

MAPBIOMAS
ECUADOR

Land Cover and Land Use

Transversal Map - Infrastructure

Algorithm Theoretical Base Document (ATBD)

Collection 4.0

Version 1.0

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1. Introduction

The MapBiomás Ecuador map collection, version 4.0, incorporates Urban Infrastructure mapping as a binary transversal layer covering the entire Ecuadorian territory for the period from 1985 to 2025. This land-cover class consists of human settlement areas associated with large and small urban centers (towns), including built-environment infrastructure such as road and railway networks and associated land. It also includes other artificialized areas, such as hydrocarbon exploitation facilities, hydroelectric power plants, military bases, airports, port areas, and unconventional airstrips in rural areas. Peripheral areas undergoing gradual urbanization for residential purposes and/or industrial areas are also considered.

Globally, several initiatives have developed urban land mapping using different remote sensing techniques and data sources (Schneider *et al.*, 2010). These products include FROM-GLC, developed by Gong *et al.* (2013), and GlobeLand30, developed by Chen *et al.* (2015). However, much of this information is available for a limited number of years, which has made it difficult to monitor urban dynamics over long historical periods.

The availability of the Landsat image time series has enabled the generation of annual information for the Ecuadorian territory, becoming a fundamental input for the multitemporal mapping developed by MapBiomás Ecuador. In the present collection, automated processing on the Google Earth Engine platform generates information on the distribution and dynamics of Urban Infrastructure (ID: 24) for the period from 1985 to 2025, equivalent to 41 years of information.

2. Construction and Definition of Landsat Mosaics

The first step in generating land-cover and land-use maps is the construction of annual mosaics from satellite images acquired by the Landsat program. For the MapBiomás Ecuador initiative, mosaic construction and processing have been carried out using different spatial reference units according to the processing area and period:

1. **For the area within the RAISG boundary:** the mosaics were processed using a uniform grid based on the International Map of the World at the Millionth scale, at a scale of 1:250,000. Each map sheet covers an area of 1°30' of longitude by 1° of latitude (see Figure 1).

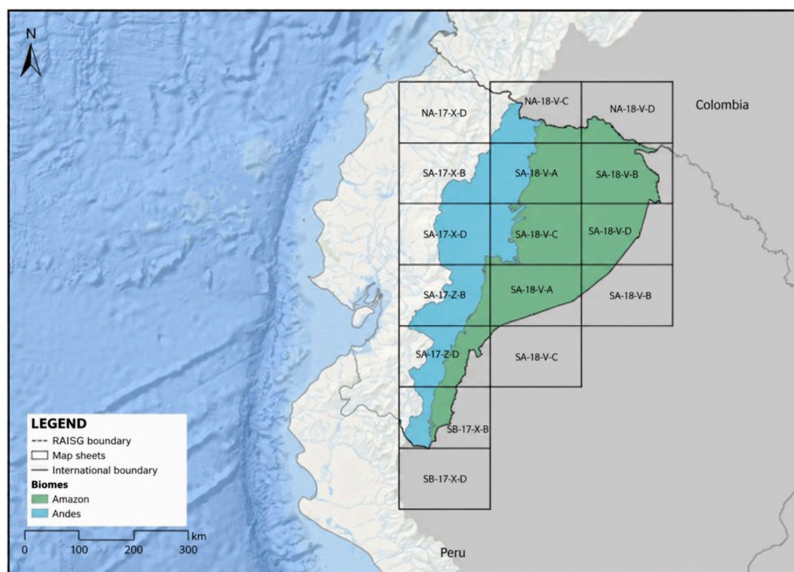


Figure 1: Distribution of the grid of the International Map of the World at the Millionth scale for mosaic processing of the infrastructure transversal map. Prepared by EcoCiencia.

2. **For the area outside the RAISG boundary:** the spatial reference unit used for mosaic construction and processing corresponded to the Path/Row grid. The Ecuadorian territory, both mainland and insular, is covered by 17 Path/Row combinations (see Figure 2).

