Coastal Zone – Appendix

MapBiomas 10m - Collection 4

Version 1

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1 Overview

The Brazilian coastal zone presents diverse environments that evolved during the Quaternary in response to climate and sea-level changes. These environments show an interaction between different sediment supplies and a geologic heritage that dates back to the breakup of South America and Africa (Dominguez, 2009; Souza-Filho et al., 2023). Among this diversity of coastal features, five classes are mapped in the MapBiomas 10m Collection 4: Mangroves, Beaches, Dunes and Sand Spots, Aquaculture, Hypersaline Tidal Flats, and Shallow Coral Reefs.

Table 1 shows the evolution of coastal features mapped in each collection and the changes in its methodological aspects.

Table 1 - Overview of the Coastal MapBiomas Collections since their first version. In the method column, 'RF' refers to 'Random Forest,' and U-Net refers to a CNN-based Deep-Learning method.

Collection	Range	Method	Classes	Improvements
1.0	2016-2022	RF and U-Net	Mangroves, Beaches & Dunes, Hypersaline tidal flats and Aquaculture	- First collection
2.0	2016-2023	RF and U-Net	Same as previous collections	- Methodology consolidation
3.0	2016-2024	RF and U-Net	Mangroves, Beaches & Dunes, Hypersaline tidal flats, Aquaculture and Shallow coral Reefs	- New samples for BDS and Mangroves. - Addition of Shallow coral reefs - extent, benthic and geomorphic mapping - Nationwide aquaculture mapping - 3rd gen U-Net for Apicum
4.0	2016-2025	RF and U-Net	Same as previous collections	- Epoch testing (30, 40, 60) with mode, max, and standardization

Compared to Collection 2, Collection 3 of the coastal zone mapping presents a new class of coastal features, the Shallow Coral Reefs, here defined as "an underwater ecosystem characterized by reef-building corals, formed of colonies of coral polyps held together by calcium carbonate" (Ferreira and Maida, 2006). Most coral reefs are built from stony corals, whose polyps cluster in groups. However, small methodological changes were made. Furthermore, in this collection there is the preliminar mapping of benthic and geomorphic features of coral reefs.

In the current collection, two machine learning techniques were used: Random Forest was the bese for Mangrove, Beach, Dunes and Sand Spots, Shallow Coral Reefs, and Aquaculture and Hypersaline Tidal Flat are U-net derived. In Collection 4, the “Apicum”/Hypersaline Tidal Flat theme gained its third generation of the U-Net learning model, which helped reduce its area oscillation and commission and omission errors. For both Apicum and Aquaculture, new tests were carried out implementing a new morphological post-processing filter. Additionally, experiments evaluating mode, maximum (max), and standardization were conducted across three deep learning training epochs: 30, 40, and 60.

In addition, Aquaculture has been mapped throughout the whole country, not only on the Coastal Zone, and Beaches, Dunes and Sand Spots has been resampled, aiming to fix some issues the class had with the limits used in the integration process in the previous collections, which cropped parts of it.

Mangroves also had an extra filter in this collection: a morphological filter for closing small holes in mangrove areas.

The classification/segmentation, validation, and publication workflow is described in Figure 1. The code repository can be accessed:

- Aquaculture: https://github.com/mapbiomas/brazil-aquaculture
- Coastal Zone: https://github.com/mapbiomas/brazil-coastal-zone

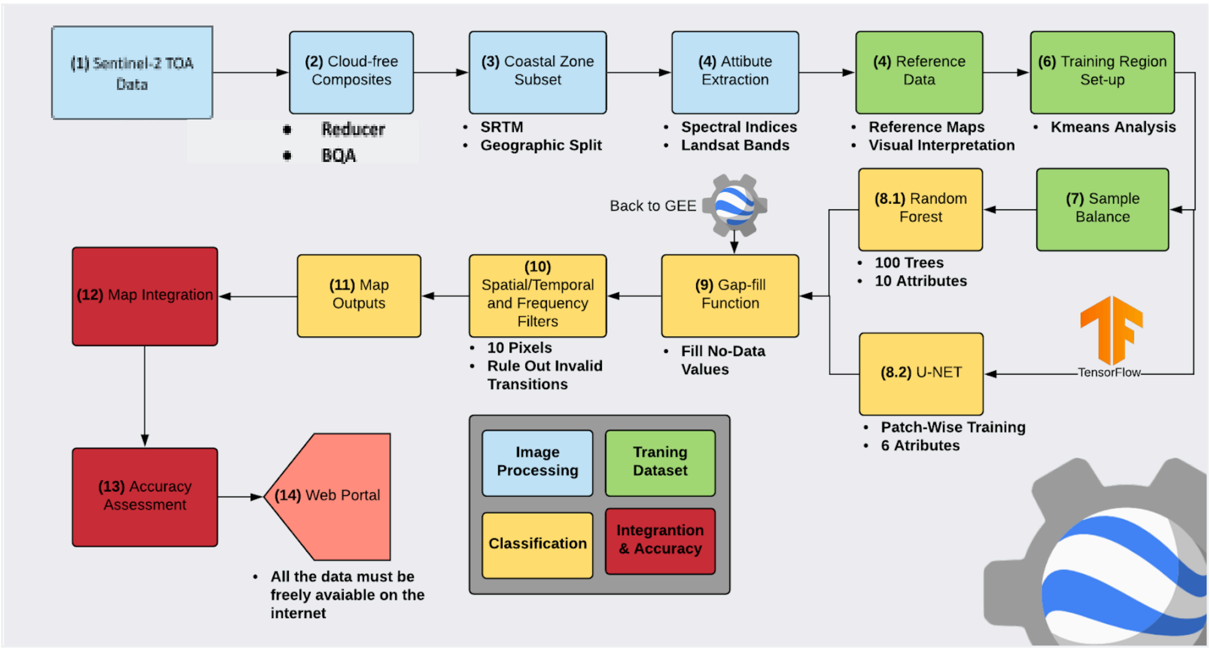

Figure 1 - Workflow of Coastal Zone mapping, validation, and publication. All data processing occurs within the Google Earth Engine - GEE platform, except for the aquaculture/saline pattern and hypersaline tidal flats segmentation, dependent on the TensorFlow library. In green are steps related to sampling design. In yellow are steps related to classification. The mapping accuracy evaluation stage is in red. **(1)** Range from 2016 to 2025.

1.1 Document Scope and Purpose

This document serves as an Appendix to the MapBiomas General Algorithm Theoretical Basis Document (ATBD), 10 Meters, Collection 4. Its primary purpose is to detail the specific methodology, dataset requirements, classification strategies, and post-processing protocols applied to map the coastal features across Brazil for Collection 4 of the 10m product (2016–2025).

While the MapBiomas General ATBD outlines the overarching technical framework, platform infrastructure, and general principles shared across all biomes, this Appendix addresses the specialized workflows unique to the Brazilian Coastal Zone (BCZ) and national cross-cutting coastal themes. Specifically, this document covers:

2 Target Classes: Mangroves; Hypersaline Tidal Flats (Apicuns); Beaches, Dunes, and Sand Spots; Aquaculture; and Shallow Coral Reefs.

