MAPBIOMAS
ECUADOR

Land Cover and Land Use

Mining - Transversal Map

Algorithm Theoretical Basis Document (ATBD)

Collection 4.0

Version 1.0

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1. Introduction

The land cover associated with mining is classified as a transversal (cross-cutting) theme within the MapBiomas methodology because it is spectrally similar to other classes, such as urban centers, sandbanks and other non-vegetated areas. This methodology has previously been implemented in several countries, such as Bolivia, Peru and Venezuela, with positive results in identifying the class. In Ecuador, the mapping methodology has been applied since Collection 3 of MapBiomas Amazonía, released in 2021.

This document describes the methodology used in MapBiomas Ecuador Collection 4.0 to classify areas with mining activity in the Ecuadorian territory, defined as surface areas where stone (aggregate) materials or minerals are extracted, with clear exposure of the soil. No distinction is made as to whether the mining is industrial or artisanal, legal or illegal, metallic or non-metallic (aggregates). Most of it is alluvial; activity that may be taking place in underground mines is not captured.

It is important to note that the original methodology was based on the experience of the MapBiomas Brazil team, and in particular of Cesar Diniz (Solutions in Geoinformation, Solved, Brazil), who gave a presentation to the MapBiomas team on the identification of industrial mining in that country. It was implemented in Google Earth Engine with adjustments to improve the performance and quality of the classified product.

2. Construction and Definition of Landsat Mosaics

The first step in generating land cover and land use maps is building mosaics from satellite images captured by the Landsat program. Due to the characteristics of the MapBiomas Ecuador initiative, two methods were used for the annual mosaics for the 1985-2024 period, depending on location:

1. Area within the RAISG boundary: the mosaics were processed using a uniform grid based on the International Map of the World at the Millionth Scale (1:250,000 scale), where each sheet covers a total of 1°30' of longitude by 1° of latitude (see Fig. 1).

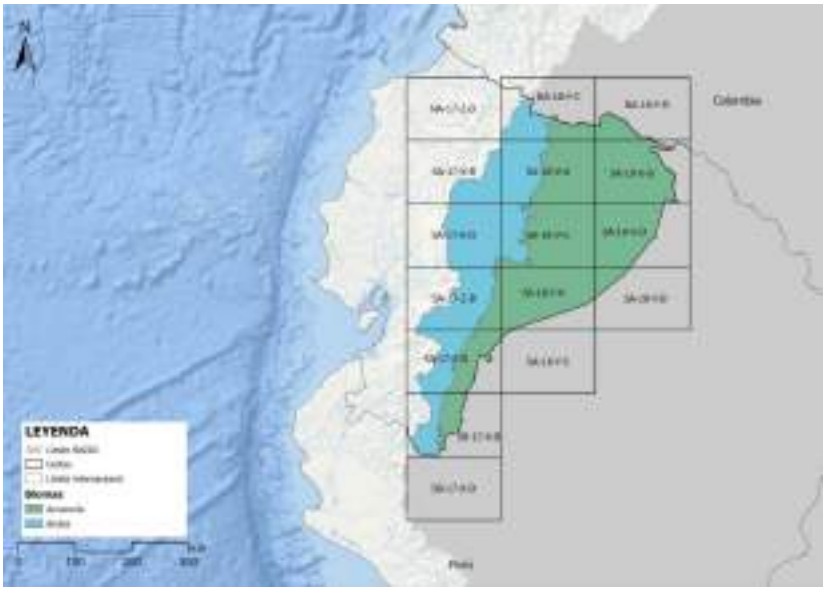


Figure 1: Distribution of the International Map of the World grid at a scale of one to one million, used for mosaic processing in the cross-cutting mining map. Source: Ecociencia

2. Area outside the RAISG boundary: the reference unit for building the mosaics was the path/row grid. The entire Ecuadorian territory, both mainland and insular, is covered by 17 path/row combinations.

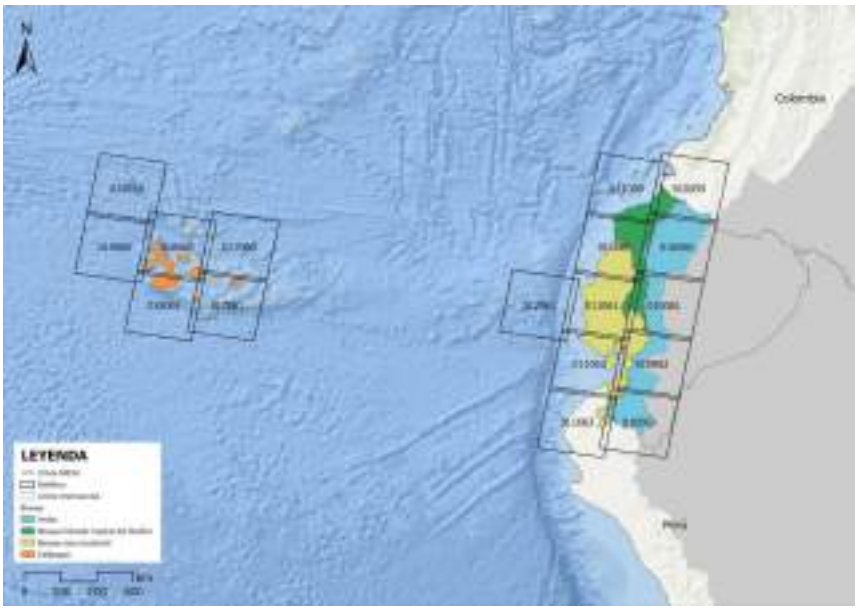


Figure 2: Distribution of Path/Row combinations used for mosaic processing in the cross-cutting mining map. Source: Ecociencia

For each map sheet and path/row, annual mosaics are built from Landsat images, with the aim of generating periodic cloud-free images that allow classification and change detection. For more details, see section 4 of the Algorithm Theoretical Basis Document (ATBD) for Ecuador - Collection 4.0.

For Collection 4.0, the mosaic for 2025 was built exclusively with the Path/Row method, as a first step towards unifying the methodologies used to generate mosaics.

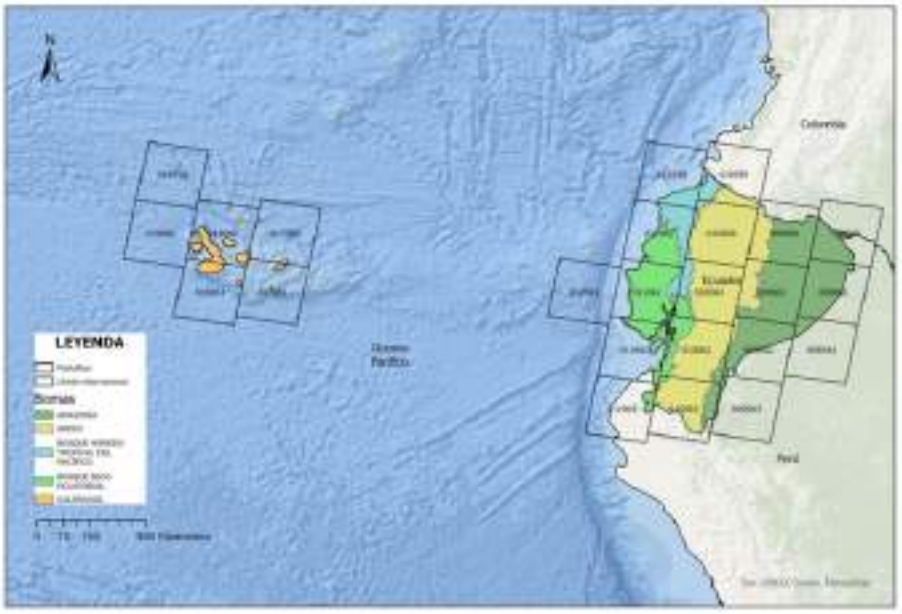


Figure 3: Distribution of the Path/Row tiles used for processing the 2025 mosaic. Source: Ecociencia.

