



MAPBIOMAS
[AGUA]



Algorithm Theoretical Basis Document (ATBD)

Appendix - Water

MapBiomas Water – Ecuador Collection 4, Version 2

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September 2026

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1. Introduction

1.1. Scope and Content of the Document

The primary objective of MapBiomass Water Ecuador is to map the dynamics of surface water across the continental territory on a monthly and annual basis from 1985 to 2025.

A notable outcome of this initiative is the set of maps with annual data on water surface area, which have been integrated as a cross-cutting theme in Collection 4 of Land Cover and Land Use of MapBiomass Ecuador.

In addition to this integration, MapBiomass Water has developed additional applications, including the publication of the dataset in the Water module of the MapBiomass Ecuador web platform. This information is publicly available to improve the management and use of water resources across the country.

The purpose of this Algorithm Theoretical Basis Document (ATBD) is to provide users with a guide to understanding the methodological steps used to produce the annual surface water data for Ecuador.

1.2. General Description

The MapBiomass Water initiative stems from a previous study conducted by Imazon and WWF-Brazil in the Brazilian Amazon biome, extended to the Upper Paraguay basin in the Chaco biome, published five years ago (Souza et al. 2019). This study demonstrated the potential to enhance the capability of the MapBiomass Initiative to detect and monitor surface water dynamics across all Brazilian biomes. Based on this context, the MapBiomass Water working group expanded the same approach and methodology to the entire Brazilian territory.

In 2022, thanks to the partnership between MapBiomass and the Amazonian Network of Georeferenced Socio-Environmental Information (RAISG), it was decided to adapt, expand, and apply the MapBiomass Water methodology to the territories of Amazonian countries (Figure 1), with the aim of mapping and understanding water dynamics in the diverse biomes of the region. As a result, the first collection of surface water maps for the entire Pan-Amazon was launched in September 2023.



Figure 1. Amazon countries.

The methodology for mapping and monitoring surface water is based on the subpixel classification of satellite images from Landsat 5, 7, and 8. This methodology enables spatial analysis of surface water bodies, allowing us to understand the changes that have occurred over the last 40 years due to anthropogenic impacts and the potential effects of climate variability and change.

All data processing was conducted within the Google Earth Engine platform to reconstruct a monthly time series of changes in surface water dynamics in Amazonian countries between 1985 and 2025. Additionally, all mapped water bodies were classified into natural and anthropogenic categories. The main results related to surface water mapping, transitions, and temporal trends were uploaded to an interactive dashboard within the water platform for end users.

With the update of this platform and the launch of Collection 4, the initiative plans to train end users in the use of the platform, including representatives from academia, the private sector, and government. The availability of reliable information on water resources constitutes an essential tool for decision-makers, facilitating the prioritization of actions aimed at protecting, restoring, and sustainably managing water use and freshwater ecosystems.

1.3. Regionalization

Regionalization in Ecuador (Figure 2) arises due to the heterogeneity and uniqueness that characterize the national territory. Consequently, the water body classification methodology applied by MapBiomass Brazil was adapted for specific regions within each country.

In this context, each country chose to establish its own regionalization approach based on specific units to achieve a deeper understanding of water body dynamics, addressing the particularities of its territory.

