



MAPBIOMAS
AGUA

Algorithm Theoretical Basis Document (ATBD)

Methodology for monthly and annual surface water mapping,
1985–2025

Collection 4, Version 1

An initiative of:



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Table of Contents

Executive Summary.....	4
1. Introduction.....	5
1.1 Scope and content of the document.....	5
1.2 General description.....	5
1.3 Key science and applications.....	6
2. General information and background.....	6
2.1 Context and key information.....	6
2.2 Historical perspective: existing maps and mapping initiatives.....	7
3. Data and regionalization.....	7
3.1 Landsat imagery.....	7
3.2 Auxiliary variables.....	8
3.3 Regionalization.....	8
4. Methodology.....	10
4.1 Image preparation.....	10
4.2 Spectral Mixture Analysis.....	11
4.3 Surface Water Subpixel Classifier.....	11
4.4 Monthly water classification and hierarchical gap filling.....	12
4.4.1 Original methodology for monthly water detection.....	12
4.4.2 Modified temporal probability (membership).....	13
4.4.3 Spectral and topographic controls.....	14
4.5 Post-classification.....	15
4.5.1 Biome-specific masks.....	15
4.5.2 Time-series frequency filter.....	15
4.5.3 Recovery and remapping.....	15
4.5.4 National integration.....	16
4.6 Derivation of annual water data.....	16
4.7 Water-body categorization methodology.....	16
4.7.1 Object vector delineation.....	17
4.7.2 Assignment of object properties.....	17
4.7.3 Object classification using training samples.....	17
5. Products and analyses.....	18
5.1 Annual surface water.....	18
5.2 Monthly surface water.....	19
5.3 Water-body types.....	20
5.4 Surface water transitions.....	21
5.5 Surface water trend.....	22
5.6 Surface water frequency.....	23
5.7 Time since last occurrence.....	24
6. Practical considerations and limitations.....	24
7. Conclusions and outlook.....	25
8. References.....	26
Appendix A.....	27

Executive Summary

Collection 4 of MapBiomass Water Bolivia produces a 30 m monthly surface water time series for 1985–2025 and derived annual products. It retains the water-body typology of the previous collection but substantially modifies detection and post-classification. Its main innovation is a hierarchical temporal inference that combines evidence from the observed month with short moving windows, interannual recurrence, and annual context. The workflow is implemented across 31 classification regions and adapted to the spectral, topographic, and hydrological conditions of each biome.

After fuzzy classification, biome-specific masks, a frequency filter based on the full time series, targeted recovery and remapping rules, and national integration are applied. This architecture reduces dependence on decadal windows, better preserves seasonality, and explicitly separates initial detection from commission- and omission-error corrections.

Surface water production workflow

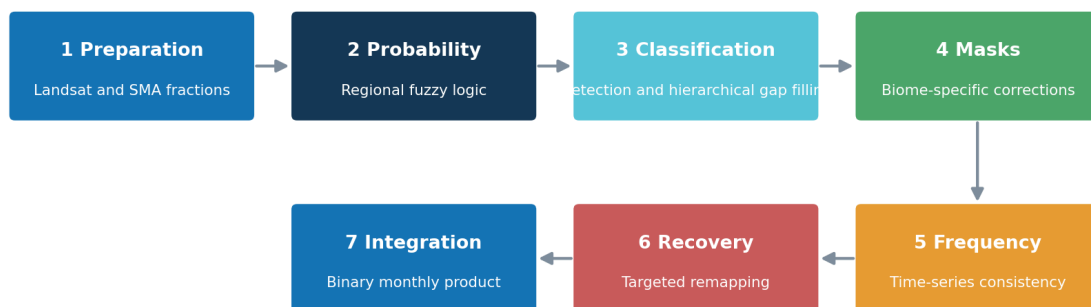


Figure 1. General production workflow for Collection 4.

1. Introduction

1.1 Scope and content of the document

MapBiomass Water aims to map and monitor surface water dynamics in Bolivia through monthly observations and annual aggregations. Collection 4 covers 1985–2025, uses Landsat imagery and Google Earth Engine processing, and generates temporally comparable information to support water-resource management, aquatic-ecosystem analysis, and the assessment of natural and anthropogenic changes.

The purpose of this Algorithm Theoretical Basis Document (ATBD) is to provide users with a guide to the updated methodological steps of Collection 4, including substantial improvements in classification logic, biome-based masking, temporal-frequency filters, and time-series recovery.

1.2 General description

MapBiomass Water is an initiative of the MapBiomass network whose main objective is to map surface water bodies throughout Bolivia on a monthly and annual basis from 1985 to 2025.

The MapBiomass Water initiative originated from an earlier study conducted by Imazon and WWF-Brazil in the Brazilian Amazon biome and later extended to the Upper Paraguay Basin in the Chaco biome (Souza et al. 2019). The study demonstrated the potential to improve the MapBiomass Initiative's capacity to detect and monitor surface water dynamics across all Brazilian biomes. In this context, the MapBiomass Water working group expanded the same approach and methodology to the entire Brazilian territory.

In 2022, through the partnership between MapBiomass and the Amazon Network of Georeferenced Socio-Environmental Information (RAISG), the MapBiomass Water methodology was adapted, extended, and applied to the full territories of the Amazonian countries to characterize water dynamics across the region's diverse biomes (Collections 1 and 2). Since Collection 3, each country has independently produced surface water data following the same methodology used in previous collections. In Collection 4, the Google Earth Engine (GEE) workflow was restructured into advanced modular phases to strengthen detection and reduce commission errors across several biomes (Amazon, Andes, Chaco, Chiquitano, Pantanal, Tukumano-Boliviano, and Valleys).

The methodology for mapping and monitoring surface water is based on subpixel classification of Landsat 5, 7, 8, and 9 imagery, together with spatial analysis of

surface water bodies to identify anthropogenic impacts and the potential effects of climate change. All data processing was performed on the Google Earth Engine cloud platform.

The initiative produced a map collection that includes monthly and annual surface water, transitions, trends, and the classification of surface water into natural and anthropogenic water bodies.

All data are publicly available in the Water module of the MapBiomass Bolivia web platform.

1.3 Key science and applications

The surface water dynamics dataset helps users understand aquatic systems and their interactions with other environmental components. It is therefore important for decision-making and supports water-resource management from a sustainable-development perspective.

Surface water mapping can support integrated land-use planning, monitoring of the Sustainable Development Goals, sustainable water-management initiatives, monitoring of water concessions and small dams, assessment of freshwater ecosystem condition, and research on 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 because of human activities in recent decades. Drastic changes in land use and land cover, hydroelectric dam construction, 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 have extinction rates twice as high as terrestrial species. In addition, climate-related extreme droughts and floods have increased pressure on water reserves and aquatic ecosystems.

This situation is likely to worsen as the global population and resource use increase. Unless integrated water-management strategies are developed, achieving the global Sustainable Development Goals will be impossible. From this perspective, continuously and historically assessing changes in surface water dynamics at continental scale is one of the main challenges for decision-making concerning this vital resource (Oliveira and Souza, 2019).

These challenges also apply to the Amazonian countries, which have the planet's highest proportion of water per capita but where distribution and quality are uneven. This requires context-specific decisions that consider regional characteristics and the interconnected, cumulative effects of water use. Such decisions depend on detailed and consistent data and information on surface water dynamics.

The innovative surface water mapping methodology adopted by MapBiomass Water has previously made it possible to identify and quantify freshwater surface dynamics in the Amazonian countries, particularly in wetlands (Souza *et al.* 2019).

2.2 Historical perspective: existing maps and mapping initiatives

Satellite data have transformed our ability to map inland surface waters and their dynamics. The combination of freely available Landsat data and cloud-computing capabilities enabled the release of multi-decadal global surface water datasets:

Global Surface Water (GSW) (Donchyts *et al.* 2016; Pekel *et al.* 2016) provides information on surface water extent and dynamics across the Earth based on pixel-level analysis of more than 30 years of Landsat imagery, with numerous scientific and management applications. However, its direct use at national scale remains challenging because of methodological limitations in detecting water in floodplains, wetlands, and small water bodies.

