Algorithm Theoretical Basis Document (ATBD)

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

Collection 1, Version 1

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Executive Summary

Collection 1 of MapBiomas Water Uruguay produces a 30 m monthly surface water time series for 1985–2025 and derived annual products for the whole national territory. The workflow follows the methodology developed by the MapBiomas Water network (Souza et al. 2019), based on subpixel classification of Landsat imagery with Spectral Mixture Analysis, fuzzy logic and temporal gap filling, processed in Google Earth Engine.

The main adaptations for Uruguay are: a single national parameter set; fuzzy-logic membership thresholds of 65–90% for Shade, 15–5% for GV + Soil and a trapezoidal function for Cloud (0–8% and 12–30%); temporal evidence from a 13-year interannual window (±6 years) and an 11-month moving intra-annual window, except in ten dry years (annual precipitation more than 15% below the 40-year mean), for which a 7-year interannual window and a 5-month moving intra-annual window were used; control of shadow and slope with an SRTM-derived slope threshold of 20°; an object-based post-classification mask based on the frequency and mean slope of water objects together with annual CSF and soil criteria; recovery of non-observed pixels from the nearest valid month within a five-year window; and an annual water map defined by at least six months classified as water. The products are the monthly classification (12 bands per year) and the annual surface water map and the frequency map (41 bands).



Figure 1. General production workflow for Collection 1.

1. Introduction

1.1 Scope and content of the document

MapBiomas Water aims to map and monitor surface water dynamics in Uruguay through monthly observations and annual aggregations. Collection 1 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 methodological steps used to produce Collection 1 of MapBiomas Water Uruguay.

1.2 General description

MapBiomas Water is an initiative of the MapBiomas network whose main objective is to map surface water bodies on a monthly and annual basis. The 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 (Souza et al. 2019). The MapBiomas Water working group subsequently expanded the same approach to the entire Brazilian territory, and in 2022, through the partnership between MapBiomas and the Amazon Network of Georeferenced Socio-Environmental Information (RAISG), the methodology was adapted and applied to the Amazonian countries.

In Uruguay, MapBiomas Water is developed as a thematic module of MapBiomas Uruguay, the initiative that produces annual land use and land cover (LULC) maps of the country from 1985 onward (Baeza et al. 2022; Gallego et al. 2026). The module is carried out by researchers of the Universidad de la República (Facultad de Agronomía and Facultad de Ciencias), the Ministerio de Ambiente and the Instituto Nacional de Investigación Agropecuaria (INIA). Collection 1 adopts the workflow of the MapBiomas Water network (lowlands module of the Southern Cone) and adapts it to Uruguay.

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.

All data are publicly available in the Water module of the MapBiomas Uruguay 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 (tajamares and reservoirs), assessment of freshwater ecosystem condition, and research on changes in water bodies and their relationship with climate variability and change.

In Uruguay, surface water data are particularly relevant for: (i) livestock production, since farm ponds (tajamares) are widely used to supply water to cattle and, secondarily, for irrigation; (ii) irrigation, whose reservoirs are regulated by Law 16.858 on irrigation for agricultural use, as modified by Law 19.553 of 2017; (iii) drinking-water supply, as the 2022–2023 drought showed the vulnerability of the reservoirs that supply the metropolitan area; and (iv) the study of coastal lagoons, wetlands and floodplains and their response to climate variability. Monthly data also allow droughts and floods to be placed in a 41-year historical context.

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, 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.

Continuously and historically assessing changes in surface water dynamics is one of the main challenges for decision-making concerning this resource (Oliveira and Souza, 2019).

Uruguay lies entirely within the Río de la Plata grasslands (Pampa) biome, and the mapped area is 17.8 million hectares. Its surface water is organized in four main hydrographic regions: the Uruguay River, the Río de la Plata, the Merín Lagoon and the Atlantic Ocean basins. The territory includes large rivers (Uruguay and Negro), hydroelectric reservoirs (Salto Grande on the Uruguay River and Rincón del Bonete, Baygorria and Palmar on the Negro River), coastal lagoons, wetlands, and a large number of small artificial water bodies. According to the MapBiomas Uruguay LULC maps, water bodies and rivers covered approximately 1.5% of the national territory in 2023 (Gallego et al. 2026).

Between 1985 and 2023, natural grasslands decreased by 21.4% and were mostly replaced by annual crops (+77.4%) and forest plantations (+857%) (Gallego et al. 2026), changes that can alter water demand and runoff. In addition, the 2022–2023 drought strongly reduced the reserves of the Santa Lucía basin (Paso Severino and Canelon Grande reservoirs; Figure 2) that supply the metropolitan area of Montevideo and affected agricultural production.

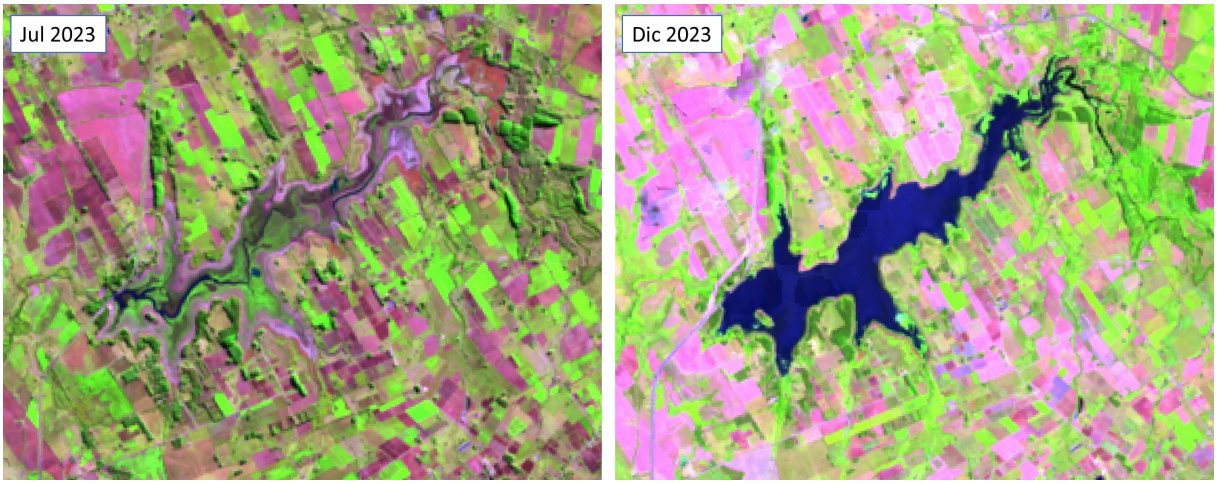


Figure 2. Water extent for the Canelon Grande reservoir during the 2022–2023 drought for Jul 2023 (left) and Dec 2023 (right).

