MAPBIOMAS

[FIRE · CHILE]

Algorithm Theoretical Basis Document

(ATBD)

MapBiomas Fire Chile

Collection 1 · Version 1

Time series 2013–2025

General Coordinator:
Jaime Hernández P.

Technical Coordinator:
Felipe Lepín S.

Team Chile:
Felipe Lepín
Alejandro Miranda
Sophia Barria
Adison Altamirano
Danniela Espinoza

Lissette Cortes
Ernesto Castillo
Jaime Hernández P.

Table of Contents

1. Introduction

1.1. Overview of MapBiomas Fire Chile

This document sets out the theoretical basis, rationale, and methodology behind the monthly and annual burned-area maps produced for Chile over the 2013–2025 period, corresponding to Version 1 of MapBiomas Fire Chile (MbFCL). As an Algorithm Theoretical Basis Document (ATBD), its purpose is to lay out the methodological steps used to build this collection and to describe the underlying datasets and analyses. All MapBiomas Chile maps and data are openly available on the project platform (https://chile.mapbiomas.org/).

This is the first fire product released for Chile, so there is no earlier national precedent within the MapBiomas project. There is, however, a well-established precedent in Brazil, where MapBiomas Fire launched its first collection in 2021 and, as of the date of this document (2026), has reached its fifth version, covering the 1985–2025 historical series. The methodological and operational experience developed in Brazil is a key reference for the design of MapBiomas Fire Chile.

The maps are built on annual mosaics of Landsat satellite imagery at 30 m spatial resolution. Processing is distributed across three platforms: Google Earth Engine (GEE), used to retrieve and process Landsat spectral data and to build the annual mosaics; Google Cloud Storage (GCS), used to store the resulting data; and the Leftraru cluster of the National Laboratory for High-Performance Computing (NLHPC) at Universidad de Chile, where model training, classification, and data filtering were carried out.

Classification was organized by Chilean ecoregions, focusing on four ecoregions that span the central-southern zone of the country, from the Valparaíso Region to La Araucanía. Training samples were collected through direct visual review of the GEE-generated mosaics, delineating burned and unburned areas within the same working environment.

The products released in Version 1 of MapBiomas Fire Chile are:

- Annual burned area
- Monthly burned area
- Burned area by scar size
- Accumulated burned area
- Fire frequency
- Year of last fire
- Fire return interval

The classification algorithms are available in the MapBiomas Fire Chile GitHub repository (https://github.com/mapbiomas-chile/fire).

1.2. How we are organized

MapBiomas is a multi-institutional initiative that brings together non-governmental organizations, universities, and technology companies around a shared goal: to produce open, free, and publicly accessible information on land dynamics from time series of satellite imagery. It operates as a collaborative network in which different technical and scientific teams specialize in specific thematic modules —such as land cover and land use, water, or fire— contributing their regional and disciplinary expertise to the joint development of the products.

MapBiomas Fire Chile is developed jointly by Universidad de La Frontera (UFRO) and Universidad de Chile, whose teams make up the project's fire module. Their collaboration spans the full workflow, from methodological design through to validation of the final products, drawing on the processing infrastructure and technical capacities of each institution.

1.3. Historical perspective: existing maps and mapping initiatives

MapBiomas Fire Chile builds on an already consolidated trajectory within the MapBiomas network, which has produced burned-area products across several countries in the region. The most advanced precedent is MapBiomas Fire Brazil, whose first collection was released in 2021 and which has since reached its fifth version (Collection 5), covering the 1985–2025 series through deep learning models applied to annual Landsat mosaics. Other members of the network have recently released their first fire collections as well: MapBiomas Fire Peru, with six sub-products derived from annual, monthly, and accumulated burned area, and MapBiomas Fire Paraguay, whose Collection 1 mapped fire dynamics between 1999 and 2024. This accumulated experience across the network —particularly Brazil's— provides the methodological foundation adapted here for the Chilean case.

Beyond the precedents within the MapBiomas network itself, the validation and comparison of MapBiomas Fire Chile results rely on global and national reference products. Global references include the MODIS burned-area product (MCD64A1), the active-fire detections of NASA's FIRMS (Fire Information for Resource Management System), and the 30 m Global Annual Burned Area Map (GABAM). At the national level, the product draws on the official fire records of the National Forestry Corporation (CONAF), as well as the fire-scar database reconstructed by Miranda et al. (2022), which documents historical burned area and fire severity in Chile through a Google Earth Engine workflow. Together, these references make it possible to contrast the spatial and temporal accuracy of the classification against independent sources of differing resolution and origin.

2. Methodological description

Processing for MapBiomas Fire Chile combines two complementary computing environments: Google Earth Engine (GEE), where the annual mosaics are generated from Landsat imagery, and the Leftraru cluster at NLHPC, where model training, classification, filtering, and vectorization are run on the mosaics once they have been exported as local rasters. The full classification, filtering, and validation pipeline is available in the project repository (https://github.com/mapbiomas-chile/fire).

