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DEVELOPMENT**

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**MONITORING SUSTAINABLE FOREST MANAGEMENT IN THE AMAZON:
STRATEGIES, CHALLENGES, AND ADVANCED REMOTE SENSING
TECHNOLOGIES**

**SANTARÉM - PA
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TECHNOLOGIES**

Thesis submitted to the Postgraduate Program in Society, Nature, and Development at the Federal University of Western Pará, as part of the requirements for obtaining the title of Doctor in Environmental Sciences. Research line: Environmental and Social Impacts of Land Use Change in the Amazon.

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ATA DE DEFESA DE TESE


Aos vinte dias do mês de dezembro do ano de dois mil e vinte e quatro, às quinze horas, através da plataforma virtual (<https://meet.google.com/fyt-qaho-pqt>) e Câmara de Vereadores de Belterra (Pará), instalou-se a banca examinadora de tese de doutorado do discente **Afonso Henrique Moraes Oliveira** do PPGSND/UFOPA. A banca examinadora foi composta pela Dra. Lucieta Guerreiro Martorano, PPGSND/UFOPA e Embrapa Amazônia Oriental, orientadora e presidente da banca, pelo co-orientador o Dr. Mauro Mendonça Magliano (PF/INC), e pelos examinadores, os professores Dr. Edson José Vidal da Silva – USP/ESALQ (examinador externo), Dr. Eraldo Aparecido Trondoli Matricardi - UnB (examinador externo), Dr. Leonardo Pequeno Reis - UFRA (examinador externo), Dr. Thiago Almeida Vieira - PPGSND/UFOPA (examinador interno) e Dr. Rodrigo da Silva - PPGSND/UFOPA (examinador interno). Deu-se início à abertura dos trabalhos, pela presidente professora Lucieta Martorano, que, após apresentar os membros da banca examinadora e esclarecer a tramitação da defesa, solicitou ao candidato que iniciasse a apresentação da tese, intitulada **“MONITORAMENTO DO MANEJO FLORESTAL NA AMAZÔNIA: ESTRATÉGIAS, DESAFIOS E TECNOLOGIAS AVANÇADAS EM SENSORIAMENTO REMOTO”**, informando ao discente que possuía de 30 a 60 minutos para a apresentação. Concluída a exposição, a Profa. Lucieta Martorano, presidente da banca, passou a palavra ao examinador externo, Dr. Thiago Vieira para arguir o candidato, e em seguida, aos professores examinadores Dr. Leonardo Reis, Dr. Edson Vidal, Dr. Rodrigo da Silva e Dr. Eraldo Matricardi, para que fizessem o mesmo, nesta ordem. Após o término das arguições, a orientadora solicitou que o público se retirasse da sala para que ocorresse a reunião exclusiva entre os membros da banca para o julgamento do trabalho. Após a deliberações da banca examinadora, a orientadora convocou o candidato e o público ouvinte de volta para divulgação do resultado. A banca examinadora decidiu por unanimidade pela **APROVAÇÃO** do candidato, conforme as normas vigentes na Universidade Federal do Oeste do Pará. A versão final da tese deverá ser entregue ao programa, no prazo de trinta dias após a defesa, contendo as modificações sugeridas pela banca examinadora. Nada mais havendo por constar, lavrou-se e fez-se a leitura da presente ata que segue assinada pelos membros da Banca Examinadora, Presidente da Banca e Doutorando. Santarém (PA), vigésimo dia do mês de dezembro do ano de dois mil e vinte e quatro, às dezoito horas.

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Dedication

I dedicate this work to God, whose guidance and blessings have illuminated my path, providing strength and purpose in every moment of this journey.

To my parents, Áurea Lúcia and Franciso Oliveira, for their unconditional love, sacrifices, and unwavering support, which have been the foundation of all my achievements.

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*"What we do to the forests of the world is but a mirror reflection of what we are doing
to ourselves and to one another."*

— Mahatma Gandhi

GENERAL ABSTRACT

MONITORING SUSTAINABLE FOREST MANAGEMENT IN THE AMAZON: STRATEGIES, CHALLENGES, AND ADVANCED REMOTE SENSING TECHNOLOGIES

The Amazon rainforest is one of the most biodiverse and essential ecosystems on the planet, playing a crucial role in climate regulation and ecosystem services. However, human pressures such as deforestation and degradation have significantly impacted its structure and functioning. Forest degradation, characterized by repeated interventions like fires, illegal logging, and edge effects, differs from disturbances, which are abrupt and localized events, such as treefalls, storms, and legal selective logging. While disturbances do not necessarily lead to long-term degradation, these processes are often conflated. The lack of clear differentiation highlights the need for the development of robust methodologies to distinguish between these processes. Advancing these methodologies, particularly through remote sensing technologies, is critical for accurately assessing the extent and impact of disturbances and degradation, enabling more targeted management strategies and conservation efforts in the Amazon. In Chapter 1, 80 scientific articles on anthropogenic impacts on the Amazon using remote sensing were analyzed. Although methodological advances were evident, gaps in monitoring less-studied regions, such as the central and western Amazon, highlighted the need for advanced tools in sustainable forest management (SFM). Chapter 2 focused on the Saracá-Taquera National Forest, examining the effects of logging intensity on volumetric stock, commercial species abundance, and forest cover. Using forest inventory data, elevation, and PlanetScope images, analyses structured in 1-hectare cells for pre-, during, and post-logging periods (t_0 , t_1 , t_2) revealed that higher commercial stocks were located farther from water bodies. Logging was concentrated on a few trees per hectare, intensifying in areas with higher timber volumes. In Chapter 3, the integration of LiDAR data and PlanetScope images improved the detection of disturbances caused by selective logging. LiDAR identified 15.48% of impacted areas, surpassing PlanetScope's 13.69% sensitivity, particularly for subtle changes like clearings smaller than 0.2 hectares. PlanetScope, however, outperformed systems like DETER and SAD in identifying clearings under 1 hectare. The combined use of these technologies proved critical for impact monitoring, strengthening sustainable management, and supporting public policies. A key aspect of SFM is its socio-environmental dimension. The Amazon is home to many traditional and indigenous communities whose livelihoods depend on the forest. Ensuring resource sustainability requires their inclusion in management processes, valuing traditional knowledge, and addressing equitable benefit-sharing and economic opportunities. Strategies must prioritize long-term resilience by balancing environmental conservation with the well-being of local populations. This study underscores the importance of integrating advanced technologies and adaptive strategies to balance economic exploitation and environmental conservation. These initiatives are essential for promoting sustainable management and protecting Amazonian forest resources.

Keywords: Selective logging, change detection, monitoring system, forest management, forest degradation, forest disturbance.

RESUMO GERAL

MONITORAMENTO DO MANEJO FLORESTAL SUSTENTÁVEL NA AMAZÔNIA: ESTRATÉGIAS, DESAFIOS, E TECNOLOGIAS AVANÇADAS EM SENSORIAMENTO REMOTO

A floresta amazônica é um dos ecossistemas mais biodiversos e essenciais do planeta, desempenhando um papel crucial na regulação do clima e na provisão de serviços ecossistêmicos. No entanto, pressões humanas, como o desmatamento e a degradação, têm impactado significativamente sua integridade. A degradação florestal, caracterizada por intervenções repetidas, como incêndios, exploração ilegal de madeira e efeitos de borda, difere de distúrbios, que são eventos abruptos e localizados, como quedas de árvores, tempestades e exploração seletiva legal. Embora os distúrbios não levem necessariamente à degradação a longo prazo, esses processos são frequentemente confundidos. A falta de uma diferenciação clara ressalta a necessidade de desenvolver metodologias robustas para distinguir esses processos. O avanço dessas metodologias, particularmente por meio de tecnologias de sensoriamento remoto (SR), é fundamental para avaliar com precisão a extensão e o impacto dos distúrbios e da degradação, permitindo estratégias de manejo e conservação mais direcionadas na Amazônia. No Capítulo 1, foram analisados 80 artigos científicos sobre os impactos antrópicos na Amazônia utilizando SR. Apesar dos avanços metodológicos observados, foram identificadas lacunas no monitoramento de regiões menos estudadas, como a Amazônia central e ocidental, destacando a necessidade de ferramentas mais avançadas no contexto do manejo florestal sustentável (MFS). O Capítulo 2 focou na Floresta Nacional Saracá-Taquera, examinando os efeitos da intensidade da exploração madeireira sobre o estoque volumétrico, a abundância de espécies comerciais e a cobertura florestal. Utilizando dados de inventário florestal, elevação e imagens do PlanetScope, as análises estruturadas em células de 1 hectare para os períodos pré, durante e pós-exploração (t0, t1, t2) revelaram que os estoques comerciais mais elevados estavam localizados mais distantes de corpos d'água. A exploração concentrou-se em poucas árvores por hectare, intensificando-se em áreas com maiores volumes de madeira. No Capítulo 3, a integração de dados LiDAR e imagens do PlanetScope melhorou a detecção de distúrbios causados pela exploração seletiva. O LiDAR identificou 15.48% das áreas impactadas, superando a sensibilidade do PlanetScope (13,69%), especialmente para mudanças sutis, como clareiras menores que 0.2 hectares. No entanto, o PlanetScope superou sistemas como o DETER e o SAD na identificação de clareiras menores que 1 hectare. O uso combinado dessas tecnologias mostrou-se essencial para monitorar os impactos, fortalecendo o MFS e apoiando políticas públicas. Um aspecto fundamental do MFS é sua dimensão socioambiental. A Amazônia abriga muitas comunidades tradicionais e indígenas, cujos meios de subsistência dependem da floresta. Garantir a sustentabilidade dos recursos requer a inclusão dessas comunidades nos processos de manejo, valorizando seus conhecimentos tradicionais e abordando questões como a repartição equitativa de benefícios e oportunidades econômicas. As estratégias devem priorizar a resiliência de longo prazo, equilibrando a conservação ambiental com o bem-estar das populações locais. Este estudo destaca a importância de integrar tecnologias avançadas e estratégias adaptativas para equilibrar a exploração econômica e a conservação ambiental. Essas iniciativas são essenciais para promover o manejo sustentável e proteger os recursos florestais da Amazônia.

Palavras-chave: extração seletiva, detecção de mudanças, sistema de monitoramento, manejo florestal, degradação florestal, distúrbio florestal.

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CHAPTER I - Introduction and Research Framework

1.1 Definition of the Problem and Research Questions

The Amazon rainforest plays a crucial role in maintaining global biodiversity, regulating the Earth's climate, and sequestering carbon. However, forest disturbances, such as selective logging, pose significant threats to forest structure, biodiversity, and ecosystem functions. While sustainable forest management aims to mitigate these impacts, effective monitoring systems are necessary to ensure compliance with sustainable practices and to detect unauthorized disturbances.

Traditional monitoring methods, such as field inspections and coarse-resolution satellite imagery, often lack the spatial and temporal resolution needed to capture the heterogeneity of selective logging activities. This creates challenges in identifying subtle forest changes and delays in responding to disturbances. Emerging remote sensing technologies, including high-resolution satellite imagery (e.g., PlanetScope) and LiDAR, offer promising solutions due to their ability to provide detailed spatial information on forest structure and canopy dynamics.

Despite the advancements in remote sensing, several knowledge gaps remain. There is a need for an integrated approach that combines multiple data sources to improve the detection of forest disturbances, particularly within federal concession areas where sustainable forest management plans (SFMPs) are implemented. Additionally, the effectiveness of these combined technologies in assessing the spatial and temporal impacts of selective logging remains underexplored.

Furthermore, scientific literature on remote sensing applications for sustainable forest management is growing, but a comprehensive analysis of trends, advancements, and persistent gaps is necessary to guide future research and policy development. Addressing these gaps will require the validation of innovative methodologies to ensure their accuracy and reliability for large-scale, continuous monitoring of SFMPs in the Amazon.

In this context, this study seeks to enhance forest disturbance detection and monitoring by integrating high-resolution remote sensing technologies. By leveraging a scientometric approach, systematic reviews, and field-based validations, the research aims to contribute to the development a propose of an effective monitoring methodology that supports sustainable forest management and conservation efforts in the Amazon.

Within this context, the study seeks to address the following research questions:

- How can innovative remote sensing technologies improve the detection and monitoring of forest disturbances to support sustainable forest management and conservation in the Amazon?

To delve deeper, the following specific questions are examined:

- What are the current trends, gaps, and advancements in the application of remote sensing technologies for monitoring forest disturbances and sustainable management in the Amazon? *Sub-question:* What insights can be derived from a scientometric approach and systematic review of existing studies on this topic?
- How does selective logging influence forest structure and heterogeneity over time in a federal concession area before and after exploitation in the Amazon? *Sub-question:* What can integrate analyses of forest inventory data and satellite imagery reveal about the spatial and temporal impacts of selective logging?
- What is the potential of a combined methodology using LiDAR and PlanetScope data for detecting and monitoring forest disturbances in sustainable forest management plans? *Sub-question:* How can this methodology be validated to ensure accuracy and reliability in monitoring systems?

1.2 General Objectives of the Thesis

General Objective

To enhance the detection and monitoring of forest disturbances in the Amazon using innovative remote sensing technologies to support sustainable forest management and conservation strategies.

Specific Objectives

- To analyze the trends, gaps, and advancements in remote sensing applications for monitoring forest disturbances and sustainable management in the Amazon through a scientometric approach and systematic review.
- To assess the spatial and temporal impacts of selective logging on forest structure and heterogeneity using integrated forest inventory and satellite data in a federal concession area.

- To develop and validate a methodology combining LiDAR and PlanetScope data for accurate detection and monitoring of forest disturbances within sustainable forest management plans.

1.3 Main Hypotheses

General Hypothesis

H1: Innovative remote sensing technologies, when effectively integrated, significantly enhance the accuracy and efficiency of detecting and monitoring forest disturbances, contributing to improved sustainable forest management and conservation strategies in the Amazon.

Hypotheses for Specific Objectives

Objective 1: Trends, gaps, and advancements in remote sensing applications

- **H1.1:** The current body of literature on remote sensing technologies for forest disturbance monitoring demonstrates significant advancements but reveals critical gaps in spatial and temporal resolution for addressing the complexity of Amazonian ecosystems.
- **H1.2:** A scientometric approach and systematic review will identify underexplored areas, particularly the integration of advanced sensor technologies like LiDAR and high-resolution satellite imagery.

Objective 2: Impacts of selective logging on forest structure and heterogeneity

- **H2.1:** Selective logging causes detectable changes in forest structure and heterogeneity over time, which vary spatially across the federal concession area.
- **H2.2:** The integration of forest inventory data and high resolution satellite imagery provides a more comprehensive understanding of these spatial and temporal impacts compared to using either dataset independently.

Objective 3: Methodology combining LiDAR and PlanetScope data

- **H3.1:** A combined methodology using LiDAR and PlanetScope data significantly improves the detection and monitoring of forest disturbances compared to conventional methods.

- **H3.2:** The validation process will demonstrate that this integrated approach achieves higher accuracy and reliability for monitoring forest disturbances within sustainable forest management plans.

1.4 Theoretical Framework

The Amazon rainforest, one of the planet's most biodiverse ecosystems, is crucial for global climate regulation, biodiversity preservation, and supporting indigenous and traditional communities (MALHI *et al.*, 2008; LOVEJOY & NOBRE, 2019). However, it faces growing threats from deforestation, illegal logging, land-use changes, and climate change impacts (LAURANCE *et al.*, 2011; BRANDO *et al.*, 2020), demanding sustainable management practices to preserve its ecological integrity.

Beyond its ecological importance, the Amazon holds significant economic value through its timber market and non-timber forest products (NTFPs). The legal timber industry supports local livelihoods, regional development, and revenue generation via domestic and international trade (VERÍSSIMO *et al.*, 2000). However, challenges such as illegal logging, mismanagement, and ineffective monitoring systems threaten sustainable exploitation, forest conservation, and the credibility of legal timber markets (OLIVEIRA *et al.*, 2024). Addressing these issues is essential to promote sustainable practices and maintain market competitiveness, ensuring the Amazon's resources contribute to both economic growth and environmental preservation (MATRICARDI *et al.*, 2020).

Sustainable Forest Management (SFM) in the Amazon entails carefully planned practices that allow resource extraction while preserving the forest's structure and functionality. Among these practices, Reduced Impact Logging (RIL) has emerged as a pivotal strategy to mitigate ecological damage during selective logging operations (PEREIRA-JUNIOR *et al.*, 2002; COSTA PINTO *et al.*, 2024). However, the effectiveness of these practices is often hindered by the inherent complexity and heterogeneity of the Amazon's forest ecosystems, characterized by diverse topoclimatic, pedological, and hydrological conditions (OLIVEIRA *et al.*, 2024b).

In this context, advances in remote sensing (SR) technologies, such as high-resolution satellite imagery, LiDAR, and classification techniques, have revolutionized forest monitoring. These innovations enable precise detection of changes in forest cover, facilitating the identification of both legal and illegal activities and improving the

understanding of forest dynamics (ASNER *et al.*, 2005; SOUZA *et al.*, 2020; MATRICARDI *et al.*, 2020). This thesis explores the integration of these cutting-edge technologies to address the key challenges in monitoring and managing forest resources in the Amazon.

This study underscores the importance of leveraging advanced remote sensing technologies and adaptive strategies to address the challenges of forest management in the Amazon. By bridging scientific knowledge with practical applications, the research aims to contribute to the sustainable exploitation of forest resources while safeguarding the ecological and socio-economic values of the Amazon, ensuring that its economic potential, including both timber and non-timber products, is harnessed responsibly for future generations.

1.5 General Comments

- **Relevance of the Study**

The thesis addresses a critical issue by focusing on the detection and monitoring of forest disturbances in the Brazilian Amazon, specifically within sustainably managed areas of dense ombrophilous forest. The emphasis on supporting sustainable forest management plans (SFMPs) through innovative remote sensing technologies highlights the importance of ensuring the preservation of forest ecosystems and their services, such as carbon sequestration and biodiversity conservation.

- **Scientific Contribution**

The integration of LiDAR data, PlanetScope satellite imagery, and forest inventory data is a novel approach to improving the detection of subtle forest changes caused by selective logging. This combination enhances the precision of spatial and temporal analyses compared to traditional monitoring methods. The validation of this integrated methodology using LiDAR flyover data and forest inventory data strengthens the contribution of research to remote sensing and forest management fields.

- **Interdisciplinary Approach**

The incorporation of a scientometric analysis and systematic review provides a robust foundation for understanding the trends, gaps, and advancements in remote sensing applications for forest disturbance monitoring. This interdisciplinary approach ensures

that the work is informed by a comprehensive synthesis of the scientific literature, reinforcing its credibility and impact.

- Innovation in Methodology

Development of a remote sensing system that combines high spatial and temporal resolution data demonstrates innovation in the field of forest monitoring. The use of PlanetScope imagery to capture frequent changes and LiDAR to assess vertical forest structure addresses key limitations of single-sensor approaches. This methodological innovation positions the thesis as a significant contribution to the development of next-generation monitoring systems.

- Application to Forest Management Plans

By focusing on federal concession areas, the research has practical implications for sustainable resource management and policy enforcement. Demonstrating how the proposed methodology can detect unauthorized disturbances and improve the efficiency of SFMPs aligns your study with real-world needs for monitoring compliance and supporting certification programs for responsible forest management.

- Challenges and Validation

The validation of the proposed methodology is a key component of the research. Addressing potential challenges, such as image inconsistencies due to cloud cover or spatial misalignment, will be critical. The use of ground-truth data from forest inventories and high-resolution LiDAR scans provides a robust framework for ensuring the accuracy and reliability of the system.

- Broader Implications

The findings of the thesis have the potential to contribute not only to the academic field of remote sensing and forestry but also to environmental governance and conservation strategies. By improving the detection of selective logging impacts, your work can support more effective policy decisions and promote transparency in forest resource management.

- Future Perspectives

The research can pave the way for future studies aimed at scaling monitoring systems for larger areas or applying similar methodologies to different forest biomes. Additionally, it can inspire new research into the integration of machine learning

algorithms for automated detection and classification of different types and intensities of forest disturbances.

1.6 Thesis Structure

This thesis is structured into three chapters that are interconnected by their shared focus on improving the understanding, monitoring, and management of forest disturbances caused by selective logging in the Amazon. Together, they build a comprehensive narrative that integrates foundational knowledge, applied methodologies, and innovative frameworks to address the challenges in SFM.

Chapter I lays the groundwork by conducting a systematic review and scientometric analysis of the applications of RS technologies in monitoring forest degradation and selective logging. It identifies current trends, highlights gaps in literature, and underscores the potential of integrating optical and LiDAR remote sensing data for improving monitoring systems. This chapter provides a broad perspective, emphasizing the critical need for accurate and efficient technologies to detect and differ subtle and large-scale forest disturbances, setting the stage for the applied analyses in Chapters II and III.

Chapter II transitions from a theoretical overview to a practical application by analyzing the spatio-temporal intensity of logging within a federal concession in the Brazilian Amazon. This chapter leverages forest inventory data, topographic information, and high-resolution optical satellite imagery to assess the impacts of selective logging on forest structure. The analysis focuses on heterogeneity within the logged areas, addressing some of the research gaps identified in Chapter I, particularly the need for precise methodologies to evaluate forest management practices under real-world conditions.

Chapter III builds on the findings and methodologies of the previous chapters by proposing an integrated framework for monitoring SFM plans using LiDAR and PlanetScope data. This chapter combines the insights from Chapter I on the benefits of multi-sensor approaches with the practical challenges observed in Chapter II, where optical data alone showed limitations in detecting subtle structural changes. The integration of LiDAR provides a complementary perspective, enabling a more detailed assessment of forest canopy disturbances and validating optical data, ultimately enhancing the monitoring accuracy and reliability.

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CHAPTER II – Assessing Forest Degradation Through Remote Sensing In The Brazilian Amazon: Implications And Perspectives For Sustainable Forest Management¹

Abstract: Forest degradation and forest disturbance are distinct yet often conflated concepts, complicating their definition and monitoring. Forest degradation involves interrupted succession and a severe reduction in forest services over time, caused by factors like fires, illegal selective logging, and edge effects. Forest disturbance, on the other hand, refers to abrupt, localized events, natural or anthropogenic, such as legal selective logging, tropical blowdowns, storms, or fires, without necessarily leading to long-term degradation. Despite the varying intensity and scale of forest degradation and disturbance, systematic studies distinguishing its types and classes are limited. This study reviews anthropogenic impacts on forests in the Brazilian Amazon, analyzing 80 scientific articles using remote sensing techniques and data. Most research focuses on the “arc of deforestation,” characterized by intense human activity, showcasing methodological advancements but also revealing gaps in monitoring less-studied regions like the central and western Amazon. The findings emphasize the need for advanced remote sensing tools to differentiate degradation types, particularly in sustainable forest management (SFM) contexts. Expanding research to underrepresented regions and refining methodologies are crucial for better understanding forest dynamics and improving conservation strategies. These efforts are essential to support effective forest management and informed policy development across the Amazon.

Keywords: *forest disturbance; selective logging; anthropogenic impacts; conservation strategies*

Resumo: A degradação florestal e o distúrbio florestal são conceitos distintos, mas muitas vezes confundidos, comprometendo sua definição e monitoramento. A degradação florestal envolve intervenções sucessivas e uma redução severa nos serviços florestais ao longo do tempo, causada por fatores como incêndios, extração seletiva ilegal de madeira e efeitos de borda. O distúrbio florestal, por outro lado, refere-se a eventos abruptos e localizados, naturais ou antropogênicos, como extração seletiva legal, quedas de árvores pelo vento, tempestades ou incêndios, sem necessariamente levar à degradação a longo prazo. Apesar da intensidade e escala variáveis da degradação e distúrbio florestal, estudos sistemáticos que distinguem seus tipos e classes são limitados. Este estudo analisou os impactos antrópicos sobre as florestas na Amazônia brasileira, analisando 80 artigos científicos utilizando técnicas e dados de sensoriamento remoto. A maioria das pesquisas se concentra no "arco do desmatamento", caracterizado por intensa atividade humana, apresentando avanços metodológicos, mas também revelando lacunas no monitoramento de regiões menos estudadas, como a Amazônia central e ocidental. Os resultados enfatizam a necessidade de ferramentas avançadas de sensoriamento remoto para diferenciar os tipos de degradação, particularmente em contextos de manejo florestal sustentável (SFM). Expandir a pesquisa para regiões subrepresentadas e refinar metodologias são cruciais para entender melhor a dinâmica florestal e melhorar as

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estratégias de conservação. Esses esforços são essenciais para apoiar o manejo florestal eficaz e o desenvolvimento de políticas informadas em toda a Amazônia.

Palavras-chave: *perturbação florestal; exploração seletiva; impactos antrópicos; estratégias de conservação.*

1. Introduction

1.1. Sustainable Forest Management in the Amazon: Importance and Challenges

Tropical forests are one of the world's largest and most productive ecosystems. They also play an essential role in the global carbon cycle, containing 44% of the world's above-ground biomass (LIU *et al.*, 2019; XU *et al.*, 2021). The Brazilian Amazon contains one-third of the world's tropical forests. Its commercial roundwood stocks are estimated to be around 60 billion m³ (2118 trillion ft³), making it the world's largest tropical timber reserve (WWF, 2012; FAO, 2020; IBGE, 2024; BRASIL, 2012).

Sustainable forest management (SFM) is an approach to managing forests that balances environmental, social, and economic objectives to meet the needs of present and future generations (BRASIL, 2012). SFM encompasses practices that maintain and enhance forest health, productivity, biodiversity, and ecological functions (BRASIL, 2012). Reduced impact logging (RIL) is a forest management practice designed to minimize the ecological damage that typically accompanies selective logging and is widely applied in SFM in the Amazon (BRASIL, 2012; PEREIRA-JUNIOR *et al.*, 2022). RIL involves practices that significantly reduce impacts compared to conventional logging; some of these practices include pre-harvest planning, targeted felling techniques, log drag control, and continuous monitoring (PEREIRA-JUNIOR *et al.*, 2002). Selective logging is a stage of management that aims to harvest specific trees while preserving the structure of the forest, contributing to sustainability when rigorously planned and monitored (PEREIRA-JUNIOR *et al.*, 2022; LAMB *et al.*, 2005). These practices minimize unnecessary canopy openings, protect surrounding vegetation, and maintain the overall forest structure, thereby mitigating the ecological impacts typically associated with logging activities (PEREIRA-JUNIOR *et al.*, 2022).

In contrast, conventional logging often results in significant forest degradation due to uncontrolled felling, poorly planned roads, and extensive canopy gaps (PEREIRA-JUNIOR *et al.*, 2022). This unregulated approach compromises forest health and

biodiversity, leading to a decline in ecosystem services, prolonged carbon emissions, and challenges in forest regeneration (LAMB *et al.*, 2005; OLIVEIRA *et al.*, 2024; PUTZ *et al.*, 2012; CHAZDON, 2008). By comparison, RIL reduces these impacts, promoting sustainability and aligning with the principles of SFM.

Pereira-Jr *et al.* (2002) highlights the differences in canopy gap fractions caused by conventional logging (CL) and RIL in 1996 and 1998. CL consistently resulted in higher canopy gaps, with total gap percentages of 16.5% and 21.6% in 1996 and 1998, respectively, primarily driven by tree felling and skidding activities. In contrast, RIL demonstrated significantly lower impacts, with total gap percentages of 4.9% and 10.9%, emphasizing its effectiveness in minimizing forest canopy disruption. The data reinforce the value of RIL as a sustainable logging practice that reduces environmental impacts while maintaining forest structure.

Nevertheless, under Brazilian standards, specific values are established for harvesting intensity per hectare (BRASIL, 2012). The authorized harvesting intensity of Brazilian forests is not associated with data on the heterogeneity of the original forest structure, i.e., the volumes determined for extraction are fixed and standardized (OLIVEIRA *et al.*, 2024). In the SFM for the Saracá-Taquera National Forest in the Brazilian Amazon, logging intensity surpassed 100 m³ ha⁻¹, with more than 20 trees harvested per hectare in certain areas (OLIVEIRA *et al.*, 2024). Putz *et al.* (2012) they mentioned that the challenge in managing tropical forests arises from their complex and diverse ecosystems. Chazdon *et al.* (2008), mentioned that the challenge in managing tropical forests stems from their complex and diverse ecosystems. According to Chazdon *et al.* (2008), improper use of natural forests can disrupt logging cycles and harm ecosystems.

SFM is recognized as a forest conservation strategy, but gaps remain in evaluating indicators that point to more appropriate ways of exploiting forest resources (PEREIRA-JUNIOR *et al.*, 2002; MACDICKEN *et al.*, 2015).

These challenges related to conducting SFM raise the following guiding questions: (i) What is the temporal trend in publications on remote sensing techniques and sustainable forest management? (ii) Which institutions and countries are leading this research? (iii) Which approaches are most commonly used? (iv) What are the main techniques and sensors used? (v) What is the spatial distribution and territorial scope of the studies throughout the Amazon biome?

1.2. Remote Sensing in Tropical Forest Monitoring

Remote sensing (RS) plays an important role in monitoring and quantifying canopy disturbance caused by selective logging (NEPSTAD *et al.*, 1999; ASNER *et al.*, 2005; SAATCHI *et al.*, 2011). Studies have shown that high spatial and temporal resolution images are necessary to monitor selective logging in the Amazon (ASNER *et al.*, 2005; MATRICARDI *et al.*, 2013). In addition, the remote sensing techniques and products used for mapping and monitoring studies of selective logging have been insufficient for large-scale assessments (ARAGÃO *et al.*, 2014; ABDLLAHNEJAD *et al.*, 2019; MATRICARDI *et al.*, 2020).

Abdollahnejad *et al.* (2019) have proposed an advanced approach integrating geographic information systems (GISs) and remote sensing using high-resolution images to monitor logging areas. Their research suggests that high spectral and spatial resolution images are necessary to increase the accuracy of volume estimates. Petri *et al.* (2022) also tested using images from the *PlanetScope* nanosatellite constellation for vegetation studies in the Amazon. They concluded that high spatial and temporal resolution images are essential for understanding forest dynamics in the Amazon. Yet, for extensive areas like the Amazon, these costs can quickly escalate, posing a challenge for continuous and largescale monitoring efforts (ABDLLAHNEJAD *et al.*, 2019).

Advances in RS technologies, such as high-resolution satellites, drones, and LiDAR (*Light Detection and Ranging*) sensors, combined with machine learning techniques, have provided new possibilities for effectively and sustainably monitoring and managing forests (ABDLLAHNEJAD *et al.*, 2019; WINSTANLEY *et al.*, 2024). These technologies enable precise detection and monitoring of changes in forest cover, making it easier to identify illegal activities and assess the impacts of logging (WINSTALEY *et al.*, 2024; DALAGNOL *et al.*, 2023). However, the application of high spatial resolution sensors to the analysis of forest degradation in SFM is still limited to smaller areas, as evidenced by the scope of the studies conducted.

1.3 Defining Forest Degradation and Forest Disturbance

The literature is rife with dozens of definitions of forest degradation regarding partial changes to the forest canopy. Categorizing forest degradation is challenging due to its dependence on the study's objective, biophysical conditions, causes, and

spatiotemporal scales (SASAKI & PUTZ, 2009; THOMPSON *et al.*, 2013). Simula (2009) e Thompson *et al.* (2013) argue that the lack of scientific consensus on forest degradation has led to many definitions and multiple ways of measuring it, particularly by RS. More recently, the term forest disturbance has been increasingly used to describe more subtle changes in forest structure and function (PEREIRA-JUNIOR *et al.*, 2002; ASNER *et al.*, 2005; MATRICARDI *et al.*, 2013; OLIVEIRA *et al.*, 2024). These disturbances often include events that do not result in outright deforestation but still alter the forest's composition, canopy cover, or ecosystem services, such as selective logging, fires, and small-scale natural events. This shift in terminology reflects an effort to capture a broader spectrum of forest dynamics and to better align with advances in RS technologies that can detect such nuanced changes (ASNER *et al.*, 2005; MATRICARDI *et al.*, 2013; OLIVEIRA *et al.*, 2024; ABDLLAHNEJAD *et al.*, 2019).

In this analysis, forest degradation can be defined as a condition of interrupted succession due to human actions, leading to a severe reduction in the forest's services over a certain period. It is a temporal process in which forest services decline and can be caused by forest fires, illegal selective logging, and edge effects, among others (THOMPSON *et al.*, 2013; SIMULA, 2009; GHAZOUL *et al.*, 2015; VÁSQUEZ-GRADÓN *et al.*, 2018). In contrast, forest disturbance refers to any abrupt and localized event, natural or anthropogenic, that disrupts forest structure or function, such as legal selective logging, tropical blowdowns, storms or even forest fires, without necessarily causing long-term degradation (ASNER *et al.*, 2005; MATRICARDI *et al.*, 2013; OLIVEIRA *et al.*, 2024; ABDLLAHNEJAD *et al.*, 2019). Thus, while forest degradation implies a sustained loss of ecosystem services, forest disturbance can be temporary and sometimes even a part of natural forest dynamics (PEREIRA-JUNIOR *et al.*, 2002; ASNER *et al.*, 2005; MATRICARDI *et al.*, 2013).

In this context, the Reducing Emissions from Deforestation and Forest Degradation (REDD+) program is an international initiative aimed at combating climate change by addressing forest loss and degradation. Figure 1 illustrates the relationship between degradation, deforestation, and sustainable practices such as SFM in the context of REDD +. Each component of the acronym REDD+ represents a key focus area. The first D (deforestation) focuses on preventing the permanent removal of forests (clear-cut), which releases significant amounts of stored carbon into the atmosphere (line C, Figure 1). The second D (degradation) addresses the decrease in forest quality and carbon storage capacity caused by activities such as illegal selective logging, fires, edge effects, or other

human-induced action. At this stage, the services provided by the forest are significantly reduced and CO₂ emissions are prolonged over time, but the vegetation is not completely removed (line B, Figure 1). The plus sign (+) extends the scope of the program to include some sustainable practices like the conservation of forest carbon stocks and the sustainable management of forests (line A, Figure 1) (UNFCCC, 2012). Here, forest disturbances resulting from legal selective logging are represented as critical factors, emphasizing the need to mitigate their impact to ensure the effectiveness of these sustainable practices. This expanded framework aims to address a broader set of activities to promote sustainable development while mitigating climate change impacts (NASI *et al.*, 2011; MORALES-BARQUERO *et al.*, 2014).

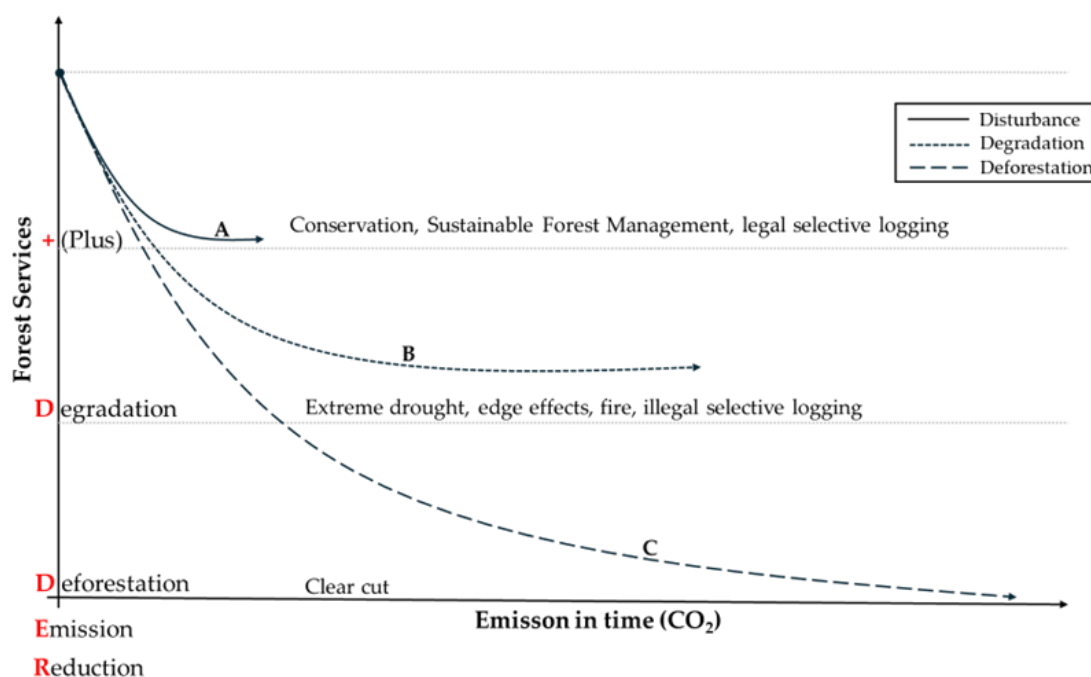


Figure 1. The graph illustrates the impact of human activities on forest ecosystem services in the context of REDD+ (red letters on the Y axis). Curve A (disturbance) represents forest carbon stock conservation practices and sustainable forest management, where forest interventions cause low CO₂ emissions and favorable variations in forest services, represented by the REDD+ “plus” (+) symbol. Curve B (degradation) represents a forest degraded by anthropogenic events such as extreme droughts, edge effects, fire, and illegal logging that persist over time. Curve C (deforestation) represents the maximum stage of anthropogenic intervention and the complete absence of forest services, since at this stage the vegetation has been completely removed (clear-cutting), represented by the first D in the REDD+ acronym. Source: adapted from (THOMPSON *et al.*, 2013; GHAZOUL *et al.*, 2015; VÁSQUEZ-GRANDÓN *et al.*, 2018; DUPUIS *et al.*, 2020).

Source: OLIVEIRA, 2024.

However, the term “forest degradation” is often used to describe legal selective logging activities (DALAGNOL *et al.*, 2023; MATRICARDI *et al.*, 2010; KUCK *et al.*, 2021; LAPOLA *et al.*, 2023; MORENO *et al.*, 2023). It is essential to point out that

although legal selective logging can be considered forest degradation from an anthropological perspective or by generic definitions, this classification is inadequate (FERREIRA *et al.*, 2015). The selective extraction of legal timber is an activity integrated into SFM and is considered a mechanism of REDD+ policies and, therefore, in first approximation, should not be categorized as forest degradation (FERREIRA *et al.*, 2015), but rather as forest disturbance, as it should not cause de-characterization or damage to the environmental function of the managed forest ecosystem (MATRICARDI *et al.*, 2013; FERREIRA *et al.*, 2015).

It is essential to consider a more comprehensive approach that considers broader ecological processes, regardless of their impact on human society, such as forest dynamics and resilience (MORALES-BARQUERO *et al.*, 2014; GHAZOUL *et al.*, 2015; VÁSQUES-GRANDÓN *et al.*, 2018). Ecosystem resilience is the capacity to return to its original state in terms of structure and function after a disturbance without requiring external intervention (VÁSQUES-GRANDÓN *et al.*, 2018).

1.4 Mapping Forest Degradation and Legal Selective Logging

The techniques, methods, and data sources used for mapping and monitoring forest degradation and selective logging in the Amazon are essentially the same, as both detect and analyze changes in forest cover when the forest is not entirely removed (MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020; KUCK *et al.*, 2021). Although, from the point of view of remote sensing, the equivalence in detection between these two actions is to be expected, and several studies treat both in a similar way (MATRICARDI *et al.*, 2013; KUCK *et al.*, 2021; DALAGNOL *et al.*, 2023; LAPOLA *et al.*, 2023; MORENO *et al.*, 2023), some important points need to be kept in mind.

The intensity and types of disturbance are different in the various types of degradation, including the partial loss of living biomass and forest quality, without the complete removal of vegetation cover. This can include the death of trees, damage to soil and under-story vegetation, and a reduction in biodiversity (MATRICARDI *et al.*, 2013). However, in legal selective logging with reduced impact, the disturbances are smaller and relate to the specific removal of trees of high commercial value, usually with openings in the forest, logging trails, and collateral damage to other trees and understored vegetation (PEREIRA-JUNIOR *et al.*, 2002; BROADBENT *et al.*, 2008; SEBBENN *et al.*, 2008). Therefore, disturbances caused to forests by selective logging are of lesser intensity in

cases of forest management implementation and, for this reason, should be distinctly mapped and considered (PEREIRA-JUNIOR et al., 2022; MATRICARDI et al., 2013; SEBBENN et al., 2008). Although using RIL reduces disturbance, these disturbances can still be classified as low intensity, since they cause changes to the forest's structure and the ecosystem's dynamics (MATRICARDI et al., 2013; BROADBENT *et al.*, 2008).

Taking the above points into account, it should be noted that the simplest and most effective way of differentiating the intensities of forest degradation processes is by observing selectively logged areas in sustainable management plans, where there are Forest Management Unit (FMU) boundaries, as well as timber unit (TU) boundaries, allowing for auxiliary information in classifying the changes detected. In SFM, the FMU represents the designated portion of the property allocated for forest management. The specific area designated for logging activities is referred to as a timber unit (TU) (BRASIL, 2012; Oliveira et al., 2004).

In contrast, in areas affected by fire or high-intensity or illegal selective logging, the intensities of forest degradation are much higher, indicating that monitoring systems must be more specific in order to discriminate between the different types of forest disturbance, which result in very different impacts and levels of degradation (MATRICARDI *et al.*, 2013). Figure 2 shows a cross-section of forest change detection alerts from the systems (A) DE-TER/INPE, (B) SAD/IMAZON, and (C) Brazilian Forestry Service (BFS)/SCCON, respectively, which intersect the TU in the FMU inside the Saracá-Taquera National Forest. Systems A and B are used in command-and-control policies and operate throughout the Amazon using low and medium spatial resolution images. System C monitors and maps forest disturbances in specific areas within the limits of the SFM boundaries using *PlanetScope* high spatial and temporal resolution images carried out by the Brazilian Forestry Service (BFS). System C shows greater consistency and precision in relation to the extracted areas of vegetation, using selective logging practices, and consequently with more coherent classification related to the phenomenon (SOUZA-JUNIOR *et al.*, 2005; DINIZ *et al.*, 2015; SFB, 2024).

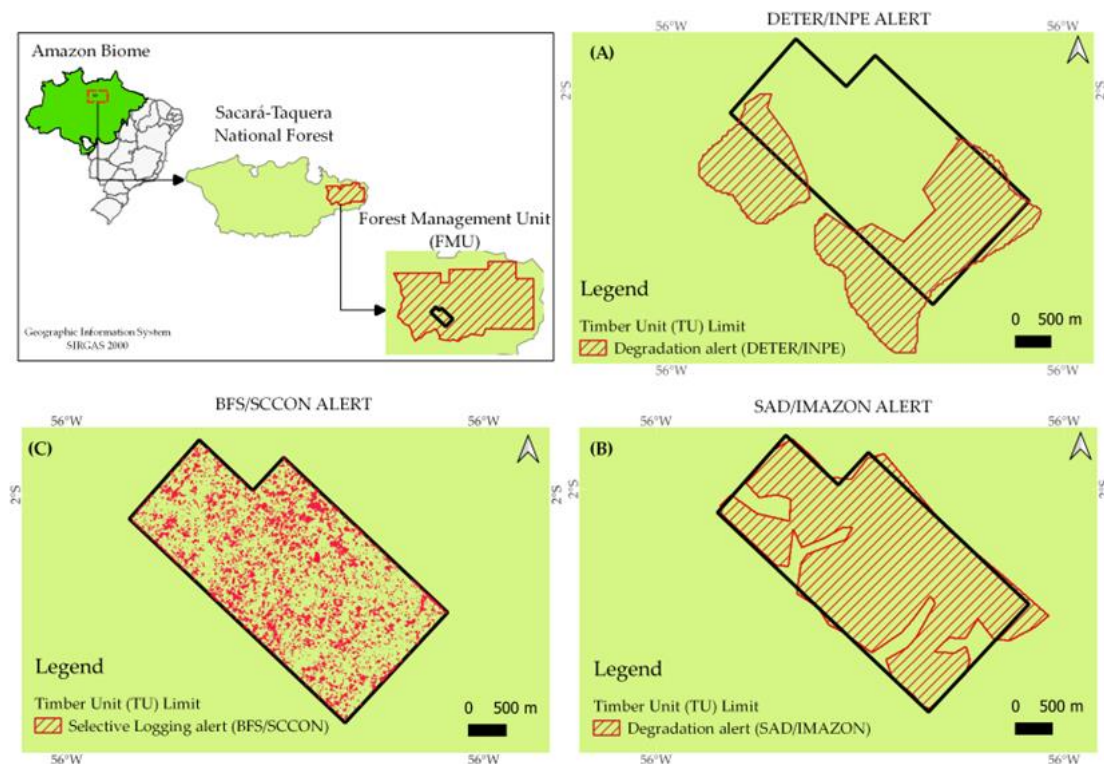


Figure 2. Forest degradation alerts from the systems (A) DETER/INPE (Real-Time Deforestation Detection System, developed by the National Institute for Space Research—INPE); (B) SAD/IMAZON (De-forestation Alert System, developed by the Amazon Institute for Man and the Environment—IMAZON); and Selective Logging alert (disturbance) (C) Brazilian Forestry Service (BFS)/SCCON (Brazilian Forestry Service system, developed by SCCON Geospatial). These systems intersect the timber unit in the Forest Management Unit inside the Saracá-Taquera National Forest, Brazilian Amazon.

Source: OLIVEIRA, 2024.

Misclassifications of different levels of forest disturbance can underestimate or over-estimate the extent of the impacts caused on forests, particularly in the case of selective logging in the Amazon. When conducted legally and under sustained management, selective logging is thought to have a low intensity of disturbance and minimal effects on the forest ecosystem (PEREIRA-JUNIOR *et al.*, 2002). However, generalized classifications of forest degradation areas without distinguishing between different types of disturbance can compromise the credibility of regulated forest conservation and management initiatives in the Amazon (VELASCO *et al.*, 2022; PINAGÉ *et al.*, 2023).

The lack of differentiation between forest extraction practices associated with SFM and other degradation processes with different impacts can lead to difficulties raising funds for conservation projects and discourage investment in sustainable management practices in the Amazon. Public policies and regulations based on incorrect data can be ineffective or harmful (KREMEM *et al.*, 2000; SAGOBAL *et al.*, 2013). This

can result in an inadequate allocation of resources for forest conservation and management, as well as hindering the implementation of effective strategies for forest protection (NASI *et al.*, 2011). Accuracy in classifying the different intensities of forest disturbances or degradation is crucial for environmental, economic, and social sustainability in forest management in the Amazon (SASAKI & PUTZ, 2009; MORALES-BARQUERO *et al.*, 2014).

1.5. Objective

In order to better distinguish anthropogenic forest disturbances and degradation in different intensities, spatial dimensions, and temporality, detected by remote sensing in the Amazon forest, we aim to map the spatial distribution and temporal evolution of studies in the Amazon biome by means of remote sensing and identifying the main techniques and sensors used to better understand the patterns, trends, and gaps associated with monitoring anthropogenic forest disturbances, generically referred to as forest degradation.

2. Materials and Methods

2.1. Search Process and Article Selection

We conducted a systematic literature review on the remote monitoring of anthropo-genic forest disturbances and their impact on sustainable forest management. The review was based on a spatiotemporal evaluation of the main techniques and sensors used to monitor and map forest degradation and legal selective logging in the Amazon. As they have a specific focus on conservation and environmental management, the systematic re-view guidelines proposed by Pullin and Sterward (2006) were followed.

This study used only articles that explicitly applied RS techniques and images aimed at detecting anthropogenic forest disturbances, in order to contribute to advancing the discussion on distinguishing forest degradation from legal selective logging in the Amazon. In this way, the main approaches, trends, and gaps in research on anthropogenic forest disturbances, notably, forest degradation and legal selective logging in the Amazon, were analyzed.

Only peer-reviewed articles published between January 2003 (the year the first article appeared) and July 2024 were selected from the *Scopus* and *Web of Science* databases (ZHU *et al.*, 2020; HERNÁNDEZ-GONZÁLEZ *et al.*, 2016). The search considered synonyms found in the literature based on the keywords in the title, abstract, and keywords, and the ALL option was chosen in the search (Table 1). These terminologies are widely used in literature for remote monitoring studies of forest disturbances and degradation in the Amazon. Reviews, conferences, and book chapters were excluded, as peer-reviewed articles are considered the most reliable source for reviewing the literature among the documents available (DE OLIVEIRA *et al.*, 2019; GARZA-REYES, 2015).

Table 1. Search expression encoded in Web of Science and Scopus and applied to titles, abstracts, and keywords.

Criteria	Search Expression	
What?	"Selective Logging" OR "Selective Harvesting" OR "Selective Cutting" OR "Disturbance" OR "Forest Disturbance" OR "Illegal Logging" OR "Degradation" OR "Forest Degradation"	
How?	AND	"Monitoring" OR "Remote Sensing" OR "Satellite"
Where?	AND	"Amazon"
Limited to?	Articles	
Data range	2003/January to 2024/July	

Source: OLIVEIRA, 2024, adapted from DUPUIS *et al.*, 2020.

In addition to articles written in English, papers written in Portuguese were also analyzed, as the subject is geographically related to Brazil, and some references are in Portuguese. We expanded the language filter to ensure that a thorough analysis of the scientific literature identifies and synthesizes relevant evidence, regardless of geographical origin or language of publication. Non-English publications may contain ideas or provide context not available in English articles (WALPOLE, 2019).

2.2. Data Selection and Integration

With the keywords mentioned, 136 articles were identified in Web of Science and 81 articles were identified in Scopus (as of 1 July 2024), which were compiled into CSV (comma-separated values) and TXT (text format) files from the respective databases. After debugging duplicate articles in different databases with the help of RStudio software (Version 4.3.1) using the `mergeDbSource` and `remove.duplicated` functions of the Bibliometrix package (ARIA, 2017), 158 articles remained.

After carefully selecting articles, we reviewed each paper to remove duplicates from the database. We specifically checked each article to ensure it focused on the Amazon biome and used remote sensing products, techniques, and images to map and monitor forest degradation and forest disturbances. After this thorough process, we selected 80 articles for analysis (Figure 3).

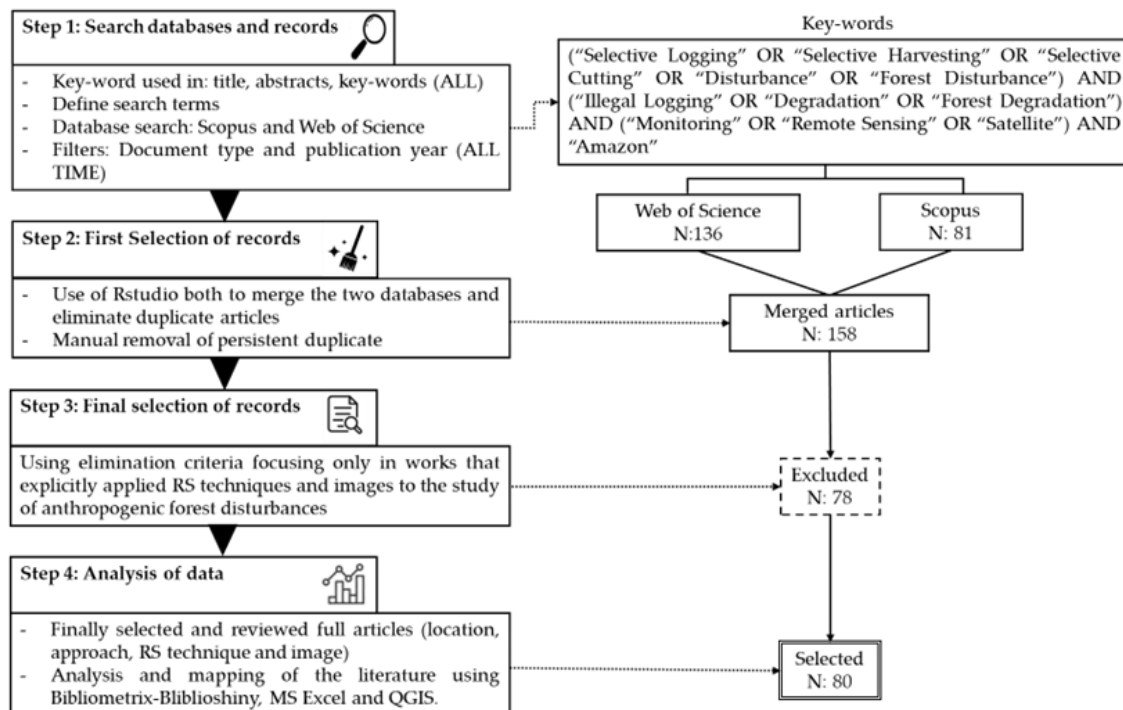


Figure 3. An overview of the criteria and procedure for the bibliographic search for a systematic review of the literature on works that explicitly apply RS techniques and images to the study of anthropogenic forest disturbances. N = Number of articles.

Source: OLIVEIRA, 2024.

2.3 Classification, Organization of Information, and Data Analysis

Based on this number, we proceeded to organize and classify the information contained in the articles. To systematize the evaluation of the approaches used, trends, and gaps in research, the information was listed in chronological order, starting with the most recent year. The information gleaned from the articles was categorized in terms of the exact location of the study area (geographical coordinates), the digital processing techniques used in the satellite images, and the sensors used.

Additionally, the articles were categorized based on the type of anthropogenic forest disturbance presented and classified accordingly:

- (a) Legal selective logging: for works that applied RS techniques to map or monitor anthropogenic forest disturbances arising exclusively from logging activities in authorized sustainable forest management areas.
- (b) Forest degradation: for works that applied RS techniques to map or monitor anthropogenic forest degradation of any nature other than legal selective logging.
- (c) Legal selective logging + forest degradation: for works that applied RS techniques to map or monitor both anthropogenic actions simultaneously.

Based on the criteria provided, we have established the following analysis parameters: (a) annual global publication trend; (b) analysis of emerging patterns and trends; (c) spatial distribution and approach of the work; (d) the main techniques used for mapping or monitoring; (e) the main RS images used for monitoring or mapping; and (f) teaching and research institutions that have published the most on the subject.

3. Results

3.1. Global Publication Trends

The red dotted regression line shows a positive slope, indicating a general increase in the number of scientific publications over time. This reflects the growing attention to monitoring degradation and anthropogenic forest disturbances in the Amazon biome. This upward trend suggests growing interest and research activity in this topic area over the years. Although there is an overall upward trend, individual years show considerable variation in production. For example, the years that showed the highest scientific productivity were 2019, 2020, and 2023, accounting for 26 articles, approximately one-third of all publications (32.5%). Among these, 2019 and 2023 have stood out with nine publications each. Conversely, 2003, 2004, 2011, and 2015 had the lowest number of publications, with only one article each year (5%) (See Figure 4).

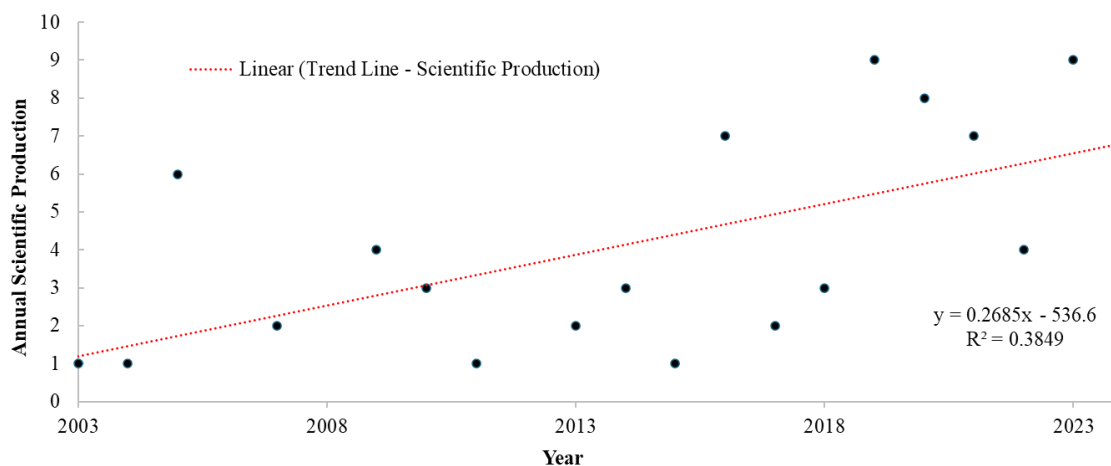


Figure 4. Evolution of annual scientific production per year for monitoring and mapping anthropogenic forest disturbances and forest degradation in the Amazon biome (2003-July/2024).

Source: OLIVEIRA, 2024.

3.2. Keyword Analyses of Emerging Patterns and Trends

Review articles often use keyword analyses to identify central themes, patterns, and trends in different research fields (GAO *et al.*, 2019; CASTAGNA *et al.*, 2024; GUERRERO-MORENO & OLIVEIRA-JUNIOR, 2024). Figure 5 illustrates the relative occurrence of key terms - biomass, carbon, degradation, disturbance, logging, and selective - in texts from 2003 to 2024. Each color in the stacked bars represents one of the selected words, with the height of each color segment within a given year indicating the proportional frequency of that word. These words were selected for their relevance to the discussion of forest management topics, highlighting trends and shifts in focus over time. The graph enables a visual assessment of the prominence of each word across different years, reflecting evolving research or policy interests in these areas.

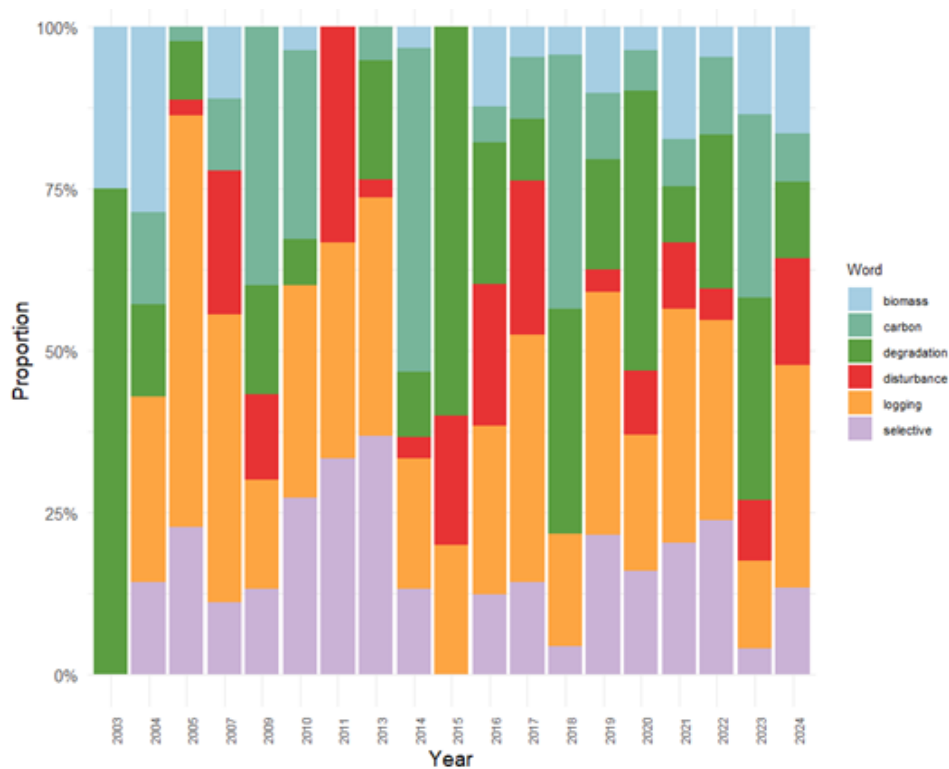


Figure 5. relative occurrence of key terms - biomass, carbon, degradation, disturbance, logging, and selective - in texts from 2003 to 2024.

Source: OLIVEIRA, 2024.

The results show that each year presents a different distribution of proportions among the words, suggesting a shift in focus over time. Carbon and degradation maintain a consistent presence throughout the years, indicating a continuous interest during the entire period analyzed. The term biomass gains prominence, starting in 2016, possibly reflecting a growing interest in its role in carbon sequestration. Although disturbance, selective, and logging are consistently present over time, these terms show a marked increase from 2020 to 2024, indicating a rise in discussions about logging and the impacts of forest disturbances. Carbon and biomass have gained relevance in recent years, especially between 2016 and 2024. This increase may be related to the role of biomass and carbon in climate change mitigation policies, with biomass increasingly being considered a renewable energy alternative.

3.3. Spatial Distribution of Studies and Approaches

A total of 25 studies were applied to the entire Amazon biome. Of these, we found that 72% (18 articles) used forest degradation exclusively (even though they may have

included SFM areas) to map anthropogenic forest disturbances. Five articles studied forest degradation and selective logging together. Only two articles discussed the region's selective ex-traction of legal timber and its impacts. Figure 6 presents the spatial distribution of studies on mapping forest degradation and forest disturbance in the Amazon biome by type of detection.

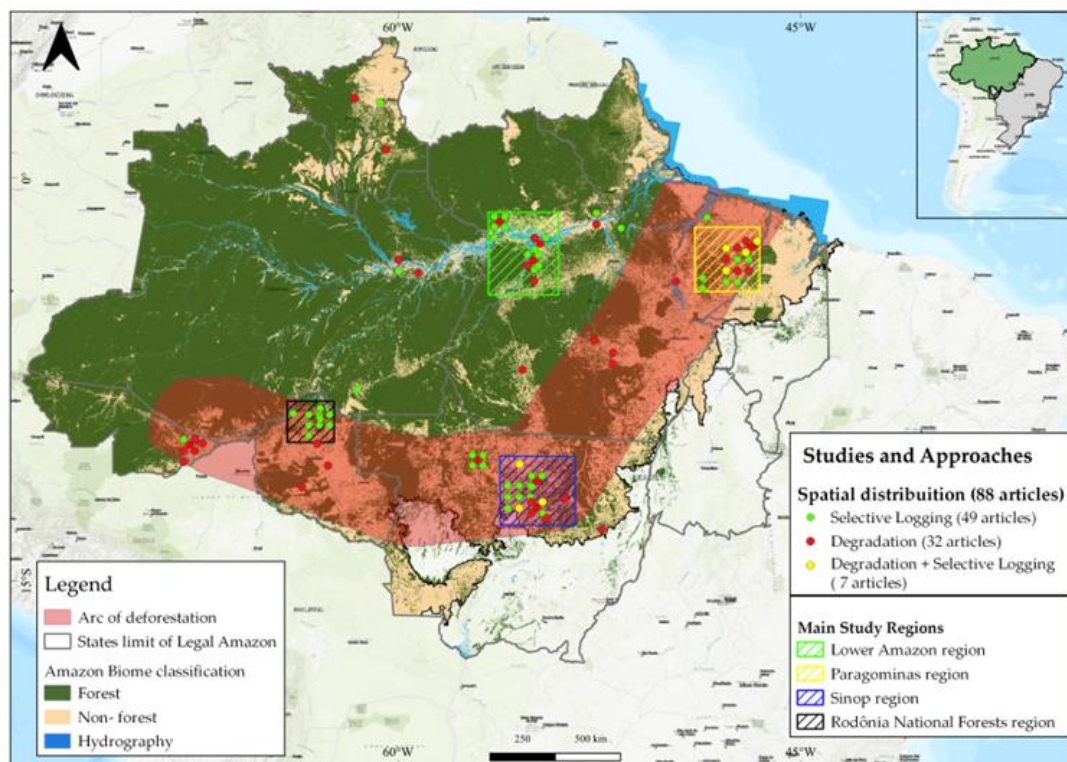


Figure 6. Categorization of the spatial distribution of studies on mapping degradation forest and selective logging in the Amazon biome by type of disturbance.

Source: OLIVEIRA, 2024.

For regional studies (55 articles), the assessment of the categorization and spatial distribution in the Amazon biome revealed that out of the 88 study areas sampled (where co-ordinates were available), 75 were concentrated in just three states (85.2%): Pará (44.3%); Mato Grosso (26.1%); and Rondônia (14.7%). In Pará, there were two notable regions. The Paragominas region in the northeast of the state had 14 articles, including studies on the former selective exploitation of legal timber (4), forest degradation (6), and articles dealing with both selective exploitation and forest degradation (4). Additionally, in the far west of Pará, the Lower Amazon region also featured 14 articles, with the focus being on legal selective logging (11) and some studies on forest degradation (3).

The state of Mato Grosso, particularly the region around the municipality of Sinop, had the second-highest number of research papers, totaling 23 articles. Most of

these articles focused on studies related to legal selective logging (11), followed by forest degradation (4). The region of the National Forests (Flona) located in the state of Rondônia had 13 articles, all of which dealt with the monitoring and mapping of legal selective logging within the Jamari and Jacundá National Forests (Figure 6).

3.4. Main Techniques Used

The results show the main approaches used in the studies evaluated and demonstrate the frequency of various techniques employed in scientific articles focused on monitoring anthropogenic forest disturbances and forest degradation. Each technique plays a specific role in monitoring and mapping (Figure 7).

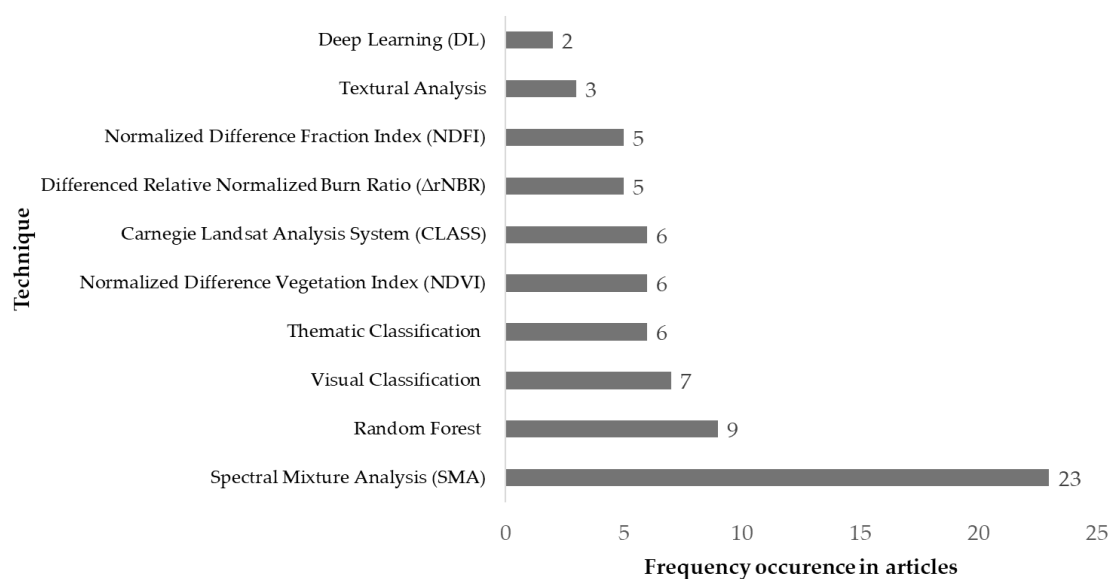


Figure 7. Frequency of occurrence of the ten main techniques used in the 80 articles evaluated.

Source: OLIVEIRA, 2024.

The Linear Spectral Mixture Model (LSMM) is the most used technique, with 23 occurrences, highlighting its importance in decomposing spectral signals into individual components (fraction images). Random Forest appears with nine occurrences, which shows that it is a frequently used technique for classifying vegetation and monitoring changes in forest cover. Visual classification, although a more traditional technique and a pioneer in this type of study (SOUZA JR *et al.*, 2003), is still relevant (seven occurrences), especially in areas where human interpretation is required to identify specific vegetation characteristics. The Carnegie Landsat Analysis System (CLASS), with six occurrences, is highly frequent in the studies evaluated.

The Normalized Difference Vegetation Index (NDVI) is widely used to monitor vegetation vigor, which is essential for identifying areas of degradation and helping to implement practices that promote forest recovery (six occurrences) (GAO *et al.*, 2020; YENGOH *et al.*, 2016). The Normalized Difference Fraction Index (NDFI) (five occurrences) helps to detect and monitor forest degradation in areas subject to sustainable forest management, allowing targeted interventions to recover intensely degraded areas. This is an essential component of sustainable management (SOUZA JR *et al.*, 2005). The Difference Relative Normalized Burn Ratio ($\Delta rNBR$) (five occurrences) is essential for assessing the severity of forest fires and their impacts, providing important data for post-fire recovery and the prevention of future fires (SOFAN *et al.*, 2016; JI *et al.*, 2011). Texture analysis (three occurrences) allows for a detailed assessment of the structural complexity of vegetation, helping to distinguish between different types of vegetation and levels of degradation (MATRICARDI *et al.*, 2005; MATRICARDI *et al.*, 2010; MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020). Deep Learning—DL (two occurrences) is a set of machine learning techniques that uses deep neural networks to recognize complex patterns in large datasets.