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

MapBiomas 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).

Before MapBiomas Water, national information on water bodies in Uruguay came mainly from LULC and wetland products. The integrated LULC map of Uruguay for 2018, produced by the Ministerio de Ganadería, Agricultura y Pesca (Petraglia et al.), maps artificial water bodies (hydroelectric dams, reservoirs for human supply and tajamares) and irrigation reservoirs from Sentinel-2 images of January–March 2018, at a scale of 1:50,000 and with a minimum mapping unit of 0.25 ha. Such products refer to a single date and do not describe intra-annual or long-term dynamics. The MapBiomas Uruguay LULC collection includes an annual water class from 1985 onward (Gallego et al. 2026), but it is not designed to describe monthly dynamics. MapBiomas Water Uruguay complements these sources with a monthly time series from 1985.

3. Data and spatial coverage

3.1 Landsat imagery

Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 and 9 OLI imagery available in Google Earth Engine are used. The collections are harmonized, spectral bands are prepared, cloud and shadow masks are applied, and the fractions required for classification are calculated.

Monthly classification uses scenes filtered by a cloud-cover threshold of 50%, whereas the annual statistics used in the post-classification mask use scenes filtered by a threshold of 70%.

3.2 Auxiliary variables

Table 1. Auxiliary variables used in Collection 1.

Input	Use in the methodology
SMA fractions	Shade, GV, Soil and Cloud fractions, used in the fuzzy rules (Table 3), and Shade, GV, NPV and Soil fractions, used in the CSF and in the soil mask of step 3.
SRTM slope (30 m)	Water on slopes of 20° or more is reassigned to class 9, and objects with a mean slope of 20° or more are excluded in the step 3 mask.
slppost2	SRTM-derived relative slope-position index: defines the direct-detection threshold (0.67 where slppost2 > 1; 0.40 where slppost2 ≤ 1; section 4.4.6).
shademask2_v3	Topographic shadow mask: water that coincides with the mask is reassigned to class 8 (section 4.4.5).
CHIRPS precipitation	Mean annual precipitation of each year and of the whole series, used to identify dry and wet years (section 4.4.1).

3.3 Spatial coverage and processing units

Processing was carried out for the whole national territory with a single set of parameters (Appendix A). The vectorization of water objects (section 4.5) was carried out by chart, using nine charts of the national chart grid, each subdivided

into 0.25° subgrids.

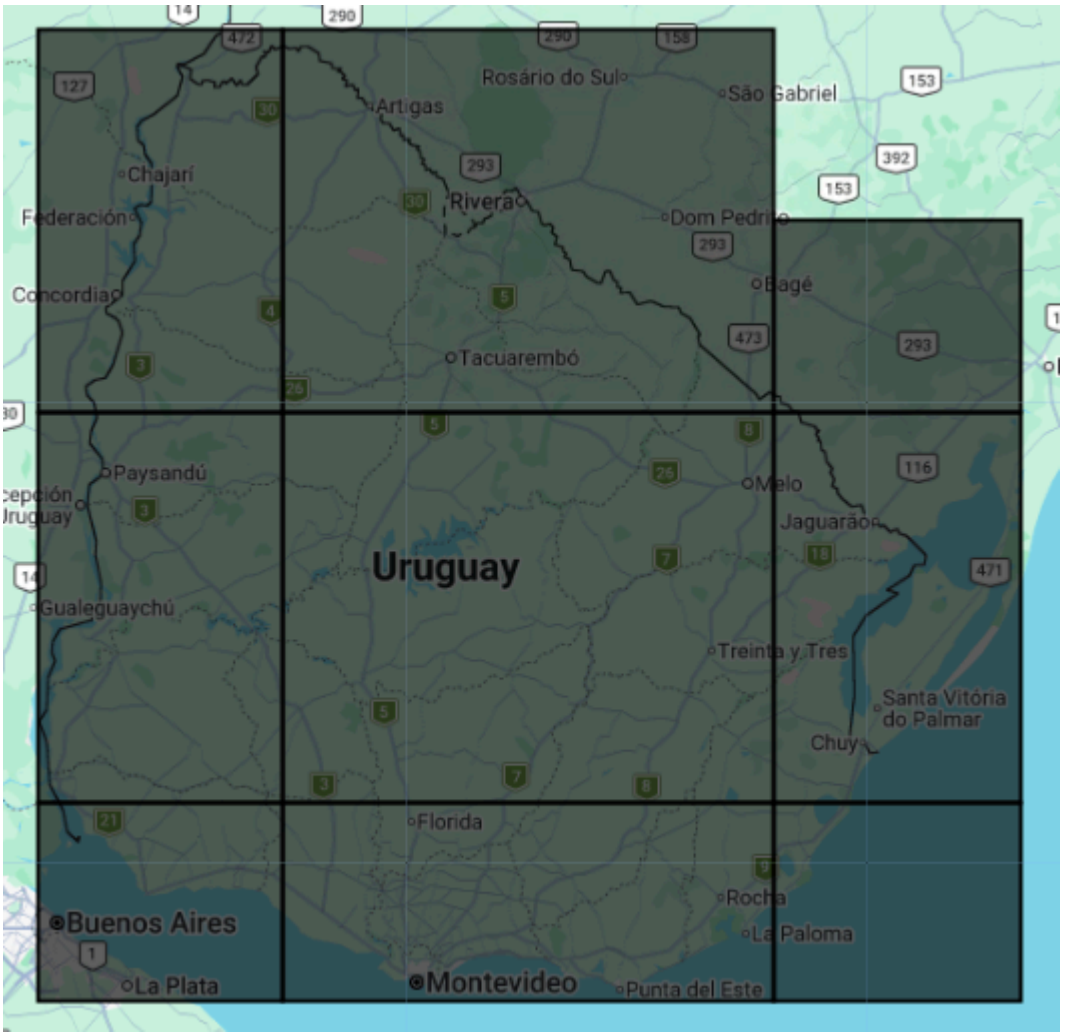


Figure 2. Charts and subgrids used for vectorization.

