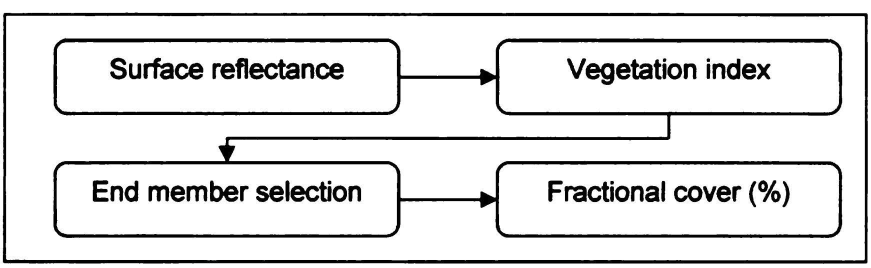


Figure 2.2. Procedure for calculating fractional cover

Forest canopy disturbances and regeneration were estimated using fractional cover derived from the discussed vegetation indices previously (NDVI, MSAVI, GEMI, AFRI, $MSAVI_{af}$, and $GEMI_{2.1}$, and GV), all retrieved from remotely sensed data. The performance of each vegetation index was observed based on the statistical results of Pearson correlations among the vegetation indices retrieved from a Landsat image acquired in August 6, 2003, under clear sky and in the presence of smoke for a variety of land cover types. The optimum vegetation index was defined based on its performance under smoke conditions and on the results of the empirical linear relationship between fractional cover retrieved from a Landsat image acquired in June 21, 2004 and fractional cover calculated from hemispherical photos also acquired during June, 2004, for different sites within the study area. Forest canopy degradation of selectively logged and burned forests, selectively logged only, and undisturbed forests were also compared.

2.4.2.5. Burned forest detection

Burned forests were detected using non-photosynthetic vegetation fraction images derived from the linear mixing model. This technique was first developed by Cochrane and Souza Jr. (1998) to detect selective logging sites and burned forests using Spot images in a case study in Para, Brazil. I improved this approach to a fully automated technique to detect and map burned forests using non-photosynthetic vegetation fraction image derived from Landsat imagery. Therefore, burned forests were detected and mapped in the study area from 1992 to 2004. Additional details of this remote sensing approach for detecting burned forests are described bellow.

2.4.2.5.1. Burned forest detection approach

This approach consisted in: 1) masking Landsat images in forest and non-forest, and 2) unmixing multispectral images using shade, green vegetation, and non-photosynthetic vegetation (NPV) endmembers. In this case, multispectral images were unmixed based on Adams et al (1995) who observed that fraction images could be generated considering particular endmembers (spectral pure signature) that represent specific components such as green vegetation, soil, non-photosynthetic vegetation, and shade. The Landsat imagery was processed as described on Figure 2.3.

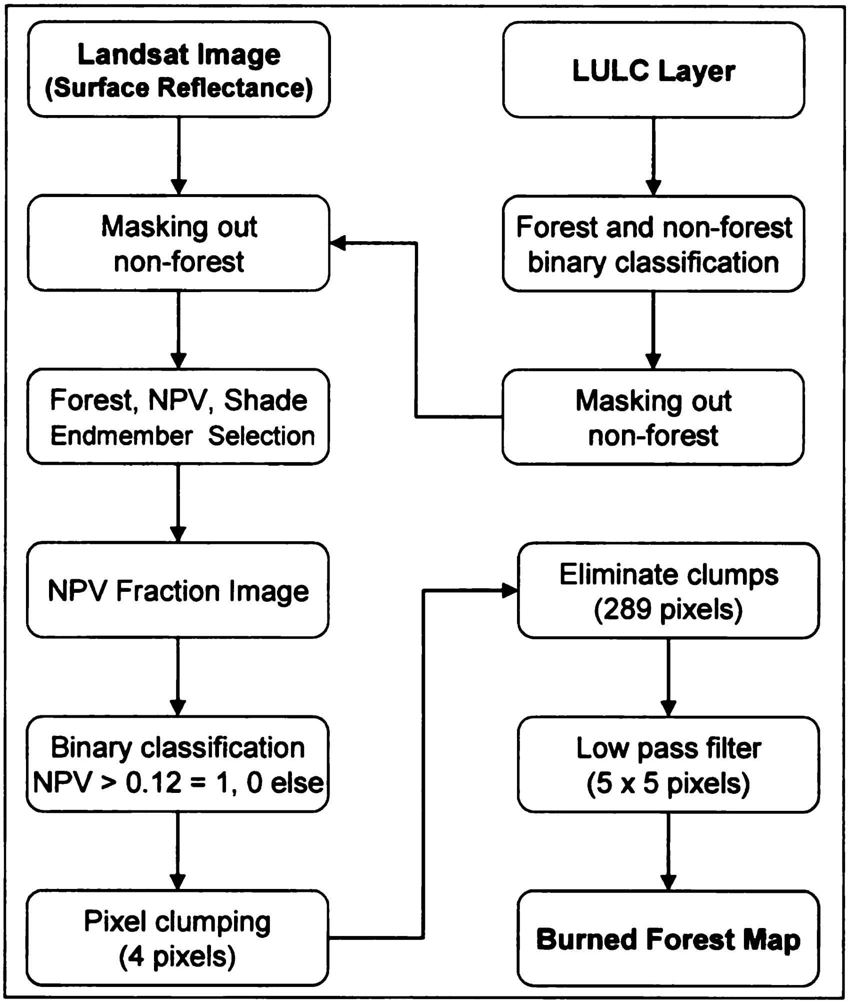


Figure 2.3. Flow diagram for burned forest automated detection technique

The NPV fraction images were classified following a binary labeling (burned forests = 1 if NPV value was greater or equal 0.12; and unburned forests = 0 otherwise). Subsequently, these classified images (burned and non-burned forests) were 4 pixels clumped using the clump algorithm from Erdas Image software. Clumps lesser than or equal 289 pixels were eliminated to remove small pixel clusters (noise) of misclassified unburned forests. Finally, a low pass filter was applied on clump eliminated images to smooth out limits of the detected burned forests.

2.4.3. Forest canopy degradation assessment

Forest canopy degradation by selective logging, forest fire, logging and fire combined and forest regeneration following each of these forest disturbances in the study area was assessed using multiple regression analysis. Multiple regression analysis is useful technique to estimate partial effects of the independent variable by controlling many other factors that simultaneously affect the dependent variable (Wooldridge, 2000).

By using the pixel as the unit of observation and based on (Wooldridge, 2000), the multiple linear regression model for green fractional percentage was defined as:

$$FC\% = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_{24} x_{24} + u \,, \qquad (16)$$

where *FC%* is the observed continuous variable (green fractional percentage derived from remotely sensed data), and β_0 is the intercept or constant, β_1 is the parameter associated with x_1 (independent variable 1), β_2 is the parameter associated with x_2 (independent variable 2) and so on. The variable u is the error term, which contains factors other than the independent variables included in this model that affect *FC%*.

The vector of independent variables (x) tested are the following:

- x_1 = Deforestation areas
- x_2 = Newly logged forests
- x_3 = Old logged forest detectable
- x_4 = Old logged forest non-detectable
- x_5 = Newly logged and burned forests
- x_6 = Newly burned forests
- x_7 = Old logged and burned forest detectable
- x_8 = Old logged and burned forest non-detectable
- x_9 = Old burned forest detectable
- x_{10} = Old burned forest non-detectable
- x_{11} = Year of 1993
- x_{12} = Year of 1994
- x_{13} = Year of 1995
- x_{14} = Year of 1996
- x_{15} = Year of 1997
- x_{16} = Year of 1998
- x_{17} = Year of 1999
- x_{18} = Year of 2000
- x_{19} = Year of 2001
- x_{20} = Year of 2002
- x_{21} = Year of 2003
- x_{22} = Year of 2004
- x_{23} = Longitude or x location (kilometer)
- x_{24} = Latitude or y location (kilometer)

Note: U*ndisturbed forest* and the year of *1992* were used as *omitted variables* for the land use classes and annual changes, respectively.

By using this multiple regression analysis, I was able to measure the effect of each land use or year of analysis on forest canopy cover in the study area, holding the other independent variables fixed.

2.4.3.1. Testing Hypotheses

Based on field observations, I expected that impacts by any anthropogenic activities should have effects on forest canopy coverage. Therefore, any particular land use and land cover type should affect (increase or decrease) values of fractional coverage when compared to undisturbed forest. I also expected that effects of non-controlled seasonal and natural variations (e.g. El

Nino effects, extreme droughts, etc.) would impact values of fractional coverage. Finally, I expected that values of fractional coverage could be affected by uncontrolled spatial variability of natural forests (e.g. response of vegetation phenology to precipitation) and human activities in the study area. I hypothesized about each value of twenty four slope coefficients ($\beta_1, \beta_2, \ldots, \beta_{24}$), once the effect of other coefficients had been account for, and used statistical inferences to test these hypotheses as following:

H_0: **Null hypothesis:**

Land use and land cover change variables (β_1 to β_{10}):

β_1 = 0: Deforestation has no effect on fractional coverage.
β_2 = 0: Newly logged forest has no effect on fractional coverage.
β_3 = 0: Old logged forest detectable has no effect on fractional coverage.
β_4 = 0: Old logged forest non-detectable has no effect on fractional coverage.
β_5 = 0: Newly logged and burned forest has no effect on fractional coverage.
β_6 = 0: Newly burned forest has no effect on fractional coverage.
β_7 = 0: Old logged and burned detectable forest has no effect on fractional coverage.
β_8 = 0: Old logged and burned non-detectable forest has no effect on fractional coverage.
β_9 = 0: Old burned forest detectable has no effect on fractional coverage.
β_{10} = 0: Old burned forest non-detectable has no effect on fractional coverage.

Temporal variables (β_{11} to β_{22}):

β_{11} = 0: Non-controlled seasonal or temporal variations for 1993 have no effect on fractional coverage.
β_{12} = 0: Non-controlled seasonal or temporal variations for 1994 have no effect on fractional coverage.
β_{13} = 0: Non-controlled seasonal or temporal variations for 1995 have no effect on fractional coverage.
β_{14} = 0: Non-controlled seasonal or temporal variations for 1996 have no effect on fractional coverage.
β_{15} = 0: Non-controlled seasonal or temporal variations for 1997 have no effect on fractional coverage.

$\beta_{16} = 0$: Non-controlled seasonal or temporal variations for 1998 have no effect on fractional coverage.

$\beta_{17} = 0$: Non-controlled seasonal or temporal variations for 1999 have no effect on fractional coverage.

$\beta_{18} = 0$: Non-controlled seasonal or temporal variations for 2000 have no effect on fractional coverage.

$\beta_{19} = 0$: Non-controlled seasonal or temporal variations for 2001 have no effect on fractional coverage.

$\beta_{20} = 0$: Non-controlled seasonal or temporal variations for 2002 have no effect on fractional coverage.

$\beta_{21} = 0$: Non-controlled seasonal or temporal variations for 2003 have no effect on fractional coverage.

$\beta_{22} = 0$: Non-controlled seasonal or temporal variations for 2004 have no effect on fractional coverage.

Spatial variables (β_{23} to β_{24}):

$\beta_{23} = 0$: Anthropogenic and natural spatial variations over longitude (x) direction have no effect on fractional coverage.

$\beta_{24} = 0$: Anthropogenic and natural spatial variations over latitude (y) direction have no effect on fractional coverage.

H_1: **Alternative hypothesis:**

Land use and land cover change variables (β_1 to β_{10}):

$\beta_1 \neq 0$: Deforestation has effect on fractional coverage.

$\beta_2 \neq 0$: Newly logged forest has effect on fractional coverage.

$\beta_3 \neq 0$: Old logged forest detectable has effect on fractional coverage.

$\beta_4 \neq 0$: Old logged forest non-detectable has effect on fractional coverage.

$\beta_5 \neq 0$: Newly logged and burned forest has effect on fractional coverage.

$\beta_6 \neq 0$: Newly burned forest has effect on fractional coverage.

$\beta_7 \neq 0$: Old logged and burned detectable forest has effect on fractional coverage.

$\beta_8 \neq 0$: Old logged and burned non-detectable forest has effect on fractional coverage.

$\beta_9 \neq 0$: Old burned forest detectable has effect on fractional coverage.

$\beta_{10} \neq 0$: Old burned forest non-detectable has effect on fractional coverage.

Temporal variables (β_{11} to β_{22}):

$\beta_{11} \neq 0$: Non-controlled seasonal and temporal variations for 1993 have effect on fractional coverage.

$\beta_{12} \neq 0$: Non-controlled seasonal and temporal variations for 1994 have effect on fractional coverage.

$\beta_{13} \neq 0$: Non-controlled seasonal and temporal variations for 1995 have effect on fractional coverage.
$\beta_{14} \neq 0$: Non-controlled seasonal and temporal variations for 1996 have effect on fractional coverage.
$\beta_{15} \neq 0$: Non-controlled seasonal and temporal variations for 1997 have effect on fractional coverage.
$\beta_{16} \neq 0$: Non-controlled seasonal and temporal variations for 1998 have effect on fractional coverage.
$\beta_{17} \neq 0$: Non-controlled seasonal and temporal variations for 1999 have effect on fractional coverage.
$\beta_{18} \neq 0$: Non-controlled seasonal and temporal variations for 2000 have effect on fractional coverage.
$\beta_{19} \neq 0$: Non-controlled seasonal and temporal variations for 2001 have effect on fractional coverage.
$\beta_{20} \neq 0$: Non-controlled seasonal and temporal variations for 2002 have effect on fractional coverage.
$\beta_{21} \neq 0$: Non-controlled seasonal and temporal variations for 2003 have effect on fractional coverage.
$\beta_{22} \neq 0$: Non-controlled seasonal and temporal variations for 2004 have effect on fractional coverage.

Spatial variables (β_{23} to β_{24}):

$\beta_{23} \neq 0$: Anthropogenic and natural spatial variations over longitude (x) direction have effect on fractional coverage.
$\beta_{24} \neq 0$: Anthropogenic and natural spatial variations over latitude (y) direction have effect on fractional coverage.

2.4.3.2. Data sampling

Spatial autocorrelation can substantially increase the error term in the regression model. Anselin (2002) suggested that these effects of spatial autocorrelation can be minimized by systematically sampling the dataset. Therefore, in this analysis, a vector file of 3 km x 3 km sample points distributed over the study area was generated. By sampling each point at a fixed distance from the others, potential contagion between neighboring cells is isolated (Arima et al. 2007) and the error term in the regression model due to spatial autocorrelation in the dataset is reduced (Anselin 2002, Arima 2007). The study area was systematically sampled by acquiring unique values for the dependent and independent variables at each sampling point location, all derived from remotely sensed data.

In addition, each cell location was identified by its longitude (x) and latitude (y) locations in the study area. The cell x and y locations were used in the regression model as an additional set of independent variables. This procedure helps to identify spatial trends and also to mitigate potential effects of spatial autocorrelation in the data population (Chomitz and Gray, 1996).

2.5. Results and Discussions

2.5.1. Relationships among various Vegetation Indices

In this analysis, the relationship among NDVI, MSAVI, GEMI, AFRI, $MSAVI_{af}$, $GEMI_{2.1}$, and GV retrieved from a Landsat image acquired in August 6, 2003 were tested under smoke and smoke free atmospheric conditions. Table 2.3 shows the relationship among these vegetation indices under clear sky for the study area.

This correlation matrix demonstrates high correlation ($r > 0.90$) among all vegetation indices under clear sky atmospheric condition. Although a perfect correlation ($r= 1$) was not observed among different vegetation indices, as observed by (Karnieli et al., 2001), these research results showed high correlations between NDVI and AFRI ($r = 0.99$), GEMI and $GEMI_{2.1}$ ($r= 0.98$), and MSAVI and $MSAVI_{af}$ ($r = 0.98$), which are the modified vegetation indices that use an empirical linear relationship observed by (Karnieli et al., 2001) to predict red band reflectance from shortwave infrared at 2.1. High correlation ($r \geq 0.98$) also was observed between GV and GEMI, GV and $GEMI_{2.1}$, GV and MSAVI, and GV and $MSAVI_{af}$.

Table 2.3. Correlation matrix among various vegetation indices under smoke-free atmospheric condition for the study site

Vegetation Index	NDVI	AFRI	GEMI	$GEMI_{2.1}$	MSAVI	$MSAVI_{af}$	GV
NDVI	1						
AFRI	**0.99**	1					
GEMI	0.97	0.96	1				
$GEMI_{2.1}$	0.93	0.94	**0.98**	1			
MSAVI	0.96	0.94	0.98	0.96	1		
$MSAVI_{af}$	0.93	0.94	0.97	0.97	0.98	1	
GV	0.95	0.96	**0.99**	**0.99**	**0.98**	**0.98**	1

Correlation is significant at the 0.01 level (1-tailed). N= 2000. Bold values represent special interest in this analysis.

Vegetation indices, however, are very sensitive to atmospheric conditions, especially on visible bands, which can strongly affect their results (Karnieli et al., 2001, Huete et al., 2003, Moura and Galvão, 2003). In this study, sensitivity of each vegetation index to presence of aerosol was tested. Table 2.4 demonstrates the performance of various vegetation indices under smoke condition in the study site.

In this case, high correlation among aerosols resistant vegetation indices (AFRI, $GEMI_{2.1}$, $MSAVI_{af}$, GV) and those more sensitive vegetation indices (NDVI, GEMI, MSAVI) to atmospheric effects indicated low performance in penetrating through the aerosols and depicting the vegetation cover under heavy smoke atmospheric condition. Therefore, low correlation between them was desired. Lowest correlation was observed for $GEMI_{2.1}$and NDVI ($r= 0.87$),

$MSAVI_{af}$ and NDVI (r= 0.87), and AFRI and NDVI (R=0.89). Relatively low correlation also was observed between $MSAVI_{af}$ and MSAVI (r= 0.90).

Table 2.4. Correlation matrix among various vegetation indices for areas in the presence of heavy smoke in the study site.

Vegetation Index	NDVI	AFRI	GEMI	$GEMI_{2.1}$	MSAVI	$MSAVI_{af}$	GV
NDVI	1						
AFRI	**0.89**	1					
GEMI	0.95	0.84	1				
$GEMI_{2.1}$	**0.87**	0.88	0.96	1			
MSAVI	0.96	0.78	0.98	0.90	1		
$MSAVI_{af}$	**0.87**	0.87	0.94	0.97	**0.90**	1	
GV	0.93	0.88	0.99	0.99	0.95	0.97	1

Pearson correlation is significant at the 0.01 level (1-tailed). N= 2000. Bold values represent special interest in this analysis.

The Appendix B.7 demonstrates MSAVI and $MSAVI_{af}$ performances under smoke condition. Although GV derived from SMA was highly correlated to $GEMI_{2.1}$ (r= 0.99) and $MSAVI_{af}$ (r= 0.97), it was also highly correlated (r> 0.90) with those more sensitive vegetation indices (NDVI, GEMI, and MSAVI) to atmospheric influences, which indicated that GV was more sensitive than AFRI and $MSAVI_{af}$ to the presence of heavy smoke in this study area.

Low correlation (r < 0.90) also was observed between AFRI and all other vegetation indices, which may indicate that each index has a different response to atmospheric effects when compared to AFRI.

2.5.2. Optimum Vegetation Index

In addition to the previously discussed relationships among various vegetation indices, empirical linear relationship between fractional coverage values derived from each vegetation index and from forest canopy coverage calculated using hemispherical photos acquired in the study site. A total of 423 hemispherical photos were used to calculate 47-canopy fraction points on the ground, estimated based on the average of 9 hemispherical photos each point. The hemispherical photos were located over the study area using GPS. Likewise, 47-canopy fraction points were calculated from NDVI, MSAVI, GEMI, GV, AFRI, $GEMI_{2.1}$, and $MSAVI_{af}$ fractional coverage derived from Landsat image, based on the average of a group of 9 pixels (window 3 x 3) each point.

The table 2.5 shows the statistical results of the linear relationship between each fractional coverage image derived from various vegetation indices and canopy coverage estimated using hemispherical photos acquired in the study area.

Table 2.5. Empirical linear relationship between various vegetation indices and forest canopy coverage based on field measurements in the study site

Vegetation Index	R-Square	Prob > F	F(1, 45)
MSAVI	**0.84**	0.000	236.83
GEMI	**0.80**	0.000	182.21
NDVI	0.67	0.000	92.26
$MSAVI_{af}$	**0.81**	0.000	191.90
$GEMI_{2.1}$	0.78	0.000	155.79
AFRI	0.60	0.000	68.25
GV	0.76	0.000	144.24

N= 47. Bold values represent special interest in this analysis

MSAVI showed the highest R^2 (0.84) indicating that 84% of the sample variation in fractional coverage derived from ground measurements can be explained by fractional coverage derived from MSAVI model. $MSAVI_{af}$ and GEMI showed slightly lower R^2 (0.81 and 0.80, respectively), and NDVI, $GEMI_{2.1}$, AFRI, and GV showed R^2 lower than 0.80. Indeed, a good performance by MSAVI had been observed for this study region by (Wang et al., 2005). In that study, the authors selected MSAVI as the optimum vegetation index to estimate fractional coverage derived from ETM+ image using Ikonos image as a ground truth for validation. Any abnormal atmospheric condition, however, was not reported by (Wang et al., 2005).

AFRI, $GEMI_{2.1}$, and $MSAVI_{af}$ presented great potential to estimate fractional coverage from Landsat imagery for this study area, if considered that these indices fitted fairly well the fractional coverage derived from hemispherical photos acquired in the field and showed good capability to penetrate the atmosphere when aerosols is present.

Based on these previously discussed limitation and potential of various vegetation indices, I selected $MSAVI_{af}$ as the optimum vegetation index for this study site given its good performance under clear sky for the study area, high correlation with its non-modified version (MSAVI), slightly better fitting to field measurements compared to other modified vegetation indices, and, most importantly, its good performance under smoke conditions.

2.5.3. Accuracy assessment of burned forest detection technique

The accuracy assessment was conducted by comparing binary classification (1 = burned forest, 0 = non-burned forest) from the burned forest map derived from Landsat TM5 image with 120 randomly distributed points in forested area, checked during the field observation within the study site. Both remotely sensed and fieldwork data were acquired in June 2004. Kappa statistics and standard Producer's, User's, and overall accuracies of this burned forest detection technique are presented in Table 2.6.

Table 2.6. Accuracy assessment results of detecting burned forests using non-photosynthetic vegetation (NPV) fraction image derived from Spectral Mixture Analysis (SMA) for the study area in 2004.

Land Use	Reference Points (*)	Classified points	Number Correct	Accuracy	
				Producer	User
Burned forests	79	80	77		
non-burned forests	41	40	38	92.7%	95.0%
Overall accuracy =	96.0%				
Overall Kapa Statistic =	0.91				

* 120 randomly distributed sampling points within forested area

The commission and omission errors were 7.3% and 5%, respectively. The accuracy assessment results demonstrated that this remote sensing approach could correctly classify 96% of burned forest if the source of error (commission and omission errors) is not accounted for. Appendix B.8 shows a sample of burned forests mapped using this remote sensing approach.

2.5.4. Multi-annual land use and land cover change

Based on these research results, it was observed that deforestation increased from approximately 3400 km^2 by 1992 to 8500 km^2 by 2004, an average increase of 426 km^2 yr^{-1} (± 202 km^2, standard deviation). The greatest deforestation increase, however, was observed between 2003 and 2004, at 980 km^2. The total disturbed forests within the study region (path 226 and row 068) increased from 5.4% to 40.1%, by 1992 and by 2004, respectively. These forest disturbances correspond to an annual increase of 1,270 km^2 yr^{-1} (±482 km^2) of forests selectively logged and/or burned. Only 30.5% of the study area was considered undisturbed forest by 2004. Table 2.7 shows the annual land use and land cover change over the study site.

Table 2.7. Cumulative deforestation and undisturbed and disturbed forests in the study area from 1992 to 2004.

Year	Undisturbed forest (km^2)	Logged forest only (km^2)	Logged & Burned forest (km^2)	Burned forest only (km^2)	Deforestation (km^2)
1992	24,131.5	1,120.9	45.1	395.7	3,403.6
1993	22,472.1	2,243.7	56.1	424.5	3,900.3
1994	21,441.7	2,911.7	70.6	426.5	4,246.4
1995	20,378.1	3,441.9	144.9	468.6	4,663.3
1996	19,284.9	4,142.8	176.5	455.8	5,036.8
1997	17,909.8	5,089.3	181.3	495.6	5,420.8
1998	16,554.8	6,069.1	246.1	493.3	5,733.4
1999	14,160.6	7,522.0	486.9	705.8	6,221.4
2000	12,515.9	7,560.2	1,491.7	1,171.3	6,357.7
2001	11,128.7	8,553.0	1,508.5	1,062.6	6,844.0
2002	10,422.2	8,975.8	1,553.2	1,028.1	7,117.5
2003	9,606.4	9,440.2	1,570.0	939.2	7,541.0
2004	8,894.1	9,274.7	1,549.3	857.8	8,520.7

A mask of 972 km^2 of the cumulative clouds and shadows was applied. Approximately 36.3 km^2 of water bodies that were annually detected on all scenes were not included.

In this given period, selective logging alone was responsible for disturbing a large extent of natural forests, equivalent to more than 31% of this study area by 2004. An additional of 5.5% and 2.9% of the study site forest was disturbed by selective logging and fire combined and forest fire only, respectively. By 2002, the total area of disturbed forests already had surpassed by more than 1,100 km^2 the total area of undisturbed forest in this study site. Figure 2.4 shows the annual change of undisturbed into disturbed forests and the forest conversion into agricultural lands (deforestation) in the study region.

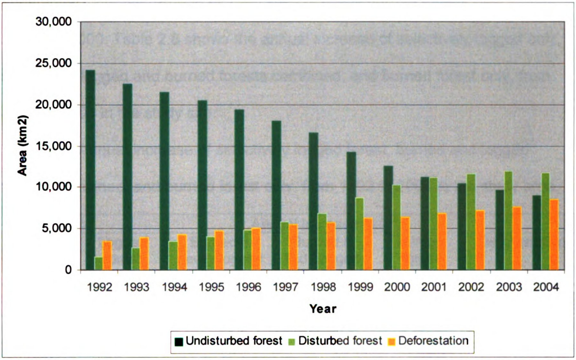


Figure 2.4. Land use and land cover change from 1992 to 2004 in the study site

These results also show that more than 10,000 km^2 of remnant logged and burned forests had recovered sufficiently to be undetected (non-persistent) by 2004 using Landsat imagery. Appendix B.9 shows annual changes of persistent and not persistent disturbed forests by selective logging and forest fire in this study area.

New areas of selective logging only increased around of 904 km^2 yr^{-1} (±354 km^2) from 1992 to 2004 in this study area. An annual average of 422 km^2 yr^{-1} (±440 km^2) of logged forests were burned, and around of 426 (±202 km^2) and 102 km^2 yr^{-1} (±152 km^2) of undisturbed forests were deforested and burned, respectively.

The greatest annual increase (around of 1728 km^2) of selective logging only occurred in 1999. Immediately following this year, it was observed a substantial increase (around of 1370 km^2) of newly burned forests over logged forest by 2000. Table 2.8 shows the annual increase of selectively logged only, selectively logged and burned forests combined, and burned forest only, from 1992 to 2004 in the study site.

Table 2.8. Annual increase of selectively logged forest, burned and logged forests combined, and burned forest only, from 1992 to 2004 in the study area.

	Annual Increase (km^2)				
Year	Logged forest	Burned & newly logged forest	Burned & Old Logged forest	Burned forest	Deforestation
1992	1,120.9	45.1	-	395.7	
1993	1,158.1	14.0	0.8	88.7	496.7
1994	708.9	11.1	1.6	22.5	346.0
1995	634.2	42.0	25.9	70.2	416.9
1996	785.2	17.2	23.1	23.6	373.5
1997	1,022.3	11.6	0.5	66.9	384.0
1998	1,072.0	41.0	11.9	38.9	312.6
1999	1,727.9	111.0	145.4	249.4	488.0
2000	873.1	296.8	721.0	539.5	136.3
2001	1,116.6	64.4	6.3	10.5	486.3
2002	540.5	34.9	14.5	50.2	273.5
2003	834.8	22.2	37.2	33.9	423.5
2004	375.7	10.2	63.2	24.1	979.7

The analysis of the land use dynamics over the study site showed that previously logged and burned sites could be revisited by loggers and recurrent forest fires, respectively. Revisited logging accounted for more than 3300 km^2 by 2004, an average of 276 km^2 yr^{-1} (±197 km^2) from 1992 to 2004. Recurrent fires accounted for 866 km^2, an average of 72 km^2 yr^{-1} (±50 km^2) in the same interval. It was also observed that more than 1756 km^2 of selectively logged forests and an additional 368 km^2 of burned forests had been deforested by 2004.

Table 2.9. Multi-annual land use dynamics in the study site from 1992 to 2004

Year	Revisited logging (km^2)	Recurrent fire (km^2)	Disturbed forests deforested by 2004		
			By logging only (km^2)	By logging & Fire (km^2)	By Fire only (km^2)
1992			372.9	25.1	211.5
1993	0	0	337.2	1.4	46.4
1994	32	61.8	307.2	0.8	9.2
1995	51.4	54.95	191.2	15.6	44.5
1996	101.6	37.2	154.8	3.3	12.8
1997	148.9	82.58	135.9	3.0	19.2
1998	319.3	74.78	175.5	10.1	20.6
1999	431.7	181.52	137.4	16.2	68.1
2000	491.6	92.43	85.6	44.5	134.9
2001	394.5	23.34	70.4	2.2	2.6
2002	455.3	73.71	-	-	-
2003	537.3	142.09	62.4	1.9	10.2
2004	350.1	41.63	-	-	-
Total	3,313.7	866.0	1,657.7	99.0	368.3

2.5.5. Assessment of forest canopy cover impacts

In this analysis, I was primarily concerned in assessing impacts of temporal and land use and land cover changes on forest canopy cover. Therefore, multiple regression analysis was applied to measure partial effect of each of factor of interest, holding fixed all other factors affecting the fractional coverage. The results of this analysis showed that the multiple regression equation (16) can significantly explain 63.07% of the dependent variable (fractional coverage) at $\alpha = 0.01$ (probability of 99%). Additionally, the hypothesis testing for measuring partial effect of each land use and land cover on fractional coverage was conducted as following.

I could not reject the Null Hypothesis for the old burned forest non-detectable, year of 2004, and longitude (x) direction variables. More specifically, the fractional coverage values for old burned forest non-detectable and undisturbed forest (the land use omitted variable) derived from Landsat imagery were not significantly different, at $\alpha = 0.01$. Similarly, fractional coverage values for the years of 2004 and 1992 (the temporal omitted variable) also were not significantly different, at $\alpha = 0.01$. Fractional coverage values did not significantly change according to longitude (x) location, at $\alpha = 0.01$, which means that there is no spatial trend in east-west direction. I could reject, however, the null hypotheses for all other tested coefficients and accepted the alternative hypotheses that there were statistically significant differences between fractional coverage values of each coefficient and its corresponding omitted variable (undisturbed forest or year of 1992).