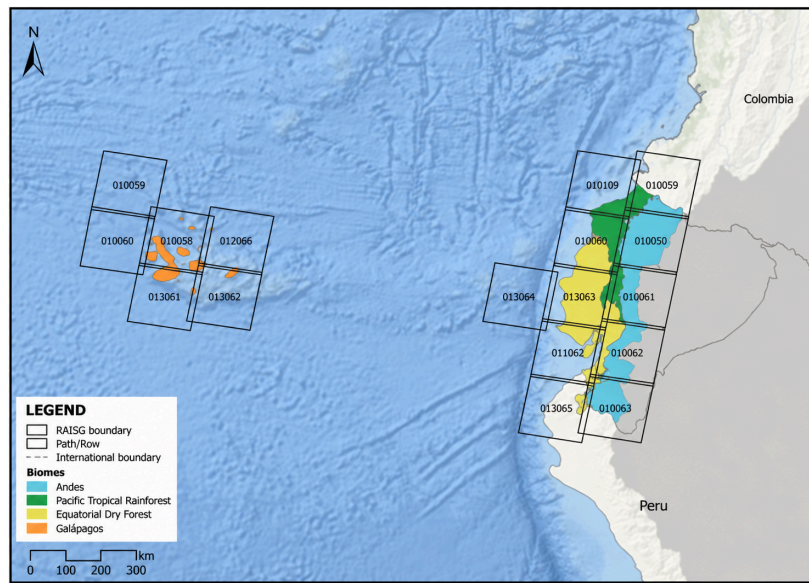


Figure 2: Distribution of Path/Row for mosaic processing of the infrastructure transversal map. Prepared by EcoCiencia.

3. **For the present collection:** the parameterization was expanded through the use of the Path/Row grid for the entire Ecuadorian territory, both mainland and insular. This modification allowed the use of a single spatial reference unit for mosaic parameterization, with the aim of optimizing memory usage and reducing processing times, while maintaining the same mosaic construction process (see Figure 3).

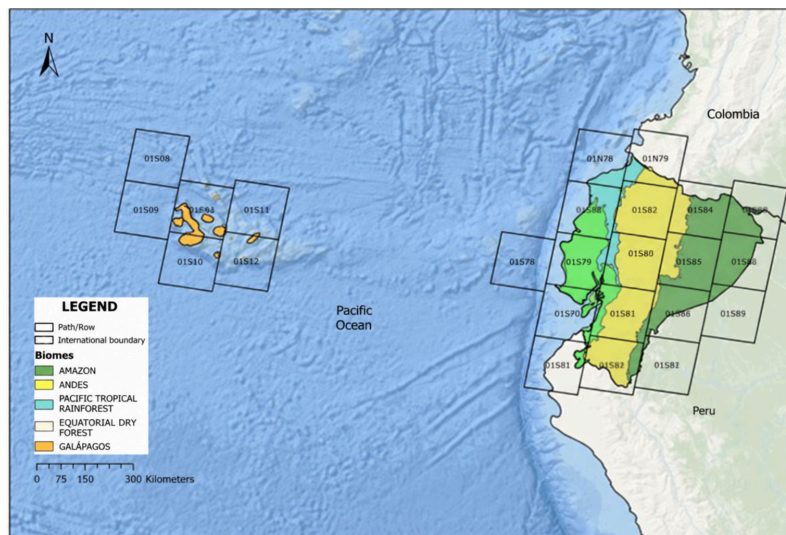


Figure 3: Distribution of the Path/Row used for parameterization and processing of Landsat image mosaics for the entire Ecuadorian territory.

Elaboración: EcoCiencia.

Within each spatial unit used for processing, annual Landsat image mosaics are constructed. The objective is to generate periodic cloud-free images that allow classification and change detection. For further details, see Section 4 of the document: *Algorithm Theoretical Base Document (ATBD) of Ecuador – Collection 4.0*.