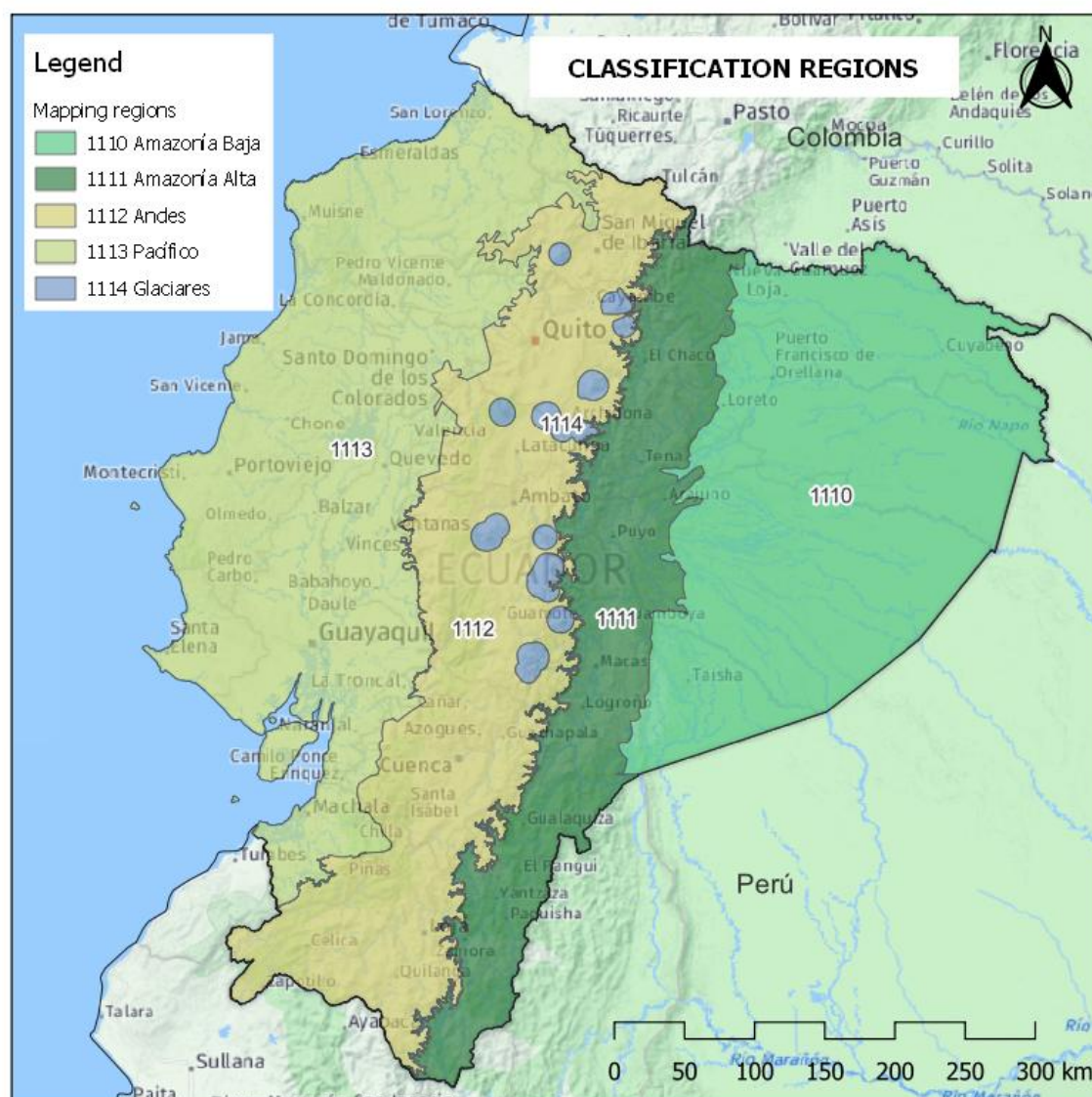


Figure 2. Regionalization of Ecuador

1.4. Science and Key Applications

The dataset on the dynamics of surface water bodies contributes to a better understanding of aquatic systems and their interaction with other environmental components. It is crucial for decision-making and significantly supports water resource management with a focus on sustainable development.

Information on surface water mapping can assist in:

- Integrated territorial planning
- Monitoring sustainable development goals
- Initiatives for sustainable water management
- Monitoring of water concessions/small dams
- Assessment of freshwater ecosystem quality

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 condition of many freshwater ecosystems has deteriorated due to anthropogenic activities in recent decades. Drastic changes in land use and land cover, the construction of hydroelectric dams, pollution, and the overuse of water resources to produce goods and services have altered water quality and availability worldwide. Recent evidence shows that freshwater species face extinction rates twice as high as terrestrial species (WWF, 2020). Additionally, extreme droughts and floods linked to climate change have increased pressure on water reservoirs and aquatic ecosystems.

This scenario is likely to worsen further, given the growing global population and resource use. Without the development of integrated water management strategies, it will be impossible to achieve global sustainable development goals. In this context, continuously and historically assessing changes in surface water dynamics at a continental scale is one of the main challenges in decision-making regarding this precious resource (Oliveira and Souza, 2019).

These challenges are particularly relevant for Amazonian countries, which possess the highest proportion of water per capita on the planet but face uneven distribution and quality. This highlights the need for specific decision-making that considers regional characteristics and the interconnected and cumulative effects of water use. Such decisions can only be made with detailed and consistent data and information on surface water dynamics.

The innovative surface water mapping methodology adopted by the MapBiomass Water initiative has previously enabled the identification and quantification of freshwater surface dynamics in Amazonian countries, particularly in wetlands (Souza et al., 2019).

2.2. Historical Perspective: Existing Maps and Cartographic Initiatives

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

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

MapBiomass 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 employs a subpixel-level surface water 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

The combination of the historical series of Landsat images with the cloud processing capabilities provided by the Google Earth Engine platform enabled the MapBiomás Water initiative to produce the first surface water dataset for all Amazonian countries. Figure 4 illustrates the main methodological steps, which include a subpixel-level surface water classifier (SWSC), decision trees, and post-classification procedures to generate annual and monthly surface water datasets.

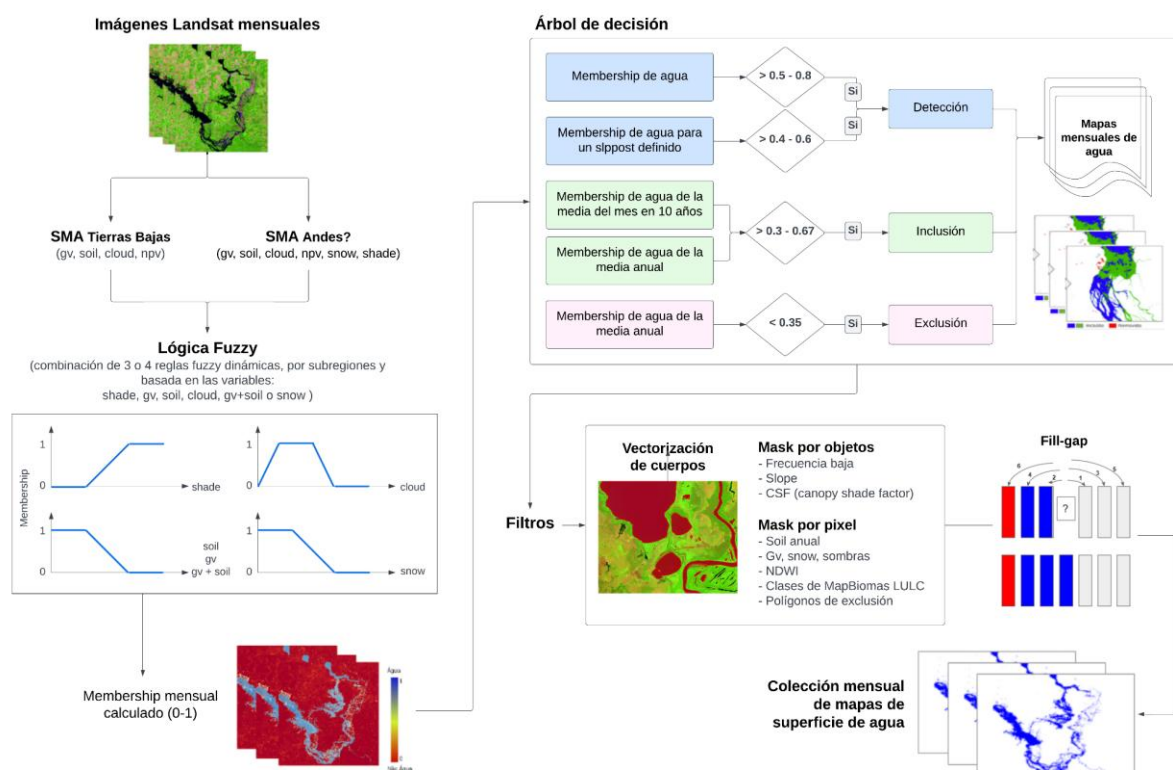


Figure 3. Diagram of the Methodological Process for Producing Surface Water Data, 1985-2025.

