



Mining – Appendix

Collection 6

Version 1

General coordinator

Pedro Walfir Martins e Souza Filho

Team

Alexandre Filho

Cesar Guerreiro Diniz

Luis Waldir Rodrigues Sadeck

Luiz Cortinhas Ferreira Neto

Maria Luize Silva Pinheiro

1 Overview

Today, Brazil is among the five largest producers of iron ore, niobium, bauxite, and manganese in the world (Bray, 2020), exporting varied mineral inputs, with a high level of purity and internationally recognized quality.

Despite its low representativeness in area, as it is a rare coverage class, the national trend associated with this land use shows a frank expansion, jumping from ~ 30,000 hectares in 1985 to ~ 200,000 hectares in 2020, a value ~6 times higher than reported in 1985. Three biomes together are responsible for much of the country's mined area: Amazon (149 thousand hectares - 72%), Atlantic Forest (~ 30 thousand hectares - 14 %), Cerrado (~20 thousand hectares - 9%).

In comparison to Collection 5, the Collection 6 mining mapping presents a severe methodological shift. The U-Net classifier (Ronneberger et al., 2015), a CNN classifier based on Deep Learning model, replaced the use of the Random Forest algorithm. Meanwhile the sample training strategy was modified, leaving the use of "Concession Areas" behind and started to use of a stack reference data from multiple sources of mining mapping projects. The stack of reference samples include data from: CPRM (Brazilian Geological Service), AhkBrasilien (Camara de Comercio e Industria), INPE (Instituto Nacional de Pesquisas Espaciais) and from ISA (Instituto Socioambiental). Once stacked the samples are converted into larger grids. Inside each grid the U-net classifier is run. The whole classification process is described below, Figure 1.

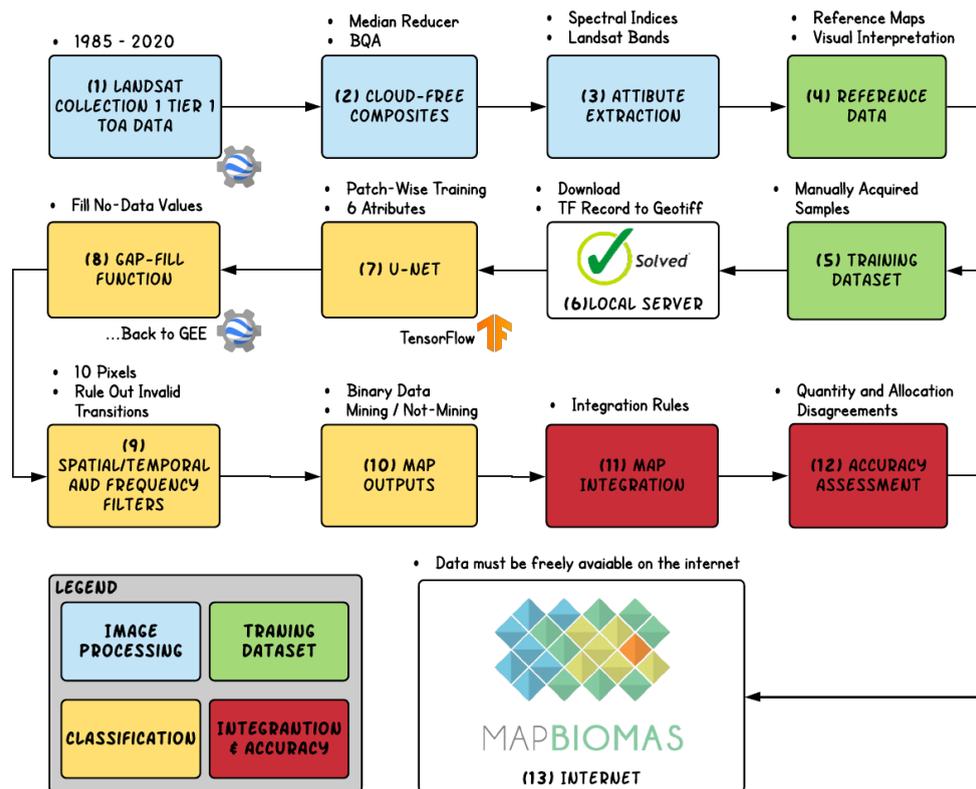


Figure 1 – Processing diagram. The steps related to image processing are in blue. The steps in green are related to the sample design. Classification procedures are in yellow. The accuracy assessment phase is in red and, finally, the data availability is in salmon. BQA denotes Band Quality Assessment.

