



MAPBIOMAS
AGUA

Algorithm Theoretical Basis Document (ATBD)

Methodology for Annual Mapping of Glacier Surface (1985-2025)
and Snow Cover (2000–2025) in Bolivia

Collection 4, Version 1



An initiative of:

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1. Introduction

Glaciers are persistent accumulations of ice and snow that flow slowly under their own weight. Their dynamics depend strongly on elevation: snow accumulation predominates at higher elevations, whereas melting and ice-calving rates increase at lower elevations (NSIDC, n.d.). Although most of the world's glaciers are located in Antarctica, some occur in the Andes, where Bolivia contains approximately 20% of the world's tropical mountain glaciers. This makes them an important component of high-elevation ecosystems and watershed water resources.

Since the 1970s, numerous studies have documented accelerated retreat of Andean glaciers. Their loss reflects rapid responses to short-term climatic variability and poses a risk to water availability, high-elevation ecosystems, and the livelihoods of communities that depend on them. However, their location in one of the world's highest mountain ranges makes field monitoring a logistical and safety challenge.

In this context, satellite imagery—particularly the Landsat series—makes it possible to identify and map glacier surfaces systematically over broad areas. Appropriate selection of spectral bands and classification methods improves the delineation of ice, snow, and other high-mountain land covers (Philip & Ravindran, 1998; Huang et al., 2021).

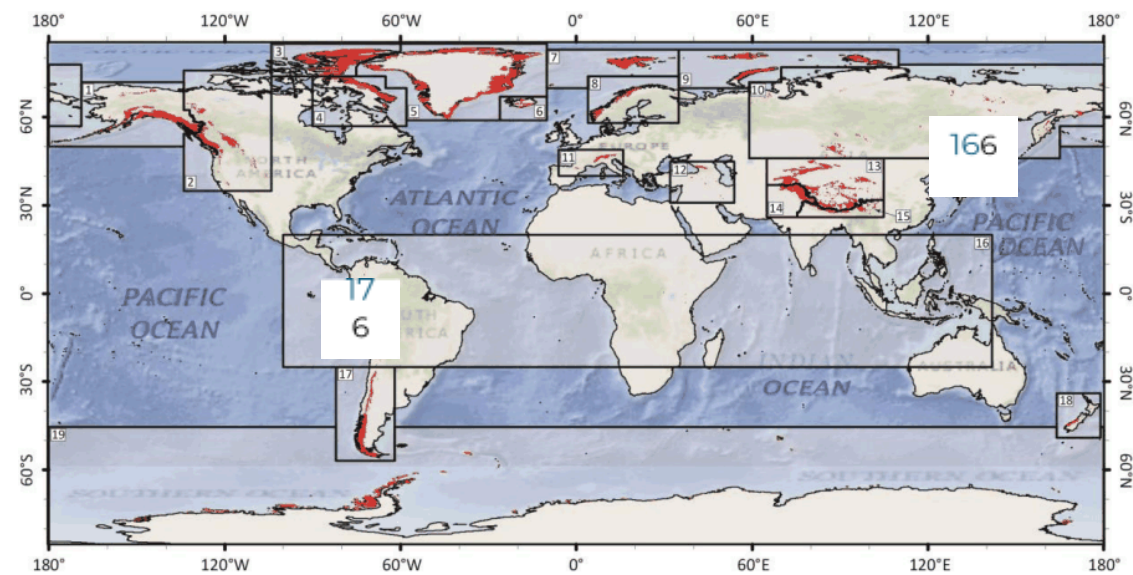
Under this approach, MapBiomass combines automated classification techniques with satellite-image time series to generate consistent, comparable annual information on the distribution of glaciers and snow cover. This document describes the methodology used to produce these products and clearly presents its main stages and procedures.

2. Context and Key Information

2.1. Global Information

The Randolph Glacier Inventory (RGI) is a global inventory of glacier outlines that complements the Global Land Ice Measurements from Space (GLIMS) initiative. The RGI was developed in support of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5). The dataset is available for download as a complete, non-overlapping, version-controlled collection with a standard set of attributes.

Figure 1. Regions according to the Randolph Glacier Inventory



First-order regions 01, 10, and 19 extend across both sides of the 180° meridian, as do second-order regions 01-03 and 19-15.

