Pantanal - Appendix

Collection 10

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. Despite being the smallest Brazilian biome in area, it boasts 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).

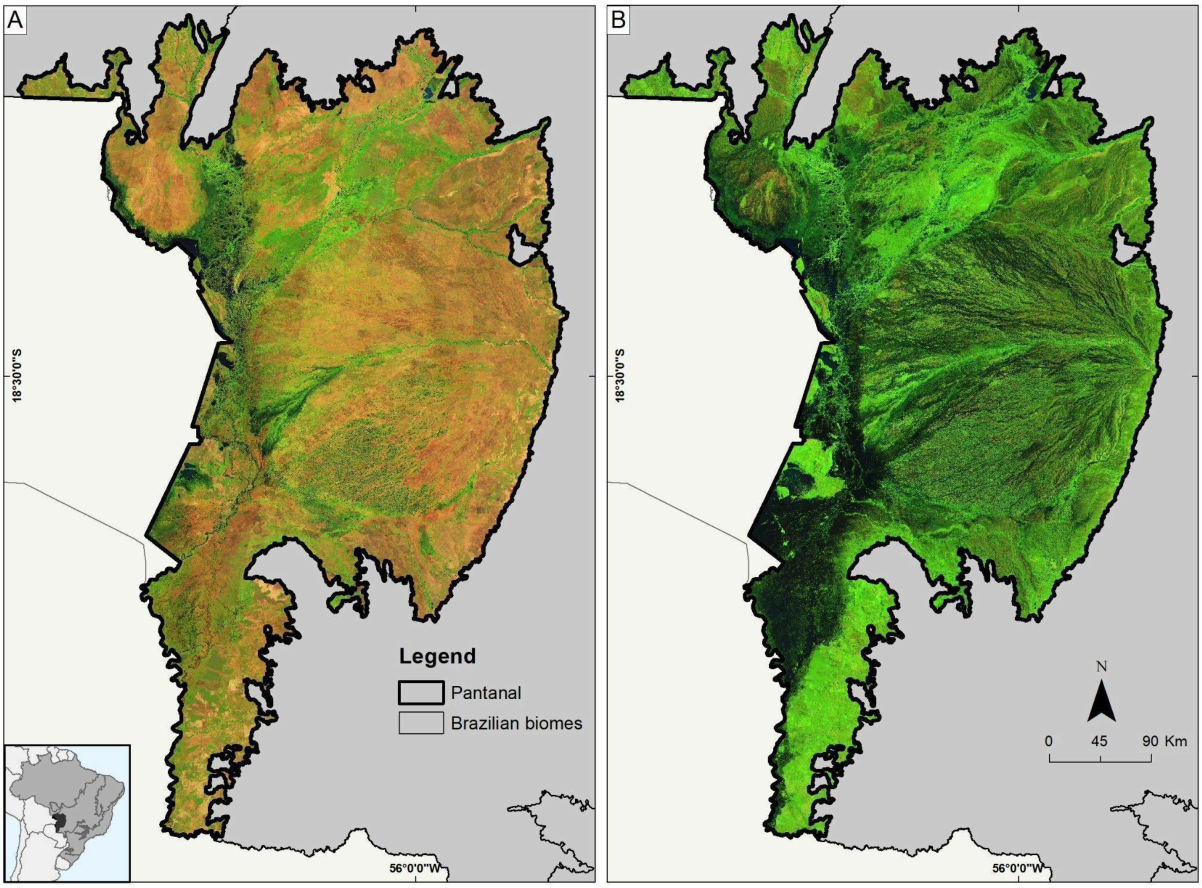


Figure 1: Location of the Pantanal biome showing RGB color composites of TM bands 5, 4 and 3 for Landsat mosaics of the year 1988 for. A) dry season Landsat mosaic; B) wet season Landsat mosaic.

Understanding the dynamics of flooding in the biome is crucial to comprehending changes in land use and land cover over time. As part of MapBiomas Collection 10, we conducted monthly mapping of water and wetland classes and made other improvements compared to previous collections, for example, the addition of the rocky outcrop class to the maps.

This document describes the methodological flow used to map the land use and land cover in the Pantanal biome from 1985 to 2024. Also, all codes used are available on our public GitHub (https://github.com/mapbiomas/brazil-pantanal).

2. Overview of classification method

The initial classification of the Pantanal biome within the MapBiomas project consisted of applying decision trees to generate annual maps of the predominant native vegetation (NV) types, distinguished in: Forest, Savanna, and Grassland and antrophic classes such as Pasture and Agriculture. The method used to generate these annual maps evolved, with significant improvements from the first MapBiomas Collection to the present. Collection 1.0 covered the period of 2008 to 2015 and was published in 2016. Collections 2.0 and 2.3 covered the period of 2000 to 2016 and were published in 2018.

The classification using Random Forest was implemented in Collection 2.3, and from this point onward, the empirical decision tree was used to generate stable samples, which were classified as the same NV type over the considered period (2000-2016). These stable samples were used to train the Random Forest models to classify the entire time series. Collections 3 and 3.1 expanded the period covered to 1985–2017.

Collections 4 and 5 used training samples based on the stable samples from the previous collection and reference maps. Collection 6.0 used stable samples from collection 5.0. Collections 7 and 7.1 (published in 2022) used stable samples from collection 6.0. Collection 8.0 used stable samples from Collection 7.1. Collection 9.0 used stable samples from Collection 8.0. This Collection 10 covered the period from 1985 to 2024 and used stable samples from Collection 9.0, and also stable samples between collections 9.0, 8.0 and 7.1 (Table 1).

