

MAPBIOMAS
INDONESIA | FIRE

Algorithm Theoretical Basis Document (ATBD)

MapBiomass Fire

Collection 2.0

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1. Introduction

1.1. Overview of MapBiomias Fire

This document presents the theoretical framework, conceptual basis, and methodological procedures used to generate burned area maps for Indonesia covering the period 2000–2024 under MapBiomias Fire Collection 2.0.

The MapBiomias Fire project released its first annual collection in 2024, mapping burned areas from 2013 to 2023. Collection 2.0, released in 2025, extends the time series to cover 2000–2024.

This collection applies a more robust and automated approach compared to semi-automatic techniques commonly used in fire mapping in Indonesia. Using Landsat satellite imagery with 30-meter spatial resolution, the mapping workflow was refined to enable comprehensive coverage of Indonesia’s diverse landscapes.

Collaboration among institutions within the MapBiomias network has played a crucial role in improving machine learning algorithms, particularly deep learning approaches. These methods are implemented on cloud-based platforms such as Google Earth Engine (GEE) and Google Cloud Storage, which provide large-scale computational capacity for efficient processing of extensive datasets.

The fire classification process is structured regionally, based on Indonesia’s major island groups, to accommodate differences in fire characteristics across regions. Fire and non-fire samples were collected to train the algorithm and were complemented by reference datasets such as the MODIS Burned Area product (MCD64A1, 500 m resolution).

MapBiomias Fire Indonesia Collection 2.0 provides:

- Annual and monthly burned area maps (2000–2024)
- Burned area frequency maps
- Cumulative burned area maps (2000–2024)
- Burned area by Land Use and Land Cover class (MapBiomias Collection 4)

1.2. How is the MapBiomias Fire Organized?

MapBiomias is a multi-institutional initiative coordinated by the Climate Observatory (a Brazilian NGO network focused on climate change). The initiative brings together NGOs, universities, research institutions, and technology companies. For MapBiomias Fire, IPAM initially developed the technological and operational framework, which was subsequently adapted by the MapBiomias Fire Indonesia team. The Indonesian team conducts sampling, evaluation, and refinement of burned area mapping. The MapBiomias Indonesia network includes partner organizations across the regions: HAKA (Hutan Alam dan Lingkungan Aceh), HaKI (Hutan Kita Institute), Genesis Bengkulu in Sumatra; Sampan Kalimantan, Green of Borneo, Save Our Borneo in Borneo; Auriga Nusantara, Woods & Wayside International in Java, Bali, and Moluccas; Komiu in Sulawesi; and Jerat Papua, also Mnuqwar in Papua. The geospatial technology company *Ecostage* is responsible for backend infrastructure, dashboards, website management, and front-end development.

1.3. Historical Perspective: Existing Fire Mapping Products

Only a limited number of global products map burned areas at large scales with high temporal frequency (e.g., every two days). One example is the MODIS MCD64A1 Collection 6 burned area product (500 m resolution) provided by NASA (Giglio et al., 2016), which was used as a reference dataset in this study. We also used the Global Annual Burned Area Map (GABAM) at 30 m resolution (Long et al., 2019), which maps annual burned areas globally using Landsat imagery processed in Google Earth Engine. Another key reference dataset is the burned area product published by Indonesia's Ministry of Environment and Forestry (KLHK) for 2015–2024, generated using Landsat imagery through a semi-automatic approach.

These existing burned area datasets provide important benchmarks for assessing and improving the accuracy of MapBiomias Fire outputs, contributing to a comprehensive understanding of burned area dynamics in Indonesia.

2. Methodology

We used the complete Landsat 5, 7, and 8 Surface Reflectance collections and a Deep Neural Network (DNN) model to detect and map burned areas regionally between January 2000 and December 2024.

The DNN model applies artificial intelligence and machine learning algorithms to perform deep learning classification of complex phenomena, producing improved mapping performance (Langford et al., 2018).

