Pantanal - Appendix
(Sentinel 10m)

MapBiomas Brasil – Cobertura e Uso da Terra

Algorithm Theoretical Basis Document (ATBD)

Collection 3 (beta)

Version 1

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1. Introduction

The Pantanal biome is located within Brazilian territory between the Mato Grosso and Mato Grosso do Sul states. It also extends into the territories of Bolivia, and Paraguay. It covers an area of 150,000 km² and is surrounded by the Amazon, Cerrado, and Atlantic Forest biomes. Although it is the smallest Brazilian biome in terms of area, it has the highest proportion of remaining native vegetation.

The Pantanal is renowned as one of the largest continuous wetlands in the world, characterized by a vast alluvial plain subject to seasonal flooding due to a flood pulse, with pronounced flood and dry periods. (Figure 1). This flood pulse is influenced by global and regional climatic conditions and the hydro-sedimentological dynamics of the rivers in the Upper Paraguay Basin (Hamilton; Souza; Coutinho, 1998; Padovani, 2010).

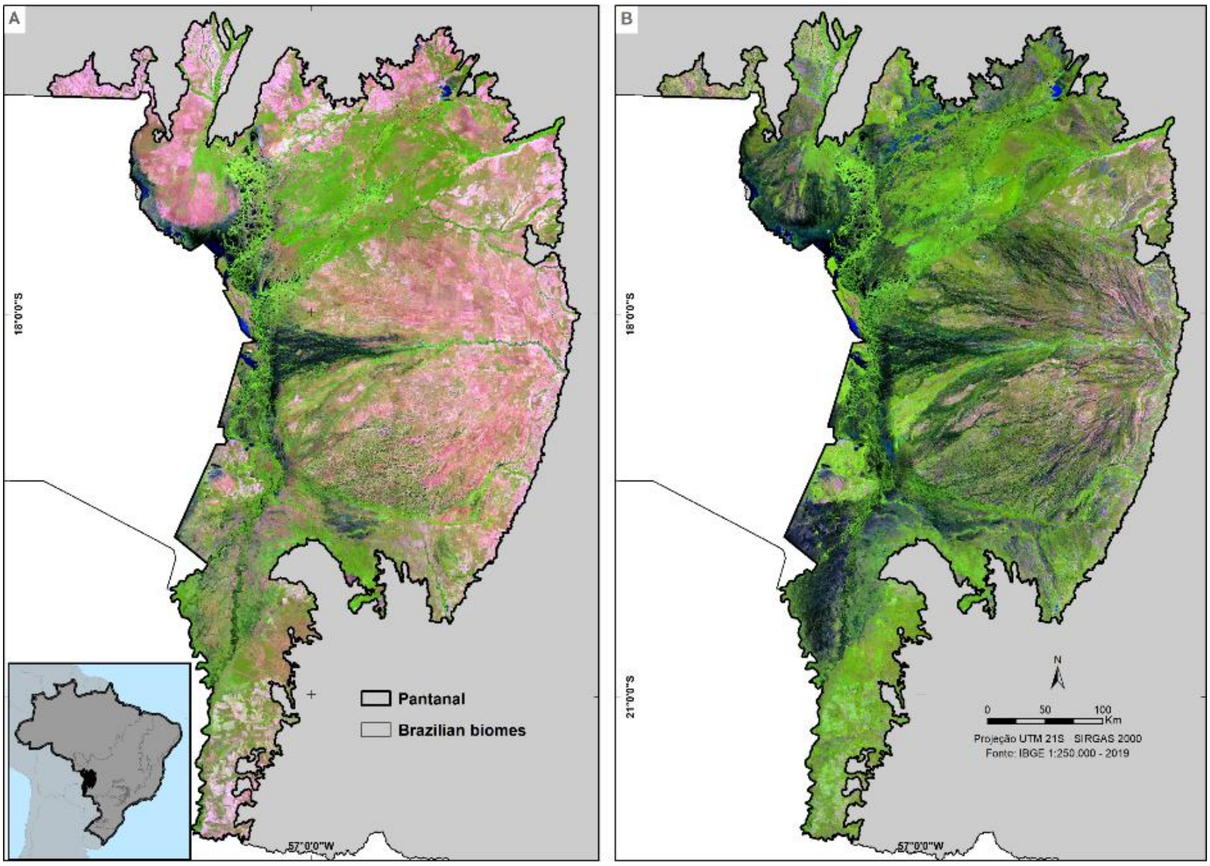


Figure 1: Location of the Pantanal biome showing RGB color composites of bands 11, 8 and 4 for Sentinel mosaics of the year 2018. A) dry season; B) wet season.

