

MAPBIOMAS
[FUEGO]

MapBiomas Fire Algorithm Theoretical Basis Document (ATBD)

Collection 1.0

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1. EXECUTIVE SUMMARY

The document presents the theoretical and methodological foundations of the Mapbiomas Fire Colombia Algorithm Theoretical Basis Document (ATBD), Collection 1.0, which provides the first monthly and annual maps of burned areas in Colombia from 2000 to 2025. The methodology relies on the processing of high-quality annual image mosaics constructed from 3 Landsat 5,7,8 and 9 images, with a spatial resolution of 30 meters, using the Google Earth Engine cloud computing platform, and on the classification of the burn scars using Deep Neural Network (DNN) model that was trained independently for the classification of natural regions representing the country's bioclimatic heterogeneity (Amazonia, Andes, Caribe, Insular, Orinoquía, Pacífico and Inter-Andean Valleys).

The classification process is supplemented by post-classification routines—thematic masking by land cover, spatial and temporal filters, and targeted manual correction—that reduce the noise and errors of commission inherent in pixel-by-pixel mapping over a time window of more than two decades. As a result, Collection 1.0 makes six products publicly available: annual burned area, monthly burned area, cumulative burned area, burning frequency, year of the last fire, and extent of burning, classified according to the land cover and land use classes of MapBiomas Colombia's Collection 3. The initiative is jointly led by the Gaia Amazonas Foundation and the Universidad del Rosario within the framework of the MapBiomas network, with technical support from the MapBiomas Fuego Brasil team, whose methodology forms the conceptual basis adapted in this document to the Colombian context. The resulting products aim to strengthen the prevention, monitoring, and assessment of the country's fire regime and are available free of charge on the MapBiomas Colombia platform.

2. INTRODUCTION

Fire is considered one of the most significant disturbance agents in terrestrial ecosystems (Bond & Keeley, 2005; Pausas & Ribeiro, 2017), and its effect on vegetation — in terms of composition, structure, and function — varies according to the specific characteristics of the fire regime: its recurrence, severity, seasonality, return intervals, and extent (Falk et al., 2007; Key & Benson, 2006; White & Pickett, 1985). In turn, fire regimes have undergone significant transformations worldwide due to multiple causes (Hardesty et al., 2005). On one hand, human activity has had a direct impact by introducing new ignition sources, altering the availability and accumulation of vegetative fuel, and modifying ecosystem functioning (Hardesty et al., 2005; Mouillot & Field, 2005). On the other hand, climate change acts as an amplifying factor by creating conditions more conducive to fire occurrence, primarily through rising temperatures and decreasing rainfall, which in turn leads to a higher frequency of extreme climate events (Dale et al., 2001; Gonzalez et al., 2010; Seidl et al., 2017).

The repercussions of these changes in fire regimes are far-reaching and include the degradation of natural resources, the release of greenhouse gases into the atmosphere, the alteration of water cycles, increased erosion processes, soil impoverishment through nutrient loss, and landscape transformation. Taken together, these effects compromise the capacity of ecosystems to provide essential environmental services (Bowman et al., 2009; Certini, 2005; Roces-Díaz et al., 2022; Shakesby & Doerr, 2006; van der Werf et al., 2017).

Within this context, Colombia presents particular conditions that make it especially important to have data that can help build an understanding of the fire regime across its different ecosystems and regions. Its bioclimatic diversity — spanning the Amazon and the Pacific to the Orinoquía, the Andes, and the Caribbean — means that fires have very different causes, dynamics, and consequences depending on the region (Armenteras et al., 2020). In the Orinoquía, burning is frequent during the dry season, mainly between January and March, and affects extensive natural savannas, arising mostly from productive activities, hunting, and pasture renewal (Armenteras et al., 2005). In the Colombian Amazon, fire is closely linked to deforestation and agricultural expansion, constituting one of the main drivers of forest cover loss (Armenteras et al., 2013). In the Andes, frequent vegetation fires threaten highly fragile ecosystems such as páramos and tropical dry forests, affecting their structure, composition, and capacity for recovery (Armenteras et al., 2020).

Given this scenario, having comparable and standardized historical records for Colombian territory is an essential condition for understanding the true magnitude of the problem and designing appropriate responses (IDEAM, n.d.). This information is key throughout the integrated fire management cycle: from prevention, by identifying areas with high recurrence and a history of burning, to monitoring and evaluation, by providing data to analyze disturbance parameters and affected land covers over time.

MapBiomás Fuego is a regional collaborative initiative that leverages the potential of satellite remote sensing, geographic information systems, and artificial intelligence algorithms to systematically and continuously map fire-affected areas. The platform is part of the MapBiomás network, present in more than 14 countries, and its central purpose is to transform satellite data into accessible, reliable, and useful information for environmental land management. Its

products are available as open, freely accessible data, which significantly broadens their reach: environmental authorities and response teams can identify areas of high recurrence and prioritize prevention actions; researchers can analyze historical trends and relate fire to climatic, socioeconomic, or land-use variables; and local communities can access objective information about fire behavior in their territories.

From a data life cycle perspective, MapBiomass Fuego Colombia operates under an annual collection scheme: each new collection extends the historical series, incorporates methodological improvements, and updates the classification models with new training samples. This scheme ensures that the products evolve alongside scientific knowledge and the availability of higher-quality satellite data, while maintaining backward compatibility across collections to allow for consistent interannual comparisons (A. A. C. Alencar et al., 2022).

The purpose of this document is to describe the methodology used by MapBiomass Fuego to generate the annual burned area maps that constitute the initiative's main product. This ATBD covers the context and background of the initiative (Section 3), the details of the implemented methodology (Section 4), and the limitations and artifacts observed in the results (Section 5), concluding with the bibliographic references (Section 6). The document is aimed at a broad audience and does not require prior knowledge of remote sensing or geographic information systems; the necessary technical concepts are explained throughout the text, along with examples applied to Colombian territory.

3. CONTEXT AND BACKGROUND

3.1 MapBiomass Fire Colombia

The network operates within the framework of: (i) the use of technology for cloud-based processing of large volumes of spatial data through Google Earth Engine algorithms; (ii) the production of data and methodologies that are entirely free, replicable, and improvable every year (collections); (iii) a multidisciplinary technical team that carries out territorial monitoring based on its expertise; and (iv) the support of institutions and funders who back the network's vision.

MapBiomass Fuego Colombia presents its first collection of annual burned area maps for the years 2000 to 2025. The methodology used employed Deep Learning algorithms based on a Deep Neural Network (DNN) model, with Landsat satellite imagery at 30-meter spatial resolution. The initiative was developed through the co-creation of Universidad del Rosario and Fundación Gaia Amazonas.

The MapBiomass collections aim to contribute to the development of a fast, reliable, collaborative, and low-cost method for processing large-scale datasets and generating historical time series of annual maps. All data, processes, code, statistics, and other analyses are freely accessible through the MapBiomass Colombia platform (<https://colombia.mapbiomas.org/>).

The data generated for Collection 1.0 comprise the following information products:

- Annual national-level burned areas from 2000 to 2025
- Burned areas according to MapBiomass Colombia Collection 3 Land Use and Land Cover classes
- Annual burned area frequency in Colombia
- Monthly burned area in Colombia from 2000 to 2025
- Cumulative burned areas in Colombia
- Annual burned area by burn scar size interval
- Year of the most recent fire/burn event

The products can be freely accessed on the MapBiomass Colombia network website, and the classification algorithms are available on the MapBiomass Colombia GitHub repository (<https://github.com/mapbiomas/colombia-fire>).

3.2 Other initiatives to monitor burned areas

In recent years, numerous initiatives have emerged aimed at mapping and monitoring burned areas and vegetation fires, both on a global and national scale, incorporating a variety of methodological approaches. These tools can be grouped into three distinct functional categories, the distinction between which is relevant for calibration and validation purposes: (i) systems for detecting hotspots or thermal anomalies in near real time, which identify the specific occurrence of active fire but do not delineate its extent; (ii) burned area or scar products, which spatially delineate the area actually affected by fire—a category to which MapBiomass Fuego Colombia belongs; and (iii) aggregation platforms, which integrate various data sources (hotspots, burned area, forest cover, deforestation alerts) into a single visualization or analysis

system. These initiatives address the need to understand the impacts of fires in the context of climate change, as well as their effects on ecological dynamics, fire regimes, and carbon cycles, and have contributed to monitoring deforestation and strengthening conservation efforts and the detection of forest degradation in Colombia and the region.

In this context, the calibration, contextualization, and cross-validation of the products generated by MapBiomás Fuego Colombia (a 30-meter-resolution burned area product derived from Landsat) require comparison with official systems administered by the Colombian government, as well as with global platforms and transnational regional networks. The most relevant initiatives are presented below, with the type of product to which each corresponds—according to the above categorization—indicated in parentheses.

Global Initiatives

NASA / FIRMS (Fire Information for Resource Management System)(*hot spots*): This is NASA's global reference information system for fire management. It distributes the locations of active fires in near real time (NRT), with a delay of less than three hours after the satellite passes over the area. It uses thermal anomaly detections from the MODIS sensors (on board Terra and Aqua, 1 km resolution) and VIIRS (on board Suomi-NPP and NOAA-20, 375 m resolution). In the MapBiomás Fuego Colombia workflow, these hotspots are used during the construction of the annual Landsat mosaics. Available at: <https://firms.modaps.eosdis.nasa.gov/>

MODIS MCD64A1 (*burned area*): Corresponde al producto global estándar de área quemada de la NASA, con periodicidad mensual y resolución espacial de 500 m. Utiliza un algoritmo basado en cambios abruptos de la reflectancia espectral diaria, calibrado con detecciones de focos de calor para acotar la fecha de quema (Giglio et al., 2016). Su resolución geométrica moderada tiende a subestimar (omisión) huellas del fuego pequeñas en paisajes altamente fragmentados como la cordillera de los Andes colombianos, un sesgo documentado en la literatura de validación del producto (Giglio et al., 2016). Con todo, al contar con la serie temporal continua más larga entre los productos de área quemada de resolución moderada (desde el año 2000), constituye un referente clave para la calibración de tendencias históricas de largo plazo. Disponible en: https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MCD64A1

VIIRS VNP64A1 (*burned area*): This is the global burned area product derived from the VIIRS (Visible Infrared Imaging Radiometer Suite) sensor, generated on the same 500-meter sinusoidal grid as MCD64A1 to ensure compatibility between the two products (Giglio et al., VNP64 User's Guide, LP DAAC). Its main advantage over MCD64A1 lies not in spatial resolution but in temporal continuity: it extends the moderate-resolution burned area series from 2012 to the present, and its integration with VIIRS active fire detections improves the sensitivity of detecting small fires in certain contexts. Available at: https://developers.google.com/earth-engine/datasets/catalog/NOAA_VIIRS_001_VNP64A1?hl=es-419

Global Nature Watch Fires (GNW Fires) (*aggregation platform*): This is a World Resources Institute (WRI) platform that combines satellite data (VIIRS, MODIS) with forest cover layers and fire alerts, designed to detect, visualize, and analyze active fires, agricultural burning, and

deforestation in near-real time, especially in tropical regions such as the Amazon (Peru, Brazil, Colombia, Bolivia, among others). Available at: <https://globalnaturewatch.org/>

ESA FireCCI (Climate Change Initiative) (*burned area*): This is a set of burned area products developed by the European Space Agency within its essential climate variables program. Originally based on MODIS (the FireCCI51 product, 250 m resolution; Chuvieco et al., 2018) and recently expanded with data from the Sentinel constellation, its methodology is oriented toward global climate modeling and the quantification of greenhouse gas emissions from biomass burning. Available at: <https://cds.climate.copernicus.eu/datasets/satellite-fire-burned-area>

GABAM (Global Annual Burned Area Map)(*burned area*): This is a global annual burned area map with a spatial resolution of 30 m, generated by the Chinese Academy of Sciences through massive cloud-based processing of complete Landsat image time series, using automatic thresholds and adaptive spectral indices (Long et al., 2019). Sharing the same native 30 m resolution as MapBiomass, it serves as a direct methodological reference for consistency assessments. Available at: <https://gee-community-catalog.org/projects/gabam/>

Global Wildfire Information System (GWIS) (*aggregation platform*):: It is a joint initiative of GEO (Group on Earth Observations) and the Copernicus Program, with the participation of NASA, GOFC-GOLD, and numerous national agencies, that integrates global wildfire data into a single platform. Its goal is to harmonize global wildfire information and strengthen countries' capacity to monitor, prevent, and manage fire-related events, with coverage across all continents and a particular focus on the Amazon. Available at: <https://gwis.jrc.ec.europa.eu/>

Regional Initiatives

MAAP (Monitoring of the Andes Amazon Program) – Dashboard (*aggregation platform, with optical verification*): This is an initiative of the Amazon Conservation Association (ACA) and the Amazon Basin Conservation Association (ACCA) that operates a near-real-time monitoring system for the Amazon Basin. It implements a double-verification protocol: it detects smoke plumes and aerosol dispersion using the VIIRS sensor and performs optical confirmation with daily high-resolution satellite imagery (Planet Labs, <5 m), which allows for the differentiation between low-intensity agricultural burning and fires that affect the forest canopy. Available at: <https://www.maaprogram.org/fire/fires/>

INPE – Queimadas (Brasil) (*hot spots*): This is Brazil's system for monitoring hotspots and fire occurrences, whose dataset (BDQueimadas) has been continuously available since 1998. It uses data from sensors such as MODIS, VIIRS, and GOES to detect and report, in near real time, the location and extent of hotspots throughout Brazil and South America; its data are publicly available and updated daily. Available at: <https://www.gov.br/pt-br/servicos/obter-dados-de-queimadas>

Nacional Initiatives

IDEAM – Sistema de Monitoreo de Bosques y Carbono (SMBYC) (hot spots): This is the official platform of the Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM), which is responsible for monitoring forest cover and issuing early warnings for wildfires through its “Heat Spot Monitoring in Colombia” portal. This system processes thermal anomalies from the MODIS and VIIRS sensors on a daily basis to generate a national report on heat spots. IDEAM itself specifies that these hotspots are an indirect indication of fire occurrence, not a confirmation: they correspond to the center of a pixel where a thermal anomaly was detected, and while in most cases they indicate fire on some type of vegetation, they can also be caused by gas combustion, thunderstorms, or other sources; since satellite data alone does not allow for distinguishing the type of anomaly, additional inputs and analyses are required to confirm a vegetation fire, although there is a documented link between the occurrence of fires and changes in land cover, particularly deforestation (IDEAM, n.d.). This institutional clarification directly supports the distinction made at the beginning of this section between heat source products and burned area products proper: IDEAM serves as the primary national reference for heat sources, but—unlike MapBiomass Fuego Colombia—it is not an institutional source for delineating burn scars; therefore, the comparison between the two products should be understood as complementary rather than as a direct validation of burned area. For MapBiomass, IDEAM represents the primary institutional and data governance framework in the country. Available at: <https://puntosdecalor.ideam.gov.co/>

Instituto SINCHI – Sistema de Información Ambiental Territorial (SIAT-AC): This system specializes in analyzing fire dynamics in the Colombian Amazon. Developed by the Amazonian Institute for Scientific Research, its algorithms focus on the spatial density of fire events and their relationship to frontiers of colonization and land-use change. Its methodological significance lies in the fact that it not only quantifies hotspots but also evaluates the “edge effect” and the fragmentation patterns that fire generates in the transition zones between the Orinoquía and the continuous Amazon rainforest block, providing a high-resolution ecological context for the calibration of spectral signatures in dense tropical forests. Available at: <https://siatac.co/cicatrices-de-quema/>

Universidad del Rosario (Interacciones Clima-Ecosistemas - ICE): The Climate–Ecosystem Interactions (ICE) research group at the School of Sciences and Engineering of Universidad del Rosario focuses on identifying, measuring, and evaluating the impacts of the various interactions between climate, its variability, land-use change, and other anthropogenic factors on ecosystems, society, and biodiversity, using quantitative methods such as global, regional, and statistical modeling. The research group covers several lines of research, including Fires in the Earth System; preliminary burned area mapping data contributed to the sample collection process and remain unpublished.

