

Gaia Amazonas

RAISG
RED AMAZÓNICA DE INFORMACIÓN SOCIOAMBIENTAL GEORREFERENCIADA

Algorithm Theoretical Basis Document - ATBD

Water - Appendix: MapBiomas Water - Colombia
Mapbiomas Agua - Colombia
Collection 3, Version 1
2025

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1. Introduction

1.1. Scope and content of the document

The primary objective of MapBiomas Water is to map surface water dynamics within the Colombian territory on a monthly and annual basis from 1998 to 2024. Additionally, a section identifying Colombia's glaciers is included, covering the same time series.

One of the main outputs is a set of maps containing annual surface water data, partially incorporated as a cross-cutting theme into Collection 3 of MapBiomas Colombia to strengthen the integration of land cover and land use maps.

Beyond the integration with Collection 3, other applications produced by the MapBiomas Water initiative include the publication of datasets publicly available on a web platform to improve the management and use of water resources throughout the Pan-Amazon region.

The purpose of this Algorithm Theoretical Basis Document (ATBD) is to provide users with a guide to understanding the methodological steps for producing annual surface water data in Colombia. In the case of glaciers, the methodological steps are described by Turpo et al. (2022).

1.2. General Description

The MapBiomas Water initiative stems from a previous study conducted by Imazon and WWF-Brazil in the Brazilian Amazon biome, later expanded to the Upper Paraguay basin in the Chaco biome, published six years ago (Souza et al. 2019). This study demonstrated the possibility of improving the MapBiomas Initiative's capacity to detect and monitor surface water dynamics across Brazilian biomes. Within this context, the MapBiomas Water working group expanded the same approach and methodology to the entire Brazilian territory.

In 2022, thanks to the alliance between MapBiomas and the Amazon Network of Georeferenced Socio-Environmental Information (RAISG), it was decided to adapt, expand, and apply the MapBiomas Water methodology in Amazonian countries (Figure 1), with the objective of understanding water dynamics in the diverse biomes of the region. Consequently, the first collection of surface water maps for the Pan-Amazon was launched in September 2023, giving rise to the respective initiatives of each country, including MapBiomas Water Colombia.



Figure 1. Amazonian countries. Source: own elaboration adapted from RAISG (2025).

The methodology used to map and monitor surface water in Colombia is based on the supervised classification of satellite imagery from Landsat (5, 7, 8, and 9). The results obtained allow for a detailed spatial analysis of surface water bodies, facilitating the understanding of changes occurring over the last 27 years, whether due to anthropogenic impacts or the potential effects of climate variability and change.

For data processing, the Google Earth Engine platform was employed, which enabled the reconstruction of a monthly time series of surface water dynamics in Colombia between 1998 and 2024. Furthermore, all identified water bodies were classified into natural and anthropogenic categories. Key results related to surface water mapping, as well as transitions and temporal trends, were integrated into an interactive dashboard within the MapBiomas Water web platform, facilitating access and analysis for end users.

With the update of this platform and the launch of Collection 3, the MapBiomas Water Colombia initiative plans to train end users—including representatives from academia, the private sector, and the government—in its use. Thus, the availability of reliable information on the nation's water resources becomes an essential tool for decision-makers, allowing for the prioritization of actions aimed at protecting, restoring, and sustainably managing water use and freshwater ecosystems.

1.4. Key science and applications

The dataset on surface water body dynamics assists in a better understanding of aquatic systems and their interaction with other environmental components, being crucial for decision-making and contributing significantly to water resource management with a focus on sustainable development.

Surface water mapping information can support integrated territorial planning, monitoring of Sustainable Development Goals (SDGs), sustainable water management initiatives, monitoring of water concessions/small dams, assessment of freshwater ecosystem quality, and research and evaluation of changes in water bodies and their relationship with climate change.

2 General information and background

2.1. Context and key information

The conditions of many freshwater ecosystems have been degraded by anthropogenic activities in recent decades. Drastic changes in land use and land cover, the construction of hydroelectric dams, pollution, and the excessive use of water resources for the production of goods and services have altered water quality and availability worldwide. Recent evidence shows that freshwater species have extinction rates twice as high as terrestrial species (WWF, 2020). Additionally, extreme droughts and floods related to climate change have increased pressure on water reservoirs and aquatic ecosystems.

This scenario is likely to worsen, given the global population growth—which surpassed 8 billion inhabitants in 2022—and resource use; unless integrated water management strategies are developed, it will be impossible to achieve global sustainable development goals. From this perspective, continuous and historical evaluation of changes in surface water dynamics at a continental scale is one of the primary challenges in decision-making regarding this precious resource (Oliveira et al., 2019).

These challenges apply to Amazonian countries, which hold the highest proportion of water per capita on the planet, though with non-homogeneous distribution and quality. This implies the need for specific decision-making that considers different regional characteristics and the interconnected and cumulative effects of water use. This will only be possible through detailed and consistent data and information on surface water dynamics (MapBiomas Agua, 2023).

The novel surface water mapping methodology adopted by the MapBiomas Water initiative has previously allowed for the identification and quantification of freshwater dynamics in

Amazonian countries, particularly in wetlands (Souza et al. 2019). These results have been corroborated by a NASA-JPL study that also points to a reduction in atmospheric water vapor in the Amazon basin (Barkhordarian et al., 2019).

2. Historical perspective: existing maps and cartographic initiatives

The use of satellite data revolutionized the human capacity to map continental surface waters and their dynamics. The combination of free access to Landsat data linked with cloud processing capabilities enabled the launch of multi-decadal global datasets on surface waters:

Global Surface Water (GSW) (Donchyts et al. 2016, Pekel et al. 2016): This initiative provides information on the extent and dynamics of surface water across the entire Earth's surface, based on an analysis of over 30 years of Landsat imagery at the pixel level, with various scientific and management applications. However, the direct use of GSW at the national level remains a challenge due to methodological limitations in detecting water in floodplains, wetlands, and small water bodies.

MapBiomas Water seeks to overcome some of these limitations by adopting the same general approach of combining Landsat data with cloud computing capabilities, but adding methodological innovations to improve the detection and mapping of surface waters. Specifically, the initiative adopts a Subpixel-level Surface Water Spectral Classifier (SWSC), initially applied to the Brazilian Amazon biome (Souza et al. 2019). Details of this methodology are presented in the following sections.

3 Methodology

3.1. Landsat Imagery

The project utilized Landsat image collections available on the Google Earth Engine platform, specifically those corresponding to the Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) sensors, aboard the Landsat 5, 7, 8, and 9 satellites, respectively. With a spatial resolution of 30 meters per pixel, the Collection 3 Level 1 Surface Reflectance (SR) orthorectified image collection was used. All Landsat scenes covering the Colombian territory between 1998 and 2024 were utilized, filtering through their metadata for those with cloud cover of less than 70%.

3.2. Regionalization

For the classification of surface water in the Colombian territory, the country was divided into working areas of 100 x 100 km², recording a total of 133 work zones, as shown in Figure 2.