Understanding flooding dynamics is essential for accurately interpreting land use and land cover (LULC) changes in the Pantanal. The seasonal pulse of water is the primary driver of ecological processes in this biome, influencing vegetation phenology and human activities alike. The MapBiomas Collection 3.0 (10-meter resolution) for the Pantanal biome provides a high-resolution temporal series of LULC maps from 2017 to 2024. Additionally, the 'Google Satellite Embeddings' annual embeddings dataset developed by Google' was not present in the Sentinel Collection 2 (2017 - 2023), but it is included in Collection 3. Consequently, while the mapping of rocky outcrops was conducted as a parallel process in Collection 2, the introduction of these Google embeddings has allowed it to be fully integrated alongside the other classes. This collection aims not only to classify terrestrial land cover but also to delineate the maximum annual flooded area for each year in the series, offering a comprehensive view of the biome's hydrological extremes. This document describes the overarching methodological framework to map the Pantanal biome from 2017 to 2024, using images of Sentinel-2, 10-meter.

In alignment with the principles of transparency and open science, all processing scripts and classification algorithms used in this methodology are publicly available. The codebase can be accessed at the official MapBiomas Pantanal GitHub repository: https://github.com/mapbiomas/brazil-pantanal.

2. Methodology Overview

The generation of land use and land cover (LULC) maps for the Pantanal biome is based on a supervised classification workflow utilizing the Random Forest machine learning algorithm. The entire processing chain is implemented within the Google Earth Engine (GEE) cloud computing platform using the JavaScript API. The input data consists of two primary sources: Sentinel-2 annual mosaics (2017–2024) and Google Satellite Embeddings annual embeddings dataset developed by Google (Brown et al., 2025).

The integration of these foundational embeddings has enhanced the classification performance of the map series. The primary objective of this methodology is to map the diverse LULC classes characteristic of the Pantanal, while also identifying the maximum flooded area for each year in the temporal series.

The classification process is divided into three fundamental stages: 1. Training Sample Generation: Samples were derived from the MapBiomas Collection 10.0. To ensure high-quality training data, only "stable pixels", those that maintained the same class for at least 10 consecutive years (2014–2024) across the biome, were selected; 2. Feature Space Construction: A set of variables was incorporated, including common spectral bands and indices used across all biomes, as well as specific variables tailored to the Pantanal's unique ecological characteristics; 3. Classification and Thematic Mapping: The model considers 7 primary LULC classes: Forest Formation, Savanna Formation, Grassland, Rocky Outcrop, Pasture, Agriculture, and Non-Vegetated Areas.

The Wetland and Water classes are integrated during the post-classification stage. This is achieved by reclassifying initial outputs based on a specific humidity index threshold, which identifies the maximum annual flooded extent. Furthermore, a sequence of spatial and temporal filters is applied to the raw classification results. These filters aim to enhance spatial consistency removing salt-and-pepper noise, ensure temporal coherence preventing illogical year-to-year transitions and eliminate gaps or null values (NoData pixels).

The complete classification workflow is illustrated in Figure 2, with detailed descriptions of each step provided in the following sections.