3.1. Landsat Imagery

The project utilized images from the Landsat data archive available on the Google Earth Engine platform, including imagery from the Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) sensors aboard the Landsat 5, Landsat 7, and Landsat 8 satellites, respectively. With a spatial resolution of 30 meters per pixel, the project employed Collection 2 Level 2 orthorectified surface reflectance images.

All Landsat scenes covering the Amazonian countries ($n = 211,348$) between 1985 and 2025 were used, filtering the scenes through their metadata to retain those with less than 70% cloud cover.

3.2. Algorithm for Surface Water Detection

3.2.1. Spectral Mixture Analysis

Spectral Mixture Analysis (SMA) allows for the estimation of the fractional composition of pure pixels (endmembers) such as green vegetation (GV), non-photosynthetic vegetation (NPV), soil, clouds, shade, and snow. The subpixel-level information obtained through SMA is particularly useful for characterizing surface water mixed with other components, such as soil and vegetation. This approach overcomes the limitations of full-pixel classifiers, enabling the mapping of wetlands, floodplains, narrow rivers, and small water bodies.

In the application of this SMA model, a generic endmember library for Landsat images is used to calculate the percentage of each component. This is based on the spectral unmixing algorithm available on the Google Earth Engine platform. Two specific cases are considered:

Amazon/Lowland Regions:

SMA is applied to each pixel using four endmembers to calculate the fractions of GV, Soil, NPV, and Cloud.

The shade fraction is derived from photometric shadow (zero reflectance in all bands) and is calculated by subtracting the sum of GV, Soil, Cloud, and NPV from 1.

Andes, Transition to Amazon, and Pacific Regions:

The fractions are calculated directly using six endmembers in the SMA: GV, Soil, NPV, Cloud, Snow, and Shade.

3.2.2. Subpixel Surface Water Classifier (SWSC)

The original Subpixel Surface Water Classifier (SWSC) algorithm uses three hierarchical binary decision rules (e.g., true, false) based on fractional information of Shade, GV, Soil, and Cloud.

First Rule:

Since water absorbs a significant portion of electromagnetic radiation in the visible, near-infrared, and shortwave infrared bands of Landsat, the SWSC uses an image with a Shade fraction $> 65\%$ to classify most Landsat pixels as surface water.

Second Rule:

The combined fractions of GV and Soil ($< 10\%$) are used to quantify the mixture of surface water with vegetation and soil. This mixed surface water is typically found along the edges of water bodies, in narrow rivers, floodplain ecosystems, and wetlands.

Third Rule:

The residual Cloud fraction ($< 25\%$) is included to detect surface water with high sediment loads. This residual Cloud fraction arises due to the spectral ambiguity between the Cloud and Soil endmembers. In fact, the residual Cloud fraction model is based on the spectral response of the Soil endmember in cloud-free pixels.

An empirical evaluation of surface water mapped using the hierarchical binary decision rules described above revealed that the thresholds still exclude some surface water. Therefore, transition rules (Figure 5) were defined along the fractional thresholds using a set of linear functions. As a result, the original binary SWSC decision was transformed into three

independent fuzzy logics (fuzzy rules), where the degree of truth/certainty (membership) that a Landsat pixel is classified as water is determined.

The average degree of truth is then calculated to produce a continuous map of memberships with values ranging between 0 and 1. Based on these memberships, Landsat pixels are classified to produce monthly surface water layers.

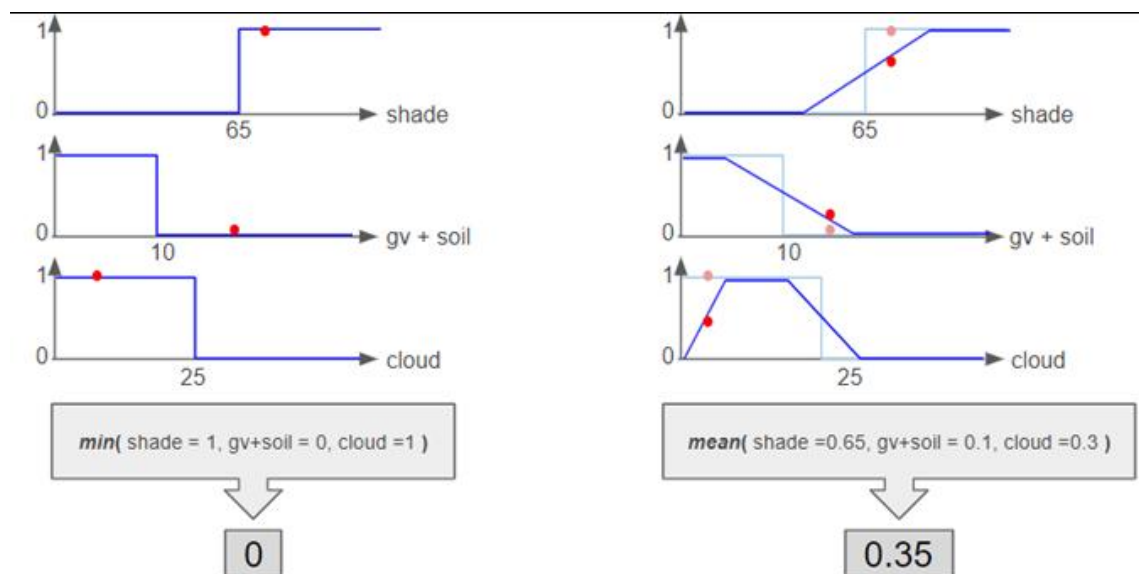


Figure 4. Binary Rules of the Subpixel Surface Water Classifier. The diagram on the left illustrates an example of undetected surface water for a pixel with fractional values indicated by the red dots (the value of GV + Soil exceeds the threshold > 10, preventing it from being classified as water).

The example on the right applies a fuzzy linear logic to the variable, and the mean value allows the pixel (red dot) to be correctly classified as surface water.

3.2.3. Adjustments Based on the Use of Masks

Topographic Slope:

To produce monthly surface water maps, monthly membership maps were first generated by calculating the median of pixel memberships from the available Landsat scenes for each month. Pixels were then classified as water based on defined thresholds for membership > 0.5 - 0.8 (the threshold varies depending on the classification regions). In some regions, a mask with low SLPPOST (stratified slope) values was applied to reduce the threshold (> 0.4 - 0.6) to enhance the detection of narrow rivers or water mixed with soil and vegetation. This process results in a monthly time series of surface water from 1985 to 2025.