Due to limited image availability in 2000 and 2012, Landsat 5 and Landsat 7 imagery were combined for those years. Landsat 8 imagery was used for 2013–2024.

Landsat 5, 7, and 8 imagery was processed in GEE to produce annual Landsat mosaics, which were used to aggregate spectral values from fires and non-fires, serving as training examples for model classification. The training samples and annual mosaics were then exported to Google Drive, where they were processed using a DNN model on a local server. The resulting map showed burned areas from 2000 to 2024.

The image processing and classification procedure for burned areas in Indonesia follows six steps:

- (1) Defining regions: Indonesia is divided into seven regions for processing to improve classification accuracy.
- (2) Construction of annual Landsat imagery: High-quality annual mosaics are generated from Landsat imagery as the dataset used in classification.
- (3) Training sample collection: Spectral values of fire and non-fire events are collected from annual Landsat image mosaics as training samples.
- (4) Training and developing a fire classification model using a DNN prediction model: The DNN model is trained using the collected samples and annual imagery from a local server.
- (5) Post-classification: The burned area classification results are masked and spatial filters are applied to improve accuracy and reduce classification errors.
- (6) Evaluation and validation of fire classification results using visual observation. The classification results are validated using reference data. This validation involves visually checking the burned area map to ensure the accuracy of the data.

Our approach combines deep learning capabilities with comprehensive satellite data, enabling the creation of detailed and reliable maps of burned areas in Indonesia, as illustrated in Figure 1.