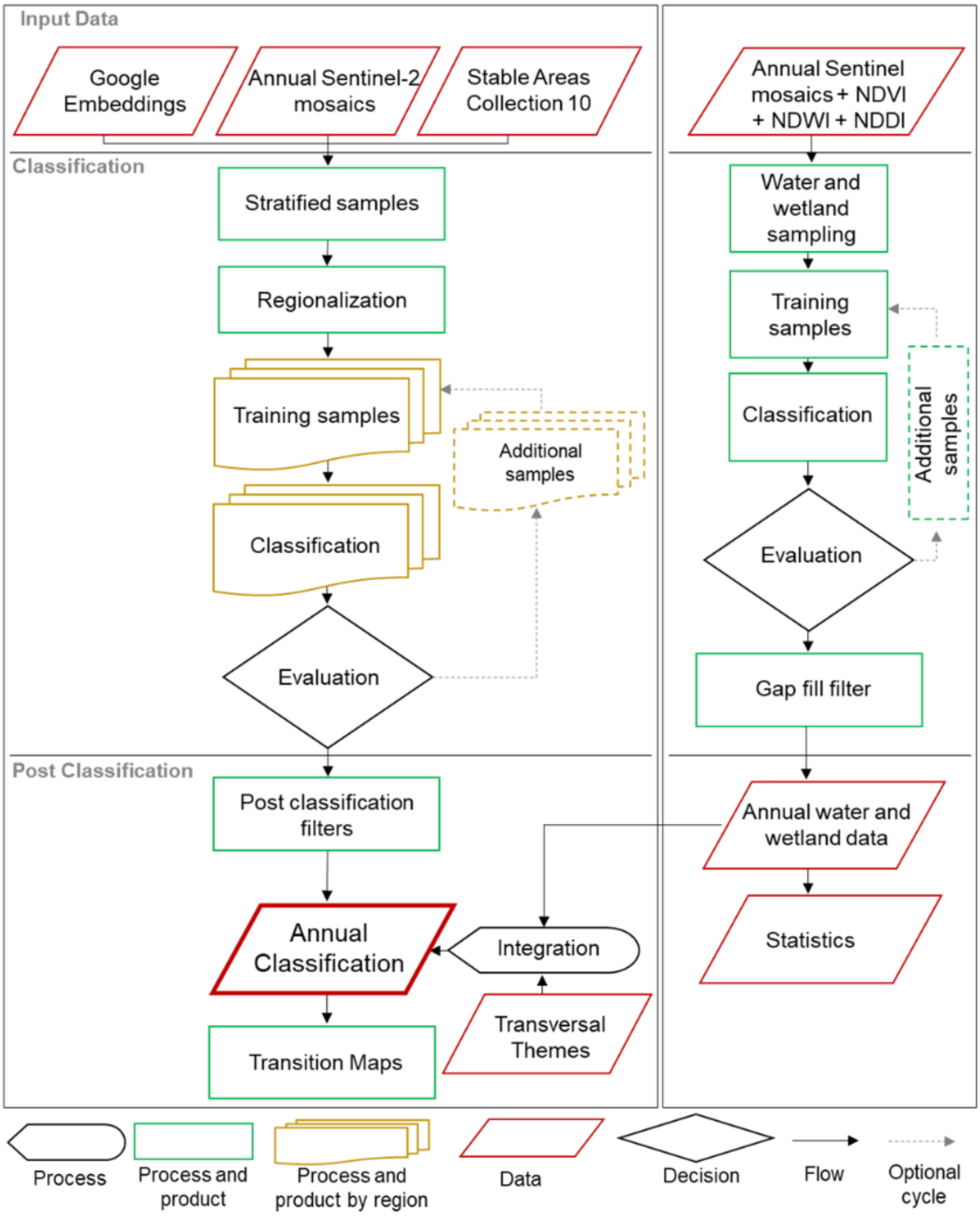


Figure 2: Classification workflow.

3. Regionalization

The Pantanal biome was divided into eight regions based on drought and flooding patterns, sub-basin watersheds, and the distribution of native vegetation as presented in different regionalization approaches (Silva & Abdon, 1998; Assine, 2015). The goal of this process was to reduce confusion and noise in the classification, improving sample balance in more homogeneous regions.

