Mining – Appendix

Collection 10

Version 1

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1 Overview

Today, Brazil is among the five largest producers of iron ore, niobium, bauxite, and manganese in the world (Bray, 2020), exporting a variety of mineral inputs with a high level of purity and internationally recognized quality. Despite its low area representation, mining expansion has been rising across the country, reaching ~440,000 hectares in 2023, an ~8-times higher value than reported in 1985 (~55,000 hectares), according to MapBiomas Collection 9.

Mining mapping in the new Collection 10 carries the same overall method as in Collections 9, 8, and 7 in most of Brazil's territory. It includes updates on the quantity and quality of the training samples, and a larger number of activation grids were used in the processing steps of the mining recognition algorithm. In addition, in Collection 10, the sampling, training, and prediction were performed separately for each Brazilian biome. The method still uses U-Net (Ronneberger et al., 2015), a CNN detection based on Deep Learning. However, Collection 10 is composed of six U-Nets, each targeting a specific Brazilian biome.

The stack of reference data now includes information from additional sources: CPRM (Brazilian Geological Service), AhkBrasilien (Brazil-Germany Chamber of Commerce and Industry), INPE (National Institute for Space Research), ISA (Instituto Socioambiental), and AMW (Amazon Mining Watch). Details regarding the segmentation process are described below in Figure 1 and on GitHub:
[https://github.com/mapbiomas/brazil-mining/tree/mapbiomas10.](https://github.com/mapbiomas/brazil-mining/tree/mapbiomas10)

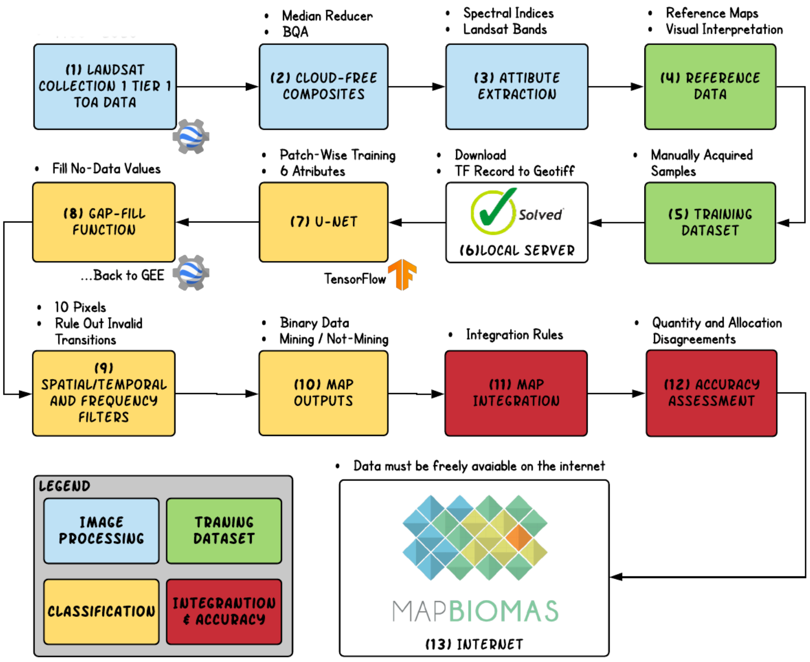


Figure 1 – Processing diagram. The steps related to image processing are in blue. The steps in green are related to the sample design. Segmentation procedures are in yellow. The accuracy assessment phase is in red. BQA stands for Band Quality Assessment. **(1)** Range from 1985 to 2024.

2 Landsat Mosaics

The segmentation of the cross-cutting theme “**Mining**” uses Landsat “Top of Atmosphere—TOA” mosaics, which differ from the “Surface Reflectance—SR” processing level used in the land use and land cover segmentation of the Brazilian biomes. The Landsat mosaics prepared for the mining mapping were cropped to comprise areas where mining sites are known to exist. These mosaics are the third generation of the methodology developed specifically for these cross-cutting themes.