2 Landsat image mosaics

The classification of the cross-cutting themes “Mining” uses Landsat mosaics that differs from the mosaics used to classify the natural vegetation of the Brazilian biomes. The Mining mosaics were cropped to comprise areas where mining sites are known to exist. These Landsat mosaics are the third generation of the methodology developed specifically for these cross-cutting themes.

2.1 Definition of the temporal period

The Mining annual cloud-free composites are generated by calculating the median pixel value from January 1 to December 31 of each year.

2.2 Mosaic Subsets

2.2.1 Mining

The definition of the mining mosaic subset is made based on a set of reference maps covering artisanal mining spots (garimpos) and industrial mining sites as well, highlighting the 300+ most crucial mine site in Brazil. The mining geographical references were extracted from the CPRM (Brazilian Geological Service), AhkBrasilien (Camara de Comercio e

Industria), INPE (Instituto Nacional de Pesquisas Espaciais) and from ISA (Instituto Socioambiental).

The references formerly constituted of georeferenced dots (location points). The dots were visually analyzed and converted to bounding boxes (grids), covering the entire mining site. Figure 2 shows the location mining grids, as well as a zoom-in one of its adjusted bounding boxes.

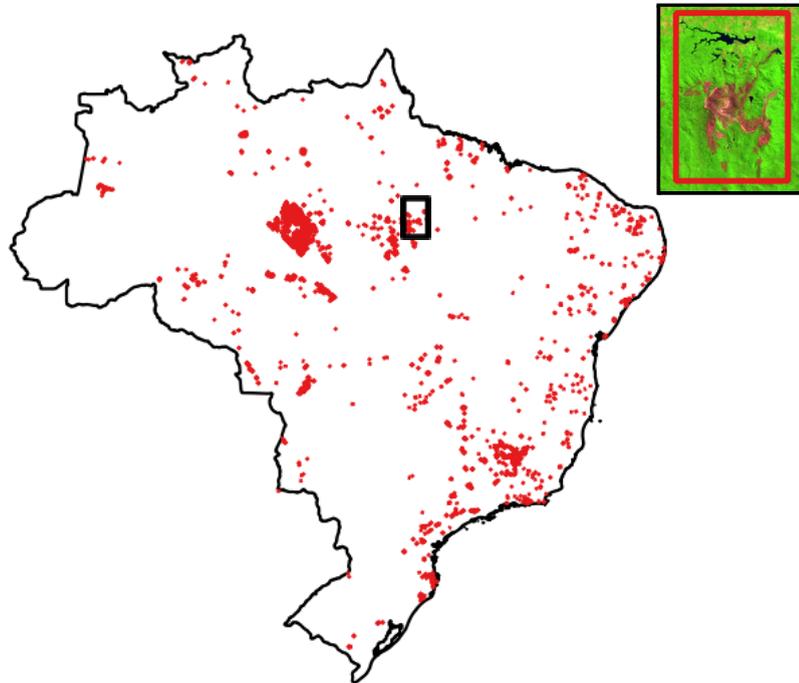


Figure 2 – In red (dots), the location of mining sites. In the top-right corner, zoom in on one of the visually adjusted bounding boxes.

2.3 Image selection

The cloud/shadow removal script takes advantage of the Landsat Collection 1 Level-1 QA band and the GEE median reducer. In Collection 1 Tier 1 data, each pixel in the QA band contains unsigned integers values that represent a particular surface, atmospheric, and sensor conditions that may affect the overall usefulness of a given pixel. When effectively used, QA values can improve data integrity by indicating which pixels might be affected by instrument artifacts or subject to cloud contamination (USGS, 2017). In conjunction with that, GEE can be instructed to pick the median pixel values in a stack of images. By doing so, GEE rejects values that are too high (e.g., clouds) or too low (e.g., shadows) and picks the median pixel value in each band, over time, Figure 3.



