SPATIOTEMPORAL DYNAMICS OF FOREST DISTURBANCES CAUSED BY SELECTIVE LOGGING IN THE BRAZILIAN AMAZON

by

Thais Almeida Lima

B.Sc., Universidade de Brasília, 2006
M.Sc., Instituto Nacional de Pesquisas da Amazônia, 2009

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The following individuals certify that they have read, and recommend to the Faculty of Graduate and Postdoctoral Studies for acceptance, the dissertation entitled:

Spatiotemporal dynamics of forest disturbances caused by selective logging in the Brazilian Amazon

submitted by Thais Almeida Lima in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Forestry

Examing Committee:

Verena C. Griess, Forestry

Supervisor

René Beuchle, Joint Research Centre of the European Commission

Supervisory Committee Member

Agni Boedihartono, Forestry

University Examiner

Mark Johnson, Resources, Environment and Sustainability

University Examiner

Britaldo Silveira Soares-Filho, Department of Geography, Universidade Federal de Minas Gerais

External Examiner
Abstract

Selective logging is one of the main causes of forest degradation in the Brazilian Amazon. However, when compared to deforestation, logged forests retain much more biomass and carbon stocks, maintaining important ecosystem services. In several tropical countries selective logging has been promoted as an alternative to the conversion of forests into other land use types. In Brazil, legal logging activities are mainly conducted in privately owned forests, hereafter called forest management units (FMUs). Little is known about the implementation of authorized logging in these areas. This thesis had the objective of characterizing selective logging activities in FMUs located in a focused area within the Brazilian State of Amazonas.

The performance of two satellites, Landsat 8 and Sentinel-2, for mapping selective logging were compared. A robust change detection approach was applied for imagery of both satellites. Based on these analyses, Sentinel-2 was chosen as input data set for a spatial pattern analysis. Landscape metrics were computed over multiple scales and then combined into a single map, with five classes of disturbances. Then, this map was used to produce a forest disturbance intensity score. Different weights, meant to account for the heterogeneity associated with harvest operations, were assigned for each disturbance class to score and rank FMUs.

Both satellites showed the same performance in terms of accuracy. However, due to its larger spatial resolution, Landsat 8 overestimated the area of logging compared to Sentinel-2. Therefore, Sentinel-2 data was chosen for all further analyses. The five disturbance intensity classes showed a good association with real disturbances. The ranking system, compared to a traditional disturbance indicator, showed very different results for FMUs with intermediate disturbance scores. The most disturbed and the least disturbed areas kept the same position wherever weighting system was assigned. This thesis presents important results towards a better understanding of the spatiotemporal patterns of logging related disturbances in tropical forests. The methodology developed here is simple but robust, it is transparent and easy to be reproduced. The mapping scheme, the spatial pattern analysis and the score system can be used by institutions concerned with the monitoring of tropical forests.
Lay Summary

Unsustainable logging is a major problem in tropical forests. A better understanding of the spatiotemporal patterns of logging activities is crucial. This study addressed whether two freely available satellites were suitable for mapping selective logging activities in the Brazilian Amazon. Later on, using the most suitable satellite, Sentinel-2, a spatial pattern analysis was carried out with the objective of categorizing areas of selective logging according to their disturbance intensities. These areas were later scored and ranked, using an innovative indicator. Results from this thesis can be promptly used by anyone interested in monitoring selective logging in tropical forests.
Preface

This Dissertation is an original research, proposed and designed by me, Thais Almeida Lima, with support of my PhD Supervisory Committee. The research, field data collection, data analyses, interpretation of results, and manuscript preparation were done by me. The co-authors in the following list of publications, advised me on methodological aspects of my work and helped me to improve the manuscripts. René Beuchle provided particular help with the grid-based analysis presented in Chapter 4 of this thesis.

Chapters 4, 5 and 6 are independent research chapters that have been structured and written as scientific articles. A list of publications for each research chapter is presented as follows:

Chapter 4

Published


Submitted

Chapter 5

Submitted
Lima TA, Beuchle R, Verhegghen A, Griess VC, Vogt P. Spatial patterns of logging-related disturbance events: preliminary results from a multi-scale analysis on forest management units
located in the Central Brazilian Amazon. Submitted and accepted for oral presentation at the XXV IUFRO World Congress, Curitiba, Brazil.

In preparation

Lima TA, Griess VC, Beuchle R, Larson, B. How has disturbance intensity been defined and measured in tropical forests landscapes? Ecography.

Chapter 6
In preparation
Lima TA, Beuchle R, Griess VC, Fusco E. Landscape indicators for evaluating the performance of selective logging activities in forest management units located in the Brazilian Amazon. Ecological Indicators.
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<td>AOI</td>
<td>Area of Interest</td>
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<td>AUTEX</td>
<td>Authorization for Logging</td>
<td>Autorização de Exploração</td>
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<td>BFC</td>
<td>Brazilian Forest Code</td>
<td>Código Florestal Brasileiro</td>
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<tr>
<td>C&amp;I</td>
<td>Criteria and Indicators</td>
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<tr>
<td>CE</td>
<td>Commission Errors</td>
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<td>CEMAAM</td>
<td>Environmental Council of Amazonas State</td>
<td>Conselho Estadual de Meio Ambiente do Amazonas</td>
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<tr>
<td>CI</td>
<td>Confidence Interval</td>
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<tr>
<td>CIFOR</td>
<td>Center for International Forestry Research</td>
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<td>CIRAD</td>
<td>French Agricultural Research Centre for International Development</td>
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<td>CL</td>
<td>Conventional Logging</td>
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<td>CLARA</td>
<td>Clustering Large Applications</td>
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<td>CONAMA</td>
<td>National Council of Environment</td>
<td>Conselho Nacional de Meio Ambiente</td>
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<tr>
<td>COP</td>
<td>Conference of the Parties</td>
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<tr>
<td>DEGRAD</td>
<td>Forest Degradation Mapping in the Brazilian Amazon</td>
<td>Mapeamento da Degradação Florestal na Amazônia Brasileira</td>
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<td>DETER</td>
<td>Deforestation Detection at Almost Real Time system</td>
<td>Sistema de Detecção do Desmatamento na Amazônia Legal em Tempo Real</td>
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<td>DN</td>
<td>Digital Numbers</td>
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<td>DOF</td>
<td>Document of Forest Origin</td>
<td>Documento de Origem Florestal</td>
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<td>EPSG</td>
<td>European Petroleum Survey Group</td>
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<td>Food and Agriculture Organization of the United Nations</td>
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<td>Forest Law Enforcement, Governance and Trade</td>
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<td>FMP</td>
<td>Forest Management Plan</td>
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<td>GFC</td>
<td>Global Forest Change</td>
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<td>GloVis</td>
<td>Global Visualization Viewer</td>
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<td>IBAMA</td>
<td>Brazilian Institute of Environment and Renewable Natural Resources</td>
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<td>ITTO</td>
<td>International Tropical Timber Organization</td>
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<td>IUFRO</td>
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<tr>
<td>IVI</td>
<td>Importance Value Index</td>
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<tr>
<td>JRC</td>
<td>Joint Research Centre</td>
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<tr>
<td>LiDAR</td>
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<td>MMA</td>
<td>Brazilian Ministry of Environment</td>
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<td>MMU</td>
<td>Minimum Mapping Unit</td>
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<tr>
<td>MODIS</td>
<td>Moderate-resolution Imaging Spectroradiometer</td>
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<td>MSI</td>
<td>Multispectral Instrument</td>
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<td>NBR</td>
<td>Normalized Burn Ratio</td>
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<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
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<td>NIR</td>
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<td>OECD</td>
<td>Organization for Economic Co-operation and Development</td>
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<td>OLI</td>
<td>Operational Land Imager</td>
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<td>Settlement Project</td>
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<td>Proportion</td>
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<td>Pdd</td>
<td>Adjacency</td>
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<td>Action Plan for the Prevention and Control of Deforestation in the Legal Amazon</td>
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<td>PRODES</td>
<td>Satellite Monitoring System for the Brazilian Amazon Deforestation</td>
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<td>PropArea</td>
<td>Proportion of the area</td>
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<tr>
<td>REDD+</td>
<td>Reducing Emissions from Deforestation and Forest Degradation in Developing Countries</td>
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<td>RGB</td>
<td>Red, green, and blue color system</td>
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Dedication

To my husband, Eliano Rossi

Para meu marido, Eliano Rossi
1 Introduction

1.1 Background and rationale

Over the past centuries, human activities have changed natural landscapes at a rapid pace. One of the most dramatic consequences of these actions has been the alteration of the global carbon cycle (Falkowski et al. 2000; Bruhwiler et al. 2018). Among other factors, tropical forest loss increases the amount of carbon in the atmosphere and is a key component of the climate change phenomenon (Gibbs et al. 2007; Lewis et al. 2015). In this context, research on the role played by land use and land cover change in the tropics as a driver of climate change has been a focal interest of the scientific community for many decades (Lambin et al. 2003; IPCC 2019). During the 2000s the gross loss of tropical forests was approximately 7.6 million ha.year\(^{-1}\) (Achard et al. 2014). In the period from 2000-2005, for instance, forests from tropical South and Central America lost 4.4 million ha.year\(^{-1}\), with Brazil accounting for 69% of the total losses (Eva et al. 2012). In fact, when compared with other climate domains, the tropics continue to show higher rates of forest loss (Hansen et al. 2013; GFC 2019).

The United Nations Framework Convention on Climate Change (UNFCCC) was implemented in 1994, recognizing that climate change was a phenomenon that needed to be tackled globally. In the year 2015 at the Conference of the Parties (COP 21), in Paris, parties to the UNFCCC met to find a common solution to tackle climate change. The document resulting from this conference is now known as the “Paris Agreement”. In the year of 2016 countries started to sign this agreement, which entered into force later in the same year (UNFCCC 2019). The UNFCCC addresses specific policies to deal with tropical deforestation. The initiative “Reducing Emissions from Deforestation and Forest Degradation in Developing Countries” (REDD+) was created specifically to curb tropical deforestation and forest degradation. In order to be efficient, this policy requires reliable methods to measure carbon emissions from both phenomena (Gibbs et al. 2007; Pelletier et al. 2013; Goetz et al. 2015).

The forests in the Amazon Basin are the largest remaining area of tropical forest in the world, sheltering the richest biological diversity on Earth (Hoorn et al. 2010). The area stores more carbon than any other tropical region and has a substantial influence on regional and global climates (Malhi et al. 2008). Brazil holds the biggest portion of the Amazon biome, and, at the same time, has the highest level of forest loss among all countries in the pan-Amazon region (Coca-Castro et al. 2013). Between 1988 and 2018 Brazil has lost more than 400,000 km\(^2\) of primary forests, an area as large as the area of Germany (INPE 2019a). Since 2004, however, annual deforestation rates in the Brazilian Amazon have reduced drastically, from 27,772 km\(^2\), recorded for this year, to 4,571 km\(^2\) recorded for the year 2012 (INPE 2019a).
Many studies tried to disentangle the possible drivers of the deforestation slowdown recorded 2004-2012. Amongst the possible reasons, new forest protection laws (e.g. Federal Decree Nº6.514/2008), satellite monitoring, such as the “Near Real-Time Deforestation Detection” system (DETER), policy interventions and law enforcement, private sector initiatives, such as beef and soybean moratoria, and market conditions were cited (Malingreau et al. 2012; Boucher et al. 2013; Nepstad et al. 2014; Gibbs et al. 2016; Soares-Filho and Rajão 2018; Carvalho et al. 2019). Despite being a contentious issue, the decrease in the deforestation rates is credited mostly to market conditions and to effective and strong law enforcement actions against illegal deforestation (Fearnside 2017; Carvalho et al. 2019; Tacconi et al. 2019). Public policies and the overall political scenario also play a major role in explaining the variations in the deforestation trends in the Brazilian Amazon (Soares-Filho and Rajão 2018).

Since 2012 the deforested area within the Brazilian Amazon is on the rise again, with a recorded 7,536 km$^2$ lost in the year 2018 (INPE 2019a). Despite the recorded rates in the period post-2012 have not (yet) exceeded 8,000 km$^2$ per year, this rising trend has been object of concern, not just among scientists at research institutions and universities, but also across different sectors of the civil society. Since the controversial changes in the Brazilian Forest Code in the year 2012, which was driven primarily by an increasing pressure from the agribusiness sector (Soares-Filho et al. 2014), there has been apprehension that the relaxing of forest legislation would promote a rise in the deforestation rates (Fearnside 2015; Soares-Filho and Rajão 2018).

While it is difficult to impute a causal effect on the rise of deforestation solely to changes in the forest legislation, it is necessary to agree that they do play a major role in explaining fluctuations in the deforestation rates. The same is also true for the overall political scenario. Since 2016 there has been a change in the environmental policies in Brazil, with a continuous weakening of the environmental institutions responsible for the prevention and control of deforestation activities (Pereira et al. 2019). At the beginning (2016) these changes were represented by budget constraints, as Brazil was facing an economic recession (Pereira et al. 2019). Since the beginning of this year (2019) the new Brazilian government has started to implement a political agenda which is clearly against environmental conservation (Ferrante and Fearnside 2019; Artaxo 2019). As a possible result of these changes, deforestation and fire outbreaks recorded for the last three months (August, July and June 2019) skyrocketed in relation to the same period of the last year (INPE 2019b; INPE 2019c).

Conservation efforts, despite being primarily implemented by governments through command and control policies, are also a result of the engagement of the scientific community and the civil society in general. The success reached in curbing deforestation rates in the period of 2004-2012 was, in part, explained by the work done collectively by different actors interested in implementing an environmental
agenda based on scientific evidence and also based on dialogue (Soares-Filho and Rajão 2018). From the lessons learned in the past 20 years, perhaps the most important one is that environmental conservation and sustainable development policies need to be based on strong scientific evidence. For instance, part of the success reached in curbing deforestation is credited to the DETER system, a pillar component of the Action Plan to Prevent and Control Deforestation in the Brazilian Amazon (PPCDAm), implemented in 2004 (Boucher et al. 2013; Tacconi et al. 2019). Regardless of the inherent problems associated with its coarse spatial resolution, based on MODIS data, DETER has 90% of overall accuracy and it was successful in doing exactly what it was created to do: give alert reports in areas with high deforestation rates, allowing law enforcement agencies to take action (Shimabukuro et al. 2013). Therefore, despite the possible overturn in the environmental agenda implemented by the new Brazilian government, the scientific community must continue to work together to find possible strategies to curb illegal deforestation, as well as to propose solutions towards sustainable development for the Amazon (Artaxo 2019).

While we have seen a major effort to develop systems for monitoring deforestation (Shimabukuro et al. 2013; Hansen et al. 2013), another anthropogenic activity, forest degradation, is still poorly understood. Therefore, another big challenge Brazil and other tropical countries are currently facing is related to the assessment of forest degradation, which is defined by the Food and Agriculture Organization of the United Nations (FAO) as “the reduction of the capacity of a forest to provide goods and services” (FAO 2010). Forest degradation due to selective logging and forest fires is an alarming reality in the Brazilian Amazon (Asner et al. 2005; Matricardi et al. 2010; Shimabukuro et al. 2019). Selective logging is defined as the practice of harvesting just few valuable trees in a given area and it is the main harvest method employed in tropical forests (Johns 1985; Edwards et al. 2014).

Although emissions caused by forest degradation in the tropics are somewhat compensated by forest regrowth (Pan et al. 2011; Houghton 2012), they may account for carbon emissions of up to 40% of the levels caused by deforestation (Berenguer et al. 2014). Additionally, previously logged forests, especially in the Brazilian Amazon, are at a high risk of being converted into non-forest land use types (Asner et al. 2005). Anthropogenic forest disturbances, like selective logging and forest fires, reduce biodiversity and conservation values in the remaining primary forest areas (Barlow et al. 2016) and can have negative impacts on ecosystems services (more than reduced carbon stocks), such as watershed services (Edwards et al. 2014). Despite the uncertainties in the estimates, it is important to highlight that the majority of selective logging operations in the Amazon are illegal (Lawson and MacFaul 2010; Wellesley 2014). Illegal and unsustainable logging results in forest degradation, and forest degradation lowers the opportunities for sustainable development (Fearnside 2003; Brancalion et al. 2018; Lima et al. 2018). Therefore, discussions
about the effectiveness of REDD+ projects need a stronger emphasis on the processes of forest degradation (Sasaki and Putz 2009).

The long-term success Brazil has had in measuring deforestation does not apply to forest degradation. The country does not have an official definition for forest degradation and it does not have a consistent, long-term monitoring system to address this type of anthropogenic activity. In the submission of its Forest Reference Emission Level (FREL) for the UNFCCC-REDD+ program, Brazil did not take into account carbon emissions from forest degradation, despite the evident importance (Brazil 2014). In fact, the technical analysis of the Brazil’s FREL report recommended, as one of the priority actions, to improve the method for monitoring forest degradation (UNFCCC 2015). Therefore, to get a better understanding about the forest degradation dynamics in Brazil, especially in the Amazon, is an urgent need. As forest disturbances caused by selective logging are a key component of the forest degradation phenomenon, understanding its pattern and dynamics is critical.

Forest canopy cover disturbances, resulting in forest degradation, are not a transition between land cover classes, but a change within one class (Eva et al. 2015). This makes the detection process more difficult when compared with deforestation. This is the case, because, in general, tropical forests recover really fast after disturbances, making the detection difficult (Verhegghen et al. 2015; Langner et al. 2016). This vegetation regrowth, however, does not necessarily mean a recovery in forest structure or biomass, since the “greenness” detected by satellite sensors is often a result of the reflectance of fast-growing pioneer vegetation (Asner et al. 2009). In addition, some of the impacts caused by selective logging, for instance, skid trails and, in some cases, logging roads, are not even visible using optical remote sensing techniques (Lima et al. 2019).

In the last two decades many studies investigated the detection of forest disturbances caused by selective logging and/or forest fires in the Brazilian Amazon using remote sensing techniques (Asner et al. 2002; Hurtt et al. 2003; Monteiro et al. 2003; Read et al. 2003; Asner et al. 2004; Souza and Roberts 2005; Souza Jr et al. 2005; Asner et al. 2005; Monteiro et al. 2007; Matricardi et al. 2010; Souza Jr et al. 2013; Cunha et al. 2016; Pinheiro et al. 2016; Tritsch et al. 2016; Grecchi et al. 2017; Shimabukuro et al. 2019). Almost all of these studies used medium resolution satellites, such as Landsat, to assess the extent of degraded forests. However, the Landsat spatial resolution (30 m) has often been considered as too coarse for reliably mapping small-scale selective logging. Imagery from the recently launched Sentinel-2 sensor, with a 10 m spatial resolution, may improve the detection of forest disturbances and the understanding of the forest degradation process. In addition, in Brazil, the vast majority of these remote sensing studies were conducted in old logging frontiers (Asner et al. 2009), mainly in the states of Pará and Mato Grosso. However, there is evidence that logging patterns may not be the same across the entire region (Ahmed and
Ewers 2012; Pinheiro et al. 2016). Hence, there is a necessity to test novel methods to map selective logging in new logging frontiers in the Brazilian Amazon.

Some authors have used the terms “forest degradation” and “selective logging” interchangeably (Foley et al. 2007; Matricardi et al. 2010; Souza Jr et al. 2013; Pinheiro et al. 2016). In addition, the role of selective logging activities in tropical forests as a catalyst of forest degradation or as an ally of sustainable development is a contentious issue in the scientific community (Zimmerman and Kormos 2012; Putz et al. 2012; Sist et al. 2012; Kormos and Zimmerman 2014; Putz et al. 2014). For some authors, of the principles of sustainable forest management are respected within a forest stand, the area should not be considered degraded (e.g. Thompson et al. 2013). Even with a lower commercial value compared to planted forests (Paul and Knoke 2016), a large part of the globally commercialized tropical hardwoods originate from native forests, a fact which is not going to change soon (Putz and Romero 2014). Despite the controversy, what is clear is that a large amount of tropical forests are or will be designated as production forests, therefore, acknowledge it and work towards better management alternatives is crucial (Edwards et al. 2014; Putz et al. 2014; Runting et al. 2019).

If properly managed, selectively logged forests retain substantial biodiversity and are clearly a better alternative compared to deforestation (Putz et al. 2012). In addition, logged forests still remain as a forest stand and, in comparison with agricultural lands, they can still provide a variety of ecosystem services, especially when Reduced Impact Logging (RIL) techniques are employed (Edwards et al. 2014; Ellis et al. 2019). In recent years, Brazil has shown considerable progress in promoting a legal framework to encourage the sustainable use of forests (Blaser et al. 2011). However, only 5% of Brazilian forests under sustainable forest management are currently monitored (FAO 2015). In addition, there is evidence that the current Brazilian sustainable forest management is imperfectly implemented, giving margin to corruption and increasing the likelihood for further forest degradation (Brancalion et al. 2018). To ensure the sustainable management of tropical production forests as a conservation strategy, reliable methods of forest monitoring are required. Furthermore, studies on the monitoring of selective logging activities using remote sensing techniques, associated with field data, are mostly concentrated in small experimental plots. Therefore, there is a gap in knowledge about the implementation of authorized (legal) harvest in licensed forest management units within the Brazilian Amazon. In addition, forest conservation policy in Brazil has substantial implementation costs (Cunha et al. 2016) and this reinforces the need for more cost-effective monitoring systems, such as remote sensing-based technologies.

Selective logging mapped using remote sensing technologies usually is presented as a binary map composed by two classes: undisturbed forests and areas considered “disturbed”, “degraded” or “logged”, depending on the adopted method and terminology (Asner et al. 2005; Souza Jr et al. 2013; Tritsch et al. 2015).
These binary maps are then used as indicators, for instance, for evaluating the amount of forest considered “logged” or “degraded” among different regions (Asner et al. 2005; Souza Jr et al. 2013). A step further into the evaluation of forest disturbances caused by selective logging is going beyond the binary maps and assigning to the disturbed areas “classes of disturbances”, so the mapped areas are scored depending on the defined disturbance intensity (Pinheiro et al. 2016; Grecchi et al. 2017). These last two studies addressed disturbance intensity within large grid cells. If the monitoring is focused within a specific authorized logging area (a forest management unit – FMU) keeping the pixel resolution may be a better alternative. Assigning classes of forest disturbances for each one of the areas previously mapped as selectively logged can be done with a spatial pattern analysis (Riitters 2018), and currently this approach was never tested exclusively in selectively logged forests.

In addition to furthering the selective logging monitoring into discrete classes (beyond the binary maps), there is a need to evaluate selectively logged areas using indicators. Composite indicators and scoreboards are used extensively to evaluate countries performances and/or to guide public policies (Nardo et al. 2008; Gan et al. 2017; Greco et al. 2019). Currently, there are few attempts of using composite indicators for assessing forest disturbance intensities (e.g. Pinheiro et al. 2016). This kind of score system could be used for planning law enforcement actions, for instance, in areas with high score of forest disturbance intensities.
1.2 Research objectives

The overall aim of this thesis is to enhance the understanding of forest disturbances, caused by logging activities, in the Brazilian Amazon: its extent and intensity, with the goal to develop a pathway towards better management approaches. A focus area, located in the State of Amazonas, Brazil, with high rates of deforestation and forest degradation was chosen as a case study. By using the same area, the methodologies developed for answering the research questions could be applied in a progressive and concise manner. My specific research objectives are (Figure 1.1):

- Research Objective 1 (Chapter 4): To map forest disturbances caused by selective logging and to compare the effectiveness of different satellite imagery for such purpose;
- Research Objective 2 (Chapter 5): To propose a methodology to assess forest disturbance intensities in selectively logged forests;
- Research Objective 3 (Chapter 6): To develop an index capable of reflecting the intrinsic heterogeneity of logging impacts within different forest management units.
Figure 1.1. Overall thesis structure.
2 General concepts

2.1 Geographical and political boundaries of Amazonia

Eva et al. (2005) proposed boundaries of the Amazon biome based on hydrographical, ecological and biogeographical criteria (Figure 2.1). An “Amazonia sensu stricto” sub-region was defined by “the limit of the Amazon Basin in the north, the 700 m contour in the west and the lowland Amazon rainforest biome in the south and south-east” (Eva et al. 2005). The Brazilian Institute of Geography and Statistics (IBGE) defined the boundaries of the Amazon biome within Brazil. This definition was used in Brazil’s FREL report in order to estimate the amount of carbon emissions due to deforestation (Brazil 2014). Not surprisingly, the two different boundaries, which were drawn using different definitions and methodologies, do not match perfectly. In fact, the definition of the boundaries of the Amazon biome is still under scientific debate (Marques et al. 2019). This research is focused within Brazil, and accordingly, when I mention the Brazilian Amazon, the Amazon biome and Amazonia, I am referring to the area geographically delimited by IBGE (Figure 2.1).

