



MapBiomass General “Handbook”

Algorithm Theoretical Basis Document (ATBD)

Collection 2

Version 1

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1. Executive Summary

MapBiomias initiative was formed in Brazil in 2015 by universities, NGOs, and tech companies to develop a fast, reliable, collaborative, and low-cost method to produce an annual time series of Brazil's land cover and land use maps from 1985 to 2023 at 30 m resolution.

In Paraguay, Guyra Paraguay began collaborating with the MapBiomias network in 2018 through the **MapBiomias Chaco initiative**, contributing to the annual monitoring of land use and land cover dynamics in the Paraguayan Chaco. Through its technical expertise in remote sensing and biodiversity monitoring, Guyra supported the development of consistent time series aligned with MapBiomias methodology, strengthening the representation of the Chaco biome within the regional platform.

In 2019, WWF Paraguay joined the MapBiomias network through the **MapBiomias Atlantic Forest initiative**, contributing to the trinational monitoring of the Atlantic Forest across Argentina, Brazil, and Paraguay. This collaboration focused on understanding land-use change dynamics in the Tri-Border region through annual mapping and a coordinated network of specialists.

The consolidation of these two efforts led to the formal creation of **MapBiomias Paraguay in 2023**, integrating the Atlantic Forest and Chaco initiatives under a unified national platform. WWF Paraguay and Guyra Paraguay assumed joint co-leadership, harmonizing methodologies and strengthening national governance within the global MapBiomias network.

This Algorithm Theoretical Basis Document (ATBD) aims to provide the methodological steps to produce MapBiomias Paraguay Collection 2 and describe the datasets and analysis. All the MapBiomias maps and datasets are freely available on the project platform (<https://paraguay.mapbiomas.org/>), as well as all computational algorithms used in the MapBiomias classifications are available on Github (<https://github.com/mapbiomas>).

2. Introduction

2.1. Scope and content of the document

This document describes the theoretical basis, justification, and methods applied to produce annual maps of land cover and land use (LCLU) in Paraguay from 1985 to 2023 of the MapBiomias Collection 2.