3. Methodological Summary

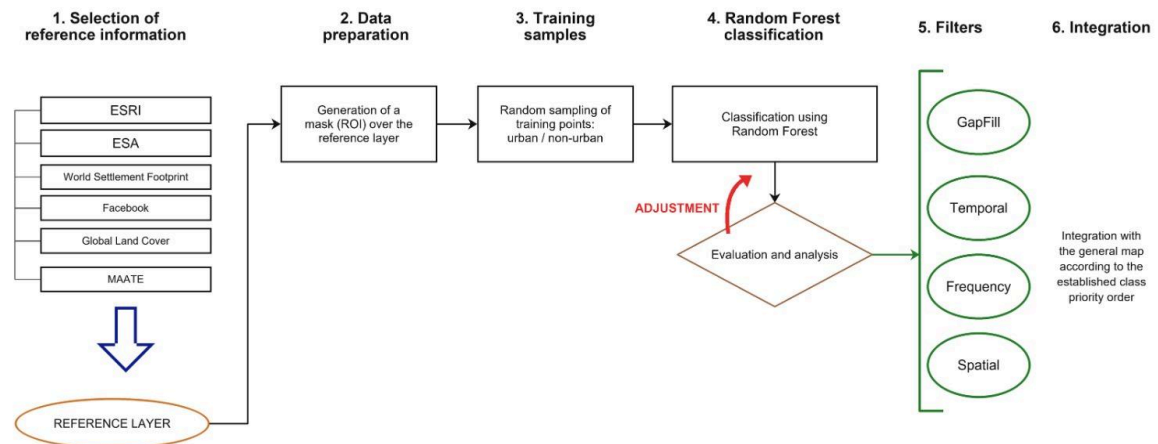


Figure 4. Methodological workflow for the classification of Urban Infrastructure, Collection 4.0. Prepared by EcoCiencia.

4. Classification Variables

The next step consisted of calculating spectral indices and fractions for each satellite observation (feature space). Landsat spectral bands, spectral indices, fractional information, and texture information derived from the previous indices and fractions were used. Additionally, static variables such as *HAND*, *shademask2*, *slppost*, *altitude*, *slope*, *latitude*, and *longitude* were used as complementary information to discriminate between classes that exhibit similar spectral characteristics but can be differentiated based on their topographic and spatial conditions.

Table 1. Feature space: Variables for the detection of Urban Infrastructure surfaces with the associated reducer.

Variable	Description	Reducer
blue	Landsat BLUE band	Median
green	Landsat GREEN band	Median
red	Landsat RED band	Median
nir	Landsat NIR band	Median
swir1	Landsat SWIR1 band	Median
swir2	Landsat SWIR2 band	Median
soil	Soil Fraction	Median
snow	Snow Fraction	Median
cloud	Cloud Fraction	Median
slope	Slope	Static topographic variable
ndvi	Normalized Difference Vegetation Index	Median
ndwi_mcfeters	Normalized Difference Water Index (Mcfeters)	Median
ndbi	Normalized Difference Built-up	Median
nuaci	Normalized Urban Areas Composite Index	Median

Finally, a representative mosaic was created for each year, consisting of a total of 151 bands, through the application of statistical reducers to the satellite observations. These reducers provide representative values for each pixel based on the different observations available for the same period. The reducers used were.

Table 2. Statistical reducers used in the composition of Urban Infrastructure images, Collection 4.0.