The annual cloud-free mosaics were generated in the Google Earth Engine (GEE) platform, with all raster data and sub-products derived from the United States Geological Survey (USGS) Landsat Collection 2 Tier 1 Top of Atmosphere (TOA) imagery, which includes Level-1 Precision Terrain (L1TP).

2.1 Temporal coverage

The annual cloud-free composites used in the mining segmentation are generated by calculating the median pixel value of all images available in the GEE image collection from January 1 to December 31 of each year.

2.2 Mosaic Subsets

2.2.1 Mining

For each year, Landsat Collection 2, Tier 1, TOA data were used to produce annual cloud-free composites of imagery acquired from January 1st to December 31st. The quality assessment (QA) band and a median filter remove clouds and shade from the imagery. QA values improve data integrity by indicating which pixels might be affected by artifacts or subject to cloud contamination. In addition, we use a GEE function that gets the median pixel value of an image stack (i.e., the entire image collection available for a predefined area and dates of interest). This function rejects values that are too bright (e.g., clouds) or too dark (e.g., shadows), returning the median pixel value (of all images available in our stack) in each band for each year of our time series. Then, the annual mosaics were clipped to grid polygons that are known to have mining activity according to our reference dataset, and large areas where these activities are not expected to occur were excluded.

2.2.2 Reference Data

Brazil, especially the Brazilian Amazon (BA), has many publicly available datasets, from geological surveys and change detection platforms to deforestation early-warning systems. Mining data availability is highly diverse in scale, type, and timeframe. Spatially explicit data may be found at a higher or lower resolution, with a greater or lesser degree of human intervention, for scientific or journalistic use, but from which a great set of spatial references of artisanal and industrial mining sites can be acquired/inferred. The reference dataset used in our segmentation comprises multiple data sources: Deter-B (http://terrabrasilis.dpi.inpe.br/), MapBiomas Alert (http://alerta.mapgiomas.org), RAISG (http://www.amazoniasocioambiental.org), ISA (https://www.socioambiental.org/), CPRM-GeoSGB (https://geosgb.cprm.gov.br/), Ahkbrasilien (https://www.ahkbrasilien.com.br/), AMW (https://amazonminingwatch.org/), and additional visual interpretations.

Table 1 – Reference data used in our products. References were visually analyzed and converted to bounding boxes.

Class	**References**
Mining	Deter: http://terrabrasilis.dpi.inpe.br/ MapBiomas Alert: http://alerta.mapgiomas.org RAISG: http://www.amazoniasocioambiental.org ISA: https://www.socioambiental.org/ CPRM-GeoSGB: https://geosgb.cprm.gov.br/ Ahkbrasilien: https://www.ahkbrasilien.com.br/ AMW: https://amazonminingwatch.org/ and Additional visual interpretations

Reference data were visually analyzed and converted to bounding boxes (Figure 2), which were overlaid on grids used to process the deep-learning mining recognition algorithm in a parallel fashion. In Figure 2, the grids used in Collection 10 are in yellow. The number of searching grids has increased compared to the previous collection.