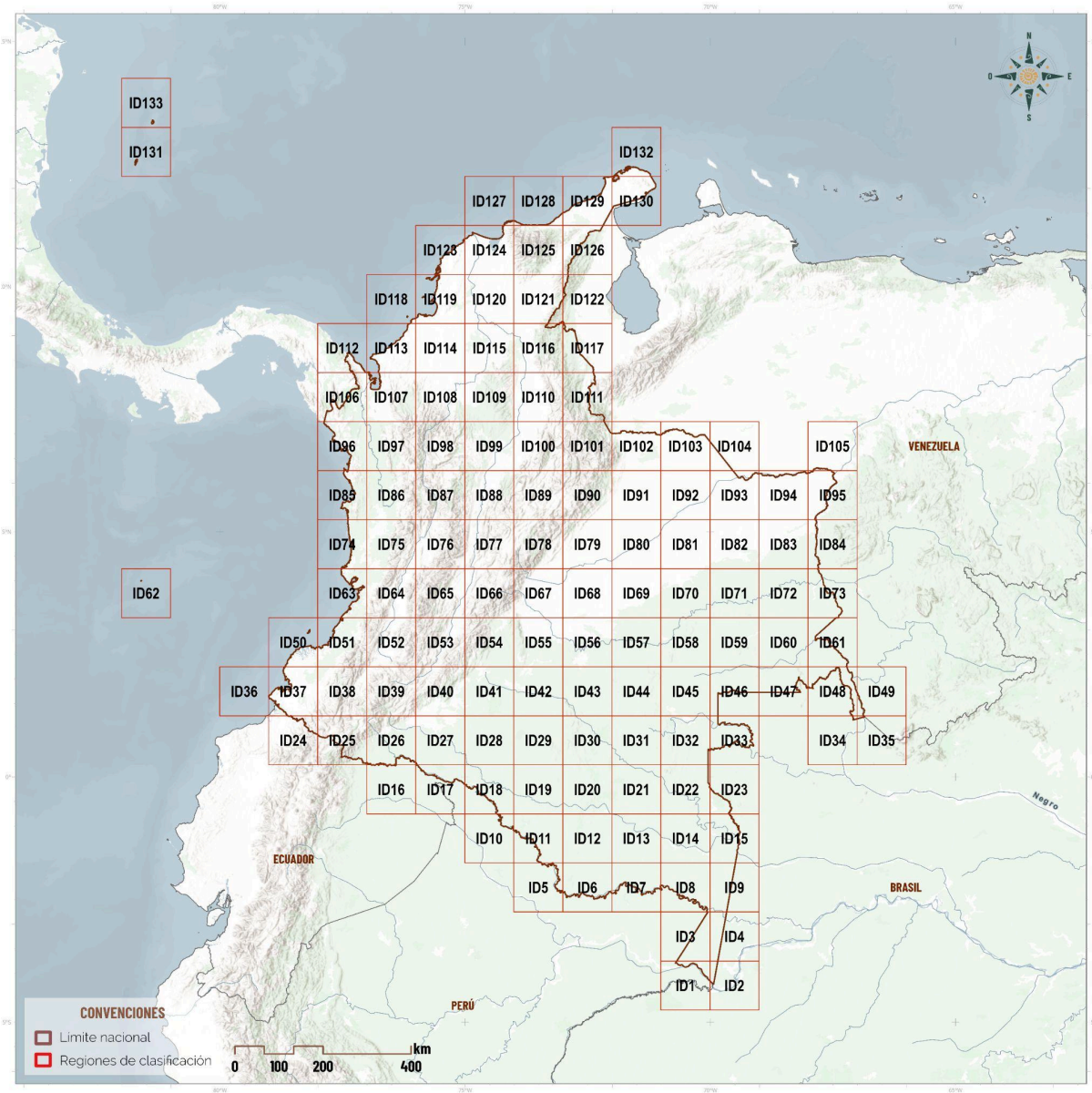


Figure 2. Classification regions. Source: own elaboration.

3.3. Algorithm for Surface Water Detection

The classification methodology was based on Spectral Mixture Analysis (SMA) applied to the Landsat imagery described in the previous section. This analysis generates a set of predictor variables that serve as the primary input for the Random Forest supervised classification model.

3.3.1. Spectral Mixture Analysis

SMA allows for the estimation of the fractional composition of pure pixels (endmembers) of Green Vegetation (GV), Non-Photosynthetic Vegetation (NPV), Soil, Cloud, Shade, and Snow. The information obtained with SMA enables subpixel detection, which is useful for characterizing surface water mixed with other components, such as soil and vegetation. This

approach overcomes the limitations of full-pixel classifiers and allows for the mapping of wetlands, floodplains, narrow rivers, and small water bodies.

In the application of this SMA model, a generic endmember library for Landsat imagery is used, allowing for the calculation of component percentages based on the spectral unmixing algorithm available in Google Earth Engine.

3.3.1.1. Annual Water Data Acquisition

Annual surface water maps include identification between permanent and seasonal water. This classification is based on thresholds corresponding to the number of months a pixel is classified as water. In the case of permanent water in the Colombian territory, a frequency equal to or greater than 6 months was considered, and for seasonal water, a frequency between 1 and 5 months. The definition of the permanent water threshold is based on the existence of a dry and a wet season in much of the country's regions, thus encompassing all permanent water bodies that are naturally more dynamic.

3.3.2. Classification methodology

The general supervised classification method is based on the Random Forest algorithm, which uses data obtained from Spectral Mixture Analysis (SMA) to predict the categories of interest. The process is developed as follows (Figure 3):

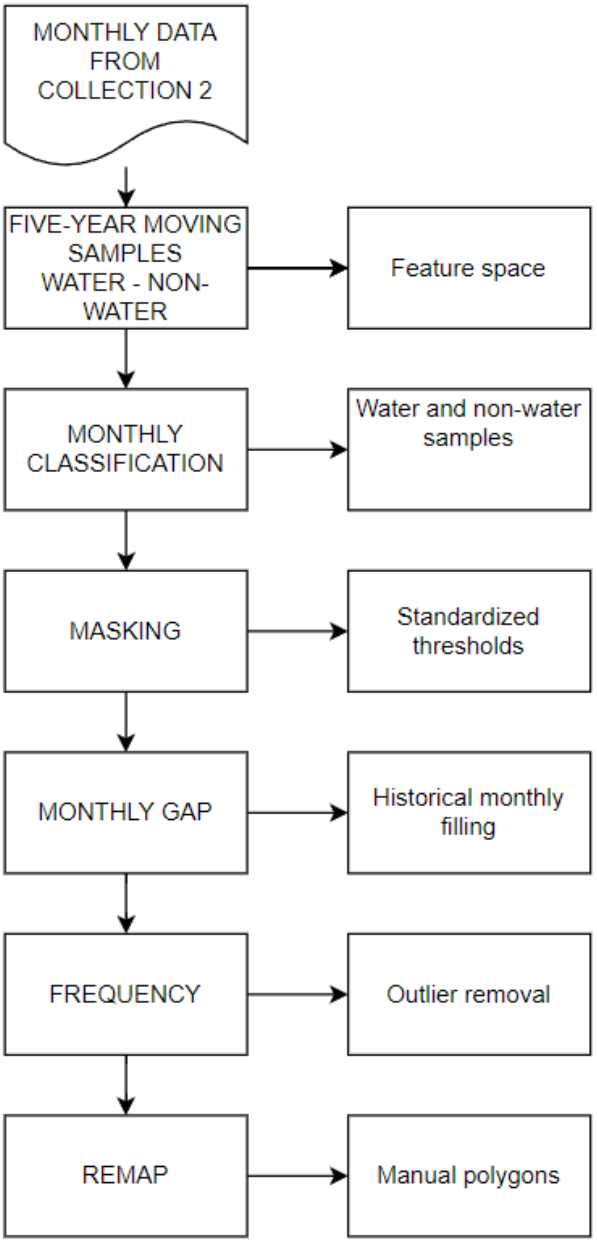


Figure 3. Classification workflow. Source: own elaboration.

3.3.2.1. Point sampling

Point sampling is performed based on Collection 2 of MapBiomas Water Colombia, conducted for each year and month. This ensures a balanced set of representative samples from areas with water bodies (water) and without water bodies (non-water) (Figure 4).

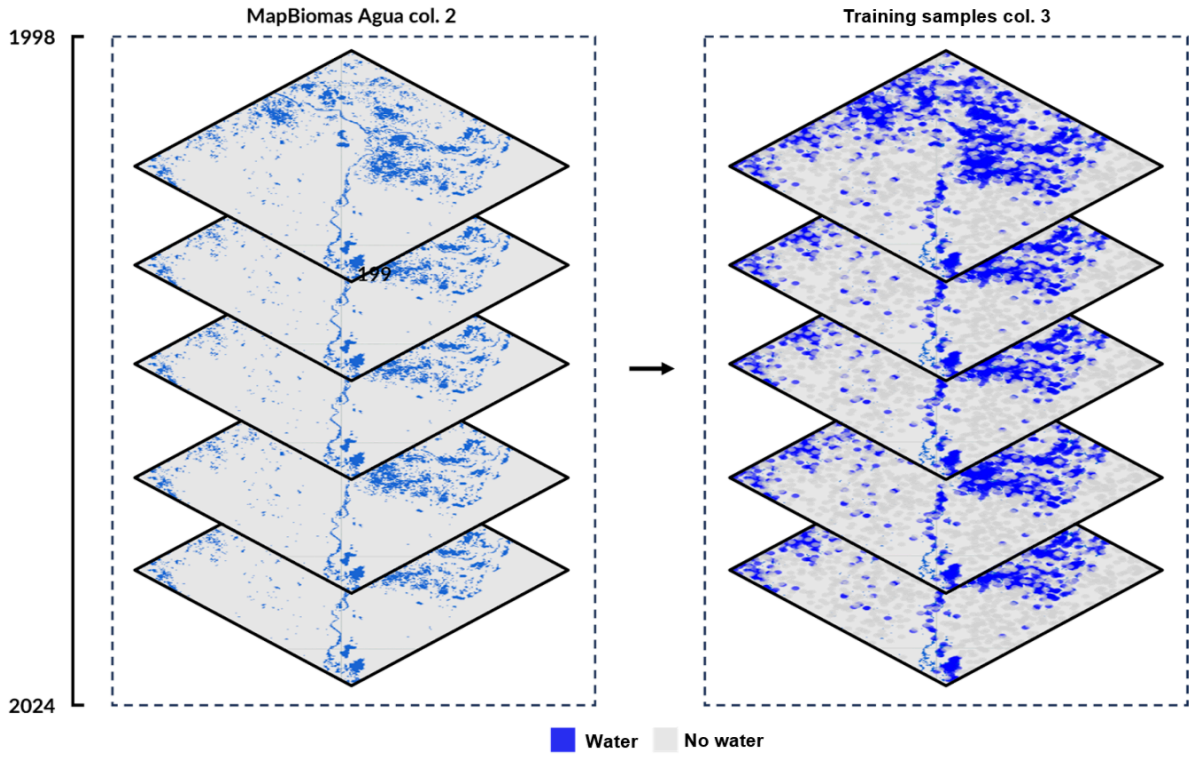


Figure 4. Sample generation. Source: own elaboration.