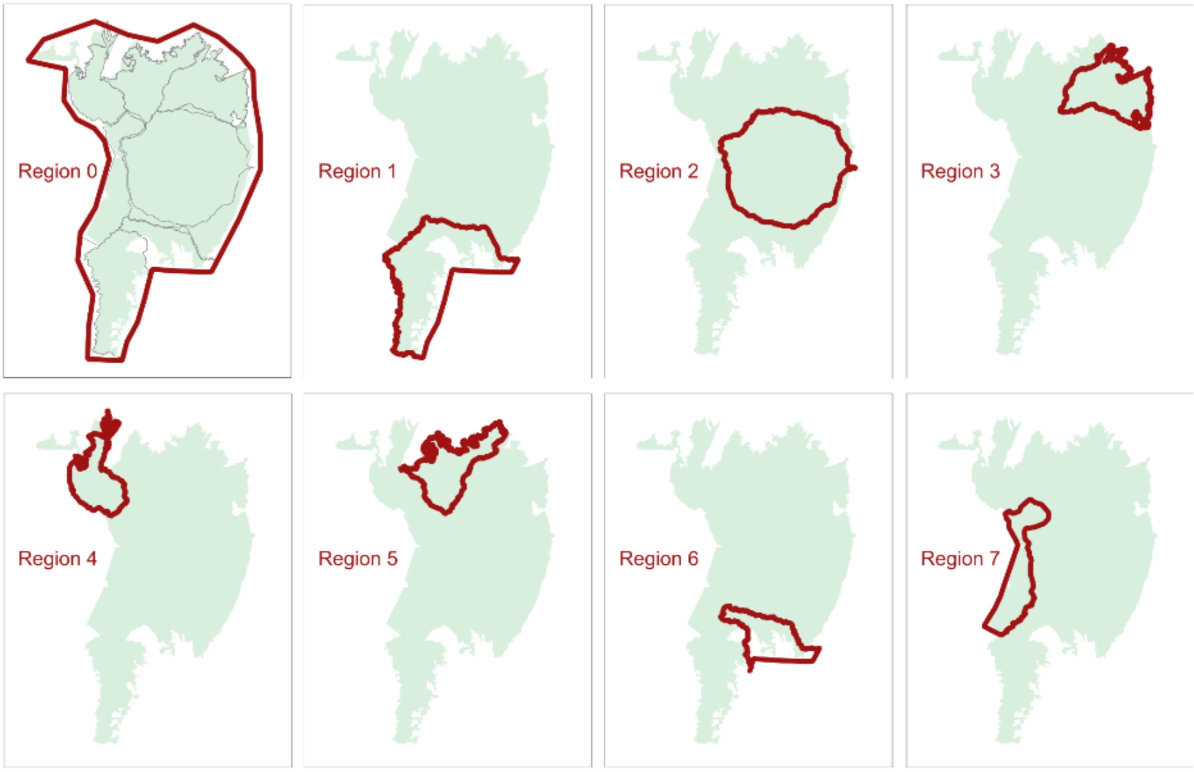
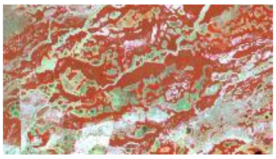
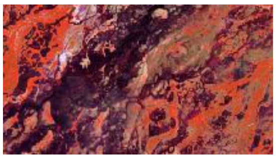


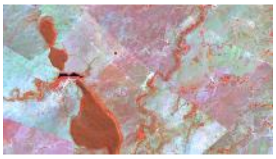
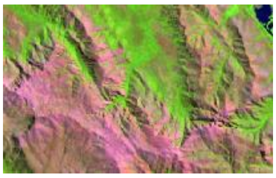
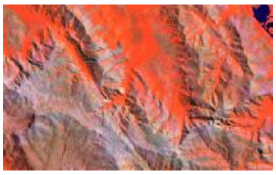
Figure 3: Regionalization for the Pantanal biome

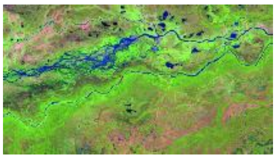
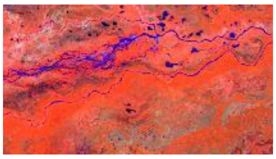
4. Mapped Classes

The primary LULC classes identified through the machine learning process are detailed in Table 1. In subsequent processing stages, these baseline classes were integrated with cross-cutting themes (such as specialized mapping of infrastructure or specific crops), the details of which are further elaborated in Section 8 (Integration and Post-processing)

Table 1: Classes mapped by the Pantanal biome in the MapBiomas Collection 3.