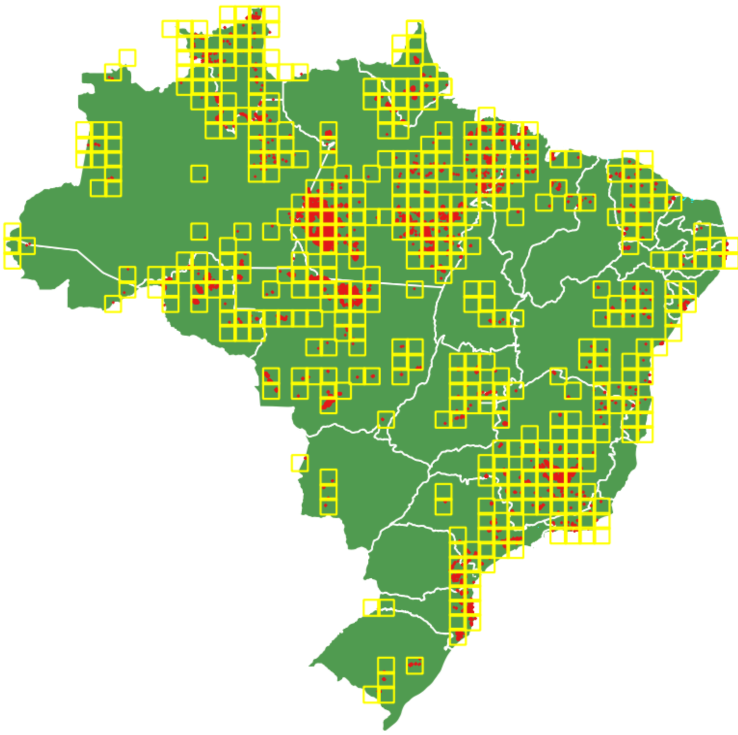


Figure 2—Reference sites are in red. The yellow grids are present exclusively in Collection 10.

3 Segmentation

In Collection 10, the U-net classifier was retained, but its implementation was restructured. Pixel-wise classification between mining and non-mining areas now incorporates statistical techniques such as majority voting and biome-specific regionalization. For each biome, five U-net models—trained over different epochs—are combined to generate the final classification. The class receiving the highest number of votes across the models (majority voting) is assigned as the final label on the map.

The semi-automatic segmentation of Landsat mosaics was performed entirely on local servers. Once the sample collection is finished, the U-net segmentation results in the pre-filtered segmentation product. The segmented data is injected back into GEE, where spatial-temporal filters and visual inspection occur (Figure 3).

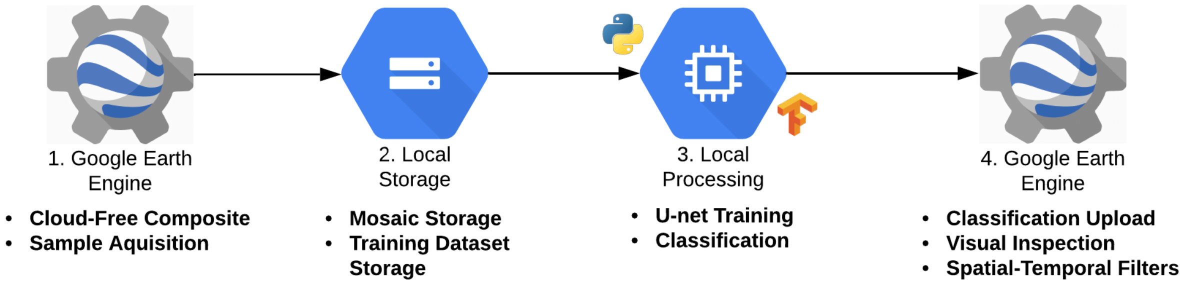


Figure 3 - Mining Detection Earth Engine-TensorFlow pipeline. The process is structured in 4 steps. First (1), GEE generates the cloud-free composites and creates the initial training dataset. Second (2), the mosaics and training data are downloaded and stored locally. Three (3) initiate patch-wise training and segmentation. In the fourth step (4), the segmented product is spatially and temporally filtered. The filtered product is visually and statistically inspected. Multiple iterations may be used until a satisfactory spatial and temporal quality is achieved.

3.1 Segmentation scheme

For the supervised segmentation of the Landsat mosaics, we selected training samples (geometries) from the previously generated bounding boxes (grids). Like any supervised algorithm, our U-net-based approach depends on human-labeled training data, categorized as mining (Mi) and non-mining (N-Mi). Guided by the reference dataset, the mining and non-mining samples are visually delineated. It is essential to highlight that no differentiation was made between artisanal and industrial mining samples. Therefore, from this point on, every time mining samples or classes are mentioned, it includes both artisanal and industrial patterns. The dissociation between such patterns, *garimpo* or industrial, and the exploited main substance results from post-segmentation and visual analysis.