3.3.2.2. Classifier training

The Random Forest algorithm is trained using stratified samples, considering the regional proportion occupied by each class (water / non-water). This approach ensures that the model is adjusted to the specific characteristics of each region and period, improving the accuracy of the final classification (Figure 5).

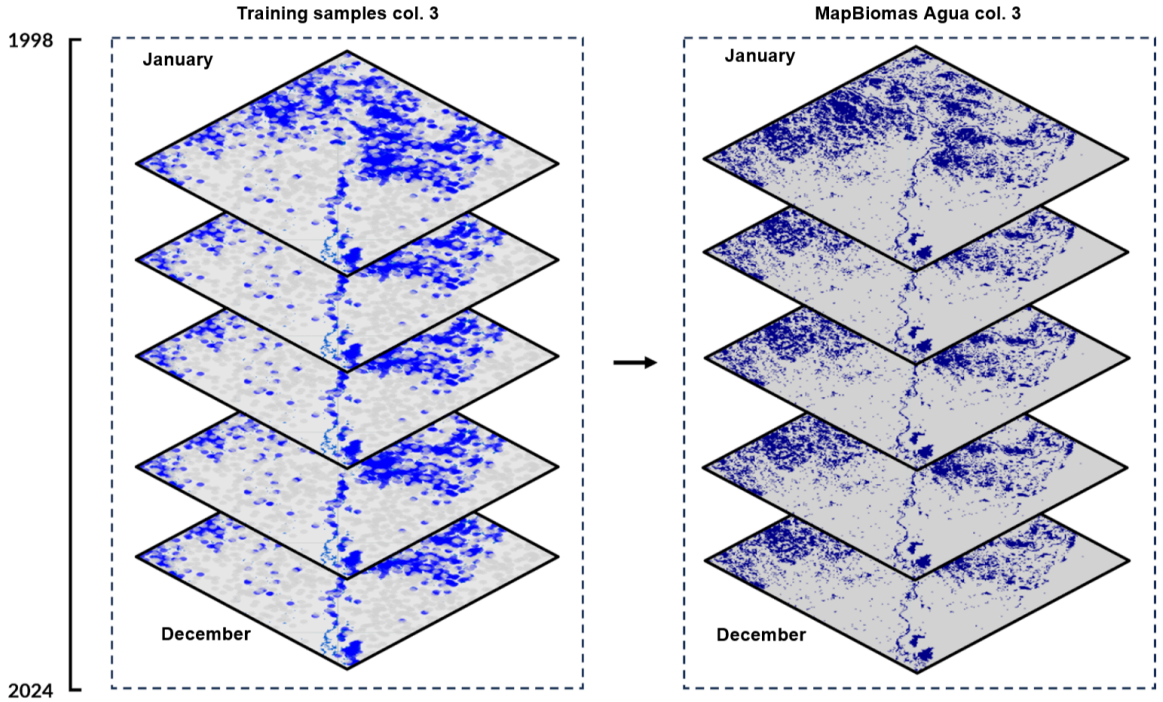


Figure 5. Classification process. Source: own elaboration.

3.3.3. Post-classification

The post-classification process is implemented to improve the accuracy and coherence of the generated maps, minimizing errors and ensuring the quality of the final results. This process includes:

3.3.3.1. Post-classification masking using spectral indices

Additional thresholds are applied to relevant spectral indices (Table 1) to refine the delineation of areas classified as water and reduce possible commission and omission errors (Figure 6).

Table 1. Spectral indices used in masking

Index	Description	Reference
MNDWI	Modification of the Normalized Difference Water Index (NDWI). Uses the green (GREEN) and shortwave infrared (SWIR) bands, allowing water bodies to be highlighted and reducing noise generated by urbanized areas.	(Xu, H, 2006)
NDVI	Normalized Difference Vegetation Index to calculate biomass, derived from the red (RED) and near-infrared (NIR) bands.	(Szabo, Gácsi & Balázs, 2016)
CSF	The CSF (Canopy Shade Factor) is a parameter used to quantify the amount of shade generated by vegetation and is applied to reduce false positives in the detection of water bodies in areas with vegetation cover.	(Schmidt y Van der Sluis 2021., 46).
HAND	The HAND (Height Above the Nearest Drainage) variable correlates terrain elevation relative to the nearest drainage, derived from a Digital Elevation Model (DEM).	(Rennó et al., 2008)
AWEI	The Automated Water Extraction Index improves the ability to correctly classify dark and shadowed areas, which represent a common challenge for conventional classification techniques.	(Feyisa et al., 2014)
GV	Green Vegetation (GV) enhances	(Souza et al., 2019)

	water detection in floodplains, wetlands, and along river and lake margins.	
SHADE	Water pixels often present high fractional shade values (>65%) due to their low reflectance.	(Souza et al., 2019)

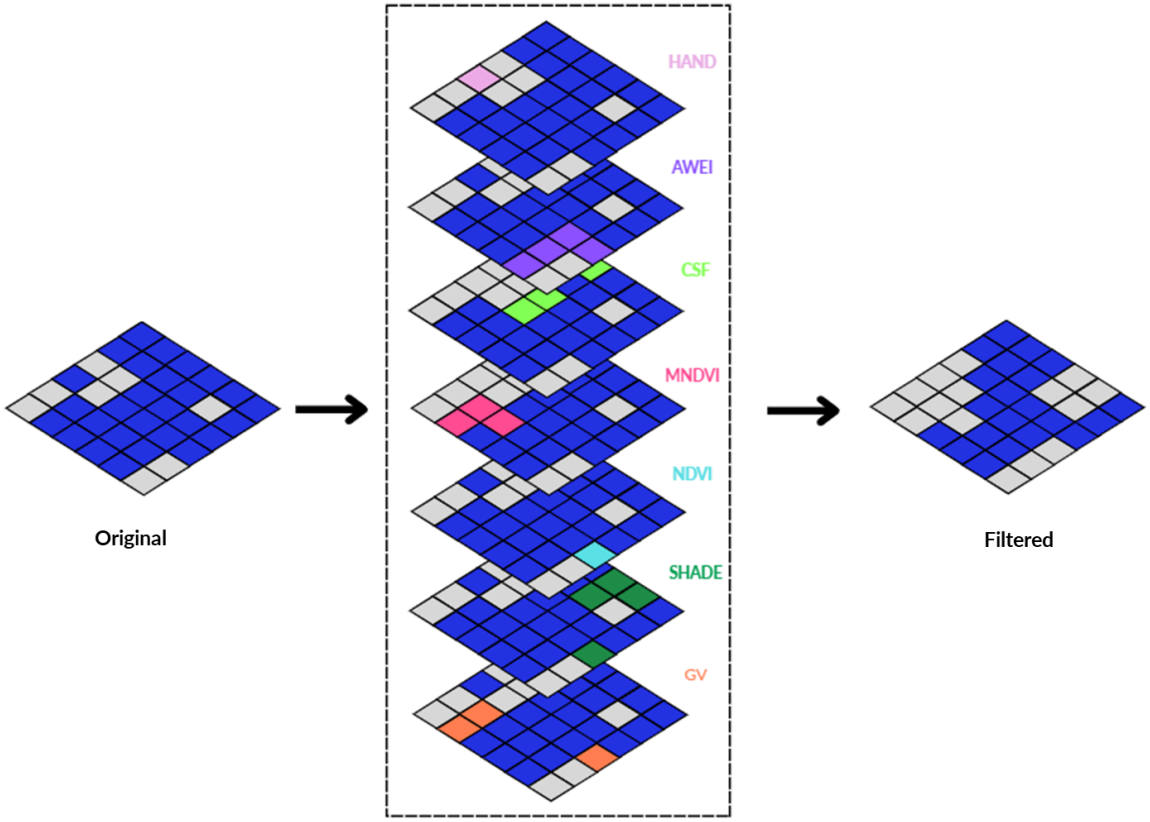


Figure 6. Operation of masking for each index employed. Source: own elaboration.