3.5. Main Satellites Used

For SFM, it is essential to use RS products to monitor and manage forests. An analysis of the frequency of occurrence in articles reveals the importance of different satellites and technologies in forest management research and practice (Figure 8).

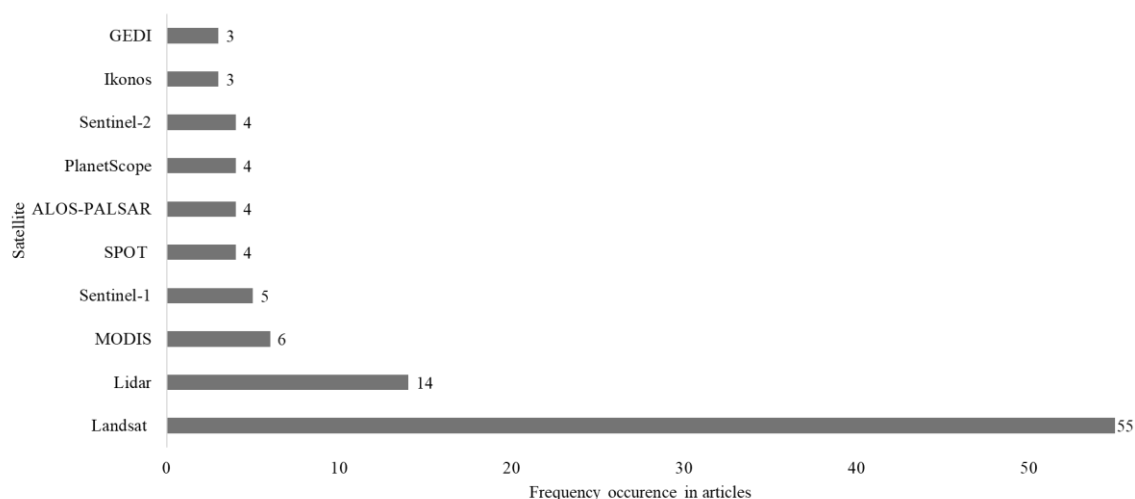


Figure 8. The frequency of occurrence of the ten main satellites used in 80 articles was evaluated.

Source: OLIVEIRA, 2024.

The main satellites' classification results to monitor anthropogenic forest disturbance and degradation indicate that the Landsat series is the most used (55 occurrences). This is mainly because of its extensive historical data and its capability to offer detailed multi-spectral data over several decades (BARROS FERRAZ *et al.*, 2002; SOUZA *et al.*, 2005; SHIMABUKURO *et al.*, 2014; SOUZA *et al.*, 2024).

LiDAR technology, with 14 occurrences, recently incorporated into forest cover monitoring studies, is highly valued for its ability to accurately measure the three-dimensional structure of forests (WINSTANLEY *et al.*, 2024).

The MODIS (Moderate Resolution Imaging Spectroradiometer), with six hits, despite its low spatial resolution, is widely used to monitor large areas of forest cover due to its high temporal frequency, which enables rapid detection of changes such as forest fires and large-scale forest degradation (PINAGÉ *et al.*, 2023; LIZUNDIA-LOIOLA *et al.*, 2020).

The Sentinel-1 and Sentinel-2 satellites mentioned nine occurrences when combined, providing optical (Sentinel-2) and radar (Sentinel-1) data. This combination is crucial for monitoring forests in adverse weather conditions and detecting subtle changes in forest cover (HETHCOAT *et al.*, 2022; LIMA *et al.*, 2019).

ALOS-PALSAR, SPOT, GEDI, and IKONOS had a combined 14 occurrences. These satellites and sensors provide valuable additional data, complementing the information obtained by the main satellites mentioned. They are used for specific applications, such as detecting small changes in forest cover, assessing biomass, and monitoring small area changes. ALOS-PALSAR helps with monitoring in tropical regions using synthetic aperture radar (SAR). SPOT is mainly used for monitoring land use, land cover, and vegetation changes. GEDI (Global Ecosystem Dynamics Investigation), which is NASA's tool to measure how deforestation has contributed to atmospheric CO₂ concentrations, is an innovative orbital LiDAR technology that helps assess the vertical structure of forests, including tree height and biomass. Ikonos, with its high spatial resolution, is used for detecting small changes in forest cover, detailed mapping, and monitoring specific areas of interest (WANG *et al.*, 2005 ASNER *et al.*, 2009; WIEDERKEHR *et al.*, 2020 HOLCOMB *et al.*, 2024).

PlanetScope is the only satellite mentioned comprising a constellation of imaging nanosatellites. It provides daily high spatial resolution images of the Earth's entire land cover. Its capability to capture detailed daily data makes it a powerful tool for monitoring

forest disturbances and sustainable forest management (OLIVEIRA *et al.*, 2024; DALAGNOL *et al.*, 2023; BRASILMAIS, 2024).

3.6. Main Research Institutions

Based on our dataset, Figure 9 shows the affiliations of the top 10 institutions worldwide that have published the most on this subject. These institutions significantly generate knowledge and advance technology for implementing and monitoring tropical forests and sustainable forest management practices.

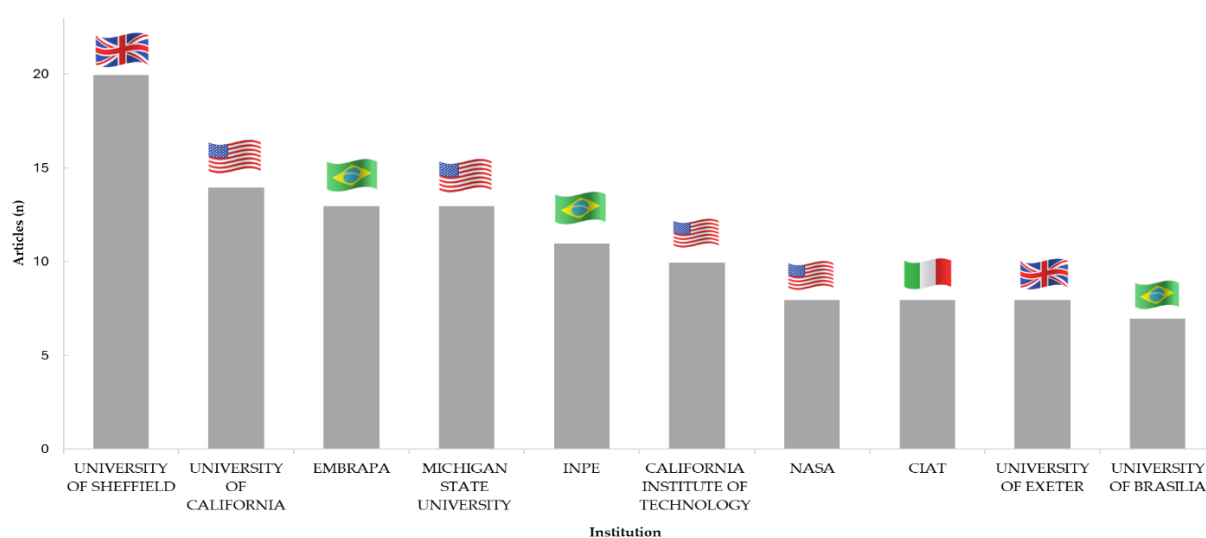


Figure 9. A hierarchical graph displays the top 10 countries and institutions worldwide with the highest publications on monitoring anthropogenic forest disturbance and degradation in the Amazon biome.

Source: OLIVEIRA, 2024.

The University of Sheffield (20 articles) is known for its significant research in ecology and environmental science, focusing on understanding the impacts of human activities on forests and developing strategies to promote forest sustainability (HETHCOAT *et al.*, 2019; HETHCOAT *et al.*, 2021). The University of California's research (14 articles) has focused on emerging remote sensing technologies, such as terrestrial and orbital LiDAR, environmental data analysis, and methods for monitoring changes in forest cover

In Brazil, EMBRAPA (13 articles) has played a vital role in developing robust technologies, including sustainable forest management practices, pioneering studies into post-harvest forest monitoring, and implementing RIL practices in the Amazon, most

recently working with LiDAR technology (SILVA & LOPES, 1984; SILVA, 1985; BERENGUER *et al.*, 2014).

Several studies from Michigan State University (13 articles) focus on using emerging remote sensing technologies for managing natural resources, particularly forests (SMITH *et al.*, 2023). The National Institute for Space Research (INPE) (11 articles) is crucial in monitoring and developing remote sensing methodologies for the Amazon and other tropical forests. INPE uses a series of satellites to gather data on deforestation, forest degradation, and biomass, which are crucial for the sustainable management of Brazilian forests (DINIZ *et al.*, 2015; SHIMABUKURO *et al.*, 2018; FONSECA *et al.*, 2019).

NASA (eight articles), through its satellite missions such as GEDI and Landsat, provides essential data used to monitor global forest cover and study the impacts of climate change, deforestation, and anthropogenic disturbances (WINSTANLEY *et al.*, 2024; MORTON *et al.*, 2011).

The Alliance Biodiversity & International Center for Tropical Agriculture (CIAT) (eight articles) promotes biodiversity conservation and the sustainable use of tropical resources, including forests. CIAT's research often deals with the sustainability of agroforestry systems and sustainable forest management (DYSON *et al.*, 2024). The University of Exeter (eight articles) research biodiversity conservation and the development of environmental policies that promote forest sustainability (FAWCETT *et al.*, 2023).

Finally, the University of Brasilia (seven articles) conducts significant research into tropical forest ecology and sustainable management practices, contributing to the development of public conservation policies in Brazil (MATRICARDI *et al.*, 2005; MATRICARDI *et al.*, 2010; MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020).

These institutions, with their research and innovations, play a key role in advancing sustainable forest management, helping to develop and implement practices that balance the conservation of forest ecosystems with economic and social needs.

4. Discussion

4.1. Need to Differentiate Forest Degradation from SFM and Policy Implications

The concept of forest degradation has not yet reached a scientific consensus, resulting in a variety of definitions and different approaches to its detection and measurement, especially by means of remote sensing, as demonstrated in this literature review (SIMULA, 2009; THOMPSON *et al.*, 2013; CHAZOUL *et al.*, 2015; VÁSQUES-GRANDÓN *et al.*, 2018). The impacts of activities related to forest management and the monitoring of selective logging have mainly been viewed from an ecological standpoint (CHAZDON, 2008; ASNER *et al.*, 2005). As a result, the term “forest degradation” is often used to describe the effects of selective logging activities ((DALAGNOL *et al.*, 2023; MATRICARDI *et al.*, 2010; KUCK *et al.*, 2021; LAPOLA *et al.*, 2023; MORENO *et al.*, 2023), fire (MATRICARDI *et al.*, 2010; MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020), and landscape fragmentation (MATRICARDI *et al.*, 2020). It is important to note that although legal selective logging can be considered degradation from an ecological perspective or by generic definitions, it is temporary degradation. Selective logging is an activity that is part of SFM and, therefore, at first glance, should be categorized distinctly within the term forest degradation (FERREIRA *et al.*, 2015).

A group of experienced researchers from Embrapa Amazonia Oriental have emphasized the need for a deeper reflection on the concept of forest degradation and its role in decision-making. They suggest that forest management, when based on good forest practices and techniques, causes temporary forest disturbances responsible only for a low level of forest degradation, contributing to forest conservation from a broad perspective when good management practices are applied (FERREIRA *et al.*, 2015). Another point is the fact that production forests, such as areas oriented for SFM, at the same time as generating environmental impact, advocate ways of mitigating them, such as reduced impact techniques and enrichment of clearings (PUTZ *et al.*, 2008; SCHWARTZ *et al.*, 2013).

Pereira-Jr *et al.* (2002) provides a comparative analysis of canopy gap fractions resulting from CL and RIL in 1996 and 1998. The study demonstrates that CL consistently caused greater canopy disruption, with total gap percentages reaching 16.5% in 1996 and 21.6% in 1998, predominantly driven by tree felling and skidding operations. Conversely, RIL exhibited significantly lower impacts on the canopy, with total gap percentages of 4.9% and 10.9% for the same years. These findings underscore the efficacy of RIL in

minimizing disturbances to forest canopy structure, highlighting its role as a sustainable logging practice that mitigates environmental degradation while preserving forest integrity.

Matricardi *et al.* (2013) observed that selective logging impacted, on average, less than 4% of the forest canopy in the Amazon between 1992 and 1999, while in forest degradation caused by forest fires, forest canopies were affected by more than 30% in the same period of analysis. In addition, recurrent fires and the opening up of the forest canopy intensify the drying out of the soil and biomass, degrading the forest and creating favorable conditions for subsequent fires (LAURENCE *et al.*, 2001; HOLDSWORTH & UHL, 1997). This cycle compromises the recovery capacity of tropical forests, making them more susceptible to clear-cutting. This highlights the need for management and protection strategies to break this cycle of degradation and conservation (COCHRANE *et al.*, 1998; COCHRANE *et al.*, 1999; COCHRANE *et al.*, 2004; MMA, 2006).

Recently, Matricardi *et al.* (2000) identified and classified two types of forest degradation in the Brazilian Amazon: forest degradation dependent on deforestation, which is closely associated with landscape fragmentation (fragment size and edge effect) in the region, and degradation independent of deforestation, which is driven by selective logging and forest fires. The authors observed that most forests selectively logged between 1992 and 2014 remained in the Brazilian Amazon, even when later affected by fires. As a result, they argue that the conversion of forests for other land uses, such as agriculture or pasture (deforestation), is a distinct process from selective logging, even though selective logging of valuable trees is part of the deforestation process (MATRICARDI *et al.*, 2020).

In this context, an important contribution of this study is to indicate that although several studies treat forest disturbances from legal selective logging as forest degradation, in practice there are several types of dynamics in the forest canopy, varying in intensity, size, and impacts resulting from anthropogenic interventions. Therefore, the different types of anthropogenic interventions need to be properly differentiated and considered, especially for cases of selective logging and timber harvesting in SFM projects.

Even though areas with SFM have high logging intensities of more than 30 m³·ha⁻¹ and more than 20 individuals logged per hectare, resulting in large and persistent clearings, these areas are supported by technical and legal aspects, which ensures the sustain-ability/legality of the activity and guarantees that the area has a legal obligation to remain intact for at least 35 years, as determined by law (MMA, 2006; OLIVEIRA *et*

al., 2024). In this sense, as proposed by Oliveira *et al.* (2024), areas within SFM with high logging intensities should be monitored after logging to assess the dynamics and resilience of the trees and, if necessary, possible adjustments to improve the current legislation, which defines the temporal, physical, and ecological parameters for extracting native timber in the Amazon (MMA, 2006; OLIVEIRA *et al.*, 2024).

It is therefore important to clearly distinguish disturbances that occur within the boundaries of sustainably managed areas from those in areas that do not follow these practices. This definition suggests that any human intervention that occurs outside sustainable management areas, which does not result in total deforestation, can be considered forest degradation. On the other hand, sustainable management activities, even if they are intense, are processes of temporary forest disturbance in which the forest recovers and can be exploited again within cutting cycles and are therefore not associated with deforestation (MATRICARDI *et al.*, 2020; MMA, 2006). Analyzing forest disturbances from the perspective of forest dynamics and resilience offers numerous opportunities, but also presents significant challenges (PEREIRA-JUNIOR *et al.*, 2002; CHAZDON, 2008). In particular, this approach would allow this definition to be generalized and distinguished from any biases introduced by biased human perspectives (CHAZDON, 2003; CHAZDON, 2008; SONG *et al.*, 2018).

Furthermore, mistakes in identifying degraded areas and selective logging can undermine the credibility of forest conservation and management efforts. This can make securing funding for conservation projects harder and discourage investment in SFM practices (JUGULUM, 2014). Public policies and regulations based on incorrect data can be ineffective or have negative consequences (NESHA *et al.*, 2021). This can lead to inadequate allocation of public resources for forest conservation and management and hinder the implementation of effective strategies for forest protection (CUTLER *et al.*, 2007; BARLOW *et al.*, 2020). Improving the accuracy in classifying forest degradation and selective logging is crucial for the environmental, economic, and social sustainability of SFM. Investments in modern monitoring technologies, such as remote sensing and GIS, combined with robust field validation, are essential to ensure the integrity of forest ecosystems and the effectiveness of management and conservation policies (DALAGNOL *et al.*, 2023; OLIVEIRA *et al.*, 2024; WINSTANLEY *et al.*, 2024).

4.2. *The Evolution of Monitoring Approaches for Forest Degradation*

The evolution of forest degradation mapping highlights significant advancements in technology, methodology, and understanding of forest dynamics over time. This progress reflects a transition from traditional techniques to sophisticated technologies like machine learning and advanced satellite systems.

Early efforts, such as the pioneering study by Nepstad *et al.* (1999), relied on indirect methods like sawmill records to estimate forest areas impacted by selective logging due to the scarcity of RS technologies. These methods, while innovative at the time, provided limited spatial and temporal insights (NEPSTAD *et al.*, 1999).

The late 1990s and early 2000s marked the beginning of remote sensing applications for forest degradation mapping. Souza and Barreto (2000) introduced a remote sensing approach to detect forests impacted by selective logging in Pará, Brazil, utilizing a linear mixture model and buffer zones (SOUZA & BARRETO *et al.*, 2000). Shortly after, Souza-Jr *et al.* (2003) advanced these techniques with the use of Spectral Mixture Analysis and Landsat imagery (SOUZA-JR *et al.*, 2003). Matricardi *et al.* (2005) further refined the use of Landsat images, employing texture analysis to estimate selectively logged areas in Mato Grosso, Brazil (MATRICARDI *et al.*, 2005). These studies signaled the transition to satellite-based mapping, enabling broader spatial coverage and more detailed assessments.

The mid-2000s saw a leap in the adoption of new satellite technologies. The Landsat series became essential for forest monitoring due to its extensive historical archive and multispectral capabilities. Asner *et al.* (2005) utilized the Carnegie Landsat Analysis System (CLAS) to map selectively logged forests across the Brazilian Amazon (ASNER *et al.*, 2005), while Matricardi *et al.* (2013) applied semi-automatic approaches and texture analysis to achieve similar goals (MATRICARDI *et al.*, 2013). These advancements highlighted the growing reliance on Landsat's medium-resolution imagery for large-scale assessments. Low-resolution satellites like MODIS also contributed, particularly in monitoring large-scale degradation due to its high temporal frequency (LIZUNDIA-LOIOLA *et al.*, 2020; PINAGÉ *et al.*, 2023). Yet, limitations in spatial resolution meant these technologies were less effective in detecting subtle disturbances, such as low-intensity selective logging (MORTON *et al.*, 2011).

However, studies began identifying limitations in detecting low-intensity logging and subtle degradation using medium-resolution sensors, as they often failed to capture

approximately 50% of canopy damage caused by logging operations (PEREIRA-JUNIOR *et al.* 2002; MATRICARDI *et al.*, 2005).

The past two decades have seen the integration of high-resolution satellites and advanced technologies into forest monitoring (SAATCHI *et al.*, 2011; ABDOLLAHNEJAD *et al.*, 2019; OLIVEIRA *et al.*, 2024; WINSTANLEY *et al.*, 2024; DALAGNOL *et al.*, 2023). Platforms like PlanetScope and Sentinel-2 now provide daily, high-resolution imagery, enabling more detailed assessments of forest structure and disturbances (LIMA *et al.*, 2019; PETRI *et al.*, 2022; HEATCOAT *et al.*, 2022; DALAGNOL *et al.*, 2023). LiDAR technology has become highly valued for its ability to capture three-dimensional forest structure, tree height, and biomass (WINSTANLEY *et al.*, 2024; HUDAK *et al.*, 2002). LiDAR-based platforms like NASA's GEDI have revolutionized large-scale carbon and biomass quantification (HOLCOMB *et al.*, 2024).

Simultaneously, advancements are marked by the introduction of machine learning and artificial intelligence (AI) techniques (BARLOW *et al.*, 2020; WINSTANLEY *et al.*, 2024; DALAGNOL *et al.*, 2023). These technologies have revolutionized forest monitoring by enabling the processing of vast datasets and improving accuracy when detecting and classifying disturbances (KUCK *et al.*, 2021; HEATCOAT *et al.*, 2021). Algorithms such as Random Forest and Deep Learning have been increasingly employed to differentiate between natural disturbances (e.g., storms) and anthropogenic impacts (e.g., selective logging and fires), offering a higher level of precision than traditional methods (HEATCOAT *et al.*, 2019; KUCK *et al.*, 2021; DALAGNOL *et al.*, 2023; WINSTANLEY *et al.*, 2024). Moreover, machine learning models have been integrated with data from high-resolution satellites and Li-DAR, providing a multi-faceted approach to monitoring forest degradation (HUDAK *et al.*, 2022; WINSTANLEY *et al.*, 2024).

Key research institutions have driven these advancements. For example, EMBRAPA and INPE in Brazil have been pivotal in developing methodologies for monitoring tropical forests and implementing sustainable forest management practices (FERREIRA *et al.*, 2015; SILVA & LOPES *et al.*, 1984; SILVA *et al.*, 1985; BERENGUER *et al.*, 2014). Internationally, universities like that of Sheffield and California have contributed to ecological research and the application of RS technologies (HETHCOAT *et al.*, 2021; HETHCOAT *et al.*, 2021), while NASA has played a central role through missions like Landsat and GEDI (HOLCOMB *et al.*, 2024; MORTON *et al.*, 2011).

Despite these advancements, challenges persist, particularly the costs and high computational demands associated with high-resolution data and LiDAR technologies. These limitations restrict their accessibility to well-funded projects and institutions. Nevertheless, initiatives like Brazil's RedeMAIS and Norway's NICFI program have made high-resolution satellite data more accessible to public institutions (BRASIL MAIS, 2024; NICFIC, 2020). These efforts have democratized forest monitoring by providing high-resolution imagery for use in conservation and sustainable management (OLIVEIRA *et al.*, 2024; DALAGNOL *et al.*, 2023).

The evolution of forest degradation to disturbance mapping reflects a dynamic trajectory of technological innovation. From early manual methods to the adoption of satellite platforms and the integration of machine learning, these advancements have significantly enhanced the capacity to monitor and manage forest resources. These technological innovations also allow for better categorization of forest degradation, enabling the distinction between different types and intensities of disturbances, such as selective logging, fires, and edge effects. Moving forward, the combination of high-resolution imagery, advanced algorithms, and collaborative global initiatives will continue to shape the future of forest monitoring, ensuring more effective and sustainable management practices.

4.3. Regional Focus of Studies and the Need for Expansion

SFM areas within conservation units have played a key role in advancing techniques and tools capable of capturing and quantifying in detail the dynamics of disturbances and forest regeneration resulting from the selective logging of trees (LIMA *et al.*, 2019; OLIVEIRA *et al.*, 2024; DALAGNOL *et al.*, 2023; WINSTANLEY *et al.*, 2024). These studies are essential to refine and validate strategies that can eventually be applied more widely across the Amazon biome. This includes developing remote sensing tools that accurately capture changes in forest cover and different disturbance intensities, regardless of geo-graphical location (ASNER *et al.*, 2005). In protected areas, like in the National Forests of Rondônia, Flona Jamari was the country's first forest concession in 2008 and Flona Jacundá began logging in 2014. Both units' conservation are managed by the Brazilian Forest Service and operated by private companies (MERRY *et al.*, 2009; RODRIGUES *et al.*, 2020; VIDAL *et al.*, 2020). The Lower Amazon region has several

sustainable use conservation units with a long history of forest management, making it a natural source of research of this nature (OLIVEIRA *et al.*, 2024; BACHA *et al.*, 2007).

On the other hand, the Paragominas region in the northeast of the state of Pará is a model for forest management in the private areas and for being a pioneer in studies of SFM and the mapping of selective logging using remote sensing (VERISSÍMO *et al.*, 1992; SOUZA-JR *et al.*, 2003; BARRETO *et al.*, 1998). The Sinop region has the highest concentration of SFM plans in private areas within the Amazon. It is one of the largest timber-exporting regions, with numerous companies operating in the timber sector (MATRICARDI *et al.*, 2005; FEARNSSIDE *et al.*, 2003; FEARNSSIDE *et al.*, 2005).

In this regard, studies monitoring anthropogenic forest disturbances and degradation are mainly focus on the “arc of deforestation” in the Brazilian Amazon (Figure 6) (CSILLIK *et al.*, 2024; DE FIGUEIREDO *et al.*, 2019; PINHEIRO *et al.*, 2016). The concentration of studies in this area is largely due to the intense human activity and rapid land use changes occurring there (PINAGÉ *et al.*, 2023; PINHEIRO *et al.*, 2016). This region, which spans the south-ern and eastern edges of the Amazon, has become a focal point for deforestation due to factors such as mechanized agriculture, cattle ranching, and logging—often conducted illegally (PINHEIRO *et al.*, 2016). These activities contribute to a high visibility of forest loss, making it an attractive region for researchers aiming to study anthropogenic impacts on tropical forests (BARROS FERRAZ *et al.*, 2005; SOUZA *et al.*, 2005; SHIMABUKURO *et al.*, 2014; PINHEIRO *et al.*, 2016; SOUZA *et al.*, 2024).

However, despite regional focus, this study has been significantly advanced through RS techniques, each offering distinct capabilities for monitoring and analysis. The Linear Spectral Mixture Model (LSMM) excels in decomposing spectral signals into individual components, enabling the detection of subtle changes in forest composition (SOUZA-JR *et al.*, 2003; SHIMABUKURO & PONZONI, 2018). Random Forest is widely used for classifying vegetation and monitoring changes in forest cover (BARLOW *et al.*, 2020), while visual classification remains relevant in scenarios requiring human interpretation of specific vegetation characteristics (SOUZA-JR *et al.*, 2003). Tools like the Carnegie Landsat Analysis System (CLAS) and indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Fraction Index (NDFI) are critical for monitoring vegetation vigor and identifying degraded areas, particularly within SFM con-texts (SOUZA-JR *et al.*, 2005; YENGOH *et al.*, 2016; SOFAN *et al.*, 2016). Additionally, the Difference Relative Normalized Burn Ratio

(Δ rNBR) is vital for assessing fire severity and informing recovery efforts (SOFAN *et al.*, 2016; JI *et al.*, 2011), while texture analysis provides detailed insights into vegetation structure (MATRICARDI *et al.*, 2005; MATRICARDI *et al.*, 2010; MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020). Advanced techniques such as Deep Learning (DL) leverage neural networks to detect complex patterns in large datasets, further expanding the potential of remote sensing in forest monitoring (ASNER *et al.*, 2010; DALAGNOL *et al.*, 2023; WINSTANLEY *et al.*, 2024).

To enhance the practical value of this research for decision-makers, there is a need to align technical advancements with real-world applications. For instance, integrating NDVI and Δ rNBR can provide actionable insights for post-fire recovery planning and monitoring the impacts of climate change on vegetation health (YENGOH *et al.*, 2016; JI *et al.*, 2011). Similarly, advanced techniques like Deep Learning could be applied to predict degradation hotspots under future climate scenarios by combining satellite data with local environmental variables (DALAGNOL *et al.*, 2023). By combining advanced remote sensing techniques, such as LSMM, NDVI, and Deep Learning, with on-the-ground validation in less-studied regions, researchers can generate a holistic understanding of forest dynamics (JI *et al.*, 2011; YENGOH *et al.*, 2016; DALAGNOL *et al.*, 2023; WINSTANLEY *et al.*, 2024). This comprehensive approach will inform adaptive management strategies and policies that promote the resilience of Amazonian forests, ensuring their ecological, economic, and social benefits for future generations (CSILLIK *et al.*, 2024; DE FIGUEIREDO *et al.*, 2019).

With climate change intensifying extreme events and altering climate patterns in the Amazon, there is an increasing need to expand the focus of forest degradation and disturbances studies beyond the “arc of deforestation” (ARAGÃO *et al.*, 2014; LAPOLA *et al.*, 2023; CSILLIK *et al.*, 2024). Although this region is a critical point of research due to intense human activities, forests located in more remote and dense areas of central and western Amazon are also vulnerable to the impacts of climate change and anthropogenic actions (MARENGO *et al.*, 2018). These historically less-studied areas may face new challenges, such as severe droughts and more frequent fires, which compromise the natural regeneration of forests and increase the risks of degradation (ARAGÃO *et al.*, 2014; DUPUIS *et al.*, 2020; MARENGO *et al.*, 2018; BOURGOIN *et al.*, 2024). Expanding research to include less-studied, densely forested regions in the central and western Amazon, where traditional, community-based, and low-impact logging practices may be more prevalent, would provide a more comprehensive understanding of forest

disturbance and degradation patterns across the Amazon (BOURGOIN *et al.*, 2024). This broader approach could improve forest management practices by incorporating the diversity of forest conditions and disturbances across different parts of the biome (REICHE *et al.*, 2016; WINSTANLEY *et al.*, 2024). Comprehensive data from underrepresented regions can guide public policies and management practices, promoting the resilience and long-term sustainability of Amazonian forests (HANSEN *et al.*, 2013; ARAGÃO *et al.*, 2014; DUPUIS *et al.*, 2020; DENNIG *et al.*, 2021).

Expanding the focus of studies to include these less-impacted regions is essential for understanding how different parts of the biome respond to the combined pressures of human activities and extreme climate events (IPCC, 2014; DE ARMOND *et al.*, 2023; DA SILVA *et al.*, 2022). This enables the development of adaptive monitoring and management strategies that consider the diverse environmental conditions across the Amazon, ensuring a more robust approach to conservation (SUAB *et al.*, 2024). Comprehensive and context-specific data on these areas could guide public policies and management practices that promote the resilience of Amazonian forests to climate change, supporting the long-term sustainability of the entire ecosystem (ASNER *et al.*, 2010; ARAGÃO *et al.*, 2014; MARENGO *et al.*, 2018; DUPUIS *et al.*, 2020).

In summary, while the focus of research has been on the arc of deforestation, it is crucial to expand research and discussion to monitor degradation and anthropogenic disturbances in the forest on a broader scale (BOURGOIN *et al.*, 2024). This expansion should include other regions of the Amazon that are less studied but equally important, as they are heavily forested and face serious challenges that warrant balanced scientific attention (KUCK *et al.*, 2021; DE FIGUEIREDO *et al.*, 2019; MARENGO *et al.*, 2018). Notably, further research is needed to monitor selective logging across the entire Amazon. To date, only one notable study (MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020) has distinguished selective logging from fire-affected areas throughout the legal boundaries of the Amazon. Here, we have addressed the main achievements of remote sensing and new technologies in assessing forest disturbances in tropical regions, as well as the challenges related to the concepts of forest degradation and forest management. Altogether, this work provides a valuable contribution to researchers, policymakers, and forest practitioners, helping to improve forest management, regulation, and conservation.

5. Conclusions

This study highlights advancements in monitoring forest degradation and disturbances within the Amazon biome, emphasizing the critical role of remote sensing technologies and sustainable forest management (SFM) practices. By synthesizing key methodologies, such as Linear Spectral Mixture Models (LSMM), Normalized Difference Vegetation Index (NDVI), and emerging techniques and technologies like Deep Learning and LiDAR, we demonstrate how these tools have transformed our ability to monitor and assess forest dynamics. These advancements allow for more precise categorization of disturbances, distinguishing temporary impacts associated with SFM from more severe degradation caused by illegal logging, fires, and other anthropogenic activities.

While much of the research remains concentrated in the “arc of deforestation”, the need to expand the geographic focus of studies to include less-impacted and under-researched regions is critical. Areas in the central and western Amazon, characterized by dense forests and traditional or low-impact logging practices, offer valuable insights into forest resilience and the diverse impacts of anthropogenic and climatic pressures. Addressing this research gap would provide a more comprehensive understanding of forest degradation across the entire biome, ensuring that findings are representative of the Amazon’s full complexity.

Climate change adds urgency to this endeavor, as the intensification of extreme events, such as severe droughts and fires, threatens the regeneration capacity of Amazonian forests. Expanding studies to underrepresented regions will enable the development of adaptive management strategies that are responsive to local environmental conditions and resilient to climatic variations. This approach is essential to support the long-term sustainability of the Amazon and its vital ecological, economic, and social functions.

Policymakers and forest practitioners can benefit greatly from the integration of advanced monitoring tools with field-based validation. Providing actionable insights, such as identifying degradation hotspots and assessing post-disturbance recovery, will help refine forest management policies, improve REDD+ initiatives, and promote more effective conservation strategies. The distinction between forest degradation and SFM must be clear in policy frameworks to ensure that temporary, managed disturbances are

not conflated with permanent degradation, preserving the credibility and sustainability of SFM practices.

The proposal presented here, which calls for differentiating types of forest disturbance, especially to separate low-impact sustainable management areas from other forms of medium- and high-intensity degradation, represents a significant advancement in assessing forest disturbance in terms of intensity, size, agents, causes, and impacts. These criteria help make a clearer distinction between sustainable management practices and other levels of disturbance that structurally compromise forest integrity and conservation.

Future research should focus on refining definitions of forest degradation and enhancing monitoring methods. This includes developing a more precise, standardized criteria for defining and assessing forest degradation across different regions and contexts. Further research could also explore advanced remote sensing techniques, such as machine learning models integrated with high-resolution data, to improve the classification and discrimination of various forest disturbance types. Additionally, long-term studies on the ecological recovery and resilience of forests after different intensities of disturbance could provide valuable insights for sustainable management practices. Such research would contribute to a more comprehensive understanding of degradation processes, ultimately supporting more effective conservation and management strategies.

In summary, this study underscores the need for a broader, more inclusive research agenda that captures the full spectrum of forest dynamics across the Amazon. By combining technological innovations, regional insights, and robust monitoring strategies, researchers and practitioners can contribute to the resilience and sustainability of Amazonian forests, ensuring their preservation for future generations. This comprehensive understanding is indispensable for shaping effective public policies and advancing global efforts to mitigate climate change and protect tropical forests.

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CHAPTER III – Spatio-Temporal Assessment Of Heterogeneity By Logging Intensity In A Federal Concession Area In The Brazilian Amazon²

The logging intensity does not take into account the spatial heterogeneity of the forest volume of commercial native species in the Brazilian Amazon. This study aims to evaluate spatio-temporal heterogeneity distribution by assessing logging intensity and its effects on the volumetric stock and abundance of commercial species, with a focus on sustainable management practices. This study was conducted in the Saracá-Taquera National Forest in the Amazon. Forest inventory data, elevation, and PlanetScope satellite images were integrated into a geographic information system. The information was aggregated into regular 1-hectare cells for the times before, during, and after logging (t0, t1, and t2). The unsupervised classification algorithm k-means with four clusters was used to analyze heterogeneity. Before logging, areas with higher commercial volumes were distant from water bodies, while areas with lower elevation had lower wood stocks. Logging intensity was generally low, concentrating on a few trees per hectare. Logging in the study area revealed heterogeneous spatial distribution by intensifying in areas with the highest wood stocks. In addition to the recommended logging intensity according to legislation, forest heterogeneity should be considered by the manager, promoting adaptive strategies to ensure the conservation of forest resources.

Keywords: *sustainable forest management; logging intensity; tropical forest; reduced impact logging; geoprocessing; volumetric heterogeneity*

Resumo: A intensidade de corte não leva em consideração a heterogeneidade espacial do volume florestal de espécies nativas comerciais na Amazônia Brasileira. Este estudo objetvou avaliar a distribuição da heterogeneidade espaço-temporal, avaliando a intensidade de corte e seus efeitos sobre o estoque volumétrico e a abundância de espécies comerciais, com foco em práticas de manejo sustentável. A pesquisa foi realizada na Flona de Saracá-Taquera, na Amazônia. Dados de inventário florestal, elevação e imagens de satélite *PlanetScope* foram integrados em um sistema de informação geográfica. As informações foram agregadas em células regulares de 1 hectare para os tempos antes, durante e após a exploração (t0, t1 e t2). O algoritmo de classificação não supervisionada k-means, com quatro clusters, foi utilizado para analisar a heterogeneidade. Antes da exploração, as áreas com volumes comerciais mais altos estavam distantes dos corpos d'água, enquanto áreas com menor elevação apresentavam estoques de madeira mais baixos. A intensidade de corte foi geralmente baixa, concentrando-se em poucas árvores por hectare. A exploração na área de estudo revelou uma distribuição espacial heterogênea, intensificando-se em áreas com os maiores estoques de madeira. Além da intensidade de corte recomendada pela legislação, a heterogeneidade florestal deve ser considerada pelo gestor, promovendo estratégias adaptativas para garantir a conservação dos recursos florestais.

Palavras-chave: *manejo florestal sustentável; intensidade de corte; floresta tropical; corte de impacto reduzido; geoprocessamento; heterogeneidade volumétrica.*

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1. Introduction

Primary forests represent some of the most vital ecosystems on Earth (GIBSON *et al.*, 2011). Approximately 1.6 billion people rely directly on forests, with the forestry industry contributing approximately US \$661 billion to the global GDP, and forests absorb an estimated 7.6 billion tons of CO₂ annually (FAO, 2015; BUSTAMANTE *et al.*, 2015; HARRIS *et al.*, 2021). The Brazilian Amazon alone encompasses one third of the world's tropical forests, boasting commercial roundwood reserves totaling around 60 billion cubic meters, thereby establishing itself as the largest repository of tropical timber worldwide (WWF, 2012; FAO, 2020; BRASIL, 2024; IBGE, 2024).

In the Amazon, owing to its high species diversity, there remain few studies on the volumetric distribution of the forest (COLPINI *et al.*, 2009). Despite extensive discussion among researchers on the topic of volume, there are still gaps in the findings concerning the spatial distribution of volume among native Amazonian species (COLPINI *et al.*, 2009; CHAPMAN & MEYER 1949; BRUCE & SCHUMACHER, 1950; SPURR, 1952; HIGUCHI *et al.*, 1979; FELDSPAUSCH *et al.*, 2011; SAATCHI *et al.*, 2011).

When observed at a synoptic scale, the terra firme Amazon Forest seems like a plain with homogeneous vegetation cover. However, local analysis unveils a diversity of environments influenced by factors such as topoclimatic and pedological conditions, as well as water availability and physiographic characteristics (MARTORANO *et al.*, 2018; QUESADA *et al.*, 2011; HILKER *et al.*, 2014; NOBRE *et al.* 2014). This typological heterogeneity significantly impacts the composition and volumetric distribution of vegetation in terra firme forests in Amazonia (PELLISSIER *et al.*, 2001; QUEASADA *et al.*, 2012; COSTA *et al.*, 2015).

The joint use of remote sensing products and forest inventory data applied to forest management has been gaining ground (WOLF *et al.*, 2012; ABDOLLAHNEJAD *et al.*, 2017; ABDOLLAHNEJAD *et al.*, 2019). As the topography of the site has a direct influence on the occurrence of species and most of them are distributed non-randomly, information from remote sensing, such as elevation, plays a crucial role in mapping and monitoring species (PEREIRA-JR *et al.*, 2021; HIGUCHI *et al.*, 1981; SOUZA *et al.*, 2005; GUO *et al.*, 2016; NOGUEIRA *et al.*, 2007). Wolf *et al.*, (2012) assessed the spatial distribution of species richness in tropical forests using lidar data and found significant differences in richness associated with topographic variation. Dong *et al.* (2020) used

optical images from the Landsat series together with topographic correction models and forest inventory data to classify groups of forest species according to topography and obtained satisfactory results.

Remote sensing can also play an important role in monitoring and quantifying canopy disturbance caused by selective logging (BUSTAMANTE *et al.*, 2016; SAATCHI *et al.*, 2011; WOLF *et al.*, 2012; ABDOLLAHNEJAD *et al.*, 2017; ABDOLLAHNEJAD *et al.*, 2019). Fortunately, damage to the canopy is highly correlated with the volume of timber removed from the forest (PEREIRA-JR *et al.*, 2021; ABDOLLAHNEJAD *et al.*, 2019). The disturbances caused by logging also vary depending on the logging practice used; the recommended logging practice in the Amazon is known as reduced impact logging (RIL) and should be incorporated into management plans to minimize impacts (PEREIRA-JR *et al.*, 2021).

Previous studies have shown the need for high spatial and temporal resolution images for monitoring selective logging in the Amazon (WOLF *et al.*, 2012; DONG *et al.*, 2020; ASNER *et al.*, 2005). In addition, most of the remote sensing techniques and products used for mapping and monitoring studies of selective logging have been insufficient for large-scale assessments (ABDOLLAHNEJAD *et al.*, 2019). A comparison using field data of crown disturbance with satellite imagery from the Landsat series after logging proved that traditional analytical methods and medium spatial resolution imagery fail to detect around 50% of the crown damage caused by forest harvesting operations (PEREIRA-JR *et al.*, 2021). Abdollahnejad *et al.*, (2019) proposed an advanced approach integrating geographic information systems (GISs) and remote sensing using very high spatial resolution images to monitor logging areas and pointed to an increase in the accuracy of volume estimates as a function of the spectral and spatial resolution of the images. Petri *et al.*, (2022) tested the use of images from the PlanetScope nanosatellite constellation for vegetation studies in the Amazon and concluded that high spatial and temporal resolution images are fundamental for understanding forest dynamics in the Amazon. Sustainable forest management (SFM) is recognized as a strategy and indicator of forest conservation, but there are gaps in the appropriate conditions for exploiting forest resources (PUTZ *et al.*, 2020; LAMB *et al.*, 2021). Brazilian standards establish specific values for harvesting intensity per hectare. On the other hand, when assessing sustainability indicators, factors such as the distribution of the diameter class structure and the availability of species to constitute the cutting rate in the forest management process must be considered (CARVALHO & PARROTA, 2017).

The authorized intensity of logging in tropical forest management is not associated with data on the heterogeneity of the original forest structure; that is, the volumes determined for extraction are fixed and standardized (PUTZ *et al.*, 2012). Carvalho (1999) considered the difficulty of tropical forest management due to the complexity and heterogeneity of its ecosystems (CARVALHO, 1999). According to Chazdon, the inappropriate use of natural forests can disrupt extraction cycles and degrade ecosystems (CHAZDON *et al.*, 2008).

Cutting intensity is one of the most important aspects of forestry and refers to the commercial volume of the trees to be harvested, estimated using volumetric equations provided in the sustainable forest management plans (SFMPs) and based on data from the pre-harvest forest inventory, expressed in cubic meters per unit area ($\text{m}^3 \text{ha}^{-1}$). Currently, Brazilian legislation authorizes a maximum cutting intensity of $30 \text{ m}^3 \text{ha}^{-1}$ for 35-year cutting cycles (BRASIL, 2000; ASNER & ALENCAR, 2010).

Although Brazilian legislation establishes a maximum limit for logging intensity, this fixed limit is indiscriminately applied to the entire Annual Production Unit (APU) area, disregarding possible forest heterogeneity. This becomes a sensitive issue as managers can exploit the forest without respecting its original structure and spatial distribution (CHAZDON & GUARIGUATA *et al.*, 2008; BRASIL, 2006). Therefore, the objective of this study is to evaluate the spatio-temporal heterogeneity by logging intensity in a federal concession area in the Brazilian Amazon within an SFM area following logging activities subjected to the reduced impact logging (RIL) technique.

2. Materials and Methods

2.1 Study Area

The study was carried out on a federal forest concession area in the Brazilian Amazon, situated within the Saracá-Taquera National Forest in the western part of the state of Pará, covering an area of 441,152 hectares (Figure 1). This sustainable Use Conservation Unit (UCS) was established by Decree No. 98.704 on 27 December 1989, with the objective of conducting research projects and initiatives aimed at the sustainable utilization of forest resources and the wellbeing of the populations residing within the UCS. These conservation units (UCs) were established under the National System of

Nature Conservation Units and managed by the Chico Mendes Institute for Biodiversity Conservation (ICMbio) (BRASIL, 2006).

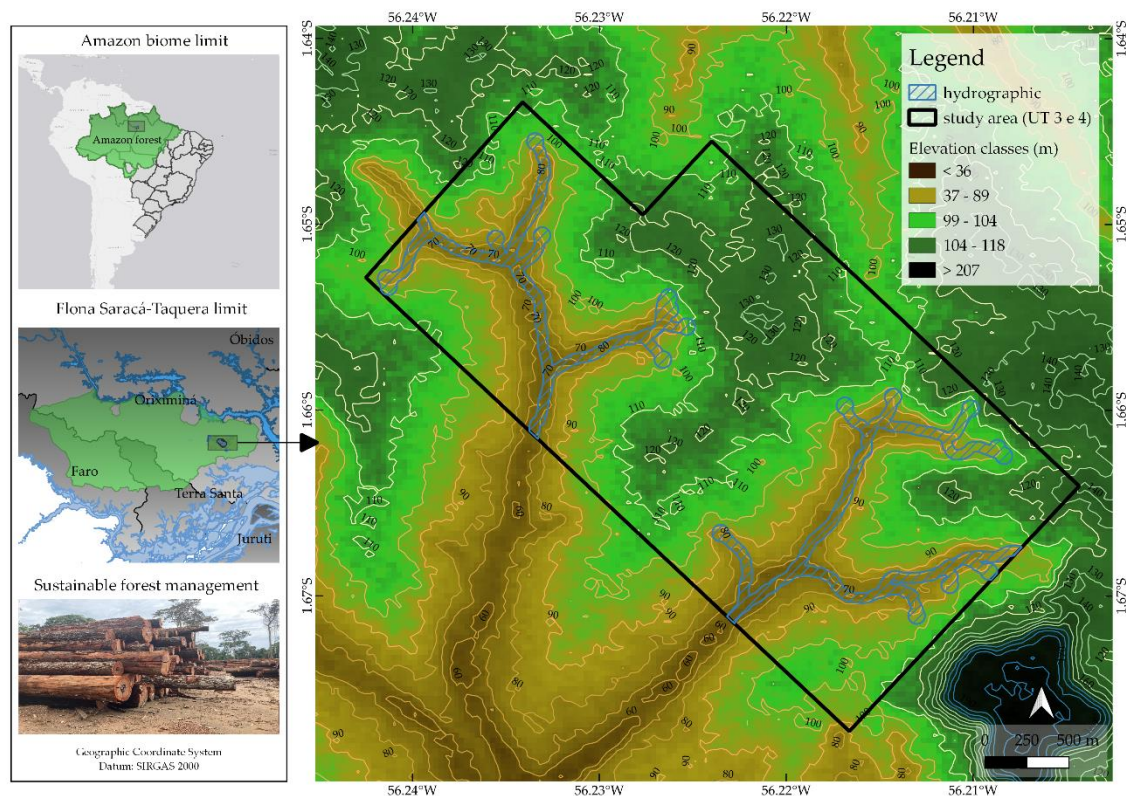


Figure 1. Location of the study area.

Source: OLIVEIRA, 2024.

The analyses were carried out in the eastern section of the national forest, specifically within Forest Management Unit II (FMU II). In SFM, the FMU represents the designated portion of the property allocated for forest management. The specific area designated for logging activities is referred to as a timber unit (TU). The portion of forest slated for management each year is termed an annual production unit (APU), and an APU may encompass one or more TUs.

The APU under evaluation was harvested between May 2022 and May 2023, with an initial authorization to exploit 1629 hectares and a total roundwood volume of 39,031 m³, comprising 30 commercial species selected by the concessionaire. TUs 3 and 4 of APU 11 were chosen to test the hypothesis proposed in this study. TU 3 covers an area of 339 hectares, while TU 4 covers 369 hectares, resulting in a total effective study area of 735 hectares, which also includes areas forming part of the hydrographic network in the analyzed area (Figure 1).

2.2 Vegetation

The national forest is covered by tropical rainforest, with variations typically linked to geomorphological features. The regional vegetation can be categorized as submontane and lowland ombrophilous dense forest, distinguished by two distinct strata: one emergent, featuring *Dinizzia excelsa*, *Bertholletia excelsa*, and *Cedrelinga catanaeformis* as primary species, and the other uniform, marked by the presence of *Manilkara spp.*, *Protium spp.*, and *Pouteria spp.* (IBGE, 2012).

The two primary facies, submontane and lowlands, comprise 94.1% of the Flona's area, while pioneer formations influenced by rivers account for 2.7%, and campinarana for 0.2%. Primary natural vegetation formations constitute 97% of the Flona's vegetation cover, whereas areas affected by anthropogenic activities represent 2% of the national forest's total area (ICMBIO, 2015).

2.3. Forest Inventory Data Extraction

The data from the pre-harvest inventory of commercial tree species and the inventory of harvested trees were obtained from the Brazilian Forestry Service (BFS) in the form of an electronic spreadsheet in .xlsx format. The BFS oversees concessions for sustainable forest management in public forests in the Amazon. Additionally, the BFS provided the post-harvest forestry report for APU 11, which included geospatial data on all inventoried commercial trees, along with an extra column containing the date of tree felling. Spatio-temporal analyses were conducted based on the 'cutting date' information to compare the original forest structure, the logged structure, and the structure remaining after logging.

Under the New Forest Code (Federal Law 12.651/12), harvesting trees within permanent preservation areas (PPAs), such as those near watercourses, is prohibited. Consequently, trees located within PPAs were excluded from the analysis to focus solely on potential trees for harvesting (Figure 2). The legislation also mandates a minimum cutting diameter (MCD) of 50 cm, meaning trees smaller than this diameter would not be felled and were thus excluded from the analysis as well. Pre-harvest inventory requirements stipulate that trees with a minimum diameter at breast height (DBH) of 10 cm below the MCD should be included (BRASIL, 2006). Thus, the study focused on

evaluating only commercial trees available for cutting outside the limits of PPAs and with a DBH greater than 50 cm.

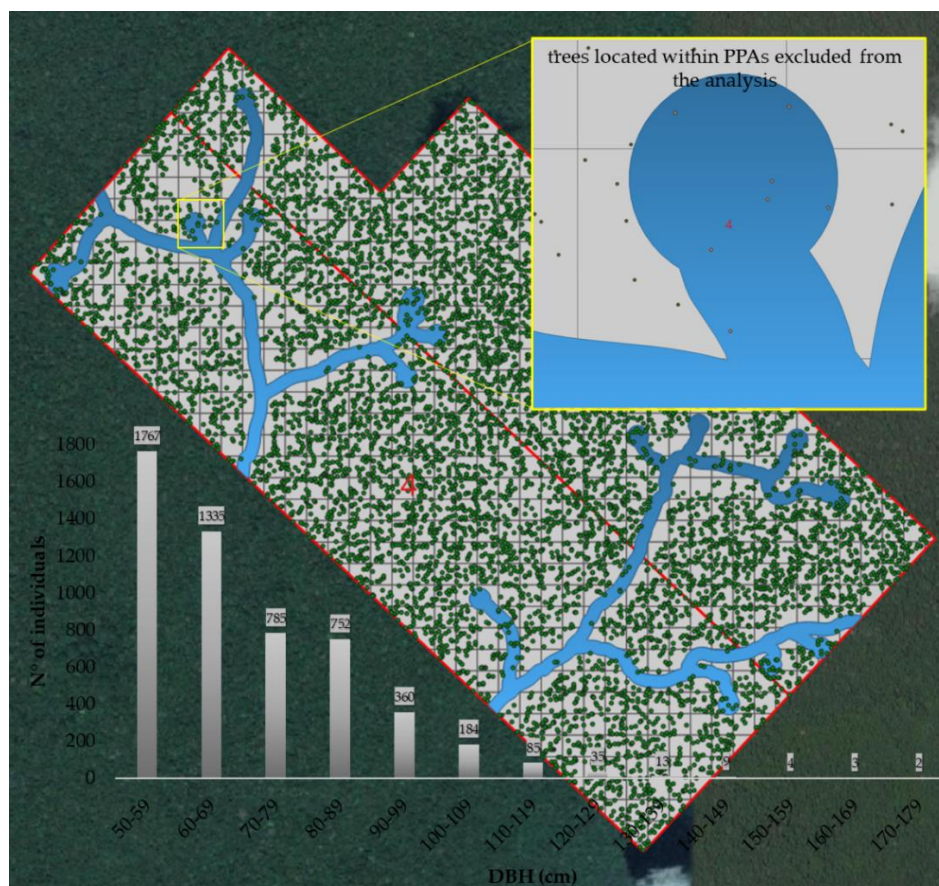


Figure 2. Spatialization of the inventory trees (points in green) with a focus on the exclusion of areas within PPAs (in blue) and the diametric distribution graph.

Source: OLIVEIRA, 2024.

2.4. Measuring Topographical Variables

The topographic variable of elevation (m) was utilized, based on the hypothesis that this variable can influence the spatial distribution of commercial species volume (WOLF *et al.*, 2012; COSTA & GUILLAUMET, 2015; ABDOLLAHNEJAD *et al.*, 2017; ABDOLLAHNEJAD *et al.*, 2019). Elevation was calculated using the average altitude for each 1-hectare cell. The Copernicus Global DSM Digital Elevation Model (DEM) at 30 m resolution was employed. The data have an absolute vertical accuracy >4 m (90% linear error) and absolute horizontal accuracy >6 m (90% linear error). These data originated from the TanDEM-X mission between 2011 and 2015 and were made available for free use in 2019. They are widely used in research employing the approach utilized in this work (WAGNER *et al.*, 2015; RIZZOLI *et al.*, 2017).

2.5. Assessment of Forest Canopy Openings Caused by Selective Logging

To evaluate the gradient of forest canopy openings resulting from tree felling in relation to logging intensity, satellite images from the PlanetScope constellation were employed. A pair of images before and after the exploitation were used for change detection analysis. This was based on the premise that higher logging intensities lead to larger openings in the forest canopy, thereby resulting in variations in the gradient of forest cover changes (ABDOLLAHNEJAD *et al.*, 2019; PEREIRA-JR *et al.*, 2001; ASNER & MASCARO, 2014).

The PlanetScope constellation comprises multiple launches of individual satellite groups (DOVEs), each consisting of a constellation of 3U CubeSats (i.e., $10 \times 10 \times 30$ cm) with over 120 active DOVEs. These sensors operate in at least four spectral bands; blue (455–515 nm), green (500–590 nm), red (590–670 nm), and near-infrared (780–860 nm), offering 3 m of spatial resolution and 12 bits of radiometric resolution (PETRI *et al.*, 2022). Band 3 was utilized individually due to its heightened spectral response to exposed soil and dry vegetation targets, making it highly recommended for vegetation studies in the Amazon (BROWN, 1997; PINARD *et al.*, 2000; JESEN, 2015) (Figure 3).

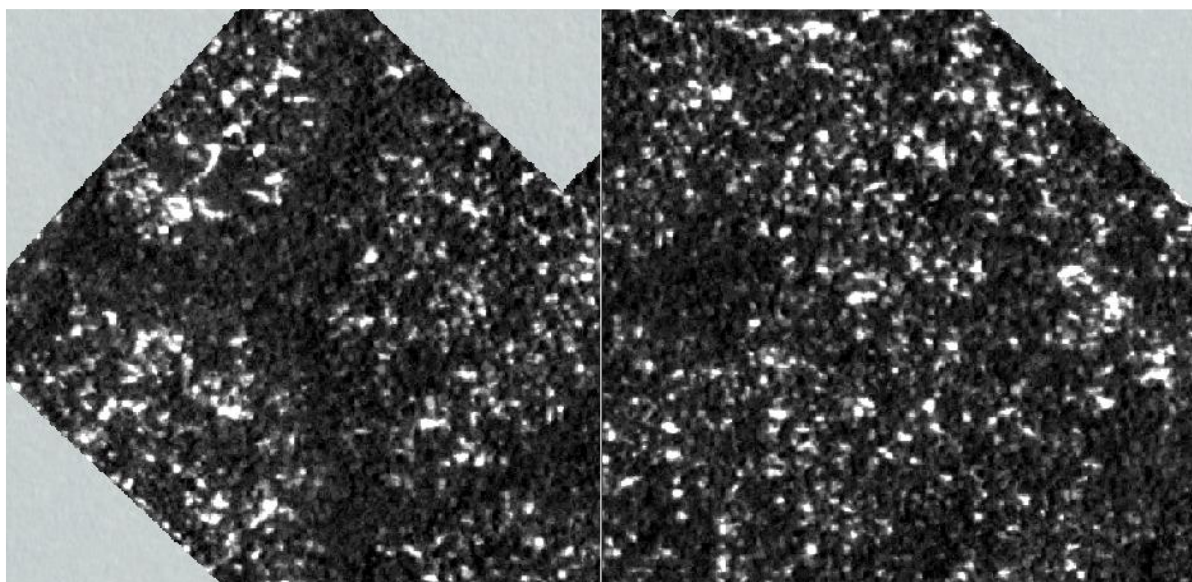


Figure 3. In the lighter tones of the band 3 images, there are higher spectral response values for areas with exposed soil and dry vegetation (clearings).

Source: OLIVEIRA, 2024.

Figure 4 and Figure 5 illustrate, didactically, the process of harvesting a tree and the impact its toppling can have on the forest canopy, resulting in the opening of a clearing. Thus, based on the variations in signal intensity captured by the sensor and the

frequency histogram of the image using band 3, a threshold was empirically defined based on the RGB (3,2,1) composition to classify areas with and without change. Digital number (DN) values greater than 2550 were considered canopy, and DN values less than 2550 were considered gaps.

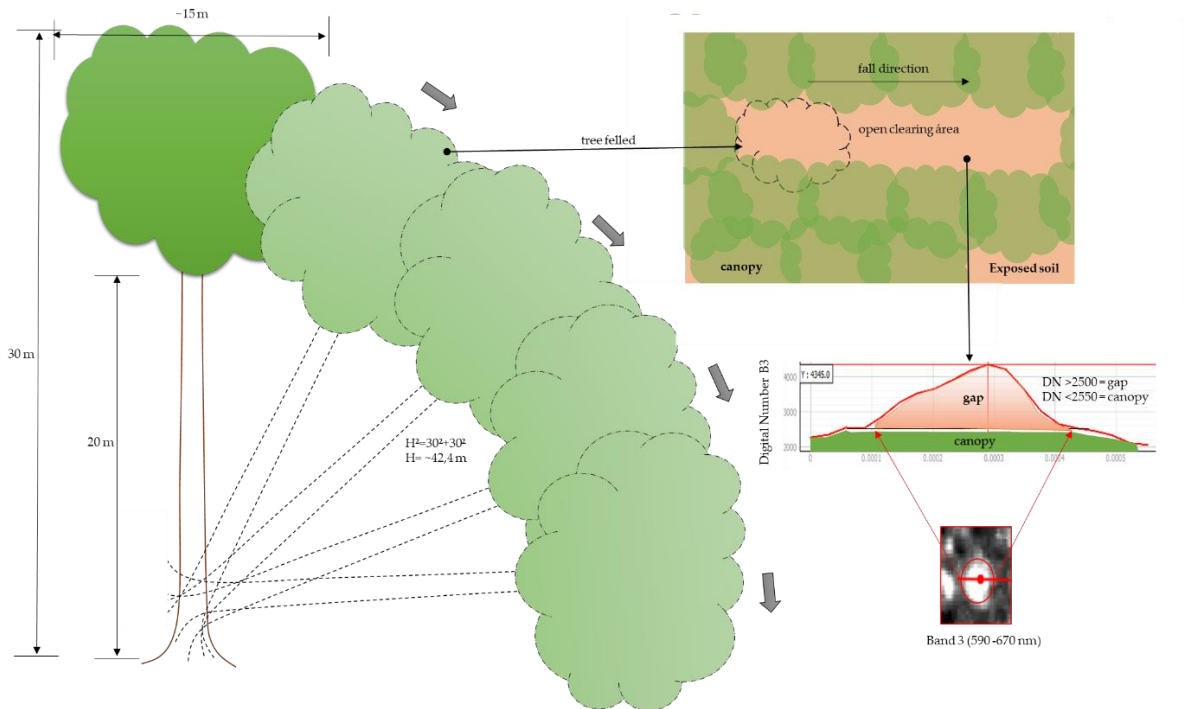


Figure 4. Illustration of the felling of a tree and its impact on the forest cover.

Source: OLIVEIRA, 2024.

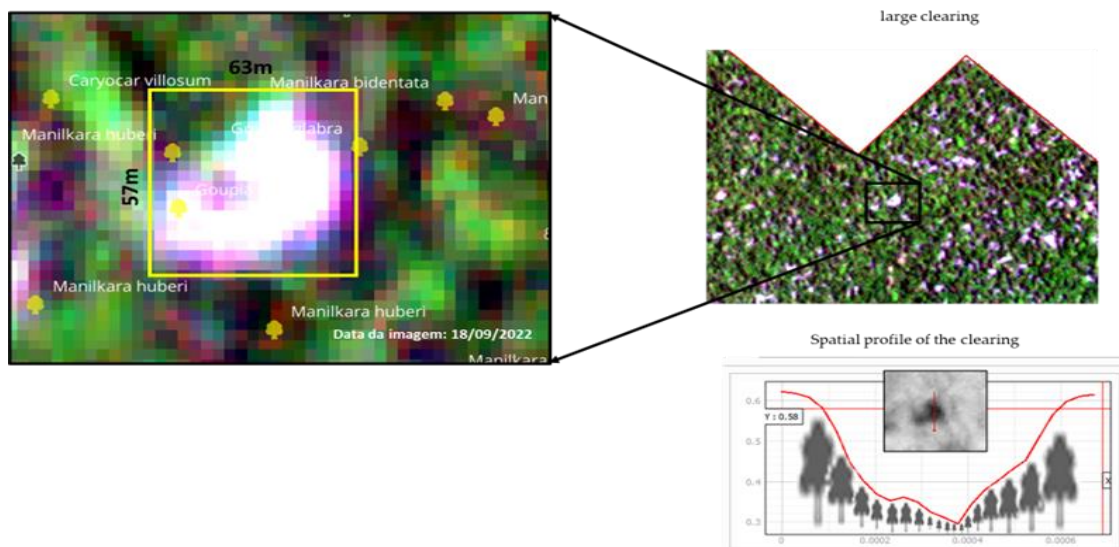


Figure 5. Empirical analysis of the size of the glades as a function of the areas extracted.

Source: OLIVEIRA, 2024.

After classification, binary thresholding or binarization of the image in raster format was performed to separate areas of dense forest from other areas (such as exposed soil and dry vegetation, among others). Following binarization, the forest and clearing classes were analyzed by converting the file to vector format. Only the clearings were then extracted to calculate the area of each class, excluding individual $3\text{ m} \times 3\text{ m}$ (9 m^2) pixels. The data were subsequently verified through visual interpretation. For visual analysis, we used the coordinates of all the trees that had been logged and the result of the classification of the clearings, so that for each tree or group of trees logged, a polygon was assigned and classified as a clearing.

Thus, except for the individual pixels, all other data points were validated and aggregated into 1-hectare cells. The metrics employed to aggregate the clearing vectors into 1-hectare cells included the percentage of the area within the cell and the total clearing area. Linear correlation analysis was conducted to assess the correlation between the area of clearings and logging intensities.

2.6. Analysis of Changes in the Spatial Distribution of Tree Volume and Abundance

The inventory information was spatialized and aggregated into 1-hectare cells. This decision was made for two main reasons: firstly, to enable the application of zonal statistics, and secondly, to facilitate understanding and discussion of the information. Since 1 hectare is a widely used unit of area in discussions of this nature, it allows for easier understanding, interpretation, and comparison between different studies and regions (LAMB, 1998; DE'ATH, 2002; ASNER *et al.*, 2005; PHILLIPS *et al.*, 2004).

The data were spatialized considering three time classes. Class "t0" refers to all the individuals inventoried before logging, class "t1" refers to the trees that were actually extracted from the forest, and class "t2" refers to the trees remaining in the area after logging. The diagram shown in Figure 6 illustrates the aggregation of individuals in the 1-hectare cells. For each cell, in each time class, the values contained in the inventory were assigned a tree abundance ($\text{n}^\circ\text{ ind. ha}^{-1}$) and volume ($\text{m}^3\text{ ha}^{-1}$) (Figure 6).

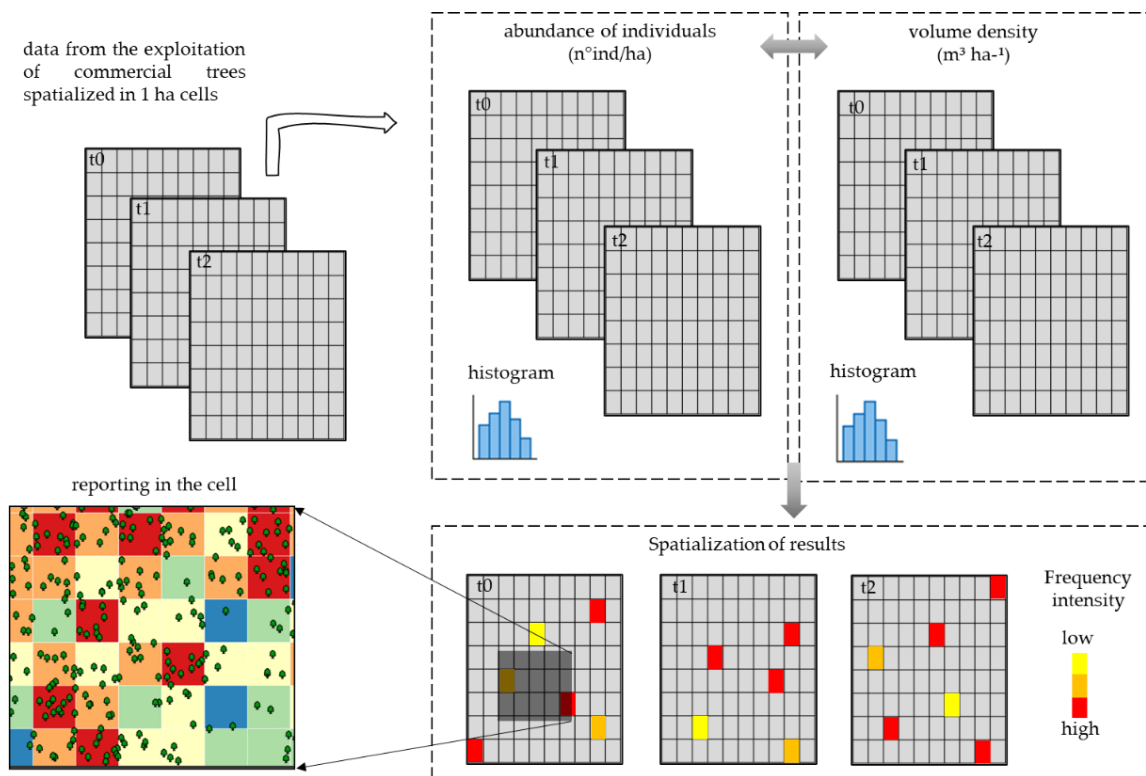


Figure 6. Schematic drawing of the aggregation of trees into 1 ha cells.

Source: OLIVEIRA, 2024.

2.7. Determining the Number of Clusters and Analyzing the Spatial Distribution of Logging

Cluster analysis was conducted using the k-means algorithm to classify the area into groups based on the topographic variable and the volumes of timber extracted (t2). The algorithm identifies objects or entities with similar characteristics, creating groups or classes with high internal homogeneity (within clusters) and high external heterogeneity (between clusters) (WANG & YANG, 2011; SANTOS & GLERIANI, 2017; KASSAMBARA, 2017; GOWER & ROSS, 1969).

To determine the optimal number of clusters (k), the elbow method was employed through visual analysis of the graph. Utilizing the elbow method with k-means clustering in the context of forest analysis is a conventional approach in data science and ecology (MACQUEEN, 1965; CUTLER *et al.*, 2007; HARIRI & JAVADI, 2000; CHÁVEZ-DURÁN *et al.*, 2022; GEORGAKIS *et al.*, 2023). An evaluation of the dissimilarity of the variables (SSEs) among each cluster was conducted to identify potential heterogeneities in forest exploitation. At the conclusion of the process, 746 1-hectare cells (100 m × 100 m) were considered.

3. Results

3.1. Analysis of the Change in the Spatial Distribution of Tree Volume and Abundance Due to Logging Activity

The spatial distribution of commercial volume before logging indicates that the interval between 45 and 60 $\text{m}^3 \text{ha}^{-1}$ had the highest number of cells with significant volume (199). For the higher volume ranges, above 120 $\text{m}^3 \text{ha}^{-1}$, only five cells were observed. It should also be noted that the lowest commercial volume ranges, from 0 to 15 $\text{m}^3 \text{ha}^{-1}$, are mostly located close to water bodies (Figure 7). In terms of tree abundance, the intermediate ranges of commercial tree abundance of 5–10, 10–15, and 15–20 individuals per hectare concentrate the largest number of cells, with the range of 10 to 15 individuals being the most representative, with 306 cells counted, and consequently, the range with the largest number of total trees.