MapBiomass Water seeks to overcome some of these limitations by combining Landsat data with cloud computing while adding methodological innovations to improve surface water detection and mapping. In particular, the initiative adopts a Surface Water Subpixel Classifier (SWSC), initially applied to the Brazilian Amazon biome (Souza *et al.* 2019). The following sections describe this methodology in detail.

3. Data and regionalization

3.1 Landsat imagery

Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 and 9 OLI imagery available in Google Earth Engine are used. Regional modules harmonize the collections, prepare spectral bands, apply cloud and shadow masks, and calculate the fractions required for classification. Depending on the processing stage and region, scripts filter scenes with cloud cover between 60% and 70%.

3.2 Auxiliary variables

Table 1. Auxiliary variables used in Collection 4

Input	Use in the methodology
SMA fractions	Shade, GV, NPV, Soil, Cloud, and Snow where applicable.
HAND	Vertical difference from the drainage network; allows more flexible thresholds in low-lying areas.
Narrow rivers	Auxiliary mask used to preserve channels with a weak spectral signal.
SRTM and slope	Topographic context and control of shadows or slopes.
Shademask	Identification of persistent topographic shadow.
MapBiomas LULC	Control of false positives in urban areas, forest, mining, and other land-cover classes.
CSF, NDWImf, and mNDWI	Auxiliary variables for biome-specific masking and recovery.
Inclusion and exclusion polygons	Documented spatial corrections for specific cases.

3.3 Regionalization

Bolivia is divided into 31 classification regions organized by biome (using Collection 2 LULC biomes): Lower Amazon, Chiquitano, Pantanal, Chaco, Tucumano-Boliviano, Andes, and Upper Amazon. Regionalization makes it possible to adjust the treatment of turbid water, narrow rivers, floodplains, terrain shadows, snow, salt flats, and land covers with spectral confusion.

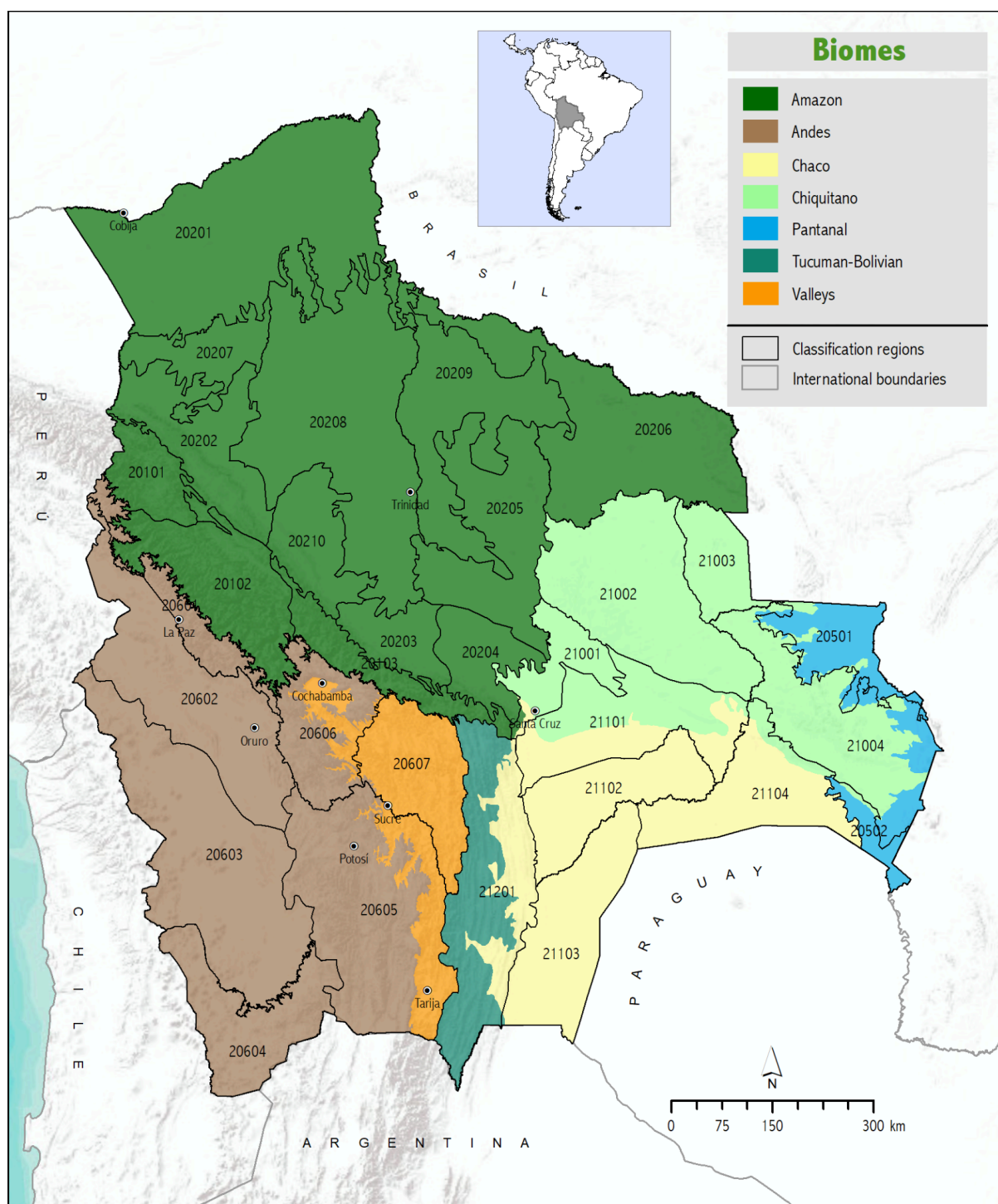


Figure 2. Regionalization used. Source: FAN.

4. Methodology

Combining the historical Landsat image archive with the cloud-processing capabilities of Google Earth Engine enabled MapBiomass Water to produce the monthly surface water dataset. Figure 3 presents the main methodological steps, including a Surface Water Subpixel Classifier (SWSC), decision trees, and post-classification procedures used to generate annual and monthly surface water data.