CSF (Canopy Shade Factor):

The Canopy Shade Factor (CSF) is an estimate of vegetation cover and its density, based on the amount of sunlight intercepted by tree canopies and other plants. This index is used to mask specific sites that were misclassified as water within vegetated areas. In Ecuador, this index is particularly used as an additional mask to remove false positives.

NDWI (Normalized Difference Water Index):

The Normalized Difference Water Index (NDWI) is a widely used spectral index in satellite image processing, especially for mapping water bodies. It leverages differences in light reflectance in the green and near-infrared (NIR) bands of the electromagnetic spectrum to

highlight the presence of water. For all countries, Landsat surface reflectance images were used to calculate NDWI.

Land Cover Masks:

Using the land cover and land use (LCLU) product from MapBiomás Amazonía (Collection 6) and national initiatives of MapBiomás (Collection 4) for different countries, a set of classes (such as urban use, agricultural use, etc.) is available as input for a masking process. This helps spatially reduce potential false positives in the surface water classification.

3.2.4. Obtaining monthly water data

The monthly maps were enhanced with procedures to restore false negatives and remove false positives, based on temporal metrics (Figure 6). The steps are as follows:

Calculation of Median Memberships:

The median water membership for the entire year (i.e., intra-annual median) was calculated. Additionally, the decadal median for each month was computed.

Gap Filling:

A gap-filling procedure was applied to reclassify as water those pixels that were temporarily covered by clouds or fell within areas where no Landsat scenes were available for a given month. This was done using a combination of two rules:

- Annual median probability $> 0.3 - 0.67$
- Decadal median for the corresponding month $> 0.3 - 0.67$

The threshold varies depending on the classification regions.

False Positive Removal:

The presence of cloud shadows or other dark objects in the Landsat scenes can lead to false positives in the water classification. A removal filter was applied to reclassify as non-water those pixels with a monthly median membership < 0.35 .

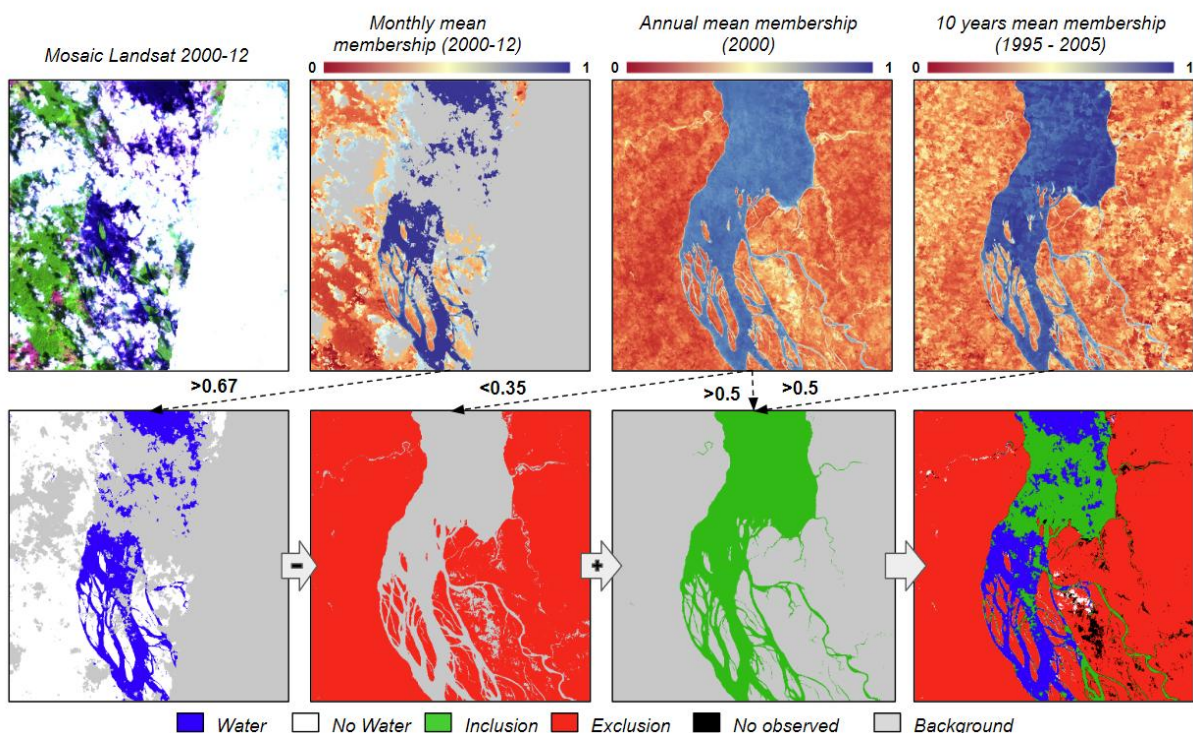


Figure 5. a: Monthly Landsat Mosaic; b: *Membership monthly median* of SWSC; c: *Membership median annual* of SWSC; d: *Membership decadal median monthly* of SWSC; e: Monthly Surface Water Classification; f: Total Surface Water per Decade; g: Likely Surface Water Area Based on Thresholds from c and d. h: Final Monthly Surface Water Map, incorporating inclusions (gap-filled areas) and exclusions (false positives removed).

3.2.5 Obtaining Annual Water Data

The annual surface water maps include a distinction between permanent and seasonal water. This classification is based on thresholds corresponding to the number of months a pixel is classified as water:

Permanent Water:

A pixel is classified as permanent water if it is detected as water for ≥ 6 months in a year.

Seasonal Water:

A pixel is classified as seasonal water if it is detected as water for 1 to 5 months in a year. The threshold for permanent water is defined based on the existence of distinct dry and wet seasons in most regions. This ensures that all naturally dynamic permanent water bodies are accurately captured.

3.2.6 Categorization of water bodies

The mapping of surface water was organized into a classification scheme for water bodies, divided into six categories:

Natural (Rivers and lakes):

Water bodies formed by natural processes, such as rivers, lakes, and wetlands.