Figure 3 - Left, Collection 2 "cloud-free composite". Right, Collection 3 "cloud-free".

3 Classification

The automatic classification of the Landsat mosaics was performed entirely on the Google Earth Engine platform, based on the U-Net classifier, a deep learning model.

3.1 Classification scheme

Each class was classified separately, in a binary fashion. For this matter, the classification process was carried out, always considering only two possible classes for each pixel, the interest class (mining) or non-interest class (non-mining).

For the supervised classification of the Landsat mosaics, we have selected training samples (geometries) captured inside of the previously generated bounding boxes (grids). The details of the parameters used in the U-Net classifier, the reference maps used for each interest class, and the feature space produced for each classification are presented in the sections to follow.

3.2 Mining Feature Space

A Landsat median composite, from January 1 to December 31, was clipped by the "Reference grid vector," obtained through visual analysis of the reference data. Subsequently, spectral indices were also used to help within the identification of surface mineral activity are added to the set of classification inputs, see table 3.

Table 3 – Indices and Landsat Bands used to classification

Band Name	Expression	Reducer	Reference
NDSI	$(GREEN - SWIR2) / (GREEN + SWIR2)$	Median	(Deng et al., 2015)

NDVI	$(NIR - RED) / (NIR + RED)$	Median	(Tucker, 1979)
SWIR2	Landsat Swir2 band median value	Median	USGS
SWIR1	Landsat Swir1 band median value	Median	USGS
NIR	Landsat Nir band median value	Median	USGS
RED	Landsat Red band median value	Median	USGS
GREEN	Landsat Green band median value	Median	USGS

3.3 Classification algorithm, training samples, and parameters

When lacking a reference map that precisely matches the annual mosaic to be classified, the closest possible reference was used. When no reference map was available, then the results of the classification of the previous year were used to guide the training of the subsequent one. Table 4 shows the Random Forest parameters used to classify each one of the years.

Table 4 - Random Forest parameters used to classify each one of the years.

Parameter	Value
Classifier	U-Net
Tile-Size	256 × 256 pixels
Optimizer	SGD
Learning Rate	0.1
Momentum	0.9
Decay	1e-4
Samples	8400 (geometries)
Attributes	NDVI, NDSI, Landsat bands

3.3.1 Mining

As in any supervised method, the U-Net classifier needs to rely on a training dataset. For the mining recognition, the training data was references were extracted from the CPRM (Brazilian Geological Service), AhkBrasilien (Camara de Comercio e Industrial), INPE (Instituto

Nacional de Pesquisas Espaciais) and from ISA (Instituto Socioambiental), posteriorly converted into grids, where geometric samples were draw, Figure 5.