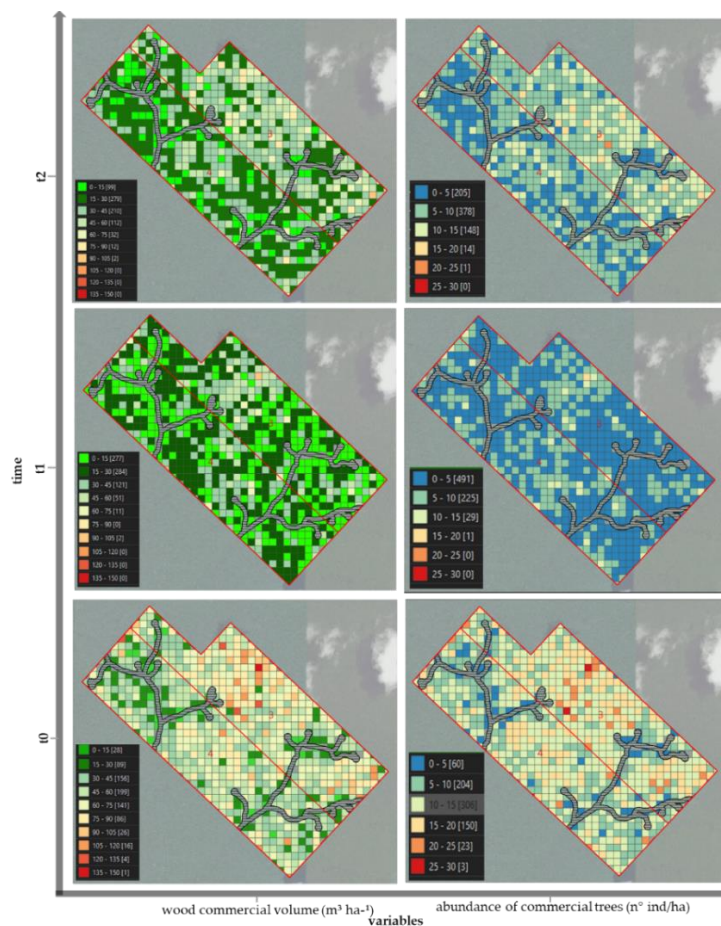


Figure 7. Spatial distribution of commercial volume and tree abundance before (t0), during (t1), and after logging (t2).

Source: OLIVEIRA, 2024.

There was a gradient in the spatial distribution of both the commercial volume and the abundance of trees in the area before logging, with three cells having an abundance between 25 and 30 individuals per hectare and 60 cells with an abundance between 0 and 5 individuals per hectare. The range of variation in the stock of commercial volume before logging is also extremely high, with 117 cells below $30 \text{ m}^3 \text{ ha}^{-1}$ and 21 cells between 105 and $150 \text{ m}^3 \text{ ha}^{-1}$ (Figure 7).

Regarding the remaining volume in the area, for didactic and visual purposes, it was decided to use shades of green to represent the volume bands below $30 \text{ m}^3 \text{ ha}^{-1}$, which is currently the maximum intensity of exploitation per hectare stipulated by the legislation. Thus, it can be observed that before logging, the forest exhibited a wide distribution of cells in bands greater than $30 \text{ m}^3 \text{ ha}^{-1}$ (Figure 7). After logging, the range between 15 and $30 \text{ m}^3 \text{ ha}^{-1}$ concentrates the largest number of cells (279), suggesting a systematic reduction across the area, but leaving areas with a considerable volume of stored wood, such as areas with a volume of $75 \text{ m}^3 \text{ ha}^{-1}$ or more, where 14 active cells remained. The map depicted in Figure 7 illustrates that the spatial distribution patterns of abundance and volume are similar throughout the area, both before (t_0) and after logging (t_2) (Figure 7).

After logging (t_2), there was no significant change in the normal distribution curve of individual abundance, suggesting that the area was logged following the natural spatial distribution of the forest. However, a shift in the number of cells towards lower abundance ranges can be observed, with the range between 5 and 10 being the most representative after logging (Figure 8).

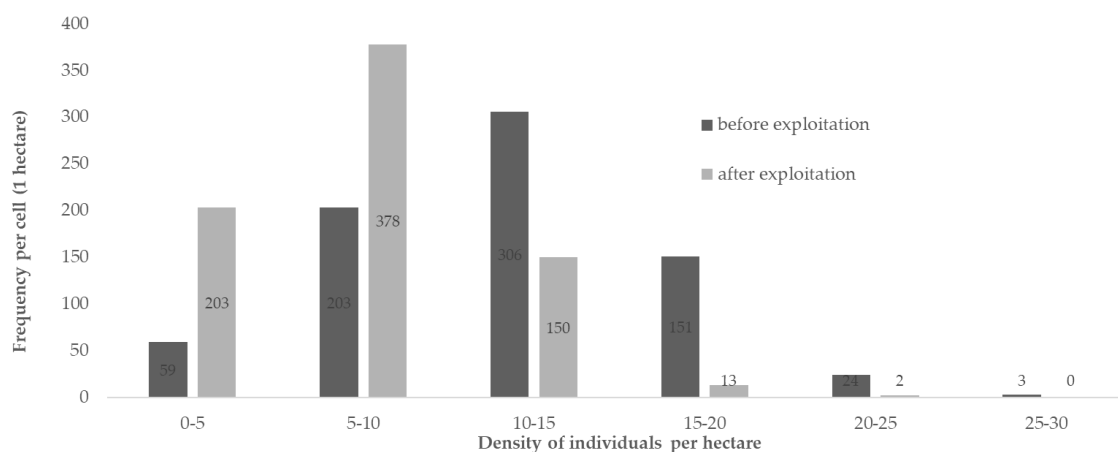


Figure 8. Frequency distribution histogram of the occurrence of 1-hectare cells in the abundance classes of commercial trees before and after logging.

Source: OLIVEIRA, 2024.

While before logging, the largest number of cells was in the commercial volume range between 45 and 60 m³ ha⁻¹, after logging, the class with the largest number of cells was concentrated in the range between 15 and 30 m³ ha⁻¹, indicating the migration of cells to lower volume classes. However, it is still possible to identify areas with a high-volume stock, such as areas with a volume greater than 75 m³ ha⁻¹, which represented 14 cells. The average volume per hectare decreased from 48 m³ ha⁻¹ to 28 m³ ha⁻¹, and the average number of individuals decreased from 12 to 7, considering the time before and after logging (Figure 9).

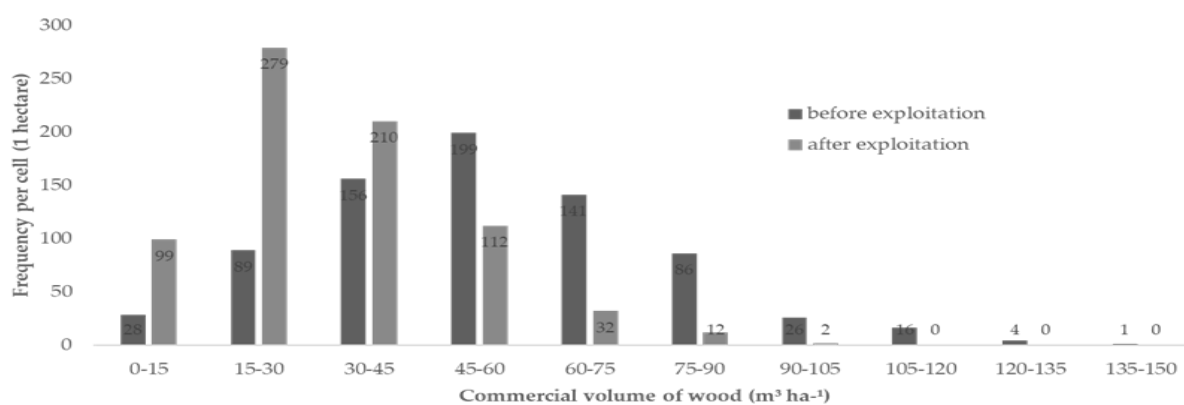


Figure 9. Frequency distribution histogram of the occurrence of 1-hectare cells in the commercial wood volume ranges before and after harvesting.

Source: OLIVEIRA, 2024.

3.2. Analysis of the Harvested Trees

Assessing the results of the commercial trees actually harvested, it is evident that harvesting was concentrated on felling a few trees per hectare, with 65.5% of the cells showing the harvesting of between 0 and 5 individuals per hectare. However, 29 cells had a logging intensity between 10 and 15 individuals per hectare, and only one cell had a logging intensity above 20 individuals per hectare, as shown in Figure 10.

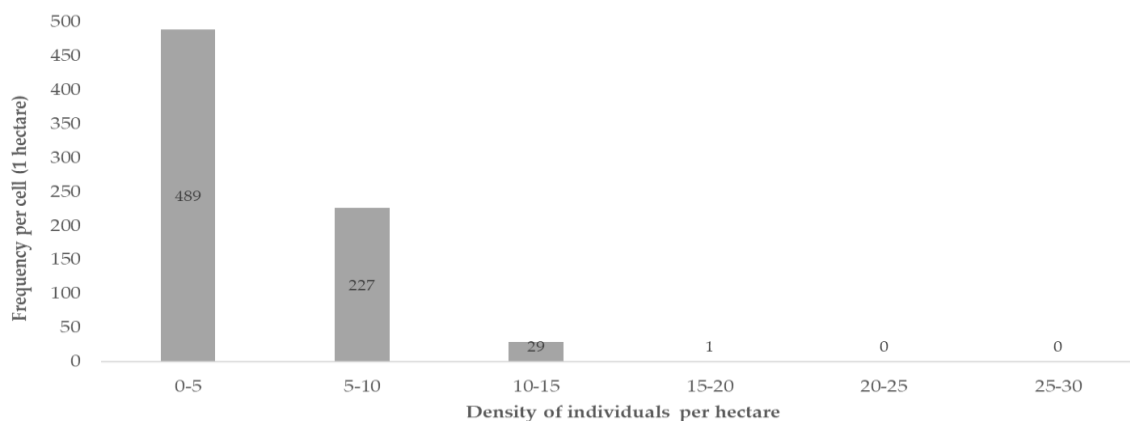


Figure 10. Class frequency distribution histogram of the number of trees logged per 1-hectare cell.

Source: OLIVEIRA, 2024.

Examining the distribution map of the abundance of commercial trees logged in Figure 7 (t1), it is evident that most of the logging was concentrated on felling a few individuals per hectare, with more logging occurring in areas with a larger stock of trees, particularly in the plateau areas farthest from the water bodies.

In terms of the volume that was effectively logged, the highest number of sensitized cells was in the range between 15 and 30 $\text{m}^3 \text{ha}^{-1}$, comprising 284 cells (Figure 11). It was observed that approximately 75% of the cells were below 30 $\text{m}^3 \text{ha}^{-1}$, which is the maximum volume allowed by law. However, it should be noted that the remaining 25% were exploited, showing harvesting above 30 $\text{m}^3 \text{ha}^{-1}$, with two cells having an exploitation intensity between 90 and 105 $\text{m}^3 \text{ha}^{-1}$.

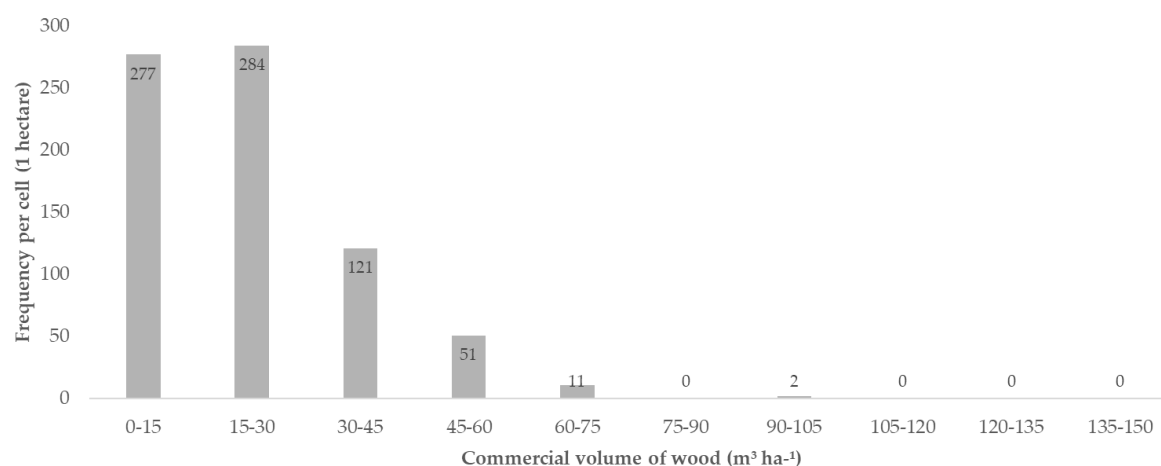


Figure 11. Frequency distribution histogram of logging intensity classes ($\text{m}^3 \text{ha}^{-1}$).

Source: OLIVEIRA, 2024.

3.3. Digital Elevation Model and Its Relationship with the Distribution of Harvested Commercial Timber Volume

Elevation ranged from 50 to 200 m. The highest values for the volume of harvested commercial timber were found away from the water bodies and close to the plateau areas (48.6 to 98.4 m^3 ha^{-1}). The lowest volume values are mostly concentrated in the lower elevation regions, such as the water bodies present in the area (0 to 8.9 m^3 ha^{-1}) (Figure 12).

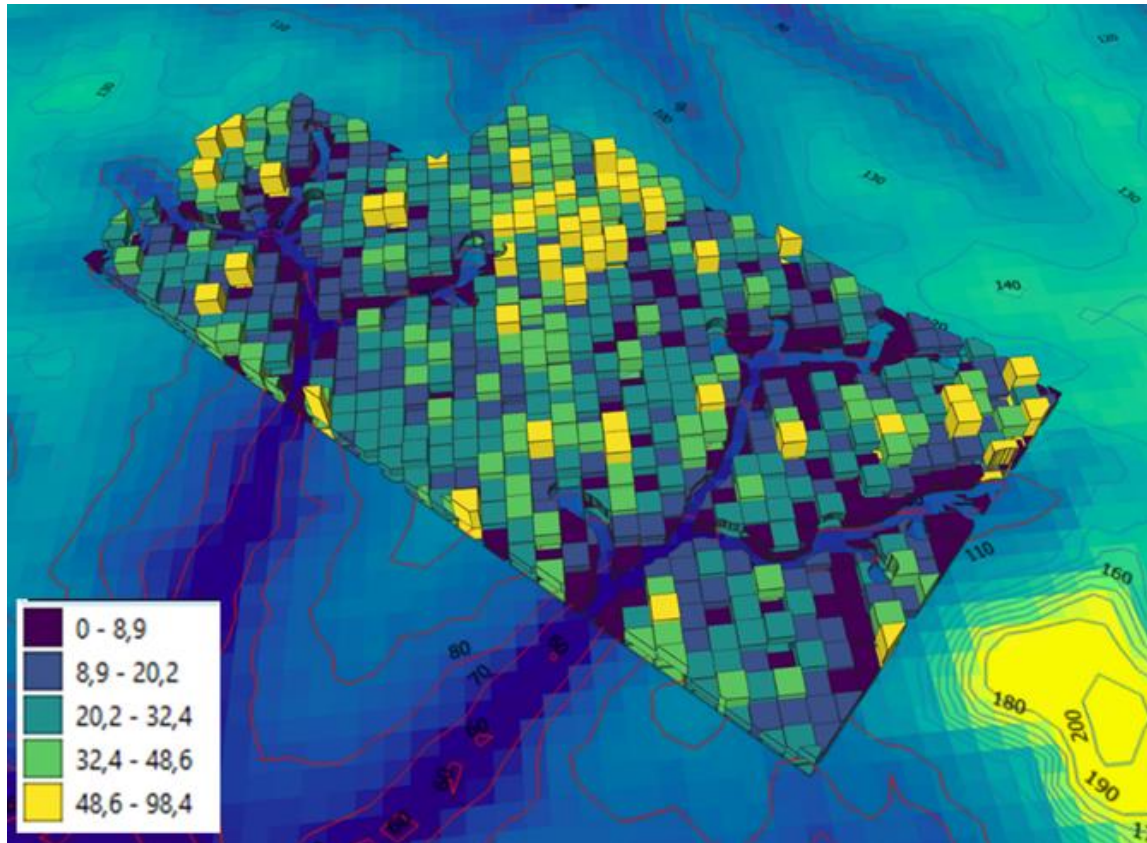


Figure 12. Relationship between elevation (m) and the volume of commercial timber actually harvested (m^3 ha^{-1}).

Source: OLIVEIRA, 2024.

3.4. Digital Elevation Model and the Relationship with the Distribution of the Volume of Commercial Timber Harvested

Based on the slope of the distortion curve in relation to the number of clusters, four clusters (k) were defined for the data set (Figure 13).

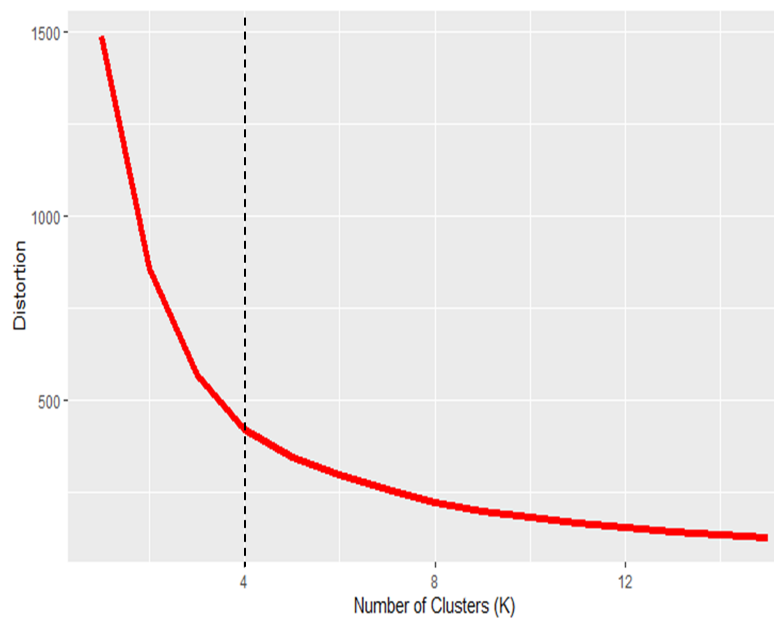


Figure 13. Definition of the best number of groups (k) using the elbow method.

Source: OLIVEIRA, 2024.

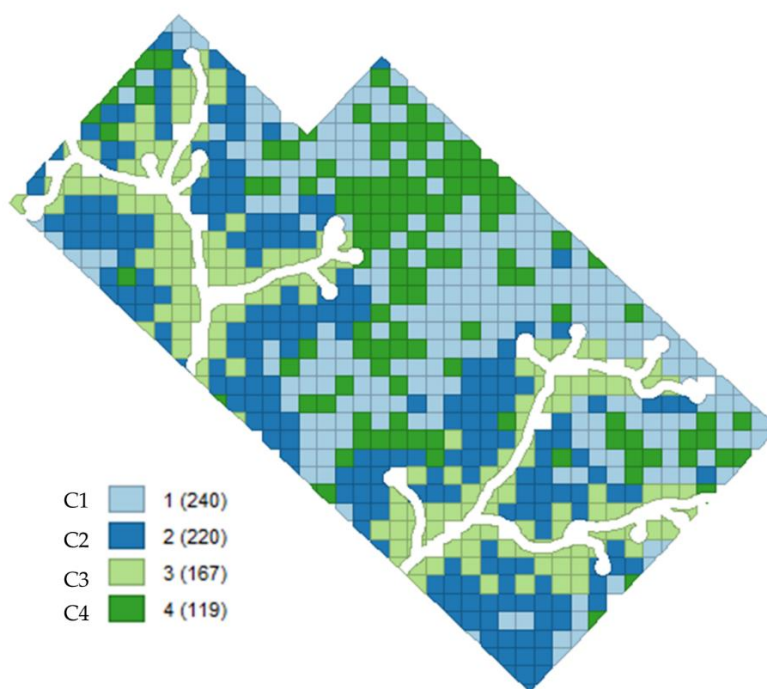
Cluster 1 (C1), comprising 240 observations and representing 32% of the data, has average values of $14.7 \text{ m}^3 \text{ ha}^{-1}$ and 113 m for the volume exploited and elevation, respectively, making it a transition group between low and high relief areas. Cluster 2 (C2) includes 220 observations (29%), with an average of $26.4 \text{ m}^3 \text{ ha}^{-1}$ and 97.6 m for volume and elevation, respectively. Cluster 3 (C3), with 167 observations (22%), had volume and elevation values of $5.9 \text{ m}^3 \text{ ha}^{-1}$ and 84.7 m, respectively, indicating a group with a spatial association with water bodies. Cluster 4 (C4) had 119 observations (16%) with volume and elevation values of $46.6 \text{ m}^3 \text{ ha}^{-1}$ and 115.2 m, respectively, indicating a spatial association of high-volume extraction in a plateau region (Table 1).

Table 1. Results of the cluster analysis in relation to volume extracted and elevation.

Cluster Centers					
Cluster	Proportion (%)	Volume Explored ($\text{m}^3 \text{ha}^{-1}$)	Elevation (m)	SSE	Cluster Name
C1	32.17%	14.70	113.30	132.30	Low volume, high elevation
C2	29.49%	26.42	97.64	105.60	Medium volume, medium elevation
C3	22.39%	5.90	84.79	77.58	Low volume, low elevation
C4	15.95%	46.66	115.29	103.78	High volume, high elevation

Source: OLIVEIRA, 2024.

Regarding the dissimilarity of the groups, expressed through the sum of squares within the clusters (SSEs), the cluster with the least variance in the Euclidean distances is the “low volume low elevation” group, with the lowest SSE value of 77.5. This indicates that in these areas, close to the water bodies, logging occurred in a homogeneous manner and with few individuals per hectare (Figure 14). On the other hand, the most heterogeneous group was the “low volume high elevation” group, with an SSE value of 132. Since this group has the largest number of cells (240) distributed throughout the area, it naturally exhibits a high degree of heterogeneity among its internal observations. The “medium volume medium elevation” and “high volume high elevation” groups have intermediate SSE values, indicating a medium degree of heterogeneity.

**Figure 14.** Spatial distribution of logging clusters using the k-means method.

Source: OLIVEIRA, 2024.

3.5. Evaluation of the Relationship between Canopy Openness and Selective Logging Intensity

Figure 15 depicts the correlation graph between the volume of timber extracted ($\text{m}^3 \text{ha}^{-1}$) by intensity class and the area of the mapped clearing. A strong correlation ($r^2 = 0.93$) is observed, confirming the hypothesis of a positive relationship between the volume of wood extracted from the forest and the area of the clearing. In other words, this suggests that there is a correlation between the spatial and spectral information extracted by SR, representing the canopy opening resulting from logging activity.

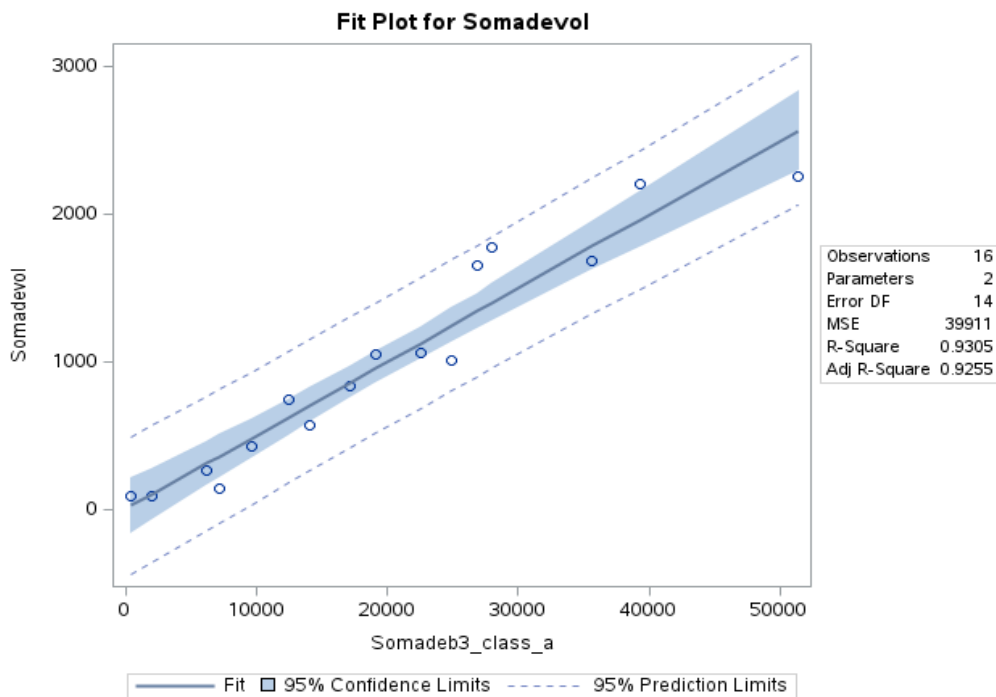


Figure 15. Positive correlation between the volume of timber extracted and the areas of clearing mapped.

Source: OLIVEIRA, 2024.

4. Discussion

The main finding of this study demonstrates that the logging intensity in SFMPs using RIL techniques in the Amazon is not uniform and follows the natural heterogeneous distribution of the stand, with high logging intensity occurring in highly stocked areas. Despite the legislation setting a maximum cutting intensity of $30 \text{ m}^3 \text{ha}^{-1}$, there are areas within the work unit that have values above this limit, and areas that have intensity values lower than this limit. However, the study indicates that areas highly stocked with timber

also exhibit higher logging intensity. One of the cells with high logging intensity (95 to 105 m³ ha⁻¹) was also the cell with the highest available volume (120 to 135 m³ ha⁻¹).

The results suggest the need to monitor forest recovery in areas with high logging intensity, to allow for the revision of forest management guidelines. This revision should consider the heterogeneous distribution of forest stands and adjust logging intensities according to the available wood stock in each management area (CHAZDON, 2008; PUTZ & REDFORD, 2009). The identification of non-uniform patterns in logging intensity indicates the necessity of developing adaptive management strategies that can be adjusted based on the specific characteristics of each management area (BERKER & FOLKE, 1998; ARMITAGE *et al.*, 2008). Understanding the heterogeneous natural distribution of forest stands and their relationship with logging intensity can contribute to promoting the sustainability and conservation of forest resources by enabling more efficient and sustainable forest management (PUTZ & ROMERO, 2020; TURNER *et al.*, 2001; PERES & LAKE, 2003).

These findings could inform new discussions regarding how legislation authorizes cutting intensity in management areas. By setting the intensity at 30 m³ ha⁻¹, the legislation does not consider the spatial heterogeneity of the distribution of forest volume evidenced in this study (PUTZ & ROMERO, 2020; LARSON & RIBOT., 2007; NASI *et al.*, 2012). The uniform application of this limit could lead managers to overexploit areas with low volume and underexploit areas with high stock. The decision to harvest is influenced by factors such as the species present, topography, or market demand for specific species or wood types. These factors can interact in complex and dynamic ways, influencing the logging strategies and intensities adopted by forest managers (SODHI *et al.*, 2010; SILLS *et al.*, 2014). The results suggest that, in addition to the criteria adopted today, such as rarity and maximum volume per authorized area, among others, the inclusion of a criterion for maximum volume or maximum number of individuals exploited per hectare could be considered, taking into account spatialization on a more refined scale, rather than for the authorized area as a whole, as is currently conducted (BRASIL, 2006). Currently, in Brazil, these criteria are defined by the Ministry of the Environment (BRASIL, 2000).

As demonstrated in this study, logging intensity is directly correlated with the available wood stock in specific areas and is more intense where stock is higher and less intense where it is lower (PUTZ *et al.*, 2012; ABDOLLAHNEJAD *et al.*, 2019). These findings are crucial for gaining a clear understanding of the spatial distribution of logging

intensity in the Amazon and for guiding future enhancements in forestry legislation (BLASER *et al.*, 2011). The results indicate that after logging, the spatial distribution of remaining volume and abundance per hectare remains proportionally similar to the original forest. It should be noted, however, that high logging intensities can leave the forest more vulnerable to collateral damage, such as forest fires (Romero *et al.*, 2021).

The heterogeneity of logging was evidenced by several factors contributing to the spatial scale. Firstly, the topography of the study area varies between plateau areas with altitudes of 200 m and lowland areas with altitudes of 50 m. It is apparent that areas farther from water bodies had the highest concentration of logging, while in areas of lower altitude and those closer to water bodies, where it is likely more difficult for heavy machinery to operate, logging was less intense. Our classification was able to clearly define the relationship between average logging intensity ($28 \text{ m}^3 \text{ ha}^{-1}$) and elevation. The spatial distribution of commercial species and their preferences for different types of soil and terrain should be considered in further analyses.

The selection of commercial species for exploitation is determined by commercial interests rather than their spatial distribution characteristics, highlighting the importance of further research in this direction. This approach can lead to unsustainable logging practices and negatively impact the genetic diversity of species populations if these factors are not considered when deciding which trees to harvest. The polycyclic forestry system with production regulation by area relies on selective logging being conducted properly. In other words, this selection stage is crucial for ensuring that viable populations can remain in managed forests (PUTZ & ROMERO, 2020; VOGT *et al.*, 1995; NEPSTA *et al.*, 2006). In addition, Romero *et al.*, (2021) points out that the productive capacity of a managed area depends on the intensity of harvesting applied by the manager and the correct use of reduced impact harvesting techniques, resulting in direct implications for climate change mitigation.

It is widely recognized that biomass and floristic composition are naturally influenced by relief and soil type (HIGUCHI *et al.*, 1981; ABDOLLAHNEJAD *et al.*, 2019). Based on forest inventories conducted by INPA in the 1980s, significant differences in basal area were observed because of relief variation. Samples taken on plateaus exhibited wood volumes of up to $210 \text{ m}^3 \text{ ha}^{-1}$, with 155 different species and a density of 155 to 170 trees ha^{-1} , for DBHs greater than 25 cm. In contrast, samples in flat areas, but at lower elevations, showed values of $136 \text{ m}^3 \text{ ha}^{-1}$, with 95 botanical species and a tree density of 135 trees ha^{-1} (CARVALHO & PORROTA, 2017). The

PROFLAMA, in an inventory also conducted in this area, observed a similar difference in volume (PROFLAMA, 1972).

Cluster analysis indicates that the topography of the site is a determining factor in the spatial arrangement and exploitation of the commercial species selected by the manager (FERRETTI *et al.*, 2020). Hartemink *et al.*, (2016) discusses soil geography and classification, including soil texture variation in different landscapes and its influence on the spatial distribution of species, ecological dynamics, and sustainable management of forest ecosystems. These results demonstrate a progressive differentiation in volume as one move down the relief positions. Denser forests with a greater volume of larger trees are observed on the plateaus. Intuitively or not, logging followed this pattern throughout the area, aligning with the natural distribution of the stand.

To reinforce this, the study enabled a direct comparison between the conditions before and during logging. The graphs in Figure 16 illustrate that the forest before logging resembled the logged forest. This indicates that logging adhered to the natural distribution of the forest. (Figure 16).

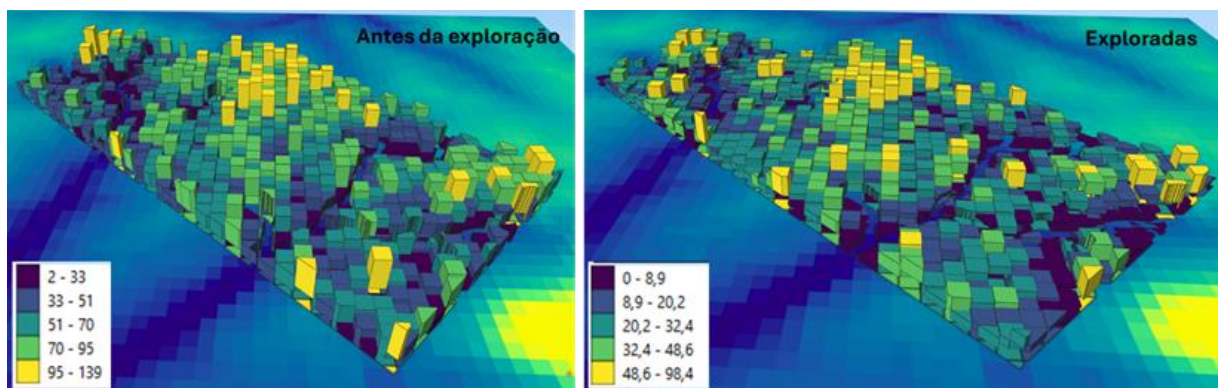


Figure 16. 3D representation of the volume before logging and of the trees actually logged ($\text{m}^3 \text{ha}^{-1}$).

Source: OLIVEIRA, 2024.

Understanding that the Brazilian government has implemented forest management across more than 220 million hectares in the Amazon, it is crucial to emphasize the necessity of developing metrics and monitoring methods that consider the forest's heterogeneity and the specific distribution of individuals and volume in each area. This includes assessing the remaining stock to inform potential future interventions, such as cutting cycles (BARRETO *et al.*, 2006; VERISSIMO *et al.*, 2011; SAWYER & SAWYER, 2018).

It is important to note that relying solely on reduced impact logging (RIL) does not ensure the sustainability of forest management (PUTZ *et al.*, 2008). For timber production to truly contribute to conservation efforts, additional measures must be implemented (CHAZDON & GUARIGUATA, 2016). Our methodology was instrumental in evaluating changes in the spatial distribution of commercial tree volume and abundance before, during, and after logging in concession areas. By utilizing simple inventory data and remote sensing imagery within a geographic information system, our approach shows promise in supporting effective and sustainable forest management in the Amazon.

Spatial and temporal analyses conducted within standardized cells, along with cluster analyses, proved to be effective in examining the spatial distribution and changes in forest structure within forest concession areas in the Brazilian Amazon. It is important to note that our study focused exclusively on public concession areas, as logging areas within private sustainable forest management plans were not included. This limitation should be considered, since public concession areas represent only a fraction of forest logging activities in the Amazon (VIDAL *et al.*, 2020).

The study was centered on a single public concession area and may not fully represent logging practices across the entire Amazon region. Specifically, it focused on a particular area within FMU II (TUs 3 and 4) and exclusively examined spatial and temporal characteristics related to commercial volume and tree occurrence per hectare in aggregated form.

It is important to acknowledge that the data analyzed originates from a commercial inventory, focusing solely on species of economic value to the concessionaire. Therefore, it does not encompass the entire population of species within the area. Additionally, while the study area is situated in a region with a rich history of human presence, including communities such as quilombolas and indigenous peoples with deep connections to the forest, social and cultural factors were not incorporated into the analysis.

The expectation is that the findings of this study will encourage forest concessions to adopt the methodology proposed here, thereby aiding in the management of forest exploitation in the Amazon. Additionally, it is recommended that the methods employed to assess the impacts of logging and the forest's capacity for recovery, such as permanent plots, consider the insights provided by this study.

5. Conclusions

Logging within the forest management area in the study exhibits heterogeneity in terms of the spatial distribution of logging intensity, encompassing both commercial volume and abundance. In this study's conditions, logging intensity aligned with the natural distribution of the forest, where the largest stocks were proportionally more exploited, and the greatest logging intensity occurred in areas with a greater stock of available timber. We recommend that managers consider this forest heterogeneity for forest exploitation using RIL techniques.

These findings hold significant implications for forest management and suggest constant monitoring in highly exploited areas and future improvements to current regulations to develop adaptive and more nuanced management strategies and foster the sustainability and conservation of forest resources.

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CHAPTER IV - Monitoring System For Sustainable Forest Management Plans In The Amazon: Integration Of Lidar Data And Planetscope Imagery³

Abstract: The growing pressure on natural resources in the Amazon underscores the need for sustainable forest management practices that balance the economic use of forest resources with environmental conservation. Sustainable Forest Management Plans (PMFS) aim to exploit timber resources while minimizing the impacts of selective logging. However, illegal logging and overly generic classifications undermine the reliability and economic feasibility of PMFS activities, necessitating improved monitoring and control to ensure their sustainability. This study proposes the integration of LiDAR data and PlanetScope imagery to enhance monitoring of forest disturbances caused by selective logging in the Amazon. LiDAR mapping detected 15.5% of the total impacted area, compared to 13.7% detected by PlanetScope. LiDAR achieved higher accuracy in detecting subtle structural changes, such as small clearings (<0.2 ha). Globally, PlanetScope mapping underestimated the total area of clearings, identifying 63.3 ha, whereas LiDAR detected 113.8 ha. The global accuracy of PlanetScope mapping was moderate ($P = 0.62$) with low recall ($R = 0.41$), indicating significant underestimation of disturbed forest areas. Metrics such as the global F1-Score (0.50), IoU (0.33), and relatively high RMSE (50.51) further highlight the differences between the two methods. Despite these limitations, PlanetScope mapping was more effective than systems like DETER and SAD in detecting clearings smaller than 1 ha, while LiDAR excelled in identifying small-scale vertical canopy changes. The integration of these technologies provides more precise and reliable data, strengthening sustainable forest management monitoring and offering critical insights to inform public policies for the Amazon forest sector.

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Keywords: forest disturbance; selective logging; monitoring system; change detection.

Resumo: A crescente pressão sobre os recursos naturais na Amazônia impõe a necessidade de práticas de manejo florestal sustentável com potencial de conciliar o aproveitamento econômico de recursos florestais e a conservação ambiental. O objetivo principal do Plano de Manejo Florestal Sustentável (PMFS) é aproveitar os recursos florestais madeireiros, minimizando os impactos da exploração seletiva de madeira. Entretanto, a ilegalidade na exploração madeireira ameaça economicamente as atividades florestais conduzidas sob PMFS, requerendo maior efetividade no monitoramento e controle da clandestinidade na atividade florestal para viabilizar economicamente o PMFS. No presente estudo, propõem-se a integração de dados LiDAR e imagens PlanetScope como alternativa para aprimorar o monitoramento dos distúrbios florestais causados pelas atividades de extração seletiva de madeira na Amazônia. Os resultados indicam que o mapeamento com dados LiDAR possibilitou a detecção de 15.5% da área total impactada pela exploração seletiva de madeiras, enquanto o mapeamento usando dados PlanetScope possibilitou a detecção de 13.7%. A maior exatidão do mapeamento alcançada com dados LiDAR em alterações estruturais sutis na floresta, tais como pequenas clareiras (<0,2 ha). A análise global aponta que o mapeamento usando dados PlanetScope subestimou o total de clareiras, detectando corretamente um total de 63,3 ha, enquanto o mapeamento usando dados LiDAR detectou um total de 113,8 ha. Como consequência, a acurácia global foi moderada ($P = 0,62$) e o recall baixo ($R = 0,41$), indicando expressiva subestimação das florestas como perturbadas. O F1-Score global (0,50) e o índice IoU (0,33), aliados a um RMSE relativamente alto (50,51), reforçam as diferenças observadas entre os métodos de mapeamento analisados. O mapeamento PlanetScope foi considerado mais eficaz que sistemas como DETER, SAD e GLAD na detecção de clareiras menores que 1 hectare na floresta, enquanto o LiDAR se destacou pela sensibilidade a alterações verticais e de pequena escala no dossel florestal. A integração dessas tecnologias oferece dados mais exatos e precisos, essenciais para fortalecer o monitoramento do manejo florestal sustentável e embasar políticas públicas para o setor florestal na Amazônia.

Palavras-chave: distúrbio florestal; exploração seletiva, sistema de monitoramento.

1. Introduction

The Amazon is recognized as the world's largest tropical forest, playing a crucial role in global climate regulation and biodiversity maintenance (MALHI *et al.*, 2008; LOVEJOY & NOBRE, 2019). However, increasing pressure on natural resources has heightened the need for forest management practices that balance economic exploitation with environmental preservation (GUARRIDO FILHA, 2002; RODRIGUES *et al.*, 2020).

The Sustainable Forest Management Plan (PMFS) is a viable strategy that ensures the rational use of forest resources and seeks to minimize the negative impacts of selective logging (BRASIL, 2006; ÂNGELO *et al.*, 2014). However, the effective implementation and monitoring of these plans have faced significant challenges, particularly concerning the precision, the detection of illegal or inefficient management practices, and the accurate classification of current monitoring systems (GUARRIDO FILHA, 2002; OLIVEIRA *et al.*, 2024).

With advancements in remote sensing (RS) technologies, the development of a detection and monitoring system utilizing high spatial and temporal resolution imagery to track sustainable forest management (SFM) activities in real-time in the Amazon has become increasingly feasible (ASNER *et al.*, 2005; ZEFERINO *et al.*, 2023; WAGNER *et al.*, 2023; OLIVEIRA *et al.*, 2024).

The advancement of these technologies, particularly the development of nanosatellites, has revolutionized environmental monitoring, making it more accessible, comprehensive, and precise (PETRI *et al.*, 2022; OLIVEIRA *et al.*, 2024). Among the most promising solutions are *PlanetScope* images, provided by a constellation of high-resolution nanosatellites managed by Planet Labs (OLIVEIRA *et al.*, 2024). These images play a strategic role in forest management monitoring, enabling the high-frequency temporal tracking and excellent spatial resolution of vegetation cover changes, the opening of clearings, and compliance with sustainable management plans (PETRI *et al.*, 2022; DALAGNOL *et al.*, 2023; OLIVEIRA *et al.*, 2024).

The adoption of spectral mixture models (SMM) for processing these images enables a more detailed analysis of forest cover composition, identifying subtle variations caused by selective logging (ZEFERINO *et al.*, 2023; OLIVEIRA *et al.*, 2024). The soil fraction represents the relative proportion of exposed soil within an image pixel (SHIMABUKURO & SMITH, 1991). In the context of forest monitoring, the model

provides critical indicators of clearing openings, vegetation removal, and changes in the forest canopy (DINIZ *et al.*, 2015). For instance, during selective logging operations, an increase in the soil fraction indicates ground exposure due to tree removal or machinery movement. This indicator is particularly useful in densely forested tropical regions, where vegetation typically dominates the landscape, making exposed soil a distinctive feature of impacted areas.

The use of LiDAR (*Light Detection and Ranging*) technology is another promising approach to enhance the monitoring of SFM in the Amazon (HUDAK *et al.*, 2002; LOKS & MATRICARDI, 2019; XU *et al.*, 2021; WINSTALEY *et al.*, 2024). LiDAR provides high-precision three-dimensional data on forest structure, enabling detailed analysis of parameters such as tree height (Canopy Height Model - CHM), canopy density, and biomass volume (XU *et al.*, 2021; WINSTALEY *et al.*, 2024). This information is critical for validating remote sensing data and detecting subtle disturbances in forest structure caused by selective logging practices (LOKS & MATRICARDI, 2019; SPARKS & SMITH, 2021; WINSTALEY *et al.*, 2024).

Additionally, LiDAR enables the creation of Digital Terrain Models (DTM) and Digital Surface Models (DSM), which aid in detecting human interventions such as roads and clearings. These capabilities contribute to a more comprehensive and effective monitoring of PMFS (WINSTALEY *et al.*, 2024).

In the present study, we evaluated the methodology and presented the results of applying an alert system using integrated LiDAR and PlanetScope data. By combining high-resolution optical imagery, LiDAR and field data, and digital image classification methods, this system provides more detailed, precise, and accurate information to support the monitoring and enforcement of forest activities in the Amazon. This approach ensures forest resource conservation while enabling efficient management and the sustainable use of forests.

2. Material and Methods

2.1. Study Area

The analyses were conducted in the eastern portion of the Saracá-Taquera National Forest (Flona), Pará state, specifically in Forest Management Unit II (FMU II). In SFM, the FMU represents the designated portion of the property for forest management. The forest area managed annually is referred to as the Annual Production Unit (APU), which may contain one or more timber unit (TU). The TU is the delimited

area for active logging activities. For this experiment, TU 3 and 4 of APU 11 were selected, corresponding to an area of 735 hectares, including regions within the hydrographic network under analysis (Figure 01).

The Saracá-Taquera National Forest is covered by tropical forest, with variations generally associated with geomorphological features. The local vegetation can be classified as Dense Ombrophilous Forest in both Submontane and Lowland formations. It is characterized by two distinct strata: an emergent layer dominated by *Dinizia excelsa* and *Cedrelinga cateniformis*, and a uniform layer with species such as *Manilkara spp.*, *Protium spp.*, and *Pouteria spp.* (IBGE, 2012). The two primary vegetation types, Submontane and Lowland, occupy 94.1% of the Flona area. Pioneer formations influenced by fluvial processes account for 2.7%, and campinarana vegetation covers 0.2%. Primary natural vegetation represents 97% of the Flona's vegetation cover, while areas impacted by human activities account for 2% of the total area (ICMBIO, 2015).

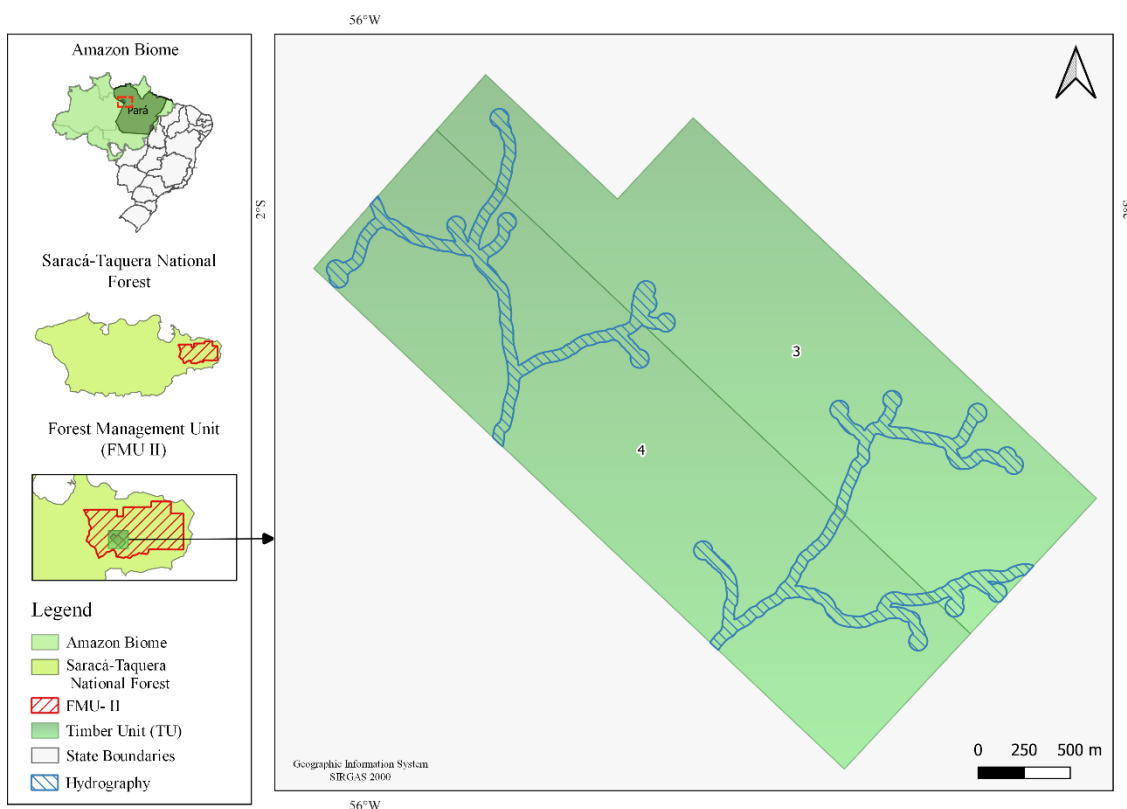


Figure 01. Location of the study area in the Saracá-Taquera National Forest, Pará state, Amazon biome.

Source: OLIVEIRA, 2024.

2.2 Execution Flowchart Details

The alert generation process involves two complementary approaches: the use of PlanetScope imagery and LiDAR data, each with specific methodologies to identify changes in forest cover (gaps). Below, in Figure 02, is a detailed explanation of each step, as well as the metrics used to evaluate the precision and accuracy of the mapping.

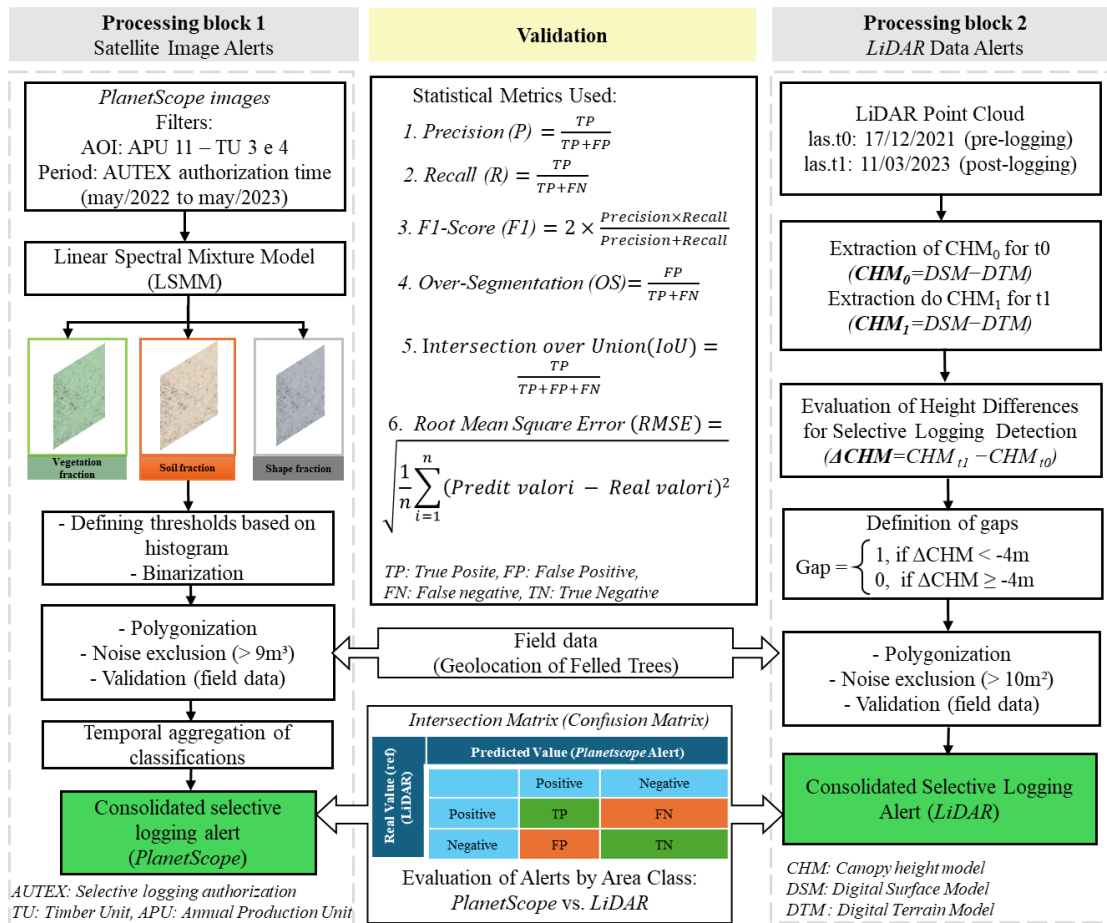


Figure 02. General flowchart of the methodology for the detection system of forests impacted by selective logging activities in the Saracá-Taquera National Forest, Pará state

Source: OLIVEIRA, 2024.

2.2.1 PlanetScope Images and Alert Generation (Block 1)

Block 1 in Figure 2 presents the process of using PlanetScope images processed through the Linear Spectral Mixture Model (LSMM), which enabled the calculation of vegetation, shadow, and soil fraction of images in the study area. The PlanetScope constellation consists of several launches of individual satellite groups (DOVEs), including a constellation of 3U CubeSats (10 × 10 × 30 cm) with over 120 active DOVEs.

These sensors operate in at least four spectral bands: blue (455–515 nm), green (500–590 nm), red (590–670 nm), and near-infrared (780–860 nm), with a spatial resolution of 3 meters and a radiometric resolution of 12 bits (PETRI *et al.*, 2022). Table 1 presents the images used in the classification.

Table 1. PlanetScope images used for generating selective logging alerts in the Saracá-Taquera National Forest, Pará state.

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20220927_134541_10_2498_3B_Analytic MS_SR_8b	70,50	57,80	1,00	30/08/20 22	Durante
20221208_131040_46_2427_3B_Analytic MS_SR_8b	123,60	48,70	2,90	08/12/20 22	Após

Source: OLIVEIRA, 2024.

From the soil fraction image, empirical thresholds were defined based on the frequency histogram and binarization, enabling the identification of areas with changes in forest cover. After classification, the identified areas were polygonized, followed by the exclusion of noise (individual polygons of $3 \times 3 \text{m} - 09 \text{m}^2$). Subsequently, the data were checked and validated through visual interpretation. Finally, the temporal classifications were aggregated, resulting in a consolidated alert of the detected changes over the entire period.

2.2.2 LiDAR Point Cloud and Alert Generation (Block 2)

LiDAR is a RS technology that uses light pulses to measure distances and create highly detailed three-dimensional representations of the Earth's surface and its cover. This study utilized LiDAR data acquired at two distinct times: pre-logging (t_0 , on 12/17/2021) and post-logging (t_1 , on 03/11/2023). Table 2 presents the details of the LiDAR data acquisition used for the clearing detection analyses.

Table 2. Acquisition details of airborne LiDAR data used for tree loss analyses.

Information	LiDAR Date 1 (Before)	LiDAR Date 2 (After)
Sensor	OPTECH/ GEMINI/07SEN213	OPTECH/ ORION M300/13SEN324
Capture Time	17/12/2021	11/03/2023
Acquisition Altitude	700 m	700 m
Scanning Frequency	57 kHz	64 kHz
Scan Angle	15°	15°
Data Type and Spatial Resolution	Point cloud (x, y, z) with 34.47 points/m ²	Point cloud (x, y, z) with 53.08 points/m ²

Source: OLIVEIRA, 2024.

The collected data were processed to generate three types of digital models: i) DSM (Digital Surface Model), which represents the total height of the terrain, including vegetation and artificial structures; ii) DTM (Digital Terrain Model), which reflects only the ground height, excluding vegetation and structures; and iii) CHM (Canopy Height Model), obtained by subtracting the DTM from the DSM, representing vegetation height.

The variation in vegetation height between periods was calculated based on the difference between CHM models, enabling the identification of areas with significant height loss ($\Delta\text{CHM} < -4$ m), classified as clearings (gaps). Detected clearing areas were polygonized, subjected to noise filters (excluding areas smaller than 10 m²), and validated with field data (felled trees), ensuring the accuracy and reliability of this technology for mapping assessments. These data were used as a reference for validating the alerts generated from PlanetScope imagery.

2.2.3 Field Data (Geolocation of Felled Trees)

Pre-exploratory inventory data for commercially valuable tree species, as well as inventory data for trees actually harvested, were provided by the Brazilian Forest Service (SFB) in the form of an electronic spreadsheet (.xlsx format). The SFB is the agency responsible for managing forest concessions for sustainable forest management in public forests within the Amazon.

The SFB also provided the post-exploratory forest report for UPA 11, which included geospatial information for all inventoried commercial trees, along with an additional column containing the logging dates for each tree. The volume extracted from each felled tree was used to evaluate the accuracy and reliability of the monitoring system.

2.2.4 Validation and Accuracy

An intersection matrix was constructed to compare the selective logging alerts detected by the *LiDAR* method (reference) and PlanetScope. The matrix contains four elements: i) True Positives (TP) - areas correctly identified as logged; ii) False Positives (FP) - areas incorrectly identified as logged (false alert); iii) True Negatives (TN) - areas correctly identified as not logged; and iv) False Negatives (FN) - areas that should have been identified as logged but were not.

The geolocation of felled trees was intersected and counted within each element (TP, FP, FN, and TN) and categorized by area size intervals to assess the spatial reliability

and accuracy of the mapping based on the size of the detected polygons (Figure 3). The validation of alerts generated by both methodologies was initially performed using the geolocation of felled trees through the correlation between the mapped alert area and the volume of wood extracted ($\text{m}^3/\text{ha}^{-1}$).

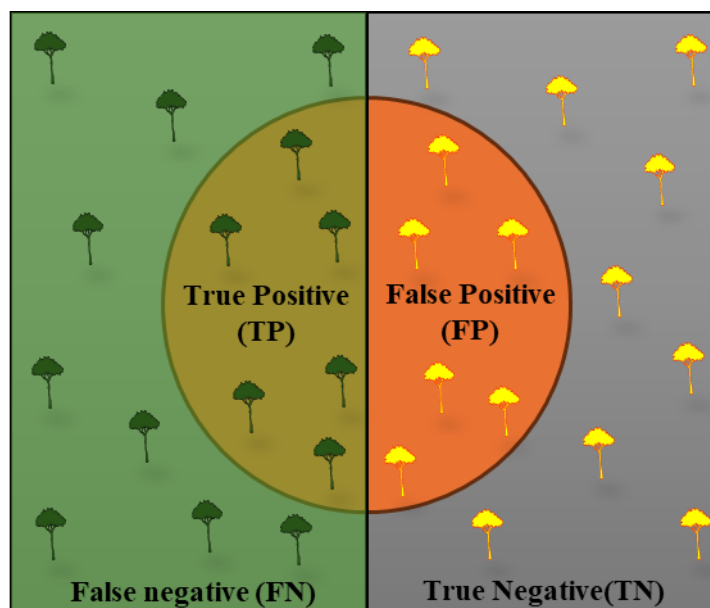


Figure 3. Evaluation criteria for the reliability and accuracy of forest disturbance detections based on felled trees.

Source: OLIVEIRA, 2024.

To evaluate the accuracy of the PlanetScope alerts, an intersection matrix was used to compare the predicted results (PlanetScope alerts) with the reference data (LiDAR). The statistical metrics used to assess the mapping accuracy are presented in Table 3 and are employed to quantify the methods' accuracy and ensure the reliability of the results.

Table 3. Statistical metrics used to evaluate the precision and accuracy of the mappings.

Metric	Formula	Description
Precision (P)	$\frac{TP}{TP+FP}$	Measures the proportion of correct classifications among all positive classifications. TP: True Positives, FP: False Positives
Recall (R)	$\frac{TP}{TP+FN}$	Measures the proportion of true positive areas correctly identified. FN: False Negatives
F1-Score (F1)	$2 \times \frac{Precision \times Recall}{Precision + Recall}$	Combines precision and recall into a single balanced metric.
Over-Segmentation (OS)	$\frac{FP}{TP+FN}$	Evaluates the proportion of false positives relative to the detected areas.

Intersection over Union (IoU)	$\frac{TP}{TP+FP+FN}$	Measures the overlap between the detected areas and the real areas.
Root Mean Square Error (RMSE)	$\sqrt{\frac{1}{n} \sum_{i=1}^n (\text{Predict Value}_i - \text{Real Value}_i)^2}$	Evaluates the average difference between predicted values and real values.

Source: OLIVEIRA, 2024.

3. Results

3.1 Correlation between the mappings and the effectively felled trees

Figure 4 shows the correlation between the volume of wood extracted and the respective areas mapped by both systems. While the correlation of wood volume with PlanetScope alerts is moderate ($r^2=0.7$) (a), there is a high correlation with LiDAR alerts ($r^2=0.9$) (b). The high correlation between the volume of wood extracted and LiDAR data demonstrates that this mapping provides greater accuracy for detecting areas impacted by logging. Therefore, it confirms the viability of this technology for evaluating the accuracy of mapping using PlanetScope images.

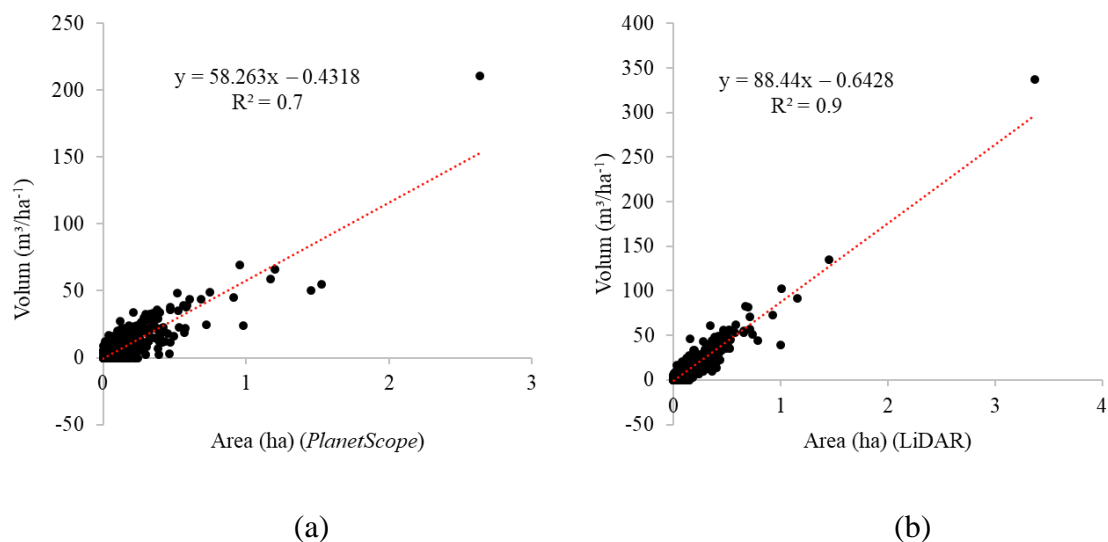


Figure 4. Correlation between the volume of wood extracted and the respective mapped areas (ha) using PlanetScope (a) and LiDAR data (b).

Source: OLIVEIRA, 2024.

3.2 PlanetScope Images Classification

Figure 5 presents the results of mapping using PlanetScope images, highlighting the classification of disturbances caused by selective logging identified through the Linear Spectral Mixture Model (LSMM). The mapping of impacted areas, highlighted in red on the map, totaled 100.91 hectares, representing 13.69% of the total area. Figure 5 also includes photos taken from different perspectives in the study area, showcasing the changes in the landscape.

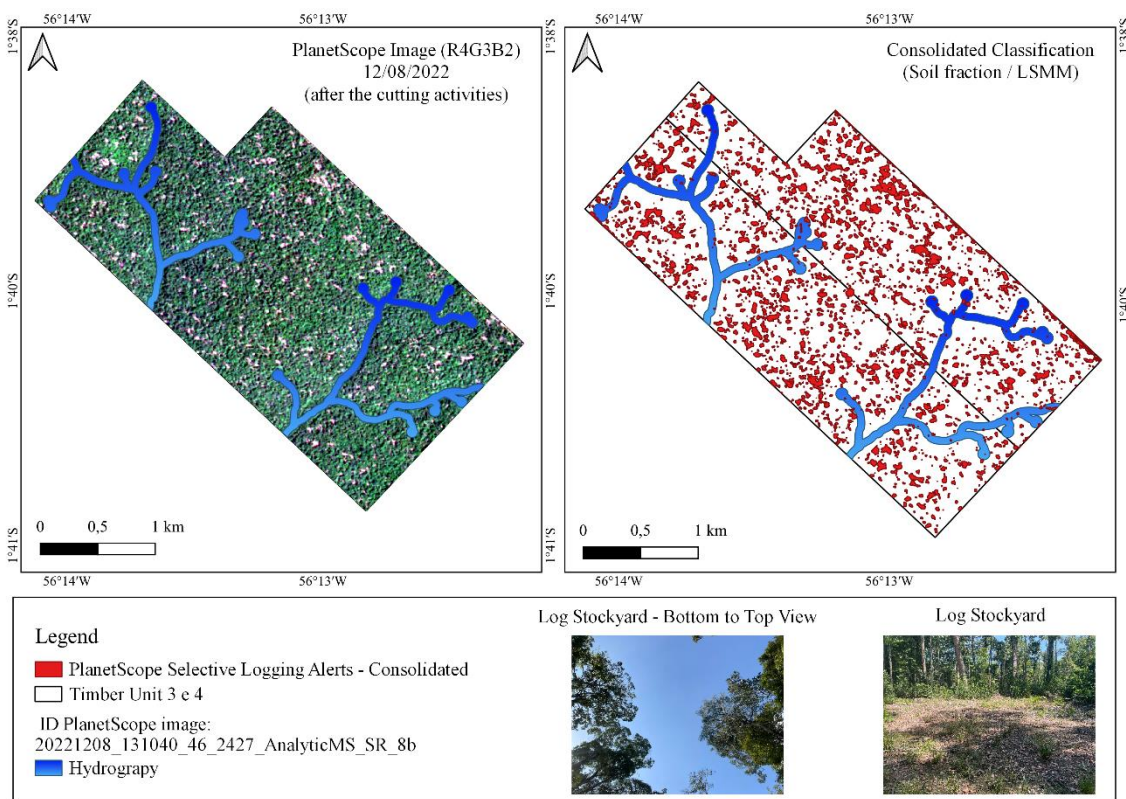


Figure 5. PlanetScope RGB color image and LSMM classification results of areas impacted by logging activities

Source: OLIVEIRA, 2024.

3.3 Classification with LiDAR Data

Figure 6 presents the results of canopy height monitoring before and after selective logging, based on Canopy Height Models (CHM). The Pre-Logging CHM, derived from data collected on 17/12/2021, represents the original vegetation structure, with heights ranging from 0 to 60 meters. Yellow regions indicate taller canopies, while dark blue areas reflect the absence of cover or low vegetation.

The Post-Logging CHM, dated 03/11/2023, highlights changes in canopy structure caused by selective logging. The differential map ($\Delta\text{CHM} = \text{CHM}_{t1} - \text{CHM}_{t0}$) emphasizes areas with canopy height reductions, with red areas indicating a loss greater than 4 meters ($\Delta\text{CHM} < -4 \text{ m}$), while areas with no significant change ($\Delta\text{CHM} \geq -4 \text{ m}$) appear in white. Enlarged circles detail the impacted regions.

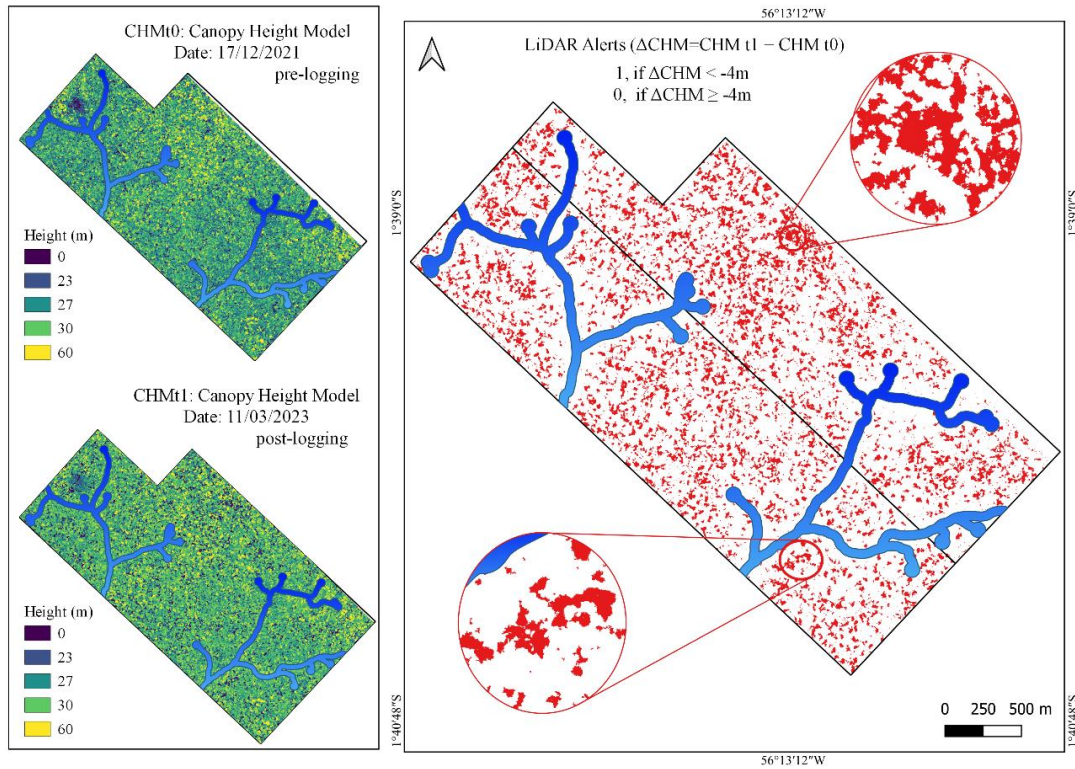


Figure 6. Forest disturbance alerts mapped through differences in LiDAR data before and after logging.

Source: OLIVEIRA, 2024.

The mapping conducted with LiDAR data identified a total of 113.77 hectares impacted by selective logging, representing an increase of 13.16 hectares compared to the mapping using PlanetScope images and 15.48% of the total area.