3. Methodological summary

The mining classification methodology consists of six stages: generation of reference layers, data preparation, definition of training samples, classification with Random Forest, application of spatial and temporal filters, and final integration in GEE. The process includes an iterative stage of adjustment and evaluation of the classification to improve its consistency before integration. The six classification steps of the mining transversal theme are shown schematically in the following diagram (see Fig. 4).

Figure 4: Steps for mining classification. Source: Ecociencia.

4. Classification variables

Selecting variables from the mosaics to identify mining areas in Ecuador is the first step of the classification. Tests were carried out to identify a specific set of variables for mining detection. The variables used are presented in Table 1.

Band	Expression / Description	Reducer
blue	Blue band value	Median
green	Green band value	Median
red	Red band value	Median
nir	Near-infrared (NIR) band value	Median
swir1	SWIR1 band value	Median
swir2	SWIR2 band value	Median
ndfi		Median
ndfib		Median
npv		Median
soil		Median, Amplitude
evi2	2.5 * ((NIR - Red) / (NIR + 2.4*Red + 1))	Median
ndvi	(NIR - Red) / (NIR + Red)	Median
ndwi_gao	(Green - SWIR1) / (Green + SWIR1)	Median
ndwi_mcfeeters	(Green - NIR) / (Green + NIR)	Median
mndwi	(Green-NIR)/(Green+NIR)	Median
gcvi	(nir / green) - 1	Median
nuaci	$UNTL*(1-\sqrt{(NDWIi-aNDWI)2+(NDVIi-aNDVI)2+(NDBIi-aNDBI)2})$	Median
		Median
pri	(blue - green)/(blue + green)	Median

Table 1 - Variables used to classify mining areas in Collection 4, MapBiomas Ecuador.

5. Classification

To generate the classification, a methodological scheme divided into six stages was developed: four correspond to the classification process and the remaining two to the post-classification stage. The process involved (1) identifying mining areas using official external sources, gathering information from reports, complaints and surveys in the Coast and Andes regions, and a general sweep of the Amazon, where a visual inspection was carried out by an interpreter specialized in mining detection; (2) sampling and classification in each of the identified regions, after which the result for the mining class was integrated into a single layer and, finally, into the general map of MapBiomas Ecuador Collection 4.0. Each step of the classification is described below.

5.1. Generation of reference layer and data preparation

A search was carried out for official auxiliary data sources that report the presence of mining activity, including the mining cadastre (ARCERNNR, 2022) and the quarry and mine classes of the land cover and land use and agricultural production systems map of mainland Ecuador (MAG, 2021).

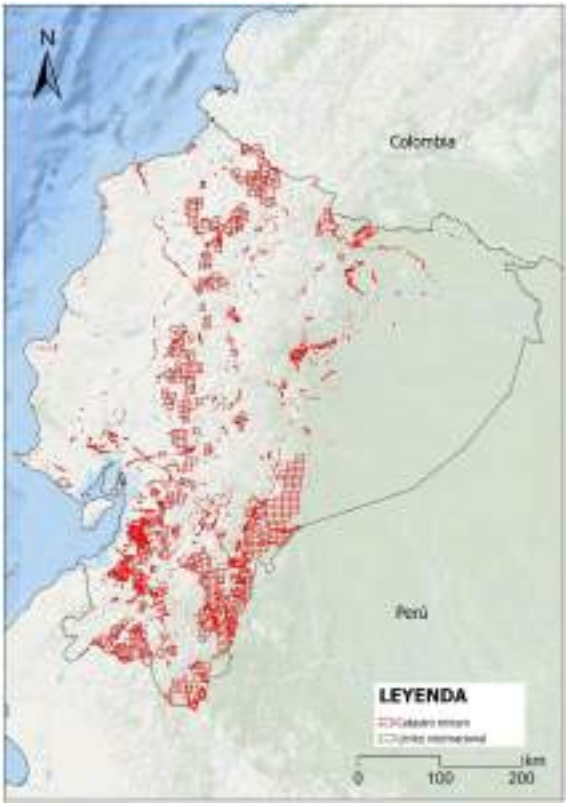
Mining cadastre	Quarries and mines from the land cover, land use, and agricultural production systems map of continental Ecuador
	

Figure 5. Presence of mining identified by each reference source. Source: EcoCiencia.

5.1.1. Amazon

In the Amazon region, the reference data were used as input to guide the identification of areas with mining activity through a systematic manual sweep of the entire study area. To do this, a reference grid was first laid over the region, which made it possible to organize the review and ensure complete spatial coverage.

For each year of the collection, ROIs were generated independently. Areas potentially affected by mining activity were identified through visual interpretation of the annual Landsat mosaics, complemented with higher spatial resolution Planet imagery. Based on this review, areas with evidence of mining activity were delineated and digitized manually as ROIs (see Fig. 8).

The resulting ROIs were the initial input for identifying and classifying mining areas in the Ecuadorian territory, and were later used as a reference for the training and classification stages.