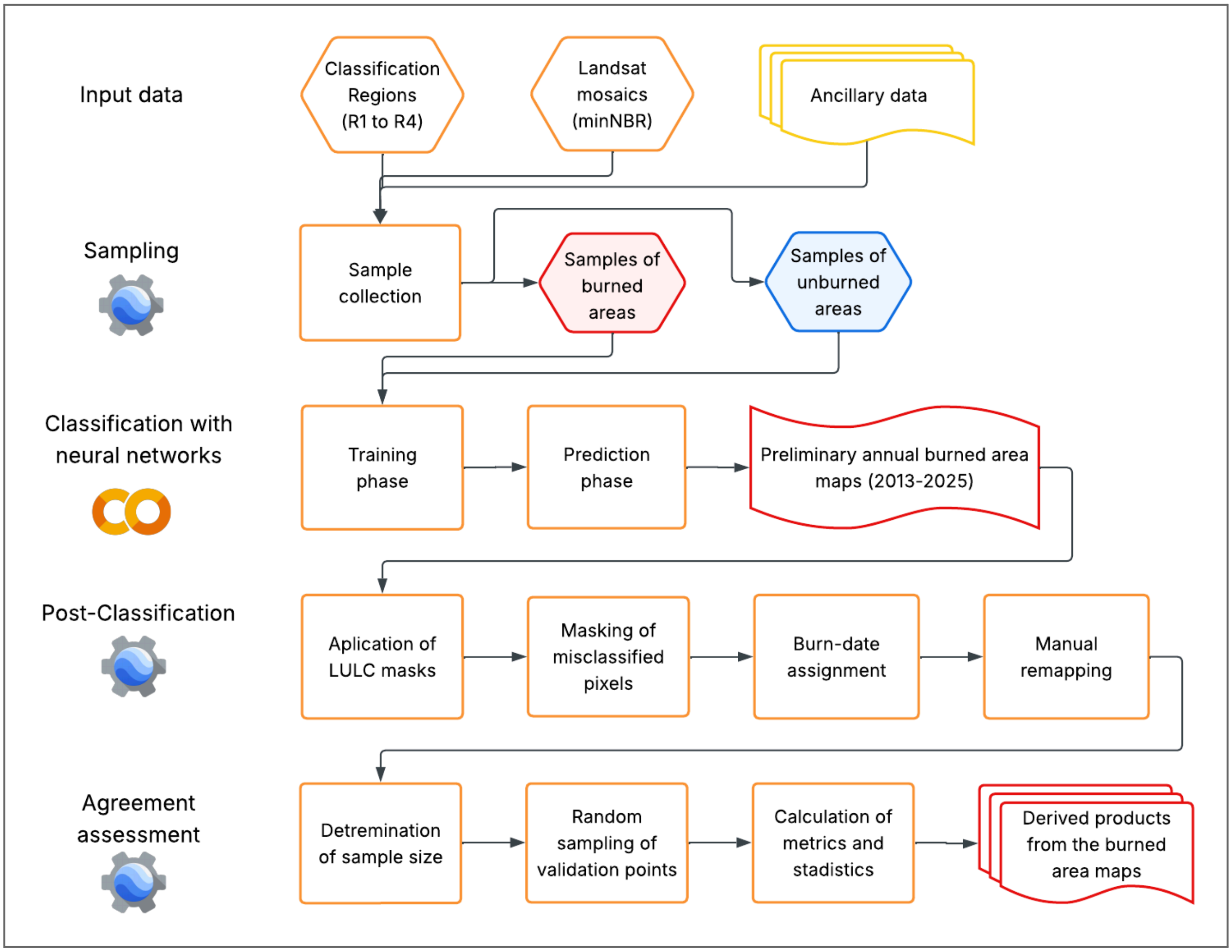

Figure 1. Methodological workflow of MapBiomas Fire Chile Collection 1.

2.1. Definition of regions

The classification regions used by MapBiomas Fire Chile are based on the WWF vegetation belts, adapted and revised by the project team to reflect the vegetation patterns, land cover, and fire regimes most relevant to the central-southern zone of the country.

The decision to focus on these ecoregions responds mainly to the strong spatial concentration of fire activity in central-southern Chile. The four ecoregions delineated span the seven administrative regions —from Valparaíso to La Araucanía— that historically account for the largest burned area in the country. According to CONAF records, these seven regions concentrated roughly 95% of the fires that occurred in Chile over the last decade. Restricting the classification to this zone therefore captures the overwhelming majority of the national fire regime while keeping the training and validation effort focused where fire is most recurrent and its impact greatest.