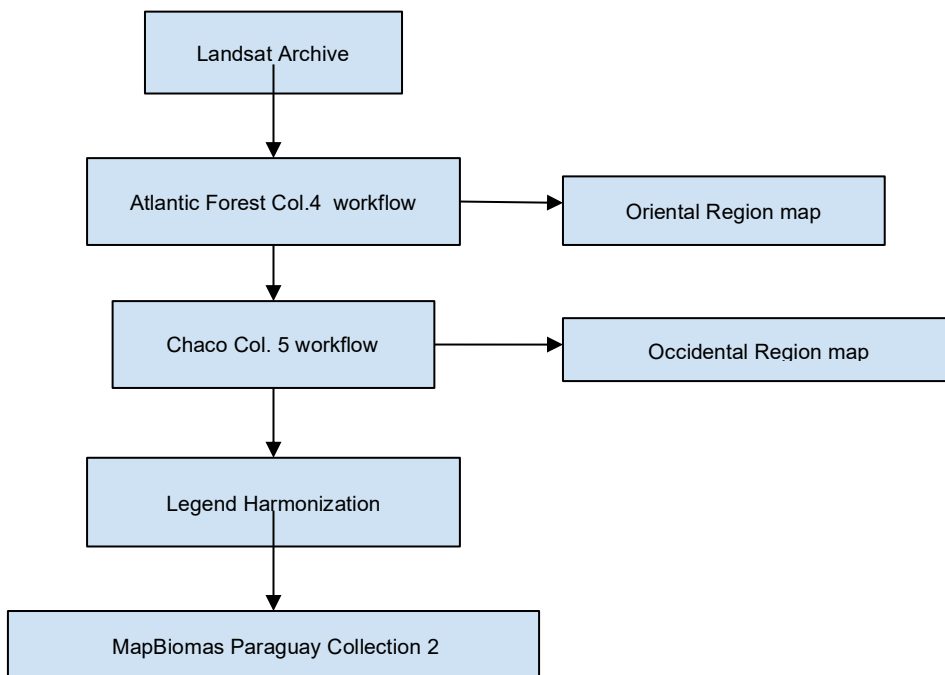
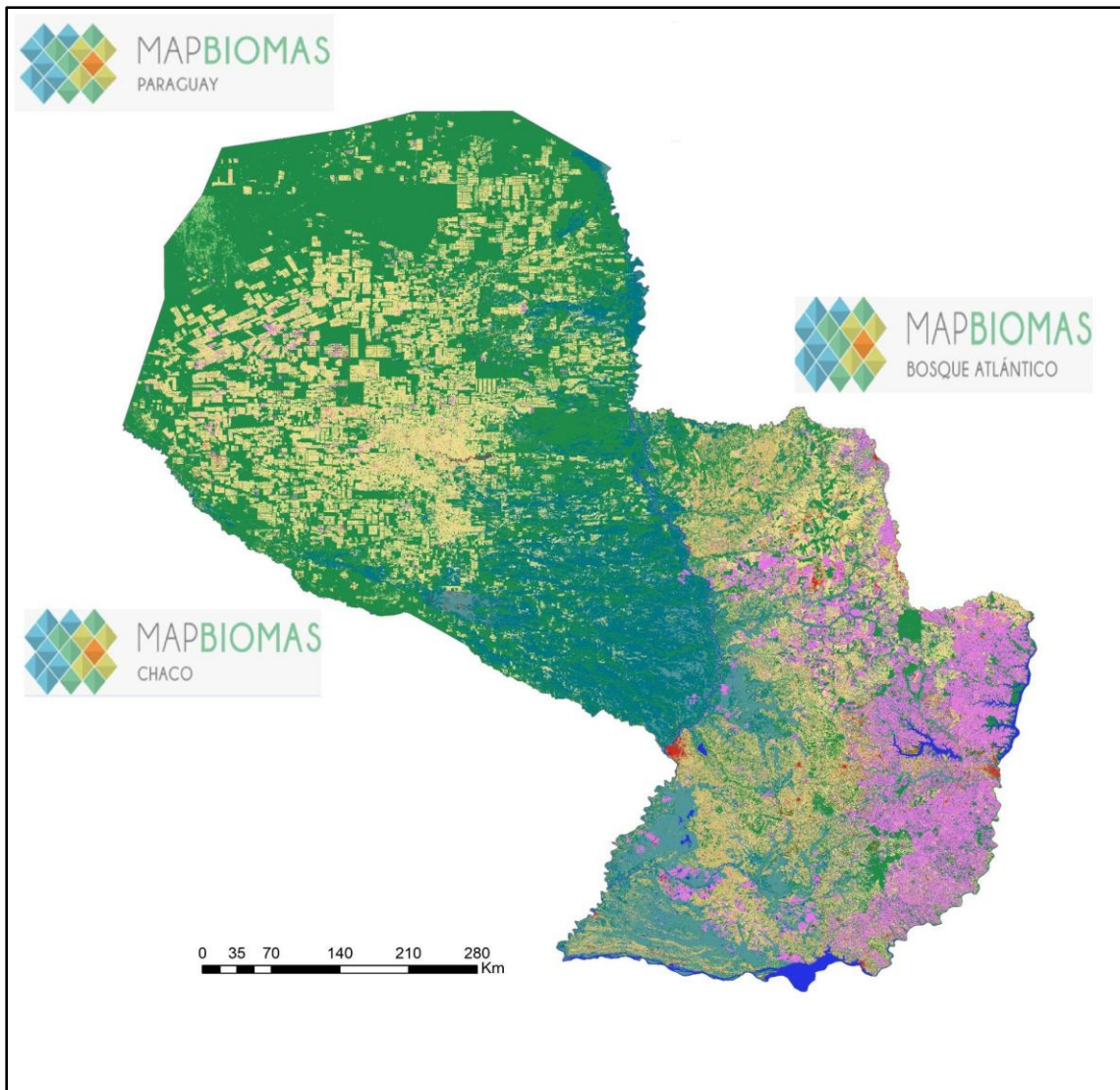
MapBiomias Paraguay is not an independent classification process but rather the integration of biome-specific classifications produced by MapBiomias Atlantic Forest and MapBiomias Chaco. The methodological procedures described in the following sections correspond to those implemented in each biome classification.