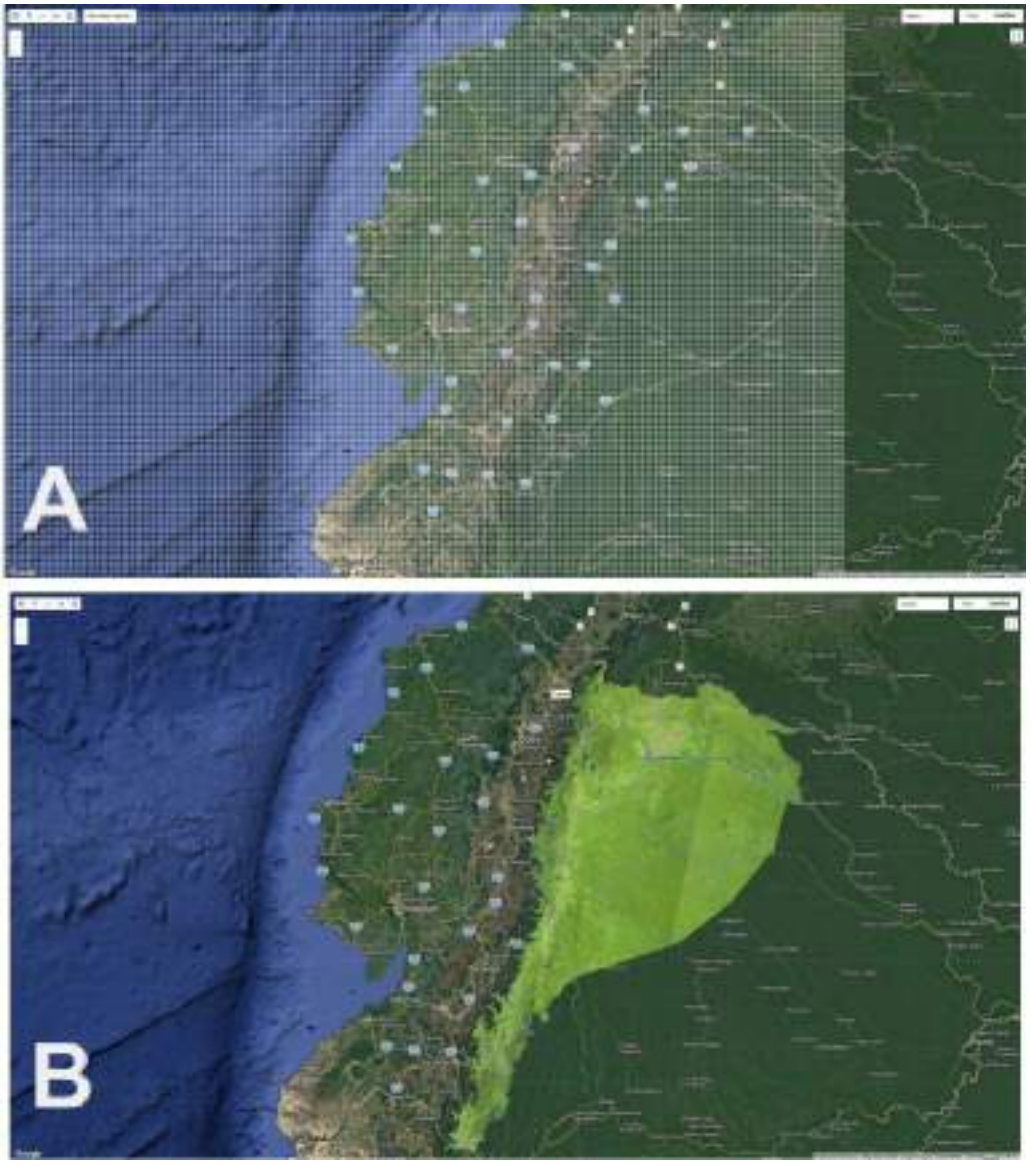


Figure 6: Script used to identify mining through a manual sweep. A. Grid used for the sweep. B. Landsat 2025 mosaic (RGB 654 L8). Prepared by: EcoCiencia.

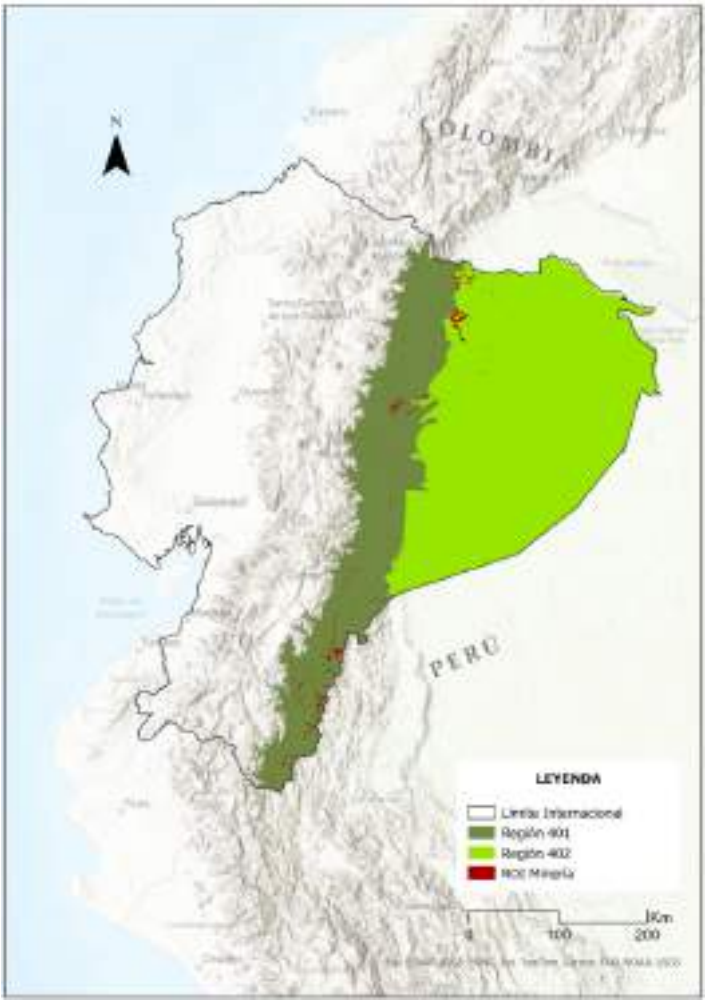


Figure 7: Mining classification ROIs for the Amazon, Collection 4.0. Prepared by: EcoCiencia.

Figure 8: Example of ROIs for mapping mining areas - Tundayme sector. Landsat 2025 mosaic (RGB 654 L8). Prepared by: Ecociencia.

5.1.2. Coast and Andes

For the Coast and Andes regions, information was gathered through surveys. These surveys were shared with key stakeholders, who contributed geographic information on areas with mining. Reports, complaints and news, among other sources, were also consulted in order to identify additional mining areas (see Fig. 9). In addition, an exhaustive sweep of the entire study area was carried out to include areas that had not been considered in the initial survey.

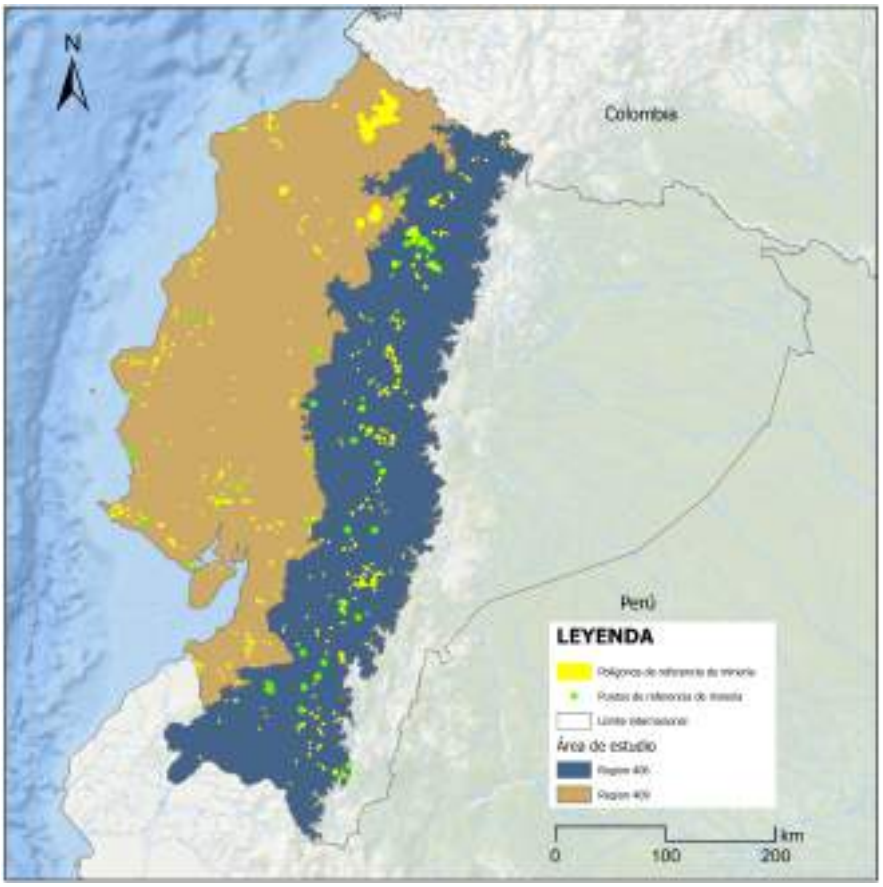


Figure 9: Reference for mining area mapping in the Coast–Andes regions. Source: EcoCiencia.

