Algorithm Theoretical Basis Document (ATBD)

MapBiomas Degradation Module

Version 2

Coordination

Ane Alencar

Tasso Azevedo

Technical coordinator

Dhemerson Conciani

Team

Amazon: Bruno Gama Ferreira, Camila Damasceno, Luis Oliveira Jr

Caatinga: Deorgia Souza, Diego Pereira Costa, Soltan Galano, Washington de Jesus da Franca-Rocha

Cerrado: Ana Gabriela de Souza, Bárbara Costa, Felipe Martenexen, Julia Shimbo, Vera Arruda, Wallace Silva

Atlantic Forest: Marcos Rosa, Natalia Crusco

Pantanal: Eduardo Rosa, Mariana Dias

Pampa: Eduardo Vélez-Martín

Technological support: Diego Pereira Costa, João Siqueira, Mauricio Vancine, Sergio Oliveira

May, 2026

Table of Contents

1. Introduction	**2**
1.1. Overview	**2**
1.2. Project Context	**2**
1.3. Degradation scope and definition	**2**
1.4. How we are organized	**3**
2. Methodological description	**4**
2.1. Definition of native vegetation for each biome	**4**
2.2. Patch ID	**4**
2.3. Patch Size	**6**
2.4. Edge Area	**7**
2.5. Edge Age	**7**
2.6. Patch Isolation	**8**
2.7. Patch Morphology	**10**
2.8.2. Fire Frequency	**11**
2.8.3 Time Since Last Fire	**11**
2.9. Secondary Vegetation Age	**12**
2.10 Forest Canopy Disturbance	**13**
2.11 Selective Logging	**13**
3. Accessing the data	**14**
4. References	**14**

1. Introduction

1.1. Overview

Since 2015, the MapBiomas network has produced annual land-use and land-cover (LULC) maps for Brazil. This extensive data collection, using Landsat satellite imagery with a spatial resolution of 30 meters, provides a comprehensive understanding of the country's land-use patterns (Souza et al., 2020). Every year, MapBiomas releases a new collection of these annual maps, with new classes, improvements across the entire time series, and the addition of the last year. The latest LULC data collection (Collection 10.1) covers the period from 1985 to 2024 (ATBD Collection 10). In this context, Brazil's network provides detailed information on the history of native vegetation and various anthropogenic uses, including planted pastures, agriculture, and urban areas. In addition to the land cover data, MapBiomas has expanded to include products for other themes, such as the historical mapping of fire scars, water surfaces, soil properties, secondary vegetation, and deforestation alerts, with degradation added as one of these themes since 2024, the publication year of the first beta version of the degradation module.

This document describes the methods used for the second beta version of the degradation module, available in the MapBiomas Brazil platform (https://plataforma.brasil.mapbiomas.org). This module enables analysis of native vegetation degradation across all Brazilian biomes and across different territories (country, state, municipality, biome, protected areas), considering different degradation drivers from 1986 to 2023. In the first version of the degradation module, we included the size and isolation of native vegetation patches, their edge areas, fire frequency and time since the last fire, and the age of secondary vegetation as degradation drivers. In this second version, we added the edge ages, landscape morphology (including perforations), and the identity (ID) of each native vegetation patch (which enables computation of fragment number and other landscape metrics). Furthermore, we included forest canopy disturbance and selective logging specifically for the Legal Amazon. These two Amazon-specific products cover 1988 to 2024 and are restricted to Forest formation (class 3) and Floodplain Forest (class 6).