Farming and others:

Water bodies created or significantly altered by human activities, such as reservoirs, canals, and irrigation ponds.

Hydroelectric:

Water bodies associated with hydroelectric power generation, including dams and reservoirs.

Mining Water:

Water bodies related to mining activities, such as tailings ponds or water used in extraction processes.

Aquaculture:

Water bodies used for fish farming or other forms of aquaculture.

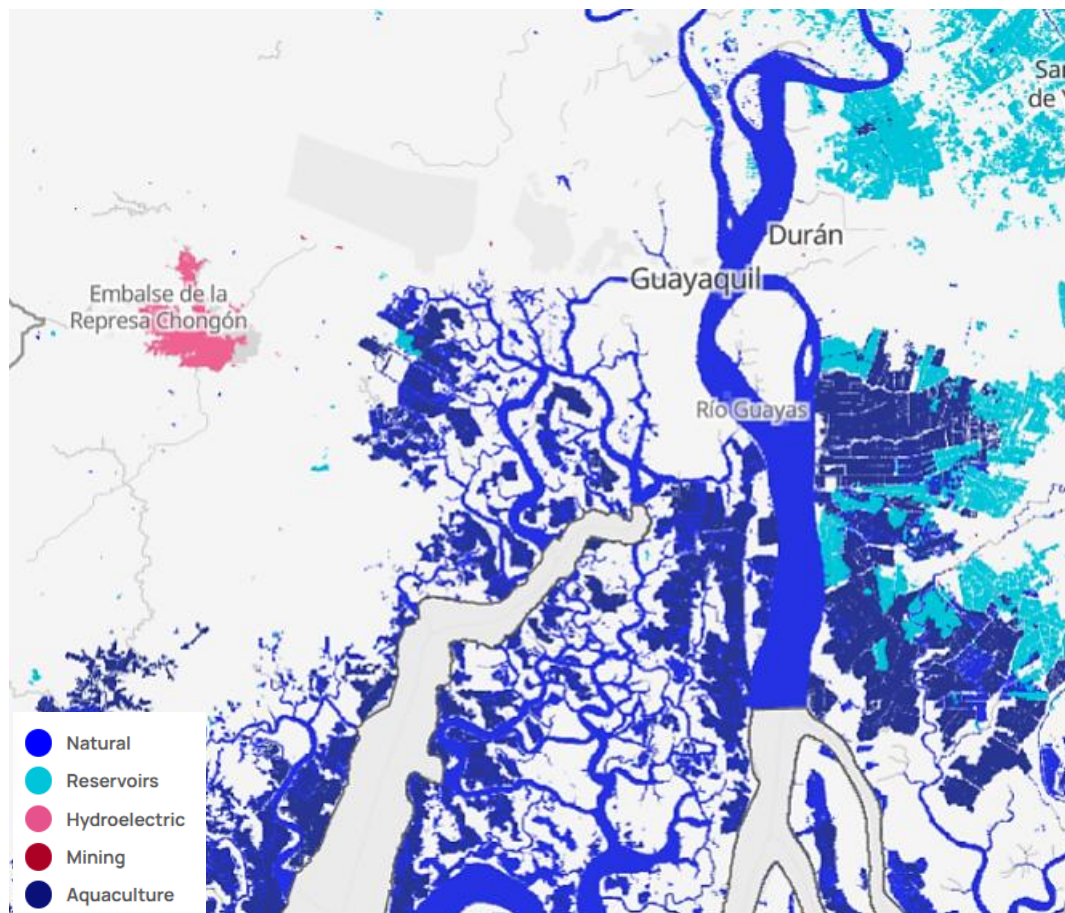


Figure 6. Example of water body categories in the lower Guayas River basin.

The classification of water bodies included the following steps:

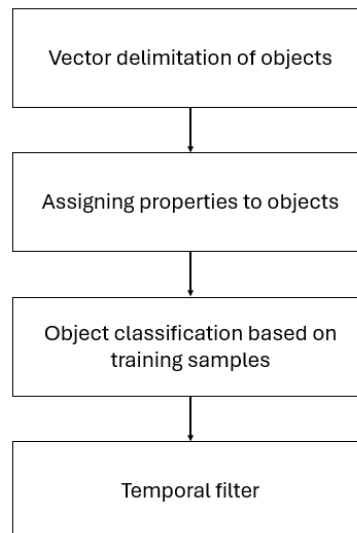


Figure 7. Sequence of steps for classification

1. Vector Delimitation of Objects

The vector delimitation of objects is referred to as annual vectorization. This process involves converting the monthly frequency maps of surface water (raster data) for each year into regular polygons (vector data) within the spatial boundaries of water bodies.

This procedure was carried out using a segmentation tool, where a particular water body could be divided into one or more polygons. The SNIC (Simple Non-Iterative Clustering) function available in Google Earth Engine was used to generate small and relatively regular segments. Figure 9 shows some examples of segmentation based on monthly frequency data for a given year.

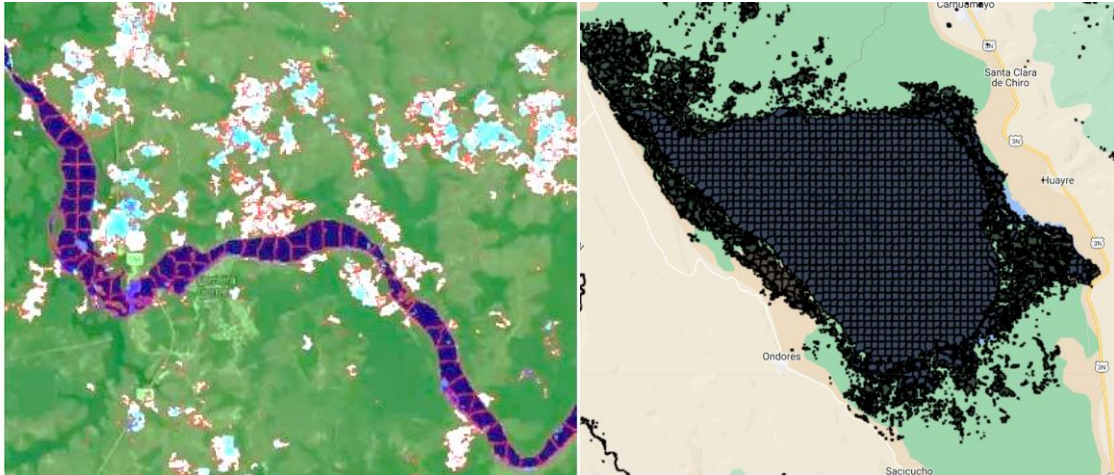


Figure 8. Examples of the segmentation process that converts raster data (monthly frequency within each year) into a regular vector mesh.