4. METHODOLOGY

4.1. General Methodological Workflow

The MapBiomass processing chain relies on Google’s cloud computing ecosystem, combining two layers of infrastructure with distinct functions. On one hand, Google Earth Engine (GEE) serves as the geospatial processing engine: a global analysis platform that integrates, within a single distributed computing environment, the public catalog of satellite imagery (including the

complete historical Landsat archive) with the ability to run algorithms on that catalog without needing to download the images locally. Processing scripts are developed on GEE, either using its JavaScript API (Code Editor, used primarily for prototyping and visual quality control) or its Python API (used for batch task automation and version control). On the other hand, the persistence and publication of the generated products—annual mosaics, burned area classifications, statistics, and methodological metadata—are handled through Google Cloud Platform’s storage and deployment services: intermediate results are stored as assets within GEE (image collections, tables), while final products are exported to Google Cloud Storage buckets and served through the public web platform, available at <http://plataforma.colombia.mapbiomas.org>.

The workflow of MapBiomas Fuego Colombia's Collection 1, summarized in Figure 1, is organized into the following stages: identification of input data, comprising the reference information used, the delimitation of classification regions, and the generation of annual mosaics (Section 4.2); collection of reference samples by biome (Section 4.3); classification of burned areas using neural networks (Section 4.4); post-classification (Section 4.5); and generation of output products (Section 4.6).

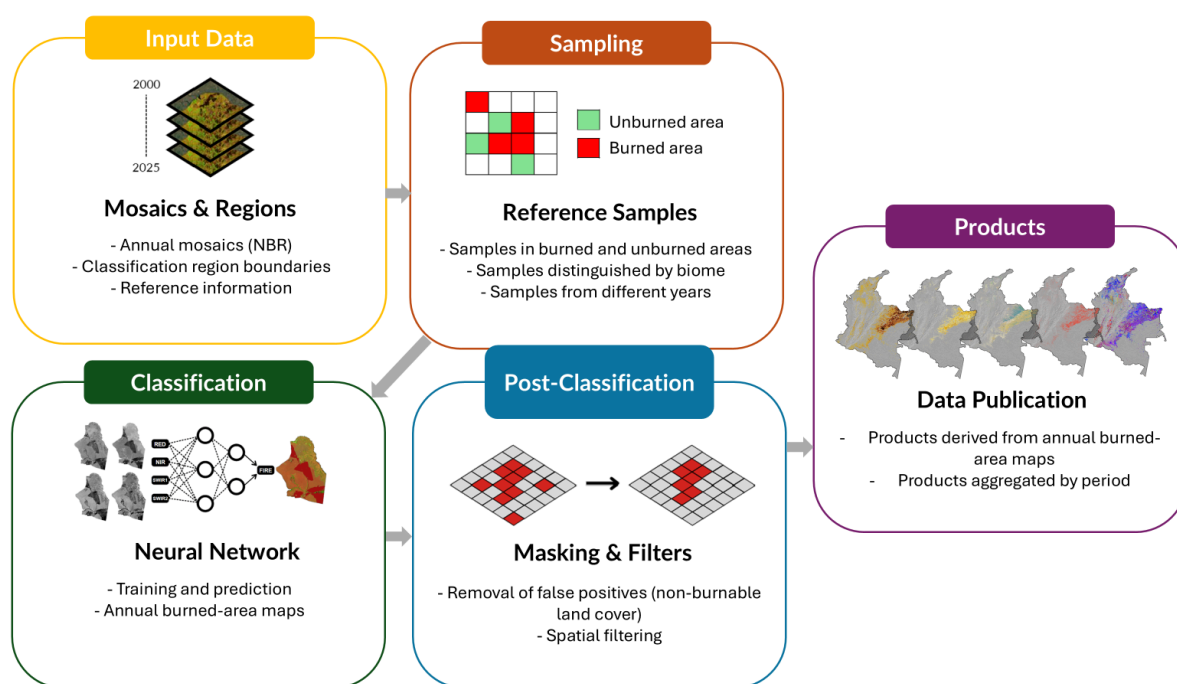


Figure 1. Methodological workflow for classifying burned areas in MapBiomas Fire. Prepared by: MapBiomas Colombia

4.2. Input Data

The generation of annual maps of burned areas is based on the large-scale processing of geospatial data using the Google Earth Engine platform, which enables the efficient analysis of historical time series. The workflow for classification using the Deep Neural Network (DNN) algorithm requires the precise integration of various inputs that ensure the representativeness of fire scars across the territory. The following section provides a more detailed look at the inputs used.

4.2.1. Reference Information Used

The MapBiomass Fuego Colombia classification methodology integrates multiple global, regional, and national reference data sources, which serve three distinct functions within the workflow: the collection of training samples, filtering and masking during post-processing, and the validation of the thematic accuracy of the final product (Chapter 6). The integration of these sources is part of a cross-validation strategy across different spatial and temporal scales, rather than a comparison with a single reference product. Table 1 summarizes the sources used, their resolution, their origin, and their specific function.

Tabla 1. Summary of regional products.

Initiative / Platform	Product type	Coverage age/ Scope	Spatial resolution	Update frequency	Temporal coverage
NASA / FIRMS	Active fire hotspot	Global	375 m (VIIRS) / 1 km (MODIS)	Near real-time (NRT, <3 h)	2000–present (MODIS) / 2012–present (VIIRS)
MODIS MCD64A1	Burned area	Global	500 m	Monthly	2000–present
VIIRS VNP64A1	Burned area	Global	500 m	Monthly	2012–present
GABAM (China)	Burned area	Global	30 m	Annual	1990–2021 (with documented missing years)
MAAP Dashboard	Aggregation platform (active fire hotspots + optical verification)	Regional (Amazon)	High (<5 m, Planet) / 375 m (VIIRS)	Near real-time	Program launched in 2015
GFW Fires	Aggregation platform	Global	375 m (VIIRS) / 1 km (MODIS)	Near real-time (hotspots) / annual (deforestation)	2000–present (MODIS) / 2012–present (VIIRS)
ESA FireCCI	Burned area	Global	250 m (FireCCI51)	Monthly	2001–2020
GWIS	Aggregation platform	Global	Variable (MODIS, VIIRS, FireCCI51)	Variable	2000–present (MODIS) / 2012–present (VIIRS) / 2001–2020 (FireCCI)

INPE Queimadas	Active hotspot	fire	Continental (South America)	Variable (MODIS, VIIRS, GOES)	Daily	1998–present	
IDEAM (SMBYC)	Active hotspot	fire	National (Colombia)	1 km (MODIS) / 375 m (VIIRS)	Daily	2000–present (MODIS) 2012–present (VIIRS)	/
Instituto SINCHI (SIAT-AC)	Burned (scar)	area	Regional (Colombian Amazon)	Medium–High (Landsat/Sentinel)	Monthly	2017–present	

FIRMS hotspots serve a purpose beyond that of a simple training reference: they are used as a temporal filter to distinguish active fire scars (with evidence of recent thermal activity) from residual scars whose spectral signature persists in the Landsat mosaic from years following the original event, thereby reducing temporal commission errors (i.e., the attribution of a scar to a year other than the one in which it actually occurred) in dense forested regions such as the Colombian Amazon.

GABAM, by sharing Landsat’s native 30-meter resolution, serves as a benchmark for geometric consistency in relation to the MapBiomass Fuego Colombia classification. MODIS’s MCD64A1 and ESA’s FireCCI, despite their moderate spatial resolution, provide longer historical time series, which are useful for calibrating long-term temporal trends.

The land cover and land use maps from MapBiomass Colombia Collection 3 also serve a masking function: they allow non-combustible features (urban infrastructure, bodies of water, rocky outcrops, among others) to be excluded from the final classification, as detailed in section 4.5.1.

4.2.2. Definition of Classification Regions

The study area covers the entire Colombian mainland and islands, with a total area of approximately 113,696,382.4 ha.

Due to the heterogeneity of the Colombian territory in terms of land cover, land use, and the distribution of burned areas, the country was divided into 99 classification regions for processing and analysis (Figure 2). This segmentation is necessary to manage the complexity inherent in machine learning algorithms when dealing with the heterogeneity of the seven biomes adapted by MapBiomass Colombia: Amazon, Andes, Inter-Andean Valleys, Caribbean, Orinoquía, Pacific, and island regions (Caribbean Islands and Pacific Islands). These seven biomes are in turn subdivided into reference landscape complexes, which are ultimately disaggregated into the 99 operational classification regions used for sample collection and the independent training of models by region. Table 2 presents this complete hierarchy (biome → landscape complexes → number of operational regions), including, among others, páramos, the Andean mountain ranges, the eastern foothills, the Magdalena Valley, the Cauca and Patía

Valleys, the Sinú Valley, the savannas of the Orinoco plains, the Caribbean marsh complex, and the subxerophytic Guajira.

Table 2. Distribution of operational regions for burned area classification (Adapted for MapBiomass Fire Colombia)

Biome	Reference Ecoregions	No. of Operational Regions
Amazonia	Amazonia	34
Andes	Andes	25
	Páramos	5
Caribbean	Caribbean Swampland	4
	Guajira Subxerophytic	1
	Sinú Valley	3
Insular	Caribbean Insular	1
	Pacific Insular	1
Orinoquía	Eastern Foothills	3
	Orinoco Plains Savannas	9
Pacífico	Pacific	6
Valles interandinos	Cauca Valley	3
	Magdalena Valley	4
Total		99

The segmentation into 99 operational classification regions represents a key methodological adaptation compared to the MapBiomass Fogo Brasil approach, which defined 28 regions (A. Alencar et al., 2026) for a larger territory but, as argued here, one with lower bioclimatic heterogeneity per unit area. In Colombia, the orographic complexity of the Andes (which generates extreme altitudinal gradients over short horizontal distances) and the coexistence of contrasting hydrological regimes—ranging from the humid Amazon to the subxerophytic Guajira—require classification models trained independently for each region, thereby preventing the model from learning from spectral signatures in incompatible ecological contexts. This design maximizes the sensitivity of the DNN classifier to the spectral signatures characteristic of each ecosystem type (A. A. C. Alencar et al., 2022; Arruda et al., 2021).

To delineate the regions, technical criteria regarding ecosystem distribution were used, based on national reference maps, the historical distribution of burned areas nationwide, and the experience gained in compiling the land cover and land use datasets for MapBiomass Colombia. The following reference layers were used:

- Map of Natural Vegetation (Rangel-Ch & Suárez-M, 2022)
- State of Colombian Ecosystems (Etter et al., 2017)

- Map of Colombia's Continental, Coastal, and Marine Ecosystems (IDEAM et al., 2017)
- Biogeographic Units of Colombia at a scale of 1:100,000 (PNN, 2022)
- Global Ecoregions (terrestrial) (WWF, 2004)
- Land Cover and Land Use Map, Collection 3 (FGA, 2025)

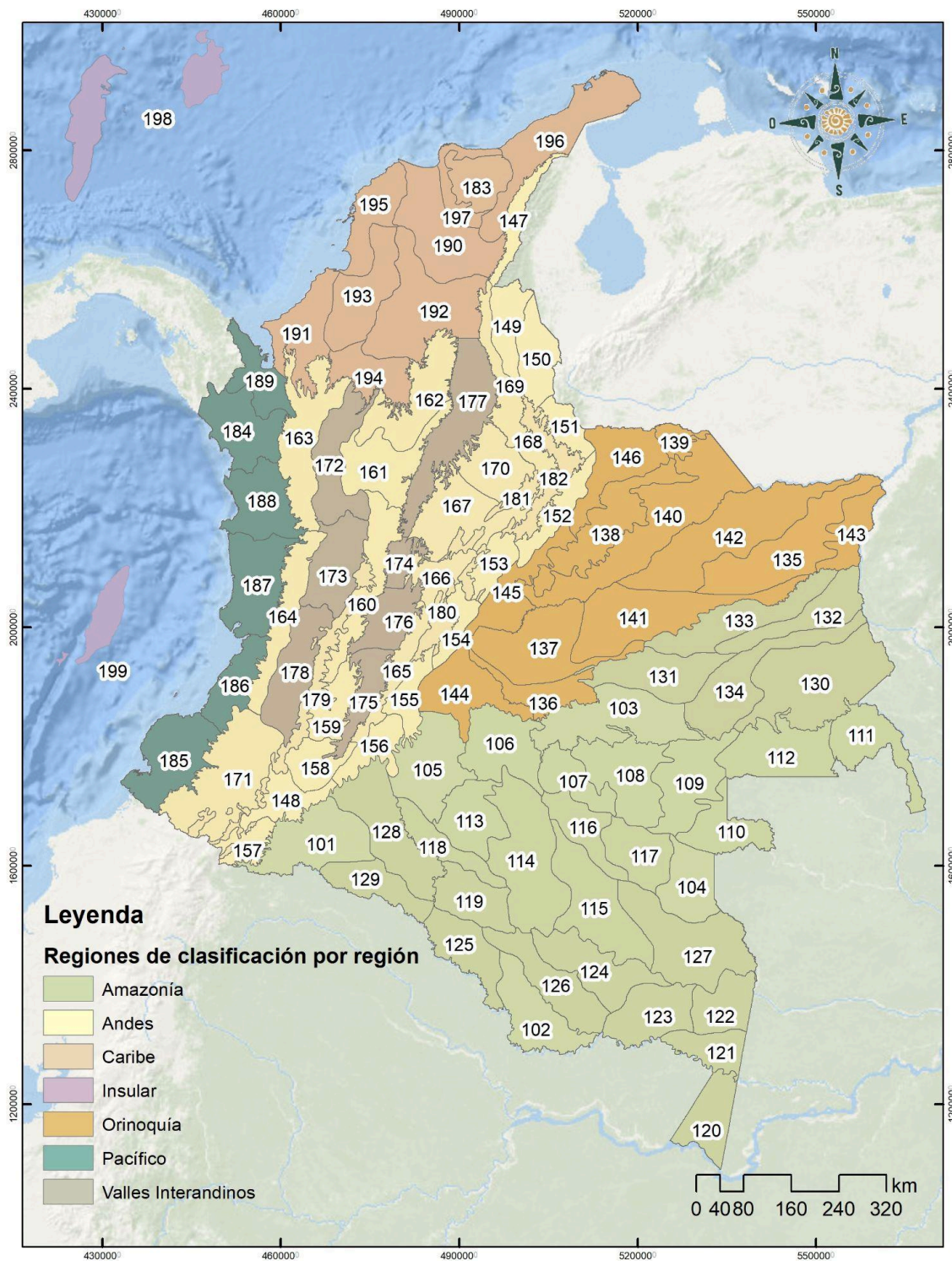


Figure 2. Regional classification for MapBiomass Fire.