In addition to the definition of the Amazon biome, the Brazilian Government has (politically) defined an area called the “Legal Amazon” (Figure 2.1). It was outlined in 1953 during the first efforts to integrate the Brazilian Amazon into the national economy (Federal Law Nº 1.806/1953). It does not reflect biome boundaries, but the political boundaries of the federal States containing parts of the Amazon biome. Many public policies are implemented on the basis of the Legal Amazon boundaries, e.g. the Brazilian Forest Code (Federal Law Nº 12.651/2012). Lastly, Amazonas is an administrative state of Brazil, located entirely in the Amazonia biome, it is one of the nine states that form the Legal Amazon.

The agricultural expansion into the areas of natural forests, promoted mainly in the mid-1960s by the Brazilian military government, occurred along the roads built to foster the region’s economic development. This colonization dynamic shaped a deforested area with a geographical form of an “arc”, from eastern Pará to Mato Grosso and Rondônia (Figure 2.2). At some stage the term “arc of deforestation” started to be widely used. According to Velasco Gomez et al. (2015), a region was defined by the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) in the early 1990s encompassing 256 municipalities with the most intensive deforestation activities. However, there is no official description or definition of the arc of deforestation. Besides, it includes municipalities in the Amazonas state that have lower rates of deforestation when compared to eastern and southern states in the Amazon (see Figure 2.2).
2.2 Land occupation in the Brazilian Amazon: A historical background

Humans have been changing Amazonian ecosystems since the early Holocene (Chazdon 2014; Clement et al. 2015; Levis et al. 2017) and the view of Amazonia as “virgin” or “pristine” is no longer supported (Willis et al. 2004; Erickson 2008; Chazdon 2014). While there is still a debate about the degree of anthropogenic disturbances caused by an indigenous population in the pre-Columbian period (Erickson 2008), it seems obvious that the most substantial changes in the landscape took place after the European conquest.

The first European settlements in the Brazilian Amazon were founded in the mid-sixteenth century mainly in the lower Amazon river region (Tavares 2011). The intensification of the settlement was motivated primarily by the threat of invasion from other colonial powers, like France, the Netherlands and England. At first, the occupation was focused on an area close to mission villages, located along the riverbanks of the main Amazon River tributaries. The villages were first controlled by Jesuit priests, who used indigenous people as a slave labor force (Tavares 2011). After the separation of church and state
during the political reforms in Portugal, the administration of the villages was taken over by civilian directories. From this period onwards, a hybrid culture between the indigenous people and the Europeans emerged in the Amazon, shaping what is now known as the “caboclo”, or “ribeirinho” culture (Brondizio and Siqueira 1992).

For over two centuries, European colonists focused on extractive industries and small-scale farming, until the “rubber boom” started in the late-nineteenth century. Fostered by the increasing demands of the industrialized countries, thousands of people were attracted to the region to feed the international need for rubber (Bezerra 2015). However, the rubber boom ended at the beginning of the twentieth century with the establishment of rubber-tree plantations in Malaysia. Although the rubber boom led to a significant increase in population of the Amazon, the rubber industry was primarily extractive and did not cause land cover changes comparable to the scale of recent transformations. The new inhabitants, migrants from Northeastern Brazil, eventually assimilated the local ribeirinho culture (Brondizio and Siqueira 1992). Thus, life in the remote villages of the Amazon continued to be based on extractive industry and small-scale farming.

In 1953, the Brazilian government launched its first national plan with the objective of promoting agriculture and cattle ranching in the Amazon region, starting the era of deforestation (Bezerra 2015). Amazon forests were conceived as an empty and economically unproductive space. Large-scale deforestation in the Brazilian Amazon began in 1958 with the construction of the Belém-Brasília (BR 010) and the BR 364 highways. In 1971 the military government launched the Program of National Integration, which led to the construction of other highways, such as the Cuiabá-Santarém (BR 163), and the Transamazon Highway (BR 230) (Moran 1993; Bezerra 2015).

As part of the national plan, thousands of families were settled by the National Institute for Colonization and Agrarian Reform (INCRA) along the roads, and governmental subsidies were provided to promote forest clearance (Peres and Schneider 2012). These areas are called Land Agrarian Reform Settlements (Alencar et al. 2016). The promises of cheap, free land also attracted other people into the region, such as land grabbers, loggers and gold miners (Fearnside 2008). Additionally, waves of migrants arrived in the region, which led to a second, informal colonization process (Simmons et al. 2016). This second group of migrants, mostly working on small farms, was considered a group of “squatters” or “landless” (Fearnside 2008).

Ranchers and capitalized farmers settled on large farms with a different colonization style. They converted forests to cattle pastures and fields for soybean production, which were both mainly for export markets (Fearnside 2008). Farmers were mainly responsible for the intensive deforestation in the 1990’s
and early 2000’s (Boucher et al. 2013). The Arc of Deforestation was consolidated at this time (Becker 2005) and gradually, the small-scale agriculture carried out, in a relatively sustainable way, by traditional communities, was replaced by unsustainable practices, such as large scale cattle ranching (Brown et al. 2016).

Forest degradation, through selective logging, fragmentation and forest fires (Asner et al. 2005; Matricardi et al. 2010; Souza Jr et al. 2013; Shimabukuro et al. 2019; Silvério et al. 2019), followed the patterns of deforestation. For more than 300 years, the timber industry was restricted to low impact logging in the floodplain forests (várzeas) of the main Amazon rivers (Barros and Uhl 1995; Asner et al. 2009). At this time, logging activity was secondary compared to the exploitation of non-timber forest products, like rubber and Brazil nut (Bertholletia excelsa) (Asner et al. 2009). After the construction of the Belém-Brasilia highway, the logging dynamic in the Amazon was profoundly altered. Once restricted to várzeas, the new roads provided unprecedented access to the timber resources of upland (terra-firme) forests. The agricultural and logging frontier expansion continued their expansion (Brown et al. 2016; Schielein and Börner 2018), moving into more remote areas of the Amazon, particularly in the southern part of the State of Amazonas.

2.3 Land use and land cover change

According to Moran et al. (2004) “land-cover refers to the land’s physical attributes, whereas land-use expresses the purpose to which those attributes are put or how they are transformed by human action”. In other words, land use can be defined as a “social concept” and land cover as an “environmental concept” (Moran et al. 2005). Land cover can express, for instance, how much of an area is covered by forests, grasslands, rivers, or other land cover classes. It can be mapped using remote sensing data, which also allows measuring the extent of changes within each land cover class over time. As land use reflects how people use the landscape, it cannot always be mapped using remote sensing techniques. Currently, some of the most important land cover changes are deforestation and forest degradation in tropical countries. To detect, map, monitor and understand both phenomena, it is necessary to further define what is meant by forest, deforestation and forest degradation.

The Food and Agriculture Organization of the United Nations (FAO) defined forests as “land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ” (FAO 2010). In the UNFCCC context forest is defined as “a minimum area of land of 0.05-1.0 hectares with tree crown cover (or equivalent stocking level) of more than 10-30 percent with trees with the potential to reach a minimum height of 2-5 meters at maturity in situ” (COP-7, 2001). A more feasible assessment of a forest area, using medium spatial resolution satellite imagery, could be achieved by adopting a threshold, such as 40% (Sasaki and Putz 2009)
or 30% (Eva et al. 2012) for the forest canopy cover. According to Achard et al. (2014) most countries require a minimum crown cover of 30% for forests in their individual land classification systems.

Figure 2.2. Deforestation in Amazon between the years 2000-2017 (Land cover composition data from PRODES-INPE, available at: http://www.dpi.inpe.br/prodesdigital/prodes.php, accessed on 1 May 2019).

Lund (1999) suggested a generic definition for deforestation as “the act or process of changing forest land to non-forest land”. More than clear-cutting, deforestation is a change in land use from forest to non-forest (Chazdon et al. 2016). Therefore, according to the FAO (2010), deforestation is “the conversion of forest to another land use or the long-term reduction of the tree canopy cover below the minimum 10 percent threshold”, with a long-term or permanent loss of forest cover. For the Brazilian government, deforestation in the Amazon biome “is not associated with thresholds, but simply with canopy cover equals to zero” (Brazil 2014). Within this context only areas of forests that were never deforested before count for the total deforested area (INPE 2008).

While deforestation seems relatively simple to identify, the same cannot be said for forest degradation. So far, forest degradation has been vaguely defined. According to the FAO (2010) forest degradation is defined as “the reduction of the capacity of a forest to provide goods and services”. In this sense, forest degradation could include all types of human induced disturbances, such as unsustainable
logging, agriculture, invasive species, forest fire, fuel wood gathering, and livestock grazing (Thompson et al. 2013). In addition, many drivers of forest degradation act synergically (Silvério et al. 2019).

The monitoring of forest degradation depends on the operational definitions, which can be limited by the accuracy of measurement approaches employed (Bustamante et al. 2016). According to Sasaki and Putz (2009), the definition of forest degradation should be focused on readily verifiable parameters (i.e., canopy cover and tree heights). Considering that unsustainable selective logging is one of the main factors for the forest degradation process, at least in the Brazilian Amazon, efforts should start with a more consistent program for mapping and monitoring selective logging activities. Selective logging is not necessarily a synonym of forest degradation (Thompson et al. 2013). Therefore, areas under sustainable forest management and following RIL techniques (Putz et al. 2008) should not be automatically classified as degraded in large scale remote sensing assessments (e.g. Vancutsem and Achard 2016; Bullock et al. 2018). The present study was carried out in forest management units with low impact logging, therefore, hereafter, the term “forest disturbance” is used to refer to the areas impacted by selective logging activities (Bustamante et al. 2016).

2.4 Logging, illegal logging and sustainable forest management

Selective logging is the act of harvesting a limited number of commercial tree species in a given area (Johns 1985). In the Amazon, selective logging without any planning and without techniques to minimize environmental impacts is called conventional logging (CL) (Asner et al. 2009). On the other hand, RIL stands for a selective logging following technical recommendations to reduce environmental impacts. Therefore, RIL is defined as “intensively planned and carefully controlled timber harvesting conducted by trained workers in ways that minimize the deleterious impacts of logging” (Putz et al. 2008). At the very beginning RIL was intended both to minimize logging impacts and to reduce the high cost of logging operations, in addition, discussions about minimizing carbon emissions were also present (Putz and Pinard 1993). Today, discussions around the bottlenecks for the large scale implementation of RIL throughout the tropics, as well as standards for evaluating RIL performance are also present (Ellis and Putz 2019). In the natural forests of the Brazilian Amazon, selective logging is the main harvest technique employed, therefore in this research the term “logging” and “selective logging” are used interchangeably.

In Brazil, forests within the Legal Amazon region can just be harvested via sustainable forest management (SFM), which is implemented through selective logging and employing some of the RIL techniques (Macpherson et al. 2012; Zimmerman and Kormos 2012). In the Brazilian Forest Code (BFC) “sustainable management”, is defined as “the management of natural vegetation to obtain economic, social and environmental goods, respecting the supporting mechanisms of the target ecosystem, and considering the use of multiple products and species, as well as, other goods and services” (Federal Law
Nº12.651/2012). This concept is similar to the one proposed by FAO, which defines SFM as “as the sustainable use and conservation of forests with the aim of maintaining and enhancing multiple forest values through human interventions” (FAO 2016), once both imply a “maintenance” of the benefits provided by forests as well as its multiple use. A unique definition for SFM will never be reached, and the use of the word “sustainable” within it is even more contentious (Putz 2018). Herein, the term “sustainable forest management” follows the Brazilian legislation definition and is used to define an area with governmental authorization for harvesting timber.

If an area is harvested without a governmental authorization (or in disagreement with it) the area is said to be “illegally logged”. Illegal logging is a complex issue. In general, it is defined as “the harvest, transport, purchase, or sale of timber in violation of national laws” (Sheikh 2010). However, there is a long standing debate about the definitions of illegal logging, as well as the context behind the so-called “illegal forest activities” (Ravenel and Granoff 2004). It is not the scope of this research to discuss all political and sociological questions surrounding the definitions of illegal logging. Therefore, illegal logging is defined as forest harvest done without any government permit. In cases where the forest stand has a logging permit, but the harvest is done in disagreement with the approved Sustainable Forest Management Plan (SFMP), the action is also referred “illegal logging”.

A SFMP is a technical document that contains all information about the forest that will be harvested, as well as all technical procedures to be applied, based on several rules and constraints established in the Brazilian forest legislation. The most important constraints in these regulations are the minimum cutting rotation of 25-35 years; the maximum annual allowable cut of 25-30 m³/ha/year; the minimum cut diameter of 45-50 cm; standardized seed-tree retention rates and maximum levels of forest clearance to build roads and log landings. Therefore, in practice, the SFM in the Brazilian Amazon is an activity carried out through selective logging with an incorporation of some RIL techniques to minimize environmental damage and protect future forest productivity (Macpherson et al. 2012). It is important to make it clear that SFM for the current Brazilian forest legislation does not necessarily imply RIL. This is the case because a landowner with an approved SFMP is obliged, by law, to comply with just few mandatory RIL techniques. Examples of RIL Guidelines, tailored for the Amazonian forests, can be found at Sabogal et al. (2000) and Espada et al. (2018). The current Brazilian forest legislation, regarding the implementation of SFMP, can be found at: CONAMA Resolution Nº406/2006 (CONAMA 2009), Normative Instruction from the Brazilian Ministry of Environment Nº005/2006 (MMA 2006) at the federal level, and CEMAAM Resolution Nº017/2013 (CEMAAM 2013) for the State of Amazonas.

Timber companies, working on private or public lands, are obliged to supply a SFMP to the Brazilian Government as a requirement to obtain an Environmental License, which is a formal authorization to use
natural resources in Brazil (Eve et al. 2000). If the SFMP is approved, an “Authorization for Logging” (AUTEX) is issued. This document is generally valid for one or two years and contains all information about the harvestable trees in a given area. This clearly defined area is generically known as forest management unit (FMU) (ITTO 2016). The AUTEX issued for a FMU is the starting point in the Brazilian timber chain of custody. The data from each AUTEX is used to feed an electronic system called Document of Forest Origin (DOF), which is used to track and control all forest products from Brazilian native forest (MMA 2016).
3 Study area

The study area is located in the southern part of the state of Amazonas, Brazil (Figure 3.1). Amazonas state covers 1.5 million km$^2$ and had an estimated population of 4.0 million in 2018, mostly living in the city of Manaus (IBGE 2019). Amazonas is the biggest state of Brazil and holds the largest area of intact forests within the Brazilian Amazon (INPE 2019a). According to INPE-PRODES the State lost 1,045 km$^2$ of primary forests in the year 2018, contributing to 13.2% of the total deforested area within the Brazilian Legal Amazon (INPE 2019a) for this year. Most of the deforestation recorded within Amazonas State occurred in its southern region, notably in the surrounding areas of Santo Antônio do Matupi, Apuí and Boca do Acre (Figure 3.1). The study carried out in this thesis was focused in the region of Santo Antônio do Matupi.

Figure 3.1. Political boundaries of the State of Amazonas. Land cover map (year 2017): deforestation (white), non-forest vegetation (yellow) and forests (green). Source: from PRODES (INPE 2019a).
3.1 Santo Antônio do Matupi

The study area is located in the region surrounding the town of Santo Antônio do Matupi, which is located on the Transamazon Highway (BR 230). Hereafter, the region surrounding the Village of Santo Antônio do Matupi is called “area of interest” (AOI) Matupi (Figure 3.2). Two additional AOIs were also included in the study (Chapter 6). These areas are called AOI Maravilha and AOI Tenharim (Figure 3.2). Together, the AOIs of Matupi, Maravilha and Tenharim form the full study area described in the Figure 3.1. Chapters 4 and 5 of this thesis were focused on the AOI Matupi, while the analyses in the Chapter 6 are focused on the three AOIs.

The region of Santo Antônio do Matupi has a tropical monsoon climate (Am) according to the Köppen climate classification system, with a recorded mean air temperature higher than 26º C and with annual rainfall ranging from 2,800 to 3,100 mm (Alvares et al. 2013). The short dry season (precipitation less than 60 mm per month) occurs between June and August (INMET 2016).

The study area is characterized by the presence of a mosaic of different vegetation types, which includes forested ecosystems, savannas and grassland pioneer vegetation associated with flooded areas (Veloso et al. 1991; IBGE 2012). The tropical forest can be further classified as “dense humid forest” and “open humid forest”. The main difference between the dense humid forest and open humid forest are explained by the length of the dry season (Veloso et al. 1991). In general, the dry season lasts less than 60 days in dense forests, whereas in the open forests it can last more than 60 days. The extended dry season in open forests leads to a development of distinguished flora, characterized by the presence of palms and bamboos. In this work, the differences between dense and open forests are not crucial, as both floristic domains belong to the humid forest classification (Veloso et al. 1991) and they are located in the same climate domain. In addition, it is not my intention to scrutinize different floristic patterns in my analyses.

Although Amazonia is home to an estimated 16,000 tree species, the Amazon biome is dominated by 227 species that represent 50% of all Amazonian trees (ter Steege et al. 2013). However, the most abundant tree species recorded by ter Steege et al. (2013) are not commercially exploitable, with the exception of *Eperua* spp. Based on commercial tree inventories carried out in the SFMP licensed in 2016 (in the study area), the most common commercial tree species present in the study area are *Eperua oleifera*, *Hymenolobium petraeum*, *Dinizia excelsa*, *Dipteryx trifoliolata*, *Allantoma lineata*, *Brosimum* spp. and *Qualea* spp. (IPAAM 2016).

The study area partly covers the municipalities of Humaitá, Manicoré, Novo Aripuanã and Apuí (Figure 3.2). This subset was chosen because this region is one of the main timber production zones within the State of Amazonas (IPAAM 2019), the surrounding region is known as a deforestation hotspot (INPE
2019a). This seems to be a contradiction, however, both activities (deforestation and selective logging) usually occur together in new colonization frontiers (Asner et al. 2009; Fearnside 2017).

The colonization of the region started in 1992 with the establishment of the Matupi Settlement Project (Projeto de Assentamento Matupi), hereafter called “PA Matupi”. In addition to the PA Matupi, a number of individual farm-lots have been regularized south of the Transamazon Highway by the “Terra Legal” program. This program was put in place by the Brazilian government in 2009 to regularize individual farm-lots within the Brazilian Amazon.

In the last demographic census, the population inside the PA Matupi was estimated at 6,833 inhabitants (IBGE 2010). The colonists in the region are represented by migrants from older development frontiers, mainly from Rondônia State (Fearnside 2008). PA Matupi has lost 66% of its original forest (Yanai et al. 2019), following the deforestation pattern associated with other Settlement Projects (Yanai et al. 2017). The loss of primary forests within the PA Matupi has pushed the logging frontier far from its center; in consequence, selective logging currently occurs mainly in areas of primary forests outside the Settlement Project.

Figure 3.2. Location of the study area in the Municipalities of Manicoré, Humaitá and Novo Aripuanã, State of Amazonas, Brazil. PA Matupi appears as a red polygon. Protected area are represented by the line pattern fill and indigenous land by the point pattern fill. Background map (year 2018) from PRODES (INPE 2019): deforestation (white), non-forest vegetation (yellow) and forests (green).
4 Comparing Sentinel-2 MSI and Landsat 8 OLI imagery for monitoring selective logging in the Brazilian Amazon

4.1 Introduction

Selective logging is a pervasive activity in tropical forests. In the Brazilian Amazon it is a major source of forest degradation, possibly encompassing an area larger than that reported as deforested (Asner et al. 2005). Despite the fact that carbon emissions caused by forest degradation in the tropics are to some extent compensated by forest regrowth (Pan et al. 2011), forests that have been selectively logged or burned store up to 40% less carbon than undisturbed forest stands (Berenguer et al. 2014). Furthermore, previously logged forests, especially in the Brazilian Amazon, are at a higher risk of being converted into non-forest land use types (Asner et al. 2005).

The assessment of deforestation and forest degradation is a key component of international policies such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation in Developing Countries). REDD+ policies require the use of reliable methods to measure carbon emissions from deforestation and forest degradation (Goetz et al. 2015). While Brazil has a consistent methodology for measuring deforestation (Shimabukuro et al. 2013), the approach used to estimate greenhouse gas emissions from forest degradation still needs improvement (UNFCCC 2015). Forest degradation is defined by the Food and Agriculture Organization of the United Nations (FAO) as “the reduction of the capacity of a forest to provide goods and services” (FAO 2010), a broad definition that needs to be contextualized for each country. Brazilian institutions still have to decide on a consistent and operational definition of “forest degradation”, while the development of a reliable monitoring methodology based on large-scale remote sensing analysis is equally indispensable. Brazil has a prototype program to map forest degradation since 2007, called DEGRAD (Forest Degradation Mapping in the Brazilian Amazon) (INPE 2008). DEGRAD is based on a visual interpretation of moderate spatial resolution satellite imagery and has been used to map areas in process of deforestation, where the forest canopy cover has not yet been completely removed (INPE 2008). Therefore, research on automatic methods for mapping selective logging, a source of forest degradation, is imperative. As a result, the term “forest disturbance” is preferred, given that not all forest disturbance events necessarily result in forest degradation (Bustamante et al. 2016).

Despite the attempts to map anthropogenic forest disturbances in tropical forests using instruments such as the airborne Light Detection and Ranging (LiDAR) (Asner et al. 2013; Ellis et al. 2016; de Carvalho et al. 2017), the use of freely available satellite imagery is currently the only feasible way of mapping changes over large areas of remote tropical forests. In the last two decades, several studies were carried out in the Brazilian Amazon with the objective of mapping or estimating areas of selective logging through
optical remote sensing techniques (Watrin and Rocha 1992; Stone and Lefebvre 1998; Souza and Barreto 2000; Asner et al. 2002; Hurtt et al. 2003; Monteiro et al. 2003; Read et al. 2003; Asner et al. 2004; Matricardi et al. 2005; Souza Jr. et al. 2005; Souza Jr et al. 2005; Asner et al. 2005; Monteiro et al. 2007; Matricardi et al. 2007; Matricardi et al. 2010; Anwar and Stein 2012; Monteiro and Souza 2012; Souza Jr et al. 2013; Matricardi et al. 2013; Shimabukuro et al. 2014; Pinheiro et al. 2016; Tritsch et al. 2016; Grecchi et al. 2017; Tyukavina et al. 2017; Bullock et al. 2018; Hethcoat et al. 2019; Shimabukuro et al. 2019). These studies differ in terms of mapping units and protocols, type of remote sensing data analyzed, image processing techniques employed, geographic extent and location, total period of observation and accuracy assessment. Some studies used very-high resolution satellite imagery, such as IKONOS, to infer the total logged area and/or forest canopy disturbance size (Hurtt et al. 2003; Read et al. 2003; Souza and Roberts 2005; Monteiro et al. 2007). However, the vast majority of studies relied on moderate spatial resolution satellite imagery, notably from the Landsat program. Initially, these studies employed visual interpretation techniques to assess the total logged area (Watrin and Rocha 1992; Stone and Lefebvre 1998). At a later stage, a combination of (semi-)automated techniques, comprising a spectral mixture analysis (SMA) combined with a GIS analysis, were used to estimate the total logged area based on the location of log landings (Souza and Barreto 2000; Monteiro et al. 2003). Automatic classification, based on fraction images derived from SMA, is currently the most common methodology used to detect and monitor selective logging in the Amazon (Souza and Barreto 2000; Souza Jr. et al. 2005; Souza Jr et al. 2005; Asner et al. 2005; Matricardi et al. 2010; Souza Jr et al. 2013; Shimabukuro et al. 2014; Pinheiro et al. 2016; Grecchi et al. 2017; Bullock et al. 2018).