This document covers the classification methods of Collection 2, the image processing architecture, and the approach to integrating the biomes. In addition, the document presents a historical context and background information, a general description of the satellite imagery datasets, feature inputs, and the accuracy assessment method applied.

2.2. Region of interest

MapBiomias Paraguay was established to produce annual LULC (Land Use and Land Cover) maps for the entire Paraguayan territory, encompassing the country's two main geographic regions: the Occidental Region and the Oriental Region, which are defined based on vegetation types associated with geomorphological and climatic conditions. This initiative supports the classification of distinct LULC classes and landscape patterns across the country.

MapBiomias Paraguay was developed by integrating the mapping collections of two major biomes: the Gran Chaco and the Atlantic Forest of Alto Paraná.



3. Overview and Background Information

3.1. MapBiomass Network in Paraguay

MapBiomass Paraguay is an initiative of WWF and Guyra Paraguay. These organizations play specific or multiple roles and contribute to the project's overall development. Each biome has a lead organization in Paraguay, as shown in the box below.

Biome
Atlantic Forest – WWF Paraguay
Chaco – Guyra Paraguay

3.1.2. Remote Sensing Data

The imagery dataset used in the MapBiomass project, was obtained by the Landsat sensors Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and the Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS), onboard of Landsat 5, Landsat 7, and Landsat 8, respectively. The Landsat imagery collections with 30 meters pixel resolution were accessible via Google Earth Engine and produced by NASA and USGS.

In earlier collections, MapBiomass primarily utilized USGS Collection 1 Tier 1 from the top of the atmosphere reflectance (TOA). Then new Landsat mosaics were processed using surface reflectance (SR) data. However, this collection uses the USGS Landsat Collection 2 (Tier 1).

3.1.3. Google Earth Engine and MapBiomass Computer Applications

MapBiomass image processing is based on Google technology, which includes image processing in cloud computing infrastructure, programming with Javascript and Python via Google Earth Engine, and data storage using Google Cloud Storage.

The MapBiomass project has developed the following computer applications based on Google Earth Engine:

- **Javascript scripts** - these computer codes were written directly in the Google Earth Engine Code Editor and were used to prototype new image processing algorithms and test large-scale image processing. Most image classification and post-classification of Collections 1 and 2 were written in Javascript.
- **Python scripts** – This code category was used to optimize the image processing of large datasets in Google Earth Engine. In addition, the map integration, some post-classification tasks, and statistical analysis were all performed in Earth Engine Python API.

- **Toolkits** – User’s Toolkits are collections of scripts with a friendly user interface in Google Earth Engine to download MapBiomias data by state, biome, municipality, or any other geometry. These toolkits were developed for the general public that is not familiar with programming languages used in Google Earth Engine. They are often reviewed and improved. The toolkits for MapBiomias Paraguay are available at <https://paraguay.mapbiomas.org/herramientas/>.
- **Github repository** - All Javascript, Python, R, toolkit, and dashboard codes are available at the public GitHub repository: (<https://github.com/mapbioma>).
- **Mapbiomas.org (Dashboard)**. The web platform of the MapBiomias initiative presents the Landsat image mosaics and their quality, land cover and land use annual maps of Collection 8, transitions analysis, statistics, and all the methodological information about the ATBD, tools, scripts, fact sheets, tutorial videos, and accuracy analysis.

3.2. Historical Perspective: Existent Mapping Initiatives

Systematic monitoring of land use and land cover (LULC) dynamics in Paraguay has evolved substantially over the past three decades, transitioning from isolated regional assessments to nationally coordinated monitoring systems and, more recently, to globally harmonized datasets.

Early initiatives focused primarily on forest cover change detection in the Atlantic Forest and Chaco regions using Landsat imagery (Huang et al., 2006; Huang et al., 2008). These studies laid the methodological foundation for later national and global-scale monitoring efforts. The expansion of cloud-computing platforms, increased data availability, and advances in machine learning have further enabled the development of higher-resolution, near-real-time and globally consistent LULC products.

3.2.1. Global Land Cover and Land Use Data

Among the most influential global datasets used in Paraguay is the Global Forest Change dataset (Hansen et al., 2013), derived from Landsat time series analysis to quantify annual forest loss and gain at 30 m resolution. This dataset has been widely used to characterize deforestation dynamics in both the Atlantic Forest and the Gran Chaco regions.