3 Tailored Composites: Selection, pre-processing, and sectoral division (7 coastal sectors plus continental expansion for aquaculture) of annual cloud-free Landsat mosaics, designed to minimize atmospheric nebulosity in coastal regions.

4 Detection Framework: Binary classification methodologies combining Random Forest algorithms (for Mangroves, Beaches, Dunes & Sand Spots and Shallow Coral Reefs) and Deep-Learning U-Net architectures (for Aquaculture and Hypersaline Tidal Flats).

5 Post-Processing & Integration: Custom gap-filling, temporal and spatial filters tailored to coastal dynamics, alongside the hierarchical integration rules used to combine coastal mapping outputs with the general biome classifications.

For general information regarding the overarching MapBiomas mapping strategy, cloud computing architecture (Google Earth Engine), or validation procedures common across all themes, please refer to the MapBiomas General ATBD.

6 Sentinel image mosaics

The cross-cutting theme “Coastal Zone” classification used Sentinel-2 mosaics that differed from those used to classify the natural vegetation of the Brazilian biomes. The coastal mosaics were defined to preserve the maximum of the coastal zone land area while capturing the minor possible cloud cover. These mosaics are the second generation of the methodology developed specifically for these cross-cutting themes.

6.1 Definition of the temporal period

Coastal areas are severely affected by atmospheric nebulosity, intensified by their proximity to the oceans and tropical locations. On the other hand, the attempt to identify a time interval that covers only the driest season of the year as an alternative to reduce cloud persistence severely reduces the number of images available to cover the entire coastal region. Thus, the annual cloud-free composites are generated, ranging from the 1st of January to the 31st of December.

6.2 Mosaic Subsets

Since the Brazilian coastal zone (BCZ) is an extensive region, approximately 8,500 kilometers from Oiapoque to Chui (not taking reentrances into account), and affected by various atmospheric systems with lesser or greater nebulosity influence, the BCZ is divided into seven different sectors: Amapá (AP), Marajó Island (MAR), Pará/Maranhão (PAMA), Piauí/Bahia (PIBA), Espírito Santo/São Paulo (ESSP), Paraná/Laguna (PRLA), and Laguna/Rio Grande do Sul (LARS) (Figure 2, LEFT).

In contrast, to accommodate the nationwide mapping of aquaculture and salt-culture, an extended continental grid system was incorporated (Figure 2, RIGHT), covering both the coastal sectors and all inland Brazilian hydrographic basins based on the search areas defined by São José et al. (2022).

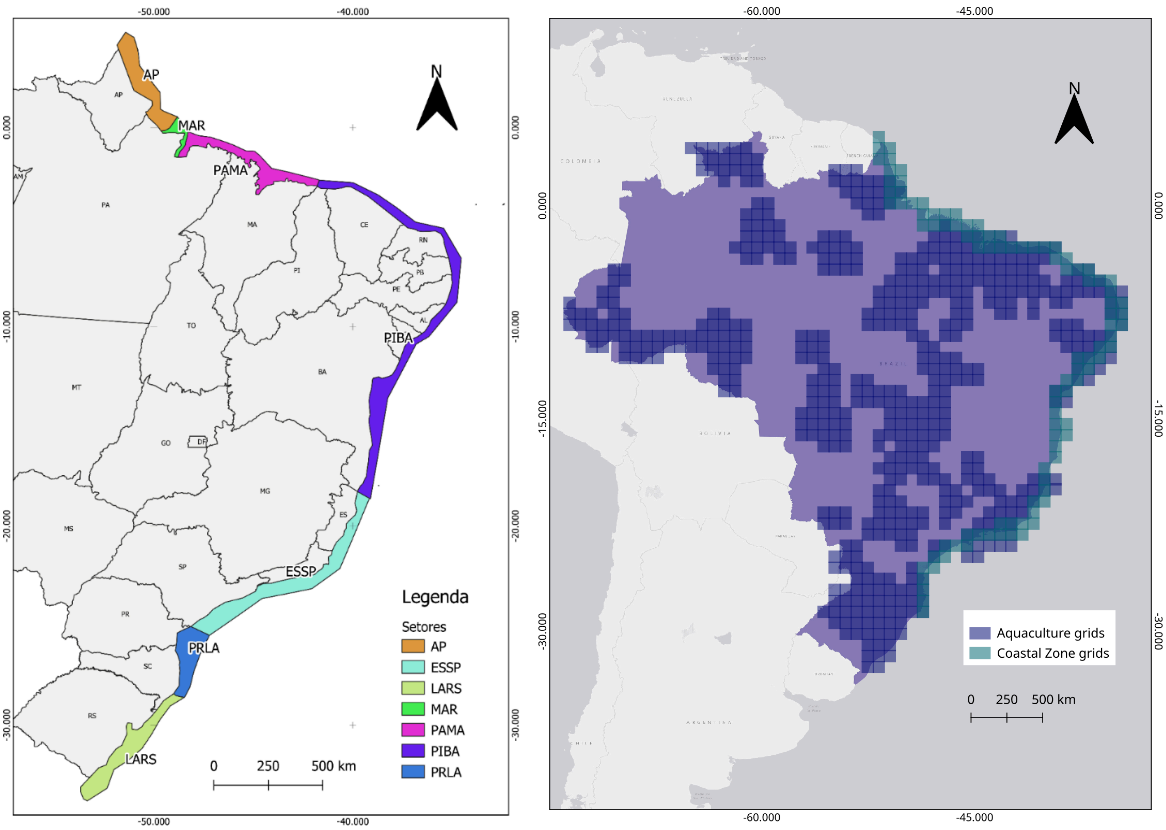

Figure 2 (**LEFT**) - The seven Brazilian Coastal Zone sectors used for mosaic subsets and image classification. Sector 1 - Amapá (AP), coastal region of Amapá. Sector 2 - Marajó Island (MAR), coastal region of Marajó Island. Sector 3 - Pará / Maranhão (PAMA), a coastal sector of the states of Pará and Maranhão. Piauí / Bahia (PIBA) is a coastal sector of the states of Piauí to Bahia. Sector 5 - Espírito Santo / São Paulo (ESSP), a region that includes the states of Espírito Santo and São Paulo. Sector 6 – Paraná/Laguna (PRLA), a coastal area that goes from the state of Paraná to the municipality of Laguna in Santa Catarina, and finally, Sector 7 (LARS), a region that ranges from Laguna to the state of Rio Grande do Sul. (**RIGHT**) - Search areas used for Aquaculture class, based on São José et al. (2022).

6.3 Image selection

We have updated the mosaic acquisition process from the Sentinel-2 Collection 2 to this current workflow, which represents Collection 3 onwards. The mosaic generation process utilizes Sentinel-2 data (Harmonized collection) combined with the Sentinel-2 Cloud Probability collection. Google Earth Engine (GEE) evaluates the cloud probability of each pixel, automatically masking those with a probability of 50% or higher.