Despite the remarkable improvements in mapping tropical forest disturbances in recent years, research gaps persist. For instance, the spatial resolution of Landsat imagery (30 m) can be too coarse to map small-scale forest disturbances in tropical forests, such as those resulting from selective logging (Verhegghen et al. 2015). The methodology proposed by Souza Jr et al.(2013), based on Landsat data, only detects forest disturbances that result in canopy openings of more than 25% within single Landsat pixels. However, disturbances caused by selective logging do not necessarily cause such large canopy openings. Consequently, there is a need to investigate the potential to map patterns of forest disturbances with finer spatial resolution. For many years, the lack of freely available imagery was the main barrier for doing so. However, the European Space Agency (ESA) recently launched the Sentinel-2A and Sentinel-2B satellites (in June 2015 and March 2017, respectively), making the data freely accessible. Sentinel-2A and 2B are “twin” satellites with the same optical sensor, providing multi-spectral imagery in 13 spectral bands at different spatial resolutions (10 to 60 m) with a revisiting time frequency of 5 days (Drusch et al. 2012). In the field of land use and land cover change, Sentinel-2 imagery has been used to map burned areas
Previous studies have mapped forest disturbances using single-scene analysis of Landsat imagery per time period, which is usually one year (Matricardi et al. 2010; Souza Jr et al. 2013; Pinheiro et al. 2016; Tritsch et al. 2016; Grecchi et al. 2017). However, in tropical evergreen forests small-scale forest disturbance caused by selective logging activities can be recovered very fast (within a few months) by vegetation regrowth (Verhegghen et al. 2015; Langner et al. 2016). Therefore, the use of a single image for a given year can underestimate the amount of forest disturbances. For instance, in the Central Amazon, if a tree harvest is carried out in early dry season, with an image used in the analysis of 4-6 months after the disturbance occurred, the mapped area is potentially underestimated due to the rapid vegetation regrowth. On the other hand, if the satellite image analyzed is acquired before a logging activity, the forest disturbance may not be detected at all in the subsequent year (Hethcoat et al. 2019). In addition, persistent cloud cover is a known problem in optical remote sensing analysis in tropical regions (Beuchle et al. 2011). Since the opening of the Landsat archive, the analysis of image time series has become feasible, allowing the retrieval of spectral information without data gaps due to cloud cover (Wulder and Coops 2014).

Against this background, this study has two main objectives: (1) the mapping of forest disturbances caused by selective logging in seven sites under sustainable forest management (SFM) within the Brazilian State of Amazonas and (2) the comparison of the effectiveness of Landsat 8 data versus Sentinel-2 imagery for such purpose. To accomplish these objectives, a change detection approach called ∆rNBR was employed. The ∆rNBR approach is a modification of the Normalized Burn Ratio (NBR) index and it has successfully been used to map forest disturbances in (semi-)evergreen forests in continental southeast Asia (Langner et al. 2018). Instead of working with single satellite scenes, this approach uses a time series analysis of all available satellite images and calculates the changes between two periods. Here, the ∆rNBR methodology was applied on imagery from both sensors during the dry seasons of years 2016 and 2017. The resulting maps were compared using an accuracy assessment based on the visual interpretation of high resolution images. To increase the robustness of the approach applied here, three unlogged areas were also analyzed. Additionally, field data regarding logging infrastructure was collected and also used to assess the quality of the final maps.
4.2 Materials and Methods

4.2.1 Study area

The study area is located in the south of the Brazilian State of Amazonas. Amazonas is the largest state in Brazil (1.5 million km$^2$) and holds the largest area of intact forests within the Brazilian Amazon (INPE 2019a). This study was carried out in a focus area, bisected by the Transamazon Highway (BR 230), near the Village of Santo Antonio do Matupi (Figure 4.1). The area is one of the main timber production zones within the State of Amazonas (IPAAM 2019); the surrounding region is known as a deforestation hotspot (INPE 2019a).

The region has a tropical monsoon climate (Am) according to the Köppen climate classification system, with a recorded annual mean air temperature higher than 26º C and with annual rainfall ranging from 2,800 to 3,100 mm (Alvares et al. 2013). The short dry season (precipitation less than 60 mm per month) occurs between June and August (INMET 2016). The study area is covered by a mosaic of different vegetation types; with terra-firme forests (non-flooded) covering most of the region. These forests are classified as dense ombrophilous forest (IBGE 2012), with a tall, closed canopy.

To compare both sensors, the analysis was focused on seven study sites where logging happened (areas Nº1 to 7) (Figure 4.1). These study sites are rectangular areas cropped from the satellite images and they overlap SFM areas, called Forest Management Units (FMUs). A further assessment of the present approach was also carried out in three areas without logging activities (areas Nº8 to 10) (Figure 4.1). These areas were licensed as a SFM, however, harvest activities were not recorded for the time period where the mapping was performed. Herein, the term “sustainable forest management” follows the Brazilian legislation definition (CONAMA 2009) and is used to define an area with governmental authorization for harvesting timber (the AUTEX, see Chapter 2). In the State of Amazonas, by law, logging intensity is limited to 25 m$^3$/ha/year, within areas suitable for timber extraction within each FMU (CEMAAM 2013). However, in general, the logging intensity is much lower than 25m$^3$/ha (Table 4.1). All FMUs comprise privately owned forests licensed in the years 2016 and 2017. In Brazil, the states have the responsibility of controlling the licensing process and issuing logging permits. In Amazonas, the Institute of Environmental Protection of Amazonas State (IPAAM) is responsible for issuing these permits. The FMUs were chosen from the IPAAM’s database, which contains all FMU licensed in the region of Santo Antônio do Matupi in the years 2016 and 2017. These areas were selected based on their ease of access and geographic distribution. The fact that each study site was located in an authorized logging area was crucial for security during field work.
Figure 4.1 Location of the study area, the study sites (in red: selectively logged areas, in blue: unlogged areas) and the forest management units (black polygons, numbered from 1 to 10). Background map (year 2017): deforestation (white), non-forest vegetation (yellow) and forests (green).

4.2.2 Canopy disturbance mapping

4.2.2.1 Satellite imagery and pre-processing

Landsat 8 images (OLI/TIRS C1 Level-1) were obtained from the United States Geological Survey (USGS) Global Visualization Viewer (GloVis, https://glovis.usgs.gov). Sentinel-2 images (MSI Level-1C) were obtained from the European Space Agency (ESA) Copernicus portal (https://scihub.copernicus.eu). All images (with less than 10% cloud cover) available for a 4 month time period from 1 June to 30 September, for 2016 and 2017 were analyzed. Choosing this timeframe allowed us to detect the temporal change in the spectral signal as close as possible to the canopy disturbance events. This is the case because logging activities in this region occur in the dry season and as explained before, this type of canopy cover disturbance recovers really fast. Therefore, by adopting this timeframe the chance of getting a “logging event” can increase. A total of 17 images (eight from Landsat 8 and nine from Sentinel-2) were suitable and used in the consequent analyses (Table 4.2). A Sentinel-2A image from August 2015 was used to ratify that the target areas had not been disturbed in the previous year.
Table 4.1. Information about the sustainable forest management (SFM) plans implemented in the seven forest management units (FMU) analyzed in this study (FMU Nº1 to 7). Areas Nº8 to 10 are unlogged FMUs used for comparisons. These data were disclosed by Institute of Environmental Protection of Amazonas State (IPAAM), under the Administrative Process Nº1946/2017.

<table>
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<th>Geographic Coordinates*</th>
<th>License/Authorization Nº</th>
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<th>Total area of the SFM (ha)***</th>
<th>Logging intensity (m³/ha)</th>
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*Centroid of the FMU’s polygon (EPSG:4326, WGS 84). **Volume authorized for logging present in the License/Authorization, according to the data provided by IPAAM. It does not necessarily represent the actual volume of logged trees in the moment the mapping was done. ***Area of the polygon representing the FMU.

For Landsat data, raw digital numbers (DN) were converted to top-of-atmosphere (TOA) reflectance values following (Simonetti et al. 2015). For Sentinel-2, the original Level-1C TOA reflectance values were kept. The corresponding spectral bands available for both sensors were taken into account in this process: blue, green, red, near infrared (NIR), short wave infrared 1 (SWIR-1) and short wave infrared 2 (SWIR-2). The SWIR-2 band in Sentinel-2 imagery comes at a 20 m resolution, therefore it was resampled to 10 m resolution using the nearest neighbor resampling method. For Sentinel-2 imagery, considering land use and land cover maps, downscaling has been shown to have superior performance compared to upscaling, even when based on the most straightforward technique, the nearest neighbor resampling (Zheng et al. 2017). For this reason and also because the study aimed at small-scale disturbances, downscaling was preferred over upscaling. Subsequently, all images were cropped to match the study sites. These steps were completed using the Image Processing (IMPACT) toolbox from the European Commission (Simonetti et al. 2015).
Even though images with low cloud cover were selected, clouds could not be fully avoided. Thus, a semi-automatic object-oriented approach was applied to mask out the clouds and cloud shadows. First, a multiresolution segmentation (Baatz and Schape 2000), using the three visible bands of the electromagnetic spectrum, was performed in eCognition® software. Afterwards, given the small size of the study sites and the limited cloud cover, it was possible to carry out a visual interpretation to remove image objects labelled as clouds and cloud shadows. Despite being labor intensive, a careful visual interpretation was preferred over a fully automatic approach for the limited-extent study areas, to avoid cloud omission errors which may have led to false disturbance detections.

<table>
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</tr>
<tr>
<td><strong>Sentinel-2A MSI</strong></td>
<td>2017-09-03</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

*MSI: MultiSpectral Instrument; OLI: Operational Land Imager

### 4.2.2.2 Building a forest/non-forest mask

To eliminate non-forested areas from the data set, an object-based image analysis on the latest Landsat 8 image from the second year (2017) was applied, following a methodology proposed by Grecchi et al. (2017). Non-forested areas included water bodies, natural vegetation not classified as forests (e.g. savannas) and deforested areas. For this study deforestation follows the definition of FAO (FAO 2010) meaning “the conversion of forest to other land use”. This step was required to avoid wrongly classifying some areas of selective logging as deforestation (e.g. log landings). Therefore, logging infrastructure, such as log landings and logging roads, were kept inside the forest mask and were mapped as a part of the forest disturbance process. To build this forest mask, a segmentation process, aiming at a minimum mapping unit (MMU) of 3 hectares (ha), was performed in eCognition®. Objects smaller than 3 ha were then merged to comply with the defined requirements for MMU. A decision-tree classification approach was applied to categorize image objects into three main classes: forest, non-forest and water. Previously, an unconstrained linear spectral mixture analysis was performed (Shimabukuro and Ponzoni 2017) and three fraction images, soil, vegetation and water/shadow were created. This step was completed using the IMPACT toolbox,
where unconstrained values were rescaled to values between 0-255 (Simonetti et al. 2015). All image objects with a soil fraction mean ≥ 108 were classified as non-forest and all objects with a water fraction mean ≥ 185 and a mean value for the NIR band < 70 were classified as water. All remaining objects were classified as forest.

Finally, the classification was exported as a raster file, with a binary classification: forest with value 1 and non-forest with value 0. As this binary forest mask was built using a Landsat image, a nearest neighbor resampling technique was carried out to convert the forest mask to the spatial resolution and the geolocation of the Sentinel-2 images. The quality of the forest mask was assessed in the seven study sites were logging occurred, based on the visual interpretation of the latest Landsat image from the year 2017, which was carried out by an external expert. A stratified random sampling scheme was applied for the two strata (forest and non-forest areas) with 150 sampling points for each one, distributed randomly over this seven study sites. The area adjusted overall accuracy (Olofsson et al. 2014) was 98.6%, with adjusted producer’s accuracy of 99% for the forest class and 95.7% for the non-forest class. The area adjusted user’s accuracy was 99.3% for the forest class and 94% for the non-forest class.

4.2.2.3 Applying the ΔrNBR approach

To detect canopy cover disturbance, a ratio-based vegetation index called Normalized Burn Ratio (NBR) was used. The NBR index is based on the normalized difference of the NIR and the SWIR-2 bands (Equation 4.1). NBR is particularly sensitive to changes in live green vegetation (Miller and Thode 2007). Like the Normalized Difference Vegetation Index (NDVI), the NBR output is composed by floating point values ranging from -1 to 1, where larger positive values are linked to closed forest canopy cover and smaller positive or even negative values indicate openings in the canopy cover (Langner et al. 2018). The NBR was calculated for all images used in this study.

Equation 4.1

\[
NBR = \frac{NIR - SWIR2}{NIR + SWIR2}
\]

The NBR index has been traditionally used to map burn severity (Miller and Thode 2007). However, recently, it also has been used to assess forest disturbances, such as those caused by selective logging (Shimizu et al. 2017). To detect changes in a given area, the NBR is assessed before (period 1) and after (period 2) the disturbance event. The difference between the values calculated for period 1 and period 2 is called ΔNBR.
When used to assess small-scale forest disturbances, NBR values can be different for two dates, even in the absence of forest cover change. This NBR difference can be due to unequal atmospheric conditions or illumination geometries (Langner et al. 2016). To avoid assigning such change as a signal of forest disturbance, Langner et al. (2018) further developed the initial NBR methodology by introducing a self-referencing step. This approach is based on a moving window concept, which aims to account for the similarity (or dissimilarity) a given pixel has in comparison with its neighborhood (Rocchini et al. 2016a). Therefore, this self-referencing step shifts the NBR values to zero by subtracting the original NBR values at each pixel location from the median of the NBR values within a circular window centered at the pixel (Equation 4.2). By following this method, intact forest canopies result in values close to 0, while openings in the canopy cover that expose bare soil or non-photosynthetic vegetation show positive values. Following (Langner et al. 2018) a 210 m radius was chosen as the size of the moving window.

Equation 4.2

\[ r_{NBR} = NBR_{n,\text{median}} - NBR \]

As the impacts of logging infrastructures on spectral signatures are ephemeral, the rNBR was calculated for all available images from the beginning to the end of the dry season (June to September) of a given year and then aggregated the maximum rNBR values into a single annual composite. The ΔrNBR image was then produced from the two annual image composites of max rNBR of years 2016 and 2017 (Equation 4.3). All these steps (Figure 4.2) were developed with “R” software (R Core Team 2018), using the raster package (Hijmans 2017). Image composites were created using a Python script provided by (Holden and Bullock 2015).

Equation 4.3

\[ \Delta r_{NBR} = r_{NBR_{\text{Period 2}}} - r_{NBR_{\text{Period 1}}} \]
Figure 4.2 Flowchart of the steps used to generate the delta self-referenced normalized burn ratio (ΔrNBR) image. MSI: MultiSpectral Instrument; OLI: Operational Land Imager; DN: digital numbers; TOA: Top of Atmosphere reflectance; NBR: normalized burn ratio; rNBR: self-referenced normalized burn ratio.
4.2.2.4 Detecting forest disturbances from optimized thresholds

A common approach used to assess the spectral signals of forest disturbances from remote sensing analyses is the empirical definition of thresholds (Coops and Tooke 2017). Accordingly, an empirical threshold value is defined to build a binary map, encompassing areas considered “disturbed”, “degraded” or “logged”, depending on the adopted method and terminology (Souza Jr et al. 2013; Tritsch et al. 2016; Grecchi et al. 2017). For both Landsat 8 and Sentinel-2 imagery, binary maps for different ΔrNBR thresholds, ranging from 0.001 to 0.200 (200 values in total), were produced and to compare the resulting sets of binary maps with a reference data set, in order to define an optimum threshold value.

The seven FMUs where selective logging occurred (areas Nº1 to 7, Figure 4.1) were used to define the threshold values for both sensors. The reference data set used for choosing the best threshold values was built using a combination of high and high very resolution imagery (spatial resolution < 10 m). PlaneScope® images, with a 3 m spatial resolution, from the end of the dry season of both years (2016 and 2017), covering five of the seven FMUs, were used to assess if the areas were logged or not (Table 4.3). For two areas a GeoEye-1 image (0.43 m spatial resolution), available in the Google Maps API®, was used for the interpretation of logging activities for the year 2017, while PlaneScope® imagery were used to assess the pre-logging status of the forests in 2016. To label the reference data set in two distinct classes, disturbed or undisturbed, a visual interpretation was carried out for 600 sample points. To be included as a change event, the areas needed to be clearly identified in the images as logging areas or logging infrastructure. Areas with doubtful interpretation were not included in the reference data set.

The number of sampling points was chosen based on the assumption that the areas would not have experienced more the 15% of land cover change. This assumption is reasonable because the change event is considered as a rare event in the landscape (Congalton and Green 2009), and even rarer if we take into account that the study areas are under sustainable forest management. Therefore, assuming area proportions for the stable class forest (i.e. undisturbed class) as 0.85 and 0.15 for the change class (disturbed), a target user’s accuracy of 0.95 and 0.80 for the undisturbed and disturbed class, respectively, and a standard error for the overall accuracy of 0.01, leads to the number of sample points of approximately 600, according to the equation for stratified random sampling presented by (Olofsson et al. 2014). Considering the stratified random sampling scheme, different distributions of the total number of samples amongst different strata will favor different estimation objectives (Olofsson et al. 2014). In the present case, it was preferred that the areas of logging were correctly included in the map (i.e. minimizing errors of omission), therefore 100 sample points were chosen for the class of disturbance and 500 sample points for the forest (undisturbed) class, with 100 of them allocated in the three FMUs known to be unlogged.
To determine optimum threshold values a bootstrapping procedure was applied (Chernick 2007). The use of resampling methods, such as bootstrapping, has been reported as a more robust approach than a single split of the data into training and test sets (Lyons et al. 2018). From a total of 600 sample points, a random sample of 350 points was extracted and the estimated overall accuracy (Olofsson et al. 2014) was calculated from this sub-sample for each of the 200 binary maps. This procedure was iterated 1000 times while for each iteration the ΔrNBR value that maximized the overall accuracy was recorded. Subsequently, the average threshold values for each satellite sensor, herein called “optimized thresholds”, was computed. These optimized thresholds were then used to build the final canopy disturbance maps used for comparisons between Landsat 8 and Sentinel-2 imagery (Figure 4.3).

4.2.2.5 Assessing forest area affected by selective logging using a grid approach

In order to assess the forest area impacted by selective logging a regular grid of 300 m × 300 m spatial resolution was applied on the pixel-based results from both sensors, leading to 252 full grid cells over the forest of the seven FMU. The size of the grid cells is similar to a radius of 180 m from the mapped disturbance areas, as proposed by Souza and Barreto (2000) and Matricardi et al. (2005), to assess the forest area directly or indirectly affected by selective logging. The grid area typically contains features such as smaller sized logging infrastructure (small felling gaps, narrow logging roads, skid trails) and residual damaged vegetation due to the logging operations (Amaral et al. 2019), which are not detectable by remote sensing imagery. In addition, due to the use of permanent assessment units, a grid cell approach has the advantage of enabling a long-term assessment of the forest disturbances related to selective logging, which is highly dynamic in space and time. A grid approach with the same grid cell dimensions has been used to monitor selective logging with Landsat imagery over 15 years in Mato Grosso State by Grecchi et al. (2017). Grid cells which contained less than 5% of pixel-based mapped selective logging area were not taken into account in order to avoid results compromised by random effects.

4.2.3 Accuracy assessment and field data collection

For the accuracy assessment of the disturbance maps, the entire reference data set (i.e. all 600 sampling points mentioned above) was used for building the error matrix, and for estimating accuracies and areas for both sensors (Olofsson et al. 2014). The method was further applied to three unlogged forest management units (areas 8 to 10, see Figure 4.1) and an additional accuracy assessment was done after the inclusion of these new areas. The three unlogged areas were mapped using the same approach adopted for the forest management units were logging occurred (areas Nº1 to 7, see Figure 4.1). The binary maps, derived from the best threshold values were compared with a new reference data set built to include sampling points also in these three unlogged areas. Accordingly, 200 sampling points were randomly
assigned for the forest (undisturbed) class. Therefore, the new reference data set had 800 points, 700 for undisturbed forest and 100 for the disturbed forest.

Table 4.3. Reference data set used in the Accuracy Assessment.

<table>
<thead>
<tr>
<th>Source</th>
<th>Acquisition date (year-month-day)</th>
<th>Image</th>
<th>FMU covered</th>
</tr>
</thead>
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<tr>
<td>PlanetScope</td>
<td>2016-08-14</td>
<td>133358_0e0d_3B_AnalyticMS</td>
<td>1</td>
</tr>
<tr>
<td>PlanetScope</td>
<td>2016-08-14</td>
<td>133456_0e3a_3B_AnalyticMS</td>
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</tr>
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<td>133443_0e0f_3B_AnalyticMS</td>
<td>2</td>
</tr>
<tr>
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<td>133500_0e16_3B_AnalyticMS</td>
<td>3</td>
</tr>
<tr>
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<td>133458_0e3a_3B_AnalyticMS</td>
<td>3</td>
</tr>
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<td>3</td>
</tr>
<tr>
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<td>133456_0e16_3B_AnalyticMS</td>
<td>4</td>
</tr>
<tr>
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<td>133453_0e3a_3B_AnalyticMS</td>
<td>4</td>
</tr>
<tr>
<td>PlanetScope</td>
<td>2016-07-30</td>
<td>202333_0c81_3B_AnalyticMS</td>
<td>4</td>
</tr>
<tr>
<td>PlanetScope</td>
<td>2016-07-30</td>
<td>133441_0e0f_3B_AnalyticMS</td>
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</tr>
<tr>
<td>PlanetScope</td>
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</tr>
<tr>
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<td>5</td>
</tr>
<tr>
<td>PlanetScope</td>
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</tr>
<tr>
<td>PlanetScope</td>
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</tr>
<tr>
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<td>4</td>
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<td>PlanetScope</td>
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<tr>
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<td>2017-08-30</td>
<td>134034_102e_3B_AnalyticMS</td>
<td>6</td>
</tr>
<tr>
<td>PlanetScope</td>
<td>2017-09-03</td>
<td>134120_1041_3B_AnalyticMS</td>
<td>7</td>
</tr>
<tr>
<td>PlanetScope</td>
<td>2017-08-26</td>
<td>134145_103c_3B_AnalyticMS</td>
<td>8</td>
</tr>
<tr>
<td>PlanetScope</td>
<td>2017-09-11</td>
<td>134052_1018_3B_AnalyticMS</td>
<td>9</td>
</tr>
<tr>
<td>PlanetScope</td>
<td>2017-09-03</td>
<td>134116_1041_3B_AnalyticMS</td>
<td>10</td>
</tr>
</tbody>
</table>
With support of the State of Amazonas Government through IPAAM, I visited FMUs near the Village of Santo Antônio do Matupi. The field data collection was carried out during IPAAM’s law enforcement inspections in the region in the first and second weeks of October 2017. In the seven FMUs I collected GPS locations and information regarding the type of logging infrastructure: log landings, felling gaps (canopy gaps created by the process of felling trees), logging roads and skid trails (Figure 4.3).