Earlier Landsat-based assessments of Paraguay’s forest cover change include the work of Huang et al. (2006, 2008), which documented rapid forest loss in the Atlantic Forest and evaluated protected area effectiveness. These studies demonstrated the feasibility of multi-temporal Landsat analysis for national-scale forest monitoring.

In recent years, global LULC datasets have diversified considerably:

- **Dynamic World** (Brown et al., 2022) provides near-real-time (NRT) global LULC classifications derived from Sentinel-2 imagery at 10 m resolution, including per-pixel class probabilities.

- **ESRI 10 m Annual Land Use Land Cover** (Karra et al., 2021) delivers annual global maps (2017–present) based on Sentinel-2 imagery and deep learning models.
- **ESA GlobCover** (Arino et al., 2012) and **ESA WorldCover 10 m 2020** (Zanaga et al., 2021) offer globally consistent land cover products at medium to high resolution.

While global datasets provide spatial consistency and frequent updates, they often present limitations in local thematic accuracy due to generalized legends, limited regional training data, and ecological heterogeneity. In highly dynamic frontiers such as the Paraguayan Chaco, regionally calibrated models frequently outperform global products in class discrimination and thematic detail.

MapBiomass Paraguay addresses this gap by combining global methodological advances with region-specific training data and expert validation

3.2.2. National Land Cover and Land Use Data

At the national level, Paraguay has developed several LULC mapping initiatives over time, primarily focused on forest monitoring, deforestation tracking, and REDD+ reporting.

One of the earliest comprehensive efforts was the Vegetation and Land Use Map of the Western Region (CIF/FIA/UNA/GTZ, 1991), derived from Landsat imagery for 1986–1987. Subsequent work by the SACH/SERMA-DOA/BGR Project (1998) produced a vegetation map of the Paraguayan Chaco at 1:250,000 scale based on Landsat TM imagery.

The Global Land Cover Facility (GLCF) produced forest cover change maps for 1985–2001 using Landsat TM and ETM+ imagery, in collaboration with Guyra Paraguay and the University of Maryland (GLCF, 2009).

Within the REDD+ framework, the Joint National Programme on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD+, 2016) generated historical deforestation maps (2000, 2005, 2011, 2015) based on supervised classification of Landsat imagery, distinguishing forest and non-forest categories.

Similarly, the National Forestry Institute (INFONA) has produced annual Land Use Change maps since 2016, supporting official forest monitoring and emissions reference levels.

Additional relevant national or regional products include:

- FCA/CIF/FFPRI (2013): National Land Cover Map (2011) based on Landsat 5 TM (minimum mapping unit: 100 ha).
- Caldas et al. (2013): Annual land-cover change maps in the Paraguayan Chaco (2000–2011) derived from MODIS Terra imagery (250 m resolution).
- Guyra Paraguay (2019): Monthly deforestation monitoring in the Gran Chaco Americano (2010–2018) using Landsat time series.

- DLR/INFONA/WWF (2018): Land use and cover map of the Paraguayan Chaco (2016) using Landsat 8 OLI.

Despite these advances, most national products were either limited temporally, restricted geographically (e.g., Chaco only), binary (forest/non-forest), or produced at coarse spatial resolution. Furthermore, methodological heterogeneity has historically hindered long-term harmonized time-series analysis.

MapBiomias Paraguay overcomes these limitations by:

1. Providing annual wall-to-wall national coverage (1985–2022);
2. Applying a standardized hierarchical legend;
3. Using consistent Landsat surface reflectance imagery;
4. Ensuring temporal consistency through post-classification filters;
5. Maintaining full transparency of algorithms and open data access.

In this context, MapBiomias Paraguay represents the first nationally integrated, open-access, high-resolution historical LULC time series for the country, aligning Paraguay with international best practices in land monitoring systems.

4. Methodological Description

MapBiomias Paraguay does not implement an independent methodological pipeline. Instead, the national product results from the **integration of two biome-level classifications produced within the MapBiomias Network**:

- **MapBiomias Atlantic Forest Trinational Col.4** – covering the Oriental Region of Paraguay.
- **MapBiomias Chaco Col. 5** – covering the Occidental Region of Paraguay.