Table 1. The evolution of the Pantanal mapping collections in the MapBiomas Project, its periods, hierarchical level and number of classes, brief methodological description, and overall accuracy in level 1 and level 2.

Collection	Period	Levels /N. Classes	Method	Overall Accuracy
Beta & 1	8 years 2008-2015	1 / 7	Empirical Decision Tree	
2.0 & 2.3	16 years 2000-2016	3 / 13	Empirical Decision Tree & Random Forest (2.3)	
3.0 & 3.1	33 years 1985-2017	3 / 19	Random Forest	Level 1: 73.2% Level 3: 62.1% *
4.0 & 4.1	34 years 1985-2018	3 / 19	Random Forest	Level 1: 80.7% Level 3: 71.0% *
5.0	35 years 1985-2019	4 / 21	Random Forest	Level 1: 85.1% Level 3: 78.3% *
6.0	36 years 1985-2020	4 / 24	Random Forest	Level 1: 81.6% Level 2: 73.5%
7.0	37 years 1985-2021	4 / 27	Random Forest	Level 1: 85.9% Level 2: 79.5%
7.1	37 years 1985-2021	4 / 27	Random Forest	Level 1: 85.6% Level 2: 77.3%
8.0	38 years 1985-2022	4 / 29	Random Forest	Level 1: 84.0% Level 2: 77.6%
9.0	39 years 1985-2023	4 / 29	Random Forest	Level 1: 85.4% Level 2: 79.2%
10.0	40 years 1985-2024	4 / 29	Random Forest	Level 1: 87.5% Level 2: 81.3%

* Due to hierarchy changes in the forest classes, level 2 of Collections 6 - 10 are being compared to level 3 of previous collections.

The production of the Collection 10.0 land use and land cover maps in the Pantanal biome followed steps similar to those used in the previous Collections (4 - 9). The use of monthly data for mapping water and flooded areas follows the methodology used in Collection 9.0. However, some improvements were implemented, particularly in the mosaics, a new balance of samples, improvement in the feature space, the annual wetland and water classification based on monthly data, improvement in the post-classification filters and a new class mapped: Rocky Outcrop.

The classification workflow is shown in Figure 2 and each step is described in the following sessions.

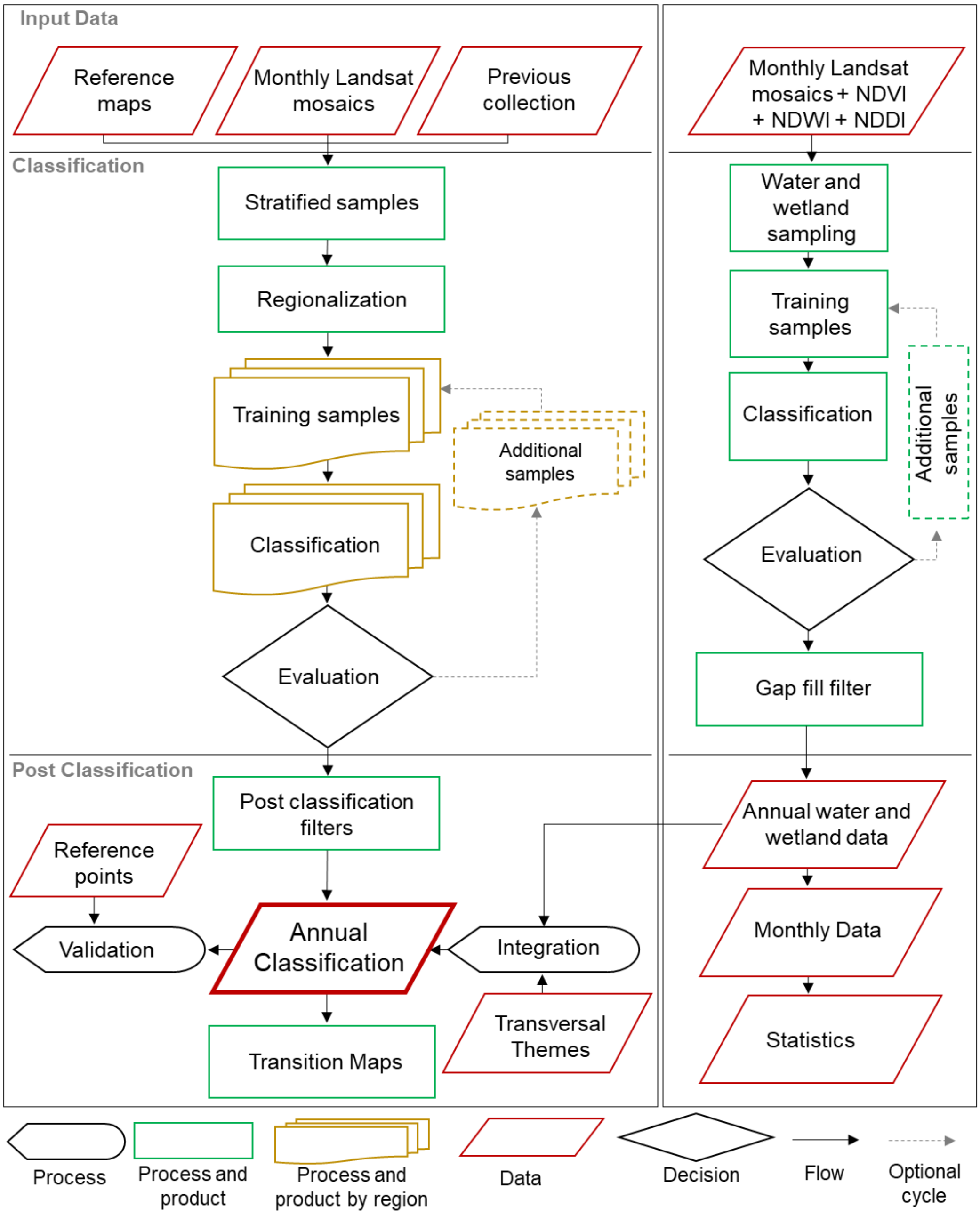


Figure 2: Workflow to generate Collection 10.0 land use and land cover maps for Pantanal biome.