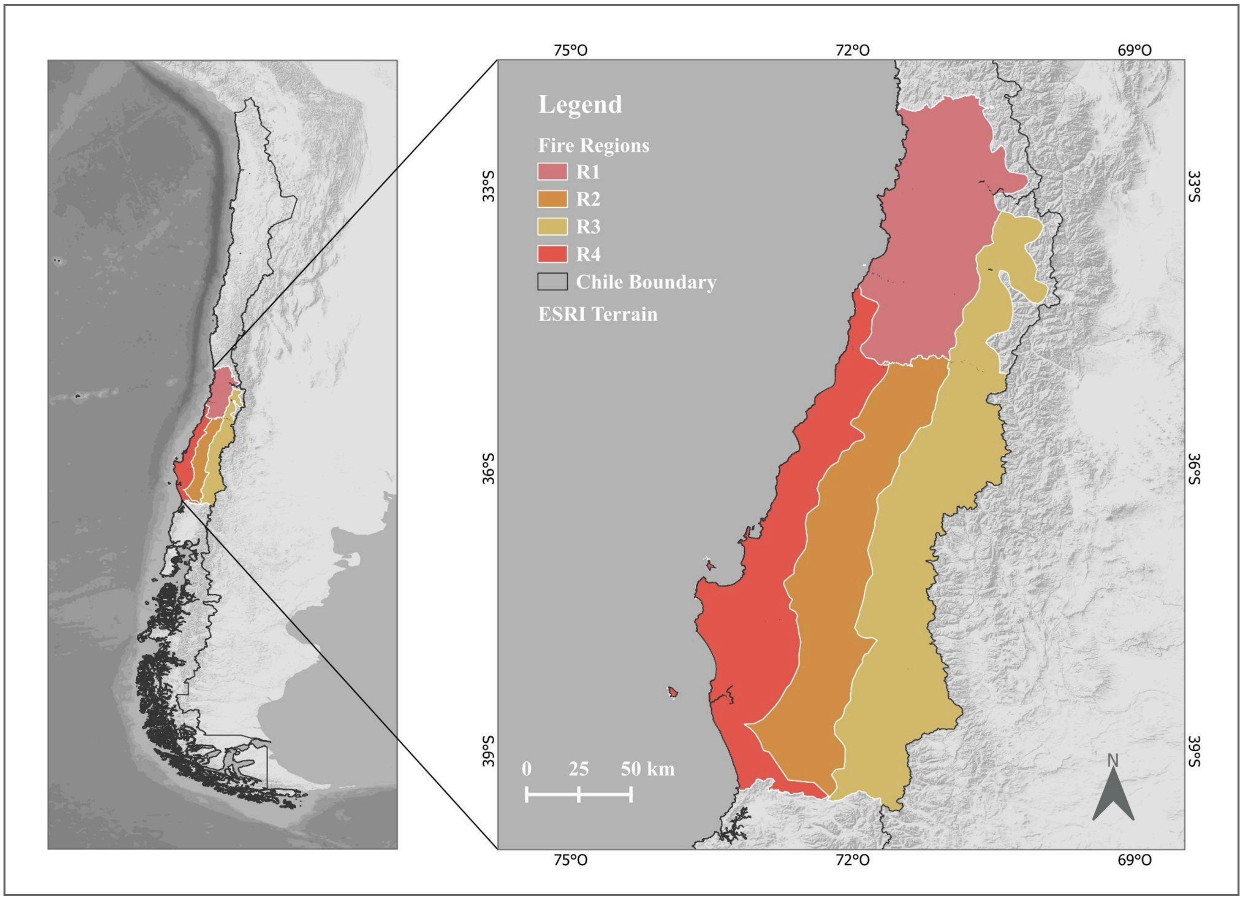

Figure 2. Map of the MapBiomas Fire Chile classification regions.

2.2. Annual multiband mosaics

This section describes the theoretical and methodological basis of the algorithm used to build 30 m annual multiband mosaics for the Chilean classification regions, using the annual minimum NBR as a temporal anchor from which to extract spectral metrics over 6- and 12-month pre/post windows. The final product comprises 26 bands derived from Landsat 7/8/9 imagery —the annual minimum NBR, the minimum NIR/SWIR1/SWIR2 values, the pre- and post-event spectral medians over 6- and 12-month windows (NDVI, NBR, NIR, SWIR1, SWIR2), and the annual dNBR and RdNBR— and serves as the standardized input for burned-area detection, severity assessment, post-fire recovery analysis, and the classification steps described in the following sections.

The algorithm draws on surface reflectance (SR) imagery from Landsat 7 ETM+, 8 OLI, and 9 OLI-2, USGS Collection 2 Level-2, accessed through Google Earth Engine. Landsat 8 and 9 serve as the primary source, given their stronger radiometric performance and higher temporal frequency in recent years, while Landsat 7 is used as a fallback to fill temporal or spatial gaps. Scenes are standardized through atmospheric screening —using the QA_PIXEL and QA_RADSAT bands to mask clouds, shadows, snow, ice, cirrus, and radiometric saturation— and radiometric harmonization across sensors, converting digital values to surface reflectance with the Collection 2 scaling factors (multiplication by 2.75×10^{-5} and an offset of −0.2). Finally, pixels with negative surface-reflectance values are discarded to remove anomalies and noise from the annual mosaic composition.

A per-year statistical approach was used to summarize the large volume of available scenes and to optimize classification without discarding pixel-level spectral information. Under this approach, the annual mosaic is built by compositing every image of the year into a single quality mosaic (QM), using the minimum NBR (Normalized Burn Ratio) spectral index as a per-pixel ordering function (eq. 1; Key and Benson, 2006). For each pixel, the date on which the minimum NBR value occurs is selected, and all of that pixel's reflectance characteristics —including the scene metadata with the corresponding acquisition date— are used to compose the annual quality mosaic:

$$\lambda_{QM} = [Blue, Green, Red, NIR, SWIR1, SWIR2] = date\ with\ min\ (\ (\lambda NIR - \lambda SWIR1) / (\lambda NIR + \lambda SWIR1)\ )\ [x_{i...j}] \quad \text{(eq. 1)}$$

Here, λ denotes the reflectance values of the quality bands that make up the mosaic (QM), retrieved on the date when each pixel reaches its minimum (min) NBR value in a given year (x), across the full set of available scenes from the first (i) to the last (j). λNIR is the near-infrared surface reflectance and λSWIR1 the shortwave-infrared-1 surface reflectance, both used to compute the NBR index.

In other words, the NBR is computed for every pixel with a valid observation within a given year and stacked into a multiband image. The pixels holding the lowest NBR value within that stack are selected, and their spectral information (Table 1) is used to compose the annual quality mosaic (QM), while also retaining the date on which each pixel reached its minimum NBR.

Table 1. Spectral bands used as predictors in the burned-area classification process.