1.1. Forest Formation			
Numeric ID: 3		Color	
Google Earth	Landsat (RGB 654)	Landsat (RGB 564)	Photo
			
Description: Tall trees and shrubs in the lower stratum: Deciduous and Semi-deciduous Seasonal Forest, Wooded Savanna, Wooded Steppe Savanna, and Fluvial and/or Lacustre Influenced Pioneer Formations.			
1.2. Savanna Formation			
Numeric ID: 4		Color	
Google Earth	Landsat (RGB 654)	Landsat (RGB 564)	Photo
			
Description: Small tree species, sparsely arranged in the shrub and herbaceous continuous vegetation. The herbaceous vegetation mixes with erect and decumbent shrubs.			
2.1. Wetland			
Numeric ID: 11		Color	
Google Earth	Landsat (RGB 654)	Landsat (RGB 564)	Photo
			
Description: Herbaceous vegetation with a predominance of grasses subject to permanent or temporary flooding (at least once a year) according to the natural flood pulses. The woody element can be present on the country 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 lagoons occupied by emergent, submerged or floating aquatic plants (e.g. swamps and barns). Areas with a water surface, but difficult to classify due to the amount of macrophytes, eutrophication or sediments, were also included in this category.			

<table>
<tr><th colspan="4">2.2. Grassland Formation</th></tr>
<tr><td colspan="2">Numeric ID: 12</td><td>Color</td><td></td></tr>
<tr><td>Google Earth</td><td>Landsat (RGB 654)</td><td>Landsat (RGB 564)</td><td>Photo</td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="4">Description: Vegetation with a predominance of grassy stratum, with the presence of isolated and stunted woody shrubs. The botanical composition is influenced by the edaphic and topographic gradients and pasture management (livestock). Patches of invasive exotic vegetation or forage use (planted pasture) may be present, forming mosaics with native vegetation.</td></tr>
<tr><th colspan="4">2.4. Rocky Outcrop</th></tr>
<tr><td colspan="2">Numeric ID: 29</td><td>Color</td><td></td></tr>
<tr><td>Google Earth</td><td>Landsat (RGB 654)</td><td>Landsat (RGB 564)</td><td>Photo</td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="4">Description: Naturally exposed rocks without soil cover, often with the partial presence of rupicolous vegetation and high slope.</td></tr>
<tr><th colspan="4">3.1. Pasture</th></tr>
<tr><td colspan="2">Numeric ID: 15</td><td>Color</td><td></td></tr>
<tr><td>Google Earth</td><td>Landsat (RGB 654)</td><td>Landsat (RGB 564)</td><td>Photo</td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="4">Description: Pasture area, predominantly planted, linked to livestock production activities. Areas of natural pasture are predominantly classified as grassland or wetland, that may or may not be grazed.</td></tr>
<tr><th colspan="4">3.2.1.5. Other Temporary Crops</th></tr>
<tr><td colspan="2">Numeric ID: 41</td><td>Color</td><td></td></tr>
<tr><td>Google Earth</td><td>Landsat (RGB 654)</td><td>Landsat (RGB 564)</td><td>Photo</td></tr>
</table>

			
Description: Areas occupied by short- or medium-duration agricultural crops, generally with a vegetative cycle of less than one year.			
4. Non-Vegetated Areas			
Numeric ID: 25		Color	
Google Earth	Landsat (RGB 654)	Landsat (RGB 564)	Photo
			
Description: Areas of exposed soil (mainly sandy soil) not classified under the Grassland Formation or Pasture classes.			
5. Water			
Numeric ID: 33		Color	
Google Earth	Landsat (RGB 654)	Landsat (RGB 564)	Photo
			
Description: Rivers, lakes, dams, reservoirs and other water bodies.			

5. Sentinel image mosaics

The mapping process is based on Sentinel-2 Surface Reflectance (Level-2A) imagery. As part of the European Space Agency (ESA) Copernicus program, the Sentinel-2 mission provides multispectral data with a high temporal resolution of 5 days (with two satellites, 2A and 2B) and a spatial resolution of 10 meters for the visible and near-infrared bands.

Annual mosaics are generated by applying a reducer to the image collection available for each year. This process collapses the temporal stack into a single representative product by calculating the median values for the dry and wet seasons independently. This seasonal approach is crucial for the Pantanal, where the spectral response of vegetation and water bodies varies significantly throughout the hydrological cycle. The feature space includes: Spectral Bands: Median annual values for Blue, Green, Red, Red-Edge (1, 2, and 3), SWIR1, and

SWIR2; Spectral Indices; Temporal Metrics: The standard deviation of the annual bands to capture phenological and flood-driven variability.