3. Landsat image mosaics

Until Collection 5.0, the classification was performed by using top-of-atmosphere (TOA) data from the Landsat 5 (TM), 7 (ETM+), and 8 (OLI) sensors. In Collection 6.0, we discontinued the use of TOA data and adopted surface reflectance (SR) data. From Collection 7.0 until Collection 9.0, we adopted the 'USGS Landsat Level 2, Collection 2, Tier 1' dataset available on the Google Earth Engine platform, maintaining the use of SR data.

The Landsat mosaics for Collection 10 were generated 'on the fly' from the Landsat series monthly mosaic asset, which is already atmospherically corrected and provides surface reflectance values (specifically, the 'LANDSAT/COMPOSITES/C02/T1_L2_32DAY' asset). Due to these corrections and the use of Deep Learning methods to recover data information, the mosaics have fewer gaps than those used in previous collections. With reduced noise from cloud and shadow removal, it was possible to use all monthly images to generate the annual mosaic.

The mosaic is generated using six original Landsat spectral bands: blue, red, green, NIR, SWIR1, and SWIR2. Afterwards, spectral indexes are calculated and appended as bands to the mosaic. Auxiliary layers, such as slope and entropy, are also added as bands. Using the Landsat image segmentation function (ee.Algorithms.Image.Segmentation.SNIC), clustered bands were generated from the median of several input bands (blue, green, red, NIR, SWIR1, NDFI, and green texture) and were also integrated into the mosaic. All of these bands (184) constitute the candidate feature space used to classify the Pantanal biome.

This process was conducted for each year (1985 - 2024), resulting in the annual Landsat mosaics that were subsequently submitted for classification. Most of the annual mosaics exhibit high quality and coverage rates; however, some years, such as 1985, 1986, and 1992, have lower image availability and thus require a more extensive post-classification procedure.

4. Regionalization

The Pantanal biome was divided into seven regions (Figure 3) based on dry and wet patterns, sub basins and native vegetation distribution presented on different regionalization approaches (Silva & Abdon, 1998; Assine, 2015). The aim of this process was to reduce the confusion and noise classification, improving the sample's balance in regions more homogeneous.

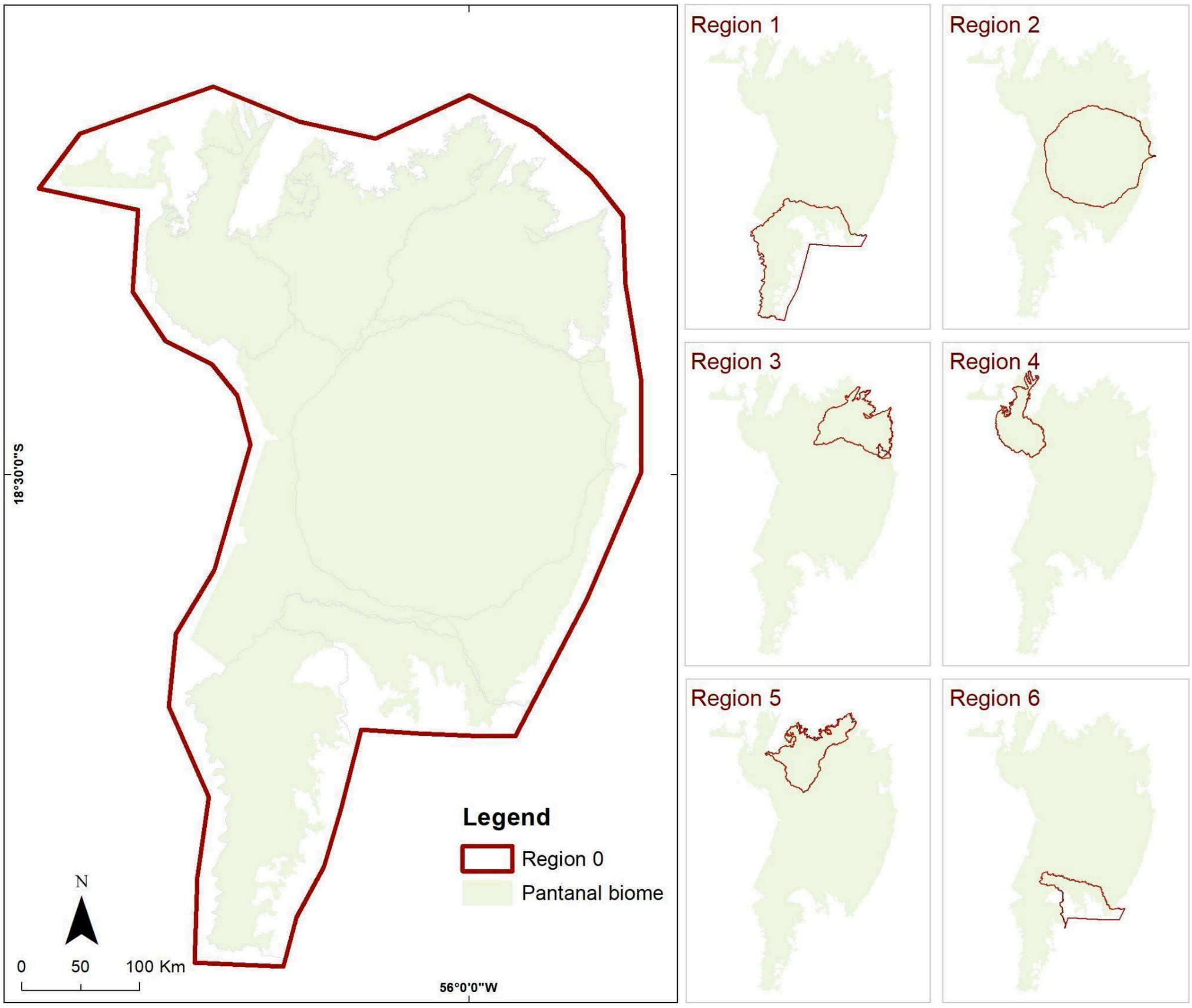
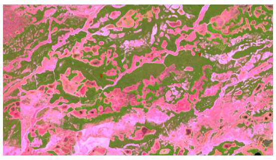
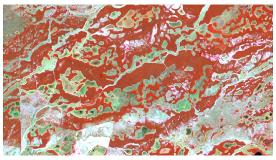
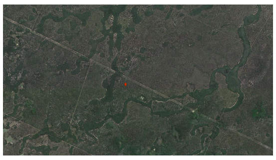
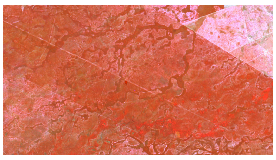
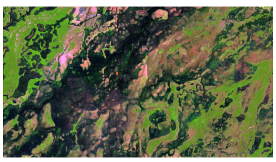
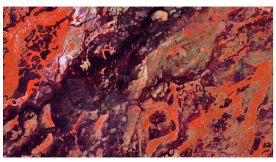
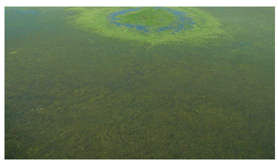