Part of the degradation drivers were computed using the annual maps of LULC provided by the MapBiomas Brazil Collection 10.1 (edge area and age, patch size, habitat isolation, landscape morphology, secondary vegetation age, and patch ID), and the other part was produced by using the annual fire-scar maps provided by the MapBiomas Fire Collection 4.1 (fire frequency and time since the last fire). In addition, forest canopy disturbance and selective logging were derived from Landsat 32-day mosaics in Google Earth Engine (GEE). Canopy disturbance is detected from NDFI changes relative to the preceding three years, and selective logging is subsequently extracted from the canopy-disturbance product using spatial-pattern and reference-data filters (Souza Jr et al., 2005)

1.2. Project context

Despite the LULC and other themes provided by MapBiomas that map targets quantitatively, the first version of the degradation module was created to address the lack of information on the integrity and quality of native vegetation, which can be affected by disturbances and perturbations in various ways. These disturbances may initiate degradation, leading to the loss of the ecosystem's functions, properties, and services, including deleterious changes in vegetation structure, diversity, carbon storage, productivity, and climate regulation (Gatti et al. 2021; Lapola et al., 2023). These direct impacts on native vegetation and the lack of information underscore the urgency of implementing a framework that enables national-scale degradation monitoring to support public policies, research, and evidence-based decision-making.

1.3. Degradation scope and definition

Degradation is defined as a process triggered by disturbances that leads to deleterious changes in the ecosystem properties, functions, or services (Lapola et al., 2023), potentially affecting both natural and anthropogenic areas. According to MapBiomas, 65% of Brazil's territory is covered by native vegetation (forests, savannas, grasslands, and wetlands), while anthropogenic activities cover 35% of the total area. In the first and second versions of the degradation module, we focused on mapping the degradation drivers affecting the native vegetation, while degradation in anthropogenic areas is being addressed by other MapBiomas Initiatives, such as the Pasture Vigour Module. Detailed information on the native vegetation classes included in the scope of the degradation module is provided in Table 1 (see section 2.1).

1.4. How we are organized

MapBiomas is a multi-institutional initiative of the Climate Observatory, co-created in 2015 by a set of NGOs, universities, and technology companies in Brazil that collaborates to use historical remote sensing data, cloud computing, and experts' knowledge to map transformations in the national territory over the past four decades. Currently, the MapBiomas Degradation Working Group comprises 13 different institutions, with the Instituto de Pesquisa Ambiental da Amazônia (IPAM) facilitating the technical coordination. Below is a list of institutions and their respective area of expertise:

- **Amazon** – Instituto do Homem e Meio Ambiente da Amazônia (IMAZON)
- **Atlantic Forest** – SOS Mata Atlântica and ArcPlan
- **Caatinga** – Geodatin and Universidade Estadual de Feira de Santana (UEFS)
- **Cerrado** – Instituto de Pesquisa Ambiental da Amazônia (IPAM)
- **Pampa** – GeoKarten and Universidade Federal do Rio Grande do Sul (UFRGS)
- **Pantanal** – SOS Pantanal and ArcPlan
- **Technological support** – e-Code, EcoStage, Geodatin, and Universidade Estadual de Campinas (Unicamp).

2. Methodological description

This document outlines the theoretical concepts and methods used in the second version (beta) of the module to create yearly maps of native vegetation exposed to degradation drivers. Most drivers cover Brazil from 1986 to 2024, while forest canopy disturbance and selective logging are mapped for the Legal Amazon from 1988 to 2024. All the code used to process and generate the degradation drivers is open source and available in the GitHub repository (https://github.com/mapbiomas/brazil-degradation).

2.1 Definition of native vegetation for each biome

The MapBiomas project uses a unified LULC legend. However, each biome has distinct characteristics. For a comprehensive understanding, Table 1 provides a detailed description of each native vegetation class and its meaning for each Brazilian biome.

