Agriculture - Land Use Land Cover 10m Appendix

Collection 3

Version 1

General coordinator
Eliseu Weber

Team
Kênia Samara Mourão Santos
Paulo Domingos Pires Teixeira Junior
Clebson Ismael dos Santos e Silva

April, 2026

1. OVERVIEW

This document describes the methodology employed in MapBiomas Collection 3 for mapping agricultural crops at 10 meters spatial resolution in the Brazilian territory, using Sentinel-2 images and satellite embeddings derived from deep learning models.

The product consists of annual land use and land cover maps with a spatial resolution of 10 meters, covering the period from 2017 to 2025, generated in the distributed processing environment of Google Earth Engine (GEE).

The mapped agricultural classes were:

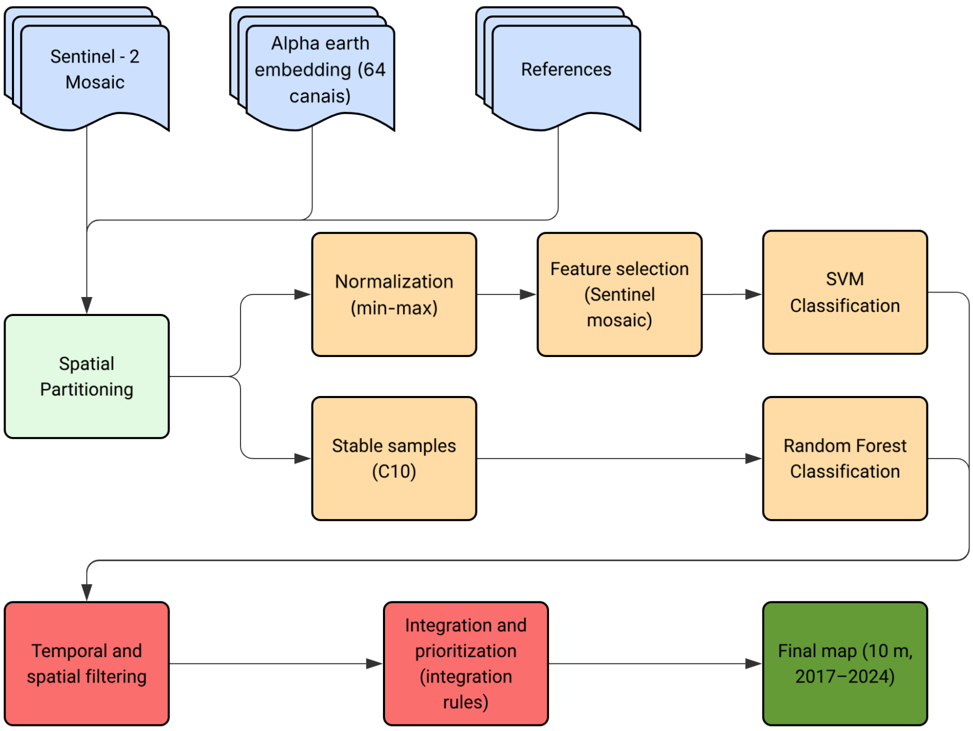
- Temporary crops;
- Perennial crops;
- Forest Plantation.

The methodological approach integrates optical remote sensing data and high-dimensionality vector representations (embeddings) into a single attribute space, allowing for the discrimination of agricultural classes with high spectral complexity and temporal variability.

Classification is performed using a supervised procedure, whose implementation incorporates variations in the training step depending on the nature and availability of the reference samples. The input data consists of seasonal Sentinel-2 surface reflectance mosaics and 64 embedding channels from the GOOGLE/SATELLITE_EMBEDDING/V1/ANNUAL dataset.

The methodological workflow is organized into sequential steps that include spatial partitioning, data preparation, attribute space construction, supervised classification, post-classification refinement, and thematic integration of results.

Figure 1 — General methodological workflow of the classification (complete pipeline)



The implementation of the methodological workflow incorporates operational variations conditioned by the nature of the reference samples, maintaining consistency in the general classification process.

2. METHODOLOGY

The adopted methodology is structured as a sequential processing workflow composed of interdependent steps, from the preparation of input data to the generation of the final product.