Collection 9 testified to the necessity of observing each Brazilian biome more closely regarding the mining presence. Therefore, in Collection 10, the training samples were collected following the Brazilian biomes' subdivision, aiming to better characterize the mining activity within each biome. Table 2 presents the parameters used in each U-net instance.

Table 2 - Model attributes and segmentation parameters. In total, six (6) distinct attributes were used.

Parameters	**Values**		
Model	U-Net		
Patch Size	256 x 256 px		
Optimizer	Nadam		
Learning Rate	5×10^{-6}		
	Biome	**Train**	**Validation**
Samples	Amazon	54777	15015
	Atlantic Forest	100000	20000
	Cerrado	21170	5790
	Caatinga	42400	9600
	Pampas	23552	9598
	Pantanal	6400	2400
Attributes	Green, Red, Nir, Swir 1, NDVI & MNDWI		
Output	Mining and Not-Mining		

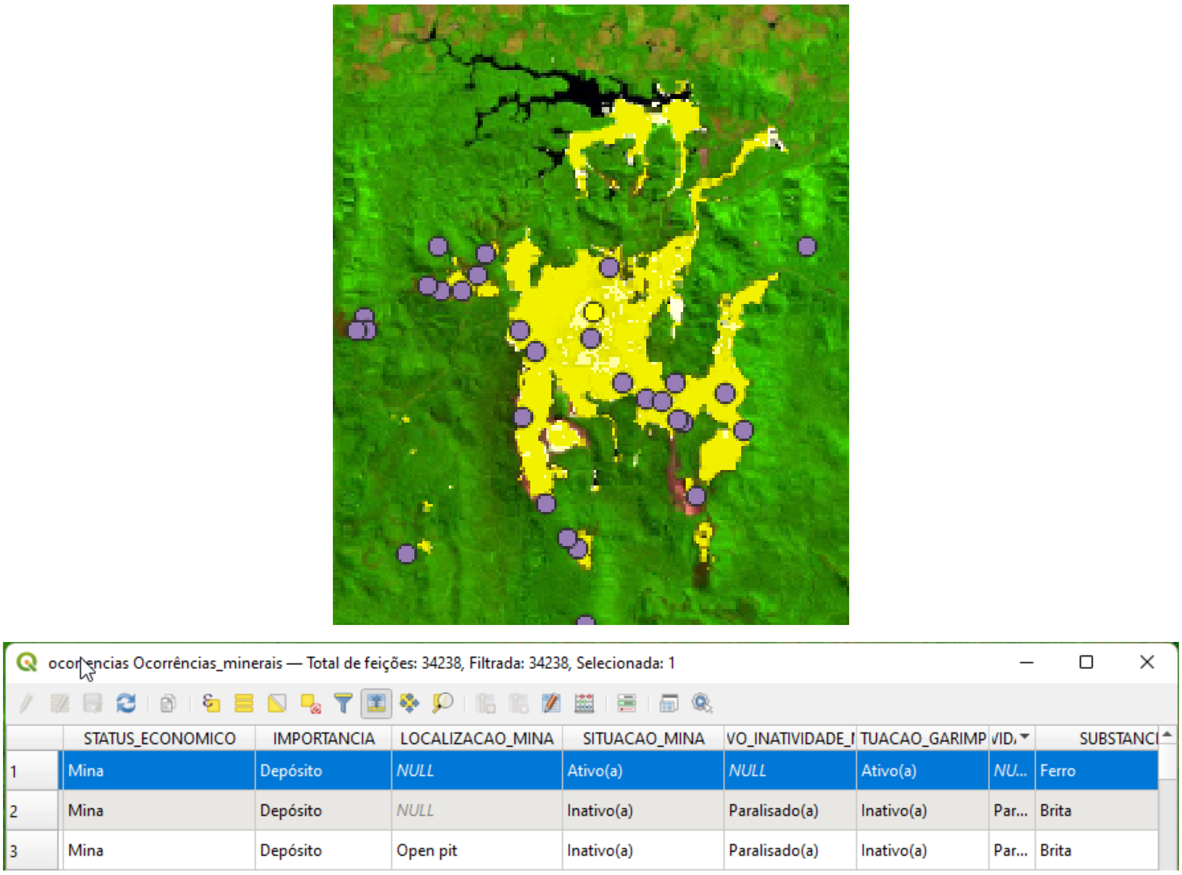
Once the sample collection and the U-net segmentation are done, the segmented data is injected back into GEE, where spatial-temporal filters and visual inspection occur. This phase was undertaken to correct segmentation errors and evaluate the need to collect (or not) additional training samples.