Spectral band	Landsat 7		Landsat 8 and 9	
	Band no.	Width (µm)	Band no.	Width (µm)
Red	3	0.63 – 0.69	4	0.64 – 0.67
NIR	4	0.76 – 0.90	5	0.85 – 0.88
SWIR1	5	1.55 – 1.75	6	1.57 – 1.65
SWIR2	7	2.08 – 2.35	7	2.11 – 2.29

On the screened imagery, two spectral indices are also computed: the NDVI, as an indicator of photosynthetic vigor and canopy biomass, and the NBR, as a direct descriptor of fire damage. The date of the annual minimum NBR serves as the central reference for building retrospective and prospective windows of six and twelve months, within which medians of the main spectral variables are computed to dampen the influence of residual cloudiness or isolated anomalies. All of this information —the annual minimum NBR, its associated dates, and the pre/post window spectral statistics— is integrated into a single multiband mosaic per region and year, together with two derived change metrics: the dNBR (difference between the median NBR of the twelve months before and after the minimum) and the RdNBR (a normalization of that change relative to the pre-fire NBR value).

Given the number of bands generated and the correlation expected among spectral variables drawn from the same set of images, a principal component analysis (PCA) was applied to the 26 mosaic bands to reduce redundancy and retain only those contributing most to the explained variance. This step reduced the mosaic to 14 bands, dropping the 6- and 12-month window bands corresponding to the original NIR, SWIR1, and SWIR2 values.

2.3. Training samples

Training samples were drawn from the same annual multiband mosaic described in Section 2.2, already reduced to the 14 bands resulting from the PCA, which allowed burned and unburned areas to be visually distinguished directly on this product within GEE. The reviewer had access to the full set of 14 bands for visual identification of scars, with NBR and its differential metrics (dNBR and RdNBR) proving the most useful for this purpose.

The sampling years were selected across two distinct periods of the time series: 2013–2018 and 2019–2025, the latter following the mega- and hyper-drought that affected central-southern Chile. For each classification region (r1, r2, r3, and r4), the reference year for sampling was the one with the largest burned area within each of the two periods, maximizing the availability and spectral representativeness of burned pixels in the training set. This same two-period logic underlies the existence of two model versions per region (v1 for 2013–2018 and v2 for 2019–2025, as described in Section 2.4), allowing the model to capture possible shifts in post-fire spectral signature associated with prolonged drought.

2.4. Classification

The classification model is a deep neural network (DNN) of the Multi-Layer Perceptron type, implemented in TensorFlow and trained locally on the spectral samples extracted from the annual mosaics. Unlike the mosaic-generation stage, classification requires no runtime connection to Google Earth Engine: it operates entirely on the exported mosaics stored as local rasters on the Leftraru cluster at NLHPC, where both training and inference run as batch jobs managed with Slurm.

For each classification region, two models were trained, corresponding to the two variable groups associated with the sampling periods described in Section 2.3 (2013–2018 and 2019–2025). Training used the 14 PCA-reduced mosaic bands as input variables, with burned and unburned as the output classes.

The architecture is a fully connected network with five hidden layers plus the output layer, using ReLU activation in the hidden layers and weights initialized from a truncated normal distribution (standard deviation = $1/\sqrt{n\_in}$). Input variables are standardized using the mean and standard deviation of the training set. The network structure is summarized in Table 2.

Table 2. Architecture of the neural network used in burned-area classification.

Layer	Neurons
Input	No. of bands in the sample scheme (standardized)
Hidden 1	7
Hidden 2	14

Hidden 3	7
Hidden 4	14
Hidden 5	7
Output (logits)	2 (unburned / burned), with softmax at inference

The training parameters defined for the Version 1 production model were as follows:

- **Learning rate:** 0.001, with the Adam optimizer.
- **Batch size:** 1000.
- **Number of iterations:** 7000.
- **Loss function:** cross-entropy weighted by inverse class frequency, to offset the natural imbalance between burned and unburned pixels.
- **Random seed:** 42, to ensure reproducibility of training.

The input data were split into two sets: 70% of the samples for training and 30% for testing, in order to estimate the algorithm's ability to map burned areas accurately. The split used spatial holdout by sampling scene (holdout by source file), preventing information leakage between neighboring pixels belonging to the same image. The training set was capped at 2,000,000 pixels and the validation set at 500,000 pixels, through random subsampling controlled by the seed.

The prediction phase was applied to the annual mosaics of each region across the full 2013–2025 period, producing a binary mask (burned / unburned) per mosaic. A morphological opening-and-closing operation was then applied to each mask, solely to smooth scar edges and remove isolated-pixel noise; area-based filtering proper is carried out in the post-classification and vectorization stages described in the following sections.