To create the cloud-free composite, GEE applies a reducer to the stack of clear images over time. The script also computes various spectral and water quality indices (such as NDVI, MNDWI, and MMRI). Finally, the optical bands undergo a radiometric normalization based on the 5th and 95th percentiles and are rescaled to 8-bit (Byte), optimizing the export of the final mosaics for each biome. This operation has improved over several collections, and it is possible to see the difference between two "cloud-free composites" from different collections below (Figure 3).

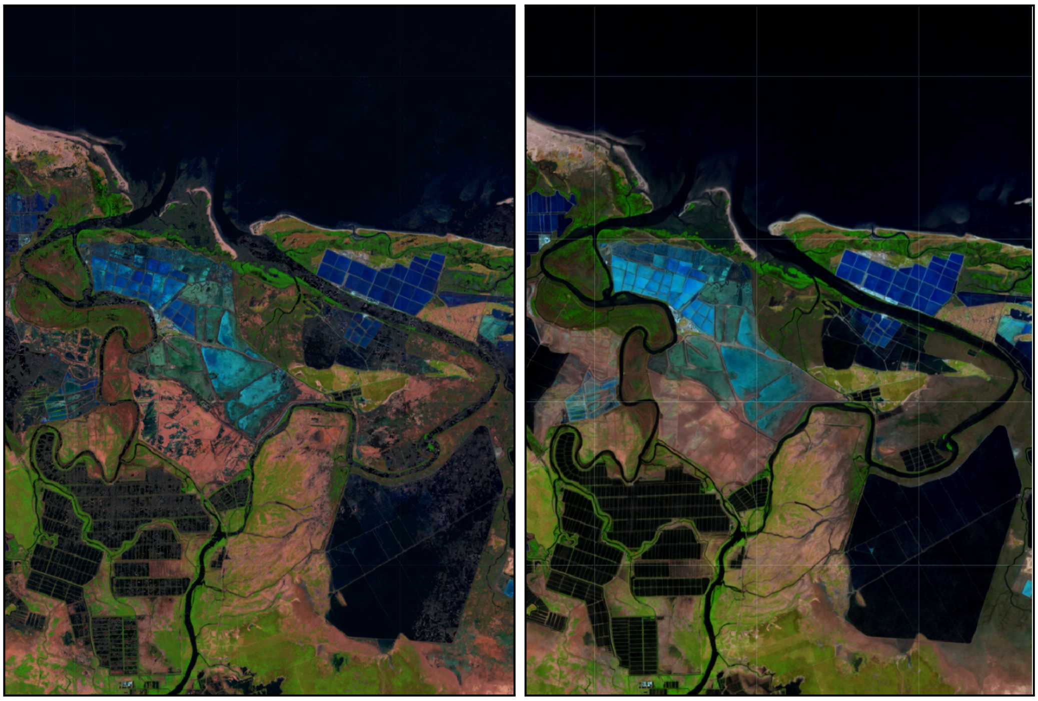

Figure 3 - Left, MapBiomas 10-meters Collection 2 “cloud-free composite.” Right, MapBiomas 10-meters Collection 3 and onwards “cloud-free composite.”

7 Detection

The automatic classification of the Sentinel mosaics was mainly performed on the Google Earth Engine platform, based on the Random Forest classifier (Breiman, 2001). The Hypersaline Tidal Flat and the Aquaculture classes were deep-learning derived and thus segmented on local environment.

7.1 Detection scheme

Each class was mapped separately as a binary variable. Therefore, five independent detection processes were performed: 1) Mangrove, 2) Beaches and Dunes and Sand Spots,

3) Hypersaline Tidal Flats , 4) Aquaculture, and 5) Shallow Coral Reefs. The mapping process was carried out considering only two possible classes for each pixel: the interest class (Mangrove, Beaches, Dunes and Sand Spots, Hypersaline Tidal Flat (HTF), Aquaculture, and Shallow Coral Reef) or the non-interest class (all the non-classes of each target of interest).

After mapping Shallow Coral Reef extent, a new classification process was performed in these regions - for benthic and geomorphic maps, there were, respectively 5 and 7 classes, in which RF mode multiprobability was employed.

We have selected training points based on the availability of reference maps and the previous MapBiomas Collection. The following sections present the details of the parameters used in the image classifiers, the reference maps used for each interest class, and the feature space produced for each classification.

7.2 Reference Data

A dataset of reference data was used to guide the generation of training samples for each class. Table 2 shows the references used for each of the coastal zone classes.

Table 2 - Reference datasets to guide training samples of coastal zone classes in Collection 4 onwards.

Class	References
Mangrove	MapBiomas 10m Collection 3, Giri et al., 2011, ICMBio Mangrove Attlas (ICMBio, 2018), Global Mangrove Watch (Bunting *et al.*, 2018; Thomas *et al.*, 2018), Diniz et al., 2019, Panorama da Conservação dos Ecossistemas Costeiros e Marinhos no Brasil (MMA, 2010), plus visual inspection.
Aquaculture/Salt-Culture	MapBiomas 10m Collection 3, Atlas Dos Remanescentes Florestais da Mata Atlântica (SOS Mata Atlântica, 2020), Barbier and Cox, 2003; Guimarães et al., 2010; Prates, Gonçalves and Rosa, 2010, Queiroz et al., 2013; Tenório et al., 2015; Thomas et al., 2017, Diniz et al., 2021, São José, F. F. de et al., 2022, plus visual inspection
Apicum/Hypersaline Tidal Flat	MapBiomas 10m Collection 3, Atlas Dos Remanescentes Florestais da Mata Atlântica (SOS Mata Atlântica, 2020), Prates, Gonçalves and Rosa, 2010, Panorama da Conservação dos Ecossistemas Costeiros e Marinhos no Brasil (MMA, 2010), plus visual inspection.
Beaches, Dunes and Sand Spots	MapBiomas 10m Collection 3, Atlas Dos Remanescentes Florestais da Mata Atlântica (SOS Mata Atlântica, 2020), Prates, Gonçalves and Rosa, 2010, Panorama da Conservação dos Ecossistemas Costeiros e Marinhos no Brasil (MMA, 2010), plus visual inspection.

Shallow Coral Reef	Áreas Prioritárias para Conservação da Biodiversidade (MMA), Panorama da Conservação dos Ecossistemas Costeiros e Marinhos no Brasil (MMA, 2010), Atlas dos Recifes de Corais nas Unidades de Conservação Brasileiras (MMA), Allen Coral Reef Atlas, and UNEP-WCMC Global Distribution of Coral Reefs.

7.3 Coastal Zone Feature Space

Tables 3 and 4 show all spectral indices and bands used for the BCZ detection.

Table 3 – Spectral Indices used for coastal zone classification.