2.1 Input Data

The main data source consists of Sentinel-2 surface reflectance mosaics (Level-2A), organized into seasonal and annual compositions from image time series. These mosaics are defined from temporal statistics, including measures of central tendency and dispersion, with the aim of representing the spectral behavior of the targets throughout the phenological cycle.

The use of compositions based on the seasonal median reduces the influence of residual atmospheric interference, lighting variations, and discrepant observations, representing the predominant state of each pixel during phenologically relevant periods.

The spectral bands used comprise:

- visible light (green and red);

- red edge bands;
- near-infrared (NIR);
- shortwave infrared (SWIR1 and SWIR2).

From these bands, a set of spectral variables is defined, structured by combining temporal statistics, spectral indices, and composition metrics. The variables are organized according to three dimensions: type of spectral variable, temporal statistic, and aggregation scale, as presented in Table 1.

Table 1 — Structure of the spectral variables used

Dimension	Elements
Spectral Bands	green, red, red_edge_1, nir, swir1, swir2
Spectral Indices	EVI2, NDWI
Temporal Statistics	median, stdDev, p20, p85, qmo
Temporal Scale	seasonal, annual

The combination of spectral components, derived indices, temporal statistics, and aggregation scales results in a set of approximately 80 variables. This set simultaneously describes instantaneous spectral properties and temporal patterns of the Earth's surface, and is used as the basis for the classification step.

2.1.2 Satellite Embeddings

The second component of the input set consists of the GOOGLE/SATELLITE_EMBEDDING/V1/ANNUAL dataset, composed of 64 annual embedding channels. The embeddings represent each pixel in a high-dimensional vector space, incorporating structural, contextual, and temporal information of the Earth's surface.

Unlike spectral bands, which describe physical properties in a specific observation, embeddings aggregate information from multiple data sources, including optical sensors, radar, and environmental variables. This representation allows for the separation of classes with similar spectral signatures in point observations, based on differences associated with temporal behavior

2.1.3 Temporal Stratification of Training

The definition of training data considers the variability of regional agricultural calendars, and is carried out based on the characteristics of the available reference samples. For datasets associated with specific temporal references, a training structure based on a defined reference year is adopted. For datasets derived from the MapBiomas historical series, stable samples over time are used, defined as pixels that remain in the same class for multiple (at least five) consecutive years.

2.2 Spatial Partitioning

Spatial partitioning is defined based on the processing strategies adopted throughout the methodological workflow, reflecting differences in the structure of the reference samples and operational requirements. These variations correspond to distinct configurations applied in specific processing steps, not representing independent processes. The main configurations adopted are presented in Table 2.

Table 2 — Spatial partitioning configurations

Parameter	Configuration A	Configuration B
Application criterion	Processing with defined temporal reference	Processing with stable samples
Spatial unit	Regular grid (tiles)	Vector geometries (MapBiomas grid)
Tile extension	~100 km (~10,000 × 10,000 pixels)	Variable according to geometry
Spatial resolution	10 m	10 m
Buffer	50 m	~10 km
Coordinate system	Regular projection (orthogonal grid)	Original system of geometries
Identification	Unique ID per tile	Geometry ID

These configurations are applied according to the availability and structure of the reference samples, maintaining consistency in the global processing. A well defined temporal reference (usually meaning a land cover map made with visual inspection) is prioritized when available. Most reference maps used in Configuration A were derived from non-public datasets, with exception of ANA (2021).

2.3 Construction of the Attribute Space

2.3.1 Variable Selection

Before the final classification, a Random Forest model with 200 decision trees is applied to the mosaic corresponding to the reference year of each class with training based on a defined temporal reference. The objective of this step is to estimate the relative importance of the spectral variables for class discrimination. From this analysis, the 10 most relevant bands are selected based on importance metrics. These variables are combined with the 64 embedding channels, forming a hybrid attribute space that integrates spectral information and high-dimensional contextual representation.

2.3.2 Attribute Normalization

Min-Max normalization is applied exclusively in the procedure based on defined reference years, with the objective of ensuring consistency in the scale of the attributes used by the classifier. The minimum and maximum parameters are estimated from samples of the reference year and subsequently fixed for the entire time series (2017–2024), ensuring intertemporal comparability.