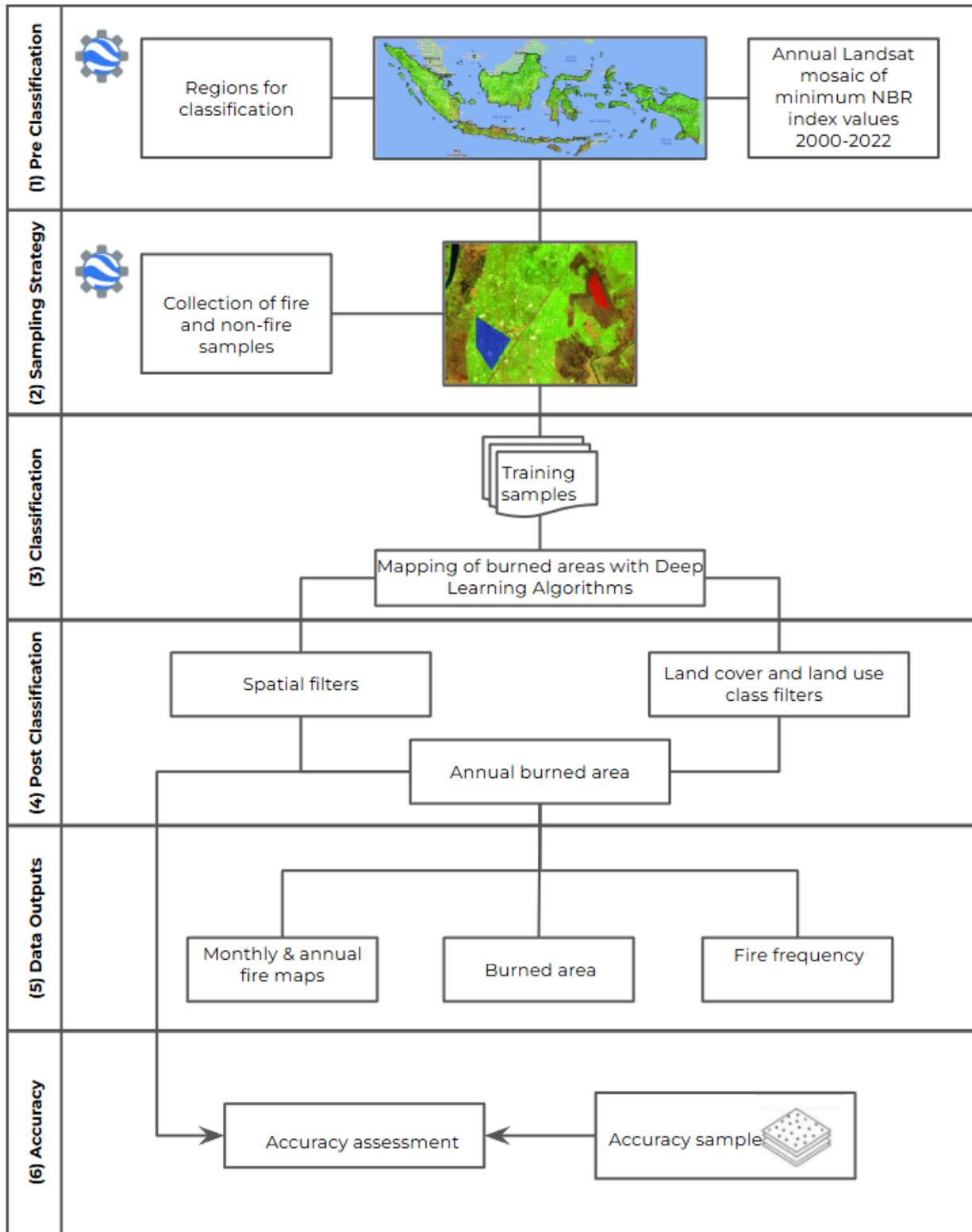


Figure 1. MapBiomass Fire Indonesia Collection 1.0 fire classification method in flowchart

2.1 Definition of Region

Given the differences in fire characteristics and spectral values due to climatic conditions and land cover and use, we combined edaphic and morphoclimatic factor data with annual maps from MapBiomas Land Use & Land Cover 4.0 (Figure 2). We also considered the zoning of Indonesia's major islands. This process resulted in seven regional classifications, addressing regional patterns and providing a more accurate classification of burned areas.

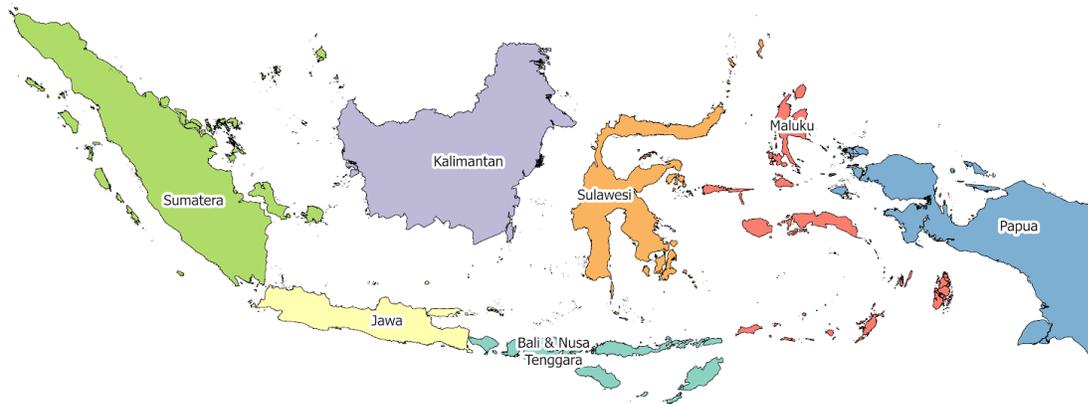


Figure 2. Indonesia is divided into 7 regions, namely Sumatera, Kalimantan, Jawa, Bali-Nusa, Sulawesi, Maluku and Papua in the collection of training samples and classification of fire areas in MapBiomas Indonesia Fire Collection 2.0.

2.2 Annual Mosaic

Classification was performed using Landsat Collection 2 (Tier 1) Surface reflectance mosaics by the USGS with a spatial resolution of 30m x 30m. Mosaics were created annually from 2000 to 2024. We examined all available Landsat 5 and 7 imagery (2000 to 2012), as well as 8 imagery (2013 to 2024) with a temporal resolution of 16 days.