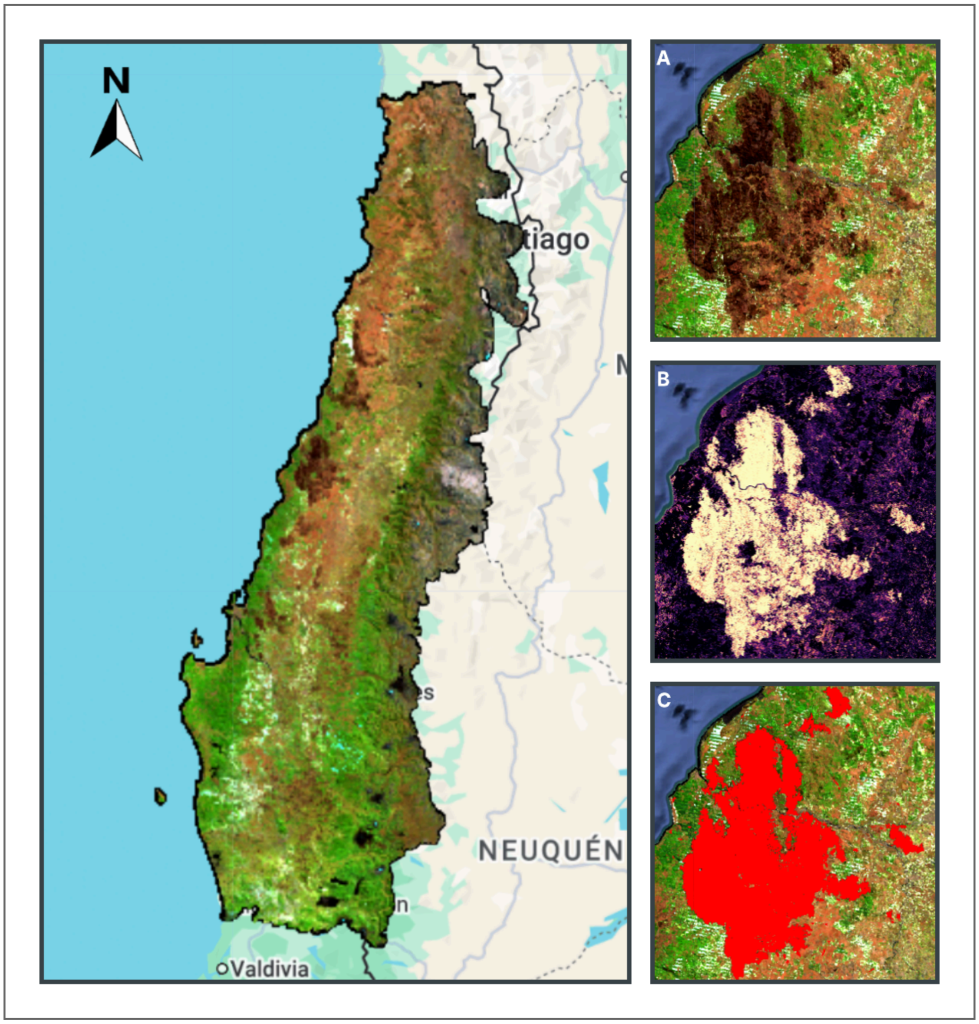

Figure 3.Example of burned area mapping for the 2017 Las Máquinas wildfire in MapBiomas Fire Chile. (A) 2017 Landsat mosaic, (B) burned area probability map, and (C) resulting burned area classification.

2.5. Post-classification

Once the classified masks are generated, a sequence of post-classification routines is applied, designed for the conditions of central-southern Chile and structured as a deterministic chain of raster filters. The order of application is: (1) temporal first-burn-year filter, (2) internal hole filling, (3) thematic land-use/land-cover filter, (4) agricultural-enclave filling, and (5) minimum-patch filter. The output of this stage is a set of clean binary masks, ready for the vectorization described in Section 2.6.

1. **Temporal filter (first burn year).** Because a scar can remain spectrally visible for more than one year, the same pixel may be detected as burned in consecutive years, leading to double counting of the event. For each pixel (same row/column across all years of a tile), the filter keeps the burn only in the first calendar year in which it occurs and clears it in later years, following the chronological priority 2013 > 2014 > … > 2025. In addition, through spatial merging —enabled in the Version 1 production configuration— pixels newly burned in year Y that are 8-connected to a

scar from an earlier year are reassigned to that origin year, resolving cases of scars split across December and January.

2. **Internal hole filling.** On the deduplicated masks, unburned pixels fully enclosed by the burned area within a single scar are filled in, without altering the outer boundary. In the production configuration, all internal holes are filled, regardless of size. This step corrects spurious voids generated by the classifier inside otherwise homogeneous scars.
3. **Thematic land-use/land-cover filter.** Masks derived from the MapBiomas Chile land-use and land-cover classes are applied to remove pixels wrongly classified as burned over non-combustible covers or covers whose spectral signature can be confused with a recent scar. The classes are grouped by temporal stability:

- **Stable classes (masked cumulatively across the whole series, via an OR operation over all bands):** rocky outcrop (code 29), sand/beach/dune (23), salt flat (61), ice/snow (34), and other non-vegetated areas (25).
- **Variable classes (masked year by year):** river/lake (33), infrastructure (24), agriculture (15), and grassland/pasture (18).

For the variable classes, a four-year stability criterion is applied: a pixel in year Y is masked only if it holds that class across a four-year window of the land-use series —forward [Y, Y+1, Y+2, Y+3] in the general case, or backward [Y−3, …, Y] near the end of the series. This criterion prevents real scars from being removed by one-off land-cover reclassifications in a single year. The total mask for each year combines the cumulative and variable classes and is applied only to the classified scars of that same year.

4. **Agricultural-enclave filling.** Because MapBiomas often classifies croplands inside fire perimeters, after the thematic filter the agricultural enclaves fully enclosed by a scar are reinstated as burned: internal holes of the scar that coincide with the annual agriculture mask —built in its strict version, with a one-year stability window— are restored to the burned class.
5. **Minimum-area patch filter.** Finally, small connected patches remaining after the previous filters (edge fragments and salt-and-pepper noise) are removed. Rather than applying a single threshold across the whole territory, a region-specific minimum-area threshold was determined: for each region, histograms of scar-area distribution were built and an elbow analysis was used to identify the area beyond which the hectare-based filter ceased to be effective. From that analysis, each region's minimum-area threshold was set and applied to the polygons in the vectorization stage (Section 2.6), summarized in Table 3.

Table 3. Minimum-area threshold applied per region, determined from the elbow analysis of the scar-area histograms (Section 2.5).

Region	Minimum-area threshold
R1	0.89 ha
R2	0.43 ha
R3	0.42 ha

R4	0.29 ha

2.6. Vectorization

Once the post-classification masks described in Section 2.5 are finalized, they are converted into vector fire-scar polygons, the format used by several of the project's final products. Vectorization is carried out in two stages: tile-level vectorization and national annual vectorization.

Tile-level vectorization. Each filtered raster mask is polygonized tile by tile, producing a GeoPackage per tile with year and region attributes.