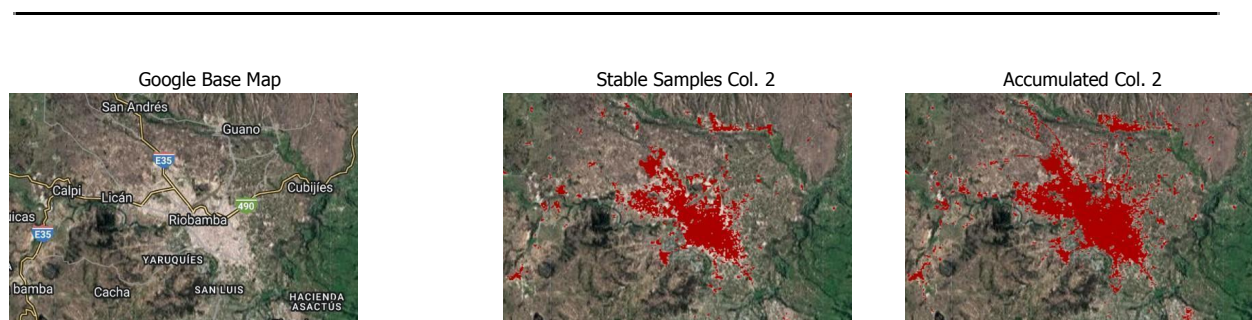
Reductor	Descripción
Median	Median of all available values in the annual mosaic for a given pixel location.
Dry-season median	Calculation of the statistical median applied to the pixels of the 25th quartile (with the values) of NDVI (proxy for the dry season).
Wet-season median	Calculation of the statistical median applied to the pixels of the 75th quartile (with the highest values) of NDVI (proxy for the rainy season).
Amplitude	Range of variation among all available pixels in the annual mosaic.
Standard deviation	Standard deviation of the values of all available pixels in the annual mosaic for a given location.
Minimum	Lowest value of all available pixels in the annual mosaic at a given location.
Maximum	Highest value of all available pixels in the annual mosaic at a given location..
Dry-period minimum	Calculation of the lowest value of all available pixels from the images in the quartile with the lowest NDVI values (proxy for the dry season).
Wet-period minimum	Calculation of the lowest value of all available pixels from the images in the quartile with the highest NDVI values (proxy for the rainy season).
Dry-period maximum	Calculation of the highest value of all available pixels from the images in the quartile with the lowest NDVI values (proxy for the dry season).
Wet-period maximum	Calculation of the highest value of all available pixels from the images in the quartile with the highest NDVI values (proxy for the rainy season).
QMO of the dry period	The highest value of the EVI2 band during the dry season. QMO of the rainy period. The highest value of the EVI2 band during the wet season.