Table 1. Detailed description of the native vegetation classes for each biome

Forest Formation	Amazon	Dense Ombrophilous Forest, Evergreen Seasonal Forest, Open Ombrophilous Forest, Semideciduous Seasonal Forest, Deciduous Seasonal Forests, Wooded Savanna. Bamboo forest (Acre).
	Caatinga	Vegetation types with a continuous canopy - Seasonal Forested Savanna, Semi-Deciduous and Deciduous Seasonal Forest.
	Cerrado	Vegetation types with a predominance of tree species, with continuous canopy formation ('Floresta Ripária', 'Mata de Galeria', 'Mata Seca', and 'Cerradão') (Ribeiro & Walter, 2008), as well as semideciduous seasonal forests.
	Atlantic Forest	Dense, Open, and Mixed Ombrophilous Forest, semi-deciduous Seasonal Forest, Deciduous Seasonal Forest, and Pioneer Tree Formation.
	Pampa	Woody vegetation with tree or tree and shrub species, with a predominantly continuous canopy. It includes the following forest types: ombrophilous, deciduous, semi-deciduous, and part of the pioneer formations.
	Pantanal	Tall trees and shrubs in the lower stratum: Seasonal Deciduous and Semideciduous Forest, Forested Savanna, Forested Seasonal Savanna, and Pioneer Formations with fluvial and/or lacustrine influence.
Savanna Formation	Amazon	Open vegetation with a rare shrub and/or tree layer, herbaceous layer is always present.
	Caatinga	Vegetation types with a predominance of semi-continuous canopy species - Wooded Seasonal Savanna, Wooded Savanna
	Cerrado	Savanna formations with defined woody and shrub-herbaceous stratum ('Cerrado Sentido Restrito', 'Cerrado denso', 'Cerrado típico', 'Cerrado ralo', and 'Cerrado rupestre')
	Atlantic Forest	Savannas, Forested and Wooded Seasonal Savannas
	Pantanal	Small tree species, sparsely distributed and arranged in the middle of continuous shrubby and herbaceous vegetation. The herbaceous vegetation is mixed with shrubs.
Mangrove	All biomes	Dense, evergreen forest formations are often flooded by the tide and associated with the coastal mangrove ecosystem.
Flooded Forest	Amazon	Alluvial Open Ombrophilous Forest, established along watercourses, occupies the periodically or permanently flooded plains, which in the Amazon constitute the 'Mata de Várzea' or 'Igapó', respectively.

Wooded Sandbank Vegetation	All biomes	Forest formations that grow on sandy soils or dunes in the coastal zone.
Wetland	Amazon	Floodplain or grassland vegetation that is influenced by rivers and/or lakes.
	Cerrado	Vegetation with a predominance of herbaceous stratum subject to seasonal flooding (e.g. 'Campo Úmido') or under fluvial/lacustrine influence (e.g. 'Brejo'). In some regions, the herbaceous matrix is associated with tree species of savanna formation (e.g., 'Parque de Cerrado') or palm trees ('Vereda', 'Palmeiral').
	Atlantic Forest	Vegetation influenced by rivers and/or lakes.
	Pampa	Swampy areas, regionally known as 'banhados' or 'marismas' (saline influence). Typically hygrophilous vegetation, with emergent, submerged, or floating aquatic plants. They occupy plains and depressions of the land with waterlogged soil, and also the shallow margins of lakes or water reservoirs.
	Pantanal	Herbaceous vegetation with a predominance of grasses subject to permanent or temporary flooding (at least once a year) according to natural flood pulses. The woody element may be present on the grassland matrix, forming a mosaic with shrub or tree plants (e.g., 'cambarazal', 'paratudal', and 'carandazal'). Swampy areas generally occur on the banks of temporary or permanent ponds occupied by emergent, submerged, or floating aquatic plants (e.g., 'brejos' and 'baceiros').
Grassland	Amazon	Savanna, 'Savana Parque' (Marajó), Seasonal Savanna (Roraima), Woody-Grassy Savanna, 'Campinarana' for regions outside the Amazon/Cerrado Ecotone. For regions within the Amazon/Cerrado Ecotone, the herbaceous stratum predominates.
	Atlantic Forest	'Savana Parque' and Woody-Grassy Savanna. Includes Steppe, Shrubby, and Herbaceous Pioneers.
	Caatinga	Vegetation types with a predominance of herbaceous species ('Savana Parque', Woody-Grassy Savanna) and Flooded areas with a network of interconnected ponds, located along watercourses and in lowlands that accumulate water, composed predominantly of herbaceous to shrubby vegetation.
	Cerrado	Grassland formations with the predominance of a herbaceous stratum ('campo sujo', 'campo limpo', and 'campo rupestre') and some areas of savanna formations such as the 'cerrado rupestre'.
	Pampa	Vegetation with a predominance of herbaceous-grassy stratum, with the presence of herbaceous dicotyledons and shrubs. Occur on deep to shallow soils, including rocky ('campos rupestres') and sandy soils ('campos arenosos' or 'psamófilos'). They range from well-drained soils (mesic grasslands) to soils with a higher moisture content ('campos úmidos').
	Pantanal	Vegetation with the predominance of herbaceous-grassy stratum, with the presence of isolated shrubs and woody plants. The botanical composition is influenced by edaphic and topographic gradients and by pastoral management.
Herbaceous Sandbank Vegetation	All biomes	Herbaceous vegetation with fluvial and marine influence.