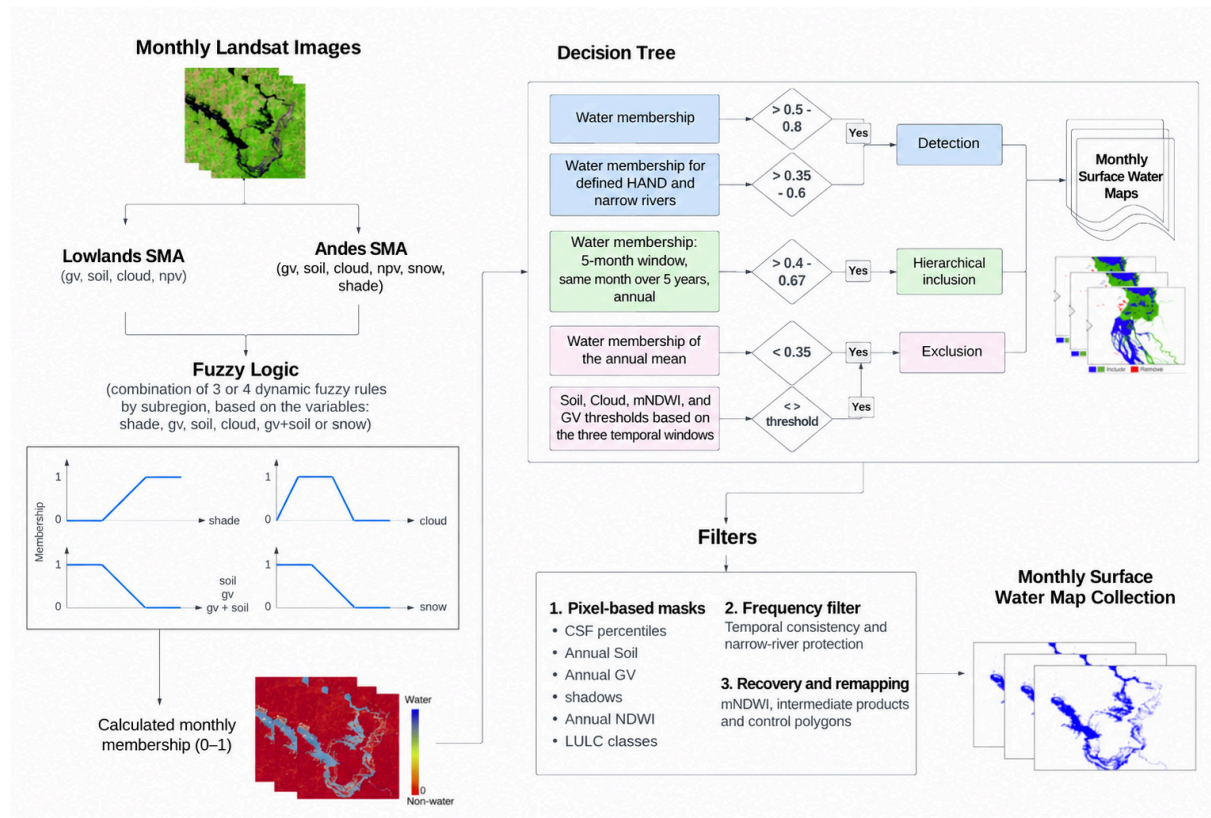


Figure 3. Methodological process used to produce surface water data, 1985–2025.

4.1 Image preparation

Each regional module retrieves and harmonizes Landsat scenes, applies atmospheric masking, and generates spectral bands and mixture fractions. Scenes identified as problematic during visual inspection may be excluded through an explicit list. Scene identifiers are retained during processing to ensure traceability.

4.2 Spectral Mixture Analysis

Spectral Mixture Analysis (SMA) estimates the fractional composition of pure pixels, or endmembers, representing green vegetation (GV), non-photosynthetic vegetation (NPV), soil, cloud, shade, and snow. The subpixel information obtained with SMA is useful for characterizing surface water mixed with other components, such as soil and vegetation. It therefore overcomes limitations of whole-pixel classifiers and supports the mapping of wetlands, floodplains, narrow rivers, and small water bodies.

A generic Landsat endmember library is used to calculate component percentages with the unmixing algorithm available in Google Earth Engine. Two cases are implemented:

- i) In Amazon and lowland regions, SMA is applied to every pixel using four endmembers to calculate GV, Soil, NPV, and Cloud fractions. The Shade fraction uses photometric shade, corresponding to zero reflectance in all bands, and is calculated by subtracting the sum of GV, Soil, Cloud, and NPV from 1.
- ii) In the Andes and transition regions with the Amazon, six SMA endmembers are calculated directly: GV, Soil, NPV, Cloud, Snow, and Shade.

Table 2. Description of spectral mixture components used in the fuzzy logic.

Component	Direction of the fuzzy rule	Example transition
Shade	A larger fraction increases water membership.	75–85
GV + Soil	A larger sum reduces membership in the Lowlands.	5–20
Cloud	Triangular function used to separate turbid water from cloud or bright soil.	0–8 ascending and 18–30 descending
GV and Soil	Higher values reduce membership in the Andes.	0–5
Snow	Auxiliary control where confusion with snow occurs.	0–50

The intervals above are examples of parameters used in the classification regions (see Appendix A).

4.3 Surface Water Subpixel Classifier

The original Surface Water Subpixel Classifier (SWSC) uses three hierarchical binary decision rules (true or false) based on the fractional information for Shade, GV, Soil, and Cloud. First, because water absorbs much of the electromagnetic radiation in the visible, near-infrared, and shortwave-infrared Landsat bands,

SWSC uses a Shade fraction greater than 65% to classify most Landsat pixels as surface water. Second, combined GV and Soil fractions below 10% quantify surface water mixed with vegetation and soil. This mixed water occurs along water-body margins, in narrow rivers, floodplain ecosystems, and wetlands. Finally, a residual Cloud fraction below 25% is included to detect surface water with high sediment loads. This residual Cloud fraction results from the spectral ambiguity of the Cloudy Soil endmember.

An empirical evaluation showed that the threshold still excluded some surface water. Transition rules were therefore defined along the fractional thresholds using linear functions (Figure 4). As a result, the original binary SWSC decision was transformed into three independent fuzzy-logic rules that determine the degree of truth, or membership, that a Landsat pixel is water. The mean degree of truth is then calculated to obtain a continuous membership map ranging from 0 to 1. Landsat pixels are classified from these membership values to produce monthly surface water layers.

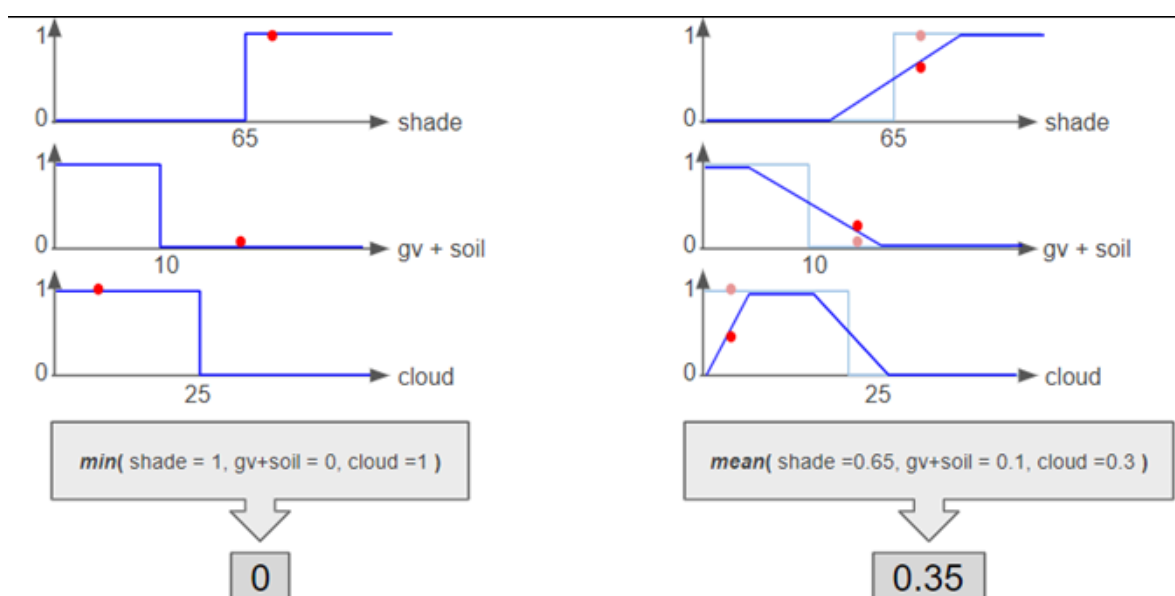


Figure 4. Binary rules of the Surface Water Subpixel Classifier. Left: example of undetected surface water for a pixel whose fractional values are shown by the red dots; GV + Soil is above the threshold of 10 required for classification as water. Right: linear fuzzy logic; the mean value correctly classifies the pixel shown by the red dot as surface water.

4.4 Monthly water classification and hierarchical gap filling

4.4.1 Original methodology for monthly water detection

Monthly maps were complemented with procedures to restore false negatives and remove false positives based on temporal metrics (Figure 5). First, median water membership was calculated for the entire year, that is, the intra-annual median, together with the decadal median for each month. Gap filling then reclassified as water pixels that had been covered by clouds or occurred where no

Landsat scene was available in a given month. Two rules were combined: median within-year probability greater than 0.3–0.67 and the decadal median for the corresponding month greater than 0.3–0.67, with thresholds varying by classification region. Finally, cloud shadows and other dark objects can produce false positives, so a removal filter reclassified as non-water pixels with median monthly membership below 0.35.