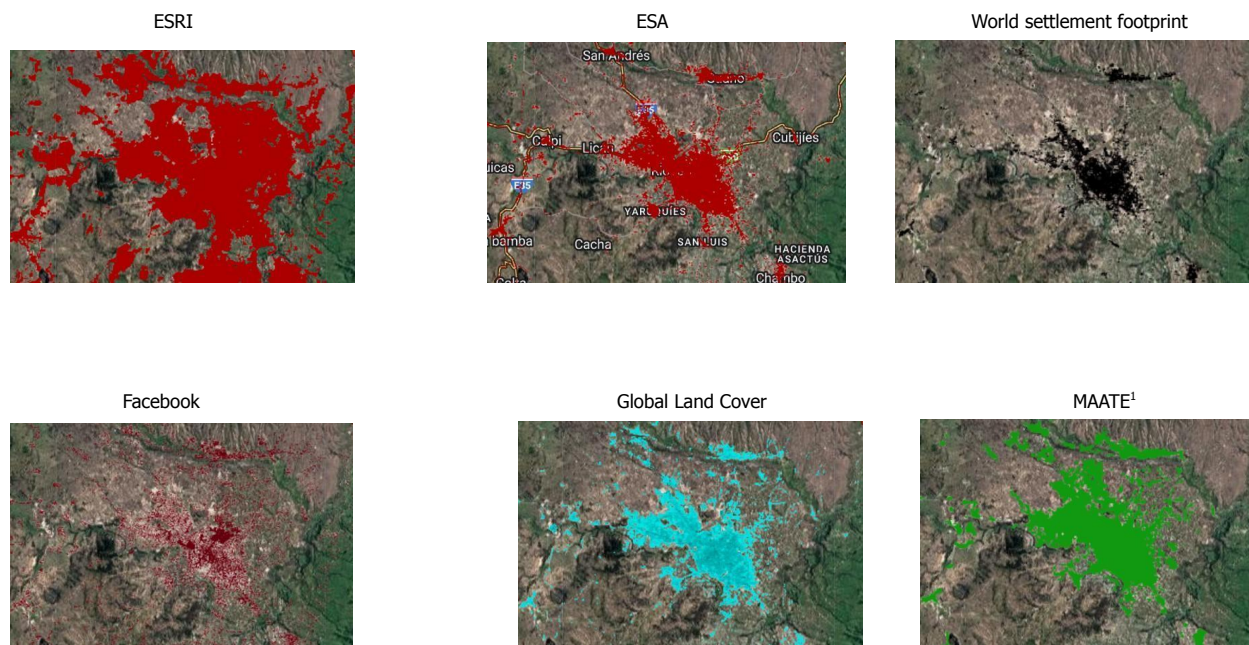
5. Clasification

5.1. Reference information

For Ecuador, thirteen reference sources were used in the Random Forest algorithm (see Table 3), compiled from projects containing geographic information from global and national datasets covering different periods. The accumulated and stable samples from previous MapBiomass Ecuador collections were also incorporated. The information was filtered according to the presence of urban infrastructure surfaces or urban clusters with residential, commercial, service, industrial, park, and other attributes.

Table 3. Reference sources available for the MapBiomass Ecuador study area





¹ The MAATE reference used (Ministry of Environment, Water and Ecological Transition) corresponds to the Ecuador Land Cover and Land Use Map for the years 1990, 2000, 2008, 2014, 2016, 2018, 2020, and 2022. Only information related to the “anthropogenic area” was extracted. This category is subdivided into populated areas (areas mainly occupied by dwellings and buildings intended for collective or public services) and infrastructure (civil works for transportation, communication, agro-industrial, and social purposes).

Table 4. Información que Ecuador emplea como referencia en el proceso de clasificación de infraestructura urbana.

Reference	MapBiomás	Global	National
Ref1_stable_pixel_of_urban_ColAnt	●		
Ref2_accumulated_of_urban_ColAnt	●		
Ref3_ESRI_Built_Area		●	
Ref4_ESA_WorldCover_project_2020_Built_up		●	
Ref5_WorldSettlementFootprint2015		●	
Ref6_WorldSettlementFootprint2019		●	
Ref7_WorldSettlementFootprintEvolution1985-2015		●	
Ref8_Mapa_densidad_población_alta_resolución_CIE SIN_Facebook		●	
Ref9_Global_land_cover_and_land_use_2019		●	
Ref10_MAATE_90 (1990)			●
Ref11_MAATE_00 (2000)			●
Ref12_MAATE_08 (2008)			●
Ref13_MAATE_14-22 (2014, 2016, 2018, 2020 y 2022)			●

Each reference was analyzed to determine which was most appropriate for application in each classification region.

Amazon Basin : The Amazon Basin was divided into five regions. The references used in each region are detailed below.

Table 5. Information used by Ecuador as a reference in the urban infrastructure classification process in the Amazon Basin.

AMAZON BASIN INFRASTRUCTURE REGIONS

	40101	40102	40201	40202	40601
Ref1_stable_pixel_of_urban_ColAnt		●			
Ref2_accumulated_of_urban_ColAnt	●		●	●	●
Ref4_ESA_WorldCover_project_2020_Built_up	●	●	●	●	●
Ref6_World Settlement Footprint 2019	●	●	●	●	●
Ref7_World Settlement Footprint		●	●		●

Pacific Basin: The Pacific Basin was divided into 13 regions. Unlike the Amazon Basin, this basin is dominated by areas that, either due to natural conditions or the influence of anthropogenic activities, have low vegetation cover density. This generated confusion in differentiating infrastructure from other land-cover and land-use classes. Therefore, an approach based on the selection of references by period was implemented in order to mitigate potential overestimation in data interpretation. The references used by region and period are detailed below.