3.4 Comparison of LiDAR and PlanetScope Classifications

Figure 7 presents the results of forest disturbance detection using PlanetScope data, based on the Linear Spectral Mixture Model (LSMM), and LiDAR data, through differential canopy height analysis (ΔCHM).

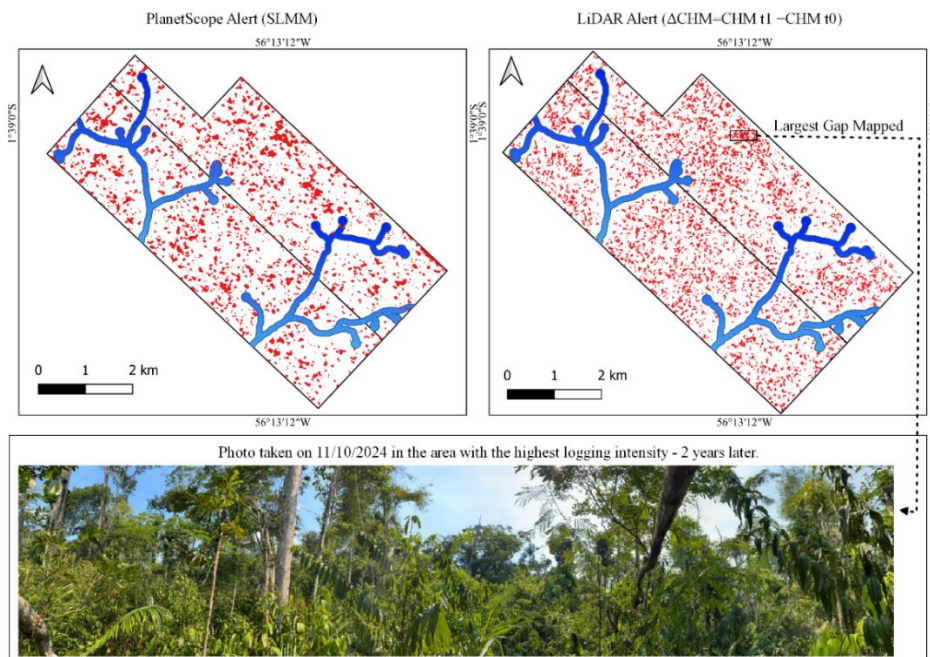


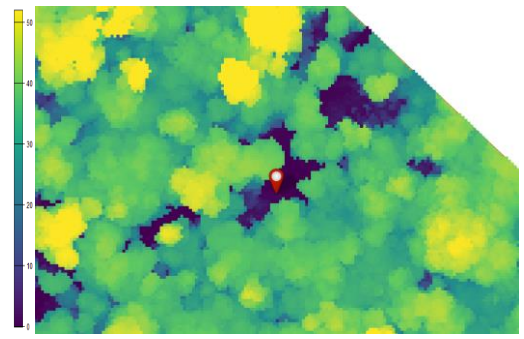
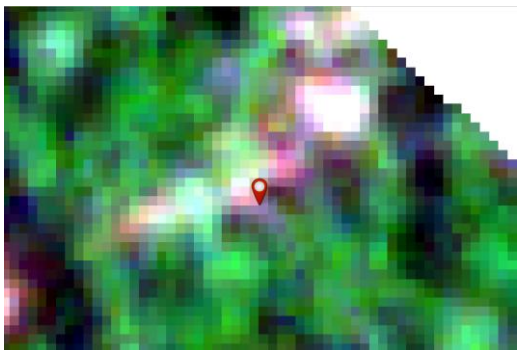

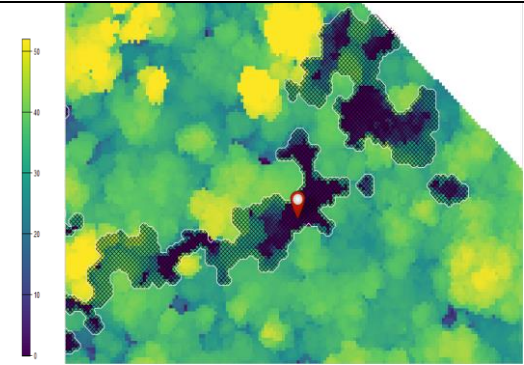
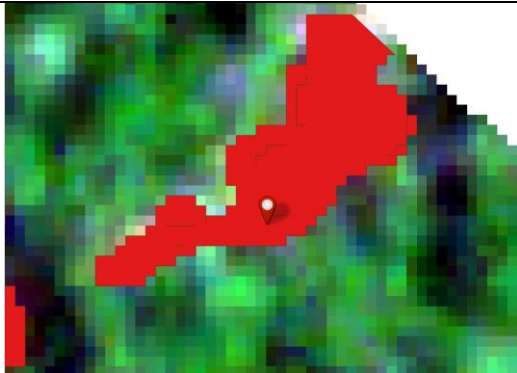

Figure 7. Comparative analysis of forest disturbance mapping results using *PlanetScope* and *LiDAR* data in the Saracá-Taquera National Forest, Pará state.

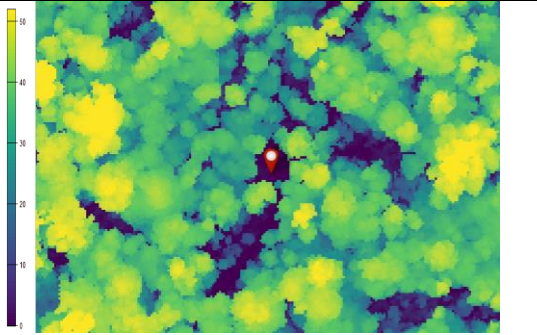
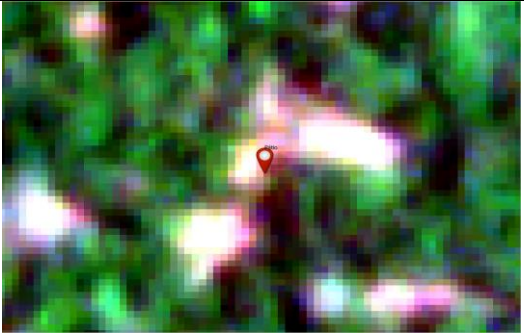

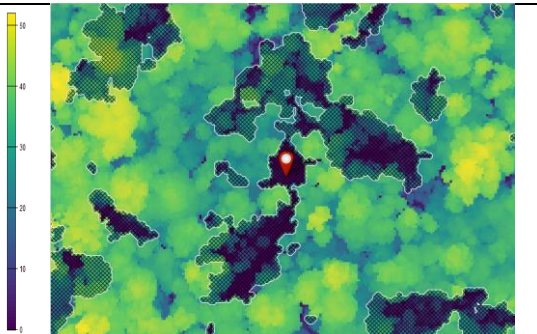
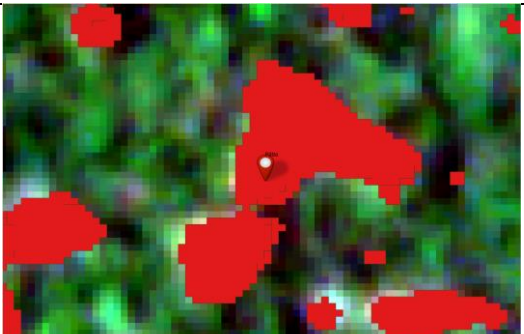

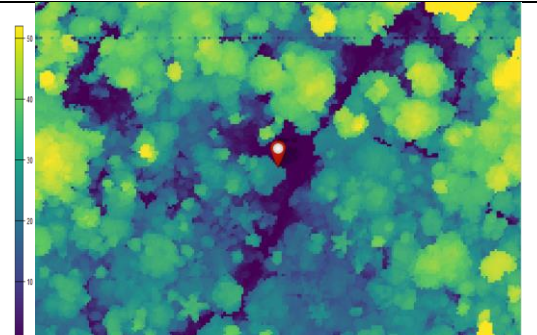
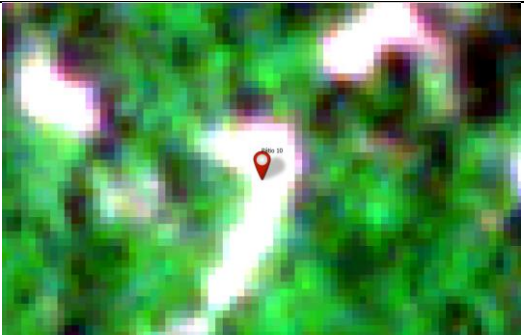

Source: OLIVEIRA, 2024.

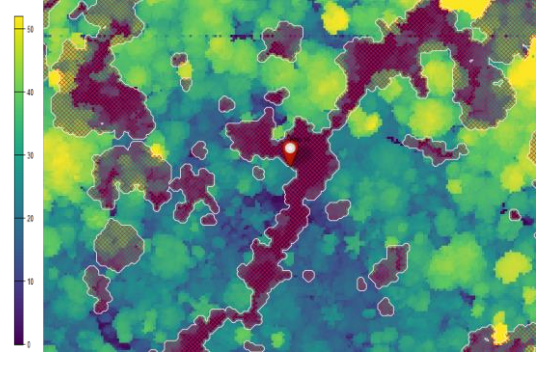
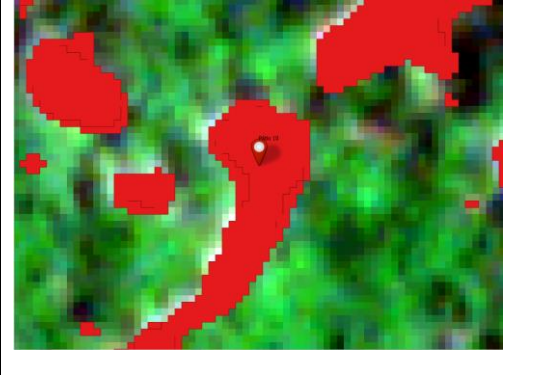

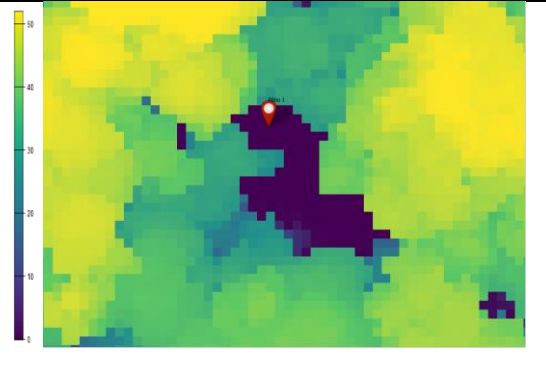
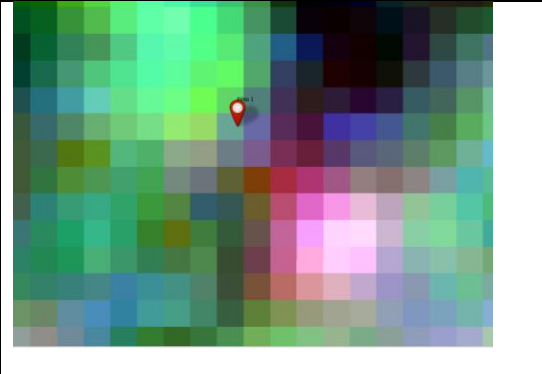

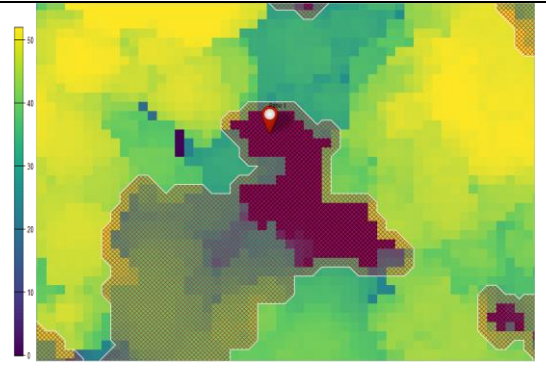
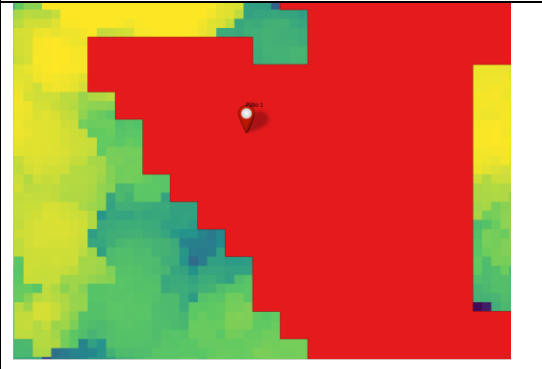

The detection using PlanetScope data (LSMM) identified disturbance areas based on the spectral response of exposed soil, dry vegetation, and other targets detected by the optical sensor. As a result, it highlights a smaller extent of impacted areas, totaling 100.61 hectares, due to limitations in detecting low-intensity changes that do not produce prominent visual responses in the imagery. The detection using LiDAR data (ΔCHM) reveals disturbance areas based on the reduction in canopy height ($\Delta\text{CHM} < -4$ m), thereby detecting a larger extent of impact, totaling 113.77 hectares, including areas where tree removal caused structural changes not perceptible in optical images. The illustrative photo, presented in Figure 7, was captured on 11/10/2024, in the area with the highest logging intensity, two years after the impact.

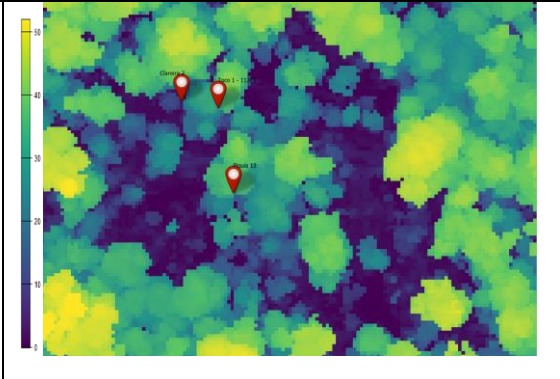


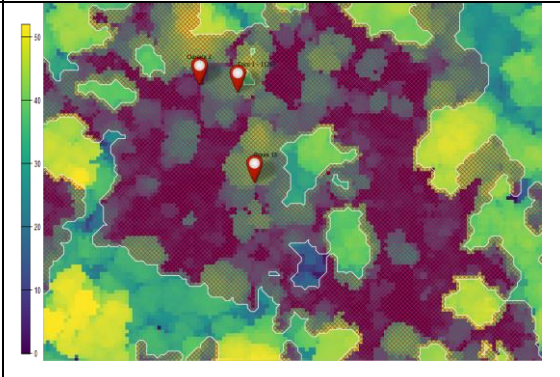

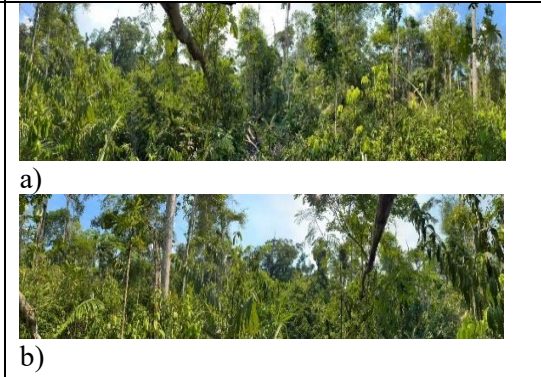
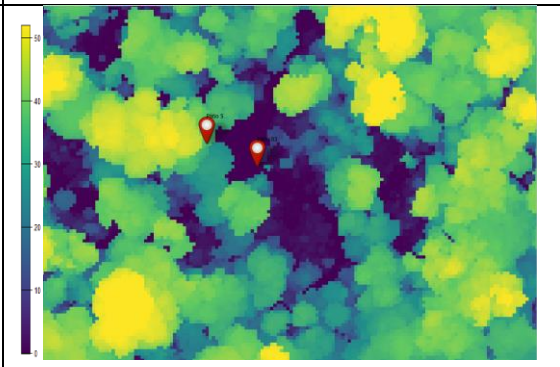
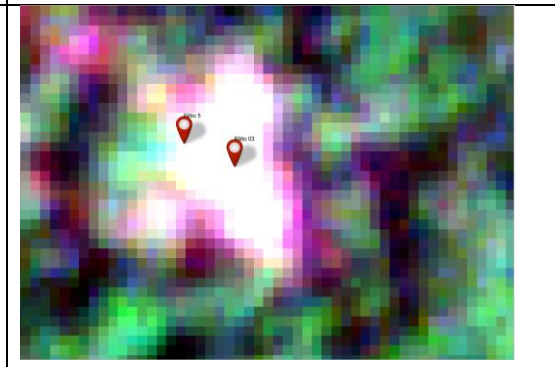

To evaluate the differences in mapping using the two data acquisition technologies in greater detail, Table 4 presents some areas that were validated and inspected in situ on 11/10/2024. During the field visits, it was observed that the most exploited areas exhibited the largest clearings, with exposed soil, forest residues, and canopy openings, confirming the accuracy of LiDAR mapping in detecting structural changes. In contrast, less exploited areas showed smaller clearings, which were often underestimated in the PlanetScope mapping due to the absence of three-dimensional data. The following photos highlight these differences, emphasizing the need to integrate both technologies for more comprehensive and effective analyses, which are essential for sustainable management.

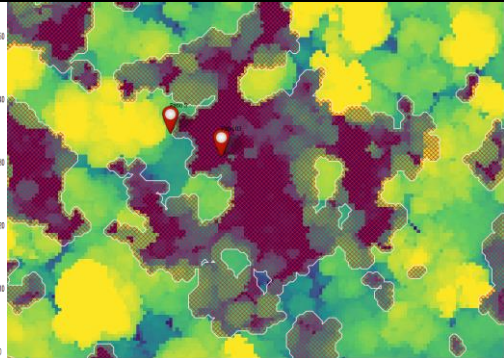


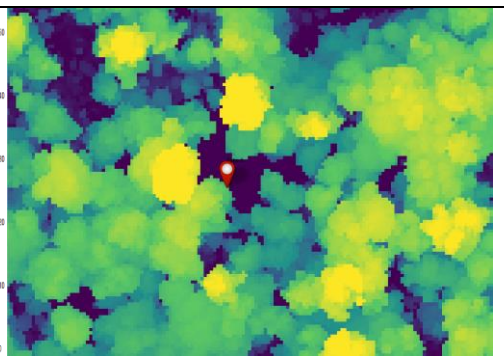
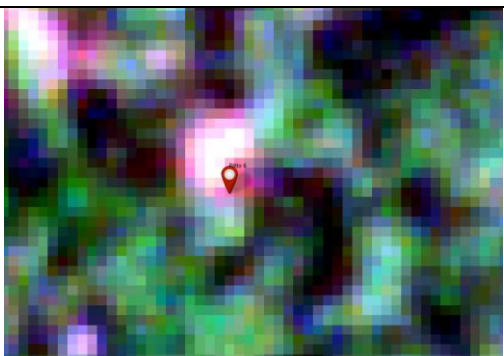

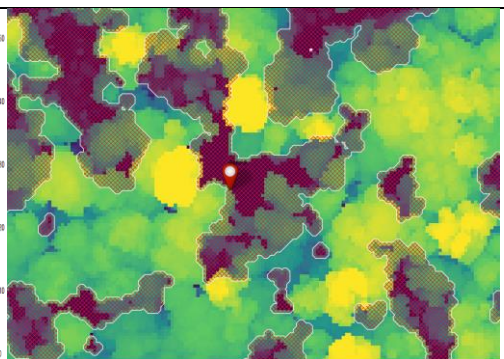
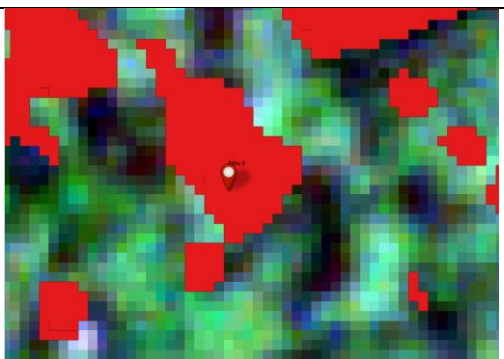

Table 4. Comparison between LiDAR and PlanetScope mappings and field photographs for visual inspection

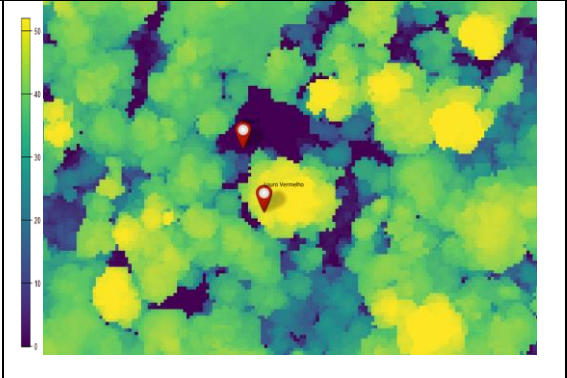


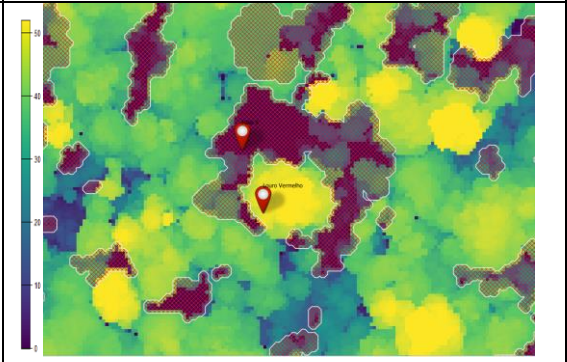
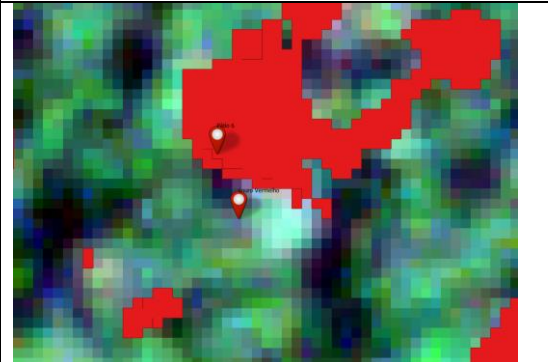

	LiDAR	PlanetScope	Photograph	Description
Image				<p><u>Stockyard 01</u></p> <p>Lat: -1.644761, Long: 56.233303</p> <p>Photo Orientation : 221176 SW</p>
Alert				<p><u>Stockyard 01</u></p> <p>Lat: -1.644831, Long: 56.233267</p> <p>Photo Orientation : 305176 NW</p>

<p>Image</p>				<p><u>Stockyard</u> <u>02</u></p> <p>Lat: - 1.646558, Long: 56.234553</p> <p>Photo Orientation: 128176 SE</p>
<p>Alert</p>				<p><u>Stockyard</u> <u>2</u></p> <p>Lat: - 1.646533, long: 56.234572</p> <p>Photo Orientation: 291176 WNW</p>
<p>Image</p>				<p><u>Stockyard</u> <u>03</u></p> <p>Lat: - 1.648361, Long: 56.236128</p> <p>Photo Orientation: 161176 SSE</p>

Alert				<p><u>Stockyard</u> <u>03</u></p> <p>Lat: - 1.648369, long: 56.236147</p> <p>Photo Orientation: 29176 NNE</p>
Image				<p><u>Stockyard</u> <u>04</u></p> <p>Lat: - 1.650739, Long: 56.220733</p> <p>Photo Orientation: 122176 ESE</p>
Alert				<p><u>Stockyard</u> <u>04</u></p> <p>Lat:- 1.650706, Long: 56.220781</p> <p>Photo Orientation: 120176 ESE</p>

<p>Image</p>				<p><u>Harvested Tree</u></p> <p>Lat: - 1.651272, Long: 56.220161</p> <p>Photo Orientation: 87176 E</p>
<p>Alert</p>				<p><u>Clearing</u></p> <p>Lat: - 1.651278, Long: 56.220161</p>
<p>Image</p>				<p><u>Stockyard 05</u></p> <p>Lat: - 1.652769, Long: 56.221225</p> <p>Photo Orientation: 14176 NNE</p>

Alert				<p><u>Stockyard 05</u></p> <p>Lat: - 1.652806, 56.221253</p> <p>Photo Orientation: 315176 NW</p>
Image				<p><u>Stockyard 06</u></p> <p>Lat: - 1.654106, Long: 56.223081</p> <p>Photo Orientation: 338176 NNW</p>
Alert				<p><u>Stockyard 06</u></p> <p>Lat: 1.654106, Long: 56.223078</p> <p>Photo Orientation: 96176 E</p>

<p style="writing-mode: vertical-rl; transform: rotate(180deg);">Image</p>				<p><u>Stockyard</u> <u>07</u></p> <p>Lat: -1.655678, Long: 56.223925</p> <p>Photo Orientation: 28176 NNE</p>
<p style="writing-mode: vertical-rl; transform: rotate(180deg);">Alert</p>				<p><u>Stockyard</u> <u>07 –</u></p> <p>Lat: 1.655678, Long: 56.223953</p> <p>Photo Orientation: 285176 WNW</p>

Source: OLIVEIRA, 2024.

3.5 Analysis in Relation to Harvested Trees

Table 5 presents the evaluation of mapping data based on FN (False Negatives), FP (False Positives), and TP (True Positives) metrics, considering the number of trees and the volume of wood (in m³) across different polygon size intervals (alert size ranges). It provides insights into the detection system's performance.

Table 5. Evaluation of FN, FP, and TP by alert polygon size, considering the number of trees and the corresponding volume of wood (m³) effectively harvested.

Intervals (ha)	FN		FP		TP	
	n° trees.	vol (m ³)	n° trees	vol (m ³)	n° trees	vol (m ³)
1- (0-0,2)	1069	5227,84	116	497,16	635	3247,55
2- (0,2-0,4)	156	877,57	10	47,95	155	807,64
3- (0,4-0,6)	16	120,35	4	12,90	67	323,66
4 - (0,6-0,8)	8	65,18	7	26,05	10	51,77
5 - (0,8-1)	21	118,02	3	23,95		
6 - (2-2,2)	-	-	-	-	34	188,52
Total	1270	6408,968	140	608,024	901	4619,139

Source: OLIVEIRA, 2024.

The mapping performance varies significantly depending on the area interval. The lower the extraction intensity, the harder it is to detect alerts. The mapping performs well in larger areas (above 0.4 ha), with low FN and FP rates, but fails to adequately detect selective logging in smaller areas, where the FN tree rate is very high (1069).

In small area intervals (0-0.2 ha), the number of trees classified as FN is significantly high, while the number of trees classified as TP is relatively low. This indicates that the model is underestimating forest extraction in small areas, likely due to the low extraction intensity, failing to correctly detect harvested trees. In intermediate intervals (0.2-0.6 ha), the balance between TP and FN improves, with a proportional increase in TP, suggesting enhanced detection capability. However, false negatives still persist, indicating that some exploited areas remain undetected. For larger areas (2-2.2 ha), the number of trees classified as FN drops to zero, demonstrating that the model can accurately identify all exploited areas. This highlights its higher effectiveness in larger-scale environments, where the distinction between exploited and non-exploited areas is clearer and easier to detect.

Figure 8 presents a section of the area with PlanetScope images (a), the Canopy Height Model (CHM) (b), and the results of the overlay between the mappings and the harvested trees (c). It is evident that in larger areas, the number of True Positive (TP) trees

(in green) is higher, demonstrating the mapping's good ability to detect large areas. However, a considerable number of False Negative (FN) trees (in yellow) is observed, reflecting areas where the mapping failed to detect accurately.

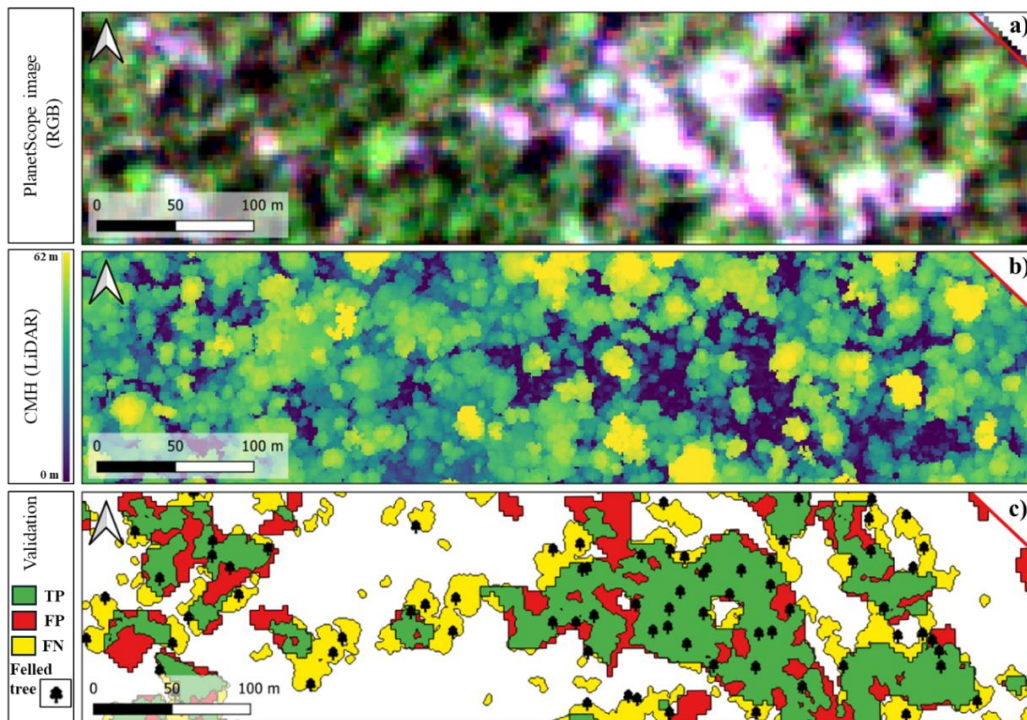


Figure 8. PlanetScope image (a), Canopy Height Model (CHM) extracted from LiDAR data (b), and the result of the overlay between trees and evaluation metrics (c).

Source: OLIVEIRA, 2024.

3.6 Regarding the Statistical Metrics

The performance results of the mapping for the different mapped area intervals are presented in Table 6, including statistical evaluation metrics such as Precision (P), Recall (R), F1-Score (F1), Overestimation Score (OS), Intersection over Union (IoU), and Root Mean Square Error (RMSE).

Table 6. Performance of forest disturbance mapping caused by selective logging across different area sizes (intervals in hectare).

Intervals (ha)	TP	FP	FN	Precision (P)	Recall (R)	F1-Score (F1)	OS	IoU	RMSE
1- (0-0,2)	46,47	32,88	77,91	0,59	0,37	0,46	0,26	0,30	45,03
2- (0,2-0,4)	9,51	2,86	9,23	0,77	0,51	0,61	0,15	0,44	6,38
3- (0,4-0,6)	4,04	1,36	0,98	0,75	0,80	0,77	0,27	0,63	0,38
4 - (0,6-0,8)	1,27	1,23	0,70	0,51	0,65	0,57	0,63	0,40	0,54
5 - (0,8-1)	0,00	0,98	1,00	0,00	0,00	0,00	0,98	0,00	0,02
6 - (2-2,2)	2,01	0,00	0,00	1,00	1,00	1,00	0,00	1,00	0,00
Total	63,30	39,31	89,82	0,62	0,41	0,50	0,20	0,33	50,51

Source: OLIVEIRA, 2024.

The main results of the PlanetScope classification, based on the reference mapping obtained with LiDAR data, reveal significant differences in the performance of clearing detection, highlighting the limitations and strengths of the mapping. Figure 9 presents a map emphasizing the results of the overlay between PlanetScope and LiDAR mappings, with a focus on different regions of the study area: a) True Positives (TP) - represent areas of agreement between the two mappings, indicating regions correctly identified by both PlanetScope and LiDAR; b) False Negatives (FN) - correspond to areas that should have been detected by the PlanetScope mapping but were only identified by LiDAR; c) False Positives (FP) - refer to areas detected by PlanetScope but not confirmed by the reference mapping conducted with LiDAR. Additionally, the felled trees, verified in the field, provide an extra layer of validation, enabling a cross-check of the accuracy of both mappings.

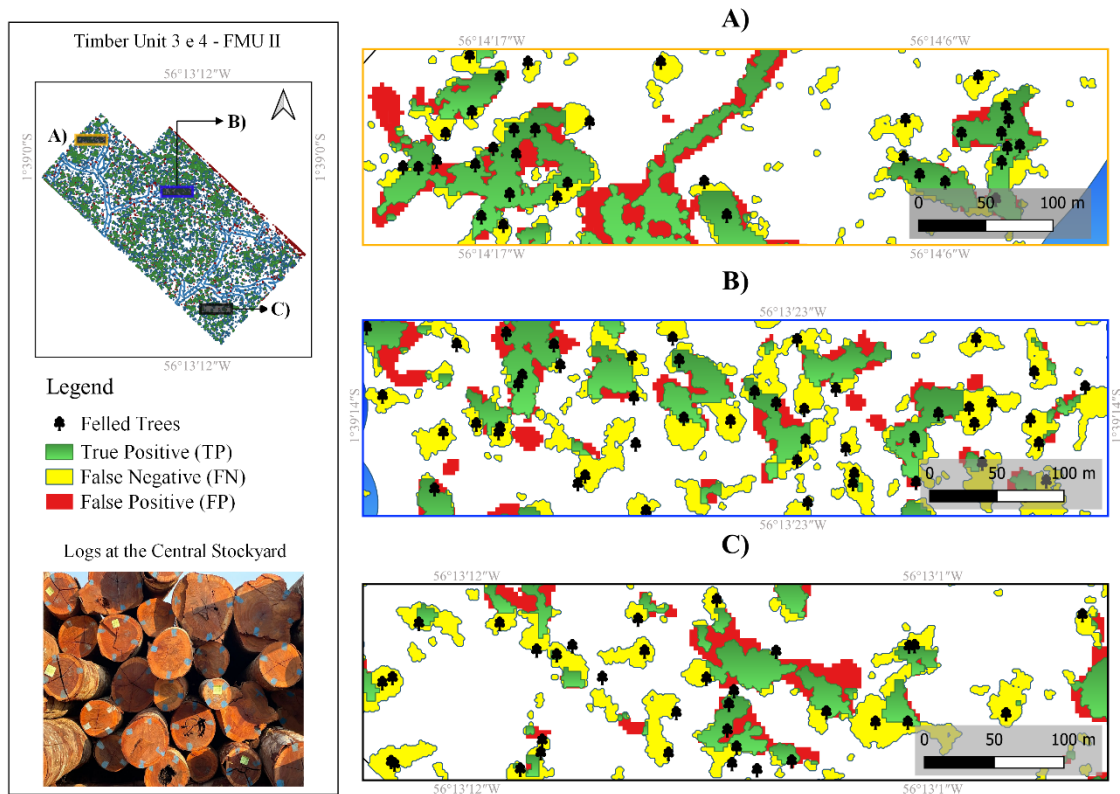


Figure 9. Results of accuracy and precision assessment of forest disturbance mapping caused by selective logging, highlighting different regions of the Saracá-Taquera National Forest

Source: OLIVEIRA, 2024.

The PlanetScope mapping exhibited variations in performance depending on the evaluated area interval, highlighting strengths and limitations in disturbance detection. In the smallest area interval (0–0.2 ha), there was the highest number of true positives (TP

= 46.47), but also a high rate of false positives (FP = 32.88) and false negatives (FN = 77.91). The moderate precision (P = 0.59) and low recall (R = 0.37) reflect PlanetScope's challenges in identifying small clearings, which are often obscured by remaining vegetation or mixed canopy cover. In contrast, LiDAR captured these areas more efficiently due to its ability to detect structural changes, demonstrating its superior sensitivity to small-scale disturbances.

In the intermediate intervals (0.2–0.6 ha), the performance of PlanetScope mapping improved considerably. For the 0.2–0.4 ha interval, precision was higher (P = 0.77), while in the 0.4–0.6 ha interval, recall reached R = 0.80, with an F1-Score of 0.77 and an IoU index of 0.63, demonstrating good agreement with the LiDAR data. This reflects greater reliability in detecting medium-sized clearings, where the spectral response is more pronounced, enhancing the accuracy of PlanetScope in these area ranges.

For larger intervals, such as 0.8–1 ha, the performance of PlanetScope mapping was inconsistent, with precision and recall both at zero, indicating a failure to detect these areas. This interval is associated with management infrastructure, such as stockyards and roads, where complex spectral patterns, like exposed soil and residual vegetation, may confuse the classification (LOCK & MATRICARDI, 2019). However, in the largest interval evaluated (1–2.2 ha), PlanetScope achieved perfect performance, with precision and recall of 1.00, demonstrating its effectiveness in areas with high impact intensity. The global analysis indicates that PlanetScope mapping underestimated the total clearings, with TP = 63.30 ha, while LiDAR identified 113.77 ha. Overall precision was moderate (P = 0.62), and the low recall (R = 0.41) highlights significant underdetection. The global F1-Score (0.50) and IoU index (0.33), combined with a relatively high RMSE (50.51), emphasize the differences between the methods, highlighting the limitations of PlanetScope mapping in smaller areas and the superiority of LiDAR in detecting smaller and low-intensity logging clearings.

3. Discussion

4.1 Regarding the Statistical Results of the Mappings

The results indicate that forest disturbance mapping using LiDAR data in the Saracá-Taquera National Forest demonstrated greater accuracy and reliability in detecting areas lower impacted by selective logging. While the mapping of impacted forests using PlanetScope data detected 100.91 hectares, LiDAR identified 113.77 hectares, an increase of 13.16 hectares. This difference reflects the superiority of LiDAR in capturing structural changes in vegetation, even in areas with lower impact intensity, which may not be detected by optical imagery (HUDAK & LEFSKY, 2002; LOCK & MATRICARDI, 2019; WINSTALEY *et al.*, 2024).

Nonetheless, it is important to highlight that the mapping of impacted forests using PlanetScope data successfully detected 63.3 hectares as true positives (TP). The 13.16-hectare difference between the two methods is directly associated with the high number of false positives (39.3 hectares) observed in the PlanetScope mapping, which partially compensated for the detection failures (false negatives) of impacted forests. This combination of errors and correct detections led to a total estimate close to the value identified by the reference LiDAR mapping, although the exact correspondence between mapped areas is limited to larger clearings (HUDAK & LEFSKY, 2002; SPARKS & SMITH, 2021).

Thus, the results highlight the importance of integrating optical and LiDAR data for forest management monitoring (HUDAK & LEFSKY, 2002; ASNER, 2009; LOCK & MATRICARDI, 2019, OLIVEIRA *et al.*, 2024). While PlanetScope mapping is useful for providing an initial overview and covering large areas, LiDAR enables validation and refinement, enhancing the detection of clearings at a local scale (OLIVEIRA *et al.*, 2024; XU *et al.*, 2021; SPARKS & SMITH, 2022).

Moreover, for smaller areas (<0.2 ha), implementing strategies to reduce false negatives is crucial, such as using algorithms that combine spectral and structural information (XU *et al.*, 2021). A promising alternative approach would involve categorizing the reliability of detected change alert polygons, assigning confidence levels from low to high based on clearing size. This technique would help reduce uncertainties and improve the robustness of the mapping process.

The limitations of mapping logged forests using PlanetScope data are directly related to the characteristics of the optical sensor, such as spectral dependency and the lack of

vertical information (ASNER, 2009; XU *et al.*, 2021; OLIVEIRA *et al.*, 2024). The detection of forest disturbances using PlanetScope imagery relies primarily on the reflectance of exposed soil, dry vegetation, and other targets. Thus, forests exhibiting low-intensity impacts or disturbances, as a result of the removal of a few trees during selective logging, may generate insufficient spectral responses to allow the identification of forest changes, leading to higher underestimation errors (elevated FN) (SHIMABUKURO & SMITH, 1991; HUDAK *et al.*, 2002; DALAGNOL *et al.*, 2023; OLIVEIRA *et al.*, 2024b). Furthermore, PlanetScope images were unable to capture changes in the three-dimensional structure of the forest, being less sensitive to alterations in canopy height compared to LiDAR data (EMMERT *et al.*, 2023).

On the other hand, LiDAR data allow for the direct measurement of changes in the forest canopy following selective logging, offering greater precision in detecting small and medium-sized clearings in the forest (WINSTALEY *et al.*, 2024; XU *et al.*, 2021; SPARKS & SMITH, 2022). LiDAR data enable the recording of height differences between pre- and post-logging periods, allowing for the identification of forest clearings regardless of spectral response (LOKS & MATRICARDI, 2019). This characteristic enhances the robustness of the method in capturing structural changes in selectively logged forests, especially in scenarios of low-impact or heterogeneous vegetation, as is the case in the Amazon rainforest (PETRI *et al.*, 2022).

The total number of trees correctly detected as harvested (1,270 trees; 6,408.97 m³) using PlanetScope images was significant but showed high underestimation in small clearings, compromising the reliability of the mapping. On the other hand, the performance of mapping harvested trees using LiDAR data was notably superior to that of PlanetScope data, as it enabled the detection of structural changes in the forest that were not captured by the PlanetScope-based mapping. The results highlight that LiDAR-based mapping is more suitable for monitoring low-impact selective logging, allowing for precise evaluation of impacted areas and providing critical information to improve the effectiveness of optical mapping (HUDAK & LEFSKY, 2002; LOCK & MATRICARDI, 2019; WINSTALEY *et al.*, 2024).

Although the mapping of selectively logged forests using PlanetScope images offers advantages in terms of cost and broad coverage, its results demonstrate limitations in detecting small clearings, especially in low-impact scenarios (DALAGNOL *et al.*, 2023; OLIVEIRA *et al.*, 2024). The mapping of altered forests using LiDAR data proved to be essential as a validation technology, showing greater sensitivity and accuracy across

all evaluated intervals. Integrating the two methods, combined with adjustments to classification algorithms, can significantly enhance the monitoring of forest disturbances and SFMP, contributing to more sustainable management of selectively logged forests (HUDAK & LEFSKY, 2002; ASNER *et al.*, 2009; LOKC & MATRICARDI, 2019). However, further evaluation is needed to assess, in detail, the cost and time required for acquiring these two types of remote sensing data.

Oliveira *et al.*, (2024b) evaluated logging intensity in the same area as the present study and highlighted the concentration of logging in areas with higher volumetric stocks of commercial species. In the present study, we observed the same pattern, where areas with higher logging intensity exhibited the largest clearings, demonstrating that the structural impact of selective tree removal is directly related to the volume or number of trees extracted from the forest. These areas were associated with regions of higher elevation and farther from water bodies, while areas of lower elevation showed lower stocks of commercial timber. Thus, adaptive management strategies that integrate spatial heterogeneity and consider structural impacts, such as the formation of clearings, are essential to balance economic exploitation with the conservation of forest resources.

4.2 Regarding the Current Monitoring Systems in the Amazon

The results obtained from forest disturbance mapping using LiDAR data and PlanetScope images highlight significant differences between the two methods in terms of both accuracy and sensitivity. These characteristics allow comparisons to be made with widely used monitoring systems in the Amazon, such as DETER/INPE and SAD/IMAZON, which use optical approaches to detect real-time changes in forest cover for monitoring selective logging (DINIZ *et al.*, 2015; SOUZA JR. *et al.*, 2005).

The DETER (Real-Time Deforestation Detection System), developed by the National Institute for Space Research (INPE) in 2004, is based on MODIS and WFI imagery and aims to monitor deforestation, selective logging, and other large-scale changes in the Brazilian Amazon (DINIZ *et al.*, 2015). Since 2015, DETER has utilized WFI (CBERS-4) and AWiFS (IRS) sensors with better resolution (56–64 m), enabling the detection of changes greater than 3 hectares. Detection relies on visual interpretation and the Linear Spectral Mixture Model (LSMM), mapping classes such as deforestation, degradation, and selective logging, among others (DINIZ *et al.*, 2015). While polygons are made publicly available starting at 6.25 hectares, the system's limited spatial resolution (~250

m for MODIS and 56–64 m for AWiFS) makes it unsuitable for detailed mapping of small disturbances, such as clearings resulting from selective logging.

Comparing with the mapping results using PlanetScope images (~3 m resolution) and LiDAR data highlights PlanetScope's superior ability to detect smaller clearings, especially in intervals below 3 hectares. Furthermore, LiDAR excels in detecting even more subtle forest disturbances, such as variations in canopy height in low-impact areas (XU *et al.*, 2023), systems like DETER cannot capture due to the lack of structural information and low spatial resolution (DINIZ *et al.*, 2015).

The Deforestation Alert System (SAD), developed by Imazon in 2008, monitors deforestation and forest degradation in the Legal Amazon on a monthly basis, using imagery from Landsat 7 and 8, Sentinel 1 and 2, and radar from Sentinel 1 for cloud-covered areas (10–30 m resolution) (Sousa Jr *et al.*, 2005). The system detects degradation caused by fire or logging and deforestation through clear-cutting in areas of at least 1 hectare (SOUSA JR *et al.*, 2005). Although SAD offers greater spatial resolution (~10–30 m) compared to DETER, it still struggles to detect selective logging and clearings smaller than 1 hectare (SOUSA JR *et al.*, 2005, MATRICARDI *et al.*, 2013). In contrast, mapping results using PlanetScope images show high performance in detecting clearings smaller than 1 hectare (0.2–0.6 ha), thanks to its higher spatial resolution and the application of the Linear Spectral Mixture Model (LSMM) (Oliveira *et al.*, 2024). However, PlanetScope mapping has limitations in detecting even smaller clearings (<0.2 ha), while LiDAR surpasses these barriers, as demonstrated in this study.

Figure 10 presents a subset of forest cover change detection alerts generated by the systems: (A) DETER/INPE, (B) SAD/IMAZON, and (C) Brazilian Forest Service (SFB)/SCCON, intersecting the Timber Unit Production (TU) within the Forest Management Unit (FMU) in the Saracá-Taquera National Forest (DINIZ *et al.*, 2015; SOUSA JR. *et al.*, 2005; SFB, 2024). Systems A and B are used in command-and-control policies, operating throughout the Amazon with low to medium spatial resolution imagery. System C monitors and maps forest disturbances in specific areas within sustainable forest management (SFM) boundaries, utilizing high spatial and temporal resolution *PlanetScope* images managed by the Brazilian Forest Service (SFB) (SFB, 2024). Visually, System C demonstrates greater consistency and accuracy in identifying selectively logged areas, resulting in classifications that align more closely with observed phenomena.

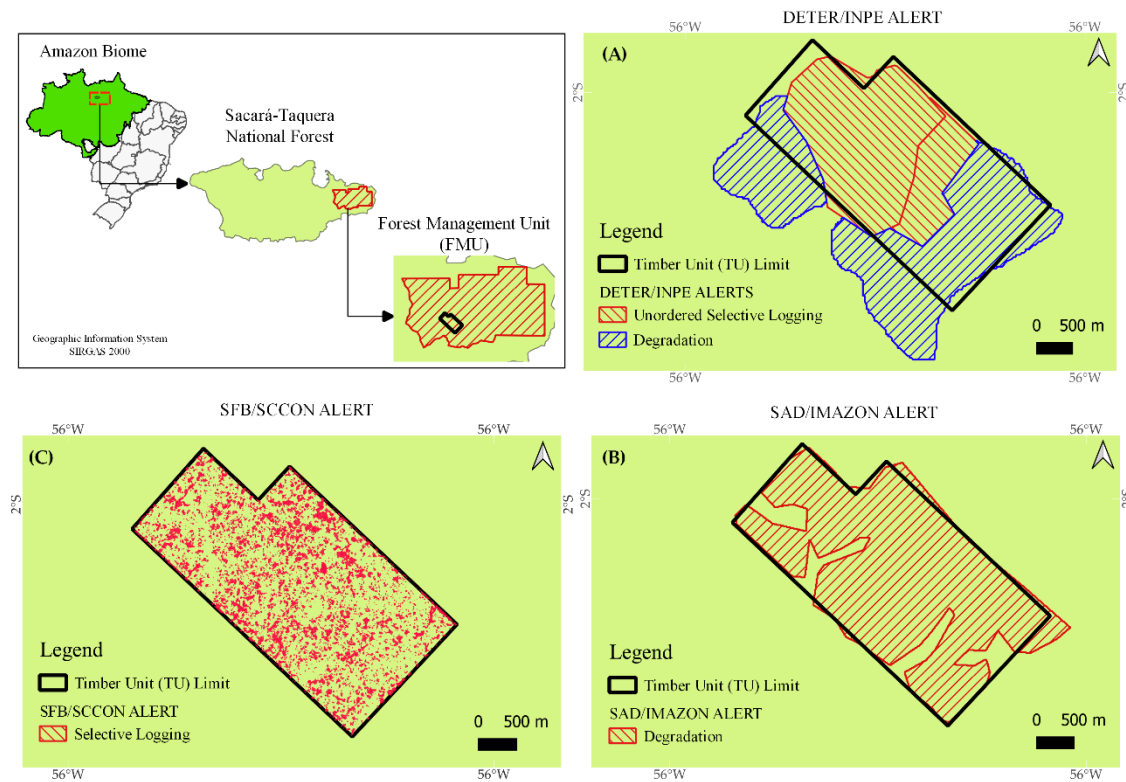


Figure 10. Forest degradation alerts from the systems: (A) DETER/INPE (Real-Time Deforestation Detection System, developed by the National Institute for Space Research—INPE); (B) SAD/IMAZON (Deforestation Alert System, developed by the Amazon Institute of People and the Environment—IMAZON); and Selective Logging Alert (C) Brazilian Forest Service (SFB)/SCCON (a system of the Brazilian Forest Service, developed by SCCON Geospatial). These systems intersect the Timber Unit Production (TU) in the Forest Management Unit (FMU) within the Saracá-Taquera National Forest, in the Brazilian Amazon.

Source: OLIVEIRA, 2024.

Systems such as DETER (INPE) and SAD (Imazon), which use low- and medium-resolution imagery, provide large-scale alerts but may fail to adequately capture low-intensity selective logging within Forest Management Units (UMFs) (DINIZ *et al.*, 2015; SOUSA JR. *et al.*, 2005; OLIVEIRA *et al.*, 2024). On the other hand, systems such as SCCON, operated by the Brazilian Forest Service (SFB), which use high-resolution PlanetScope images to exclusively monitor concession-managed areas, demonstrate greater accuracy in detecting disturbances in managed areas, enabling classifications that are more consistent with observed phenomena (OLIVEIRA *et al.*, 2024b). Table 7 presents the main differences between the systems and sensors used for monitoring forest cover in the Amazon.

Tabela 7. Principais diferenças entre as sistemas e sensores utilizados para o monitoramento da cobertura florestal na Amazônia

System	Satellite/ Sensor	Spatial resolution	Main focus	Limitation	LiDAR and PlanetScope Comparison
DETER-B (INPE)	MODIS/WFI	~250 m (56-64m)	Deforestation, degradation, and selective logging across the entire Legal Amazon	Low spatial resolution; does not detect small clearings < 3 ha	Lower sensitivity; useful for monitoring large areas
SAD (IMAZON)	Landsat 7 e 8/Sentinel-2	~10-30 m	Deforestation, degradation, and selective logging across the entire Legal Amazon	Does not detect selective logging and clearings < 1 ha	PlanetScope detects clearings smaller than 1 hectare; LiDAR outperforms both
SFB (SCCON Geospatial)	PlanetScope	~3 m	Selective logging (small and medium clearings < 1 ha)	Low sensitivity in small clearings or low-impact logging	Complements LiDAR; better performance for clearings between 0.2–2 ha
SFB – Selective logging	LiDAR 3D data (altimetry)	~1 m	Selective logging (structural changes in vegetation)	High cost; lower temporal coverage	High precision; ideal for validating other methods

Source: OLIVEIRA, 2024.

Although DETER and SAD systems are widely used due to their broad coverage and update frequency, the results of this study demonstrate that integrating LiDAR and PlanetScope data offers greater accuracy in detecting clearings and selective logging. LiDAR, in particular, stands out for its sensitivity to vertical and subtle changes in the forest canopy, while PlanetScope can be effectively used for initial monitoring or in areas with medium to high impact intensity.

4.3 Implications of Generic Classifications for SFM Sustainability

The lack of differentiation between SFM practices and other types of degradation can either underestimate or overestimate forest impacts, compromising the credibility of conservation and management initiatives in the Amazon (VELASCO *et al.*, 2022; OLIVEIRA *et al.*, 2024b). This may hinder funding opportunities, discourage sustainable practices, and result in inadequate public policies, negatively affecting resource allocation and forest protection strategies (PINAGÉ *et al.*, 2023). Thus, accurate classification of different levels of disturbance is essential for ensuring environmental, economic, and social sustainability in forest management in the Amazon (VELASCO *et al.*, 2022; PINAGÉ *et al.*, 2023).

The intensity and types of forest disturbances vary across degradation processes, including partial loss of living biomass, forest quality, and changes in biodiversity (SASAKI *et al.*, 2009; THOMPSON *et al.*, 2013; SIMULA, 2009). In the case of legal selective logging under Reduced Impact Logging (RIL) management, forest disturbances are considered low-intensity and are limited to the removal of high-value commercial trees, with canopy openings, logging trails, and collateral damage to other trees and understory vegetation (PEREIRA-JÚNIOR *et al.*, 2022; OLIVEIRA *et al.*, 2024). In contrast, processes such as wildfires, illegal selective logging, or high-intensity logging generate significantly greater impacts, requiring more specific monitoring systems to distinguish between different types of degradation (MATRICARDI *et al.*, 2020).

SFM faces a series of legal impacts with generic classifications that can compromise its effectiveness and implementation. These challenges are related to regulation, enforcement, public perception, as well as economic and social aspects (VELASCO *et al.*, 2022; PINAGÉ *et al.*, 2023; KREMEN *et al.*, 2000; SAGOBAL *et al.*, 2013; OLIVEIRA *et al.*, 2024b).

The lack of differentiation in degradation classifications made by monitoring systems often fails to adequately distinguish between SFM and other types of forest degradation, such as illegal logging, intense fires, edge effects, among others (LAPOLA *et al.*, 2020; MATRICARDI *et al.*, 2020). This generalization can lead to underestimation or overestimation of mapped areas, resulting in inconsistent data that undermine the credibility of sustainable management and conservation projects (KREMEN *et al.*, 2000).

As a consequence of classifying SFM areas as forest degradation, there are inevitable damages to the credibility and investments in the timber sector in the Amazon (FERREIRA *et al.*, 2015). The lack of precision in differentiating between legal and illegal practices can discourage investments in sustainable practices, hindering the ability to secure funding for management initiatives (VELASCO *et al.*, 2022). Moreover, legal forest management projects may be penalized or discredited due to confusion with illegal practices, generating legal uncertainty and affecting their sustainability (FERREIRA *et al.*, 2015). Another key consideration is that policies based on inaccurate or incomplete data may deprioritize or discredit sustainable management, focusing efforts on punitive measures against deforestation without providing incentives for legal practices (VELASCO *et al.*, 2022; PINAGÉ *et al.*, 2023).

From a public and political perception standpoint, the generalization of "degradation" without considering sustainable management practices can lead to the

stigmatization of legal and certified activities (FERREIRA *et al.*, 2015). Sustainable management may be perceived as less effective in combating deforestation or even associated with it due to the lack of public campaigns explaining its benefits and differences compared to predatory logging and other types of degradation (PEREIRA-JUNIOR *et al.*, 2002; OLIVEIRA *et al.*, 2024; OLIVEIRA *et al.*, 2024b). Therefore, it is essential to strengthen regulations, encourage sustainable practices, and improve monitoring systems to promote forest management as an effective tool for conservation and economic development.

4. Conclusion

The combination of LiDAR data with PlanetScope imagery significantly enhances accuracy in detecting forest disturbances caused by selective logging activities in the Amazon, particularly in areas under sustainable forest management. While optical systems such as PlanetScope images are efficient in identifying medium and large clearings, LiDAR data stand out by improving accuracy and precision in detecting subtle and structural changes in the forest, offering a complementary and robust approach. Integrating these technologies is essential for differentiating types of forest disturbances caused by selective logging activities, such as low-impact selective logging and more intense disturbances caused by illegal activities, ensuring greater data reliability. The implementation of standardized metrics for classifying disturbances can strengthen monitoring efforts and support the development of more effective public policies for conservation and sustainable management in the Amazon.

The high cost of LiDAR data acquisition remains a significant barrier to its widespread adoption in forest monitoring and management. LiDAR surveys require specialized equipment, skilled operators, and often involve aerial campaigns that add to operational expenses. Furthermore, processing the vast amounts of three-dimensional data collected requires advanced software and computational resources, further increasing costs. While the precision and depth of information provided by LiDAR are unmatched, its expense can limit its accessibility, particularly for smaller-scale projects or regions with limited funding. To address these challenges, investments in cost-reduction technologies, such as unmanned aerial vehicles (UAVs) equipped with LiDAR sensors and collaborative funding mechanisms, are essential to make this powerful tool more accessible for conservation and sustainable management initiatives.

As a future direction, it is recommended to develop more advanced algorithms using artificial intelligence to more accurately distinguish between legal and illegal logging practices, as well as areas impacted by extreme climate changes, which are increasingly frequent in the Amazon region. Additionally, it is essential to expand the use of high temporal, spectral, and spatial resolution technologies, such as nanosatellites and LiDAR, to other areas of interest in the Amazon, including Conservation Units and Indigenous Lands, with the goal of curbing illicit activities.

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CHAPTER V - Conclusions and Future Perspectives

1.1 Contextualization of Study Results in SFM and Climate Change

The findings of this study hold significant implications for the implementation of Sustainable Forest Management (SFM) and efforts to mitigate global climate change. By enhancing the detection and monitoring of forest disturbances, particularly those caused by selective logging, this research supports more precise and timely assessments of forest dynamics, a critical factor in ensuring the long-term sustainability of managed forests.

In the context of SFM, the integration of high-resolution remote sensing technologies, such as LiDAR and PlanetScope imagery, contributes to improved transparency and accountability in forest management practices. This advancement strengthens compliance monitoring within forest concessions, helping to detect unauthorized logging activities and ensuring adherence to sustainable harvesting practices. Ultimately, this promotes the conservation of biodiversity, the maintenance of ecosystem services, and the economic viability of forest-based industries.

From a global climate change perspective, the accurate detection of forest disturbances enhances the ability to quantify carbon stock changes and carbon sequestration potential more precisely. Selective logging, when poorly monitored, can lead to significant carbon emissions due to canopy openings and forest degradation. By providing tools to monitor the spatial and temporal impacts of logging activities, the study supports efforts to reduce emissions from deforestation and forest degradation (REDD+). This contributes to achieving national and international climate goals, such as those outlined in the Paris Agreement.

Moreover, the study's findings underscore the importance of scalable monitoring systems that can be adapted to large forested areas, particularly in regions vulnerable to both legal and illegal forest exploitation. These systems can serve as a model for improving the sustainability of forest management plans globally and inform policy frameworks aimed at balancing resource use with conservation priorities.

In summary, the methodologies developed in this study provide essential contributions to the advancement of sustainable forestry and the fight against climate change. By fostering more effective forest monitoring systems, this research not only strengthens forest governance but also enhances the capacity of tropical forests to function as a key component of the global climate regulation system.

1.2 Revisiting Research Questions and Objectives: General Conclusions

This study was guided by a set of research questions and objectives aimed at enhancing the detection and monitoring of forest disturbances caused by selective logging in the Amazon through innovative remote sensing technologies. The general conclusions drawn from the research are as follows:

Trends, Gaps, and Advancements in Remote Sensing Applications: the scientometric analysis and systematic review revealed key trends and gaps in the use of remote sensing for forest disturbance monitoring. While advancements have been made in integrating data from various sources, such as satellite imagery and LiDAR, challenges remain in the adoption of high-resolution and frequent temporal data to detect subtle changes associated with selective logging. This highlights the need for continued innovation and validation of monitoring methodologies in the context of Sustainable Forest Management (SFM).

Impacts of Selective Logging on Forest Structure and Heterogeneity: the integrated analysis of forest inventory data and high-resolution remote sensing imagery demonstrated that selective logging significantly affects forest structure and increases spatial heterogeneity over space and time. The study confirmed that combining ground-based measurements with high-resolution satellite data improves the assessment of logging impacts, providing a more comprehensive understanding of changes at both the stand and landscape levels. This contributes to more effective monitoring within federal concession areas, ensuring compliance with sustainable harvesting practices.

Development and Validation of an Integrated Methodology: the proposed methodology, which integrates LiDAR and PlanetScope data, proved to be an effective tool for detecting forest disturbances with greater accuracy and precision. The validation process demonstrated that this approach surpasses traditional methods by capturing both horizontal and vertical forest structure changes. This integrated system supports the implementation of continuous monitoring, which is essential for promoting transparency and accountability in forest resource management.

Broader Implications for SFM and Climate Change Mitigation: the study's results contribute to strengthening SFM frameworks by offering a replicable and scalable system for tracking selective logging impacts. Additionally, the findings support climate change mitigation efforts by improving the estimation of carbon stock changes and identifying

degradation hotspots that could lead to carbon losses if left unmanaged. This underscores the importance of high-resolution monitoring for achieving global climate targets, particularly in tropical forests that serve as critical carbon sinks.

In summary, the research objectives have been met by addressing the research questions through a robust interdisciplinary approach. The integration of scientometric insights, field-based data, and cutting-edge remote sensing technologies provides a foundation for future advancements in sustainable forest monitoring. The methodologies developed in this study can serve as a model for improving environmental governance and conservation strategies in the Amazon and beyond.

1.3 Revisiting the hypotheses

This study proposed several hypotheses to guide the investigation of forest disturbances caused by selective logging in the Amazon. Upon revisiting these hypotheses in light of the results obtained, the following conclusions are drawn:

Hypotheses Related to Trends, Gaps, and Advancements in Remote Sensing Applications:

Hypothesis H1.1: The scientific literature on remote sensing technologies for forest disturbance monitoring demonstrates significant advancements but reveals critical gaps in spatial and temporal resolution for addressing selective logging impacts.

Conclusion: This hypothesis was supported. The scientometric analysis confirmed that, despite technological progress, limitations in temporal frequency and spatial precision remain, particularly in the monitoring of forest heterogeneity and smaller canopy disturbances.

Hypothesis H1.2: A scientometric approach and systematic review will identify underexplored areas, particularly regarding the integration of advanced sensor technologies like LiDAR and high-resolution satellite imagery.

Conclusion: This hypothesis was also supported, as the review highlighted the limited number of studies combining high-resolution satellite imagery with LiDAR for selective logging detection, signaling an opportunity for further methodological integration.

Hypotheses Related to the Impacts intensity of Selective Logging on Forest Structure and Heterogeneity:

Hypothesis H2.1: Selective logging causes detectable changes in forest structure and heterogeneity over time, varying spatially across the federal concession area.

Conclusion: This hypothesis was confirmed. The analysis demonstrated that selective logging significantly alters the forest canopy and structural heterogeneity, with these impacts showing spatial variability across different logging units.

Hypothesis H2.2: The integration of forest inventory data and high resolution satellite imagery provides a more comprehensive understanding of spatial and temporal impacts compared to using either dataset independently.

Conclusion: Supported. The combined use of forest inventory data and satellite imagery improved the accuracy of assessments and revealed detailed temporal dynamics of selective logging impacts that would not have been captured by a single dataset.

Hypotheses Related to the Development of an Integrated Methodology:

Hypothesis H3.1: A combined methodology using LiDAR and PlanetScope data improves the detection and monitoring of forest disturbances compared to conventional methods.

Conclusion: This hypothesis was strongly supported. The integrated approach detected disturbances with greater spatial detail and precision, especially in identifying subtle canopy openings and patterns associated with selective logging.

Hypothesis H3.2: The validation process will demonstrate that this integrated approach achieves higher accuracy and reliability for monitoring forest disturbances within sustainable forest management plans.

Conclusion: Confirmed. The validation showed that the methodology achieved higher classification accuracy and reliability compared to conventional satellite monitoring, demonstrating its suitability for continuous monitoring of selective logging within federal concession areas.

The revisiting of these hypotheses demonstrates that the proposed methodologies effectively address key challenges in forest disturbance monitoring. By confirming these hypotheses, this study provides a validated framework that enhances the precision and reliability of forest management monitoring systems, contributing to sustainable resource use and climate change mitigation efforts.

1.4 Opportunities for future studies

Based on the findings and discussions presented in this thesis, several key opportunities for future research emerge, particularly in the context of enhancing sustainable forest management and addressing global conservation challenges:

Scaling Methodologies Across Diverse Forest Landscapes: the integration of LiDAR and PlanetScope data proved effective for detecting both large-scale clearings and small-scale disturbances. Future research could focus on adapting and scaling this methodological framework to other forest regions, such as secondary forests, mixed-use landscapes, and conservation areas. This would enable comparative studies across different biomes, providing a broader understanding of forest dynamics in various ecological contexts.

Incorporating Cost-Effective Remote Sensing Solutions: while LiDAR data has demonstrated its value for high-resolution forest monitoring, its high cost and limited accessibility remain barriers to widespread adoption. Future studies could explore the integration of lower-cost alternatives, such as drone-based LiDAR or open-access satellite platforms (e.g., GEDI), to enhance cost-effectiveness while maintaining accuracy. Additionally, exploring advancements in UAV (unmanned aerial vehicle) technology could provide new opportunities for localized and scalable forest assessments.

Expanding Data Integration and Automation: the combination of forest inventory, satellite imagery, and LiDAR data was pivotal in improving the understanding of selective logging impacts. Further research could incorporate additional datasets, such as climatic, hydrological, and socio-economic data, to explore the broader impacts of logging on ecosystem functions and forest-dependent communities. Additionally, integrating machine learning algorithms for automated detection of forest changes could improve the efficiency of monitoring systems, particularly in large and remote areas.

Long-Term Monitoring and Time-Series Analysis: Understanding the cumulative effects of selective logging requires long-term data collection and analysis. Future research could focus on creating time-series datasets to assess recovery rates, regrowth patterns, and long-term ecosystem changes following selective logging events. This would help refine adaptive management strategies that consider temporal variability and resilience dynamics.

Interdisciplinary Research and Policy Integration: the findings of this study highlight the importance of bridging technological advancements with forest governance and policy frameworks. Future research could involve collaborations between remote sensing experts, forest ecologists, policymakers, and local communities to develop decision-support tools that translate remote sensing data into actionable policies. This could also include studies on how to improve community-based forest monitoring programs by training local stakeholders in the use of accessible remote sensing tools.

Addressing Technological Accessibility and Equity: Given the challenges related to the accessibility of high-resolution data, future studies could focus on developing open-source platforms that democratize access to advanced data processing tools. These platforms could include cloud-based processing systems that enable real-time analysis of forest changes, particularly for institutions in the Global South with limited resources.

Monitoring Beyond Selective Logging: while this research focuses on forest disturbances caused by selective logging, future investigations could expand to include other disturbances, such as illegal mining, fires, and infrastructure expansion. These studies could benefit from multi-sensor approaches to capture a more comprehensive view of anthropogenic impacts on forest ecosystems.

Climate Resilience and Carbon Accounting: the integration of high-resolution forest monitoring into climate models remains an underexplored area. Future studies could focus on quantifying carbon sequestration and emissions dynamics following selective logging, which would enhance the accuracy of carbon stock assessments and inform global climate mitigation strategies, such as REDD+ initiatives.

The methodologies and findings of this thesis pave the way for more sophisticated, cost-effective, and inclusive approaches to forest monitoring and management. By addressing the outlined research opportunities, future studies can strengthen the alignment between conservation science, technological innovation, and forest policy implementation. Ultimately, these efforts will contribute to more sustainable forest governance, ensuring the Amazon's ecological and socio-economic resilience in the face of global environmental changes.