Based on these accepted alternative hypotheses, partial effect of each factor of interest was assessed. Water body significantly decreased 61.9% (± 3.6), at $\alpha = 0.01$, of fractional coverage values compared to fractional coverage for undisturbed forests (the land use omitted variable). Indeed, vegetation indices are very low for water bodies due to low reflectance on infrared wavelengths (Wang et al., 2004). The effects of deforestation were the second greatest contributor for forest canopy loss, decreasing 53.5% (± 0.8) of forest canopy values, at $\alpha = 0.01$, compared to fractional coverage values for undisturbed forests, holding all other factors (independent variable) fixed. Indeed, deforestation implies in cutting down, damaging, and burning forests, converting natural forests into other land use type Skole and Tucker (1993) and FRA (2005) where forest canopy cover is drastically reduced (FRA, 2005).

In terms of forest uses, newly logged forest only significantly decreased 5.0% (± 0.8), at $\alpha = 0.01$, forest canopy in the study area compared to fractional coverage for undisturbed forests. On the other hand, newly burned forest significantly decreased 28.9% (± 2.0), at $\alpha = 0.01$, forest canopy and, when combined selective logging and forest fires, decreased 35.6% (± 2.1) forest canopy compared to fractional coverage for undisturbed forests. Figure 2.5 shows the estimated losses and gains of canopy coverage based on the multiple regression model of fractional coverage for various forest uses classified in the study site using Landsat imagery acquired from 1992 to 2004.

The alternative hypothesis that old (previously) logged forests detectable using remotely sensed data has effect on fractional coverage also was accepted. In this case, old logged forest significantly contributed to decrease only 1.6% (± 0.7), at $\alpha = 0.01$, of fractional coverage values compared to those for undisturbed forest. On the other hand, old logged forests that recovered sufficiently to become undetectable using Landsat images, accounted for a significant increase of 3.1 (± 0.5), at $\alpha = 0.01$, of fractional coverage values, compared to undisturbed forests. These results indicate that strong forest regeneration occurred and contributed to increase vegetation greenness as well as fractional coverage values, surpassing even fractional coverage value for undisturbed forests in this study area.

Old burned forests detectable using remotely sensed data showed a significant decrease of 12.6% (± 1.5), at $\alpha = 0.01$, of fractional coverage values and, when not detectable, showed no significant change in canopy cover. In this last case, the null hypothesis that old burned forest has no effect on fractional coverage could not be rejected. And again, old areas of detectable selective logging and forest fire combined showed significant decrease of 25.6% (± 2.0), at α = 0.01, of fractional coverage values, and even when not detectable, still showed significant decrease of 4.7% (± 1.1), at α = 0.01, of fractional coverage values compared to undisturbed forests.

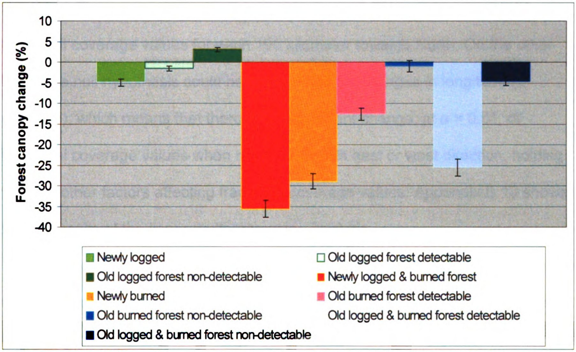


Figure 2.5. Partial effects of various forest uses on fractional coverage values in the study area estimated using linear multi-regression model and multi-annual remotely sensed derived dataset

As previously stated, in terms of temporal change, all years from 1993 to 2003 showed significant change of fractional coverage values at α = 0.01 compared to 1992 (omitted variable) and the alternative hypotheses that non-controlled seasonal and temporal variations significantly affected fractional coverage values. The greatest annual losses of fractional coverage, 8.8% (± 0.7) and 8.4% (± 0.7), were observed for 1993 and 1999, respectively. Based on these results, the average around of 3.6% and 6.4% of forest canopy losses were observed for 1994-1998 and for 1999-2003 time intervals, respectively.

The alternative hypothesis that anthropogenic and natural spatial variations over latitude (y direction) have effect on fractional coverage was accepted. These variations significantly increased 3.7% (± 0.3), at $\alpha = 0.01$, of fractional coverage values for each 100 kilometer towards North. On the other hand, the null hypothesis could not be rejected for changes in longitude (x direction), which means that there is no significant change, at $\alpha = 0.01$, of fractional coverage values when moving towards east or west direction, holding fixed all other factors affecting fractional coverage values. Appendix B.10 shows further results of the linear multi-regression analysis.

It was also observed that forest regeneration increases fractional coverage in the year immediately following selective logging activities and forest fires. The peak of this forest regeneration was observed 3 years following the harvesting year for logging and 5 years following forest fire.

2.6. Conclusions

Modified vegetation indices AFRI and $MSAVI_{af}$ showed good performance in predicting forest canopy cover under smoke condition. AFRI and $MSAVI_{af}$ also showed high correlation with NDVI and MSAVI, respectively. However, it was observed that fractional coverage derived from MSAVI and $MSAVI_{af}$ predicted fractional coverage slightly better than the other tested vegetation indices when compared to field measurements in this study area. Additionally, fractional coverage, as a linear unmixing model in vegetation index domain retrieved from Landsat TM and ETM+ imagery, showed to be useful in measuring forest canopy degradation and regeneration in tropical evergreen forests.

The land use and land cover dramatically changed from 1992 to 2004 in this study area. More than 29% of the study area, approximately 8,521 km^2, was converted into agricultural land by 2004. More than 19%, 4%, and 1% of the deforested area was previously detected as logged forest, burned forest, and logged and burned forest, respectively, in the 1992-04 time period. In addition to outright deforestation, forests disturbed by selective logging and forest fires represented approximately 40% of this study area by that year. Assuming that this observed trend of land use and land cover conversion continues, there will be no undisturbed forests remaining by 2011.

In this context, selective logging only is by far the most important factor of forest disturbances of large extent in the study site. Selective logging only was responsible for the disturbance of more than 9,200 km^2 of natural forests by 2004, which corresponds to more than 31% of the total study area. Indeed, large areas of tropical forests have been damaged or impoverished each year by selective logging activities in the Brazilian Amazon (Uhl and Vieira, 1989, Verissimo et al., 1995, Houghton, 1997, Nepstad et al., 1999). Roughly 2350 km^2 were degraded by forest fire or a combination of forest fires and selective logging by 2004. This corresponds to less than 26% of the total forest disturbed by selective logging only.

During this given period of analysis, there was a large increase of revisited logging and recurrent forest fires. In this study area, more than 3,300 km^2 and 800 km^2 of cumulative area of revisited logging and recurrent fire was observed by 2004, respectively. I defined revisit logging and recurrent fire as logging and burned forest detected in areas of previous logging and forest fire, respectively, that had recovered sufficiently to become undetectable for one or more years prior to the return of the loggers or forest fire. An annual average of 27.8 km^2 (± 26), 256.4 km^2 (± 152.8), and 445.8 km^2 (± 74.8) of revisit logging was observed for 1992-95, 1996-99, and 2000-04, respectively. An annual average of 38.9 km^2 (± 33.9), 38.5 km^2 (± 61.6), and 59.1 km^2 (± 46.3) of recurrent fire was observed for 1992-95, 1996-99, and 2000-04, respectively. Recurrent forest fire is likely to increase even more in the next years in this region. According to (Cochrane and Schulze, 1998), once burned for the first time, chances of recurring fires are increased as well.

Based on the results of this multi-temporal analysis of fractional coverage derived from Landsat TM and ETM+ imagery, new areas of selective logging only decreased fractional coverage by an average of 4.8% in the study area. Newly burned forests alone and selectively logged and burned forests combined decreased an additional 24% and 31% of forest canopy cover, respectively, compared to newly logged forests only. Old areas of selective logging and forest fire combined that were still detectable, also showed a substantial decrease of 25.1% of fractional coverage values compared to undisturbed forests. A fractional coverage decrease of 4.3% was observed for old selectively logged and burned forest even after they become undetectable on Landsat images. Although forest fires disturbed a smaller extent of natural forest than selective logging in this study site, when it occurs, as observed by Uhl and Kauffman (1990), its impacts can be devastating for tropical rainforests.

Fractional coverage values for old selectively logged forests were 3.3% greater than fractional coverage values for undisturbed forests. These previously selectively logged forests accounted for more than 60% of the total disturbed forest in the study site by 2004. This finding implies that selective logging may be a carbon source immediately following its activities but it may become a carbon sink in the subsequent years. Therefore, further research is required to accurately infer how much selective logging has been contributing to the carbon cycle either as source or as sink in tropical areas. This amount may vary according to forest characteristics, logging and fire intensity, and forest capacity of regeneration of each site.

These research results indicate that forests are capable of a strong canopy regeneration following logging activities and forest fires. Approximately 70% of the total area of disturbed forests by logging and fire had sufficiently recovered to become undetectable on satellite imagery by 2004. Forest regeneration, however, may vary according to logging and fire intensity, but in general it takes more time if burned. Selectively logged forests can be detected using Landsat imagery from 3 to 5 years following logging activities and burned forests may persist detectable from 3 to 10 years, depending on fire intensity and forest regeneration capacity.

CHAPTER III

Basin-Wide Assessment of Forest Disturbances by Selective Logging and Forest Fires

3.1. Abstract

The rapid and drastic environmental changes happening in the Brazilian Amazon because of widespread deforestation have attracted the attention of the scientific community for several decades. An area of particular interest involves the assessment of the impacts of selective logging and forest fires. Forest disturbances by selective logging and forest fires may vary in scale, from local damages to the local environment (microclimate, habitats destruction, species extirpation, etc.), to global changes, mostly related to the increase of atmospheric carbon dioxide released into the atmosphere. Selective logging activities and forest fires have been reported by many studies as important agents of land use and land cover changes but yet have to be properly addressed, especially at large scale in tropical regions. Previous studies have focused on a few study sites or were limited to estimate the extent of selective logging. Therefore, this study involved a more comprehensive study of multi-temporal and basin-wide changes of forest disturbances by selective logging and forest fires using remotely sensed data acquired in 1992, 1996, and 1999. Methods for detecting burned forests and estimating forest canopy cover were researched. Finally, I conducted rigorous ground measurements and observations for assessing local impacts of selective logging and forest fires in three different states in the Brazilian Amazon. The results of this study showed a substantial increase in total

areas of selectively logged and burned forests, changing from approximately 11800 km^2 to 35600 km^2 by 1992 and 1999, respectively. Selective logging only was responsible for 60.4% of this forest disturbance in the studied period. Approximately 33% and 7% of forest disturbances detected in the same period were due to impacts of forest fire only and selective logging and forest fire combined, respectively. Most of the degraded forests (~90%) were detected in the States of Mato Grosso and Para. My estimates indicate that approximately 5467 km^2, 7618 km^2, and 17437 km^2 were new areas of selective logging and/or forest fires in 1992, 1996, and 1999, respectively. Protected areas seemed to be very effective in constraining these types of forest degradation. Approximately 2.4% and 1.3% of the total detected selectively logged and burned forests, respectively, were geographically located within protected areas. I observed, however, an increasing trend for these anthropogenic activities to occur within the limits of protected areas from 1992 to 1999. Although forest fires impacted the least extent of natural forests, new areas of burned forests detected in 1996 and 1999 were responsible for the greatest impact on canopy cover, with an estimated loss of 18.8% of forest canopy when compared to undisturbed forests. Selective logging and forest fire combined impacted even more those canopies, with an estimated loss of 27.5% of forest canopy. Selectively logged forest only showed the least impact on canopy cover, with an estimated loss of 5% of forest canopy. Field measurements indicated a significant positive correlation between forest canopy openness and tree mortality rate and dead basal area, and a negative correlation between canopy openness and tree diversity. Selectively logged forests had lesser impacts on tree species diversity than did those burned forests. Selectively logged forests also showed stronger and faster forest regeneration than burned forests, following these forest impact events.

3.2. Introduction

Natural forests in the Brazilian Amazon have been increasingly exposed to selective logging activities and forest fires (Nepstad et al., 1999, Cochrane et al., 2004, Asner et al., 2005, Matricardi et al., 2005, Matricardi et al., 2007). In contrast to deforestation that converts large extents of natural forests into agricultural lands, selective logging targets cutting down a few most marketable tree species and leave behind of its activities highly disturbed forest patches in which tree fall gaps, access roads, logging patios, and damaged trees are abundant (Stone and Lefebvre, 1998, Nepstad et al., 1999, Souza and Barreto, 2000). Similarly to forest fragmentation that frequently occurs between the edges of deforestation and forested areas, selective logging can increase forest fire susceptibility as tropical forest becomes more fragmented (Cochrane, 2001). Agricultural plots that frequently use fire as land management technique serve as ignition sources and fragmented forests increase the chance of spreading forest fire throughout the Amazon region (Uhl and Buschbacher, 1985, Uhl and Kauffman, 1990, Cochrane, 2001). The consequences of forest fires, however, can be devastating for those natural forests (Uhl and Kauffman, 1990).

Although selective logging and forest fires are considered important anthropogenic activities in tropical regions, only a few attempts towards a spatially explicit classification of both activities using remotely sensed data have been conducted in the Brazilian Amazon. The first basin-wide selective logging estimate was conducted by Nepstad et al. (1999) and it was based on a survey of sawmills' production in the Amazon. These authors estimated that 9,000 to 15,000 km^2 of natural forest had been selectively logged in 1996-97 period. Matricardi et al. (2007) detected and mapped selectively logged areas in the Brazilian Amazon using Landsat imagery acquired in 1992, 1996, and 1999. In that study, a total of 5980 km^2, 10064 km^2, and 26085 km^2 of selectively logged forests were detected by 1992, 1996, and 1999, respectively. Matricardi et al. (2007) estimated an increase of new areas of selective logging in the Brazilian Amazon around of 2547 km^2, 4361 km^2, 11889 km^2 in 1992, 1996, and 1999, respectively. A more recent multi-annual analysis of selective logging from 1999 to 2002 was conducted by Asner et al. (2005) in five major timber centers of the Brazilian Amazon, using remotely sensed data. These authors observed an increase around of 19800 km^2, 14200 km^2, and 12000 km^2 of selectively logged forests in 1999-00, 2000-01, 2001-02 periods, respectively.

In addition to selective logging activities, forest fires are increasingly contributing to forest degradation in the Amazon region. Although fire is an important agent of land use and land cover change, it has yet to be properly assessed (Schroeder et al., 2005). Most large scale analyses of fire in the Amazon region have been based on general information, manly focusing on the geographic location of fires based on thermal bands and course spatial resolution satellite products. Maps of fire locations or fire pixels have been generated in a daily basis by the National Institute for Space Research (INPE) in Brazil. Most of those maps are based on NOAA[3] and MODIS[4] products (http://www.cptec.inpe.br/queimadas/) and are available for the entire South America continent. Schroeder et al. (2005) used the INPE products to analyze spatiotemporal dynamics of fire in the Brazilian Amazon. These authors had to integrate various datasets to improve spatial scale and reduce analytical uncertainties caused by the use of a single sensor. Complementary and more detailed researches have been restricted to small study areas (e.g. Cochrane and Schulze, 1998, Souza et al., 2005) and are not sufficient for a more comprehensive analysis of forest fires (Schroeder et al., 2005) and selective logging in the Amazon region (Matricardi et al., 2007).

Based on the existing knowledge gaps, I conducted a comprehensive research of forest degradation due to selective logging activities and forest fires based on remotely sensed data and ground measurements in the Brazilian Amazon. In addition to employing the selective logging dataset created by Matricardi et al. (2007), I developed and applied a fully automated remote sensing approach based on SMA (Spectral Mixture Analysis) to detect and map burned forests basin-wide. Fractional coverage was retrieved from Landsat imagery and used to assess forest canopy impacts by selective logging and forest fires. This analysis was conducted on a time-series of Landsat TM and ETM+ imagery acquired in 1992, 1996, and 1999. Field measurements and observations included three different regions in the Amazon States of Acre,

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[3] NOAA: A series of Geostationary and Polar-Orbiting Weather Satellites operated by the National Oceanic and Atmospheric Administration, USA;
[4] MODIS: Moderate Resolution Imaging Spectroradiometer sensor aboard of Terra and Aqua satellites, both operated by the National Aeronautics and Space Administration, USA.

Rondônia, and Mato Grosso. The field information was used to assess forest impacts caused by selective logging and forest fires on forested areas and to validate remote sensing approaches. The results of this study will contribute to improve land use classification maps and to expand current understanding of the characteristics and interactions between forest fire and selective logging, and fire and other land management practices in the study region. The applied use of these results by governmental and non-governmental organizations may contribute to improve sustainable forest management, environmental monitoring, and law enforcement activities in the Brazilian Amazon.

3.3. Methods

3.3.1. Regional setting

The study region was Brazil's Legal Amazon, a territory with approximately 5 million km^2. The so-called Legal Amazon includes the totality of Acre, Amapá, Amazonas, Pará, Rondônia, and Roraima States, plus parts of Mato Grosso, Maranhão, and Tocantins (see Appendix C.1). The Legal Amazon is a political-administrative region in Brazil, created by the Brazilian Federal Law 1806 in 1953. This analysis was conducted using more than 600 Landsat images of the Legal Amazon, previously used for deforestation analysis at the Tropical Rain Forest Information Center (TRFIC), of the Michigan State University. Signs of selective logging and forest fire were searched throughout the study region. Matricardi et al. (2007) found evidences of selective logging in 31 Landsat TM scenes acquired in 1992 and 1996, and in 38 Landsat ETM+ scenes acquired in 1999. Evidence of forest fires also was found on these scenes and, complementarily, for 1992 and 1996, additional 6 scenes acquired in 1992 and 1996 were used and for 1999, additional 7 scenes acquired in 1999 were used. These Landsat scenes defined the subsequent effective areas of study used in this analysis (Appendix C.1).

3.3.2. Dataset

3.3.2.1. Deforestation dataset

The Brazilian Amazon is one of the regions covered by the deforestation monitoring project implemented by the Tropical Rain Forest Information Center (http://www.trfic.msu.edu) at Michigan State University, which involved a multi-annual classification of 229 Landsat scenes. In that study, Landsat images were individually classified into seven thematic classes: forest, deforestation, regrowth, *cerrado* [5], cloud, cloud shadow, and water using unsupervised image classification procedures. Classified Landsat scenes (path/row) were available individually and placed together as deforestation mosaics for the entire Brazilian Amazon. These deforestation mosaics preserved the original spatial resolution (30 meters). Additional details of the deforestation dataset are presented in Table 3.1.

Selectively logged and burned forests were not included in these land use and land cover classes. Both individual Landsat scenes and deforestation mosaics for 1992, 1996, and 1999, produced by the TRFIC at Michigan State University, were used to perform the intended analytical procedures.

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[5] Cerrado is a vegetation type similar to African Savannah.

Table 3.1 Deforestation dataset characteristics

Dataset	Features	Format	Spatial resolution	Period of Analysis	Projection
Land use and land cover GIS layers by Landsat scene (path/row)	Forest, deforestation, secondary regrowth, cerrado, clouds, and shadows	Arc/Info grid	30m x 30m	1992, 1996, and 1999	UTM, Zones 19 through 23. Projection, Datum, and Spheroid WGS84
Land use and land cover mosaic	Forest, deforestation, secondary regrowth, cerrado, clouds, and shadows	Arc/Info vector and grid	30m x 30m	1992, 1996, and 1999	Sinusoidal projection, Datum and Spheroid WGS84

3.3.2.2. Selective logging dataset

Unsupervised classification has frequently been applied to assess land use and land cover change in the Brazilian Amazon. This procedure does not detect most of the selectively logged forests. As a result, additional remote sensing techniques were required to accurately detect and map them.

Matricardi et al. (2007) conducted a multi-temporal analysis of selective logging of the entire Brazilian Amazon. In that study, forests showing evidences of selective logging were mapped and estimated for up to 38 Landsat scenes throughout the Brazilian Amazon for 1992, 1996 and 1999. The authors used semi-automated (texture algorithm) analysis of Landsat band 5 to detect log landings (i.e. log storage patios) and, subsequently, applied variable buffer zones (180 and 450 meters) around patios to estimate areas affected by selective logging. In addition, Matricardi et al. (2007) mapped selectively logged forests with visible canopy disturbance on Landsat images through visual interpretation, and circumscribed them digitally on a computer screen. In that analysis, visual interpretation and semi-automated method could detect 83.4% and 63.7% of the total logged forests, respectively. Common areas between these two techniques were around 50% but they were not double-counted. Areas that had been previously missed using automatic analysis were added by visual interpretation and vice-versa. Moreover, semi-automated and visual interpretation technique combined showed 92.9% and 0.82 of overall accuracy and overall kappa statistic, respectively. Concomitantly, a deforestation dataset was produced for 1992, 1996, and 1999 and composed by individual Landsat scenes and mosaics for the entire region. Characteristics of the logging dataset are presented in Table 3.2.

Table 3.2 Selective Logging dataset characteristics

Dataset	Classification Features	Format	Spatial resolution	Period of Analysis	Projection
Selectively logged forest GIS layers (Landsat path/row)	Binary classes (1 = logging, 0 = no data)	Arc/Info grid	30m x 30m	1992, 1996, and 1999	UTM, Zones 19, through 23. Datum and Spheroid WGS84
Selectively logged forest GIS layers (mosaic)	Binary classes (1 = logging, 0 = no data)	Arc/Info grid	30m x 30m	1992, 1996, and 1999	Sinusoidal, Datum and Spheroid WGS84

The present study included the previously described selective logging dataset, involving multi-annual measurements for1992, 1996, and 1999 of selectively logged forests in *terra-firme* (upland) of the Brazilian Amazon. In addition, information derived from a multi-annual analysis of selective logging from 1992 to 2002 for a case study (Landsat scene path226 and row 068) in the

State of Mato Grosso, conducted by Matricardi et al. (2005), was used to estimate annual increase of selectively logged forests in the study region.

3.3.2.3. Landsat imagery

The Landsat imagery used in this analysis were drawn from the Tropical Rain Forest Information Center (http://www.trfic.msu.edu) at Global Observatory for Ecosystem Services, Michigan State University. For 1992 and 1996, 38 Landsat TM5 images were used for the analyses, and for 1999, 46 Landsat ETM+ images were used. Three years (1992, 1996, and 1999) were used as reference for measurements and analytical purposes. Some Landsat images, however, were acquired on previous or following year of reference, according to remotely sensed data availability and quality. Acquisition dates of each Landsat scene used in this analysis are provided in Appendix C.2.

3.3.2.3.1. Radiometric correction

Remotely sensed data is affected by changes in the instrument over time. In this case, radiometric correction can be used to normalize the sensor degradation to generate products suitable for multi-temporal analysis, especially when the remotely sensed data is derived from different sensors and acquisition dates (Chander and Markham, 2003). Therefore, radiometric correction was conducted for all Landsat scenes used in this analysis. Further details on this correction procedure were shown in Chapter 2.

3.3.2.3.2. Landsat imagery normalization

Multi-temporal analysis using satellite imagery may be affected by seasonal variations of landscape components such as soil and vegetation characteristics (Mas, 1999). To prevent this sort of distortion, image normalization may be applied to reduce seasonality effects and atmospheric and sensor variations (Elvidge et al., 1995).

Image normalization was applied for all Landsat scenes used in this analysis. A good quality Landsat image, p226/r068 acquired in 1999, was selected as reference. As suggested by Elvidge et al. (1995), the brightest and darkest pixels or sample points were selected from the reference Landsat image and from the corresponding scene acquired in 1996. Sample points consisted of areas of undisturbed forests, soil exposure, and deep water bodies. Around 20 sample points of reflectance values from the reference image (dependent variable) and from the corresponding image acquired in 1996 (independent variable) were used to generate coefficients for a linear regression model. Normalization coefficients (slope and intercept) for each band of interest were produced. The acceptable R^2 for each equation was greater than 0.95, and, when needed, additional sample points were acquired to increase it. The equation 1 describes the linear regression model used for image normalization.

$$y = \beta_0 + \beta_1 x_1 \tag{1}$$

where *y* is the reference image reflectance (dependent variable), β_0 is the intercept or constant coefficient, β_1 is the parameter associated with x_1, and x_1 is the reflectance of the normalizing image (independent variable).

The estimated coefficients and Landsat image acquired in 1996 (independent variable) were used as input to the equation 1, which generated a spectrally adjusted (normalized) image to the reference image. The same procedure was applied to normalize the Landsat image (p226/r068) acquired in 1992.

Common areas (overlaps) observed between Landsat scenes were used to obtain reflectance values of brightest and darkest pixels. In this case, each previously normalized image served as a reference image for its neighboring scene. This procedure was applied for all images acquired in 1999. Consequently, the normalized Landsat imagery acquired in 1999 were used as reference to normalize those acquired in 1992 and 1996.

3.3.2.3.3. Geometric correction

The Landsat imagery used in this analysis was previously system-corrected at the TRFIC using sensor geometry and a polynomial distortion model. The root-mean-square (RMS) positional errors resulting from this geometric correction varied from 0.20 to 0.47 pixels. Additionally, ground control points at known locations and intersections of road segments acquired during fieldwork in 2004 were used to test geometric accuracy of three Landsat scenes (p002/r067, p232/r067, and p226/068) located in the States of Acre, Rondônia, and Mato Grosso. The measurements between these three Landsat scenes and the ground control locations averaged less than 36 meters ± 31.4 meters and 32 meters ± 37.1 meters for x and y directions, respectively.

3.3.3. Field study

The fieldwork observations and measurements were conducted during June 2003, June and July 2004 in study sites in the States of Acre, Rondônia, and Mato Grosso (Appendix C.3). Various types of selective logging (ongoing and previous logging), logged and burned forests, and undisturbed forests were sampled across the study sites. The study site locations and characteristics are described in Appendix C.4. The field studies were designed to enhance the accuracy assessment of remote sensing approaches and to support further analysis of forest disturbances.

3.3.3.1. Field sampling and measurement

Field survey sampling was necessary to estimate the potential biological composition changes of several forest use types (undisturbed, selective logging, and forest fire). Fuel load such as dead trees, wood debris, and litter were also quantified in each study site. Moreover, various forest degradation types and intensities were identified and sampled (Appendix C.4). Therefore, this survey included simultaneous measurements of fuel load and forest composition and regeneration assessments.

A sampling design scheme developed by Cochrane and Schulze (1998) was used to guarantee accuracy and precision of the field survey. As a result, the sample unit was the same for all sampled sites (Appendix C.5). Twenty transects (approximately 9.4 hectares) were plotted and measured in Acre, Rondônia, and Mato Grosso. Each sampled site was geographically located using a GPS. The sample unit on the ground consisted of one transect of 500 x 10 m in which the number of trees, tree identification, tree condition (i.e. dead, alive, rotten, or broken), and DBH measurement of trees greater than 10 cm DBH were recorded. Within the main transect, a quadrat of 10 × 10 m was also plotted every 25 m. Each 10 × 10 m quadrat contained a nested sub-quadrat of 5 × 5 m for sampling tree regeneration and trees within two different diameter classes (< 5 cm and 5-10 cm). Secondary regrowth species and biomass (i.e. dry, rotten, alive, broken, etc.) were identified within the sub-quadrats (DBH < 10 cm) and main transects (DBH >10 cm). Additionally, along each main transect a 10 m fuel line was plotted every 25 m. Each fuel line started at the center of every quadrat (Q1, Q2, Q3, or Q4) towards a randomized direction (0° to 90°, 90° to 180°, 180° to 270°, and 270° to 360° for Q1, Q2, Q3, and Q4, respectively). Subsequently, litter depth was measured at the beginning, middle, and end of the line. In addition, the remaining biomass under the last meter, under the last three meters, and under the entire line for classes of diameter less than 2.5 cm, between 2.5 and 7.6 cm, and greater than 7.6 cm were also counted.

Finally, hemispherical photos were acquired every 10 m along the main transect line. These photos were used to measure canopy openness in each location.

3.3.3.2. Identification of species

Identification of tree species was one of the most difficult tasks during the field survey. In theory, plant components could be collected and properly identified in a herbarium (e.g. Emilio Goeldi Museum in the State of Pará). However, in practical terms, a great amount of time, energy, and financial resources would be required to fulfill this task. To avoid such logistical trap, I used the help of a *Mateiro*[6] in each study area to make an approximate

[6] A *Mateiro* is a knowledgeable local person whom has been working in a given area long enough to have the ability to identify most of the tree species using common or local names.

identification of most tree species. Finally, I used a description of trees produced by the Brazilian Institute of Environment and Renewable Natural Resources- IBAMA to provide the scientific name for each tree species previously identified in the field. Scientific names helped to avoid double counting of the tree species identified by local names.

3.3.3.3. Data processing for biodiversity

Forest diversity can be quantified in many different ways. Key measurement concepts of the measurement of diversity include specie richness, heterogeneity, and equitability. Alternative approaches to measure biological diversity suggested by Peet (1974) are based on specie richness and heterogeneity indices. Species richness is an indicator of species diversity based on the number of species per sample. As a result, biological richness will increase as the number of species observed in a sample increases. Therefore, richness is dependent of the sample size. Following this reasoning, a larger sample size with more species present will be understood as a 'richer' sample. Alternatively, heterogeneity indices can measure diversity by taking into account the number and equitability (relative diversity) of species and, because of that, these indices are less sensitive to sample size (Peet, 1974).

To compare tree species diversity of different sample sizes conducted in the State of Acre, Rondônia, and Mato Grosso, I applied two heterogeneity indices that are not sensitive to sample size, the Simpson's Index of Diversity (1-D) and the Simpson's Reciprocal Index (1/D), both variants of Simpson's Index (D) (Peet, 1974). The Simpson's Index of Diversity varies directly with heterogeneity and ranges between 0 and 1, where higher values indicate greater species diversity. This index can be defined as:

$$D = 1 - \sum_{i=1}^{S} p_i^2 \tag{2}$$

The Simpson's Reciprocal Index starts with 1 as the lowest possible value, representing a community containing only one species, and the maximum value is the number of species in the sample. It can be defined as:

$$\tilde{D} = 1 / \sum_{i=1}^{S} p_i^2 \tag{3}$$

where D and $\tilde{D}$ is the Simpson's Index of Diversity and the Simpson's Reciprocal Index, respectively, p_i is the proportion of individuals in species *i*, and *S* is the number of species (Peet, 1974).

3.3.3.4. Field validation for remote sensing approaches

Canopy openness was measured for both disturbed and undisturbed forests using hemispherical photos (further details are provided below). Similarly, tree species diversity (including secondary tree species) was qualitatively and quantitatively established for each site. Hemispherical photos acquired with "fish eye" lens and digital camera (3.2 mega pixels resolution) beneath undisturbed and disturbed forest canopies were used to estimate canopy openness. The photo-shots follow 500 meter transect trails, for each 10-meter intervals. Canopy openness measurement for each individual location was calculated using the Gap Light Analyzer (GLA) software. Fraction canopy openness was estimated using a semi-automated technique because each individual photo requires a threshold empirically defined by the photo interpreter (Appendix B.6). Subsequently, the canopy fraction was obtained by calculating the difference between 100% and forest canopy openness (%) calculated from the hemispherical photos.

Finally, potential occurrences of forest fires were surveyed in 120 randomly distributed locations of forested lands within the Landsat path 226 and row 068. The resulting information was used to perform an accuracy assessment of the burned forest detection technique. Further details of the accuracy assessment of burned forest detection are described in Chapter 2.