Each biome classification follows its own methodological workflow developed within the MapBiomias network and documented in their respective ATBDs. The MapBiomias Paraguay Collection 2 dataset is therefore produced by **integrating these two biome-level classifications into a harmonized national map**, using the standardized MapBiomias legend.

The methodological descriptions below summarize the approaches used in each biome.

4.1 Methodology for the Atlantic Forest Territory (Oriental Region)

The classification of the Oriental Region of Paraguay follows the methodology of **MapBiomias Atlantic Forest Trinational Collection 4**, which produces annual land use and

land cover maps for the Atlantic Forest region of Argentina and Paraguay using Landsat imagery and the MapBiomas processing framework.

Remote sensing data

The classification is based on Landsat satellite imagery from the following sensors:

- Landsat 5 TM (1985–1999 and 2003–2011)
- Landsat 7 ETM+ (2000–2002 and 2012)
- Landsat 8 OLI (2013–2023)

All imagery corresponds to **USGS Landsat Tier 1 surface reflectance products**, available in Google Earth Engine.

Annual mosaics were generated using images distributed throughout the year, applying cloud and shadow masking using the **QA band** and selecting representative pixels through a **median compositing approach**.

Subregional classification approach

To reduce spectral confusion and improve classification accuracy, the Atlantic Forest region was divided into **seven homogeneous subregions**, four of which correspond to Paraguay.

Each subregion was classified independently, allowing training samples and classification parameters to be adjusted according to local ecological conditions.

Feature space

The classification uses a feature space derived from Landsat spectral information, including:

- Spectral bands
- Vegetation indices
- Spectral mixture fractions
- Texture metrics

A subset of **37 selected variables** from the full feature space was used as input to the classifier, selected according to their ability to discriminate land cover classes.

Temporal statistical reducers were applied to generate annual features such as:

- median reflectance
- median_dry
- median_wet
- amplitude
- standard deviation
- minimum values

These features capture seasonal variability and phenological behavior of vegetation.

Training samples and classification

Training samples were generated through a multi-step procedure:

1. **Manual delineation of temporally stable polygons** based on visual interpretation of Landsat time series.
2. **Generation of stable samples** from preliminary classifications.
3. **Balancing of sample numbers** based on class proportions within each subregion.
4. **Collection of complementary samples** to correct classification errors.

Random Forest classification was then applied **year-by-year for each subregion**, using **100 decision trees** implemented within Google Earth Engine.

Post-classification filtering

After classification, the following filters were applied:

- spatial filters to remove isolated pixels
- temporal filters to ensure interannual consistency
- gap filters to fill missing observations

Finally, subregional classifications were integrated using **prevalence rules**, generating the final annual maps.

4.2 Methodology for the Chaco Territory (Occidental Region)

The classification of the Paraguayan Chaco follows the methodology of **MapBiomass Chaco Collection 5**, which produces annual land use and land cover maps for the Gran Chaco Americano region using Landsat imagery and a zonal classification framework.

Remote sensing data

The classification is based on Landsat imagery from:

- Landsat 5
- Landsat 7
- Landsat 8

All imagery corresponds to **Landsat Collection 2 Tier 1 Level-2 surface reflectance data**, accessed through Google Earth Engine.

Annual mosaics were generated by stacking all available scenes within the calendar year and applying cloud masking using the **QA band**.

Synthetic Landsat scenes

To reduce missing observations due to cloud cover or limited image availability, **synthetic Landsat scenes were generated using cubic interpolation** based on cloud-free observations from the target year and the following two years.

This process generates:

- 23 synthetic scenes per year
- temporal resolution of approximately 16 days

The interpolation allows reconstruction of spectral time series where observations are limited.

Feature space

The classification uses a feature space derived from spectral, temporal and structural variables, including:

- spectral bands
- vegetation indices
- spectral mixture fractions
- temporal statistics
- slope and terrain variables

These features describe both the spectral characteristics and phenological dynamics of land cover classes.

Zonation

To improve classification accuracy across heterogeneous landscapes, the Gran Chaco region was divided into **23 ecological zones**, defined using biophysical variables and ecoregion boundaries.