3.3.3.2. Filling information at the monthly level

A temporal integration of the monthly results is carried out, ensuring continuity and consistency of the information throughout the series. This step allows the identification and correction of possible gaps or inconsistencies in the detection of water bodies in months without information (Figure 7).

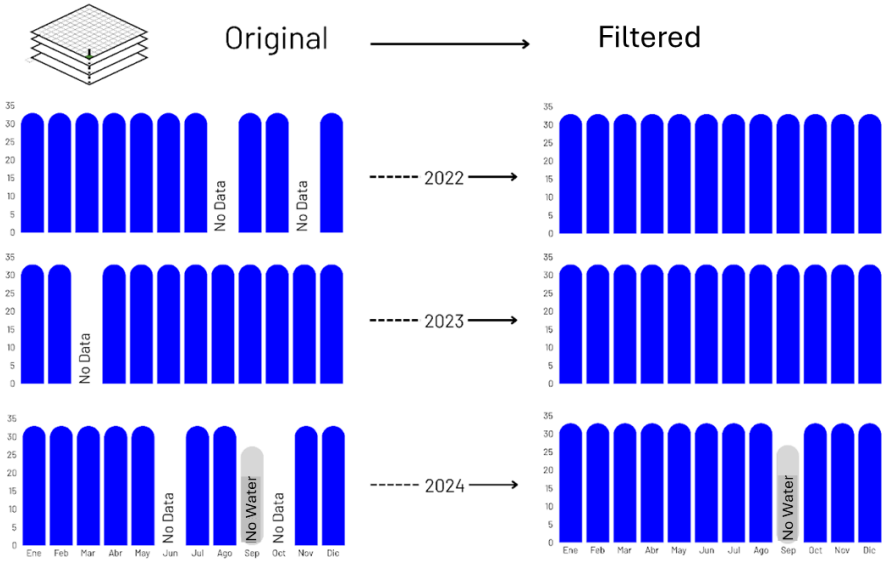


Figure 7. Operation of the monthly information filling filter. Source: own elaboration.

3.3.3.3. Removal of commissions based on the overall frequency of the time series

Detections classified as water that show low occurrence throughout the analyzed period are eliminated, since they usually correspond to classification errors or atypical events not representative of the real dynamics of water bodies in the country **(Figure 8).**

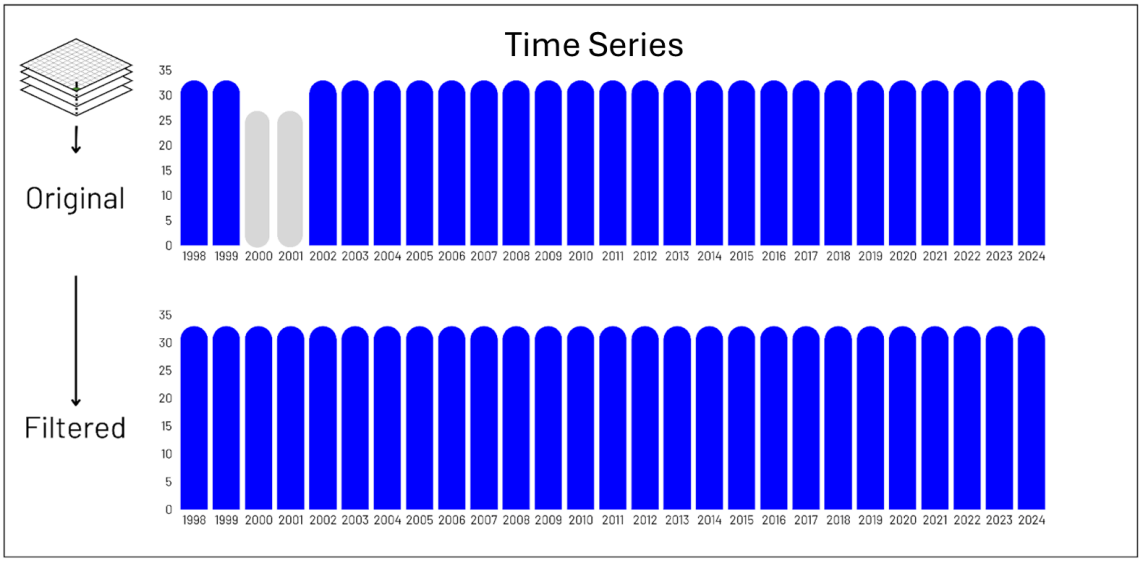


Figure 8. Operation of the frequency filter. Source: own elaboration.

3.3.3.4. Additional cleaning based on geometries and reference layers.

Finally, a spatial refinement is carried out using auxiliary information, such as hydrological reference layers and geometric boundaries, to correct possible artifacts, remove spurious objects, and ensure that the areas classified as water effectively correspond to real water bodies (Figure 9).

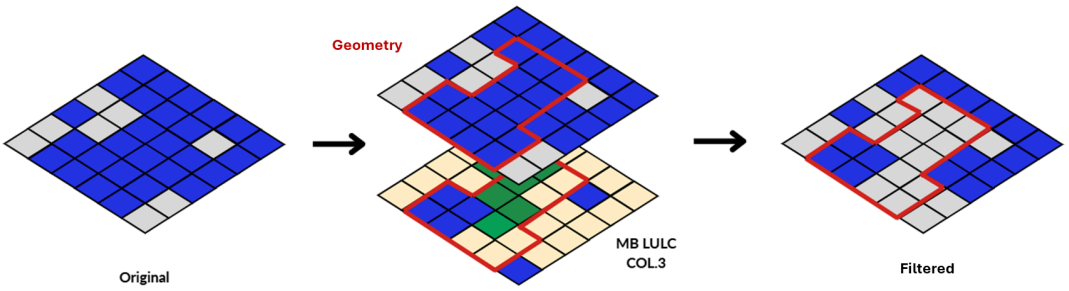


Figure 9. Operation of the additional cleaning based on geometries and reference layers, using MapBiomas Colombia Collection 3 (2025). Source: own elaboration.

3.4. Categorization of water bodies

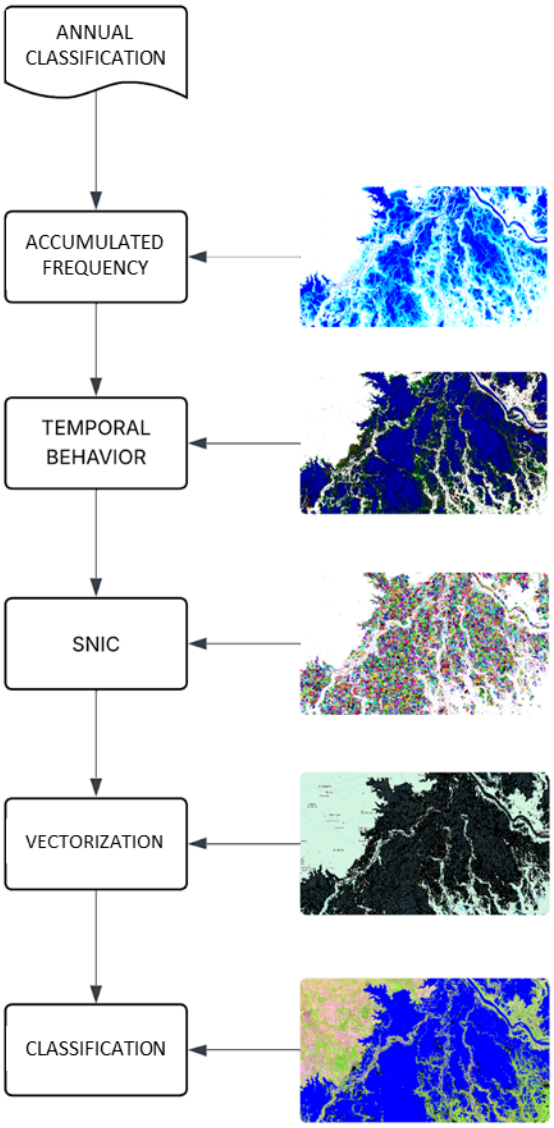


Figure 10. Methodology for categorization of water bodies. Source: own elaboration.

The annual delineation and analysis of water bodies consisted of converting monthly frequency data into vector polygons through segmentation, using the SNIC function of Google Earth Engine to generate small and regular objects.

Each resulting object (segment) was assigned morphological, geomorphological, and thematic properties (including area, perimeter, compactness, elongation, convexity, maximum extent, number of neighbors, land cover and land use (MapBiomas Colombia), anthropic and hydroelectric classification, SRTM elevation, and mean total frequency) in order to characterize its structure and surroundings.

Finally, these objects were classified with the Random Forest algorithm, using as input the water bodies with detection frequency greater than or equal to six months and a systematic set of training samples per biome, corresponding to the five naturalness classes shown in Table 2. The general workflow is presented in Figure 10.