3.3.4. Remote sensing approaches

3.3.4.1. Burned forests detection

Burned forests were detected and mapped using a remote sensing approach based on Spectral Mixture Analysis. This approach was successfully applied by Cochrane and Sousa Jr (1998) and Souza et al. (2003) to detect selectively logged and burned forests using Spot imagery in a case study in the State of Para, Brazil. Cochrane and Sousa Jr (1998) used fraction images based on particular endmembers (spectral pure signatures) that represented specific image components such as green vegetation, soil, non-photosynthetic vegetation, and shade. Based on this approach, a fully automated technique was developed and tested to detect burned forests using non-photosynthetic vegetation fraction image from Spectral Mixture Analysis (SMA), retrieved from Landsat imagery. This technique was developed and tested for a 30000 km^2 study site in the Amazon State of Mato Grosso. Accuracy assessment results indicated 96.0% and 0.91 of overall accuracy and overall kappa statistic, respectively. Additional details regarding this technique and its usage can be found in Chapter 2.

The approach introduced in Chapter 2 was applied where signs of burned forest were observed throughout the Brazilian Amazon. Burned forests were detected and binary classified (1 = burned forest, 0 = non-burned forest) in raster format for 1992, 1996, and 1999.

3.3.4.2. Fractional coverage

The theoretical foundation for the assessment of forest canopy impacts by selective logging and forest fires using vegetation index derived from remotely sensed data was previously described in Chapter 2 for a case study in the State of Mato Grosso. In that study, Modified Soil-Adjusted Vegetation Index - MSAVI, Global Environmental Monitoring Index - GEMI, modified $GEMI_{2.1}$, Normalized Difference Vegetation Index - NDVI, Aerosol Free Vegetation Index - AFRI, Modified Soil-Adjusted Vegetation Index aerosol free – $MSAVI_{af}$, and Green Vegetation derived from Spectral Mixture Analysis were retrieved from the Landsat path 226 and row 068, and their performance was assessed under different atmospheric conditions and forest characteristics.

For the basin-wide analysis purposes, two additional case studies in the Amazon States of Rondônia and Acre (Appendix C.3) were conducted in the present study. Vegetation indices' performances were assessed again for different Amazon sub-regions and forest sites by comparing fractional coverage values derived from remotely sensed data to canopy cover measurements from hemispherical photos acquired in the field. This assessment contributed to select the optimum vegetation index to be applied in the basin-wide analysis.

Time-scale variation of forest canopy also was verified through multi-temporal analysis of fractional coverage retrieved from Landsat imagery acquired in 1992, 1996, and 1999. Finally, partial effects of each land use and land cover change on fractional coverage were identified using multiple regression analysis. Further details of this multiple regression analysis are described bellow.

3.3.5. Forest canopy impact assessment

Forest canopy degradation by selective logging, forest fire, logging and forest fire combined, and forest regeneration following each of these forest disturbances in the study area were assessed using multiple regression analysis. Multiple regression analysis is useful to estimate partial effects of a given independent variable by controlling other independent variables that simultaneously affect the dependent variable (Wooldridge, 2000).

Based on Wooldridge (2000), the multiple linear regression model can be defined as:

$$FC\% = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_{14} x_{14} + u \,, \tag{4}$$

where *FC%* is the observed continuous variable (green fractional percentage derived from remotely sensed data), and β_0 is the intercept or constant, β_1 is the parameter associated with x_1 (independent variable 1), β_2 is the parameter associated with x_2 (independent variable 2) and so on. The variable *u* is the error term, which contains factors other than the independent variables included in this model that affect *FC%*.

The vector of independent variables (x) tested is described as following:

- x_1 = Deforestation
- x_2 = Secondary regrowth
- x_3 = Water body
- x_4 = Cerrado or Savannah
- x_5 = Newly logged forest
- x_6 = Newly logged and burned forest
- x_7 = Newly burned forest
- x_8 = Previously logged forest
- x_9 = Previously burned forest
- x_{10} = Previously logged and burned forest
- x_{11} = Year 1996
- x_{12} = Year 1999
- x_{13} = Longitude or x location (kilometer)
- x_{14} = Latitude or y location (kilometer)

Note: Undisturbed forest and the year *1992* were used as *omitted variables* for the land use classes and annual changes, respectively.

By using this multiple regression analysis, I was able to measure the effect of each land use or year of analysis on forest canopy cover in the study area, holding constant the other independent variables.

3.3.5.1. Testing Hypotheses

Based on field observations, I expected that impacts by anthropogenic activities should produce measurable effects on forest canopy. Therefore, any observed type of land use and land cover should affect (increase or decrease) values of fractional coverage derived from Landsat imagery when compared to undisturbed forests. I also expected that effects of non-controlled seasonal and natural variations should have effects on values of fractional coverage, which ultimately could be observed by using multi-temporal dataset. Finally, I expected that values of fractional coverage could be affected by uncontrolled spatial variability of natural forests and human activities in the study area. In this case, location itself could be used to identify potential spatial variation of fractional coverage values throughout the study region. Based on these assumptions, I hypothesized about each value of the fourteen slope coefficients (β_1, β_2, ..., β_{14}), once the effect of other coefficients had been account for, using statistical inferences to test the following hypothesis:

H_0: **Null hypothesis:**

Land use and land cover change variables (β_1 to β_{10}):

β_1 = 0: Deforestation has no effect on fractional coverage.
β_2 = 0: Secondary regrowth has no effect on fractional coverage.
β_3 = 0: Cerrado has no effect on fractional coverage.
β_4 = 0: Water body has no effect on fractional coverage.
β_5 = 0: Newly logged forest has no effect on fractional coverage.
β_6 = 0: Newly burned forest has no effect on fractional coverage.
β_7 = 0: Newly logged and burned forest has no effect on fractional coverage.
β_8 = 0: Previously logged forest has no effect on fractional coverage.
β_9 = 0: Previously burned forest has no effect on fractional coverage.
β_{10} = 0: Previously logged and burned forest has no effect on fractional coverage.

Temporal variables (β_{11} to β_{12}):

β_{11} = 0: Non-controlled seasonal or temporal variations for 1996 have no effect on fractional coverage.
β_{12} = 0: Non-controlled seasonal or temporal variations for 1999 have no effect on fractional coverage.

Spatial variables (β_{23} to β_{24}):

β_{13} = 0: Anthropogenic and natural spatial variations over longitude (x) direction have no effect on fractional coverage.
β_{14} = 0: Anthropogenic and natural spatial variations over latitude (y) direction have no effect on fractional coverage.

H_1: **Alternative hypothesis:**

Land use and land cover change variables (β_1 to β_{10}):

$\beta_1 \neq 0$: Deforestation has effect on fractional coverage.
$\beta_2 \neq 0$: Secondary regrowth has effect on fractional coverage.
$\beta_3 \neq 0$: Cerrado has effect on fractional coverage.
$\beta_4 \neq 0$: Water body has effect on fractional coverage.

$\beta_5 \neq 0$: Newly logged forest has effect on fractional coverage.

$\beta_6 \neq 0$: Newly burned forest has effect on fractional coverage.

$\beta_7 \neq 0$: Newly logged and burned forest has effect on fractional coverage.

$\beta_8 \neq 0$: Previously logged forest has effect on fractional coverage.

$\beta_9 \neq 0$: Previously burned forest has effect on fractional coverage.

$\beta_{10} \neq 0$: Previously logged and burned forest has effect on fractional coverage.

Temporal variables (β_{11} to β_{12}):

$\beta_{11} \neq 0$: Non-controlled seasonal and temporal variations for 1996 have effect on fractional coverage.

$\beta_{12} \neq 0$: Non-controlled seasonal and temporal variations for 1999 have effect on fractional coverage.

Spatial variables (β_{13} to β_{14}):

$\beta_{13} \neq 0$: Anthropogenic and natural spatial variations over longitude (x) direction have effect on fractional coverage.

$\beta_{14} \neq 0$: Anthropogenic and natural spatial variations over latitude (y) direction have effect on fractional coverage.

3.3.5.2. Data Sampling

As previously discussed in Chapter 2, multiple linear regression models are sensitive to spatial auto-correlation in the dataset. The auto-correlation effects can be minimized by systematically sampling the dataset (Anselin 2002, Arima et al. 2007). Therefore, I used a 5km x 5km point grid to sample all variables of interest over the study region (Appendix C.1). Since pixel was used as the unit of observation in this analysis, a unique value of the dataset was acquired for each point of the sampling grid to represent each of the studied variables. Additionally, each grid cell was located with *x* and *y* coordinates, which also were used as independent variables. This procedure is expected to allow the identification of spatial trends in the data and to reduce the error term in the regression model due to spatial autocorrelation in the data population (Chomitz and Gray 1996, Arima et al. 2007).

3.4. Results and Discussion

3.4.1. Multi-temporal assessment of selective logging and forest fires

Matricardi et al. (2007) developed remote sensing approaches to detect selectively logged forests in the entire Brazilian Amazon. Using such approaches, a total of 5980 km^2, 10064 km^2, and 26085 km^2 of selectively logged forests were detected in 1992, 1996, and 1999, respectively. By using linear mixture analysis, I could detect 6280 km^2, 7580 km^2, and 11508 km^2 of burned forests in the Brazilian Amazon in 1992, 1996, and 1999, respectively. The total area of tropical forests impacted by selective logging and forest fire and detected using remotely sensed data were 11800 km^2, 16500 km^2, and 35600 km^2 in 1992, 1996, and 1999, respectively. This magnitude of degraded forests had not been reported in previous studies of deforestation (Skole et al., 2004). Table 3.3 shows further details of the detected areas of selectively logged and burned forests, taking into account the overlap between both types of forest disturbances.

Table 3.3 Detected selective logging, burned forests, and dataset characteristics

Year	Burned only (km^2)	Burned & Logged (km^2)	Logged only (km^2)	Total degraded (km^2)
1992	5,889.4	391.6	5,588.2	11,869.3
1996	6,177.7	1,403.3([a])	8,951.0	16,532.0
1999	9,038.4	2,470.7([b])	24,188.1	35,697.3

[a] Total includes 290.2 km^2 of burned forest detected in 1996, which was previous logging detected in 1992 and not detected in 1996;
[b] Total includes 573.4 km^2 of burned forest detected in 1999, which was previous logging detected by 1996 and not detected in 1999.

Landsat path and row analysis indicated that 1205 km^2, 1719 km^2, and 4241 km^2 of selective logging were detected in 1992, 1996, and 1999, respectively, within the path 226 and row 068, located in Mato Grosso. This was the greatest forest extension impacted by selective logging for a particular Landsat scene (path/row) in the entire Brazilian Amazon. Meanwhile, the greatest extension of burned forest detected was observed within the path 222 and row 063 in 1992 (around of 644 km^2) and within the path 224/068 in 1996 and 1999 (around of 605 km^2 and 1227 km^2, respectively). Appendix C.9 shows basin-wide results of selectively logged and burned forest detected within each Landsat path and row in 1992, 1996, and 1999.

Most of the detectable burned and selectively logged forests were observed in Mato Grosso and Pará. These two states accounted for more than 90% of total selective logging only, 89% of total burned forest only, and 87% of total selectively logged and burned forest combined detected in 1992, 1996, and 1999. Mato Grosso was responsible for approximately 59% of burned forest in 1992 and Para was responsible for approximately 76% of selectively logged and burned forests detected in 1996 (Appendix C.10).

An additional element of concern in this analysis was related to the occurrence of forest disturbances within the borders of land set aside from economic development for different types of non-economic uses. Around 1.8%, 2.3%, and 4.7% of the total selectively logged forests were detected within the limits of Amerindian reserves, protected lands, and military areas in 1992, 1996, and 1999, respectively (Matricardi et al., 2007). Approximately 0.6%, 2.6%, and

5.1% of the total forests burned were detected within these areas in 1992, 1996, and 1999, respectively. Amerindian reserves constituted the vast majority of the detected selectively logged and burned forests within these areas (Table 3.4).

Table 3.4.Total area of selectively logged and burned forests detected in 1992, 1996, and 1999 within protected areas (indigenous land, conservation unit, and military area)

	Indigenous land		Conservation units		Military area	
Year	Burned forest (km^2)	Logged Forest (*) (km^2)	Burned forest (km^2)	Logged Forest (*) (km^2)	Burned forest (km^2)	Logged Forest (*) (km^2)
1992	33.3	106.5	2.8	3.6	0.0	0.0
1996	193.2	216.6	0.5	11.1	0.0	0.0
1999	574.3	1189.8	17.3	44.7	0.4	0.0
Total	800.8	1512.8	20.5	59.4	0.4	0.0

* Source: Matricardi et al. (2007)

Multi-temporal analysis between forest fire and deforestation indicated that 2968 km^2 of burned forest only detected in 1992 were deforested by 1996 and an additional 546 km^2 by 1999. Around of 3225 km^2 of burned forest only detected in 1996 were deforested by 1999. Comparisons between selective logging and deforestation in this period of analysis indicated that 651 km^2 of logged forest only detected in 1992 was deforested by 1996 and an additional 708 km^2 by 1999. Meanwhile, 984 km^2 of logged forest detected in 1996 were deforested by 1999. Additionally, comparisons between deforestation, selective logging, and forest fire indicated that around of 145 km^2 of selectively logged and burned forest combined in 1992 were cleared by 1996 and an additional 188 km^2 were cleared by 1999. Around of 720 km^2 of selectively logged forest in 1992 and/or

1996 and burned forest in 1996, were deforested by 1999. These results also showed that around of 457 km^2 and 148 km^2 of forest disturbances detected could be considered recurrent fires and revisited logging, respectively. I defined recurrent fire and revisited logging as burned and logged forests, respectively, detected in 1992 that had formerly recovered sufficiently to become undetectable in 1996 and again were detected in 1999 as burned or logged forests.

3.4.2. Optimum vegetation index selection

In Chapter 2, an optimum vegetation index was selected based on the estimated relationships among various vegetation indices retrieved from a Landsat image and canopy cover derived from hemispherical photos. The statistical results showed that AFRI could perform slightly better than $MSAVI_{af}$ under clear sky and anomalous atmospheric conditions for the study region in Mato Grosso. However, linear relationship between fractional coverage values derived from each vegetation index and those calculated from hemispherical photos acquired in the field indicated that MSAVI and its modified version ($MSAVI_{af,}$) could better estimate forest canopy cover for the same region. Finally, $MSAVI_{af}$ was selected as the optimum vegetation index given its property of acquiring more accurate ground information than the other indices in the presence of smoke and aerosols.

Additional hemispherical photos were acquired in the field sites located in Acre and Rondônia. MSAVI showed highest R-squared for Rondônia and Acre study sites (0.74 and 0.81, respectively). Immediately following MSAVI, $MSAVI_{af}$, GEMI, $GEMI_{2.1}$, and GV showed the same R-squared (0.69) for the Rondônia study site. $MSAVI_{af}$ showed the second highest R-squared (0.80) for the Acre study site. Based on these statistical results and on its performance under clear and smoke sky condition, I selected $MSAVI_{af}$ as the optimum vegetation index to be used in this basin-wide analysis. The Appendix C.8 shows the statistical results of the empirical linear relationship between various vegetation indices and forest canopy coverage based on field measurements for the study sites in Mato Grosso, Rondônia, and Acre.

3.4.3. Forest canopy impact assessment based on remotely sensed data

Impacts on forest canopy by selective logging and forest fire were estimated using a multiple regression model (Equation 4) and land use and fractional coverage derived from remotely sensed data. The statistical results indicated that this equation can significantly explain 52.8% of the dependent variable (fractional coverage).

Analysis of the partial effects of different anthropogenic activities that potentially could be affecting fractional coverage derived from vegetation index domain in the study region from 1992 to 1999 indicated that deforestation alone was responsible for a decrease of 49% (± 0.38) in the fractional coverage values when compared to fractional coverage values for undisturbed forests and holding fixed all other factors. Although secondary regrowth is defined as a formerly deforested area, this land use was much less responsible for the reduction of fractional coverage values (around of 7%) than was deforestation itself.

In terms of forest uses, around of 28%, 19.8%, and 2% of estimated forest canopy decreases in the studied period were due to new areas of selective logging and forest fire combined, forest fire only, and selective logging only, respectively. Previously burned and logged forests were responsible to decrease approximately 10% of fractional coverage values. When considered previously burned forest only, I could not reject the null hypothesis that fractional coverage values for this forest use are not significantly different from fractional coverage values for undisturbed forests (omitted variable). My analysis also indicated that forest canopy is sufficiently recovering after selective logging activities throughout the Legal Amazon and such recovery was responsible for an increase of approximately 6% in fractional coverage values when compared to undisturbed forests. Figure 3.1 shows partial effects of each anthropogenic activity on forest canopy change.

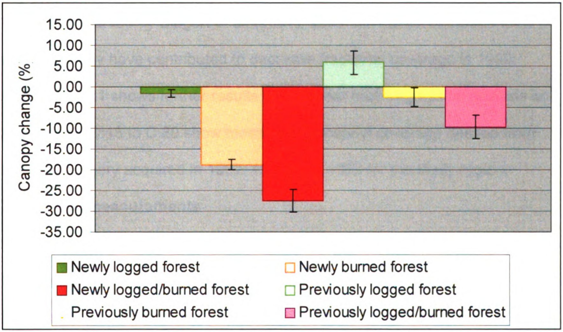

Figure 3.1. Partial effects of various anthropogenic activities on forest canopy cover in the Brazilian Amazon using linear multiple-regression model and multi-temporal remotely sensed data

The null hypothesis that anthropogenic and natural spatial variations over longitude and latitude (x and y) directions have no effect on fractional coverage values could be rejected and the alternative hypothesis was consequently accepted. Fractional coverage values significantly decrease 0.8% (± 0.03 standard deviation) each 100 km towards east direction and significantly increase 1.2% (± 0.04) each 100 km towards north direction.

In terms of temporal change, the results indicated an increase of 1% of fractional values in 1996 compared to year 1992 and by holding all other independent variables fixed. The greatest annual loss of fractional coverage, around 5% (± 0.3), was observed in 1999. A possible explanation is related to the factors that vary annually, such as the rainfall reduction caused by the 1997-1998 “El Nino” observed by Siegert et al. (2001), absent in the list of independent variables, may have contributed to decrease fractional coverage in 1999. Appendix C.11 shows further results of the linear multi-regression analysis and Appendices C.18 to C.20 show mosaics of fractional coverage derived from Landsat imagery acquired in 1992, 1996, and 1999 for the study region.

3.4.4. Field measurements

In the field survey conducted in the States of Acre, Rondônia, and Mato Grosso, a total of 3269 individuals of tree species (DBH > 10 cm) were recorded for an area of 9.38 hectares, an average greater than 348 tree individuals per hectare. This estimate is well in the range of Whitmore’s (1984) estimate that indicated 250 or more species of trees DBH greater than 10 cm for tropical rain forests. Approximately 80% of the total observed tree species observed in the present study could be identified by the *Mateiros*, which indicated that a minimum of 119 different tree species were observed in those sampled sites (Appendix C.6).

The number of new tree species decreased as the sample size (number of transects) increased. The number of tree species also increased between the transects #3 and #4 and between transects #8 and #9, which represented the transition sites between the State of Acre and Rondônia and between the State of Rondônia and Mato Grosso, respectively. The observed increase of new tree species in the first samples for each sampled region indicated potential differences in tree species diversity among the study sites. However, the fact that the same *Mateiro* was not available to assist the field work data gathering process in three regions, could have affected the detected number of unknown species.

Based on field observations, the sites sampled in Acre and Rondônia seemed to have greater number of tree species (DBH > 10 cm) than did those sites located in Mato Grosso. Forest disturbances by selective logging and forest fire were also visually more intensive in Mato Grosso. Based on these facts, I expected that tree species diversity would be higher in Acre and Rondônia. Statistical results (t-test for independent groups, $\mu_1 \neq \mu_2$) confirmed that sampled sites in Rondônia and Acre combined had higher Simpson's Diversity Index ($\underline{M}$ = 0.94, $\underline{SD}$ = 0.008) than did those sites sampled in Mato Grosso only ($\underline{M}$ = 0.81, $\underline{SD}$ =0.087). This difference was significant, $\underline{t}(18) = 3.9937$, $\underline{p} = .0004$. Similarly, sites in Rondônia and Acre combined had significantly higher Simpson's

Reciprocal Index (M = 16.3, SD = 2.31) than did those sites in Mato Grosso only (M = 6.1, SD =1.88), $t(18)$ = 10.8658, p = .0000. The greatest decrease of tree species diversity index was observed for a severely burned site (transect # 20) in Mato Grosso. The Simpson's Index of Diversity, Simpson's Reciprocal Index, and the number of tree species variation across the sampled sites are shown in Figure 3.2.

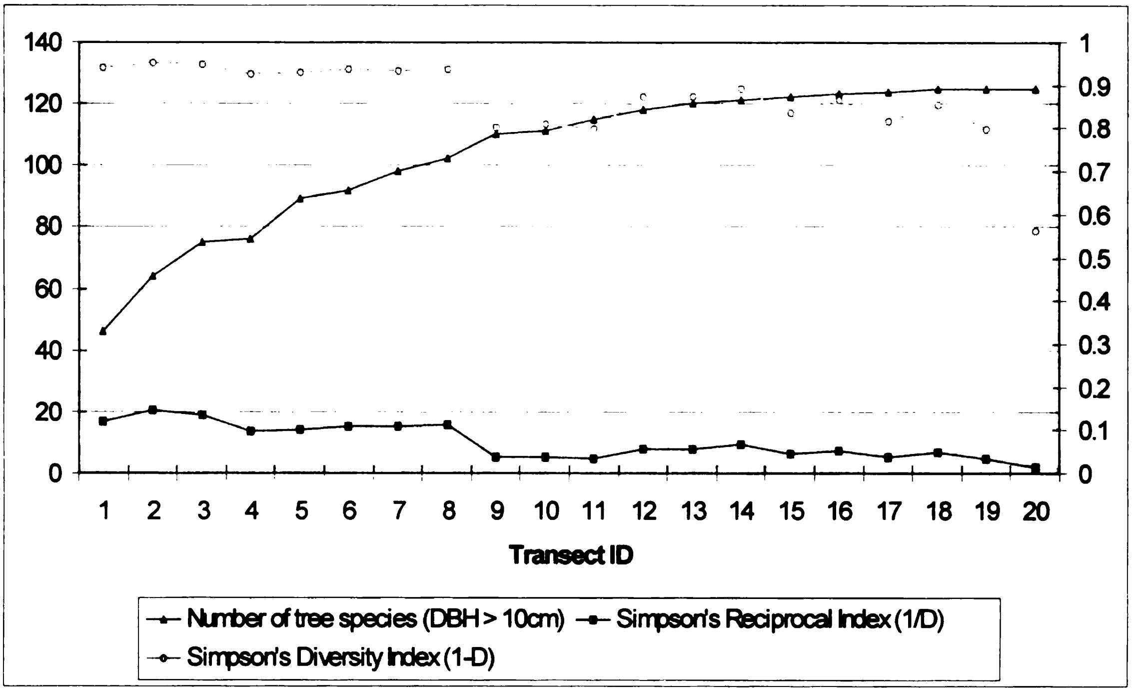

Figure 3.2. Number of tree species, Simpson's index of diversity, and Simpson's reciprocal index against number of sampling (transect)

By grouping the sampled sites in undisturbed and disturbed (logged and/or burned) forests, the difference of mean values of Simpson's Index of Diversity for these two groups was not significantly different from zero (undisturbed M = 0.90, SD = 0.06, disturbed M = 0.85, SD = 0.1, $t(18)$ = 0.9199, p = 0.1849). Similarly, the difference of mean values of the Simpson's Reciprocal

Index was not significantly different for undisturbed (M = 12.03, SD = 5.38) and disturbed (M = 9.53, SD = 5.59) forests, $t(18) = 0.8742$, $p = 0.1965$). However, the combination of undisturbed and logged forest sites (M = 0.892, SD = 0.05) produced significantly higher Simpson's Index of Diversity than did those burned forest sites (M = 0.796, SD = 0.13), $t(18) = 2.401$, $p = 0.0135$.

Undisturbed forest sites had significantly higher canopy cover (M = 87.7, SD = 2.7) than did the forest sites disturbed by selective logging and forest fires (M = 80.1, SD = 7.7), $t(18) = 2.138$, $p = 0.0232$. Undisturbed forest sites also had higher canopy cover (M = 88.6, SD = 1.8) than did the forest sites disturbed by forest fire only (M = 76.6, SD = 11.1), $t(9) = 2.37$, $p = 0.021$. Similarly, undisturbed forests had higher canopy cover (M = 88.6, SD = 1.8) than did the forest sites disturbed by selective logging only (M = 81.9, SD = 2.886), $t(12) = 4.627$, $p = 0.001$.

Mean values of fuel load (metric tons per hectare) and litter depth (cm) did not show substantial difference among various types of forest uses. For example, the estimated difference of mean values of fuel load for undisturbed (M = 68.1, SD = 42.1) and disturbed forests (M = 60.5, SD = 36.5) was not significant, $t(18) = 0.380$, $p = 0.351$. This result showed, however, that variance (standard deviation) is substantial among those forest sites. The greatest fuel loads of approximately 141 and 138 metric tons per hectare were observed in previously logged forests in Mato Grosso and Rondônia, respectively. As opposed to forest uses, amount of fuel load seemed to vary significantly among the study regions. Study sites located in Rondônia and Mato Grosso (M = 71.1, SD = 35.8) had higher fuel loads than did those located in Acre (M = 27.9, SD = 14.8), $t(18)$ = 2.32, p = 0.016. Similarly, study sites located in Rondônia and Mato Grosso (M = 4.6, SD = 2.3) had higher litter depth than did those located in Acre (M = 2.1, SD = 1.1), $t(18)$ = 2.157, p = 0.023.

The difference of mean of mortality rates of tree species (DBH > 10 cm) for undisturbed (M = 7.3, SD = 3.9) and disturbed forests (M = 15.9, SD = 15.5) was not significantly different from zero, $t(18)$ = -1.2163, p = 0.12. Undisturbed and logged forest combined had significantly lower tree mortality rates (M = 7.6, SD = 4.5) than did those burned forest sites (M = 28.1, SD = 18.2), $t(18)$ = -4.064, p = 0.000. Undisturbed and logged forest combined also had lower rates of dead basal area (M = 8.47, SD = 5.2) than did those burned forest only (M = 22.7, SD = 17.2), $t(18)$ = -2.897, p = 0.000. The difference of mean values of the rate of dead basal area for undisturbed and disturbed forests was not significantly different from zero, $t(18)$ = -0.9060, p = 0.1885.

3.4.5. Links between forest canopy and further ecological indicators

Pearson correlation values among various field measurements that indicate different level of forest disturbances are presented in Table 3.5. Further estimates of forest disturbance indicators based on field measurements are presented in Appendix C.7.

High negative correlation values were observed between forest canopy cover, tree mortality rate, and dead basal area. These results indicate that tree mortality rate and dead basal area increase when there is a decrease in forest canopy cover.

Table 3.5 Correlation matrix among various forest parameters measured in the study sites in the State of Acre, Rondônia, and Mato Grosso.

	FC	TMR	DBA	REG	REG^5	REG^{10}	Fuel load	Litter depth	SID	SRI
FC	1									
TMR	**-0.77**	1								
DBA	**-0.78**	**0.93**	1							
REG	0.03	-0.19	-0.17	1						
REG^5	0.14	-0.02	-0.01	-0.29	1					
REG^{10}	0.31	-0.24	-0.18	-0.18	**0.79**	1				
Fuel load	-0.13	0.28	0.17	-0.27	-0.40	-0.41	1			
Litter depth	0.40	-0.22	-0.17	-0.37	-0.04	-0.08	0.37	1		
SID	**0.70**	**-0.74**	**-0.73**	0.37	0.02	0.22	-0.20	0.10	1	
SRI	0.36	-0.47	-0.43	0.35	-0.02	0.26	-0.25	-0.19	0.82	1

Pearson correlation is significant at the 0.01 level (1-tailed) for bold values, which represent special interest in this analysis. N= 20

FC = Canopy cover (%) derived from hemispherical pictures; TMR = Tree mortality rate; DBA = Dead basal area; REG = Tree regeneration > 10 cm DBH; REG^5 = Tree regeneration < 5 cm DBH; REG^{10} = Tree regeneration between 5 and 10 cm DBH; SID = Simpson's Index of Diversity; RSI = Simpson's Reciprocal Index

The Simpson's Diversity Index showed a high positive Pearson correlation value with forest canopy cover, indicating that tree diversity increases when canopy cover increases. On the other hand, the Simpson's Diversity Index had high negative Pearson correlation values with tree mortality rate and dead basal area. These results indicate that tree diversity decreases when tree mortality rate and dead basal area increase. Tree mortality rate and dead basal area had high positive correlation. Finally, two size groups (i.e. <5 cm DBH and 5-10 cm DBH) of regeneration tree species had high positive correlation. These results indicate that forest regeneration is not only a process with temporal fluctuations but dependent on the existence of viable tree individuals.

3.5. Conclusions

The present results showed a substantial increase (~300%) of forest degradation by selective logging and forest fires in the Brazilian Amazon between 1992 and 1999. The total area of forest impacted by these activities was around of 11800 km^2, 16500 km^2, and 35600 km^2 in 1992, 1996, and 1999, respectively. Total estimates indicated that at least 52859 km^2 of natural forests (1.1% of the entire Brazilian Amazon) were selectively logged and/or burned between 1992 and 1999. From this total, approximately 10000 km^2 were deforested by 1999. Selective logging alone was responsible for more than 60% of forest disturbances detected in the studied period and, approximately, 33% and 7% of forest disturbances were due to forest fire alone and forest fire and selective logging combined, respectively. The States of Mato Grosso and Pará were affected by approximately 90% of this forest degradation detected using remotely sensed data acquired in 1992, 1996, and 1999 (see the spatial distribution of selectively logged and burned forests detected on maps presented in Appendices C.12 to C.17).

These amounts of forest disturbances detected in 1992, 1996, and 1999 do not represent, however, annual rates because they did not occur exclusively on these given years. Most of selectively logged forests are detectable on satellite imagery up to a year following logging activities, but none of the disturbed forests should remain detectable more than 2-3 years due to rapid forest regeneration in tropical regions (Stone and Lefebvre, 1998, Sousa Jr and Barreto, 2000). Evidences of burned forests can be even more persistent on satellite data. However, their accurate detection would require multi-annual dataset in order to calculate annual rates of these types of forest disturbances (Souza et al., 2005). Based on this assumption, I used the results of the multi-annual analyses conducted by Matricardi et al. (2005) and the results of the analysis presented in Chapter 2 to estimate the increase of new areas of selectively logged and burned forests, which were then extrapolated to the entire Brazilian Amazon.

In the case of selective logging, I used the average relations between total detected and the increase of logging areas from 1992 to 1999 observed by Matricardi et al. (2005) in the Mato Grosso and Rondônia study cases, 39.5% and 91.4%, respectively. Furthermore, Matricardi et al. (2005) assumed that logging activities may persist up to 3 years on satellite imagery and high intensity logging occurred on those Landsat scenes that showed an average of total detected logging areas greater than 100 $km^2 yr^{-1}$ in 1996 and 1999. Low intensity logging where fewer marketable trees are harvested, lesser infra-structure built, and, consequently, lower forest disturbances, was assumed to occur on Landsat scenes that showed an average of total detected logging areas below 100 $km^2 yr^{-1}$ in 1996 and 1999. Finally, the States of Mato Grosso and Rondônia average relations (39.5% and 91.4%) were assumed to represent Landsat scenes showing high and low intensity logging activities, respectively.