4. Methodology

Combining the historical Landsat image archive with the cloud-processing capabilities of Google Earth Engine enabled MapBiomas Water to produce the monthly surface water dataset. After image preparation, spectral mixture analysis and the subpixel classifier (sections 4.1 to 4.3), processing is organised in five sequential steps (Table 2), namely (1) preliminary classification, (2) vectorization, (3) false-positive masking, (4) gap filling and (5) removal of water detected in urban and non-vegetated areas, such as dunes and beaches. Steps 1, 3 and 4 each produce a 12-band monthly image (w_1 to w_12) with the classes of Table 5, step 2 produces the vector objects used by step 3, and step 5 applies a final filter to the gap-filled monthly image. Step 1 is parameterised differently for dry years and for normal and wet years (section 4.4.1). Figure 3 presents the classification logic of step 1.

Table 2. Steps of the monthly surface water processing.

Step	Process	Input	Output
1	Preliminary classification (section 4.4)	Per-image water membership (SWSC); SRTM slope and shadow mask	Monthly classification in classes 1 to 9; 13-year windows (7 in dry years)
2	Vectorization (section 4.5)	Classes 1 to 3 of the preliminary classification	Eight-connected water objects at 30 m, with mean frequency and mean slope
3	False-positive masking (section 4.6)	Preliminary classification, object attributes, CSF and soil fraction	Water pixels reassigned to class 4 (non-water); classes 4 to 9 preserved
4	Gap filling (section 4.7)	Masked classification	Class 5 pixels recovered with the nearest valid month, 5-year window
5	Removal of water detected in urban and non-vegetated areas, such as dunes and beaches	Gap-filled classification; urban area and non-vegetated area masks (beaches, dunes and sand spots) from the MapBiomas land cover collection	Final monthly water classification, with water pixels within the masks reassigned to class 4 (non-water)

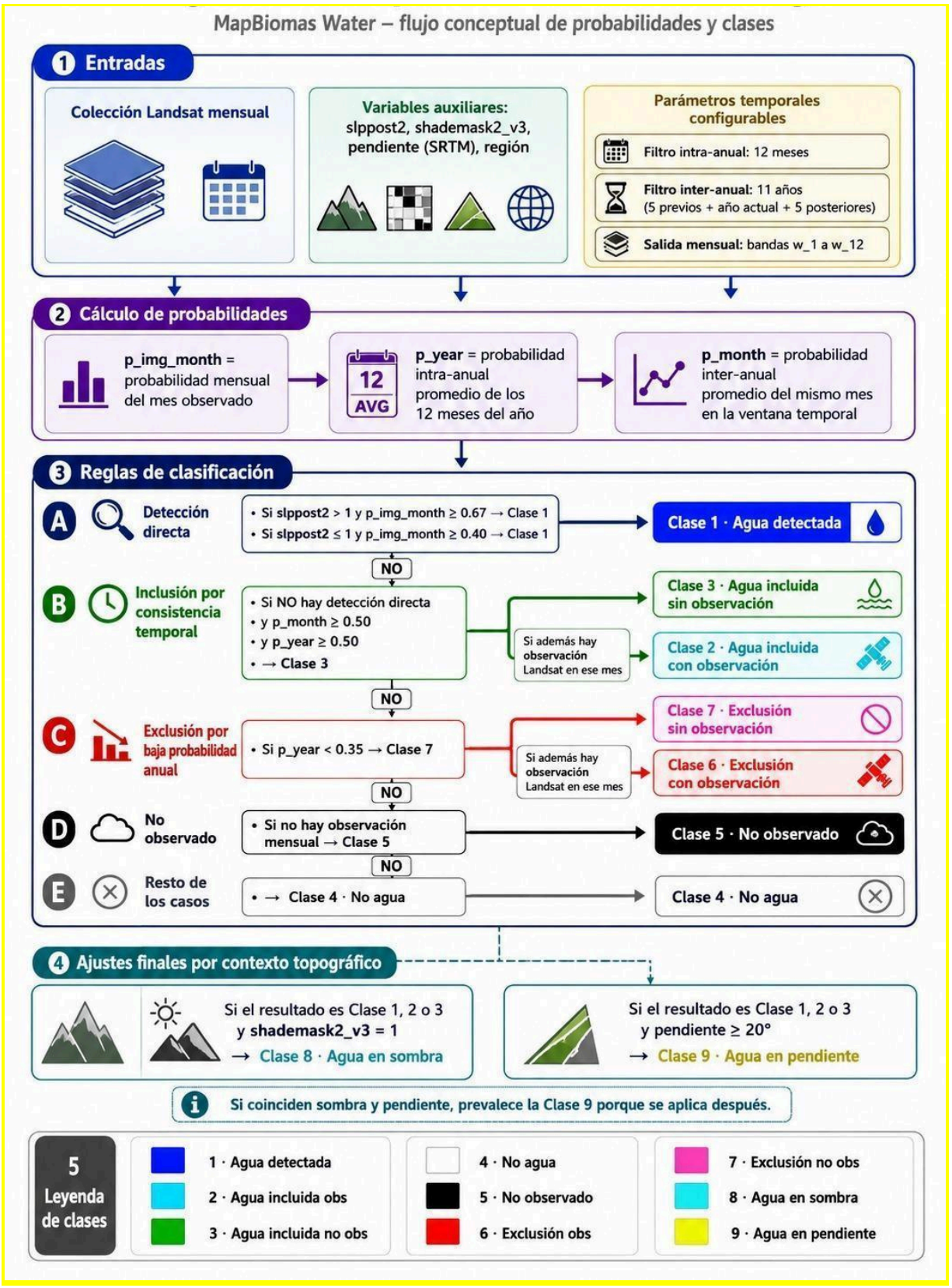


Figure 3. Methodological process used to produce surface water data, 1985–2025.