Index	Expression	Reducer	Reference
EVI2	2.5 * ((NIR - RED) / (NIR + 2.4*RED + 1))	Median and Standard Deviation	Liu and Huete, 1995
NDVI	(NIR - RED) / (NIR + RED)	Median and Standard Deviation	Tucker, 1979
MNDWI	(GREEN - SWIR1) / (GREEN + SWIR1)	Median and Standard Deviation	Xu, 2006
NDSI	(SWIR1 - NIR) / (SWIR1 + NIR)	Median and Standard Deviation	Rogers and Kearney, 2004
MMRI	Modular Mangrove Recognition Index	Median and Standard Deviation	Diniz et al., 2019
GBNDVI	The Green Blue NDVI	Median and Standard Deviation	Wang et al., 2007
GRNDVI	The Green Red NDVI	Median and Standard Deviation	Wang et al., 2007
GARI	Green Atmospherically Resistant Vegetation Index	Median and Standard Deviation	Gitelson et al., 2003
CI	Coloration Index	Median and Standard Deviation	Escadafal et al., 1994

Table 4 - Table of bands used to classify coastal zone classes.

Variable	Description	Reducer
BLUE	Sentinel-2 Blue band	Mean and Standard Deviation
GREEN	Sentinel-2 Green band	Mean and Standard Deviation
RED	Sentinel-2 Red band	Mean and Standard Deviation

NIR	Sentinel-2 NIR band	Mean and Standard Deviation
SWIR1	Sentinel-2 SWIR1 band	Mean and Standard Deviation

7.4 Detection strategy, training samples, and parameters

When reference maps that match the classes and/or year to be mapped, reference maps of the closest possible timeframe to the median composites were used. When no reference map was available, then the detection results of the previous year were used for subsequent training. Tables 5 and 6 show the Random Forest and U-net parameters used to detect each one of the years.

Table 5 - Random Forest parameters used to classify each one of the years. Mangroves, beaches, dunes, sand spots, and shallow coral reefs.

Parameter	**Value**
Number of trees	100
Samples	50000 (non-target), 5000 (target)
Classes	2 (binary classification)

Table 6—U-Net parameters used to segment each year. The U-Net-derived classes are the aquaculture and HTF classes.

Parameter	**Value**
Model	U-Net
Patch Size	Aqua: 512 x 512 px | HTF: 256 x 256 px
Optimizer	Nadam
Learning Rate	5×10^{-6}
Samples	Aqua: 61370 (train), 14412 (validation) | HTF: 22459 (train), 4421 (validation)
Attributes	Green, Red, Nir, Swir 1, NDVI, MNDWI
Output	binary segmentation

7.4.1 Mangroves

As with any supervised method, the Random Forest classifier must rely on a training dataset. For mangrove cover recognition, the training data was obtained from MapBiomas previous collections, Giri et al., 2011, Atlas dos Manguezais do Brasil (ICMBio, 2018), Global Mangrove Watch (Bunting *et al.*, 2018; Thomas *et al.*, 2018) and visual inspection (Figure 5). The consolidated results of the mangrove distributions on Landsat images are available in Diniz et al., 2019.

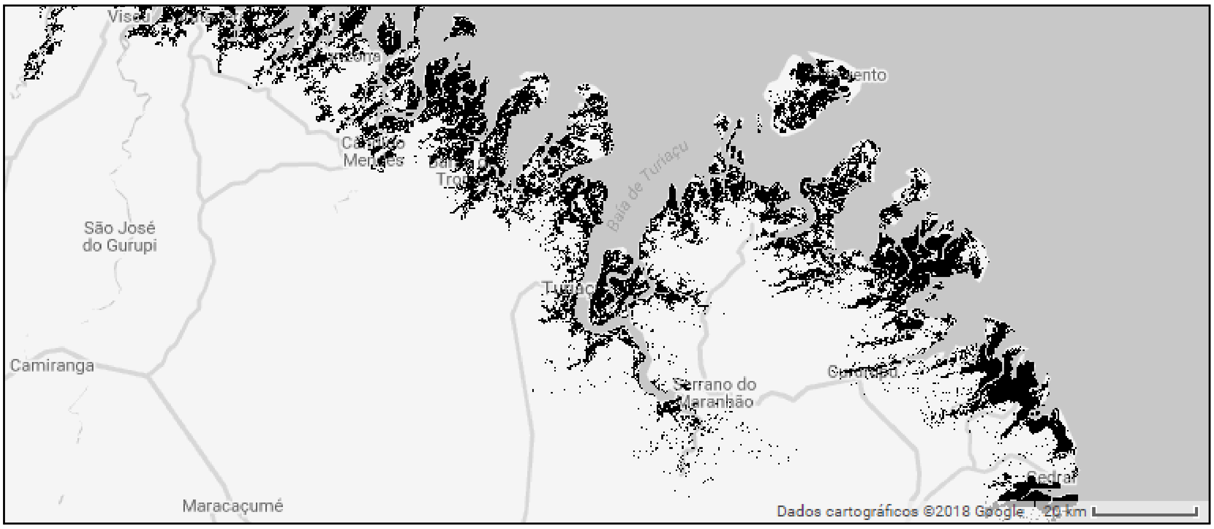

Figure 5 - Global Mangrove Cover data was used as a mangrove mapping reference.

7.4.2 Hypersaline Tidal Flat

Generally, a mangrove swamp's less frequently flooded area, in the transition to topographically elevated lands, is usually devoid of arboreal vegetation. This area is called "Apicum" in Brazil. In the international scientific literature, this transition zone is usually called hypersaline tidal flat. As shown in Table 1, three different reference maps were here used: the "Atlas dos Remanescentes Florestais da Mata Atlântica" (SOS Mata Atlântica, 2020) from 2019/2020, covering the Mata Atlantica coastal region and the "Carta de Sensibilidade Ambiental ao Óleo - Pará-Maranhão-Barreirinhas" referent to 2017 and covering most of the Brazilian north coastal area and the data from the MapBiomas 10-meters Collection 3.