Landsat Surface Reflectance is accompanied by two Bitwise Quality Assessment Bands (QA_PIXEL and QA_RADSAT) that will identify pixels with problematic radiometry and instruments, including possible markings on bands and pixels. We use the QA_PIXEL band to select and sort "cloud" and "shadow" pixels with a high confidence level (67-100%). Then, we use QA_RADSAT to avoid pixels with radiometric saturation across all Surface Reflectance bands. Finally, we remove pixels with negative surface reflectance values to eliminate anomalies and noise in the annual mosaic.

We use a statistical approach on an annual basis to summarize all data and optimize the classification process without discarding the spectral information contained in the pixel data. This approach allows us to create an annual mosaic by combining all 16-day temporal resolution images into one quality mosaic (QM), using the pixel sorting function, minimum NBR

(Normalized Burn Ratio) spectral index (formula — Key and Benson, 2006), the pixel with the lowest NBR value will be selected along with all its spectral reflectance characteristics, including metadata for each scene in the form of pixel dates, used to create an annual mosaic.

$$\lambda QM = [Blue, Green, Red, NIR, SWIR1, SWIR2] = \text{date in with } \min \left(\frac{\lambda NIR - \lambda SWIR1}{\lambda NIR + \lambda SWIR1} \right) [xi... j]$$

Where λ represents the reflectance value of the quality bands that form the quality mosaic (QM), where the date of each pixel with the minimum NBR value in a given year (x) is taken, considering the aggregate of all available images, from the beginning (i) to the end (j); λ NIR (Near-Infrared surface reflectance) and λ SWIR1 (Short-Wave Infrared surface reflectance) are used to calculate the NBR spectral index. In other words, we calculate the NBR value for each observed pixel in a given year and stack them into a multi-band image. The pixel with the lowest NBR value in the multi-band image will be selected along with its spectral information (table 1) to construct the annual quality mosaic (QM). In addition to the spectral information, we store image metadata information including the date at each displayed pixel, the pixel with the lowest NBR value. The mosaic created with the minimum NBR information, shows good performance in distinguishing fire and non-fire in land cover and land use in Indonesia (figure 3).

Table 1. Bands used in Mosaic to predict and classify fire areas.

Spectral band	Landsat 5 dan 7		Landsat 8	
	Band number	Band width (μm)	Band number	Band width (μm)
Red	3	0.63 - 0.69	4	0.64 - 0.67
NIR	4	0.76 - 0.90	5	0.85 - 0.88
SWIR ₁	5	1.55 - 1.75	6	1.57 - 1.65
SWIR ₂	7	2.08 - 2.35	7	2.11 - 2.29