2. Assignment of Properties to Objects

After generating the objects for each year, a dataset of characteristics with new properties was assigned to each object for subsequent use in classification. These properties include information related to:

- Object morphology and geomorphology
- Qualitative information from other studies on water body classification and land cover/land use mapping

The following variables were associated with each object:

- Area
- Perimeter
- Area/Perimeter ratio
- Compactness
- Roundness
- Degree of elongation
- Laenge-Breite ratio
- Convexity
- Maximum extent
- Number of neighbors
- Number of neighbors within a 50-meter buffer
- ANA classification - Anthropogenic
- ANA classification - Hydroelectric
- MapBiomass land cover and land use classes (urban, mining, forest, non-forest, pasture)
- Maximum SRTM value

- Mean of total frequency

3. Object Classification Based on Training Samples

The classification of water bodies was performed using the Random Forest algorithm. Training samples were collected across different biomes for each of the five classes. These samples were gathered using a set of pre-drawn grids for each biome, covering various years of the time series.

4. Temporal Filter

After classification, the results underwent a post-classification routine by applying a temporal filter. The logic of the temporal filter was to eliminate improbable transitions between classes within the same segment over the time series.

Finally, all polygons classified as false positives within each year were converted back to raster format and used to filter the annual and monthly surface water datasets, removing any remaining false positives.

4. Collection of maps and analysis

The main results of Collection 4 are available on the public web platform: <https://plataforma.ecuador.mapbiomas.org/> The platform includes three data layers:

- Surface Water,
- Transitions, and
- Trends.

4.1. Surface Water Area

This layer corresponds to the annual surface water cover data. The data includes surface water mapped across different time ranges within the period from 1985 to 2025, along with its respective relative frequency. The total mapped surface area covers the countries of Colombia, Brazil, Bolivia, Ecuador, French Guiana, Guyana, Peru, Suriname, and Venezuela. The available data is organized into different territorial units, such as:

- Biomes
- Hydrographic basins
- States (Level 1 political-administrative units)
- Municipalities (Level 2 political-administrative units)
- Protected areas
- Indigenous territories

Users can select different territories and time ranges, causing the map, graphs, and statistics to update accordingly (Figure 10).

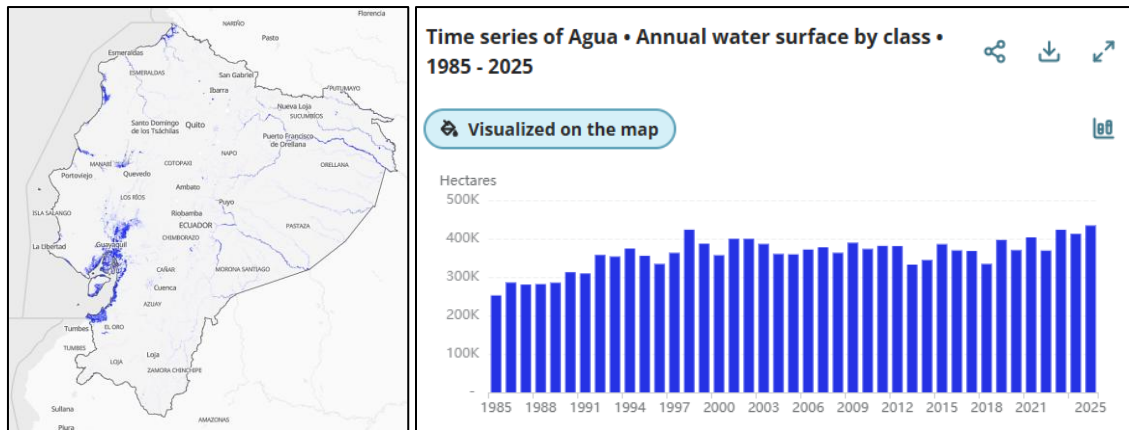


Figure 10. Example of visualization of water surface layer data (map and graph) on the MapBiomias Water platform.

4.2. Water surface transitions

This layer represents surface water areas that have decreased, increased, remained constant, or appeared sporadically over the time series. These areas were identified using the total number of pixels classified as water across the entire annual series (e.g., 40 years). An RGB color composition was created to facilitate the visualization and identification of these categories (Figure 11).

Persistence:

Blue was assigned to the total number of years classified as surface water to characterize persistence.

Increase:

The number of years from the beginning of the time series to the first classification of water was selected and assigned green to characterize increase.

Decrease:

The number of years from the last observation of surface water to the end of the time series was selected and assigned red to indicate a decrease in surface water.

As a result:

Permanent water surfaces appear predominantly blue.

Temporary water surfaces appear black if they occurred sporadically.

Lost water surfaces appear red.

New water surfaces appear green.

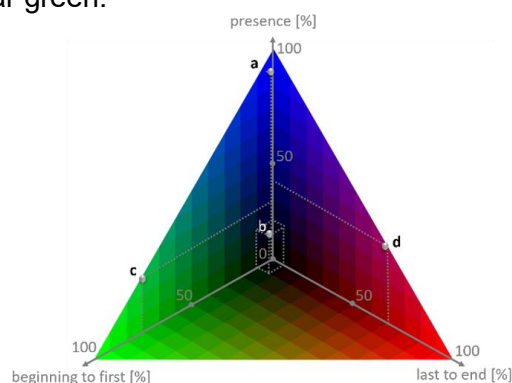


Figure 11. RGB water surface dynamics. Blue indicates persistence, as all years were classified as water surface; green, increased (years from the beginning of the time series to

the first classification); and red, decreased. Black and dark colors indicate sporadic or non-permanent water surfaces.