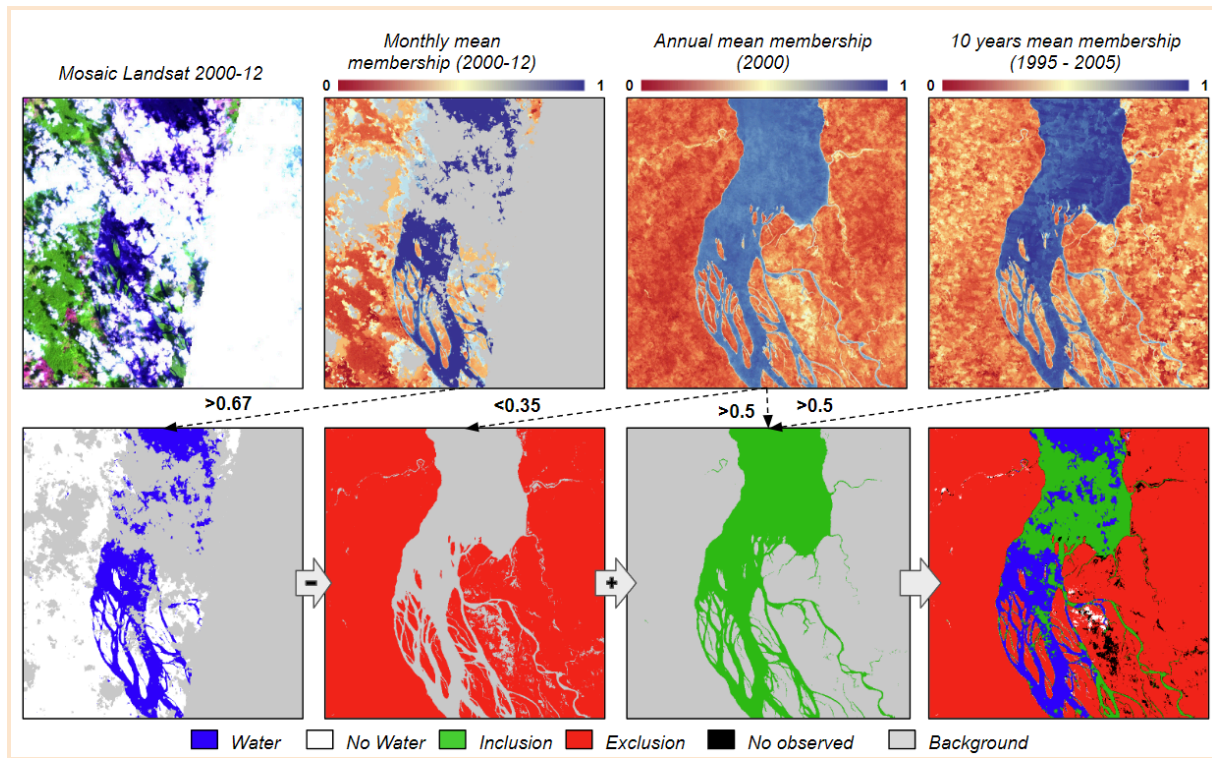


Figure 5. Methodological process for the original surface water classification. a: monthly Landsat mosaic; b: median monthly SWSC membership; c: median annual monthly SWSC membership; d: median decadal monthly SWSC membership; e: monthly surface water classification; f: total surface water per decade; g: probable surface water based on the thresholds in c and d; h: final monthly surface water map with the corresponding inclusion and removal.

4.4.2 Modified temporal probability (membership)

Four complementary probability surfaces are calculated for every year and month. This combination replaces the decadal median used as the main gap-filling source in Collections 1–3 (Figure 5) and limits the temporal context to windows that better preserve seasonality and rapid channel changes.

Temporal evidence used in monthly classification

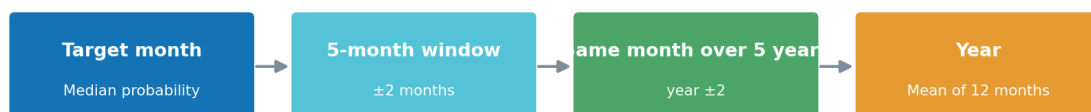


Figure 6. Hierarchy of temporal evidence in Collection 4.

Table 3. Description of the function of each probability p

Surface	Calculation	Function
monthly p	Median probability of scenes in the target month.	Direct detection.
5-month p	Median of scenes from two months before to two months after.	Short-term seasonal gap filling.
same-month 5-year p	Median for the same month in the target year ± 2 years.	Interannual recurrence without mixing seasons.
annual p	Mean monthly probabilities for the year.	Annual context and control of omission or commission errors.

Initial detection compares monthly probability with thresholds differentiated by HAND and with specific rules for narrow rivers. A more flexible threshold can be used in low-HAND areas because their topographic position increases the likelihood of water. A dedicated threshold is applied in narrow channels to retain mixed signals.

When the month has no valid observation or direct detection does not identify water, the algorithm sequentially evaluates the 5-month probability, the same-month 5-year probability, and the annual probability. Each source only fills pixels not yet classified as water. Cases with very low temporal evidence remain non-water or are assigned an internal removal label. This priority prevents a broad temporal source from overwriting valid monthly evidence.

Table 4. Hierarchical implementation order

Order	Evidence	Conceptual condition	Internal result
1	monthly p	Exceeds the regional threshold.	Detected water
2	5-month p	The month was not detected and the short window exceeds the threshold.	Gap-filled water
3	same-month 5-year p	Water remains undetected and interannual recurrence is present.	Gap-filled water
4	annual p	Water remains undetected and annual support is high.	Gap-filled water
5	Low evidence	Annual or window probability is insufficient.	Non-water or removal

4.4.3 Spectral and topographic controls

The provisional classification is corrected using cloud, soil, topographic shade, and annual probability information. Detections within the shade mask and pixels with high Soil or Cloud fractions are removed when annual support is low. In certain months, from July to November, and regions such as the Amazon, Pantanal, and

Chiquitanía, additional annual thresholds control seasonal confusion such as that caused by dry-season fires. Nearly permanent pixels may also be recovered when annual probability is high.

4.5 Post-classification

4.5.1 Biome-specific masks

The second stage groups classification regions by biome and applies adapted commission-error rules. For example, the Lower Amazon uses annual percentiles of the Canopy Shade Factor (CSF), Soil and GV fractions, land-use and land-cover classes, and the narrow-river mask. Missing values in the mosaics used for masking at the beginning of the series are complemented with data from the following year.

Table 5. Details of masks applied by biome

Regional group	Dominant issues	Available controls
Lower Amazon	Canopy shadow, wet soil, and floodplains.	CSF, GV, Soil, LULC, and narrow rivers.
Andes	Topographic shadow, snow, salt flats, and bare soil.	Shade mask and mNDWI
Chaco and Chiquitano	Turbid water, dry soil, and pronounced seasonality.	SMA fractions, indices, and regional rules.
Pantanal	Extensive flooding and aquatic-vegetation mosaics.	Flexible thresholds, HAND, and temporal recurrence.
Upper Amazon and Tucumano	Relief, shadow, and elevation gradients.	Cloud and shadow modules, topography, and specific masks.

4.5.2 Time-series frequency filter

This stage counts the total number of months classified as water during 1985–2025. The cumulative frequency distinguishes persistent signals from isolated detections. The example applies different rules inside and outside narrow rivers: very-low-frequency pixels are remapped to an internal removal class, whereas almost-complete-frequency pixels may be consolidated as observed water if they are detected as water in the last year.

The minimum threshold is not applied blindly across the country. Its interaction with the narrow-river mask prevents the removal of small channels that are observable in only a fraction of the months.

4.5.3 Recovery and remapping

This step compares the filtered result with intermediate products from Collection 4 itself, first the mask and, when necessary, the classification, and applies targeted

comparisons with a previous version. Control polygons indicate where pixels should be recovered from the classification, masks, or previous remapping. Annual mNDWI and its 75th percentile support recovery during periods with consistent spectral evidence. Other areas are remapped to an internal exclusion class.

4.5.4 National integration

The final stage creates a single mosaic of the regions, limits the result to the national territory, and reduces the internal classes to a monthly binary mask. Internal values 1, 2, and 3—classification, inclusion in observed areas, and inclusion in unobserved areas, respectively—are interpreted as water and converted to 1; all other values are masked. Each annual image contains 12 monthly bands and metadata for year, country, collection, source, version, and cadence.