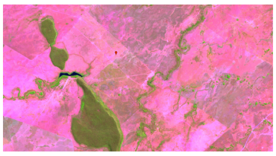
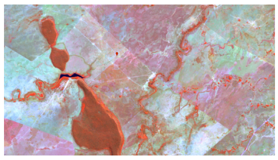
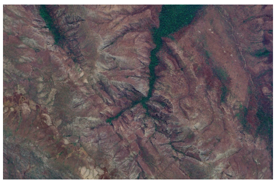
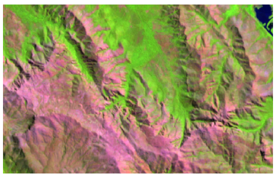
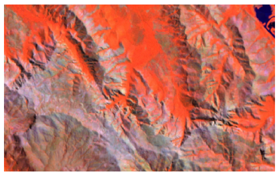
Figure 3: Regionalization used in the classification of the Collection 10 in the Pantanal biome.

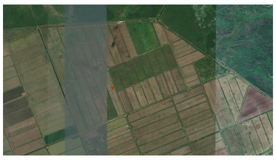
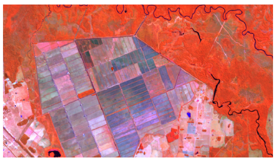
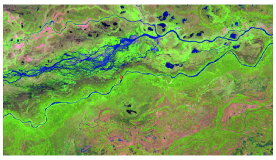
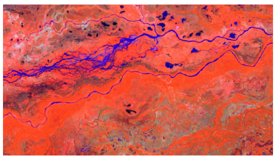
5. Classification

The digital classification of the Landsat mosaics for the Pantanal biome aimed to individualize a subset of 8 classes from the complete legend of MapBiomas Collection 10 (Table 2), which were subsequently integrated with the cross-cutting themes in a further step (see section 7).

Table 2: Classes mapped by the Pantanal biome in the MapBiomas Collection 10.

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.			
2.2. Grassland Formation			
Numeric ID: 12		Color	
Google Earth	Landsat (RGB 654)	Landsat (RGB 564)	Photo
			
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.			
2.4. Rocky Outcrop			
Numeric ID: 29		Color	
Google Earth	Landsat (RGB 654)	Landsat (RGB 564)	Photo
			
Description: Naturally exposed rocks without soil cover, often with the partial presence of rupicolous vegetation and high slope.			
3.1. Pasture			
Numeric ID: 15		Color	
Google Earth	Landsat (RGB 654)	Landsat (RGB 564)	Photo
			
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. This class may occur on recently deforested areas, even without farming activities having started yet.			
3.2.1.5. Other Temporary Crops			

Numeric ID: 41		Color	
Google Earth	Landsat (RGB 654)	Landsat (RGB 564)	Photo
			
Description: Areas occupied with agricultural crops with a long vegetative cycle (more than one year), which allow successive harvests, without the need for new planting.			
5. Water			
Numeric ID: 33		Color	
Google Earth	Landsat (RGB 654)	Landsat (RGB 564)	Photo
			
Description: Rivers, lakes, dams, reservoirs and other water bodies.			