UNIVERSIDADE FEDERAL DO OESTE DO PARÁ
INSTITUTO DE BIODIVERSIDADE E FLORESTAS
PROGRAMA DE PÓS-GRADUAÇÃO EM SOCIEDADE, NATUREZA E DESENVOLVIMENTO

ATA DE DEFESA DE TESE

Aos vinte dias do mês de dezembro do ano de dois mil e vinte e quatro, às quinze horas, através da plataforma virtual (<https://meet.google.com/fyt-qaho-pqt>) e Câmara de Vereadores de Belterra (Pará), instalou-se a banca examinadora de tese de doutorado do discente **Afonso Henrique Moraes Oliveira** do PPGSND/UFOPA. A banca examinadora foi composta pela Dra. Lucieta Guerreiro Martorano, PPGSND/UFOPA e Embrapa Amazônia Oriental, orientadora e presidente da banca, pelo co-orientador o Dr. Mauro Mendonça Magliano (PF/INC), e pelos examinadores, os professores Dr. Edson José Vidal da Silva – USP/ESALQ (examinador externo), Dr. Eraldo Aparecido Trondoli Matricardi - UnB (examinador externo), Dr. Leonardo Pequeno Reis - UFRA (examinador externo), Dr. Thiago Almeida Vieira - PPGSND/UFOPA (examinador interno) e Dr. Rodrigo da Silva - PPGSND/UFOPA (examinador interno). Deu-se início à abertura dos trabalhos, pela presidente professora Lucieta Martorano, que, após apresentar os membros da banca examinadora e esclarecer a tramitação da defesa, solicitou ao candidato que iniciasse a apresentação da tese, intitulada **“MONITORAMENTO DO MANEJO FLORESTAL NA AMAZÔNIA: ESTRATÉGIAS, DESAFIOS E TECNOLOGIAS AVANÇADAS EM SENSORIAMENTO REMOTO”**, informando ao discente que possuía de 30 a 60 minutos para a apresentação. Concluída a exposição, a Profa. Lucieta Martorano, presidente da banca, passou a palavra ao examinador externo, Dr. Thiago Vieira para arguir o candidato, e em seguida, aos professores examinadores Dr. Leonardo Reis, Dr. Edson Vidal, Dr. Rodrigo da Silva e Dr. Eraldo Matricardi, para que fizessem o mesmo, nesta ordem. Após o término das arguições, a orientadora solicitou que o público se retirasse da sala para que ocorresse a reunião exclusiva entre os membros da banca para o julgamento do trabalho. Após a deliberações da banca examinadora, a orientadora convocou o candidato e o público ouvinte de volta para divulgação do resultado. A banca examinadora decidiu por unanimidade pela **APROVAÇÃO** do candidato, conforme as normas vigentes na Universidade Federal do Oeste do Pará. A versão final da tese deverá ser entregue ao programa, no prazo de trinta dias após a defesa, contendo as modificações sugeridas pela banca examinadora. Nada mais havendo por constar, lavrou-se e fez-se a leitura da presente ata que segue assinada pelos membros da Banca Examinadora, Presidente da Banca e Doutorando. Santarém (PA), vigésimo dia do mês de dezembro do ano de dois mil e vinte e quatro, às dezoito horas.

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**FEDERAL UNIVERSITY OF WESTERN PARÁ
INSTITUTE OF BIODIVERSITY AND FORESTS
POSTGRADUATE PROGRAM IN SOCIETY, NATURE, AND
DEVELOPMENT**

AFONSO HENRIQUE MORAES OLIVEIRA

**MONITORING SUSTAINABLE FOREST MANAGEMENT IN THE AMAZON:
STRATEGIES, CHALLENGES, AND ADVANCED REMOTE SENSING
TECHNOLOGIES**

**SANTARÉM - PA
2024**

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TECHNOLOGIES**

Thesis submitted to the Postgraduate Program in Society, Nature, and Development at the Federal University of Western Pará, as part of the requirements for obtaining the title of Doctor in Environmental Sciences. Research line: Environmental and Social Impacts of Land Use Change in the Amazon.

Advisor: Dra. Lucietta Guerreiro Martorano

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SANTARÉM - PA

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Dedication

I dedicate this work to God, whose guidance and blessings have illuminated my path, providing strength and purpose in every moment of this journey.

To my parents, Áurea Lúcia and Franciso Oliveira, for their unconditional love, sacrifices, and unwavering support, which have been the foundation of all my achievements.

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*"What we do to the forests of the world is but a mirror reflection of what we are doing
to ourselves and to one another."*

— Mahatma Gandhi

GENERAL ABSTRACT

MONITORING SUSTAINABLE FOREST MANAGEMENT IN THE AMAZON: STRATEGIES, CHALLENGES, AND ADVANCED REMOTE SENSING TECHNOLOGIES

The Amazon rainforest is one of the most biodiverse and essential ecosystems on the planet, playing a crucial role in climate regulation and ecosystem services. However, human pressures such as deforestation and degradation have significantly impacted its structure and functioning. Forest degradation, characterized by repeated interventions like fires, illegal logging, and edge effects, differs from disturbances, which are abrupt and localized events, such as treefalls, storms, and legal selective logging. While disturbances do not necessarily lead to long-term degradation, these processes are often conflated. The lack of clear differentiation highlights the need for the development of robust methodologies to distinguish between these processes. Advancing these methodologies, particularly through remote sensing technologies, is critical for accurately assessing the extent and impact of disturbances and degradation, enabling more targeted management strategies and conservation efforts in the Amazon. In Chapter 1, 80 scientific articles on anthropogenic impacts on the Amazon using remote sensing were analyzed. Although methodological advances were evident, gaps in monitoring less-studied regions, such as the central and western Amazon, highlighted the need for advanced tools in sustainable forest management (SFM). Chapter 2 focused on the Saracá-Taquera National Forest, examining the effects of logging intensity on volumetric stock, commercial species abundance, and forest cover. Using forest inventory data, elevation, and PlanetScope images, analyses structured in 1-hectare cells for pre-, during, and post-logging periods (t_0 , t_1 , t_2) revealed that higher commercial stocks were located farther from water bodies. Logging was concentrated on a few trees per hectare, intensifying in areas with higher timber volumes. In Chapter 3, the integration of LiDAR data and PlanetScope images improved the detection of disturbances caused by selective logging. LiDAR identified 15.48% of impacted areas, surpassing PlanetScope's 13.69% sensitivity, particularly for subtle changes like clearings smaller than 0.2 hectares. PlanetScope, however, outperformed systems like DETER and SAD in identifying clearings under 1 hectare. The combined use of these technologies proved critical for impact monitoring, strengthening sustainable management, and supporting public policies. A key aspect of SFM is its socio-environmental dimension. The Amazon is home to many traditional and indigenous communities whose livelihoods depend on the forest. Ensuring resource sustainability requires their inclusion in management processes, valuing traditional knowledge, and addressing equitable benefit-sharing and economic opportunities. Strategies must prioritize long-term resilience by balancing environmental conservation with the well-being of local populations. This study underscores the importance of integrating advanced technologies and adaptive strategies to balance economic exploitation and environmental conservation. These initiatives are essential for promoting sustainable management and protecting Amazonian forest resources.

Keywords: Selective logging, change detection, monitoring system, forest management, forest degradation, forest disturbance.

RESUMO GERAL

MONITORAMENTO DO MANEJO FLORESTAL SUSTENTÁVEL NA AMAZÔNIA: ESTRATÉGIAS, DESAFIOS, E TECNOLOGIAS AVANÇADAS EM SENSORIAMENTO REMOTO

A floresta amazônica é um dos ecossistemas mais biodiversos e essenciais do planeta, desempenhando um papel crucial na regulação do clima e na provisão de serviços ecossistêmicos. No entanto, pressões humanas, como o desmatamento e a degradação, têm impactado significativamente sua integridade. A degradação florestal, caracterizada por intervenções repetidas, como incêndios, exploração ilegal de madeira e efeitos de borda, difere de distúrbios, que são eventos abruptos e localizados, como quedas de árvores, tempestades e exploração seletiva legal. Embora os distúrbios não levem necessariamente à degradação a longo prazo, esses processos são frequentemente confundidos. A falta de uma diferenciação clara ressalta a necessidade de desenvolver metodologias robustas para distinguir esses processos. O avanço dessas metodologias, particularmente por meio de tecnologias de sensoriamento remoto (SR), é fundamental para avaliar com precisão a extensão e o impacto dos distúrbios e da degradação, permitindo estratégias de manejo e conservação mais direcionadas na Amazônia. No Capítulo 1, foram analisados 80 artigos científicos sobre os impactos antrópicos na Amazônia utilizando SR. Apesar dos avanços metodológicos observados, foram identificadas lacunas no monitoramento de regiões menos estudadas, como a Amazônia central e ocidental, destacando a necessidade de ferramentas mais avançadas no contexto do manejo florestal sustentável (MFS). O Capítulo 2 focou na Floresta Nacional Saracá-Taquera, examinando os efeitos da intensidade da exploração madeireira sobre o estoque volumétrico, a abundância de espécies comerciais e a cobertura florestal. Utilizando dados de inventário florestal, elevação e imagens do PlanetScope, as análises estruturadas em células de 1 hectare para os períodos pré, durante e pós-exploração (t0, t1, t2) revelaram que os estoques comerciais mais elevados estavam localizados mais distantes de corpos d'água. A exploração concentrou-se em poucas árvores por hectare, intensificando-se em áreas com maiores volumes de madeira. No Capítulo 3, a integração de dados LiDAR e imagens do PlanetScope melhorou a detecção de distúrbios causados pela exploração seletiva. O LiDAR identificou 15.48% das áreas impactadas, superando a sensibilidade do PlanetScope (13,69%), especialmente para mudanças sutis, como clareiras menores que 0.2 hectares. No entanto, o PlanetScope superou sistemas como o DETER e o SAD na identificação de clareiras menores que 1 hectare. O uso combinado dessas tecnologias mostrou-se essencial para monitorar os impactos, fortalecendo o MFS e apoiando políticas públicas. Um aspecto fundamental do MFS é sua dimensão socioambiental. A Amazônia abriga muitas comunidades tradicionais e indígenas, cujos meios de subsistência dependem da floresta. Garantir a sustentabilidade dos recursos requer a inclusão dessas comunidades nos processos de manejo, valorizando seus conhecimentos tradicionais e abordando questões como a repartição equitativa de benefícios e oportunidades econômicas. As estratégias devem priorizar a resiliência de longo prazo, equilibrando a conservação ambiental com o bem-estar das populações locais. Este estudo destaca a importância de integrar tecnologias avançadas e estratégias adaptativas para equilibrar a exploração econômica e a conservação ambiental. Essas iniciativas são essenciais para promover o manejo sustentável e proteger os recursos florestais da Amazônia.

Palavras-chave: extração seletiva, detecção de mudanças, sistema de monitoramento, manejo florestal, degradação florestal, distúrbio florestal.

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CHAPTER I - Introduction and Research Framework

1.1 Definition of the Problem and Research Questions

The Amazon rainforest plays a crucial role in maintaining global biodiversity, regulating the Earth's climate, and sequestering carbon. However, forest disturbances, such as selective logging, pose significant threats to forest structure, biodiversity, and ecosystem functions. While sustainable forest management aims to mitigate these impacts, effective monitoring systems are necessary to ensure compliance with sustainable practices and to detect unauthorized disturbances.

Traditional monitoring methods, such as field inspections and coarse-resolution satellite imagery, often lack the spatial and temporal resolution needed to capture the heterogeneity of selective logging activities. This creates challenges in identifying subtle forest changes and delays in responding to disturbances. Emerging remote sensing technologies, including high-resolution satellite imagery (e.g., PlanetScope) and LiDAR, offer promising solutions due to their ability to provide detailed spatial information on forest structure and canopy dynamics.

Despite the advancements in remote sensing, several knowledge gaps remain. There is a need for an integrated approach that combines multiple data sources to improve the detection of forest disturbances, particularly within federal concession areas where sustainable forest management plans (SFMPs) are implemented. Additionally, the effectiveness of these combined technologies in assessing the spatial and temporal impacts of selective logging remains underexplored.

Furthermore, scientific literature on remote sensing applications for sustainable forest management is growing, but a comprehensive analysis of trends, advancements, and persistent gaps is necessary to guide future research and policy development. Addressing these gaps will require the validation of innovative methodologies to ensure their accuracy and reliability for large-scale, continuous monitoring of SFMPs in the Amazon.

In this context, this study seeks to enhance forest disturbance detection and monitoring by integrating high-resolution remote sensing technologies. By leveraging a scientometric approach, systematic reviews, and field-based validations, the research aims to contribute to the development a propose of an effective monitoring methodology that supports sustainable forest management and conservation efforts in the Amazon.

Within this context, the study seeks to address the following research questions:

- How can innovative remote sensing technologies improve the detection and monitoring of forest disturbances to support sustainable forest management and conservation in the Amazon?

To delve deeper, the following specific questions are examined:

- What are the current trends, gaps, and advancements in the application of remote sensing technologies for monitoring forest disturbances and sustainable management in the Amazon? *Sub-question:* What insights can be derived from a scientometric approach and systematic review of existing studies on this topic?
- How does selective logging influence forest structure and heterogeneity over time in a federal concession area before and after exploitation in the Amazon? *Sub-question:* What can integrate analyses of forest inventory data and satellite imagery reveal about the spatial and temporal impacts of selective logging?
- What is the potential of a combined methodology using LiDAR and PlanetScope data for detecting and monitoring forest disturbances in sustainable forest management plans? *Sub-question:* How can this methodology be validated to ensure accuracy and reliability in monitoring systems?

1.2 General Objectives of the Thesis

General Objective

To enhance the detection and monitoring of forest disturbances in the Amazon using innovative remote sensing technologies to support sustainable forest management and conservation strategies.

Specific Objectives

- To analyze the trends, gaps, and advancements in remote sensing applications for monitoring forest disturbances and sustainable management in the Amazon through a scientometric approach and systematic review.
- To assess the spatial and temporal impacts of selective logging on forest structure and heterogeneity using integrated forest inventory and satellite data in a federal concession area.

- To develop and validate a methodology combining LiDAR and PlanetScope data for accurate detection and monitoring of forest disturbances within sustainable forest management plans.

1.3 Main Hypotheses

General Hypothesis

H1: Innovative remote sensing technologies, when effectively integrated, significantly enhance the accuracy and efficiency of detecting and monitoring forest disturbances, contributing to improved sustainable forest management and conservation strategies in the Amazon.

Hypotheses for Specific Objectives

Objective 1: Trends, gaps, and advancements in remote sensing applications

- **H1.1:** The current body of literature on remote sensing technologies for forest disturbance monitoring demonstrates significant advancements but reveals critical gaps in spatial and temporal resolution for addressing the complexity of Amazonian ecosystems.
- **H1.2:** A scientometric approach and systematic review will identify underexplored areas, particularly the integration of advanced sensor technologies like LiDAR and high-resolution satellite imagery.

Objective 2: Impacts of selective logging on forest structure and heterogeneity

- **H2.1:** Selective logging causes detectable changes in forest structure and heterogeneity over time, which vary spatially across the federal concession area.
- **H2.2:** The integration of forest inventory data and high resolution satellite imagery provides a more comprehensive understanding of these spatial and temporal impacts compared to using either dataset independently.

Objective 3: Methodology combining LiDAR and PlanetScope data

- **H3.1:** A combined methodology using LiDAR and PlanetScope data significantly improves the detection and monitoring of forest disturbances compared to conventional methods.

- **H3.2:** The validation process will demonstrate that this integrated approach achieves higher accuracy and reliability for monitoring forest disturbances within sustainable forest management plans.

1.4 Theoretical Framework

The Amazon rainforest, one of the planet's most biodiverse ecosystems, is crucial for global climate regulation, biodiversity preservation, and supporting indigenous and traditional communities (MALHI *et al.*, 2008; LOVEJOY & NOBRE, 2019). However, it faces growing threats from deforestation, illegal logging, land-use changes, and climate change impacts (LAURANCE *et al.*, 2011; BRANDO *et al.*, 2020), demanding sustainable management practices to preserve its ecological integrity.

Beyond its ecological importance, the Amazon holds significant economic value through its timber market and non-timber forest products (NTFPs). The legal timber industry supports local livelihoods, regional development, and revenue generation via domestic and international trade (VERÍSSIMO *et al.*, 2000). However, challenges such as illegal logging, mismanagement, and ineffective monitoring systems threaten sustainable exploitation, forest conservation, and the credibility of legal timber markets (OLIVEIRA *et al.*, 2024). Addressing these issues is essential to promote sustainable practices and maintain market competitiveness, ensuring the Amazon's resources contribute to both economic growth and environmental preservation (MATRICARDI *et al.*, 2020).

Sustainable Forest Management (SFM) in the Amazon entails carefully planned practices that allow resource extraction while preserving the forest's structure and functionality. Among these practices, Reduced Impact Logging (RIL) has emerged as a pivotal strategy to mitigate ecological damage during selective logging operations (PEREIRA-JUNIOR *et al.*, 2002; COSTA PINTO *et al.*, 2024). However, the effectiveness of these practices is often hindered by the inherent complexity and heterogeneity of the Amazon's forest ecosystems, characterized by diverse topoclimatic, pedological, and hydrological conditions (OLIVEIRA *et al.*, 2024b).

In this context, advances in remote sensing (SR) technologies, such as high-resolution satellite imagery, LiDAR, and classification techniques, have revolutionized forest monitoring. These innovations enable precise detection of changes in forest cover, facilitating the identification of both legal and illegal activities and improving the

understanding of forest dynamics (ASNER *et al.*, 2005; SOUZA *et al.*, 2020; MATRICARDI *et al.*, 2020). This thesis explores the integration of these cutting-edge technologies to address the key challenges in monitoring and managing forest resources in the Amazon.

This study underscores the importance of leveraging advanced remote sensing technologies and adaptive strategies to address the challenges of forest management in the Amazon. By bridging scientific knowledge with practical applications, the research aims to contribute to the sustainable exploitation of forest resources while safeguarding the ecological and socio-economic values of the Amazon, ensuring that its economic potential, including both timber and non-timber products, is harnessed responsibly for future generations.

1.5 General Comments

- **Relevance of the Study**

The thesis addresses a critical issue by focusing on the detection and monitoring of forest disturbances in the Brazilian Amazon, specifically within sustainably managed areas of dense ombrophilous forest. The emphasis on supporting sustainable forest management plans (SFMPs) through innovative remote sensing technologies highlights the importance of ensuring the preservation of forest ecosystems and their services, such as carbon sequestration and biodiversity conservation.

- **Scientific Contribution**

The integration of LiDAR data, PlanetScope satellite imagery, and forest inventory data is a novel approach to improving the detection of subtle forest changes caused by selective logging. This combination enhances the precision of spatial and temporal analyses compared to traditional monitoring methods. The validation of this integrated methodology using LiDAR flyover data and forest inventory data strengthens the contribution of research to remote sensing and forest management fields.

- **Interdisciplinary Approach**

The incorporation of a scientometric analysis and systematic review provides a robust foundation for understanding the trends, gaps, and advancements in remote sensing applications for forest disturbance monitoring. This interdisciplinary approach ensures

that the work is informed by a comprehensive synthesis of the scientific literature, reinforcing its credibility and impact.

- Innovation in Methodology

Development of a remote sensing system that combines high spatial and temporal resolution data demonstrates innovation in the field of forest monitoring. The use of PlanetScope imagery to capture frequent changes and LiDAR to assess vertical forest structure addresses key limitations of single-sensor approaches. This methodological innovation positions the thesis as a significant contribution to the development of next-generation monitoring systems.

- Application to Forest Management Plans

By focusing on federal concession areas, the research has practical implications for sustainable resource management and policy enforcement. Demonstrating how the proposed methodology can detect unauthorized disturbances and improve the efficiency of SFMPs aligns your study with real-world needs for monitoring compliance and supporting certification programs for responsible forest management.

- Challenges and Validation

The validation of the proposed methodology is a key component of the research. Addressing potential challenges, such as image inconsistencies due to cloud cover or spatial misalignment, will be critical. The use of ground-truth data from forest inventories and high-resolution LiDAR scans provides a robust framework for ensuring the accuracy and reliability of the system.

- Broader Implications

The findings of the thesis have the potential to contribute not only to the academic field of remote sensing and forestry but also to environmental governance and conservation strategies. By improving the detection of selective logging impacts, your work can support more effective policy decisions and promote transparency in forest resource management.

- Future Perspectives

The research can pave the way for future studies aimed at scaling monitoring systems for larger areas or applying similar methodologies to different forest biomes. Additionally, it can inspire new research into the integration of machine learning

algorithms for automated detection and classification of different types and intensities of forest disturbances.

1.6 Thesis Structure

This thesis is structured into three chapters that are interconnected by their shared focus on improving the understanding, monitoring, and management of forest disturbances caused by selective logging in the Amazon. Together, they build a comprehensive narrative that integrates foundational knowledge, applied methodologies, and innovative frameworks to address the challenges in SFM.

Chapter I lays the groundwork by conducting a systematic review and scientometric analysis of the applications of RS technologies in monitoring forest degradation and selective logging. It identifies current trends, highlights gaps in literature, and underscores the potential of integrating optical and LiDAR remote sensing data for improving monitoring systems. This chapter provides a broad perspective, emphasizing the critical need for accurate and efficient technologies to detect and differ subtle and large-scale forest disturbances, setting the stage for the applied analyses in Chapters II and III.

Chapter II transitions from a theoretical overview to a practical application by analyzing the spatio-temporal intensity of logging within a federal concession in the Brazilian Amazon. This chapter leverages forest inventory data, topographic information, and high-resolution optical satellite imagery to assess the impacts of selective logging on forest structure. The analysis focuses on heterogeneity within the logged areas, addressing some of the research gaps identified in Chapter I, particularly the need for precise methodologies to evaluate forest management practices under real-world conditions.

Chapter III builds on the findings and methodologies of the previous chapters by proposing an integrated framework for monitoring SFM plans using LiDAR and PlanetScope data. This chapter combines the insights from Chapter I on the benefits of multi-sensor approaches with the practical challenges observed in Chapter II, where optical data alone showed limitations in detecting subtle structural changes. The integration of LiDAR provides a complementary perspective, enabling a more detailed assessment of forest canopy disturbances and validating optical data, ultimately enhancing the monitoring accuracy and reliability.

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CHAPTER II – Assessing Forest Degradation Through Remote Sensing In The Brazilian Amazon: Implications And Perspectives For Sustainable Forest Management¹

Abstract: Forest degradation and forest disturbance are distinct yet often conflated concepts, complicating their definition and monitoring. Forest degradation involves interrupted succession and a severe reduction in forest services over time, caused by factors like fires, illegal selective logging, and edge effects. Forest disturbance, on the other hand, refers to abrupt, localized events, natural or anthropogenic, such as legal selective logging, tropical blowdowns, storms, or fires, without necessarily leading to long-term degradation. Despite the varying intensity and scale of forest degradation and disturbance, systematic studies distinguishing its types and classes are limited. This study reviews anthropogenic impacts on forests in the Brazilian Amazon, analyzing 80 scientific articles using remote sensing techniques and data. Most research focuses on the “arc of deforestation,” characterized by intense human activity, showcasing methodological advancements but also revealing gaps in monitoring less-studied regions like the central and western Amazon. The findings emphasize the need for advanced remote sensing tools to differentiate degradation types, particularly in sustainable forest management (SFM) contexts. Expanding research to underrepresented regions and refining methodologies are crucial for better understanding forest dynamics and improving conservation strategies. These efforts are essential to support effective forest management and informed policy development across the Amazon.

Keywords: *forest disturbance; selective logging; anthropogenic impacts; conservation strategies*

Resumo: A degradação florestal e o distúrbio florestal são conceitos distintos, mas muitas vezes confundidos, comprometendo sua definição e monitoramento. A degradação florestal envolve intervenções sucessivas e uma redução severa nos serviços florestais ao longo do tempo, causada por fatores como incêndios, extração seletiva ilegal de madeira e efeitos de borda. O distúrbio florestal, por outro lado, refere-se a eventos abruptos e localizados, naturais ou antropogênicos, como extração seletiva legal, quedas de árvores pelo vento, tempestades ou incêndios, sem necessariamente levar à degradação a longo prazo. Apesar da intensidade e escala variáveis da degradação e distúrbio florestal, estudos sistemáticos que distinguem seus tipos e classes são limitados. Este estudo analisou os impactos antrópicos sobre as florestas na Amazônia brasileira, analisando 80 artigos científicos utilizando técnicas e dados de sensoriamento remoto. A maioria das pesquisas se concentra no "arco do desmatamento", caracterizado por intensa atividade humana, apresentando avanços metodológicos, mas também revelando lacunas no monitoramento de regiões menos estudadas, como a Amazônia central e ocidental. Os resultados enfatizam a necessidade de ferramentas avançadas de sensoriamento remoto para diferenciar os tipos de degradação, particularmente em contextos de manejo florestal sustentável (SFM). Expandir a pesquisa para regiões subrepresentadas e refinar metodologias são cruciais para entender melhor a dinâmica florestal e melhorar as

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estratégias de conservação. Esses esforços são essenciais para apoiar o manejo florestal eficaz e o desenvolvimento de políticas informadas em toda a Amazônia.

Palavras-chave: *perturbação florestal; exploração seletiva; impactos antrópicos; estratégias de conservação.*

1. Introduction

1.1. Sustainable Forest Management in the Amazon: Importance and Challenges

Tropical forests are one of the world's largest and most productive ecosystems. They also play an essential role in the global carbon cycle, containing 44% of the world's above-ground biomass (LIU *et al.*, 2019; XU *et al.*, 2021). The Brazilian Amazon contains one-third of the world's tropical forests. Its commercial roundwood stocks are estimated to be around 60 billion m³ (2118 trillion ft³), making it the world's largest tropical timber reserve (WWF, 2012; FAO, 2020; IBGE, 2024; BRASIL, 2012).

Sustainable forest management (SFM) is an approach to managing forests that balances environmental, social, and economic objectives to meet the needs of present and future generations (BRASIL, 2012). SFM encompasses practices that maintain and enhance forest health, productivity, biodiversity, and ecological functions (BRASIL, 2012). Reduced impact logging (RIL) is a forest management practice designed to minimize the ecological damage that typically accompanies selective logging and is widely applied in SFM in the Amazon (BRASIL, 2012; PEREIRA-JUNIOR *et al.*, 2022). RIL involves practices that significantly reduce impacts compared to conventional logging; some of these practices include pre-harvest planning, targeted felling techniques, log drag control, and continuous monitoring (PEREIRA-JUNIOR *et al.*, 2002). Selective logging is a stage of management that aims to harvest specific trees while preserving the structure of the forest, contributing to sustainability when rigorously planned and monitored (PEREIRA-JUNIOR *et al.*, 2022; LAMB *et al.*, 2005). These practices minimize unnecessary canopy openings, protect surrounding vegetation, and maintain the overall forest structure, thereby mitigating the ecological impacts typically associated with logging activities (PEREIRA-JUNIOR *et al.*, 2022).

In contrast, conventional logging often results in significant forest degradation due to uncontrolled felling, poorly planned roads, and extensive canopy gaps (PEREIRA-JUNIOR *et al.*, 2022). This unregulated approach compromises forest health and

biodiversity, leading to a decline in ecosystem services, prolonged carbon emissions, and challenges in forest regeneration (LAMB *et al.*, 2005; OLIVEIRA *et al.*, 2024; PUTZ *et al.*, 2012; CHAZDON, 2008). By comparison, RIL reduces these impacts, promoting sustainability and aligning with the principles of SFM.

Pereira-Jr *et al.* (2002) highlights the differences in canopy gap fractions caused by conventional logging (CL) and RIL in 1996 and 1998. CL consistently resulted in higher canopy gaps, with total gap percentages of 16.5% and 21.6% in 1996 and 1998, respectively, primarily driven by tree felling and skidding activities. In contrast, RIL demonstrated significantly lower impacts, with total gap percentages of 4.9% and 10.9%, emphasizing its effectiveness in minimizing forest canopy disruption. The data reinforce the value of RIL as a sustainable logging practice that reduces environmental impacts while maintaining forest structure.

Nevertheless, under Brazilian standards, specific values are established for harvesting intensity per hectare (BRASIL, 2012). The authorized harvesting intensity of Brazilian forests is not associated with data on the heterogeneity of the original forest structure, i.e., the volumes determined for extraction are fixed and standardized (OLIVEIRA *et al.*, 2024). In the SFM for the Saracá-Taquera National Forest in the Brazilian Amazon, logging intensity surpassed 100 m³ ha⁻¹, with more than 20 trees harvested per hectare in certain areas (OLIVEIRA *et al.*, 2024). Putz *et al.* (2012) they mentioned that the challenge in managing tropical forests arises from their complex and diverse ecosystems. Chazdon *et al.* (2008), mentioned that the challenge in managing tropical forests stems from their complex and diverse ecosystems. According to Chazdon *et al.* (2008), improper use of natural forests can disrupt logging cycles and harm ecosystems.

SFM is recognized as a forest conservation strategy, but gaps remain in evaluating indicators that point to more appropriate ways of exploiting forest resources (PEREIRA-JUNIOR *et al.*, 2002; MACDICKEN *et al.*, 2015).

These challenges related to conducting SFM raise the following guiding questions: (i) What is the temporal trend in publications on remote sensing techniques and sustainable forest management? (ii) Which institutions and countries are leading this research? (iii) Which approaches are most commonly used? (iv) What are the main techniques and sensors used? (v) What is the spatial distribution and territorial scope of the studies throughout the Amazon biome?

1.2. Remote Sensing in Tropical Forest Monitoring

Remote sensing (RS) plays an important role in monitoring and quantifying canopy disturbance caused by selective logging (NEPSTAD *et al.*, 1999; ASNER *et al.*, 2005; SAATCHI *et al.*, 2011). Studies have shown that high spatial and temporal resolution images are necessary to monitor selective logging in the Amazon (ASNER *et al.*, 2005; MATRICARDI *et al.*, 2013). In addition, the remote sensing techniques and products used for mapping and monitoring studies of selective logging have been insufficient for large-scale assessments (ARAGÃO *et al.*, 2014; ABDLLAHNEJAD *et al.*, 2019; MATRICARDI *et al.*, 2020).

Abdollahnejad *et al.* (2019) have proposed an advanced approach integrating geographic information systems (GISs) and remote sensing using high-resolution images to monitor logging areas. Their research suggests that high spectral and spatial resolution images are necessary to increase the accuracy of volume estimates. Petri *et al.* (2022) also tested using images from the *PlanetScope* nanosatellite constellation for vegetation studies in the Amazon. They concluded that high spatial and temporal resolution images are essential for understanding forest dynamics in the Amazon. Yet, for extensive areas like the Amazon, these costs can quickly escalate, posing a challenge for continuous and largescale monitoring efforts (ABDLLAHNEJAD *et al.*, 2019).

Advances in RS technologies, such as high-resolution satellites, drones, and LiDAR (*Light Detection and Ranging*) sensors, combined with machine learning techniques, have provided new possibilities for effectively and sustainably monitoring and managing forests (ABDLLAHNEJAD *et al.*, 2019; WINSTANLEY *et al.*, 2024). These technologies enable precise detection and monitoring of changes in forest cover, making it easier to identify illegal activities and assess the impacts of logging (WINSTALEY *et al.*, 2024; DALAGNOL *et al.*, 2023). However, the application of high spatial resolution sensors to the analysis of forest degradation in SFM is still limited to smaller areas, as evidenced by the scope of the studies conducted.

1.3 Defining Forest Degradation and Forest Disturbance

The literature is rife with dozens of definitions of forest degradation regarding partial changes to the forest canopy. Categorizing forest degradation is challenging due to its dependence on the study's objective, biophysical conditions, causes, and

spatiotemporal scales (SASAKI & PUTZ, 2009; THOMPSON *et al.*, 2013). Simula (2009) e Thompson *et al.* (2013) argue that the lack of scientific consensus on forest degradation has led to many definitions and multiple ways of measuring it, particularly by RS. More recently, the term forest disturbance has been increasingly used to describe more subtle changes in forest structure and function (PEREIRA-JUNIOR *et al.*, 2002; ASNER *et al.*, 2005; MATRICARDI *et al.*, 2013; OLIVEIRA *et al.*, 2024). These disturbances often include events that do not result in outright deforestation but still alter the forest's composition, canopy cover, or ecosystem services, such as selective logging, fires, and small-scale natural events. This shift in terminology reflects an effort to capture a broader spectrum of forest dynamics and to better align with advances in RS technologies that can detect such nuanced changes (ASNER *et al.*, 2005; MATRICARDI *et al.*, 2013; OLIVEIRA *et al.*, 2024; ABDLLAHNEJAD *et al.*, 2019).

In this analysis, forest degradation can be defined as a condition of interrupted succession due to human actions, leading to a severe reduction in the forest's services over a certain period. It is a temporal process in which forest services decline and can be caused by forest fires, illegal selective logging, and edge effects, among others (THOMPSON *et al.*, 2013; SIMULA, 2009; GHAZOUL *et al.*, 2015; VÁSQUEZ-GRADÓN *et al.*, 2018). In contrast, forest disturbance refers to any abrupt and localized event, natural or anthropogenic, that disrupts forest structure or function, such as legal selective logging, tropical blowdowns, storms or even forest fires, without necessarily causing long-term degradation (ASNER *et al.*, 2005; MATRICARDI *et al.*, 2013; OLIVEIRA *et al.*, 2024; ABDLLAHNEJAD *et al.*, 2019). Thus, while forest degradation implies a sustained loss of ecosystem services, forest disturbance can be temporary and sometimes even a part of natural forest dynamics (PEREIRA-JUNIOR *et al.*, 2002; ASNER *et al.*, 2005; MATRICARDI *et al.*, 2013).

In this context, the Reducing Emissions from Deforestation and Forest Degradation (REDD+) program is an international initiative aimed at combating climate change by addressing forest loss and degradation. Figure 1 illustrates the relationship between degradation, deforestation, and sustainable practices such as SFM in the context of REDD +. Each component of the acronym REDD+ represents a key focus area. The first D (deforestation) focuses on preventing the permanent removal of forests (clear-cut), which releases significant amounts of stored carbon into the atmosphere (line C, Figure 1). The second D (degradation) addresses the decrease in forest quality and carbon storage capacity caused by activities such as illegal selective logging, fires, edge effects, or other

human-induced action. At this stage, the services provided by the forest are significantly reduced and CO₂ emissions are prolonged over time, but the vegetation is not completely removed (line B, Figure 1). The plus sign (+) extends the scope of the program to include some sustainable practices like the conservation of forest carbon stocks and the sustainable management of forests (line A, Figure 1) (UNFCCC, 2012). Here, forest disturbances resulting from legal selective logging are represented as critical factors, emphasizing the need to mitigate their impact to ensure the effectiveness of these sustainable practices. This expanded framework aims to address a broader set of activities to promote sustainable development while mitigating climate change impacts (NASI *et al.*, 2011; MORALES-BARQUERO *et al.*, 2014).

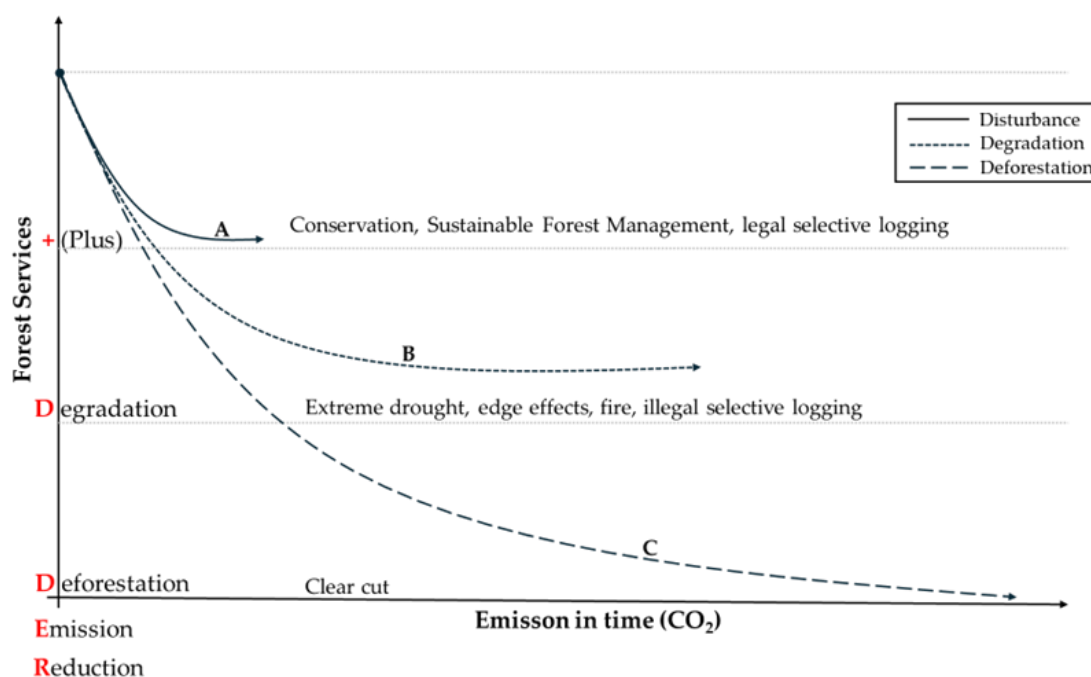


Figure 1. The graph illustrates the impact of human activities on forest ecosystem services in the context of REDD+ (red letters on the Y axis). Curve A (disturbance) represents forest carbon stock conservation practices and sustainable forest management, where forest interventions cause low CO₂ emissions and favorable variations in forest services, represented by the REDD+ “plus” (+) symbol. Curve B (degradation) represents a forest degraded by anthropogenic events such as extreme droughts, edge effects, fire, and illegal logging that persist over time. Curve C (deforestation) represents the maximum stage of anthropogenic intervention and the complete absence of forest services, since at this stage the vegetation has been completely removed (clear-cutting), represented by the first D in the REDD+ acronym. Source: adapted from (THOMPSON *et al.*, 2013; GHAZOUL *et al.*, 2015; VÁSQUEZ-GRANDÓN *et al.*, 2018; DUPUIS *et al.*, 2020).

Source: OLIVEIRA, 2024.

However, the term “forest degradation” is often used to describe legal selective logging activities (DALAGNOL *et al.*, 2023; MATRICARDI *et al.*, 2010; KUCK *et al.*, 2021; LAPOLA *et al.*, 2023; MORENO *et al.*, 2023). It is essential to point out that

although legal selective logging can be considered forest degradation from an anthropological perspective or by generic definitions, this classification is inadequate (FERREIRA *et al.*, 2015). The selective extraction of legal timber is an activity integrated into SFM and is considered a mechanism of REDD+ policies and, therefore, in first approximation, should not be categorized as forest degradation (FERREIRA *et al.*, 2015), but rather as forest disturbance, as it should not cause de-characterization or damage to the environmental function of the managed forest ecosystem (MATRICARDI *et al.*, 2013; FERREIRA *et al.*, 2015).

It is essential to consider a more comprehensive approach that considers broader ecological processes, regardless of their impact on human society, such as forest dynamics and resilience (MORALES-BARQUERO *et al.*, 2014; GHAZOUL *et al.*, 2015; VÁSQUES-GRANDÓN *et al.*, 2018). Ecosystem resilience is the capacity to return to its original state in terms of structure and function after a disturbance without requiring external intervention (VÁSQUES-GRANDÓN *et al.*, 2018).

1.4 Mapping Forest Degradation and Legal Selective Logging

The techniques, methods, and data sources used for mapping and monitoring forest degradation and selective logging in the Amazon are essentially the same, as both detect and analyze changes in forest cover when the forest is not entirely removed (MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020; KUCK *et al.*, 2021). Although, from the point of view of remote sensing, the equivalence in detection between these two actions is to be expected, and several studies treat both in a similar way (MATRICARDI *et al.*, 2013; KUCK *et al.*, 2021; DALAGNOL *et al.*, 2023; LAPOLA *et al.*, 2023; MORENO *et al.*, 2023), some important points need to be kept in mind.

The intensity and types of disturbance are different in the various types of degradation, including the partial loss of living biomass and forest quality, without the complete removal of vegetation cover. This can include the death of trees, damage to soil and under-story vegetation, and a reduction in biodiversity (MATRICARDI *et al.*, 2013). However, in legal selective logging with reduced impact, the disturbances are smaller and relate to the specific removal of trees of high commercial value, usually with openings in the forest, logging trails, and collateral damage to other trees and understored vegetation (PEREIRA-JUNIOR *et al.*, 2002; BROADBENT *et al.*, 2008; SEBBENN *et al.*, 2008). Therefore, disturbances caused to forests by selective logging are of lesser intensity in

cases of forest management implementation and, for this reason, should be distinctly mapped and considered (PEREIRA-JUNIOR et al., 2022; MATRICARDI et al., 2013; SEBBENN et al., 2008). Although using RIL reduces disturbance, these disturbances can still be classified as low intensity, since they cause changes to the forest's structure and the ecosystem's dynamics (MATRICARDI et al., 2013; BROADBENT *et al.*, 2008).

Taking the above points into account, it should be noted that the simplest and most effective way of differentiating the intensities of forest degradation processes is by observing selectively logged areas in sustainable management plans, where there are Forest Management Unit (FMU) boundaries, as well as timber unit (TU) boundaries, allowing for auxiliary information in classifying the changes detected. In SFM, the FMU represents the designated portion of the property allocated for forest management. The specific area designated for logging activities is referred to as a timber unit (TU) (BRASIL, 2012; Oliveira et al., 2004).

In contrast, in areas affected by fire or high-intensity or illegal selective logging, the intensities of forest degradation are much higher, indicating that monitoring systems must be more specific in order to discriminate between the different types of forest disturbance, which result in very different impacts and levels of degradation (MATRICARDI *et al.*, 2013). Figure 2 shows a cross-section of forest change detection alerts from the systems (A) DE-TER/INPE, (B) SAD/IMAZON, and (C) Brazilian Forestry Service (BFS)/SCCON, respectively, which intersect the TU in the FMU inside the Saracá-Taquera National Forest. Systems A and B are used in command-and-control policies and operate throughout the Amazon using low and medium spatial resolution images. System C monitors and maps forest disturbances in specific areas within the limits of the SFM boundaries using *PlanetScope* high spatial and temporal resolution images carried out by the Brazilian Forestry Service (BFS). System C shows greater consistency and precision in relation to the extracted areas of vegetation, using selective logging practices, and consequently with more coherent classification related to the phenomenon (SOUZA-JUNIOR *et al.*, 2005; DINIZ *et al.*, 2015; SFB, 2024).

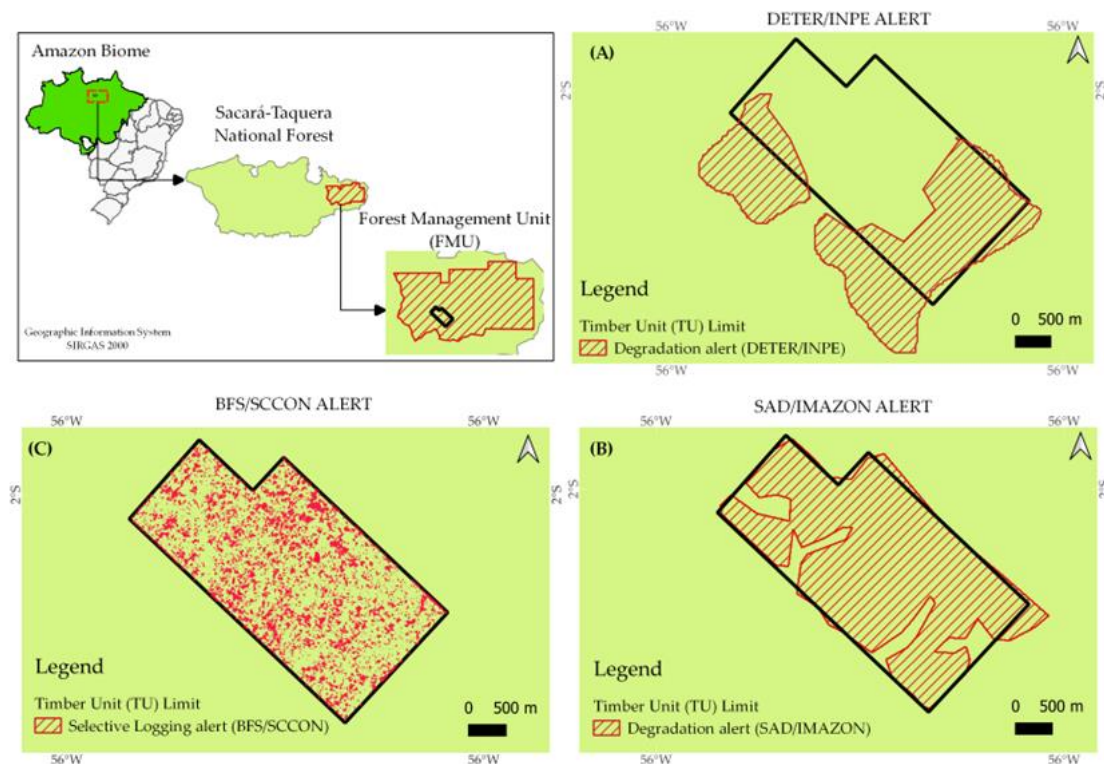


Figure 2. Forest degradation alerts from the systems (A) DETER/INPE (Real-Time Deforestation Detection System, developed by the National Institute for Space Research—INPE); (B) SAD/IMAZON (De-forestation Alert System, developed by the Amazon Institute for Man and the Environment—IMAZON); and Selective Logging alert (disturbance) (C) Brazilian Forestry Service (BFS)/SCCON (Brazilian Forestry Service system, developed by SCCON Geospatial). These systems intersect the timber unit in the Forest Management Unit inside the Saracá-Taquera National Forest, Brazilian Amazon.

Source: OLIVEIRA, 2024.

Misclassifications of different levels of forest disturbance can underestimate or over-estimate the extent of the impacts caused on forests, particularly in the case of selective logging in the Amazon. When conducted legally and under sustained management, selective logging is thought to have a low intensity of disturbance and minimal effects on the forest ecosystem (PEREIRA-JUNIOR *et al.*, 2002). However, generalized classifications of forest degradation areas without distinguishing between different types of disturbance can compromise the credibility of regulated forest conservation and management initiatives in the Amazon (VELASCO *et al.*, 2022; PINAGÉ *et al.*, 2023).

The lack of differentiation between forest extraction practices associated with SFM and other degradation processes with different impacts can lead to difficulties raising funds for conservation projects and discourage investment in sustainable management practices in the Amazon. Public policies and regulations based on incorrect data can be ineffective or harmful (KREMEM *et al.*, 2000; SAGOBAL *et al.*, 2013). This

can result in an inadequate allocation of resources for forest conservation and management, as well as hindering the implementation of effective strategies for forest protection (NASI *et al.*, 2011). Accuracy in classifying the different intensities of forest disturbances or degradation is crucial for environmental, economic, and social sustainability in forest management in the Amazon (SASAKI & PUTZ, 2009; MORALES-BARQUERO *et al.*, 2014).

1.5. Objective

In order to better distinguish anthropogenic forest disturbances and degradation in different intensities, spatial dimensions, and temporality, detected by remote sensing in the Amazon forest, we aim to map the spatial distribution and temporal evolution of studies in the Amazon biome by means of remote sensing and identifying the main techniques and sensors used to better understand the patterns, trends, and gaps associated with monitoring anthropogenic forest disturbances, generically referred to as forest degradation.

2. Materials and Methods

2.1. Search Process and Article Selection

We conducted a systematic literature review on the remote monitoring of anthropo-genic forest disturbances and their impact on sustainable forest management. The review was based on a spatiotemporal evaluation of the main techniques and sensors used to monitor and map forest degradation and legal selective logging in the Amazon. As they have a specific focus on conservation and environmental management, the systematic re-view guidelines proposed by Pullin and Sterward (2006) were followed.

This study used only articles that explicitly applied RS techniques and images aimed at detecting anthropogenic forest disturbances, in order to contribute to advancing the discussion on distinguishing forest degradation from legal selective logging in the Amazon. In this way, the main approaches, trends, and gaps in research on anthropogenic forest disturbances, notably, forest degradation and legal selective logging in the Amazon, were analyzed.

Only peer-reviewed articles published between January 2003 (the year the first article appeared) and July 2024 were selected from the *Scopus* and *Web of Science* databases (ZHU *et al.*, 2020; HERNÁNDEZ-GONZÁLEZ *et al.*, 2016). The search considered synonyms found in the literature based on the keywords in the title, abstract, and keywords, and the ALL option was chosen in the search (Table 1). These terminologies are widely used in literature for remote monitoring studies of forest disturbances and degradation in the Amazon. Reviews, conferences, and book chapters were excluded, as peer-reviewed articles are considered the most reliable source for reviewing the literature among the documents available (DE OLIVEIRA *et al.*, 2019; GARZA-REYES, 2015).

Table 1. Search expression encoded in Web of Science and Scopus and applied to titles, abstracts, and keywords.

Criteria	Search Expression	
What?	"Selective Logging" OR "Selective Harvesting" OR "Selective Cutting" OR "Disturbance" OR "Forest Disturbance" OR "Illegal Logging" OR "Degradation" OR "Forest Degradation"	
How?	AND	"Monitoring" OR "Remote Sensing" OR "Satellite"
Where?	AND	"Amazon"
Limited to?	Articles	
Data range	2003/January to 2024/July	

Source: OLIVEIRA, 2024, adapted from DUPUIS *et al.*, 2020.

In addition to articles written in English, papers written in Portuguese were also analyzed, as the subject is geographically related to Brazil, and some references are in Portuguese. We expanded the language filter to ensure that a thorough analysis of the scientific literature identifies and synthesizes relevant evidence, regardless of geographical origin or language of publication. Non-English publications may contain ideas or provide context not available in English articles (WALPOLE, 2019).

2.2. Data Selection and Integration

With the keywords mentioned, 136 articles were identified in Web of Science and 81 articles were identified in Scopus (as of 1 July 2024), which were compiled into CSV (comma-separated values) and TXT (text format) files from the respective databases. After debugging duplicate articles in different databases with the help of RStudio software (Version 4.3.1) using the `mergeDbSource` and `remove.duplicated` functions of the Bibliometrix package (ARIA, 2017), 158 articles remained.

After carefully selecting articles, we reviewed each paper to remove duplicates from the database. We specifically checked each article to ensure it focused on the Amazon biome and used remote sensing products, techniques, and images to map and monitor forest degradation and forest disturbances. After this thorough process, we selected 80 articles for analysis (Figure 3).

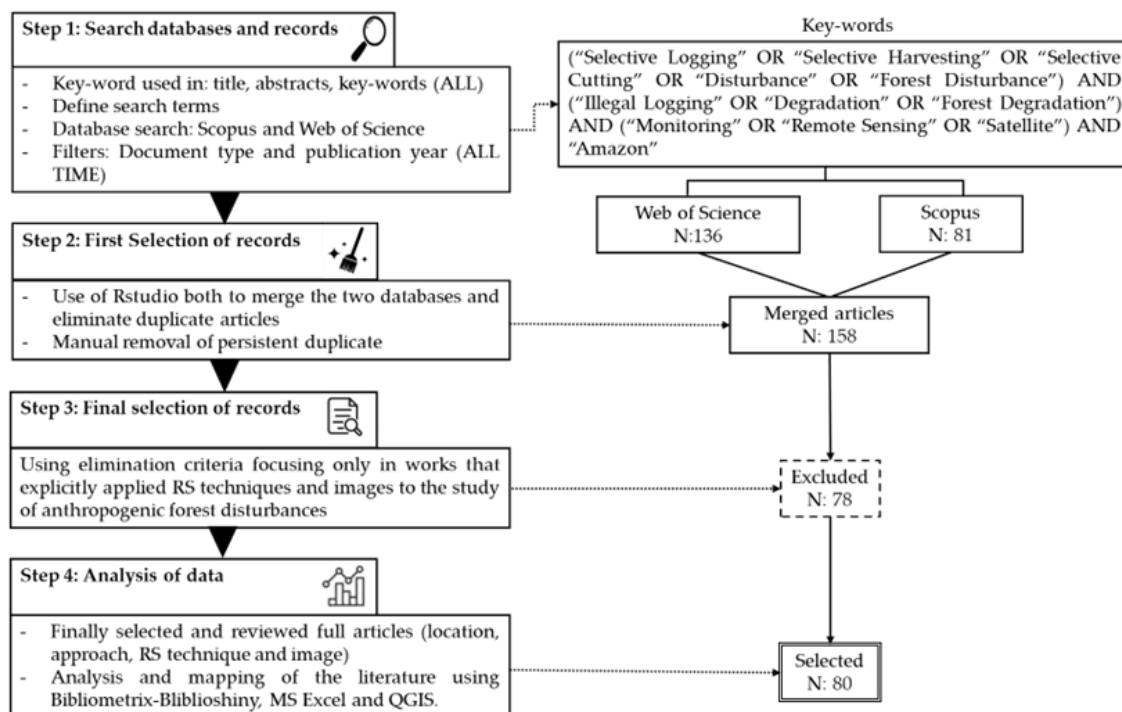


Figure 3. An overview of the criteria and procedure for the bibliographic search for a systematic review of the literature on works that explicitly apply RS techniques and images to the study of anthropogenic forest disturbances. N = Number of articles.

Source: OLIVEIRA, 2024.

2.3 Classification, Organization of Information, and Data Analysis

Based on this number, we proceeded to organize and classify the information contained in the articles. To systematize the evaluation of the approaches used, trends, and gaps in research, the information was listed in chronological order, starting with the most recent year. The information gleaned from the articles was categorized in terms of the exact location of the study area (geographical coordinates), the digital processing techniques used in the satellite images, and the sensors used.

Additionally, the articles were categorized based on the type of anthropogenic forest disturbance presented and classified accordingly:

- (a) Legal selective logging: for works that applied RS techniques to map or monitor anthropogenic forest disturbances arising exclusively from logging activities in authorized sustainable forest management areas.
- (b) Forest degradation: for works that applied RS techniques to map or monitor anthropogenic forest degradation of any nature other than legal selective logging.
- (c) Legal selective logging + forest degradation: for works that applied RS techniques to map or monitor both anthropogenic actions simultaneously.

Based on the criteria provided, we have established the following analysis parameters: (a) annual global publication trend; (b) analysis of emerging patterns and trends; (c) spatial distribution and approach of the work; (d) the main techniques used for mapping or monitoring; (e) the main RS images used for monitoring or mapping; and (f) teaching and research institutions that have published the most on the subject.

3. Results

3.1. Global Publication Trends

The red dotted regression line shows a positive slope, indicating a general increase in the number of scientific publications over time. This reflects the growing attention to monitoring degradation and anthropogenic forest disturbances in the Amazon biome. This upward trend suggests growing interest and research activity in this topic area over the years. Although there is an overall upward trend, individual years show considerable variation in production. For example, the years that showed the highest scientific productivity were 2019, 2020, and 2023, accounting for 26 articles, approximately one-third of all publications (32.5%). Among these, 2019 and 2023 have stood out with nine publications each. Conversely, 2003, 2004, 2011, and 2015 had the lowest number of publications, with only one article each year (5%) (See Figure 4).

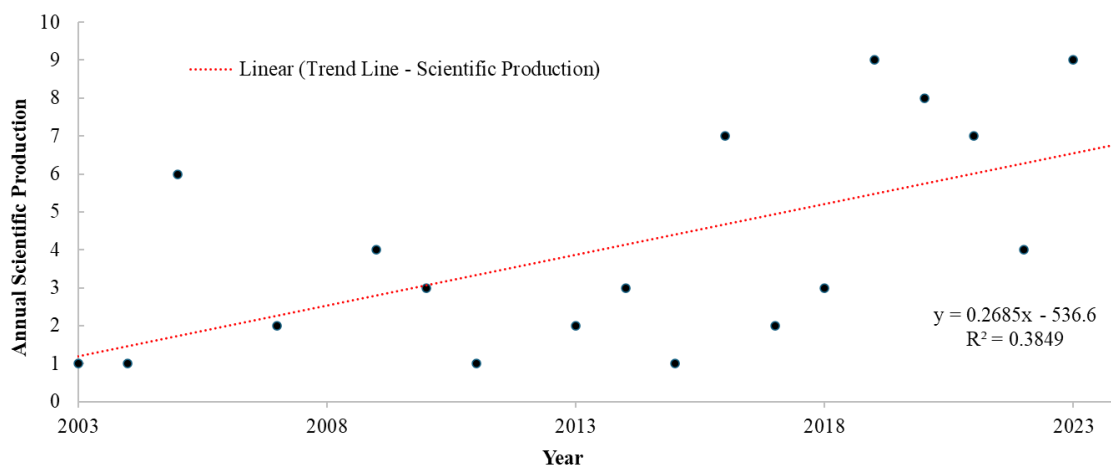


Figure 4. Evolution of annual scientific production per year for monitoring and mapping anthropogenic forest disturbances and forest degradation in the Amazon biome (2003-July/2024).

Source: OLIVEIRA, 2024.

3.2. Keyword Analyses of Emerging Patterns and Trends

Review articles often use keyword analyses to identify central themes, patterns, and trends in different research fields (GAO *et al.*, 2019; CASTAGNA *et al.*, 2024; GUERRERO-MORENO & OLIVEIRA-JUNIOR, 2024). Figure 5 illustrates the relative occurrence of key terms - biomass, carbon, degradation, disturbance, logging, and selective - in texts from 2003 to 2024. Each color in the stacked bars represents one of the selected words, with the height of each color segment within a given year indicating the proportional frequency of that word. These words were selected for their relevance to the discussion of forest management topics, highlighting trends and shifts in focus over time. The graph enables a visual assessment of the prominence of each word across different years, reflecting evolving research or policy interests in these areas.

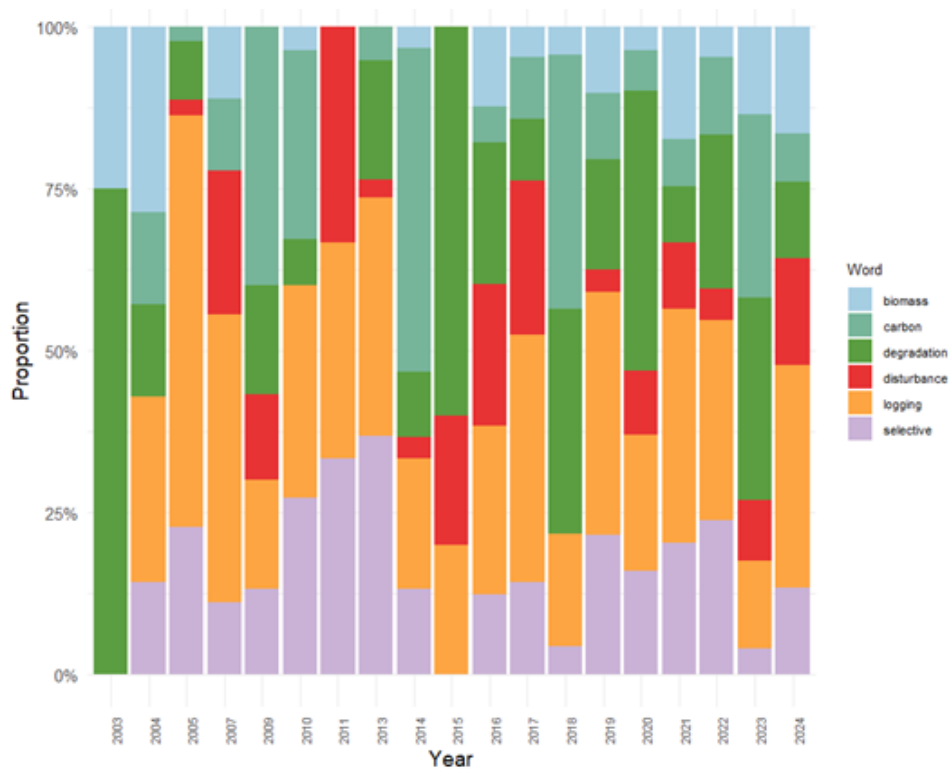


Figure 5. relative occurrence of key terms - biomass, carbon, degradation, disturbance, logging, and selective - in texts from 2003 to 2024.

Source: OLIVEIRA, 2024.

The results show that each year presents a different distribution of proportions among the words, suggesting a shift in focus over time. Carbon and degradation maintain a consistent presence throughout the years, indicating a continuous interest during the entire period analyzed. The term biomass gains prominence, starting in 2016, possibly reflecting a growing interest in its role in carbon sequestration. Although disturbance, selective, and logging are consistently present over time, these terms show a marked increase from 2020 to 2024, indicating a rise in discussions about logging and the impacts of forest disturbances. Carbon and biomass have gained relevance in recent years, especially between 2016 and 2024. This increase may be related to the role of biomass and carbon in climate change mitigation policies, with biomass increasingly being considered a renewable energy alternative.

3.3. Spatial Distribution of Studies and Approaches

A total of 25 studies were applied to the entire Amazon biome. Of these, we found that 72% (18 articles) used forest degradation exclusively (even though they may have

included SFM areas) to map anthropogenic forest disturbances. Five articles studied forest degradation and selective logging together. Only two articles discussed the region's selective ex-traction of legal timber and its impacts. Figure 6 presents the spatial distribution of studies on mapping forest degradation and forest disturbance in the Amazon biome by type of detection.

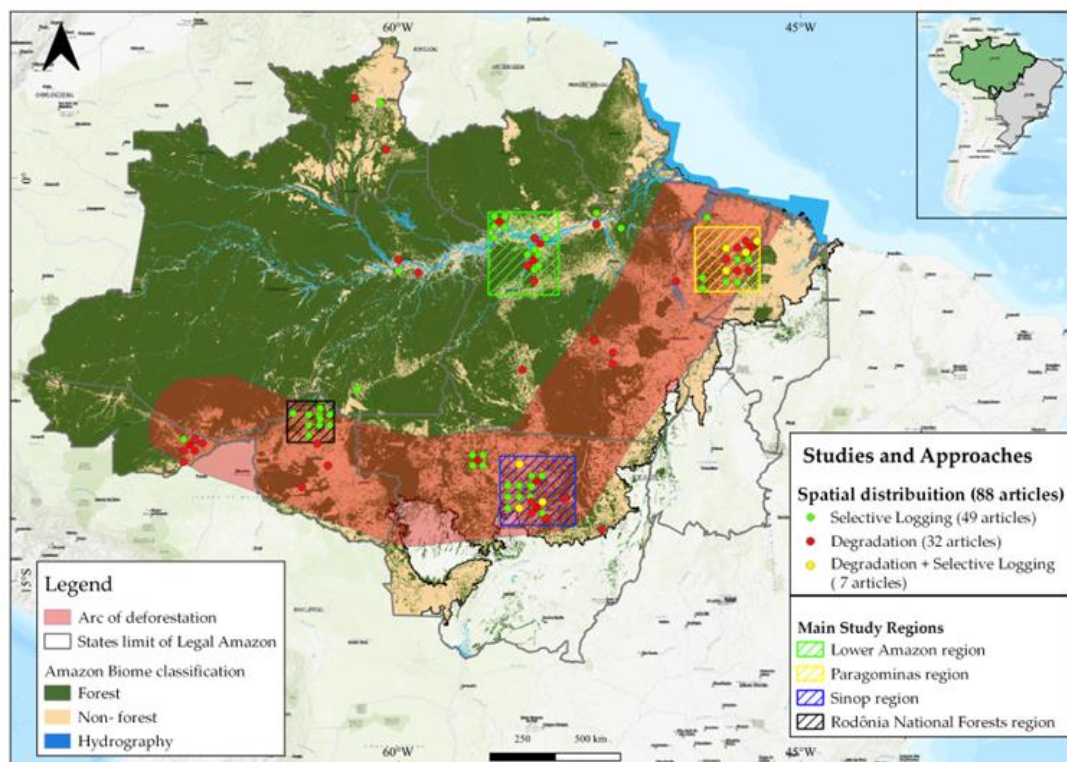


Figure 6. Categorization of the spatial distribution of studies on mapping degradation forest and selective logging in the Amazon biome by type of disturbance.

Source: OLIVEIRA, 2024.

For regional studies (55 articles), the assessment of the categorization and spatial distribution in the Amazon biome revealed that out of the 88 study areas sampled (where co-ordinates were available), 75 were concentrated in just three states (85.2%): Pará (44.3%); Mato Grosso (26.1%); and Rondônia (14.7%). In Pará, there were two notable regions. The Paragominas region in the northeast of the state had 14 articles, including studies on the former selective exploitation of legal timber (4), forest degradation (6), and articles dealing with both selective exploitation and forest degradation (4). Additionally, in the far west of Pará, the Lower Amazon region also featured 14 articles, with the focus being on legal selective logging (11) and some studies on forest degradation (3).

The state of Mato Grosso, particularly the region around the municipality of Sinop, had the second-highest number of research papers, totaling 23 articles. Most of

these articles focused on studies related to legal selective logging (11), followed by forest degradation (4). The region of the National Forests (Flona) located in the state of Rondônia had 13 articles, all of which dealt with the monitoring and mapping of legal selective logging within the Jamari and Jacundá National Forests (Figure 6).

3.4. Main Techniques Used

The results show the main approaches used in the studies evaluated and demonstrate the frequency of various techniques employed in scientific articles focused on monitoring anthropogenic forest disturbances and forest degradation. Each technique plays a specific role in monitoring and mapping (Figure 7).

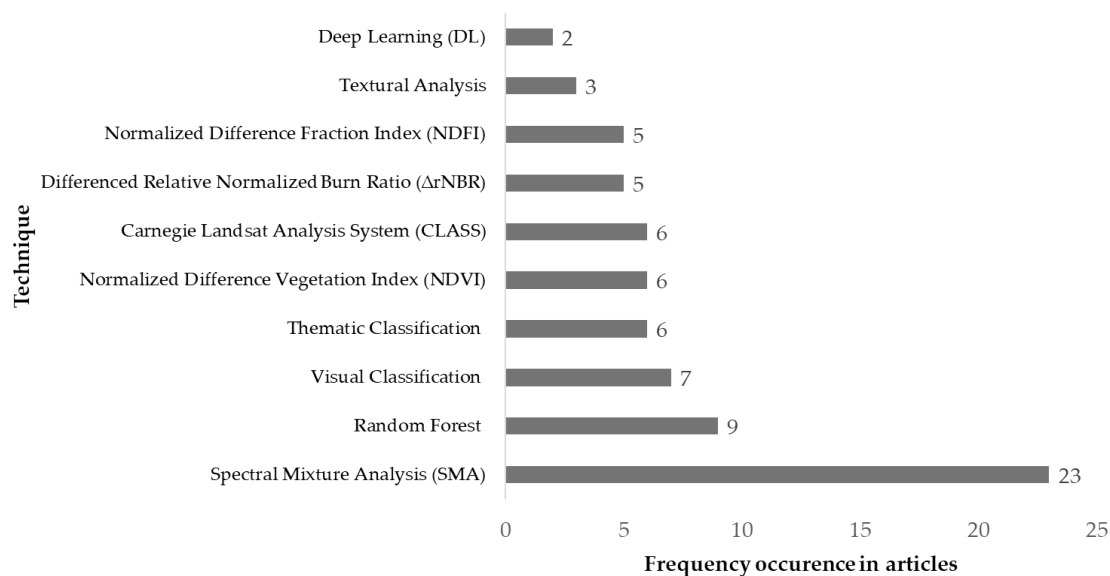


Figure 7. Frequency of occurrence of the ten main techniques used in the 80 articles evaluated.

Source: OLIVEIRA, 2024.

The Linear Spectral Mixture Model (LSMM) is the most used technique, with 23 occurrences, highlighting its importance in decomposing spectral signals into individual components (fraction images). Random Forest appears with nine occurrences, which shows that it is a frequently used technique for classifying vegetation and monitoring changes in forest cover. Visual classification, although a more traditional technique and a pioneer in this type of study (SOUZA JR *et al.*, 2003), is still relevant (seven occurrences), especially in areas where human interpretation is required to identify specific vegetation characteristics. The Carnegie Landsat Analysis System (CLASS), with six occurrences, is highly frequent in the studies evaluated.

The Normalized Difference Vegetation Index (NDVI) is widely used to monitor vegetation vigor, which is essential for identifying areas of degradation and helping to implement practices that promote forest recovery (six occurrences) (GAO *et al.*, 2020; YENGOH *et al.*, 2016). The Normalized Difference Fraction Index (NDFI) (five occurrences) helps to detect and monitor forest degradation in areas subject to sustainable forest management, allowing targeted interventions to recover intensely degraded areas. This is an essential component of sustainable management (SOUZA JR *et al.*, 2005). The Difference Relative Normalized Burn Ratio ($\Delta rNBR$) (five occurrences) is essential for assessing the severity of forest fires and their impacts, providing important data for post-fire recovery and the prevention of future fires (SOFAN *et al.*, 2016; JI *et al.*, 2011). Texture analysis (three occurrences) allows for a detailed assessment of the structural complexity of vegetation, helping to distinguish between different types of vegetation and levels of degradation (MATRICARDI *et al.*, 2005; MATRICARDI *et al.*, 2010; MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020). Deep Learning—DL (two occurrences) is a set of machine learning techniques that uses deep neural networks to recognize complex patterns in large datasets.

3.5. Main Satellites Used

For SFM, it is essential to use RS products to monitor and manage forests. An analysis of the frequency of occurrence in articles reveals the importance of different satellites and technologies in forest management research and practice (Figure 8).