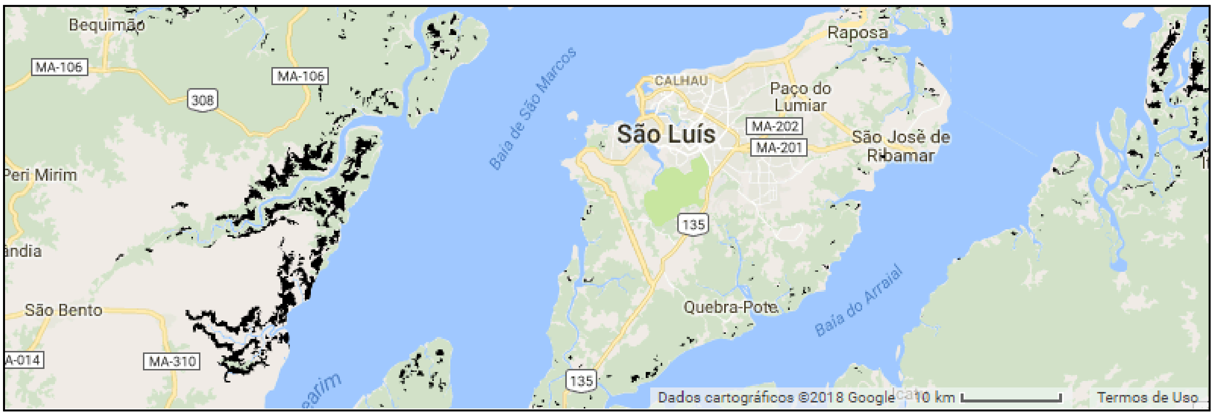

Figure 6 – Apicum reference maps, the "Atlas Dos Remanescentes Florestais da Mata Atlântica" from 2019/2020, covering the Forest Atlantic coastal region and the "Carta de Sensibilidade Ambiental ao Óleo -Pará-Maranhão-Barreirinhas 2017", covering most of the Brazilian north coast region.

7.4.3 Beaches, Dunes and Sand Spots

Mapped in a single class, here "Beaches, Dunes and Sand Spots" refers to sandy strands, bright white, with no vegetation predominance. As shown in Table 1, the training data for this land cover was obtained from MapBiomas Collection 3 and other available reference data (Table 2; Figure 7).

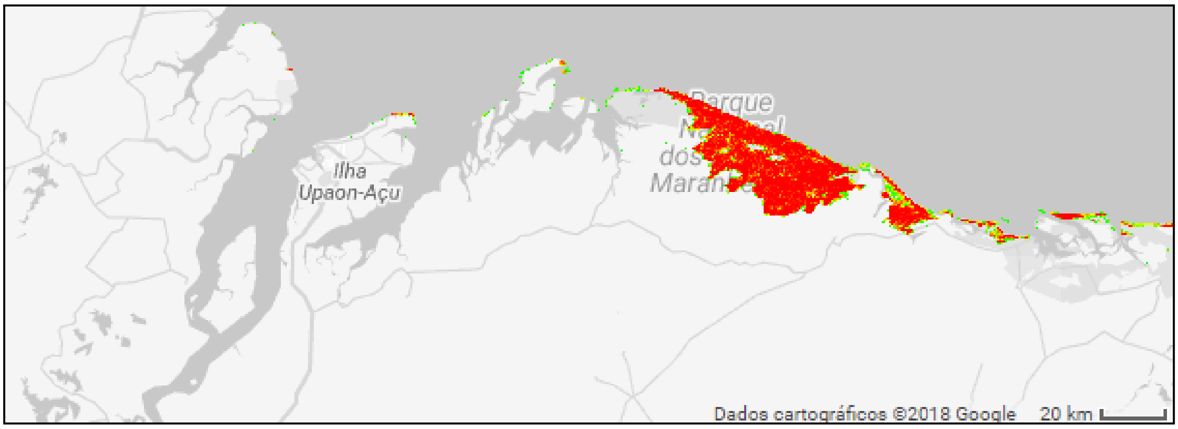

Figure 7 - The training data for this land cover was obtained from MapBiomas Collection 2 and available reference, as table 2.

7.4.4 Aquaculture/Salt Culture

Compared to previous Mapbiomas 10-meters Collections, Collection 3 aquaculture mapping consolidated the use of the Deep-Learning model in replacement of the traditional Random Forest Algorithm (Diniz *et al.*, 2021), and has detected aquaculture beyond BCZ. In this scenario, conventional machine learning algorithms use spectral-temporal data to classify targets according to similarities of their spectral-temporal patterns (Breiman, 2001). However, temporal and spectral properties might not be enough to discriminate "super-similar" targets (targets that behave similarly in both spectral and temporal domains). That is the case for most surface water targets, such as aquaculture ponds, rivers, lakes, and open waters (Figure 8).

Unless water presents a high concentration of external compounds (minerals, suspended sediments, algae, and others), not much can be done to spectrally differentiate between numerous surface water targets. On the other hand, the temporal domain may not present much valid discriminatory data either. In Brazil, aquaculture is a traditional and coastal-related economic activity. Thus, in 11 years of data, a diverse set of aquaculture frequencies may exist (Barbier and Cox, 2003; Guimarães *et al.*, 2010; Queiroz *et al.*, 2013; Tenório *et al.*, 2015; Thomas *et al.*, 2017). As a result, the temporal domain fails to distinguish between well-consolidated aquaculture, main river channels, and open waters once all these features present high temporal persistence throughout the entire time series.