Additionally, bands from the new Google Satellite Embedding dataset were incorporated (Brown et al., 2025). This asset consists of self-supervised learned representations (embeddings) derived from a large-scale Vision Transformer (ViT) model. These embeddings capture complex spatial and contextual patterns that traditional spectral bands might miss, providing a more robust "feature signature" for each pixel and significantly improving the model's ability to differentiate between subtle land cover classes in the Pantanal biome.

6. Feature Space

For this collection, a feature importance analysis was conducted for each region. A feature importance test was performed using a pool of 250 different bands, which included annual median, standard deviation, and quartile values from the spectral bands and a wide range of indices, in addition to texture and embeddings bands. The test involved running the classifier with the full set of candidate bands for multiple years and for each region. By using a classifier composed of 500 decision trees, it was possible to obtain a ranking of the most relevant bands considered in the classification.

Subsequently, the 60 most important bands for each region were selected. The composition of the feature space subset for final classification is region-specific. Table 2 presents the list of the most important bands for the classification of the Pantanal biome.

Table 2. Feature space subset with the most frequent variables between regions considered in the classification of the Pantanal biome in Landsat image mosaics in the MapBiomas Collection (2017-2024).

Type	Name	Formula	Statistics	Reference
	Blue	Band 2	median, median_dry, median_wet	ESA
	Green	Band 3	median, median_dry, median_wet, median_texture	ESA
	Red	Band 4	median, median_dry, median_wet	ESA
Sentinel band	Red Edge 1	Band 5	median, median_dry, median_wet	ESA
	Red Edge 2	Band 6	median, median_dry, median_wet	ESA
	Red Edge 3	Band 7	median, median_dry, median_wet	ESA

Type	Name	Formula	Statistics	Reference
	NIR	Band 8	median, median_dry, median_wet	ESA
	SWIR 1	Band 11	median, median_dry, median_wet	ESA
	SWIR 2	Band 12	median, median_dry, median_wet	ESA
Spectral Index	Advanced Vegetation Index	AVI = (NIR × (1.0 - Red) × (NIR - Red))$^{1/3}$	median, median_dry, median_wet	
	Automated Water Extraction Index	AWEI = Blue + 2.5 × Green- 15 × (NIR + SWIR1) - 0.25 × SWIR2	median, median_dry, median_wet	Feyisa et al., 2014
	Band Ratio for Built-up Area	BRBA = Red / SWIR2	median, median_dry, median_wet	Waqar et a., 2012
	Brightness Index	BI = ((Red^2 + Green^2) / 2)$^{1/2}$	median, median_dry, median_wet	Escadafal, 1989
	Enhanced Vegetation Index	EVI = 2.5 × (NIR - Red) / (NIR + 2.4 × Red + 1)	median_wet,	Parente et al., 2018
	Enhanced Vegetation Index 2	EVI 2 = 2.5 × (NIR - Red) / (NIR + 2.4 × Red + 1)	median, median_dry, median_wet, stdDev	Parente et al., 2018
	Global Environment Monitoring Index	GEMI = (2 * (NIR^2 - Red^2) + 1.5 * NIR + 0.5 * Red) / (NIR + Red + 0.5)	median, median_dry, median_wet	Pinty & Verstraete, 1992
Spectral Index	Green Chlorophyll Vegetation Index	GCVI = (NIR / Green - 1)	amplitude, median, median_dry, median_wet	Burke et al., 2017
	Modified Normalized Difference Water Index	MNDWI = (Green - SWIR1) / (Green + SWIR1	median, median_dry, median_wet,	Xu, 2006
	Normalized Difference Drought Index	NDDI = (NDVI - NDWI) / (NDVI + NDWI)	median_wet	Gu et al., 2007
	Normalized Difference Vegetation Index	NDVI = (NIR - Red) / (NIR + Red)	amplitude, median,	Rouse et al., 1974