As a starting point, the historical series was divided into seven periods, to which the year 2024 was added in Collection 3.0 and the year 2025 in Collection 4.0 (see Table 2). For each period, the areas affected by mining activity were identified and ROIs were drawn manually. For this task, the information gathered, the official reference data and visual identification through a sweep of the entire study area, supported by Planet imagery and Landsat mosaics, were used as a guide.

As a result, nine ROI layers were generated, one for each period. These ROIs serve as the starting point for the identification and classification of mining in the country (see Fig. 10).

Period No.	Years
PERIOD 1	1985-1992
PERIOD 2	1993-1997
PERIOD 3	1998-2002
PERIOD 4	2003-2007
PERIOD 5	2008-2012
PERIOD 6	2013-2018
PERIOD 7	2019-2023
PERIOD 8	2024
PERIOD 9	2025

Table 2 - Analysis periods for identifying mining in the Andes and Coast regions for Collection 4.0, MapBiomas Ecuador.

Period 1 (1985 - 1992)

Period 2 (1993 - 1997)

Period 3 (1998 - 2002)

Period 4 (2003-2007)

Period 5 (2008 - 2012)

Period 6 (2013 - 2018)

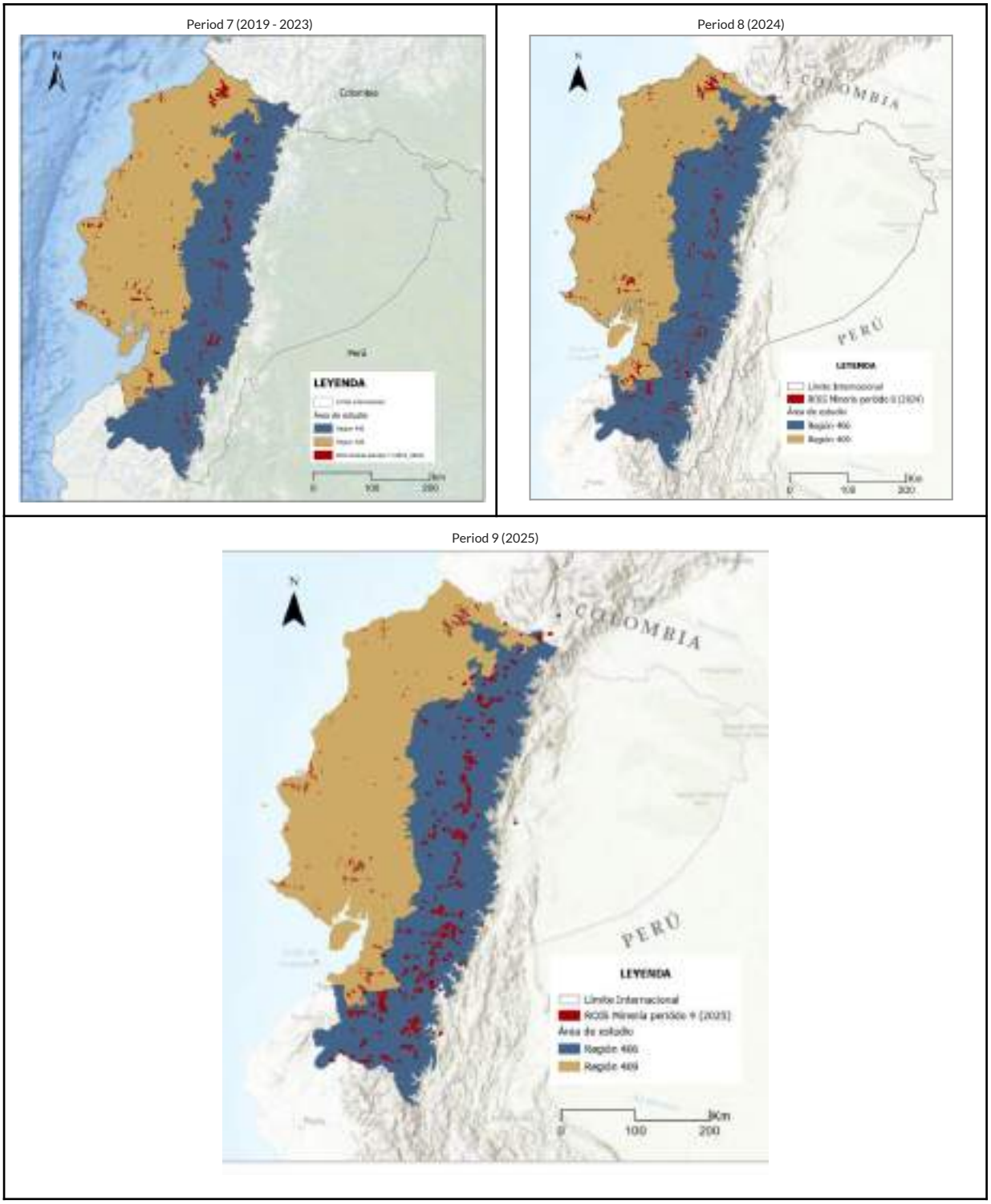


Figure 10: Mining classification ROIs for the Coast-Andes, Collection 4.0. Prepared by: Ecociencia

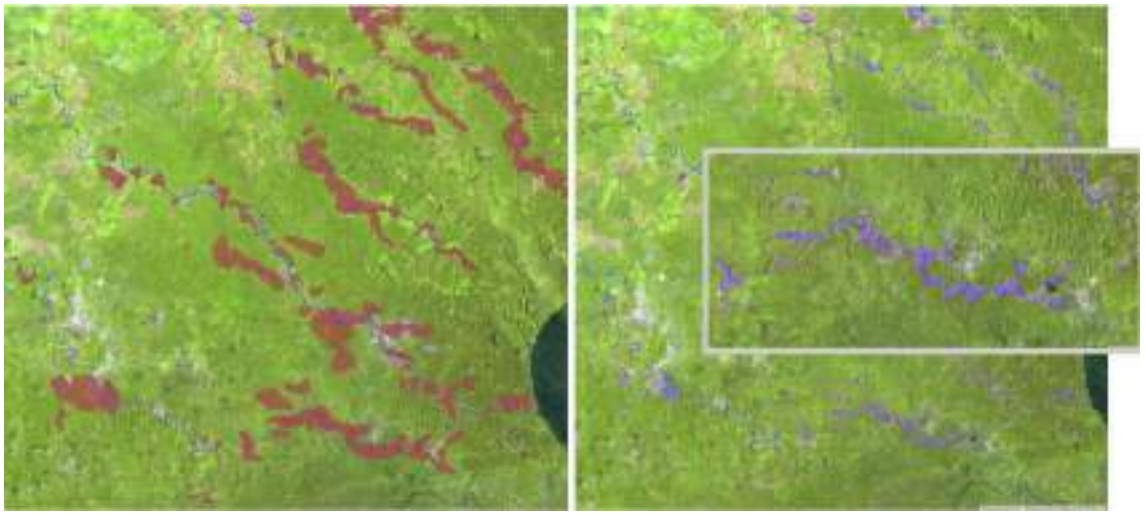


Figure 11: Example of ROIs for mapping mining areas - Esmeraldas. Landsat 2025 mosaic (RGB 654 L8). Prepared by: Ecociencia.

5.2. Training samples (mining / non-mining)

Within the ROIs (see Figures 7 and 8), two types of training points were defined manually: the first, 'New_samples_30' (ID 30), contains strictly pixels that are part of the mining extraction area, and the second polygon covers the class 'New_samples_27', i.e. areas that do not correspond to mining activity, covering all classes other than mining (ID 27) (see Fig. 12). The training samples are used to classify pixels as mining or non-mining. The area outside the zone delimited as the region of interest is not classified within this transversal theme.