The classes known as Forest, Savanna, Grassland, Pasture, Rocky Outcrop, Other Temporary Crops and Other non-vegetated areas were mapped based on annual Landsat mosaics. On the other hand, the water and wetland classes represent a minimum frequency of two monthly Landsat mosaics classified as these humid classes.

5.1 Stable Samples

The extraction of stable samples from the previous Collection 9.0 followed several steps, aiming to ensure their confidence for use as training areas. The areas that did not change class from 1985 to 2023 in Collection 9.0 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 7.1, 8 and 9 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.

5.2 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 Landsat mosaics for all the 40 years during the polygon drawing. Based on the knowledge of each region, samples of forest, savanna, grassland, agriculture or pasture were added.

5.3 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 clustering 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 relevant bands for each region were selected to compose the feature space subset used in the final classification of each respective region. Table 3 shows the list of the most important bands for the classification of the Pantanal biome.

Table 3. 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 10 (1985-2024).

Type	Name	Formula	Statistics	Reference
Landsat band	Blue	Band 1 (L5 and L7) Band 2 (L8)	median, median_dry, median_wet	USGS
	Green	Band 2 (L5 and L7) Band 3 (L8)	median, median_dry, median_wet, median_texture	USGS
	Red	Band 3 (L5 and L7) Band 4 (L8)	median, median_dry, median_wet	USGS
	NIR	Band 4 (L5 and L7) Band 5 (L8)	median, median_dry, median_wet	USGS
	SWIR 1	Band 5 (L5 and L7) Band 6 (L8)	median, median_dry, median_wet	USGS
	SWIR 2	Band 7 (L5 and L7) Band 8 (L8)	median, median_dry, median_wet	USGS
Spectral Index	Advanced Vegetation Index	$AVI = (NIR \times (1.0 - Red) \times (NIR - Red))^{1/3}$	median, median_dry, median_wet	
	Automated Water Extraction Index	$AWEI = Blue + 2.5 \times Green - 15 \times (NIR + SWIR1) - 0.25 \times SWIR2$	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,	Escadafal, 1989

Type	Name	Formula	Statistics	Reference
			median_wet	
	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
	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
Spectral Index	Normalized Difference Vegetation Index	NDVI = (NIR - Red) / (NIR + Red)	amplitude, median, median_dry, median_wet	Rouse et al., 1974
	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

Type	Name	Formula	Statistics	Reference
	Hall's Forest Height	HFH = −0.039 × RED − 0.011 × NIR − 0.026 × SWIR1 + 4.13	median, median_dry, median_wet	
Terrain	Slope	ALOS DSM: Global 30 m	identity	Tadono et al., 2014
Coords	Latitude and Longitude		Latitude, Longitude	

5.4 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.

5.5 Rocky Outcrop Classification

For the first time, this class has been mapped in the Pantanal biome using Landsat imagery. The mapping of the rocky outcrop was conducted in a parallel process, starting with a specific regionalization of the Serra do Amolar area. This was followed by clustering of the region and a supervised classification using the Random Forest algorithm with manually collected samples. The feature space for this binary classification was composed of the SAVI, EVI, GCVI and BSI indexes.

Considering that the rocky outcrop in this region is a stable area over the time series, a frequency filter was applied to stabilize the raw mapping, which had shown a tendency to vary depending on wetter and drier years. This class can be found on the map with the code 29.

5.6 Water and Wetland Monthly and Annual Classification

We performed a monthly classification to map water and wetland classes, aiming to map the maximum floodplain area each year. To guarantee the monthly classification of the maximum available images, we used monthly mosaics of each satellite and also mosaics composed of data from different satellites, if they were available for the same period (Table 4).

Table 4: Satellites for each period

Satellite	Years
Landsat 5	1985-1999; 2003
Landsat 5 + 7	2000-2002; 2004-2011
Landsat 7	2012
Landsat 8	2013-2021
Landsat 8 + 9	2022-2024

A sampling toolkit was developed to collect water and wetland points on the monthly Landsat mosaics (Figure 4).