National annual vectorization. All regional tiles for a given year are merged into a single national mosaic. A sieve step removes isolated patches smaller than approximately 112 connected pixels (~1 ha), followed by polygonization and application of the region-specific minimum-area threshold defined in Section 2.5 (Table 3). Scars located within 200 m of each other are then grouped into fire events, represented as multipolygons with attributes including a unique event identifier, year, number of fragments, area (ha and m^2), and geometry. The result is the annual national catalog of fire events used by the downstream MapBiomas Fire Chile products.

2.7. Classification evaluation

The MapBiomas Fire Chile classification was evaluated by comparing the burned-area surfaces estimated by the product against global and national reference datasets. Global references included the MODIS burned-area product (MCD64A1), FIRMS active-fire detections, and the global GABAM map, while at the national level the comparison drew on the official records of the National Forestry Corporation (CONAF) and on the fire-scar database reconstructed by Miranda et al. (2022). The evaluation combined two complementary approaches: a comparison by affected area, focused on the total estimated surfaces, and a spatial validation based on the Jaccard index, focused on the geometric overlap of the scars.

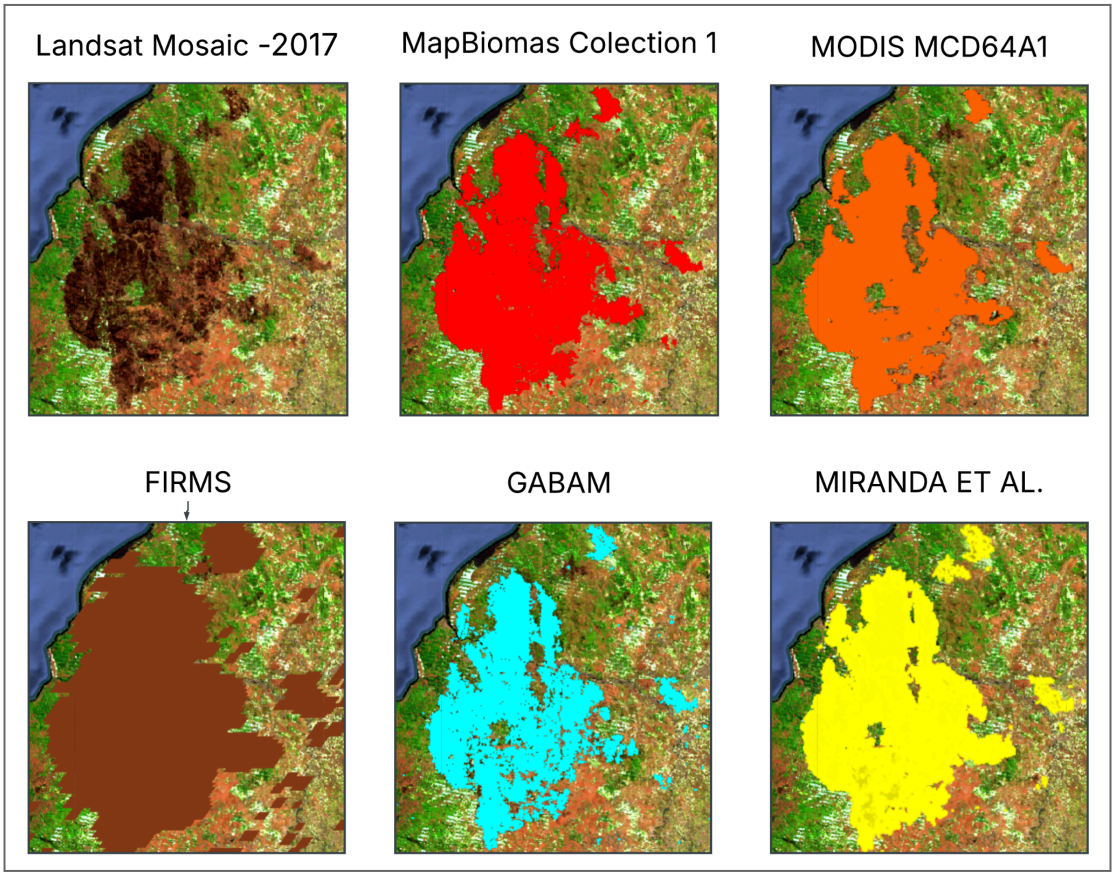

Figure 4. Comparison of the 2017 Las Máquinas wildfire burned area across different datasets: Landsat mosaic L7 (30 m), MapBiomas Fire Collection 1 (30 m), MODIS MCD64A1 (500 m), FIRMS (1 km), GABAM (30 m), and Miranda et al.

Comparison by affected area.

Emphasis was placed on the comparison with CONAF's official figures for the fire seasons of the 2013–2025 series, contrasting the burned area by region and season. For this collection, agreement is reported through a single aggregate metric: the difference over the accumulated surface of the series, computed as the sum of the surface differences between MapBiomas Fire Chile and CONAF across the whole period, divided by the total surface reported by CONAF.

Under this metric, the total burned surface estimated by the product for 2013–2025 is about 24.95% lower than the surface reported by CONAF (a difference of roughly 431,000 ha over the series). Rather than a mapping error, this gap is interpreted as burned area that the product is not yet detecting: as the Jaccard analysis below shows, the scars that MapBiomas Fire Chile does map are geometrically consistent with independent references, but around a quarter of the surface reported by CONAF is not being captured. This is most likely associated with agricultural and forestry burns and other controlled, lower-magnitude fire activity that the current filtering and model-calibration process does not yet delineate reliably.

Spatial validation (Jaccard index).