Although, initially, the use a random sampling scheme was intended, the field data collection was changed towards the selection of points close to logging roads. I collected field data for 155 sample locations, distributed over the 7 FMUs. Consequently, the collected field data was not used for accuracy assessment, but for a quantitative comparison with the resulting disturbance maps to infer the degree of “detectability” of disturbances from the mapping approach. The field points could not have been used for accuracy assessment due to the limited number of sampling points. Also because some of the impacts provoked by logging activities do not result in canopy cover removal, as in the case of some portions of logging roads and skid trails (Figure 4.3). In spite of this, the field points helped to distinguish the logging infrastructure when the reference data set was built. The percentage of GPS points corresponding to logging infrastructure that overlap the final (optimized) disturbance maps was used as detectability performance criteria.
Figure 4.3. Detail of the FMU area N°3, showing: A) the field data collected, B) the areas classified as disturbed according the Sentinel-2 and C) Landsat 8. Background image: very high resolution image from 8 September 2017, available in Google Maps API and accessed via QGIS OpenLayers plugin.
4.3 Results

4.3.1 Optimized thresholds

The bootstrapping approach used to retrieve the optimized thresholds (Figure 4.4) shows that the overall accuracy has low values for the lowest threshold values (due to a high error of commission) and then increases strongly until peak threshold values at around 0.03 and 0.06 for Landsat 8 and Sentinel-2, respectively. Subsequently, the overall accuracy drops with increasing threshold values, due to a high error of omission. The simulations of disturbance maps resulted in optimized threshold averages for ΔrNBR at 0.035 (±0.005) and 0.065 (±0.009) for Landsat 8 and Sentinel-2 images respectively.

![Figure 4.4 Estimated overall accuracies (Olofsson et al. 2014) of disturbance maps derived from 200 ΔrNBR thresholds, based on the bootstrapping approach applied for Landsat 8 and Sentinel-2 data (bootstrap average appears as a smooth curve).](image)

4.3.2 Sentinel-2 vs. Landsat 8

4.3.2.1 Accuracy of disturbance detection

The overall accuracy of the two mapped classes (disturbed forest and undisturbed forest), taking into account the original, uncorrected error matrices, was 94.8% for Landsat 8 and 94.3% for Sentinel-2. When adjusted to account for area proportion, these values increased. The area adjusted overall accuracies for Landsat 8 and Sentinel-2 were 95.7% and 96.7%, respectively (Table 4.4). The omission error was higher for the disturbed class for both satellites. Here, the area adjusted producer’s accuracy for the disturbed class was 59.3% for Landsat 8 and 63.3% for Sentinel-2. On the other hand, the area adjusted producer’s accuracy for the undisturbed class (stable class, with no change) was 99.2% and 98.9% for Landsat 8 and Sentinel-2, respectively (Table 4.4).
No substantial differences in terms of accuracy were found by adding three unlogged areas to the original seven FMUs. Taking into account the ten areas, the area adjusted overall accuracies for Landsat 8 and Sentinel-2 increased marginally, with values of 96.7% and 97.5%, respectively. This can be explained by the high accuracies recorded for the undisturbed class. For this class, the area adjusted user’s accuracy was 97.4% and 98.3% for Landsat 8 and for Sentinel-2, respectively. The area adjusted producer’s accuracy was 99.1% for both sensors. However, for the disturbed class, the area adjusted producer’s accuracy showed a slightly decrease for the Sentinel-2 map (62.1%) while for Landsat 8 it was recorded the same accuracy of before (59.3%). The area adjusted user’s accuracy for the disturbance class also decreased, with new values of 80.4% and 77.2% for Landsat 8 and Sentinel-2, respectively.

Table 4.4 Area adjusted accuracies for the maps of forest canopy disturbance obtained from Landsat 8 (a) and Sentinel-2 data (b). CE: Commission error, OE: omission error and OA: overall accuracy.

(a) Landsat 8

<table>
<thead>
<tr>
<th>Classification</th>
<th>Undisturbed</th>
<th>Disturbed</th>
<th>Total</th>
<th>User's accuracy (%)</th>
<th>CE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Undisturbed</td>
<td>0.906</td>
<td>0.035</td>
<td>0.941</td>
<td>96.3</td>
<td>3.7</td>
</tr>
<tr>
<td>Disturbed</td>
<td>0.008</td>
<td>0.051</td>
<td>0.059</td>
<td>87.1</td>
<td>12.9</td>
</tr>
<tr>
<td>Total</td>
<td>0.913</td>
<td>0.087</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Producer's accuracy (%)

|          | 99.2 | 59.3 |
OE (%)    | 0.8  | 40.7 |
OA (%)    | 95.7 |

(b) Sentinel-2

<table>
<thead>
<tr>
<th>Classification</th>
<th>Undisturbed</th>
<th>Disturbed</th>
<th>Total</th>
<th>User's accuracy (%)</th>
<th>CE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Undisturbed</td>
<td>0.927</td>
<td>0.023</td>
<td>0.950</td>
<td>97.6</td>
<td>2.4</td>
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<tr>
<td>Disturbed</td>
<td>0.010</td>
<td>0.040</td>
<td>0.050</td>
<td>80.0</td>
<td>20.0</td>
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<tr>
<td>Total</td>
<td>0.937</td>
<td>0.063</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Producer's accuracy (%)

|          | 98.9 | 63.3 |
OE (%)    | 1.1  | 36.7 |
OA (%)    | 96.7 |      |
**4.3.2.2 Forest area affected by selective logging: pixel based approach**

Considering the disturbance maps derived from the proposed approach and calculating the area covered by pixels with values greater than the optimized thresholds, Landsat 8 imagery leads to the detection of a larger logging-affected area than Sentinel-2 imagery (Table 4.5). The adjusted area for the disturbance class was 282.7 ± 52.5 ha for Landsat 8 and 206.5 ± 44.1 ha for Sentinel-2. The map based on Landsat 8 leads to an area affected by selective logging 17.8% higher than the map based on Sentinel-2 data, considering the simple pixel counting. However, when adjusted areas are taken into account this value is 36.9%. There is an uncertainty associated with the choice of the best threshold value, particularly for Sentinel-2 (ΔrNBR ≥ 0.065 ± 0.009). If we were to consider the lower end of this uncertainty interval (i.e. ΔrNBR ≥ 0.056) and the areas computed by simple pixel counting (Table 4.5), the logged areas mapped by Sentinel-2 would be substantially higher (163.4 ha for ΔrNBR ≥ 0.065 and 201.3 ha for ΔrNBR ≥ 0.056). Even if the differences in the overall accuracy for the lower end (96.6% for ΔrNBR ≥ 0.056) seem to be minimal, the commission error increased, reaching a value of 26.6%. By choosing to use the optimized threshold, i.e. the mean of all values that maximized the overall accuracy in 1000 simulations (ΔrNBR ≥ 0.065), this problem could be avoided.

Table 4.5. Mapped and adjusted areas for the maps of forest canopy disturbance obtained from Landsat 8 (a) and Sentinel-2 data (b). CI: confidence interval.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Landsat 8</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Map area (ha)</td>
<td>Adjusted area (ha)</td>
<td>±95% CI (ha)</td>
<td>±95% CI (%)</td>
<td></td>
</tr>
<tr>
<td>Undisturbed</td>
<td>3,069.3</td>
<td>2,979.1</td>
<td>52.5</td>
<td>1.8</td>
<td></td>
</tr>
<tr>
<td>Disturbed</td>
<td>192.5</td>
<td>282.7</td>
<td>52.5</td>
<td>18.6</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>3,261.8</td>
<td>3,261.8</td>
<td></td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>Classification</th>
<th>Sentinel-2</th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Map area (ha)</td>
<td>Adjusted area (ha)</td>
<td>±95% CI (ha)</td>
<td>±95% CI (%)</td>
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<td>Disturbed</td>
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<td>206.5</td>
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</tbody>
</table>

The percentages of logged area in relation to the total FMU areas (Table 4.6) vary from 2.43% to 14.28% for Landsat 8 and from 1.91% to 11.60% for Sentinel-2. In total, over the 7 areas, the percentages are 5.73% and 4.87% for Landsat 8 and Sentinel-2 respectively. If we analyze the sum of pixels classified as disturbed within the three unlogged sites the resulting areas are negligible for Sentinel-2, with 0.6% of
the total area accounting for disturbed pixels, for all sites. However, for Landsat 8 these disturbed pixels result in 1.2% - 2.6% of the total areas.

Table 4.6. Comparison of logging-affected areas derived from Landsat 8 and Sentinel-2 imagery through the ΔrNBR approach for the seven FMU. Areas extracted from the maps are derived from pixel counting and were not adjusted.

<table>
<thead>
<tr>
<th>FMU</th>
<th>Total area of the FMU (ha)**</th>
<th>Logging intensity (m³/ha)</th>
<th>Landsat 8</th>
<th>Sentinel-2</th>
<th>Landsat 8</th>
<th>Sentinel-2</th>
</tr>
</thead>
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<td>4.87</td>
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</tbody>
</table>

* Percentage of logged area (%) mapped in relation to the total FMU area (ha). ** Area of the polygon representing the SFM test sites.

4.3.2.3 Forest area affected by selective logging: grid-based approach

From the 252 full grid cells of 300 m × 300 m over forest in the seven FMU areas, 127 grid cells (1,143 ha - 50.4%) and 133 grid cells (1197 ha - 52.8%) contained more than 5% of pixels of mapped selective logging in Sentinel-2 and Landsat 8 data, respectively (Figure 4.5). The difference between the two sensors thus resulted in a 4.7% larger area with Landsat imagery. The grid cells appearing as disturbed in both datasets amounted to 116, accounting for 91.3% and 87.2% in Sentinel-2 and Landsat 8 data, respectively. In addition, a sensitivity analysis was applied on the position of the grid cells by calculating the statistics over ten different grids, nine of them shifted by 75 m steps in E-W, N-S and both directions from the original grid. In all cases Landsat 8 – based results showed a larger area of impacted forest by selective logging, ranging from 1.6 to 12.5%, with an average of 6.8%, compared to results based on Sentinel-2 imagery.
4.3.3 Detectability of logging infrastructure: results from field data collection

During field data collection, the geolocation of 155 sampling points was collected, and distributed throughout the seven FMUs. Data were collected for the geographic location and major types of logging infrastructure present. Logging infrastructure catalogued includes log landings (30), felling gaps (61), logging roads (32) and skid trails (32).

When comparing the field information to the disturbance maps, it appeared that Sentinel-2 imagery had a better capability for detecting logging infrastructure than Landsat 8 imagery (Figure 4.6). For log landings, the percentage of correct detection was 93.3% and 80% for Sentinel-2 and Landsat 8 imagery, respectively. However, for other types of logging infrastructure the same pattern was not observed. Felling gaps, with the second highest percentage of correct detection, reached 47.5% and 34.4% for Sentinel-2 and Landsat 8 imagery respectively. Logging roads (Landsat 8 = 21.9% and Sentinel-2 = 25%) and skid trails (Landsat 8 = 9.4% and Sentinel-2 = 6.3%) show very low percentage values of detectability.
4.4 Discussion

4.4.1 Detection of logging impacts: comparison with other studies in the Amazon

Based on the ΔrNBR approach proposed by Langner et al. (2018), selective logging activities were mapped in the seven FMUs near the town of Santo Antônio do Matupi, State of Amazonas, Brazil. The area-adjusted overall accuracies in the present study were satisfactorily high, with 95.7% for Landsat 8 and 96.7% for Sentinel-2, respectively. Similar values were obtained by Grecchi et al. (2017) for a forest disturbance mapping performed in the Brazilian Amazon, using SMA analysis on Landsat imagery – as well as in other studies (Souza Jr et al. 2013; Shimabukuro et al. 2014).

Instead of choosing arbitrary thresholds, the methodology employed in this study allows for the selection of an optimized threshold for each sensor, Landsat 8 and Sentinel-2, through the use of a reference data set. The optimized thresholds were defined using a bootstrapping approach with numerous simulations of accuracy assessments, with the goal of minimizing commission and omission errors, leading to the highest overall accuracy. For both satellites, the user’s and producer’s accuracies for the disturbed forest class was much lower than for the undisturbed class (Table 4.4). Omission errors play a major role in lowering the overall accuracy at the best possible threshold. With decreasing threshold values, overall accuracies also decreased considerably (Figure 4.4), indicating a strong increase of commission errors due to noise effects over non-disturbed areas. Therefore, it is possible that the key to more accurately identify disturbed areas does not lie in the lack of “detectability” through the ΔrNBR index, but rather in the capacity to separate real forest disturbances from noise. Notwithstanding, the range of all accuracies found here are
well within the range of previous works, or exceed them (Souza Jr et al. 2013; Shimabukuro et al. 2014; Grecchi et al. 2017; Langner et al. 2018; Shimabukuro et al. 2019).

4.4.2 Sentinel-2 versus Landsat 8

4.4.2.1 Accuracy assessment

Several studies have been carried out on sensor comparison and synergistic use of Landsat 8 and Sentinel-2 (Flood 2017; Forkuor et al. 2017; Korhonen et al. 2017; Wang et al. 2017; Quintano et al. 2018; Stumpf et al. 2018). However, more information is needed regarding the differing capabilities of the two sensors for land cover mapping and the consequences of these differences in the context of forest cover monitoring and forest cover change assessment. The results of mapping forest disturbances with the ΔrNBR approach reveal that, although Sentinel-2 shows a better performance, the overall accuracy (96.7%) is just marginally higher than the one reported for Landsat 8 (95.7%). Similar values were reported in other studies on land cover changes when comparing Landsat 8 and Sentinel-2 based results. For instance, Forkuor et al. (2017) mapping land use and land cover in Burkina Faso, found that the usage of Sentinel-2 data can improve image classification accuracy by 4%. In another study, Sentinel-2 was also shown to better map burn scars and fire severity in Greece from a ΔNBR approach with a 2.7% higher overall accuracy compared to Landsat based results (Mallinis et al. 2017). A study in Finland (Korhonen et al. 2017) compared the retrieval of biophysical variables for forests, concluding that Sentinel-2 performed better when the red-edge band was taken into account, however, the improvements in accuracy were marginal.

Sentinel-2 has very similar spectral bands compared to Landsat 8, therefore a better detectability of selective logging was expected due to the finer spatial resolution of Sentinel-2. However, Landsat 8 based results have similar overall accuracy. This could indicate that despite its coarser spatial resolution, Landsat 8 has good potential to identify logging features. These results agree with recent studies carried out in a region near the study area, in the State of Rondônia, Brazil (Bullock et al. 2018; Hethcoat et al. 2019). However, the area mapped as logged with Landsat imagery is considerably larger in comparison with Sentinel-2 – based results.

4.4.2.2 Forest area affected by selective logging

Landsat 8 data increased the estimated area of selective logging by 36.9%, compared to Sentinel-2 (Table 4.5). Logging infrastructure, such as log landings and logging roads, are generally smaller than the Landsat spatial resolution (Shimabukuro et al. 2019). In consequence, the possible area overestimation can be attributed to the high response values of mixed pixels in Landsat 8, that show up as a set of “pure” pixels in Sentinel-2, for the same corresponding area. Even though Sentinel-2 – based results have a higher commission error for the disturbed class (20%) compared to Landsat 8 results (12.9%), this was not
reflected in an increase of the mapped area. From Figure 4.3 it is clearly visible that Landsat 8 correctly
detects most of the logging infrastructure that results directly in canopy cover reduction. However, with its 30
m spatial resolution, it will also include “non-directly affected” logging areas in the same mapping unit (i.e.
the pixel), leading to a larger mapped area. The three areas without logging activities showed a minimal
amount of pixels classified as disturbed (0.6% for Sentinel-2). For Landsat 8 these disturbed areas
represented from 1.2 to 2.6% of the total areas, reflecting its coarse spatial resolution. Given the high
response values of the ΔrNBR for these pixels and the scattered spatial distribution of them, it is possible
that they represent natural disturbance events, such as natural tree falls. A further spatial pattern analysis
could be useful to “filter” these isolated pixels from the original mapping, if one is interested in reporting
disturbed areas in a regional scale, for example.

Deleterious effects of selective logging in tropical forests are not restricted to canopy cover reduction,
but have cascading effects on rates of forest growth, hydrological processes and carbon cycling (Asner et
al. 2009) and can have negative impacts on wildlife (Meijaard et al. 2005). Artificial gaps created by
selective logging activities, despite being designed to emulate natural systems (gap phase dynamics), lead
to a larger disturbance area than expected to occur under natural gap phase dynamics (Chazdon 2014).
Previous remote sensing studies deduced the area affected by selective logging, using buffers around key
logging infrastructure (Souza and Barreto 2000; Anwar and Stein 2012), as a way to estimate logging
impacts throughout surrounding forests. However, considering the areas under investigation, it is virtually
impossible to affirm that the non-directly affected areas of forests mapped from Landsat 8 imagery are
necessarily disturbed or even degraded, without consistent field data and a reliable methodology for
concluding so.

Logging authorizations within the State of Amazonas are valid for 24 months. Therefore, logging
activities can be carried out over the course of three consecutive years. This research focused on areas with
logging authorizations starting in 2016. In consequence it was probable that logging activities would be
carried out within the following 12 months. During the field campaign (carried out in 2017), it was observed
that the SFM activities were almost completely finished, however, a small percentage of the authorized
logging could potentially have occurred also within 2018. There is no clear relationship between logging
intensity and the percentage of the FMU mapped as logged (Table 4.6). This can be explained by two main
reasons. First of all, the logging intensity is quite similar amongst areas. Second, logging intensity is just a
ratio between the volume authorized for logging and the total area of the FMU. The percentage of disturbed
areas will also be dependent on the spatial distribution of logging activities and on the impacts of selective
logging on the remaining vegetation during the harvest process. For instance, if two areas have the same
logging intensity, but one of them did not follow the guidelines for minimizing harvest impacts, this area
will have a high percentage of disturbed areas. In spite of this, the percentages of logged forest area, considering all FMUs analyzed (Landsat 8 = 5.73%; Sentinel-2 = 4.87%), were similar to those reported from other studies carried out in areas under Reduced Impact Logging (RIL) techniques and/or subjected to legal harvest constraints (like SFM). The logging intensity in the FMUs is lower in comparison with the maximum volume authorized by law (CONAMA 2009; CEMAAM 2013) and more related to other studies carried out following RIL and/or low impact logging (Asner et al. 2002; de Carvalho et al. 2017). Asner et al. (2002), working in the Eastern Brazilian Amazon, found that the ground disturbance in areas subjected to RIL (logging intensity 23 m³/ha) was circa 4.6-4.8%, in relation to the total area authorized for selective logging. Authors of a different study (Tritsch et al. 2016), also focusing on the Eastern Brazilian Amazon, reported an average of 5% disturbance in RIL logging plots. While mapping selective logging with aerial LiDAR and field data in the State of Acre, in a public forest following very low harvest intensities (up to 13.3 m³/ha), de Carvalho et al. (2017), recorded areas of logging ranging from 7% to 8.6%. However, in areas undergoing illegal/conventional logging these percentages could be higher (Asner et al. 2002; Tritsch et al. 2016).

All RIL practices are not mandatory by law and SFM plans only need to comply with constraints present in the current Brazilian environmental legislation. These may include RIL practices or they may not (Zimmerman and Kormos 2012). One of the few constraints that allows monitoring with remote sensing techniques is related to the authorized area of forest openings for the construction of log landings and logging roads, currently limited to 2.5% of the total area of the management unit (CEMAAM 2013). However, the legislation does not establish any limits for the openings of felling gaps. It was not possible to clearly separate the damage caused by log landings and felling gaps in the FMUs. In this context it would be reasonable, as a suggestion for decision makers, to adapt the law to set a limit for the “total area under disturbance” which would include also the disturbances caused by felling gaps, rather than to specify maximum percentages by the type of logging infrastructure.

4.4.2.3 Grid cell approach measuring affected forest area by selective logging

The grid-based comparison of forest area affected by selective logging in Sentinel-2 and Landsat 8 data does not reflect the large difference of 36.9% between the sensors in the pixels-based forest disturbance mapping approach. The respective value for the grid-based area comparison (6.1% overestimation with Landsat 8) shows that most of the pixel-based overestimation by Landsat data was compensated in the grid by the spatial proximity of the Landsat 8 and Sentinel-2 disturbance pixels. In consequence, as for the pixel-based approach, the overestimation of the Landsat-based analysis is mostly linked to the coarser resolution.
4.4.2.4 Detectability of logging infrastructure

The logging infrastructure detectability was calculated using data collected from 155 field plots across the seven FMUs. Sentinel-2 has a better capability for detecting logging features (43.2%) compared to Landsat 8 (35.5%), which can most likely be attributed to its finer spatial resolution. The detectability over all the types of logging features was similar to values reported by Asner et al. (2005).

In a study performed in Guyana that mapped logging activities with Sentinel-2 data, it was noted that skid trails could not be identified using Sentinel-2 imagery (Masiliūnas 2017). This highlights the fact that skid trail damage is almost impossible to detect with optical remote sensing data available today because of its “below canopy” location (Figure 4.3). The logging roads in the study areas are secondary roads, built to be temporary and ranging from 4 m to 6 m in width. This could explain the lack of “detectability” for this kind of infrastructure. Nonetheless, the detectability of logging features confirms a better performance by Sentinel-2 (Figure 4.6), even if the difference from Landsat 8-based values is small. However, given the higher spatial resolution of Sentinel-2, these differences between the sensors are smaller than expected.

4.5 Conclusions

In this study the performance of Sentinel-2 MSI and Landsat 8 OLI for detecting forest canopy disturbances caused by selective logging was compared. A novel approach for detecting forest disturbances, the ΔrNBR index (Langner et al. 2018), was combined with a robust methodology to select optimized ΔrNBR thresholds for mapping forest disturbances in seven sustainable forest management areas harvested during years 2016 and 2017. The area adjusted overall accuracy for both sensors were similar, with a slightly higher accuracy recorded for Sentinel-2. No large differences in terms of accuracy were found by adding three unlogged areas to the original seven FMUs. Taking into account the area mapped as disturbed, it was found that Landsat 8 overestimates the detection of logging by approximately 36.9%, when compared to Sentinel-2 data. Using field data collected in the seven sustainable forest management areas, it was reported that Sentinel-2 imagery allows for the better detection of log landings and felling gaps than Landsat 8 imagery. However, other logging features had a small detection percentage for both satellites.

It was expected to find more substantial differences between the maps derived from Landsat 8 versus Sentinel-2 data, given the nature of the forest disturbances investigated. However, the results show similarities between the two sensors, both in terms of accuracy and logging infrastructure detectability using field data. This provides evidence of the potential for interoperability of the two sensors’ data in the context of forest canopy cover change. Moreover, it was shown that Landsat 8 maps larger areas containing forest disturbances, compared to Sentinel-2, both in the pixel-based and grid-based approaches, due to the lower spatial resolution. However, the two approaches deliver very different figures of Landsat overestimation,
with the grid-based overestimation being much smaller than the pixel-based approach. The higher spatial resolution of Sentinel-2 leads to a more precise pixel-based mapping of forest disturbance by selective logging, making it possible to map smaller disturbances and to map larger disturbances more precisely. For pixel-based forest disturbance maps it becomes clear that results should be called “areas of occurrence of selective logging” rather than “areas of selective logging” because considerable parts within Landsat pixels do not cover logging infrastructure. This is reflected by the large difference of pixel-based mapping results with Landsat and Sentinel-2 sensors. Future research could focus on more precise estimates of Landsat products for mapping areas directly affected by logging, using e.g. a change area correction factor, as suggested for MODIS products (Lunetta et al. 2006). In addition to this, future comparisons of Landsat 8 and Sentinel-2 could analyze possible synergies with the additional bands present in Sentinel-2, such as the red edge bands and the narrow NIR band, which were not investigated in the present study.
5 Spatial patterns of logging-related disturbance events: a multi-scale analysis on forest management units located in the Brazilian Amazon

5.1 Introduction

Selective logging is a major human activity in tropical forests. In the Brazilian Amazon it can reach an area as big as that reported as deforested (Asner et al. 2005). The impacts of selective logging have been documented for a wide variety of biotic and abiotic indicators (Meijaard et al. 2005; Olander et al. 2005; Burivalova et al. 2014; Darrigo et al. 2016; de Carvalho et al. 2017). While there are inevitable impacts associated with logging, it has been advocated that this activity is less deleterious to the environment than deforestation (Putz et al. 2012), which is a complete land cover and land use change. Therefore, despite the possible negative outcomes, selective logging has been promoted as an alternative to the conversion of forests into another land use type (Nasi et al. 2011; Putz et al. 2012; Edwards et al. 2014; Putz et al. 2014). In this context, sustainable forest management (SFM), has been presented as an opportunity to promote the sustainable use of forests while economic profits can still be assured. It is important to highlight that SFM activities differ from unsustainable/conventional logging. In the recent decades many policies were created to foster the sustainability of tropical forest products, such as the Forest Law Enforcement, Governance and Trade (FLEGT) policy of European Union (Tegegne et al. 2014). Therefore, research to improve the reliability of monitoring tools used to evaluate SFM activities is of high interest.