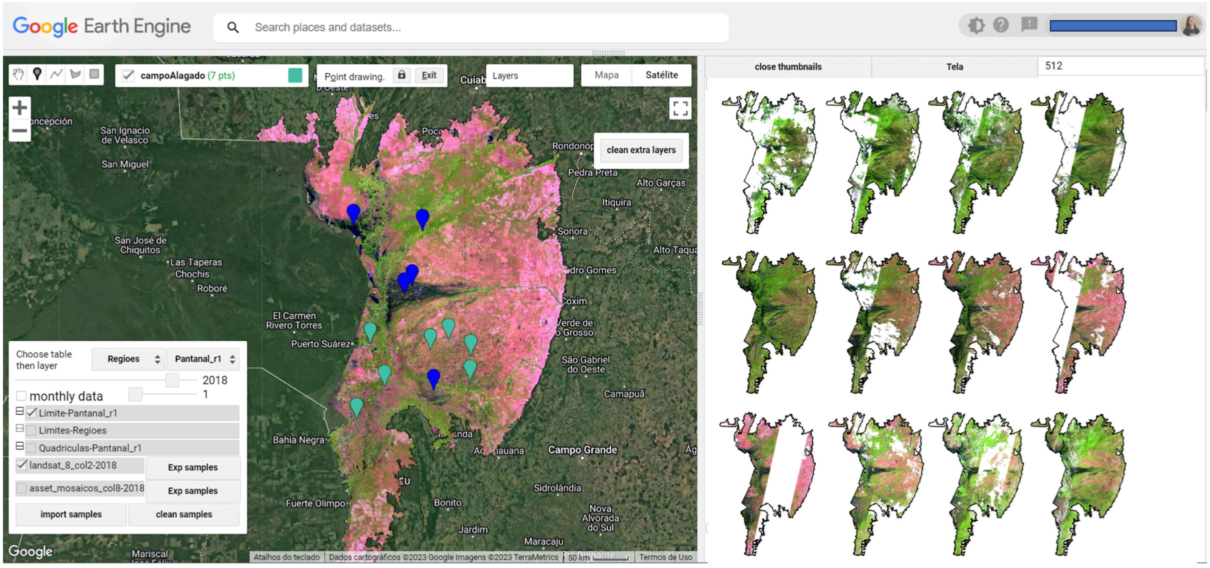


Figure 4: Monthly sampling toolkit.

For classes considered 'non-wet', we raffled points in pixels that had a stable classification over the 39 years of the Collection 9.0. Each sample point was trained by Random Forest and all Landsat bands plus Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Normalized Difference Drought Index (NDDI).

Then, a supervised classification was carried out using the Random Forest (RF) algorithm (Breiman, 2001) to classify each monthly mosaic into three classes: water, wetland and 'non-wet' areas.

The RF classification result was used to mask the 'non-wet' monthly mosaic areas, and then a water-wetland separation threshold was defined for each satellite based on the NDDI value and applied on the 'wet' RF masked area.

Some monthly Landsat mosaics had no data pixels because of a lack of images or the cloud mask filter action. To overcome this challenge, we developed a 'gap fill' filter on the classified data. The filter considered the local precipitation pattern (Figure 5) to fill each no data pixel with the classification of the closest and driest month available. We consider this a conservative strategy to not overestimate the mapping of the Pantanal flooded areas in periods without images, since the wettest months are also those with the highest levels of rainfall and, therefore, the cloudiest.

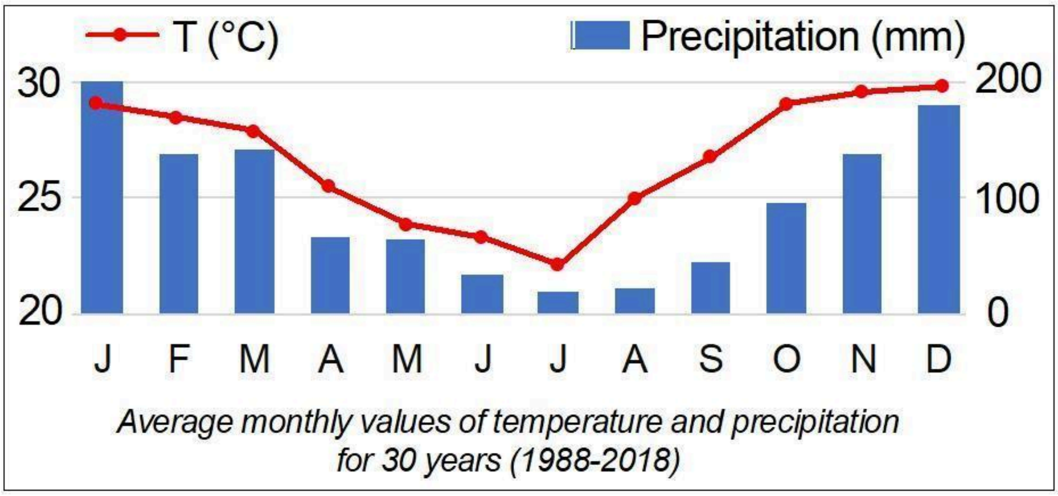


Figure 5: Climograph from 1988 to 2018 with CHIRPS (Climate Hazards Group InfraRed Precipitation with Station) precipitation data and MODIS (Moderate-Resolution Imaging Spectroradiometer) temperature data. (Funk; Peterson; Landsfield, 2015).

With the available monthly water and wetland classifications for each year since 1985, it was possible to generate frequency data. To integrate these into the annual maps for MapBiomas Collection 10.0, we included all pixels classified as either water or wetland in at least two months of a given year. In cases where a pixel was classified as both within the same year, the water class was given precedence over the wetland class.

Furthermore, we incorporated the annual data classified by the MapBiomas Water methodology to supplement the mapped water surface area for each year. This was done because the MapBiomas Water data tends to provide an information gain for both smaller and more stable (permanent) water bodies.

6. Post Classification

6.1 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 exposure during a dry period. To avoid this misclassification, a mask of 'non-pasture' was manually drawn based on historical reference maps (Ci et al., 2009), PRODES data (Assis et al., 2019) and high resolution images, and then applied to exclude pixels misclassified as pasture. For the same purpose, a second 'non-pasture' mask was applied considering flooded pixels (classified monthly as water or wetland) in more than 75% of the entire 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.

6.2 Water and Wetland data integration

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 savanna. This is also a strategy to avoid false positives from humid areas in the shade of the relief, urban areas or roads.

6.3 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.

6.3.1 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.

6.3.2. Transitions Forest Formation x Savanna Formation

A frequency filter was applied only in pixels that are considered forest or savanna formation (classes 3 and 4 in Table 3). If a “stable natural vegetation” pixel is at least 60% of years of the same class and the first and last year are of this class, all years are changed to this class. The result of this frequency filter is a more stable classification of these natural classes (forest and savanna). Another important result is the removal of noises in the first and last year in classification.