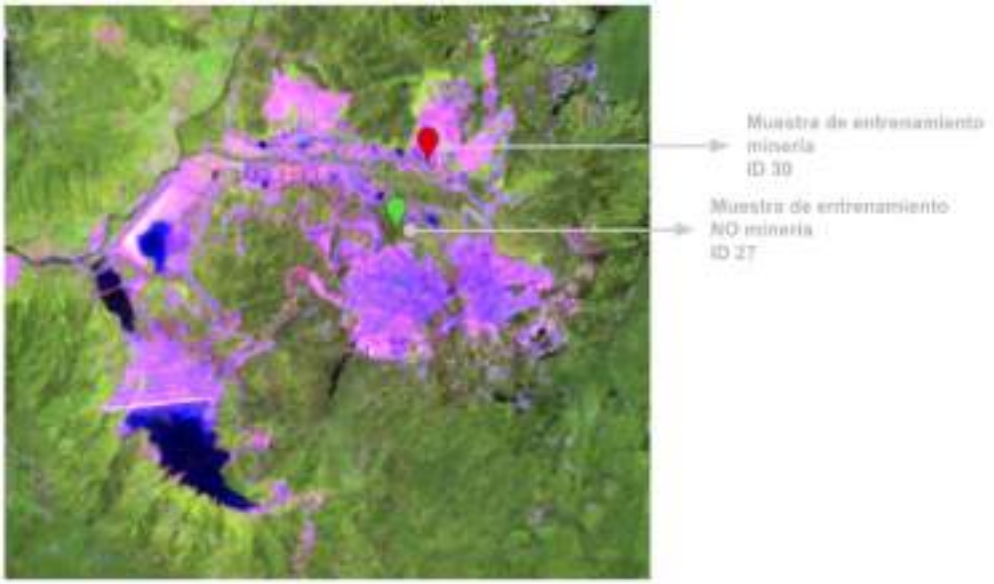


Figure 12: Mining and non-mining polygons - Tundayme sector. Landsat 2025 mosaic (RGB 654 L8). Prepared by: Ecociencia

5.3. Classification using the Random Forest algorithm

The classification process is based on the Random Forest classifier, which uses artificial intelligence (AI) algorithms and machine learning to distinguish areas with mining within the regions of

interest. By building a collection of independent decision trees, a class is assigned to each pixel (Breiman, 2001) through a series of binary splits. This makes it possible to make predictions based on that classification. The decision trees are generated randomly to reduce the correlation between them and improve the accuracy of the model.

The classification of mining areas was carried out on the Google Earth Engine platform, based on the methodology implemented by the MapBiomas Brazil team (Solutions in Geoinformation, Solved, Brazil) for identifying mining.

The classification was run within the ROIs (see Figs. 7 and 10) in each region in order to identify areas with mining activity. The result was an image composed of pixels indicating the presence of mining (area shown in red in Figs. 13 and 14), within the limits previously defined by the ROIs.

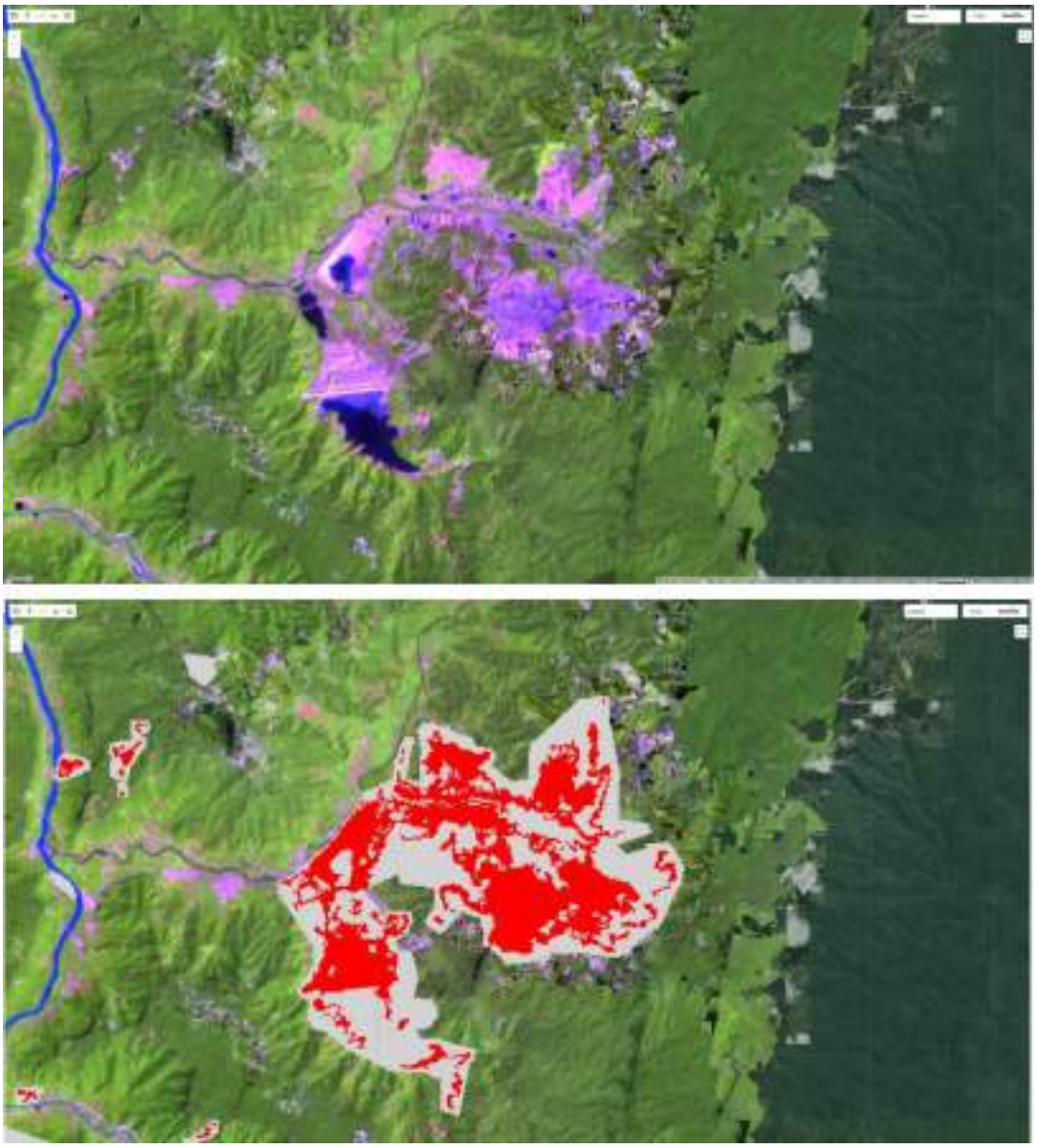


Figure 13: Mining classification in the Amazon. Top: open-pit mine, Landsat 2025 mosaic (RGB 654 L8). Bottom: polygons filled in red indicate the 2025 mining classification.

Figure 14: Mining classification in the Coast region. Top: river (alluvial) mining, Landsat 2025 mosaic (RGB 654 L8). Bottom: polygons filled in red indicate the 2025 mining classification. Prepared by: Ecociencia

5.4. Post-classification

The classification results were subjected to a sequence of filters in order to reduce temporal inconsistencies, data gaps, overestimation noise and other common classification errors. Three types of filters were applied: gap fill, a spatial filter and a temporal filter.