Table 1. Regions according to the Randolph Glacier Inventory

First-order region		Second-order regions (code, glacier area, name)		
16	Low latitudes	16-01	2338	Low-latitude Andes
17	Southern Andes	17-02	3976	C. Andes

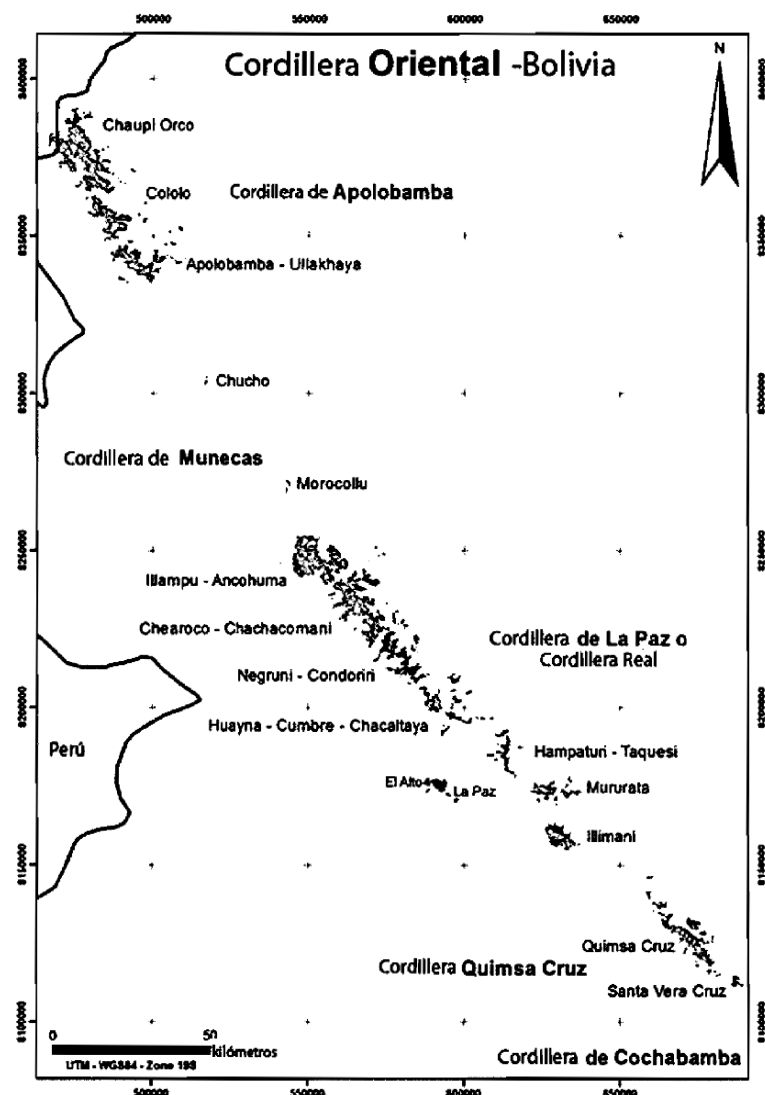
2.2. National Information

In Bolivia, the first glaciological inventory was produced in 1975 by Ekkehard Jordán using photogrammetric restitution of aerial photographs. The work focused on delineating glacier outlines, major moraines, selected

three-dimensional points in stereoscopic models, major lakes, and glacier-fed headwater basins. However, the photographs had low contrast because of fresh snow at high elevations associated with the 1975–76 La Niña event (Figure 2).

Satellite-image studies in Bolivia have been limited. In 2000, one study focused on identifying the snowline of Sajama volcano using IRS-2 SAR imagery. It used seven ascending-orbit acquisitions collected between August 1998 and June 1999. Although the study was not validated, it remains one of the few efforts to use an active sensor for glacier monitoring in the country (Soruco, 2012).

Figure 2. *Glacier Map of the Cordillera Oriental, Bolivia*



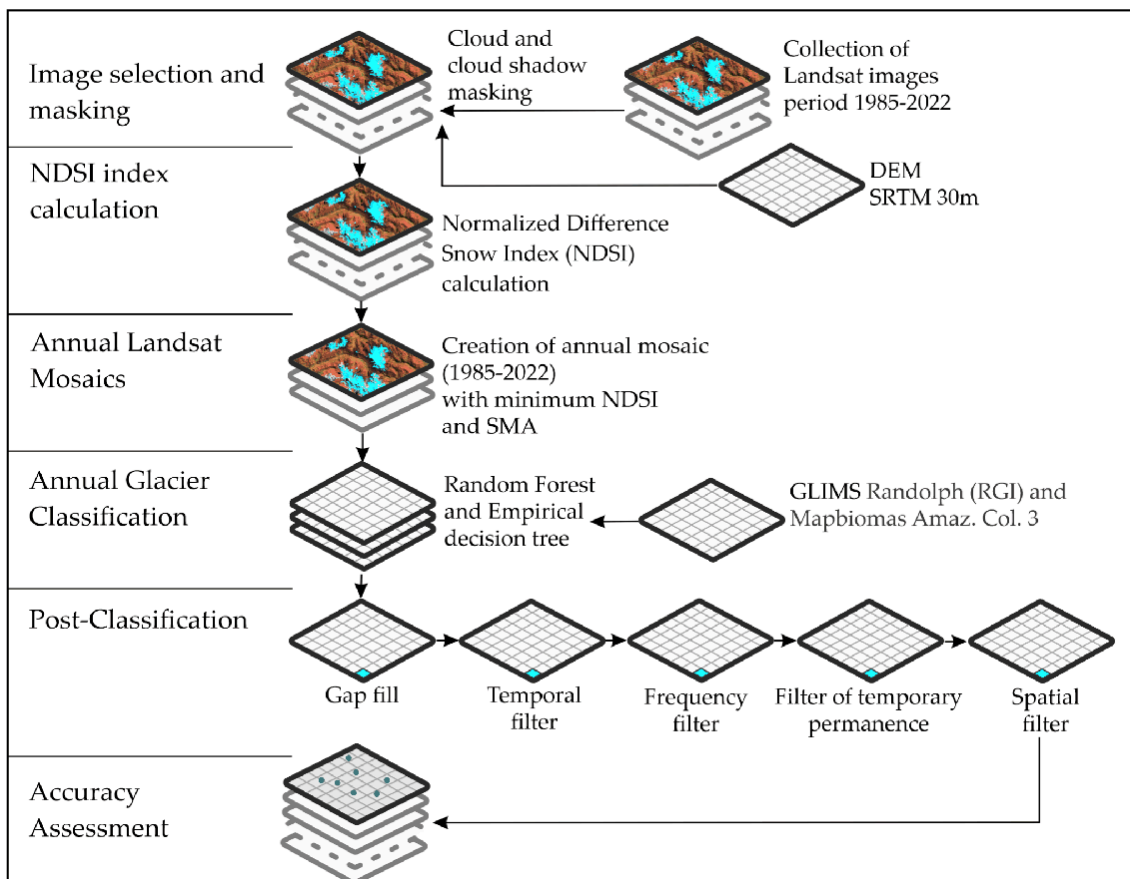
Jordán inventory based on 1975 aerial photographs; digitized on a DAO platform from 16 maps produced by Jordán