6.3.3. Moving window temporal filter

The temporal filter uses the subsequent years to replace pixels that have invalid transitions, and is applied in three steps. The first step looks in a 3-year moving window to correct any value that is changed in the middle year and return to the same class next year. This process is applied in this sequential order [41, 3, 4, 15, 12] (classes listed in Table 3) .

The second step is similar to the first process, but it is a 4-years moving window that corrects all middle years.

In the third step the filter looks at any native vegetation class [12, 3, 4] that is not this class in 1985 and is equal in 86 and 87 and then corrects 85 values to avoid any changes in the first year. In the last process, the filter looks for the pixel value in 2024 that is not [12,15] and is equal to 15 in 2022 and 2023. The value in 2024 is then converted to [12,15] to avoid any false regeneration in the last year.

6.3.4. Regeneration filter

A filter was applied to prevent Forest or Savanna Formations converted to anthropic to regenerate as Natural Grassland Formation. Thus, it eliminated part of the confusion of pasture areas and Grassland Formation. This filter is used to ensure that any area converted to pasture stays as pasture for, at least, seven consecutive years to avoid some confusion in the classification.

Additionally, a forest stabilization filter was implemented in the time series from 1985 to 2024. By using the Stable Forest data, we corrected classification confusion between savanna and wetland areas, overestimating the Forest classification, especially in the early years.

Still,to avoid false regeneration in agriculture areas, we use the data of agriculture in last year and increment year by year the classification since 1985. This filter considers the field knowledge in the Pantanal (in the southern part of subregion 6).

6.3.5. 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 stabilises these two classes.

6.3.6. Spatial filter

A spatial filter was also applied to avoid unwanted modifications to the edges of the pixel groups, using the "connectedPixelCount" function. Native to the GEE platform, this function locates connected pixels (neighbors) with the same value. Thus, only pixels that do not share connections to a predefined number of identical neighbors are considered isolated. In this filter, at least six connected pixels are needed to reach the minimum connection value. Consequently, the minimum mapping unit is directly affected by the spatial filter applied, and it was defined as 6 Landsat pixels (~0,5 ha). This is the final step before integration with cross-cutting themes.

7. 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). They were superimposed on the Pantanal data (Figure 7), resulting in final maps of the biome containing 14 classes (Table 5).

Table 5: Classes observed in the Pantanal biome.

Legend class of Collection 10	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	