4.2.3. Image Mosaic Generation

Using the Google Earth Engine platform, surface reflectance (SR) data from the Landsat Collection 2 (C2), Tier 1 catalog were used, with a spatial resolution of 30 m × 30 m. The analysis period spans from 2000 to 2025, using satellite images according to the following temporal distribution: Landsat 5 and Landsat 7 (2000–2012), Landsat 7 and Landsat 8 (2013–2021), and Landsat 8 and Landsat 9 (2022–2025). These instruments have a repeat cycle of 16 days.

Table 3. Landsat Data Collections

Sensor	Collection ID in GEE
Landsat 5 TM	LANDSAT/LT05/C02/T1_SR
Landsat 7 ETM+	LANDSAT/LE07/C02/T1_SR
Landsat 8 OLI /TIRS	LANDSAT/LC08/C02/T1_SR
Landsat 9 OLI 2 /TIRS 2	LANDSAT/LC09/C02/T1_SR

Landsat surface reflectance is accompanied by two bit-by-bit quality assessment bands: QA_PIXEL and QA_RADSAT. These bands identify pixels with radiometric and instrumental issues. In this workflow, the QA_PIXEL band was used to mask pixels with high confidence levels (67–100%) for “cloud” and “cloud shadow.” Subsequently, QA_RADSAT was used to exclude pixels with radiometric saturation in any of the optical bands. Finally, pixels with negative reflectance values were removed to suppress anomalies and background noise.

4.2.3.1. Normalized Burn Area Index (NBR)

To summarize the large volume of annual data and optimize cassification without discarding pixel-level spectral information, (Step 0 in Figure 3) all valid observations for a specific year—defined as those Landsat scenes filtered using the QA_PIXEL band to exclude pixels with a high confidence level (67–100%) of clouds and shadows— the QA_RADSAT band to exclude pixels with radiometric saturation, and the exclusion of negative surface reflectance values—following the same masking criteria applied by MapBiomas Fuego Brasil (A. Alencar et al., 2026)—are stacked into a temporal multiband image. On this stack (Steps 1 and 2 in Figure 3) a statistical pixel-by-pixel composition approach is applied, adapted from that same methodology, using the Normalized Burn Area Index (NBR) as the pixel-level ordering function (Equation 1; Key & Benson, 2006)

For each pixel (Step 3 in Figure 3), the date on which the NBR reaches its minimum value within the year is selected, and from that specific date, all spectral reflectance bands are extracted along with the scene metadata (including the exact date of observation) to compose the annual quality mosaic (QM):

$$\lambda_{QM} = [\text{Blue, Green, Red, NIR, SWIR1, SWIR2}] = \text{date of measurement for } \min [(NIR - SWIR1) / (NIR + SWIR1)] [x_i \dots x_j]$$

Equation 1. Equation describing mosaic composition based on NBR (Key & Benson, 2006)

Where λ represents the reflectance values of the quality bands that make up the mosaic (QM), obtained on the date when each pixel (x) reached its minimum NBR value in a given year, considering all available scenes, from the first (i) to the last (j). NIR and SWIR1 are the near-infrared and short-wave infrared 1 surface reflectances, respectively, used to calculate the NBR.

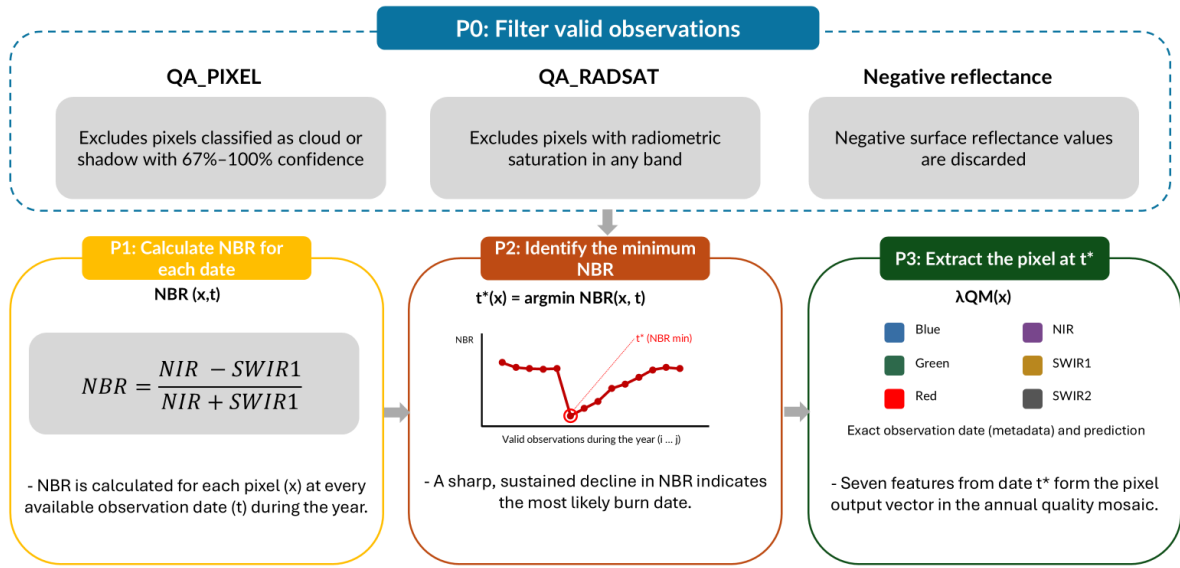


Figure 3. Method for Generating Annual Mosaics and Calculating the Minimum NBR Spectral Index for MapBiomass Fire Colombia.

The quality mosaic based on the minimum NBR has demonstrated good performance in distinguishing between burned and unburned land cover in Brazilian biomes (A. Alencar et al., 2026), and in the case of Colombia, it effectively separates burned areas from unburned areas across the various classification regions of the country.

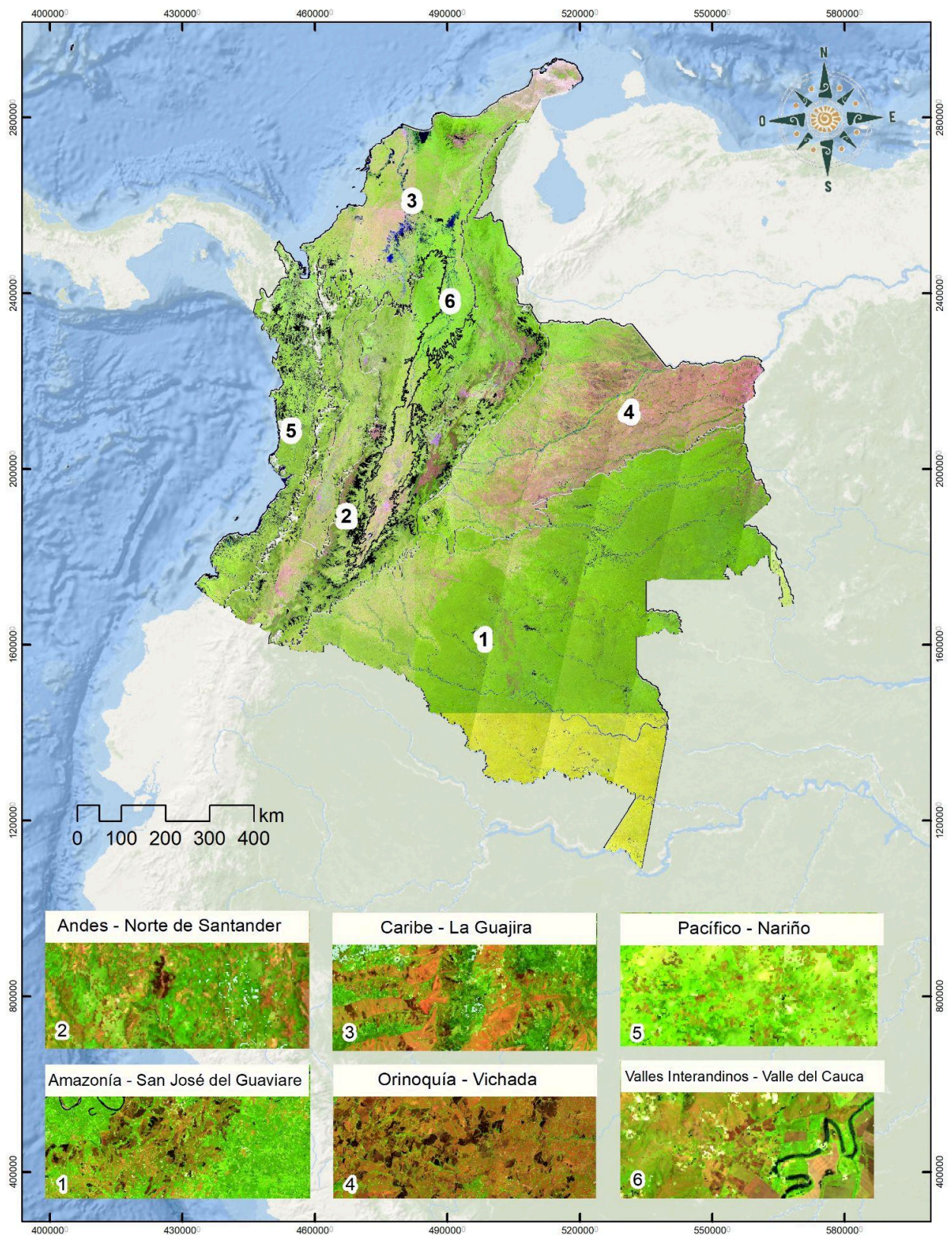


Figure 4. 2025 Quality Map (QM) for Colombia (RGB SWIR-1, NIR, Red), with examples of burned areas: (1) Amazon, (2) Andes, (3) Caribbean, (4) Orinoquia, (5) Pacific, and (6) Inter-Andean Valleys.

4.2.3.2. Selección de variables de clasificación Selection of classifications variables

Based on the annual quality mosaics generated, preliminary classification tests were conducted to identify the spectral variables with the greatest discriminatory power between burned and unburned areas, thereby reducing the number of variables needed for the final classification. Based on the results of these tests, the classification model was implemented using the four surface reflectance bands: Red (RED), Near Infrared (NIR), Shortwave Infrared 1 (SWIR1), and Shortwave Infrared 2 (SWIR2). Details for each band are shown in Table 4 below.

Table 4. Variables for Fire Classification from Collection 1 of MapBiomass Fire Colombia

Variable	Description	Approx. wavelen gth	Landsat Band 5/7	Landsa t Band 8/9	Relevance to fire discrimination
RED	Red reflectance	0.63–0.69 μm	Band 3	Band 4	Ash and residual charcoal reduce reflectance in this region compared to healthy vegetation
NIR	Near-Infrar ed Reflectance	0.76–0.90 μm	Band 4	Band 5	The loss of photosynthetically active vegetation following a fire sharply reduces NIR reflectance
SWIR1	Short-Wave Infrared Reflectance 1	1.55–1.75 μm	Band 5	Band 6	Sensitive to the moisture content of vegetation and exposed soil following a fire
SWIR2	Short-Wave Infrared Reflectance 2	2.08–2.35 μm	Band 7	Band 7	Together with NIR, it makes up the Normalized Burn Area Index (NBR); fire scars exhibit high reflectance in this band

4.3. Sampling

In the sampling phase, the concept of burned area was first defined as the total surface affected by fire during an event or season, in which combustion fully or partially consumed biomass (vegetation and surface organic matter).

In remote sensing, this category excludes surfaces whose spectral response is due to processes unrelated to fire, such as volcanic deposits, oil spills, rocky outcrops, water bodies, floodable zones, naturally dark soils (andisols, peatlands, or soils rich in organic matter), and shadows caused by clouds or relief (Chuvienco et al., 2019; Fidelis & Pivello, 2025).

Given the above, burned area sampling was adjusted by biome/region and by Landsat sensor cutover (L5/L7, L7/L8, and L8/L9), covering three sampling periods: 2000 to 2012, 2013 to 2021, and 2022 to 2025. Sample collection was carried out across the 99 classification regions to ensure representativeness of their different spectral signatures.

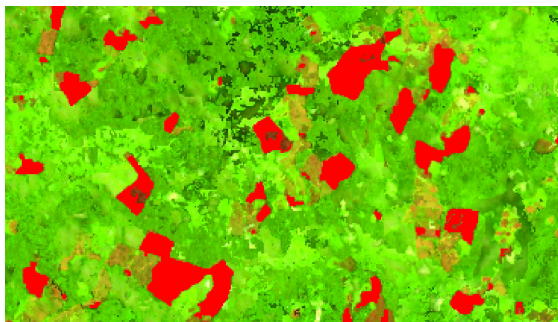
Some inputs used during this stage were:

- MODIS burned areas (MCD64A1) (500 m spatial resolution) (2000–2025);
- Global Annual Burned Area Map (GABAM) (30 m spatial resolution) (1985–2021);
- Fire scars from the Fire Information for Resource Management System (FIRMS) (1 km spatial resolution) (2000–2025);
- Fire CCI Burned Area Climate Data Record Version 5.1 (250 m spatial resolution) (2001–2020);
- MapBiomass Colombia Collection 3 Land Cover and Land Use (30 m spatial resolution) (1985–2024);
- Reflectance and hotspots from the TERRA satellite (MODIS) (250 m to 1 km spatial resolution) (2000–2025); and
- Reflectance and hotspots from the AQUA satellite (MODIS) (250 m to 1 km spatial resolution) (2002–2025).

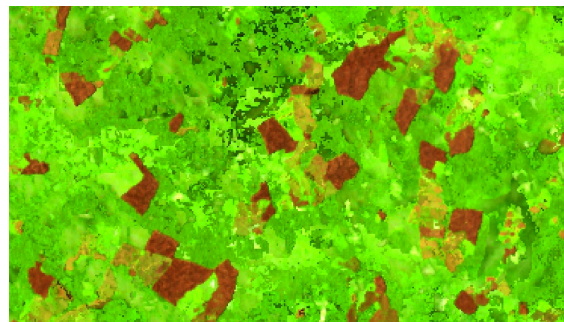
Some examples of burned area sample collection by biome are shown below.

4.3.1 Burned areas in the Amazon

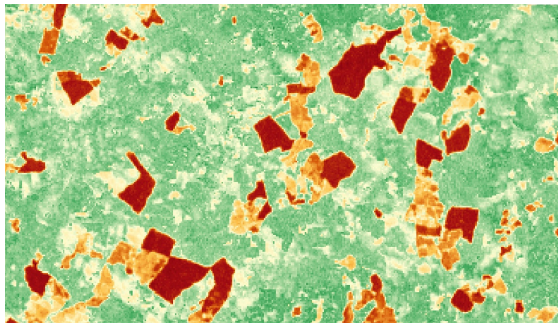
In the Amazon region, areas classified as burned tend to be associated with anthropogenic land uses, mainly agriculture-or-pasture mosaics, as well as natural land covers such as herbaceous formations, natural non-forest floodable formations, and forest. Likewise, the departments of Guaviare, Caquetá, and Meta stand out for recording the largest annual burned area throughout the historical series. It is worth noting that these same departments also show the greatest loss of forest cover due to deforestation, where fire acts as a risk agent for natural ecosystems (mainly humid forest) when used for land-use change.