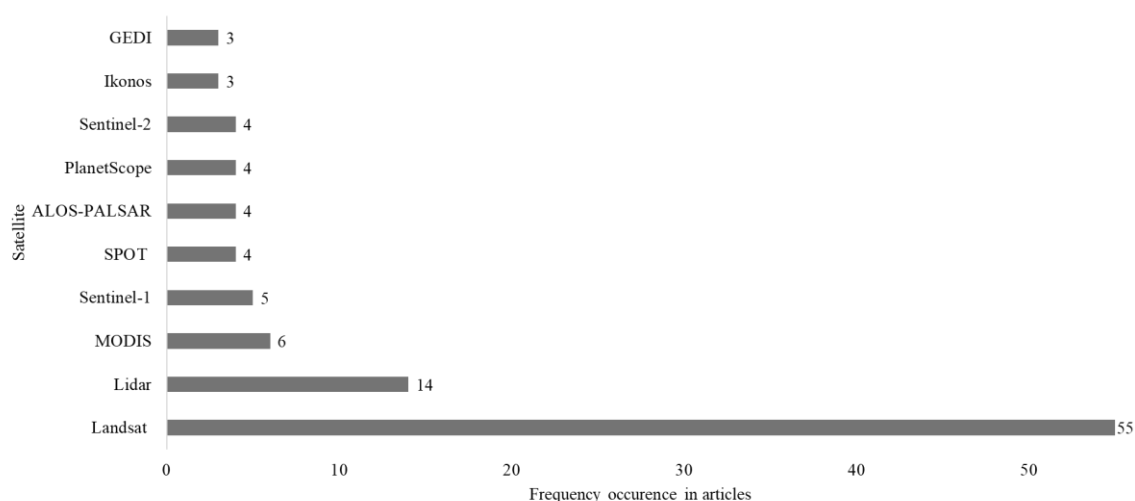


Figure 8. The frequency of occurrence of the ten main satellites used in 80 articles was evaluated.

Source: OLIVEIRA, 2024.

The main satellites' classification results to monitor anthropogenic forest disturbance and degradation indicate that the Landsat series is the most used (55 occurrences). This is mainly because of its extensive historical data and its capability to offer detailed multi-spectral data over several decades (BARROS FERRAZ *et al.*, 2002; SOUZA *et al.*, 2005; SHIMABUKURO *et al.*, 2014; SOUZA *et al.*, 2024).

LiDAR technology, with 14 occurrences, recently incorporated into forest cover monitoring studies, is highly valued for its ability to accurately measure the three-dimensional structure of forests (WINSTANLEY *et al.*, 2024).

The MODIS (Moderate Resolution Imaging Spectroradiometer), with six hits, despite its low spatial resolution, is widely used to monitor large areas of forest cover due to its high temporal frequency, which enables rapid detection of changes such as forest fires and large-scale forest degradation (PINAGÉ *et al.*, 2023; LIZUNDIA-LOIOLA *et al.*, 2020).

The Sentinel-1 and Sentinel-2 satellites mentioned nine occurrences when combined, providing optical (Sentinel-2) and radar (Sentinel-1) data. This combination is crucial for monitoring forests in adverse weather conditions and detecting subtle changes in forest cover (HETHCOAT *et al.*, 2022; LIMA *et al.*, 2019).

ALOS-PALSAR, SPOT, GEDI, and IKONOS had a combined 14 occurrences. These satellites and sensors provide valuable additional data, complementing the information obtained by the main satellites mentioned. They are used for specific applications, such as detecting small changes in forest cover, assessing biomass, and monitoring small area changes. ALOS-PALSAR helps with monitoring in tropical regions using synthetic aperture radar (SAR). SPOT is mainly used for monitoring land use, land cover, and vegetation changes. GEDI (Global Ecosystem Dynamics Investigation), which is NASA's tool to measure how deforestation has contributed to atmospheric CO₂ concentrations, is an innovative orbital LiDAR technology that helps assess the vertical structure of forests, including tree height and biomass. Ikonos, with its high spatial resolution, is used for detecting small changes in forest cover, detailed mapping, and monitoring specific areas of interest (WANG *et al.*, 2005 ASNER *et al.*, 2009; WIEDERKEHR *et al.*, 2020 HOLCOMB *et al.*, 2024).

PlanetScope is the only satellite mentioned comprising a constellation of imaging nanosatellites. It provides daily high spatial resolution images of the Earth's entire land cover. Its capability to capture detailed daily data makes it a powerful tool for monitoring

forest disturbances and sustainable forest management (OLIVEIRA *et al.*, 2024; DALAGNOL *et al.*, 2023; BRASILMAIS, 2024).

3.6. Main Research Institutions

Based on our dataset, Figure 9 shows the affiliations of the top 10 institutions worldwide that have published the most on this subject. These institutions significantly generate knowledge and advance technology for implementing and monitoring tropical forests and sustainable forest management practices.

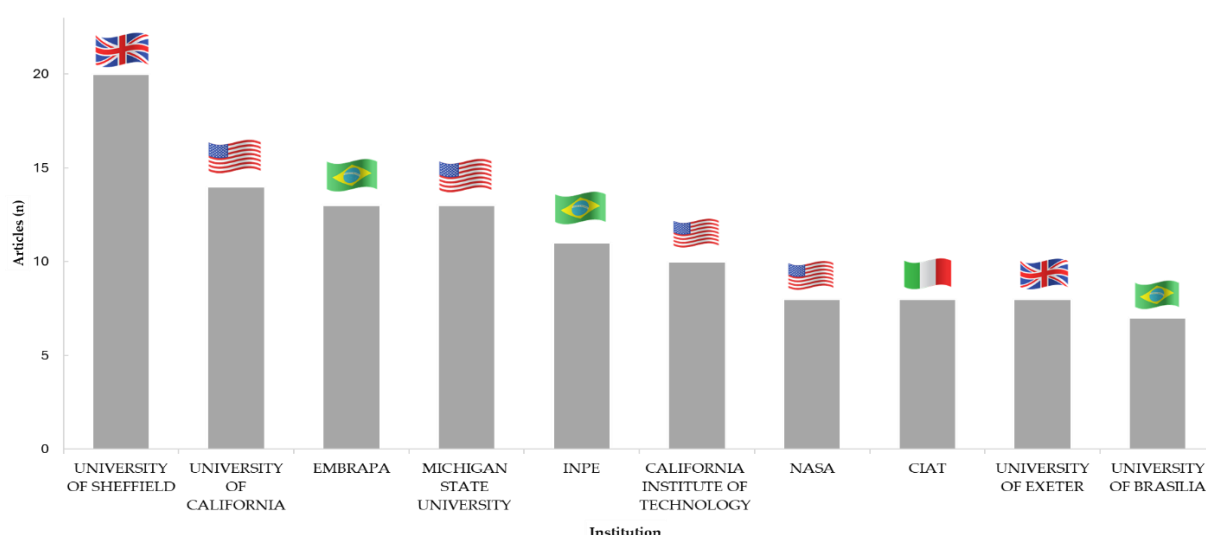


Figure 9. A hierarchical graph displays the top 10 countries and institutions worldwide with the highest publications on monitoring anthropogenic forest disturbance and degradation in the Amazon biome.

Source: OLIVEIRA, 2024.

The University of Sheffield (20 articles) is known for its significant research in ecology and environmental science, focusing on understanding the impacts of human activities on forests and developing strategies to promote forest sustainability (HETHCOAT *et al.*, 2019; HETHCOAT *et al.*, 2021). The University of California's research (14 articles) has focused on emerging remote sensing technologies, such as terrestrial and orbital LiDAR, environmental data analysis, and methods for monitoring changes in forest cover

In Brazil, EMBRAPA (13 articles) has played a vital role in developing robust technologies, including sustainable forest management practices, pioneering studies into post-harvest forest monitoring, and implementing RIL practices in the Amazon, most

recently working with LiDAR technology (SILVA & LOPES, 1984; SILVA, 1985; BERENGUER *et al.*, 2014).

Several studies from Michigan State University (13 articles) focus on using emerging remote sensing technologies for managing natural resources, particularly forests (SMITH *et al.*, 2023). The National Institute for Space Research (INPE) (11 articles) is crucial in monitoring and developing remote sensing methodologies for the Amazon and other tropical forests. INPE uses a series of satellites to gather data on deforestation, forest degradation, and biomass, which are crucial for the sustainable management of Brazilian forests (DINIZ *et al.*, 2015; SHIMABUKURO *et al.*, 2018; FONSECA *et al.*, 2019).

NASA (eight articles), through its satellite missions such as GEDI and Landsat, provides essential data used to monitor global forest cover and study the impacts of climate change, deforestation, and anthropogenic disturbances (WINSTANLEY *et al.*, 2024; MORTON *et al.*, 2011).

The Alliance Biodiversity & International Center for Tropical Agriculture (CIAT) (eight articles) promotes biodiversity conservation and the sustainable use of tropical resources, including forests. CIAT's research often deals with the sustainability of agroforestry systems and sustainable forest management (DYSON *et al.*, 2024). The University of Exeter (eight articles) research biodiversity conservation and the development of environmental policies that promote forest sustainability (FAWCETT *et al.*, 2023).

Finally, the University of Brasilia (seven articles) conducts significant research into tropical forest ecology and sustainable management practices, contributing to the development of public conservation policies in Brazil (MATRICARDI *et al.*, 2005; MATRICARDI *et al.*, 2010; MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020).

These institutions, with their research and innovations, play a key role in advancing sustainable forest management, helping to develop and implement practices that balance the conservation of forest ecosystems with economic and social needs.

4. Discussion

4.1. Need to Differentiate Forest Degradation from SFM and Policy Implications

The concept of forest degradation has not yet reached a scientific consensus, resulting in a variety of definitions and different approaches to its detection and measurement, especially by means of remote sensing, as demonstrated in this literature review (SIMULA, 2009; THOMPSON *et al.*, 2013; CHAZOUL *et al.*, 2015; VÁSQUES-GRANDÓN *et al.*, 2018). The impacts of activities related to forest management and the monitoring of selective logging have mainly been viewed from an ecological standpoint (CHAZDON, 2008; ASNER *et al.*, 2005). As a result, the term “forest degradation” is often used to describe the effects of selective logging activities ((DALAGNOL *et al.*, 2023; MATRICARDI *et al.*, 2010; KUCK *et al.*, 2021; LAPOLA *et al.*, 2023; MORENO *et al.*, 2023), fire (MATRICARDI *et al.*, 2010; MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020), and landscape fragmentation (MATRICARDI *et al.*, 2020). It is important to note that although legal selective logging can be considered degradation from an ecological perspective or by generic definitions, it is temporary degradation. Selective logging is an activity that is part of SFM and, therefore, at first glance, should be categorized distinctly within the term forest degradation (FERREIRA *et al.*, 2015).

A group of experienced researchers from Embrapa Amazonia Oriental have emphasized the need for a deeper reflection on the concept of forest degradation and its role in decision-making. They suggest that forest management, when based on good forest practices and techniques, causes temporary forest disturbances responsible only for a low level of forest degradation, contributing to forest conservation from a broad perspective when good management practices are applied (FERREIRA *et al.*, 2015). Another point is the fact that production forests, such as areas oriented for SFM, at the same time as generating environmental impact, advocate ways of mitigating them, such as reduced impact techniques and enrichment of clearings (PUTZ *et al.*, 2008; SCHWARTZ *et al.*, 2013).

Pereira-Jr *et al.* (2002) provides a comparative analysis of canopy gap fractions resulting from CL and RIL in 1996 and 1998. The study demonstrates that CL consistently caused greater canopy disruption, with total gap percentages reaching 16.5% in 1996 and 21.6% in 1998, predominantly driven by tree felling and skidding operations. Conversely, RIL exhibited significantly lower impacts on the canopy, with total gap percentages of 4.9% and 10.9% for the same years. These findings underscore the efficacy of RIL in

minimizing disturbances to forest canopy structure, highlighting its role as a sustainable logging practice that mitigates environmental degradation while preserving forest integrity.

Matricardi *et al.* (2013) observed that selective logging impacted, on average, less than 4% of the forest canopy in the Amazon between 1992 and 1999, while in forest degradation caused by forest fires, forest canopies were affected by more than 30% in the same period of analysis. In addition, recurrent fires and the opening up of the forest canopy intensify the drying out of the soil and biomass, degrading the forest and creating favorable conditions for subsequent fires (LAURENCE *et al.*, 2001; HOLDSWORTH & UHL, 1997). This cycle compromises the recovery capacity of tropical forests, making them more susceptible to clear-cutting. This highlights the need for management and protection strategies to break this cycle of degradation and conservation (COCHRANE *et al.*, 1998; COCHRANE *et al.*, 1999; COCHRANE *et al.*, 2004; MMA, 2006).

Recently, Matricardi *et al.* (2000) identified and classified two types of forest degradation in the Brazilian Amazon: forest degradation dependent on deforestation, which is closely associated with landscape fragmentation (fragment size and edge effect) in the region, and degradation independent of deforestation, which is driven by selective logging and forest fires. The authors observed that most forests selectively logged between 1992 and 2014 remained in the Brazilian Amazon, even when later affected by fires. As a result, they argue that the conversion of forests for other land uses, such as agriculture or pasture (deforestation), is a distinct process from selective logging, even though selective logging of valuable trees is part of the deforestation process (MATRICARDI *et al.*, 2020).

In this context, an important contribution of this study is to indicate that although several studies treat forest disturbances from legal selective logging as forest degradation, in practice there are several types of dynamics in the forest canopy, varying in intensity, size, and impacts resulting from anthropogenic interventions. Therefore, the different types of anthropogenic interventions need to be properly differentiated and considered, especially for cases of selective logging and timber harvesting in SFM projects.

Even though areas with SFM have high logging intensities of more than 30 m³·ha⁻¹ and more than 20 individuals logged per hectare, resulting in large and persistent clearings, these areas are supported by technical and legal aspects, which ensures the sustain-ability/legality of the activity and guarantees that the area has a legal obligation to remain intact for at least 35 years, as determined by law (MMA, 2006; OLIVEIRA *et*

al., 2024). In this sense, as proposed by Oliveira *et al.* (2024), areas within SFM with high logging intensities should be monitored after logging to assess the dynamics and resilience of the trees and, if necessary, possible adjustments to improve the current legislation, which defines the temporal, physical, and ecological parameters for extracting native timber in the Amazon (MMA, 2006; OLIVEIRA *et al.*, 2024).

It is therefore important to clearly distinguish disturbances that occur within the boundaries of sustainably managed areas from those in areas that do not follow these practices. This definition suggests that any human intervention that occurs outside sustainable management areas, which does not result in total deforestation, can be considered forest degradation. On the other hand, sustainable management activities, even if they are intense, are processes of temporary forest disturbance in which the forest recovers and can be exploited again within cutting cycles and are therefore not associated with deforestation (MATRICARDI *et al.*, 2020; MMA, 2006). Analyzing forest disturbances from the perspective of forest dynamics and resilience offers numerous opportunities, but also presents significant challenges (PEREIRA-JUNIOR *et al.*, 2002; CHAZDON, 2008). In particular, this approach would allow this definition to be generalized and distinguished from any biases introduced by biased human perspectives (CHAZDON, 2003; CHAZDON, 2008; SONG *et al.*, 2018).

Furthermore, mistakes in identifying degraded areas and selective logging can undermine the credibility of forest conservation and management efforts. This can make securing funding for conservation projects harder and discourage investment in SFM practices (JUGULUM, 2014). Public policies and regulations based on incorrect data can be ineffective or have negative consequences (NESHA *et al.*, 2021). This can lead to inadequate allocation of public resources for forest conservation and management and hinder the implementation of effective strategies for forest protection (CUTLER *et al.*, 2007; BARLOW *et al.*, 2020). Improving the accuracy in classifying forest degradation and selective logging is crucial for the environmental, economic, and social sustainability of SFM. Investments in modern monitoring technologies, such as remote sensing and GIS, combined with robust field validation, are essential to ensure the integrity of forest ecosystems and the effectiveness of management and conservation policies (DALAGNOL *et al.*, 2023; OLIVEIRA *et al.*, 2024; WINSTANLEY *et al.*, 2024).

4.2. *The Evolution of Monitoring Approaches for Forest Degradation*

The evolution of forest degradation mapping highlights significant advancements in technology, methodology, and understanding of forest dynamics over time. This progress reflects a transition from traditional techniques to sophisticated technologies like machine learning and advanced satellite systems.

Early efforts, such as the pioneering study by Nepstad *et al.* (1999), relied on indirect methods like sawmill records to estimate forest areas impacted by selective logging due to the scarcity of RS technologies. These methods, while innovative at the time, provided limited spatial and temporal insights (NEPSTAD *et al.*, 1999).

The late 1990s and early 2000s marked the beginning of remote sensing applications for forest degradation mapping. Souza and Barreto (2000) introduced a remote sensing approach to detect forests impacted by selective logging in Pará, Brazil, utilizing a linear mixture model and buffer zones (SOUZA & BARRETO *et al.*, 2000). Shortly after, Souza-Jr *et al.* (2003) advanced these techniques with the use of Spectral Mixture Analysis and Landsat imagery (SOUZA-JR *et al.*, 2003). Matricardi *et al.* (2005) further refined the use of Landsat images, employing texture analysis to estimate selectively logged areas in Mato Grosso, Brazil (MATRICARDI *et al.*, 2005). These studies signaled the transition to satellite-based mapping, enabling broader spatial coverage and more detailed assessments.

The mid-2000s saw a leap in the adoption of new satellite technologies. The Landsat series became essential for forest monitoring due to its extensive historical archive and multispectral capabilities. Asner *et al.* (2005) utilized the Carnegie Landsat Analysis System (CLAS) to map selectively logged forests across the Brazilian Amazon (ASNER *et al.*, 2005), while Matricardi *et al.* (2013) applied semi-automatic approaches and texture analysis to achieve similar goals (MATRICARDI *et al.*, 2013). These advancements highlighted the growing reliance on Landsat's medium-resolution imagery for large-scale assessments. Low-resolution satellites like MODIS also contributed, particularly in monitoring large-scale degradation due to its high temporal frequency (LIZUNDIA-LOIOLA *et al.*, 2020; PINAGÉ *et al.*, 2023). Yet, limitations in spatial resolution meant these technologies were less effective in detecting subtle disturbances, such as low-intensity selective logging (MORTON *et al.*, 2011).

However, studies began identifying limitations in detecting low-intensity logging and subtle degradation using medium-resolution sensors, as they often failed to capture

approximately 50% of canopy damage caused by logging operations (PEREIRA-JUNIOR *et al.* 2002; MATRICARDI *et al.*, 2005).

The past two decades have seen the integration of high-resolution satellites and advanced technologies into forest monitoring (SAATCHI *et al.*, 2011; ABDOLLAHNEJAD *et al.*, 2019; OLIVEIRA *et al.*, 2024; WINSTANLEY *et al.*, 2024; DALAGNOL *et al.*, 2023). Platforms like PlanetScope and Sentinel-2 now provide daily, high-resolution imagery, enabling more detailed assessments of forest structure and disturbances (LIMA *et al.*, 2019; PETRI *et al.*, 2022; HEATCOAT *et al.*, 2022; DALAGNOL *et al.*, 2023). LiDAR technology has become highly valued for its ability to capture three-dimensional forest structure, tree height, and biomass (WINSTANLEY *et al.*, 2024; HUDAK *et al.*, 2002). LiDAR-based platforms like NASA's GEDI have revolutionized large-scale carbon and biomass quantification (HOLCOMB *et al.*, 2024).

Simultaneously, advancements are marked by the introduction of machine learning and artificial intelligence (AI) techniques (BARLOW *et al.*, 2020; WINSTANLEY *et al.*, 2024; DALAGNOL *et al.*, 2023). These technologies have revolutionized forest monitoring by enabling the processing of vast datasets and improving accuracy when detecting and classifying disturbances (KUCK *et al.*, 2021; HEATCOAT *et al.*, 2021). Algorithms such as Random Forest and Deep Learning have been increasingly employed to differentiate between natural disturbances (e.g., storms) and anthropogenic impacts (e.g., selective logging and fires), offering a higher level of precision than traditional methods (HEATCOAT *et al.*, 2019; KUCK *et al.*, 2021; DALAGNOL *et al.*, 2023; WINSTANLEY *et al.*, 2024). Moreover, machine learning models have been integrated with data from high-resolution satellites and Li-DAR, providing a multi-faceted approach to monitoring forest degradation (HUDAK *et al.*, 2022; WINSTANLEY *et al.*, 2024).

Key research institutions have driven these advancements. For example, EMBRAPA and INPE in Brazil have been pivotal in developing methodologies for monitoring tropical forests and implementing sustainable forest management practices (FERREIRA *et al.*, 2015; SILVA & LOPES *et al.*, 1984; SILVA *et al.*, 1985; BERENGUER *et al.*, 2014). Internationally, universities like that of Sheffield and California have contributed to ecological research and the application of RS technologies (HETHCOAT *et al.*, 2021; HETHCOAT *et al.*, 2021), while NASA has played a central role through missions like Landsat and GEDI (HOLCOMB *et al.*, 2024; MORTON *et al.*, 2011).

Despite these advancements, challenges persist, particularly the costs and high computational demands associated with high-resolution data and LiDAR technologies. These limitations restrict their accessibility to well-funded projects and institutions. Nevertheless, initiatives like Brazil's RedeMAIS and Norway's NICFI program have made high-resolution satellite data more accessible to public institutions (BRASIL MAIS, 2024; NICFIC, 2020). These efforts have democratized forest monitoring by providing high-resolution imagery for use in conservation and sustainable management (OLIVEIRA *et al.*, 2024; DALAGNOL *et al.*, 2023).

The evolution of forest degradation to disturbance mapping reflects a dynamic trajectory of technological innovation. From early manual methods to the adoption of satellite platforms and the integration of machine learning, these advancements have significantly enhanced the capacity to monitor and manage forest resources. These technological innovations also allow for better categorization of forest degradation, enabling the distinction between different types and intensities of disturbances, such as selective logging, fires, and edge effects. Moving forward, the combination of high-resolution imagery, advanced algorithms, and collaborative global initiatives will continue to shape the future of forest monitoring, ensuring more effective and sustainable management practices.

4.3. Regional Focus of Studies and the Need for Expansion

SFM areas within conservation units have played a key role in advancing techniques and tools capable of capturing and quantifying in detail the dynamics of disturbances and forest regeneration resulting from the selective logging of trees (LIMA *et al.*, 2019; OLIVEIRA *et al.*, 2024; DALAGNOL *et al.*, 2023; WINSTANLEY *et al.*, 2024). These studies are essential to refine and validate strategies that can eventually be applied more widely across the Amazon biome. This includes developing remote sensing tools that accurately capture changes in forest cover and different disturbance intensities, regardless of geo-graphical location (ASNER *et al.*, 2005). In protected areas, like in the National Forests of Rondônia, Flona Jamari was the country's first forest concession in 2008 and Flona Jacundá began logging in 2014. Both units' conservation are managed by the Brazilian Forest Service and operated by private companies (MERRY *et al.*, 2009; RODRIGUES *et al.*, 2020; VIDAL *et al.*, 2020). The Lower Amazon region has several

sustainable use conservation units with a long history of forest management, making it a natural source of research of this nature (OLIVEIRA *et al.*, 2024; BACHA *et al.*, 2007).

On the other hand, the Paragominas region in the northeast of the state of Pará is a model for forest management in the private areas and for being a pioneer in studies of SFM and the mapping of selective logging using remote sensing (VERISSÍMO *et al.*, 1992; SOUZA-JR *et al.*, 2003; BARRETO *et al.*, 1998). The Sinop region has the highest concentration of SFM plans in private areas within the Amazon. It is one of the largest timber-exporting regions, with numerous companies operating in the timber sector (MATRICARDI *et al.*, 2005; FEARNSIDE *et al.*, 2003; FEARNSIDE *et al.*, 2005).

In this regard, studies monitoring anthropogenic forest disturbances and degradation are mainly focus on the “arc of deforestation” in the Brazilian Amazon (Figure 6) (CSILLIK *et al.*, 2024; DE FIGUEIREDO *et al.*, 2019; PINHEIRO *et al.*, 2016). The concentration of studies in this area is largely due to the intense human activity and rapid land use changes occurring there (PINAGÉ *et al.*, 2023; PINHEIRO *et al.*, 2016). This region, which spans the south-ern and eastern edges of the Amazon, has become a focal point for deforestation due to factors such as mechanized agriculture, cattle ranching, and logging—often conducted illegally (PINHEIRO *et al.*, 2016). These activities contribute to a high visibility of forest loss, making it an attractive region for researchers aiming to study anthropogenic impacts on tropical forests (BARROS FERRAZ *et al.*, 2005; SOUZA *et al.*, 2005; SHIMABUKURO *et al.*, 2014; PINHEIRO *et al.*, 2016; SOUZA *et al.*, 2024).

However, despite regional focus, this study has been significantly advanced through RS techniques, each offering distinct capabilities for monitoring and analysis. The Linear Spectral Mixture Model (LSMM) excels in decomposing spectral signals into individual components, enabling the detection of subtle changes in forest composition (SOUZA-JR *et al.*, 2003; SHIMABUKURO & PONZONI, 2018). Random Forest is widely used for classifying vegetation and monitoring changes in forest cover (BARLOW *et al.*, 2020), while visual classification remains relevant in scenarios requiring human interpretation of specific vegetation characteristics (SOUZA-JR *et al.*, 2003). Tools like the Carnegie Landsat Analysis System (CLAS) and indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Fraction Index (NDFI) are critical for monitoring vegetation vigor and identifying degraded areas, particularly within SFM con-texts (SOUZA-JR *et al.*, 2005; YENGOH *et al.*, 2016; SOFAN *et al.*, 2016). Additionally, the Difference Relative Normalized Burn Ratio

(Δ rNBR) is vital for assessing fire severity and informing recovery efforts (SOFAN *et al.*, 2016; JI *et al.*, 2011), while texture analysis provides detailed insights into vegetation structure (MATRICARDI *et al.*, 2005; MATRICARDI *et al.*, 2010; MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020). Advanced techniques such as Deep Learning (DL) leverage neural networks to detect complex patterns in large datasets, further expanding the potential of remote sensing in forest monitoring (ASNER *et al.*, 2010; DALAGNOL *et al.*, 2023; WINSTANLEY *et al.*, 2024).

To enhance the practical value of this research for decision-makers, there is a need to align technical advancements with real-world applications. For instance, integrating NDVI and Δ rNBR can provide actionable insights for post-fire recovery planning and monitoring the impacts of climate change on vegetation health (YENGOH *et al.*, 2016; JI *et al.*, 2011). Similarly, advanced techniques like Deep Learning could be applied to predict degradation hotspots under future climate scenarios by combining satellite data with local environmental variables (DALAGNOL *et al.*, 2023). By combining advanced remote sensing techniques, such as LSMM, NDVI, and Deep Learning, with on-the-ground validation in less-studied regions, researchers can generate a holistic understanding of forest dynamics (JI *et al.*, 2011; YENGOH *et al.*, 2016; DALAGNOL *et al.*, 2023; WINSTANLEY *et al.*, 2024). This comprehensive approach will inform adaptive management strategies and policies that promote the resilience of Amazonian forests, ensuring their ecological, economic, and social benefits for future generations (CSILLIK *et al.*, 2024; DE FIGUEIREDO *et al.*, 2019).

With climate change intensifying extreme events and altering climate patterns in the Amazon, there is an increasing need to expand the focus of forest degradation and disturbances studies beyond the “arc of deforestation” (ARAGÃO *et al.*, 2014; LAPOLA *et al.*, 2023; CSILLIK *et al.*, 2024). Although this region is a critical point of research due to intense human activities, forests located in more remote and dense areas of central and western Amazon are also vulnerable to the impacts of climate change and anthropogenic actions (MARENGO *et al.*, 2018). These historically less-studied areas may face new challenges, such as severe droughts and more frequent fires, which compromise the natural regeneration of forests and increase the risks of degradation (ARAGÃO *et al.*, 2014; DUPUIS *et al.*, 2020; MARENGO *et al.*, 2018; BOURGOIN *et al.*, 2024). Expanding research to include less-studied, densely forested regions in the central and western Amazon, where traditional, community-based, and low-impact logging practices may be more prevalent, would provide a more comprehensive understanding of forest

disturbance and degradation patterns across the Amazon (BOURGOIN *et al.*, 2024). This broader approach could improve forest management practices by incorporating the diversity of forest conditions and disturbances across different parts of the biome (REICHE *et al.*, 2016; WINSTANLEY *et al.*, 2024). Comprehensive data from underrepresented regions can guide public policies and management practices, promoting the resilience and long-term sustainability of Amazonian forests (HANSEN *et al.*, 2013; ARAGÃO *et al.*, 2014; DUPUIS *et al.*, 2020; DENNIG *et al.*, 2021).

Expanding the focus of studies to include these less-impacted regions is essential for understanding how different parts of the biome respond to the combined pressures of human activities and extreme climate events (IPCC, 2014; DE ARMOND *et al.*, 2023; DA SILVA *et al.*, 2022). This enables the development of adaptive monitoring and management strategies that consider the diverse environmental conditions across the Amazon, ensuring a more robust approach to conservation (SUAB *et al.*, 2024). Comprehensive and context-specific data on these areas could guide public policies and management practices that promote the resilience of Amazonian forests to climate change, supporting the long-term sustainability of the entire ecosystem (ASNER *et al.*, 2010; ARAGÃO *et al.*, 2014; MARENGO *et al.*, 2018; DUPUIS *et al.*, 2020).

In summary, while the focus of research has been on the arc of deforestation, it is crucial to expand research and discussion to monitor degradation and anthropogenic disturbances in the forest on a broader scale (BOURGOIN *et al.*, 2024). This expansion should include other regions of the Amazon that are less studied but equally important, as they are heavily forested and face serious challenges that warrant balanced scientific attention (KUCK *et al.*, 2021; DE FIGUEIREDO *et al.*, 2019; MARENGO *et al.*, 2018). Notably, further research is needed to monitor selective logging across the entire Amazon. To date, only one notable study (MATRICARDI *et al.*, 2013; MATRICARDI *et al.*, 2020) has distinguished selective logging from fire-affected areas throughout the legal boundaries of the Amazon. Here, we have addressed the main achievements of remote sensing and new technologies in assessing forest disturbances in tropical regions, as well as the challenges related to the concepts of forest degradation and forest management. Altogether, this work provides a valuable contribution to researchers, policymakers, and forest practitioners, helping to improve forest management, regulation, and conservation.

5. Conclusions

This study highlights advancements in monitoring forest degradation and disturbances within the Amazon biome, emphasizing the critical role of remote sensing technologies and sustainable forest management (SFM) practices. By synthesizing key methodologies, such as Linear Spectral Mixture Models (LSMM), Normalized Difference Vegetation Index (NDVI), and emerging techniques and technologies like Deep Learning and LiDAR, we demonstrate how these tools have transformed our ability to monitor and assess forest dynamics. These advancements allow for more precise categorization of disturbances, distinguishing temporary impacts associated with SFM from more severe degradation caused by illegal logging, fires, and other anthropogenic activities.

While much of the research remains concentrated in the “arc of deforestation”, the need to expand the geographic focus of studies to include less-impacted and under-researched regions is critical. Areas in the central and western Amazon, characterized by dense forests and traditional or low-impact logging practices, offer valuable insights into forest resilience and the diverse impacts of anthropogenic and climatic pressures. Addressing this research gap would provide a more comprehensive understanding of forest degradation across the entire biome, ensuring that findings are representative of the Amazon’s full complexity.

Climate change adds urgency to this endeavor, as the intensification of extreme events, such as severe droughts and fires, threatens the regeneration capacity of Amazonian forests. Expanding studies to underrepresented regions will enable the development of adaptive management strategies that are responsive to local environmental conditions and resilient to climatic variations. This approach is essential to support the long-term sustainability of the Amazon and its vital ecological, economic, and social functions.

Policymakers and forest practitioners can benefit greatly from the integration of advanced monitoring tools with field-based validation. Providing actionable insights, such as identifying degradation hotspots and assessing post-disturbance recovery, will help refine forest management policies, improve REDD+ initiatives, and promote more effective conservation strategies. The distinction between forest degradation and SFM must be clear in policy frameworks to ensure that temporary, managed disturbances are

not conflated with permanent degradation, preserving the credibility and sustainability of SFM practices.

The proposal presented here, which calls for differentiating types of forest disturbance, especially to separate low-impact sustainable management areas from other forms of medium- and high-intensity degradation, represents a significant advancement in assessing forest disturbance in terms of intensity, size, agents, causes, and impacts. These criteria help make a clearer distinction between sustainable management practices and other levels of disturbance that structurally compromise forest integrity and conservation.

Future research should focus on refining definitions of forest degradation and enhancing monitoring methods. This includes developing a more precise, standardized criteria for defining and assessing forest degradation across different regions and contexts. Further research could also explore advanced remote sensing techniques, such as machine learning models integrated with high-resolution data, to improve the classification and discrimination of various forest disturbance types. Additionally, long-term studies on the ecological recovery and resilience of forests after different intensities of disturbance could provide valuable insights for sustainable management practices. Such research would contribute to a more comprehensive understanding of degradation processes, ultimately supporting more effective conservation and management strategies.

In summary, this study underscores the need for a broader, more inclusive research agenda that captures the full spectrum of forest dynamics across the Amazon. By combining technological innovations, regional insights, and robust monitoring strategies, researchers and practitioners can contribute to the resilience and sustainability of Amazonian forests, ensuring their preservation for future generations. This comprehensive understanding is indispensable for shaping effective public policies and advancing global efforts to mitigate climate change and protect tropical forests.

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CHAPTER III – Spatio-Temporal Assessment Of Heterogeneity By Logging Intensity In A Federal Concession Area In The Brazilian Amazon²

The logging intensity does not take into account the spatial heterogeneity of the forest volume of commercial native species in the Brazilian Amazon. This study aims to evaluate spatio-temporal heterogeneity distribution by assessing logging intensity and its effects on the volumetric stock and abundance of commercial species, with a focus on sustainable management practices. This study was conducted in the Saracá-Taquera National Forest in the Amazon. Forest inventory data, elevation, and PlanetScope satellite images were integrated into a geographic information system. The information was aggregated into regular 1-hectare cells for the times before, during, and after logging (t0, t1, and t2). The unsupervised classification algorithm k-means with four clusters was used to analyze heterogeneity. Before logging, areas with higher commercial volumes were distant from water bodies, while areas with lower elevation had lower wood stocks. Logging intensity was generally low, concentrating on a few trees per hectare. Logging in the study area revealed heterogeneous spatial distribution by intensifying in areas with the highest wood stocks. In addition to the recommended logging intensity according to legislation, forest heterogeneity should be considered by the manager, promoting adaptive strategies to ensure the conservation of forest resources.

Keywords: *sustainable forest management; logging intensity; tropical forest; reduced impact logging; geoprocessing; volumetric heterogeneity*

Resumo: A intensidade de corte não leva em consideração a heterogeneidade espacial do volume florestal de espécies nativas comerciais na Amazônia Brasileira. Este estudo objetvou avaliar a distribuição da heterogeneidade espaço-temporal, avaliando a intensidade de corte e seus efeitos sobre o estoque volumétrico e a abundância de espécies comerciais, com foco em práticas de manejo sustentável. A pesquisa foi realizada na Flona de Saracá-Taquera, na Amazônia. Dados de inventário florestal, elevação e imagens de satélite *PlanetScope* foram integrados em um sistema de informação geográfica. As informações foram agregadas em células regulares de 1 hectare para os tempos antes, durante e após a exploração (t0, t1 e t2). O algoritmo de classificação não supervisionada k-means, com quatro clusters, foi utilizado para analisar a heterogeneidade. Antes da exploração, as áreas com volumes comerciais mais altos estavam distantes dos corpos d'água, enquanto áreas com menor elevação apresentavam estoques de madeira mais baixos. A intensidade de corte foi geralmente baixa, concentrando-se em poucas árvores por hectare. A exploração na área de estudo revelou uma distribuição espacial heterogênea, intensificando-se em áreas com os maiores estoques de madeira. Além da intensidade de corte recomendada pela legislação, a heterogeneidade florestal deve ser considerada pelo gestor, promovendo estratégias adaptativas para garantir a conservação dos recursos florestais.

Palavras-chave: *manejo florestal sustentável; intensidade de corte; floresta tropical; corte de impacto reduzido; geoprocessamento; heterogeneidade volumétrica.*

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1. Introduction

Primary forests represent some of the most vital ecosystems on Earth (GIBSON *et al.*, 2011). Approximately 1.6 billion people rely directly on forests, with the forestry industry contributing approximately US \$661 billion to the global GDP, and forests absorb an estimated 7.6 billion tons of CO₂ annually (FAO, 2015; BUSTAMANTE *et al.*, 2015; HARRIS *et al.*, 2021). The Brazilian Amazon alone encompasses one third of the world's tropical forests, boasting commercial roundwood reserves totaling around 60 billion cubic meters, thereby establishing itself as the largest repository of tropical timber worldwide (WWF, 2012; FAO, 2020; BRASIL, 2024; IBGE, 2024).

In the Amazon, owing to its high species diversity, there remain few studies on the volumetric distribution of the forest (COLPINI *et al.*, 2009). Despite extensive discussion among researchers on the topic of volume, there are still gaps in the findings concerning the spatial distribution of volume among native Amazonian species (COLPINI *et al.*, 2009; CHAPMAN & MEYER 1949; BRUCE & SCHUMACHER, 1950; SPURR, 1952; HIGUCHI *et al.*, 1979; FELDSPAUSCH *et al.*, 2011; SAATCHI *et al.*, 2011).

When observed at a synoptic scale, the terra firme Amazon Forest seems like a plain with homogeneous vegetation cover. However, local analysis unveils a diversity of environments influenced by factors such as topoclimatic and pedological conditions, as well as water availability and physiographic characteristics (MARTORANO *et al.*, 2018; QUESADA *et al.*, 2011; HILKER *et al.*, 2014; NOBRE *et al.* 2014). This typological heterogeneity significantly impacts the composition and volumetric distribution of vegetation in terra firme forests in Amazonia (PELLISSIER *et al.*, 2001; QUEASADA *et al.*, 2012; COSTA *et al.*, 2015).

The joint use of remote sensing products and forest inventory data applied to forest management has been gaining ground (WOLF *et al.*, 2012; ABDOLLAHNEJAD *et al.*, 2017; ABDOLLAHNEJAD *et al.*, 2019). As the topography of the site has a direct influence on the occurrence of species and most of them are distributed non-randomly, information from remote sensing, such as elevation, plays a crucial role in mapping and monitoring species (PEREIRA-JR *et al.*, 2021; HIGUCHI *et al.*, 1981; SOUZA *et al.*, 2005; GUO *et al.*, 2016; NOGUEIRA *et al.*, 2007). Wolf *et al.*, (2012) assessed the spatial distribution of species richness in tropical forests using lidar data and found significant differences in richness associated with topographic variation. Dong *et al.* (2020) used

optical images from the Landsat series together with topographic correction models and forest inventory data to classify groups of forest species according to topography and obtained satisfactory results.

Remote sensing can also play an important role in monitoring and quantifying canopy disturbance caused by selective logging (BUSTAMANTE *et al.*, 2016; SAATCHI *et al.*, 2011; WOLF *et al.*, 2012; ABDOLLAHNEJAD *et al.*, 2017; ABDOLLAHNEJAD *et al.*, 2019). Fortunately, damage to the canopy is highly correlated with the volume of timber removed from the forest (PEREIRA-JR *et al.*, 2021; ABDOLLAHNEJAD *et al.*, 2019). The disturbances caused by logging also vary depending on the logging practice used; the recommended logging practice in the Amazon is known as reduced impact logging (RIL) and should be incorporated into management plans to minimize impacts (PEREIRA-JR *et al.*, 2021).

Previous studies have shown the need for high spatial and temporal resolution images for monitoring selective logging in the Amazon (WOLF *et al.*, 2012; DONG *et al.*, 2020; ASNER *et al.*, 2005). In addition, most of the remote sensing techniques and products used for mapping and monitoring studies of selective logging have been insufficient for large-scale assessments (ABDOLLAHNEJAD *et al.*, 2019). A comparison using field data of crown disturbance with satellite imagery from the Landsat series after logging proved that traditional analytical methods and medium spatial resolution imagery fail to detect around 50% of the crown damage caused by forest harvesting operations (PEREIRA-JR *et al.*, 2021). Abdollahnejad *et al.*, (2019) proposed an advanced approach integrating geographic information systems (GISs) and remote sensing using very high spatial resolution images to monitor logging areas and pointed to an increase in the accuracy of volume estimates as a function of the spectral and spatial resolution of the images. Petri *et al.*, (2022) tested the use of images from the PlanetScope nanosatellite constellation for vegetation studies in the Amazon and concluded that high spatial and temporal resolution images are fundamental for understanding forest dynamics in the Amazon. Sustainable forest management (SFM) is recognized as a strategy and indicator of forest conservation, but there are gaps in the appropriate conditions for exploiting forest resources (PUTZ *et al.*, 2020; LAMB *et al.*, 2021). Brazilian standards establish specific values for harvesting intensity per hectare. On the other hand, when assessing sustainability indicators, factors such as the distribution of the diameter class structure and the availability of species to constitute the cutting rate in the forest management process must be considered (CARVALHO & PARROTA, 2017).

The authorized intensity of logging in tropical forest management is not associated with data on the heterogeneity of the original forest structure; that is, the volumes determined for extraction are fixed and standardized (PUTZ *et al.*, 2012). Carvalho (1999) considered the difficulty of tropical forest management due to the complexity and heterogeneity of its ecosystems (CARVALHO, 1999). According to Chazdon, the inappropriate use of natural forests can disrupt extraction cycles and degrade ecosystems (CHAZDON *et al.*, 2008).

Cutting intensity is one of the most important aspects of forestry and refers to the commercial volume of the trees to be harvested, estimated using volumetric equations provided in the sustainable forest management plans (SFMPs) and based on data from the pre-harvest forest inventory, expressed in cubic meters per unit area ($\text{m}^3 \text{ha}^{-1}$). Currently, Brazilian legislation authorizes a maximum cutting intensity of $30 \text{ m}^3 \text{ha}^{-1}$ for 35-year cutting cycles (BRASIL, 2000; ASNER & ALENCAR, 2010).

Although Brazilian legislation establishes a maximum limit for logging intensity, this fixed limit is indiscriminately applied to the entire Annual Production Unit (APU) area, disregarding possible forest heterogeneity. This becomes a sensitive issue as managers can exploit the forest without respecting its original structure and spatial distribution (CHAZDON & GUARIGUATA *et al.*, 2008; BRASIL, 2006). Therefore, the objective of this study is to evaluate the spatio-temporal heterogeneity by logging intensity in a federal concession area in the Brazilian Amazon within an SFM area following logging activities subjected to the reduced impact logging (RIL) technique.

2. Materials and Methods

2.1 Study Area

The study was carried out on a federal forest concession area in the Brazilian Amazon, situated within the Saracá-Taquera National Forest in the western part of the state of Pará, covering an area of 441,152 hectares (Figure 1). This sustainable Use Conservation Unit (UCS) was established by Decree No. 98.704 on 27 December 1989, with the objective of conducting research projects and initiatives aimed at the sustainable utilization of forest resources and the wellbeing of the populations residing within the UCS. These conservation units (UCs) were established under the National System of

Nature Conservation Units and managed by the Chico Mendes Institute for Biodiversity Conservation (ICMbio) (BRASIL, 2006).

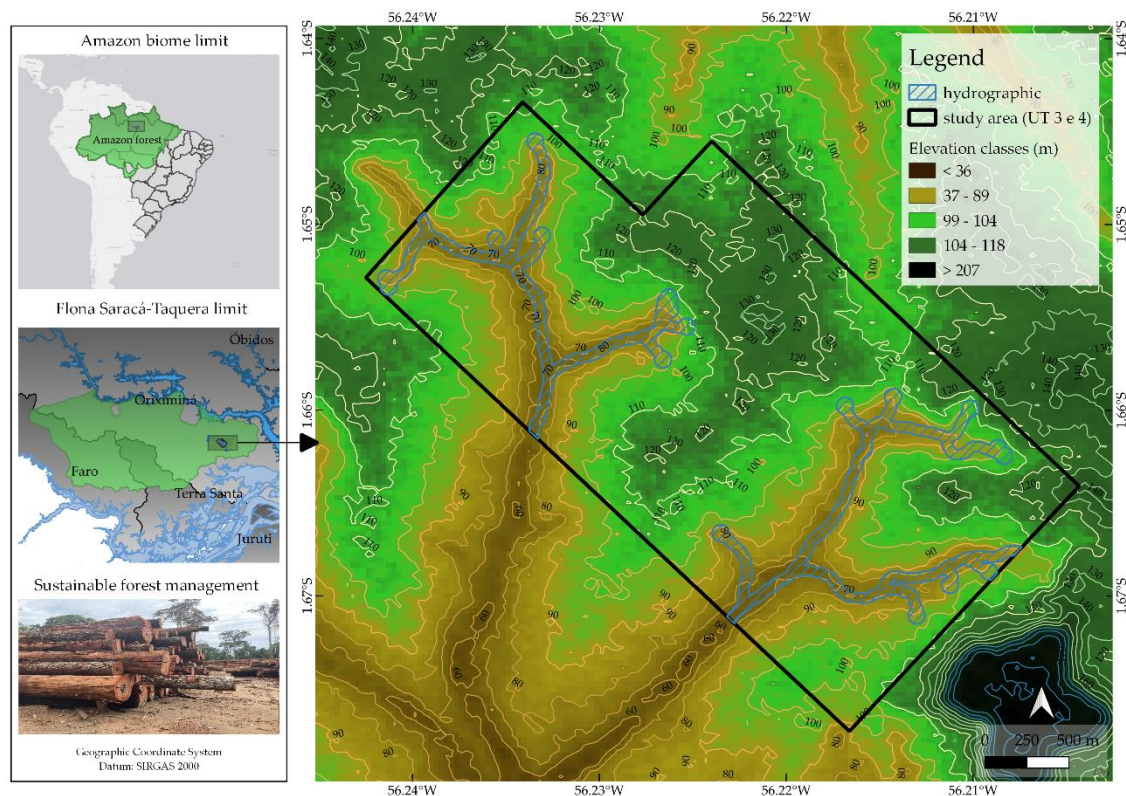


Figure 1. Location of the study area.

Source: OLIVEIRA, 2024.

The analyses were carried out in the eastern section of the national forest, specifically within Forest Management Unit II (FMU II). In SFM, the FMU represents the designated portion of the property allocated for forest management. The specific area designated for logging activities is referred to as a timber unit (TU). The portion of forest slated for management each year is termed an annual production unit (APU), and an APU may encompass one or more TUs.

The APU under evaluation was harvested between May 2022 and May 2023, with an initial authorization to exploit 1629 hectares and a total roundwood volume of 39,031 m³, comprising 30 commercial species selected by the concessionaire. TUs 3 and 4 of APU 11 were chosen to test the hypothesis proposed in this study. TU 3 covers an area of 339 hectares, while TU 4 covers 369 hectares, resulting in a total effective study area of 735 hectares, which also includes areas forming part of the hydrographic network in the analyzed area (Figure 1).

2.2 Vegetation

The national forest is covered by tropical rainforest, with variations typically linked to geomorphological features. The regional vegetation can be categorized as submontane and lowland ombrophilous dense forest, distinguished by two distinct strata: one emergent, featuring *Dinizzia excelsa*, *Bertholletia excelsa*, and *Cedrelinga catanaeformis* as primary species, and the other uniform, marked by the presence of *Manilkara spp.*, *Protium spp.*, and *Pouteria spp.* (IBGE, 2012).

The two primary facies, submontane and lowlands, comprise 94.1% of the Flona's area, while pioneer formations influenced by rivers account for 2.7%, and campinarana for 0.2%. Primary natural vegetation formations constitute 97% of the Flona's vegetation cover, whereas areas affected by anthropogenic activities represent 2% of the national forest's total area (ICMBIO, 2015).

2.3. Forest Inventory Data Extraction

The data from the pre-harvest inventory of commercial tree species and the inventory of harvested trees were obtained from the Brazilian Forestry Service (BFS) in the form of an electronic spreadsheet in .xlsx format. The BFS oversees concessions for sustainable forest management in public forests in the Amazon. Additionally, the BFS provided the post-harvest forestry report for APU 11, which included geospatial data on all inventoried commercial trees, along with an extra column containing the date of tree felling. Spatio-temporal analyses were conducted based on the 'cutting date' information to compare the original forest structure, the logged structure, and the structure remaining after logging.

Under the New Forest Code (Federal Law 12.651/12), harvesting trees within permanent preservation areas (PPAs), such as those near watercourses, is prohibited. Consequently, trees located within PPAs were excluded from the analysis to focus solely on potential trees for harvesting (Figure 2). The legislation also mandates a minimum cutting diameter (MCD) of 50 cm, meaning trees smaller than this diameter would not be felled and were thus excluded from the analysis as well. Pre-harvest inventory requirements stipulate that trees with a minimum diameter at breast height (DBH) of 10 cm below the MCD should be included (BRASIL, 2006). Thus, the study focused on

evaluating only commercial trees available for cutting outside the limits of PPAs and with a DBH greater than 50 cm.

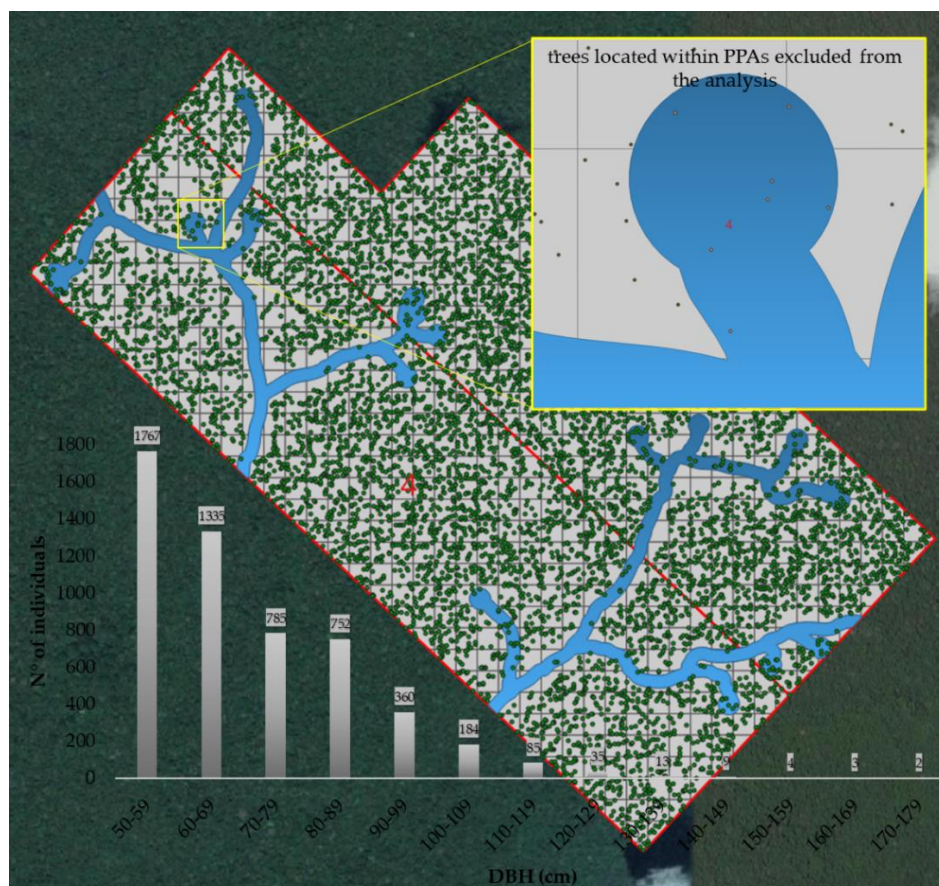


Figure 2. Spatialization of the inventory trees (points in green) with a focus on the exclusion of areas within PPAs (in blue) and the diametric distribution graph.

Source: OLIVEIRA, 2024.

2.4. Measuring Topographical Variables

The topographic variable of elevation (m) was utilized, based on the hypothesis that this variable can influence the spatial distribution of commercial species volume (WOLF *et al.*, 2012; COSTA & GUILLAUMET, 2015; ABDOLLAHNEJAD *et al.*, 2017; ABDOLLAHNEJAD *et al.*, 2019). Elevation was calculated using the average altitude for each 1-hectare cell. The Copernicus Global DSM Digital Elevation Model (DEM) at 30 m resolution was employed. The data have an absolute vertical accuracy >4 m (90% linear error) and absolute horizontal accuracy >6 m (90% linear error). These data originated from the TanDEM-X mission between 2011 and 2015 and were made available for free use in 2019. They are widely used in research employing the approach utilized in this work (WAGNER *et al.*, 2015; RIZZOLI *et al.*, 2017).

2.5. Assessment of Forest Canopy Openings Caused by Selective Logging

To evaluate the gradient of forest canopy openings resulting from tree felling in relation to logging intensity, satellite images from the PlanetScope constellation were employed. A pair of images before and after the exploitation were used for change detection analysis. This was based on the premise that higher logging intensities lead to larger openings in the forest canopy, thereby resulting in variations in the gradient of forest cover changes (ABDOLLAHNEJAD *et al.*, 2019; PEREIRA-JR *et al.*, 2001; ASNER & MASCARO, 2014).

The PlanetScope constellation comprises multiple launches of individual satellite groups (DOVEs), each consisting of a constellation of 3U CubeSats (i.e., $10 \times 10 \times 30$ cm) with over 120 active DOVEs. These sensors operate in at least four spectral bands; blue (455–515 nm), green (500–590 nm), red (590–670 nm), and near-infrared (780–860 nm), offering 3 m of spatial resolution and 12 bits of radiometric resolution (PETRI *et al.*, 2022). Band 3 was utilized individually due to its heightened spectral response to exposed soil and dry vegetation targets, making it highly recommended for vegetation studies in the Amazon (BROWN, 1997; PINARD *et al.*, 2000; JESEN, 2015) (Figure 3).

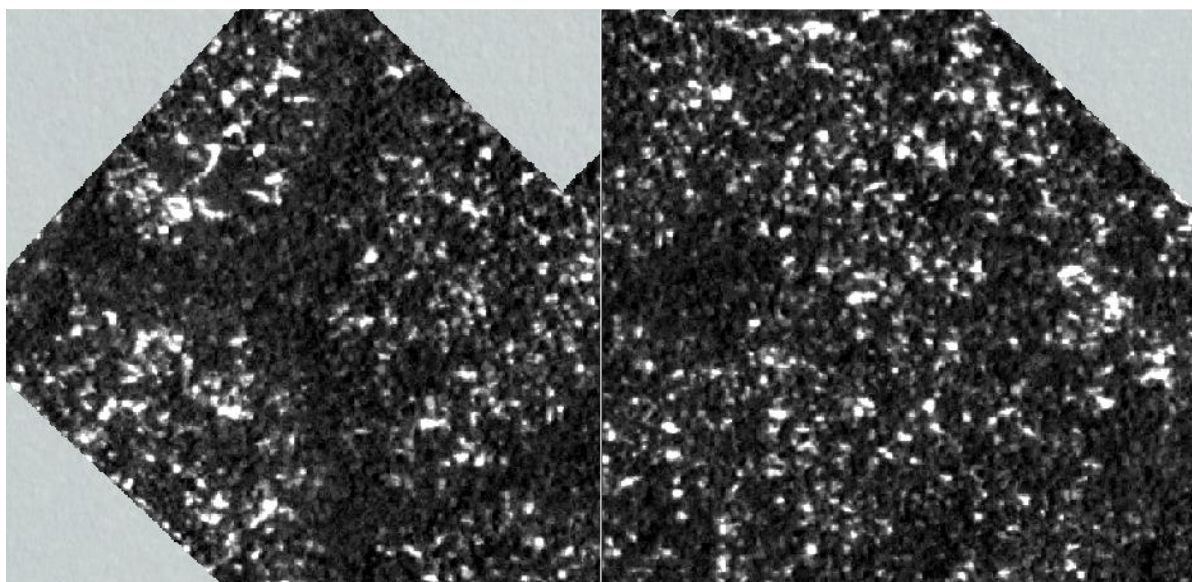


Figure 3. In the lighter tones of the band 3 images, there are higher spectral response values for areas with exposed soil and dry vegetation (clearings).

Source: OLIVEIRA, 2024.

Figure 4 and Figure 5 illustrate, didactically, the process of harvesting a tree and the impact its toppling can have on the forest canopy, resulting in the opening of a clearing. Thus, based on the variations in signal intensity captured by the sensor and the

frequency histogram of the image using band 3, a threshold was empirically defined based on the RGB (3,2,1) composition to classify areas with and without change. Digital number (DN) values greater than 2550 were considered canopy, and DN values less than 2550 were considered gaps.

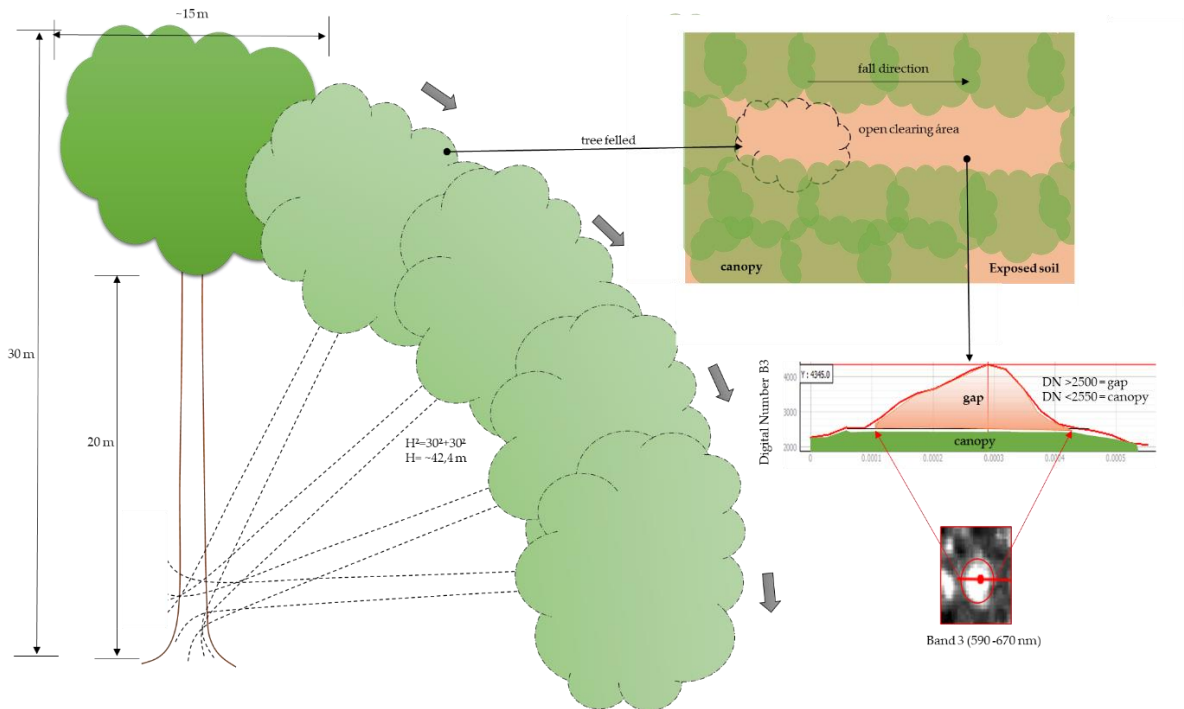


Figure 4. Illustration of the felling of a tree and its impact on the forest cover.

Source: OLIVEIRA, 2024.

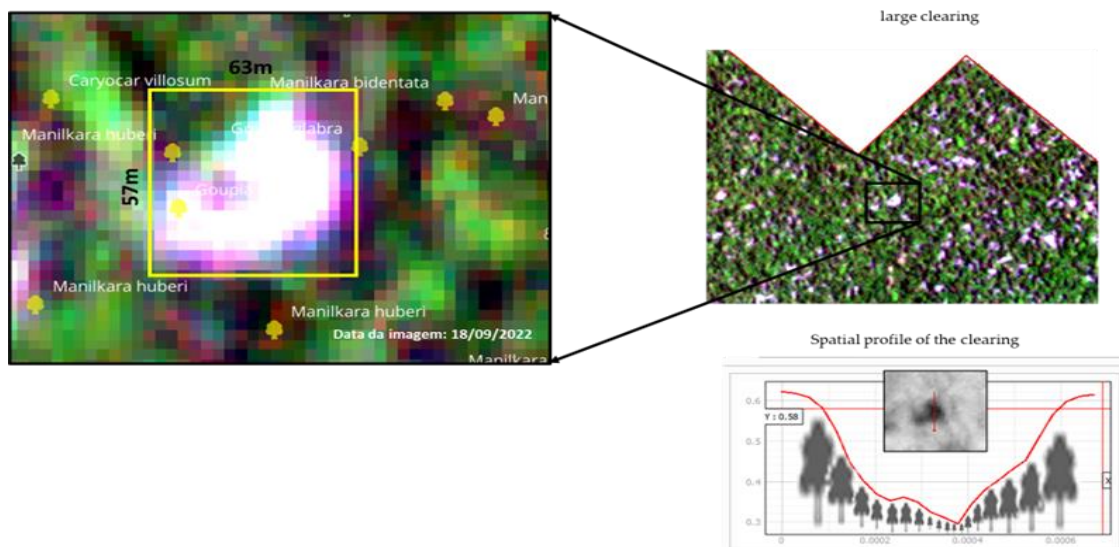


Figure 5. Empirical analysis of the size of the glades as a function of the areas extracted.

Source: OLIVEIRA, 2024.

After classification, binary thresholding or binarization of the image in raster format was performed to separate areas of dense forest from other areas (such as exposed soil and dry vegetation, among others). Following binarization, the forest and clearing classes were analyzed by converting the file to vector format. Only the clearings were then extracted to calculate the area of each class, excluding individual $3\text{ m} \times 3\text{ m}$ (9 m^2) pixels. The data were subsequently verified through visual interpretation. For visual analysis, we used the coordinates of all the trees that had been logged and the result of the classification of the clearings, so that for each tree or group of trees logged, a polygon was assigned and classified as a clearing.

Thus, except for the individual pixels, all other data points were validated and aggregated into 1-hectare cells. The metrics employed to aggregate the clearing vectors into 1-hectare cells included the percentage of the area within the cell and the total clearing area. Linear correlation analysis was conducted to assess the correlation between the area of clearings and logging intensities.

2.6. Analysis of Changes in the Spatial Distribution of Tree Volume and Abundance

The inventory information was spatialized and aggregated into 1-hectare cells. This decision was made for two main reasons: firstly, to enable the application of zonal statistics, and secondly, to facilitate understanding and discussion of the information. Since 1 hectare is a widely used unit of area in discussions of this nature, it allows for easier understanding, interpretation, and comparison between different studies and regions (LAMB, 1998; DE'ATH, 2002; ASNER *et al.*, 2005; PHILLIPS *et al.*, 2004).

The data were spatialized considering three time classes. Class “t0” refers to all the individuals inventoried before logging, class “t1” refers to the trees that were actually extracted from the forest, and class “t2” refers to the trees remaining in the area after logging. The diagram shown in Figure 6 illustrates the aggregation of individuals in the 1-hectare cells. For each cell, in each time class, the values contained in the inventory were assigned a tree abundance ($\text{n}^\circ\text{ ind. ha}^{-1}$) and volume ($\text{m}^3\text{ ha}^{-1}$) (Figure 6).

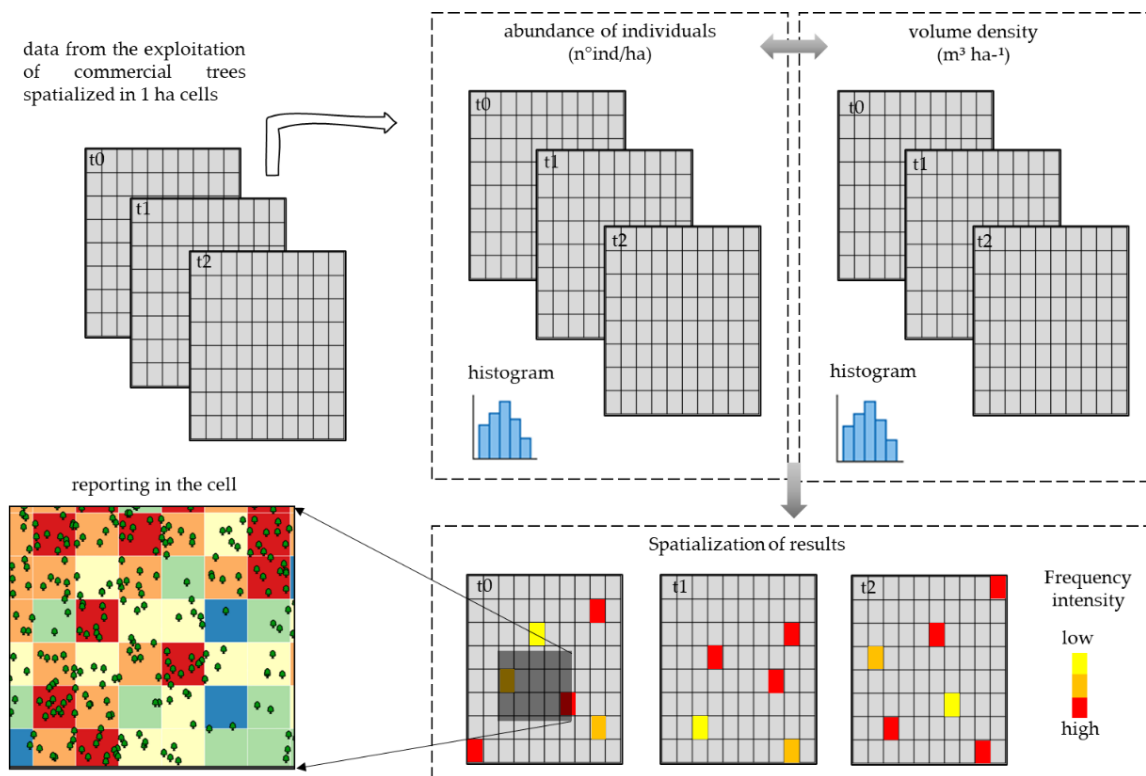


Figure 6. Schematic drawing of the aggregation of trees into 1 ha cells.

Source: OLIVEIRA, 2024.

2.7. Determining the Number of Clusters and Analyzing the Spatial Distribution of Logging

Cluster analysis was conducted using the k-means algorithm to classify the area into groups based on the topographic variable and the volumes of timber extracted (t_2). The algorithm identifies objects or entities with similar characteristics, creating groups or classes with high internal homogeneity (within clusters) and high external heterogeneity (between clusters) (WANG & YANG, 2011; SANTOS & GLERIANI, 2017; KASSAMBARA, 2017; GOWER & ROSS, 1969).

To determine the optimal number of clusters (k), the elbow method was employed through visual analysis of the graph. Utilizing the elbow method with k-means clustering in the context of forest analysis is a conventional approach in data science and ecology (MACQUEEN, 1965; CUTLER *et al.*, 2007; HARIRI & JAVADI, 2000; CHÁVEZ-DURÁN *et al.*, 2022; GEORGAKIS *et al.*, 2023). An evaluation of the dissimilarity of the variables (SSEs) among each cluster was conducted to identify potential heterogeneities in forest exploitation. At the conclusion of the process, 746 1-hectare cells ($100 \text{ m} \times 100 \text{ m}$) were considered.

3. Results

3.1. Analysis of the Change in the Spatial Distribution of Tree Volume and Abundance Due to Logging Activity

The spatial distribution of commercial volume before logging indicates that the interval between 45 and 60 $\text{m}^3 \text{ha}^{-1}$ had the highest number of cells with significant volume (199). For the higher volume ranges, above 120 $\text{m}^3 \text{ha}^{-1}$, only five cells were observed. It should also be noted that the lowest commercial volume ranges, from 0 to 15 $\text{m}^3 \text{ha}^{-1}$, are mostly located close to water bodies (Figure 7). In terms of tree abundance, the intermediate ranges of commercial tree abundance of 5–10, 10–15, and 15–20 individuals per hectare concentrate the largest number of cells, with the range of 10 to 15 individuals being the most representative, with 306 cells counted, and consequently, the range with the largest number of total trees.