5.4.1. Gap fill

Due to its geographic position and topography, the Ecuadorian territory has high cloud cover throughout the year. In addition, the striping problem of the Landsat 7 sensor produces mosaics with missing information or pixels without data (No Data). For this reason, these gaps or null values must be filled using Gap fill, which reduces them by using the temporally closest pixel value.

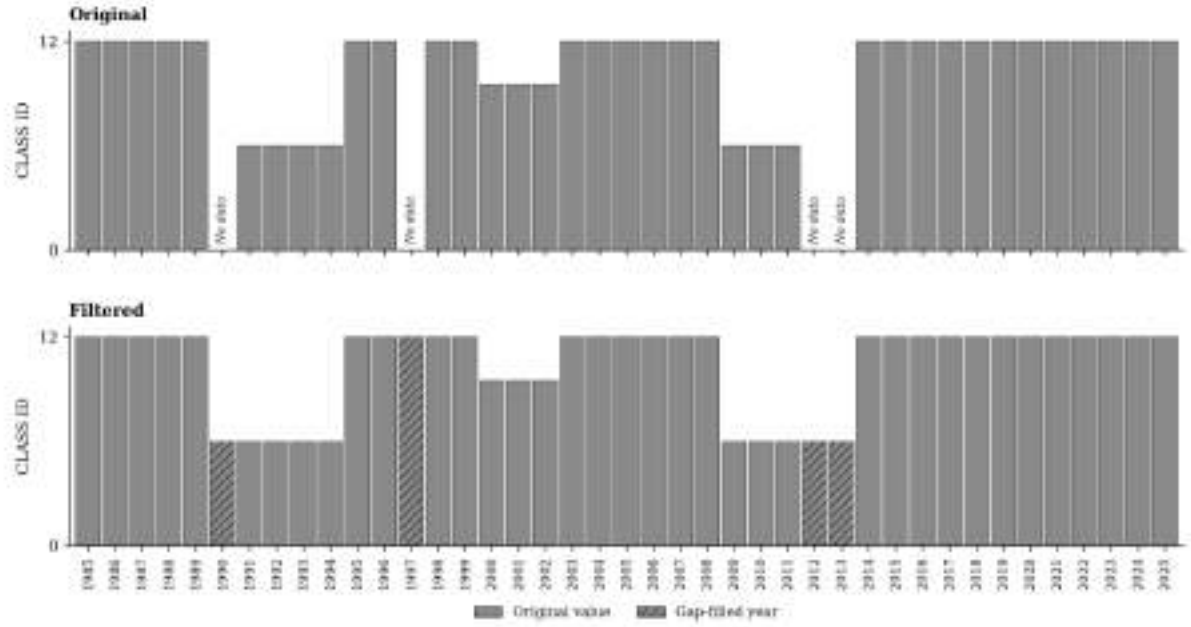


Figure 15: Diagram illustrating the functionality of the Gap Fill filter. Source: MapBiomas.

5.4.2. Spatial filter

The spatial filter is based on the Google Earth Engine function "connectedPixelCount", which identifies groups of neighboring pixels that share the same value. Using this function, and considering a preset minimum number of identical pixels, pixels that are not connected (i.e., have different values) are considered isolated and are reclassified (see Fig. 16).

For both classes (ID 27, ID 30), a minimum connection of 5 pixels (approx. 0.5 ha) was set.

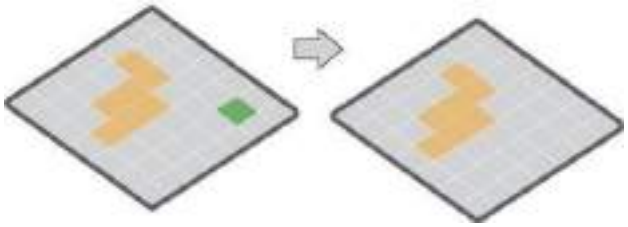


Figure 16: Diagram of how the spatial filter works. Prepared by: MapBiomas

5.4.3. Temporal filter

This filter replaces pixels considered to be noise or a "salt and pepper" effect, which represent inconsistencies caused by misclassification of land cover given its gradual year-to-year changes, as well as missing or distorted information in a mosaic. The temporal filter includes three sub-types: intermediate year, first year and last year, explained below.

Intermediate year: The filter is applied taking into account the first and last pixel of the time series, changing the classification of pixels in the intermediate years to the classes of the pixels at the ends of the time series (1985-2025). The lower part of Figure 17 shows that, for the 3-year rule, a pixel is classified as presence of the class of interest (in green: forest, agriculture, mining, etc.) in years t1 and t3, while in t2 it shows absence of the class of interest (in beige). After the filter is applied, it stabilizes these abrupt changes in the classification by changing the intermediate pixel to the class of its initial and final pairs. Likewise, it is applied to 4- and 5-year time series, and in the inverse way, as explained in the upper part of Figure 17. It is important to clarify that the intermediate-year rule is not applied to the first and

last years of the analyzed period, in this case 1985 and 2025, because there are no years to compare them with.

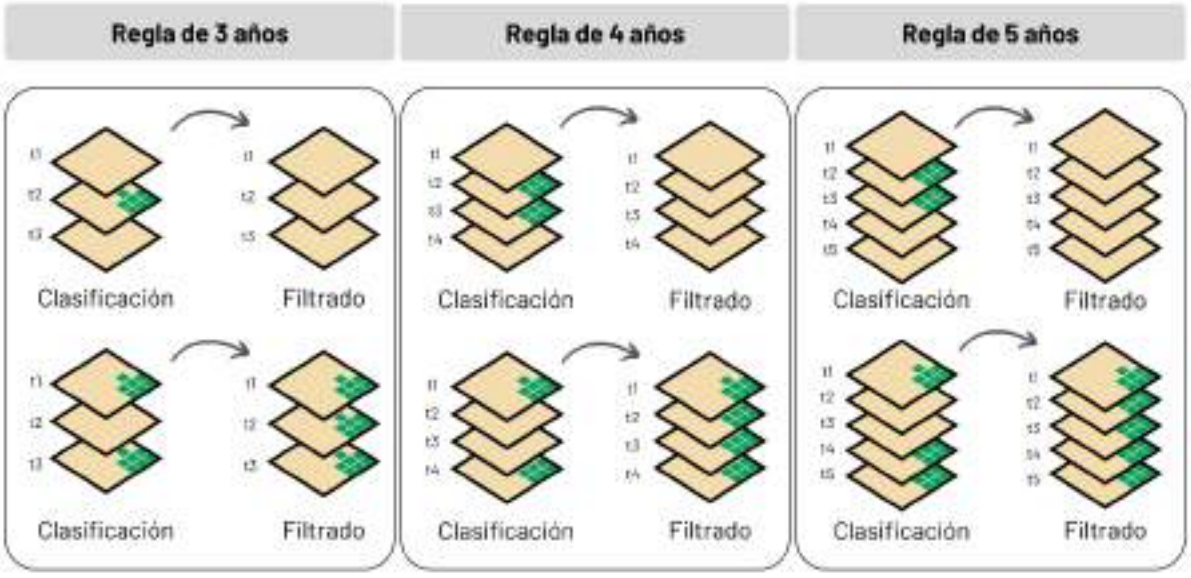


Figure 17: Effect of the temporal filter. Source: MapBiomas.

First and last year: The first-year rule corrects inconsistencies in the time series caused by missing information for 1985. The following example shows a transition from absence of areas of the class of interest (mining) in the first year to presence of mining areas in the first year.