Burned area classification (2023)



False-color composite B6-B5-B4 (2023)



NBR (2023)

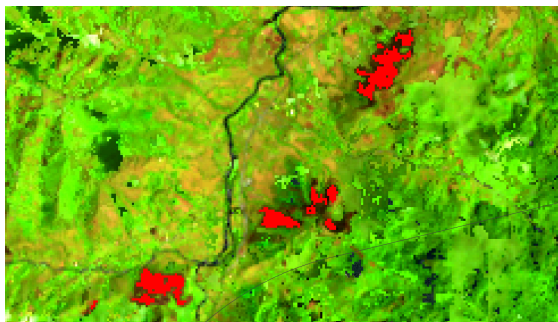


Google Maps base map

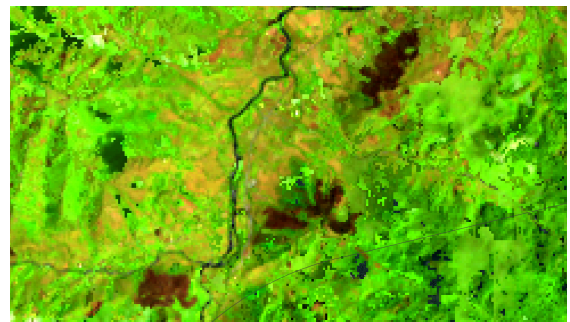
Figure 5. Comparison between the burned area classification and the mosaics used for sampling in the Amazon, Puerto Guzmán municipality, Putumayo.

4.3.2 Burned areas in the Andes

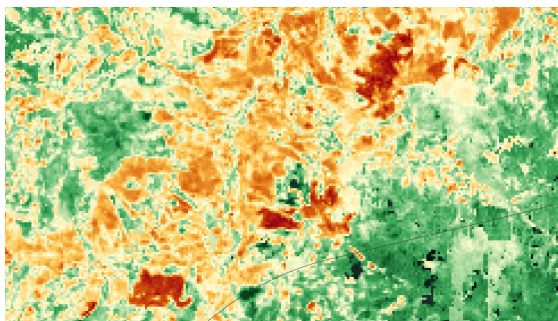
In the Andes region, agriculture-or-pasture mosaic covers show the highest concentration of burned area in the biome, mainly related to burning associated with the renewal of agricultural and livestock activities. However, 10.6% of the burned area corresponds to natural covers, such as forests, grasslands, and Andean shrublands. In terms of territorial distribution, Antioquia, Boyacá, Huila, and Tolima stand out as the departments with the greatest presence of burned surface.



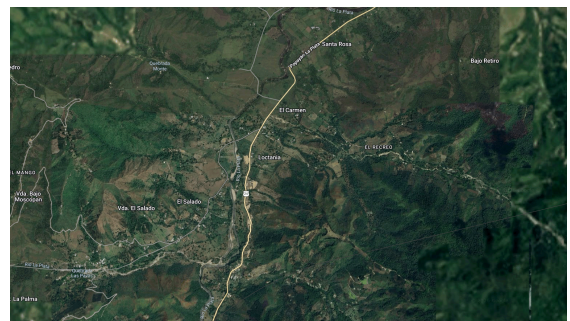
Burned area classification



False-color composite B6-B5-B4 (2023)



NBR (2023)

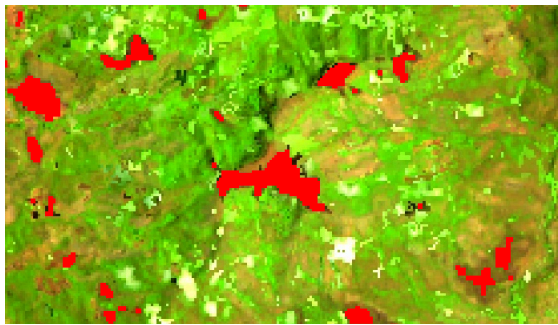


Google Maps base map

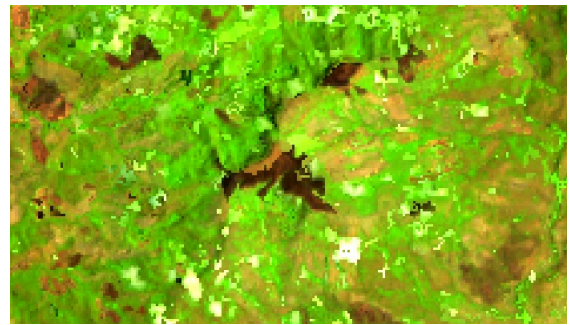
Figure 6. Comparison between the burned area classification and the mosaics used for sampling in the Andes, La Plata municipality, Huila.

4.3.3 Burned areas in the Caribbean

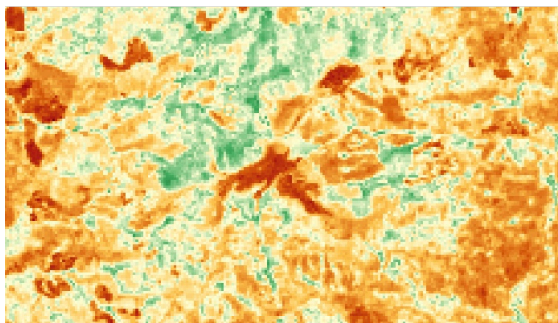
In the Caribbean region, the fire regime is mainly associated with the burning of anthropogenic land covers (agriculture and/or pasture mosaics) and natural vegetation in tropical dry forests and semi-arid areas, concentrated in the dry season that generally runs from December to April. Fire is strongly concentrated in the departments of Magdalena, Cesar, and Bolívar, which together account for around 74% of the cumulative regional burned surface between 2000 and 2025. Unlike the Amazon, where fire acts as a land-use change agent over humid forest, in the Caribbean the recurrence regime is predominantly sporadic – most of the area burned only once throughout the historical series – suggesting a fire that disperses spatially rather than becoming established recurrently on the same territory.



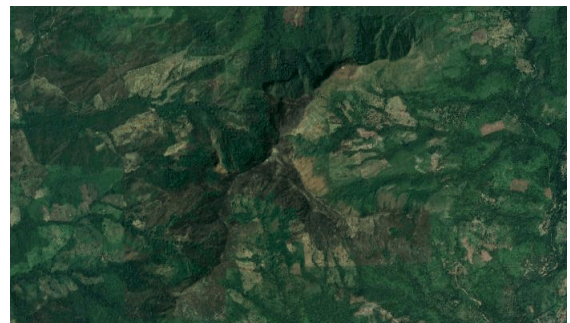
Burned area classification (2025)



False-color composite B6-B5-B4 (2025)



NBR (2025)



Google Maps base map

Figure 7. Comparison between the burned area classification and the mosaics used for sampling in the Caribbean, Valledupar municipality, Cesar.

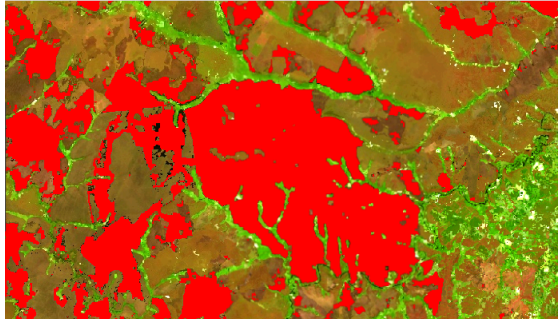
4.3.4 Burned areas in the Insular biome

In the Insular biome, the classification did not report any detection of burned areas during the time series evaluated.

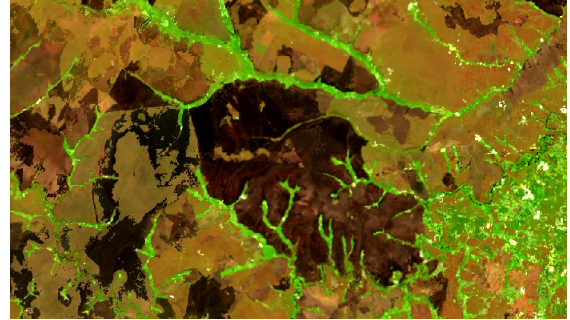
4.3.5 Burned areas in the Orinoquía

In the Orinoquía, fire is a structural component of the disturbance regime of natural savannas, with marked seasonality concentrated between January and March, coinciding with the low-water (dry) period, and causality mainly associated with productive practices, pasture

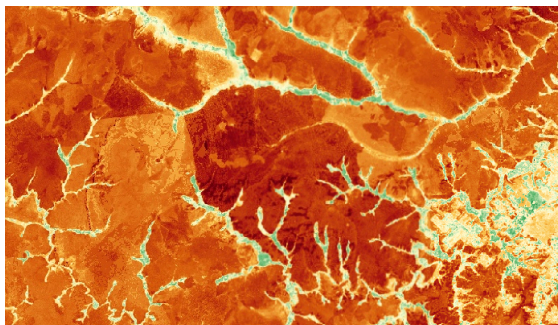
renewal, and hunting (IDEAM, n.d.). This is the region with the greatest fire impact at the national level: 10.2 Mha burned at least once between 2000 and 2025 (73.2% of the country's accumulated burned area), concentrated mainly in the departments of Vichada and Meta. Unlike the dispersed regime observed in the Caribbean (section 4.3.3), in the Orinoquía fire shows the highest recurrence pattern in the country, with savannas burning repeatedly over the same territory throughout the entire historical series.



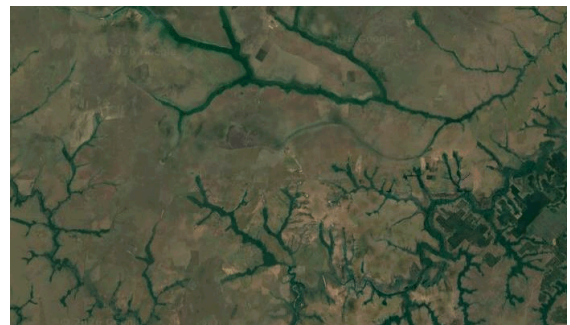
Burned area classification (2024)



False-color composite B6-B5-B4 (2024)



NBR (2024)

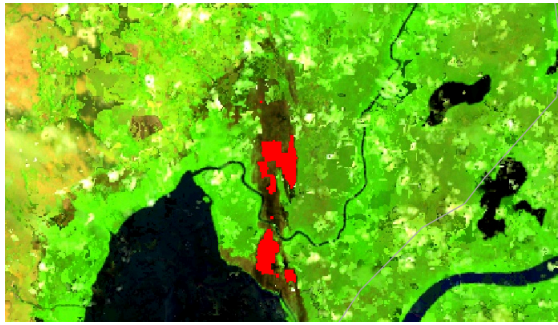


Google Maps base map

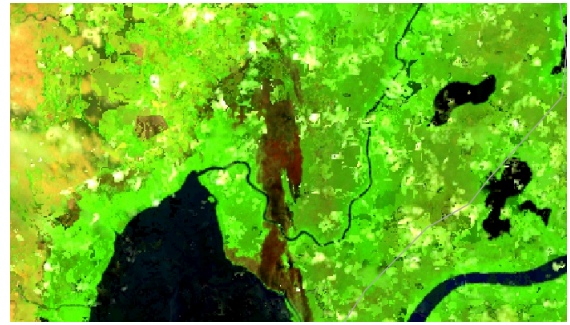
Figure 8. Comparison between the burned area classification and the mosaics used for sampling in the Orinoquía, La Primavera municipality, Vichada

4.3.6 Burned Areas in the Pacific

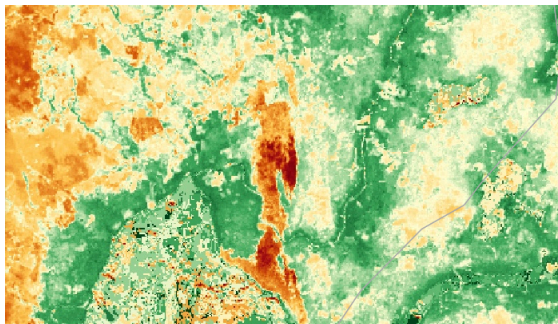
The Pacific region is dominated by conditions of high rainfall and relative humidity that naturally limit the occurrence and spread of fire, which is why this biome has the lowest incidence of burned area in the country, concentrated mainly in the departments of Valle del Cauca and Cauca. Unlike the rest of the national territory, Valle del Cauca shows an inverted fire calendar, with a burning peak toward September instead of the December-to-March dry season, associated almost entirely with the burning of agricultural/livestock land covers. The region also shows marked internal heterogeneity in its recurrence regime: while in Valle del Cauca fire tends to disperse spatially, in Chocó it is concentrated much more persistently over the same territory.



Burned area classification (2024)



False-color composite B6-B5-B4 (2024)



NBR (2024)

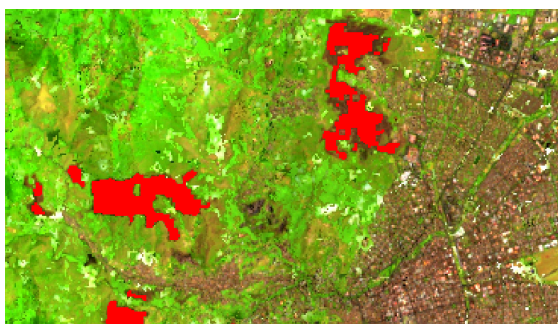


Google Maps base map

Figure 9. Comparison between the burned area classification and the mosaics used for sampling in the Pacific, Unguía municipality, Chocó.

4.3.7 Burned areas in the Interandean Valleys

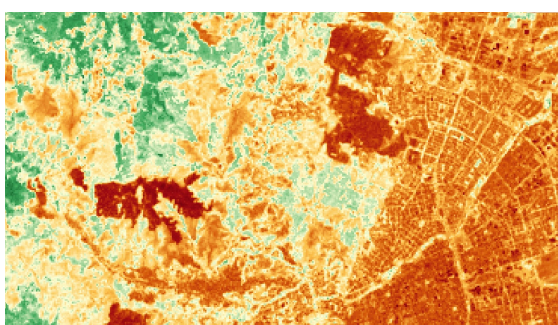
In the Interandean Valleys, located between the Andean mountain ranges, the departments of Valle del Cauca, Tolima, and Santander account for 67.8% of the burned area recorded throughout the biome's historical series. In terms of land cover, agriculture-or-pasture mosaics predominate as the most affected surface, representing 95.0% of the total burned area throughout the entire time series — a figure associated, among other agricultural practices, with the scheduled pre-harvest burning of sugarcane, historically widespread in Valle del Cauca. This near-absolute predominance of anthropogenic land covers contrasts with the 10.6% of burned natural cover reported for the Andes region (section 4.3.2), suggesting an even more pronounced anthropogenic pressure on the fire regime in the interandean valleys than in the surrounding mountain ranges.