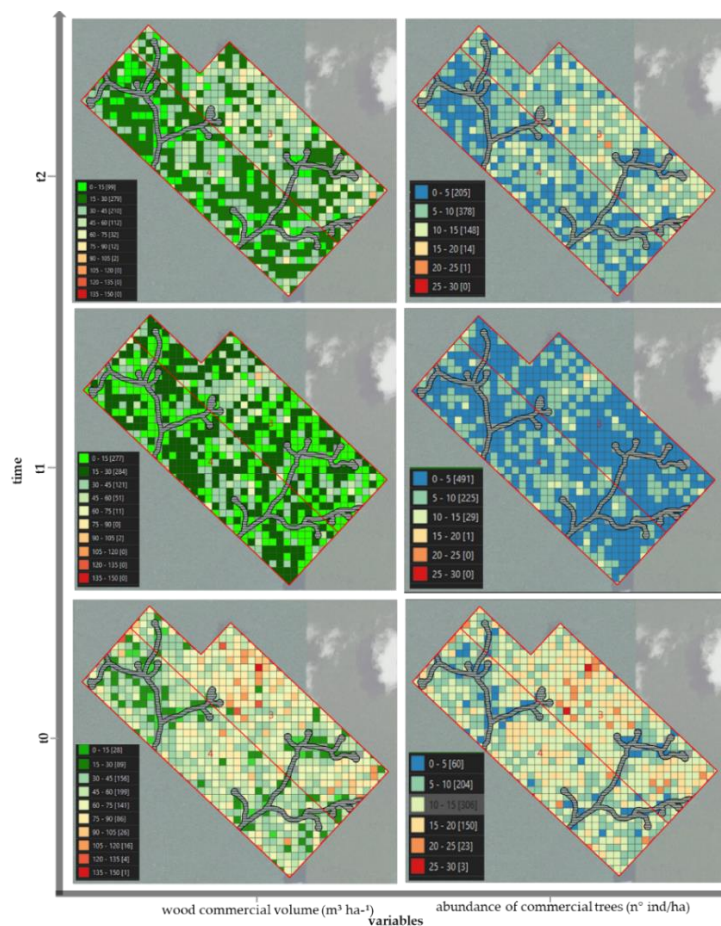


Figure 7. Spatial distribution of commercial volume and tree abundance before (t0), during (t1), and after logging (t2).

Source: OLIVEIRA, 2024.

There was a gradient in the spatial distribution of both the commercial volume and the abundance of trees in the area before logging, with three cells having an abundance between 25 and 30 individuals per hectare and 60 cells with an abundance between 0 and 5 individuals per hectare. The range of variation in the stock of commercial volume before logging is also extremely high, with 117 cells below $30 \text{ m}^3 \text{ ha}^{-1}$ and 21 cells between 105 and $150 \text{ m}^3 \text{ ha}^{-1}$ (Figure 7).

Regarding the remaining volume in the area, for didactic and visual purposes, it was decided to use shades of green to represent the volume bands below $30 \text{ m}^3 \text{ ha}^{-1}$, which is currently the maximum intensity of exploitation per hectare stipulated by the legislation. Thus, it can be observed that before logging, the forest exhibited a wide distribution of cells in bands greater than $30 \text{ m}^3 \text{ ha}^{-1}$ (Figure 7). After logging, the range between 15 and $30 \text{ m}^3 \text{ ha}^{-1}$ concentrates the largest number of cells (279), suggesting a systematic reduction across the area, but leaving areas with a considerable volume of stored wood, such as areas with a volume of $75 \text{ m}^3 \text{ ha}^{-1}$ or more, where 14 active cells remained. The map depicted in Figure 7 illustrates that the spatial distribution patterns of abundance and volume are similar throughout the area, both before (t_0) and after logging (t_2) (Figure 7).

After logging (t_2), there was no significant change in the normal distribution curve of individual abundance, suggesting that the area was logged following the natural spatial distribution of the forest. However, a shift in the number of cells towards lower abundance ranges can be observed, with the range between 5 and 10 being the most representative after logging (Figure 8).

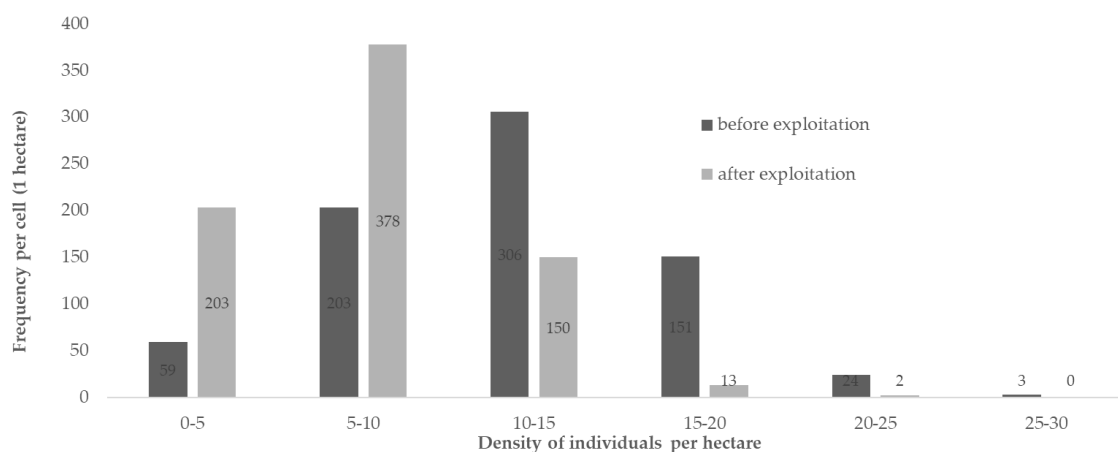


Figure 8. Frequency distribution histogram of the occurrence of 1-hectare cells in the abundance classes of commercial trees before and after logging.

Source: OLIVEIRA, 2024.

While before logging, the largest number of cells was in the commercial volume range between 45 and 60 m³ ha⁻¹, after logging, the class with the largest number of cells was concentrated in the range between 15 and 30 m³ ha⁻¹, indicating the migration of cells to lower volume classes. However, it is still possible to identify areas with a high-volume stock, such as areas with a volume greater than 75 m³ ha⁻¹, which represented 14 cells. The average volume per hectare decreased from 48 m³ ha⁻¹ to 28 m³ ha⁻¹, and the average number of individuals decreased from 12 to 7, considering the time before and after logging (Figure 9).

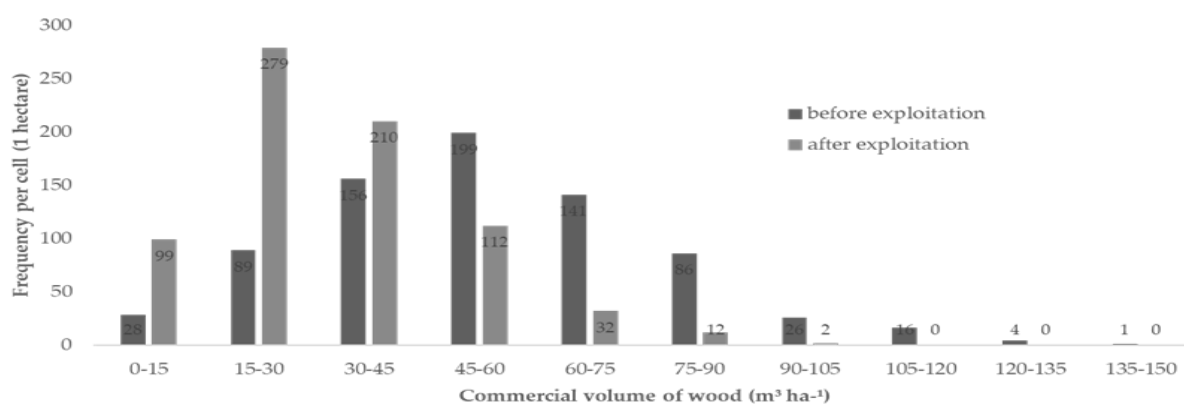


Figure 9. Frequency distribution histogram of the occurrence of 1-hectare cells in the commercial wood volume ranges before and after harvesting.

Source: OLIVEIRA, 2024.

3.2. Analysis of the Harvested Trees

Assessing the results of the commercial trees actually harvested, it is evident that harvesting was concentrated on felling a few trees per hectare, with 65.5% of the cells showing the harvesting of between 0 and 5 individuals per hectare. However, 29 cells had a logging intensity between 10 and 15 individuals per hectare, and only one cell had a logging intensity above 20 individuals per hectare, as shown in Figure 10.

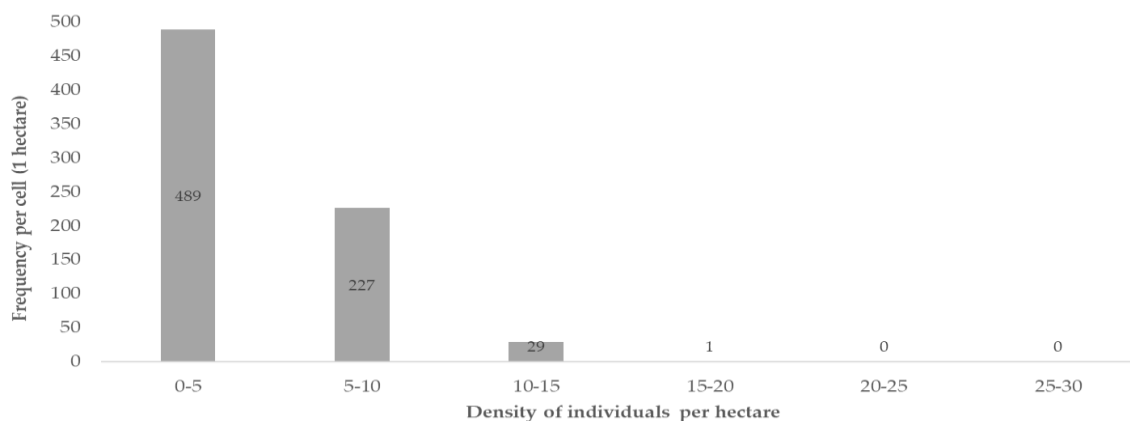


Figure 10. Class frequency distribution histogram of the number of trees logged per 1-hectare cell.

Source: OLIVEIRA, 2024.

Examining the distribution map of the abundance of commercial trees logged in Figure 7 (t1), it is evident that most of the logging was concentrated on felling a few individuals per hectare, with more logging occurring in areas with a larger stock of trees, particularly in the plateau areas farthest from the water bodies.

In terms of the volume that was effectively logged, the highest number of sensitized cells was in the range between 15 and 30 $\text{m}^3 \text{ha}^{-1}$, comprising 284 cells (Figure 11). It was observed that approximately 75% of the cells were below 30 $\text{m}^3 \text{ha}^{-1}$, which is the maximum volume allowed by law. However, it should be noted that the remaining 25% were exploited, showing harvesting above 30 $\text{m}^3 \text{ha}^{-1}$, with two cells having an exploitation intensity between 90 and 105 $\text{m}^3 \text{ha}^{-1}$.

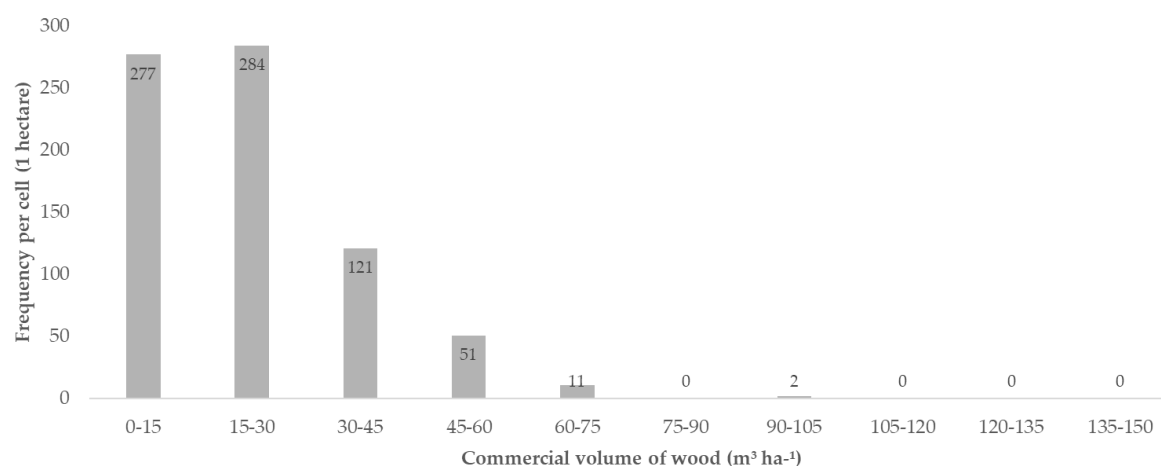


Figure 11. Frequency distribution histogram of logging intensity classes ($\text{m}^3 \text{ha}^{-1}$).

Source: OLIVEIRA, 2024.

3.3. Digital Elevation Model and Its Relationship with the Distribution of Harvested Commercial Timber Volume

Elevation ranged from 50 to 200 m. The highest values for the volume of harvested commercial timber were found away from the water bodies and close to the plateau areas (48.6 to 98.4 m³ ha⁻¹). The lowest volume values are mostly concentrated in the lower elevation regions, such as the water bodies present in the area (0 to 8.9 m³ ha⁻¹) (Figure 12).

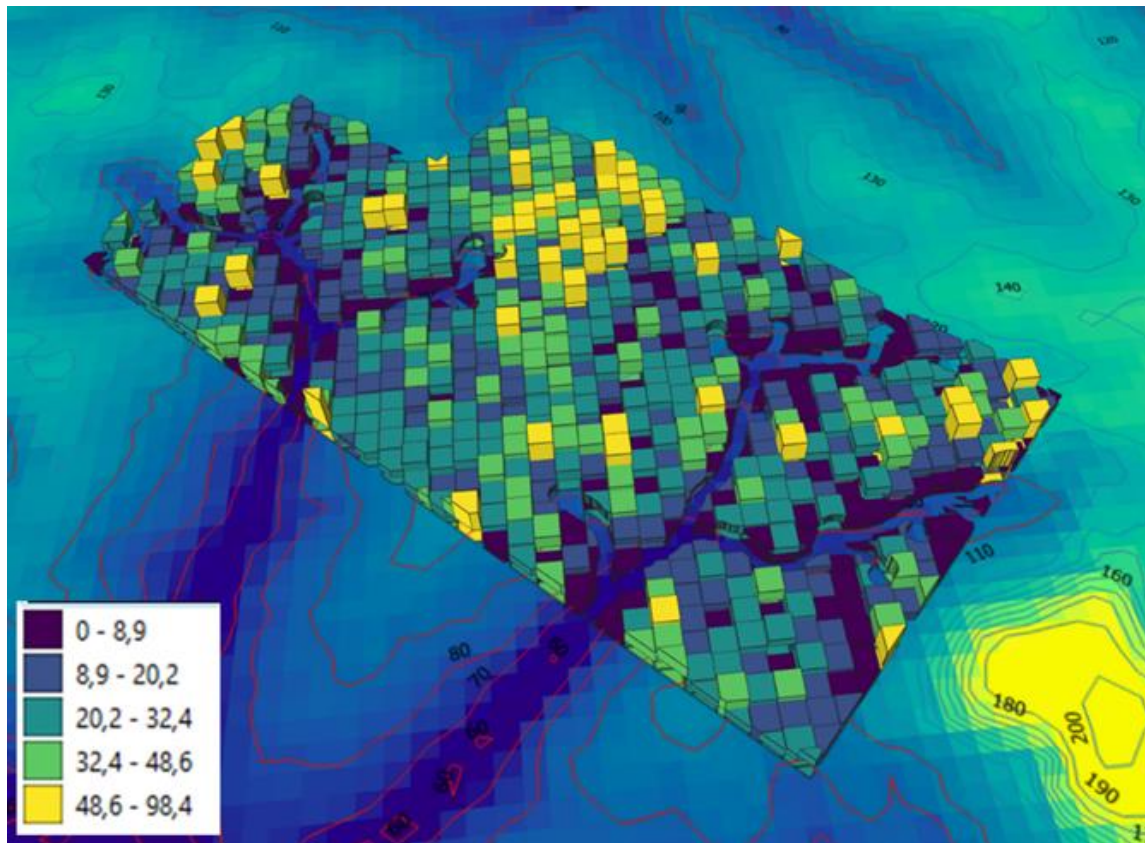


Figure 12. Relationship between elevation (m) and the volume of commercial timber actually harvested (m³ ha⁻¹).

Source: OLIVEIRA, 2024.

3.4. Digital Elevation Model and the Relationship with the Distribution of the Volume of Commercial Timber Harvested

Based on the slope of the distortion curve in relation to the number of clusters, four clusters (k) were defined for the data set (Figure 13).

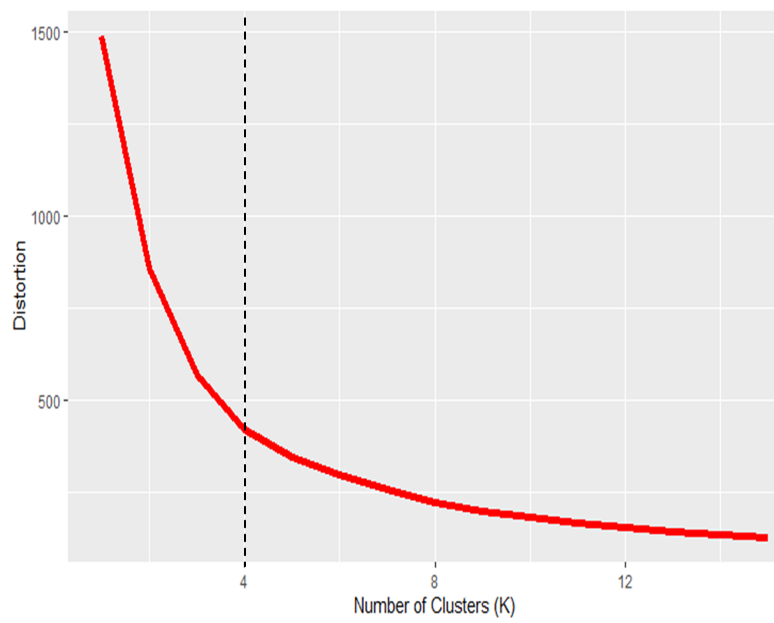


Figure 13. Definition of the best number of groups (k) using the elbow method.

Source: OLIVEIRA, 2024.

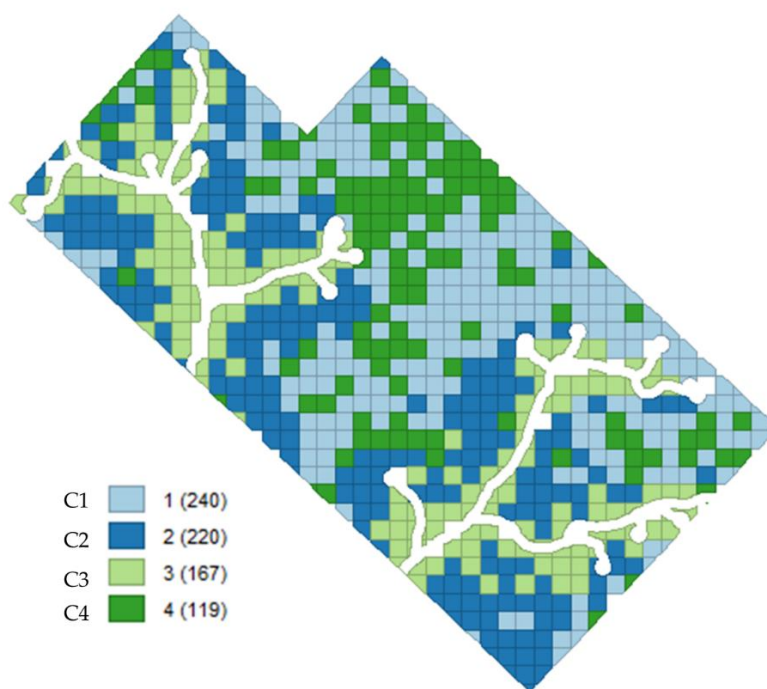
Cluster 1 (C1), comprising 240 observations and representing 32% of the data, has average values of $14.7 \text{ m}^3 \text{ ha}^{-1}$ and 113 m for the volume exploited and elevation, respectively, making it a transition group between low and high relief areas. Cluster 2 (C2) includes 220 observations (29%), with an average of $26.4 \text{ m}^3 \text{ ha}^{-1}$ and 97.6 m for volume and elevation, respectively. Cluster 3 (C3), with 167 observations (22%), had volume and elevation values of $5.9 \text{ m}^3 \text{ ha}^{-1}$ and 84.7 m, respectively, indicating a group with a spatial association with water bodies. Cluster 4 (C4) had 119 observations (16%) with volume and elevation values of $46.6 \text{ m}^3 \text{ ha}^{-1}$ and 115.2 m, respectively, indicating a spatial association of high-volume extraction in a plateau region (Table 1).

Table 1. Results of the cluster analysis in relation to volume extracted and elevation.

Cluster	Cluster Centers				Cluster Name
	Proportion (%)	Volume Explored ($\text{m}^3 \text{ha}^{-1}$)	Elevation (m)	SSE	
C1	32.17%	14.70	113.30	132.30	Low volume, high elevation
C2	29.49%	26.42	97.64	105.60	Medium volume, medium elevation
C3	22.39%	5.90	84.79	77.58	Low volume, low elevation
C4	15.95%	46.66	115.29	103.78	High volume, high elevation

Source: OLIVEIRA, 2024.

Regarding the dissimilarity of the groups, expressed through the sum of squares within the clusters (SSEs), the cluster with the least variance in the Euclidean distances is the “low volume low elevation” group, with the lowest SSE value of 77.5. This indicates that in these areas, close to the water bodies, logging occurred in a homogeneous manner and with few individuals per hectare (Figure 14). On the other hand, the most heterogeneous group was the “low volume high elevation” group, with an SSE value of 132. Since this group has the largest number of cells (240) distributed throughout the area, it naturally exhibits a high degree of heterogeneity among its internal observations. The “medium volume medium elevation” and “high volume high elevation” groups have intermediate SSE values, indicating a medium degree of heterogeneity.

**Figure 14.** Spatial distribution of logging clusters using the k-means method.

Source: OLIVEIRA, 2024.

3.5. Evaluation of the Relationship between Canopy Openness and Selective Logging Intensity

Figure 15 depicts the correlation graph between the volume of timber extracted ($\text{m}^3 \text{ha}^{-1}$) by intensity class and the area of the mapped clearing. A strong correlation ($r^2 = 0.93$) is observed, confirming the hypothesis of a positive relationship between the volume of wood extracted from the forest and the area of the clearing. In other words, this suggests that there is a correlation between the spatial and spectral information extracted by SR, representing the canopy opening resulting from logging activity.

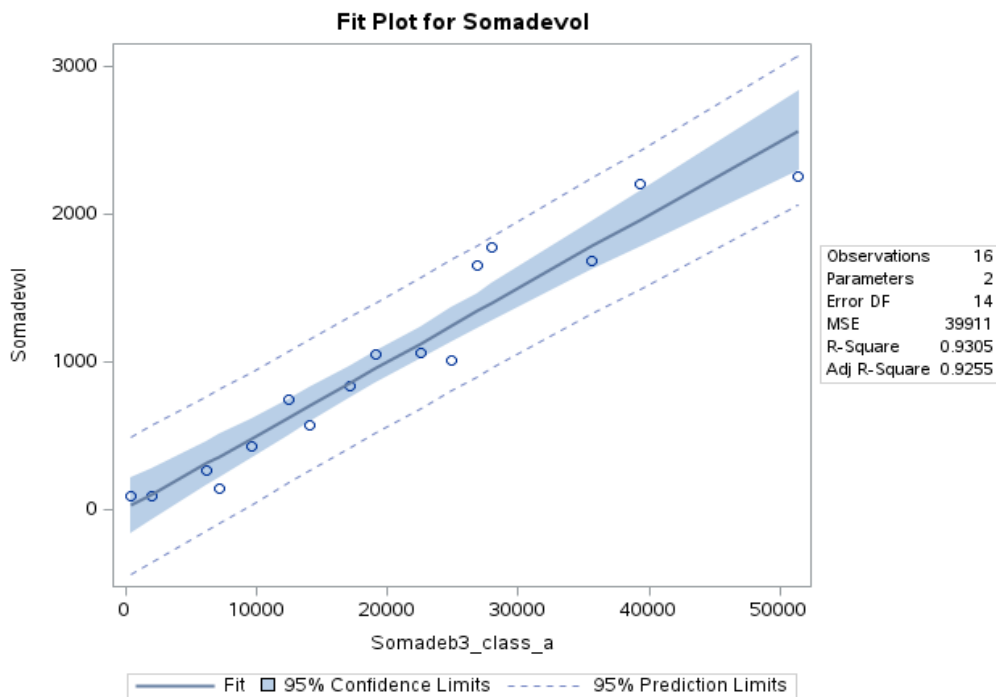


Figure 15. Positive correlation between the volume of timber extracted and the areas of clearing mapped.

Source: OLIVEIRA, 2024.

4. Discussion

The main finding of this study demonstrates that the logging intensity in SFMPs using RIL techniques in the Amazon is not uniform and follows the natural heterogeneous distribution of the stand, with high logging intensity occurring in highly stocked areas. Despite the legislation setting a maximum cutting intensity of $30 \text{ m}^3 \text{ha}^{-1}$, there are areas within the work unit that have values above this limit, and areas that have intensity values lower than this limit. However, the study indicates that areas highly stocked with timber

also exhibit higher logging intensity. One of the cells with high logging intensity (95 to 105 m³ ha⁻¹) was also the cell with the highest available volume (120 to 135 m³ ha⁻¹).

The results suggest the need to monitor forest recovery in areas with high logging intensity, to allow for the revision of forest management guidelines. This revision should consider the heterogeneous distribution of forest stands and adjust logging intensities according to the available wood stock in each management area (CHAZDON, 2008; PUTZ & REDFORD, 2009). The identification of non-uniform patterns in logging intensity indicates the necessity of developing adaptive management strategies that can be adjusted based on the specific characteristics of each management area (BERKER & FOLKE, 1998; ARMITAGE *et al.*, 2008). Understanding the heterogeneous natural distribution of forest stands and their relationship with logging intensity can contribute to promoting the sustainability and conservation of forest resources by enabling more efficient and sustainable forest management (PUTZ & ROMERO, 2020; TURNER *et al.*, 2001; PERES & LAKE, 2003).

These findings could inform new discussions regarding how legislation authorizes cutting intensity in management areas. By setting the intensity at 30 m³ ha⁻¹, the legislation does not consider the spatial heterogeneity of the distribution of forest volume evidenced in this study (PUTZ & ROMERO, 2020; LARSON & RIBOT., 2007; NASI *et al.*, 2012). The uniform application of this limit could lead managers to overexploit areas with low volume and underexploit areas with high stock. The decision to harvest is influenced by factors such as the species present, topography, or market demand for specific species or wood types. These factors can interact in complex and dynamic ways, influencing the logging strategies and intensities adopted by forest managers (SODHI *et al.*, 2010; SILLS *et al.*, 2014). The results suggest that, in addition to the criteria adopted today, such as rarity and maximum volume per authorized area, among others, the inclusion of a criterion for maximum volume or maximum number of individuals exploited per hectare could be considered, taking into account spatialization on a more refined scale, rather than for the authorized area as a whole, as is currently conducted (BRASIL, 2006). Currently, in Brazil, these criteria are defined by the Ministry of the Environment (BRASIL, 2000).

As demonstrated in this study, logging intensity is directly correlated with the available wood stock in specific areas and is more intense where stock is higher and less intense where it is lower (PUTZ *et al.*, 2012; ABDOLLAHNEJAD *et al.*, 2019). These findings are crucial for gaining a clear understanding of the spatial distribution of logging

intensity in the Amazon and for guiding future enhancements in forestry legislation (BLASER *et al.*, 2011). The results indicate that after logging, the spatial distribution of remaining volume and abundance per hectare remains proportionally similar to the original forest. It should be noted, however, that high logging intensities can leave the forest more vulnerable to collateral damage, such as forest fires (Romero *et al.*, 2021).

The heterogeneity of logging was evidenced by several factors contributing to the spatial scale. Firstly, the topography of the study area varies between plateau areas with altitudes of 200 m and lowland areas with altitudes of 50 m. It is apparent that areas farther from water bodies had the highest concentration of logging, while in areas of lower altitude and those closer to water bodies, where it is likely more difficult for heavy machinery to operate, logging was less intense. Our classification was able to clearly define the relationship between average logging intensity ($28 \text{ m}^3 \text{ ha}^{-1}$) and elevation. The spatial distribution of commercial species and their preferences for different types of soil and terrain should be considered in further analyses.

The selection of commercial species for exploitation is determined by commercial interests rather than their spatial distribution characteristics, highlighting the importance of further research in this direction. This approach can lead to unsustainable logging practices and negatively impact the genetic diversity of species populations if these factors are not considered when deciding which trees to harvest. The polycyclic forestry system with production regulation by area relies on selective logging being conducted properly. In other words, this selection stage is crucial for ensuring that viable populations can remain in managed forests (PUTZ & ROMERO, 2020; VOGT *et al.*, 1995; NEPSTA *et al.*, 2006). In addition, Romero *et al.*, (2021) points out that the productive capacity of a managed area depends on the intensity of harvesting applied by the manager and the correct use of reduced impact harvesting techniques, resulting in direct implications for climate change mitigation.

It is widely recognized that biomass and floristic composition are naturally influenced by relief and soil type (HIGUCHI *et al.*, 1981; ABDOLLAHNEJAD *et al.*, 2019). Based on forest inventories conducted by INPA in the 1980s, significant differences in basal area were observed because of relief variation. Samples taken on plateaus exhibited wood volumes of up to $210 \text{ m}^3 \text{ ha}^{-1}$, with 155 different species and a density of 155 to 170 trees ha^{-1} , for DBHs greater than 25 cm. In contrast, samples in flat areas, but at lower elevations, showed values of $136 \text{ m}^3 \text{ ha}^{-1}$, with 95 botanical species and a tree density of 135 trees ha^{-1} (CARVALHO & PORROTA, 2017). The

PROFLAMA, in an inventory also conducted in this area, observed a similar difference in volume (PROFLAMA, 1972).

Cluster analysis indicates that the topography of the site is a determining factor in the spatial arrangement and exploitation of the commercial species selected by the manager (FERRETTI *et al.*, 2020). Hartemink *et al.*, (2016) discusses soil geography and classification, including soil texture variation in different landscapes and its influence on the spatial distribution of species, ecological dynamics, and sustainable management of forest ecosystems. These results demonstrate a progressive differentiation in volume as one move down the relief positions. Denser forests with a greater volume of larger trees are observed on the plateaus. Intuitively or not, logging followed this pattern throughout the area, aligning with the natural distribution of the stand.

To reinforce this, the study enabled a direct comparison between the conditions before and during logging. The graphs in Figure 16 illustrate that the forest before logging resembled the logged forest. This indicates that logging adhered to the natural distribution of the forest. (Figure 16).

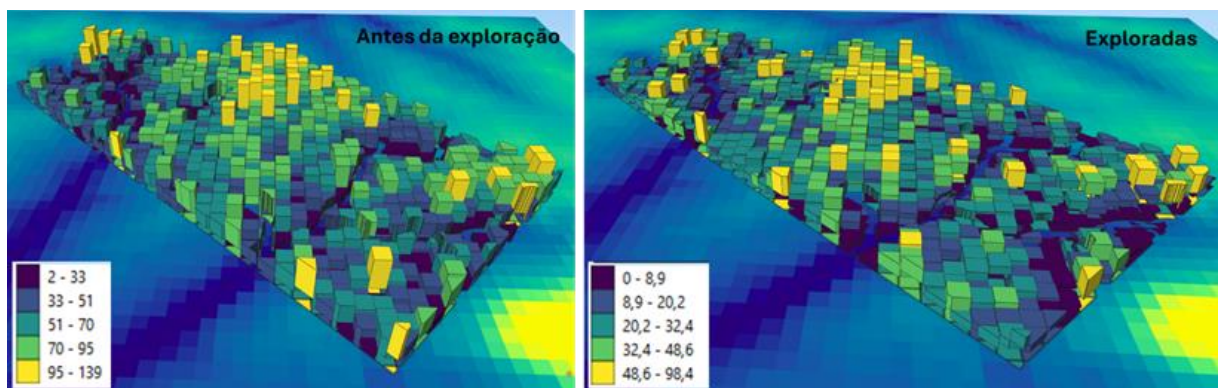


Figure 16. 3D representation of the volume before logging and of the trees actually logged ($\text{m}^3 \text{ha}^{-1}$).

Source: OLIVEIRA, 2024.

Understanding that the Brazilian government has implemented forest management across more than 220 million hectares in the Amazon, it is crucial to emphasize the necessity of developing metrics and monitoring methods that consider the forest's heterogeneity and the specific distribution of individuals and volume in each area. This includes assessing the remaining stock to inform potential future interventions, such as cutting cycles (BARRETO *et al.*, 2006; VERISSIMO *et al.*, 2011; SAWYER & SAWYER, 2018).

It is important to note that relying solely on reduced impact logging (RIL) does not ensure the sustainability of forest management (PUTZ *et al.*, 2008). For timber production to truly contribute to conservation efforts, additional measures must be implemented (CHAZDON & GUARIGUATA, 2016). Our methodology was instrumental in evaluating changes in the spatial distribution of commercial tree volume and abundance before, during, and after logging in concession areas. By utilizing simple inventory data and remote sensing imagery within a geographic information system, our approach shows promise in supporting effective and sustainable forest management in the Amazon.

Spatial and temporal analyses conducted within standardized cells, along with cluster analyses, proved to be effective in examining the spatial distribution and changes in forest structure within forest concession areas in the Brazilian Amazon. It is important to note that our study focused exclusively on public concession areas, as logging areas within private sustainable forest management plans were not included. This limitation should be considered, since public concession areas represent only a fraction of forest logging activities in the Amazon (VIDAL *et al.*, 2020).

The study was centered on a single public concession area and may not fully represent logging practices across the entire Amazon region. Specifically, it focused on a particular area within FMU II (TUs 3 and 4) and exclusively examined spatial and temporal characteristics related to commercial volume and tree occurrence per hectare in aggregated form.

It is important to acknowledge that the data analyzed originates from a commercial inventory, focusing solely on species of economic value to the concessionaire. Therefore, it does not encompass the entire population of species within the area. Additionally, while the study area is situated in a region with a rich history of human presence, including communities such as quilombolas and indigenous peoples with deep connections to the forest, social and cultural factors were not incorporated into the analysis.

The expectation is that the findings of this study will encourage forest concessions to adopt the methodology proposed here, thereby aiding in the management of forest exploitation in the Amazon. Additionally, it is recommended that the methods employed to assess the impacts of logging and the forest's capacity for recovery, such as permanent plots, consider the insights provided by this study.

5. Conclusions

Logging within the forest management area in the study exhibits heterogeneity in terms of the spatial distribution of logging intensity, encompassing both commercial volume and abundance. In this study's conditions, logging intensity aligned with the natural distribution of the forest, where the largest stocks were proportionally more exploited, and the greatest logging intensity occurred in areas with a greater stock of available timber. We recommend that managers consider this forest heterogeneity for forest exploitation using RIL techniques.

These findings hold significant implications for forest management and suggest constant monitoring in highly exploited areas and future improvements to current regulations to develop adaptive and more nuanced management strategies and foster the sustainability and conservation of forest resources.

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CHAPTER IV - Monitoring System For Sustainable Forest Management Plans In The Amazon: Integration Of Lidar Data And Planetscope Imagery³

Abstract: The growing pressure on natural resources in the Amazon underscores the need for sustainable forest management practices that balance the economic use of forest resources with environmental conservation. Sustainable Forest Management Plans (PMFS) aim to exploit timber resources while minimizing the impacts of selective logging. However, illegal logging and overly generic classifications undermine the reliability and economic feasibility of PMFS activities, necessitating improved monitoring and control to ensure their sustainability. This study proposes the integration of LiDAR data and PlanetScope imagery to enhance monitoring of forest disturbances caused by selective logging in the Amazon. LiDAR mapping detected 15.5% of the total impacted area, compared to 13.7% detected by PlanetScope. LiDAR achieved higher accuracy in detecting subtle structural changes, such as small clearings (<0.2 ha). Globally, PlanetScope mapping underestimated the total area of clearings, identifying 63.3 ha, whereas LiDAR detected 113.8 ha. The global accuracy of PlanetScope mapping was moderate ($P = 0.62$) with low recall ($R = 0.41$), indicating significant underestimation of disturbed forest areas. Metrics such as the global F1-Score (0.50), IoU (0.33), and relatively high RMSE (50.51) further highlight the differences between the two methods. Despite these limitations, PlanetScope mapping was more effective than systems like DETER and SAD in detecting clearings smaller than 1 ha, while LiDAR excelled in identifying small-scale vertical canopy changes. The integration of these technologies provides more precise and reliable data, strengthening sustainable forest management monitoring and offering critical insights to inform public policies for the Amazon forest sector.

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Keywords: forest disturbance; selective logging; monitoring system; change detection.

Resumo: A crescente pressão sobre os recursos naturais na Amazônia impõe a necessidade de práticas de manejo florestal sustentável com potencial de conciliar o aproveitamento econômico de recursos florestais e a conservação ambiental. O objetivo principal do Plano de Manejo Florestal Sustentável (PMFS) é aproveitar os recursos florestais madeireiros, minimizando os impactos da exploração seletiva de madeira. Entretanto, a ilegalidade na exploração madeireira ameaça economicamente as atividades florestais conduzidas sob PMFS, requerendo maior efetividade no monitoramento e controle da clandestinidade na atividade florestal para viabilizar economicamente o PMFS. No presente estudo, propõem-se a integração de dados LiDAR e imagens PlanetScope como alternativa para aprimorar o monitoramento dos distúrbios florestais causados pelas atividades de extração seletiva de madeira na Amazônia. Os resultados indicam que o mapeamento com dados LiDAR possibilitou a detecção de 15.5% da área total impactada pela exploração seletiva de madeiras, enquanto o mapeamento usando dados PlanetScope possibilitou a detecção de 13.7%. A maior exatidão do mapeamento alcançada com dados LiDAR em alterações estruturais sutis na floresta, tais como pequenas clareiras (<0,2 ha). A análise global aponta que o mapeamento usando dados PlanetScope subestimou o total de clareiras, detectando corretamente um total de 63,3 ha, enquanto o mapeamento usando dados LiDAR detectou um total de 113,8 ha. Como consequência, a acurácia global foi moderada ($P = 0,62$) e o recall baixo ($R = 0,41$), indicando expressiva subestimação das florestas como perturbadas. O F1-Score global (0,50) e o índice IoU (0,33), aliados a um RMSE relativamente alto (50,51), reforçam as diferenças observadas entre os métodos de mapeamento analisados. O mapeamento PlanetScope foi considerado mais eficaz que sistemas como DETER, SAD e GLAD na detecção de clareiras menores que 1 hectare na floresta, enquanto o LiDAR se destacou pela sensibilidade a alterações verticais e de pequena escala no dossel florestal. A integração dessas tecnologias oferece dados mais exatos e precisos, essenciais para fortalecer o monitoramento do manejo florestal sustentável e embasar políticas públicas para o setor florestal na Amazônia.

Palavras-chave: distúrbio florestal; exploração seletiva, sistema de monitoramento.

1. Introduction

The Amazon is recognized as the world's largest tropical forest, playing a crucial role in global climate regulation and biodiversity maintenance (MALHI *et al.*, 2008; LOVEJOY & NOBRE, 2019). However, increasing pressure on natural resources has heightened the need for forest management practices that balance economic exploitation with environmental preservation (GUARRIDO FILHA, 2002; RODRIGUES *et al.*, 2020).

The Sustainable Forest Management Plan (PMFS) is a viable strategy that ensures the rational use of forest resources and seeks to minimize the negative impacts of selective logging (BRASIL, 2006; ÂNGELO *et al.*, 2014). However, the effective implementation and monitoring of these plans have faced significant challenges, particularly concerning the precision, the detection of illegal or inefficient management practices, and the accurate classification of current monitoring systems (GUARRIDO FILHA, 2002; OLIVEIRA *et al.*, 2024).

With advancements in remote sensing (RS) technologies, the development of a detection and monitoring system utilizing high spatial and temporal resolution imagery to track sustainable forest management (SFM) activities in real-time in the Amazon has become increasingly feasible (ASNER *et al.*, 2005; ZEFERINO *et al.*, 2023; WAGNER *et al.*, 2023; OLIVEIRA *et al.*, 2024).

The advancement of these technologies, particularly the development of nanosatellites, has revolutionized environmental monitoring, making it more accessible, comprehensive, and precise (PETRI *et al.*, 2022; OLIVEIRA *et al.*, 2024). Among the most promising solutions are *PlanetScope* images, provided by a constellation of high-resolution nanosatellites managed by Planet Labs (OLIVEIRA *et al.*, 2024). These images play a strategic role in forest management monitoring, enabling the high-frequency temporal tracking and excellent spatial resolution of vegetation cover changes, the opening of clearings, and compliance with sustainable management plans (PETRI *et al.*, 2022; DALAGNOL *et al.*, 2023; OLIVEIRA *et al.*, 2024).

The adoption of spectral mixture models (SMM) for processing these images enables a more detailed analysis of forest cover composition, identifying subtle variations caused by selective logging (ZEFERINO *et al.*, 2023; OLIVEIRA *et al.*, 2024). The soil fraction represents the relative proportion of exposed soil within an image pixel (SHIMABUKURO & SMITH, 1991). In the context of forest monitoring, the model

provides critical indicators of clearing openings, vegetation removal, and changes in the forest canopy (DINIZ *et al.*, 2015). For instance, during selective logging operations, an increase in the soil fraction indicates ground exposure due to tree removal or machinery movement. This indicator is particularly useful in densely forested tropical regions, where vegetation typically dominates the landscape, making exposed soil a distinctive feature of impacted areas.

The use of LiDAR (*Light Detection and Ranging*) technology is another promising approach to enhance the monitoring of SFM in the Amazon (HUDAK *et al.*, 2002; LOKS & MATRICARDI, 2019; XU *et al.*, 2021; WINSTALEY *et al.*, 2024). LiDAR provides high-precision three-dimensional data on forest structure, enabling detailed analysis of parameters such as tree height (Canopy Height Model - CHM), canopy density, and biomass volume (XU *et al.*, 2021; WINSTALEY *et al.*, 2024). This information is critical for validating remote sensing data and detecting subtle disturbances in forest structure caused by selective logging practices (LOKS & MATRICARDI, 2019; SPARKS & SMITH, 2021; WINSTALEY *et al.*, 2024).

Additionally, LiDAR enables the creation of Digital Terrain Models (DTM) and Digital Surface Models (DSM), which aid in detecting human interventions such as roads and clearings. These capabilities contribute to a more comprehensive and effective monitoring of PMFS (WINSTALEY *et al.*, 2024).

In the present study, we evaluated the methodology and presented the results of applying an alert system using integrated LiDAR and PlanetScope data. By combining high-resolution optical imagery, LiDAR and field data, and digital image classification methods, this system provides more detailed, precise, and accurate information to support the monitoring and enforcement of forest activities in the Amazon. This approach ensures forest resource conservation while enabling efficient management and the sustainable use of forests.

2. Material and Methods

2.1. Study Area

The analyses were conducted in the eastern portion of the Saracá-Taquera National Forest (Flona), Pará state, specifically in Forest Management Unit II (FMU II). In SFM, the FMU represents the designated portion of the property for forest management. The forest area managed annually is referred to as the Annual Production Unit (APU), which may contain one or more timber unit (TU). The TU is the delimited

area for active logging activities. For this experiment, TU 3 and 4 of APU 11 were selected, corresponding to an area of 735 hectares, including regions within the hydrographic network under analysis (Figure 01).

The Saracá-Taquera National Forest is covered by tropical forest, with variations generally associated with geomorphological features. The local vegetation can be classified as Dense Ombrophilous Forest in both Submontane and Lowland formations. It is characterized by two distinct strata: an emergent layer dominated by *Dinizia excelsa* and *Cedrelinga cateniformis*, and a uniform layer with species such as *Manilkara spp.*, *Protium spp.*, and *Pouteria spp.* (IBGE, 2012). The two primary vegetation types, Submontane and Lowland, occupy 94.1% of the Flona area. Pioneer formations influenced by fluvial processes account for 2.7%, and campinarana vegetation covers 0.2%. Primary natural vegetation represents 97% of the Flona's vegetation cover, while areas impacted by human activities account for 2% of the total area (ICMBIO, 2015).

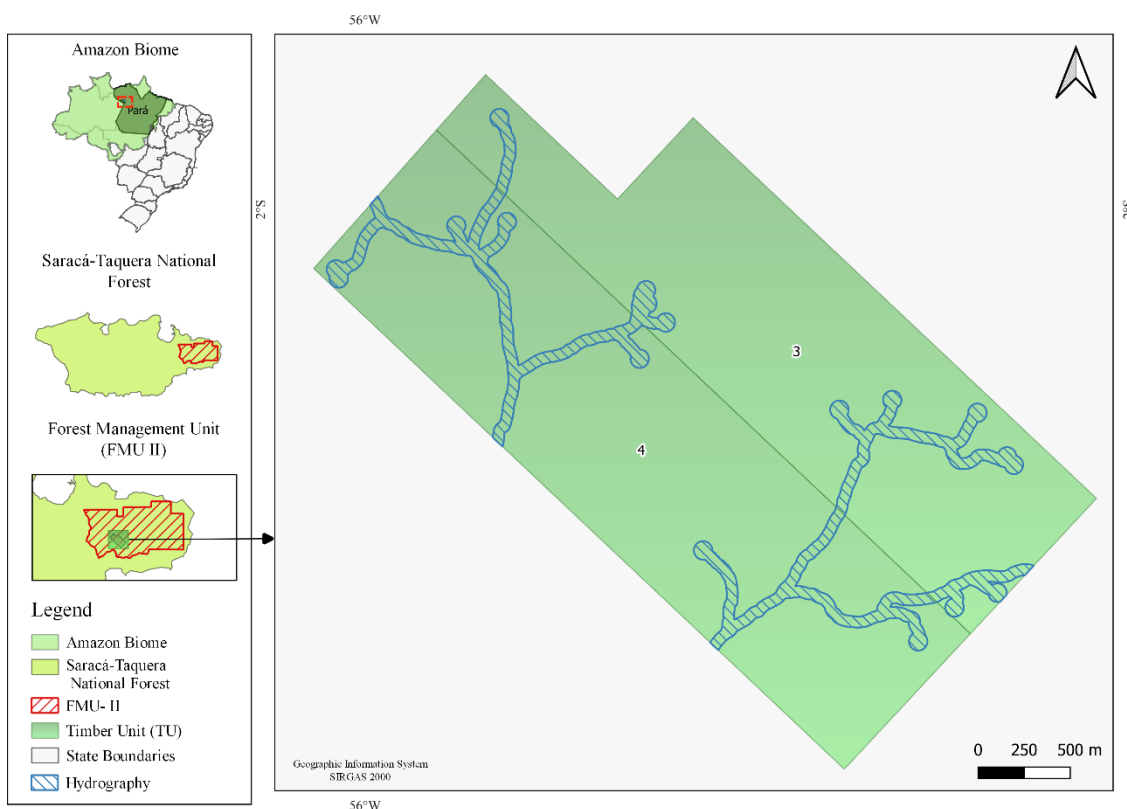


Figure 01. Location of the study area in the Saracá-Taquera National Forest, Pará state, Amazon biome.

Source: OLIVEIRA, 2024.

2.2 Execution Flowchart Details

The alert generation process involves two complementary approaches: the use of PlanetScope imagery and LiDAR data, each with specific methodologies to identify changes in forest cover (gaps). Below, in Figure 02, is a detailed explanation of each step, as well as the metrics used to evaluate the precision and accuracy of the mapping.

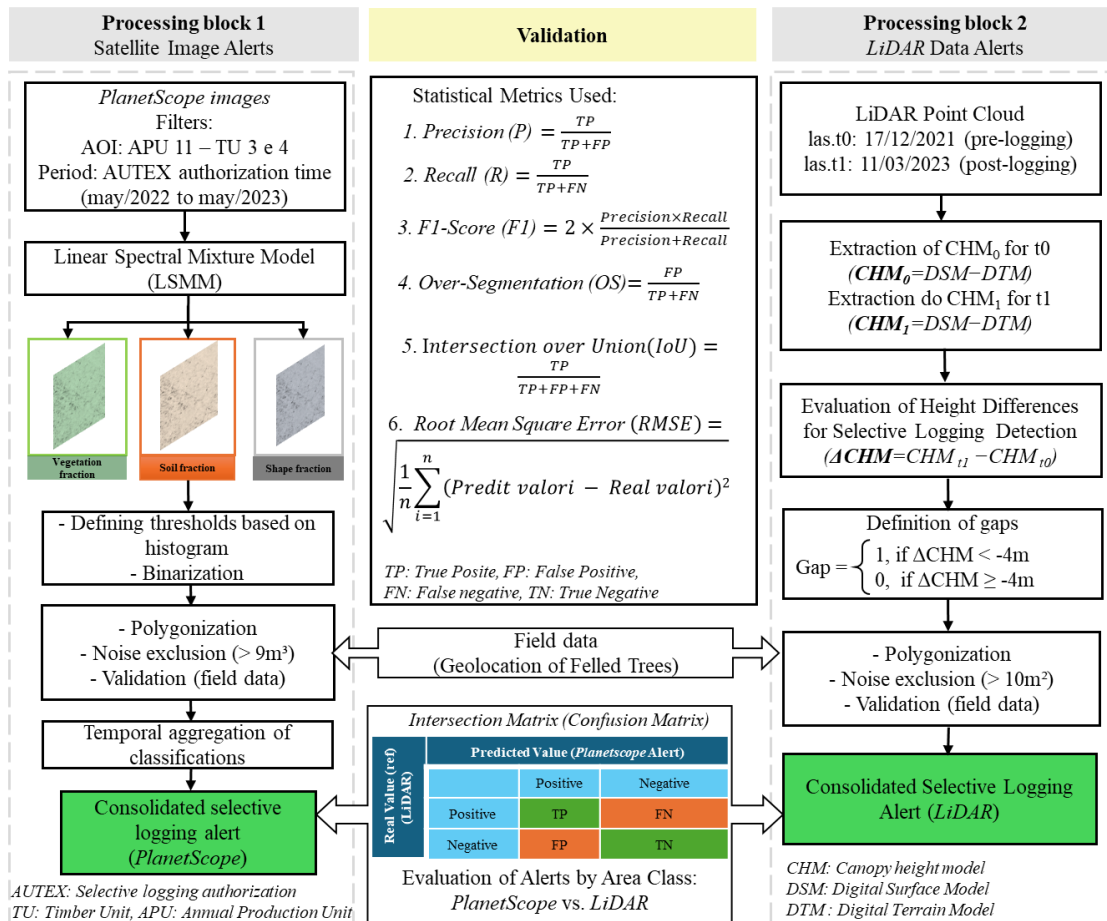


Figure 02. General flowchart of the methodology for the detection system of forests impacted by selective logging activities in the Saracá-Taquera National Forest, Pará state

Source: OLIVEIRA, 2024.

2.2.1 PlanetScope Images and Alert Generation (Block 1)

Block 1 in Figure 2 presents the process of using PlanetScope images processed through the Linear Spectral Mixture Model (LSMM), which enabled the calculation of vegetation, shadow, and soil fraction of images in the study area. The PlanetScope constellation consists of several launches of individual satellite groups (DOVEs), including a constellation of 3U CubeSats (10 × 10 × 30 cm) with over 120 active DOVEs.

These sensors operate in at least four spectral bands: blue (455–515 nm), green (500–590 nm), red (590–670 nm), and near-infrared (780–860 nm), with a spatial resolution of 3 meters and a radiometric resolution of 12 bits (PETRI *et al.*, 2022). Table 1 presents the images used in the classification.

Table 1. PlanetScope images used for generating selective logging alerts in the Saracá-Taquera National Forest, Pará state.

ID da imagem	Azimu te Sol	Elevaç ão Sol	Ângul o de visada	Data de aquisiça o	Momento de captura
20220617_131308_77_2430_3B_Analytic MS_SR_8b	53,90	45,00	3,00	17/06/20 22	Antes
20220927_134541_10_2498_3B_Analytic MS_SR_8b	70,50	57,80	1,00	30/08/20 22	Durante
20221208_131040_46_2427_3B_Analytic MS_SR_8b	123,60	48,70	2,90	08/12/20 22	Após

Source: OLIVEIRA, 2024.

From the soil fraction image, empirical thresholds were defined based on the frequency histogram and binarization, enabling the identification of areas with changes in forest cover. After classification, the identified areas were polygonized, followed by the exclusion of noise (individual polygons of $3 \times 3 \text{m} - 09 \text{m}^2$). Subsequently, the data were checked and validated through visual interpretation. Finally, the temporal classifications were aggregated, resulting in a consolidated alert of the detected changes over the entire period.

2.2.2 LiDAR Point Cloud and Alert Generation (Block 2)

LiDAR is a RS technology that uses light pulses to measure distances and create highly detailed three-dimensional representations of the Earth's surface and its cover. This study utilized LiDAR data acquired at two distinct times: pre-logging (t_0 , on 12/17/2021) and post-logging (t_1 , on 03/11/2023). Table 2 presents the details of the LiDAR data acquisition used for the clearing detection analyses.

Table 2. Acquisition details of airborne LiDAR data used for tree loss analyses.

Information	LiDAR Date 1 (Before)	LiDAR Date 2 (After)
Sensor	OPTECH/ GEMINI/07SEN213	OPTECH/ ORION M300/13SEN324
Capture Time	17/12/2021	11/03/2023
Acquisition Altitude	700 m	700 m
Scanning Frequency	57 kHz	64 kHz
Scan Angle	15°	15°
Data Type and Spatial Resolution	Point cloud (x, y, z) with 34.47 points/m ²	Point cloud (x, y, z) with 53.08 points/m ²

Source: OLIVEIRA, 2024.

The collected data were processed to generate three types of digital models: i) DSM (Digital Surface Model), which represents the total height of the terrain, including vegetation and artificial structures; ii) DTM (Digital Terrain Model), which reflects only the ground height, excluding vegetation and structures; and iii) CHM (Canopy Height Model), obtained by subtracting the DTM from the DSM, representing vegetation height.

The variation in vegetation height between periods was calculated based on the difference between CHM models, enabling the identification of areas with significant height loss ($\Delta\text{CHM} < -4$ m), classified as clearings (gaps). Detected clearing areas were polygonized, subjected to noise filters (excluding areas smaller than 10 m²), and validated with field data (felled trees), ensuring the accuracy and reliability of this technology for mapping assessments. These data were used as a reference for validating the alerts generated from PlanetScope imagery.

2.2.3 Field Data (Geolocation of Felled Trees)

Pre-exploratory inventory data for commercially valuable tree species, as well as inventory data for trees actually harvested, were provided by the Brazilian Forest Service (SFB) in the form of an electronic spreadsheet (.xlsx format). The SFB is the agency responsible for managing forest concessions for sustainable forest management in public forests within the Amazon.

The SFB also provided the post-exploratory forest report for UPA 11, which included geospatial information for all inventoried commercial trees, along with an additional column containing the logging dates for each tree. The volume extracted from each felled tree was used to evaluate the accuracy and reliability of the monitoring system.

2.2.4 Validation and Accuracy

An intersection matrix was constructed to compare the selective logging alerts detected by the *LiDAR* method (reference) and PlanetScope. The matrix contains four elements: i) True Positives (TP) - areas correctly identified as logged; ii) False Positives (FP) - areas incorrectly identified as logged (false alert); iii) True Negatives (TN) - areas correctly identified as not logged; and iv) False Negatives (FN) - areas that should have been identified as logged but were not.

The geolocation of felled trees was intersected and counted within each element (TP, FP, FN, and TN) and categorized by area size intervals to assess the spatial reliability

and accuracy of the mapping based on the size of the detected polygons (Figure 3). The validation of alerts generated by both methodologies was initially performed using the geolocation of felled trees through the correlation between the mapped alert area and the volume of wood extracted ($\text{m}^3/\text{ha}^{-1}$).

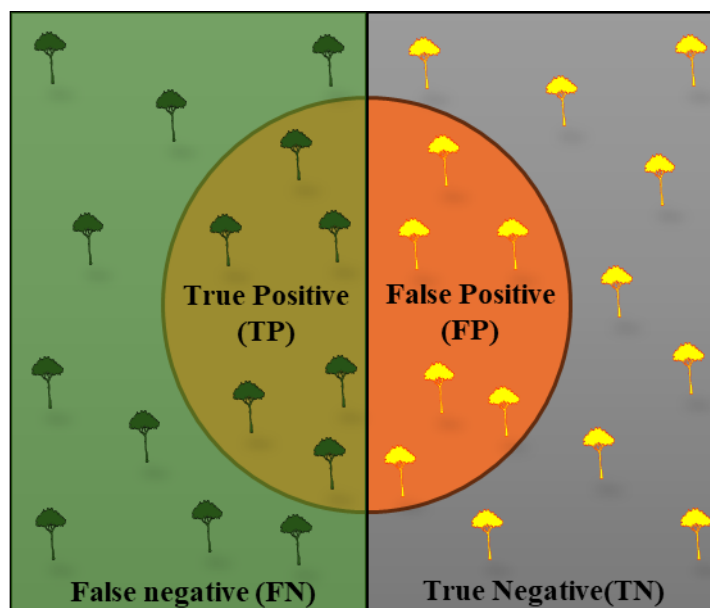


Figure 3. Evaluation criteria for the reliability and accuracy of forest disturbance detections based on felled trees.

Source: OLIVEIRA, 2024.

To evaluate the accuracy of the PlanetScope alerts, an intersection matrix was used to compare the predicted results (PlanetScope alerts) with the reference data (LiDAR). The statistical metrics used to assess the mapping accuracy are presented in Table 3 and are employed to quantify the methods' accuracy and ensure the reliability of the results.

Table 3. Statistical metrics used to evaluate the precision and accuracy of the mappings.

Metric	Formula	Description
Precision (P)	$\frac{TP}{TP+FP}$	Measures the proportion of correct classifications among all positive classifications. TP: True Positives, FP: False Positives
Recall (R)	$\frac{TP}{TP+FN}$	Measures the proportion of true positive areas correctly identified. FN: False Negatives
F1-Score (F1)	$2 \times \frac{Precision \times Recall}{Precision + Recall}$	Combines precision and recall into a single balanced metric.
Over-Segmentation (OS)	$\frac{FP}{TP+FN}$	Evaluates the proportion of false positives relative to the detected areas.

Intersection over Union (IoU)	$\frac{TP}{TP+FP+FN}$	Measures the overlap between the detected areas and the real areas.
Root Mean Square Error (RMSE)	$\sqrt{\frac{1}{n} \sum_{i=1}^n (\text{Predict Value}_i - \text{Real Value}_i)^2}$	Evaluates the average difference between predicted values and real values.

Source: OLIVEIRA, 2024.

3. Results

3.1 Correlation between the mappings and the effectively felled trees

Figure 4 shows the correlation between the volume of wood extracted and the respective areas mapped by both systems. While the correlation of wood volume with PlanetScope alerts is moderate ($r^2=0.7$) (a), there is a high correlation with LiDAR alerts ($r^2=0.9$) (b). The high correlation between the volume of wood extracted and LiDAR data demonstrates that this mapping provides greater accuracy for detecting areas impacted by logging. Therefore, it confirms the viability of this technology for evaluating the accuracy of mapping using PlanetScope images.

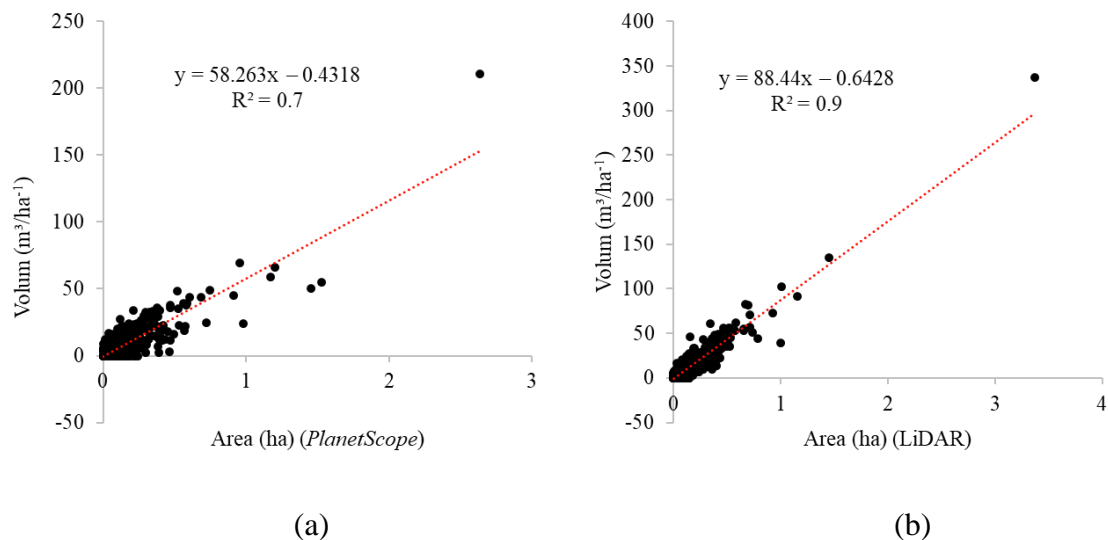


Figure 4. Correlation between the volume of wood extracted and the respective mapped areas (ha) using PlanetScope (a) and LiDAR data (b).

Source: OLIVEIRA, 2024.

3.2 PlanetScope Images Classification

Figure 5 presents the results of mapping using PlanetScope images, highlighting the classification of disturbances caused by selective logging identified through the Linear Spectral Mixture Model (LSMM). The mapping of impacted areas, highlighted in red on the map, totaled 100.91 hectares, representing 13.69% of the total area. Figure 5 also includes photos taken from different perspectives in the study area, showcasing the changes in the landscape.

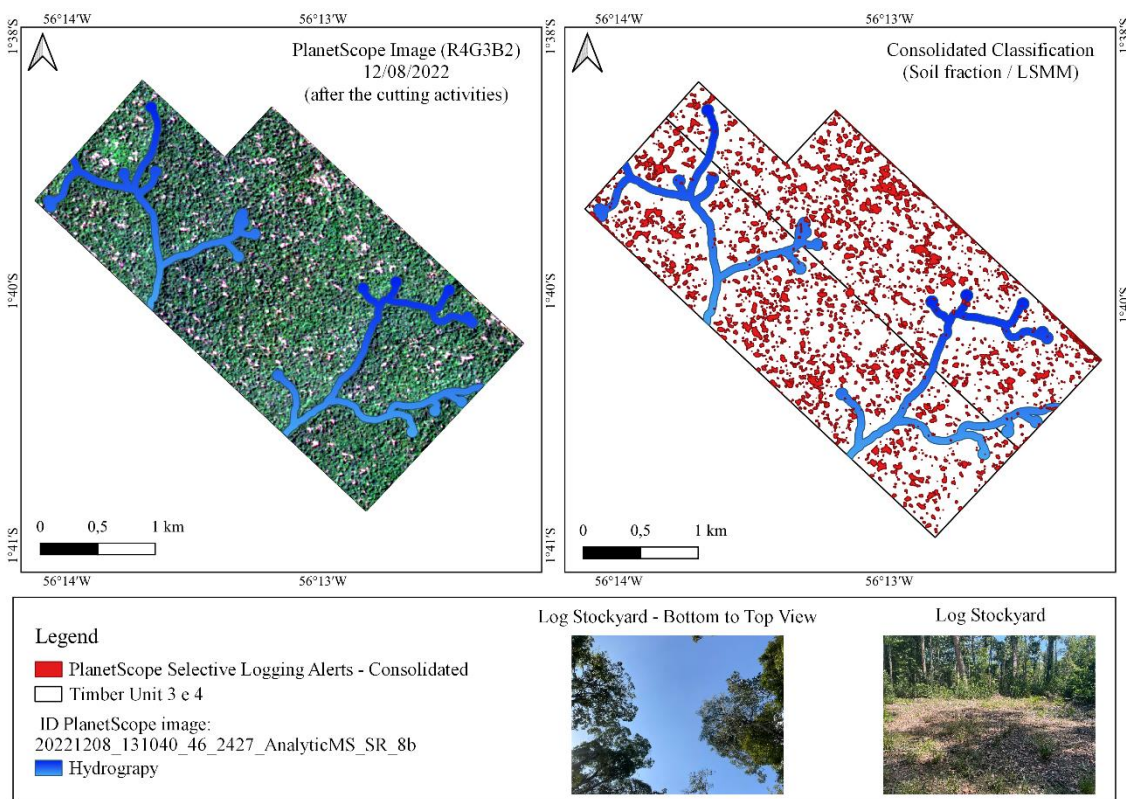


Figure 5. PlanetScope RGB color image and LSMM classification results of areas impacted by logging activities

Source: OLIVEIRA, 2024.

3.3 Classification with LiDAR Data

Figure 6 presents the results of canopy height monitoring before and after selective logging, based on Canopy Height Models (CHM). The Pre-Logging CHM, derived from data collected on 17/12/2021, represents the original vegetation structure, with heights ranging from 0 to 60 meters. Yellow regions indicate taller canopies, while dark blue areas reflect the absence of cover or low vegetation.

The Post-Logging CHM, dated 03/11/2023, highlights changes in canopy structure caused by selective logging. The differential map ($\Delta\text{CHM} = \text{CHM}_{t1} - \text{CHM}_{t0}$) emphasizes areas with canopy height reductions, with red areas indicating a loss greater than 4 meters ($\Delta\text{CHM} < -4 \text{ m}$), while areas with no significant change ($\Delta\text{CHM} \geq -4 \text{ m}$) appear in white. Enlarged circles detail the impacted regions.

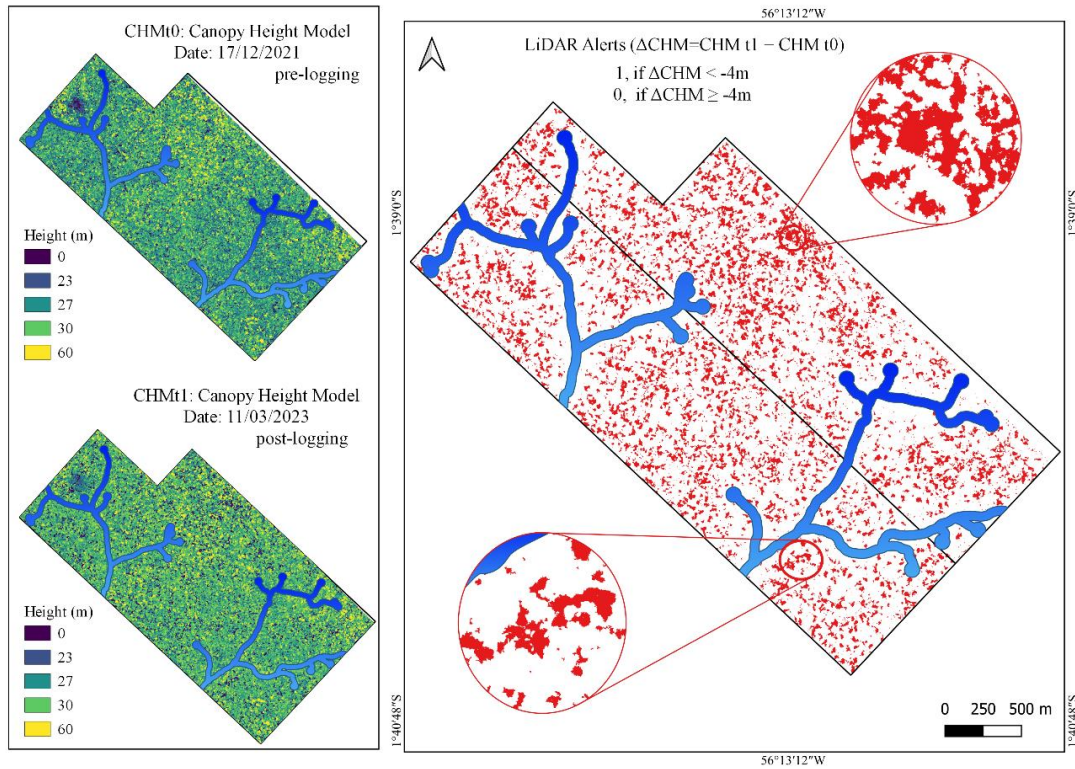


Figure 6. Forest disturbance alerts mapped through differences in LiDAR data before and after logging.