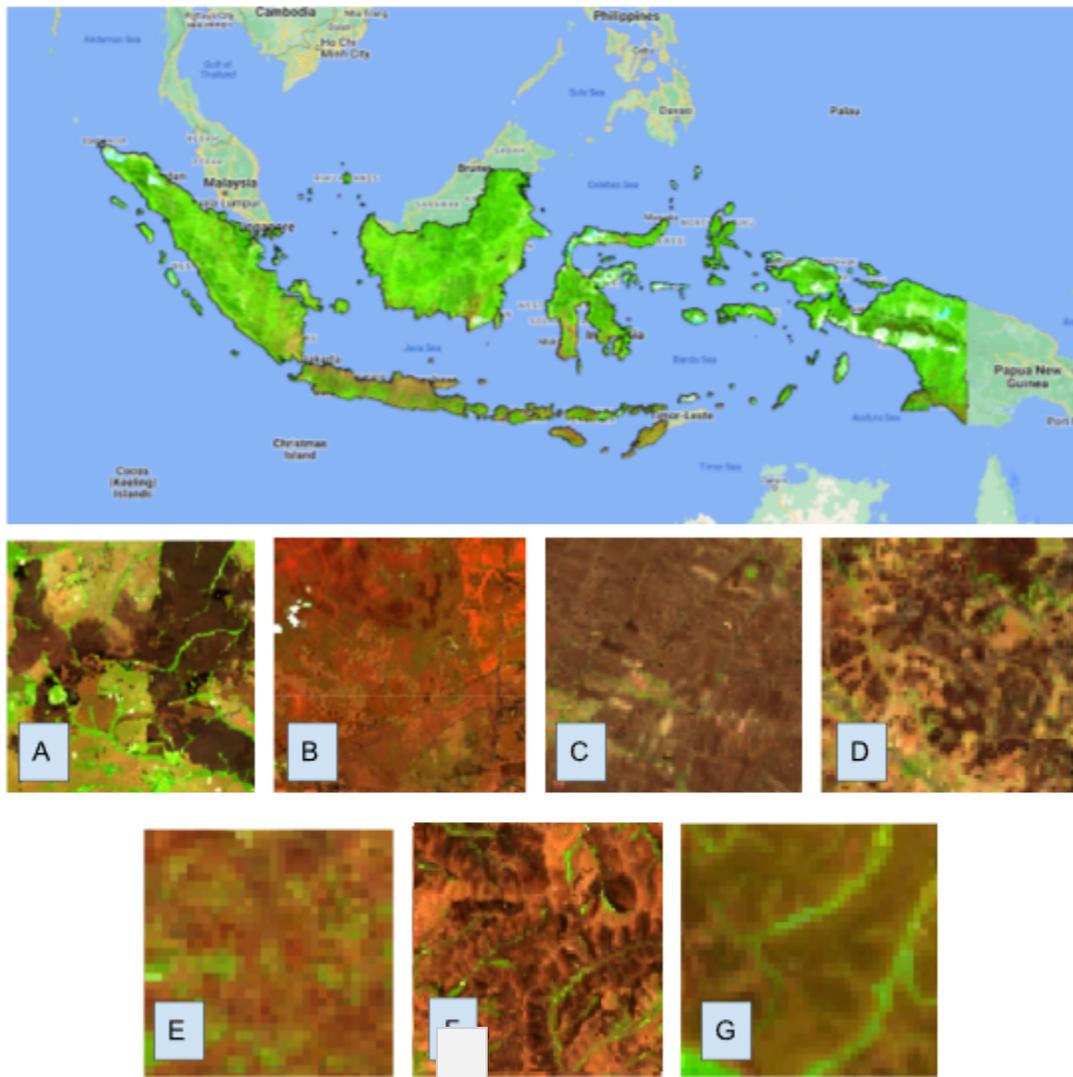


Figure 3. Annual mosaic 2023 Indonesia (RGB SWIR-1, NIR, RED), construction based on spectral information taken from pixels with minimum NBR in a year, examples of burnt scar diversity in each region: a) Sumatra, b) Kalimantan, c) Java, d) Sulawesi, e) Maluku, g) Bali-Nusa, and h) Papua.

2.3 Training Sample

We created a spectral library based on manual delineation of burned and non-burned areas to serve as training samples. The burned and non-burned samples were stratified using Landsat mosaics in each region. The samples collected in Collection 1 were derived from annual mosaics in 2015 and 2019 across seven regions. These samples were then used as input for the classification stage.

Given the diverse characteristics of fires, sampling was prioritized for land cover types: peat, forest, agriculture, rice fields, savannah, and mountains. Non-burned samples were collected from areas with fire-like features, such as settlements, mining areas, open land, and other land cover types. The collected samples were then used as input for the classification process.

2.4 Classification

The classification model used is a Deep Neural Network (DNN), which consists of computations based on mathematical calculation models capable of deep learning and visual pattern recognition. The structure we use is a Multi-Layer Perceptron Network (MLPN), which combines several layers of interconnected computational units, where each mode (neuron) in a layer is connected to a node in the next layer (Hu, Wenk, 2009). The layers are divided into: input, hidden, and output.