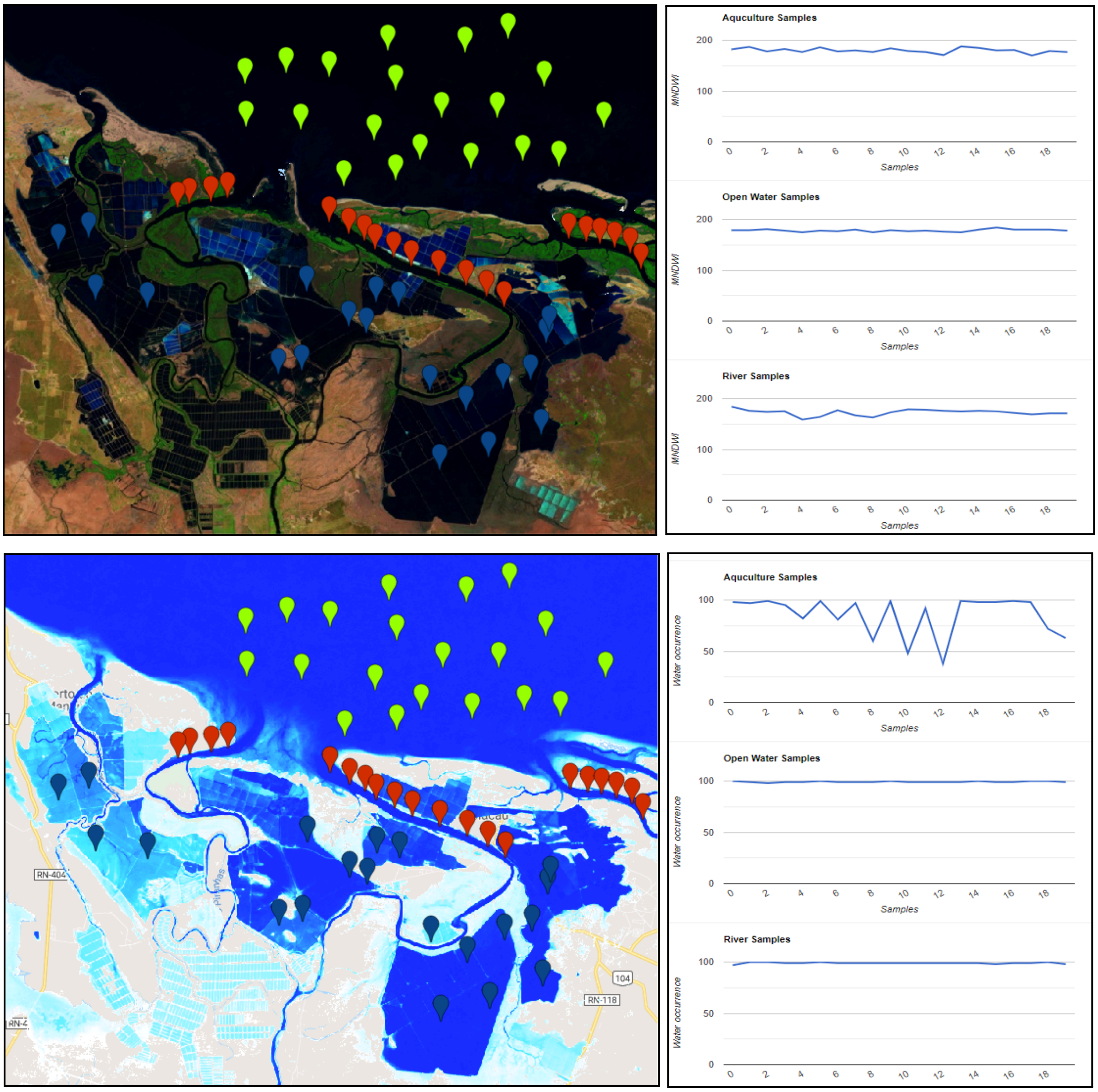

Figure 8 – Spectral and temporal patterns of the aquaculture, rivers, and open waters classes. In the top-left corner is the median cloud-free composite from Macau-RN, northeast of Brazil. The dark blue, green, and red markers represent aquaculture, open water, and river samples. On the top right are the NMDWI values for each one of the samples, in the bottom-left JRC occurrence data. The occurrence frequency of each one of the samples is at the bottom right.

In cases like this, the “context domain” may be essential to distinguishing between rivers, aquaculture, and open waters pixels. In the context analysis scenario, the U-Net: Convolutional Networks (Abadi et al., 2015) have the advantage of predicting the class label of each pixel by providing as input a local region (patches or chips) around that pixel. Such a characteristic of working with “patches” or “chips” gives the U-Net the ability to access the "context domain" of the image instead of using isolated pixels. The U-Net initial training was guided by 10-meters Collection 2, visual inspection and other available reference data (Table 2).

In addition to the Brazilian coastal zone, 10-meters Collection 3 now includes new areas for detection. The source for such investigation relies on the document provided by Embrapa

Territoral, entitled: *Mapeamento de viveiros escavados para aquicultura no Brasil por sensoriamento remoto* (São José, F. F. de et al, 2022).

To optimize model training and post-classification performance, experimental tests were conducted across three different deep learning training epochs: 30, 40, and 60 epochs. Within these training cycles, different data aggregation and scaling strategies were evaluated, specifically testing mode, maximum (max), and standardization metrics. Furthermore, these epoch trials were paired with testing a new morphological post-processing filter to eliminate edge noise, and better delineate discrete pond geometries.

7.4.5 Shallow Coastal Reef

Collection 3 was the first MapBiomas 10m Collection to map shallow tropical reef extent, and coastal reef structures visible in satellite imagery, as shown in Figure 10, and the results are presented in a separate module within the platform. This initiative is significant, as coral reefs are the most biodiversity-dense ecosystems globally and the most diverse in the sea (Adey, 2000). Yet, it is estimated that at least 25% of all marine species depend on a healthy coral reef ecosystem for shelter, food, or reproduction during at least one phase of their life (Nancy, 2010).

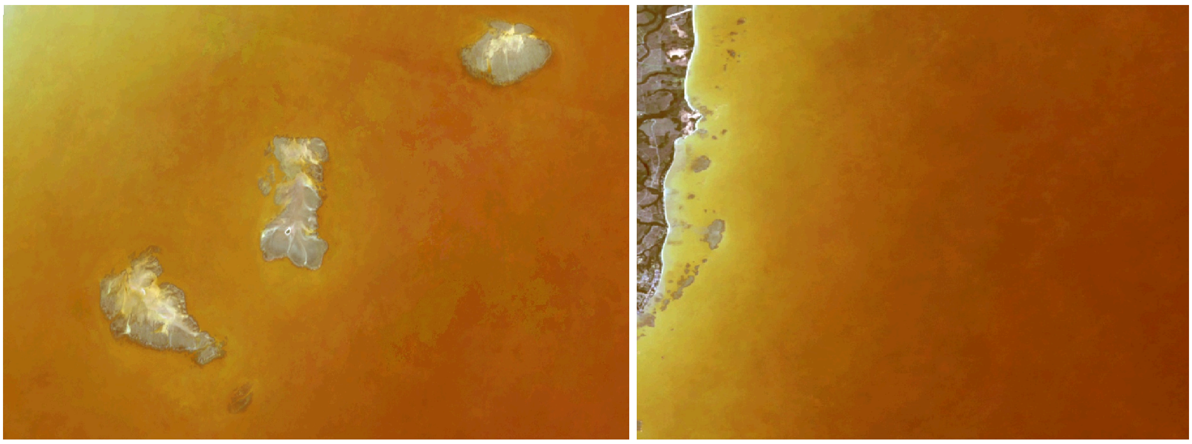

Figure 9– Example of shallow coastal reefs - visible in satellite imagery.

This collection also has the preliminary mapping of benthic and geomorphic features. Benthic mapping is the mapping of the seafloor's biological and physical habitats — like coral reefs, seagrass, sand, or rubble. Geomorphic mapping is the mapping of the seafloor's landforms and structure — such as plateaus, slopes, reefs flats — focusing on shape and geology rather than biology.

As mentioned above, this classification was made using a multiprobability RF classifier - combining Sentinel-derived bathymetry and in-situ data of benthic and geomorphic habitats in northern Brazil (Araujo *et al.,* 2023).