For annual rates of burned forest, I used the average relations between total detected and the increase of burned areas from 1992 to 1999 presented in Chapter 2 for the Mato Grosso case study. The results in this case were 41%

and 50.4% observed for burned forests and selectively and burned forests combined, respectively. I also assumed that forest fires may persist up to 5 years on satellite imagery and heavily burned forests occurred on those Landsat scenes showing an average of total detected burned forests greater than 20 km^2 yr^{-1} in 1996 and 1999. Lightly burned forests were assumed to occur on Landsat scenes showing an average of total detected logging areas less than 20 km^2 yr^{-1} in 1996 and 1999. Based on the Rondônia case study, an increase of approximately 100% of burned forests was observed from 1992 to 1999 on Landsat imagery. Additionally, field observations showed that lightly burned areas encompassed small forest plots, sparsely distributed within the Landsat path 232 row 067. Very unique site characteristics (i.e. moist microclimate and dense vegetation) may have reduced fire intensity and prevented fire propagation into neighbor forests. Finally, the average relations (41% and 50.4%) were assumed to represent Landsat scenes showing heavily burned forest only and selectively logged and burned forest combined, respectively. Landsat scenes showing less than 20 km^2 yr^{-1} in 1996 and 1999 were assumed as having an average relation of 100%. Nevertheless, these lightly burned sites represented less than 10% of the total burned forest detected in the studied period and should produce minor impact on final results.

Assuming that the average relations previously presented can be extrapolated to a basin-wide scale, the total increase of selectively logged forest only, burned forest only, and selectively logged and burned forests combined in 1992 was at least 2391 km^2, 2883 km^2, and 193 km^2, respectively. These amounts increased to 3951 km^2, 3018 km^2, and 649 km^2 by 1996. Following this increasing trend, estimates for 1999 indicated that areas of selectively logged forest only, burned forest only, and selectively logged and burned forests combined expanded to 11767 km^2, 4514 km^2, and 1156 km^2, respectively. These new areas of selective logging and forest fires represent around of 46% of the total disturbed forests detected in 1992 and 1996, and 49% in 1999. These areas were considered to have been previously impacted by selective logging and forest fire and, due to their more severe forest disturbances, were more persistent on satellite imagery. The remaining detected disturbed forests increased from 6401 km^2 in 1992 to 8913 km^2 in 1996 and 18258 km^2 in 1999. The total areas detected and annual rates of selective logging and forest fires are presented in Tables 3.3 and 3.6, respectively.

New areas of natural forests impacted by selective logging and forest fires increased 139% and 229% in the period between 1992 and 1996 and between 1996 and 1999, respectively. Matricardi et al. (2007) had estimated rather similar increases of new areas of selective logging only in the same period for the entire Brazilian Amazon. These results support previous reports of increasing trends in degradation of natural forests in the Brazilian Amazon by selective logging activities (Uhl et al., 1997, Nepstad et al., 1998, Stone and Lefebvre, 1998, Souza and Barreto, 2000) and forest fires (Uhl and Buschbacher, 1985, Uhl and Kauffman, 1990, Cochrane and Schulze, 1998, Cochrane, 2001, Cochrane et al., 2004).

Table 3.6. Estimated increase of new selectively logged, forests burned, and selectively logged and burned forests in the Brazilian Amazon.

Year	Annual increase (km^2)			
	Logged only ([1])	Burned only ([2])	Burned & Logged ([3])	Total
1992	2,391.0	2,883.6	193.5	5,468.2
1996	3,951.6	3,018.6	649.4	7,619.6
1999	11,767.9	4,514.4	1,156.9	17,439.2

[1] Logging average 1 (39.5%) and average 2 (91.4%) of selective logging increases were estimated for Mato Grosso and Rondonia study cases, respectively. (Matricardi et al. 2005)
[2] Logged and burned forest average 1 (50.4%) and average 2 (100%) of burned and logged forests combined were estimated for Mato Grosso and Rondonia study cases, respectively.
[3] Burned forest average 1 (41%) and average 2 (100%) of burned forest increases were estimated for Mato Grosso and Rondonia study cases, respectively.
These averages were calculated as total area of forest showing selectively logged and/or burned forests for the first time divided by the total area of forest wherein selective logging and/or forest fire was detected. Logging averages 1 and 2 were used to estimate new areas of forests impacted by selective logging and forest fire for all Landsat scenes showing total area of selective logging more or less than 100 $km^2\ yr^{-1}$, respectively. The burned forest averages 1 and 2 were used to estimate new areas of forests burned for all Landsat scenes showing total areas of this forest disturbance more or less than 20 $km^2\ yr^{-1}$, respectively. This last procedure was applied to estimate new areas of selective logging and forest fires using the averages 1 and 2.

The intensity of forest disturbances is also increasing in the Brazilian Amazon. Formerly logged forests are increasingly been revisited by loggers searching for the second tier economic species as raw material and undisturbed forests became scarcer (Uhl et al., 1997, Matricardi et al., 2005). Matricardi et al. (2005) reported that revisiting logging increased approximately to 7.3% of the total logged forest in the period of 1993-2002. Similar increase (7.1%) of recurrent fires was observed in the studied period in Mato Grosso (see Chapter 2). The study case results support the research conducted by Cochrane and Schulze (1998) who observed that recurrent fire and its intensity are likely to increase because of favorable local environmental created by the previous fire events.

Forest disturbances within the limits of protected areas represented an average of 2.9% and 2.8% of the total area of the detected selective logging and forest fire, respectively. The results indicated that such areas have been very effective in constraining these types of anthropogenic activities in Brazilian Amazon. The results also indicated that between 1992 and 1999 the total area detected of selectively logged and burned forests within protected areas increased 2.9% and 4.5%, respectively. This trend of increasing forest degradation within protected areas supports the analysis by Pedlowski et al. (2005) who reported that many conservation units in the Brazilian Amazon have been increasingly been exposed to logging and deforestation activities.

Finally, the results of the methods used in this analysis are considered conservative, since, in different circumstances, degraded forests by selective logging and forest fires cannot be detected. Indeed, Matricardi et al. (2005) and Matricardi et al. (2007) observed that very low intensity selective logging cannot be easily detected using remote sensing approaches, nor it may cause substantial environmental impacts on natural forests and on fluxes of carbon dioxide. However, the total areas of natural forests here classified as selectively logged and burned forests represent additional land use types that constitute major forest impacts and have not yet been properly accounted for by conventional remote sensing approaches of deforestation assessment.

CHAPTER IV

Spatially explicit probabilistic models of forest fire and selective logging in the Brazilian Amazon

4.1. Abstract

In this chapter, multivariate probit models of forest fire and selective logging were designed for the Brazilian Amazon. I developed these models using variables that affect the occurrence of forest fire and selective logging throughout the region. Therefore, the effects of each variable on likelihood of forest fire and selective logging were estimated. In spite of the results of a forest fire probit model indicated that distance to deforestation is the most correlated factor to forest fires, a combination of factors (e.g. prolonged water deficit, selective logging, vegetation type, and forest fragmentation) were apparently the more realistic causes of forest fires in the Brazilian Amazon. In apparent opposition to forest fire probability estimates, the selective logging probit model demonstrated that logging activities were not significantly related to distance to deforestation events. In fact, distance to access roads and timber centers were the most significant statically and substantively factors affecting occurrence of selective logging events. The average total timber volume per hectare was significant statistically but not substantively, which indicated that abundance of timber sources was not as important as its accessibility for loggers in the period of analysis. Like forest fire probability, all factors combined (e.g. distance to roads and timber centers, timber volume, vegetation types, land status, etc.) seemed to define chances of selective logging occurrence. Although I could observe some

synergistic interactions between selective logging and forest fire, selective logging activities were spatially located predominantly in new frontiers of undisturbed forests, while most of forest fire events occurred in more fragmented forests patches next to older deforestation areas. Finally, field information indicated that the landowner's desire of converting natural forests into agricultural land may strongly affect forest fire probability. This factor, however, was not included in the forest fire probit model because it is considered a criminal action without previous authorization from the environmental agencies and, therefore, it is very difficult to accurately survey it in the Brazilian Amazon.

4.2. Introduction

As already discussed in Chapters 1, 2, and 3, selective logging and forest fire are becoming anthropogenic activities of special concern in tropical regions due they potential impacts both on people and the environment. Various authors have been studying these phenomena in the Brazilian Amazon and the resultant synergistic interaction among them. Uhl and Buschbacher(1985) and Uhl et al. (1991) observed that impacts by selective logging on undisturbed forests can be severe, involving forest canopy damages, dead slash vegetation, and degradation by logging infrastructure such access roads, skid trails, and patios. These forest disturbances can be substantial even upon the occurrence of a very selective timber harvesting event (Frumhoff, 1995). Consequently, forests damaged by selective logging become more susceptible to fires, and fire-maintained agricultural lands work as powerful ignition sources and fire can rapidly spread into adjacent and more flammable selectively logged forests (Uhl and Buschbacher, 1985). Furthermore, forest roads left behind by logging activities provide access to occupation of new frontiers by landless peasants and squatters (Uhl and Vieira, 1989).

In addition to forest disturbances by selective logging and deforestation, several other factors might be contributing to increase forest fire in the Brazilian Amazon. Studies conducted by Kuntz and Siegert (1999) and Siegert et al. (2001) indicate that severe drought can be observed during years of climatic events such as El Nino in the Amazon region. Such events substantially increase forest susceptibility to fire (Cochrane, 2001, Laurance and Williamson, 2001, Nelson, 2001). For example, Nelson (2001) reported that area and severity of forest fires varied according to vegetation type in the state of Roraima in which secondary and *igapó* (low land) forests were the most severely damaged vegetation types during the 1997-98 dry season in that region.

Based on that the evidence present in the literature, I conducted a spatiotemporal analysis using probabilistic models to assess probability of selective logging and forest fire occurring in the Brazilian Amazon. To reach this goal, I applied multivariate probit models and variables derived from remotely sensed data. Each variable represented a specific factor potentially affecting the spatial and temporal distributions of selective logging and forest fire throughout the region. I also used multi-temporal datasets for 1992, 1996, and 1999, including variables representing climatic, landscape, and land use characteristics such as vegetation types, water deficits, deforestation, and forest fragmentation.

The results of the final probabilistic models substantially improved the current understanding of spatiotemporal distribution of forest fires, selective logging, and their interaction. These results also contribute to improve land use and land cover change modeling, and the development of forest fire control and selective logging monitoring programs by governmental agencies in Brazil.

4.3. Methods

4.3.1. The setting

This research focused on tropical rainforests located within the Brazilian Amazon, which encompasses an area of approximately 5 million square kilometers and includes all of the states of Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, and portions of the Mato Grosso, Maranhão, and Tocantins. However, I centered my spatiotemporal analysis of selective logging and forest fire occurrence in a study region (Appendix D.1) within the Brazilian Amazon where signs of selectively logged and forest fires were most evident in Landsat imagery in 1992, 1996, and 1999 (Appendices C.12 to C.17). Therefore, I excluded those areas where these types of human activities were highly unlikely.

4.3.2. Datasets

4.3.2.1. Deforestation dataset

A deforestation dataset produced by the Tropical Rain Forest Information Center (http://www.trfic.msu.edu) at the Michigan State University was used in this study. This dataset involves a multi-annual classification of 229 Landsat scenes covering the entire Brazilian Amazon. Landsat images were individually classified into seven thematic classes: forest, deforestation, regrowth, cerrado, cloud, cloud shadow, and water using unsupervised image classification procedures. Three mosaics of the Landsat scenes available for the entire Brazilian Amazon for 1992, 1996, and 1999 (Appendix D.2) were used to perform the spatially explicit probabilistic models of fire and selective logging in the study region, and details of the deforestation dataset are presented in Table 4.1.

Table 4.1 Deforestation dataset characteristics

Dataset	Features	Format	Spatial resolution	Period of Analysis	Projection
Land use and land cover mosaic	Forest, deforestation, secondary regrowth, cerrado, clouds,and shadows	Arc/Info vector and grid	30m x 30m	1992, 1996, and 1999	Sinusoidal projection, Datum and Spheroid WGS84

4.3.2.2. Selective logging dataset

As previously addressed in Chapter 2 and 3, selectively logged forests were not included as a land use class in the deforestation dataset produced by the TRFIC at MSU because more sensitive remote sensing techniques are required to accurately detect and map their presence. Therefore, selectively logged forests were detected and mapped using a semi-automated (texture algorithm) technique and Landsat band 5 to detect log landings (i.e. log storage patios) and, subsequently, variable buffer zones were applied (180 and 450 meters) around patios to estimate the size of areas affected by selective logging.

Following Matricardi et al.(2007), visual interpretation was used to map selectively logged forests with visible canopy disturbance on Landsat images.

The combination of these remote sensing approaches showed 92.9% and 0.82 of overall accuracy and overall kappa statistic, respectively.

The selective logging dataset available at Global Observatory for Ecosystem Services (GOES), Michigan State University included three multi-temporal mosaics of selective logging of the entire Brazilian Amazon (Table 4.2).

Table 4.2 Selective Logging dataset characteristics

Dataset	Classification Features	Format	Spatial resolution	Period of Analysis	Projection
Selectively logged forest GIS layers (mosaic)	Binary classes (1 if selectively logged, 0 otherwise)	Arc/Info grid	30m x 30m	1992, 1996, and 1999	Sinusoidal, WGS84 Datum and Spheroid

Such mosaics included a binary classification of natural forests (1 if selectively logged, 0 if otherwise) for up to 38 Landsat scenes throughout the Brazilian Amazon for 1992, 1996 and 1999

The present study also included the selective logging mosaics for 1992, 1996, and 1999 produced by Matricardi et al. (2007) (Appendices C.14, C.15, and C.16)

4.3.2.3. Thematic maps

The present analytical effort included thematic maps of urban areas, road network, protected areas, vegetation types, timber centers, and state borders in the Brazilian Amazon. The urban area, road network, and state maps were digitized by SIVAM (2004) from datasets produced by the Brazilian Institute of Geography and Statistics (IBGE), derived from field surveillance and remotely sensed data. The vegetation map was compiled and digitized by SIVAM (2004) from dataset produced by the RADAMBRASIL Project in 1980 (Appendix D.3).

The map of timber centers in the Brazilian Amazon was composed of timber center locations reported by Lentini et al. (2003), and the map of urban areas produced by SIVAM (2004). The timber center locations were defined based on the spatial distribution of 1190 saw mills surveyed by the Amazon Institute of Man and Environment – IMAZON throughout the Brazilian Amazon in 1998. The identification of city location for each timber center was based on Lentini et al. (2002) and their geographic location was plotted accordingly on the map of urban areas (Table 4.3).

Table 4.3. Description of the thematic maps

Dataset	Features	Format	Original scale	Projection	Source
Map of road network	Lines and table of road types (paved, unpaved, access, etc.)	Arc/Info coverage and *.dbf	Derived from Landsat imagery, 30 m spatial resolution	Geographic, Datum SAD69	SIVAM IBGE
Map of the Amazon States	Polygons, arcs, table of the State borders	Arc/Info coverage and *.dbf	1:250,000	Geographic, Datum SAD69	SIVAM IBGE
Map of urban areas	Polygons, arcs, table of city locations and urban areas	Arc/Info coverage and *.dbf	1:250,000	Geographic, Datum SAD69	SIVAM IBGE
Map of protected areas	Polygons, arcs and table	Arc/Info coverage and *.dbf	1:250,000	Geographic, Datum SAD69	ISA IBAMA
Map of vegetation	Polygons, arcs, table of vegetation types	Arc/Info coverage and *.dbf	1:250,000	Geographic, Datum SAD69	SIVAM IBGE
Timber centers	Points and tables	Arc/Info coverage and *.dbf	1:250,000	Geographic, Datum SAD69	IMAZON

The road network map included different road types, which mostly included official roads constructed by the federal, state and local governments.

The road classification includes paved road, unpaved, secondary roads, and access roads. Logging roads and trails were not included. The state map included borders of all states within the Legal Brazilian Amazon. The map of urban areas included identification, location and administrative classification (i.e. capital, city, and village) of all urban areas in the Amazon region for 1999. Indigenous land, conservation unit classification (i.e. parks, ecological reserves, extractive reserves, national and state forests, etc), and military areas were included in the protected areas map. Appendix D.5 shows a composite map of road network, protected areas, and timber center location.

Finally, the vegetation map included several vegetation types and sub-types. The present analysis included 6 classes of forest types: dense, open, semi-deciduous, deciduous, transitional, and pioneer forests. By 1999, approximately 27%, 23%, 23%, 21% of the study area was covered by dense forest, open forest, transitional forest, and cerrado (savannah), respectively. Therefore, tropical rainforest was the predominant vegetation in the study region covering 73% of its territorial area by 1999.

All these thematic maps were used to support the spatial analysis of forest degradation by selective logging and forest fires in the Brazilian Amazon.

4.3.2.4. Timber volume in the Brazilian Amazon

In the 1970s the RADAMBRASIL Project conducted a forest inventory that included tree species identification and measurements (i.e. basal area and volume) within thousands of sample units throughout the Brazilian Amazon. In this study, I used a dataset digitized by SIVAM (2004) containing the geographic location and the total timber volume of tree species measured within 57,971 sample units generated by the RADAMBRASIL Project. In addition, a variogram model was created by using these sample points, and ordinary kriging using the values derived from this model was run in ArcGIS™. The variogram model used for ordinary kriging had an exponential curve, with a nugget of 2182.8, a range of 3,076,600, and a partial sill of 4460.1. As a result, a map of the timber volume per hectare was created for the Brazilian Amazon and then converted into a grid (Appendix D.5).

4.3.2.5. Water balance

Water balance is a good measure of the moisture available in a terrestrial ecosystem and, ultimately, can be a good indicator of forest fire flammability. The water balance dataset used in this analysis was generated by (Willmott, 1999) based in a modified procedure developed by Thornthwaite and Mather in 1955. Basically, the calculation procedure for this model included multiple variables such as: soil water-holding capacity, the gridded average-monthly precipitation, evapotranspiration, and temperature. The average water balance datasets for 1992, 1996 and 1999 were then used to identify areas with water deficit during the dry season[7] in these given years. Appendix D.6 shows the water balance for the Brazilian Amazon during the dry season (May to September) in 1999.

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[7] The dry season is defined as a time period from May to September, when a prolonged low precipitation and high temperature can be observed in the Amazon region. The dry season for the Northern Amazon, however, normally occurs from January to March.

4.3.3. Forest Fragmentation

Skole and Tucker (1993) introduced the concept of fragmented forests in the context of tropical deforestation studies. Deforestation was previously addressed through a binomial classification of forest and non-forest. These authors observed that forest fragmentation could affect larger areas than deforestation itself, especially in the context of the Brazilian Amazon. In their ground-breaking research, Skole and Tucker (1993) defined fragmented forests as forested areas smaller than 100 hectares surrounded by deforested lands, and edge effects as a series of ecological responses affecting a buffer zone distant up to 1 km from adjacent deforested areas.

Concepts drawn from Landscape Ecology have also been applied to enhance the understanding of the ecological implications of anthropogenic activities on forest ecosystems (Turner et al., 2001). Accordingly, I used two of the patch-based measures (patch area and fractal dimension) of landscape patterns proposed by Skole and Tucker (2001) to assess the presence of distinct levels of forest fragmentation in the study area. Patch area can be used to display the frequency distribution of number of patches and patch size. Therefore, a high frequency of small patch size is a good indicator of forest fragmentation intensity, although it disregards the shaping of the patches. Conversely, patch shape can be a good indicator of temporal changes in landscape patterns. For example, small forest patches tend to have simpler shapes than larger ones due to human activities and natural boundary effects, respectively. Thus, fractal dimension is a useful indicator of shape complexity for patches of different sizes (Turner et al., 2001).

$$d = \frac{\ln(A)}{\ln(P) + \ln(k)} \quad (1)$$

where d = fractal dimension, *A* = area of each patch, *P* = perimeter of each patch, and *k* = 0.25 constant value if the actual patch perimeter is used to estimate *P*.

By applying the equation 1, fractal dimension can depict the shape of each forest patch that may range from 1.0 to 2.0 for a straight line and a circle or square forest patch, respectively.

These two patched based measurements were applied in the study region using land use and land cover classification maps from 1992, 1996 and 1999. I used log transformed of path size (m^2) in order to minimize the effects of very large forest patches, and fractal dimension was applied using the equation 1. The constant k = 0.25 was applied to estimate the fractal dimension of forest patches. Forested areas are shown in Appendix D.2.

4.3.4. Modeling forest fie and selective logging probabilities in the Amazon

Spatial pattern of selective logging and forest fire, their impacts and interactions with other land use and socioeconomic variables were assessed using two multivariate Probit models. The Probit is a binary response model, which implies that the estimated probabilities will range between 0 and 1. This model uses the standard normal cumulative distribution function and its use is most indicated when the dependent variable is discrete and the partial effect of any independent variable is potentially not constant (Wooldridge, 2000).

The probit models were used to identify the factors influencing the probability of selective logging and forest fire occurrence throughout the study region within the Brazilian Amazon based on their spatial distribution, local biophysical characteristics, and socioeconomic factors.

According to (Wooldridge, 2000), the probit model can be defined as:

$$y^* = \beta_0 + x\beta + \varepsilon, \quad y = 1\ [y^* > 0], \tag{2}$$

where y^* is the unobserved or latent variable (in this study, a pixel representing forest fire) that satisfies a normal, homoskedastic distribution with a linear conditional mean; x is a vector of independent variables; β is a vector of unknown coefficients; and ξ is an independently distributed error term assumed to be normal with zero mean and constant variance σ^2. The indicator function requires that observations take 1 as their value if the event (forest fire) is true, and 0 if otherwise. Therefore,

$y = 1$ if $y^* > 0$, and

$y = 0$ if $y^* \leq 0$.

Based on this approach, the probability of forest fire and selective logging in the study region can be defined using equation 3:

$$P(y = 1\ |x) = P(y^* > 0|x) = P(\varepsilon > -x\beta|x) = \Phi(x\beta) \tag{3}$$

where, Φ (.) is the standard cumulative normal distribution function (cdf); x is a vector of independent variables, and β is a vector of unknown coefficients.

4.3.4.1. Forest fire conceptual model

Previous studies have shown that forest fire is a growing problem in the Brazilian Amazon due to different factors such as: the sprawl of ignition sources from fire-managed agricultural lands Uhl and Buschbacher (1985) and the increasing forest flammability (caused by greater fuel availability and drier microclimates) as natural forests become more fragmented Cochrane(2001) and Cochrane (2004) and disturbed by deforestation and selective logging activities (Uhl and Buschbacher, 1985, Uhl and Kauffman, 1990, Holdsworth and Uhl, 1997, Cochrane et al., 2004). Environmental conditions may also substantively increase forest flammability. For example, Uhl and Buschbacher (1985), Nepstad et al. (1999), Houghton et al. (2000) , and Nelson (2001) reported that fires are more likely during years of prolonged drought.

Many authors (Uhl and Buschbacher, 1985, Uhl and Kauffman, 1990, Holdsworth and Uhl, 1997, Cochrane and Schulze, 1998, Cochrane, 2001, Nelson, 2001, Cochrane et al., 2004) have observed that agricultural land is a major ignition source for forest fires in the Brazilian Amazon. In addition to that, I could observe during the fieldwork that fires frequently occur along roads and, consequently, one may need to take into account the importance of transportation networks as ignition sources. I could not find evidences, however, of lightning strikes as important ignition sources of forest fire. This finding is probably explained by the fact that most lightning strikes occur during the rainy season when forests are too moist to allow fire ignition. Therefore, I hypothesized that any forest fires observed in this study would be human-driven whether accidentally or intentionally.

In addition to the ignition sources of fire, forests are becoming increasingly fragmented and, hence, more susceptible to fires. Consequently, selective logging which has been reported as a major source of forest disturbances in the Brazilian Amazon (Nepstad et al., 1999, Skole et al., 2004, Asner et al., 2005, Matricardi et al., 2007) also is deemed as a cause of increased forest fire (Uhl and Buschbacher, 1985, Uhl and Kauffman, 1990, Holdsworth and Uhl, 1997, Cochrane and Schulze, 1998, Nepstad et al., 1999, Cochrane, 2001, Nelson, 2001, Cochrane et al., 2004). Additionally, small forest patches and larger forest edges left behind by the deforestation contribute substantially to forest fragmentation (Skole and Tucker, 1993, Cochrane et al., 2004, Skole et al., 2004). Once fragmented, tropical forests become more susceptible to fires (Cochrane, 2001, Cochrane et al., 2004).

Water balance is an important environmental factor that may contribute to increase forest fire susceptibility in tropical regions (Cochrane, 2001, Laurance and Williamson, 2001, Nelson, 2001). Forest fires are more likely to occur in tropical regions during the dry season, when precipitation is very low (Uhl and Buschbacher, 1985, Houghton et al., 2000) and during years of extreme moisture deficit and prolonged drought , where even undisturbed forests may become flammable (Nepstad et al., 1999, Nelson, 2001). For example, a prolonged water deficit such as the extreme drought observed during year of climatic events such as the 1997-98 El Niño (Kuntz and Siegert, 1999, Siegert et al., 2001) substantially increased forest flammability in the Amazon region.

The forest fire conceptual model was based on the assumption that three major factors may increase the probability of forest fire in the study region: ignition sources, forest disturbances, and environmental conditions. I created a vector of independent variables, which included the previously discussed biophysical and socioeconomic factors that affect forest susceptibility to fire. First, a dummy variable was created for the land status (1 if within protected areas, 0 if otherwise). It is expected that the land status of protected areas (e.g. ecological reserves, indigenous land, extractive reserves, national parks) should be a legal barrier for deforestation and selective logging activities (Pedlowski et al., 2005) and, therefore, a grid cell (unit of observation) representing forest fire is less likely to occur within their territorial borders. Dummy variables for each year of selective logging (1 if logged, 0 if otherwise) also were created. It is expected that selectively logged forests are more susceptible to fire than undisturbed forests because of the canopy degradation caused by logging lead to a rapid decrease moisture and humidity in logged forests (Uhl and Kauffman, 1990).

Subsequently, I created two continuous variables based on the Euclidean distances to agricultural lands (i.e. deforestation) and roads, which estimated the proximity of grid cells representing burned and non-burned forests to roads and deforested areas. Another continuous variable was created to represent the water deficit during the dry season of each year of analysis. As previously discussed, it is expected that forests under prolonged water deficit would be more vulnerable to fire than those under moisture conditions. Two other continuous variables (logarithm of forest patch size and fractal dimension) were created to represent landscape fragmentation, since smaller forest patch sizes and lower values of fractal dimension are likely to be more fragmented, therefore, more susceptible to fire.

I also created a set of dummy variables to represent vegetation factors, assuming that forest fires are more likely to occur in drier microclimate observed in deciduous, semi-deciduous, and transitional forests than in moisture microclimate observed in dense and open forests.

Finally, dummy variables were created to represent each state within the study region, which were intended to capture potential variations at state level due to different environmental legislation and law enforcement capabilities. As previously presented in Chapter 3, the bulk of selective logging and forest fire activities were detected in the states of Mato Grosso, Pará, and Maranhão in 1992, 1996, and 1999. These states are located within the so-called Arc of Deforestation created by the Brazilian Institute of Environment and Renewable Natural Resources- IBAMA as a priority region for forest fire control and prevention in the Brazilian Amazon (IBAMA, 2007).

Based on that, I tested the vector of the following independent variables (*x*) for the Probit model described in Equation 2:

- Protected areas (1 if within protected areas, 0 if otherwise)
- Proximity to agricultural lands (deforestation) (km)
- Proximity to agricultural lands squared
- Proximity to roads (km)
- Proximity to roads squared
- Logging in 1999 (1 if selectively logged in 1999, 0 if otherwise)
- Logging in 1996 (1 if selectively logged in 1996, 0 if otherwise)
- Logging in 1992 (1 if selectively logged in 1992, 0if otherwise)
- Water deficit (1 if water deficit persisted ≥ 5 months, 0 if otherwise)
- Forest patch size (ln transformed area)
- Fractal dimension (1 to 2)
- Vegetation type 1 (1 dense forest, 0 if otherwise)
- Vegetation type 2 (1 open forest, 0 if otherwise)
- Vegetation type 3 (1 semi-deciduous forest, 0 if otherwise)
- Vegetation type 4 (1 deciduous forest, 0 if otherwise)
- Vegetation type 5 (1 transitional forest, 0 if otherwise)

- Vegetation type 6 (1 pioneer forest0 if otherwise)
- Temporal variable 1 (1 if forest was burned in 1999, 0 if otherwise)
- Temporal variable 2 (1 if forest was burned in 1996, 0 if otherwise)

The control variables were indexed to a time scale (temporal variables) in the model. Thus, the interaction between time and other variables was assessed, which contributed to explain spatiotemporal changes of forest. Additionally, potential interactions between forest fires and very large distance from agricultural lands and roads (ignition sources) were also considered. This procedure required creating two new variables, distances to deforested areas and roads squared, which represented spatial patterns of forest fires geographically located at large distance from deforestation and roads.

4.3.4.2. Selective logging conceptual model

A multi-temporal assessment of selective logging in the Brazilian Amazon conducted by (Matricardi et al., 2007) showed that selectively logged forests increased more than 336% between 1992 and 1999. The vast majority of these anthropogenic activities were observed within the states of Para and Mato Grosso (Matricardi et al., 2007) and the logging industrial centers were clustered along major Amazon transportation axis (Nepstad et al., 1999, Lentini et al., 2003, Lentini, 2005). (Matricardi et al., 2007) also speculated that some biophysical and socioeconomic factors such as raw material for saw mills, environmental law changes occurred in 1996, and extreme droughts, might have contributed to increase intensity and area of selective logging. Indeed, (Uhl et al., 1997) reported that loggers were increasing both volume and number of tree species harvested in more mature logging regions in which timber products are becoming scarcer. As in the case of forest fires, given their legal status, protected areas also are deemed as offering a barrier for logging activities (Pedlowski et al., 2005). In this case, although the raw material may be abundant and economically viable, it is not legally accessible.

Therefore, it was assumed for the selective logging conceptual model that land legal status, raw material availability, transportation networks, and the geographic locations of the timber centers were the major factors driving loggers over natural forests. A dummy variable was created for the land status (1 if within protected areas, 0 otherwise). A grid cell (unit of observation) representing selective logging within protected lands is less likely to be observed. Dummy variables for each year of selective logging (1 if logged, 0 otherwise) also were created. (Matricardi et al., 2007) observed that selective logging substantially increased in area and intensity in Brazilian Amazon, growing approximately 73% and 345% in 1992-96 and 1992-99 periods, respectively.

Three continue variables were created to measure selective logging proximity to logging centers, roads, and deforestation. I expected that loggers have to operate at certain buffer distances from logging centers due to the transportation costs and, therefore, selective logging areas would tend to decrease as distance to logging centers increase. I also assumed that saw mills can not be easily relocated closer to sources of raw material because they are strongly attached to the consumption markets, major transportation axis, and labor and electricity availability. Similarly to logging centers, it was expected that undisturbed forests closer to the road networks and previous deforestation are more accessible and, therefore, more likely to be selectively logged than those located at larger distance from access roads and agricultural lands.