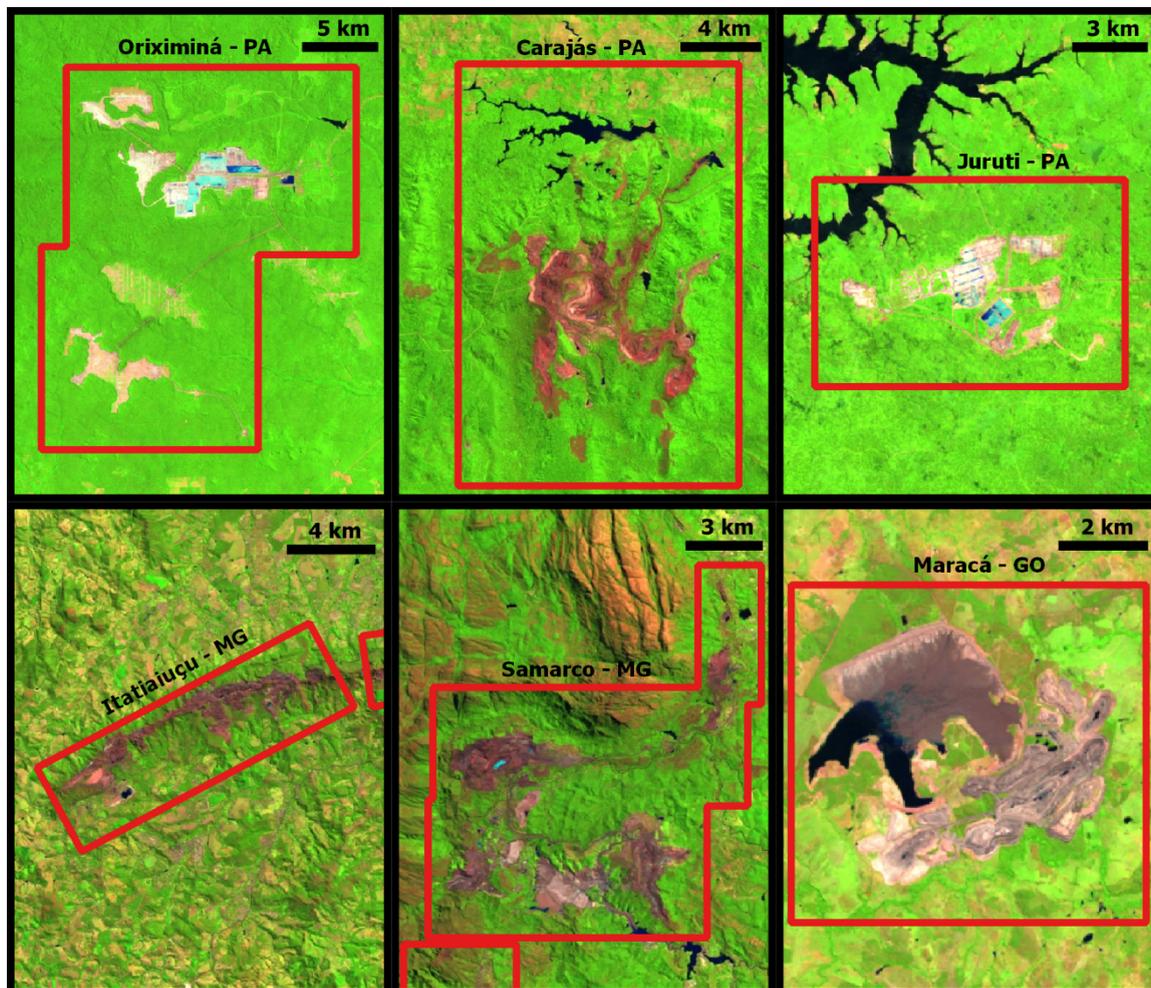


Figure 5 – The training samples were collected only inside of the Reference Grids (red polygons). From left-to-right and top-to-bottom, the mine grids of Oriximina-PA, Carajas-PA, Juruti-PA, Itatiaiuçu-MG, Samrco-MG, Maracá-GO.

4 Post-classification

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

4.1 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, then 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. To keep track of pixel temporal origins, a mask of years was built, as shown in Figure 9.

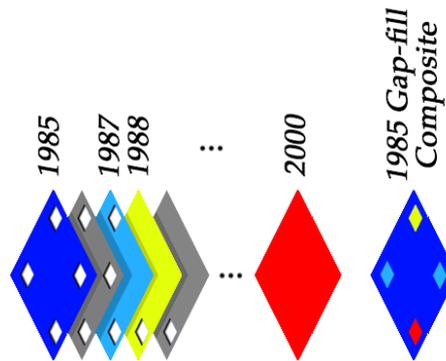


Figure 9 – Gap-filling mechanism. The next valid classification replaces existing no-data values. If no “future” valid position is available, then the no-data value is replaced by its previous valid classification, based on up to a maximum of three (3) prior years. To keep track of pixel temporal origins, a mask of years was built.

4.2 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”), and 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 of 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 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

4.3 Spatial filter

Next, 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 10. In this filter, at least ten 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 10 pixels (~1 ha).

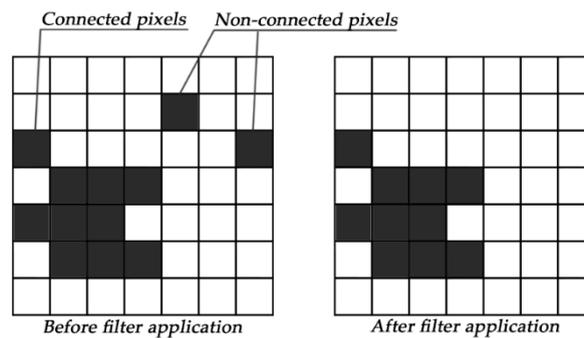


Figure 10 – The spatial filter removes pixels that do not share neighbors of identical value. The minimum connection value was 10 pixels.