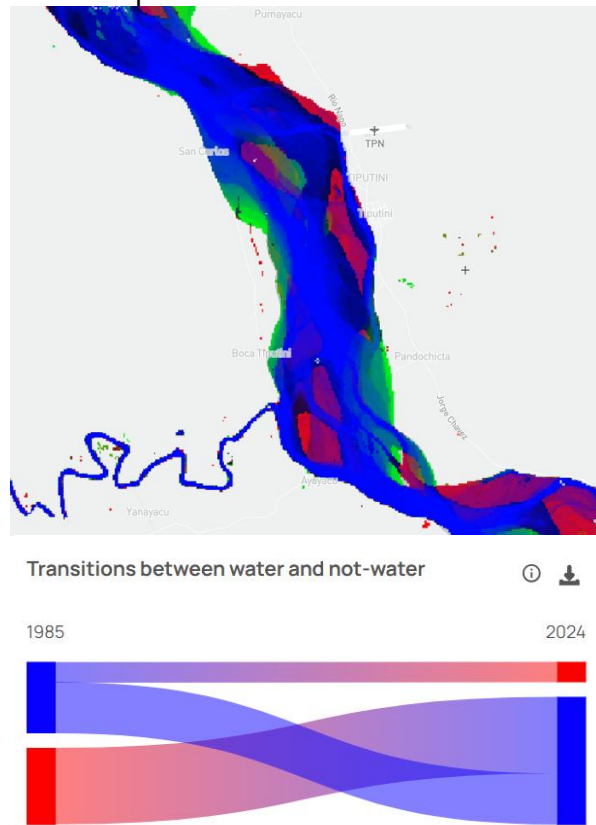


Figure 12. Example of water surface transition at Tiputini, Ecuadorian Amazon. A specific transition in the region is illustrated using the previously described color composition.

4.3. Surface Water Trends

Analysis of surface water trends was conducted using the monthly water database.

4.3.1 Harmonic Model Fitting

To describe and test changes in seasonal variation patterns, including phase shifts, amplitude changes, and variation rates, while identifying seasonal patterns and potential trends in the monthly surface water mapping data for the 1985-2025 time series, the harmonic model described by Shumway and Stoffer (2006) was used (Figure 13).

Let $x_1, x_2, \dots, x_n$ be a set of n data points, where x_t represents the variable surface water area at time t in the time series, for $t \in [1, n] \in \mathbb{N}$, on the data $n=468$ (months). The harmonic value for each element of the series was calculated using the following formula:

$$\hat{x}_t = \beta_0 + \beta_1 * t + \beta_2 * \cos(2\pi * t) + \beta_3 * \sin(2\pi * t)$$

The estimated coefficients $\beta_0, \beta_1, \beta_2, \beta_3$ were calculated using the ordinary least squares (OLS) method (Shumway and Stoffer, 2006).

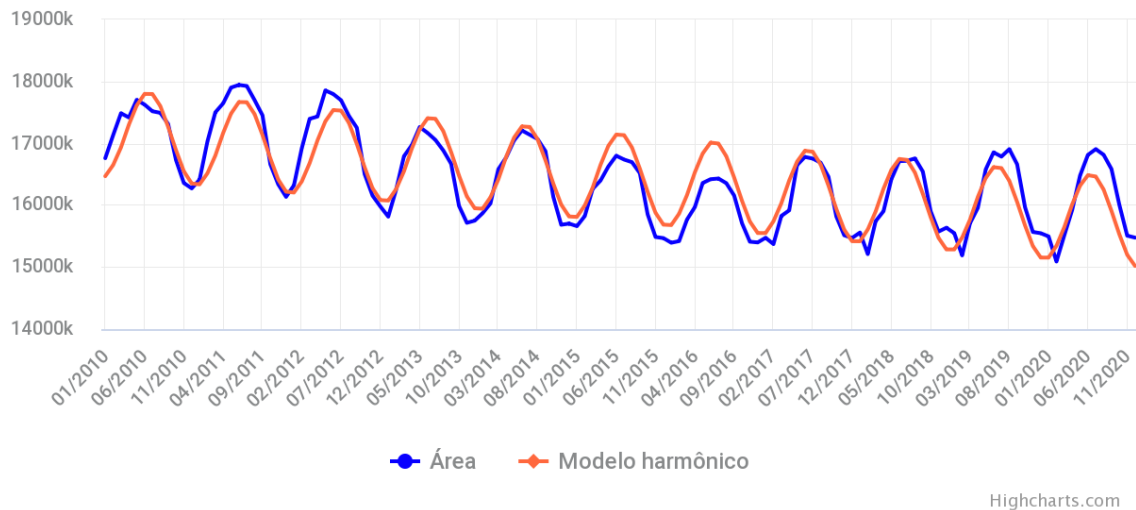


Figure 13. Example of harmonic series fit to monthly mapped water surface results. The blue line corresponds to the mapped water surface, the red line indicates the harmonic model fit.

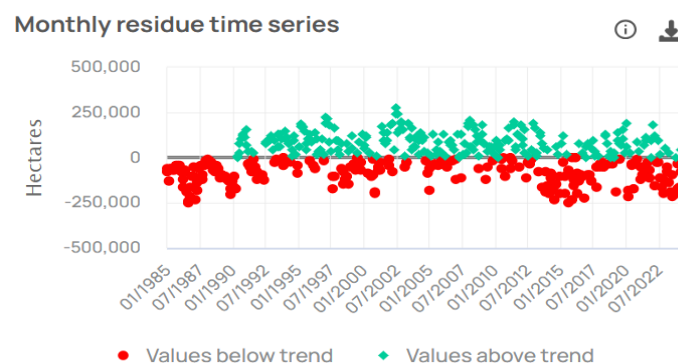
4.3.2 Differences Between the Harmonic Model and Observed Data

To detect increasing or decreasing trends over the time series, the difference between the harmonic model and the mapped surface water data was calculated. This analysis aims to more clearly identify which monthly periods exhibited more significant deviations from the model's expectations.

4.3.3 Temporal Trends

Trends of increase, decrease, or stability in the mapped surface water over the 1985-2025 time series were identified. The analysis was conducted using the Seasonal Mann-Kendall (MK) Test, which is used to analyze data collected over time for increasing or decreasing trends with monotonic behavior in the Y-axis values (Figure 14).