The transformation follows the expression:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

2.4 Supervised Classification

Classification is performed based on training strategies defined according to the characteristics of the available reference samples, maintaining consistency in the general classification process.

2.4.1 Strategy based on temporal reference

For datasets associated with specific temporal references, a training strategy based on a defined reference year is adopted. In this context, steps for variable selection, attribute normalization, and classification by Support Vector Machine (SVM) with RBF kernel γ (gamma) = 0.1 and C (cost) = 10 are applied.

2.4.2 Strategy based on stable samples

For datasets derived from the MapBiomas (Collection 10) historical series, classification is performed using stable samples over time. In this approach, the Random Forest algorithm with 100 trees is used, without applying attribute normalization

3. Post-Classification and Temporal Coherence

After the supervised classification step, the results are subjected to spatial and temporal refinement procedures, with the objective of reducing noise, eliminating inconsistencies, and ensuring coherence throughout the time series. The post-classification steps are applied uniformly to the results generated throughout the classification process. These procedures are structured into three main steps: (i) spatial filtering; (ii) temporal persistence-based filtering; and (iii) logical adjustment applied to the final year of the series

3.1 Spatial Filtering

The first refinement stage consists of removing classified regions with small spatial extent. The criterion adopted is based on the minimum area of polygons, eliminating regions with an area less than 0.3 hectare, which corresponds to approximately 30 connected pixels at 10-meter resolution. This procedure reduces the occurrence of “salt and pepper” patterns, frequently associated with classification noise, geometric registration errors, or local variations that do not represent consistent spatial units.

3.2 Temporal Persistence Filtering

The temporal consistency of the classifications is ensured by persistence rules applied in three-year moving windows, an approach widely used in the analysis of remote sensing time series (Jönsson & Eklundh, 2004; Zhou et al., 2023). For each pixel, permanence in a given class is conditioned on its occurrence in at least two of the three years considered (2 out of 3 rule). This approach reduces the incidence of transient detections associated with seasonal variations, temporary changes in land use, or punctual classification noise.

After applying the temporal filtering, a new spatial filter is executed, using the same minimum area criterion, with the objective of removing residual fragments resulting from the temporal combination

3.3 Logical Adjustment for the Final Year of the Series

The application of temporal filters based on moving windows imposes a limitation on the final year of the time series, since there are no subsequent observations for persistence evaluation. To mitigate the underestimation of areas in this period, an OR-type logical operation is applied between the result of the last available year and the immediately preceding year. This operation preserves consistent occurrences observed in the previous year, compensating for the structural limitation of the temporal analysis at the upper limit of the series

4. Internal Integration

The thematic integration of classification results is performed using a set of deterministic rules that define the priority between classes and the way different intermediate products are consolidated into a single final map. This step is responsible for resolving spatial conflicts between classes originating from different classification pipelines, ensuring thematic coherence and hierarchical consistency in the final product.

4.1 Hierarchical Prioritization between Classes

The resolution of spatial conflicts between classes is performed using a hierarchy of precedence defined a priori. For each pixel, the final class is assigned by selecting the highest priority among the candidate classes, ensuring the assignment of a single class per pixel. Precedence is implemented by associating integer values to the classes, followed by applying a pixel-by-pixel maximum operation. This approach ensures a deterministic resolution of overlaps, eliminating ambiguities in the final classification

4.1.1 Class ordering

After applying the precedence rules, the intermediate classes are grouped. The classes are consolidated in the following order of priority:

- Temporary Crops;
- Perennial Crops;
- Forest Plantation.

This grouping ensures compatibility with previous collections and consistency in the interpretation of results throughout the time series

References

AGÊNCIA NACIONAL DE ÁGUAS (ANA). Mapeamento do arroz irrigado no Brasil. Brasília: ANA; Companhia Nacional de Abastecimento (CONAB), 2021.

JÖNSSON, P.; EKLUNDH, L. TIMESAT — a program for analyzing time-series of satellite sensor data. Computers & Geosciences, v. 30, n. 8, p. 833–845, 2004.

ZHOU, J. et al. A scalable software package for time series reconstruction of remote sensing datasets on the Google Earth Engine platform. International Journal of Digital Earth, v. 16, n. 1, p. 988–1007, 2023.