Table 6. Information used by Ecuador as a reference in the urban infrastructure classification process in the Pacific Basin regions.

	40907	40905	40908	40901	40902	40903	40904	40906	40603	40604	40605	40606	40607
Ref7_World Settlement Footprint Evolution 1985-2015	●	●	●	●	●	●	●	●	●	●	●	●	●
Ref10_MAATE_90	●	●	●	●	●	●	●	●	●	●	●	●	●
Ref11_MAATE_00	●	●	●	●	●	●	●	●	●	●	●	●	●
Ref12_MAATE_08	●	●	●	●	●	●	●	●	●	●	●	●	●
Ref13_MAATE_14-22	●	●	●	●	●	●	●	●	●	●	●	●	●

Table 7. Information used by Ecuador as a reference in the urban infrastructure classification process for the periods defined for each region of the Pacific Basin.

	Ref7_World Settlement Footprint Evolution 1985-2015	Ref10_MAATE_90	Ref11_MAATE_00	Ref12_MAATE_08	Ref13_MAATE_14-22
1985 - 1990	●	●			
1991 - 2000	●		●		
2001 - 2008	●			●	
2009 - 2023	●				●
2024	●				●

5.2. Training Samples (Urban/Non-Urban)

Training samples were randomly selected within the references (see Tables 6 and 7). For this purpose, the number of points to be randomly selected for each class was defined. Two types of points were sampled: Urban (ID 24), containing exclusively pixels corresponding to urban infrastructure areas, and Non-Urban (ID 27), comprising areas that do not correspond to urban infrastructure, i.e., all classes other than urban infrastructure (see Figure 4).

Depending on the region, the number of references to be used was established. Of the 13 available references, the number to be employed was determined. A point is considered valid as a training sample only when all selected references agree in classifying it as urban or non-urban.

Training samples are used to generate the classification of pixels corresponding to urban and non-urban areas. Areas outside the region of interest defined by the references are not classified within this transversal theme.

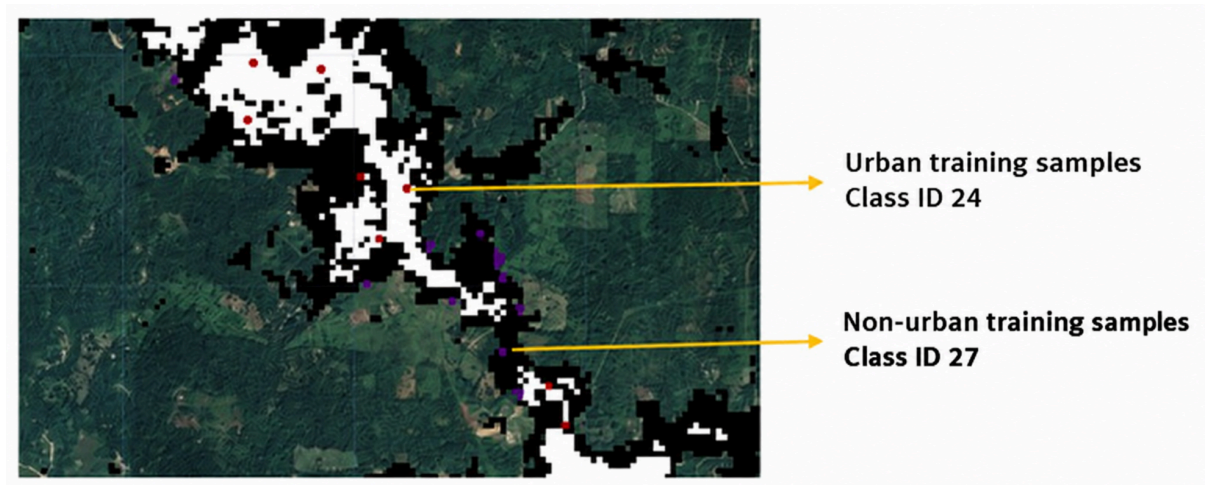


Figure 5. Urban and Non-Urban training samples. Prepared by EcoCiencia.