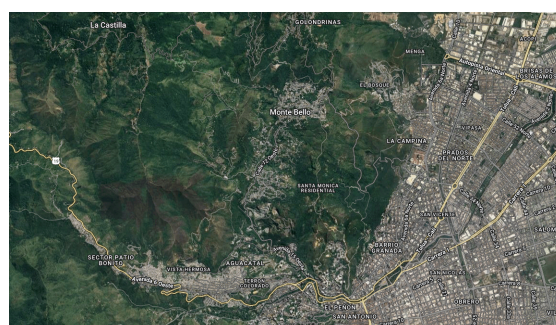
Clasificación de área quemada (2023)



Combinación falso color B6-B5-B4 (2023)



NBR (2023)



Mapa base de Google Maps

Figure 10. Comparison between the burned area classification and the mosaics used for sample collection in the Interandean Valleys, Cali municipality, Valle del Cauca.

4.4 Classification of burned areas using neural networks

The classification of fire footprints in MapBiomás Fuego Colombia was carried out using a Deep Learning model, specifically a Deep Neural Network (DNN), capable of identifying and generalizing complex spectral patterns associated with fire occurrence from large volumes of remote sensing data. The architecture used corresponds to a Multi-Layer Perceptron Network (MLPN), structured in layers of interconnected neurons (input, hidden, and output), in which each neuron receives the input values, applies a set of weights and a bias to them, and produces an output that is passed to the next layer (Hu & Weng, 2009). For this model, five layers with 7, 14, 7, 14, and 7 neurons respectively were used, defined based on tests carried out by the MapBiomás Fuego Brasil team and adopted as the baseline configuration for application in Colombia.

The classification process was implemented independently for each of the country's 99 classification regions (Section 4.2.2), training a specific model per region using the burned and unburned area samples collected for each one (Section 4.3), producing as a result a binary pixel-by-pixel classification — burned/unburned — on the annual Landsat quality mosaics described in Section 4.2.3. This regionalized approach allows the model to capture the spectral particularities of fire in each biome, without the country's ecological and climatic heterogeneity affecting classification accuracy. The following sections describe in detail the sampling strategy, the input bands, the architecture and training parameters, and the model's inference process.

4.4.1 Sampling

Analysts visually interpret Landsat images in Google Earth Engine and digitize polygons over burned and unburned areas. These polygons are rasterized and exported as GeoTIFF files at 30 m resolution. A set of training files covers one biome, sub-region, and satellite sensor combination.

4.4.2 Input bands

The four bands exported to the training files and used as model variables are raw **surface reflectance** values, not derived indices:

Tabla 5. Bands exported to the training files.

Band	Name	Wavelength
1	Red	0.64 - 0.67
2	Nir	0.85 - 0.88
3	Swir 1	1.57 - 1.65
4	Swir 2	2.11 - 2.29

These four bands contain the signal that the NBR compresses into a single number. The model learns the complete pattern directly from the raw values. A fifth band is added by the analyst during sample collection (1 = burned, 0 = unburned) and stored as the last band of each training file.

4.4.3 Data Preparation

Each TIFF file contains a raster image of $H \times W$ pixel dimensions and 5 bands (Red, NIR, SWIR1, SWIR2, and label). To feed the neural network, the spatial structure is flattened: each pixel becomes an independent row in a table of $N \times 5$ values, where $N = H \times W$. All files available for a given biome and region are concatenated into a single table before proceeding to the next step (see Figure 11).

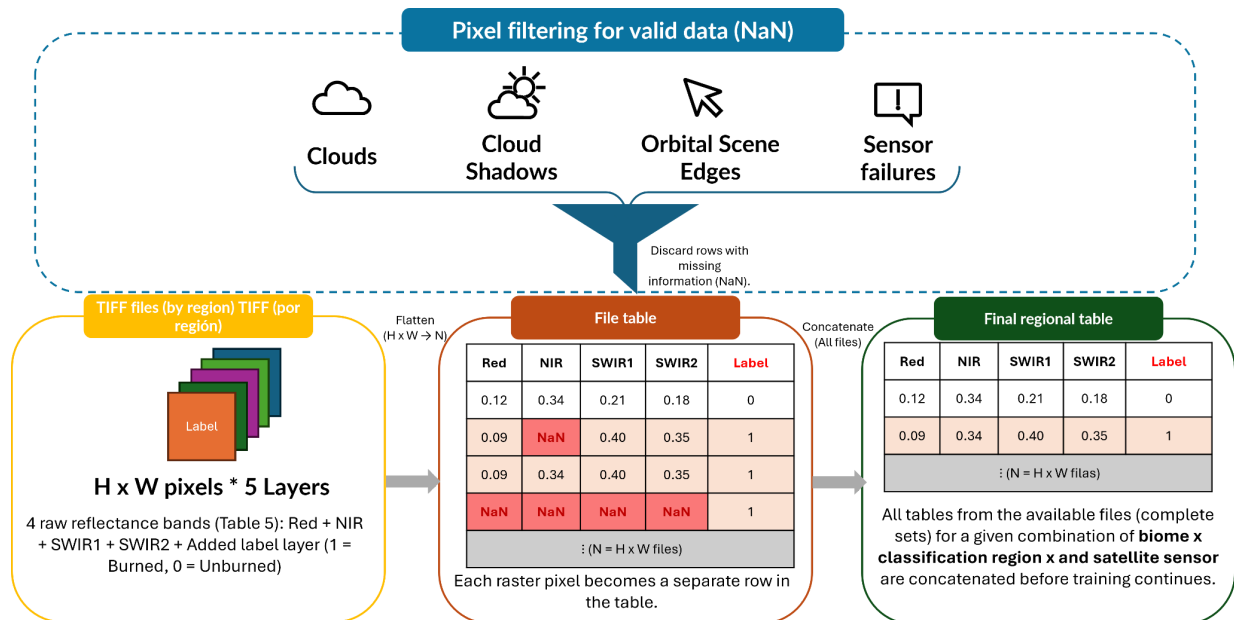


Figure 11. Data preparation: from raster to training table, flattening each TIFF file ($H \times W \times 5$) into an $N \times 5$ table, filtering out data with no valid values, and concatenating by region.

Landsat images contain pixels with no valid data in areas covered by clouds, shadows, orbital scene edges, or sensor failures. These pixels are identified as having at least one NaN value in any of their bands and are completely discarded from the table. Their inclusion in training would introduce noise and could bias the parameters learned by the model (Figure 11).

The data are randomly shuffled and split into a training set (70%) and a validation set (30%). The split is stratified: the proportion of burned and unburned pixels is kept the same in both subsets. This is especially important because, in most regions, burned pixels represent between 5% and 25% of the total. A non-stratified split could produce a validation set with very few examples of the burned class, making the evaluation metrics unrepresentative of the model's actual performance.

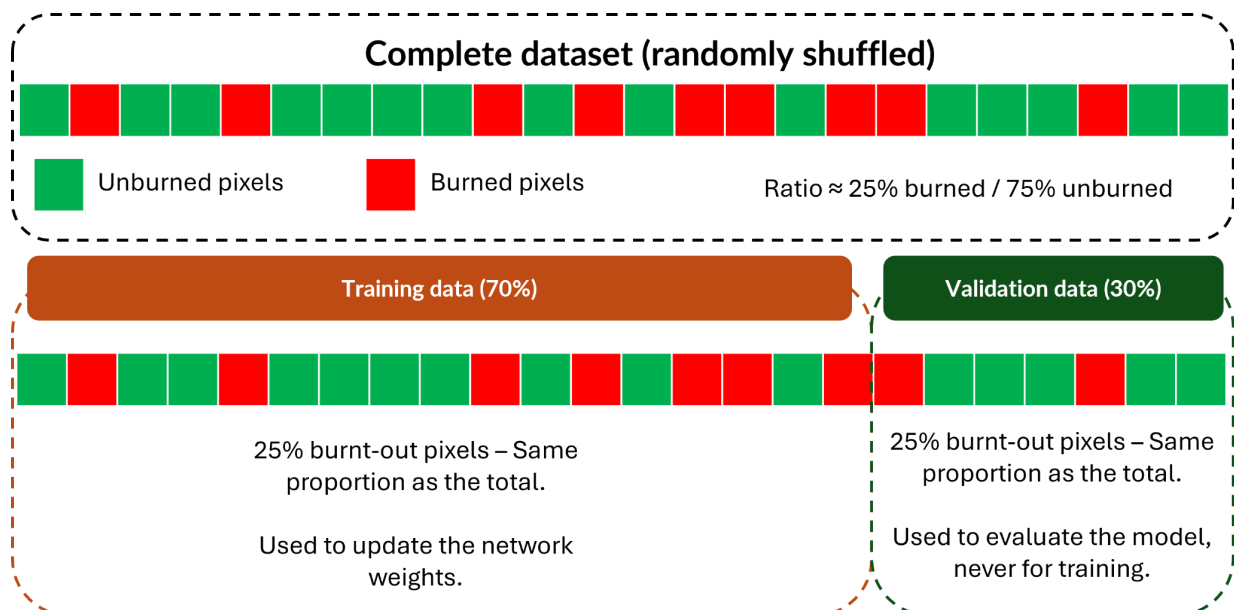


Figure 12. Stratified data split to preserve the proportion of burned and unburned pixels.

Each of the four spectral bands is centered at zero and scaled to unit variance using the mean and standard deviation calculated exclusively from the training set. This normalization ensures that all bands contribute equally to the learning process, regardless of their original reflectance ranges. The mean and standard deviation values are stored alongside the model and applied identically during inference, ensuring consistency between the training and prediction phases.

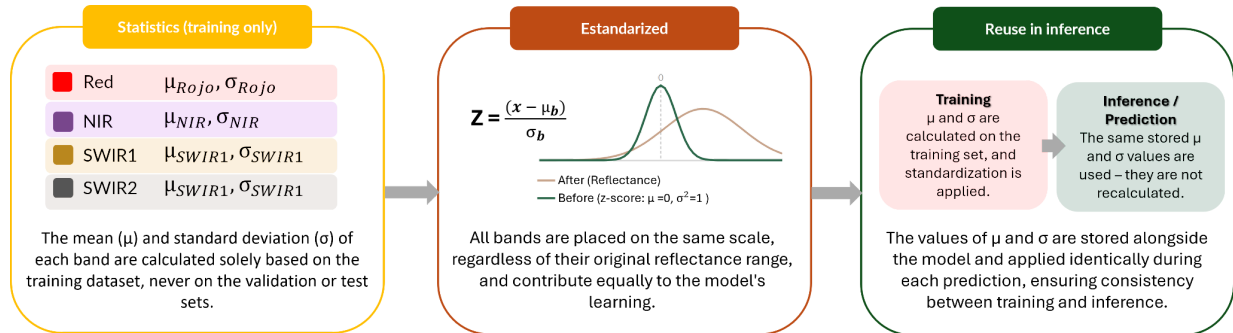


Figure 13. Standardization of spectral bands (z-score), centered on zero and scaled to unit variance, with statistics fixed on the training dataset

4.4.4 Model Architecture

The chosen architecture is a multilayer perceptron (MLP) with five hidden layers and a small number of parameters (~700 in total). This choice reflects the nature of the problem: the spectral signal of fire scars is sufficiently distinctive across the four bands to be separated by a piecewise linear classifier, without the need for convolutional layers or the incorporation of spatial information. The alternating layers of 7 and 14 neurons form an expansion-contraction pattern that allows the network to learn richer intermediate representations before compressing the information toward the final binary decision.

The ReLU (Rectified Linear Unit) activation function is applied in all hidden layers. This function introduces the nonlinearity necessary to learn complex decision boundaries in the spectral space, while avoiding the vanishing gradient problem that affects activations such as the sigmoid in deep networks.

The output layer produces two logits—one per class—whose argmax determines the final classification. No thresholding is applied: the class with the highest activation is directly assigned as the result.

It is important to note that the model does not learn the spatial shape of the scars. The geometric consistency of the burned areas in the final map is introduced exclusively through post-classification morphological filtering (see Section 2.3), not through the model's architecture.

The five-layer MLP architecture with a configuration of 7-14-7-14-7 neurons was adopted directly from the methodology developed by the MapBiomass Fuego Brasil team (Alencar et al., 2022; Arruda et al., 2021), where it proved sufficient to distinguish the spectral signatures of burned and unburned areas in Brazilian biomes. For Colombia, the technical team confirmed that this architecture maintains its discriminatory efficiency across different classification

regions, including spectrally challenging contexts such as Andean cloud forests and the Orinoquia savannas, where the NBR signal can be partially confused with seasonally bare soil or senescent vegetation. The low total number of parameters (~700) also facilitates rapid model convergence even with moderately sized training datasets, which is particularly relevant in regions with limited availability of cloud-free imagery.

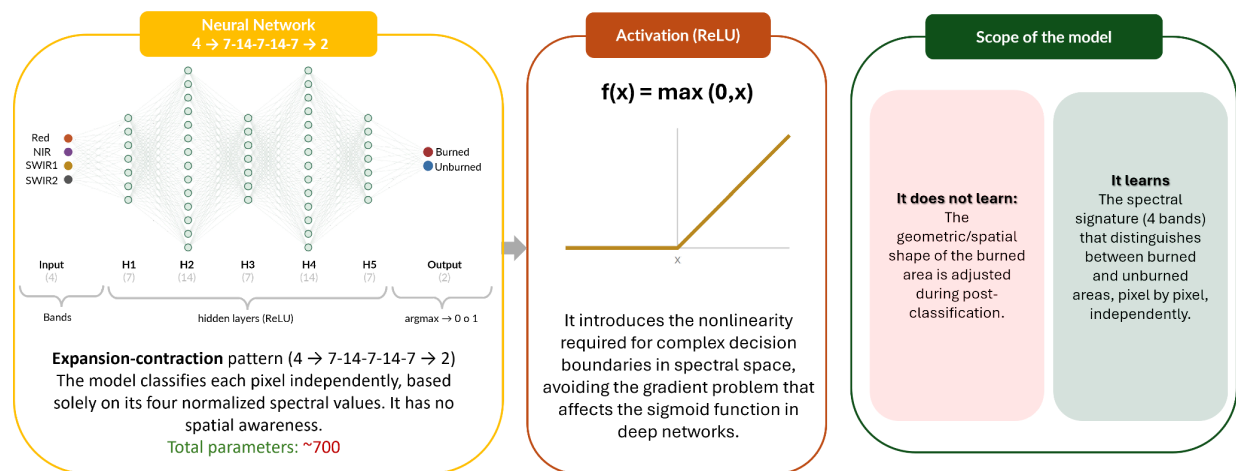


Figure 14. Architecture of the classification model (MLP): five-hidden-layer multi-layer perceptron — separation of the spectral signature of burned areas using the four bands.

4.4.5 Model Training

Training is performed using the Adam (Adaptive Moment Estimation) optimizer, which adaptively adjusts the learning rate for each parameter based on the first- and second-order moments of the gradient. This property makes it particularly efficient for problems with sparse or noisy gradients, such as remote sensing data with high spectral variability across scenes and sensors.