Post-classification sequence

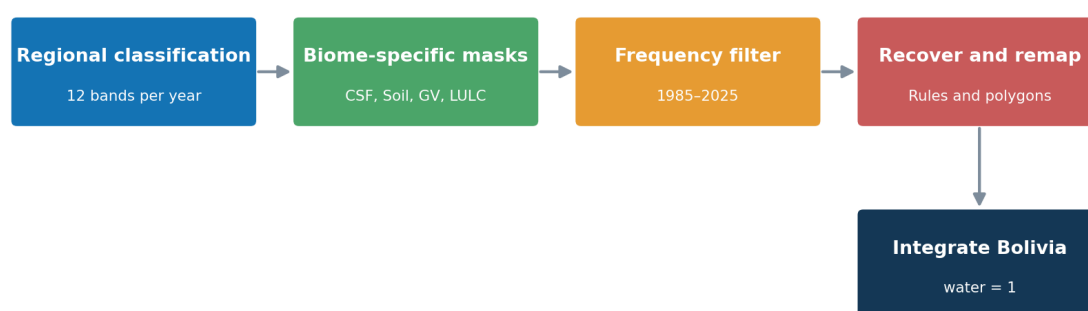


Figure 7. Post-classification and national integration sequence.

4.6 Derivation of annual water data

Annual surface water maps distinguish permanent and seasonal water according to the number of months in which a pixel is classified as water. Permanent water has a frequency of at least 6 months, whereas seasonal water has a frequency of 1 to 5 months. The permanent-water threshold reflects the presence of a dry and a wet season in most regions and therefore includes permanent water bodies that are naturally more dynamic.

4.7 Water-body categorization methodology

Surface water mapping was used in a water-body classification scheme with the following classes: 1. Natural, 2. Saline lakes, 3. Anthropogenic, 4. Water associated with mining activity, and 5. Aquaculture. This classification is a by-product used to remove some unwanted false positives remaining in the monthly and annual surface water collections.

4.7.1 Object vector delineation

Object vector delineation was termed annual vectorization because it converts monthly surface water frequency maps for each year from raster data into regular vector polygons within the spatial extent of the water bodies. A segmentation tool was used, and a particular water body may have been converted into one or more polygons. The SNIC function available in Google Earth Engine generated small, relatively regular segments. Figure 8 presents examples of segmentation based on monthly frequency data for a given year.

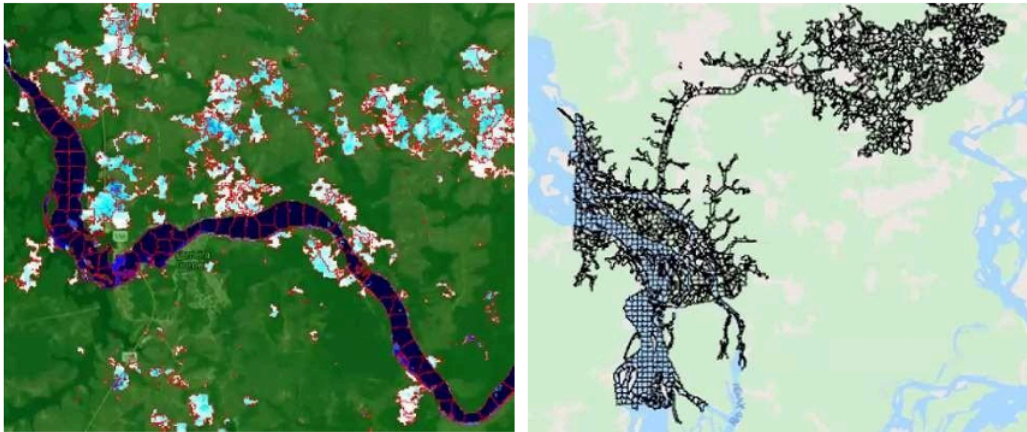


Figure 8. Examples of the segmentation process that converts raster data, representing monthly frequency within each year, into a regular vector mesh.

4.7.2 Assignment of object properties

After objects were generated for each year, a feature dataset with new properties was assigned to each object for subsequent classification. These properties include information on object morphology, geomorphology, and qualitative data from other water-body classification and land-use and land-cover mapping studies. The following variables were assigned to each object: area, perimeter, area-to-perimeter ratio, compactness, roundness, elongation, Laenge–Breite ratio, convexity, maximum extent, number of neighbors, number of neighbors within a 50 m buffer, MapBiomass land use and land cover (urban, mining, forest, non-forest class, pasture), maximum SRTM value, and mean total frequency.

4.7.3 Object classification using training samples

Water bodies were classified using the Random Forest algorithm. Training samples for the five classes were collected across the different biomes using a set of previously defined grids and covering different years of the time series.

After classification, the results underwent a post-classification routine using a temporal filter. The temporal filter removed unlikely transitions between classes for the same segment throughout the time series.

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

5. Products and analyses

The main results of Collection 4 are available on the public web platform at <https://plataforma.bolivia.mapbiomas.org/agua> and include: <https://plataforma.mapbiomas.org/projects/mapbiomas/bolivia>

- Annual surface water
- Monthly surface water
- Water-body types
- Surface water trend
- Surface water transitions
- Annual surface water frequency
- Time since last occurrence

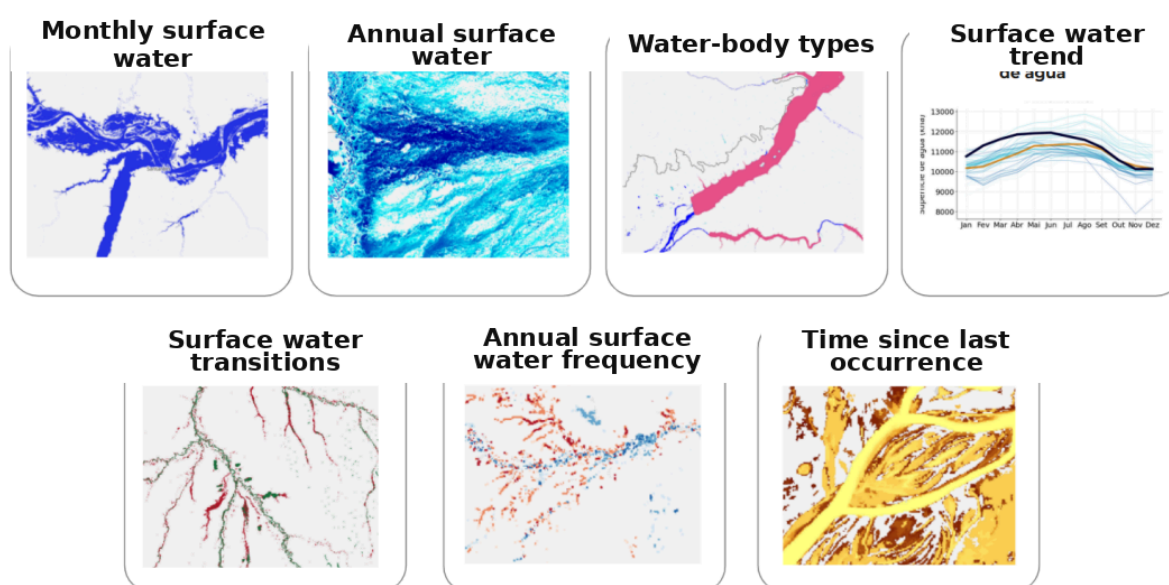


Figure 9. Products derived from monthly surface water data and available on the platform.

5.1 Annual surface water

This variable corresponds to annual surface water data, which can be viewed for any year from 1985 to 2025 (Figure 10). The data are available for different territorial units, including biome, watershed, and department. Users can select different territories and time ranges, which updates the map, charts, and statistics.