Each zone was classified independently using training samples representative of local land cover conditions.

Training samples

Training samples were derived from **stable pixels identified in previous MapBiomias Chaco collections**, defined as pixels that remained in the same class across the time series.

A **stratified random sampling approach** was used to generate training samples for each class and zone.

Sample balancing procedures were applied to reduce class imbalance in the Random Forest classifier.

Iterative classification

The classification process is iterative and includes:

1. preliminary classification using stable samples
2. identification of classification errors in hotspot areas
3. addition of complementary samples
4. reclassification using expanded training datasets

This iterative process continues until classification stability is achieved.

Post-classification filters

Several filters are applied to improve temporal consistency and remove noise:

- gap filters
- spatial filters
- temporal filters
- frequency and incidence filters

These filters correct spurious class transitions and reduce classification noise.

4.3 Landsat Mosaics

Landsat cloud-free composites were generated based on specific periods of time to optimize the spectral contrast and help within the discrimination of LCLU classes. The cloud/shadow removal script takes advantage of the quality assessment (QA) band and the GEE median reducer. The QA values can improve data integrity by indicating which pixels might be affected by artifacts or subject to cloud contamination (USGS, 2017). In conjunction, GEE can be instructed to pick the median pixel value in a stack of images. By doing so, the engine rejects values that are too bright (e.g., clouds) or too dark (e.g., shadows) and picks the median pixel value in each band over time.

In Collection 7 and 8, new USGS Landsat surface reflectance images (Collection 2, Tier 1) were used in the classification. For each chart, a specific temporal mosaic of Landsat images was built based on the following selection criteria/parameters: 1. The selected Landsat data must enable an annual analysis, and 2. The period for Landsat scene selection (t0 and t1 in day/month/year) must provide enough spectral contrast to distinguish LCLU classes better.

4.4 MapBiomass feature space

The feature space for LCLU classification is composed of 90 input variables per year, including the original Landsat bands and fractional and textural information derived from those bands (Table 2). Table 2 presents the formula or the description to obtain these variables, as well as highlights in green all the bands, indices, and fractions available in the feature space. In addition, statistical reducers were used to generate temporal features such as:

- Median: median of the pixel values within the defined stack of images
- Median_dry: median of the quartile of the lowest pixel NDVI values
- Median_wet: median of the quartile of the highest pixel NDVI values

- Amplitude: amplitude of variation of the index considering all the year's images
- stdDev: stdDev of the pixel values within the defined stack of images
- Min: the lower annual value of the pixels of each band

Table 1. List, description, and reference of bands, fractions and indices available in the feature space.

	band or index name	formula	Reducer					
			median	median_dry	median_wet	amplitude	stdDev	min
bands	blue	B1 (L5 e L7); B2 (L8)						
	green	B2 (L5 e L7); B3 (L8)						
	red	B3 (L5 e L7); B4 (L8)						
	nir	B4 (L5 e L7); B5 (L8)						
	swir1	B5 (L5 e L7); B6 (L8)						
	swir2	B7 (L5); B8 (L7); B7 (L8)						
	temp	B6 (L5 e L7); B10 (L8)						
index	ndvi	$(nir - red)/(nir + red)$						
	evi2	$(2.5 * (nir - red)/(nir + 2.4 * red + 1))$						
	cai	$(swir2 / swir1)$						
	ndwi	$(nir - swir1)/(nir + swir1)$						
	gcvi	$(nir / green - 1)$						
	hall_cover	$(-red * 0.017 - nir * 0.007 - swir2 * 0.079 + 5.22)$						
	pri	$(blue - green)/(blue + green)$						
	savi	$(1 + L) * (nir - red)/(nir + red + 0,5)$						
	textG	<code>('median_green').entropy(ee.Kernel.square({radius: 5}))</code>						
gv		fractional abundance of green vegetation within the pixel						
		fractional abundance of non-photosynthetic						

fraction	npv	vegetation within the pixel						
	soil	fractional abundance of soil within the pixel						
	cloud	fractional abundance of cloud within the pixel						

Each biome executed a feature selection algorithm to choose the most appropriate subset of variables to train the respective random forest classifier.