4.1 Image preparation

Landsat 5, 7, 8 and 9 surface reflectance scenes are retrieved with a function of the shared lowlands module of the MapBiomas Water network, filtered by region, period and cloud cover (50%). For each image the fractions of GV, Soil, Cloud and Shade are obtained with SMA (section 4.2) and the water membership is calculated image by image (section 4.3). For each month, the monthly membership (p_img_month) is the median of the memberships of all images of that month.

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 and shade. 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. 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.

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, which 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, a result of the spectral ambiguity of the Cloud and Soil endmembers.

An empirical evaluation showed that the thresholds 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, from which monthly surface water layers are produced.

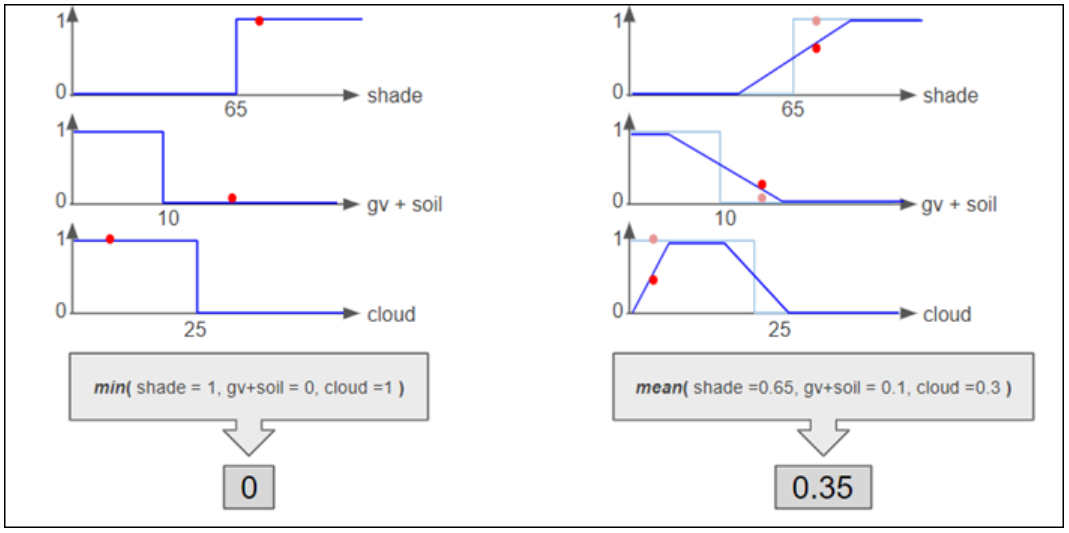


Figure 4. Binary rules of the Surface Water Subpixel Classifier. Left, example of undetected surface water for a pixel whose fractional values are shown by the red dots (GV + Soil is above the threshold of 10). Right, linear fuzzy logic, where the mean value correctly classifies the pixel as surface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

Table 3. Description of spectral mixture components used in the fuzzy logic for Uruguay.

Component	Direction of the fuzzy rule	Transition used
Shade	A larger fraction increases water membership.	Linear transition from 0 at 65% to 1 at 90%.
GV + Soil	A larger sum reduces membership.	Linear transition from 1 at 5% to 0 at 15%.
Cloud	Trapezoidal function (minimum of an ascending and a descending ramp) used to separate turbid water from cloud or bright soil.	Ascending from 0 at 0% to 1 at 8%; descending from 1 at 12% to 0 at 30%.

4.4 Step 1. Preliminary classification

Step 1 generates the preliminary monthly classification by combining the water membership calculated with the SWSC (section 4.3) with temporal and topographic evidence. Figure 3 summarises the decision logic applied to each pixel and month, and Figure 5 describes the original methodology on which this step is based.

Monthly maps are complemented with procedures to restore false negatives and remove false positives based on temporal metrics (Figure 5). In the original methodology, median water membership is calculated for the entire year together with the decadal median for each month. Gap filling then reclassifies as water those pixels that were covered by clouds or occurred where no Landsat scene was available in a given month, combining a within-year threshold and a decadal threshold for the corresponding month. Finally, a removal filter reclassifies as non-water the pixels with low median monthly membership, to eliminate false positives caused by cloud shadows and other dark objects.

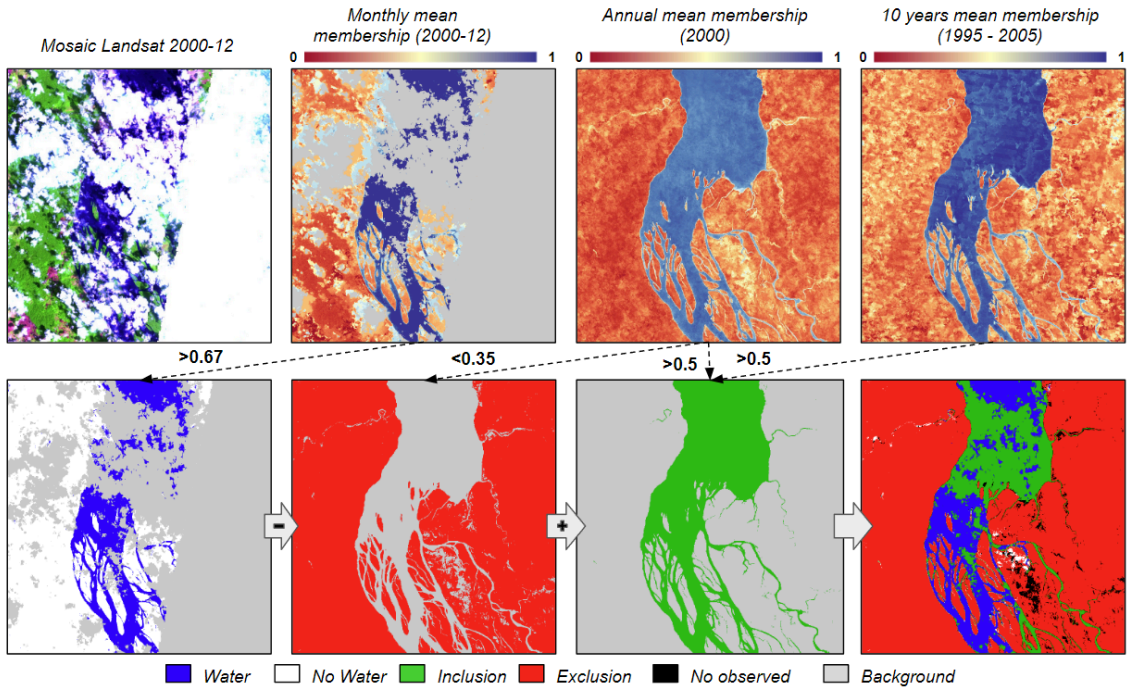


Figure 5. Methodological process for the original surface water classification. a, monthly Landsat mosaic; b, median monthly SWSC membership; c, median annual SWSC membership; d, median decadal monthly SWSC membership; e, monthly surface water classification; f, total surface water per decade; g, probable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