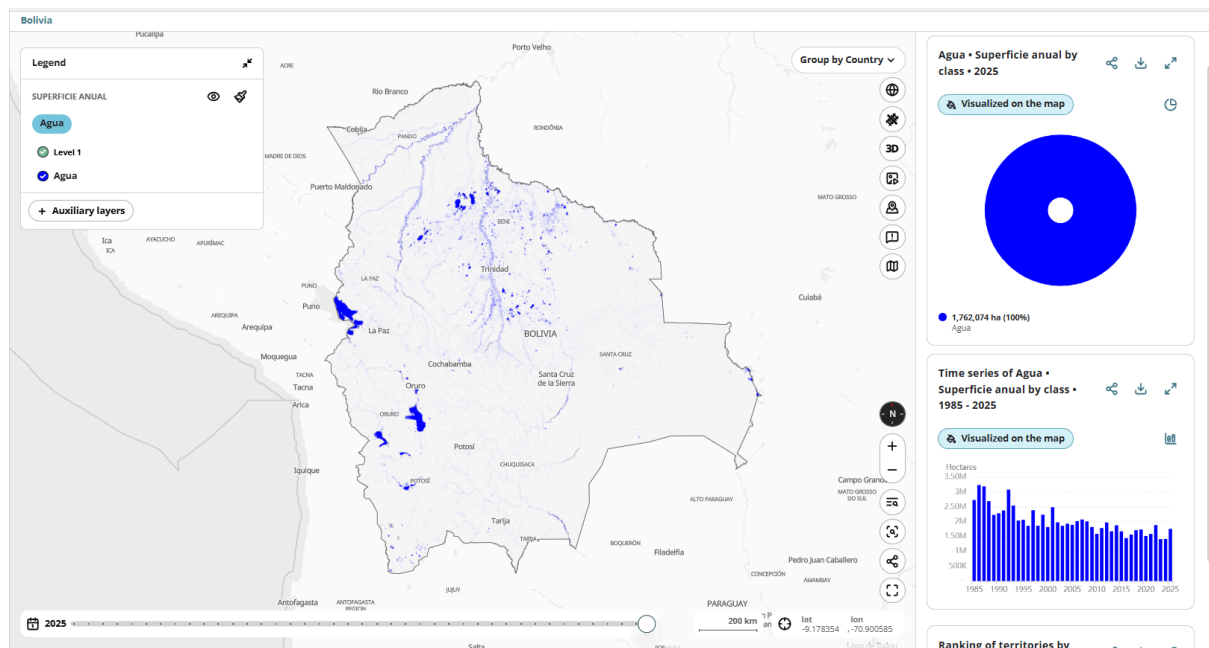


Figure 10. Example visualization of surface water layer data, including map and chart, on the MapBiomas Water platform.

5.2 Monthly surface water

This variable corresponds to monthly surface water data. All months can be displayed simultaneously using a different color for each month. In addition to the monthly map, the platform provides charts and statistics such as the months with the largest and smallest surface water areas in a given year, the mean across all months of a year, variation relative to the historical monthly mean, and monthly trends by year.

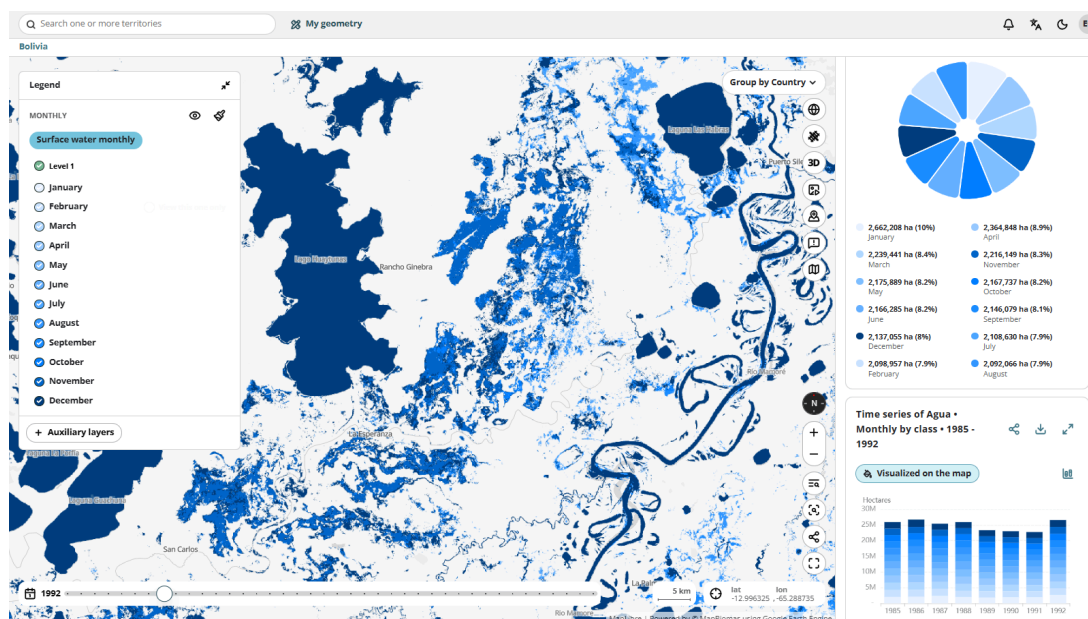


Figure 11. Example visualization of monthly surface water data, including map and chart, on the MapBiomas Water platform.

5.3 Water-body types

This variable corresponds to the classification of surface water by origin. Classification is annual and the time series covers 1985–2025. Available statistics include the surface water area in each mapped water-body class for the year of interest and selected spatial unit, together with a chart of areas throughout the full time series.

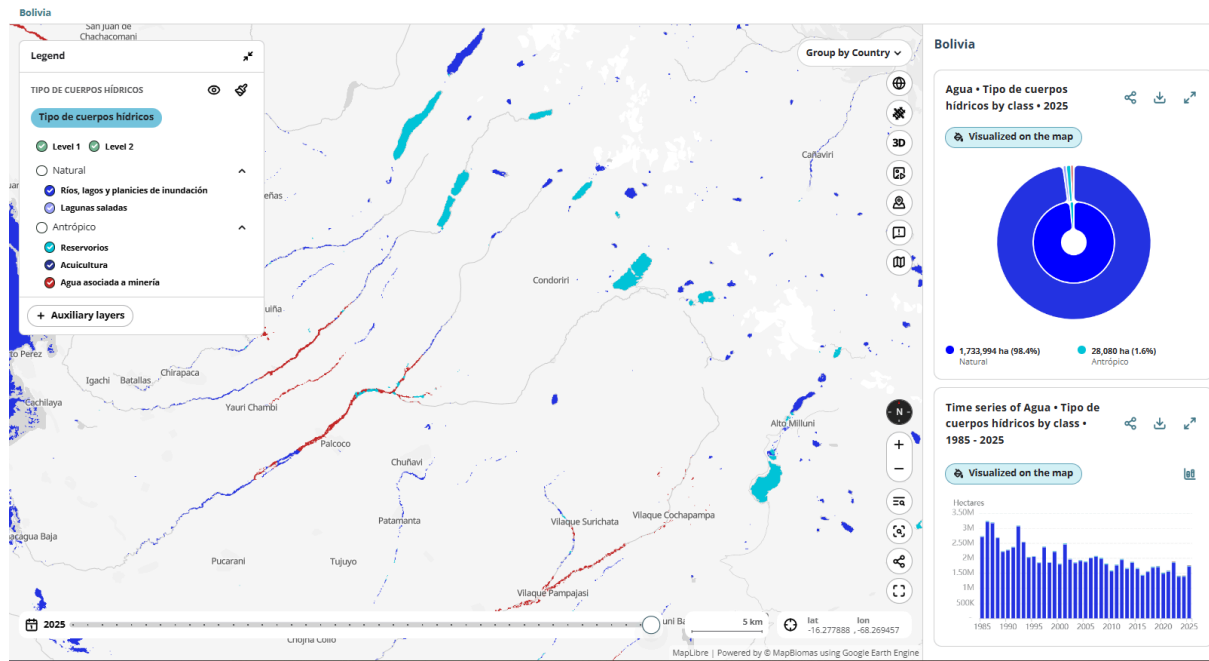


Figure 12. Example visualization of water-body types, including map and chart, on the MapBiomias Water platform.