2.2 Patch ID

2.2.1 Description

The patch ID identifies contiguous native vegetation fragments and assigns a unique identifier (ID) to each patch using the yearly maps from MapBiomas LULC Collection 10.1. Ecologically, this procedure enables the characterization of habitat configuration across the landscape by distinguishing individual habitat fragments based on cell adjacency. Fragment identification is a fundamental step in landscape ecology because the spatial arrangement of the habitat patches directly influences species movement, dispersal, population persistence, and ecological connectivity (Fahrig, 2003). The fragment ID generated by the workflow represents the spatial distribution of connected native vegetation patches, allowing subsequent analyses of fragmentation dynamics and landscape structure.

2.2.2. Method

The workflow was implemented as an adaptation of the *lsmetrics* R package (Vancine et al., 2026) that uses *rgrass* to integrate GRASS GIS geospatial processing tools. For each year, the native vegetation map was imported into GRASS GIS and converted into a binary habitat map, retaining native vegetation pixels and assigning null values to non-habitat cells. Contiguous habitat fragments were identified using the *r.clump* function, considering the queen's case (8 sides of possible connections: horizontal, vertical, and diagonal), which groups adjacent cells into unique connected components and assigns an individual identifier to each fragment.

2.3 Patch Size

2.3.1 Description

Ecological literature indicates that many native plant and animal species have minimum habitat area requirements to maintain viable, persistent populations. As remnants of native vegetation become smaller in area, the resources available to maintain a population decrease, and local extinctions of species may occur. Additionally, smaller fragments are less likely to be recolonized by migrant individuals dispersing from neighboring patches, further contributing to population declines (Lawrence et al., 2018; Magioli et al., 2015). The smaller the fragment, the greater the proportion of the area occupied by edges, which also contributes to a decrease in habitat quality. The sum of these effects results in biologically impoverished patches of habitat. These patches often exhibit reduced biodiversity and ecological function as their area decreases. Moreover, larger patches are generally more effective at providing ecosystem services, such as carbon sequestration, water regulation, and air purification, which are crucial for the health of the surrounding landscapes and human communities (Brancalion et al., 2019). In the context of edge effects, an ecosystem's species and functions are differently impacted by the minimum size of a native vegetation patch. Larger patches are typically more resilient and can sustain diverse biological communities and ecological processes (Laurance et al., 2011).

2.3.2 Method

We used the yearly native vegetation patch ID maps from the previous step as input and computed the area of each pixel using the GRASS GIS *area()* function, converted to hectares. The total area of each fragment was computed using the r.stats.zonal function, which summed the area values of all cells belonging to the same fragment ID. The resulting raster therefore represents the size of each connected habitat fragment in hectares, with all cells within a fragment receiving the same area value. Different patch size thresholds can be applied in the degradation module platform to filter patches, with pre-set values of 5, 10, 25, 50, 100, 250, 500, 1000, and 5000 hectares, but the user can define any other threshold they need.