The inputs used for the DNN model are the RED, SWIR1, and SWIR2 spectral bands, and the outputs are fire and non-fire classes. This fire mapping uses a two-step algorithm: a training phase and a prediction phase.

- **Training Phase:**

In the training phase, the following parameters were determined, based on previous testing: learning rate (0.001), batch size (1000), number of interactions (7000), and classification input (Arruda et al. 2021). The input to the classification process used in this model was SR spectral data taken from an annual quality mosaic using training samples of burned and non-burned areas.

Based on the spectral library of burned and non-burned training samples, the following spectral bands were used as input to the burned area classification model: red (RED—0.65 μm), near infrared (NIR—0.86 μm), and short-wave infrared (SWIR 1—1.6 μm and SWIR 2—2.2 μm). These Landsat spectral bands were selected based on their sensitivity to fire occurrence across different land uses and land covers.

The training input data was divided into two datasets: 70% of the samples were used for training and 30% for testing, to assess the ability of the DNN algorithm to map burned areas.

- **Prediction Phase:**

This classification was performed using annual Landsat mosaics from each region, resulting in 25 years of fire data across Indonesia (Figure 4). This approach allowed us to leverage the advanced capabilities of DNNs to accurately and efficiently map burned areas across Indonesia.

Spatial filters were applied to remove noise and fill gaps, eliminating burned areas smaller than or equal to 1.4 ha (16 pixels), and empty gaps (within burned areas) smaller than or equal to 5.8 ha (64 pixels) were classified as fires (Padilla et al. 2015). This method eliminates

isolated noisy pixels and fills small gaps, improving the overall accuracy and coherence of the burned area map.

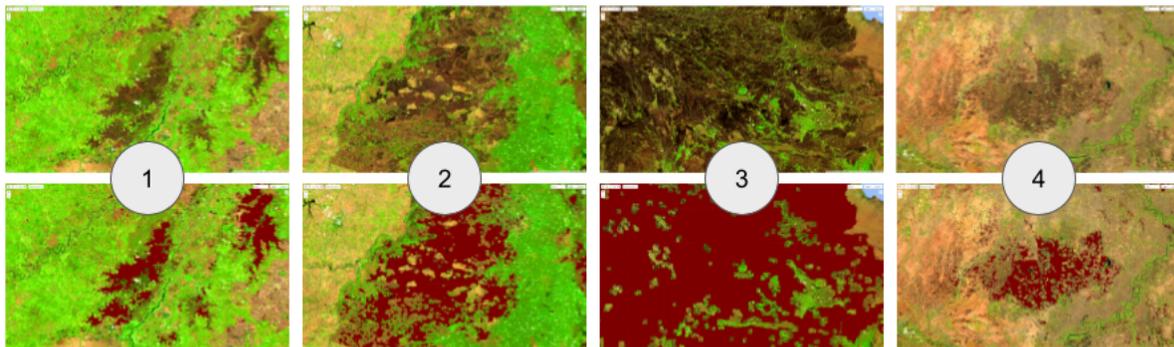


Figure 4. Examples of fire area classification results in each region, using the annual Landsat 8 mosaic, with burned areas marked in red. 1. Forest fires; 2. Mineral soil fires; 3. Fires around volcanoes; 4. Rice fields.

Because deep learning methods require powerful computational processing, we performed the analysis using a graphics processing unit (GPU) and specialized hardware components to execute parallel arithmetic operations. The computing infrastructure used was a Personal Computer with the following device specifications: Ryzen 9 750X processor, Nvidia RTX 4080 graphics card, 128 GB RAM, 1 TB SSD, 16 TB HDD. Access to the GPU in the virtual machine environment was implemented on the server location.

2.5 Post-classification

After evaluating the classification results, a post-classification masking process was also applied to reduce commission errors from land uses with spectral characteristics similar to recently burned areas, such as aquaculture areas and mining areas. We established rules to remove or mask pixels classified as burned in the land cover and land use classes of MapBiomas Landy Collection 4 according to the fire year range.