At each gradient step, a batch of 1,000 pixels is randomly selected from the training set. This stochastic gradient descent approach using mini-batches balances computational efficiency with convergence stability. Every 100 steps, accuracy is evaluated on the validation set, and a model checkpoint is saved, always preserving the weights that yield the best validation performance.

The process is repeated for 7,000 gradient steps, which is equivalent to approximately seven complete passes over a typical training set of one million pixels. The loss function used is softmax cross-entropy, which penalizes predictions with low confidence in the correct class and is standard for multiclass classification problems.

A separate model is trained for each region. This decision is justified by differences in vegetation phenology, fire regimes, and reflectance conditions across geographic regions: a single global model would tend to learn trade-offs between these differences, reducing its sensitivity in each specific context.

4.4.6 Training Results

A TensorFlow checkpoint file for each biome/region containing:

- Neural network weights (weight and bias matrices for the 5 layers)
- Normalization statistics (mean and standard deviation per band)

- Model hyperparameters (stored in an attached JSON file)

The checkpoint is self-contained: it includes both the model parameters and the normalization applied during training. This ensures that inference is reproducible without needing access to the original training data. Any new mosaic processed with this checkpoint will undergo exactly the same transformation that the model experienced during its training, which is a fundamental requirement for obtaining consistent predictions over time and across different satellite scenes.

Checkpoint files follow a naming convention that encodes the collection, region, and model version, facilitating their traceability and management in production environments with dozens of active models.

4.4.7 Inference - Input Data

The inference phase applies the trained models to new annual Landsat mosaics to produce burned area maps at 30-meter resolution. Unlike training, which is performed only once per collection, inference is repeated every year for each region as new mosaics are generated.

The input data is a cloud-free annual Landsat mosaic in Cloud-Optimized GeoTIFF (COG) format at 30-meter resolution, constructed using the same four bands used during training: RED, NIR, SWIR 1, and SWIR 2.

The mosaic is constructed by applying the same quality criteria used in the sample collection phase: for each pixel, the observation with the highest NBR value is selected from among all cloud-free images for that year. This approach ensures that the inference mosaic is spectrally consistent with the data on which the model was trained. The temporal coverage spans the entire year (January through December), integrating observations from Landsat 5, 7, 8, or 9 sensors depending on availability for each period.

It is critical that the bands of the inference mosaic be in the same spectral space as the training samples. Atmospheric corrections (USGS Collection 2, Level 2) are applied identically in both phases to ensure this consistency.

4.4.8 Scene-by-Scene Processing

The mosaic is processed in tiles that follow the Landsat orbital grid (path/row scenes). This avoids loading the entire country into memory at once.

Scene-by-scene processing addresses two practical needs. First, annual mosaics for large regions can contain tens of millions of pixels, making it infeasible to load them fully into GPU memory before classification. Second, the Landsat grid (path/row) is the natural organizational unit of the source data, and working at this scale facilitates error management and process resumption in the event of failures.

Each scene is cropped with a 100 m buffer relative to the orbital boundary to eliminate edge effects introduced by cloud masking and discontinuities between adjacent scenes. Once classified, the cropped image is merged with the other tiles through a mosaicking operation that gives priority to the first valid value in areas of overlap.

The normalization applied in step 3 uses exactly the same mean and standard deviation calculated on the training set and stored in the checkpoint. The inference mosaic does not

recompute these statistics, which ensures that the normalized values for the new year lie in the same space as the data the model saw during fitting.

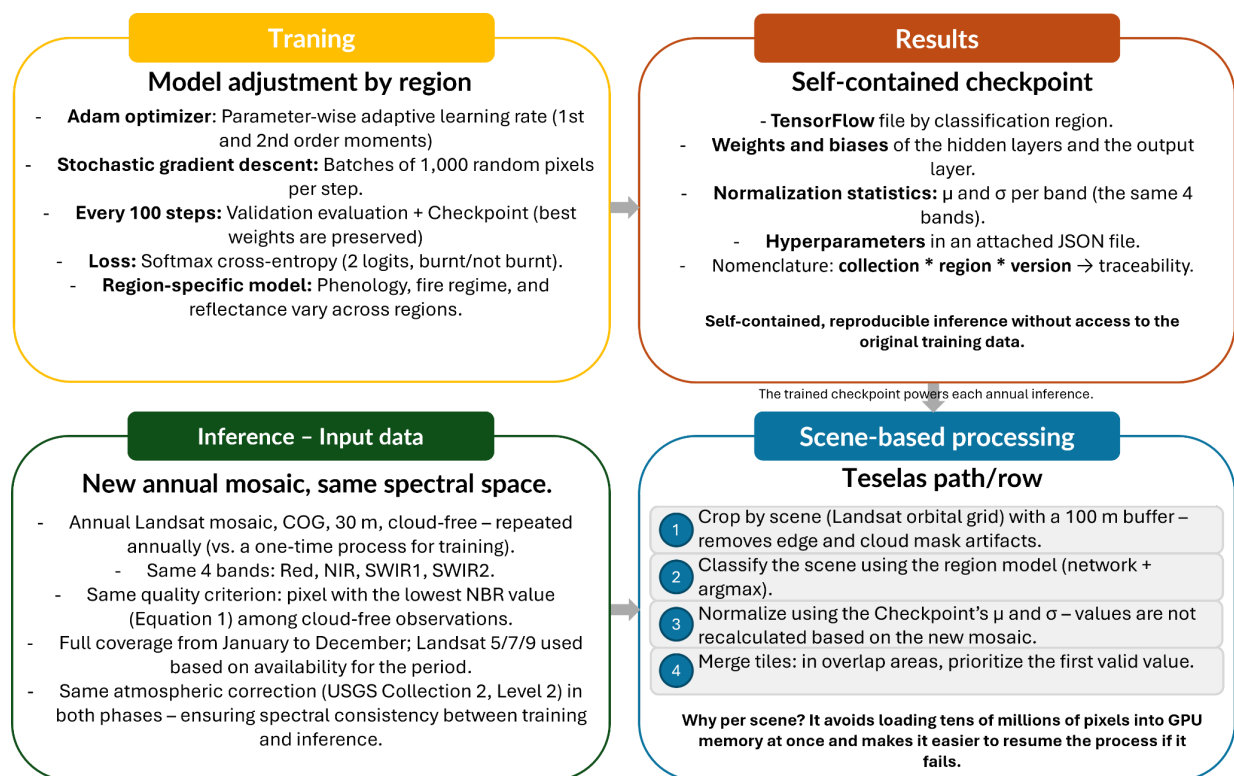


Figure 15. Model life cycle by region (from training to inference); this figure shows point 4.4.5 in yellow, point 4.4.6 in orange, point 4.4.7 in green, and point 4.4.8 in blue.

4.4.9 Inference Output

A single-band GeoTIFF file is generated per year and biome/region at 30 m resolution:

The output of the inference phase is a single-band GeoTIFF file per year and per region/biome, at 30 m spatial resolution, in which each pixel stores the class predicted by the Deep Learning model (1 = burned, 0 = unburned), derived directly from the argmax of the two output logits of the neural network described in Section 4.4.4. This output corresponds to the raw binary classification, prior to the application of the post-classification filters described in Section 4.5.

By default, the morphological opening-and-closing spatial filter described in Section 4.4.9 (2×2 and 4×4 pixel kernels, respectively) is applied to this output. These parameters can be adjusted by region when local conditions of landscape fragmentation or residual noise require it, subject to visual validation by the technical team.

4.5 Post-Classification

Because a pixel-by-pixel classification method is applied over an extensive 26-year time window, inconsistencies in the mapping are common (noise, salt-and-pepper effects, information gaps, and false positives from spectral confusion with non-combustible land covers). For this reason, a sequence of post-classification processes is applied: (1) thematic masking by land cover and land use, (2) a spatial filter that removes isolated pixels (applied

differently by region, as explained in 4.5.2), (3) a targeted manual correction tool for specific cases not resolved by the automatic filters, (4) a gap-filling filter that restores the geometric coherence of fire footprints, and (5) the extraction of the detection date for each burned pixel from the quality mosaic.

The assignment of MapBiomass Colombia (Collection 3) legend classes to each of the three decision levels is as follows:

4.5.1. Masking by Land Cover and Land Use

After classification with the Deep Learning model, thematic masking is applied to exclude from the burned area layer those land covers that, by their nature, cannot burn or for which vegetation fires are not plausible (for example, water bodies, rock outcrops, glaciers, and urban infrastructure), as well as those whose spectral signature can be confused with that of a recent fire footprint.

This procedure integrates MapBiomass Colombia's Collection 3 annual land cover and land use maps as a thematic reference mask (ImageCollection), defined independently for each of the country's classification regions and integrated into a single final version per year and region. For each region, a set of MapBiomass Colombia legend classes is defined to be reclassified as "no fire," following a three-level decision criterion:

Classes with recommended masking: systematic exclusion in all regions, as these are land covers that are by definition non-combustible or whose spectral signature is confused with a fire footprint.

Table 6. Classes with recommended masking.

Class (MapBiomass Colombia legend)	Type	Code
2. Non forest natural formation		10
2.3. Hypersaline tidal flat	Coverage	32
2.4. Rocky outcrop	Coverage	29
4. Non vegetated area		22
4.1. Beach, dune and sand spot	Coverage	23
4.2. Urban area	Use	24
4.3. Mining	Use	30
4.6. Solar panel farm	Use	75
5. Water		26
5.1. River, lake and ocean	Coverage/Use	33
5.2. Aquaculture	Use	31
5.3. Glacier	Coverage	34

Classes with masking at the technical team's discretion: based on a case-by-case evaluation by region and year, verifying the temporal stability of the land cover and the absence of evidence of actual burning.

Table 7. Classes with masking at the discretion of the professional responsible for each region.

Class (MapBiomias Colombia legend)	Type	Code
3. Farming		14
3.1. Forest plantation	Use	9
3.2. Palm oil	Use	35
3.3. Banana	Use	74
4. Non vegetated area		22
4.4. Other natural non vegetated area	Coverage	68
4.5. Other non Vegetated Areas	Use	25

Classes not recommended for masking: land covers in which fire is a documented ecological or productive process.

Table 8. Classes not recommended for masking.

Class (MapBiomias Colombia legend)	Type	Code
1. Forest		1
1.1. Forest formation	Coverage	3
1.2. Mangrove	Coverage	5
1.3. Bosque inundable	Coverage	6
1.4. Wooded sandbak vegetation	Coverage	49
2. Non forest natural formation		10
2.1. Wetland	Coverage	11
2.2. Grassland	Coverage	12
2.5. Herbaceous sandbank vegetation	Coverage	50
3. Farming		14
3.4. Mosaic of use	Use	21

It is the responsibility of each region's technical team to verify that the classes selected for masking remain stable over time (that is, that their land cover does not change) and show no evidence of burning within the time window analyzed, before applying the filter. Additionally, MapBiomias Colombia Collection 3's stable-water layers are incorporated, identifying pixels consistently classified as water bodies throughout the entire time series, further reinforcing the exclusion of false positives associated with this land cover.

4.5.2 Spatial Filter

The spatial filter is based on the "connectedPixelCount" function, which makes it possible to homogenize the classification by assigning scattered pixels the value of the predominant class

around them. Groups of connected pixels that do not reach a minimum area of 5 pixels (0.45 ha, at 30 m Landsat resolution) are reclassified, removing noise and unifying the mosaic's land covers.

The raw pixel-by-pixel classification contains two types of noise:

- **False positives:** isolated pixels marked as burned due to sensor artifacts or dark soil — removed by morphological opening.
- **Gaps:** small undetected areas within actual fire footprints — filled by morphological closing.

Morphological filtering is applied in two sequential steps to the binary image resulting from the classification.

Morphological opening (2×2 kernel). Opening is an erosion followed by a dilation using the same structuring element. Its net effect is to remove objects smaller than the kernel: pixels or groups of one or two pixels classified as burned but that are not part of a coherent burned area. These false positives mainly originate from dark bare soils, residual cloud shadows, and sensor radiometric calibration artifacts. The 2×2 kernel size (equivalent to 60×60 m) is conservative: it removes only the smallest isolated detections without affecting small-area fire footprints.

Morphological closing (4×4 kernel). Closing is a dilation followed by an erosion. Its effect is to fill discontinuities within burned regions: gaps of one to three pixels caused by residual unmasked clouds, spectral variability within the fire footprint, or areas with different post-fire vegetation behavior. The 4×4 pixel kernel (120×120 m) is calibrated to close these small gaps without merging burned areas that are genuinely independent.

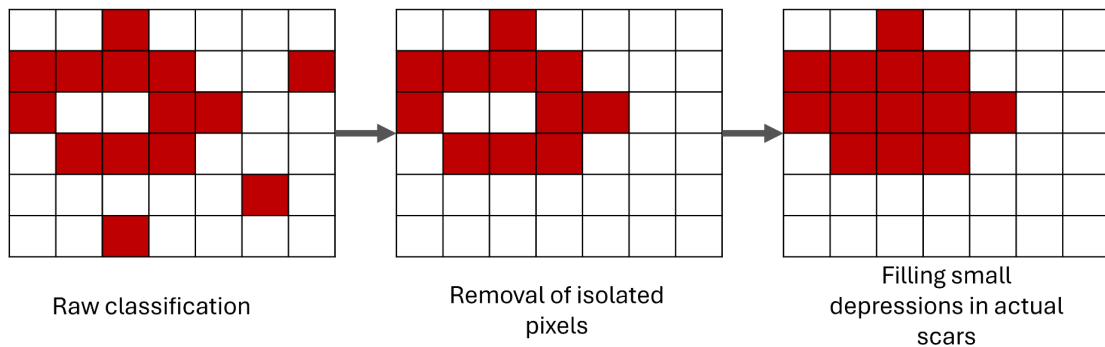
The choice to apply opening before closing (rather than the reverse) is deliberate: noise is removed first, before filling gaps, thereby preventing the opening step from removing real footprints that have already been thickened by the closing step.

This filter is not applied uniformly across the country: in the Amazon region it is deliberately omitted, in order to preserve the visibility of chagras (shifting polyculture plots that constitute a traditional food-security strategy of Indigenous communities), whose footprint is usually expressed as isolated or small-area pixels. For this reason, it is normal to find isolated burned-area pixels in the Amazon that would have been removed by the spatial filter in other regions.

4.5.3. Gap-Filling Filter (gapfill)

Finally, a gap-filling filter (gapfill) is applied, aimed at correcting small information gaps within fire footprints that would otherwise be coherent and continuous. These gaps usually originate from internal spectral variability of the fire footprint, residual clouds or shadows not removed during the construction of the annual mosaic, or differences in post-fire vegetation behavior within the same burned area. Empty areas that are completely surrounded by pixels classified as burned, and that do not exceed an area threshold defined by region, are filled and reclassified as burned, improving the geometric coherence of the final product without altering the actual total extent of the fire event.

Spatial Filter



Isolated groups are reclassified to the surrounding predominant class, while the large group is preserved.

Figure 15. Effect of applying the spatial filter and gap filling.