3. Methodology

Glacier-cover detection was developed as a processing sequence beginning with the generation of annual mosaics. Available sensors were selected and masks were applied to exclude clouds and cloud shadows. The annual minimum NDSI was then calculated and used as an input variable to represent surface conditions during the year of analysis.

Glacier cover was classified from this set of variables, considering the spectral bands most sensitive to ice and snow, such as NIR and RED, together with variables related to snow, slope, and cloud cover. Classification used an empirical decision tree and the Random Forest algorithm. Finally, the classified product underwent post-classification, in which several filters were applied to correct inconsistencies and address temporal and spatial issues (Figure 3).

Figure 3. Methodological flowchart for producing glacier-cover maps



3.1. Study Area

The study area was defined from the Randolph Glacier Inventory (RGI Consortium, 2017), clipped to Bolivia's national boundary. A 1.5 km buffer was applied to this subset to delimit the final classification area.

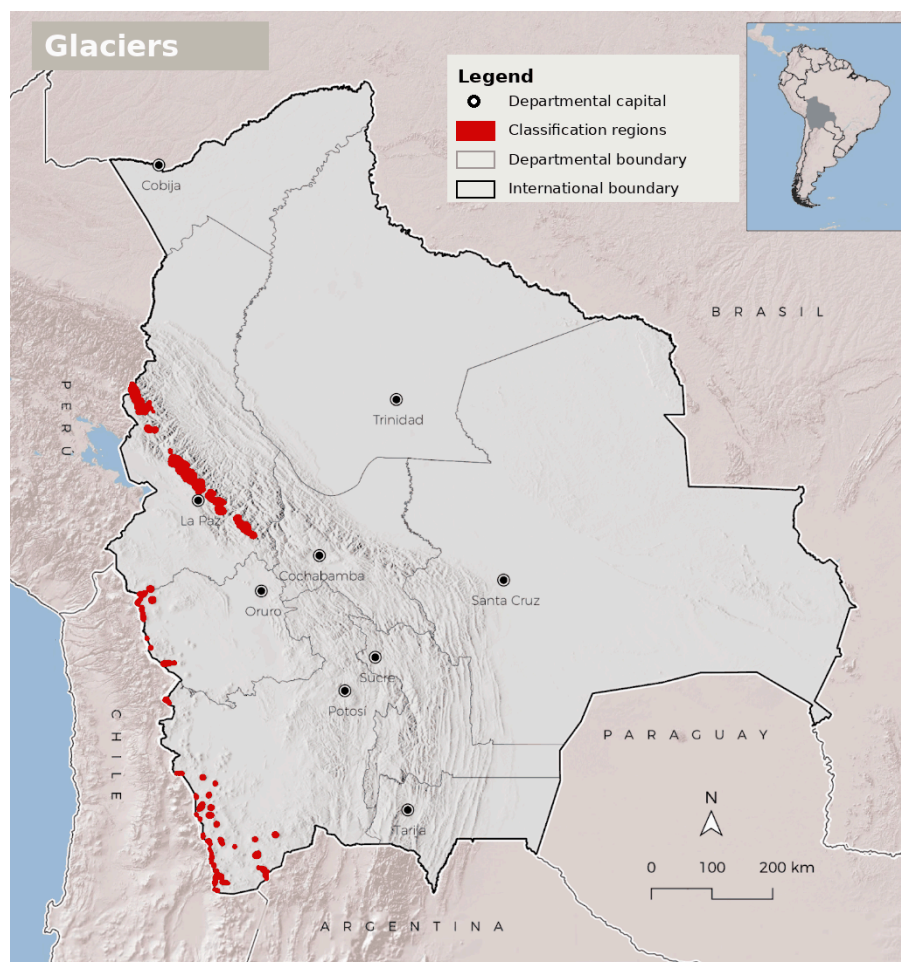
In Bolivia, glaciers occur along the Andes, the world’s longest mountain range. Geographically, the range is divided into three broad regions: the Northern Andes (Venezuela, Colombia, and Ecuador), Central Andes (Peru and Bolivia), and Southern Andes (Chile and Argentina). Climatically, the Andes comprise three main zones: tropical, wet, and dry Andes. Bolivia’s glaciers are located mainly in the tropical Andes, although a smaller portion occurs in the dry Andes (UNESCO, 2018). These climatic differences create contrasting conditions that directly influence glacier behavior and characteristics.