Type	Name	Formula	Statistics	Reference
			median_dry, median_wet	
	Normalized Difference Water Index	NDWI = (NIR - SWIR1) / (NIR + SWIR1)	amplitude, median, median_dry, median_wet	Gao et al., 1996
	Optimized Soil Adjusted Vegetation Index	OSAVI = ((NIR - Red) / (NIR + Red + 0.16)) × (1 + 0.16)	median, median_wet	Rondeaux et al., 1996
	Ratio Vegetation Index	RVI = Red/NIR	median, median_wet	Jordan, 1969
	Redness Index	RI = (Red - Green) / (Red + Green)	median, median_wet,	Escadafal & Huete, 1991
	Soil-Adjusted Vegetation Index	SAVI = 1.5 × (NIR - Red) / (NIR + Red + 0.5)	median_wet, amplitude, median, median_dry, median_wet	Huete, 1988
Surface Index	Hall's Forest Cover	HFC = −0.017 × RED − 0.007 × NIR − 0.079 × SWIR2 + 5.22	median, median_dry, median_wet	Hall et al., 2006
	Hall's Forest Height	HFH = −0.039 × RED − 0.011 × NIR − 0.026 × SWIR1 + 4.13	median, median_dry, median_wet	
Embedings	Google Satellite Embeddings	Bands A00 - A63		Brown et al., 2025
Terrain	Slope	ALOS DSM: Global 30 m	identity	Tadono et al., 2014
Coords	Latitude and Longitude		Latitude, Longitude	

6.1 Stable Samples

The extraction of stable samples from the Collection 10.0 followed several steps, aiming to ensure their confidence for use as training areas. The areas that did not change class from 2014 to 2024 in Collection 10.0 were used to generate 7,000 random training points in each region. In addition, more 7,000 random points from areas that did not change in a given year between collections 8, 9 and 10 were also used, to obtain a stratum of stable samples not over time, but over collections prepared with different approaches. During the classification, the balance was done by reducing the number of stable samples adjusted for each class.

6.2 Complementary samples

The need for complementary samples was evaluated by visual inspection. Complementary sample collection was made in Google Earth Engine Code Editor with the drawing polygons tool. The same concept of stable samples was applied, checking the false-color composites of the Sentinel mosaics for all the 8 years during the polygon drawing. Based on the knowledge of each region, samples of forest, savanna, grassland, agriculture or pasture were added.

6.3 Classification algorithm

A digital classification was performed year by year using a variation of the Random Forest algorithm (Breiman, 2001), available in Google Earth Engine. Random Forest was trained with stable and complementary samples, according to which feature space subset. Each subregion had a specific sample balance and classification. After the classification processing, the subregions were merged to form the Pantanal biome territory.

7. Post Classification

7.1. Masks

Some natural grassland areas in the western portion of the Pantanal can be easily confused and classified as exotic pastures by RF because of the overgrazing or the soils exposition during a dry period. To avoid this misclassification, a mask of 'non-pasture' was applied considering flooded pixels in more than 75% of the entire Collection 10.0 time series.

Also, in order to improve the classification for the most recent years, a mask of 'deforested areas' was built from the MapBiomas Alertas validated polygons. Following, all native vegetation pixels intercepting the mask were reclassified to farming class in the deforestation event year and in the following years. It is worth remembering that these deforestation polygons are available from 2019.

7.2. Water and Wetland data integration

To generate Water and Wetland data, the Normalized Difference Dynamic Index (NDDI) was calculated for the dry and wet periods of the annual mosaic. Once a threshold has been defined, it differentiates flooded areas from the water surface and non-flooded areas. The intention with this processing is to map the maximum flooded area each year, considering that the Pantanal is one of the largest wetlands in the world subject to a significant flood pulse that varies intra-annually and multi-annually.

This annual water and wetland data were added to the map of 'non-wet' classes only in areas classified as grasslands, considering that the methodology for the latter is not adapted to identify flooded forest and savannah. This is also a strategy to avoid false positives from humid areas in the shade of the relief, urban areas or roads.

7.3. Filters

Some temporal and spatial filters were applied to the annual maps to correct classification errors or invalid class transitions using long-term information from the temporal series.