Efforts to develop Criteria and Indicators (C&I) for monitoring SFM activities in tropical forests, ensuring its sustainability, have been made by a variety of national and international organizations (Elias 2004; McDonald and Lane 2004; ITTO 2016; Linser et al. 2018). The International Tropical Timber Organization (ITTO) developed C&I for the sustainable management of tropical forests (ITTO 2016). and the Tarapoto Process, was developed specifically for Amazonian forests (Elias 2004). Some of ITTO’s C&Is, such as “Forest Biological Diversity”, rely on field data. Others, however, can only be measured with remote sensing techniques (ITTO 2016), due to the fact that many SFM implemented in tropical forests, especially in the Amazon basin, are located in areas difficult to access. While not all indicators can be assessed using satellite imagery, this type of data can be used as a proxy to measure the impacts of selective logging over time and covering large areas.

In the last two decades, we have seen a major development of remote sensing techniques applied for the assessment of selective logging in the Brazilian Amazon (Asner et al. 2005; Matricardi et al. 2010; Souza Jr et al. 2013; Pinheiro et al. 2016; Tritsch et al. 2016; Grecchi et al. 2017; Lima et al. 2019; Shimabukuro et al. 2019). While the majority of these studies focused on the mapping of selective logging, some of them assessed the intensity of forest disturbances and/or their spatial pattern either in a grid-based
approach (Pinheiro et al. 2016; Grecchi et al. 2017) or using land tenure databases (Tritsch et al. 2016). However, there is a need to investigate patterns of forest disturbances caused by selective logging in forest management units (FMU), rather than in the artificial landscape scale units such as regular grids. Investigating actual disturbance patterns in real FMU is crucial for understanding how the SFM has been implemented. In addition, a more detailed analysis of the spatial patterns derived from forest disturbance maps are necessary. So far, the vast majority of remote sensing studies had the objective of mapping the extent of selectively logged forests from binary maps (representing disturbed/undisturbed forests) (Asner et al. 2005; Matricardi et al. 2010; Souza Jr et al. 2013; Pinheiro et al. 2016; Tritsch et al. 2016; Grecchi et al. 2017; Lima et al. 2019; Shimabukuro et al. 2019). However, selective logging activities in tropical forests are not homogeneous. Impacts of selective logging varies in function of the type of logging infrastructure created during the harvest process. Secondary roads, log landings, felling gaps and skid trails will all impact forests in a different manner (Asner et al. 2002; Pinagé et al. 2016; de Carvalho et al. 2017). Therefore, binary maps measuring the extent of selectively logged areas as an indicator of forest disturbances may not be sufficient to describe the logging impacts in areas under SFM.

The main premise of this study is that selective logging activities in tropical forests are heterogeneous and that different types of patches, with distinct disturbance intensities, are produced during the tree harvest process. A patch implies a “relatively discrete spatial pattern” and a “relationship of one patch to another in space”, considering the surrounding of affected and unaffected areas (White and Pickett 1985). Therefore, the type of spatial configuration of forest disturbance patches, formed during selective logging process, could give us important information beyond pixel counting about the selective logging impact in a given area. A spatial pattern analysis (Riitters 2018) can be used to create a map accounting for the intrinsic heterogeneity within the areas of selective logging, categorizing each pixel in a binary map according to discrete disturbance intensities classes while keeping the spatial resolution of the pixel (Buma et al. 2017; Riitters et al. 2017).

Given the above, the objective of this study is to map forest disturbance intensities in areas of selective logging, located in a focus area in the Brazilian Amazon. To reach this objective, first, logging activities were mapped using high resolution Sentinel-2 imagery, later, a spatial pattern analysis was applied to the logging map. Landscape metrics were used to derive a forest disturbance intensity map via a cluster analysis. The method used to generate the final forest disturbance intensity map is partially based on the multi-scale approach proposed by Zurlini et al. (2006) and refined by Riitters et al. (2017). By adapting this method to small scale logging-related disturbances, it was possible to discriminate five categories of logging, therefore, going beyond binary maps of disturbed/undisturbed forests.
5.2 Material and Methods

5.2.1 Study area and selection of the forest management units

The study area is located in the south of the Brazilian State of Amazonas. Amazonas is the largest state in Brazil (1.5 million km\(^2\)) and holds the largest area of intact forests within the Brazilian Amazon (INPE 2019a). The region has a tropical monsoon climate (Am) according to the Köppen climate classification system, with a recorded mean air temperature higher than 26\(^\circ\)C and with annual rainfall ranging from 2,800 to 3,100 mm (Alvares et al. 2013). The short dry season (precipitation less than 60 mm per month) occurs between June and August (INMET 2016). The study area is covered by a mosaic of different vegetation types; with terra-firme forests (non-flooded) covering most of the region. These forests are classified as dense ombrophilous forest (IBGE 2012), with a tall, closed canopy. This study was carried out in a focus area, bisected by the Transamazon Highway (BR 230), near the Village of Santo Antonio do Matupi (Figure 5.1). It is one of the main timber production zones within the State of Amazonas (IPAAM 2019), while the surrounding area is known as a deforestation hotspot (INPE 2019a).

Figure 5.1. Location of the study area and the forest management units (black polygons, numbered from 1 to 12). Background map (year 2017): deforestation (white), non-forest vegetation (yellow) and forests (green), source: PRODES (INPE 2018).
According to data obtained from IPAAM, a total of 130 SFM areas, hereafter called Forest Management Unit (FMU), received authorization for logging between 2016 and 2017, considering all municipalities in the State of Amazonas. From these areas, 24 areas (18.4% of the licensed areas) are located inside the AOI. Of these, 12 areas were selected for the spatial pattern analysis, all of which had experienced tree harvest in the year 2017. Logging authorizations in the State of Amazonas are valid for 24 months. Therefore, selective logging activities can be carried out over the course of three consecutive years. For example, if an area is licensed in July 2016, logging activities may be carried out from July 2016, may continue in the dry season of 2017 and need to be finished by the end of June 2018. The 12 areas selected for this study were harvested mostly during the year of 2017, some during the year 2016 and 2018 (Chapter 6). Focusing mainly on areas harvested in 2017 allowed us to apply the change detection approach developed in the Chapter 4 of this thesis (Lima et al. 2019).

5.2.2 Input data

Sentinel-2 (S2) imagery was used to map logging activities in the study area. Sentinel-2 images (MSI Level-1C), tile 20MPS, were obtained from the European Space Agency (ESA) Copernicus portal (https://scihub.copernicus.eu). With a spatial coverage of 100 × 100 km per image tile, they provide a good representation of the town of Santo Antonio do Matupi and its surrounding areas (Figure 5.1). All cloud free images available for a 4-month time period from 1 June to 30 September for the years 2016 and 2017 were analyzed (Table 5.1). Clouds and cloud shadows were masked out using the fmask algorithm (Zhu et al. 2015), with a 20 m spatial resolution. To accommodate the cloud detection algorithm for the 10 m resolution of Sentinel-2 data, the fmask product was resampled to 10 m using the nearest neighbor method. To improve the detection of small clouds, the cloud probability threshold was modified to 0.1 from the original value of 0.2.

Non-forested areas were masked out using PRODES forest cover mapping for the year 2017 (INPE 2019a). PRODES data was chosen for building the forest mask because it applies an object-based image analysis, with a minimum mapping unit (MMU) of 6.5 hectares. This ensures that logging infrastructure can be kept inside the forest mask and mapped as part of the forest disturbance process. Water bodies were masked out using the Global Surface Water data set (Pekel et al. 2016). Both data sets were resampled to 10 m resolution using the nearest neighbor resampling method. Forest disturbance maps were produced using an adaptation of the difference of a self-referenced normalized burn ratio, the ΔrNBR approach (Langner et al. 2018), for the years 2016 and 2017. This approach was already tested for Sentinel-2 data in the same region (Lima et al. 2019). The ΔrNBR approach was used to build a binary map of disturbed/undisturbed forests, the input data set used to calculate the forest disturbance intensity for each
FMU. All remote sensing analyses were done in R (R Core Team 2018), using raster (Hijmans 2017) and rgdal (Bivand et al. 2018) packages.

Table 5.1. Satellite imagery used in this study.

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* Values from ESA/Copernicus portal; percentage in relation to the Sentinel-2 tile area (100 x 100 km = 10,000 km²)

5.2.3 Spatial pattern analysis

The binary map produced in the first step does not discriminate between different types of disturbance patches. Therefore, the input map has only two classes for forest areas: disturbed and undisturbed forests. The justification for running a spatial pattern analysis is going beyond the binary map and assign a potential disturbance patch category for the pixels classified as disturbed, considering the context and location of each pixel. Spatial patterns of forest disturbances can be estimated by a variety of metrics (Turner and Gardner 2015). However, ultimately, the fundamental elements of landscape pattern can be described by composition and configuration (Li and Reynolds 1994; Gustafson 2018; Riitters 2018). Composition refers to the extents of the many land cover types in a landscape and configuration to their spatial arrangements (Zurlini et al. 2006).

Composition can be calculated as the proportion of the map occupied by the land cover class of interest (Pd = proportion). Therefore, pixels belonging to the disturbance class can have Pd values ranging from 0 to 100% (Vogt 2018a). An example of a Pd calculation for a square moving window of 7 × 7 pixels size is shown in (Figure 5.2). Configuration can be described by a landscape metric known as adjacency (Riitters 2018). Adjacency is also called contagion (Riitters et al. 1996), and is used to distinguish between landscape patterns that are clumped or dispersed (Turner and Gardner 2015). Here, adjacency is described as the conditional probability (using the 4-neighbor rule) that a focal class pixel is adjacent to another focal class pixel (Pdd = adjacency). Pixels belonging to the disturbance class are also going to have Pdd values ranging from 0 to 100% (Figure 5.3). Here, adjacency is defined as a “class-level contagion” because just one land cover class, the disturbance class, has been used to calculate Pdd (Vogt 2018b).
Figure 5.2. Example of the proportion (Pd) metric computation from a binary map. Left: Study area Nº6, binary map of disturbed/undisturbed forests: light grey color represents undisturbed areas and dark grey disturbed areas; Center: Moving window (7 × 7 pixels) surrounding the focal pixel (in blue); Right: Proportion (Pd) map, containing pixels with the proportion of the surrounding landscape encompassing disturbed pixels (high values are dark red, low values are light red). In the case of the focal pixel exemplified Pd = 76.

Figure 5.3 Example of the adjacency (Pdd) metric computation from a binary map. Left: Study area Nº6, binary map of disturbed/undisturbed forests: light grey color represents undisturbed areas and dark grey disturbed areas; Center: Moving window (7 × 7 pixels) surrounding the focal pixel (in blue); Right: adjacency (Pdd) map, containing pixels with the proportion of the surrounding landscape with disturbed-disturbed adjacency, represented by the grey color dotted lines (high values are dark purple, low values are light purple). In the case of the focal pixel exemplified Pdd = 77.

In the present study, Pd and Pdd values were calculated using a square moving window with different sizes. Observations of composition and configuration are scale-dependent, and are connected such that one cannot study configuration independently of composition (Zurlini et al. 2006). For this reason both metrics were chosen to describe the spatial patterns of logging-related disturbances within the study area. Both metrics were calculated using the GUIDOS TOOL Box from the European Commission (Vogt and Riitters 2017).
The spatial variation of a system property (i.e. the spatial entity being evaluated, here disturbance area) that can be detected will depend on the spatial scale at which the property is measured and the size of the mapping unit (Gustafson 1998). In this study, the size of the mapping unit (also called the grain size) is the 10 m spatial resolution of the input map, derived from Sentinel-2 data. Defining spatial scale is a problematic issue in landscape ecology (Dungan et al. 2002; Wu and Li 2006). Here, spatial scale follows the conceptual model proposed by Zurlini et al. (2006), where the scale of observation is defined by a fixed-area following square moving windows of different sizes.

The moving window algorithm (Baker and Cai 1992; Rocchini et al. 2016b) has been mentioned as a powerful approach for analyzing composition and configuration at multiple scales, considering spatial data derived from satellite imagery (Zurlini et al. 2006). Therefore, in the current study, Pd and Pdd were calculated for 8 fixed-area windows: 3 × 3 pixels (0.09 ha), 5 × 5 (0.25 ha), 7 × 7 (0.49 ha), 9 × 9 (0.81 ha), 11 × 11 (1.21 ha), 15 × 15 (2.25 ha), 21 × 21 (4.41 ha) and 25 × 25 (6.25 ha). Hereafter, the term “landscape scale” and “landscape extent” are used interchangeably to define different moving window sizes and when the fixed-area windows are described as 3 × 3, it means 3 × 3 pixels. Therefore, a moving window of 3 × 3 pixels can also be called a landscape scale of 3 × 3 pixels.

Previous studies have used larger window sizes to describe landscape patterns at multiple scales (Buma et al. 2017; Riitters et al. 2017; Wardlaw et al. 2018). For instance, in a study carried out in North America, using Landsat input maps, the landscape size ranged from 0.0081 to 179.8 km², as the authors were analyzing disturbance patterns in a continental scale (Buma et al. 2017). However, in the present study smaller moving windows were required, given that small scale disturbances were analyzed. In addition, it is expected that logging-related disturbances will not be larger in size than 6.5 ha, once this is minimum mapping unit of PRODES data set (INPE 2019a).

5.2.4 Combining composition and configuration in a forest disturbance intensity map

Having multiple maps representing distinct (although related) landscape metrics (Pd and Pdd) does not give us additional information about disturbance patterns in space. However, combined, they can provide us with insights about the spatial distribution of disturbance events. Therefore, by combining Pd and Pdd it is possible assign a number of discrete classes, representing different intensities of forest disturbances. In the following, a justification is given for using the current pattern metrics to assess disturbance intensity within the study area, before presenting the approach used to combine Pd and Pdd in a forest disturbance intensity map.
5.2.4.1 Ecological context for the use of composition and configuration to describe spatial patterns of selective logging

Ecological disturbances were defined by White and Pickett (1985) as “any relatively discrete event in time that disrupts ecosystem, community or population structure and changes resources, substrate availability or the physical environment”. Later, a definition of disturbance, specific for terrestrial forest ecosystems, was proposed by Clark (1990) as “a relatively discrete event causing a change in the physical structure of the environment”. In the present study, Clark’s definition is used. Disturbances vary in many aspects, notably size, spatial distribution, intensity, severity and frequency, which are the components of the disturbance regime (Turner and Gardner 2015). Intensity is defined as “the physical energy of the disturbance event per area per time” and severity as “the effect of the disturbance event, in organism, community, or ecosystem” (Turner and Gardner 2015). According to the authors, both components are closely related, since more intense disturbances generally are more severe. An approach to “measure” disturbance intensity is to consider the recovery process: the longer the recovery takes, the higher the intensity of the disturbance event (Chazdon 2003). For this study the approach suggested by (Chazdon 2003) is used.

Disturbances caused by single trees dying and falling (the gap phase dynamics) is the dominant reason for natural forest turnover in tropical forests (Brokaw 1985; Denslow and Hartshorn 1994; Schnitzer et al. 2008; Chazdon 2014). Most canopy gaps created by falling trees are reported to have a gap size ranging from 10-100 m² (Brokaw 1985; Denslow and Hartshorn 1994; Hunter et al. 2015). Additionally, larger canopy gaps are caused by infrequent windstorms or landslides (Nelson et al. 1994; Espírito-Santo et al. 2014; Negrón-Juárez et al. 2017). Artificial gaps created by selective logging activities, despite being designed to emulate natural systems, result in a much larger disturbance area than that caused by natural processes as those described above (Chazdon 2014). The amount and the spatial configuration of canopy openings caused by selective logging activities in a given area can be used as a proxy for measuring disturbance intensity.

Composition and configuration were combined in a forest disturbance intensity map comprising five discrete intensity classes: very low (Class I1), low (Class I2), moderate (Class I3), high (Class I4) and very high (Class I5). The reasons for adopting this classification are justified as follows:

i) Isolated pixels in the binary map have a high probability of being just noise (Langner et al. 2018) and even if they correctly represent a disturbance, it can be considered a relatively small one (1 pixel represents an area of 100 m²). The metrics employed here, particularly the contagion metric (Pdd), can be useful for identifying those kind of pixels;
The center of large disturbed patches are likely to experience different physical conditions than that of small patches (Turner and Gardner 2015). By calculating Pd and Pdd, it is possible to assign different disturbance intensities to the core and edges of the same large forest gap. The core area can be considered more severely disturbed than its edge. Ecologically, this assumption is supported by the fact that a large gap has a very different climate at its center than at the edges, which includes differences in air movement and cooling processes (Oliver and Larson 1996). Resources, such as light availability and soil nutrients, vary strongly from the edge to the interior of gaps (Schnitzer et al. 2008). Furthermore, there is also a possible slowed tree regeneration at the center of disturbed sites in comparison to its edges (Chazdon 2014).

Different categorical classes (or types) of forest disturbances are also named “disturbance profiles” (Lundquist 1995; Zurlini et al. 2006; Buma et al. 2017). These areas should be more similar to one another than among different disturbance classes.

5.2.4.2 Clustering analysis

Riitters et al. (2002) plotted Pd and Pdd values of n observations in a simple scatterplot and called it “pattern space”. Later, this pattern space was used to assign categorical classes for each observation based on the values of composition and configuration. This approach was used to classify the remaining forests of continental United States in four classes: patch, perforated, edge and core, as a proxy to assess the status of forest fragmentation. The definition of discrete classes for characterizing the spatial patterns of land cover and/or land use will depend on the context and the type of classes being analyzed. In the study done by Riitters et al. (2002), the focal class was the forest class, since they were analyzing forest fragmentation. In the present study, the focal land cover class is the disturbed forest, and the discrete classes, meant to represent different disturbance intensities, were derived solely from this land cover class.

Another approach for aggregating information on land cover into meaningful landscape classes, with distinct spatial patterns, is cluster analysis (Zurlini et al. 2006; Riitters et al. 2017; Coops et al. 2018). Cluster analysis is a type of unsupervised data analysis which classifies a collection of objects into subgroups. Objects within each group are more closely related to one another than objects assigned to different groups (Hastie et al. 2009). Amongst various clustering techniques, k-means is one of the most popular, having been used, for instance, to capture global biodiversity patterns (Coops et al. 2018) and to assess forest disturbance patterns (Riitters et al. 2017; Sommerfeld et al. 2018). Even though the k-means algorithm is widely used, for this study the k-medoids clustering algorithm was selected, due to its robustness for the analysis of large data sets (Velmurugan and Santhanam 2010).
Clustering Large Applications (CLARA), a variant of the k-medoids algorithm developed for the purpose of analyzing large data sets (Kaufman and Rousseeuw 1990), was used to generate the final disturbance intensity map. Clustering was carried out for the aggregated values (the means) of composition and configuration across the range of scales. The map, aggregate by the mean, is hereafter called “multi-scale” map. CLARA cluster map was generated for k = 5 (five disturbance intensity classes) using the cluster package (Maechler et al. 2018) developed for R environment (R Core Team 2018).

5.2.5 Assessing the reliability of the forest disturbance mapping

Two approaches were adopted to assess the correspondence of the five classes of the forest disturbance map correspond to actual forest disturbances. The first one was to compare the field data collected in the area with the classes of disturbance. The second was to assess the rate of forest regrowth amongst different forest disturbance classes. In Section 5.2.4.1 it was described that an area could have its impact (disturbance intensity) “measured” by the rate of its forest regeneration. In this case, areas classified as very high disturbance intensity (Class I5) should take more time to recover.

This “post-harvest forest recovery” (White et al. 2019) was assessed using the values of the rNBR index for the years before logging (2015-2016) and the year after logging (2018). If an area is more heavily impacted it will take more time to return to the original values of rNBR than an area with lower impact. The rNBR is built with bands of the electromagnetic spectrum which are very sensitive to any changes in the green vegetation and it is also sensitive to areas with exposed soil (Langner et al. 2016; White et al. 2017). Therefore, the values of the rNBR were used to assess if these forest disturbance classes are indeed representative of different forest disturbance types. This approach is also used in the analyses of the Chapter 6, Section 6.2.3.1, when the post-harvest recovery rate was used to derive weights for a forest disturbance score.
5.3 Results

5.3.1 Composition and configuration

Both, Pd and Pdd, showed higher ratio values at the smaller scales (Figure 5.4). However, Pdd values stabilized quickly and stayed consistent for landscape scales bigger than \(5 \times 5\) moving window size. In addition, mean values of Pdd values did not show great variation amongst different moving window sizes, ranging from 48\% at the \(3 \times 3\) and 38.6\% at the largest scale \((25 \times 25)\). On the other hand, analyzing Pd values, at \(3 \times 3\) extent the recorded mean was 52.9\%, whereas at the biggest scale \((25 \times 25)\) this value was just 10.4\%. The variance, represented by the standard deviation, changed with landscape extent: at the smaller scales, the variance is higher than at larger spatial scales, for both Pd and Pdd.

Figure 5.4. Mean Proportion (Pd) and Adjacency (Pdd) across different window sizes (grey ribbons represents mean ± standard deviation).

Figure 5.5 displays the mean values for the different FMUs analyzed. Their patterns are similar: at smaller window sizes the mean values of Pd and Pdd are high and then decrease as the moving window size increases. Areas Nº6 and Nº8 (see Figure 5.1) show the highest Pd and Pdd values, which is an indication that two these areas have (proportionally) larger disturbances in comparison with the other FMUs. The same pattern is observed for the FMUs in the analysis of the final disturbance map derived from the CLARA analysis (see more details in the Item 5.3.2).
Figure 5.5. Proportion (Pd) and adjacency (Pdd) mean values among different forest management units (FMU, values from 1 to 12) and across a range of scales. See location of FMUs in the Figure 5.1

With increasing window size, the distribution of the individual data points in the scatterplot (represented by each one of the 33,419 pixels from the original land cover map) shifted towards the lower right corner of the pattern space at 9 × 9 scale. At 25 × 25 moving window size most of the individual data points are located at lower values of Pd (< 40%) and at intermediate values of Pdd, from 30-70% (Figure 5.6), indicating a decrease in the values of both metrics. Using the mean values of Pd and Pdd (the multi-scale) in the scatterplot creates a “smoother” cloud of data points, as the values are no longer categorized following discrete classed (Figure 5.6). The set of observations at the multi-scale is similar to that obtained when using a 9 × 9 moving window size. The multi-scale values of Pd and Pdd were used to generate a map of disturbance profiles, here called “disturbance intensity map”, described in the following Section.
Figure 5.6. Distribution of disturbed pixel values (33,419 observations) in the pattern space (Pdd x Pd – sensu Riitters et al. 2002) across different landscape sizes.
5.3.2 Disturbance profiles: analysis of the disturbance intensity classes

Mean disturbance proportion (Pd) and mean disturbance adjacency (Pdd) for the moving window sizes and for each of the clusters derived from the CLARA analysis (disturbance profiles) are shown in Figure 5.7. The distinct classes of disturbances trajectories (disturbance profiles) across all landscape scales are shown in Figure 5.8. Class I1 includes pixels with low values of Pd for all window sizes. This class covers 15.9% of the disturbance map, considering all FMUs. Figure 5.9 shows that most of the Class I1 pixels can be considered as noise, being spatially distant from more clumped spatial configurations. For this reason they were assigned the arbitrary class “I1.Very low” disturbance. On the other hand, Class I5 includes pixels with the highest values of Pd, ranging from a mean value of almost 90% and decreasing monotonically to the value of 18%, at the larger spatial scale (25 × 25). This class represents 21.6% of all disturbed pixels, and it represents (mostly) the core area of clumped logging-related disturbances, such as log landings and large felling gaps (Figure 5.9). Class I4, here called “high intensity” type of disturbance, covers 24.4% of the classified area. It has high values of Pd and Pdd, however, lower than Class I5 values. In the map, class I4 can be associated with the edges of large disturbed areas (log landings and felling gaps) and with logging roads (Figure 5.9). The other categories (Class I2 and I3) cover 38% percent of the map and represent “intermediate” types of disturbances that can be associated with small felling gaps. However the distinction between these two classes is not as clear as it is for the other classes. Figure 5.10 shows the distribution of disturbance classes for the 12 FMUs.