4.4.1 Dry years and wet years

The workflow distinguishes two regimes: normal and wet years, and dry years, which are processed with a different parameterization of the temporal windows (section 4.4.2). Dry and wet years were identified with precipitation from the CHIRPS product (Funk et al. 2015), by comparing the mean annual precipitation of each year with the mean of the whole series. The dry years considered are 1988, 1989, 1995, 1996, 1999, 2008, 2020, 2021, 2022 and 2023; the processing script indicates that in them the national accumulated average was below approximately 20%. In dry years the windows are shorter (7 years and 5 months, compared with 13 years and 11 months), so that the temporal evidence reflects more the conditions of the year itself.

4.4.2 Classification time windows

For Uruguay, three probabilities are calculated for each pixel and month: (i) p_img_month, the median of the per-image water membership of the month; (ii) p_month, the mean of the monthly membership of the same calendar month over a centred interannual window; and (iii) p_year, the mean of the monthly membership over a moving intra-annual window centred on the analysed month. Two parameterizations of the windows were used (Table 6). For normal and wet years, the interannual window is 13 years (the analysed year plus six years before and six after) and the intra-annual window is 11 months (five months before and five after). For the dry years 1988, 1989, 1995, 1996, 1999, 2008, 2020, 2021, 2022 and

2023, the interannual window is 7 years (three before and three after) and the intra-annual window is 5 months (two before and two after). In both cases the interannual window is truncated at the limits of the 1985–2025 series, and the intra-annual window is shifted at the beginning and end of the year to keep the same number of months without crossing into adjacent years. p_month therefore provides the inter-annual persistence of water in a given month, and p_year its persistence within the year. The decision thresholds (section 4.4.3) and the six-month threshold of the annual map are the same in both parameterizations. These windows belong to step 1 and are independent of the five-year window used in gap filling (step 4, section 4.7.1).

4.4.3 Decision rules and classes

A pixel is classified as directly detected water (class 1) when p_img_month ≥ 0.67 where the value of the relative slope-position index (SLPPOST, slppost2; section 4.4.6) is greater than 1, and when p_img_month ≥ 0.4 where slppost2 is 1 or less (positions at the bottom of the local relief), which broadens the detection of narrow rivers and water strongly mixed with soil and vegetation. Temporal inclusion is applied only to pixels that were not detected directly. Pixels without direct detection are included as water when p_month ≥ 0.5 and p_year ≥ 0.5; pixels with p_year < 0.35 are excluded. In normal and wet years direct detection has priority and is not modified by the exclusion; in the dry-year script, in contrast, the exclusion is applied last and can also replace a direct detection (Table 4). The monthly classification has nine classes (Table 5). Figure 3 shows the order in which these rules are applied.

Table 4. Hierarchical implementation order of temporal evidence.

Order	Evidence	Conceptual condition	Internal result
1	Direct detection	p_img_month ≥ 0.67 where slppost2 > 1, or ≥ 0.4 where slppost2 ≤ 1; temporal inclusion does not apply to it.	Class 1 (detected water).
2	Temporal inclusion	No direct detection, with p_month ≥ 0.5 and p_year ≥ 0.5.	Class 3 (included, not observed) or class 2 (included, with observation in the month).
3	Temporal exclusion	p_year < 0.35 (applied last; in dry years it also replaces direct detections, and in other years it only acts where there is no direct detection).	Class 7 (exclusion, not observed) or class 6 (exclusion, with observation). Remaining pixels: class 5 (not observed) or class 4 (non-water).

Table 5. Classes of the monthly surface water classification.

Class	Label	Interpretation
1	Detected water	Direct detection: sufficient per-image membership in the month.
2	Water included, with observation	No direct detection, included by p_month and p_year; there is a valid observation in the month.
3	Water included, without observation	Included by temporal evidence; there is no valid observation in the month.
4	Non-water	All other cases.
5	Not observed	No valid observation in the month (clouds or no scene); recovered in step 4.
6	Exclusion with observation	p_year < 0.35, with a valid observation in the month.
7	Exclusion without observation	p_year < 0.35, without a valid observation in the month.
8	Water in shadow	Classes 1 to 3 that coincide with the shademask2_v3 mask.
9	Water on slope	Classes 1 to 3 with a slope of 20° or more.

4.4.4 Topographic controls

Two topographic controls are applied to the pixels classified as water (classes 1 to 3): pixels that coincide with the shadow mask shademask2_v3 are reassigned to class 8 (water in shadow), and pixels with a slope of 20° or more, derived from SRTM, are reassigned to class 9 (water on slope). These two classes are not counted as water in the frequency and annual maps.

4.4.5 Topographic shadow mask (shademask2_v3)

The shademask2_v3 mask identifies pixels that, because of relief, lie in shadow or receive low solar illumination and may be confused with water. It is generated in Google Earth Engine from the 30 m SRTM digital elevation model (USGS/SRTMGL1_003) and from the typical solar geometry of Landsat images over the country. The mean solar azimuth and mean solar angle (SUN_AZIMUTH and SUN_ELEVATION) are calculated for the Landsat 5 (2005–2006) and Landsat 8 (2012–2013) Collection 2 Level 2 scenes covering the territory, and with each pair of values the terrain cast shadow (ee.Terrain.hillShadow, with a neighbourhood of 300 and hysteresis) and the terrain shading (ee.Terrain.hillshade) are calculated. The cast shadow is averaged over a 30 m square neighbourhood. A pixel is flagged as shadow (value 1) when this average is 0.9 or lower, or when the terrain shading is 120 or lower (0–255 scale). The masks derived from Landsat 5 and Landsat 8 are combined with the maximum value, clipped to the national territory and exported as an 8-bit image at 30 m.