The last-year rule corrects misclassified pixels at the end of the time series (2025) caused by abrupt changes such as the one mentioned above. Figure 18 shows how the filter acts on a pixel classified at the end of the time series as presence of mining (in green); after the filter is run, it is reclassified as absence of mining, making the series homogeneous.

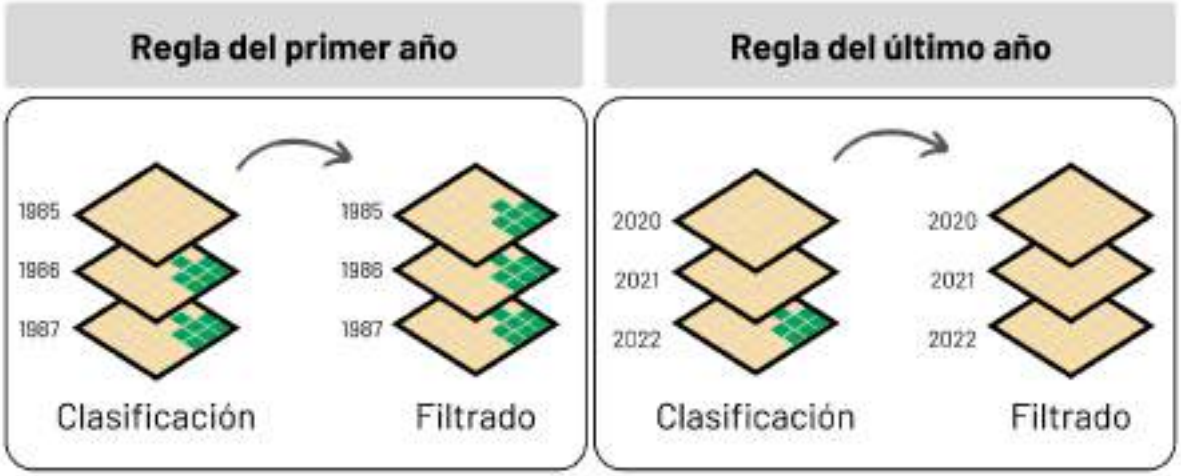


Figure 18: Temporal filter – first and last year rule. Source: MapBiomas.

Due to the dynamic nature of the mining class, which can appear and disappear in certain areas over time, the interpreter must carefully assess in which situations to run this filter and how to configure it. This is essential to avoid both overestimation and underestimation of the class throughout the time series.

In conclusion, the main objective of this set of filters is to obtain a stable time series, without inconsistent jumps that could affect statistical reports and the classification itself. Years can also be excluded from the time series to better match the behavior observed in the mosaics; this mainly happens in intermediate years, when a series of years is stable but other specific periods are not.

5.4.4. Integration

Once the classification of mining areas was obtained, a first integration of all areas identified as mines was carried out for each country, and this result was integrated into the general national classification map together with the other identified classes (see Fig. 19).

Integration is carried out based on a set of prevalence rules, or integration order, which define the priority between classes in case of overlap. Following the integration order, the result is the final map showing the presence of mining in the Amazon biome of Ecuador:

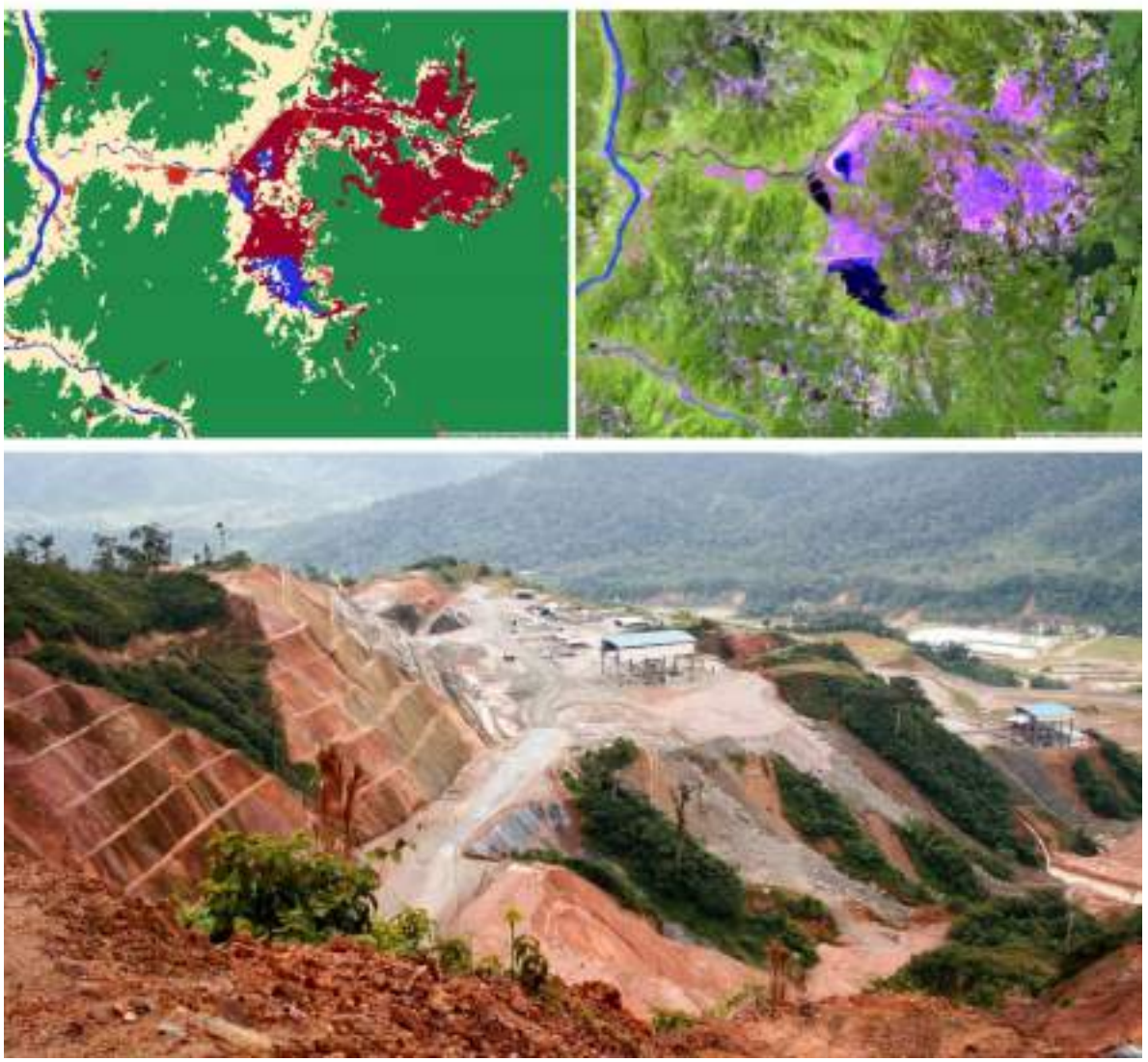


Figure 19: Integration of the mining class. Left: integrated classification of the classes identified in the general map of MapBiomas Ecuador Collection 4. Right: satellite image of the area. Bottom: landscape photo of the identified mining area. Photo: Ministerio de Energía, Flickr.