An additional continue variable was created to represent timber volume (m^3/ha. In this case, I assumed that loggers are also attracted by the amount of timber volume (m^3/ha) observed in undisturbed forest throughout a given area of interest. Finally, a set of dummy variables was created to represent vegetation factors, assuming that marketable tree species vary according to forest type and, therefore, some forest types should be more attractive for loggers than others. Based on these assumptions, I tested the vector of the following independent variables (*x*) using the Probit model described in Equation 2 for selective logging:

- Protected areas (1 if within protected areas, 0 if otherwise)
- Proximity to agricultural lands (deforestation) (km)
- Proximity to agricultural lands squared
- Proximity to roads (km)
- Proximity to roads squared
- Proximity to timber centers (km)
- Proximity to timber centers squared
- Timber volume (m^3)
- Forest patch size (ln transformed area)
- Fractal dimension (1 to 2)
- Vegetation type 1 (1 if dense forest, 0 if otherwise)
- Vegetation type 2 (1 if open forest, 0 if otherwise)
- Vegetation type 3 (1 if semi-deciduous forest, 0 if otherwise)
- Vegetation type 4 (1 if deciduous forest, 0 if otherwise)
- Vegetation type 5 (1 if transitional forest, 0 if otherwise)
- Vegetation type 6 (1 if pioneer forest, 0 if otherwise)
- Temporal variable 1 (1 if selectively logged in 1999, 0 if otherwise)
- Temporal variable 2 (1 if selectively logged in 1996, 0 if otherwise)

In the selective logging probit model the control variables were also indexed to a time scale (temporal variables), to allow the assessment of selective logging spatiotemporal changes. Finally, I created three variables (distances to deforested areas, roads, and timber centers squared) to observe the spatial distribution of selective logging at very large distances from logging centers, deforested areas, and road network.

4.3.4.3. Data sampling

As previously indicated, the present analytical exercise focused on a study region where evidences of selective logging and forest fire have been observed using remotely sensed data, including ´portions of the states of Pará, Mato Grosso, Tocantins, Acre, Rondônia, and Maranhão. This option helped to improve the sampling process and the statistical model performance. Analyses involved datasets for 1992, 1996, and 1999, which is the most recent year of mapping of forest fire and selective logging available for the Brazilian Amazon.

In this spatially explicit probabilistic analysis of selective logging and forest fires, a stratified random sampling was applied to collect spatial data from point locations. First, a vector of 5x5 km grid cell size was located evenly over the study region. Subsequently, one point was randomly located within each 25 km^2 grid cell (Figure 4.1).

The pixel was used as the unit of observation and, therefore, a unique value of the dataset was collected for each point of the sampling grid to represent forest fire (1 if burned, 0 if otherwise) and another to represent selective logging (1 if logged, 0 if otherwise) (Appendix D.1). Similarly, a pixel value was collected for each independent variable and point location.

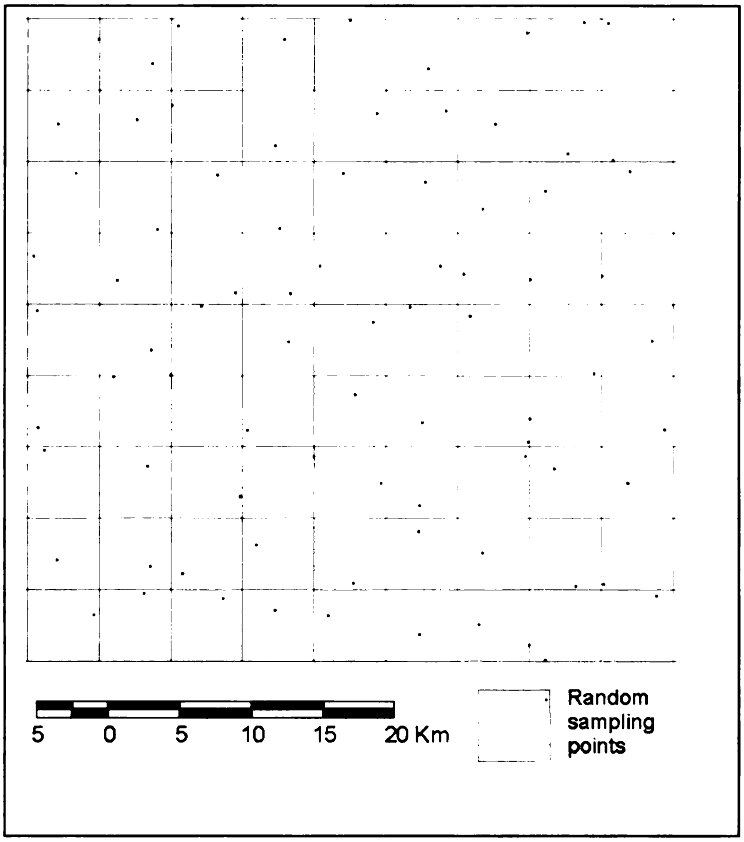


Figure 4.1 Stratified random sampling used to collect spatial data for the probit model of forest fire and selective logging in the study region.

This stratified sampling procedure was designed to reduce the effects autocorrelation in the dataset (Anselin 2002, Arima et al. 2007). The random distribution of points within a regular sampling network can reduce effects of potential coincidence between spatial patterns of landscape and sampling points (Burrough, 1998). Stratified and random sampling combined can minimize statistical biasness of as given model (Burrough, 1998, Anselin, 2002) and the error term in the probit models due to spatial autocorrelation in the data population (Chomitz and Gray 1996, Arima et al 2007).

4.4. Results and Discussion

4.4.1. Forest fire probabilistic model

The analysis of forest fire dataset showed that although forest fire observation was relatively rare (unconditional probability of forest fire = 0.77%) in the study region, encompassing more than 1.7 million km^2 of tropical rainforests by 1999, it has increasingly become a socioeconomic and environmental concern in the last decades. The statistical significances of the previously discussed factors that affect forest fire probability were estimated using a probit regression model (Table 4.4).

The estimated model predicts that forest fires are inversely related to distance to deforestation (agricultural lands). The probability of forest fires proved to be significant both statistically and substantively. Forest fires increased as distance to deforestation decreased. For example, by decreasing distance to deforestation areas from 10 to 0 km would increase forest fire by 42%. The predicted non-linear effect of distance to deforestation in the probability of forest fire is presented in Figure 4.2.

Table 4.4. Probit regression analysis results of forest fire

Variables and Constant	Coefficient	Rob. St. Error	P > |z|	dF/DX
Protected areas (1 if yes, 0 otherwise)	-0.1955	0.0681	0.004	-0.00002
Distance to deforested areas (km)	-0.1594	0.0144	0.000	-0.00002
Distance to deforested areas squared	0.0011	0.0001	0.000	0.0000001
Distance to roads (km)	-0.0294	0.0043	0.000	-0.000003
Distance to roads squared	0.0002	0.00003	0.000	0.00000002
Selectively logged 1999 (1 if yes, 0 otherwise)	0.7075	0.0567	0.000	0.0004
Selectively logged prior to 1999 (1 if yes, 0 otherwise)	0.5716	0.0853	0.000	0.0002
Water deficit between May and September	0.0021	0.0008	0.011	0.0000002
Patch size (log area m2)	-0.0113	0.0025	0.000	-0.000001
Fractal dimension (1 to 2)	-0.2445	0.0444	0.000	-0.00003
Vegetation type: (omitted Pioneer)				
Dense forest	0.2033	0.0970	0.036	0.00003
Open forest	0.4145	0.0969	0.000	0.00007
Semi-deciduous forest	0.4337	0.1591	0.006	0.0001
Deciduous forest	0.0210	0.1429	0.883	0.000003
Transitional forest (Forest/Savannah)	0.4555	0.0936	0.000	0.00009
State: (omitted Acre)				
Pará	0.9668	0.2224	0.000	0.0002
Maranhão	0.7751	0.2276	0.001	0.0005
Tocantins	0.3608	0.2517	0.152	0.0001
Mato Grosso	1.0190	0.2224	0.000	0.0005
Rondônia	0.1016	0.2342	0.664	0.00001
Year: (omitted 1992)				
1999	0.5476	0.0458	0.000	0.0001
1996	0.3067	0.0474	0.000	0.00005
Constant	-2.8753	0.2439	0.000	
Log likelihood = -4883.9944; Pseudo R^2 = 0.2517; n= 144,793				

I also estimated the effect of distance to deforestation in quadratic form. As opposed to the estimated parameter of the level term, the squared term was positive indicating that probability of forest fires eventually increases as distance to deforestation increases at very large distances from deforestation. Indeed, I could observe some isolated forest fires in the study region, geographically located away from deforestation areas, which could be associated with selective logging activities.

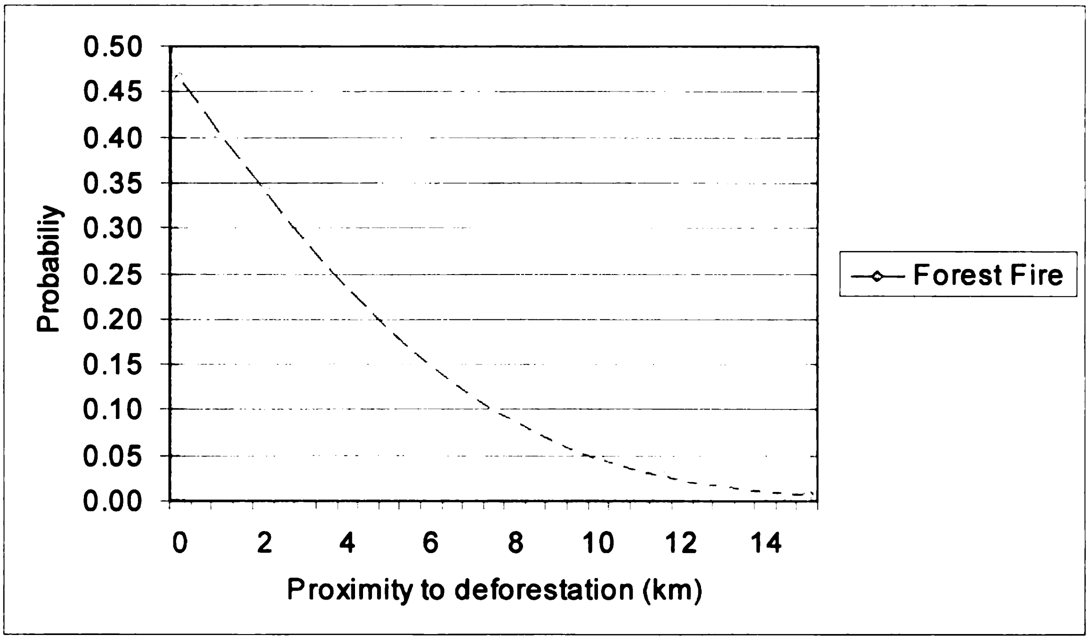


Figure 4.2. Probability of forest fire with respect to distance to deforestation

Similarly to distance to deforestation, the estimated model predicts that forest fire occurrence is inversely related to distance to roads. By decreasing distance to roads from 50 to 0 km, forest fires would increase 7%. The predicted non-linear effect of distance to roads in the probability of forest fire is presented in Figure 4.3.

The effect of distance to roads in quadratic form is positively related to forest fires, indicating that probability of forest fires eventually increases as distance to roads increases at very large distances from roads. It is likely that this type of spatial pattern of forest fire occurs during logging operations in new timber sources located at large distance from roads.

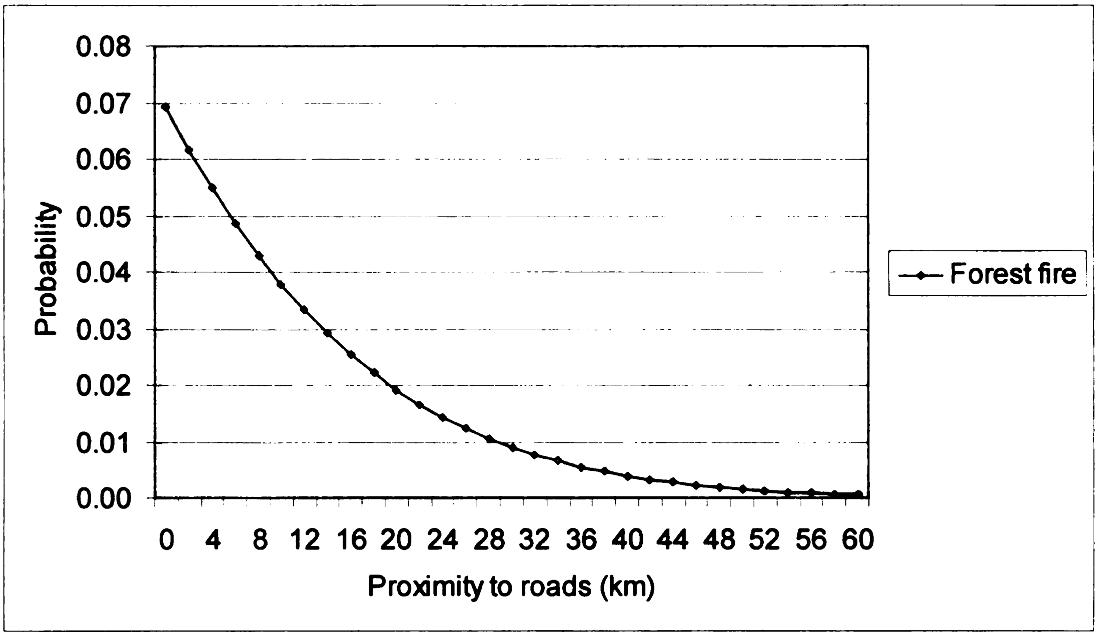


Figure 4.3. Probability of forest fire with respect to distance to roads

The water deficit observed in the study region significantly contributed to increase the likelihood of forest fires at 95% probability. The direct effect is that higher water deficit level increases forest flammability. For example, by increasing the water deficit from 0 to 200 millimeters during the dry season (May to September) forest fire likelihood would increase 2.5%. The predicted effect of water deficit in the forest fire likelihood is presented in Figure 4.4.

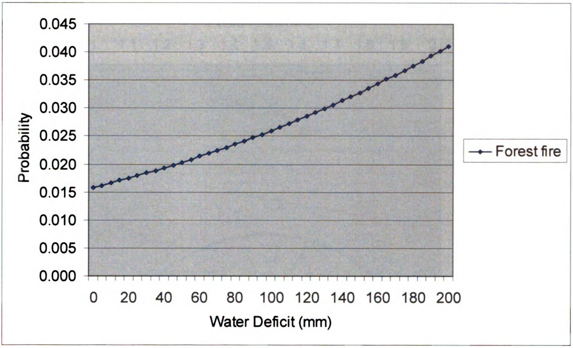


Figure 4.4. Probability of forest fire with respect to water deficit from May to September

The model predicted that the effect of an increase in forest fragmentation was significantly related to forest fires. The results showed that the applied measurements of forest fragmentation (forest patch size and fractal dimension) are significant explanatory variables, because the average probability of forest fires increased by 1% and 2% as fractal dimension decreased from 2 to 1 and forest patch size decreased from 533,000 km^2 to 1 km^2, respectively. These increases in absolute probabilities might be considered small in absolute terms, but they are relatively high considering that the unconditional probability of forest fire is 0.77% in the study region. The predicted effect of forest patch size and shape (fractal dimension) in the probability of forest fire is presented in Figure 4.5.

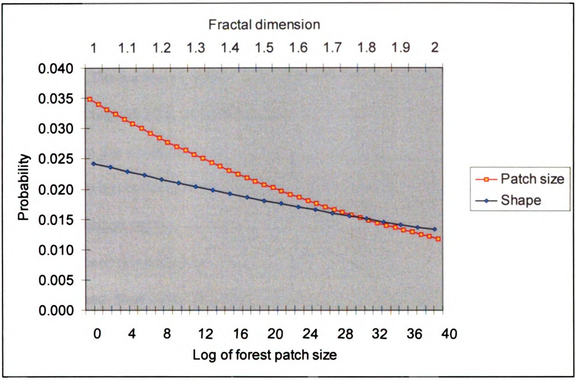


Figure 4.5. Probability of forest fire with respect to forest patch size and shape

Meanwhile, selective logging directly affects forest susceptibility to fires. When compared to undisturbed forests, newly and previously detected selective logging areas significantly increased the chance of fire 3.4% and 2.7%, respectively. Selective logging contributes to increase canopy openness and decrease moisture (Uhl and Kauffman, 1990), and hence, higher forest flammability. In addition to selective logging effects, probability of forest fires was 1% greater outside of protected areas than inside of them. This result supports, at least temporarily, the assumption that environmental laws and conservation policies for protected areas has been successfully applied in the Brazilian Amazon, contributing to impede or slow anthropogenic activities (e.g. forest fires) Most of the vegetation dummy variables were statistically significant. Open, semi-deciduous, and transitional forests with 2% of likelihood of forest fires were the most fire-prone forest types by holding all other independent variables fixed at mean value. Dense forest, with 1% of likelihood of forest fires was the least fire prone forest type at 95% probability. Deciduous forest was not statistically different from the omitted forest type (pioneer vegetation). These results show that dense forest is the predominant and least fire prone vegetation type in the Brazilian Amazon region. However, open and transitional forests become of special concern because they were two-fold more likely to fire than dense forest, and, combined, they cover approximately 46% of the study area. The predicted effect of forest types, state political-administrative peculiarities, selective logging, protected areas, and temporal variables on the probability of forest fire is presented in Figure 4.6.

The state dummy variables for Rondônia and Tocantins were not statistically different from the omitted state (Acre) in terms of forest fire probability. The dummy variables for Pará, Maranhão, and Mato Grosso were both statistically and substantively significant. Mato Grosso has 5.7% greater chance of experiencing fire than the omitted state, while Pará and Tocantins have 5.4% and 4.4% likelihood of fire, respectively. These results show that Mato Grosso, Para, and Tocantins are the most fire-prone states in the Brazilian Amazon by holding all other factors constant at mean value. However, the extent of the "arc of forest fire" as defined by the present study does match perfectly the arc of deforestation defined by (IBAMA, 2007). It can be hypothesized that potential differences in state environmental policies and legislation might be affecting forest fire likelihood in the Brazilian Amazon.

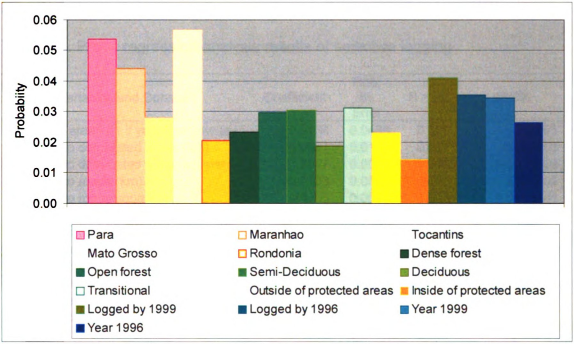


Figure 4.6. Probability of forest fire with respect to forest types, states, selective logging, protected areas, and year of analysis

Finally, the multi-temporal dummy variables proved to be statistically significant. The year 1999 and 1996 had 3.4% and 2.6% greater chance of experiencing fire than the omitted year (1992). These results contribute to explain the temporal changes of forest fires which showed to be consistently and significantly increasing along the period of analysis.

4.4.2. Selective logging model

Based on the selective logging dataset the unconditional probability of selective logging is 1.15% for the study region, which encompassed more than 1.7 million km^2 of tropical rain forests by 1999. Additionally, the statistical significances of various factors that affect selective logging probability were estimated using a probit regression model. The results of probit regression analysis of selective logging are presented in Table 4.5.

Table 4.5. Probit regression analysis results of selective logging

Variables and Constant	Coefficient	Rob. St. Error	P > |z|	dF/DX
Protected areas (1 if yes, 0 otherwise)	-0.3168	0.0486	0.000	-0.0001
Distance to deforested areas (km)	0.0051	0.0132	0.697	0.000003
Distance to deforested areas squared	-0.0017	0.0009	0.076	-0.0000009
Distance to roads (km)	-0.0383	0.0031	0.000	-0.00002
Distance to roads squared	0.0003	0.0000	0.000	0.0000001
Distance to timber center (km)	-0.0058	0.0006	0.000	-0.000003
Distance to timber center squared	-0.0000004	0.0000	0.873	-0.0000000002
Timber volume (m3/ha)	0.0009	0.0004	0.031	0.0000005
Vegetation type: (omitted Pioneer)				
Dense forest	0.4229	0.1054	0.000	0.0003
Open forest	0.3101	0.1106	0.005	0.0002
Semi-deciduous forest	0.2576	0.1754	0.142	0.0002
Deciduous forest	-0.0714	0.1596	0.655	-0.00004
Transitional forest (Forest/Savannah)	0.6567	0.1071	0.000	0.0008
State: (omitted Acre)				
Pará	0.9108	0.1948	0.000	0.0008
Maranhão	1.2005	0.1980	0.000	0.007
Tocantins	-0.4176	0.3580	0.243	-0.0001
Mato Grosso	0.9233	0.1940	0.000	0.001
Rondônia	-0.1841	0.2086	0.378	-0.00008
Year: (omitted 1992)				
1999	0.6677	0.0297	0.000	0.0007
1996	0.2478	0.0323	0.000	0.0002
Constant	-3.1936	0.2251	0.000	
Log likelihood = -6947.22 ; Pseudo R^2 = 0.236; n= 144,793				

Based on the model results, I estimated the effect of distance to deforestation in linear and quadratic forms. As opposed to the forest fire probit model, the selective logging probit model estimated that neither the parameter of the level term nor the squared term were statistically significant, indicating that distance to deforestation has no effects in probability of selective logging. The estimated model predicted that selective logging is inversely related to distance to roads and, therefore, selective logging increases as distance to roads decreases. Probability of distance to roads proved to be statistically significant. For example, a decrease in distance to roads from 30 to 0 km would increase selective logging by 2.8%. Similarly, selective logging is inversely related to distance to timber centers. The probability of distance to timber centers was also statistically significant. These results show that natural forests become less attractive to loggers if they are obligated to move away from roads and logging centers to harvest timber. The predicted non-linear effect of distance to roads and logging centers in the probability of selective logging is presented in Figure 4.7.

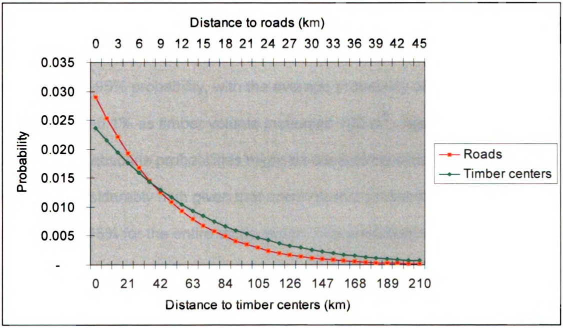


Figure 4.7. Probability of selective logging with respect to distance to roads and timber centers

Meanwhile, I also estimated the effect of distance to roads and logging centers in quadratic form. As opposed to the estimated parameter of the level term, the squared term of distance to roads was positive indicating that probability of selective logging eventually increases as distance to roads increases at very large distances from roads. This supports the assumption that loggers, although reluctantly, could direct their attention toward undisturbed forests geographically located farer away from existing road networks if timber sources become too scarce in those forests close to the road network .The estimated parameter of the squared term of distance to timber centers was not statistically significant, which indicate no effect of distance to timber centers at very large distances from saw mills in the probability of selective logging occurrence.

The model predicted that the effect of an increase in timber volume was positively related to selective logging. The results showed that timber volume is significant at 95% probability, with the average probability of selective logging increased by 0.1% as timber volume increased 100 m^3. Again, although such increases in absolute probabilities might be considered small in absolute terms, they are considerably high given that unconditional probability of selective logging is 1.15% for the entire study region. The predicted non-linear effect of timber volume in the probability of selective logging is presented in Figure 4.8.

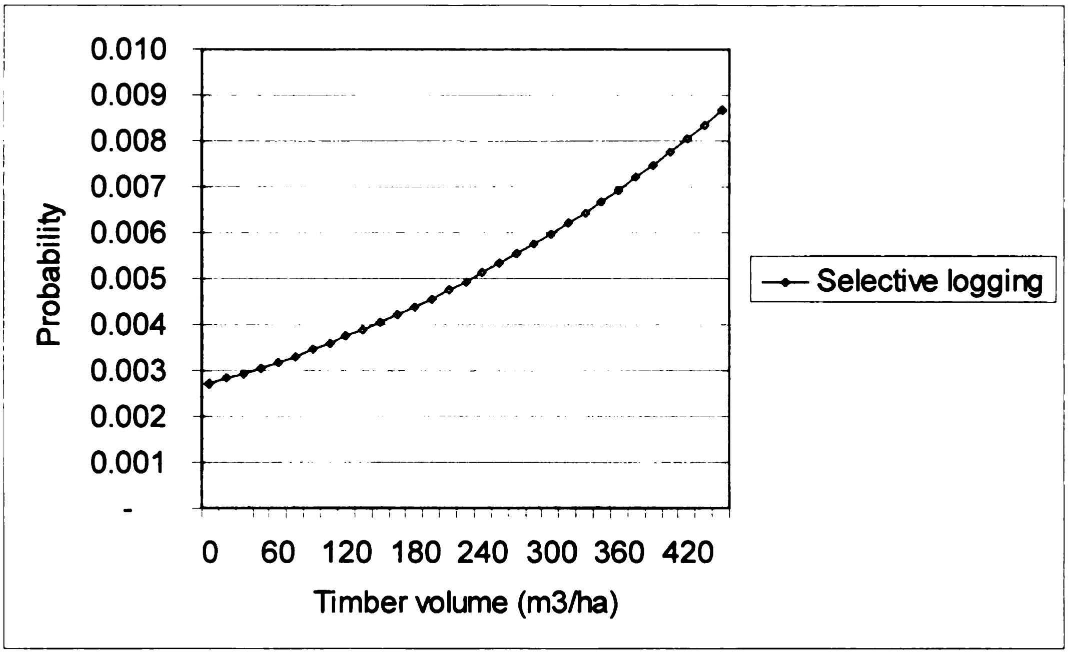


Figure 4.8. Probability of selective logging with respect to timber volume

Vegetation types

The vegetation dummy variables for dense, open, and transitional forests were all statistically significant. Transitional forest, with 0.9% of likelihood of selective logging was the most selective logging-prone forest type when all other factors are held constant at mean value. Dense and open forests showed 0.7% and 0.6% of likelihood of selective logging, respectively. Deciduous and semi-deciduous forests were not statistically different from the omitted forest type (pioneer vegetation). Although transitional forest is not the largest forest type and does not have the highest timber volume per hectare, it showed to be the most attractive ecotype to loggers. As previously presented, transitional forest also have been object of more forest fires than any other forest types. The predicted effect of forest types, states, protected areas, and temporal variables in the probability of selective logging is presented in Figure 4.9.

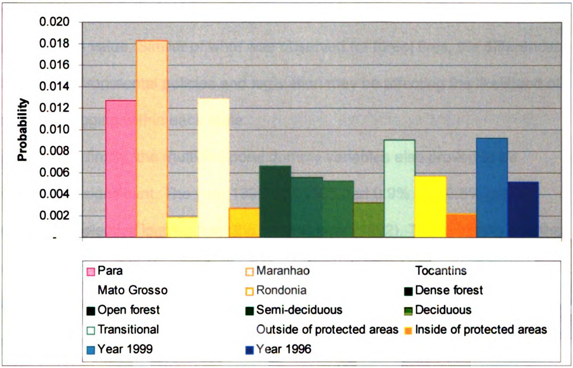


Figure 4.9. Probability of selective logging with respect to states, vegetation types, protected areas, and year of analysis

The probability of selective logging was three-fold greater outside than inside of protected areas with 0.6% and 0.2% of likelihood of selective logging, respectively. This result shows that protected areas have been reasonably effective in impeding or even slowing the pace of selective logging in the Brazilian Amazon

The state dummy variables for Rondônia and Tocantins were not statistically different from the omitted state (Acre) in terms of selective logging probability. The dummy variables for the states of Pará, Maranhão, and Mato Grosso were statistically significant. Natural forests located within the state of Maranhão have 1.8% greater chances of selective logging than the omitted state (Acre), immediately followed by forests located in Mato Grosso and Pará, both with 1.3% likelihood of selective logging and by holding all other factors constant at the mean value. Similar of what was observed for forest fires, the differences in state environmental policies and legislation may be affecting the likelihood of selective logging within each state.

And, finally, the multi-temporal dummy variables also proved to be statistically significant. The year 1999 and 1996 had 0.9% and 0.5% greater chance of selective logging than the omitted year (1992). These results and the results presented in chapter 2 and 3 show that selective logging activities are increasing in area, intensity, and over time in Brazilian Amazon. (Matricardi et al., 2007) speculated that major factors contributing to the increase of selective logging during the period of analysis were the changes in the Brazil's environmental law, the scarcity of raw material for timber industries, and the occurrence of extreme climatic events. Indeed, (Uhl et al., 1997) had observed that loggers were going farther searching for new timber sources (undisturbed forests) as well as revisiting previously logged forests for species that recently became marketable.

4.5. Conclusions

The results derived from the two probit models could explain important spatiotemporal dynamics of selective logging activities and forest fires in the Brazilian Amazon. Based on these results, the occurrence of forest fires were highly correlated with distance to deforestation. This result is supported by Uhl and Buschbacher (1985) who observed that agricultural lands are important ignition sources for forest fires in the Brazilian Amazon. The likelihood of forest fire events is even greater if additional anthropogenic and environmental factors that may increase forest flammability are considered. For example, selectively logged forests were more susceptible to fire than undisturbed forests. This fire susceptibility due to selective logging, however, tends to decrease as forests recover from logging impacts and, four years following selective logging activities, forest moisture can be similar to undisturbed forest (Holdsworth and Uhl, 1997). It is very important to point out that although selective logging seemed to be a factor fueling the increase of forest fires in the study region during the period of analysis, a large amount of selective logging activities and forest fires were spatially distinct events. While distance to deforestation is highly related to forest fires, this factor was not statistically significant in selective logging probability. For instance, the reality of timber scarcity in the old frontier has forced loggers to move ahead of deforestation frontier searching for new timber sources in undisturbed forests (Schmink and Wood, 1992, Pinedo-Vasquez et al., 2001).

.Prolonged water deficit also showed to be an important factor that might increase likelihood of forest fires. This result is also corroborated by different authors (Uhl and Buschbacher, 1985, Nepstad et al., 1999, Houghton et al., 2000, Nelson, 2001) who have observed that extreme droughts can increase likelihood of forest fires in tropical regions. Complementarily, (Nelson, 2001) reported that even undisturbed forests became flammable in the Brazilian Amazon upon a severe drought as the one related to the El Niño event of 1997/98. Similarly, forest fragmentation significantly contributed to increase the chances of forest fires. Indeed, deforestation activities are responsible for creating non-continuous and small forest patches and for increasing forest edges with agricultural lands (Skole and Tucker, 1993, Cochrane et al., 2004, Skole et al., 2004) that results in greater forest flammability (Uhl and Kauffman, 1990, Cochrane, 2001, Cochrane et al., 2004). This anthropogenic phenomenon was studied by (Cochrane, 2001), who concluded that forest fires were strongly correlated with fragmented forest edges in a study site located in the state of Para, Brazil.