3.4.1. Legend.

The mapping of water surface was organized into a water body classification scheme comprising six categories: 1) Natural, 2) Anthropic, 3) Hydroelectric, 4) Mining Water, 5) False Positives, and 6) Aquaculture. False positives are a byproduct of the classification used to eliminate certain commission errors that persisted in the monthly and annual water surface collections. An example of the classification is shown in Figure 11.

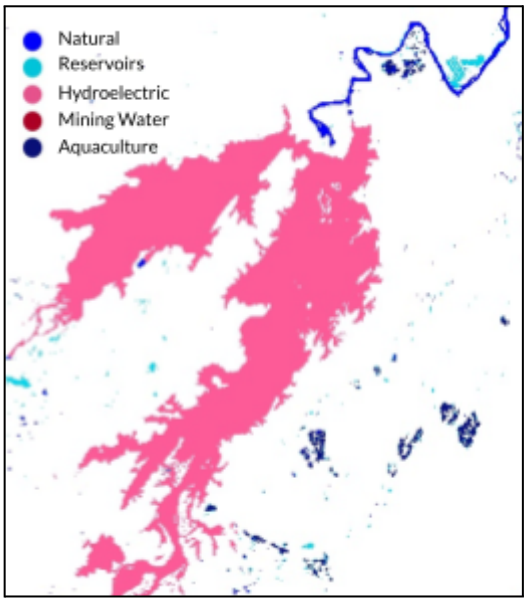


Figure 11. Example of water body categories. Source: authors' elaboration.

The categorization of water bodies was structured in a two-level hierarchical scheme based on their degree of naturalness. At the first level, water bodies were classified into two major groups: Natural and Anthropogenic. At the second level, each group is detailed into specific categories that allow for distinguishing the different types of water bodies present within the territory. In the case of natural water bodies, rivers, lakes, lagoons, and wetlands are included. Anthropogenic water bodies comprise classes associated with hydroelectric infrastructure,

mining activities, aquaculture, and other water bodies resulting from human intervention (Table 2).

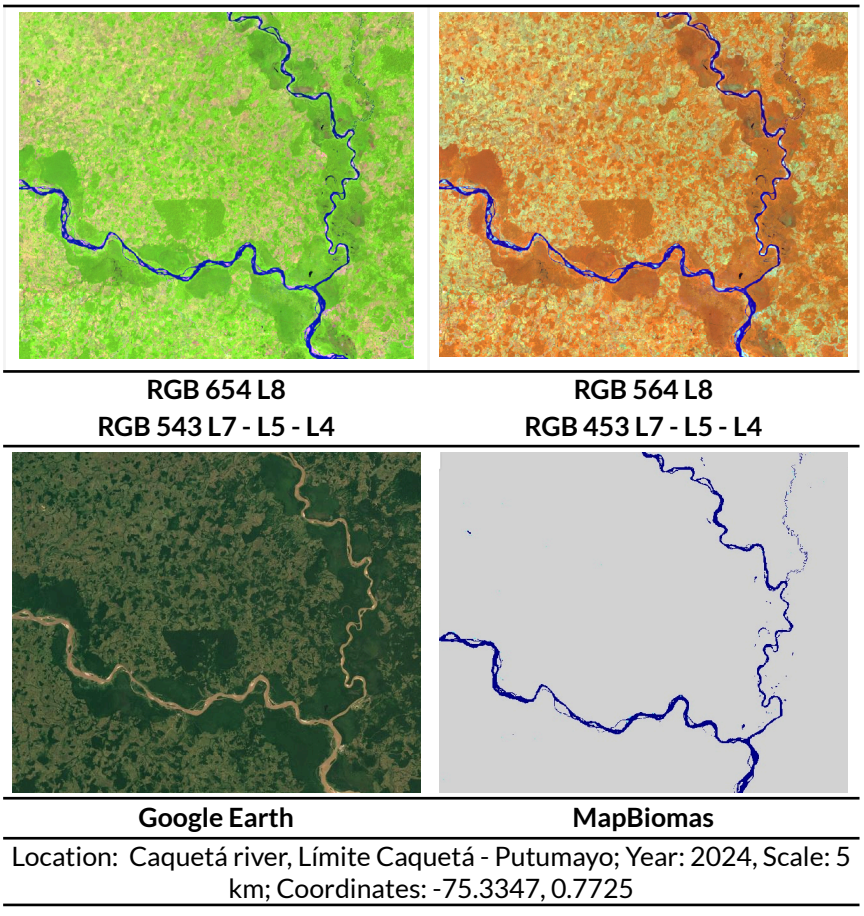
Table 2. Level 1 and Level 2 legend of naturalness for MapBiomas Agua Collection 3.0

LEVEL 1				LEVEL 2			
ID	Level 1 Class	Hexadecimal code	Color	ID	Level 2 Class	Hexadecimal code	Color
	Natural	0000FF			Rivers, lakes, lagoons, and wetlands	0000FF	
	Anthropic	00D7EE			Mining	BD0027	
					Reservoirs	00D7EE	
					Hydroelectric	FD5A98	
					Aquaculture	091182	

3.4.1.1. Natural

Rivers, Lakes, Lagoons, and Wetlands

Includes all naturally occurring water bodies that do not show significant human intervention. This class encompasses rivers, lakes, lagoons, wetlands, and natural marshes where the water surface is clearly visible (Figure 12).



RGB 654 L8
RGB 543 L7 - L5 - L4

RGB 564 L8
RGB 453 L7 - L5 - L4

Google Earth

MapBiomas

Location: Caquetá river, Límite Caquetá - Putumayo; Year: 2024, Scale: 5 km; Coordinates: -75.3347, 0.7725

Figure 12. Spectral response of the Rivers, Lakes, Lagoons, and Wetlands class. Source: authors' elaboration.

3.4.1.2. Anthropic

Mining

Water bodies associated with mining activities, formed as a result of extraction processes, material removal, sediment accumulation, or excavations generated by mining activities (Figure 13).

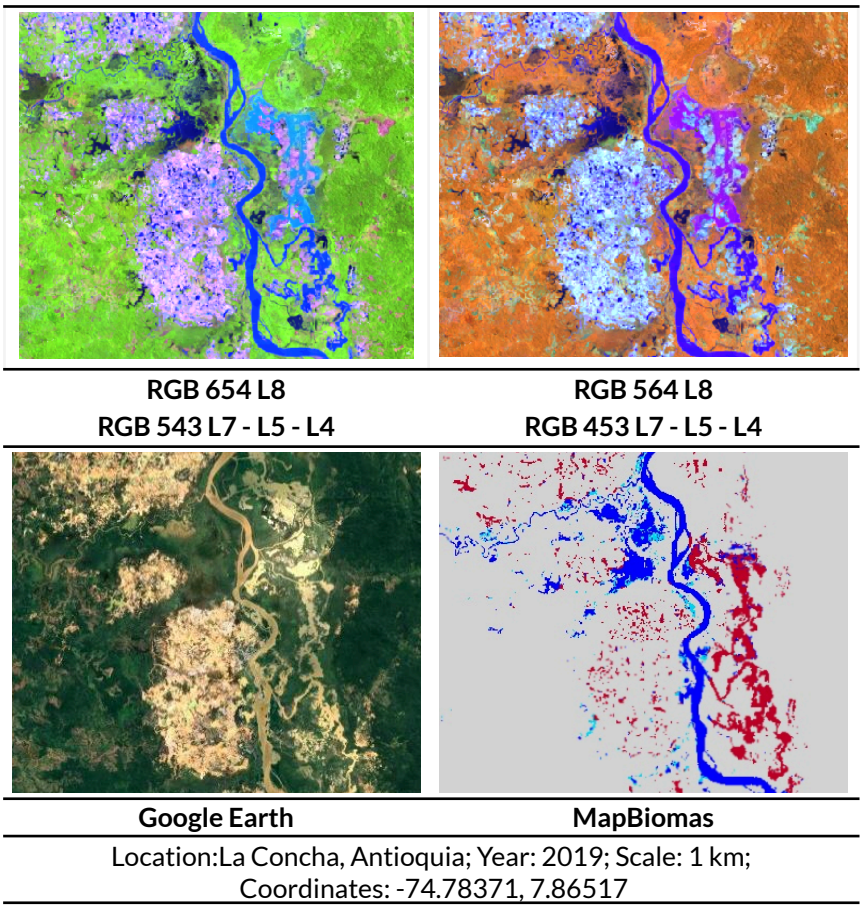
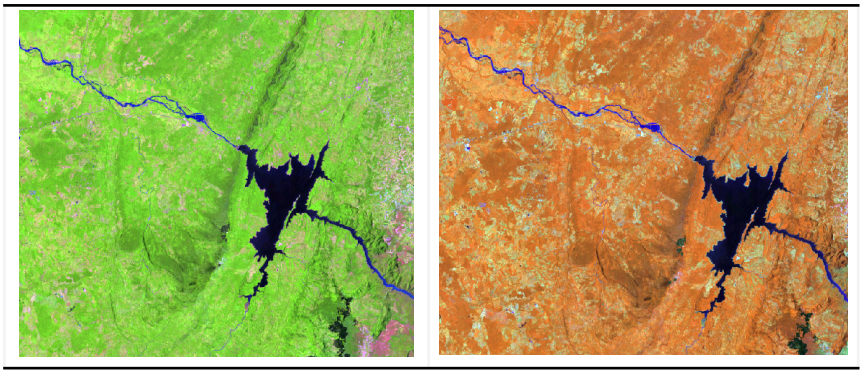