4 Mining Class, Mining Type, and Main Substances

Since Collection 6, the MapBiomas Platform has had a specific mining-related module. Thus, it is crucial to understand each mining-related product's origin. In this sense, the U-Net model performs pattern recognition of a mining site, regardless of its nature or primary substance, in a binary final output fashion [mining (Mi) and non-mining (N-Mi)], as previously explained.

Once the mining class is noise-filtered, the final version is integrated as a layer in the MapBiomas LULC data, corresponding to the class ID “30”. Then, the mining raster data intersects with the CPRM-GeoSGB dataset, from which the attributes of substances (Gold, Iron, Silver, Copper…) and extraction type (*garimpo* or industrial) are extracted. Thus, the recognition of mining sites is U-Net-related.

On the other hand, categorizing its nature/type or main substances results from a spatial operation involving a third-party reference dataset, as shown in Figure 4.



	STATUS_ECONOMICO	IMPORTANCIA	LOCALIZACAO_MINA	SITUACAO_MINA	VO_INATIVIDADE_I	TUACAO_GARIMP	VIDA	SUBSTANCI
1	Mina	Depósito	NULL	Ativo(a)	NULL	Ativo(a)	NU...	Ferro
2	Mina	Depósito	NULL	Inativo(a)	Paralisado(a)	Inativo(a)	Par...	Brita
3	Mina	Depósito	Open pit	Inativo(a)	Paralisado(a)	Inativo(a)	Par...	Brita

Figure 4 - The dots are the CPRM-GeoSGB dataset. The Yellow pixels represent the mining class. The recognition of the mine nature and the main mined substances is the resultant aggregation of both datasets.

The product published on the Mining Module aggregates both attributes in a three-digit identifier (“class_id”), resulting in the information in Table 3.

Table 3—The product published on the Mining Module aggregates both attributes in a three-digit identifier ("class_id"). In Collection 10, identifier 130 appears for the first time as a "class_id" due to adding a Zinc industrial extraction site.