Beyond agreement in total surface, the geometric overlap between the scars mapped by MapBiomas Fire Chile and those in the Miranda et al. (2022) database was also assessed. All scars larger than 250 ha were filtered, and from that subset 100 samples were randomly selected across the full series and compared against the corresponding scars in the reference database. The Jaccard index —defined as the ratio between the intersection area and the union area of the two polygons— yielded an average value of 80.1%, indicating strong spatial correspondence between the two products for the larger scars.

Taken together, the two lines of evidence offer a balanced reading of the product's performance: the difference over the accumulated surface (−24.95%) indicates that the product still underestimates the total burned area relative to CONAF, while the average Jaccard index (80.1%) confirms strong spatial agreement in the delineation of the larger scars that are detected.

Table 4. Burned area by season (2013–2025): comparison between CONAF official figures and MapBiomas Fire Chile, with the absolute difference per season.

Season	CONAF (ha)	MapBiomas (ha)	Difference (ha)
2012–2013	15,402	13,378	−2,024
2013–2014	97,590	67,764	−29,826
2014–2015	122,543	80,852	−41,691
2015–2016	33,288	33,447	+159
2016–2017	566,223	508,265	−57,958
2017–2018	37,150	15,170	−21,980
2018–2019	62,122	34,010	−28,112
2019–2020	101,099	52,210	−48,889
2020–2021	33,966	18,301	−15,665
2021–2022	119,114	85,206	−33,908
2022–2023	418,410	327,451	−90,959
2023–2024	68,296	28,219	−40,077
2024–2025	52,052	31,964	−20,088
Full series	1,727,255	1,296,237	−431,018

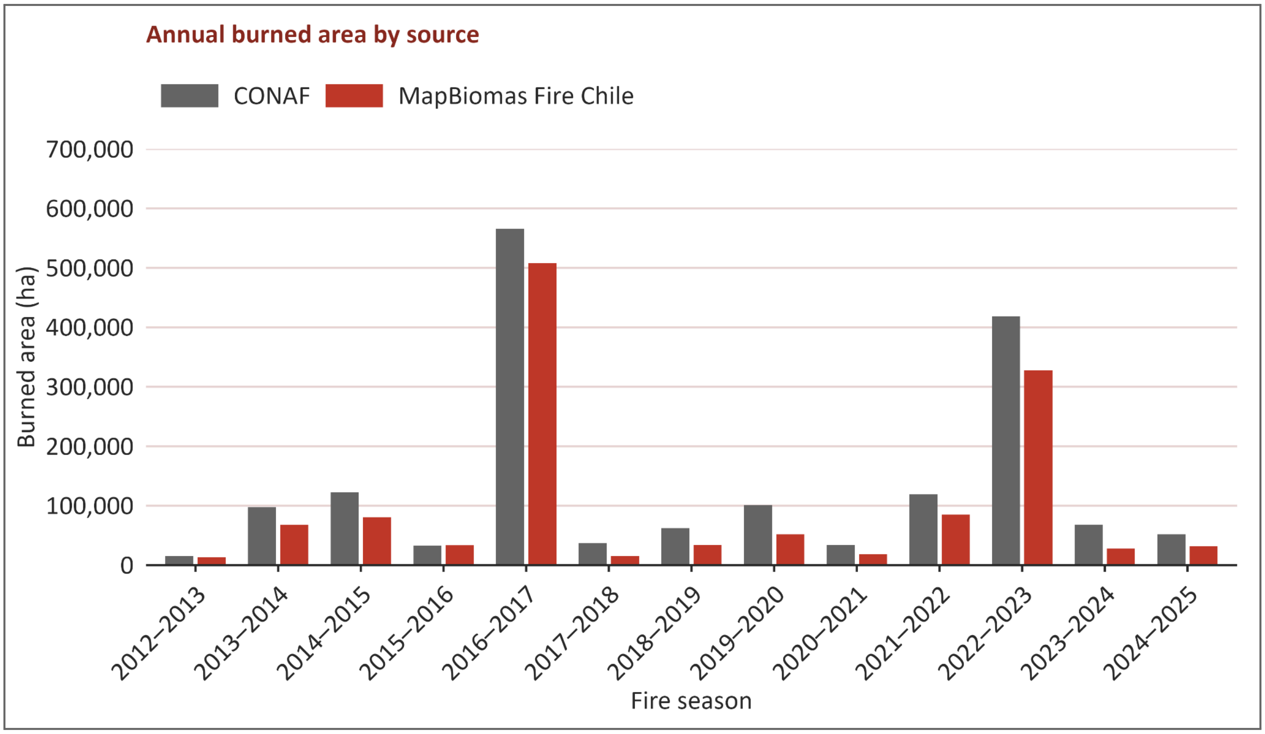

Figure 5. Annual burned area by source (MapBiomas Fire Chile vs. CONAF) for 2013–2025.

3. MapBiomas Fire Chile products

3.1. Annual burned area

This dataset comprises annual maps identifying the pixels classified as burned for each year over the 2013–2025 period. Each pixel is assigned the corresponding MapBiomas Chile land-use/land-cover class for the year in which the burn occurred, supporting temporal analysis of fire occurrence across the different land-use categories.

3.2. Monthly burned area

The monthly burned-area maps indicate the specific month (1 to 12) in which the fire event occurred for each pixel over 2013–2025. Temporal attribution is based on the acquisition date of the satellite image in which the pixel showed its minimum NBR (Normalized Burn Ratio) value, as derived from the annual quality mosaic. This product enables the study of seasonal fire patterns.

3.3. Burned area by scar size

This dataset groups annual burned areas into size intervals, measured in hectares, over 2013–2025. A fire scar is defined as a contiguous cluster of burned pixels identified within the same year. This classification helps characterize the distribution and scale of fire events.