To improve glacier-classification accuracy, Bolivian glaciers were therefore divided into three operational regions. This division allows tropical glaciers in the Cordillera Oriental and dry glaciers in the Cordillera Occidental to be mapped separately, accounting for their climatic and morphological characteristics. The separation supports a more coherent classification process adapted to the conditions of each region (Table 2).

Table 2. *Classification regions in Bolivia*

Region	Characteristic
1012	Corresponds to the tropical Andes region of the Cordillera Oriental
1014	Corresponds to the transition region between the tropical Andes and the dry Andes
1015	Corresponds to the dry Andes region

Figure 4. Classification regions



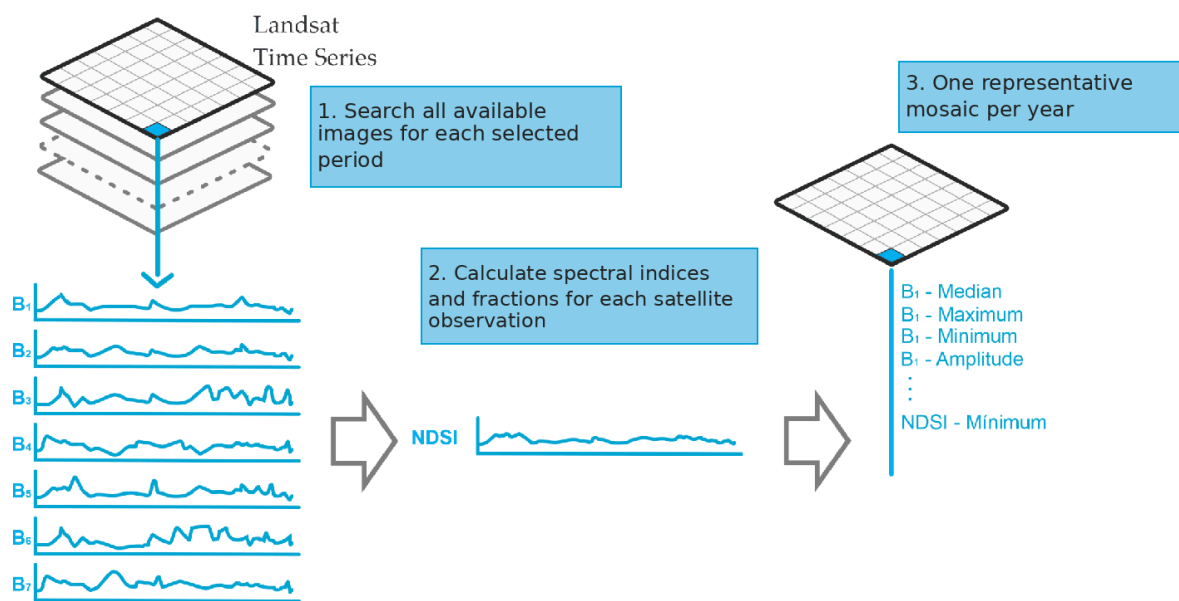
3.2. Generation of Annual Mosaics

Classification of the cross-cutting “Glaciers” theme used Landsat image mosaics generated specifically for glacier mapping. These mosaics represented the annual minimum glacier area, based on the minimum-NDSI quality pixel.

Images from the Landsat 5, 7, 8, and 9 satellites with cloud cover of 75% or less were used. They were subsequently processed with masking methods (the Cloud Score technique and the TDOM algorithm¹) and index calculations. For this methodology, the focus was the minimum Normalized Difference Snow Index (NDSI), so classification was performed on mosaics representing the annual minimum glacier and snow-covered area, as shown in Figure 5.

¹ TDOM (Temporal Dark Outlier Mask) is an automated remote-sensing tool used to detect and remove pixels contaminated by clouds and their satellite-observed shadows.