4.4.6 Relative slope-position index (slppost2)

The slppost2 index describes the relative position of each pixel between the bottom and the top of the local relief. It is calculated in Google Earth Engine from the 30 m SRTM model clipped to the national territory. In a square window of

radius 30 pixels (61 × 61 pixels, approximately 1.8 km) the minimum elevation (valley floor) and the maximum elevation (crest) are obtained. For each pixel, the index is (elevation − minimum) / (maximum − minimum) × 100 + 0.5, converted to an integer, so that 0 corresponds to the bottom of the local relief and 100 to the crest. Low values (1 or less) identify the lowest positions of the landscape, such as channels and low plains, where the direct-detection threshold is less demanding (0.4 instead of 0.67; section 4.4.3). The layer is exported as an 8-bit image at 30 m.

4.5 Step 2. Vectorization

Step 2 converts the preliminary monthly classification of each year from raster data to vector water objects, so that step 3 can evaluate each water body as a unit rather than as isolated pixels. The objects are used as the basis of the step 3 mask (section 4.6.1), where they are filtered with fixed thresholds.

4.5.1 Object vector delineation

Object vector delineation, termed annual vectorization, converts the monthly classification of each year from raster to vector data. Pixels classified as water (classes 1 to 3) in at least one month are grouped into eight-connected objects with the reduceToVectors function of Google Earth Engine at 30 m. Processing is carried out by year and by chart (nine charts), and each chart is divided into 0.25° subgrids that are vectorized separately and then merged, so objects that cross a subgrid boundary are split.

4.5.2 Assignment of object properties

Each object is assigned two attributes calculated during vectorization: the mean frequency of water (mean_freq, months per year) and the mean slope (mean_srtm, SRTM-derived slope in degrees), together with the year, chart and version.

4.6 Step 3. False-positive masking

Step 3 reassigns to non-water (class 4) the pixels classified as water in step 1 (classes 1 to 3) that correspond to false positives. The logic combines three criteria: the slope and frequency of the object (section 4.6.1), the Canopy Shade Factor (section 4.6.2) and the soil fraction (section 4.6.3). A water pixel is reassigned to class 4 if it meets any of the exclusion conditions, and classes 4 to 9 of the input are preserved unchanged. The thresholds are the same for the whole country (Appendix A).

4.6.1 Object-based mask

Each water object obtained in step 2 is characterised by its mean annual frequency (mean_freq, months per year) and its mean slope (mean_srtm,

degrees). A water pixel is reassigned to class 4 when the object has a mean slope of 20° or more, or when the object has a mean frequency below 1.8 months and the pixel was water in fewer than 8 months of the year. Put differently, the pixel is kept if the mean slope of the object is below 20° and, in addition, the mean frequency of the object is at least 1.8 months or the pixel was water for 8 months or more.

4.6.2 Canopy Shade Factor (CSF)

The Canopy Shade Factor (CSF) is an estimate of vegetation cover and its density, based on the amount of sunlight intercepted by the crowns of trees and other plants. It is calculated from the SMA fractions as CSF = (Shade − (GV + NPV + Soil)) / (Shade + GV + NPV + Soil), so that low values indicate a predominance of vegetation and soil over shade. This index is used to mask sites that were classified as water within vegetated areas, and works as an additional mask to remove false positives (its use is particularly common in Colombia).

In Uruguay, a water pixel is reassigned to class 4 when the annual median CSF is 0.35 or less, or 0.7 or less where the pixel was classified as water in 3 months or fewer of the year. The second threshold removes more pixels and is applied only to those with low annual water frequency.

4.6.3 Soil fraction

A water pixel is also reassigned to class 4 when the annual median soil fraction is 20% or more.

4.7 Step 4. Gap filling

Step 4 recovers the pixels not observed in a given month (class 5), that is, those covered by clouds or without an available Landsat scene, with the temporally nearest valid classification.

4.7.1 Filling window

For each unobserved pixel, the classifications of the neighbouring months are examined within a five-year window (the analysed year plus two years before and two after, shifted at the beginning and end of the series), alternating between the following and the preceding month at increasing distance. The first month with a valid value (different from class 5) fills the pixel, and when the following and preceding months are equally distant the following month has priority. Pixels never observed within the window remain without data.

The five-year window of step 4 is different from the windows of step 1 (section 4.4.2). The step 1 windows gather the evidence (p_month and p_year) used to decide whether a pixel is water in a given month, and are applied to all pixels. The

step 4 window only defines where a valid value is searched for a pixel without observation. Table 6 summarises the windows of both steps.

Table 6. Time windows used in the preliminary classification (step 1) and in gap filling (step 4).

Stage	Window	Scope	Function
Step 1: p_month (normal and wet years)	13 years (±6; truncated at the series limits)	Same calendar month	Inter-annual persistence
Step 1: p_month (dry years)	7 years (±3; truncated at the series limits)	Same calendar month	Inter-annual persistence
Step 1: p_year (normal and wet years)	11 moving months (±5; shifted at the year edges)	Neighbouring months within the same year	Intra-annual persistence
Step 1: p_year (dry years)	5 moving months (±2; shifted at the year edges)	Neighbouring months within the same year	Intra-annual persistence
Step 4: gap filling	5 years (±2; shifted at the series ends)	Following and preceding month, alternating at increasing distance (priority to the following)	Recover class 5 pixels

4.7.2 National integration

The workflow was executed for the entire national territory. The result of each year is a 12-band image (w_1 to w_12, 30 m) with the classes described in Table 5 (section 4.4.3), and the final version corresponds to the output of step 4 (gap filling).

4.8 Derivation of annual surface 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.

A pixel is assigned to the annual surface water map when it was classified as water (classes 1 to 3) in at least six months of the year. The frequency map records the number of months classified as water (0 to 12).

5. Accuracy assessment

Accuracy was assessed through a visual evaluation carried out basin by basin across Uruguay. For each basin, monthly satellite imagery was inspected and contrasted with the corresponding monthly water product generated by the processing chain, in order to identify omission and commission errors.