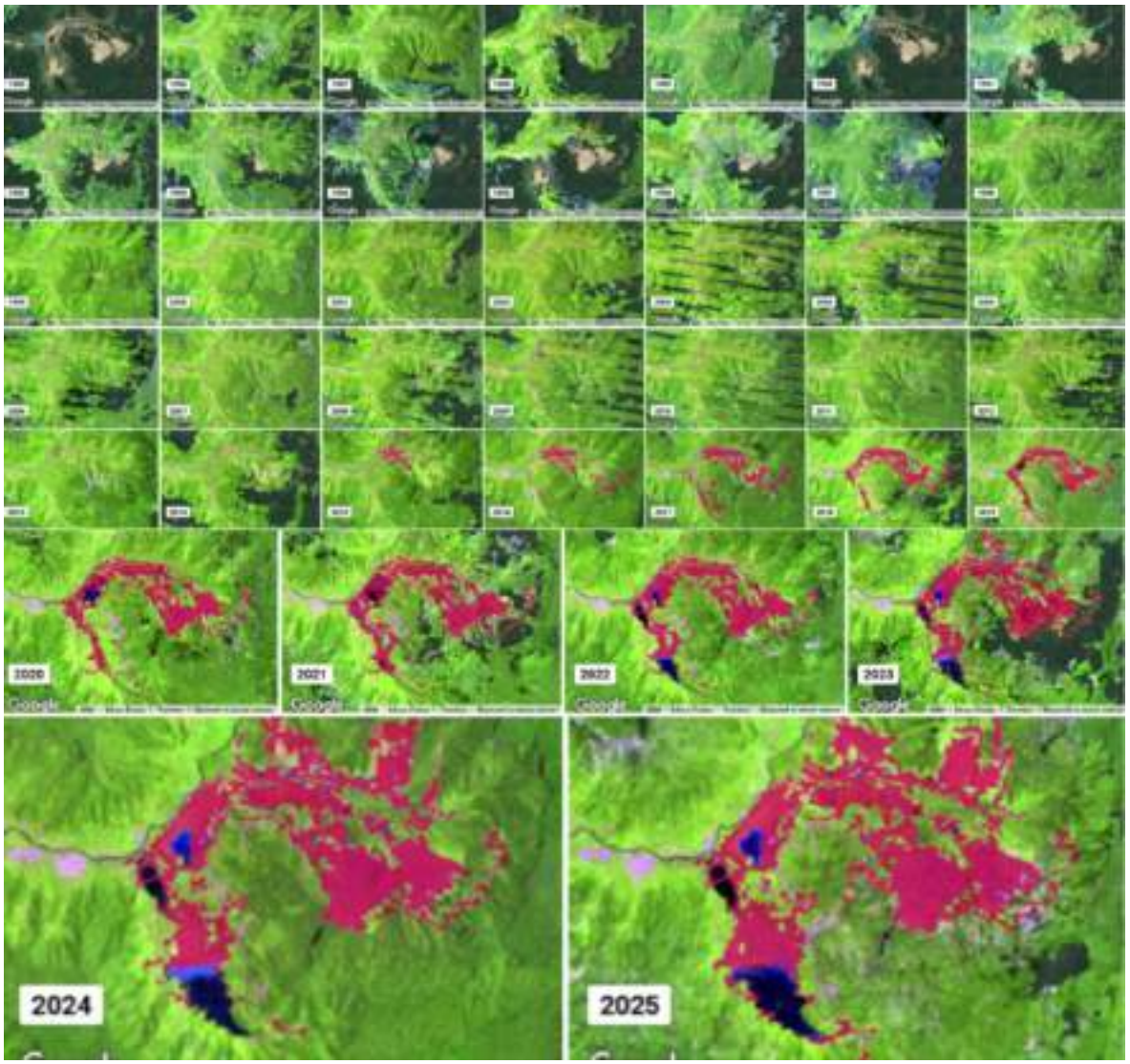


Figure 20: Multitemporal classification, Tundayme. Prepared by: EcoCiencia.

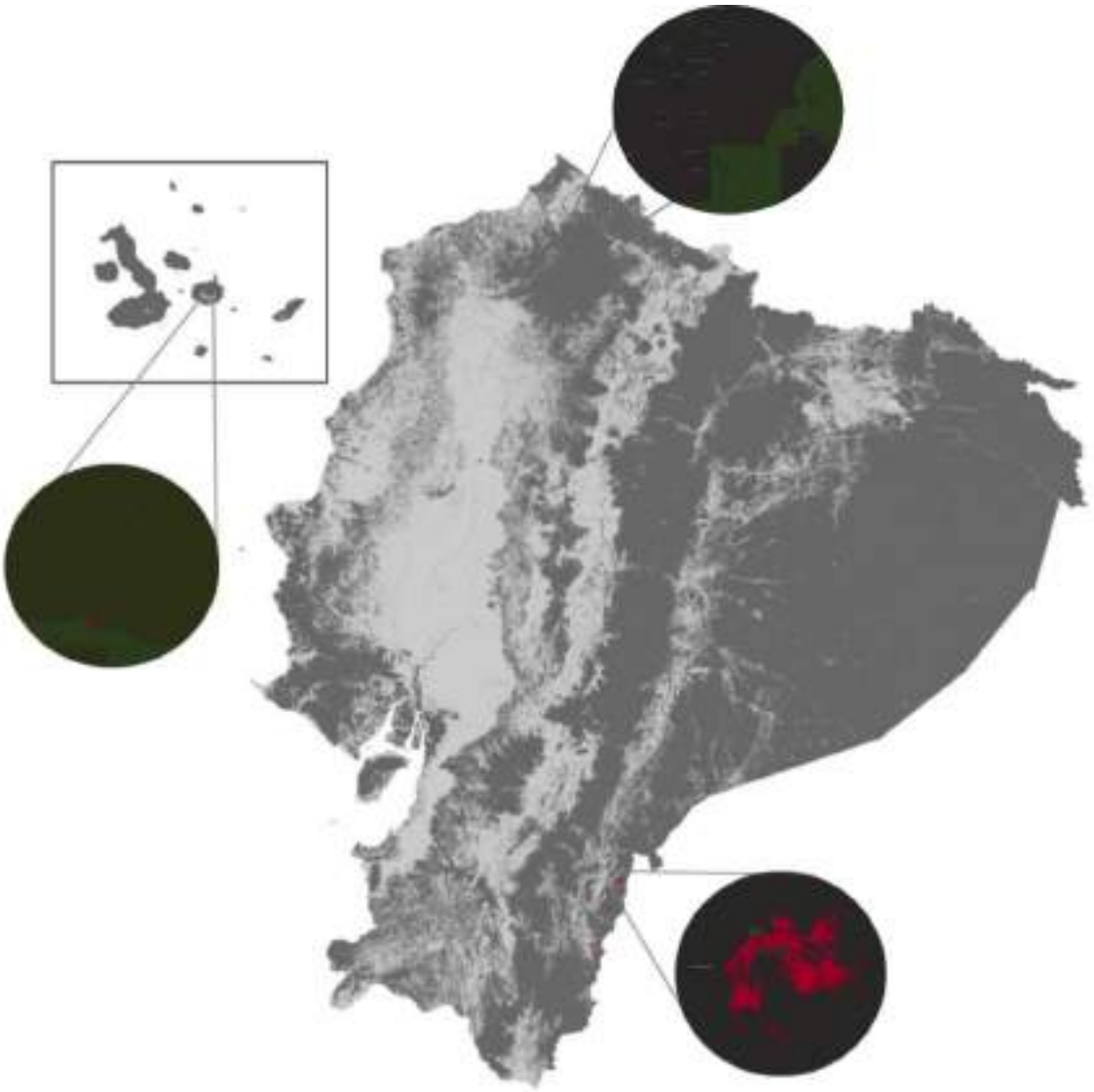


Figure 21: 2025 mining map. Prepared by: EcoCiencia

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