The test is non-parametric, meaning it does not require the data to meet normality assumptions. It is specifically designed to detect monotonic trends in seasonal data (Hirsch et al., 1982; Hirsch et al., 1984; Gilbert, 1987; Helsel and Hirsch, 1995; Morell and Fried, 2009).



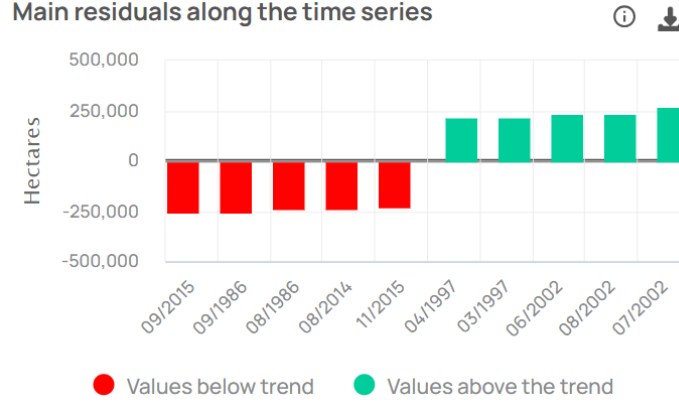


Figure 14. Example of differences between the fitted model and the observed data. Green points and bars indicate increasing values, while red points and bars indicate decreasing values relative to what was expected by the harmonic model.

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 the rest of the subsequent elements in the series. In Kendall statistics, it is considered as 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 statistics:

Being $x_1, x_2, \dots, x_n$ a set of n data where x_j represents the value of the time variable j for all $j \in [1, n] \in \mathbb{N}$, then it is calculated:

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

the function is:

$$\text{sign}(x_j - x_k) = \begin{cases} 1 & \text{if } x_j - x_k > 0 \\ 0 & \text{if } x_j - x_k = 0 \\ -1 & \text{if } x_j - x_k < 0 \end{cases}$$

Therefore:

- If $S > 0$, the trend is increasing.
- If $S < 0$, the trend is decreasing.
- Ties should be counted as 0.

Each value added to S means an increase or decrease in value with respect to the next in the series.

In the time series of area data to collect maps of water bodies, it was necessary to consider the Kendall calculation for a series with seasonal behavior. The water body surface series corresponds to a time series of 12 months over 41 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 the values corresponding to the month of January of the series, the second to all the values corresponding to February of the series, and so on, until December. Then the value of S will be the sum of all the S_j where $J = [1, 12]$ (Helsel and Hirsch 1995).

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

The Kendall value for each month is calculated as described above.

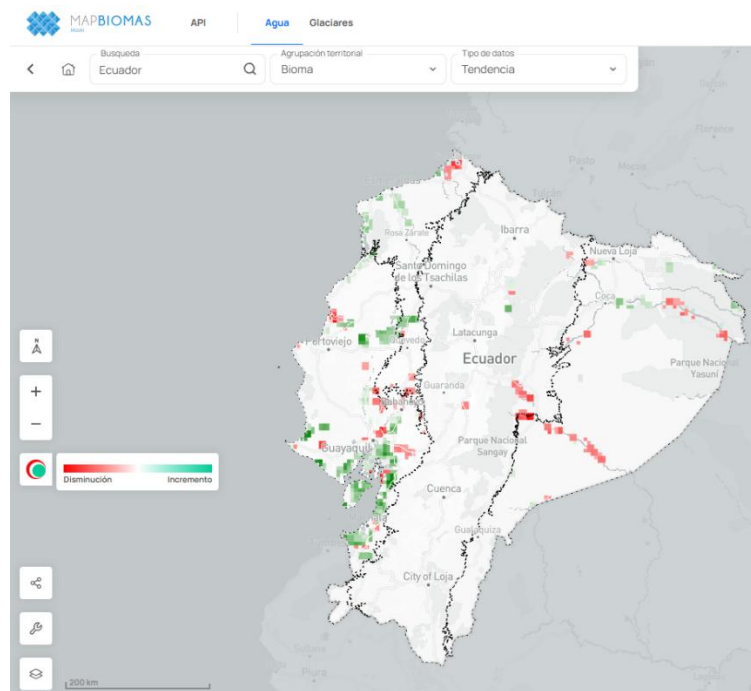


Figure 15. Example of trend calculation results for Ecuador using the Mann-Kendall seasonal test. Red data indicate a decrease, green data indicate an increase, and white data indicate stability. Only data with significant values are presented.

5. Practical Considerations

The fourth version of this product marks a significant advancement in continuous improvement, addressing feedback and suggestions from the first version's use and analysis. This new iteration is designed as a dynamic tool, intended not only to provide relevant data but also to evolve in response to user needs and technological advancements.

All generated data is publicly accessible, promoting transparency and open access. This approach encourages users to review the content, identify strengths, and propose necessary adjustments. User contributions and feedback are crucial to ensure that future versions undergo iterative refinement, keeping the product up-to-date and relevant.

Users should rigorously review the accuracy levels and associated uncertainty metrics when applying the presented quantitative data. This will enable more robust interpretation and appropriate evaluation of its applicability in various contexts. Comparing the data with other sources or complementary studies is essential to confirm its validity or highlight potential limitations.

This continuous improvement approach underscores the developers' commitment to the product's quality and utility, fostering collaboration between the scientific community and other users to maximize the dataset's positive impact.

6. Final Conclusions and Perspectives

Collection 4 of MapBiomass Water solidifies its position as a fundamental mapping product for surface water in Ecuador and the Amazonian countries. Its contribution is significant for understanding the spatial and temporal dynamics of freshwater ecosystems, providing detailed data that enables the analysis of change patterns, cycles of increase or decrease, and the estimation of gains or losses in water surface area. This product has also proven to be a key tool for linking these transformations to human activities, generating valuable knowledge about the interactions between natural systems and anthropogenic pressures.

The achievement of this result strengthens the objectives set by the MapBiomass Water initiative and RAISG, standing out as a collaborative effort that contributes to both scientific understanding and the development of sustainable management strategies. The public availability of the data encourages its use by researchers, decision-makers, and local communities, who can utilize it to plan conservation, restoration, and sustainable water resource management actions.

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