4.4 Frequency filter

The last step of the filter chain is the frequency filter, as shown in Figure 11. This filter takes into consideration the occurrence 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 33) are filtered out and incorporated into the non-class binary. This mechanism contributes to reducing the temporal oscillation of the classification signal, decreasing the number of false positives, and preserving consolidated class pixels.

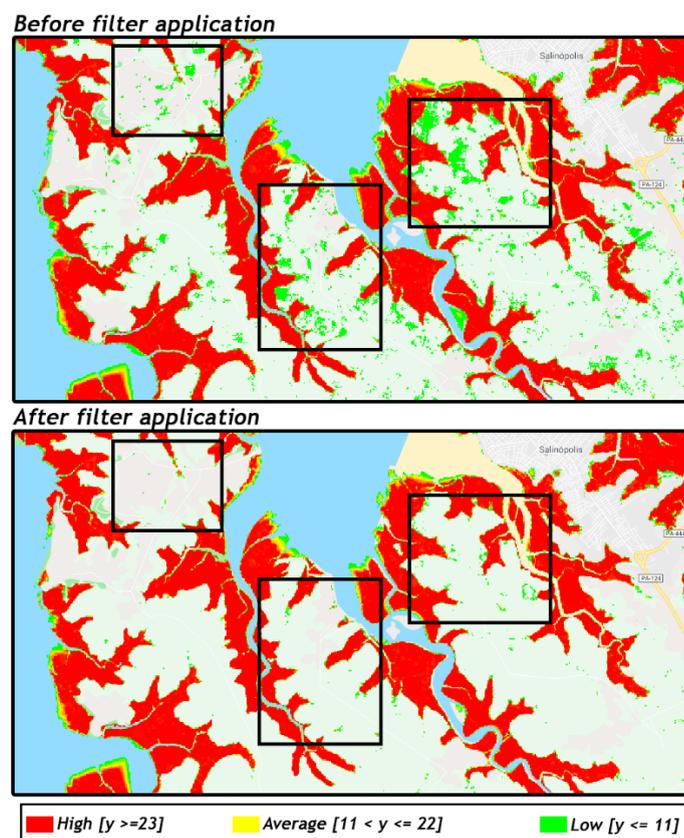


Figure 11 – Red, yellow and green represent classified pixels with high (23 or more years, $y \geq 23$), average (between 11 and 22 years, $11 \leq y \leq 22$), and low (ten years or less, $y < 11$) occurrence frequencies, respectively. The top image shows classified pixels before applying the frequency filter. The bottom image shows pixels after using the frequency filter. The black boxes are centered on areas that have been significantly affected by the filter. Note that all classification occurrences with less than 10% temporal persistence (3 years in 33 possible years) were filtered out.

4.5 Integration with biomes themes

After the application of the filter-chain, the cross-cutting themes and the Biomes data are integrated. This integration is guided by a set of specific hierarchical prevalence rules (Table 5). As output of this step, a final vegetation cover/land use map for each chart of the MapBiomias project.

Table 5 - Prevalence rules for combining the output of digital classification with the cross-cutting themes in Collection 4.

Collection 4	Prevalence Rule
4.1. Beaches and Dunes	1
1.1.3. Mangrove	2
5.2. Aquaculture	3
2.3. Apicum	4
5. Water	5
5.1. River, Lake and Ocean	5
1.2. Forest Plantations	6
4.4. Mining	7
4.2. Urban Areas	8
3.2. Farming	9
3.2.1. Annual and Perennial Crop	9
3.2.1. Cultivo semi perene	9
1.1.1. Forest Formations	10
1.1.2. Savana Formations	11
4.5. Rocky Outcrop	12
2.1. Non-Forest Formations in Wetlands	13
2.2. Grassland	14
2.4. Other Non-Forest Formations	14
3.1. Pasture	15
4.3. Other Non-Vegetated Area	16
3.3 Agriculture or Pasture	17
6. Not Observed	18

References

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