5.4 Surface water transitions

This layer represents surface water that decreased, increased, remained persistent, or occurred sporadically over the 41-year period. These areas were identified using the total number of pixels classified as water across the annual time series, i.e., 41 years. An RGB color composite was prepared to facilitate visualization and identification of these categories (Figure 13).

First, persistence was represented in blue using the total number of years classified as surface water. Second, the number of years from the beginning of the time series to the first water classification was assigned green to represent increase. Finally, the number of years from the last surface water observation to the end of the time series was assigned red to indicate decrease. Permanent water bodies therefore appear predominantly blue; temporary water surfaces appear black when they occur sporadically; surface water loss appears red; and new water surfaces appear green.

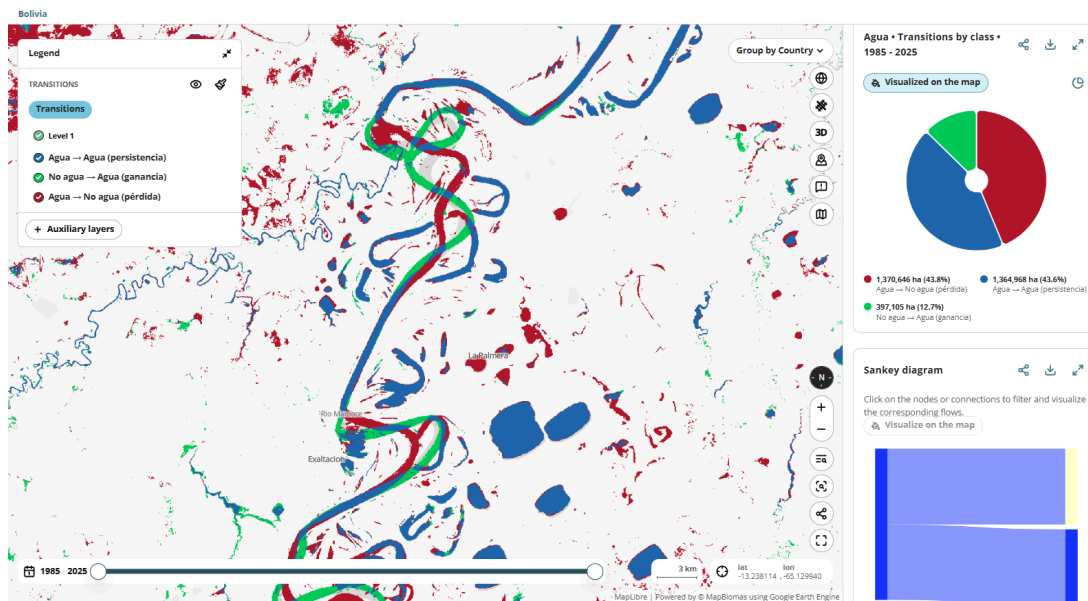


Figure 13. Example visualization of surface water transitions on the MapBiomias Water platform.

5.5 Surface water trend

Surface water trends were analyzed using the monthly water dataset. Trends of increase, decrease, or stability in mapped surface water were evaluated over 1985–2025 using the Seasonal Mann–Kendall test. This nonparametric test identifies increasing or decreasing monotonic trends in data collected over time and does not require the data to meet normality assumptions. It is appropriate for detecting monotonic trends in seasonal data (Hirsch et al., 1982; Hirsch et al., 1984; Gilbert, 1987; Helsel and Hirsch, 1995; Morell and Fried, 2009).

The platform displays the map using different color shades according to the magnitude of positive and negative trends. Only statistically significant results at the 95% confidence level are shown.

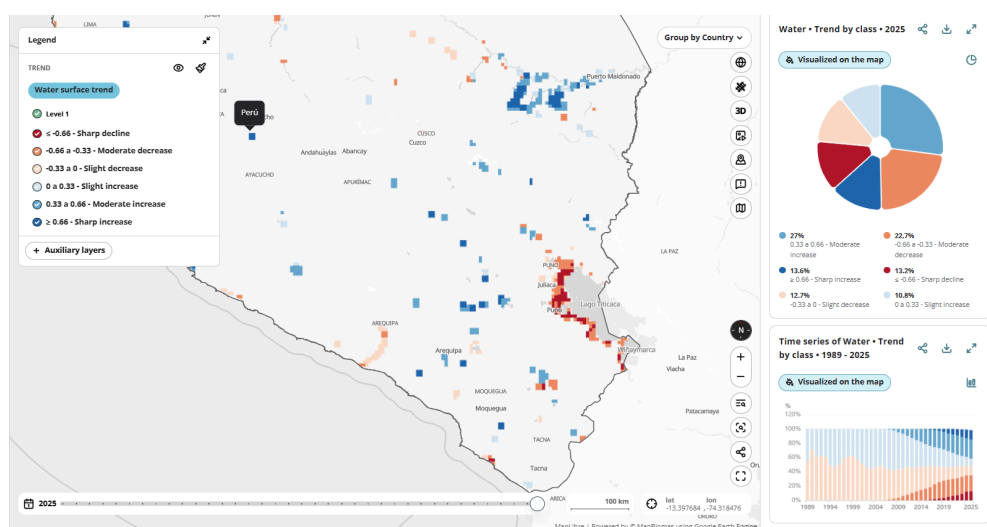


Figure 14. Example visualization of the surface water trend on the MapBiomias Water platform.

5.6 Surface water frequency

This variable represents frequency based on annual surface water data. Different color shades show the number of times a pixel was mapped as water throughout the time series.

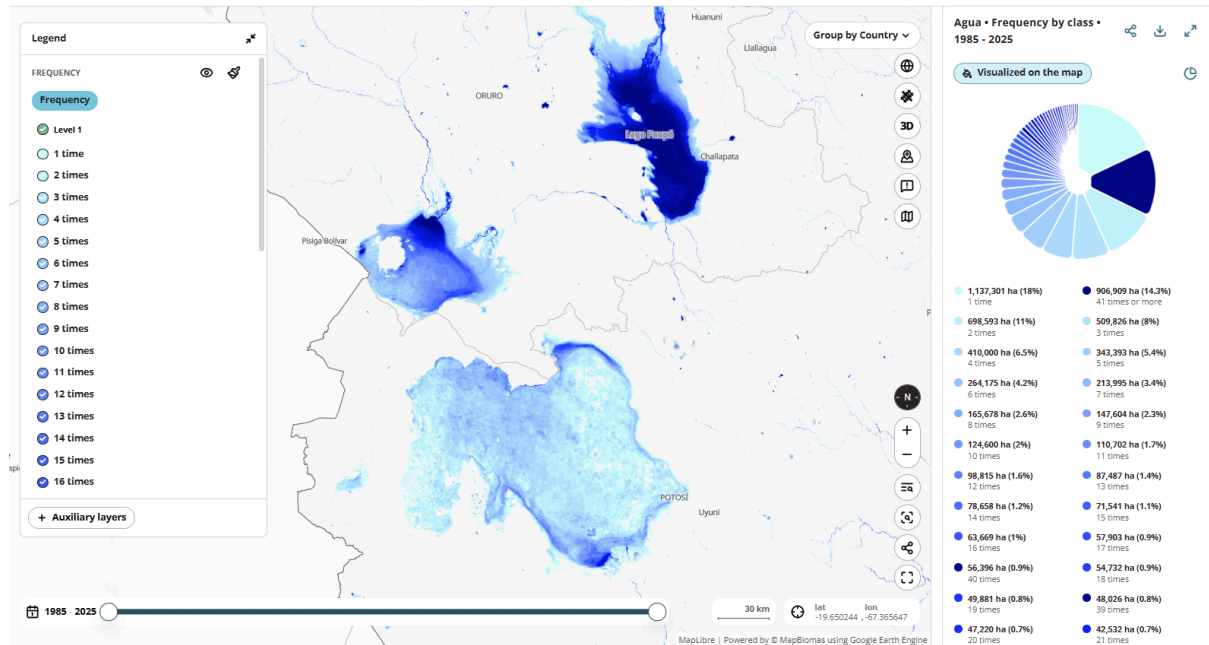


Figure 15. Example visualization of surface water frequency on the MapBiomas Water platform.