Source: OLIVEIRA, 2024.

The mapping conducted with LiDAR data identified a total of 113.77 hectares impacted by selective logging, representing an increase of 13.16 hectares compared to the mapping using PlanetScope images and 15.48% of the total area.

3.4 Comparison of LiDAR and PlanetScope Classifications

Figure 7 presents the results of forest disturbance detection using PlanetScope data, based on the Linear Spectral Mixture Model (LSMM), and LiDAR data, through differential canopy height analysis (ΔCHM).

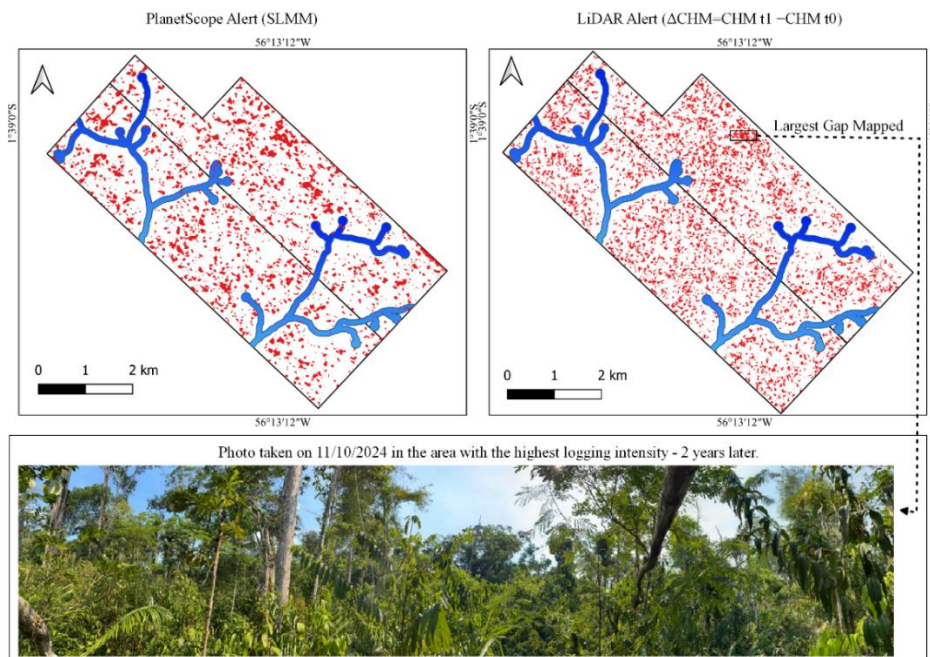


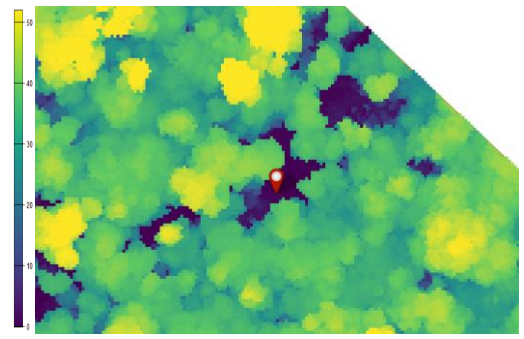
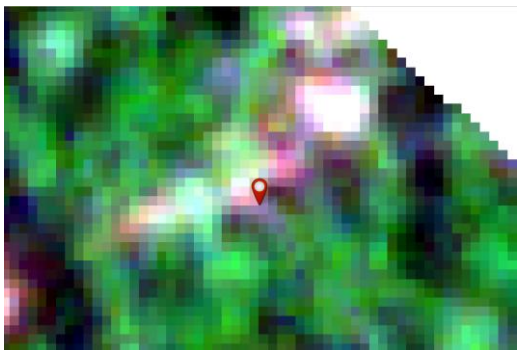

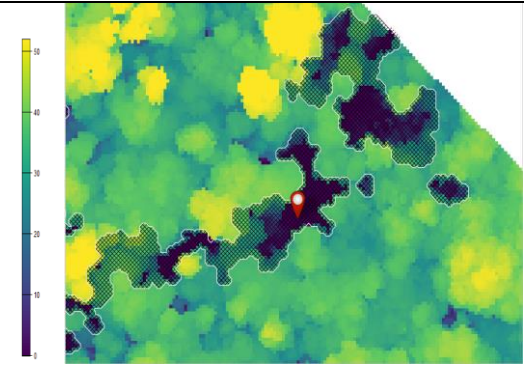
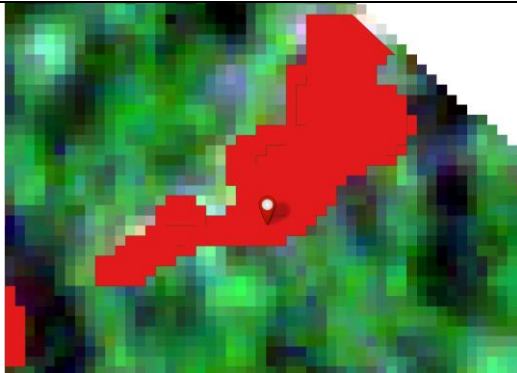

Figure 7. Comparative analysis of forest disturbance mapping results using *PlanetScope* and *LiDAR* data in the Saracá-Taquera National Forest, Pará state.

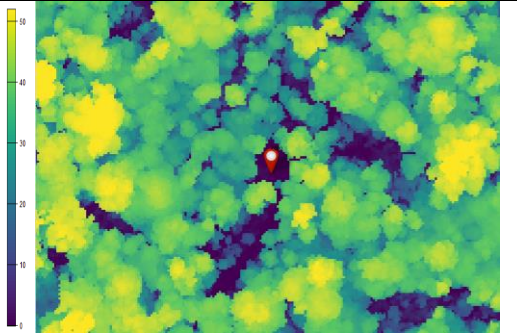
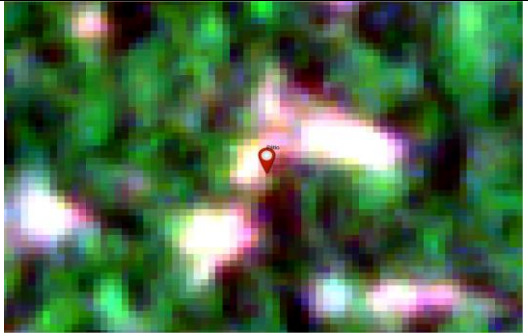

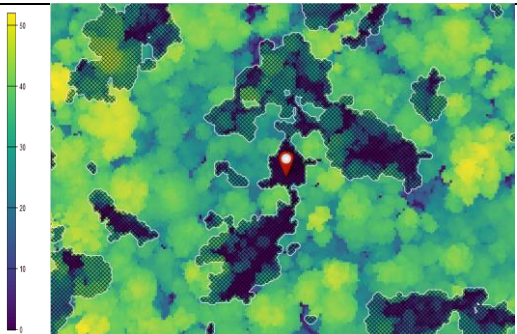
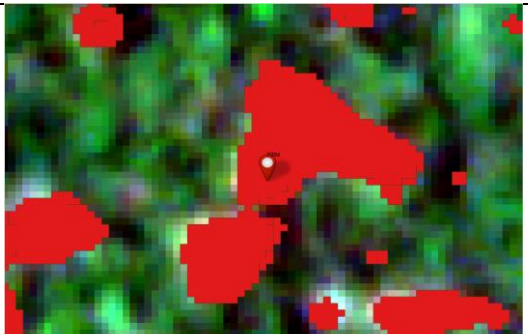

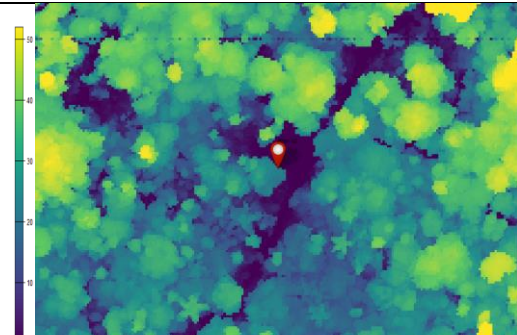
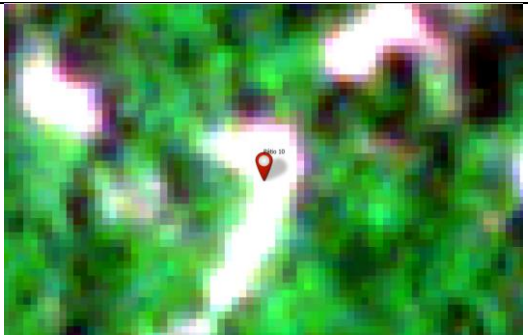

Source: OLIVEIRA, 2024.

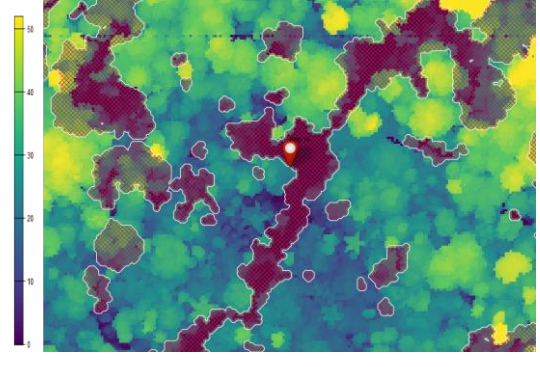
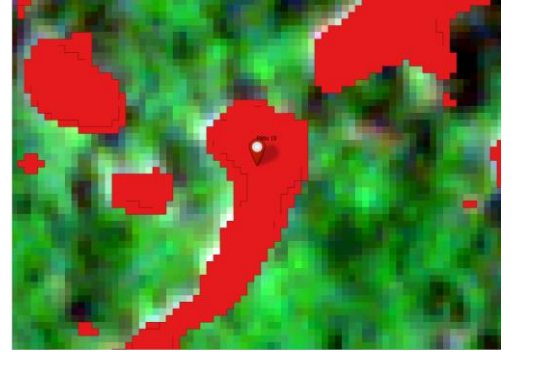

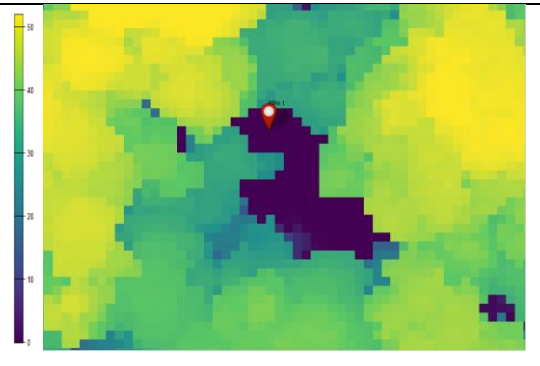
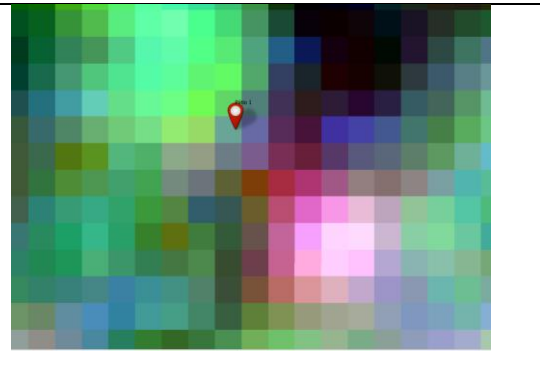

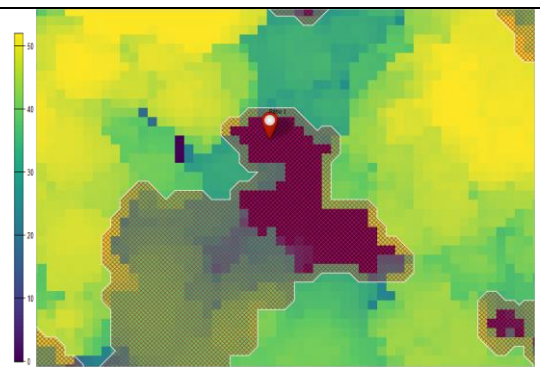
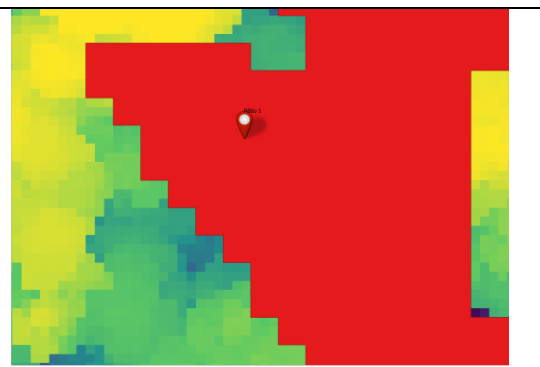

The detection using PlanetScope data (LSMM) identified disturbance areas based on the spectral response of exposed soil, dry vegetation, and other targets detected by the optical sensor. As a result, it highlights a smaller extent of impacted areas, totaling 100.61 hectares, due to limitations in detecting low-intensity changes that do not produce prominent visual responses in the imagery. The detection using LiDAR data (ΔCHM) reveals disturbance areas based on the reduction in canopy height ($\Delta\text{CHM} < -4$ m), thereby detecting a larger extent of impact, totaling 113.77 hectares, including areas where tree removal caused structural changes not perceptible in optical images. The illustrative photo, presented in Figure 7, was captured on 11/10/2024, in the area with the highest logging intensity, two years after the impact.

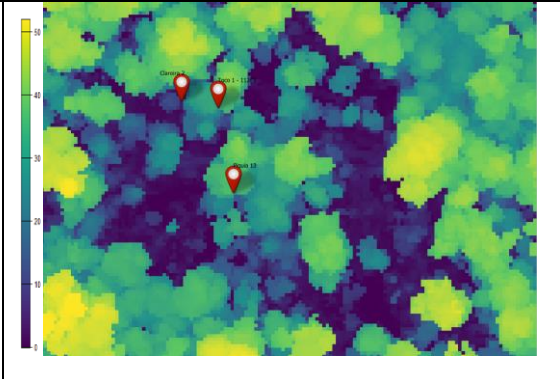


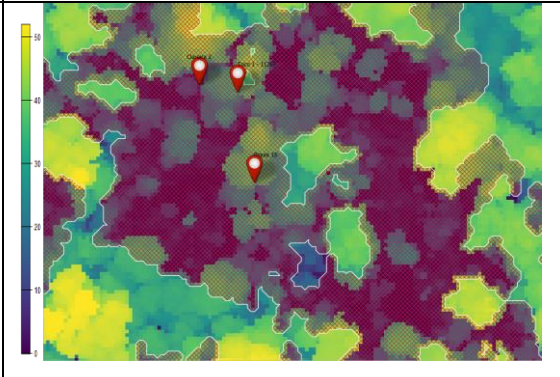

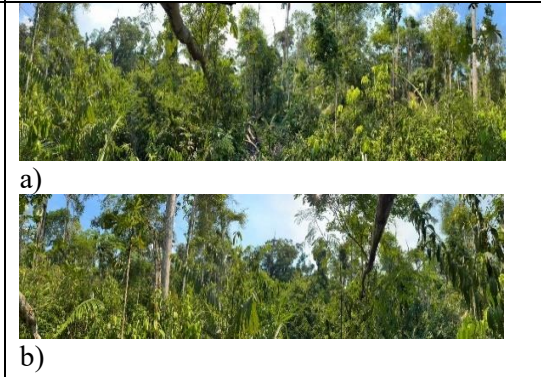
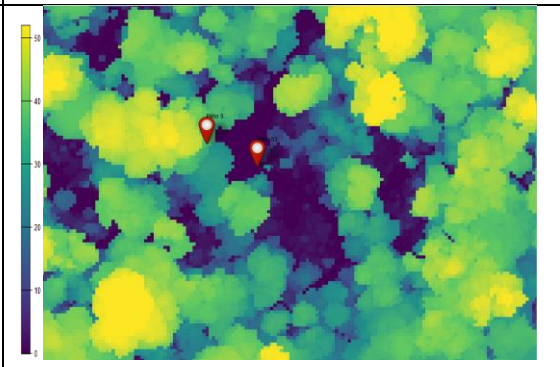
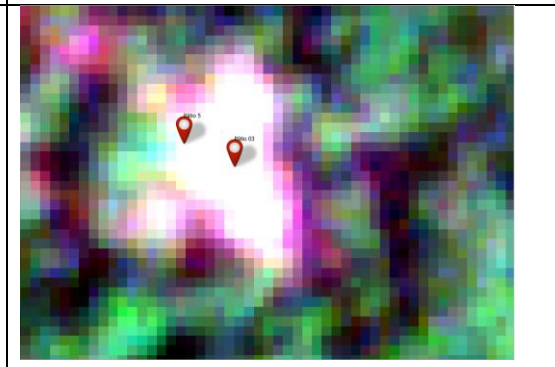

To evaluate the differences in mapping using the two data acquisition technologies in greater detail, Table 4 presents some areas that were validated and inspected in situ on 11/10/2024. During the field visits, it was observed that the most exploited areas exhibited the largest clearings, with exposed soil, forest residues, and canopy openings, confirming the accuracy of LiDAR mapping in detecting structural changes. In contrast, less exploited areas showed smaller clearings, which were often underestimated in the PlanetScope mapping due to the absence of three-dimensional data. The following photos highlight these differences, emphasizing the need to integrate both technologies for more comprehensive and effective analyses, which are essential for sustainable management.

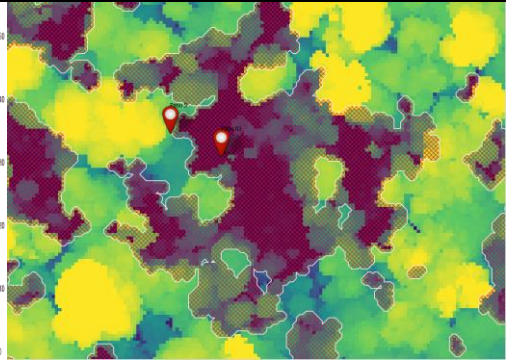
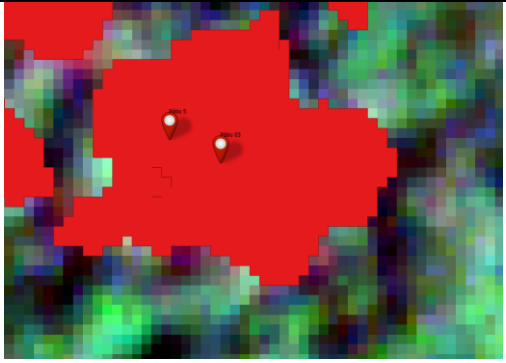

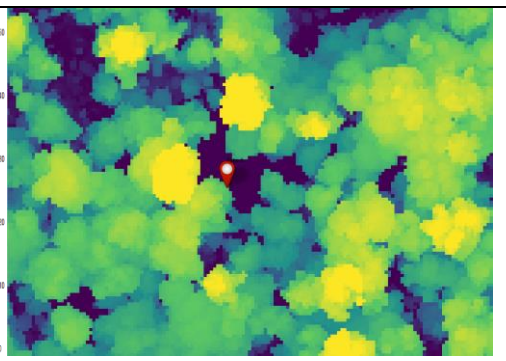
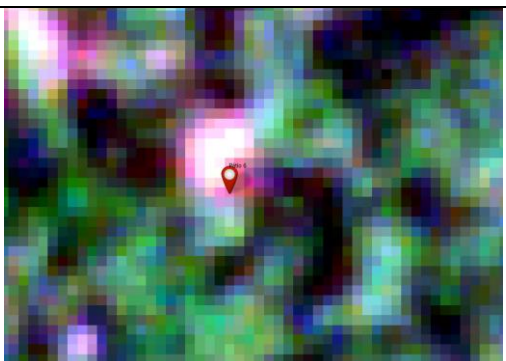

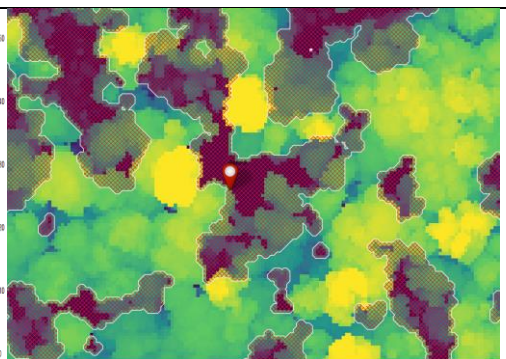
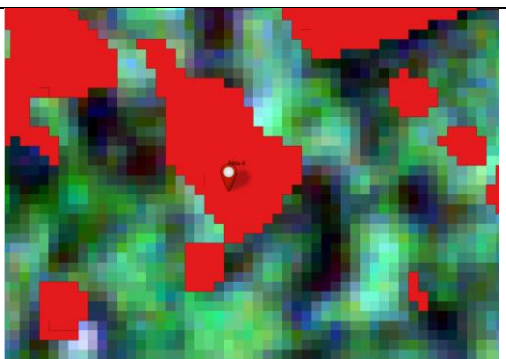

Table 4. Comparison between LiDAR and PlanetScope mappings and field photographs for visual inspection

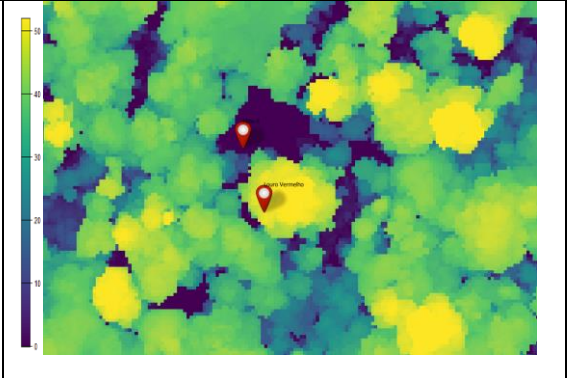


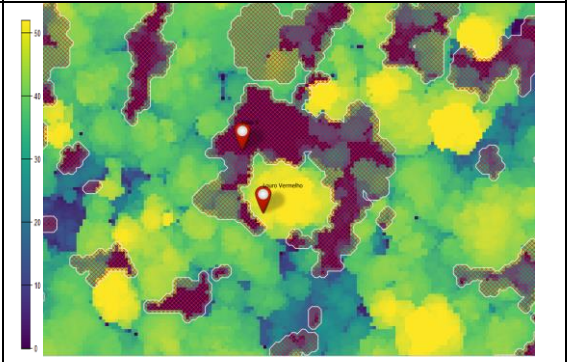
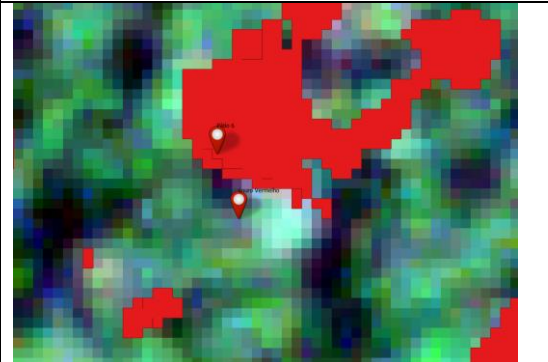

	LiDAR	PlanetScope	Photograph	Description
Image				<p><u>Stockyard 01</u></p> <p>Lat: -1.644761, Long: 56.233303</p> <p>Photo Orientation : 221176 SW</p>
Alert				<p><u>Stockyard 01</u></p> <p>Lat: -1.644831, Long: 56.233267</p> <p>Photo Orientation : 305176 NW</p>

<p>Image</p>				<p><u>Stockyard</u> <u>02</u></p> <p>Lat: - 1.646558, Long: 56.234553</p> <p>Photo Orientation: 128176 SE</p>
<p>Alert</p>				<p><u>Stockyard</u> <u>2</u></p> <p>Lat: - 1.646533, long: 56.234572</p> <p>Photo Orientation: 291176 WNW</p>
<p>Image</p>				<p><u>Stockyard</u> <u>03</u></p> <p>Lat: - 1.648361, Long: 56.236128</p> <p>Photo Orientation: 161176 SSE</p>

Alert				<p><u>Stockyard</u> <u>03</u></p> <p>Lat: - 1.648369, long: 56.236147</p> <p>Photo Orientation: 29176 NNE</p>
Image				<p><u>Stockyard</u> <u>04</u></p> <p>Lat: - 1.650739, Long: 56.220733</p> <p>Photo Orientation: 122176 ESE</p>
Alert				<p><u>Stockyard</u> <u>04</u></p> <p>Lat:- 1.650706, Long: 56.220781</p> <p>Photo Orientation: 120176 ESE</p>

<p>Image</p>				<p><u>Harvested Tree</u></p> <p>Lat: - 1.651272, Long: 56.220161</p> <p>Photo Orientation: 87176 E</p>
<p>Alert</p>				<p><u>Clearing</u></p> <p>Lat: - 1.651278, Long: 56.220161</p>
<p>Image</p>				<p><u>Stockyard 05</u></p> <p>Lat: - 1.652769, Long: 56.221225</p> <p>Photo Orientation: 14176 NNE</p>

Alert				<p><u>Stockyard 05</u></p> <p>Lat: - 1.652806, 56.221253</p> <p>Photo Orientation: 315176 NW</p>
Image				<p><u>Stockyard 06</u></p> <p>Lat: - 1.654106, Long: 56.223081</p> <p>Photo Orientation: 338176 NNW</p>
Alert				<p><u>Stockyard 06</u></p> <p>Lat: 1.654106, Long: 56.223078</p> <p>Photo Orientation: 96176 E</p>

<p style="writing-mode: vertical-rl; transform: rotate(180deg);">Image</p>				<p><u>Stockyard</u> <u>07</u></p> <p>Lat: -1.655678, Long: 56.223925</p> <p>Photo Orientation: 28176 NNE</p>
<p style="writing-mode: vertical-rl; transform: rotate(180deg);">Alert</p>				<p><u>Stockyard</u> <u>07 -</u></p> <p>Lat: 1.655678, Long: 56.223953</p> <p>Photo Orientation: 285176 WNW</p>

Source: OLIVEIRA, 2024.

3.5 Analysis in Relation to Harvested Trees

Table 5 presents the evaluation of mapping data based on FN (False Negatives), FP (False Positives), and TP (True Positives) metrics, considering the number of trees and the volume of wood (in m³) across different polygon size intervals (alert size ranges). It provides insights into the detection system's performance.

Table 5. Evaluation of FN, FP, and TP by alert polygon size, considering the number of trees and the corresponding volume of wood (m³) effectively harvested.

Intervals (ha)	FN		FP		TP	
	n° trees.	vol (m ³)	n° trees	vol (m ³)	n° trees	vol (m ³)
1- (0-0,2)	1069	5227,84	116	497,16	635	3247,55
2- (0,2-0,4)	156	877,57	10	47,95	155	807,64
3- (0,4-0,6)	16	120,35	4	12,90	67	323,66
4 - (0,6-0,8)	8	65,18	7	26,05	10	51,77
5 - (0,8-1)	21	118,02	3	23,95		
6 - (2-2,2)	-	-	-	-	34	188,52
Total	1270	6408,968	140	608,024	901	4619,139

Source: OLIVEIRA, 2024.

The mapping performance varies significantly depending on the area interval. The lower the extraction intensity, the harder it is to detect alerts. The mapping performs well in larger areas (above 0.4 ha), with low FN and FP rates, but fails to adequately detect selective logging in smaller areas, where the FN tree rate is very high (1069).

In small area intervals (0-0.2 ha), the number of trees classified as FN is significantly high, while the number of trees classified as TP is relatively low. This indicates that the model is underestimating forest extraction in small areas, likely due to the low extraction intensity, failing to correctly detect harvested trees. In intermediate intervals (0.2-0.6 ha), the balance between TP and FN improves, with a proportional increase in TP, suggesting enhanced detection capability. However, false negatives still persist, indicating that some exploited areas remain undetected. For larger areas (2-2.2 ha), the number of trees classified as FN drops to zero, demonstrating that the model can accurately identify all exploited areas. This highlights its higher effectiveness in larger-scale environments, where the distinction between exploited and non-exploited areas is clearer and easier to detect.

Figure 8 presents a section of the area with PlanetScope images (a), the Canopy Height Model (CHM) (b), and the results of the overlay between the mappings and the harvested trees (c). It is evident that in larger areas, the number of True Positive (TP) trees

(in green) is higher, demonstrating the mapping's good ability to detect large areas. However, a considerable number of False Negative (FN) trees (in yellow) is observed, reflecting areas where the mapping failed to detect accurately.

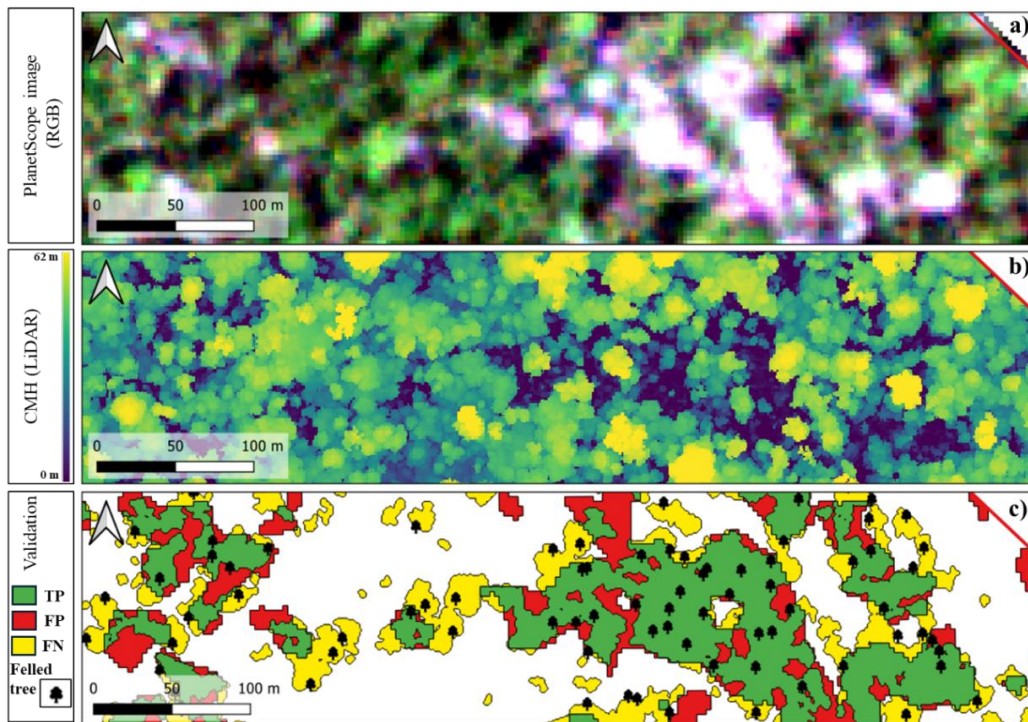


Figure 8. PlanetScope image (a), Canopy Height Model (CHM) extracted from LiDAR data (b), and the result of the overlay between trees and evaluation metrics (c).

Source: OLIVEIRA, 2024.

3.6 Regarding the Statistical Metrics

The performance results of the mapping for the different mapped area intervals are presented in Table 6, including statistical evaluation metrics such as Precision (P), Recall (R), F1-Score (F1), Overestimation Score (OS), Intersection over Union (IoU), and Root Mean Square Error (RMSE).

Table 6. Performance of forest disturbance mapping caused by selective logging across different area sizes (intervals in hectare).

Intervals (ha)	TP	FP	FN	Precision (P)	Recall (R)	F1-Score (F1)	OS	IoU	RMSE
1- (0-0,2)	46,47	32,88	77,91	0,59	0,37	0,46	0,26	0,30	45,03
2- (0,2-0,4)	9,51	2,86	9,23	0,77	0,51	0,61	0,15	0,44	6,38
3- (0,4-0,6)	4,04	1,36	0,98	0,75	0,80	0,77	0,27	0,63	0,38
4 - (0,6-0,8)	1,27	1,23	0,70	0,51	0,65	0,57	0,63	0,40	0,54
5 - (0,8-1)	0,00	0,98	1,00	0,00	0,00	0,00	0,98	0,00	0,02
6 - (2-2,2)	2,01	0,00	0,00	1,00	1,00	1,00	0,00	1,00	0,00
Total	63,30	39,31	89,82	0,62	0,41	0,50	0,20	0,33	50,51

Source: OLIVEIRA, 2024.

The main results of the PlanetScope classification, based on the reference mapping obtained with LiDAR data, reveal significant differences in the performance of clearing detection, highlighting the limitations and strengths of the mapping. Figure 9 presents a map emphasizing the results of the overlay between PlanetScope and LiDAR mappings, with a focus on different regions of the study area: a) True Positives (TP) - represent areas of agreement between the two mappings, indicating regions correctly identified by both PlanetScope and LiDAR; b) False Negatives (FN) - correspond to areas that should have been detected by the PlanetScope mapping but were only identified by LiDAR; c) False Positives (FP) - refer to areas detected by PlanetScope but not confirmed by the reference mapping conducted with LiDAR. Additionally, the felled trees, verified in the field, provide an extra layer of validation, enabling a cross-check of the accuracy of both mappings.

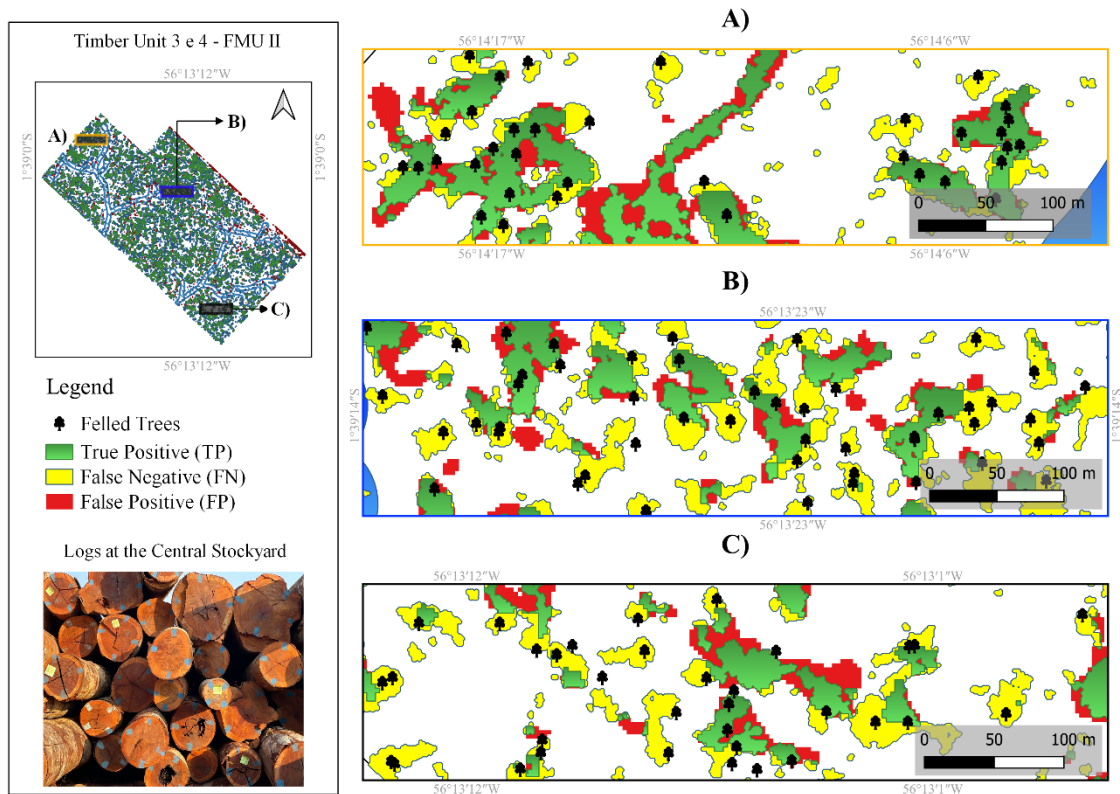


Figure 9. Results of accuracy and precision assessment of forest disturbance mapping caused by selective logging, highlighting different regions of the Saracá-Taquera National Forest

Source: OLIVEIRA, 2024.

The PlanetScope mapping exhibited variations in performance depending on the evaluated area interval, highlighting strengths and limitations in disturbance detection. In the smallest area interval (0–0.2 ha), there was the highest number of true positives (TP

= 46.47), but also a high rate of false positives (FP = 32.88) and false negatives (FN = 77.91). The moderate precision (P = 0.59) and low recall (R = 0.37) reflect PlanetScope's challenges in identifying small clearings, which are often obscured by remaining vegetation or mixed canopy cover. In contrast, LiDAR captured these areas more efficiently due to its ability to detect structural changes, demonstrating its superior sensitivity to small-scale disturbances.

In the intermediate intervals (0.2–0.6 ha), the performance of PlanetScope mapping improved considerably. For the 0.2–0.4 ha interval, precision was higher (P = 0.77), while in the 0.4–0.6 ha interval, recall reached R = 0.80, with an F1-Score of 0.77 and an IoU index of 0.63, demonstrating good agreement with the LiDAR data. This reflects greater reliability in detecting medium-sized clearings, where the spectral response is more pronounced, enhancing the accuracy of PlanetScope in these area ranges.

For larger intervals, such as 0.8–1 ha, the performance of PlanetScope mapping was inconsistent, with precision and recall both at zero, indicating a failure to detect these areas. This interval is associated with management infrastructure, such as stockyards and roads, where complex spectral patterns, like exposed soil and residual vegetation, may confuse the classification (LOCK & MATRICARDI, 2019). However, in the largest interval evaluated (1–2.2 ha), PlanetScope achieved perfect performance, with precision and recall of 1.00, demonstrating its effectiveness in areas with high impact intensity. The global analysis indicates that PlanetScope mapping underestimated the total clearings, with TP = 63.30 ha, while LiDAR identified 113.77 ha. Overall precision was moderate (P = 0.62), and the low recall (R = 0.41) highlights significant underdetection. The global F1-Score (0.50) and IoU index (0.33), combined with a relatively high RMSE (50.51), emphasize the differences between the methods, highlighting the limitations of PlanetScope mapping in smaller areas and the superiority of LiDAR in detecting smaller and low-intensity logging clearings.

3. Discussion

4.1 Regarding the Statistical Results of the Mappings

The results indicate that forest disturbance mapping using LiDAR data in the Saracá-Taquera National Forest demonstrated greater accuracy and reliability in detecting areas lower impacted by selective logging. While the mapping of impacted forests using PlanetScope data detected 100.91 hectares, LiDAR identified 113.77 hectares, an increase of 13.16 hectares. This difference reflects the superiority of LiDAR in capturing structural changes in vegetation, even in areas with lower impact intensity, which may not be detected by optical imagery (HUDAK & LEFSKY, 2002; LOCK & MATRICARDI, 2019; WINSTALEY *et al.*, 2024).

Nonetheless, it is important to highlight that the mapping of impacted forests using PlanetScope data successfully detected 63.3 hectares as true positives (TP). The 13.16-hectare difference between the two methods is directly associated with the high number of false positives (39.3 hectares) observed in the PlanetScope mapping, which partially compensated for the detection failures (false negatives) of impacted forests. This combination of errors and correct detections led to a total estimate close to the value identified by the reference LiDAR mapping, although the exact correspondence between mapped areas is limited to larger clearings (HUDAK & LEFSKY, 2002; SPARKS & SMITH, 2021).

Thus, the results highlight the importance of integrating optical and LiDAR data for forest management monitoring (HUDAK & LEFSKY, 2002; ASNER, 2009; LOCK & MATRICARDI, 2019, OLIVEIRA *et al.*, 2024). While PlanetScope mapping is useful for providing an initial overview and covering large areas, LiDAR enables validation and refinement, enhancing the detection of clearings at a local scale (OLIVEIRA *et al.*, 2024; XU *et al.*, 2021; SPARKS & SMITH, 2022).

Moreover, for smaller areas (<0.2 ha), implementing strategies to reduce false negatives is crucial, such as using algorithms that combine spectral and structural information (XU *et al.*, 2021). A promising alternative approach would involve categorizing the reliability of detected change alert polygons, assigning confidence levels from low to high based on clearing size. This technique would help reduce uncertainties and improve the robustness of the mapping process.

The limitations of mapping logged forests using PlanetScope data are directly related to the characteristics of the optical sensor, such as spectral dependency and the lack of

vertical information (ASNER, 2009; XU *et al.*, 2021; OLIVEIRA *et al.*, 2024). The detection of forest disturbances using PlanetScope imagery relies primarily on the reflectance of exposed soil, dry vegetation, and other targets. Thus, forests exhibiting low-intensity impacts or disturbances, as a result of the removal of a few trees during selective logging, may generate insufficient spectral responses to allow the identification of forest changes, leading to higher underestimation errors (elevated FN) (SHIMABUKURO & SMITH, 1991; HUDAK *et al.*, 2002; DALAGNOL *et al.*, 2023; OLIVEIRA *et al.*, 2024b). Furthermore, PlanetScope images were unable to capture changes in the three-dimensional structure of the forest, being less sensitive to alterations in canopy height compared to LiDAR data (EMMERT *et al.*, 2023).

On the other hand, LiDAR data allow for the direct measurement of changes in the forest canopy following selective logging, offering greater precision in detecting small and medium-sized clearings in the forest (WINSTALEY *et al.*, 2024; XU *et al.*, 2021; SPARKS & SMITH, 2022). LiDAR data enable the recording of height differences between pre- and post-logging periods, allowing for the identification of forest clearings regardless of spectral response (LOKS & MATRICARDI, 2019). This characteristic enhances the robustness of the method in capturing structural changes in selectively logged forests, especially in scenarios of low-impact or heterogeneous vegetation, as is the case in the Amazon rainforest (PETRI *et al.*, 2022).

The total number of trees correctly detected as harvested (1,270 trees; 6,408.97 m³) using PlanetScope images was significant but showed high underestimation in small clearings, compromising the reliability of the mapping. On the other hand, the performance of mapping harvested trees using LiDAR data was notably superior to that of PlanetScope data, as it enabled the detection of structural changes in the forest that were not captured by the PlanetScope-based mapping. The results highlight that LiDAR-based mapping is more suitable for monitoring low-impact selective logging, allowing for precise evaluation of impacted areas and providing critical information to improve the effectiveness of optical mapping (HUDAK & LEFSKY, 2002; LOCK & MATRICARDI, 2019; WINSTALEY *et al.*, 2024).

Although the mapping of selectively logged forests using PlanetScope images offers advantages in terms of cost and broad coverage, its results demonstrate limitations in detecting small clearings, especially in low-impact scenarios (DALAGNOL *et al.*, 2023; OLIVEIRA *et al.*, 2024). The mapping of altered forests using LiDAR data proved to be essential as a validation technology, showing greater sensitivity and accuracy across

all evaluated intervals. Integrating the two methods, combined with adjustments to classification algorithms, can significantly enhance the monitoring of forest disturbances and SFMP, contributing to more sustainable management of selectively logged forests (HUDAK & LEFSKY, 2002; ASNER *et al.*, 2009; LOKC & MATRICARDI, 2019). However, further evaluation is needed to assess, in detail, the cost and time required for acquiring these two types of remote sensing data.

Oliveira *et al.*, (2024b) evaluated logging intensity in the same area as the present study and highlighted the concentration of logging in areas with higher volumetric stocks of commercial species. In the present study, we observed the same pattern, where areas with higher logging intensity exhibited the largest clearings, demonstrating that the structural impact of selective tree removal is directly related to the volume or number of trees extracted from the forest. These areas were associated with regions of higher elevation and farther from water bodies, while areas of lower elevation showed lower stocks of commercial timber. Thus, adaptive management strategies that integrate spatial heterogeneity and consider structural impacts, such as the formation of clearings, are essential to balance economic exploitation with the conservation of forest resources.

4.2 Regarding the Current Monitoring Systems in the Amazon

The results obtained from forest disturbance mapping using LiDAR data and PlanetScope images highlight significant differences between the two methods in terms of both accuracy and sensitivity. These characteristics allow comparisons to be made with widely used monitoring systems in the Amazon, such as DETER/INPE and SAD/IMAZON, which use optical approaches to detect real-time changes in forest cover for monitoring selective logging (DINIZ *et al.*, 2015; SOUZA JR. *et al.*, 2005).

The DETER (Real-Time Deforestation Detection System), developed by the National Institute for Space Research (INPE) in 2004, is based on MODIS and WFI imagery and aims to monitor deforestation, selective logging, and other large-scale changes in the Brazilian Amazon (DINIZ *et al.*, 2015). Since 2015, DETER has utilized WFI (CBERS-4) and AWiFS (IRS) sensors with better resolution (56–64 m), enabling the detection of changes greater than 3 hectares. Detection relies on visual interpretation and the Linear Spectral Mixture Model (LSMM), mapping classes such as deforestation, degradation, and selective logging, among others (DINIZ *et al.*, 2015). While polygons are made publicly available starting at 6.25 hectares, the system's limited spatial resolution (~250

m for MODIS and 56–64 m for AWiFS) makes it unsuitable for detailed mapping of small disturbances, such as clearings resulting from selective logging.

Comparing with the mapping results using PlanetScope images (~3 m resolution) and LiDAR data highlights PlanetScope's superior ability to detect smaller clearings, especially in intervals below 3 hectares. Furthermore, LiDAR excels in detecting even more subtle forest disturbances, such as variations in canopy height in low-impact areas (XU *et al.*, 2023), systems like DETER cannot capture due to the lack of structural information and low spatial resolution (DINIZ *et al.*, 2015).

The Deforestation Alert System (SAD), developed by Imazon in 2008, monitors deforestation and forest degradation in the Legal Amazon on a monthly basis, using imagery from Landsat 7 and 8, Sentinel 1 and 2, and radar from Sentinel 1 for cloud-covered areas (10–30 m resolution) (Sousa Jr *et al.*, 2005). The system detects degradation caused by fire or logging and deforestation through clear-cutting in areas of at least 1 hectare (SOUSA JR *et al.*, 2005). Although SAD offers greater spatial resolution (~10–30 m) compared to DETER, it still struggles to detect selective logging and clearings smaller than 1 hectare (SOUSA JR *et al.*, 2005, MATRICARDI *et al.*, 2013). In contrast, mapping results using PlanetScope images show high performance in detecting clearings smaller than 1 hectare (0.2–0.6 ha), thanks to its higher spatial resolution and the application of the Linear Spectral Mixture Model (LSMM) (Oliveira *et al.*, 2024). However, PlanetScope mapping has limitations in detecting even smaller clearings (<0.2 ha), while LiDAR surpasses these barriers, as demonstrated in this study.

Figure 10 presents a subset of forest cover change detection alerts generated by the systems: (A) DETER/INPE, (B) SAD/IMAZON, and (C) Brazilian Forest Service (SFB)/SCCON, intersecting the Timber Unit Production (TU) within the Forest Management Unit (FMU) in the Saracá-Taquera National Forest (DINIZ *et al.*, 2015; SOUSA JR. *et al.*, 2005; SFB, 2024). Systems A and B are used in command-and-control policies, operating throughout the Amazon with low to medium spatial resolution imagery. System C monitors and maps forest disturbances in specific areas within sustainable forest management (SFM) boundaries, utilizing high spatial and temporal resolution *PlanetScope* images managed by the Brazilian Forest Service (SFB) (SFB, 2024). Visually, System C demonstrates greater consistency and accuracy in identifying selectively logged areas, resulting in classifications that align more closely with observed phenomena.

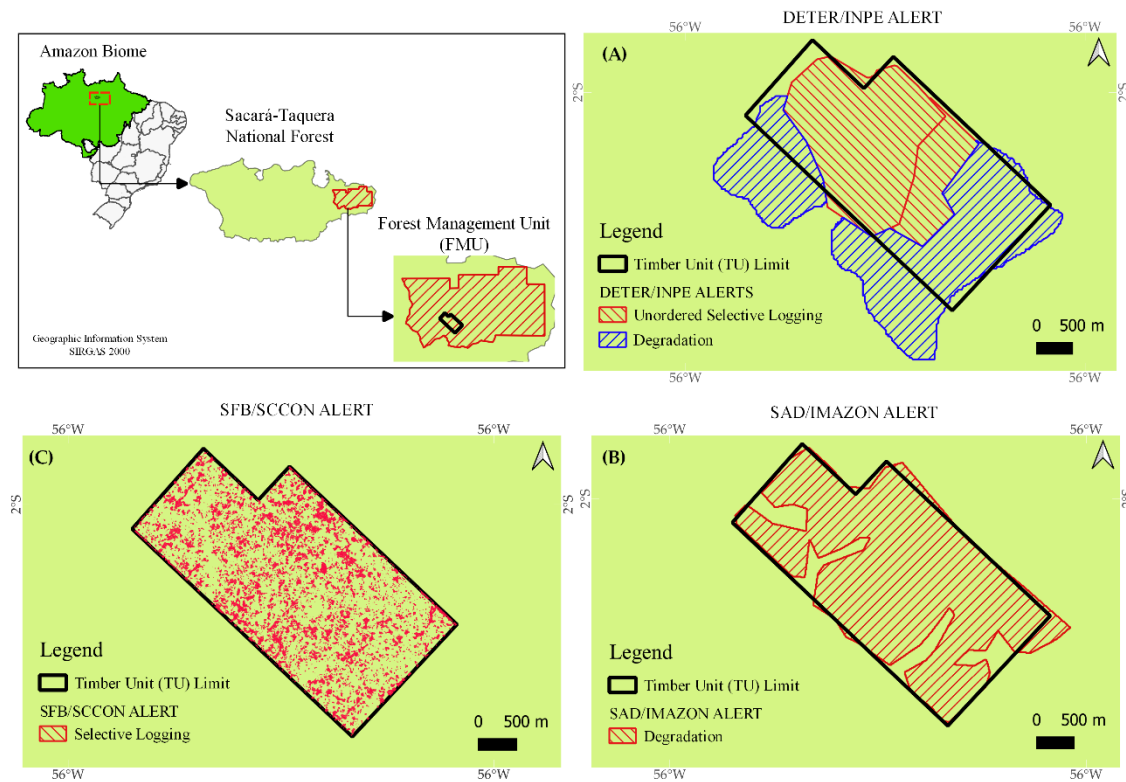


Figure 10. Forest degradation alerts from the systems: (A) DETER/INPE (Real-Time Deforestation Detection System, developed by the National Institute for Space Research—INPE); (B) SAD/IMAZON (Deforestation Alert System, developed by the Amazon Institute of People and the Environment—IMAZON); and Selective Logging Alert (C) Brazilian Forest Service (SFB)/SCCON (a system of the Brazilian Forest Service, developed by SCCON Geospatial). These systems intersect the Timber Unit Production (TU) in the Forest Management Unit (FMU) within the Saracá-Taquera National Forest, in the Brazilian Amazon.

Source: OLIVEIRA, 2024.

Systems such as DETER (INPE) and SAD (Imazon), which use low- and medium-resolution imagery, provide large-scale alerts but may fail to adequately capture low-intensity selective logging within Forest Management Units (UMFs) (DINIZ *et al.*, 2015; SOUSA JR. *et al.*, 2005; OLIVEIRA *et al.*, 2024). On the other hand, systems such as SCCON, operated by the Brazilian Forest Service (SFB), which use high-resolution PlanetScope images to exclusively monitor concession-managed areas, demonstrate greater accuracy in detecting disturbances in managed areas, enabling classifications that are more consistent with observed phenomena (OLIVEIRA *et al.*, 2024b). Table 7 presents the main differences between the systems and sensors used for monitoring forest cover in the Amazon.

Tabela 7. Principais diferenças entre as sistemas e sensores utilizados para o monitoramento da cobertura florestal na Amazônia

System	Satellite/ Sensor	Spatial resolution	Main focus	Limitation	LiDAR and PlanetScope Comparison
DETER-B (INPE)	MODIS/WFI	~250 m (56-64m)	Deforestation, degradation, and selective logging across the entire Legal Amazon	Low spatial resolution; does not detect small clearings < 3 ha	Lower sensitivity; useful for monitoring large areas
SAD (IMAZON)	Landsat 7 e 8/Sentinel-2	~10-30 m	Deforestation, degradation, and selective logging across the entire Legal Amazon	Does not detect selective logging and clearings < 1 ha	PlanetScope detects clearings smaller than 1 hectare; LiDAR outperforms both
SFB (SCCON Geospatial)	PlanetScope	~3 m	Selective logging (small and medium clearings < 1 ha)	Low sensitivity in small clearings or low-impact logging	Complements LiDAR; better performance for clearings between 0.2–2 ha
SFB – Selective logging	LiDAR 3D data (altimetry)	~1 m	Selective logging (structural changes in vegetation)	High cost; lower temporal coverage	High precision; ideal for validating other methods

Source: OLIVEIRA, 2024.

Although DETER and SAD systems are widely used due to their broad coverage and update frequency, the results of this study demonstrate that integrating LiDAR and PlanetScope data offers greater accuracy in detecting clearings and selective logging. LiDAR, in particular, stands out for its sensitivity to vertical and subtle changes in the forest canopy, while PlanetScope can be effectively used for initial monitoring or in areas with medium to high impact intensity.

4.3 Implications of Generic Classifications for SFM Sustainability

The lack of differentiation between SFM practices and other types of degradation can either underestimate or overestimate forest impacts, compromising the credibility of conservation and management initiatives in the Amazon (VELASCO *et al.*, 2022; OLIVEIRA *et al.*, 2024b). This may hinder funding opportunities, discourage sustainable practices, and result in inadequate public policies, negatively affecting resource allocation and forest protection strategies (PINAGÉ *et al.*, 2023). Thus, accurate classification of different levels of disturbance is essential for ensuring environmental, economic, and social sustainability in forest management in the Amazon (VELASCO *et al.*, 2022; PINAGÉ *et al.*, 2023).

The intensity and types of forest disturbances vary across degradation processes, including partial loss of living biomass, forest quality, and changes in biodiversity (SASAKI *et al.*, 2009; THOMPSON *et al.*, 2013; SIMULA, 2009). In the case of legal selective logging under Reduced Impact Logging (RIL) management, forest disturbances are considered low-intensity and are limited to the removal of high-value commercial trees, with canopy openings, logging trails, and collateral damage to other trees and understory vegetation (PEREIRA-JÚNIOR *et al.*, 2022; OLIVEIRA *et al.*, 2024). In contrast, processes such as wildfires, illegal selective logging, or high-intensity logging generate significantly greater impacts, requiring more specific monitoring systems to distinguish between different types of degradation (MATRICARDI *et al.*, 2020).

SFM faces a series of legal impacts with generic classifications that can compromise its effectiveness and implementation. These challenges are related to regulation, enforcement, public perception, as well as economic and social aspects (VELASCO *et al.*, 2022; PINAGÉ *et al.*, 2023; KREMEN *et al.*, 2000; SAGOBAL *et al.*, 2013; OLIVEIRA *et al.*, 2024b).

The lack of differentiation in degradation classifications made by monitoring systems often fails to adequately distinguish between SFM and other types of forest degradation, such as illegal logging, intense fires, edge effects, among others (LAPOLA *et al.*, 2020; MATRICARDI *et al.*, 2020). This generalization can lead to underestimation or overestimation of mapped areas, resulting in inconsistent data that undermine the credibility of sustainable management and conservation projects (KREMEN *et al.*, 2000).

As a consequence of classifying SFM areas as forest degradation, there are inevitable damages to the credibility and investments in the timber sector in the Amazon (FERREIRA *et al.*, 2015). The lack of precision in differentiating between legal and illegal practices can discourage investments in sustainable practices, hindering the ability to secure funding for management initiatives (VELASCO *et al.*, 2022). Moreover, legal forest management projects may be penalized or discredited due to confusion with illegal practices, generating legal uncertainty and affecting their sustainability (FERREIRA *et al.*, 2015). Another key consideration is that policies based on inaccurate or incomplete data may deprioritize or discredit sustainable management, focusing efforts on punitive measures against deforestation without providing incentives for legal practices (VELASCO *et al.*, 2022; PINAGÉ *et al.*, 2023).

From a public and political perception standpoint, the generalization of "degradation" without considering sustainable management practices can lead to the

stigmatization of legal and certified activities (FERREIRA *et al.*, 2015). Sustainable management may be perceived as less effective in combating deforestation or even associated with it due to the lack of public campaigns explaining its benefits and differences compared to predatory logging and other types of degradation (PEREIRA-JUNIOR *et al.*, 2002; OLIVEIRA *et al.*, 2024; OLIVEIRA *et al.*, 2024b). Therefore, it is essential to strengthen regulations, encourage sustainable practices, and improve monitoring systems to promote forest management as an effective tool for conservation and economic development.

4. Conclusion

The combination of LiDAR data with PlanetScope imagery significantly enhances accuracy in detecting forest disturbances caused by selective logging activities in the Amazon, particularly in areas under sustainable forest management. While optical systems such as PlanetScope images are efficient in identifying medium and large clearings, LiDAR data stand out by improving accuracy and precision in detecting subtle and structural changes in the forest, offering a complementary and robust approach. Integrating these technologies is essential for differentiating types of forest disturbances caused by selective logging activities, such as low-impact selective logging and more intense disturbances caused by illegal activities, ensuring greater data reliability. The implementation of standardized metrics for classifying disturbances can strengthen monitoring efforts and support the development of more effective public policies for conservation and sustainable management in the Amazon.

The high cost of LiDAR data acquisition remains a significant barrier to its widespread adoption in forest monitoring and management. LiDAR surveys require specialized equipment, skilled operators, and often involve aerial campaigns that add to operational expenses. Furthermore, processing the vast amounts of three-dimensional data collected requires advanced software and computational resources, further increasing costs. While the precision and depth of information provided by LiDAR are unmatched, its expense can limit its accessibility, particularly for smaller-scale projects or regions with limited funding. To address these challenges, investments in cost-reduction technologies, such as unmanned aerial vehicles (UAVs) equipped with LiDAR sensors and collaborative funding mechanisms, are essential to make this powerful tool more accessible for conservation and sustainable management initiatives.

As a future direction, it is recommended to develop more advanced algorithms using artificial intelligence to more accurately distinguish between legal and illegal logging practices, as well as areas impacted by extreme climate changes, which are increasingly frequent in the Amazon region. Additionally, it is essential to expand the use of high temporal, spectral, and spatial resolution technologies, such as nanosatellites and LiDAR, to other areas of interest in the Amazon, including Conservation Units and Indigenous Lands, with the goal of curbing illicit activities.

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CHAPTER V - Conclusions and Future Perspectives

1.1 Contextualization of Study Results in SFM and Climate Change

The findings of this study hold significant implications for the implementation of Sustainable Forest Management (SFM) and efforts to mitigate global climate change. By enhancing the detection and monitoring of forest disturbances, particularly those caused by selective logging, this research supports more precise and timely assessments of forest dynamics, a critical factor in ensuring the long-term sustainability of managed forests.

In the context of SFM, the integration of high-resolution remote sensing technologies, such as LiDAR and PlanetScope imagery, contributes to improved transparency and accountability in forest management practices. This advancement strengthens compliance monitoring within forest concessions, helping to detect unauthorized logging activities and ensuring adherence to sustainable harvesting practices. Ultimately, this promotes the conservation of biodiversity, the maintenance of ecosystem services, and the economic viability of forest-based industries.

From a global climate change perspective, the accurate detection of forest disturbances enhances the ability to quantify carbon stock changes and carbon sequestration potential more precisely. Selective logging, when poorly monitored, can lead to significant carbon emissions due to canopy openings and forest degradation. By providing tools to monitor the spatial and temporal impacts of logging activities, the study supports efforts to reduce emissions from deforestation and forest degradation (REDD+). This contributes to achieving national and international climate goals, such as those outlined in the Paris Agreement.

Moreover, the study's findings underscore the importance of scalable monitoring systems that can be adapted to large forested areas, particularly in regions vulnerable to both legal and illegal forest exploitation. These systems can serve as a model for improving the sustainability of forest management plans globally and inform policy frameworks aimed at balancing resource use with conservation priorities.

In summary, the methodologies developed in this study provide essential contributions to the advancement of sustainable forestry and the fight against climate change. By fostering more effective forest monitoring systems, this research not only strengthens forest governance but also enhances the capacity of tropical forests to function as a key component of the global climate regulation system.

1.2 Revisiting Research Questions and Objectives: General Conclusions

This study was guided by a set of research questions and objectives aimed at enhancing the detection and monitoring of forest disturbances caused by selective logging in the Amazon through innovative remote sensing technologies. The general conclusions drawn from the research are as follows:

Trends, Gaps, and Advancements in Remote Sensing Applications: the scientometric analysis and systematic review revealed key trends and gaps in the use of remote sensing for forest disturbance monitoring. While advancements have been made in integrating data from various sources, such as satellite imagery and LiDAR, challenges remain in the adoption of high-resolution and frequent temporal data to detect subtle changes associated with selective logging. This highlights the need for continued innovation and validation of monitoring methodologies in the context of Sustainable Forest Management (SFM).

Impacts of Selective Logging on Forest Structure and Heterogeneity: the integrated analysis of forest inventory data and high-resolution remote sensing imagery demonstrated that selective logging significantly affects forest structure and increases spatial heterogeneity over space and time. The study confirmed that combining ground-based measurements with high-resolution satellite data improves the assessment of logging impacts, providing a more comprehensive understanding of changes at both the stand and landscape levels. This contributes to more effective monitoring within federal concession areas, ensuring compliance with sustainable harvesting practices.

Development and Validation of an Integrated Methodology: the proposed methodology, which integrates LiDAR and PlanetScope data, proved to be an effective tool for detecting forest disturbances with greater accuracy and precision. The validation process demonstrated that this approach surpasses traditional methods by capturing both horizontal and vertical forest structure changes. This integrated system supports the implementation of continuous monitoring, which is essential for promoting transparency and accountability in forest resource management.

Broader Implications for SFM and Climate Change Mitigation: the study's results contribute to strengthening SFM frameworks by offering a replicable and scalable system for tracking selective logging impacts. Additionally, the findings support climate change mitigation efforts by improving the estimation of carbon stock changes and identifying

degradation hotspots that could lead to carbon losses if left unmanaged. This underscores the importance of high-resolution monitoring for achieving global climate targets, particularly in tropical forests that serve as critical carbon sinks.

In summary, the research objectives have been met by addressing the research questions through a robust interdisciplinary approach. The integration of scientometric insights, field-based data, and cutting-edge remote sensing technologies provides a foundation for future advancements in sustainable forest monitoring. The methodologies developed in this study can serve as a model for improving environmental governance and conservation strategies in the Amazon and beyond.

1.3 Revisiting the hypotheses

This study proposed several hypotheses to guide the investigation of forest disturbances caused by selective logging in the Amazon. Upon revisiting these hypotheses in light of the results obtained, the following conclusions are drawn:

Hypotheses Related to Trends, Gaps, and Advancements in Remote Sensing Applications:

Hypothesis H1.1: The scientific literature on remote sensing technologies for forest disturbance monitoring demonstrates significant advancements but reveals critical gaps in spatial and temporal resolution for addressing selective logging impacts.

Conclusion: This hypothesis was supported. The scientometric analysis confirmed that, despite technological progress, limitations in temporal frequency and spatial precision remain, particularly in the monitoring of forest heterogeneity and smaller canopy disturbances.

Hypothesis H1.2: A scientometric approach and systematic review will identify underexplored areas, particularly regarding the integration of advanced sensor technologies like LiDAR and high-resolution satellite imagery.

Conclusion: This hypothesis was also supported, as the review highlighted the limited number of studies combining high-resolution satellite imagery with LiDAR for selective logging detection, signaling an opportunity for further methodological integration.

Hypotheses Related to the Impacts intensity of Selective Logging on Forest Structure and Heterogeneity:

Hypothesis H2.1: Selective logging causes detectable changes in forest structure and heterogeneity over time, varying spatially across the federal concession area.

Conclusion: This hypothesis was confirmed. The analysis demonstrated that selective logging significantly alters the forest canopy and structural heterogeneity, with these impacts showing spatial variability across different logging units.

Hypothesis H2.2: The integration of forest inventory data and high resolution satellite imagery provides a more comprehensive understanding of spatial and temporal impacts compared to using either dataset independently.

Conclusion: Supported. The combined use of forest inventory data and satellite imagery improved the accuracy of assessments and revealed detailed temporal dynamics of selective logging impacts that would not have been captured by a single dataset.

Hypotheses Related to the Development of an Integrated Methodology:

Hypothesis H3.1: A combined methodology using LiDAR and PlanetScope data improves the detection and monitoring of forest disturbances compared to conventional methods.

Conclusion: This hypothesis was strongly supported. The integrated approach detected disturbances with greater spatial detail and precision, especially in identifying subtle canopy openings and patterns associated with selective logging.

Hypothesis H3.2: The validation process will demonstrate that this integrated approach achieves higher accuracy and reliability for monitoring forest disturbances within sustainable forest management plans.

Conclusion: Confirmed. The validation showed that the methodology achieved higher classification accuracy and reliability compared to conventional satellite monitoring, demonstrating its suitability for continuous monitoring of selective logging within federal concession areas.

The revisiting of these hypotheses demonstrates that the proposed methodologies effectively address key challenges in forest disturbance monitoring. By confirming these hypotheses, this study provides a validated framework that enhances the precision and reliability of forest management monitoring systems, contributing to sustainable resource use and climate change mitigation efforts.

1.4 Opportunities for future studies

Based on the findings and discussions presented in this thesis, several key opportunities for future research emerge, particularly in the context of enhancing sustainable forest management and addressing global conservation challenges:

Scaling Methodologies Across Diverse Forest Landscapes: the integration of LiDAR and PlanetScope data proved effective for detecting both large-scale clearings and small-scale disturbances. Future research could focus on adapting and scaling this methodological framework to other forest regions, such as secondary forests, mixed-use landscapes, and conservation areas. This would enable comparative studies across different biomes, providing a broader understanding of forest dynamics in various ecological contexts.

Incorporating Cost-Effective Remote Sensing Solutions: while LiDAR data has demonstrated its value for high-resolution forest monitoring, its high cost and limited accessibility remain barriers to widespread adoption. Future studies could explore the integration of lower-cost alternatives, such as drone-based LiDAR or open-access satellite platforms (e.g., GEDI), to enhance cost-effectiveness while maintaining accuracy. Additionally, exploring advancements in UAV (unmanned aerial vehicle) technology could provide new opportunities for localized and scalable forest assessments.

Expanding Data Integration and Automation: the combination of forest inventory, satellite imagery, and LiDAR data was pivotal in improving the understanding of selective logging impacts. Further research could incorporate additional datasets, such as climatic, hydrological, and socio-economic data, to explore the broader impacts of logging on ecosystem functions and forest-dependent communities. Additionally, integrating machine learning algorithms for automated detection of forest changes could improve the efficiency of monitoring systems, particularly in large and remote areas.

Long-Term Monitoring and Time-Series Analysis: Understanding the cumulative effects of selective logging requires long-term data collection and analysis. Future research could focus on creating time-series datasets to assess recovery rates, regrowth patterns, and long-term ecosystem changes following selective logging events. This would help refine adaptive management strategies that consider temporal variability and resilience dynamics.

Interdisciplinary Research and Policy Integration: the findings of this study highlight the importance of bridging technological advancements with forest governance and policy frameworks. Future research could involve collaborations between remote sensing experts, forest ecologists, policymakers, and local communities to develop decision-support tools that translate remote sensing data into actionable policies. This could also include studies on how to improve community-based forest monitoring programs by training local stakeholders in the use of accessible remote sensing tools.

Addressing Technological Accessibility and Equity: Given the challenges related to the accessibility of high-resolution data, future studies could focus on developing open-source platforms that democratize access to advanced data processing tools. These platforms could include cloud-based processing systems that enable real-time analysis of forest changes, particularly for institutions in the Global South with limited resources.

Monitoring Beyond Selective Logging: while this research focuses on forest disturbances caused by selective logging, future investigations could expand to include other disturbances, such as illegal mining, fires, and infrastructure expansion. These studies could benefit from multi-sensor approaches to capture a more comprehensive view of anthropogenic impacts on forest ecosystems.

Climate Resilience and Carbon Accounting: the integration of high-resolution forest monitoring into climate models remains an underexplored area. Future studies could focus on quantifying carbon sequestration and emissions dynamics following selective logging, which would enhance the accuracy of carbon stock assessments and inform global climate mitigation strategies, such as REDD+ initiatives.

The methodologies and findings of this thesis pave the way for more sophisticated, cost-effective, and inclusive approaches to forest monitoring and management. By addressing the outlined research opportunities, future studies can strengthen the alignment between conservation science, technological innovation, and forest policy implementation. Ultimately, these efforts will contribute to more sustainable forest governance, ensuring the Amazon's ecological and socio-economic resilience in the face of global environmental changes.