6. Products and analyses

The main results of Collection 1 are available on the public web platform of MapBiomas Uruguay

[https://plataforma.mapbiomas.org/projects/mapbiomas/uruguay] and include the products listed below.

- Annual Collection
- Monthly Collection

6.1 Annual surface water

This variable corresponds to annual surface water data, which can be viewed for any year of the series. The data are available for different territorial units [e.g. department, hydrographic basin]. Users can select different territories and time ranges, which updates the map, charts, and statistics.

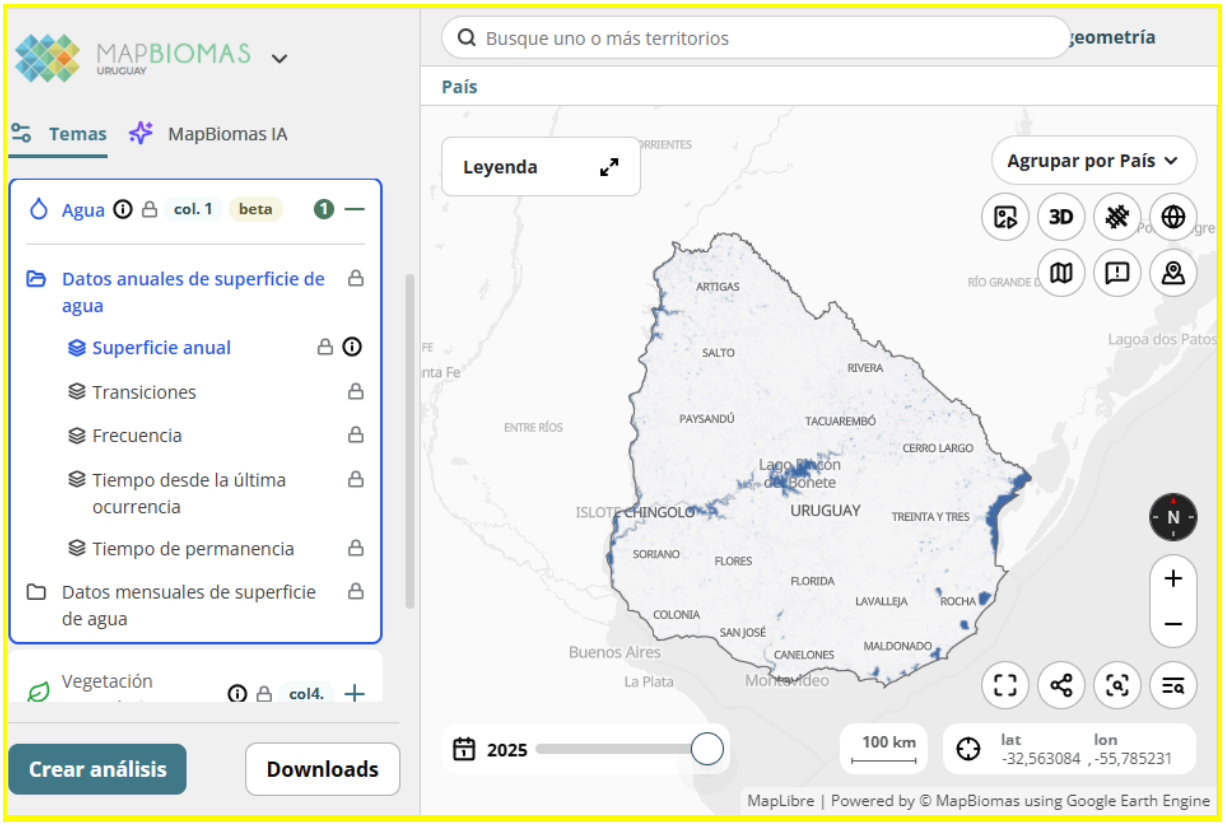


Figure 8. Example visualization of annual surface water on the MapBiomas Water platform.

6.2 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, and variation relative to the historical monthly mean.