5.7 Time since last occurrence

This variable represents the number of years elapsed since water was last detected for a given year. It is useful for viewing areas that historically contained surface water but no longer do.

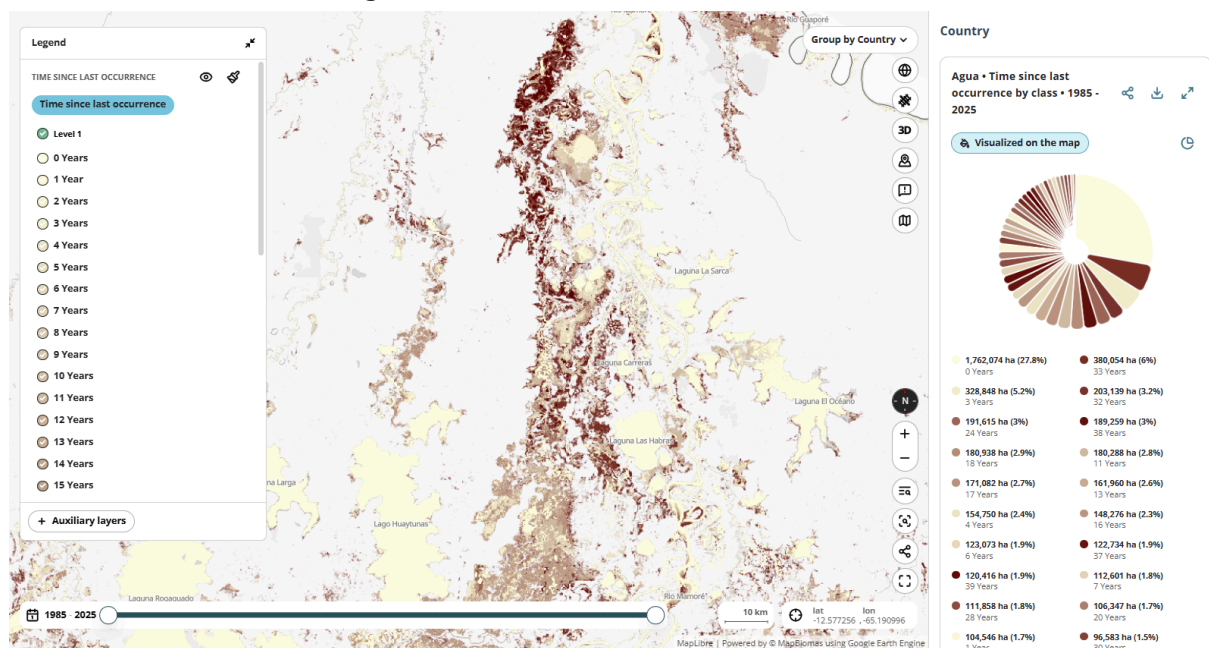


Figure 16. Example visualization of time since last occurrence on the MapBiomas Water platform.

6. Practical considerations and limitations

Users of this dataset should compare any use or application of the quantitative data presented here with the accuracy results to better understand the associated uncertainty and determine whether the data are suitable for the intended purpose.

The 30 m resolution limits detection of very narrow channels and small reservoirs. Persistent cloud cover, topographic shadows, snow, sediment, wet soil, and flooded vegetation can produce omission and commission errors. Temporal gap filling improves continuity but can also smooth abrupt changes if thresholds are not properly calibrated. The product should therefore be interpreted together with its accuracy metrics and local knowledge.

Changes relative to Collection 3 are summarized in the following table:

Table 6. Comparison of changes made in Collection 4 relative to Collection 3.

Component	Collection 3	Collection 4
Period	1985–2024	1985–2025.
Temporal gap filling	Combination of the annual median and the decadal median for the same month.	Sequence: 5 months, same month over 5 years, and annual context.
Topography and hydrology	Slpост and supplementary masks.	HAND or SLPPOST, modified shade mask, and a specific rule for narrow rivers.
Masks	CSF, NDWI, LULC, and regional rules.	CSF, mNDWI, NDWImf, SMA, and LULC.
Temporal consistency	Inclusion and removal filters.	Explicit filter based on cumulative frequency over the full time series.
Final corrections	Post-classification and false positives.	Targeted spatial recovery and remapping before integration.

The change in temporal window is particularly relevant for dynamic rivers. A decadal window can combine historical channel positions and different hydrological conditions; the five-month and five-year windows reduce this risk, although visual inspection remains necessary for highly dynamic rivers.

7. Conclusions and outlook

Collection 4 represents a significant advance in thematic accuracy over Collection 3 and constitutes an important surface water mapping product for the entire territory of Bolivia, contributing to the understanding of spatial and temporal dynamics. It meets the objectives established by MapBiomass Water Bolivia by consolidating surface water mapping that makes it possible to characterize change patterns, observe cycles of increase and decrease, estimate gains and losses, and relate changes to human interactions in order to better understand their consequences.

8. References

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Appendix A

Table A-1. Regional thresholds for fuzzy logic

Region	id_region	shade	gv_soil	cloud_asc	cloud_desc	gv	soil	snow
Tucumano	21201	55-72	4-10	2-5	27-29	-	-	-
Upper Amazon	20101 a 20103	70-72	5-25	2-5	27-29	-	-	-
Chiquitano	21001 a 21004	75-85	5-25	0-8	26-29	-	-	-
Chaco	21101 and 21102	75-80	15-20	1-7	21-27	-	-	-
Chaco	21103 and 21104	72-76	21-35	4-5	20-26	-	-	-
Pantanal	20501 and 20502	84-87	3-16	0-5	14-24	-	-	-
Lower Amazon	20201 a 20210	75-85	5-20	0-8	18-30	-	-	-
Glacier Andes	20601	55-80	-	-	-	0-7	0-7	
Western transition Andes	20605 a 20607	55-75	-	-	-	0-10	0-15	-
Southern Andes	20604	55-70	-	-	-	0-12	0-7	-
Central Andes	20602 and 20603	55-70	-	-	-	0-10	0-15	60 and 70 special months

Table A-2. Thresholds for classification parameters

Region	id_region	hand or slppost	slppost or hand cutoff ($\leq$)	detection probability	narrow-river cutoff and probability	5-month gap filling	same-month 5-year gap filling	annual gap filling
Tucumano	21201		<15(0.49)	0.66		0.5		
Amazonía alta	20101 a 20103	slppost	<12(0.5)	0.67 and 0.5	2 and 0.34	0.6 and 0.5	0.6y 0.4	0.55
Chiquitano	21001 a 21004	hand30_1000	<2(0.5)	0.67		0.5 and 0.5	0.5 and 0.45	0.62
Chaco	21101 and 21102	slppost	<10(0.5)	0.67	3 and 0.28	0.5 and 0.5	0.5 and 0.5	0.6
Chaco	21103 and 21104	hand30_1000	5	0.67	3 and 0.33	0.5 and 0.5	0.5 and 0.5	0.6

Pantanal	20501 and 20502	hand30_1000 and slppost<3	3(0.55)	0.67	2 and 0.32	0.5 and 0.48	0.5 and 0.48	0.6
Lower Amazon	20201 a 20210	hand30_1000	3.5	0.67 and 0.45	3 and 0.35	0.5 and 0.45	0.5 and 0.45	0.6
Glacier Andes	20601	hand30_1000 and slppost<4 and geo	<10(0.55)	0.6 and 0.55	2 and 0.45	0.6 and 0.55	0.6 and 0.55	0.6
Western transition Andes	20605 a 20607	hand30_1000 and slppost<4	7	0.66 and 0.5	2 and 0.4	0.6 and 0.5	0.6 and 0.5	0.6
Southern Andes	20604	modified SLPPPOST	<10(0.53)	0.66 and 0.5	2 and 0.4	0.6	0.6 and 0.5	0.6
Central Andes	20602 and 20603	hand30_1000	5	0.66 and 0.5	2 and 0.4	0.55	0.6 and 0.5	0.74