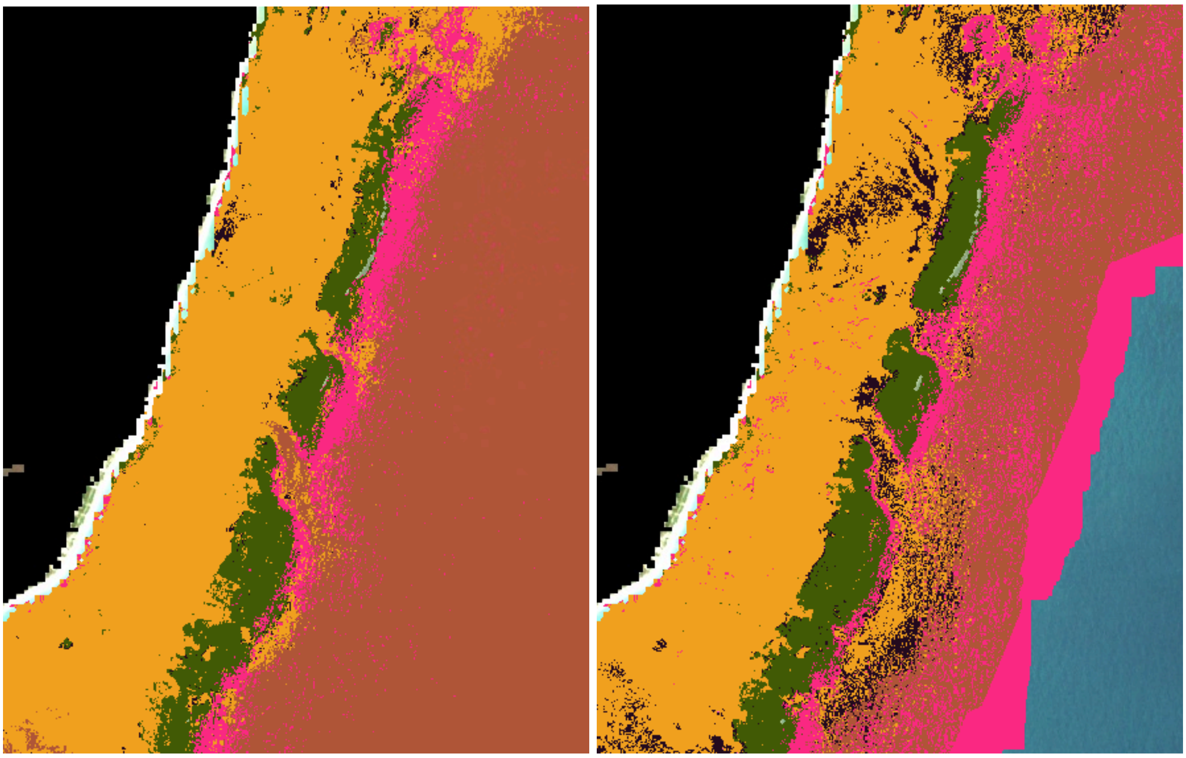

Figure 10 - Example of reference data (left) and resulting classification (right) of benthic maps.

It is important to reinforce that this is an initial approach to benthic and geomorphic mapping, the reference data was collected from a small area in Brazil and expanded throughout the coast, which means the accuracy in areas distant from the reference may vary and are not immediately verifiable - as there is not reliable data for the classes in other regions. The benthic and geomorphic mapping is a beta version and it relies on the feedback of the users for further improvement in future collections.

This is the first approach MapBiomas has made to monitor these ecosystems. Still, the goal is to expand the mapping, indicating other essential aspects regarding the health and survival of this ecosystem. Other initiatives, such as Allen Coral Atlas (2024), have successfully mapped coral areas especially vulnerable to bleaching, inspiring us to continue studying ways to further our understanding of these ecosystems through remote sensing data. Collection 3 focuses on the shallow coral reef extent and benthic and geomorphic mapping and future collections will focus on alerting whether a given reef has crossed the environmental conditions for bleaching to occur.

The most common technical challenges regarding the automatic delineation of shallow coastal reefs and its benthic and geomorphic features are interference from suspended sediments and the depth of the reef system. In both cases, but through different mechanisms, the sun's light is prevented from reaching the reef system and scattered back by the orbital optical sensor on board satellites.

8 Post-classification

Due to the classification method's pixel-based nature and the very long temporal series, a set of post-classification filters was applied. The post-classification process includes applying a gap-fill, a temporal, a spatial, and a frequency filter.

8.1 Gap-Fill filter

The chain starts by filling in possible no-data values. In a long-time series of severely cloud-affected regions, such as tropical coastal zones, it is expected that no-data values may populate some of the resultant median composite pixels. 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, the no-data value is replaced by its previous valid class. Up to three prior years can be used to fill in persistent no-data positions. Therefore, gaps should only exist if a given pixel has been permanently classified as no-data throughout the entire temporal domain. A mask of years was built to keep track of pixel temporal origins, as shown in Figure 11.

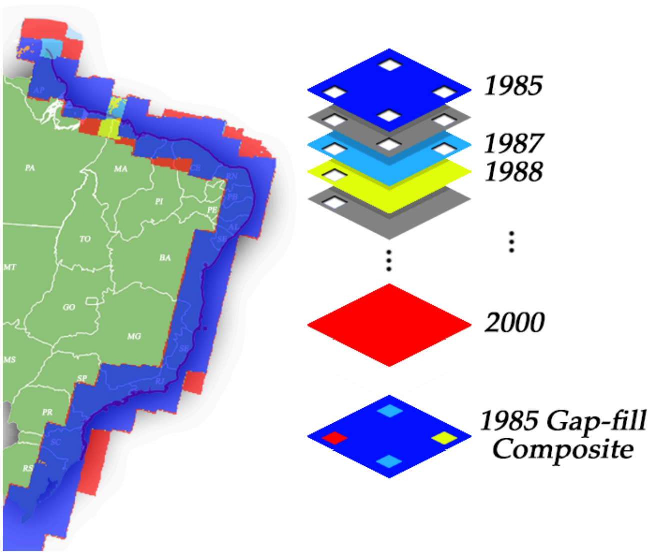

Figure 11 – Gap-filling mechanism. The following valid classification replaces existing no-data values. If no "future" valid position is available, then the no-data value is replaced by its previous valid classification based on up to a maximum of three (3) prior years. A mask of years was built to keep track of pixel temporal origins.

8.2 Temporal filter

After gap-filling, a temporal filter was executed. The temporal filter uses sequential classifications in a 3-year unidirectional moving window to identify temporally non-permitted transitions. Based on a single generic rule (GR), the temporal filter inspects the central position of three consecutive years ("ternary"). If the extremities of the ternary are identical, but the center position is not, then the central pixel is reclassified to match its temporal neighbor class, as shown in Table 6.

Table 6 - The temporal filter inspects the central position for three consecutive years, and in cases of identical extremities, the center position is reclassified to match its neighbor. T1, T2, and T3 stand for positions one (1), two (2), and three (3), respectively. GR means “generic rule”, while Mg and N-Mg represent mangrove and non-mangrove pixels.

Rule	Input (Year)			Output		
	T1	T2	T3	T1	T2	T3
GR	Mg	N-Mg	Mg	Mg	Mg	Mg
GR	N-Mg	Mg	N-Mg	N-Mg	N-Mg	N-Mg

8.3 Spatial filter

Posteriorly, a spatial filter was applied. To avoid unwanted modifications to the edges of the pixel groups (blobs), a spatial filter was built based on the "connectedPixelCount" function. Native to the GEE platform, this function locates connected components (neighbors) that share the same pixel value. Thus, only pixels that do not share connections to a predefined number of identical neighbors are considered isolated, as shown in Figure 12. This filter needs at least ten connected pixels to reach the minimum connection value. Consequently, the minimum mapping unit is directly affected by the spatial filter applied, and it was defined as 10 pixels.