2.4 Edge Area

2.4.1 Description

The edge area corresponds to the peripheral area of a native vegetation patch in contact with some anthropogenic use, such as planted pasture, agriculture, or urban areas. This condition generates negative effects from the outside to the inside of the native vegetation patch, which may include changes in the microclimate, such as greater exposure to winds and solar radiation, changes in nutrient cycling, an increase in the invasion by exotic species, and which together result in the loss of habitat quality and the impoverishment of biological and functional diversity (Silva-Junior et al., 2020; Dodonov et al., 2013; Banks-Leite et al., 2010; Broadbent et al., 2008). The distance of edge effects reported in the scientific literature varies by species and ecosystem type. In this way, we generated eight distinct layers with different distance thresholds measured from edge contacts among anthropogenic uses and native vegetation (30m, 60m, 90m, 120m, 150m, 300m, 600m, and 1000m). This practical approach allows the user to apply the information they consider most appropriate to the group of organisms or ecosystem function they are interested in evaluating.

2.4.2 Method

First, we used annual LULC data from MapBiomas Collection 10.1 and standardized all the native vegetation classes to a single class to ensure that only anthropogenic uses may cause edge areas over the native vegetation. This approach guarantees that grasslands do not cause edge areas over forests or savannas, and vice versa. Furthermore, we assumed that rocky outcrop, hypersaline tidal flat, and water do not generate edge areas over native vegetation. Finally, we applied the *ee.Kernel.euclidean()* function in Google Earth Engine to calculate the distance of edge areas over native vegetation. This was achieved by considering buffers of 30, 60, 90, 120, 150, 300, 600, and 1000 meters from the neighboring anthropogenic use. It is important to note that we did not differentiate or weight the edge area by source (e.g., Pasture, Agriculture, or Urban). All buffers were treated as equal, regardless of the source anthropogenic class.

2.5 Edge Age

2.5.1 Description

As the edge ages, native vegetation often experiences progressively stronger and more persistent edge effects, including increased light and wind exposure, temperature fluctuations, and reduced humidity. These altered microclimatic conditions can lead to higher tree mortality, lower recruitment of shade-tolerant species, and shifts in species composition toward disturbance-adapted or invasive plants. Long-term exposure to edge environments also disrupts ecological interactions such as pollination, seed dispersal, and nutrient cycling, ultimately reducing biodiversity and ecosystem resilience. Studies in tropical and temperate forests have shown that older edges may accumulate chronic degradation over time and increase fire risk, leading to declines in biomass and functional diversity compared to forest interiors (Silva-Junior et al., 2020; Harper et al., 2005; Laurance et al., 2002).

2.5.2 Method

To construct the edge ages dataset, we followed the following steps:

1. **Edge Areas Mapping**: Identify edge areas for each distance threshold and year using the edge areas dataset.
2. **Age Computation**: For each subsequent year in which a pixel was mapped as an edge, increment the edge age of each pixel by +1. The count resets if a pixel no longer forms an edge. This is done annually, starting from the year of edge detection.

The edge age for each pixel is computed by summing the years it was detected as an edge. For example, if a pixel was detected as an edge in 1993 and remained an edge in subsequent years, by 2023 the pixel would have 30 years of edge age.

2.6 Patch Isolation

2.6.1 Description

Ecological literature indicates that the persistence of species in fragmented habitats is better understood within the framework of metapopulations. In this case, the species' population is considered at the landscape scale, occupying a set of isolated habitat patches and their distances from source areas (large fragments). The presence of the species in a given habitat patch results from a balance between local extinctions and recolonization from neighboring habitat patches. As a result, the more isolated a habitat patch is from surrounding patches, the greater the risk of local species extinctions due to a lower probability of migrants arriving (Almeida et al., 2019; Hatfield et al., 2018; Martensen et al., 2008).

Isolation is not the only factor to consider. The size of the patch (target fragment) is also important. Smaller patches have fewer resources and are less likely to be reached by dispersing individuals. The size of the larger neighboring patches (source fragments) is a key consideration, as they are typically the main sources of immigrants. Large patches, with their more favorable habitat conditions, play a crucial role in maintaining species diversity by providing better conditions for species reproduction and by enabling migrants to disperse to other neighboring patches (Fahrig, 2003).

Species have different dispersal capabilities; therefore, distance influences genetic connectivity between isolated populations in small fragments and larger areas. Gene flow is essential for maintaining genetic diversity in populations, and connected landscapes facilitate the exchange of genetic variation. This connectivity helps prevent inbreeding and increases the adaptive potential of populations (Frankham, 2005). Thus, the worst-case scenario for biodiversity conservation is when the target fragment is smaller and more isolated from neighboring large fragments.