3.4. Accumulated burned area

The accumulated burned-area maps represent the total surface affected by fire across the entire study period, counting each pixel only once regardless of how many times it burned. In addition, the accumulated burned area is stratified by the land-use/land-cover classes of the final MapBiomas Chile year, offering insight into the long-term impacts of fire on the different cover types.

3.5. Fire frequency

The fire-frequency maps represent the number of times each pixel was classified as burned over 2013–2025. The data are aggregated into a single map whose classes indicate the number of occurrences (class 1 for a single occurrence, class 2 for two, and so on). Each pixel also retains its land-use/land-cover classification from the final MapBiomas Chile year, enabling analysis of fire recurrence across land uses.

3.6. Year of last fire

This dataset records the most recent year in which each pixel was identified as burned, within 2013–2025. Derived from the annual quality mosaics, it supports the assessment of time elapsed since the last fire.

3.7. Fire return interval

This product describes the temporal interval between mapped fire events at the pixel level, based on the annual burned-area series of MapBiomas Fire Chile. It includes two metrics:

- **Time since last fire:** the number of years since the previous fire at the same pixel, considering only areas burned in the analyzed year that have a prior occurrence.
- **Mean fire return interval (FRI):** the average number of years between successive fire events in the same area.

4. References

Alencar, A. A. C., Arruda, V. L. S., da Silva, W. V., Conciani, D. E., Costa, D. P., Crusco, N., Duverger, S. G., Ferreira, N. C., Franca-Rocha, W., Hasenack, H., Martenexen, L. F. M., Piontekowski, V. J., Ribeiro, N. V., Rosa, E. R., Rosa, M. R., dos Santos, S. M. B., Shimbo, J. Z., & Vélez-Martin, E. (2022). Long-term Landsat-based monthly burned area dataset for the Brazilian biomes using deep learning. *Remote Sensing, 14*(11), 2510. https://doi.org/10.3390/rs14112510

Arruda, V. L. S., Piontekowski, V. J., Alencar, A., Pereira, R. S., & Matricardi, E. A. T. (2021). An alternative approach for mapping burn scars using Landsat imagery, Google Earth Engine, and deep learning in the Brazilian savanna. *Remote Sensing Applications: Society and Environment, 22*, 100472. https://doi.org/10.1016/j.rsase.2021.100472

Corporación Nacional Forestal (CONAF). (n.d.). *Historical statistics of forest fires in Chile*. Retrieved July 24, 2026, from https://www.conaf.cl/incendios-forestales/incendios-forestales-en-chile/estadisticas-historicas/

Garreaud, R. D., Boisier, J. P., Rondanelli, R., Montecinos, A., Sepúlveda, H. H., & Veloso-Aguila, D. (2020). The Central Chile Mega Drought (2010–2018): A climate dynamics perspective. *International Journal of Climatology, 40*(1), 421–439. https://doi.org/10.1002/joc.6219

Giglio, L., Schroeder, W., & Justice, C. O. (2016). The Collection 6 MODIS active fire detection algorithm and fire products. *Remote Sensing of Environment, 178*, 31–41. https://doi.org/10.1016/j.rse.2016.02.054

Key, C. H., & Benson, N. C. (2006). Landscape assessment (LA): Sampling and analysis methods. In D. C. Lutes, R. E. Keane, J. F. Caratti, C. H. Key, N. C. Benson, S. Sutherland, & L. J. Gangi (Eds.), *FIREMON: Fire Effects Monitoring and Inventory System* (General Technical Report RMRS-GTR-164-CD, pp. LA-1–LA-55). USDA Forest Service, Rocky Mountain Research Station.

Long, T., Zhang, Z., He, G., Jiao, W., Tang, C., Wu, B., Zhang, X., Wang, G., & Yin, R. (2019). 30 m resolution global annual burned area mapping based on Landsat images and Google Earth Engine. *Remote Sensing, 11*(5), 489. https://doi.org/10.3390/rs11050489

Miller, J. D., & Thode, A. E. (2007). Quantifying burn severity in a heterogeneous landscape with a relative version of the delta normalized burn ratio (dNBR). *Remote Sensing of Environment, 109*(1), 66–80. https://doi.org/10.1016/j.rse.2006.12.006

Miranda, A., Mentler, R., Moletto-Lobos, Í., Alfaro, G., Aliaga, L., Balbontín, D., Barraza, M., Baumbach, S., Calderón, P., Cárdenas, F., Castillo, I., Contreras, G., de la Barra, F., Galleguillos, M., González, M. E., Hormazábal, C., Lara, A., Mancilla, I., Muñoz, F., Oyarce, C., Pantoja, F., Ramírez, R., & Urrutia, V.

(2022). The Landscape Fire Scars Database: Mapping historical burned area and fire severity in Chile. *Earth System Science Data, 14*(8), 3599–3613. https://doi.org/10.5194/essd-14-3599-2022

NASA. (n.d.). *Fire Information for Resource Management System (FIRMS)*. Retrieved July 24, 2026, from https://firms.modaps.eosdis.nasa.gov/

NLHPC (National Laboratory for High Performance Computing). (2024). *Leftraru 2 supercomputing infrastructure (ECM-02)*. Center for Mathematical Modeling, University of Chile. https://www.nlhpc.cl/

U.S. Geological Survey. (2021). *Landsat 4–7 Collection 2 Level-2 Science Product Guide*. U.S. Department of the Interior.

U.S. Geological Survey. (2024). *Landsat 8–9 Collection 2 Level-2 Science Product Guide* (Version 6.0). U.S. Department of the Interior.