class_id	level_1	level_2	level_3
101	2. Industrial	2.2 Metallics	Metallics
102	2. Industrial	2.2 Metallics	2.2.01 Iron
103	2. Industrial	2.2 Metallics	2.2.02 Manganese
104	2. Industrial	2.2 Metallics	2.2.03 Nickel
105	2. Industrial	2.2 Metallics	2.2.04 Asbestos
106	2. Industrial	2.2 Metallics	2.2.05 Molybdenum
107	2. Industrial	2.2 Metallics	2.2.06 Titanium
108	2. Industrial	2.2 Metallics	2.2.07 Chromium
109	2. Industrial	2.2 Metallics	2.2.08 Copper
110	2. Industrial	2.2 Metallics	2.2.09 Aluminum
111	2. Industrial	2.2 Metallics	2.2.10 Magnesium
112	2. Industrial	2.2 Metallics	2.2.11 Barium
113	2. Industrial	2.2 Metallics	2.2.12 Niobium
114	2. Industrial	2.2 Metallics	2.2.13 Tin
115	2. Industrial	2.2 Metallics	2.2.14 Gold
130	2. Industrial	2.2 Metallics	2.2.30 Zinc
116	2. Industrial	2.3 Non-Metallics	Non-Metallics
117	2. Industrial	2.3 Non-Metallics	2.3.01 Class 2 Minerals
118	2. Industrial	2.3 Non-Metallics	2.3.02 Fluorine
119	2. Industrial	2.3 Non-Metallics	2.3.03 Phosphorus
120	2. Industrial	2.3 Non-Metallics	2.3.04 Graphite
121	2. Industrial	2.3 Non-Metallics	2.3.05 Silicon
122	2. Industrial	2.3 Non-Metallics	2.3.06 Limestone
123	2. Industrial	2.4 Precious Stones & Ornamental Rocks	Precious Stones & Ornamental Rocks
124	2. Industrial	2.4 Precious Stones & Ornamental Rocks	Precious Stones
125	2. Industrial	2.4 Precious Stones & Ornamental Rocks	Ornamental Rocks
126	2. Industrial	2.1 Energetics	Energetics
127	2. Industrial	2.1 Energetics	2.1.01 Mineral Coal
128	2. Industrial	2.1 Energetics	2.1.02 Uranium
129	2. Industrial	2.1 Energetics	2.1.03 Natural Gas and Petroleum
214	1. *Garimpo*	1.1 Metallics	1.1.02 Tin
215	1. *Garimpo*	1.1 Metallics	1.1.01 Gold
216	1. *Garimpo*	1.2 Non-Metallics	Non-Metallics
217	1. *Garimpo*	1.2 Non-Metallics	1.2.01 Class 2 Minerals
223	1. *Garimpo*	1.3 Precious Stones & Ornamental Rocks	Precious Stones & Ornamental Rocks
224	1. *Garimpo*	1.3 Precious Stones & Ornamental Rocks	1.3.01 Precious Stones
225	1. *Garimpo*	1.3 Precious Stones & Ornamental Rocks	1.3.02 Ornamental Rocks

5 Post-segmentation

Due to the segmentation method's pixel-based nature and the very long temporal series, a chain of post-segmentation filters was applied to reduce the salt-and-pepper effect and add spatiotemporal consistency. The post-segmentation process includes the application of the following filters: gap-fill, temporal, spatial, and frequency.

5.1 Gap-Fill filter

The post-processing steps start by filling in possible no-data values. In a long-time series of severely cloud-affected regions, such as forested areas of tropical countries, pixels with no-data values are expected to be present in median composite mosaics. The gap-fill filter replaces the no-data values (e.g., image “gaps”) with a valid pixel from the nearest date available. In this procedure, if no “future” valid class is available, the no-data value is replaced by the nearest previous valid class. Up to three prior years can fill in persistent no-data pixels. Therefore, gaps should only exist if a given pixel has been permanently segmented as no-data throughout the entire temporal series. A year mask was built to track pixel temporal origins, as shown in Figure 5.

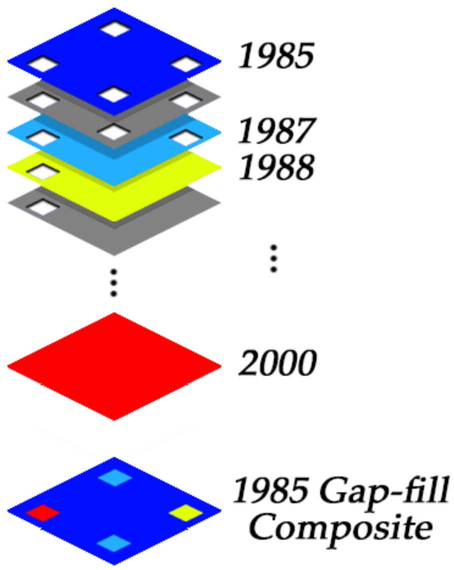


Figure 5 – Gap-filling filter mechanism. The following valid pixel data replaces existing no-data values. If no “future” valid position is available, then the no-data value is replaced by its previous valid value based on up to a maximum of three (3) prior years. To keep track of pixel temporal origins, a “year” mask was built.