2.6.2 Method

We defined three variables to be used in the analysis, each with three factors:

1) Size of Target Patch: Area equal to or less than 25 hectares (ha), 50 ha, or 100 ha. The higher the value, the more fragments are considered isolated.
2) Distance to Source Patch: Distance equal to or more than 5 kilometers (km), 10 km, or 20 km. Distance here represents an isolation-tolerance threshold. Therefore, lower values indicate less tolerance, resulting in a greater number of isolated fragments in the landscape.
3) Size of Source Patch: Area equal to or greater than 100 ha, 500 ha, or 1000 ha. The higher the value, the fewer source fragments in the landscape, resulting in more isolated fragments.

To process this information in Google Earth Engine, we followed the steps:

1. **Resampling Data**: We resampled the data from Collection 10.1, with spatial resolutions of 30m to 100m.
2. **Exporting Native Vegetation Data**: We exported native vegetation data grouped into two categories: "forest" (including Forest Formation, Savanna Formation, Mangrove, Flooded Forest, and Wooded Sandbank Vegetation) and "Non-Forest" (including Wetland, Grassland, and Herbaceous Sandbank Vegetation). Exclusively for the Pantanal, the water class was also considered a 'pseudo' native vegetation as Non-Forest.
3. **Creating Connected Natural Areas Mask**: We exported a mask of connected natural areas with up to 1024 pixels, which allowed us to separate forest and non-forest areas into categories of more than 100 hectares (100 pixels), 500 hectares (500 pixels), and 1,000 hectares (1,000 pixels), representing the "source patch" maps.
4. **Generating Distance Map**: Using the *ee.Using the Kernel.euclidean()* distance function in Google Earth Engine, we generated a distance map from source patches, classifying distances into categories of 5km, 10km, and 20km or greater.

5. **Removing Large Fragments**: We used the same databases as masks to remove all fragments larger than 100 hectares. This generated a database of natural areas with areas of 100 hectares or less.
6. **Reclassifying Target Fragments**: The remaining natural areas were reclassified to generate the layer of target fragments: natural areas with areas of 25, 50, or 100 hectares or less.

2.7 Patch Morphology

2.7.1 Description

The patch morphology is a spatial pattern analysis (MSPA) of native vegetation fragments to classify habitat structure and connectivity across the landscape. Ecologically, the workflow identifies different functional components of habitat configuration, including core areas, edges, corridors, branches, stepping stones, and perforations. These categories describe how habitat patches are spatially organized and connected, providing important information about ecological connectivity, dispersal pathways, and the influence of fragmentation on biodiversity persistence (Vogt et al., 2007; Haddad et al., 2015). The resulting morphology raster represents distinct structural classes of the landscape that are associated with different ecological functions. Core areas correspond to interior habitat with lower edge influence, while corridors and stepping stones may facilitate species movement between fragments. Edge and perforation classes indicate areas more exposed to external disturbances and edge effects.

2.7.2 Methods

The workflow was implemented in R using the *rgrass* and *lsmetrics* packages (Vancine et al. 2026) to integrate GRASS GIS spatial analysis tools. For each year, we used the native vegetation map from the MapBiomas LULC Collection 10.1, imported it into GRASS GIS, converted it to binary, and processed it with the r.clump function to identify connected habitat patches. Morphological classes were derived through a sequence of neighborhood and zonal operations. Core areas were identified using moving-window minimum filters (*r.neighbors*), while stepping stones were detected as isolated fragments lacking core habitat. Edge areas were defined in 30 meters and estimated by comparing habitat interiors and neighborhood anthropogenic areas after hole-filling operations. Corridor and branch structures were identified using connected-component analysis and spatial growth operations applied to linear habitat elements; in both cases, the maximum width considered is 90 meters. Perforation areas were mapped by detecting internal non-habitat gaps surrounded by vegetation. The final morphology raster combined all classes into a single categorical output representing core, edge, corridor, branch, stepping-stone, and perforation structures.