4.5.4. Targeted Manual Correction

In addition to the automatic filters described above, a targeted manual correction tool is available that allows specific polygons that have been incorrectly labeled as burned area due to classification errors to be reclassified as "no fire." This tool is used to correct localized aberrations in the annual mosaic, persistent cloud shadows not removed by quality masking, and outcrops or other surfaces with anomalous spectral signatures.

The correction is applied by manually drawing the polygons corresponding to the areas to be excluded, and associating each polygon with a time period (start year and end year) during which the mask should be applied; in this way, the remapping affects only the years in which the error was identified, without altering the classification of prior or subsequent years in which fire detection is in fact valid for that same location.

4.5.5. Detection Date Extraction

Once classification is complete and the masking, spatial, targeted manual correction, and gap-filling filters have been applied, the temporal information for each pixel classified as burned is retrieved from the annual minimum-NBR mosaic (Equation 1, Section 4.2.3.1). Since each pixel of the quality mosaic retains the exact date of the observation that generated the minimum NBR value, this date is assigned directly to the pixel classified as burned area, making it possible to identify the month (and, when the availability of cloud-free scenes allows it, the approximate day) on which the fire footprint was detected. This procedure underpins the "date per pixel" output product described in Section 4.6.

4.6. Output Products

Based on the burned area classification (Section 4.4) and the post-classification processes that refine its geometric and thematic quality (Section 4.5), the output products of MapBiomass Fuego Colombia Collection 1.0 are generated. All of them share the same spatial resolution (30 m) and are derived from a single base layer: the annual burned area map (4.6.1.1), to which the corresponding land cover and land use class from MapBiomass Colombia Collection 3 is attributed. From this base layer, five additional sub-products are generated, grouped into two categories: Data by year: Monthly burned area (4.6.1.2), Burn scar size (4.6.1.3); and data by period: cumulative burned area (4.6.2.1), burned area frequency (4.6.2.2), year of the last fire (4.6.2.3) – each aimed at answering a different analytical question about the country's fire regime: when it occurred, how often it recurs, how much total surface it affects, how much time has passed since the last event, and how large individual fire footprints are. These products are publicly available on the [MapBiomass Fuego Colombia web platform](#).

4.6.1 Data Grouped by Year

This group brings together the products that retain the classification's annual temporal resolution, describing each fire event within the specific year in which it occurred: the month in which it was detected, and the burn scar size it produced, both derived directly from the annual burned area base layer.

4.6.1.1 Annual Burned Area

The annual burned area dataset comprises maps identifying the pixels classified as burned for each year within the 2000–2025 period. Each pixel is assigned the corresponding land cover and land use (LULC) class from MapBiomass Colombia Collection 3 for the year in which the fire occurred. This product constitutes the base from which the remaining sub-products in Section 4.6 are derived, and allows tracking of the evolution of fire incidence over the time series across the different land covers and uses.

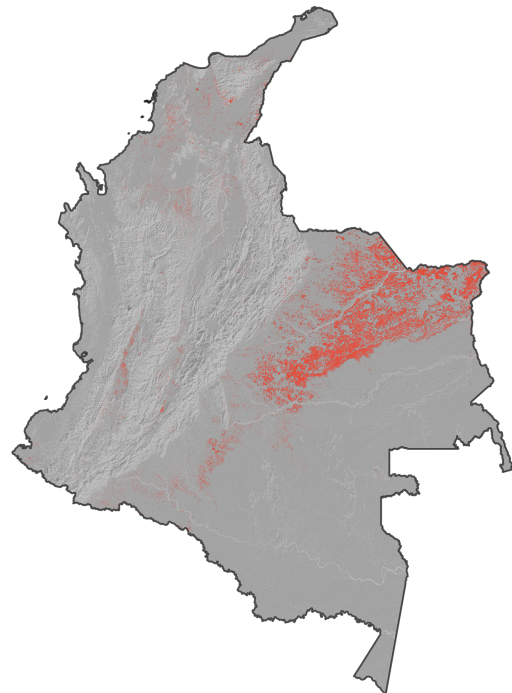


Figure 19.. Mapa de extensión de de quema (2025)

4.6.1.2 Monthly Burned Area

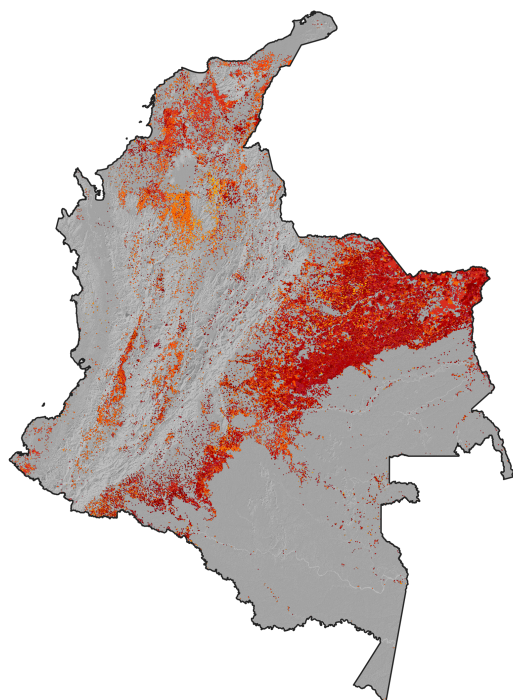


Figure 18. Monthly burned area map (2025)

The monthly burned area dataset indicates the specific month (1 to 12) in which each fire event occurred, for each pixel classified as burned in the classified year within the 2000–2025 period. The temporal attribution is derived from the date of the Landsat scene in which the pixel showed its minimum NBR value within the Quality Mosaic (Section 4.2.3.1). This product allows detailed analysis of fire seasonality across the country's regions — for example, contrasting the concentration of burning in the December–March quarter characteristic of the Orinoquía, the Amazon, and the Caribbean against the inverted calendar observed in the Pacific (Section 4.3.6) — and serves as an input for planning regional prevention and control strategies that are differentiated in time.

4.6.1.3 Burn Scar Size

This dataset records annual information on burn scar size for each year in the 2000–2025 period, classifying scars into intervals based on their surface area in hectares. Burn scar size is defined as a cluster of spatially connected burned pixels within the same year. This categorization facilitates characterizing fires by magnitude and spatial distribution, identifying large-magnitude events ($\geq 5,000$ ha) concentrated almost exclusively in the Orinoquía and, to a lesser extent, in the Amazon.

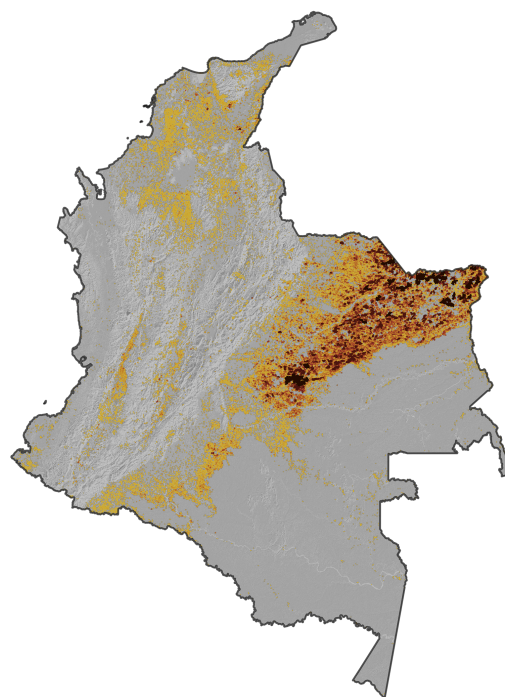


Figure 19. Burn scar size map (2025)

4.6.2 Data Grouped by Period

This group brings together the products that summarize fire behavior across the entire time series (2000–2025), rather than describing individual events: the total surface affected at least once (4.6.2.1), the number of times each pixel has burned (4.6.2.2), and the time elapsed since the most recent event (4.6.2.3).

4.6.2.1 Cumulative Burned Area

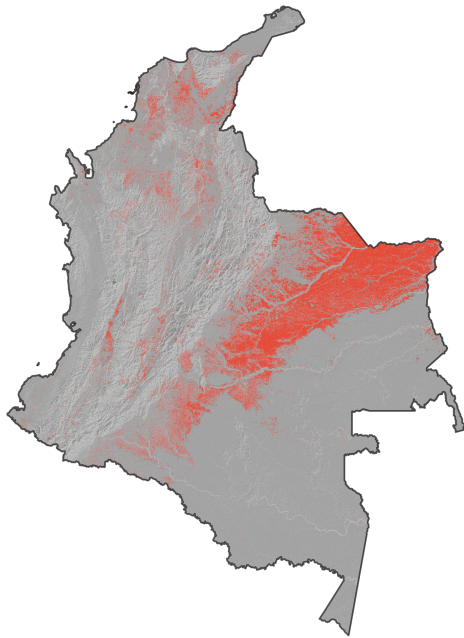


Figure 20. Cumulative burned area map for the 2000–2025 period.

Cumulative burned surface represents the total area affected by at least one fire event during the periods analyzed. This layer is generated incrementally, ensuring that each pixel is counted only once, regardless of the number of fires recorded on it throughout the time series. By cross-referencing this information with the land cover and land use (LULC) classification from the most recent year of the MapBiomass Collection, it is possible to characterize and assess the magnitude of the cumulative impact of fire on the territory's different land covers.

4.6.2.2 Burned Area Frequency

This product quantifies how many times each pixel was classified as burned over the entire series (2000–2025), summarized in a single map of discrete classes (1, 2, 3... up to the maximum number of years with recorded fire for a single pixel). Each pixel also retains the Collection 3 land cover and land use class corresponding to the most recent year of the series, making it possible to cross-reference burn recurrence with land cover type and prioritize high-recurrence areas for fire management and prevention. This is the product that reveals extreme recurrence patterns, in which some Orinoquía savannas accumulate twenty or more fire events over the 26 years of the series.

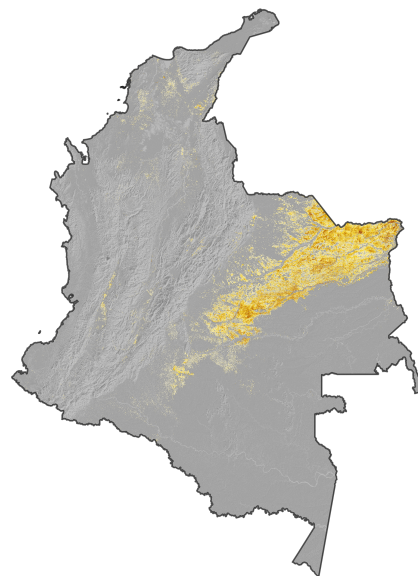
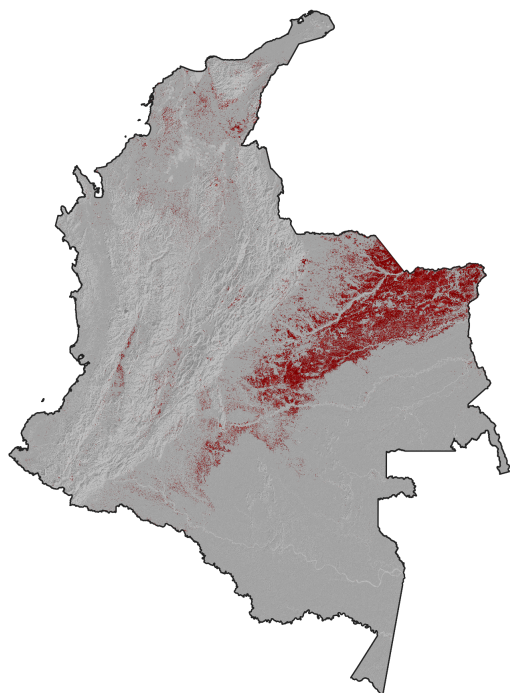


Figure 21. Burned area frequency map for the 2000–2025 period.

4.6.2.3 Year of the Last Fire



This dataset records, for each pixel, the most recent year in which a fire event was detected within the 2000–2025 period, derived directly from the annual burned area masks. This product makes it possible to estimate the time elapsed since the last burn at any point in the territory, and is a direct input for future fire return-interval analyses, as well as for identifying areas that have not recently experienced fire and that may have greater accumulation of vegetative fuel.

Figure 22. Map of the most recent burned area record for the 2000–2025 period.

5. LIMITATIONS AND ARTIFACTS

Like any detection product derived from satellite imagery, MapBiomass Fuego Colombia data are subject to methodological and technical limitations that affect their interpretation and use. This section transparently documents the main sources of uncertainty and known artifacts of the product, organized according to the stage of the process in which they originate: the characteristics of the input data (Landsat imagery), the methodological criterion for selecting the annual mosaic (minimum NBR), the design decisions of the classification model and its application by region and scene, and the dependence on external inputs such as land cover and land use data. The purpose is not to point out weaknesses of the product in the abstract, but to give users the elements needed to correctly interpret its results, recognize the valid limits of its application, and avoid erroneous conclusions arising from inappropriate use of the data.

5.1. Limitations of the Input Data

The Landsat 7 "SLC-off effect" — the failure of the Scan Line Corrector since 2003, which introduces wedge-shaped strips of missing data (approximately 22% of the scene) — is a well-known artifact in remote sensing and directly affects the L5/L7 window used in this Collection (2000–2012). It interacts with the NaN filtering described in Section 4.4.3, since scan-line gaps generate additional pixels with no valid data that are excluded from both the training tables and the annual mosaics, and it is documented here as an explicit limitation of the input data. Cloud-free image availability is also uneven across regions, which limits the temporal precision of the minimum-NBR selection in areas of chronic cloud cover, such as the Pacific and the Amazon foothills.

The mosaic quality map is incorporated precisely to characterize this spatial and temporal variability in Landsat data availability. Its purpose is to indicate, for each pixel and year, how many valid, cloud-free observations were available for building the mosaic. It therefore does not directly represent the accuracy of the burned area classification, but rather the amount of observational information available for selecting the annual NBR value. High values indicate a greater number of potentially useful observations, while low values identify areas and years in which the estimate depends on a more limited set of images and, consequently, there is greater uncertainty about the temporal timing of the selected observation.

This map was built from the Landsat 5, 7, 8, and 9 imagery available for each year. For each acquisition, pixels affected by missing data, clouds, cloud shadows, snow, cirrus (where applicable), and radiometric saturation are identified and excluded, using the quality-control bands of the Landsat image collections. Observations that pass these filters are counted cumulatively for each pixel, so that the final value corresponds to the number of valid, cloud-free observations available during that year. Processing is further restricted to the PATH/ROW grids used in mosaic generation, making it possible to spatially represent differences in data availability associated both with atmospheric conditions and with the acquisition characteristics of the different sensors.