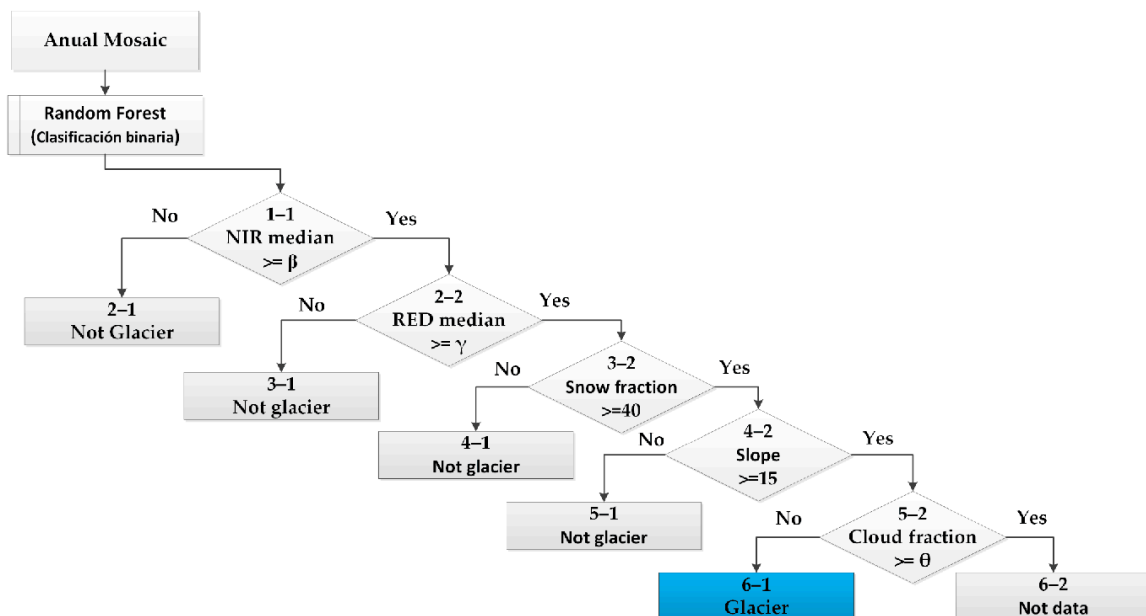
Figure 5. *Generation of Landsat Mosaics*



3.3. Classification

The Landsat mosaics were classified entirely in Google Earth Engine using an empirical decision tree (Figure 6).

Figure 6. *Empirical decision tree combined with Random Forest for glacier classification*



Classification was performed using a hybrid approach combining Random Forest and empirical rules. The model used the spectral bands, indices, and auxiliary variables described in Table 3 as inputs.

The Random Forest model was configured with 50 trees and training samples for the glacier and non-glacier classes, with 3,000 and 8,000 samples, respectively.

The resulting classification was complemented with empirical rules based on NDSI, snow fraction, slope, and spectral variables, using criteria differentiated by the sensor available for each year. Finally, quality criteria were applied to identify and exclude pixels affected by unsuitable observation conditions.

3.4. Classification Variables

Glacier-surface classification used spectral variables, spectral indices, and auxiliary variables derived from topographic information and spectral mixture analysis.

The spectral variables correspond to annual Landsat image composites previously filtered for clouds and shadows, and include bands in the visible, near-infrared, and shortwave-infrared regions. NDSI values for different periods of the year and the annual minimum value were also included.

The auxiliary variables included slope derived from the SRTM DEM, and snow, cloud, and shade fractions obtained through Spectral Mixture Analysis (SMA). Together with the spectral variables, these variables were used as inputs for classification with Random Forest and empirical rules. The variables, parameters, and criteria used are detailed in Table 3.

Table 3. *Spectral indices and bands used for classification*

Type	Name	Formula	Description	Reducer ¹				
				Median	Median-dry	Median-wet	Min	Max
Band	Blue	B1 (L5 and L7); B2 (L8)	Blue visible spectrum		X			
	Green	B2 (L5 and L7); B3 (L8)	Green visible spectrum		X			
	Red	B3 (L5 and L7); B4 (L8)	Red visible spectrum	X	X			
	Nir	B4 (L5 and L7); B5 (L8)	Near-infrared	X	X			
	Swir1	B5 (L5 and L7); B6 (L8)	Shortwave infrared 1		X			
	Swir2	B7 (L5); B8 (L7); B7	Shortwave infrared 2		X			
Indices	Ndsi	B2 (L5 and L7); B3 (L8)	green – swir1 / (green + swir1)				X	
Fractions	Cloud fraction	B3 (L5 and L7); B4 (L8)	SMA		X			
	Snow fraction	B4 (L5 and L7); B5 (L8)	SMA		X			