2.8 Fire

2.8.1 Description

Fires in native vegetation may or may not represent a degradation factor. This is because some vegetation types, such as grasslands and savannas, have an evolutionary history of coexistence and adaptation to fire triggered by natural factors (Bowman et al., 2009). On the other hand, forest formations generally lack fire adaptation, so any burning event can be considered a degradation factor.

Fire frequency is a critical factor in determining their impact. In ecosystems such as grasslands and savannas, fire regimes (including fire frequency and time since the last fire) play a significant role in maintaining ecological balance (Bond & Keeley, 2005). These ecosystems are adapted to specific fire regimes, and deviation from these natural patterns due to anthropogenic causes can lead to degradation. When fire frequency increases beyond natural levels, it can exceed the recovery capacity of these fire-adapted ecosystems, leading to significant ecological consequences (Archibald et al., 2013).

In contrast, forest ecosystems, which typically lack an evolutionary history of frequent fire exposure, are more susceptible to fire-induced degradation. Fire in these areas often results in biodiversity loss, soil degradation, and changes in vegetation structure, contributing to long-term ecological damage (Cochrane, 2003).

2.8.2 Fire Frequency Method

The burned area frequency maps show how many times each pixel was mapped as burned from 1986 to 2023. Fire frequency data is aggregated into a single map with 38 classes: Class 1 represents pixels that burned once, Class 2 represents pixels that burned twice, and so on.

To create these maps, we retrieved yearly burned areas from MapBiomas Fire Collection 4.1. We computed the fire frequency by binarizing yearly burned areas for each year (1= burned, 0= unburned) and summing the fire occurrences across years. This data also includes the LCLUC classes from MapBiomas Collection 10.1. For more details, see the MapBiomas Fire ATBD.

2.8.3 Time Since The Last Fire Method

The Time Since Last Fire represents the age (in years) since each pixel last burned based on the MapBiomas Fire Collection 2.

To construct this dataset, we followed these steps:

1. **Generate Fire Age**: For each pixel, we calculated the fire age by counting from the year after the first observed fire event. From the year following the fire, we added 1 to each subsequent year without a fire event.
2. **Determine Last Fire Year**: When a new fire event is observed, record the number of years since the last fire. The count then reset in the following year, starting again from 1.
3. **Mask Unburned Pixels**: All pixels with no observed fire events are masked in the map.

The resulting map shows the number of years since each pixel last experienced a fire, providing valuable information on fire history and intervals between fire events across the landscape.

2.9 Secondary Vegetation Age

2.9.1 Description

The removal of primary vegetation by anthropogenic and natural processes, followed by abandonment, gives rise to passive succession. The impact of secondary vegetation on the climate, soil, and hydrology differs from that of primary or anthropogenic areas. Over time, the structure and function of patches of secondary vegetation during recovery tend to improve due to increases in plant species diversity and vegetation structural complexity (Chazdon, 2014). As a result, these recovering areas are more resistant to and resilient against the effects of various degradation processes. In this context, patches of secondary vegetation can be considered susceptible to degradation, particularly those that are relatively young. Consequently, the age of secondary vegetation is an important indicator of its ecological stability and resistance to further disturbances (Arroyo-Rodríguez et al., 2017).

This layer of information was generated from the results obtained by the Deforestation and Secondary Vegetation MapBiomas dataset. By processing data from the annual MapBiomas LULC Collection 10.1 maps, this dataset identifies areas with secondary vegetation each year, enabling calculation of the age of each existing patch of secondary vegetation for the most recent year.

2.9.2 Method

Using the MapBiomas Deforestation and Secondary Vegetation dataset (see Deforestation and Secondary Vegetation ATBD), we map regrowth of native vegetation by year and compute the regrowth age (in years) for each pixel.