![Figure 5.7. Means of Proportion (Pd) and Adjacency (Pdd) for five disturbance classes across eight different landscape sizes.](image-url)
Figure 5.8. Classes of disturbance (disturbance profiles) in the pattern space (Pdd × Pd) for eight landscape scales (moving window sizes).

Assessing the reliability of the forest disturbance mapping

A total of 155 field points were collected in seven FMUs during the field work carried out in October 2017 (Lima et al. 2019). These field points represented different types of logging infrastructure: log landings (30 points), felling gaps (61), logging roads (32) and skid trails (32). Not all field points collected within the FMUs were correctly associated with the forest disturbance map (Figure 4.6, Chapter 4). This is especially true for “below canopy” disturbance types, such as skid trails. Therefore, from the total of 155 points collected in the field just 68 points were represented in the forest disturbance map. The other points were in areas classified as undisturbed forests. Consequently, these 68 points were associated with the forest disturbance classes (Figure 5.11). Considering the disturbance classes and the logging infrastructure, log landings can be associated with high and very high disturbance intensity classes. The classes I1 and I2 were not well detected with respect to the field data.

Figure 5.12 shows the post-harvest forest recovery. The classes defined by the forest disturbance intensity map are clearly distinct in terms of the rNBR values, mainly for the year 2017, the year where the selective logging activities were recorded. In addition, the classes I4 and I5, with high and very high disturbance intensities, show the highest values of rNBR during the forest recovery process in the year 2018 (post-harvest year).
Figure 5.11. Field data (logging infrastructure) distribution among different disturbance intensity classes.

Figure 5.12. Values of the self-referenced normalized-burn ratio index (rNBR) for the years 2015, 2016, 2017 and 2018, averaged by the disturbance intensity class. Note the high values of rNBR for the year of disturbance (2017) and the start of the recovery process in 2018. The arrow indicates the recovery process, from the highest rNBR value in 2017 in direction of the original pre-disturbance values (around -0.01) in the years to come.
5.4 Discussion

The main goal of this study was to produce a forest disturbance intensity map with the aim of improving the evaluation and monitoring of selective logging activities in areas licensed for timber harvest in the Brazilian Amazon. The main premise of this study is that selective logging activities in tropical forests show heterogeneous patterns and create different types of forest disturbance patches, with different disturbance intensities during the harvest process. Therefore, a well-known methodology designed for large scale studies (Zurlini et al. 2006; Riitters et al. 2017) was adapted to produce a forest disturbance intensity map that accounts for the intrinsic heterogeneity associated with selective logging activities.

The spatial patterns of logging-related disturbances were evaluated throughout multiple observation scales, with the objective of producing and analyzing a map of disturbance profiles (“disturbance intensities”). Two fundamental landscape metrics (Pd and Pdd) were calculated for such purpose, using different spatial extents. Based on the multi-scale (average) values of Pd and Pdd, a map containing discrete categories of forest disturbance was produced using a cluster analysis (Figure 5.9). By analyzing this “disturbance intensity map” it was possible to evaluate selective logging beyond counting pixels in a binary (disturbed/undisturbed) map. This is a step further, because in the categorized disturbance intensity map, pixels are classified into different classes of disturbance intensities. In simple binary maps, all logging areas have the same intensity class, based on the mapping of just two land cover classes: disturbed forest and undisturbed forest.

5.4.1 Composition and configuration variability across landscape extents

Composition and configuration, expressed as proportion (Pd) and adjacency (Pdd), respectively, describe spatial patterns of forest disturbance events in numerous landscape scale studies (Zurlini et al. 2006; Zaccarelli et al. 2008; Bourbonnais et al. 2017; Buma et al. 2017; Riitters et al. 2017). These previous studies used spatial pattern analyses to assess disturbance trajectories among different types of forest disturbances (e.g. forest fire, tree harvest, land use change), and clearly distinguish between regional and continental scales. The main goal of the present study was to assess the variation within a specific kind of forest disturbance event: tree harvest through selective logging.

Using areas of small-scale and legal (government authorized) logging it was possible to distinguish among the different types of forest disturbances caused by tree harvest activities, here called forest disturbance profiles. This methodology was originally developed for the use at regional/continental scale studies (Zurlini et al. 2006; Riitters et al. 2017), covering a variety of disturbance types, however, it was possible to show that the method can also be used at smaller scales.
Some of the points made by Zurlini et al. (2007) in their regional scale assessment can also be observed here: if the same focal pixel has a high Pd value at a small-sized moving window and a low Pd value at a large-sized moving window, the disturbance can be characterized as a “local heavy disturbance embedded in a larger region of fewer disturbances” (Zurlini et al. 2007) (Figure 5.4, Figure 5.5). This overall trend becomes even more pronounced if we consider the forest disturbance trajectory of class “I5. Very high” in Figure 5.7.

Using simulated landscapes, Riitters (2018) used the pattern metric space to infer aspects of landscape patterns derived from Pd and Pdd. It is possible to use this theoretical model to interpret the patterns observed in Figure 5.6. At small landscape scales, e.g. the 5 × 5 moving window, the cloud of data points at the upper right corner of the pattern space defines focal class pixels characterized as “clumped” and defines a landscape with larger and more distinct “perforations” or “holes”, related to the type of background/foreground map under analysis. As we move towards bigger landscape sizes (up to 25 × 25 window size), pixels in the upper right corner of the pattern space are absent. Most of the data points are located at the lower left corner of the metric space (Figure 5.6). At this landscape scale most of the observations are classified as “patchy”, ranging from many small patches to fewer larger patches (Riitters 2018). In practical terms this means that, at this landscape size, most of the observed values of Pd and Pdd are quite similar, regardless of the different assigned disturbance types.

Logging-related disturbances, as observed in the study area, are represented by a mosaic of distinct types of disturbances left after the tree harvest process (Asner et al. 2002; Chazdon 2003; Asner et al. 2004; Meijaard et al. 2005; Asner et al. 2009; Chazdon 2014; de Carvalho et al. 2017). These forest disturbances have a different spatial configuration. Recognizing spatial pattern within a given area will depend on the observation scale. The problem of changing observation scales in ecology was addressed by Levin (1992). The author pointed out that, in homogeneous environments, variability (of the system property) will decrease with increasing landscape sized (moving window sizes). These changes in variability are seen across different disturbance profiles: as the moving window size increases, the discrepancy in mean values of Pd and Pdd decreases (Figure 5.7 and Figure 5.8).

5.4.2 Disturbance intensity map: interpretation of disturbance profiles

Unlike previous studies, the approach applied here does not take into account a regional scale, which could contain more than one type of forest disturbance (e.g. forest fire, shifting cultivation, etc.). Instead it was limited to the boundaries of selected FMUs, covered largely by undisturbed forest (or not directly disturbed forest), given the small scale nature of tree harvesting activities. The assessment was done at the focal class level (Wu 2004), meaning that only the disturbance class in a binary map was under
investigation. By restricting the analysis to FMUs and focusing just on the disturbance class it was possible to group individual disturbed pixels into meaningful classes of disturbance profiles.

Disturbance profiles have been described as distinct types of disturbances grouped according to their similarity, taking into account certain landscape metrics (Zurlini et al. 2007; Zaccarelli et al. 2008; Buma et al. 2017; Riitters et al. 2017). These profiles may or may not be related with actual, real disturbances types, i.e. a land use or land cover category. For instance, while analyzing the regional patterns of disturbance in the south of Italy, Zurlini et al. (2007) observed that some of the disturbance profiles (clusters) were correlated with actual land use types, while others were not. This was also observed in the study area.

In the Brazilian Amazon, logging-related disturbances have traditionally been classified in log landings (or logging decks), logging roads (or secondary roads), felling gaps and skid trails (Asner et al. 2002; Asner et al. 2004; de Carvalho et al. 2017; Lima et al. 2019). This was the main reason for restricting the cluster analysis to few classes, differently from previous studies (Zurlini et al. 2006; Zurlini et al. 2007; Riitters et al. 2017; Wardlaw et al. 2018), and also for not running an algorithm to get a “optimal” numbers of k-classes (Riitters et al. 2017). Considering the FMUs under investigation and the aforementioned logging-related disturbance classes, disturbances caused by skid trails do not result in a large enough canopy cover removal to be captured by optical sensors (Masiliūnas 2017; Lima et al. 2019). However, the input data set captures and successfully maps most of the disturbances that result in direct canopy cover removal (log landings and felling gaps).

Through a visual analysis of Figure 5.9 some of the clusters can be associated with actual disturbance classes. Class “I5. Very high” can be e.g. associated with log landings, class “4. High” with logging roads. Class “I1. Very low” represents mainly noise (thus not real forest disturbances), as it appears in a sporadic, isolated manner, a spatial pattern atypical for selective logging activities. Field points identified as log landings are represented mostly as Classes I4 and I5. Both classes and Class I3 can be also be associated with felling gaps (Figure 5.11), reflecting the spatial heterogeneity of this kind of disturbance among the FMUs under analysis. Logging roads in this region are difficult to map even with very high resolution data (Lima et al. 2019) while skid trails are basically undetectable with optical remote sensing techniques (Masiliūnas 2017; Lima et al. 2019). In consequence, only the disturbance intensity classes I5 and I4 can be associated with logging infrastructure such as log landings and large felling gaps, on basis of the collection of 68 field point. Some of the field points taken in (probably smaller) felling gaps were mapped as Class I3, which constitutes an intermediate forest disturbance class.
The correlation of forest disturbance profiles with actual disturbances was reported to be more obvious for the extreme classes of disturbance intensities (e.g. very low and very high), considering different disturbance profiles (Zurlini et al. 2007). In Zurlini’s study, intermediate classes were more difficult to be correlated with real disturbances, which is also observed in the present study. Therefore, while it is possible, at a certain level, to associate the disturbance profiles with logging infrastructure, the forest disturbance intensity map does not perfectly distinguish categories of logging infrastructure. However, with this method it was possible to assign degrees of forest disturbance intensity, which can have important effects on the regeneration potential of forest stands after selective logging. More heavily impacted areas can present a slowed forest succession (Chazdon 2014) and a proliferation of non-commercial pioneer tree species (de Carvalho et al. 2017). This situation is not ideal from an ecological nor from an economic point of view.

Both values of the rNBR, in the year of logging (2017) and in the first year after logging (2018), show a distinct pattern among the forest disturbance intensity classes. The post-harvest values of rNBR (forest recovery), are lower for more heavily impacted areas, potentially lengthening the time period needed to return to the original, pre-disturbance rNBR values. Even though canopy closure after selective logging in tropical forest can occur really fast (Asner et al. 2004; Verhegghen et al. 2015; Langner et al. 2016) the ecological consequences can persist for a long period (Asner et al. 2009; Chazdon 2014). These ecological consequences vary among different types of selective logging infrastructure (de Carvalho et al. 2017) and this highlights the importance of having a map with categories of disturbance intensities.

This study was carried out over 12 FMUs, which in theory should have the same forest management regime. The distinction made among different classes of forest disturbances derived from logging activities was possible because the analysis was constrained to one type of forest related disturbance (i.e. selective logging). The areas of selective logging need to be clearly separated from other types of disturbances (e.g. forest fire, shifting cultivation, etc.) in order to derive detailed, specific logging-related information on forest disturbance intensities. The approach tested here, despite being successful in separating five distinct forest disturbance classes, can just partially identify logging infrastructure (log landing, felling gaps, and logging roads), due to the limitations of the optical remote sensing input data. More investigation is needed in this field, e.g. the application of the analysis over areas with a more distinct typology of selective logging infrastructure, as it appears in large forest concessions (Verhegghen et al. 2015).
5.5 Conclusions

This study had the objective to improve the mapping of selective logging activities beyond the binary maps representing two land cover classes (disturbed/undisturbed forests). A forest disturbance intensity map, accounting for the intrinsic heterogeneity associated with selective logging activities, was produced using two basic landscape metrics, composition and configuration. Based on a multi-scale analysis, similar disturbance profiles were grouped in five distinct classes. The results from this study reinforces the importance of a multi-scale analysis and highlights the consequences of choosing small moving window sizes over large ones.

Selective logging in the study area is composed by disturbances that are locally heavy, but embedded in a larger region of fewer disturbances. On this background, intermediate scale measurements are more suitable to represent actual (on the ground) forest disturbances; despite differences in the metric values (Pd and Pdd). The FMUs analyzed showed the same pattern across scales with different window sizes, while the cluster analysis (k = 5) showed non-random disturbance profiles, which were arbitrarily associated with five classes of disturbance intensity, very low, low, moderate, high and very high.

Each one of these disturbance intensity classes should be representative of a category of disturbance intensity that can be related with real forest disturbance types related to selective logging. The approach adopted in this study, despite being originally developed for regional and continental scales, was useful to distinguish among different types of logging-related disturbances. These classes were related to different categories of logging infrastructure mapped in the field. In addition, these classes can also be linked with forest recovery by post-harvest values of the rNBR index.
6 Landscape indicators for evaluating the performance of selective logging activities in forest management units located in the Brazilian Amazon

6.1 Introduction

The sustainability of selective logging operations in the tropics remains a long standing debate in the scientific community (Zimmerman and Kormos 2012; Putz et al. 2014; Brandt et al. 2016; Karsenty et al. 2017; Brandt et al. 2018). Nevertheless, selective logging has been promoted as an alternative to the conversion of forests into another land use type in several tropical countries (Nasi et al. 2011; Putz et al. 2012; Edwards et al. 2014; Putz et al. 2014). In this context, the governments of many tropical countries have produced legal frameworks to encourage the implementation of Sustainable Forest Management (SFM) as an approach to avoid deforestation and forest degradation (Nasi et al. 2011; Poudyal et al. 2018).

In Brazil, SFM activities are implemented via Forest Management Plans (FMPs) in private or public production forests. Regardless of its wide promotion, there is little data about the FMP implementation on the ground (Karsenty et al. 2017). This knowledge is essential in guiding the future development of public policies as well as in ensuring the environmental sustainability of forestry activities.

Acknowledging the importance of SFM, in recent decades, several actors have been involved in the development of criteria and indicators (C&I) for evaluating SFM activities at international, regional, and national levels (Linser et al. 2018). One integral part in the development of these C&I is the environmental component. C&I frameworks, such as the International Tropical Timber Organization (ITTO)’s C&I for the sustainable management of tropical forests (ITTO 2016) and the Tarapoto Process, developed specifically for Amazonian forests (Elias 2004), suggest the evaluation of many environmental indicators at local level. However, some very important criteria in the SFM scenario (and their related indicators), are difficult to measure periodically and at large scales.

The “Extent and Condition of Forests” criterion, proposed in the ITTO C&I framework, is one of the most important criteria for the evaluation of SFM activities. Its indicators can be measured using remote sensing and geographic information systems. In fact, selective logging activities in the Brazilian Amazon have been evaluated using optical remote sensing techniques for many years. Most of these studies had the objective of mapping the extent (the total area) impacted by selective logging (Asner et al. 2005; Matricardi et al. 2010; Souza Jr et al. 2013; Pinheiro et al. 2016; Tritsch et al. 2016; Grecchi et al. 2017; Lima et al. 2019; Shimabukuro et al. 2019). Some studies have also assessed forest disturbance intensities related to selective logging activities, acknowledging that the tree harvesting process is not homogenous across the landscape (Pinheiro et al. 2016; Tritsch et al. 2016; Grecchi et al. 2017). In some of these studies, the forest disturbance areas mapped were later summarized using indicators (indices) derived from landscape metrics.
The indices were either analyzed independently (thus not aggregated) (Tritsch et al. 2016) or they were aggregated into a single score (Pinheiro et al. 2016).

Aggregated indices, known as composite indicators (Nardo et al. 2008) are largely adopted for evaluating public policies. In this context, landscape metrics have long been used as landscape indicators for the evaluation of land use change, the status of habitat quality and biodiversity, as well as for evaluating habitat aesthetics (Uuemaa et al. 2013). Considering the importance of environmental indicators, in particular of landscape indicators, for the correct implementation of public policies, and considering the general importance of SFM implementation in tropical countries, the study of such indices in Forest Management Units (FMU) represents a step towards a better understanding of the forest policies in the Brazilian Amazon.

A FMU can be described as “a clearly defined forest area managed to a set of explicit objectives according to a long-term management plan” (ITTO 2016). Still following the ITTO’s definition, a FMU should have “a common system of forest management”, therefore making these units ideal for the assessment of SFM activities at local (within the FMU) and regional scales (among many FMUs). Pinheiro et al. (2016) did not take into account explicit areas of FMU in their evaluation of forest disturbances caused by selective logging with a composite indicator. Instead, the author used an arbitrary grid of 100 ha size over one Landsat scene, encompassing different types of forest disturbances, for instance selective logging and forest fires. Additionally, the set of independent indicators formulated by Tritsch et al. (2016) assessed forest disturbances in privately owned forests, but did not restrict the area of interest to FMUs. Therefore, there is still a research gap regarding the evaluation of tree harvest activities performed in FMUs.

In Chapter 5 of this thesis, a forest disturbance intensity map was built, taking into account high resolution remote sensing imagery with a 10 m spatial resolution and two fundamental landscape metrics, composition and configuration (Riitters 2018). However, the map alone does not give information about how each one of the FMUs performed in terms of forest disturbance impact, and does not give us means for comparison between the FMUs. Indices and scoreboards are widely used for comparisons among different units belonging to the same system (Nardo et al. 2008). The objective of this study is to develop a forest disturbance index to classify areas of selective logging, according to the amount and distribution of logging-related forest disturbances. To accomplish this objective, the analyses developed in the previous Chapters (4 and 5) were further refined and applied to additional areas (17 FMUs in total). A forest disturbance score (FDScore) was developed and tested against the most common indicator used to assess the impact of logging: the total extent of logged area.
6.2 Material and Methods

6.2.1 Study area and selection of the forest management units

The study area is located in the south of the Brazilian State of Amazonas. Amazonas is the largest state in Brazil (1.5 million km$^2$) and holds the largest area of intact forests within the Brazilian Amazon (INPE 2019a). The region has a tropical monsoon climate (Am) according to the Köppen climate classification system, with a recorded mean air temperature higher than 26º C and with annual rainfall ranging from 2,800 to 3,100 mm (Alvares et al. 2013). The short dry season (precipitation less than 60 mm per month) occurs between June and August (INMET 2016).

The study area is covered by a mosaic of different vegetation types; with terra-firme forests (non-flooded) covering most of the region. These forests are classified as dense ombrophilous forest (IBGE 2012), with a tall, closed canopy. This study was carried out in a focus area, crossed by the Transamazon Highway (BR 230), centered at the Village of Santo Antonio do Matupi, but also encompassing four FMUs alongside the Transamazon (Figure 6.1). This region is one of the main timber production zones within the State of Amazonas (IPAAM 2019), while the surrounding region is known as a deforestation hotspot (INPE 2019a).

The target year for the analysis in this chapter is 2017. Therefore all FMUs with SFMP licensed in the years 2016-2017 in the proximity of Santo Antonio do Matupi were pre-selected. Areas with a logging license but without apparent logging activities were excluded from analysis. Finally, 17 areas with substantial logging activities in 2017 were identified from IPAAM’s database and included in the study (Table 6.1). Some of the FMU are located far (up to 120 km) from Santo Antonio do Matupi, but exhibit similarities with the FMUs near the village, such as the same forest type and the same climate. In addition, all 17 FMUs are located alongside or near the Transamazon Highway (BR 230) (Figure 6.1).
Figure 6.1. Location of the study area and the location of the FMUs (areas Nº1 to 17) spanning throughout four municipalities (Humaitá, Manicoré, Novo Aripuanã and Apuí) and three Ares of Interest (AOI): Matupi, Maravilha and Tenharim. Background map (year 2018) from PRODES (INPE 2019): deforestation (white), non-forest vegetation (yellow) and forests (green).
Table 6.1. Information about the sustainable forest management (SFM) plans implemented in the 17 forest management units (FMU) analyzed in this study. These data were disclosed by the Brazilian Government, represented by the Institute of Environmental Protection of Amazonas State (IPAAM), under the Administrative Process Nº1946/2017.

<table>
<thead>
<tr>
<th>FMU</th>
<th>Geographic Coordinates*</th>
<th>License Nº</th>
<th>License validity (mm/dd/yyyy)</th>
<th>Volume authorized for logging (m$^3$) **</th>
<th>Total area of the SFM (ha)***</th>
<th>Logging intensity (m$^3$/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-61.5939, -8.0544</td>
<td>211/16</td>
<td>09/15/2016 09/15/2018</td>
<td>5,029.36</td>
<td>266.34</td>
<td>18.88</td>
</tr>
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<td>2</td>
<td>-61.7057, -7.9186</td>
<td>060/16</td>
<td>04/28/2016 04/28/2018</td>
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<td>373.62</td>
<td>18.42</td>
</tr>
<tr>
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<td>07/07/2017 07/07/2019</td>
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</tr>
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<td>08/05/2016 08/05/2018</td>
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</tr>
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<td>235/16</td>
<td>11/01/2016 11/01/2018</td>
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<tr>
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<td>91.49</td>
<td>16.71</td>
</tr>
</tbody>
</table>

*Centroid of the FMU’s polygon (EPSG:4326, WGS 84). **Volume authorized for logging present in the License/Authorization, according to the data provided by IPAAM. It does not necessarily represent the actual volume of logged trees in the moment the mapping was done. ***Area of the polygon representing the SFM test sites.
6.2.2 Spatial data set

6.2.2.1 Remote Sensing analysis

Imagery from the recently launched Sentinel-2 satellite (S2) was used to map selective logging in the study area (Figure 6.1). FMUs licensed in the years 2016-2017 were chosen, as the present study is focused on harvest activities that occurred mainly in the year 2017, (Table 6.1). The remote sensing analysis was based on the method proposed by Lima et al. (2019), which is based on a change detection approach called self-referenced normalized burn ratio (ΔrNBR) (Langner et al. 2018). The FMUs areas are located across three S2 tiles (Table 6.2), however, most of them are placed at the T20MPS tile, which covers the region of Santo Antonio do Matupi. Therefore, S2 imagery (MSI Level-1C) for these three tiles were downloaded from the European Space Agency (ESA) Copernicus portal (https://scihub.copernicus.eu), for four years since Sentinel-2 started to operate (2015, 2016, 2017 and 2018).