5.2 Temporal filter

Next, we applied a temporal filter that uses sequential segmentation 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"). It changes its value if it differs from the first and last years in the ternary, which must have identical classes. The central year of the ternary is then remapped to match its temporal neighbor class, as shown in Table 4.

Table 4 - The temporal filter inspects the central position for three consecutive years, and in cases of identical extremities, the center position is remapped to match its neighbor. T1, T2, and T3 stand for positions one (1), two (2), and three (3), respectively. GR means "generic rule," while Mi and N-Mi represent mining and non-mining pixels.

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

5.3 Spatial filter

Then, a spatial filter was applied to avoid unwanted modifications on the edges of grouping pixels (clusters) by using 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 pre-defined number of identical neighbors are considered isolated, as shown in Figure 6. 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, which was defined as 10 pixels (~1 ha).

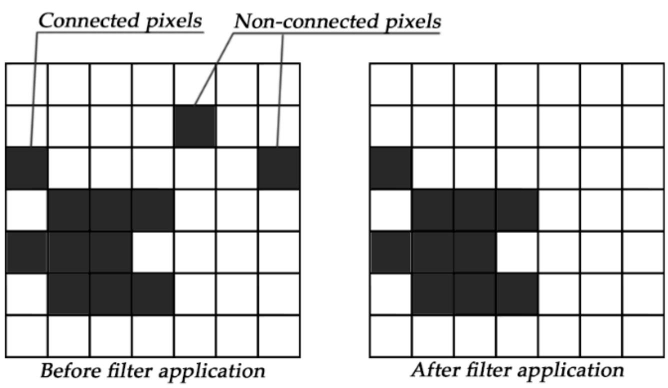


Figure 6 – The spatial filter removes pixels that do not share neighbors of identical value. The minimum connection value was 10 pixels.

5.4 Frequency filter

The last post-processing filter step is the frequency filter. This filter considers the frequency of a given class throughout the entire time series. Thus, all class occurrences with less than 10% temporal persistence (3 years or fewer out of 37) are filtered out and incorporated into the non-class binary. This mechanism reduces the temporal oscillation in the segmentation, decreases the number of false positives, and preserves consolidated classes.

5.5 Integration with biomes and cross-cutting themes

After applying the post-processing filters, we integrate the cross-cutting themes and the Biomes data into a single raster dataset. This integration is guided by a set of specific hierarchical prevalence rules (Table 5). The resulting output is a final land cover/land use map for each region of the MapBiomas project.

The top position classes in the prevalence rank are related to coastal ecosystems (such as mangroves, beaches, dunes, and sand spots; aquaculture) and anthropogenic land use (i.e., mining and urban infrastructure) present throughout the country (Table 5).

Table 5 - Prevalence rules for combining the output of digital segmentation with the cross-cutting themes in Collection 10.

Class	Pixel Value	Prevalence	Exception
Mining	30	1	Urban Infrastructure on MG state
Beach, Dune, and Sand Spot	23	2	
Mangrove	5	3	
Aquaculture/Salt-Culture	31	4	
Hypersaline Tidal Flat	32	5	
Coastal Reefs	69	-	* Coastal reefs are not integrated into the same map

6 Error/Accuracy Assessment

Once all classes from the Mining theme constitute a rare population concerning its distribution throughout Brazil’s territory, the error assessment strategy must rely on a sample design specifically focused on that matter. The error assessment of rare classes is under development and will soon be available.

7 References

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