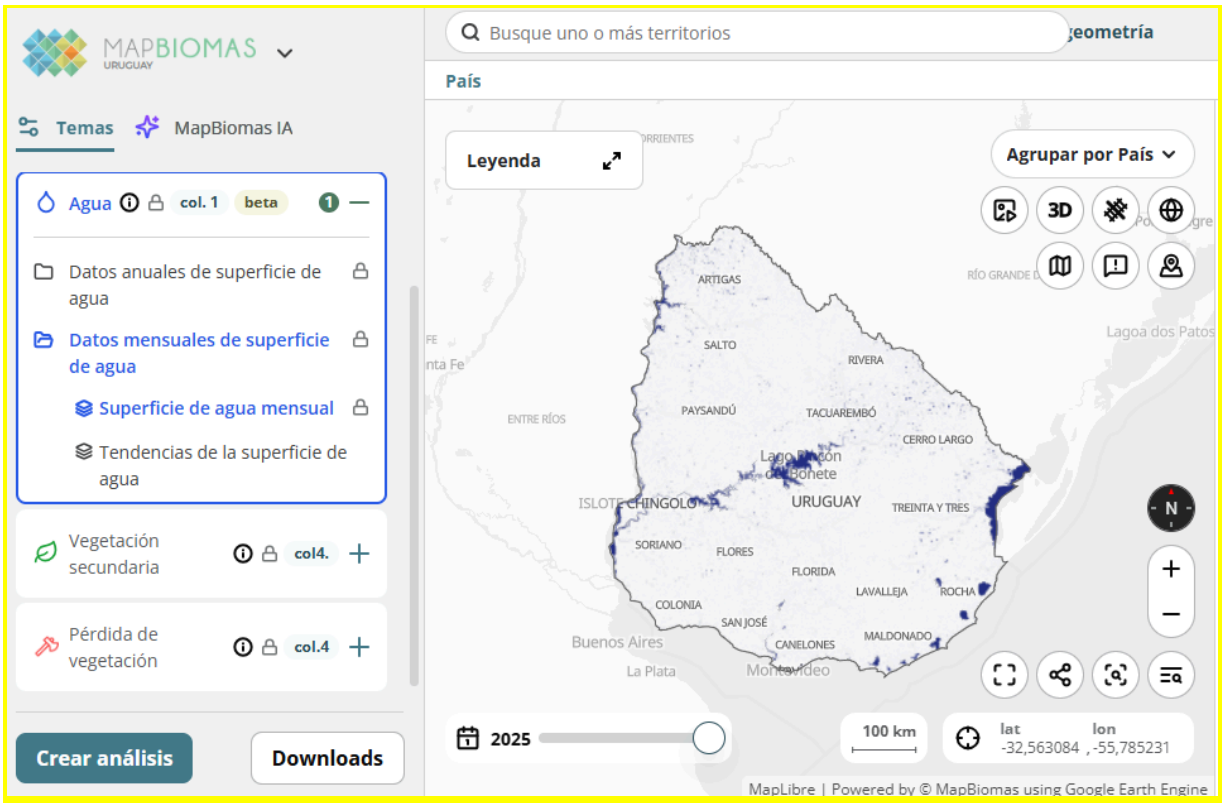


Figure 9. Example visualization of monthly surface water on the MapBiomas Water platform.

6.3 Surface water transitions

This layer represents surface water that decreased, increased or remained persistent. An RGB color composite is prepared to facilitate visualization. Persistence is represented in blue using the total number of years classified as surface water; the number of years from the beginning of the series to the first water classification is assigned green to represent increase; and the number of years from the last surface water observation to the end of the series is assigned red to indicate decrease. Permanent water bodies therefore appear predominantly blue, sporadic temporary water surfaces appear black, surface water loss appears red, and new water surfaces appear green.

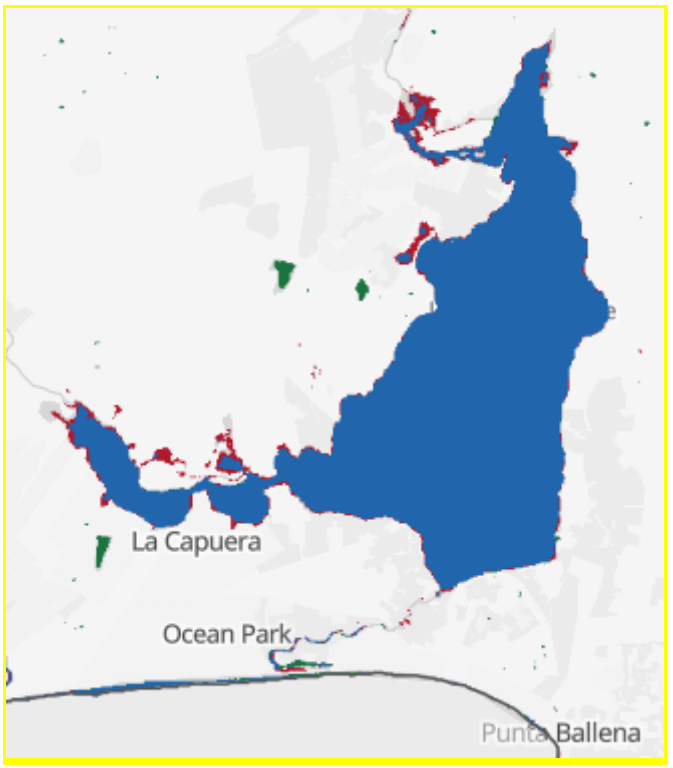


Figure 10. Example visualization of surface water transitions on the MapBiomas Water platform.

6.4 Surface water trend

Surface water trends are analyzed using the monthly water dataset. Trends of increase, decrease, or stability in mapped surface water are evaluated using the Seasonal Mann–Kendall test, a nonparametric test that identifies monotonic trends in data collected over time without requiring normality, and is appropriate for seasonal data (Hirsch et al., 1982; Hirsch and Slack, 1984; Gilbert, 1987; Helsel and Hirsch, 1995; Morell and Fried, 2009). Only statistically significant results at the 95% confidence level are shown.

6.5 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.

6.6 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.

7. 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, 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.

In Uruguay, many farm ponds (tajamares) may be only a few Landsat pixels in size (one pixel covers 0.09 ha), so the product probably underestimates the number and area of small artificial water bodies. Highly turbid water, such as in the upper Río de la Plata and shallow lagoons, can be confused with soil or cloud; coastal lagoons and estuarine waters have variable salinity and turbidity; and flooded rice paddies, mainly in the east of the country, appear as water for part of the year and are not distinguished from natural water in the surface water layer. Floodplains and wetlands with emergent vegetation can be omitted or detected only intermittently.

The methodology itself also involves some limitations. The temporal windows used as evidence (13 years and 11 months for normal and wet years, and 7 years and 5 months for dry years) can assign water to pixels that were probably not flooded, particularly in very wet and very dry years, when surface water conditions depart most from the multi-year pattern. The window lengths therefore reflect a compromise between temporal consistency and noise reduction, on the one hand, and sensitivity to interannual variability, on the other.

In addition, the final object-based mask removes low-frequency water objects in very flat areas to reduce false positives, but as a result, sporadic flooding in these areas is also removed, so short-lived inundation events in low-lying terrain are underrepresented in the product.

8. Conclusions and outlook

Collection 1 of MapBiomas Water Uruguay provides a national monthly surface water time series for 1985–2025 at 30 m resolution, with derived annual products that allow permanent and seasonal water, transitions, trends and frequency of occurrence to be analyzed. The dataset adds a long-term hydrological dimension to the MapBiomas Uruguay LULC maps and supports the study of droughts, reservoirs and land-use change. Future collections are expected to improve the detection of small water bodies, for example by incorporating Sentinel-2 imagery

(10 m), to refine the parameters and temporal filters using the validation results, and to consolidate the classification of water-body types.

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Appendix A. Classification parameters

Table A-1. Fuzzy-logic thresholds.

shade	gv_soil	cloud_asc	cloud_desc
65–90	5–15	0–8	12–30

Table A-2. Thresholds for classification parameters.

Detection probability	Gap filling	Removal	Time windows
0.67 (slppost2 > 1); 0.40 (slppost2 ≤ 1)	p_month ≥ 0.5 and p_year ≥ 0.5	p_year < 0.35	13-year interannual window and 11-month moving intra-annual window (dry years: 7-year window and 5-month moving window)