4.5 Classification

The MapBiomias classification scheme is a hierarchical system comprising four categorical levels (Table 2). At Level 1, there are six classes: 1) Woody Natural Vegetation, 2) Herbaceous Natural Vegetation, 3) Agricultural Areas, 4) Non-Vegetated Area, 5) Water, and 6) Not Observed. Level 2 has 8 classes across the six classes of the first categorical level.

Table 2. Agreement of classes between Mapbiomas Chaco and Atlantic Forest

Atlantic Forest			Chaco			Paraguay Col. 2 Legend	
Level 1	Level 2	Level 3	Class Level 1	Class Level 2	Level 3	Agreement Level 1	Agreement Level 2
Forest	Forest Formation		Natural wooded vegetation	Closed woodland		Woody Natural Vegetation	Closed Natural Woodlands
				Open woodland			Open Natural Woodlands
				Flooded woodland			Flooded Natural Woodlands
Non Forest Natural Formation	Grassland		Natural non-wooded vegetation	Grassland	Open grassland	Herbaceous Natural Vegetation	Grassland
					Sparse grassland		
Non Forest Natural Formation	Flooded grasslands				Flooded grassland		Flooded grasslands
Farming	Pasture		Agricultural Areas	Pasture		Agricultural Areas	Pasture
	Agriculture	Annual Crops		Agriculture - Annual crops	Single crop		Agriculture
		Perennial Crop - Tea			Multiple crop		
		Other Perennial Crops			Shrub Plantations		
	Forest Plantation		Tree Plantations		Forest Plantation		
Non vegetated area			Non-vegetated Areas	Beach, Dune and Sand Spot		Non vegetated area	
				Urban Area			
				Other Non-vegetated Areas			
				Salt Flat			
Water	River, Lake and Ocean		Water bodies			Water bodies	
Not observed			Not observed			Not observed	

4.5.1 Integration

In the first instance, the classes of both initiatives were recategorized in order to reach a level of common categories. After the recategorization of classes between the two collections, some adjustments were made in some specific areas:

Cerrado: in this area, the classification of the Mapbiomas Chaco collection was prioritized, but in the areas with forest and grassland categories that overlap with areas with the savanna category of Mapbiomas Atlantic Forest, they were recategorized to the savanna class.

Overlap: in the areas of overlap between collections, the classification of Mapbiomas Chaco was prioritized, but in the areas with grassland categories that overlap with areas with the wetlands category of Mapbiomas Atlantic Forest, they were recategorized to the grassland class. This is because it was known that there was a certain overestimation of wetlands in Mapbiomas Atlantic Forest.

4.5.2 Temporal filter

Some temporal filters were applied to ensure the consistency of the time series. In this case, if a pixel was classified with the pasture category in 1985 and 2023, it cannot have the pasture category in any intermediate period.

Likewise, in order to correct an overestimation of crops in pasture areas of Chaco in the last year, a rule was applied in which pasture areas in 2019 and 2020 that were classified as crops in 2022 were recategorized to pastures.

4.5.3 Frequency filter

This filter considers the frequency with which a LCLU class occurs throughout the entire time series. Thus, all natural class occurrences with less than a given percentage of temporal persistence (e.g., three or fewer years out of 38) are filtered out. This mechanism reduces the temporal oscillation associated with a given natural class, decreasing the number of false positives and preserving consolidated trajectories.

4.5.4 Spatial filter

A spatial filter that removes isolated pixels was built based on the “connectedPixelCount” function to avoid unwanted modifications to the edges of the pixel groups. This function in GEE connects components (neighbors) that share the same pixel value. A pixel that does not share connections to at least four identical neighbors is considered isolated and its value is replaced with the mode value of the surrounding. This also means that this spatial filter affects the minimum mapping unit, defined as five pixels (~0.5 ha).

5. Map Collections and Analysis

This is the second Mapbiomas Collection produced for the whole country, it comprised the period of 1985 to 2023 and was based on random forest classifications for the biomes Chaco and Atlantic Forest.

Transition analysis

LULC change transition analysis (with spatial filter application) statistics, and spatial analysis with political, watershed, protected areas, and other categorical maps, were generated to understand LULC within these boundaries.

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