For the present study some adaptations from the original method presented in the Chapters 4 and 5 were made. The approach presented by (Langner et al. 2018) and further developed for S2 images by Lima et al. (2019) is a change detection approach that accounts for the canopy cover change for a period of time after the disturbance occurrence (T2), based on the comparisons with a period of time before the forest disturbance occurred (T1). The method is useful for countries or regions interested in reporting annual forest canopy cover change in the context of UNFCCC REDD+ policy (Langner et al. 2018). It is also useful for comparison between sensors, as presented by (Lima et al. 2019). In the study done by Lima et al. (2019) most of the logging activities in the targeted FMUs (areas Nº1 to 7) were carried out in the course of one year (2017) (Table 6.2). However, some of the tree harvest activities could also have happened during the first year of the analysis (2016), as well as, in the year after (2018), as the period of a logging authorization can span across three consecutive dry seasons (Table 6.1). For instance, FMU area Nº1 received the Authorization for Logging Nº211/16 on 15 September 2016, with an expiry date of 15 September 2018. In consequence, it could have experienced tree harvest activity in 2016, 2017 and 2018.

As the main objective of this study was to derive an index for evaluating the entire selective logging activities in the FMUs over the authorized time span, the decision was made to include, if necessary, forest disturbances that started in the previous year (2016) and those eventually carried out in the 2018. Even if these logging activities were small in comparison to the activities carried out in the main year under analysis (2017) (see Table 6.1), they could impact the evaluation of each FMU. For example, a given FMU could receive a lower forest disturbance score not because it had a lower harvest impact, but because the initial impact was canceled out by the adoption of a change detection approach.
Figure 6.2 shows the possible canopy cover dynamics scenarios in the FMUs throughout the years of 2015, 2016, 2017 and 2018, with the three later years representing the time span of authorized selective logging and the first year as pre-logging status. Hereafter the canopy cover dynamics scenario is defined as the change the FMUs have experienced from undisturbed forest to selectively logged forest to post-logged forest (forest regrowth) (Figure 6.2). Figure 6.3 shows an example of canopy cover dynamics scenario 1, where an additional mapping of the selective logging activities in 2016 was required, due to the fact that the selective logging activities from 2016 do not appear in the ΔrNBR change detection approach for 2016-2017. Figure 6.4 shows an example of canopy cover dynamics scenario 2, in which all selective logging activities were performed in 2017 with vegetation regrowth to be identified for the year 2018. Hence, biannual binary maps were made for each FMU classified in the Scenarios 1 and 3 by simply adding the binary maps derived from the two change detection periods (Figure 6.3). Therefore, the remote sensing analysis follows the steps described in Chapter 5 of this thesis, the difference merely being a larger area of interest and, where necessary, a forest cover change analysis for several years, rather than only for one year (2017).

Figure 6.2. Flowchart of the possible canopy cover dynamics scenarios recorded in the 17 FMUs under analysis.

An accuracy assessment was performed in order to choose the thresholds for the binary maps. This accuracy assessment was based on the visual interpretation of Sentinel-2 image composites (Bands 11, 8 and 4 in RGB) and followed the simple error matrix (Congalton 1991) and the calculation of the overall accuracy. The number of sampling points was 500 for the forest and 50 for the logged areas, for all seven change detection maps (Table 6.3), totaling 3850 sampling points interpreted. The threshold maximizing
the overall accuracy was chosen to build the binary masks. The overall accuracy for all maps was always greater than 95% (Table 6.3). The complete list of all images used in the analysis is presented in the Table 6.4.

The fmask algorithm (Zhu et al. 2015) was used for cloud masking and it was implemented using the command line script written in Python language and provided by Flood (2019). All remote sensing analyses were done in R (R Core Team 2018), using raster (Hijmans 2017) and rgdal (Bivand et al. 2018) packages. GIS analyses were done using QGIS open source software (QGIS Development Team 2019).

Table 6.2. Information about the location of each Forest Management Unit (FMU), the years where logging activity occurred and its respective canopy cover dynamics scenario (see code’s meaning at the Figure 6.2). AOI = Area of Interest

<table>
<thead>
<tr>
<th>FMU</th>
<th>Geographic Coordinates*</th>
<th>Sentinel-2 tile</th>
<th>AOI</th>
<th>Period of time where logging activities were recorded</th>
<th>Canopy cover dynamics scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2016</td>
<td>2017</td>
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<td>1</td>
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<td>Matupi</td>
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</tr>
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<td>2</td>
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<td>Matupi</td>
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<td>X</td>
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<td>4</td>
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<td>Matupi</td>
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<td>X</td>
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<td>Matupi</td>
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<tr>
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<td>Matupi</td>
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<td>X</td>
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<td>Matupi</td>
<td>X</td>
<td>X</td>
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<td>12</td>
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<td>X</td>
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<td>Maravilha</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
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<td>Tenharim</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
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<td>T20MNS</td>
<td>Tenharim</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

* Centroid of the FMU’s polygon (EPSG:4326, WGS 84)
Figure 6.3. FMU Nº12. Example of Canopy Cover Dynamics Scenario 1, here a biannual map is required since logging started in 2016 is canceled out in the binary map 2016-2017. A) Sentinel-2 image from August 2015: no logging detected; B) Sentinel-2 image from August 2016, starting of logging activities (red box); C) Sentinel-2 image from September 2017, more logging activities detected (red boxes), D) Binary map derived from the ΔrNBR approach, years 2015-2016; E) Binary map derived from the ΔrNBR approach, years 2016-2017 (red box: logged areas erased); F) Combined biannual map, encompassing the areas disturbed in 2016 that were canceled out due to the change detection approach.
Figure 6.4. FMU Nº6: Canopy Cover Dynamics Scenario 2. Sentinel-2 images (Bands 11, 8 and 4 in RGB) for the years 2015: baseline year, 2016: no logging detected, 2017: logging detected, and 2018: post-logging scenario with vegetation in process of regrowth and no more harvest activities detected.
Table 6.3. Sentinel-2 binary maps derived from the ΔrNBR change detection approach and respective thresholds and overall accuracy (Congalton 1991).

<table>
<thead>
<tr>
<th>AOI</th>
<th>Sentinel-2 tile</th>
<th>ΔrNBR period (year 1 – year 2)</th>
<th>Threshold ΔrNBR ≥</th>
<th>Overall Accuracy (%)</th>
<th>Disturbance class</th>
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<tbody>
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<td>T20MPS</td>
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<td>0.0</td>
</tr>
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<td>T20MQS</td>
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<td>—</td>
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</table>

Table 6.4 Sentinel-2 images used in this study. AOI = Area of Interest. Components of the Sentinel-2 filename: MMM: is the mission ID (S2A/S2B), MSIL1C: denotes the Level-1C product level, YYYYMMDDHHMMSS: the datatake sensing start time, Nxxxy: the Processing Baseline number (e.g. N0204), ROOO: Relative Orbit number (R001 - R143), Txxxxx: Tile Number field.

<table>
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<th>Sentinel-2 tile</th>
<th>Year</th>
<th>Sentinel-2 image</th>
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Table 6.4 (continued).

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</tr>
<tr>
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<td>2017</td>
<td>S2A_MSIL1C_20170903T142851_N0205_R053_T20MNS</td>
</tr>
</tbody>
</table>

6.2.2.2 Spatial pattern analysis

The spatial pattern analysis is based on the method described in Chapter 5 of this thesis. In this approach, fundamental landscape metrics like proportion (Pd) and configuration (Pdd) (Zurlini et al. 2007; Buma et al. 2017; Riitters 2018) were assessed on multiple scales and then combined, via a cluster algorithm, in a categorical map containing five classes of disturbance, herein called a forest disturbance intensity map. The only difference, from the approach already described (Chapter 5), is the inclusion of binary maps on selective logging activities from the years 2016 or 2018 were necessary in order to get a complete picture of logging-related forest disturbances over the whole authorized time period (Figure 6.2).

In the forest disturbance intensity map, each disturbed pixel received a score, with disturbance intensities ranging from very low (class I1) to very high (class I5) (Figure 6.5). In general, the score assigned for each pixel is a form of composite index, based on two single indicators, each representing a different aspect of the same multi-dimensional issue (Pd and Pdd). The two different variables Pd and Pdd were
combined to produce a third variable, which is not directly measurable (the forest disturbance intensity class). The challenge now was to decide the best way to evaluate and score each of the FMUs, based on the categorical values of the respective disturbance intensity maps.

Figure 6.5. FMU Nº8, canopy cover disturbance scenario 2. Left: Sentinel-2 composite (Bands 11, 8 and 4 in RGB) showing selective logging impact recorded in the year 2017 (magenta color); Centre: Binary map derived from the ΔrNBR approach for the years 2016-2017; Right: Forest Disturbance Intensity map, classes: I1 (very low), I2 (low), I3, (moderate), I4 (high) and I5 (very high).

6.2.3 Building a forest disturbance score

The total area affected by selective logging activities is the simplest possible index for evaluating tree harvest impacts. To make it possible to compare FMUs with different sizes, the proportion of the FMU considered disturbed (PropArea), in relation to its total area, was calculated. This simple indicator was compared with an index that accounts for forest disturbance heterogeneity, hereafter called Forest Disturbance Score (FDScore). By comparing the FDScore with PropArea we can have a clear idea about the shifts in the ranking position of different areas.

The disturbance intensity map introduced five disturbance intensity classes. These classes were meant to represent a gradual increase in disturbance intensity from I1 (very low) to I5 (very high) (Figure 6.5). Therefore, different weights were assigned to each class, using two different weighting strategies.
6.2.3.1 Weighting approaches

Weighting is a sensitive step in the construction of environmental indices (Gan et al. 2017). Changes in the weighting approaches can enormously change the ranking position of the entities being evaluated (Nardo et al. 2008). Two approaches were adopted in this research. In the first one, arbitrary weights were assigned for each disturbance class: zero for undisturbed pixels (non-directly disturbed forests), one for class I1, two for class I2, three for class I3, four for class I4 and five for class I5.

The second approach, based on a post-disturbance recovery index, was meant to be more “objective”. This is the case because the weights were derived from vegetation recovery metrics. Spectral metrics, based on NBR values, have been used before to describe post-disturbance forest recovery (e.g. Kennedy et al. 2010). An “average rate of recovery” (regrowth) was computed following the approach proposed by White et al. (2019). Just FMUs fully harvested in 2017 were assessed (Scenario 2, areas Nº1, 3, 4, 6, 8, 9 and 10), in order to result with a consistent time series (2015-2018). Figure 6.6 shows the averaged values of the rNBR index for each one of the disturbance classes for the years 2015, 2016, 2017 and 2018. This simplified analysis had the objective of providing information about the recovery process of different disturbance classes. Even though a longer time series is needed to fully understand the vegetation recovery process, it is evident that the disturbance intensity classes show distinct rNBR post disturbance recovery patterns. However, I am fully aware that forest regrowth information based solely on rNBR, does neither describe forest recovery in terms of tree species composition nor does it give precise biomass gain estimates. Even though canopy closure after selective logging in tropical forest can occur really fast (Verhegghen et al. 2015; Langner et al. 2016), the ecological consequences for these areas can persist for a long period (Asner et al. 2009). With this background, the spectral response indicates a vegetation regeneration by decreasing rNBR values from the year of disturbance (2017) to the year after disturbance.

Based on the Figure 6.6 it is possible to infer that classes I1, I2 and I3 have similar rates of vegetation recovery. However, the classes of disturbance I4 and I5, with “high” and “very high” disturbance intensity, respectively, have considerably higher rNBR values compared to the other disturbance classes, in the year of the disturbance event (2017) as well as in the first year of post-disturbance (2018), thus the first year of vegetation regrowth. Therefore, in the year 2018, the rNBR of the classes I4 and I5 show the largest differences from the original, pre-disturbance values (2015-2016). A forest disturbance recovery rate was calculated, based on the rNBR pre-disturbance values and the highest rNBR value in the year of disturbance (2017). While the rNBR pre-disturbance values are at ca. -0.01 (averaged for all classes and for both years) the highest rNBR value for the year 2017 is at 0.20 (Figure 6.6). The distance for each class is from the pre-disturbance value is used as a proxy for the weighting scheme.
Figure 6.6. Values of the self-referenced normalized-burn ratio index (rNBR) for the years 20015, 2016, 2017, 2018 averaged by disturbance intensity class. Note the high values of rNBR for the year of disturbance (2017) and the starting of recovery process in 2018. The arrow indicates the recovery process, from high rNBR values in 2017 up to the original pre-disturbance values (around -0.01).

Classes I1, I2 and I3 are at the same forest recovery situation in the first post-disturbance year (2018). Even if each one of these classes had different rNBR values in the year of disturbance (2017), in the year after disturbance they showed very similar rNBR values of (I1: 0.048, I2:0.046, I3:0.049). The rNBR values of the disturbed forests represented by these classes needs to decrease by 20% to return to the pre-disturbance level. Class I5 needs to decrease by 50% and Class I4 by 30%. These percentages, based on the forest recovery rate, were used to assign the weights for each one of the forest disturbance classes, in order to build the forest disturbance score (Table 6.5). The FDScore, based on arbitrary weights, is hereafter called FDScore-I and the one based on the vegetation regrowth is the FDScore-II.

Table 6.5 Weights assigned for each forest disturbance class based on two different approaches.

<table>
<thead>
<tr>
<th>Class name</th>
<th>Intensity of disturbance</th>
<th>Subjective based</th>
<th>Based on vegetation regrowth</th>
</tr>
</thead>
<tbody>
<tr>
<td>I1</td>
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<td>2</td>
</tr>
<tr>
<td>I2</td>
<td>Low</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>I3</td>
<td>Moderate</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>I4</td>
<td>High</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>I5</td>
<td>Very High</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>
6.2.3.2 Aggregation

After defining the weights, they were aggregated into a single number as a score for each FMU. The type of weighting scheme and aggregation method applied will impact the ranking of the units being measured (Nardo et al. 2008; Gan et al. 2017; Greco et al. 2019). One of the most common aggregation methods is the weighted arithmetic average (Becker et al. 2017), being used in a variety of sustainability indices (Gan et al. 2017). This approach works when a “compensatory logic” does not need to be avoided (Fusco 2015). In the case of many independent (but somewhat) related sub-indicators to be combined into one single indicator (composite indicator), one sub-indicator can be “compensated” by another by using additive methods. This is evident from studies ranking the “relative importance” of tree species in a given forest community, using e.g. the importance value index (IVI) (Lima et al. 2010). Consequently, additive methods should not be used when interactions between indicators are significant (Gan et al. 2017). However, this is not the case for this study, as an area (a pixel) has a unique class of disturbance. Therefore, the different disturbance intensity class areas (\(Area_I\)) were multiplied by their respective weights (depending on the weighting scheme) and then divided by the total area of the respective FMU (Equation 6.1).

\[
FDScore = \frac{1}{N} \sum_{i=1}^{n} w_i Area_{I_i}
\]

Here, \(w\) is the weight given to the area (\(Area_I\), in number of pixels) of each forest disturbance class \(I\). \(N\) represents the total area under analysis, i.e. the number of pixels, disturbed or undisturbed, within the specific FMU. Following this approach the minimum value for a given unit would be zero (without disturbed pixels), the maximum value would be five (all pixels classified as “very highly” disturbed, thus belonged to the class I5). In this manner, the FDScore was normalized to a common scale (0-100) by Equation 6.2.

\[
FDScore^* = \frac{FDScore}{5} \times 100
\]
6.2.3.3 Uncertainty and Sensitivity analysis

Assigning different weights to the FDScore is, in a very general sense, a type of sensitivity analysis. Actually, the area proportion (PropArea) has the same design as the FDScore. In this case all pixels have the same weight (1). Uncertainty and sensitivity analysis, also referred as robustness analysis, are core steps on the construction of composite indices (Burgass et al. 2017; Greco et al. 2019). According to the Organization for Economic Co-operation and Development (OECD) Handbook on Composite Indicators (Nardo et al. 2008), the FDScore described here is not considered a “composite indicator”, in a sensu strictu, because it is not multidimensional. Nevertheless, the steps described by OECD guidelines to assess robustness were also applied to it.

A sensitivity analysis (SA) is “the study of how the uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input” (Saltelli 2002). A closely related analysis is the uncertainty analysis, which “refers to the changes that are observed in the final outcome from a potentially different choice made in the inputs” (Greco et al. 2019). Following the OECD guidelines, the SA approach to be adopted is dependent on the sources of uncertainty and on the assumptions considered as relevant in each specific case. The SA approach implemented here considered solely the variations on the weight values. Following Saltelli et al. (2008), Monte Carlo simulations (Gotelli and Ellison 2013) were carried out with 10,000 random combinations for weight values. The ranking position (RK) of each FMU was retrieved in each one of the simulations.

Therefore, the RK was the output of the sensitivity analysis and the average shift ($\bar{R}_S$) in the FMU’s ranking position was the metric used to assess uncertainty (Greco et al. 2019). The average shift, also called cumulative shift, captures the relative change in the ranking positions, considering the entire system, summarizing it in a single number (Saisana et al. 2005). It can be calculated as the average of the absolute differences in the FMUs’ ranks with respect to a “reference ranking” (RK$_{Ref}$), considering each one of the Monte Carlo simulations. In the present study RK$_{Ref}$ is the PropArea, since this is the most commonly used indicator to express the impact of the tree harvest within areas exposed to selective logging activities.

Equation 6.3 is an adaptation of the average shift (Nardo et al. 2008; Saltelli et al. 2008), where the average of the absolute difference between the reference ranking (RK$_{Ref}$) and the ranking position, specified by a given score RK is calculated, considering all FMUs. The difference between the approach present by Nardo et al. (2008) and Saltelli et al. (2008) and the one adopted here is that this average was originally meant to represent the cumulative shift of the entire system, including all FMUs, as a way to later identify causal sources of uncertainty in the final score scheme. Here, just one input factor has been tested: the weighting system. Therefore, the more appropriate question here is: what would the variation in the average
shift for a given FMU be like if the weights were randomly assigned? For instance, will FMU Nº6 continue to stay in the top ranking position, no matter the weighting values chosen? Or, which of the FMUs are more “sensitive” to a weighting scheme change? Hence, the approach presented here takes into account what happens to the ranking system in these situations.

Equation 6.3

\[ \bar{R}_S = \frac{1}{n} \sum_{i=1}^{n} |R_{K_{Ref}} - R_{K}| \]

Where, \( \bar{R}_S \) is the average shift, \( R_{K_{Ref}} \) is the position of the FMU in the baseline ranking, \( R_{K} \) is the position of the FMU in the simulations, from \( I = 1 \) to \( n \).
6.3 Results

6.3.1 Forest canopy disturbance maps

A total of 35 Sentinel-2 images for the years 2015, 2016, 2017 and 2018 were processed and analyzed, with the objective of mapping logging activities in 17 FMUs located in the southern region of the Brazilian State of Amazons. The overall majority of selective logging operations occurred in 2017 (Figure 6.7). However, a number of FMUs experienced some logging activity in the dry season of 2016 (areas Nº2, 7, 12, 16 and 17) and five areas (areas Nº5, 11, 13, 14, 15) had tree harvesting activities starting in 2017 and continuing in the dry season of 2018. Table 6.6 shows the total annual logged (disturbed) area for each FMU. The ΔrNBR is a change detection approach that will detect any event that causes a change in the spectral responses of the bands NIR and SWIR-2 from one period of time to another. In consequence, areas that were classified as disturbed in the first period of analysis (for instance, 2016-2017) can be classified as disturbed again in the next period of analysis (2017-2018) if i.e. an area (i.e. a group of pixels) has experienced some disturbance in both time periods. If a tree was felled in the early time period (2016-2017), followed by a logging road construction at the same place in the second period (2017-2018) a disturbance will be detected for both time periods. As a logging road is a more severe disturbance, involving canopy cover change and soil exposure, the area affected may be mapped as a “new logging area”. In consequence, forest disturbance is detected twice at the same point. However, for the biannual forest disturbance map these areas were not double counted.

From the Table 6.6 one sees that the “intersection” pixels, i.e. pixels classified as logged in both time periods, are minimal. Most of the biennial maps have less than 10% of the pixels classified as logged in both change-detection periods. An exception is area Nº13, with 24.1% of the areas classified as logged in both periods, 2016-2017 and 2017-2018. However, most of the forest disturbances were detected either in the first or second change-detection period. For instance, areas Nº7 and Nº5 were mapped by (Lima et al. 2019) just for the period 2016-2017. Area Nº7 experienced some logging at the end of 2016, which was canceled out by the change detection approach. These areas represent an increase of 25% in logged areas, to this specific FMU. In contrast, Area Nº5, which was also analyzed by Lima et al. (2019), had more logging occur in the years 2017-2018, which is understandable since the logging permit was still valid. In this case, the logging detected area doubled, it was 16.5 ha in 2016-2017 and in 2017-2018 it was 18.95 ha, for a total of 34.88 ha (excluding the intersection pixels). No logging was recorded outside the period in which the licenses were valid (Table 6.1), indicating (at least) a compliance regarding the authorized time period in which logging can occur.
Table 6.6. Areas of forest disturbance caused by selective logging computed using the ΔrNBR change detection approach for the years 2015, 2016, 2017 and 2018. FMU: forest management units, T1: period of time 1, T2: period of time 2. The symmetric difference symbol $\ominus$ refers to disturbed areas that were mapped as disturbed in T1 or T2, but not in both, and the intersection symbol $\cap$ refers to areas classified as disturbed in both T1 and T2. The original seven FMUs from (Lima et al. 2019) are highlighted in bold.

<table>
<thead>
<tr>
<th>FMU</th>
<th>AOI</th>
<th>Scenario</th>
<th>Forested area*</th>
<th>2015-2016</th>
<th>2016-2017</th>
<th>2017-2018</th>
<th>T1 $\ominus$ T2</th>
<th>T1 $\cap$ T2</th>
<th>Disturbed</th>
</tr>
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<tr>
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<td>—</td>
<td>2.65</td>
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</tr>
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<td>—</td>
<td>—</td>
<td>—</td>
<td>10.54</td>
</tr>
<tr>
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<td>21.56</td>
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<td>—</td>
<td>—</td>
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<td>—</td>
<td>—</td>
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<td>—</td>
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<td>1.77</td>
<td>64.11</td>
</tr>
</tbody>
</table>

|   |   |   | 9269.46 | 74.90 | 317.48 | 164.48 | 368.58 | 30.96 | 525.90 |

*The total deforested area (ha) here is represented by all pixels classified as forest (disturbed and undisturbed) inside each FMU. They are not necessarily the same areas of the polygons representing each FMU (described in the Table 1).

Figure 6.7. Proportional distribution of annual logged areas among the 17 FMUs under analysis. FMU: Forest Management Units.
Table 6.7 shows the total area of forests analyzed in this study, including disturbed and undisturbed forests within each FMU. From these totals we can see the amount of disturbed forests accumulated throughout the years where logging was recorded (Scenario 1 and 3). In general, these percentages are less than 10% of the original areas of undisturbed forests recorded in the pre-logging period (Table 6.7). An exception is the area N°6, which has 11.64% of area disturbed. Area N°17, even being an area mapped for two consecutive years (2015-2016, 2016-2017 – scenario 1), presented the smallest absolute area of logging (2.65 ha) and one of the smallest proportional areas of logged areas (3.98%). Area N°9 had, proportionally, the lowest area affected by logging (2.68%).

There is no clear pattern on the distribution of the mapped areas amongst the disturbance intensity classes (Figure 6.8). However, it seems that the intermediate classes (I2, I3 and I4) have more areas in comparison to the more extreme classes (I1, very low impact and I5, very high impact).

Table 6.7. Total forested area (ha), total area of disturbed forests within each FMU (ha), their respective area proportions (PropArea) and the extent of each disturbance intensity class (ha), I1: very low, I2: low, I3: moderate, I4: high and I5: very high. FMU: Forest Management Unit.