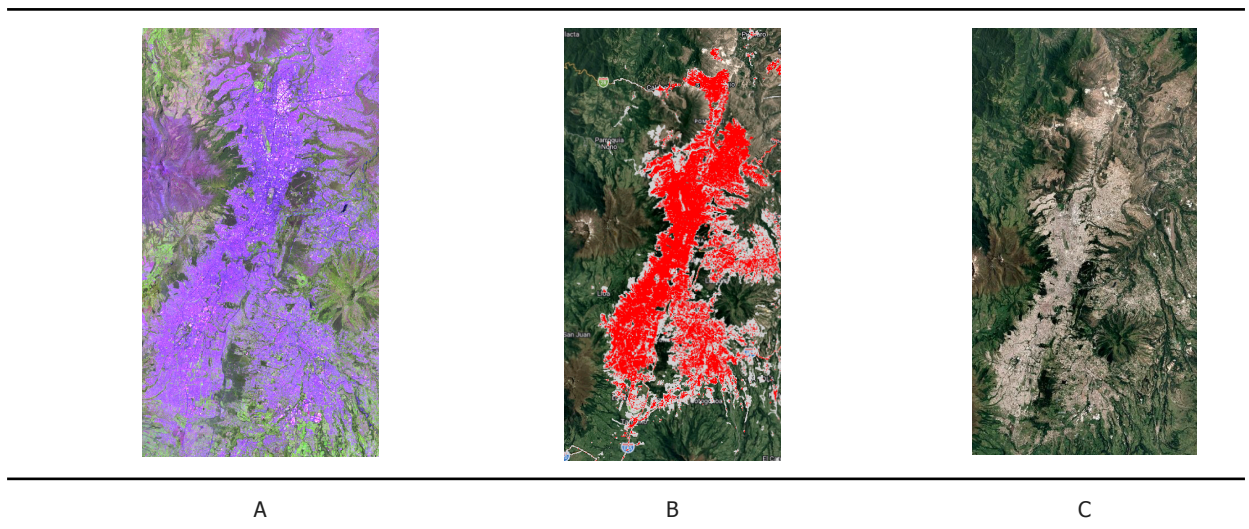
5.3. Classification Using the Random Forest Algorithm

The objective of the classification was to produce a binary layer distinguishing between urban infrastructure and non-urban areas, considering only two possibilities for each pixel: 1: Presence of Urban Infrastructure and 2: Absence of Urban Infrastructure. Classification based on training samples over the Landsat mosaics was performed using the Random Forest (RF) algorithm.

The Random Forest machine-learning algorithm (Breiman, 2001) was implemented on the Google Earth Engine platform. Training samples were generated and classification was subsequently performed based on the behavior of the indices used, supported by regional reference maps such as OpenStreetMap, as well as national and global reference information.

Classification was performed over the 13 classification regions defined for the Collection 4.0 transversal theme, considering the presence of the urban infrastructure class according to known reference sources and high-resolution imagery.

Table 8. Urban Infrastructure Detection, Collection 4.0: (A) 2025 Landsat mosaic (RGB 654), (B) 2025 urban surface classification, (C) high-resolution Google Earth image. (Quito, Ecuador).



6. Post-Classification

Due to the pixel-based nature of the classification method and the use of an extensive time series, a post-classification process was carried out, including the application of temporal and morphological filters (Gap Fill, spatial, and frequency filters) to the binary discrimination of Urban Infrastructure. The purpose was to reduce temporal inconsistencies and classification noise smaller than the minimum mapping unit, as well as to fill information gaps.