In additional to the previously discussed factors, I also observed that probability of forest fires and selective logging varied according to forest types. It is presumable that potential differences in soil and forest moisture present in these ecosystems may affect forest fire susceptibility. In this analysis, open, semi-deciduous, and transitional forests were more likely to get on fire than dense and deciduous forests. This effect of vegetation type on forest fire probability is supported by (Nelson, 2001) who observed that secondary and *igapó* forests were more vulnerable to fire than any other vegetation types during the El Niño event of 1997-98 in the state of Roraima. Similarly, selective logging activities mostly occurred in transitional, dense, and open forests, which are the predominant vegetation types in the Brazilian Amazon. Transitional forests, however, showed slightly higher probability of selective logging than dense and open forests. In this case, I hypothesized that economic factors (e.g. lower harvesting cost and higher productivity) are driving loggers towards this particular forest type.

Forest fire and selective logging likelihood also varied according to the land ownership status. The legal status of protected areas seemed sufficient to, at least, decrease the likelihood of the occurrence of fire and selective logging within their territorial boundaries. However, given the observed increase of selective logging and forest fire between 1992 and 1999, it seems reasonable to expect that human pressure will increase in the future over the natural resources existent within the protected lands established in the Brazilian Amazon. Pedlowski et al. (2005) have already detected the occupation of areas and exploitation of natural resources within the borders of protected lands in the state of Rondônia.

Meanwhile, the greatest chances of forest fire and selective logging were found in the states of Pará, Mato Grosso, and Maranhão. These states fall within the infamously famous “arc of deforestation” defined by IBAMA (2007). Additionally, the states of Mato Grosso and Para were reported as responsible by most of selective logging detected using remotely sensed data in 1992, 1996, and 1999 in the Brazilian Amazon (Matricardi et al., 2007). Eventual differences in state environmental legislation and law enforcement capabilities may be a factor that promotes or hamper the occurrence of selective logging activities and forest fires.

In terms of temporal changes, the results showed that selective logging and forest fires significantly increased between 1992 and 1999. (Matricardi et al., 2007) mentioned that scarcity of timber resources, changes in environmental law, and extreme climatic events are perhaps the most important factors that contribute to increase selective logging in the period of analysis. I would hypothesize that the process of increasing socioeconomic pressure over undisturbed forests will continue, unless intensive environmental monitoring and law enforcement combined with governmental incentives for alternative uses of land forest resources are implemented in Brazilian Amazon.

I also hypothesize that at least half of forest fires detected in 1992 and 1996 were 'intentional' rather than 'accidental' fires, which indicates that landowners intended to burn those forests in order to achieve rapid conversion to agricultural lands. This inference is supported by the results shown in Chapter 3 that indicated that more than 50% of burned forests detected in 1992 and 1996 had been deforested by 1999. This factor, however, was not included in the presented probabilistic models.

Finally, it is my hope that the bulk of the results of this research can be used in one hand the expand the modeling of land cover change in the Brazilian Amazon, and on the other hand, also be used to improve governmental programs aimed at enhancing the control of forest fires and the environmental monitoring in the Brazilian Amazon region.

CHAPTER V

Concluding Remarks

5.1. Seating the current study in the context of global change research

In 2000, the area of the Earth covered with forests was estimated as being around 39 million square kilometers. Most of those forest areas were located in tropical areas (47%) and boreal zones (33%). The rest of the forested areas (18%) were located in temperate and subtropics regions. Most of the forests (95%) were then classified as natural forests and a smaller fraction (5%) as forest plantations (WRI, 2000). Meanwhile, tropical forests are estimated to store 460 to 575 billion metric tons of carbon, an average of 180 metric tons of carbon per acre (NASA, 1998). Therefore, the highest carbon and biodiversity losses occur when a high biomass forest area is converted into low biomass systems such as pasture or agriculture; releasing carbon and other trace gases to the atmosphere while natural habitats are gravely disturbed. The release of trace gases into the atmosphere enhances the Greenhouse effect which contributes to higher temperatures and, consequently, to dramatic global climatic changes (Skole and Tucker, 1993, NASA, 1998, Skole et al., 2004).

Deforestation (i.e. conversion of natural forests to non-forest land covers) is annually destroying a significant portion of the world forests. The gross and net rates of global forest loss averaged 17 and 13 million hectares annually, in the 1980s. Moreover, the gross and net rates of global deforestation grew to an average of 14.6 and 9.4 million hectares annually in the 1990s. The 1990s rates of annual forest loss correspond to 0.4% globally and 0.8% in the tropics.

Consequently, the highest deforestation rates have been observed in developing countries in the tropics (FRA, 2005).

Deforestation in the tropics is a critical factor that has several implications for biological diversity, local habitats, and carbon cycle at global scale (Skole and Tucker, 1993, Skole et al., 2004). Approximately 15.4 and 16 million hectares of forest loss was annually observed in tropical countries during 1980-90 and 1990-00 periods, respectively (Matthews, 2001). More specifically, multi-temporal measurements of deforestation in the Brazilian Amazon provided by (INPE, 2007) demonstrate that more than 2 million hectares of natural forests were slashed annually from 1978 to 2005 in the region.

In addition to deforestation, several other processes of land use and land cover change may increase forest degradation in tropical regions such as forest disturbances by selective logging, forest fires, and forest fragmentation (Skole et al., 2004). Skole and Tucker (1993) estimated that areas of disturbed forests due to forest patch isolation and its edge effects in the 1980s were 150% larger than deforested area itself in the Brazilian Amazon. Because of fragmentation, forests will become more susceptible to fire due to an increase of forest disturbances associated to edge effects including the exposure to fires (Cochrane et al., 2004). Based on sawmill survey in the Brazilian Amazon, Nepstad et al.(1999) estimated that the current carbon flux estimates for the Amazon region may be underestimated because of logging areas that have not been accounted for.

Nevertheless, in spite of the important contribution of these land use processes to global climate change, only a few attempts have been made to detect and measure forest disturbances, and its extent and impacts using remotely sensed data gathered for tropical regions. As a result, the total area of forest damaged by human activities may have been underestimated. Therefore, relevant questions have yet to be addressed before a better understand of selective logging and forest fire dynamics, their impacts on tropical forests, and their interactions with other land use types is achieved.

In this research, based on data obtained remotely and in field studies, I presented new estimates of the extent of selectively logged and burned forests for the Brazilian Amazon basin for 1992, 1996, and 1999. I also estimated the impacts caused by selective logging and forest fire in the region. The results show that the total combined areas of selectively logged and burned forest increased from approximately 11800 km^2 to 35600 km^2 from 1992 to1999. Selective logging alone was responsible for 60.4% of forest disturbances in the studied period. My estimates indicate that the total active areas of selective logging and forest fire in the Brazilian Amazon have substantially increased from 5468 km^2 to 7620 km^2 and from 7620 km^2 to 17439 km^2 in 1992-1996 and 1996-1999 periods , respectively.

These amount of disturbed forests by selective logging and forest fires represent additional land use types that have yet to be properly accounted for. Skole et al. (2004) affirmed that these processes of forest degradation can substantially degrade tropical forests and increase loss of biomass. Furthermore, the impact of selective logging on undisturbed forests tropical forests creates a net carbon flux equal to approximately 4-7% of the annual carbon release generated by deforestation (Fearnside, 1997), which can be severely aggravated by forest fires (Uhl and Kauffman, 1990).

The intensity of forest disturbances is also increasing in the Brazilian Amazon. As previously mentioned, selective logging was responsible for the largest extent of forest disturbance Amazon-wide. Forest fires, however, were responsible for the greatest impact on canopy cover, causing an average of 18.8% of canopy loss and even greater average of 27.5% of canopy loss if forest fire and selective logging results were combined. This result is supported by (Uhl and Kauffman, 1990) who observed that forest fires in tropical forest can be devastating because of their natural low resistance to fire. Meanwhile, selective logging was responsible for around of ~2% of forest canopy losses. These results indicate that although selective logging may destroy 40-50% of canopy cover in particular study sites (Uhl and Vieira, 1989, Verissimo et al., 1992), it has lower impacts on forest canopy cover at the regional scale.

Finally, the results of this analysis must be considered conservative, since under different circumstances, the most cryptic forest degradation by selective logging and forest fires cannot be properly detected. Indeed, Matricardi et al. (2005) and Matricardi et al. (2007) observed that very low intensity selective logging cannot be easily detected using remote sensing approaches. This type of forest disturbance, however, does not cause substantial environmental impacts on natural forests and on fluxes of carbon dioxide.

5.2. Research questions revisited

- *Is selective logging and forest fire causing more forest degradation than otherwise would occur?*

According to INPE (2007) estimates, a total area of 440186 km^2, 517065 km^2, and 569269 km^2 of tropical forests in the Brazilian Amazon had been deforested by 1992, 1996, and 1999 respectively. Those estimates from INPE also indicate an average increase of deforestation of 18331 km^2 $year^{-1}$ between 1992 and 1999. The results of the present research indicate that the total area affected by selective logging and forest fire correspond to 2.7%, 3.2%, and 6.3% of total deforestation by 1992, 1996, and 1999, respectively. In addition, results showed that active selective logging and forest fire represented an additional of 27.4%, 38.1%, and 87.3% to the outright increase of deforestation in 1992, 1996, and 1999, respectively. Therefore, selective logging activities and forest fires are substantially affecting large extents of forested areas in the Brazilian Amazon. Further results from the case study in Mato Grosso indicate that this trend in forest degradation by selective logging and forest fires may persist, while natural resources are abundant and accessible in a given area. However, forest fires appeared to be the most aggressive type of forest disturbance, causing an average decrease of 18.8% in forest canopy cover. When forest fires and selective logging were combined, the effect is even greater, leading to an average decrease of 27.5% in forest canopy cover, whereas selective logging alone contributed to a decrease of 2% of forest canopies in the study region.

Despite the fact that selective logging only contributed to a decrease of 2%, this process impacted the largest extent of natural forests in the Brazilian Amazon during the period of study. Nevertheless, this study demonstrated that the area covered with natural forests under the impacts of fires and selective logging is rapidly increasing, making these land uses of greater concern. Finally, forests impacted by fires and selective logging showed the ability to rapidly recover from these disturbances if left to fallow, for periods ranging from 5 to 10 years. Therefore, forest regeneration is another very important phenomenon that must be further investigated because it may indicate forest uses and management alternatives aimed at mitigating impacts brought about by anthropogenic activities in tropical regions.

- *Can we accurately measure these anthropogenic activities in the Brazilian Amazon basin?*

The automated remote sensing technique based on Spectral Mixture Analysis was an efficient methodological approach for estimating the area affected by forest fire in the Amazon region. This approach was previously employed by Cochrane and Sousa Jr (1998) and Souza et al. (2003) to detect selectively logged and burned forests using Spot imagery in a case study in Para. I further improved, tested, and validated this remote sensing technique for a 30000 km^2 study site in the state of Mato Grosso. The accuracy assessment results of this forest fire detection approach indicated 96.0% and 0.91 of overall accuracy and overall kappa statistic, respectively. This technique showed high sensitivity to changes in Non-Photosynthetic Vegetation (NPV) within tropical forests. NPV grows substantially when forests are affected by fires, and its effects are prolonged throughout contiguous forested areas. Indeed, (Nelson, 2001) reported that even ground fires could be detected using Landsat TM imagery. Therefore, based on my remote sensing analyzes and findings of the field studies, I believe that the most fire-impacted forests were accurately detected and mapped.

The semi-automated texture analysis and visual interpretation combined also showed to be an efficient remote sensing approach to detect and estimate areas affected by selective logging. The results of the research conducted by Matricardi et al. (2007) showed that most of selectively logged forests were detected and mapped using semi-automated and visual interpretation approaches. These remote sensing approaches showed 92.9% and 0.82 of overall accuracy and overall kappa statistic, respectively.

However, I must advise that the results of these methods must be considered as conservative, since, in different circumstances, some cases of selectively logged and burned forests could not be detected. I hypothesize that very low intensity ground fires that did not affect canopy cover were difficult to detect using remote sensing approaches. Similarly, selective logging activities may not be easily detectable using Landsat imagery because of lack of soil exposure by logging features (patios, access roads, etc.) on the ground.

- Where are the most severe selective logging and forest fire occurring in that region? Why selective logging and forest fire are occurring there and not somewhere else?

Based on the findings of the basin-wide results, most of the impacted forests by selective logging and fires were detected in Mato Grosso, Pará, and Maranhão, which are geographically located within the so-called "Arc of Deforestation" defined by the Brazilian Institute of Environment and Renewable Natural Resources as a distinguished zone highly affected by anthropogenic activities in the Brazilian Amazon. While spatial distribution of forest fires were highly correlated with proximity to deforestation areas, selective logging activities were more related to proximity to logging centers and road networks. These findings are supported by Uhl and Buschbacher (1985), Uhl and Kauffman (1990), and Cochrane (2001), who observed that fires from fire-maintained agricultural lands are the main ignition sources for forest fires in the Brazilian Amazon. Additional factors such as prolonged water deficit, selective logging, and forest fragmentation also contributed to increase forest fires, though a combination of all these factors seemed to be a more probable reason for forest fire events occurring in the region. Meanwhile, I also observed that the spatial distribution of selective logging activities is strongly influenced by the distance to logging centers and road networks, which may be associated to transportation costs. As a consequence, loggers have to improve their transportation efficiency continuously to better exploit timber sources in new frontiers of undisturbed forests as the forests next to logging centers become overexploited. During the field work in Mato Grosso I could observe that loggers are commonly using heavy-load (30 to 40 tons) trailer trucks to transport logs from forest sites to sawmill. Finally, the status of land ownership seemed to play an important role in the spatial distribution of both selectively logged and burned forests. For example, only 3.7% of the total impacted forests by selective logging and fires were geographically located within protected areas in the period of analysis. There is growing evidence, however, of an increasing trend for the occurrence of anthropogenic activities within the limits of protected areas.

- Is there any spatial pattern of these activities in that region? Are those spatial patterns changing over time?

The results of this research show that forest fires and selective logging activities were occurring throughout the Brazilian Amazon at an increasing intensity during the period of 1992 to 1999 (see appendices C.12 to C.17). Forest fire events that could rarely be observed in Rondonia and Acre in 1992 were evident in 1996 and 1999 in both states. The most meaningful forest fire and logging clusters were located in the Eastern and Southern Para, Western Maranhão, and Northeastern and Mid-Northern Mato Grosso in 1992, 1996, and 1999. The analysis for 1999 logging and fire mosaics (appendices C.12 to C.17) revealed the surfacing of new logging centers and fire events in Northwestern and Southwestern Para, and Northwestern Mato Grosso. These mosaics also show that selective logging activities and forest fires have encroached on protected areas in the study region. This spatial feature is especially clear in the Northeastern Mato Grosso.

- Is there any interaction between selective logging and other land use or land cover type that may be synergistically causing even more forest disturbances?

As previously presented in Chapter 4, selective logging activities significantly increased forest fire likelihood in the Brazilian Amazon. This fact is supported by Uhl and Buschbacher (1985), Uhl and Kauffman (1990), and Cochrane (2001), who observed that selective logging increases forest fire susceptibility in tropical regions. The proximity to agricultural land, however, was the factor that most substantively and significantly affected probability of forest fires in the study region. On the other hand, this factor did not significantly affect selective logging likelihood in the study region. Further juxtaposition between selective logging and forest fire maps indicate less than 7% of overlap between these types of forest disturbances in the period of analysis. These facts indicate that, at the regional scale, most of selective logging and forest fire were spatially distinct events.

The results from the basin-wide analysis of forest fires also indicate that only around of 457 km^2 could be considered recurrent fires detected over the study period. Moreover, field measurements showed that fuel load averages for study sites in Acre, Rondonia, and Mato Grosso were not significantly different for various forest uses (i.e. logged, burned, and undisturbed forests). Altogether, these facts indicate that the positive association between selective logging and forest fires at the local scale observed by many authors (Holdsworth and Uhl et al. 1997, Cochrane 1999, and Cochrane and Schulze 1999) may not be supported by a basin-wide analysis, since most of the selective logging and forest fires detected did not occur at the same place and time. The results and field measurements also indicated that some forested areas are naturally more fire prone than others, whether logged or not, which indicates that forest fire events at a particular site require very unique local conditions. These may include, but are not limited to, water deficit, forest type, forest disturbance, and the presence of ignition sources.

5.3. Hypotheses revisited

Hypothesis 1: *Forest impacts by selective logging activities increase over time and severely disturb natural forests in the Brazilian Amazon.*

This hypothesis may be considered true since my results showed that areas of selectively logged forests detected using remotely sensed data increased 500% between 1992 and 1999. These results also showed that selective logging alone contribute to degrade around of 2% of forest canopy compared with undisturbed forests. Selective logging and forest fire combined substantively increases canopy degradation up to 27.5%. Moreover, selective logging is increasing in area and intensity throughout the Brazilian Amazon. It is also important to point out that forest canopy regeneration was very strong (~6% greater than undisturbed forests) in previously logged forest detected in the period of analysis. At the local scale, field measurements indicated that newly selectively logged forests may significantly decrease around 6.7% of canopy cover. If selective logging and fire combined, canopy cover is decreased by 7.7%. Finally, diversity index, tree mortality and fuel load rates for logged sites were not significantly different from undisturbed forests.

Hypothesis 2: *Forest fires mostly occur on fire-prone selectively logged forests and further increase forest degradation in the Brazilian Amazon.*

This hypothesis cannot be accepted as it is stated. My results showed that selective logging significantly increase forest fire probability. However, the juxtaposition of forest fire and selective logging maps showed only approximately 7% of common area between logging and fire. Additional statistical analysis indicated that proximity to deforestation was a factor that substantively and significantly affected forest fire likelihood. Therefore, fire-prone selectively logged forests may increase forest fire probability, but it did not seem to be the major factor that increases forest fire events at the regional scale. The second half of this hypothesis can be accepted as stated. Indeed, the results showed that, when taken as a singular phenomenon, forest fires severely degraded canopy cover (up to ~19%) in the study region. At the local scale, field measurements also indicated that newly burned forests significantly decreased around 12% of canopy cover when compared to undisturbed forests. Tree mortality rate was also significantly higher and diversity index was significantly lower compared to undisturbed and selectively logged forests.

Hypothesis 3: *Variables that reflect landscape and land use characteristics (e.g. vegetation type, soil, precipitation, deforestation, forest fragmentation, proximity* *to road network, etc.) explain spatial distribution and probability of selective logging and forest fire to occur in the Brazilian Amazon.*

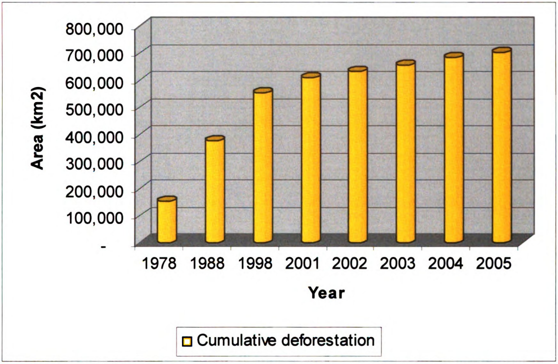
This hypothesis can be accepted. In this analysis, variables derived from remotely sensed data representing landscape and land use characteristics were used as input for forest fires and selective logging probit models. These multivariate models permitted to select statistically significant variables that represented factors influencing selective logging and forest fire occurrences in the study area. The final statistical models supported inferences of both the selective logging and forest fire probabilities throughout the study region. The effect of each variable on forest fire and selective logging probabilities was previously presented and discussed.

5.4. Opportunities for further studies

My study showed a 10 year trend of forest fire and selective logging in the Amazon, but the long-term impacts of these activities are still unknown. I also estimated the extent and impact of selective logging and forest fires on pristine forests in the Brazilian Amazon. In fact, synergistic interactions between these two land use types are poorly understood at regional scales. Therefore, new approaches using finer temporal, spatial, and spectral resolutions satellite imagery should be developed to improve the combined assessment of forest fires and selective logging in tropical regions. Field studies also should be conducted in different sub-regions in the Brazilian Amazon to better understand the process of forest degradation and its synergisms in the Brazilian Amazon. Finally, the development of simulations and scenarios of forest fires and selective logging could be useful to support public policies to achieve a sustainable development in the Amazon region.

APPENDICES

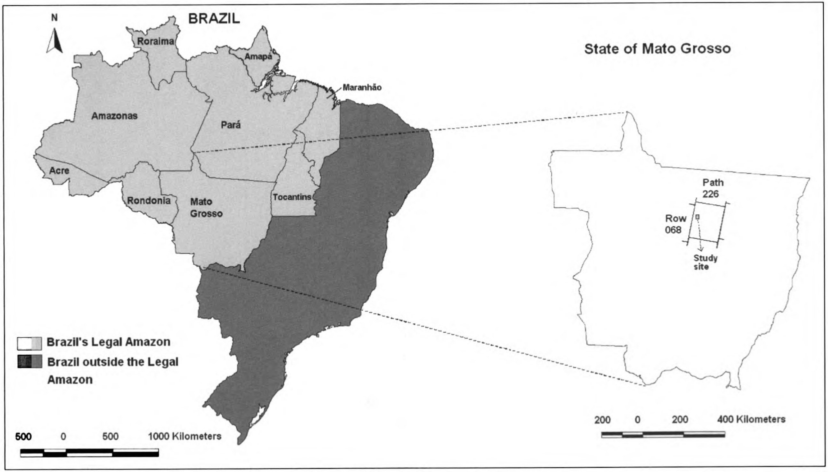
Appendix A.1. Total deforestation in the Brazilian Amazon from 1978 to 2004



Source: INPE (2007)

Appendix A.1

Appendix B.1. Study site location (Landsat path 226 row 068) in the Amazon State of Mato Grosso, Brazil.


BRAZIL
N
Roraima
Amapá
Maranhão
Amazonas
Pará
Acre
Rondonia
Mato
Grosso
Tocantins
Brazil's Legal Amazon
Brazil outside the Legal
Amazon
500 0 500 1000 Kilometers
State of Mato Grosso
Path
226
Row
068
Study
site
200 0 200 400 Kilometers

Appendix B.1

Appendix B.2. Satellite imagery used in the case study in the Amazon State of Mato Grosso, Brazil. Landsat Path 226 and Row 068

Acquisition Date	Landsat Sensor	Band	Source
19-May-92	TM	1,2,3,4,5,7	INPE
26-Aug-93	TM	1,2,3,4,5,7	INPE
12-Jul-94	TM	1,2,3,4,5,7	INPE
29-Jun-95	TM	1,2,3,4,5,7	INPE
1-Jul-96	TM	1,2,3,4,5,7	INPE
5-Aug-97	TM	1,2,3,4,5,7	INPE
5-Jun-98	TM	1,2,3,4,5,7	INPE
19-Aug-99	ETM+	1,2,3,4,5,7	TRFIC
18-Jun-00	ETM+	1,2,3,4,5,7	TRFIC
8-Aug-01	ETM+	1,2,3,4,5,7	TRFIC
4-Mar-02	ETM+	1,2,3,4,5,7	TRFIC
26-Jul-02	ETM+	1,2,3,4,5,7	TRFIC
6-Aug-03	TM	1,2,3,4,5,7	INPE
21-Jun-04	TM	1,2,3,4,5,7	INPE

Appendix B.2

Appendix B.3. Slope and intercept for atmospheric correction of the Landsat imagery using as 5S model.

Slope and intercept for atmospheric correction (5S)

Year	Band	Slope	intercept	R^2	Sig. F
1992	B1	1.2424	-0.0900	0.9993	0.000
	B2	1.2346	-0.0483	0.9996	0.000
	B3	1.1749	-0.0288	0.9998	0.000
	B4	1.1846	-0.0141	0.9999	0.000
	B5	1.1650	-0.0026	1	0.000
	B7	1.1349	-0.0010	1	0.000
1993	B1	1.2455	-0.0896	0.9993	0.000
	B2	1.2376	-0.0480	0.9996	0.000
	B3	1.1764	-0.0284	0.9998	0.000
	B4	1.1853	-0.0138	0.9999	0.000
	B5	1.1656	-0.0025	1	0.000
	B7	1.1378	-0.0010	1	0.000
1994	B1	1.2648	-0.0944	0.9992	0.000
	B2	1.2547	-0.0507	0.9996	0.000
	B3	1.1893	-0.0302	0.9998	0.000
	B4	1.1958	-0.0149	0.9999	0.000
	B5	0.1715	-0.0027	1	0.000
	B7	1.1403	-0.0012	1	0.000
1995	B1	1.2682	-0.0953	0.9992	0.000
	B2	1.2576	-0.0512	0.9996	0.000
	B3	1.1915	-0.0306	0.9998	0.000
	B4	1.1976	-0.0151	0.9999	0.000
	B5	1.1726	-0.0028	1	0.000
	B7	1.1410	0.0012	1	0.000
1996	B1	1.2728	-0.0965	0.9993	0.000
	B2	1.2582	-0.0510	0.9996	0.000
	B3	1.1915	-0.0303	0.9998	0.000
	B4	1.1972	-0.0148	0.9999	0.000
	B5	1.1723	-0.0027	1	0.000
	B7	1.138	-0.0013	1	0.000
1997	B1	1.2837	-0.0990	0.9992	0.000
	B2	1.2712	-0.0533	0.9996	0.000
	B3	1.2017	-0.0319	0.9998	0.000
	B4	1.2055	-0.0158	0.9999	0.000
	B5	1.1773	-0.0030	1	0.000
	B7	1.1443	-0.0012	1	0.000
1998	B1	1.2774	-0.0976	0.9993	0.000
	B2	1.2663	-0.0523	0.9996	0.000
	B3	1.1972	-0.0311	0.9998	0.000
	B4	1.2015	-0.0152	0.9999	0.000
	B5	1.1751	-0.0028	1	0.000
	B7	1.1447	-0.0012	1	0.000

Appendix B.3. To be continued …

Slope and intercept for atmospheric correction (5S)

Year	Band	Slope	intercept	R^2	Sig. F
1999	B1	1.2837	-0.0099	0.9992	0.000
	B2	1.2491	-0.0502	0.9996	0.000
	B3	1.1859	-0.0300	0.9998	0.000
	B4	1.1937	-0.0149	0.9999	0.000
	B5	1.1701	-0.0028	1	0.000
	B7	1.1383	-0.0012	1	0.000
2000	B1	1.2705	-0.0959	0.9993	0.000
	B2	1.2604	-0.0513	0.9996	0.000
	B3	1.1927	-0.0304	0.9998	0.000
	B4	1.1978	-0.0149	0.9999	0.000
	B5	1.1729	-0.0027	1	0.000
	B7	0.8754	0.001	1	0.000
2001	B1	1.2492	-0.0906	0.9993	0.000
	B2	1.2414	-0.0483	0.9996	0.000
	B3	1.1786	-0.0285	0.9998	0.000
	B4	1.1867	-0.0138	0.9999	0.000
	B5	1.1665	-0.0024	1	0.000
	B7	1.1373	-0.0011	1	0.000
2002	B1	1.2418	-0.0025	0.9993	0.000
	B2	1.2343	-0.0137	0.9996	0.000
	B3	1.1743	-0.0282	0.9998	0.000
	B4	1.1839	-0.0476	0.9999	0.000
	B5	1.1647	-0.0029	1	0.000
	B7	1.1349	-0.0010	1	0.000
2003	B1	1.2728	-0.0965	0.9993	0.000
	B2	1.2624	-0.0516	0.9996	0.000
	B3	1.1940	-0.0306	0.9998	0.000
	B4	1.1988	-0.0149	0.9999	0.000
	B5	1.1734	-0.0027	1	0.000
	B7	1.1382	-0.0009	1	0.000
2004	B1	1.2173	-0.0849	0.9992	0.000
	B2	1.2118	-0.0457	0.9996	0.000
	B3	1.1588	-0.0273	0.9998	0.000
	B4	1.1722	-0.0134	0.9999	0.000
	B5	1.1578	-0.0026	1	0.000
	B7	1.1381	-0.0012	1	0.000

Appendix B.3. Continued.

Appendix B.4. Slope and intercept for normalization of the Landsat imagery using as a reference the path 226 row 068, acquired in August 8, 2001.

Slope and intercept for Landsat imagery normalization

Year	Band	Slope	intercept	R^2	Sig. F
1992	B1	1.9458	-17.023	0.9877	0.000
	B2	1.7109	-10.506	0.9849	0.000
	B3	2.2996	-15.615	0.9884	0.000
	B4	1.0635	9.8466	0.9884	0.000
	B5	1.6272	-14.439	0.9761	0.000
	B7	1.5619	2.6144	0.9814	0.000
1993	B1	1.1355	-18.099	0.9053	0.000
	B2	1.0387	-9.2681	0.9202	0.000
	B3	1.655	-11.368	0.9608	0.000
	B4	0.3689	41.513	0.9771	0.000
	B5	1.1254	-5.123	0.9965	0.000
	B7	1.1151	-2.8036	0.9994	0.000
1994	B1	1.3403	-7.4632	0.9967	0.000
	B2	1.2786	-2.8302	0.9982	0.000
	B3	1.3281	-3.6665	0.9988	0.000
	B4	1.0825	-0.5237	0.9942	0.000
	B5	1.2995	-3.0316	0.9983	0.000
	B7	1.3192	0.9798	0.9963	0.000
1995	B1	1.7059	-15.641	0.9622	0.000
	B2	1.4951	-6.068	0.9703	0.000
	B3	1.7877	-8.0787	0.9934	0.000
	B4	1.2372	1.1525	0.994	0.000
	B5	1.5292	-7.2734	0.9882	0.000
	B7	1.8949	-3.7354	0.9874	0.000
1996	B1	1.5642	-12.177	0.9913	0.000
	B2	1.4677	-5.3567	0.9963	0.000
	B3	1.4836	-4.5231	0.9876	0.000
	B4	1.1978	2.3117	0.9736	0.000
	B5	1.3547	-2.1899	0.9756	0.000
	B7	1.6588	-3.297	0.9928	0.000
1997	B1	1.513	-15.815	0.9588	0.000
	B2	1.4038	-8.9126	0.9717	0.000
	B3	1.4471	-9.2322	0.9785	0.000
	B4	1.1821	-5.186	0.9756	0.000
	B5	1.3085	-3.382	0.997	0.000
	B7	1.2852	-0.4181	0.9959	0.000
1998	B1	1.0959	-0.912	0.9833	0.000
	B2	1.2526	-2.0085	0.9944	0.000
	B3	1.7138	-5.9986	0.9972	0.000
	B4	1.2153	1.1125	0.985	0.000
	B5	1.2027	0.742	0.9945	0.000
	B7	1.7216	-3.1168	0.9762	0.000

Appendix B.4. To be continued ...