The land use classes used for the masking process are: settlements, mining pits, aquaculture, and rivers, lakes, and seas. To obtain information about the month of the fire, post-classification is performed to obtain information on the date of the burned pixel. The pixel date is obtained from annual images constructed from the minimum NBR value.

2.6 Post-classification Result

Burned area classification was evaluated using Landsat mosaics through visual inspection and statistical analysis. Visual inspections were conducted by experts from each region, who thoroughly examined the burn scars classified using Landsat mosaics to ensure accuracy. Discrepancies identified during these inspections were recorded and used to refine

the samples for the algorithm. Statistical analysis was performed to validate the classification results by comparing them with the burned area product.

Evaluation of burned area classification was performed using Landsat mosaics through visual inspection and statistical analysis. Visual inspections were conducted by experts from each region, who thoroughly checked the classified burned areas against the original Landsat mosaics to ensure accuracy. Discrepancies identified during these inspections were recorded and used to refine the samples for the algorithm. Furthermore, the mapped burned areas were compared with other reference maps (Ministry of Environment and Forestry Burned Area, MODIS, GABAM, FIRMS, FireCCI, hotspots) (Figure 5). This comprehensive evaluation process ensured high quality and accuracy of burned area classification, integrating automated and expert-based assessments to produce reliable results (Figures 5 and 6).

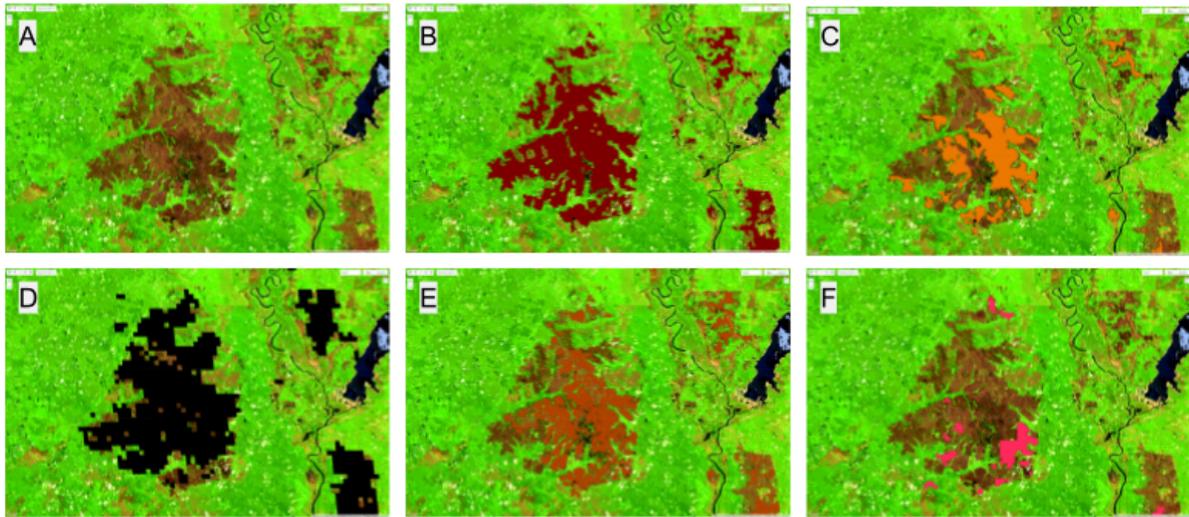


Figure 5. From top left to right and resolution, A) Landsat 8 image (30 m), B) MapBiomas Fire Collection 1 classification results (30 m), C) Fire by KLHK, D) MODIS (MCD64A1) (500 m), E) GABAM (30 m), and F) FireCCI (250 m).