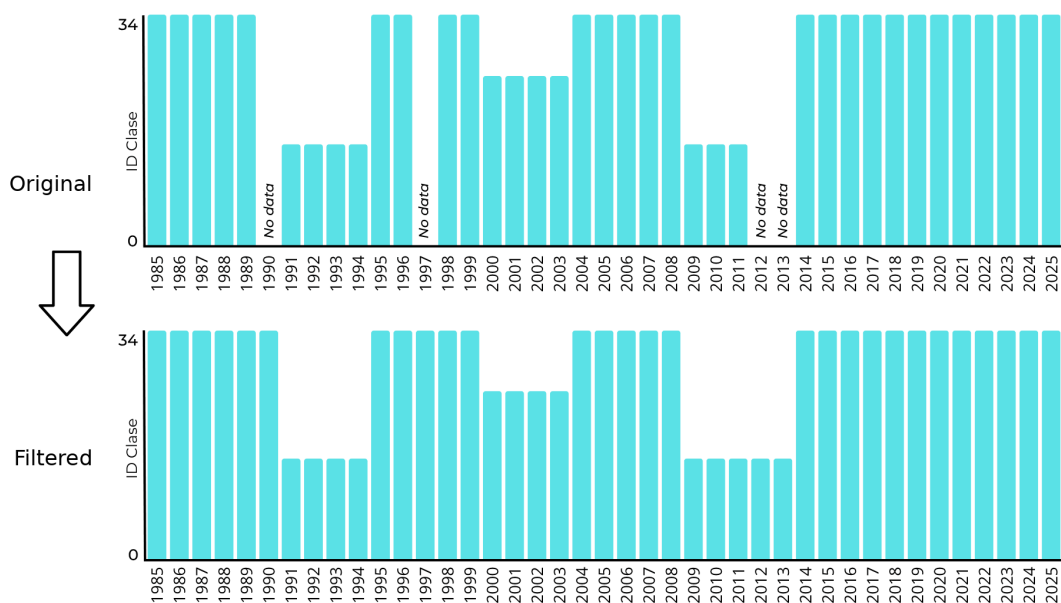
3.5. Post-classification

Because the classification method is pixel-based and was applied to an extensive time series, a sequence of post-classification filters was used. The process includes gap-filling, temporal, spatial, and frequency filters.

3.5.1. *Filling Information Gaps (Gap Fill)*

The filter sequence begins with gap filling. In a long time series for regions severely affected by clouds, gaps may occur in the median composite. This filter replaces gaps with the nearest classification in time. If no value is available for the following year, the gap is filled with the value from the preceding year. Gaps should therefore remain only when a given pixel is consistently classified as no data throughout the entire time series.

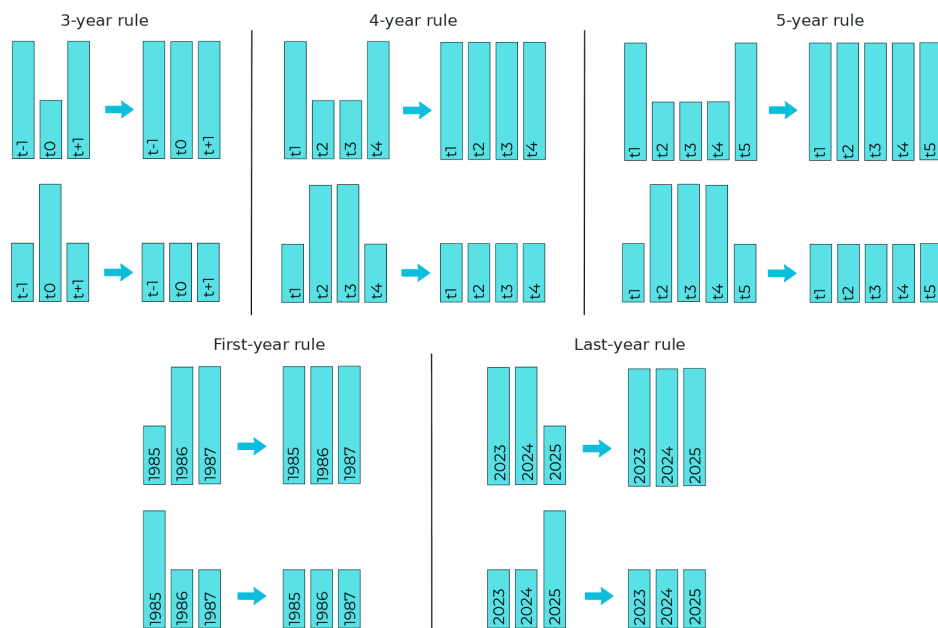
Figure 7. *Gap filling*



3.5.2. *Temporal Filter*

After gap filling, a temporal filter was applied. The filter uses sequential classifications within a one-directional moving window of three, four, or five years to identify temporally inconsistent transitions. It is based on rules for intermediate years and for the first and last years of the series.