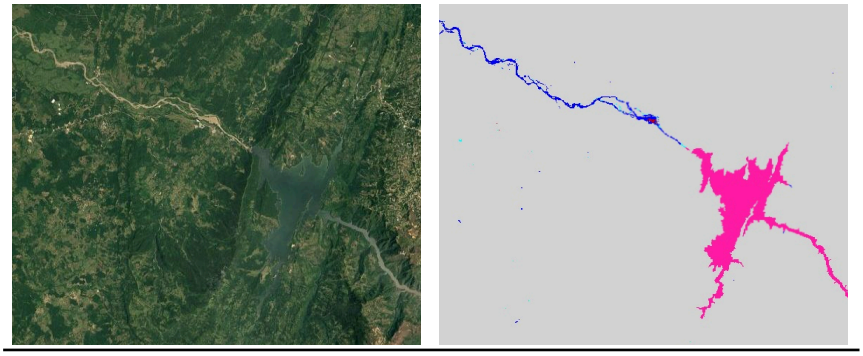
Figure 13. Spectral response of the Mining class. Source: authors' elaboration.

Hydroelectric

Includes reservoirs and impoundments created through the construction of dams and retaining structures for the accumulation and regulation of discharge from large rivers, intended for hydroelectric power generation (Figure 14).



RGB 654 L8 RGB 543 L7 - L5 - L4	RGB 564 L8 RGB 453 L7 - L5 - L4



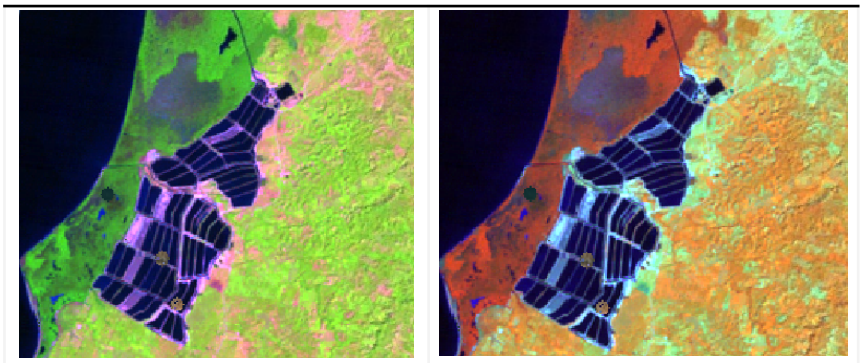
Google Earth	MapBiomas

Location: Hidrosogamoso, Santander; Year 2024; Scale: 5 km;
Coordinates -73.3614, 7.0575

Figure 14. Spectral response of the Hydroelectric class. Source: authors' elaboration.

Aquaculture

Ponds and reservoirs designated for the breeding and cultivation of fish, shrimp, and other crustaceans in freshwater or saltwater environments (Figure 15).



RGB 654 L8 RGB 543 L7 - L5 - L4	RGB 564 L8 RGB 453 L7 - L5 - L4



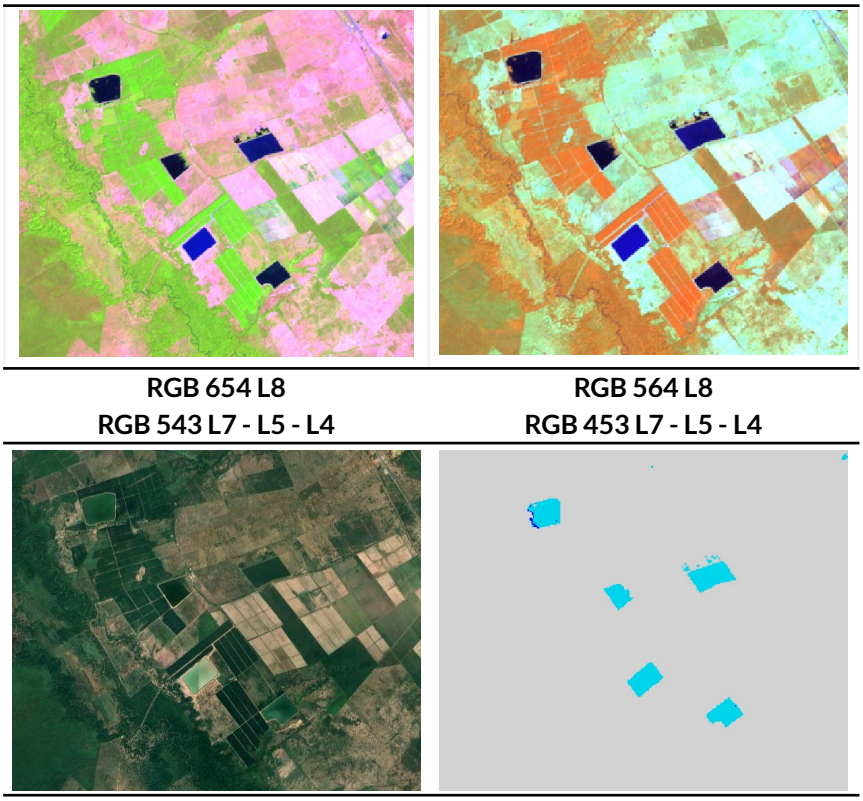
Google Earth	MapBiomas

Location: Libertad, Sucre; Year: 2000; Scale: 1 km;
Coordinates: -75.57289, 9.94051

Figure 15. Spectral response of the Aquaculture class. Source: authors' elaboration.

Reservoirs

Other water bodies created or modified by human activities, such as *jagüeyes*, reservoirs, small dams, and channels (Figure 16).



RGB 654 L8 RGB 543 L7 - L5 - L4	RGB 564 L8 RGB 453 L7 - L5 - L4
Google Earth	MapBiomas

Location: Bosconia, Cesar, Year: 2024, Scale: 2km
Coordinates: -73.888, 9.8652

Figure 16. Spectral response of the Other Anthropogenic Water Bodies class. Source: authors' elaboration.

4 Map Collection and Analysis

The main results of Collection 3 are available on the public web platform, which includes three data coverages: water surface, transitions, and trends.

4.1. Surface Water Area

This layer corresponds to the annual surface water coverage data. The data represent mapped water surface considering different temporal ranges within the interval from 1998 to 2024, including their respective relative frequency. The entirety of the mapped surface corresponds to the continental area of Colombia. The available data are organized within various territorial units such as biome, watershed, departments, municipalities, protected areas, indigenous territories, among others (refer to the MapBiomas Colombia platform to explore the available layers). Users can select different territories and temporal ranges, causing the map, graphs, and statistics to update accordingly (Figure 17).

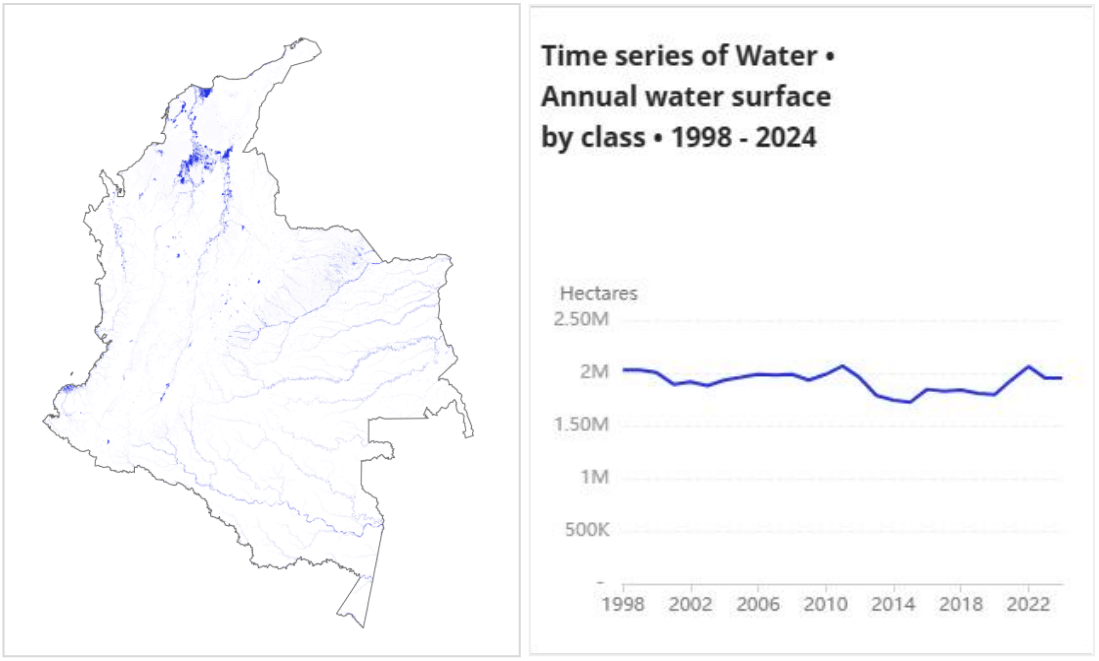


Figure 17. Example of visualization of the surface water layer data (map and graph) on the MapBiomas water platform.
Source: authors' elaboration.