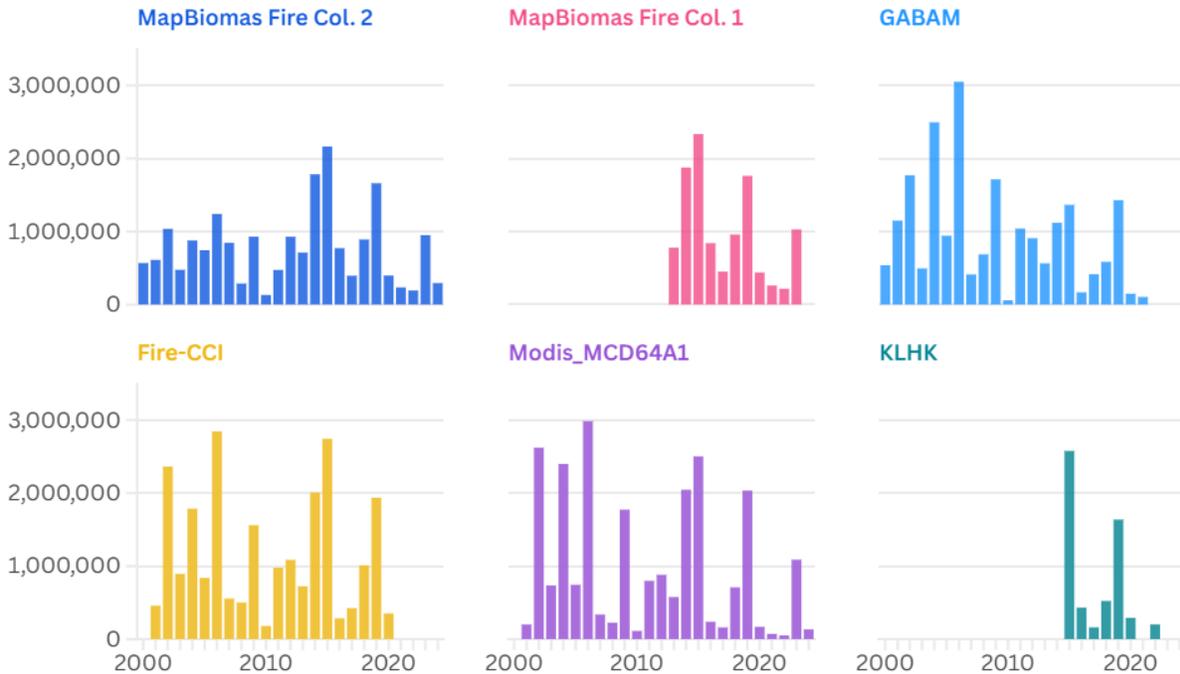


Figure 6. Burned land area based on data collections: MapBiomias Fire Collection 2 (30 m), MapBiomias Fire Collection 1 (30 m), GABAM (30 m), KLHK fire data, MODIS (MCD64A1) (500 m), GABAM (30 m), and FireCCI (250 m).

3. MapBiomias Fire Product

3.1 Annual Burned Area

Annual burned area data from 2000 to 2024, showing the area mapped as burned for each year. It also includes Annual Burns, which represents the annual burned area for each land use and land cover class, where each pixel contains land cover and land use values based on class codes according to MapBiomias collection 2.

3.2 Monthly Burned Area

Monthly burned area data covers the period 2000 to 2024, with each pixel's data taken from an annual mosaic based on the date of the satellite imagery. Monthly Burned Area Data shows the month (1 to 12) in which the fire occurred for each pixel.

3.3 Cumulative Burned Area

This cumulative data represents the accumulated area burned each year, counting the area burned once and excluding repeated fires in the same area. This data represents the area burned at least once during a given period. The cumulative burned area also represents fires across land cover and land use over a given period.

3.4 Fire Frequency data

The burned area frequency map shows the number of times the same pixel was mapped as burned within a given time period. The fire frequency data were compiled into a single map with 25 classes from 2000 to 2024. Class 1 represents pixels burned once, class 2 represents pixels burned twice, and so on. The data also includes the land cover and land use of each class from MapBiomass Landy Collection 4.

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