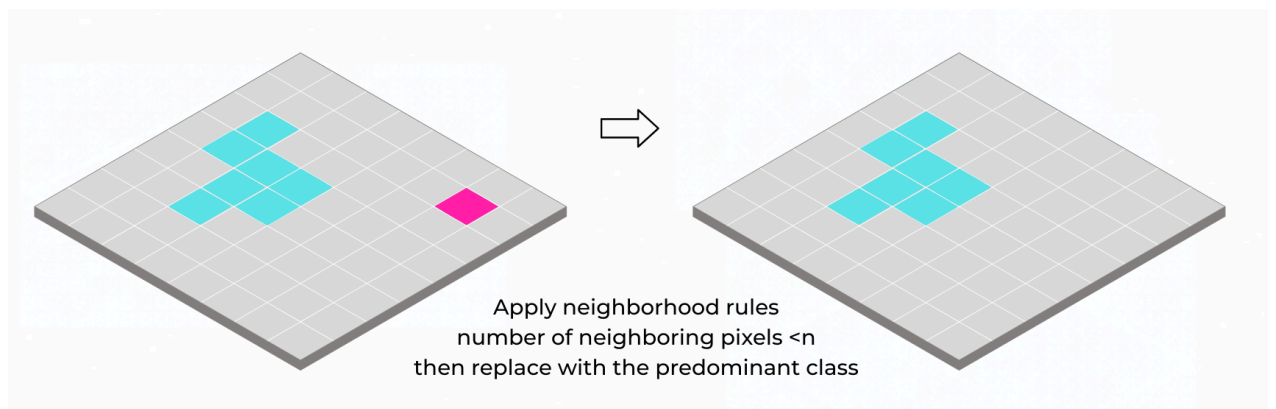
Figure 8. *Temporal Filter*



3.5.3. *Spatial Filter*

Next, a spatial filter based on the “connectedPixelCount” function identifies groups of neighboring pixels that share the same value. Pixels that are not connected to a predefined minimum number of identical pixels are treated as isolated pixels and reclassified (Figure 9).