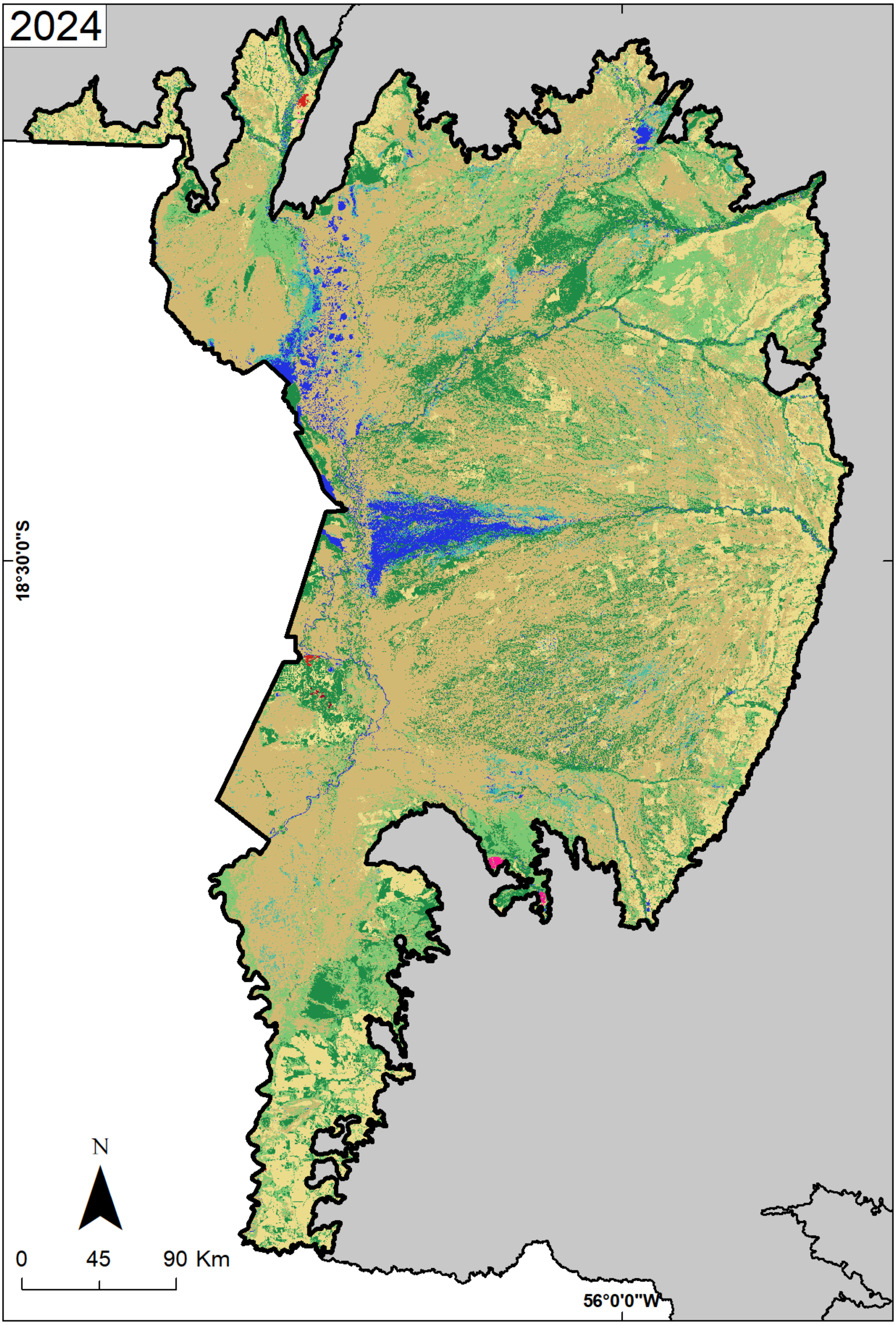


Figure 7: Final land use and land cover map of the Pantanal for the year 2024.

8. Validation

In Collection 10 the overall accuracy reached 87.5% and 81.3% in levels 1 and 2, respectively. Wetland and Water classes were added to the map by the maximum area in each year, but this criterion is different from the validation methodology. To solve that difference, the validation points of grassland or wetland that overlapped on the classified map as water were considered correct.

Considering the Global Accuracy for all collections in legend level 1 (Figure 8), the maps in Collection 10 embody a decade of expertise in mapping land use and land cover within the Pantanal. This is evident in the collection's accuracy and enhanced mapping methodologies. Time-series analysis reveals that Collection 10 is more stable and consistent. Crucially, it has demonstrated superior performance in recent years.

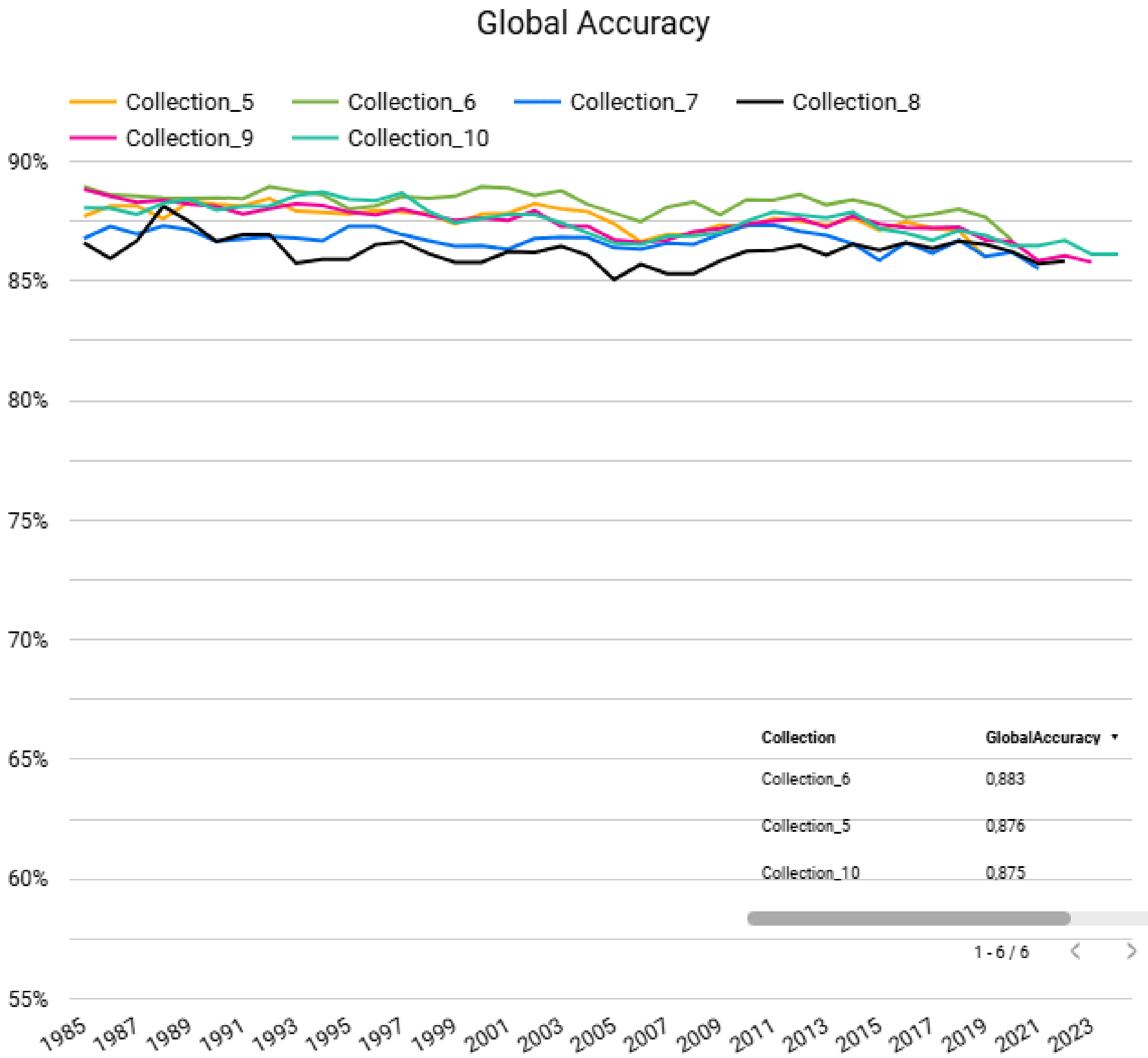


Figure 8. Global accuracy for all collections in Pantanal over the classification period.

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