4.2. Surface Water Transitions

This layer represents the water surface that has decreased, increased, remained constant, or occurred sporadically throughout the time series. These areas were identified using the total number of pixels classified as water across the entire annual series (e.g., 27 years). An RGB color composition was created to facilitate the visualization and identification of these categories (Figure 18).

First, to characterize persistence, the color blue was assigned to the total number of years classified as water surface. Second, the number of years from the beginning of the time series until the first water classification was selected and assigned the color green to characterize an increase. Finally, the number of years from the last water surface observation until the end of the time series was selected to indicate a decrease in water surface, assigned the color red. In this way, permanent water surfaces appear predominantly blue, temporary water surfaces appear black if they occurred sporadically, water surface loss appears red, and newly formed water surfaces appear green (Figure 19).

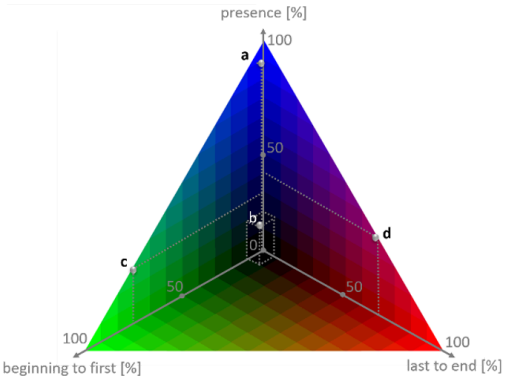
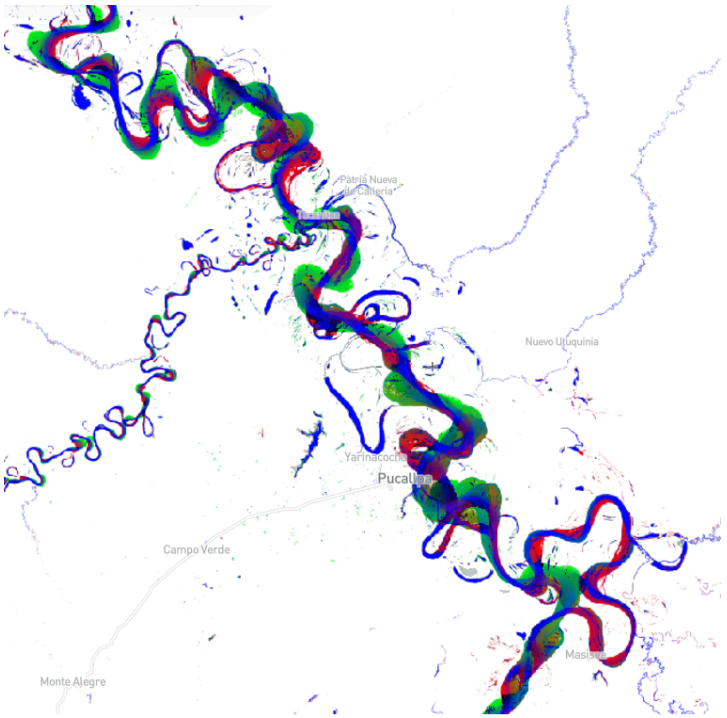


Figure 18. RGB dynamics of surface water. The color blue indicates persistence, as the total number of years were classified as water surface; green indicates increase (years from the start of the time series until the first classification); and red indicates decrease. Black and dark colors indicate sporadic or non-permanent water surfaces. Source: MapBiomas Water (2023).



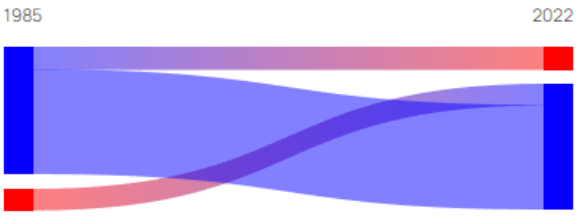


Figure 19. Example of surface water transition in Pucallpa, Ucayali, Peruvian Amazon. A specific transition in the region is illustrated using the previously described color composition. Source: MapBiomas Water (2023).

4.3. Surface Water Trend

The analysis of surface water trends was performed using the monthly water database

4.3.1 Harmonic Model Fitting

To describe and test changes in seasonal variation patterns—related to phase shifts, amplitude, and rate of change—and to identify seasonal patterns and potential trends with respect to the monthly surface water mapping data for the 1998–2024 time series, the harmonic model described by Shumway and Stoffer (2006) was used (Figure 20).

Let $x_1, x_2 \ldots, x_n$ be a set of nnn data points where xtx_txt represents the value of the variable water surface area in the time series, for t < [1,n] ∈ℵ, with = 468 (meses). The harmonic value for each element of the series was calculated using the following formula:

$$x_t = \beta_0 + \beta_1 * t + \beta_2 * \cos(2\pi * t) + \beta_3 * \sin(2\pi * t)$$

The estimated coefficients β_0, β_1, β_2, β_3 were calculated using the ordinary least squares method (Shumway and Stoffer, 2006).

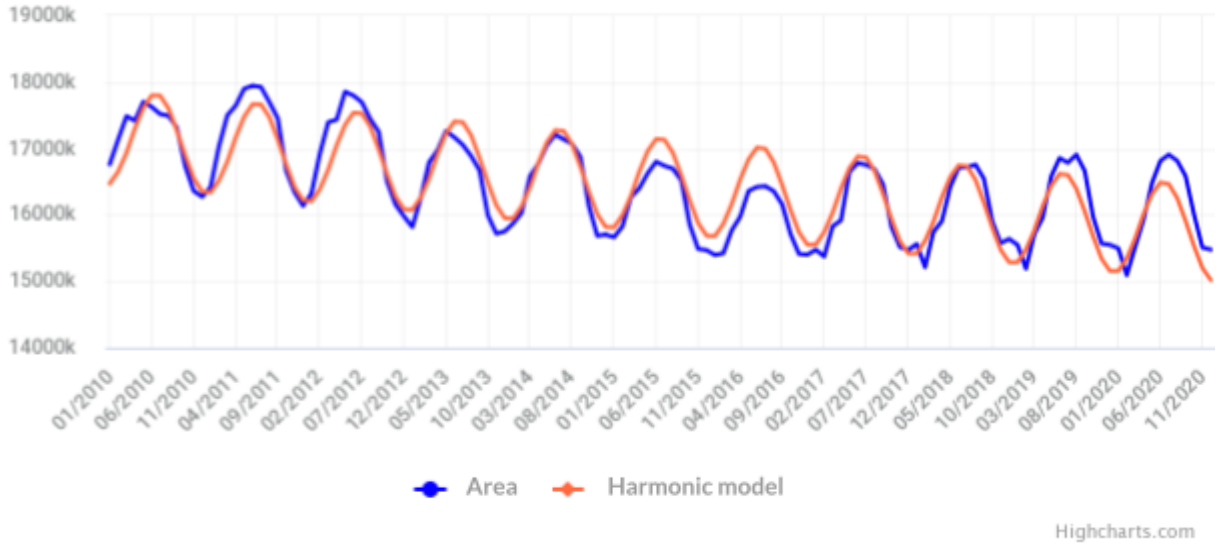


Figure 20. Example of harmonic series fitting to the monthly mapped water surface results. The blue line corresponds to the mapped water surface, and the red line indicates the harmonic model fit. Source: MapBiomas Water (2023).

4.3.2 Differences Between the Harmonic Model and Observed Data

To detect increasing or decreasing behavior throughout the time series, the difference between the harmonic model and the mapped water surface was calculated. This analysis aims to more clearly identify which monthly periods exhibited more intense deviations relative to those expected by the model.