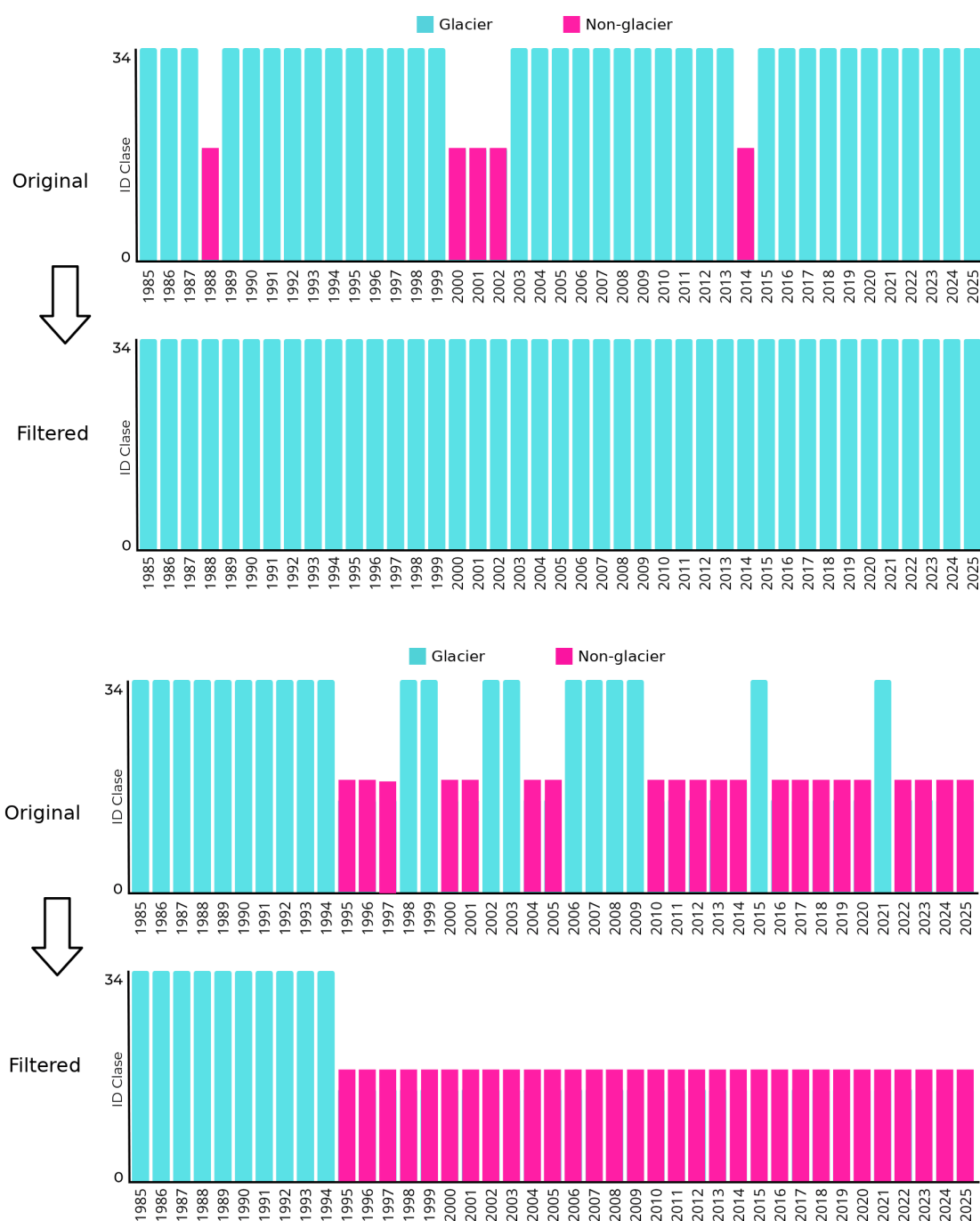
Figure 9. *Spatial Filter*



3.5.4. *Frequency and Temporal Persistence Filter*

The final filter in the post-classification sequence was the frequency filter. As shown in Figure 10, it considers class occurrence throughout the time series to clean the classification result. A complementary temporal-persistence rule is also applied in figure 10.

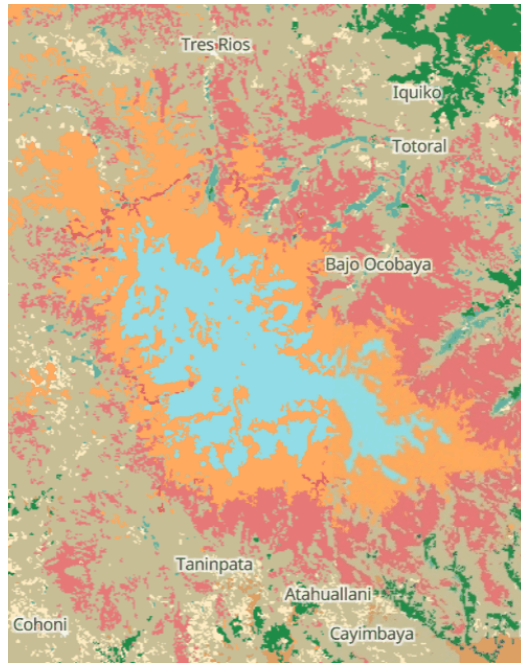
Figure 10. *Frequency and Temporal Persistence Filter*



3.5.5. Integration with the Other MapBiomass Bolivia Classes

The glacier product is integrated with the other MapBiomass Bolivia land-cover classes. This process applies priority rules among classes to resolve potential overlaps and maintain classification consistency. The result is an integrated annual land-cover and land-use product that incorporates the glacier class into the overall MapBiomass Bolivia classification (Figure 11).

Figure 11. *Integration of glacier cover with the other MapBiomass Bolivia classes on Mount Illimani, Cordillera Real.*



3.6. Snow-cover Classification

Snow-cover classification was developed from the inputs and preprocessing stages used for glacier mapping. However, differences in the spatial distribution and temporal dynamics of the two cover types required inputs and classification procedures to be adapted specifically for snow. Because of image availability, the snow-cover analysis period spans 2000–2025.

The mosaics used for snow classification differ from those used for glacier classification. For glaciers, the annual minimum value, intended to represent glacier surface consistently, is used. For snow, the 75th percentile of annual observations, is used to represent conditions of high snow presence while reducing the influence of extreme values associated mainly with residual cloud noise. Therefore, this product does not represent the absolute maximum snow extent observed during the year, but rather a spatially consistent condition of high snow cover.

Because snow cover has greater temporal variability and a broader spatial distribution than glacier surface, its classification regions also differ from those used for glaciers. These regions were defined with reference to the classification regions and grids used by MapBiomass Water, and were subsequently modified and adjusted to create classification units adapted to the spatial distribution of snow.

Unlike glacier classification, snow identification does not use an empirical decision tree or the Random Forest algorithm. Classification is based primarily on thresholds applied to NDSI and the Snow. The HAND model is incorporated as an auxiliary variable to adjust application of these thresholds

in selected areas. In addition, the NIR and RED bands are used as complementary criteria to exclude surfaces with similar spectral characteristics and reduce false positives.

Because of the temporal dynamics of snow cover, images available during the twelve months of each year from 2000 to 2025, were analyzed to adequately represent variability over the study period. Images showing noise associated with clouds that had not been fully removed were discarded. This selection reduced the misclassification of such signals as snow cover and improved delineation of its spatial distribution.

Once the annual classification was obtained, Gap Fill was applied to complete spatial and temporal discontinuities in the results. A *Spatial* filter was then applied to reduce isolated pixels or pixel groups whose distribution was inconsistent with snow. Together, these stages improved product continuity and consistency.

Finally, an additional cleaning step, identified and removed pixels that persisted after filtering but did not correspond to snow. This final stage reduced residual errors and yielded a more consistent final product representing annual snow-cover distribution.

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