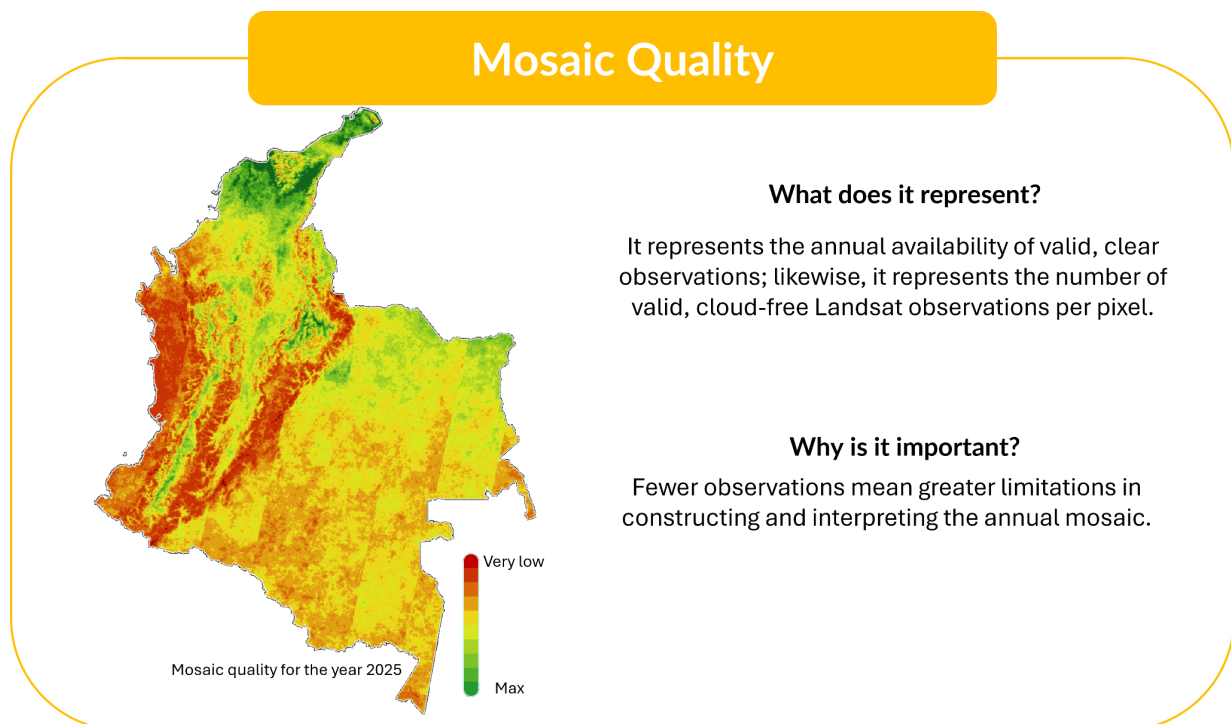


Figure 23. Representation of the quality mosaic analysis, also available on the MapBiomass Colombia platform – fire module.

In this regard, for the years 2002, 2005, and 2007 – corresponding to Path-Rows 6-56 and 6-57, which register the mosaics with the lowest data availability according to the mosaic quality map – complementary data from the MODIS sensor were incorporated. This inclusion allows the user to identify that, for these specific year-and-scene combinations, information was not captured by Landsat due to the limited availability of cloud-free imagery, and that this gap was filled using a different data source. However, caution is recommended when using these complementary data, since MODIS has a spatial resolution different from that of Landsat, as it

comes from a different sensor, and its integration should therefore not be interpreted as equivalent in geometric detail to the rest of the product.

5.2. Limitations Inherent to the Methodological Criterion (Minimum NBR)

The "single minimum NBR per year" criterion implicitly assumes one dominant burn per pixel-year; if the same pixel burns more than once within the year (common in pasture-management burning), the mosaic only captures the date of the lowest-NBR event, underestimating the true intra-annual burn frequency. It is also worth documenting that this same criterion deliberately equates "burned" with "lowest NBR," which can generate false positives if some cause unrelated to fire produces a drop in NBR (for example, defoliation that leaves bare soil exposed).

5.3. Limitations of Processing by Region and by Scene

This subsection brings together the limitations that follow directly from methodological decisions already documented: the training of independent models by region (4.4.5), the merging of tiles in scene-by-scene processing (4.4.8), and the differentiated masking and spatial-filtering criteria (4.5.1, 4.5.2).

- **Edge effects between classification regions.** Since an independent model is trained for each classification region (4.4.5), discontinuities are to be expected at the boundaries between adjacent regions, where the same land cover may be classified differently on each side of the boundary.
- **Edge effects between Landsat scenes.** Merging tiles using the first-valid-value priority criterion (4.4.8) can introduce visible artifacts at scene (path/row) boundaries when there are date or illumination differences between adjacent scenes.
- **Deliberate heterogeneity between regions.** The spatial filter is not applied in the Amazon region, in order to preserve the visibility of chagras (4.5.2); as a result, this product retains, by design, greater residual spatial noise in that region than in the rest of the country. This difference is not an error, but it must be explicitly documented so that it is not interpreted as a quality defect.
- **Subjectivity in discretionary masking classes.** The intermediate decision level of thematic masking (4.5.1) depends on case-by-case verification by each region's technical team; this verification can introduce inconsistencies between regions or between years.
- **Interpretive ambiguity in unmasked classes.** By not masking herbaceous formation, agriculture-and/or-pasture mosaic, and mining (in order to capture fire used as a management tool), the final product integrates both management fire and unplanned fire into a single layer, without distinguishing between the two. This is an interpretive limitation that must be taken into account before using these data to attribute causality to the recorded fire events.

6. REFERENCES

Alencar, A. A. C., Arruda, V. L. S., 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., 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>
- Alencar, A., Conciani, D., Reis Rosa, E., Vélez Martin, E., Andrade, G., Hasenack, H., Moraes Martenexen, L., Fernandes Márcio Ribeiro, J., Shimbo, J., Rosa, M., Dias, M., Crusco, N., Santos, N., Coelho Monteiro, N., Galano Duverger, S., Azevedo, T., Piontekowski, V., Arruda, V., Vieira, W., & da Franca Rocha, W. (2026). *Algorithm Theoretical Basis Document (ATBD) MapBiomass Fire Brasil* [Documento técnico].
- Armenteras, D., González, T. M., Vargas, J. O., Meza Elizalde, M. C., & Oliveras, I. (2020). Incendios en ecosistemas del norte de Suramérica: Avances en la ecología del fuego tropical en Colombia, Ecuador y Perú. *Caldasia*, 42(1), 1-16. <https://doi.org/10.15446/caldasia.v42n1.77353>
- Armenteras, D., Rodríguez, N., & Retana, J. (2013). Landscape Dynamics in Northwestern Amazonia: An Assessment of Pastures, Fire and Illicit Crops as Drivers of Tropical Deforestation. *PLOS ONE*, 8(1), e54310. <https://doi.org/10.1371/journal.pone.0054310>
- Armenteras, D., Romero, M., & Galindo, G. (2005). *Vegetation fire in the savannas of the Llanos Orientales of Colombia*. 17(4).
- 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>
- Bond, W. J., & Keeley, J. E. (2005). Fire as a global 'herbivore': The ecology and evolution of flammable ecosystems. *Trends in Ecology & Evolution*, 20(7), 387-394. <https://doi.org/10.1016/j.tree.2005.04.025>
- Bowman, D. M. J. S., Balch, J. K., Artaxo, P., Bond, W. J., Carlson, J. M., Cochrane, M. A., D'Antonio, C. M., DeFries, R. S., Doyle, J. C., Harrison, S. P., Johnston, F. H., Keeley, J. E., Krawchuk, M. A., Kull, C. A., Marston, J. B., Moritz, M. A., Prentice, I. C., Roos, C. I., Scott, A. C., ... Pyne, S. J. (2009). Fire in the Earth System. *Science*, 324(5926), 481-484. <https://doi.org/10.1126/science.1163886>
- Certini, G. (2005). Effects of fire on properties of forest soils: A review. *Oecologia*, 143(1), 1-10. <https://doi.org/10.1007/s00442-004-1788-8>
- Chuvieco, E., Lizundia-Loiola, J., Pettinari, M. L., Ramo, R., Padilla, M., Tansey, K., Mouillot, F., Laurent, P., Storm, T., Heil, A., & Plummer, S. (2018). Generation and analysis of a new global burned area product based on MODIS 250\,m reflectance bands and thermal anomalies. *Earth System Science Data*, 10(4), 2015-2031. <https://doi.org/10.5194/essd-10-2015-2018>

- Chuvieco, E., Mouillot, F., van der Werf, G. R., San Miguel, J., Tanase, M., Koutsias, N., García, M., Yebra, M., Padilla, M., Gitas, I., Heil, A., Hawbaker, T. J., & Giglio, L. (2019). Historical background and current developments for mapping burned area from satellite Earth observation. *Remote Sensing of Environment*, 225, 45-64. <https://doi.org/10.1016/j.rse.2019.02.013>
- Dale, V. H., Joyce, L. A., McNulty, S., Neilson, R. P., Ayres, M. P., Flannigan, M. D., Hanson, P. J., Irland, L. C., Lugo, A. E., Peterson, C. J., Simberloff, D., Swanson, F. J., Stocks, B. J., & Wotton, B. M. (2001). Climate Change and Forest Disturbances: Climate change can affect forests by altering the frequency, intensity, duration, and timing of fire, drought, introduced species, insect and pathogen outbreaks, hurricanes, windstorms, ice storms, or landslides. *BioScience*, 51(9), 723-734. [https://doi.org/10.1641/0006-3568\(2001\)051%5B0723:CCAFD%5D2.0.CO;2](https://doi.org/10.1641/0006-3568(2001)051%5B0723:CCAFD%5D2.0.CO;2)
- Etter, A., Andrade, A., Saavedra, K., Amaya, P., & Arévalo, P. (2017). *Estado de los Ecosistemas Colombianos: Una aplicación de la metodología de la Lista Roja de Ecosistemas* [Informe Final]. Pontificia Universidad Javeriana y Conservación Internacional-Colombia.
- Falk, D. A., Miller, C., McKenzie, D., & Black, A. E. (2007). Cross-Scale Analysis of Fire Regimes. *Ecosystems*, 10(5), 809-823. <https://doi.org/10.1007/s10021-007-9070-7>
- FGA, F. G. A. (2025). *Documento de Bases Teóricas de Algoritmo (ATDB) MapBiomás Colombia Colección 3* [Documento técnico].
- Fidelis, A., & Pivello, V. (2025). *Fire in the South American Ecosystems*. Springer Cham. <https://doi.org/https://doi.org/10.1007/978-3-031-89372-8>
- Giglio, L., Boschetti, L., Roy, D. P., Hall, J. V., Zubkova, M., Humber, M., Huang, H., & Oles, V. (2025). The NASA VIIRS burned area product, global validation, and intercomparison with the NASA MODIS burned area product. *Remote Sensing of Environment*, 331, 115006. <https://doi.org/10.1016/j.rse.2025.115006>
- Giglio, L., Boschetti, L., Roy, D. P., Humber, M. L., & Justice, C. O. (2018). The Collection 6 MODIS burned area mapping algorithm and product. *Remote Sensing of Environment*, 217, 72-85. <https://doi.org/10.1016/j.rse.2018.08.005>
- Gonzalez, P., Neilson, R. P., Lenihan, J. M., & Drapek, R. J. (2010). Global patterns in the vulnerability of ecosystems to vegetation shifts due to climate change. *Global Ecology and Biogeography*, 19(6), 755-768. <https://doi.org/10.1111/j.1466-8238.2010.00558.x>
- Hardesty, J., Myers, R., & Fulks, W. (2005). Fire, Ecosystems, and People: A Preliminary Assessment of Fire as a Global Conservation Issue. *The George Wright Forum*, 22(4), 78-87. JSTOR.
- Hu, X., & Weng, Q. (2009). Estimating impervious surfaces from medium spatial resolution imagery using the self-organizing map and multi-layer perceptron neural networks.

- Remote Sensing of Environment*, 113(10), 2089-2102.
<https://doi.org/10.1016/j.rse.2009.05.014>
- IDEAM, I. de H., Meteorología y Estudios Ambientales. (s.f.). *Incendios de la cobertura vegetal. Instituto de Hidrología, Meteorología y Estudios Ambientales*.
- IDEAM, I. de H., Meteorología y Estudios Ambientales, Instituto Humboldt, I. de I. de R. B. A. von H., INVEMAR, I. de I. M. y C. J. B. V. de A., & IGAC, I. G. A. C. (2017). *Mapa de ecosistemas continentales, costeros y marinos de Colombia (MEC)* [Memoria técnica]. escala 1:100.000.
- Key, C. H., & Benson, N. C. (2006). *Landscape Assessment: Ground measure of severity, the Composite Burn Index; and Remote sensing of severity, the Normalized Burn Ratio* (Report RMRS-GTR-164-CD: LA 1-51). USGS Publications Warehouse.
<https://pubs.usgs.gov/publication/2002085>
- 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>
- Mouillot, F., & Field, C. B. (2005). Fire history and the global carbon budget: A 1°× 1° fire history reconstruction for the 20th century. *Global Change Biology*, 11(3), 398-420.
<https://doi.org/10.1111/j.1365-2486.2005.00920.x>
- Pausas, J. G., & Ribeiro, E. (2017). Fire and plant diversity at the global scale. *Global Ecology and Biogeography*, 26(8), 889-897. <https://doi.org/10.1111/geb.12596>
- PNN, P. N. N. de C. (2022). *Unidades biogeográficas de Colombia a escala 1:100 000* [Dataset].
- Rangel-Ch, O., & Suárez-M, C. (2022). *Mapa de vegetación natural de Colombia* [Memoria técnica]. Ministerio de Ambiente y Desarrollo Sostenible.
- Roces-Díaz, J. V., Santín, C., Martínez-Vilalta, J., & Doerr, S. H. (2022). A global synthesis of fire effects on ecosystem services of forests and woodlands. *Frontiers in Ecology and the Environment*, 20(3), 170-178. <https://doi.org/10.1002/fee.2349>
- Seidl, R., Thom, D., Kautz, M., Martin-Benito, D., Peltoniemi, M., Vacchiano, G., Wild, J., Ascoli, D., Petr, M., Honkaniemi, J., Lexer, M. J., Trotsiuk, V., Mairota, P., Svoboda, M., Fabrika, M., Nagel, T. A., & Reyer, C. P. O. (2017). Forest disturbances under climate change. *Nature Climate Change*, 7(6), 395-402. <https://doi.org/10.1038/nclimate3303>
- Shakesby, R. A., & Doerr, S. H. (2006). Wildfire as a hydrological and geomorphological agent. *Earth-Science Reviews*, 74(3), 269-307. <https://doi.org/10.1016/j.earscirev.2005.10.006>
- van der Werf, G. R., Randerson, J. T., Giglio, L., van Leeuwen, T. T., Chen, Y., Rogers, B. M., Mu, M., van Marle, M. J. E., Morton, D. C., Collatz, G. J., Yokelson, R. J., & Kasibhatla, P. S. (2017). Global fire emissions estimates during 1997–2016. *Earth System Science Data*, 9(2), 697-720. <https://doi.org/10.5194/essd-9-697-2017>
- White, P. S., & Pickett, S. T. A. (1985). Chapter 1—Natural Disturbance and Patch Dynamics: An

Introduction. En S. T. A. Pickett & P. S. White (Eds.), *The Ecology of Natural Disturbance and Patch Dynamics* (pp. 3-13). Academic Press.

<https://doi.org/10.1016/B978-0-12-554520-4.50006-X>

WWF, W. W. F. (2004). *Ecorregiones Globales (terrestres)* [Dataset].