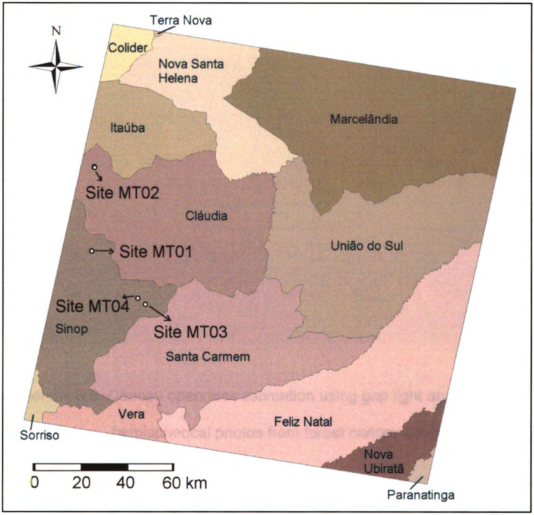
Slope and intercept for Landsat imagery normalization

Year	Band	Slope	intercept	R^2	Sig. F
1999	B1	1.0725	-4.698	0.972	0.000
	B2	1.1402	-4.7609	0.98	0.000
	B3	1.094	-2.9142	0.9919	0.000
	B4	1.0274	-1.7792	0.9919	0.000
	B5	1.0021	-0.498	0.9994	0.000
	B7	1.0361	0.00832	0.9667	0.000
2000	B1	1.136	-4.2724	0.9763	0.000
	B2	1.1361	-3.3419	0.9701	0.000
	B3	1.4985	-6.1871	0.9888	0.000
	B4	1.077	0.9588	0.9842	0.000
	B5	1.2987	-7.6197	0.9921	0.000
	B7	1.4035	-2.0002	0.9626	0.000
2002	B1	1.4999	-8.6342	0.9874	0.000
	B2	1.3816	-4.4249	0.9881	0.000
	B3	1.2784	-1.1385	0.9973	0.000
	B4	1.0682	-0.8031	0.9651	0.000
	B5	1.505	-15.125	0.9601	0.000
	B7	1.7514	-5.9245	0.9594	0.000
2003	B1	0.9417	-1.3961	0.9688	0.000
	B2	0.8743	0.0857	0.9875	0.000
	B3	1.0109	-4.7539	0.9653	0.000
	B4	0.9747	0.3068	0.9838	0.000
	B5	1.0121	-0.3465	0.9948	0.000
	B7	0.8776	1.6558	0.9995	0.000
2004	B1	0.9762	1.6281	0.9522	0.000
	B2	1.0554	0.051	0.9637	0.000
	B3	1.2116	-2.6322	0.98	0.000
	B4	1.2849	1.5652	0.9872	0.000
	B5	1.5952	-4.9404	0.9914	0.000
	B7	0.9849	2.0037	0.9986	0.000

Appendix B.4. Continued.

Appendix B.5. Fieldwork locations within the study area

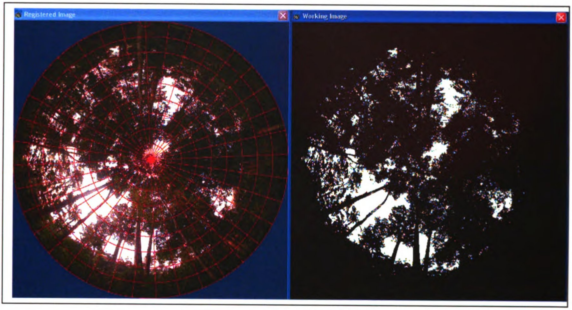
Fieldwork locations within the study area



Site ID	Latitude (degree)	Longitude (degree)	UTM X (meters)	UTM Y (meters)	Altitude (meters)
MT01	-11.5569	-55.4017	674287.6	8721959	358
MT02	-11.2263	-55.3985	674836.8	8758522	287
MT03	-11.7591	-55.186	697676.3	8699443	346
MT04	-11.7438	-55.2119	694859.5	8701157	352

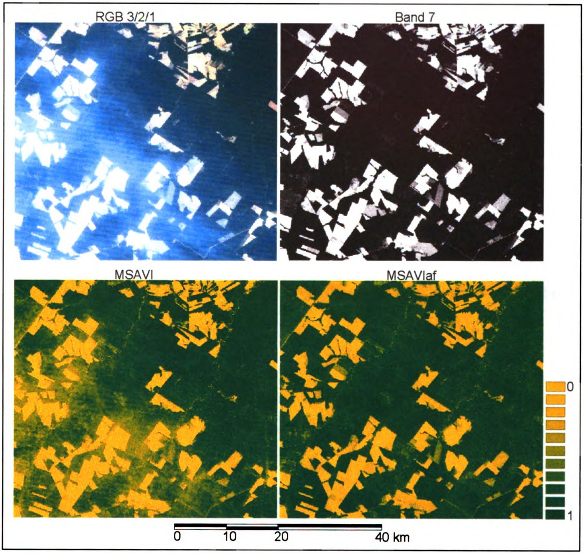
Appendix B.5

Appendix B.6. Canopy openness estimation using gap light analyzer and hemispherical photos from forest canopy cover



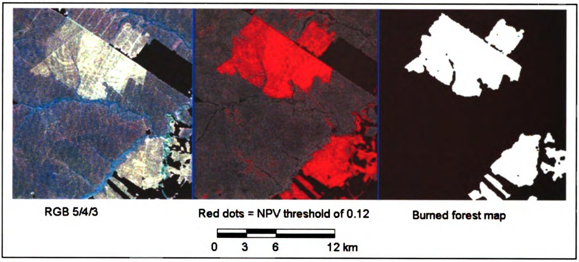
Appendix B.6

Appendix B.7. Visible and SWIR (at 2.1 μm) reflectance, and MSAVI and MSAVIaf retrieved from Landsat image acquired in 2003.



Appendix B.7

Appendix B.8. Burned forests detection based on non-photosynthetic vegetation fraction image


RGB 5/4/3
Red dots = NPV threshold of 0.12
Burned forest map
0
3
6
12 km

Appendix B.8

Appendix B.9. Cumulative deforestation and persistence of selective logging and forest fire on remotely sensed data

Year	Undisturbed Forests [a] (km²)	Disturbed forests						Cumulative Deforestation [h] (km²)
		Selectively logged only (km²)		Selectively logged & burned (km²)		Burned forest only (km²)		
		Detected[b]	Undetected[c]	Detected[d]	Undetected[e]	Detected[f]	Undetected[g]	
1992	24,131.5	1,120.9	-	45.1	-	395.7	-	3,403.6
1993	22,472.1	1,818.7	425.0	44.0	12.1	182.7	241.8	3,900.3
1994	21,446.7	1,843.4	1,063.2	47.1	23.5	89.9	336.6	4,246.4
1995	20,378.1	1,386.6	2,055.3	102.0	42.9	150.2	318.4	4,663.3
1996	19,284.9	1,534.2	2,608.6	80.7	95.8	93.8	362.0	5,036.8
1997	17,909.8	2,032.2	3,057.0	68.2	113.1	207.6	288.0	5,420.8
1998	16,554.8	2,858.9	3,210.2	162.9	83.3	128.9	364.4	5,733.4
1999	14,160.6	3,997.1	3,524.9	403.4	83.6	498.6	207.2	6,221.4
2000	12,515.9	3,261.7	4,298.5	1,370.0	121.7	878.3	293.0	6,357.7
2001	11,128.7	3,542.0	5,011.0	1,026.3	482.2	359.3	703.4	6,844.0
2002	10,422.2	3,663.1	5,312.7	820.7	732.5	273.1	754.9	7,117.5
2003	9,606.4	2,753.8	6,686.4	547.8	1,022.2	244.5	694.8	7,541.0
2004	8,894.1	2,221.7	7,053.1	393.7	1,155.6	74.3	783.5	8,520.7

[a] Total cumulative undisturbed forest; [b] Total of logged forest detected in that given year; [c] Total of logged forest detected in previous year and undetected for that given year; [d] Total of logged and burned forest detected in that given year; [e] Total of logged and burned forest detected in previous year and undetected for that given year; [f] Total of burned forest detected in that given year; [g] Total of burned forest detected in previous year and undetected for that given year; [h] Total of cumulative deforestation for that given year.
Note: A mask of 972 km^2 of the cumulative clouds and shadows was applied. Approximately 36.3 km^2 of water bodies that were annually detected on all scenes were not included.

Appendix B.9

Appendix B.10. Forest canopy losses estimated using multi-regression model for the study area

Forest canopy losses estimated using multi-regression model for the study area

N = 49583 observations (3000m x 3000m systematic sampling grid)

R^2 = 0.6307; Adj. R^2 = 0.6305; Prob > F = 0.000; F(23, 49559) = 3526.17

Constant and Variables	Coefficient	Std. Error	t	P (2-tails)	[95% Conf. Interval]	
Constant	-235.0	12.96792	-18.12	0.000	-260.46	-209.626
Deforestation	-53.9	0.20911	-257.7	0.000	-54.294	-53.474
Newly logged	-5.0	0.40512	-12.34	0.000	-5.7937	-4.2057
Old logged forest detectable(*)	-1.6	0.3423	-4.62	0.000	-2.2521	-0.9103
Old logged forest non-detectable(**)	3.1	0.2428	12.58	0.000	2.57897	3.53075
Newly logged & burned forest	-35.6	1.05498	-33.78	0.000	-37.709	-33.573
Newly burned	-28.9	0.99566	-29.05	0.000	-30.877	-26.974
Old burned forest detectable (*)	-12.6	0.76258	-16.49	0.000	-14.072	-11.082
Old burned forest non-detectable(**)	-1.0	0.71549	-1.45	0.147	-2.4412	0.36352
Old logged & burned forest detectable(*)	-25.6	1.03242	-24.75	0.000	-27.58	-23.533
Old logged & burned forest non-detectable(**)	-4.7	0.54397	-8.57	0.000	-5.7269	-3.5945
Water body	-61.3	1.81431	-33.8	0.000	-64.871	-57.759
Year of 1993	-8.8	0.36602	-24.05	0.000	-9.5186	-8.0838
Year of 1994	-4.5	0.36661	-12.23	0.000	-5.2039	-3.7668
Year of 1995	-1.2	0.3669	-3.33	0.001	-1.9414	-0.5031
Year of 1996	-3.1	0.36738	-8.45	0.000	-3.8251	-2.385
Year of 1997	-5.6	0.36799	-15.11	0.000	-6.2802	-4.8377
Year of 1998	-3.5	0.36895	-9.41	0.000	-4.1957	-2.7494
Year of 1999	-8.4	0.36992	-22.61	0.000	-9.0905	-7.6404
Year of 2000	-4.4	0.37366	-11.83	0.000	-5.1537	-3.6889
Year of 2001	-7.1	0.37501	-18.91	0.000	-7.8252	-6.3551
Year of 2002	-6.5	0.37629	-17.31	0.000	-7.2502	-5.7751
Year of 2003	-5.0	0.37739	-13.23	0.000	-5.7316	-4.2522
Year of 2004	0.1	0.37891	0.25	0.806	-0.6497	0.83561
X coordinate (km)	-0.001	0.0015	-0.43	0.669	-0.0036	0.0023
Y coordinate (km)	0.037	0.001497	24.7	0.000	0.03403	0.0399

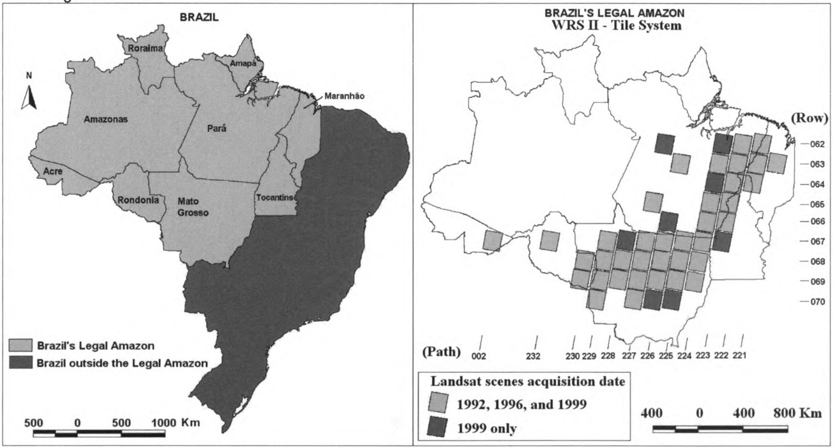
* The term *detectable* refers to previously logged and/or burned forests that persist detectable on satellite imagery. ** The term *non-detectable* refers to previously logged and/or burned forests that do not persist detectable on satellite imagery.

Note: In this multiple-regression analysis, undisturbed forest and the year of 1992 were used as **omitted variables** for land use and annual changes, respectively.

Appendix B.10

Appendix C.1. Study region location and Landsat scenes used in the spatiotemporal assessment of selective logging and forest fire in the Legal Amazon

Study region location and Landsat scenes used in the spatiotemporal assessment of selective logging and forest fire in the Legal Amazon



Appendix C.1

Appendix C.2. Acquisition dates of the Landsat imagery for 1992, 1996, and 1999

Acquisition dates of the Landsat imagery for 1992, 1996, and 1999

Path/Row	Acquisition Date		
	1992	1996	1999
221/063	July 11, 1992	May 30, 1997	May 14, 2000
222/062	July 24, 1991	July 5, 1996	July 14, 1999
222/063	July 24, 1991	June 3, 1996	August 23, 1999
222/064([1])	August 25, 1991	June 19, 1996	August 23, 1999
223/062	August 16, 1991	May 28, 1997	July 13, 1999
223/063	May 28, 1991	July 12, 1996	July 13, 1999
223/064	August 10, 1992	June 10, 1996	July 13, 1999
223/065	June 02, 1993	June 10, 1996	July 13, 1999
223/066	July 25, 1992	June 10, 1996	July 13, 1999
223/067([2])	-	-	August 30, 1999
224/062([2])	-	-	October 24, 1999
224/063	June 22, 1992	July 19, 1996	October 8, 1999
224/064([2])	-	-	October 8, 1999
224/065	July 16, 1992	June 19, 1996	October 8, 1999
224/066	July 16, 1992	July 3, 1996	October 8, 1999
224/067	July 16, 1992	July 3, 1996	October 8, 1999
224/068	July 23, 1992	July 3, 1996	August 21, 1999
224/069	July 23, 1992	July 3, 1996	August 21, 1999
225/067([1])	July 23, 1992	June 8, 1996	August 12, 1999
225/068([1])	July 23, 1992	August 11, 1996	August 12, 1999
225/069	June 21, 1992	August 11, 1996	August 12, 1999
225/070([2])	-	-	August 12, 1999
226/063	July 20, 1991	June 18, 1997	August 3, 1999
226/066([2])	-	-	August 3, 1999
226/067	May 19, 1992	July 1, 1996	August 19, 1999
226/068	May 19, 1992	July 1, 1996	August 19, 1999
226/069	May 19, 1992	July 1, 1996	August 19, 1999
226/070([2])	-	-	August 3, 1999
227/062([2])	-	-	August 10, 1999
227/065([1])	August 06, 1992	August 09, 1996	August 10, 1999
227/067	August 6, 1992	July 24, 1996	August 10, 1999
227/068	August 6, 1992	June 6, 1996	August 10, 1999
227/069	July 5, 1992	June 6, 1996	August 10, 1999
227/070	July 5, 1992	June 6, 1996	August 10, 1999
228/067([2])	-	-	August 17, 1999
228/068	June 18, 1992	June 13, 1996	August 17, 1999
228/069	June 18, 1992	June 13, 1996	August 17, 1999
229/067	July 3, 1992	July 22, 1996	August 8, 1999

[1] Selectively logged forest not mapped in 1992 and 1996.
[2] Selectively logged and burned forest not mapped in 1992 and 1996.

Appendix C.2. To be continued ...

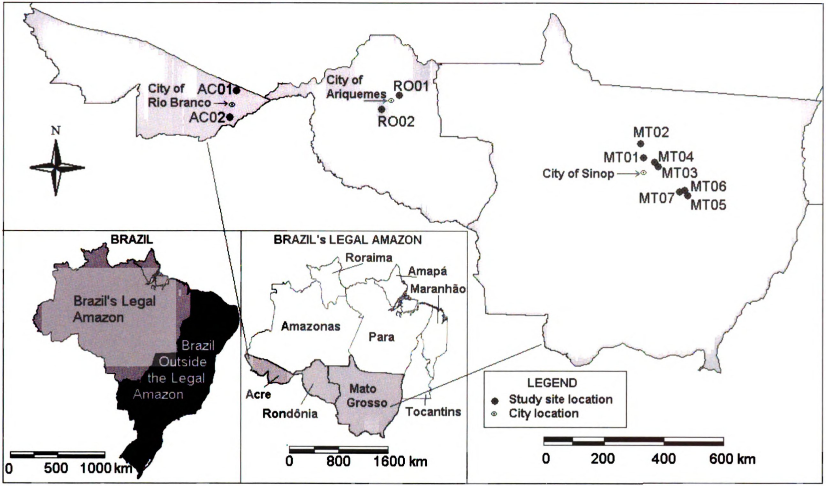
Acquisition dates of the Landsat imagery for 1992, 1996, and 1999

Path/Row	Acquisition Date		
	1992	1996	1999
229/068	July 11, 1992	July 22, 1996	October 11, 1999
229/069	June 25, 1992	July 6, 1996	August 8, 1999
229/070	July 11, 1992	June 23, 1997	August 8, 1999
230/068	July 10, 1992	October 17, 1996	August 15, 1999
230/069	May 15, 1992	October 17, 1996	July 30, 1999
232/067	June 22, 1992	June 25, 1996	June 28, 2000
002/067	August 30, 1992	August 1, 1996	August 2, 1999

Appendix C.2. Continued.

Appendix C.3. Case study (fieldwork) locations in the Brazilian Amazon

Case study (fieldwork) locations in the Brazilian Amazon



Appendix C.3

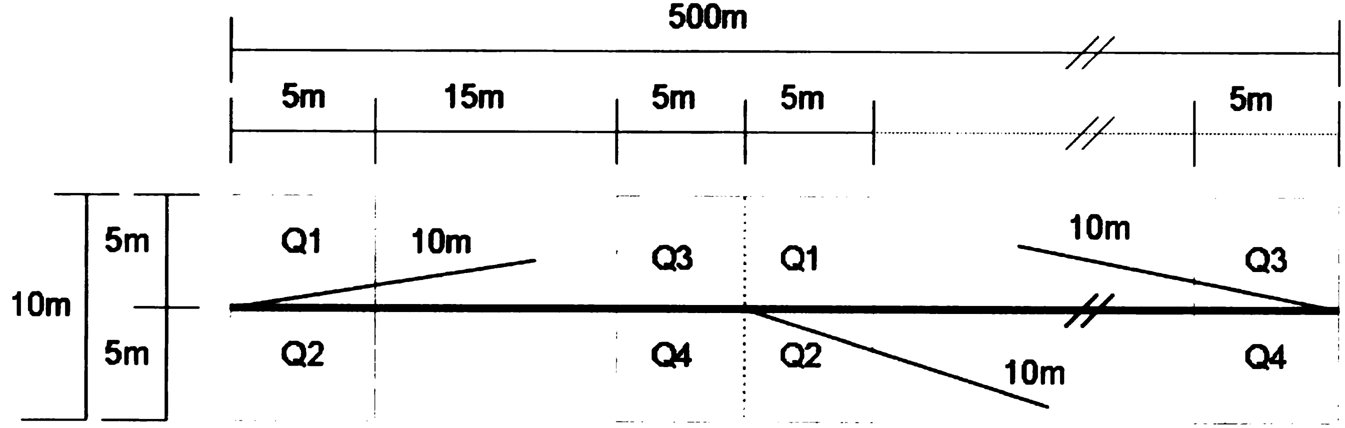
Appendix C.4. Case study and transect locations and characteristics

Site ID	State	Transect ID	Latitude (degree)	Longitude (degree)	Transect Dimension (m)	Site Characteristics
AC01	Acre	# 01	-9.574	-67.663	500 x 10	Undisturbed forest
	Acre	# 02	-9.582	-67.662	500 x 10	Ongoing selective logging
AC02	Acre	# 03	-10.410	-67.845	500 x 10	Logged/burned (1 year)
	Acre	# 04	-10.396	-66.017	125 x 10	Logged (2 years old)
RO01	Rondônia	# 05	-9.944	-62.922	500 x 10	Logged (1 year old)
	Rondônia	# 06	-9.923	-62.932	250 x 10	Logged (3 years old)
RO02	Rondônia	# 07	-10.142	-63.283	500 x 10	Undisturbed forest
	Rondônia	# 08	-10.149	-63.284	500 x 10	Undisturbed forest
MT01	Mato Grosso	# 09	-11.557	-55.402	500 x 10	Lightly burned (1 year old)
	Mato Grosso	# 10	-11.556	-55.401	500 x 10	Logged forest (3 years old)
MT02	Mato Grosso	# 11	-11.226	-55.399	500 x 10	Heavily burned (4 years old)
	Mato Grosso	# 12	-11.233	-55.393	500 x 10	On going logg./ burned (4 years old)
MT03	Mato Grosso	# 13	-11.759	-55.186	500 x 10	Logged/burned (5 years old)
MT04	Mato Grosso	# 14	-11.744	-55.212	500 x 10	Logged (1 year old)
MT05	Mato Grosso	#15	-12.525	-54.401	500 x 10	Undisturbed forest
MT05	Mato Grosso	#16	-12.532	-54.405	500 x 10	Undisturbed forest
MT05	Mato Grosso	#17	-12.533	-54.406	500 x 10	Logged forest (1 year old)
MT05	Mato Grosso	#18	-12.550	-54.399	500 x 10	Logged forest (2 years old)
MT06	Mato Grosso	#19	-12.490	-54.469	500 x 10	Heavily burned forest (2 years old)
MT07	Mato Grosso	#20	-12.486	-54.443	500 x 10	Severely burned forest (2 years old)

Appendix C.4

Appendix C.5. Transect design for fieldwork measurements

Transect design for fieldwork measurements



LEGEND

Main transect (500m)

Quadrat ($25 m^2$)

Fuel load measurements (10m length) at random direction)

FIELD MEASUREMENTS

Main transect: count of the number of trees, tree identification, tree condition (dead, alive, rotten, or broken), and DBH measurement of trees with DBH > 10 cm.

Quadrat: count of regeneration and trees within two different diameter classes: diameter < 5 cm and diameter between 5 and10 cm.

Tree identification and DBH measurement: trees DBH > 10 cm along the 500 m transect.

Fuel line: count of remaining biomass within three classes: < 2.5 cm, 2.5-7.6 cm, and > 7.6 cm, and litter depth measurement.

Appendix C.5

Appendix C.6. List of tree species identified and recorded during the field work in the States of Acre, Rondônia, and Mato Grosso.

List of tree species identified and recorded during the field work in the States of Acre, Rondônia, and Mato Grosso

Species	Scientific Name
Abacaterana	Aniba burchellii Kostern
Abiorana	*Pouteria macrophylla* (Lam.) Eyma
Abiu	*Pouteria sagotiana* (Baill) Eyma
Açai	*Euterpe oleraceae* Mart.
Acapu	*Minquartia guianensis* Aubl.
Algodao	*Bombax* sp
Amarelao	*Qualea dinizii* Ducke
Amendoim-Bravo	*Pterogyne nitens* Tul.
Amescla/Breu	*Trattinickia burseraefolia* Mart. Willd.
Angelim	*Hymenolobium sericeum* Ducke
Angelim Pedra	*Dinizia excelsa* Ducke
Angico	*Cassia fastuosa* Willd.
Apui	*Ficus trigona* L.f.
Babaçu (*)	*Attalea* sp
Bacuri	*Symphonia globulifera* L.f.
Bagaceira	*Bagassa guianensis* Aubl.
Banana-do-mato (*)	*Musa* spp
Bandarra (*)	*Schizolobium amazonicum* (Hubber) Ducke
Barriguda	*Chorisia integrifolia* Ulbr.
Bauchorana	*Ecclinusa guianensis* Eyma
Bolateira	*Manilkara huberi* (Ducke) Chevalier
Branquilho	*Albizia hasslerii* (Chodat) Burkart
Branquinho	*Sebastiana* sp
Breu grande	*Protium apiculatum* Swartz
Cafezinho	*Caesaria* sp
Caja	*Spondias dulcis* Forst.
Cambara/Cedrinho	*Erisma uncinatum* Warm.
Canafistula	*Cassia leiandra* Benth.
Canela	*Nectandra cuspidata* Nees
Capirana	*Calycophyllum spruceanum* Benth
Caraipe	*Licania pruinosa* R. Benoist
Caroba	*Jacaranda copaia* (Aubl.) D. Don
Castanheira	*Bertholletia excelsa* Humb. Bonpl
Catanudo	*Chrysophyllum* sp
Catuaba / Breu Leite	*Thyrsodium schomburgkianum* Benth.
Caucho	*Castilla ulei* Warb.
Caxeta / Mandioqueira	*Qualea albiflora* Warm.
Cedro	*Cedrela odorata* L.
Champagne/Cumaru	*Dipterix odorata* (Aubl.) Willd.
Chicha/ Capote	*Sterculia speciosa* K. Schum
Cinzeiro	*Terminalia amazonica* (J.F. Gmel) Excell.

Appendix C.6. To be continued...

List of tree species identified in the field work in the States of Acre, Rondônia, and Mato Grosso

Species	Scientific Name
Cipouba	*Parkia discolor* Spruce ex. Benth.
Copaiba	*Copaifera guianensis* Desf.
Copiuba	*Goupia graba* Ambl.
Cumaru Ferro	*Dipterix trifoliata* Ducke
Cupuacu	*Theobroma bicolor* Humb & Bonpl.
Envireira	*Rollinia* sp
Escorrega Macaco	*Capirona huberiana* Ducke
Escova de Macaco	*Apeiba* sp
Espeteiro	*Casearia sylvestris* Sw.
Farinha Seca	*Polygonanthus amazonicus* Ducke
Faveira	*Parkia nitida* Miq.
Figueira	*Ficus malacocarpa* Standl.
Freijo	*Cordia sagoti* L. M. Johnston.
Garapa/Garapeira	*Apuleia leiocarpa* (Vogel) J.F. Macbr.
Garrote	*Brosimum utile* (H.B.K.) Pittier
Goiabinha (*)	*Bellucia grossularioides* (L.) Triana
Guanandi	*Calophyllum brasiliense* Cambess.
Guaranta	*Esenbeckia leiocarpa* Engl.
Guariuba	*Clarisia racemosa* Ruiz & Pav.
Imbauba (*)	*Cecropia ulei* Snethl.
Imburana	*Amburana acreana* (Ducke) A.C. Sm.
Inga	*Inga macrophylla* H.B.K.
Ipe	*Tabebuia serratifolia* (Vahl) Nichols.
Itauba	*Mezilaurus itauba* (Meissn.) Taubert ex Mez.
Jambo	*Eugenia malaccensis* L.
Jatoba (Jatai)	*Hymenea courbaril* L.
Jenipapo	*Genipa caruto* H.B.K.
Jito	*Quarea silvatica* C.DC.
Joao Mole	*Neea opositifolia* Ruiz & Pav.
Lacre	*Vismia guianensis* Pers.
Landim	*Calophyllum brasiliense* Cambess.
Leiteiro	*Himatanthus sucuuba* (Spruce ex. Mull. Arg.) Woodson
Louro	*Ocotea rubra* Mez.
Macaranduba	*Manilkara excelsa* (Ducke) Standl.
Macuco	Hi*rtella racemosa* Lam.
Mamica de Porca	*Zanthoxylum rhoidolium* Lam
Mamui	*Jaracatia spinosa* (Aubl.) A. DC.
Mandiocao	*Schefflera morototoni* (Aubl.) Decne. & Planch.
Marapaju	*Manilkara longifolia* (A.DC.) Dubard
Marmelada	*Amaioua guianensis* Aubl.
Matamata	*Eschweilera grandifolia* (Aubl.) Sandwith

Appendix C.6. To be continued...

Species	Scientific Name
Mirindiba	*Terminalia amazonica* (J.F. Gmel) Excell.
Monjolo	*Enterolobium maximum* Ducke
Mororo	*Bauhinia macrostachya* (Raddi) J.F. Macbr.
Muiracatiara	*Astronium gracile* Engler
Mulateiro	*Pentaclethra macroloba* (Willd.) Kuntze
Mulungu	*Malouetia tamaquarina* (Aubl.) A.DC.
Murici	*Byrsonima chrysophylla* H.B.K.
Naja	*Maximiliana maripa* (Aubl.) Drude
Nao identificada	Unknown
Orelha de Negro	*Enterolobium contortisiliquum* (Vell.) Morong
Orucuri	*Siagus* sp
Paineira	*Ceiba Pentandra* (L) Gaertn.
Palheira (*)	*Geonoma* sp
Palmeira (*)	*Livistoma chinensis* (Jacq.) R.Br.
Palmeira Norjesu (*)	*Livistoma* sp
Pama	*Brosimum* sp
Pata de Vaca	*Bauhinia* sp
Pau cebola	*Clusia rosea* Jacq.
Pau d'alho	*Seguieria langsdorffii* Mog
Paxiuba (*)	PALMAE
Pente de Macaco	*Bagassa guianensis* Aubl.
Pequia	*Caryocar gracile* Wittm.
Peroba Mico	*Aspidosperma pyrifolium* Mart.
Pindaiba	*Xylobia frutescens* Aubl.
Pororoca	*Curatella americana* L.
Quina	*Coutarea hexandra* (Jack.) K. Schum.
Roxinho	*Peltogyne paradoxa* Ducke
Sangue	*Iryanthera elliptica* Ducke
Seringueira	*Hevea brasiliensis* Mull. Arg
Sucupira	*Bowdichia virgilioides* H.B.K.
Sumauma	*Ceiba Pentandra* Gaertn.
Tachi	*Tachigalia paniculata* Aublet
Tamarindo	*Martiodendron elatum* (Ducke) Gleason
Tauari	*Couratari guianensis* Aubl.
Tucuma	*Astrocaryum aculeatum* G.F. W. Meyer
Uchi	*Endopleura uchi* (Huber) Cuatr.
Unha de gato (*)	*Mimosa* sp
Urtiga (*)	*Cnidoscolus pubescens* (Pax.) PaX & k. Hoffm.
Velame	*Sclelorobium paniculata* Vogel
Violeta	*Peltogyne paradoxa* Ducke
Virola	*Virola surinamensis* (Rol.) Warb.

* Regeneration (secondary) tree species

Appendix C.6. Continued.