The process is as follows:

3. **Initial Mapping**: Identify areas of deforestation and secondary vegetation for each year using the MapBiomas dataset.
4. **Regrowth Calculation**: For each year following deforestation, increment the regrowth age of each pixel by +1. This is done annually, starting from the year of deforestation.
5. **Age Computation**: The age of regrowth for each pixel is determined by summing the years of regrowth. For example, if a pixel was deforested in 2010 and identified as secondary vegetation in subsequent years, by 2022 it would have 12 years of regrowth.

2.10 Forest Canopy Disturbance

2.10.1 Description

Forest canopy disturbance is an abrupt change in the forest canopy structure that indicates a loss of vegetation density or a canopy opening. In this module, the product is mapped in the Legal Amazon for MapBiomas Forest Formation (class 3) and Floodplain Forest (class 6). Detected disturbances may be associated with selective logging, fires, extreme climatic events, or incipient deforestation; therefore, the layer represents observed canopy change rather than a single causal agent. Detection is based on reductions in the Normalized Difference Fraction Index (NDFI) relative to the same pixel's spectral behavior over the preceding three years (Souza Jr. et al., 2005).

2.10.2 Method

We use Landsat surface reflectance mosaics with a 32-day compositing window in Google Earth Engine and calculate NDFI using Spectral Mixture Analysis (Roberts et al., 1993; Gorelick et al., 2017). For each monthly mosaic, the Median Absolute Deviation (DAM; PhamGia & Hung, 2001) compares the current NDFI with the median of the previous 36 monthly mosaics. A pixel is initially flagged as disturbed when the NDFI deviation is between -0.25 and -0.095, the historical median NDFI is at least 0.8, and the pixel belongs to Forest Formation (class 3) or Floodplain Forest (class 6). The annual disturbance maps cover the period from 1988 to 2024. Raw detections are then post-processed to reduce commission errors. Geographic and ecological filters remove recurrent spectral artifacts associated with specific high-elevation areas and lithic or rocky substrates. Remaining pixels are classified based on spatial patterns and auxiliary information, including cluster size, wetlands, rugged terrain, forest-edge context, and disturbance frequency. The resulting annual forest-canopy-disturbance product is also the input used to identify selective logging. For more information, access the “Detection of Forest Canopy Disturbances and Selective Logging - ATBD”

2.11 Selective Logging

2.11.1 Description

Selective logging is mapped as a subset of forest canopy disturbances whose spatial configuration is consistent with timber extraction features such as log decks and skid trails. It is a challenging remote-sensing target because logging features are spatially sparse, their spectral signal may disappear as neighboring crowns close gaps within one to three years, and their geometry varies with harvesting practices, species, terrain, and log-transport mode. The 13 product is restricted to the Legal Amazon forest classes used for canopy disturbance and covers the period from 1988 to 2024. "Detection of Forest Canopy Disturbances and Selective Logging - ATBD"

2.11.2 Method

Selective logging classification starts with 30 x 30 m pixels that are already classified as forest canopy disturbances. Candidate logging pixels are selected with a multi-scale kernel applied to the disturbance-frequency layer. The workflow retains small disturbance clusters with 1 to 4 months of disturbance, 1 to 6 disturbed neighbors in a 3 x 3 window, connected patches of 5 to 1,023 pixels, local density between 10% and 75% in a 5 x 5 window, a local-to-regional density ratio of at least 0.8, and frequency variance below 5 in a 7 x 7 window. Candidate pixels are then restricted to yearly valid-classification areas derived from Imazon and INPE reference databases, with additional analyst validation using annual NDFI imagery. Accepted pixels are converted to vectors and grouped into exploitation polygons. The polygon workflow uses a 500 m expansion, followed by a 300 m erosion to consolidate nearby features, then a convex-hull operation to produce the final selective-logging polygons and estimate area in hectares.

3. Accessing the data

The data, maps, and statistics can be accessed on the MapBiomas Degradation Module Platform, which allows interactive assessment by degradation driver and the combination of multiple degradation drivers to generate your own custom scenario for any territory in Brazil (country, state, municipality, protected areas, indigenous lands, or custom territory). Furthermore, statistical data for each degradation driver are available for download in Excel format (.xlsx) on the MapBiomas Download Page.

4. References

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