<table>
<thead>
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<th>FMU</th>
<th>Forested area*</th>
<th>Disturbed areas</th>
<th>PropArea (%)</th>
<th>I1</th>
<th>I2</th>
<th>I3</th>
<th>I4</th>
<th>I5</th>
</tr>
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<td>0.77</td>
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</tr>
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</table>

*The total forested area (ha) here is represented by all pixels classified as forest (disturbed and undisturbed) inside each FMU. They are not necessarily the same areas of the polygons representing each FMU (described in the Table 6.1).
6.3.2 Forest disturbance indices: comparing performances

The ranking values of different FMUs varied according to the weighting scheme adopted. Ultimately, the three scores evaluated were based on the same index, but with different weighting schemes. The area proportion is a version of the FDScore with all classes having weights equal to one. Table 6.8 shows that only three FMUs kept the same ranking position no matter which type of weighting scheme was used. Area N°6 has the highest forest disturbance intensity scores, followed by area N°15, for all weighting schemes (PropArea, FDScore-I and FDScore-II). Another area, area N°9, also kept its consistency as the area with the lowest forest disturbance score. All areas in between varied in ranking, according to the weighting scheme. Comparing the area proportion, area N°8 (4.63%) has almost the same score as area N°4 (4.21%), being at the 12th and 13th ranking position, respectively (Table 6.8). However area N°8 has shown the greatest ranking shift from 8th position for both FDScores to 12th position for area proportion.

Figure 6.9 shows the FDScores, taking into account uncertainties. The FMUs’ histograms scores look like normal distributions, from the least (FMU N°9) to the most disturbed area (FMU N°6), which becomes a flat-topped distribution, showing the wide range of possible score values.
Table 6.8 Values of the forest disturbance indices among different Forest Management Units (FMUs). FMUs are ranked, from highest to lowest score, by the area proportion index (PropArea). FDScore-I: Forest Disturbance Score based one cumulative arbitrary weights, FDScore-II: Forest Disturbance Score based on the average rate of vegetation regrowth. RK_I is the ranking position according to index I (PropArea), RK_II according to the FDScore-I and RK_III according to the FDScore-II.

<table>
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<tr>
<th>FMU</th>
<th>PropArea Value (%)</th>
<th>PropArea Ranking Position (RK_I)</th>
<th>FDScore-I Value</th>
<th>FDScore-I Ranking Position (RK_II)</th>
<th>FDScore-II Value</th>
<th>FDScore-II Ranking Position (RK_III)</th>
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</tr>
</tbody>
</table>

Figure 6.10 shows the average shift for 10,000 simulations, where in each one of the simulations weights were randomly assigned. The FMU with no change in the ranking position is again area Nº9. This area remains ranked as the least disturbed independently of the weighting scheme adopted. Area Nº6, which has the greatest values of the FDScore, considering both pre-defined weighting systems (Table 6.8), confirms this position in the average shift analysis. On the other hand, area Nº17 has the greatest variation in the ranking scheme, with an average shift of 1.42. Area Nº8, which has the greatest variation, considering the pre-defined weighting scheme, also shows high values for the average shift (Figure 6.10). Figure 6.11 shows the forest disturbance intensity mapping for area Nº8 and also for area Nº4, which had almost the same score when area proportion was compared.
Figure 6.9. Uncertainty analysis for a mapping with 5 disturbance classes. FDScores are shown for all 17 FMUs accounting for uncertainties in the weighting system. Vertical lines are the mean values for 10,000 simulations.
Figure 6.10. Average shift in the rankings’ positions of all Forest Management Units, in 10,000 simulations, where weights were randomly assigned.

Figure 6.11. Comparison between FMUs Nº4 and 8. Both have substantially the same logged area, however with a different distribution amongst the forest disturbance intensities classes.
6.4 Discussion

In this study, selectively logged areas located in the southern region of the Brazilian State of Amazonas were mapped using high resolution satellite imagery. Landscape indicators were used to build a map of forest disturbance intensities, categorizing the logged areas in five classes of disturbances, from very low (I1) to very high intensity (I5). Seventeen areas (FMUs) were assessed, all of them with authorized selective logging activities in 2016, 2017 and 2018. An alternative approach to assess the overall logging impact, going beyond the sum of disturbed forest areas, was used to rank the FMUs according to the degree of forest disturbances. The FDScore index was designed to account for the intrinsic heterogeneity of selective logging operations in tropical forests. Finally, two weighting schemes were used, assigning different degrees of importance to each of the forest disturbance classes.

6.4.1 Canopy cover disturbance maps

The canopy cover disturbance was mapped for a time period of four years in 17 FMUs exposed to different canopy cover disturbance dynamics (Figure 6.7). Table 6.6 shows the total area of forests analyzed in this study, including disturbed and undisturbed forests within each FMU. There are small differences between the forest areas here and in Chapter 4 of this thesis (Lima et al. 2019) — at least for the areas N°1 to 7. These differences are due to the forest mask used in Chapter 4. Of course an inclusion of additional maps (for the forest disturbance scenarios 1 and 3), also contributed to the change of the disturbance area.

When the analysis of Chapter 4 was done neither PRODES (INPE 2019a) nor the Global Forest Change product (GFC) (Hansen et al. 2013; GFC 2019) were available for the target year 2017. In consequence, a specific forest mask was built based on object-based image analysis (Lima et al. 2019). For Chapter 5, ancillary land cover/land use change maps were incorporated to build a forest map to make the approach proposed by Lima et al. (2019) more operational (Chapter 5). The two different forest masks used in Chapter 4 and Chapter 5 explain the small differences in forest areas in the FMUs analyzed by Lima et al. (2019). The use of ancillary data sets, such as PRODES, GFC and the Global Surface Water (Pekel et al. 2016) have been shown to be highly reliable and have been widely used in other scientific publications (Pinheiro et al. 2016; Tritsch et al. 2016; Langner et al. 2018; Beuchle et al. 2019; Shimabukuro et al. 2019).

The method presented here was tailored to map the selective logging activities in 17 targeted areas where logging was known to have occurred mostly in 2017, in contrast to previous studies that assessed all types of forest disturbances within a delimited area of interest over a longer time period (Pinheiro et al. 2016; Tritsch et al. 2016; Grecchi et al. 2017; Beuchle et al. 2019; Shimabukuro et al. 2019). By focusing the forest disturbance mapping in authorized logging areas, it was possible to reduce errors of commission. This is the case because the disturbances within each FMU were caused essentially by logging operations.
If this study were to be carried out on a regional scale, it would not be possible to assign all the disturbance mapped as being caused by selective logging. This is because on a large scale, many types of disturbances are expected to occur, such as fire and blowdowns (large scale windstorms) (Condé et al. 2019; Shimabukuro et al. 2019; Silvério et al. 2019). By working within FMUs it was possible to insure that the majority of the disturbance was caused by the logging operations. Fire and blowdowns were not recorded inside the FMUs during the analyzed timeframe. In a study carried out in Northern Mato Grosso, it was shown that while using the ΔrNBR method of Langner et al. (2018), only active delineation of anthropogenic forest disturbances (selective logging and forest fire), i.e. so-called “positive mapping”, avoided the inclusion of commission errors caused by natural events such as vegetation phenology and vegetation dynamics along river courses (Beuchle et al. 2019). Fortunately, the terra-firme forests analyzed here do not display such natural vegetation variations, differently e.g. from bamboo-dominated on southwest Brazilian Amazon (de Carvalho et al. 2013) or seasonally flooded forests in areas of várzea (floodplain forests), common in the Central Amazon (Peixoto et al. 2009).

The percentages of forest area mapped as selectively logged within each of the FMUs was 5.93%, on average, with a minimum value of 2.68% for area Nº9 and a maximum of 11.64% for area Nº6. These percentages are consistent with other studies carried out in the Brazilian Amazon, where low impact selective logging and/or reduced impact logging was implemented (Asner et al. 2002; de Carvalho et al. 2017; Pinage et al. 2019). Even with the inclusion of a second logging year (canopy cover dynamics scenarios 1 and 3), a significant increase in the total logged areas (Table 6.6) was not detected. In fact, the area with the largest selectively logged area (proportionally) is area Nº6, which was harvested only in 2017.

6.4.2 Short term forest regeneration analysis

Post-disturbance forest recovery was assessed in seven of the 17 FMUs studies (areas Nº1, 3, 4, 6, 8, 9 and 10, canopy cover dynamics scenario 2). While preliminary results, given the Sentinel-2 series is still short, we can have an idea about the vegetation regrowth dynamics in the study areas. The canopy cover disturbance classes (I1 to I5) had a distinct pattern; areas with higher disturbance intensity values had higher rNBR values in the year of disturbance (2017). The year 2018 showed greater differences from the rNBR values recorded in the pre-disturbance scenario (Figure 6.6).

Second, areas of disturbed forest recover quite fast (see Figure 6.4), confirming the findings of previous studies carried out in tropical forests (Verhegghen et al. 2015; Dalagnol et al. 2019; Pinage et al. 2019). Furthermore, selectively logged areas classified in the low to moderate disturbance classes (I1, I2 and I3) recover even more rapidly in comparison to those classified in the high (I4) and very high (I5) disturbance classes. This fast canopy closure after disturbance, detected from optical remote sensing
analysis, is in fact due to the fast regrowth of pioneer plant species which have high photosynthetic activity (Asner et al. 2009; Kleinschroth et al. 2015). In a study carried out in a forest concession in a nearby region (Jamari National Forest, Rondônia), Dalagnol et al. (2019) found a similar trend analyzing forest regrowth in function of canopy gap sizes. The authors used aerial LIDAR data which can also capture characteristics of forest structure, showing that large forest canopy gaps will need more time to fully close in comparison with medium or small gaps.

The time period analyzed here was short. However, as soon as the Sentinel-2 archive increases it will be possible to assess how forest regeneration, with a crescent complexity in the forest structure, will be reflected in the rNBR time series. This trend has already been captured for temperate forests with a long-term Landsat time series analysis, using the traditional NBR (White et al. 2017; White et al. 2019).

### 6.4.3 The Forest Disturbance Score (FDScore)

Ranking entities according to their performances is not an easy and straightforward task. More than to present a definitive approach, those building composite indicators and/or scoreboards should be interested in initiating discussions and stimulating public interest towards an index that could help governments and stakeholders to improve the efficiency of their activities (Nardo et al. 2008).

Despite the long-term discussions towards C&I for evaluating SFM from the national to local levels (Linser et al. 2018), it is still difficult to evaluate SFM activities on the ground. Tailored C&I for tropical forests have been proposed in the last decades, in an attempt to offer a more feasible solution for the implementation and monitoring of SFM in tropical forests (Elias 2004; ITTO 2016). While it is necessary to agree that the economic and social components of C&I’s are undoubtedly important, mainly when traditional communities are involved (Spies et al. 2019), many tropical countries are still struggling to assess the extent and conditions of their forests.

The “Extent and Condition of Forests” criterion, proposed in the ITTO C&I framework, is one of the most important criteria for the evaluation of SFM activities. This is especially true in the case of human-induced forest degradation, defined as “the reduction of the capacity of a forest to provide goods and services” (FAO 2010). A global forest cover change product, such as the GFC (Hansen et al. 2013; GFC 2019), made specifically for forest degradation, is still lacking and many assessments still rely on coarse resolution satellites and/or products aimed mainly at mapping deforestation, not forest degradation. For instance, Brandt et al. (2016) assessed the efficiency of timber extraction in logging concessions in the Republic of Congo, using the deforestation rates derived from the GFC product as an indicator and comparing FMUs with and without a licensed forest management plan. Such an approach would not have been possible in the study areas analyzed here, since the GFC product does not give enough information.
related to low impact logging, as the GFC mapping process was not created to provide information about forest degradation (Hansen et al. 2013). Therefore, by producing specific forest disturbance maps and categorizing these maps according to the disturbance intensity, it is possible to make a more reliable assessment of the execution of SFM activities on the ground.

This reasoning is clear when the ranking provided by the FDScore is evaluated. When only the total disturbed area is analyzed proportionally, area Nº8 (4.63%), for instance, has almost the same score of area Nº4 (4.21%), being in the 12th and 13th ranking position, respectively (Table 6.8). However, when both FMUs are analyzed using the FDScore, which accounts for the intrinsic forest disturbance heterogeneity associated with selective logging, the results are quite different. While area Nº4 still remains in 13th position, the shift in the ranking position of area Nº8 is substantial. It changes four positions, when it was expected to change, on average, one position if weights were assigned randomly (Figure 6.10). This change in four positions is mainly due to more areas classified with a very high disturbance intensity (I5), in the forest disturbance intensity map (Figure 6.11). This is an expected result by the FDScore design: penalizing FMUs with large extents of logging areas classified as very high disturbance intensity. Still, analyzing area Nº8, visually (Figure 6.11), the areas classified as I5 resemble large roads. By law, there is a limit in the area proportion, within each FMU, that can be apportioned for logging roads, which is 1.75% (CEMAAM 2013). Therefore, the FDScore presented here could also be further improved to rank FMUs according to their compliance with the forestry norms.

The ranking proposed here is based solely on the remote sensing and landscape pattern analysis, it was not meant to account for biomass removal. However, from Table 6.1 we can see that the FMUs under analysis here have similar logging intensity (< 25 m³/ha). Interestingly, area Nº4 and area Nº8 almost show the same logging intensity (~ 16 m³/ha). Therefore, it could be argued that the spatial distribution of logging activities play an important role in explaining the overall disturbance intensity within each unit and for the values of the FDScore. Considering the ranking system, areas Nº4 and Nº8 are located in the middle ranking positions. When the top ranked (e.g. area Nº6) and the least disturbed FMUs (area Nº9) are analyzed we see a different variation in the average shift values (Figure 6.10). This behavior has been described earlier by Nardo et al. (2008), when analyzing countries’ performances according to the Technology Achievement Index (TAI). The same has been has been noted here (even in the SA simulation): FMUs located in the extreme rankings’ positions keep the same place, consistently. However, FMUs in intermediate ranking positions showed greater variation, both using pre-defined and random weights.
6.5 Conclusions

In this chapter, the remote sensing and spatial pattern analyses developed in the previous chapters were expanded by applying the analysis to more FMUs, and by analyzing more years of forest disturbances with respect to the original analysis (Chapter 4). The FDScore, designed to capture the intrinsic heterogeneity inside the areas of selective logging, was applied to those areas. Two pre-defined weightings schemes were defined, with increasing weight values from lower to higher disturbance intensity classes. In the first weighting scheme, increasing arbitrary weights were assigned to each class, while in the second scheme the weights were derived from post-disturbance forest recovery rates.

For all FMUs, the forest area directly impacted by selective logging is within the range of other studies carried out in low impact and/or reduced impact logging at various locations in the Brazilian Amazon. When comparing the ranking position among different FMUs and considering the three indicators (PropArea, FDScore-I and FDScore-II) it was found that the ranking position will change for all FMUs, with an exception for the most and the least disturbed area (the extreme cases). The intermediate positions will have a substantial variation in the ranking position depending on the weighting system adopted. Considering the shift in ranking position depending on the weights assigned and using a sensitivity analysis, it was shown that for some FMUs this shift is not random. This means that, if we were to use the weights as they have been defined here (FDScore-I and FDScore-II), the performance of some FMUs would be completely different from those assigned by a traditional indicator (the proportion of disturbed areas within a given FMU).
7 General Conclusions

7.1 Overview

Deforestation and forest degradation are the main drivers of forest cover loss in tropical forests. The main causes of forest degradation in the Brazilian Amazon are forest fires and unsustainable selective logging. While deforestation has a straightforward definition and is relatively easy to map with remote sensing imagery, the same is not true for forest degradation. The process of tropical deforestation comprises a change in both land cover and land use: all canopy cover is removed and the forests are replaced by another land use type.

Forest degradation is not a transition between land cover classes, but it is a change in land cover within the forest class. A degraded forest is still a forest, but with significant losses in biomass, carbon stocks and biodiversity. Selective logging has often been directly related to forest degradation, especially in the Brazilian Amazon, where large forest areas have undergone this process. However, not all selective logging operations will necessarily result in a degradation of the forest. Areas of forest management, which respect the many legal constraints and plan the tree harvest process accordingly, should not be automatically classified as “degraded” after the logging process. This introduces us to the current “theoretical battlefield” about the definition of forest degradation, especially in the context of legal selective logging operations. This is the reason the term “disturbed forest” or “forest disturbance” have been adopted throughout this thesis. In fact, the Brazilian Government is still trying to find an operating definition for forest degradation.

The main motivation of this thesis was improve our understanding of forest disturbances caused by selective logging within the Brazilian Amazon. Prior literature on the spatiotemporal dynamics of forest disturbances has been mainly focused on regional and national scale studies, in general using medium resolution satellites, such as Landsat, to map the extent of disturbed forests. Few studies have addressed forest disturbance intensities, recognizing that the process is not homogeneous. Different from a deforested area, where all forest is replaced e.g. by pasturelands, a selectively logged forest might consist in areas of different forest disturbance classes. There are log landings, felling gaps, logging roads and skid trails, all of them with a different spatial configuration. It is well established in the scientific literature that these features are different in terms of ecological impact and post-harvest forest regeneration. Despite this, most studies treat these different logging infrastructures as homogeneous entities. Some studies categorize these areas in classes from low to high disturbance, using a grid-based approach. However, grids work on regional scale because when a grid-based method is adopted resolution is lost. In the area of interest, where most of the legal selective logging is authorized for small to medium privately owned forests (< 500 hectares), the grid approach is not applicable. The questions that were addressed are: What are the consequences of
moving the mapping of selective logging from medium to high spatial resolution? How can we address forest disturbance intensity classes while still keeping the original spatial resolution? In addition, based on the methods presented in the thesis, a new score system was proposed in order to evaluate the impact of selective logging activities within a given area.

7.2 Main findings and study limitations

Landsat satellite series have long been used to map selective logging in Amazonian forests. In this study it was confirmed that Landsat 8 detects well even small-scale selective logging, once it showed almost the same overall accuracy as Sentinel-2. However, when we need to assess the extent of selective logging, i.e. estimate disturbed forest areas, Landsat 8 showed a selectively logged area which was 36.9% larger than the area mapped by Sentinel-2. This can be explained by the high response of Landsat pixels to canopy cover changes. Sentinel-2 showed a better performance when comparing field data to the disturbance maps, and, in consequence, has a higher accuracy (even though marginal) and better detectability of selective logging features as mapped in the field. For this reason Sentinel-2 was chosen as an input data set for all analyses carried out in Chapters 5 and 6. One of the main caveats of the performance comparison of Landsat 8 and Sentinel-2 (Chapter 4) is that the selective logging areas classified in binary maps do not take in account actual canopy cover reduction within a pixel area. If there is a forest disturbance of 25 m² (e.g. a felling gap) within the area of a Sentinel-2 pixel (100 m²) the whole pixel will be classified as disturbed, not only a pixel fraction of 25%. Consequently, any sub-pixel small forest cover change detected (mix of changed forest area and unchanged forest within one pixel) of both satellite data sets will be mapped as canopy cover change of the whole pixel. Given its coarser spatial resolution, this is especially problematic for Landsat 8. Another limitation of the methodology presented here is related to the nature of both input data sets. It is not possible to map many of the secondary roads, because there is no substantial change in the forest canopy to make the disturbances detectable. Some parts of the logging roads and almost all the skid trails are not detectable using optical remote sensing due to their location under the forest canopy. Outside this issue, the forest disturbances resulting in direct change in canopy cover were satisfactorily detected by Sentinel-2.

In addition, this study had the objective of improving the mapping of selective logging activities, going beyond the ‘traditional’ binary map which represent only two land cover classes (disturbed/undisturbed forests). Based on multi-scale analysis, similar forest disturbance profiles were grouped in five distinct classes. Afterwards, each of these classes, representing one category of disturbance intensity each, were related with real disturbance types (logging landings, felling gaps and logging roads). Some of the forest disturbance intensity classes were related to different categories of logging infrastructure measured during the field work. In addition, these classes could also be linked to the forest recovery rate
by distinct post-harvest values of rNBR. The main drawbacks of this part of the study are related to the “validation” of the real disturbance classes. In the field survey carried out in seven of the 12 areas assessed (Chapter 5), 155 ground points were collected at various selective logging areas. However, only 68 points were detected in the binary map used as an input data set. In consequence, it would be good to have more field points to assess whether the forest disturbance classes are reliable over a larger area, especially for the intermediate disturbance classes (classes I2 and I3). In addition, analyzing a longer time series would improve the understanding of the post-logging recovery patterns among different forest disturbance classes.

A final product of this thesis was a forest disturbance intensity score, meant to capture the intrinsic heterogeneity inside areas of selective logging. All work developed in the previous chapters was combined, more forest areas were analyzed and a longer time-series (2015, 2016, 2017 and 2018) was assessed. The forest disturbance intensity map was used as an input data set for building a score system and FMUs were analyzed, scored and ranked. The sensitivity analysis showed that the score system is irrelevant for the two extreme scores (highest score, area N°6 and lowest score, area N°9). For all intermediate scores the ranking system is not random. For instance, for area N°8, the difference between the ranking positions assigned to the PropArea and the FDScore that we would expect to find if weights were randomly assigned was one, while the observed value is four. This highlights the fact that using just the proportion of forest disturbance area within an FMU (PropArea) as an indicator maybe not enough when selective logging is evaluated. The spatial heterogeneity of the disturbance patterns needs to be taken into account if we want to have more reliable monitoring. The main drawback of this approach is the absence of a more realistic “frontier”, as the score considers the worst case scenario possible (all pixels within the FMU are classified as I5, with a very high disturbance intensity), which practically suggests complete deforestation, and the best possible situation (all pixels within the FMU are classified as undisturbed forest, FDScore = 0, suggesting the absence of forest disturbance).

7.3 Recommendations for future research

Regarding the first study objective, the comparison of Sentinel-2 and Landsat 8 imagery for selective logging assessment, the main recommendation for future research is to further investigate on area estimations for both satellites. This future research could be done using very high resolution satellite data (such as PlanetScope and SkySat satellites) and field work measurements to get more information about the effects of the spatial resolution of Landsat 8 and Sentinel-2 on forest disturbance area estimates. Having reliable reference data would allow for the collection of information related to the percentage of canopy cover loss within pixels of high and medium spatial resolution. Another issue that was not addressed here is the comparison of the ΔrNBR with other well-established forest cover change detection methods, such as the spectral mixture analysis. Future research should also assess the potential of other Sentinel-2 spectral
bands, such as the Red Edge and narrow NIR bands, for detecting selective logging. One more practical recommendation. R is a really nice environment for statistical computing. Most of the analyses here were done in R. However, R is slow for remote sensing processing, in comparison with other programming languages such as Python. More work should be done to develop easy to use libraries (as we have for R) in Python.

Regarding Chapter 5, the main recommendations are to expand the amount of field data to be correlated with the forest disturbance intensity classes. A longer time series, for evaluating the post-harvest disturbance recovery is also needed. In addition, these forest disturbance intensity classes could be related with other types of analysis, e.g. the amount of soil in a soil fraction image derived from spectral mixture analysis. The spatial pattern analysis developed here is a “class-level” analysis, all metrics were calculated for the forest disturbance class. It could be interesting to address the forest class instead.

The FDScore is an initial attempt to build a score for assessing the performance of selective logging in FMUs, taking into account only the tree harvest process that could be detected with remote sensing. Future research should integrate more field data, and calculate, for instance, the level of compliance regarding the forest laws. This would need to be done in partnership with law enforcement institutions, given the amount of FMUs that voluntarily allow the audition by certification companies is very low. If more field data were available, the FDScore could be improved and a more reliable frontier (or frontier methods) could be used to score the areas. Additionally, the FDScore could be developed in a composite indicator, by aggregating new sub-indicators such as e.g. the degree of forest recovery.

Finally, given that selective logging is a pervasive activity within Brazilian Amazon and considering that we do not have any official system to keep track of illegal logging, research on this area is crucial. This research could be done using public domain data bases (already available) such as data from DOF system, with information regarding the timber supply chain and data bases with information regarding land tenure (e.g. Sparovek et al. 2019). By putting together reliable maps of selective logging activities and public data bases we could generate reliable information for assisting with monitoring and planning of forest management activities within the Brazilian Amazon. This will be a necessary step towards the sustainable management of Brazil’s unique natural resources in the long term.
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