4.3.3 Temporal Trends

Trends of increase, decrease, or persistence in the mapped water surface were assessed throughout the 1998–2024 time series. The analysis was performed using the Seasonal Mann–Kendall test (MK test), which is used to analyze data collected over time to identify increasing or decreasing trends with monotonic behavior in the values of the Y-axis (Figure 21). It is a non-parametric test; therefore, it does not require the data to meet normality assumptions and analyzes the data for monotonic trends within seasonal data (Hirsch et al., 1982; Hirsch et al., 1984; Gilbert, 1987; Helsel and Hirsch, 1995; Morell and Fried, 2009).

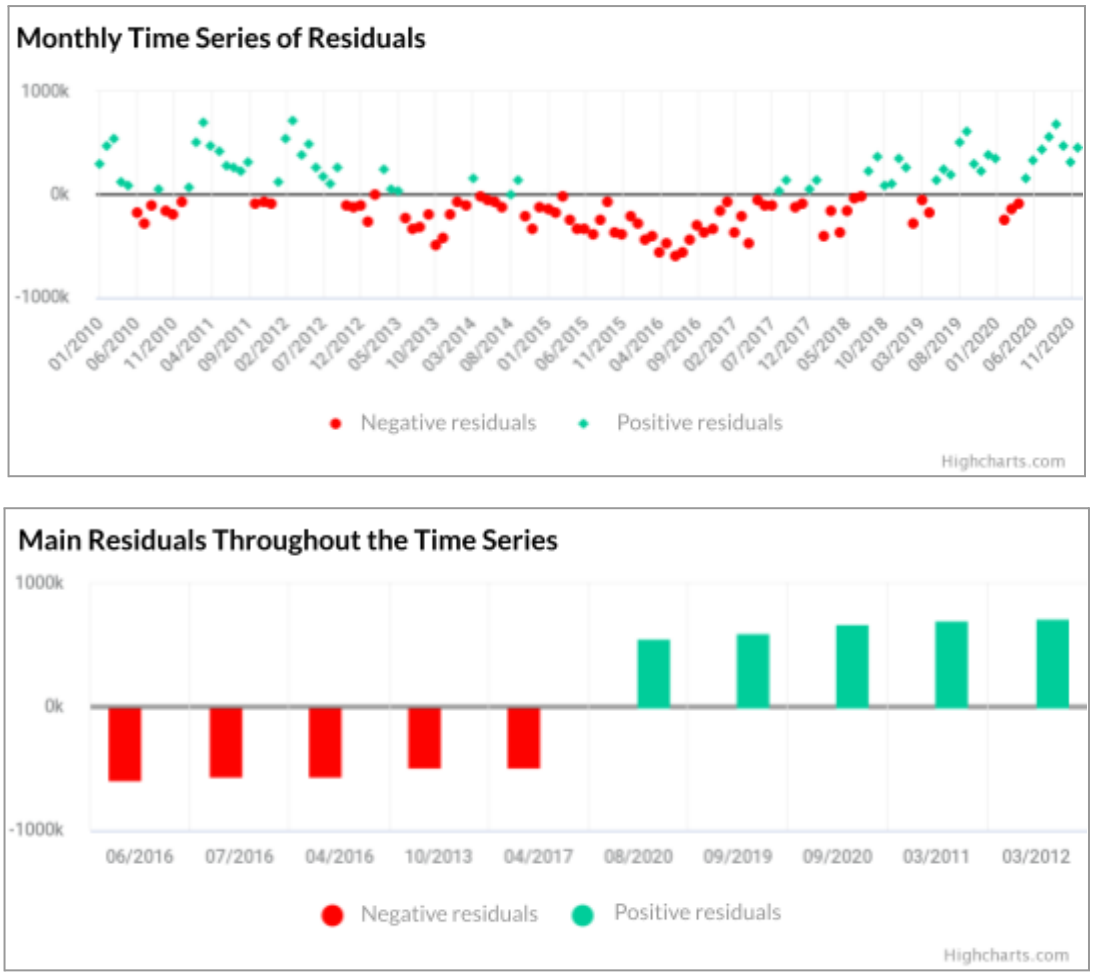


Figure 21. Example of the differences between the fitted model and the observed data. Green points and bars indicate increasing values, while red points and bars indicate decreasing values relative to those expected by the harmonic model. Source: MapBiomas Water (2023).

To perform the test on the time series, the values are considered as an ordered time series. Each value in the series is compared with all subsequent elements of the series. In Kendall's statistic, it is considered 0 when S = 0. If the value of S for the entire set of elements is greater than 0, it means that the trend of the data in the series is decreasing. Otherwise, it means that the series is increasing.

The following steps were considered to calculate the Mann–Kendall statistic:

Let $x_1, x_2, ..., x_n$ be a set of nnn data points where x_j represents the value of the variable at time *j* for all *j* < [1,n] ∈ℵ, then:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign(x_j - x_k)$$

where the function is defined as:

$$sign(x_j - x_k) = 1 \qquad se\ x_j - x_k > 0$$
$$sign(x_j - x_k) = 1 \qquad se\ x_j - x_k = 0$$
$$sign(x_j - x_k) = -1 \qquad se\ x_j - x_k < 0$$

Each value added to S represents an increase or decrease of the value with respect to the subsequent value in the series.

In the area time series used to generate water body maps, it was necessary to consider the calculation of Kendall's statistic for a series with seasonal behavior. The water body surface series corresponds to a 12-month time series over 27 years. Given this structure for the calculation of the S statistic, the data were divided into 12 subsets, where the first subset corresponds to all values associated with the month of January in the series, the second to all values associated with February, and so on, until December. The value of S is then the sum of all S_j where J = [1.12] (Helsel y Hirsch 1995).

$$S = \sum_{j=1}^{12} S_j$$

The Kendall value for each month is calculated as described above. The model results can be visualized in Figure 22.

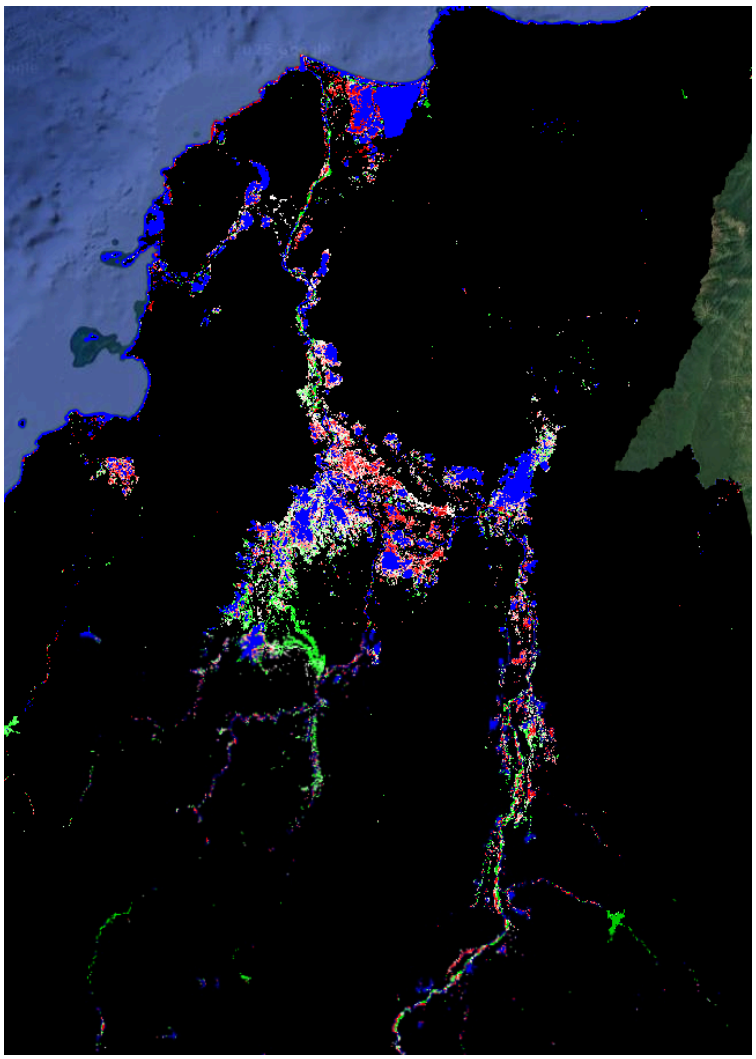


Figure 22. Example of trend calculation results for the Momposina Depression in Colombia using the Seasonal Mann–Kendall test. Data in red indicate a decrease, data in green indicate an increase, and data in white and blue indicate stability. Only data with significant values are presented.
Source: authors' elaboration.

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