7.3.1. Gap Fill filter

In this filter, no-data values ("gaps") are theoretically not allowed and are replaced by the temporally nearest valid classification. In this procedure, if no "future" valid position is available, then the no-data value is replaced by its previous valid class. Therefore, gaps should only exist if a given pixel has been permanently classified as no-data throughout the entire temporal domain.
Trajectory filter

7.3.2. Trajectory filter

To avoid false transitions between savanna formation and grassland in short time intervals, a filter was applied that considered the trajectory of the pixel according to Pontius (2022). Considering the trajectory of absence - alternation - absence, the number of changes that the class was involved in and also the pixel mode along the time series, the filter stabilizes these two classes. This filter was also implemented to prevent areas of Forest or Savanna Formations that had been converted to anthropic uses from regenerating as Natural Grassland Formation. It addressed part of the confusion between pasture areas and Grassland Formation. Specifically, the filter ensures that any area converted to pasture remains classified as pasture for at least seven consecutive years, reducing classification errors.

7.3.3. Spatial Filter

A spatial filter was applied to prevent undesired changes along the edges of pixel groups using the "connectedPixelCount" function. Native to the Google Earth Engine (GEE) platform, this function identifies connected pixels (neighbors) with the same value. Isolated pixels—those not sharing connections with a predefined number of identical neighbors—were considered separately. Similar to the implementation in Collection 10.0, this filter improved spatial consistency along pixel boundaries.

8. Integration with cross-cutting themes

The final map generated by the Pantanal biome team was integrated with maps from some cross-cutting themes, which represent rare classes or classes that demand a specific mapping strategy. These external themes comprise urban areas (24), mining (30), agriculture (39, 20, 41) and forest plantation (9). The prevalence rules for integration with the agriculture and pasture cross-cutting themes apply only to anthropic areas, while urban infrastructure and mining have prevalence over all mapped classes. They were superimposed on the Pantanal data, resulting in final maps of the biome containing 14 classes (Table 3).

Table 3: Classes observed in the Pantanal biome.

Legend class of Collection 3 - 10 Meters	Numeric ID	Color
1.1. Forest Formation	3	
1.2. Savanna Formation	4	
2.1. Wetland	11	
2.2. Grassland Formation	12	
2.4. Rocky Outcrop	29	
3.1. Pasture	15	
3.2.1.1. Soybean	39	
3.2.1.2. Sugar cane	20	
3.2.1.5. Other Temporary Crops	41	
3.3. Forest Plantation	9	
4.2. Urban area	24	
4.3. Mining	30	
4.4. Other non vegetated area	25	
5. Water	33	

9. Known Limitations and Advantages

While the data and processing scripts are public and open-access, it is essential to highlight the specific technical limitations and significant gains of the Sentinel-based Collection 3.0 (10-meter resolution) compared to previous Landsat-based efforts.

9.1 Technical Limitations and Sensor Discrepancies

Thematic Consistency vs. Spatial Resolution: Although this collection uses the same classification legend as the Landsat-based series, the differences in spectral and spatial resolutions (10m vs. 30m) introduce variations in thematic results. For instance, due to the Pantanal's characteristic low-density arboreal vegetation, the higher spatial resolution of Sentinel-2 tends to capture more Savanna Formation than Forest Formation, as it can better resolve gaps in the canopy that are "averaged out" in coarser 30m pixels.

Validation Constraints: Currently, MapBiomas does not have a dedicated independent accuracy assessment (validation points) specifically designed for the Sentinel-based maps. Users should exercise caution when comparing these results directly with the validated 40-year historical series.

Temporal Depth: The short time series (8 years, from 2017 to 2024) limits its use for long-term trend analysis or decadal climate change impact assessments when compared to the 40-year record available in the Landsat-based Collection 10.

9.2 Significant Improvements and Gains

Despite these limitations, the transition to 10-meter resolution offers substantial advantages for the Pantanal biome:

Mapping of Rare Classes: The 10m resolution allows for the identification of rare or fragmented land cover classes that are often lost at coarser scales.

Critical Features and APP Areas: There is a significant improvement in the mapping of ecologically sensitive features, such as Permanent Preservation Areas (APP), riparian corridors, and small water bodies, which are vital for the hydrological and biological connectivity of the biome.

Enhanced Spatial Detail: The inclusion of Google's Satellite Embeddings, combined with Sentinel's resolution, provides a superior level of landscape texture and detail, essential for fine-scale territorial management.

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