Appendix C.7. Estimates of indicators of forest disturbances by selective logging and forest fires based on field measurements in the States of Acre, Rondônia, and Mato Grosso

Transect	Trees (> 10 cm DBH)						
ID	Site location	Individuals (/ha)	Dead (/ha)	Species (/ha)	Basal area (m2/ha)	Dead basal area (m2/ha)	Regeneration (/ha)
# 01	Acre	310	10	130	42.82	3.38	26
# 02	Acre	326	6	118	12.54	0.10	28
# 03	Acre	354	64	106	17.12	3.34	72
# 04	Acre	440	32	248	25.04	0.95	104
# 05	Rondônia	348	20	100	28.20	1.71	80
# 06	Rondônia	372	28	132	25.06	2.52	76
# 07	Rondônia	276	26	82	20.19	3.07	46
# 08	Rondônia	266	16	88	24.23	0.30	42
# 09	Mato Grosso	374	52	42	19.84	1.97	76
# 10	Mato Grosso	584	46	50	25.91	3.53	118
# 11	Mato Grosso	262	32	62	19.53	1.16	26
# 12	Mato Grosso	280	52	70	18.89	2.45	12
# 13	Mato Grosso	216	80	50	17.69	4.21	30
# 14	Mato Grosso	432	26	68	22.36	1.56	86
#15	Mato Grosso	414	12	48	28.68	1.13	16
#16	Mato Grosso	538	26	48	31.29	3.48	14
#17	Mato Grosso	326	42	48	18.00	1.32	26
#18	Mato Grosso	358	44	52	18.69	3.27	50
#19	Mato Grosso	336	92	46	14.03	3.14	30
#20	Mato Grosso	226	136	32	12.74	6.98	16

Appendix C.7 To be continued…

Transect ID	Tree species (> 10 cm DBH)					Regeneration (individuals/ha)		Average Fuel load (Metric tons/ha)	Average Litter depth (cm)
	Mortality rate (%)		Regeneration	SDI [1]	SRI [2]	< 5 cm DBH	5-10 cm DBH		
	Trees/ha	Basal Area/ha	Trees/ha						
# 01	3.2	7.9	8.4	0.94	16.65	3276	688	40.1	3.1
105 2	1.8	0.8	8.6	0.95	20.59	3892	640	40.2	2.3
# 03	18.1	19.5	20.3	0.95	18.62	3400	528	21.1	2.2
# 04	7.3	3.8	23.6	0.93	13.63	2984	248	10.3	0.6
# 05	5.7	6.1	23.0	0.93	14.29	1074	40	60.2	6.1
# 06	7.5	10.1	20.4	0.94	15.45	560	100	137.5	6.6
# 07	9.4	15.2	16.7	0.93	15.09	896	60	48.8	2.4
# 08	6.0	1.2	15.8	0.94	15.92	828	74	66.6	2.9
# 09	13.9	9.9	20.3	0.80	5.05	1512	216	21.8	2.2
# 10	7.9	13.6	20.2	0.81	5.27	3030	552	35.8	3.3
# 11	12.2	6.0	9.9	0.80	4.95	3002	252	80.8	4.3
# 12	18.6	13.0	4.3	0.87	7.74	1608	174	111.1	6.3
# 13	37.0	23.8	13.9	0.87	7.87	3688	368	83.4	5.0
# 14	6.0	7.0	19.9	0.89	9.35	2102	302	44.8	4.6
#15	2.9	3.94	3.9	0.84	6.06	2944	306	26.1	5.0
#16	4.8	11.13	2.6	0.87	7.47	3296	390	44.01	10.9
#17	12.9	7.33	8.0	0.80	5.02	2068	274	141.17	5.13
#18	12.3	17.49	14.0	0.85	6.78	3256	196	69.86	4.0
#19	27.4	22.38	8.9	0.80	4.98	2104	164	88.75	2.8
#20	60.2	54.82	7.1	0.56	2.27	1864	114	76.67	1.8

Appendix C.7 Continued.

Appendix C.8. Empirical linear relationship between various vegetation indices and forest canopy coverage based on field measurements for the study sites in Mato Grosso, Rondônia, and Acre.

Mato Grosso site, N= 47

Vegetation Index	R^2	df	F(1,45)	Sigf.
MSAVI	0.840	45	236.83	0.000
GEMI	0.802	45	182.21	0.000
NDVI	0.672	45	92.26	0.000
$MSAVI_{af}$	0.810	45	191.9	0.000
$GEMI_{2.1}$	0.776	45	155.79	0.000
AFRI	0.603	45	68.25	0.000
GV	0.762	45	144.24	0.000

Rondônia study site, N= 32

Vegetation Index	R^2	df	F(1,30)	Sigf.
MSAVI	0.7374	30	84.26	0.000
GEMI	0.6991	30	69.7	0.000
NDVI	0.6018	30	45.35	0.000
$MSAVI_{af}$	0.6983	30	69.44	0.000
$GEMI_{2.1}$	0.6972	30	69.07	0.000
AFRI	0.5772	30	40.96	0.000
GV	0.6897	30	66.67	0.000

Acre study site, N = 30

Vegetation Index	R^2	df	F(1,28)	Sigf.
MSAVI	0.8125	28	121.3	0.000
GEMI	0.7304	28	75.85	0.000
NDVI	0.7181	28	71.34	0.000
$MSAVI_{af}$	0.8035	28	114.49	0.000
$GEMI_{2.1}$	0.705	28	66.9	0.000
AFRI	0.7147	28	70.14	0.000
GV	0.7416	28	80.34	0.000

Appendix C.8

Appendix C.9. Basin-wide results of selective logging and burned forest detection for 1992, 1996, and 1999

Path & Row	1992			1996			1999		
	Burned only (km^2)	Burned & Logged (km^2)	Logged only (km^2)	Burned only (km^2)	Burned & Logged (*) (km^2)	Logged only (km^2)	Burned only (km^2)	Burned & Logged (**) (km^2)	Logged only (km^2)
002/067	5.1	-	7.8	11.8	-	29.5	25.7	-	23.9
221/063	203.9	23.2	23.0	77.8	19.7	7.9	53.6	14.1	34.1
222/062	296.7	33.3	482.4	574.6	264.9	689.7	440.7	293.1	931.7
222/063	644.5	49.8	594.5	464.3	136.4	586.5	709.5	603.5	2,231.0
222/064([a])	17.7	0.2	-	44.7	5.1	7.6	31.8	3.3	17.4
223/062	180.3	40.1	644.5	411.6	556.5	1,549.7	422.7	259.7	3,382.1
223/063	66.1	25.5	489.8	538.4	147.1	1,413.0	360.9	246.2	2,748.0
223/064	14.5	-	27.4	55.2	0.8	27.3	40.2	2.5	235.5
223/065	111.8	1.1	25.5	277.9	3.5	14.3	28.6	-	60.5
223/066	21.3	7.3	66.5	60.1	4.2	5.3	34.1	3.6	37.4
223/067([d])	-	-	-	0.3	-	-	3.6	-	
224/062([c])	-	-	-	24.4	2.8	11.2	159.7	16.8	681.3
224/063	28.7	-	7.6	44.0	2.1	18.1	46.4	8.4	34.7
224/065	69.0	-	47.2	71.6	0.4	60.2	75.1	19.1	95.9
224/066	493.0	90.0	205.9	159.3	30.5	191.8	1,048.1	88.1	689.5
224/067	518.3	0.5	23.1	37.8	1.9	72.4	151.6	6.6	316.3
224/068([b])	189.8	-	-	605.8	-	0.1	1,227.6	-	0.2
224/069([b])	140.6	-	-	225.0	-	-	474.0	-	
225/067([a])	297.1	-	-	333.2	-	-	305.2	-	15.6
225/068([a])	159.3	-	-	228.0	-	-	136.9	5.0	88.6
225/069	296.2	0.3	1.4	322.0	1.9	15.9	473.4	2.4	60.8
225/070([d])	-	-	-	-	-	-		-	
226/063	7.3	-	5.0	9.3	0.1	68.4	9.9	-	8.2
226/066([c])	-	-	-	-	-	-	2.2	-	35.6
226/067	313.3	1.5	16.0	384.7	4.2	24.2	169.0	11.2	359.8

Appendix C.9 To be continued …

Path & Row	1992 Burned only (km^2)	1992 Burned & Logged (km^2)	1992 Logged only (km^2)	1996 Burned only (km^2)	1996 Burned & Logged (*) (km^2)	1996 Logged only (km^2)	1999 Burned only (km^2)	1999 Burned & Logged (**) (km^2)	1999 Logged only (km^2)
226/068	397.4	39.6	1,205.2	121.9	43.6	1,719.6	569.3	292.5	4,241.2
226/069	144.2	29.6	844.2	215.4	86.7	1,087.1	397.4	350.6	2,990.5
226/070(d)	-	-	-	-	-	-	31.6	-	1.3
227/062(a)	-	-	-	0.1	0.1	13.3	57.8	0.2	443.2
227/065(a)	6.4	-	-	7.5	-	-	38.1	1.2	110.0
227/067	564.9	0.7	3.7	190.8	0.4	12.7	164.1	2.2	159.2
227/068	310.5	28.9	274.8	234.9	35.2	296.8	365.3	131.3	1,168.6
227/069	52.5	8.4	358.1	86.5	14.8	437.2	188.2	21.6	846.8
227/070	-	-	2.3	-	-	0.6	85.8	0.1	14.7
228/067(d)	-	-	-	3.2	-	12.1	66.1	-	11.1
228/068	166.1	5.2	134.9	195.3	34.2	178.3	140.8	41.7	695.3
228/069	11.1	4.7	15.8	11.5	3.5	83.9	50.7	8.0	375.7
229/067	18.5	-	5.7	13.5	-	72.3	19.6	0.4	244.5
229/068	22.7	0.1	6.6	11.2	0.7	34.2	155.9	28.5	411.9
229/069	5.9	-	5.0	59.0	0.6	5.9	45.6	0.4	17.3
229/070	40.2	0.3	23.5	6.0	-	28.9	28.0	1.8	54.7
230/068	46.7	-	12.2	35.0	0.7	81.8	146.4	2.2	104.3
230/069	22.8	1.2	18.1	15.9	0.5	93.0	53.7	4.2	84.8
232/067	5.1	-	10.3	8.5	-	-	3.8	-	125.0
Total	5,889.3	391.6	5,588.1	6,177.8	1,403.3	8,951.0	9,038.4	2,470.7	24,188.1

Appendix C.9. Continued .

Appendix C.10. Selectively logged and burned forests detected by State in the Brazilian Amazon

State	1992			1996			1999		
	Burned only (km^2)	Burned & Logged (km^2)	Logged only (km^2)	Burned only (km^2)	Burned & Logged [a] (km^2)	Logged only (km^2)	Burned only (km^2)	Burned & Logged [b] (km^2)	Logged only (km^2)
Acre	2.9	2.2	5.6	11.5	-	30.8	24.7	-	20.5
Amapá	-	-	-	-	-	-	-	-	-
Amazonas	-	-	-	-	-	-	-	-	-
Maranhão	772.0	44.0	462.2	380.2	110.7	526.2	489.7	350.9	2,022.9
Mato Grosso	3,521.8	108.1	2,905.5	3,222.6	225.6	4,013.9	5,221.9	899.3	11,864.8
Pará	1,486.6	228.5	2,176.9	2,295.1	1,064.8	4,199.9	3,078.9	1,213.8	9,956.4
Rondônia	71.0	8.8	33.0	90.8	1.9	168.6	186.4	6.8	305.6
Roraima	-	-	-	-	-	-	-	-	-
Tocantins	35.1	0.0	5.0	177.5	0.3	11.6	36.9	-	17.8
Total	5,889.5	391.6	5,588.1	6,177.8	1,403.3	8,951.0	9,038.4	2,470.7	24,188.1

Appendix C.10

Appendix C.11. Forest canopy losses estimated using multi-regression model for the study region

Variables and Constant	Coef.	Std. Err.	t	P (2 tails)	[95% Conf.	Interval]
Constant	95.5	0.2461	387.83	0.000	95.0	95.9
Deforestation	-49.0	0.1724	-284.30	0.000	-49.4	-48.7
Secondary Regrowth	-6.8	0.2297	-29.74	0.000	-7.3	-6.4
Cerrado (Savannah)	-39.2	0.1573	-249.37	0.000	-39.5	-38.9
Water body	-66.8	0.5647	-118.36	0.000	-67.9	-65.7
Newly logged ([1])	-1.6	0.4895	-3.28	0.001	-2.6	-0.6
Newly burned ([1])	-18.8	0.6250	-30.12	0.000	-20.1	-17.6
Newly logged & burned ([1])	-27.5	1.3681	-20.07	0.000	-30.1	-24.8
Previously logged ([2])	5.8	1.4327	4.05	0.000	3.0	8.6
Previously burned ([2])	-2.5	1.1203	-2.25	0.024	-4.7	-0.3
Previously logged & burned ([2])	-9.7	1.4907	-6.48	0.000	-12.6	-6.7
Year 1996	1.0	0.1381	7.19	0.000	0.7	1.3
Year 1999	-5.1	0.1324	-38.29	0.000	-5.3	-4.8
Longitude (km)	-0.008	0.0001	-59.48	0.000	-0.008	-0.007
Latitude (km)	0.012	0.0002	58.34	0.000	0.011	0.012

[1] The term *newly* refers to logging and/or burning activities occurred during 1993-96 and 1997-99 intervals, detected by 1996 and 1999, respectively. [2] The term *previously* refers to logging and/or burning activities detected by 1992 and 1996 that persisted detectable on Landsat imagery by 1996 and 1999, respectively.

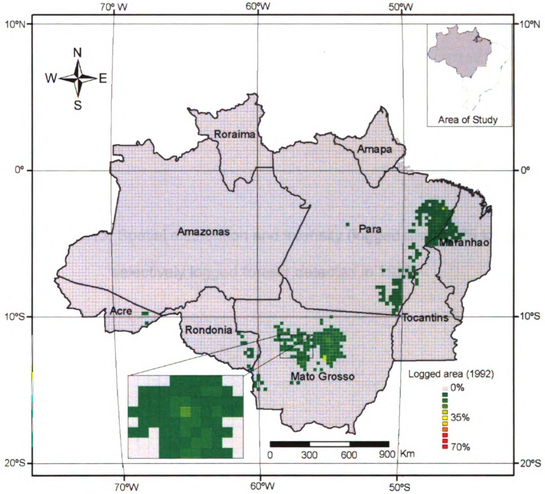
N = 154635 observations (5000m x 5000m systematic sampling grid)

R2 = 0.5285; Adj. R2 = 0.5284; Prob > F = 0.000; F(14, 154620) = 12377.16

Appendix C.11

Appendix C.12. Spatial distribution and intensity (logged area / 625 km2) of selectively logged forests detected in 1992

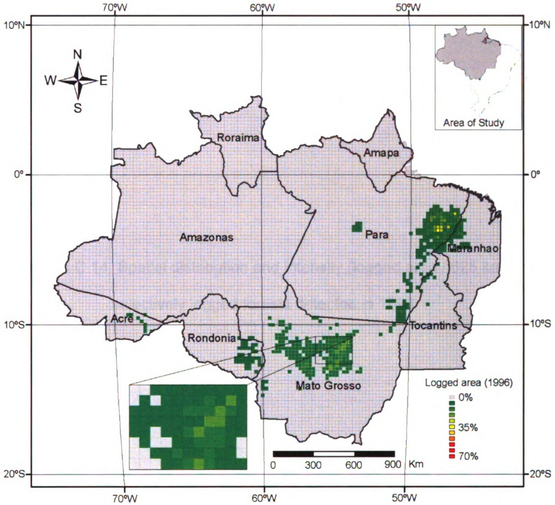
Spatial distribution and intensity (logged area / 625 km2) of selectively logged forests detected in 1992



Appendix C.12

Appendix C.13. Spatial distribution and intensity (logged area / 625 km2) of selectively logged forests detected in 1996

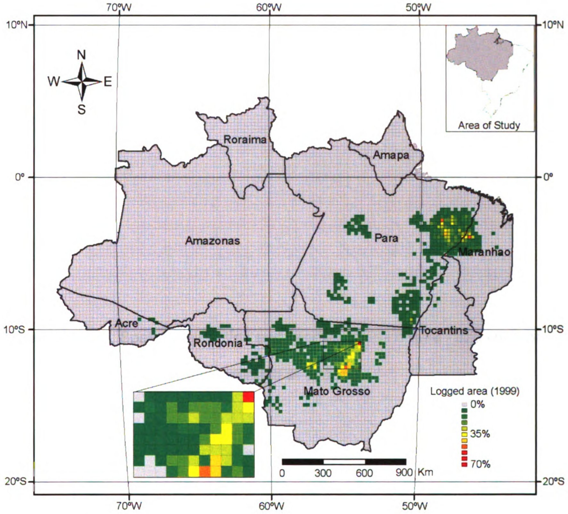
Spatial distribution and intensity (logged area / 625 km2) of selectively logged forests detected in 1996



Appendix C.13

Appendix C.14. Spatial distribution and intensity (logged area / 625 km2) of selectively logged forests detected in 1999

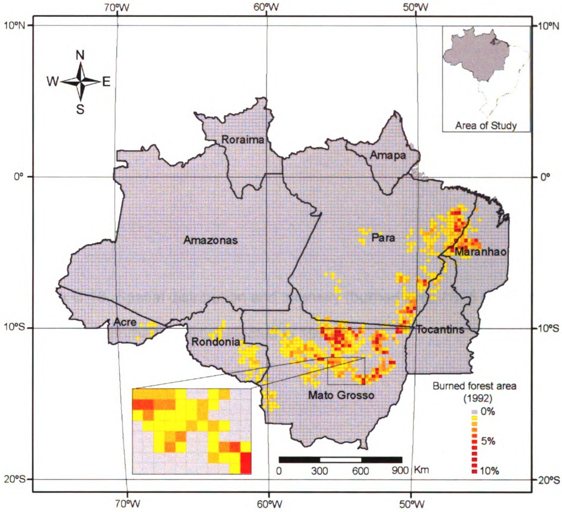
Spatial distribution and intensity (logged area / 625 km2) of selectively logged forests detected in 1999



Appendix C.14

Appendix C.15. Spatial distribution and intensity (burned area / 625 km2) of burned forests detected in 1992

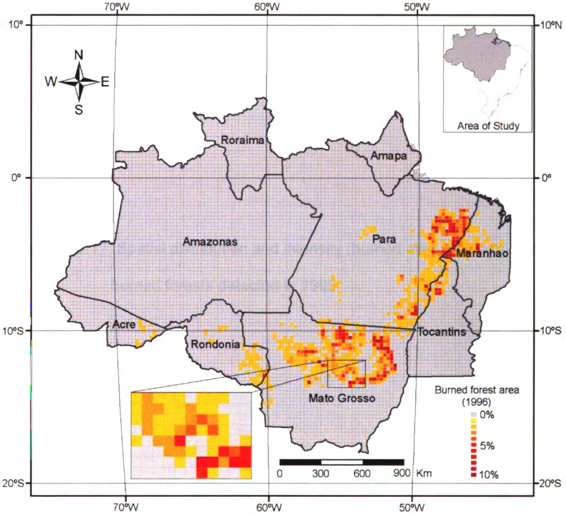
Spatial distribution and intensity (burned area / 625 km2) of burned forests detected in 1992



Appendix C.15

Appendix C.16. Spatial distribution and intensity (burned area / 625 km2) of burned forests detected in 1996

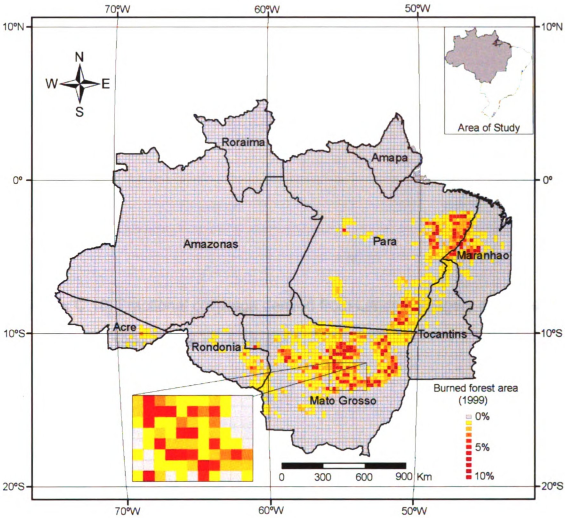
Spatial distribution and intensity (burned area / 625 km2) of burned forests detected in 1996



Appendix C. 16

Appendix C.17. Spatial distribution and intensity (burned area / 625 km2) of burned forests detected in 1999

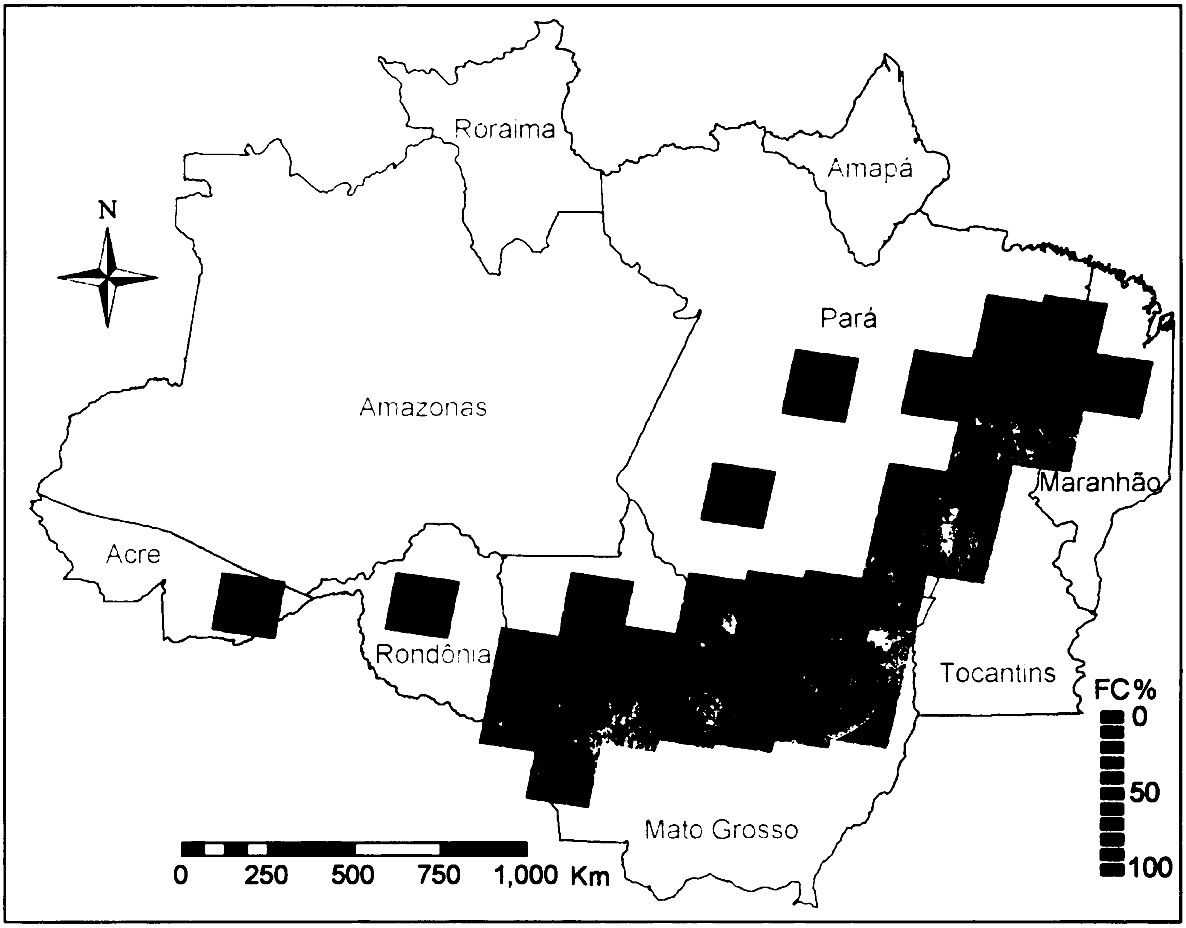
Spatial distribution and intensity (burned area / 625 km2) of burned forests detected in 1999



Appendix C. 17

Appendix C.18. Fractional coverage derived from Landsat imagery acquired in 1992 for the study region

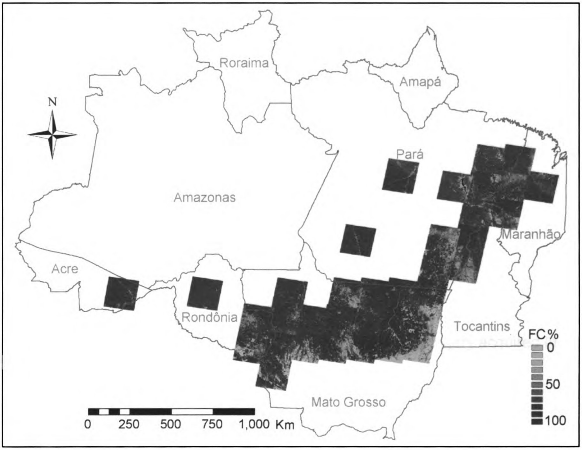
Fractional coverage derived from Landsat imagery acquired in 1992 for the study region



Appendix C.18

Appendix C.19. Fractional coverage derived from Landsat imagery acquired in 1996 for the study region

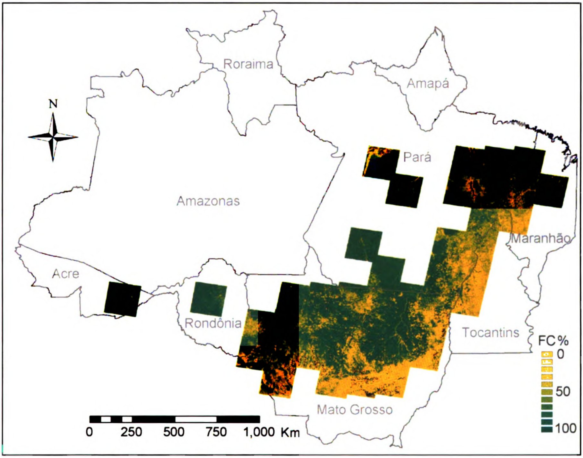
Fractional coverage derived from Landsat imagery acquired in 1996 for the study region



Appendix C.19

Appendix C.20. Fractional coverage derived from Landsat imagery acquired in 1999 for the study region

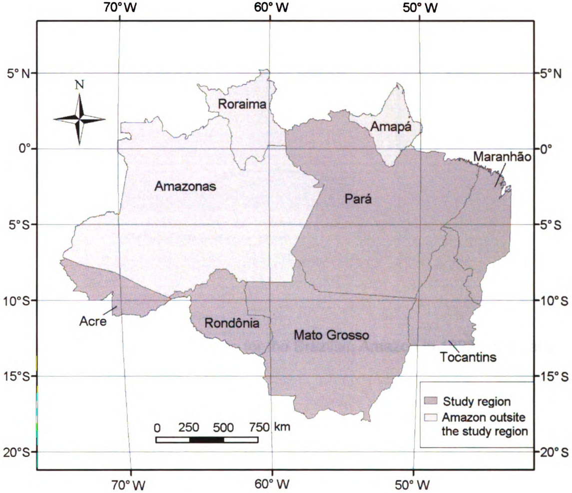
Fractional coverage derived from Landsat imagery acquired in 1999 for the study region



Appendix C.20

Appendix D.1. The study region location within the Brazilian Amazon

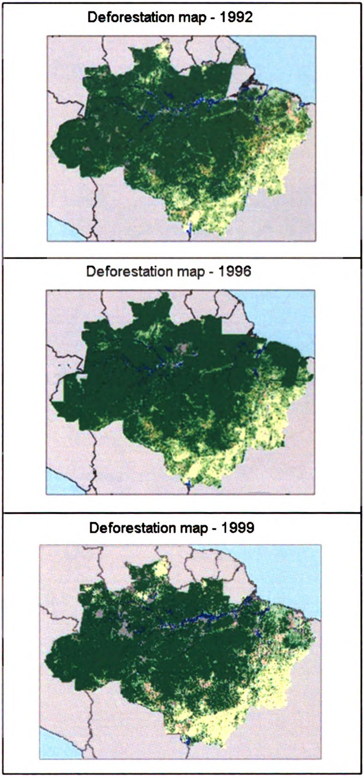
The study region location within the Brazilian Amazon



Appendix D.1.

Appendix D.2. Deforestation map for the Brazilian Amazon in 1992, 1996, and 1999

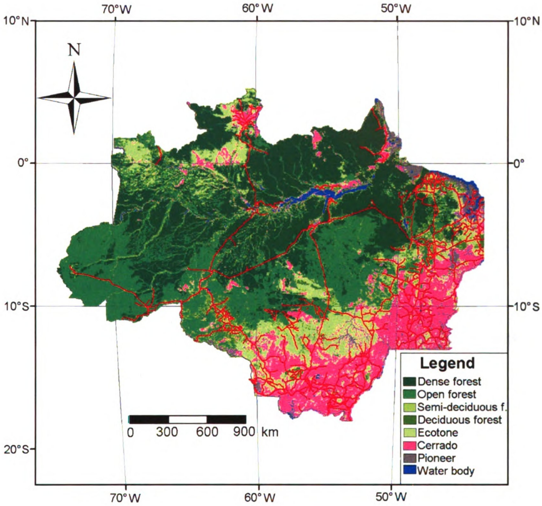
Deforestation map for the Brazilian Amazon in 1992, 1996, and 1999



Appendix D.2

Appendix D.3. Vegetation map of the Brazilian Amazon in 1999.

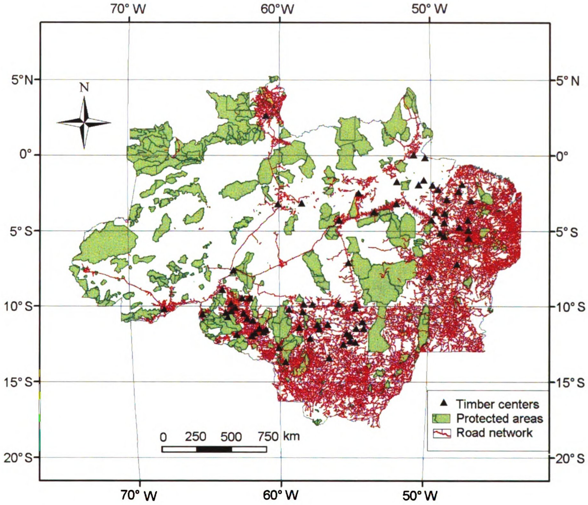
Vegetation map of the Brazilian Amazon in 1999.



Appendix D.3

Appendix D.4. Map of road network, protected areas, and timber centers in the Amazon

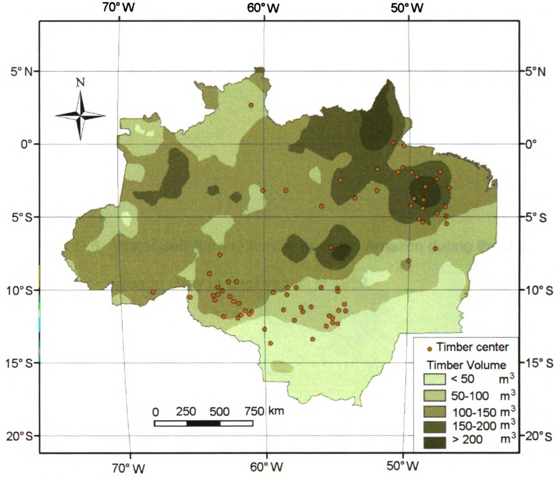
Map of road network, protected areas, and timber centers in the Amazon



Appendix D.4

Appendix D.5. Map of timber volume generated using ordinary kriging interpolation and the dataset derived from forest inventory conducted by RADAMBRASIL project

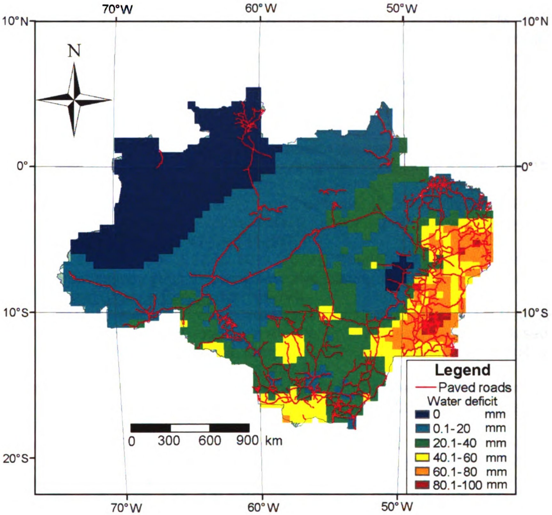
Map of timber volume generated using ordinary kriging interpolation and the dataset derived from forest inventory conducted by RADAMBRASIL project



Appendix D.5.

Appendix D.6. Water deficit (mm) for the Brazilian Amazon during the dry season (May to September) in 1999.

Water deficit (mm) for the Brazilian Amazon during the dry season (May to September) in 1999.



Appendix D.6

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