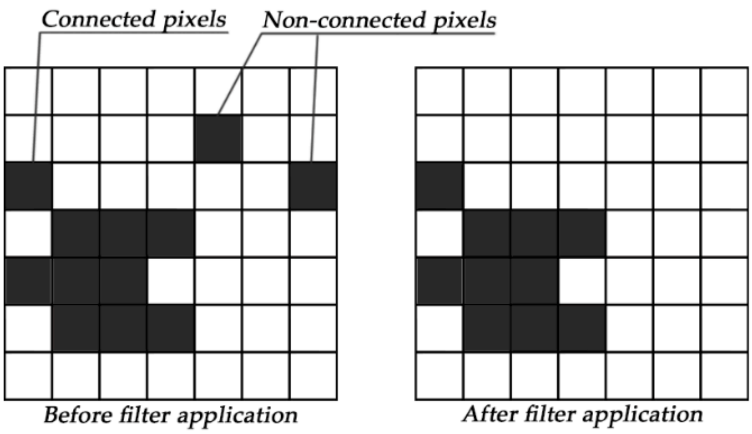

Figure 12 – The spatial filter removes pixels that do not share neighbors of identical value. The minimum connection value was 10 pixels.

In the case of mangroves, a new spatial filter was developed for Collection 3 and 4 - small holes surrounded by mangrove-classifed areas were filled, aiming to reduce inconsistencies throughout the years and the pixel alternance between forest and mangrove classes.

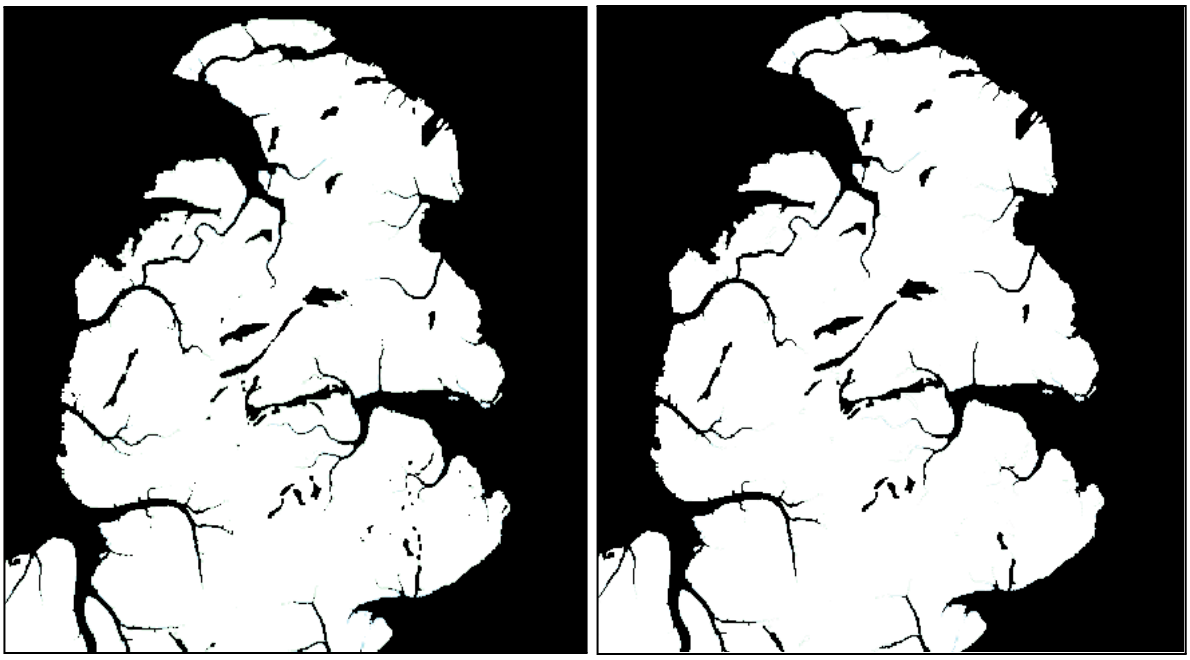

Figure 13 – Morphological filter results - before (left) and after (right).

8.4 Integration with biomes and cross-cutting themes

After applying the filter chain, the cross-cutting themes and the biome data are integrated. This integration is guided by specific hierarchical prevalence rules (Table 7). As the output of this step, a final land cover/land use map of Brazil for each year.

Coastal-related features such as Mangroves, Beaches, Dunes, Aquaculture, and anthropic transitions widely distributed throughout Brazil's territory tend to occupy the top positions of the prevalence rank, as seen below in Table 7.

Table 7- Prevalence rules for combining the output of digital classification with the cross-cutting themes in Collection 11 and 10-meters Collection 4. Shallow coral reefs are not integrated into the same map, thus the concept of prevalence does not apply.

Classes Level 1	Classes Level 2	Pixel Value	Prevalence	Legend Color	Description
Non Vegetated Area	Beach, Dune and Sand Spot	23	4	**#ffa07a**	Sandy areas, with bright white color, with no predominance of vegetation of any kind.
Forest	Mangrove	5	5	**#04381d**	Dense, evergreen forest and/or shrub formations, frequently flooded by tides and associated with the coastal mangrove ecosystem.

Water	Aquaculture /Salt-Culture	31	6	**#091077**	Artificial lakes where aquaculture and/or salt production activities predominate.
Herbaceous and Shrubby Vegetation	Hypersaline Tidal Flat	32	7	**#fc8114**	"Apicuns" or hypersaline tidal flats are formations almost always devoid of tree and shrub vegetation, associated with a topographically higher, hypersaline sector of the coastal plain, flooded less frequently than mangroves, generally occurring in the transition between mangroves and uplands or dune fields.
Shallow Coral Reefs	—	69	-	**#4cd0e2**	Rigid structures along the Brazilian coastline that include both biogenic reefs — features built by marine organisms, such as corals and calcareous algae — and sandstone reefs, formed by sandstones cemented with carbonate.

9 Accuracy Assessment and Validation

Although the mapping workflow includes an explicit accuracy evaluation stage (Figure 1), the statistical validation and accuracy assessment for the presented class targets are conducted independently through the centralized MapBiomas Quality Control and Accuracy Assessment framework, managed in partnership with the Remote Sensing and Geoprocessing Laboratory - Lapig (UFG).

Due to the rare nature and specialized distribution of coastal land cover features (e.g., Mangroves, Hypersaline Tidal Flats, and Shallow Coral Reefs), the accuracy assessment is performed entirely by Lapig and the central MapBiomas team on the integrated national product.

For further information regarding the accuracy assessment methodology, sampling design, and detailed validation metrics (such as confusion matrices, user/producer accuracies, and quantity/allocation disagreements), please consult the MapBiomas General ATBD, or visit the official MapBiomas platform statistics dashboard (https://brasil.mapbiomas.org/en/analise-de-acuracia/).

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