6.1. Gap Fill Filter

The sequence of filters for the urban infrastructure thematic layer begins with the filling of information gaps—*Gap Fill*—considering that the area covered by MapBiomias Ecuador and urban surfaces are subject to atmospheric and climatic conditions that result in annual mosaics containing some pixels without information or an absence of observations by the satellite (“gaps”).

This filter is capable of reducing these residual gaps by replacing missing values with the temporally closest available value. When a “future” pixel lacks a value (no data), the Gap Fill filter assigns it the value from the closest available year. This filter reviews the time series and first fills gaps by scanning “backward to forward,” where gaps are filled with data from the nearest preceding years. If gaps remain, they are filled using data from the nearest subsequent year.

For each pixel whose value has been completed using this filter, the change is recorded in a metadata file that stores the pixel's history. Several years can be used to fill gaps. Therefore, information gaps persist only if a given pixel has been permanently classified as having no information throughout the entire time series.

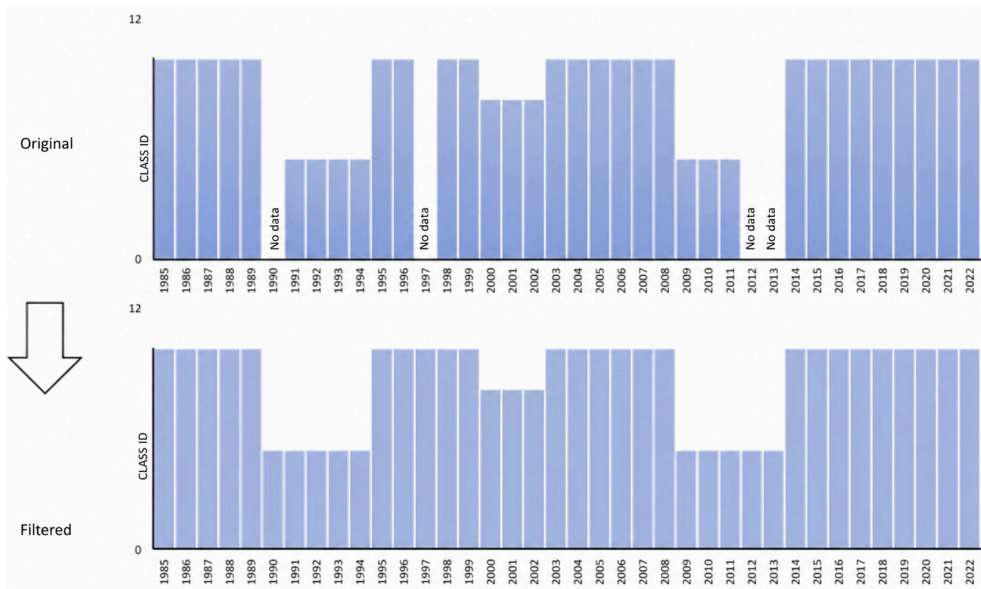


Figure 6: Functional scheme of the Gap Fill Filter. Prepared by MapBiomass.

6.2. Temporal Filter

A temporal filter using 3-, 4-, and 5-year windows was applied throughout the entire time series. The filter examines the value of each classified pixel in relation to the value of that same pixel in temporally consecutive classifications. It uses a one-directional moving window that considers sequences of 3 to 5 years and identifies disallowed temporal transitions.

The temporal filter is applied to each pixel for all years in the collection. Depending on the year whose value will be modified, there are three types of rules:

General Rules (GR). Applied to pixels corresponding to years in intermediate positions within sequences of 3 to 5 years. This rule is applied only when there is a temporal inconsistency; for example, when sequences of consecutive years have identical values except for the pixel in the central position. In these cases, the filter modifies the value of the central pixel so that it is consistent with the pixels preceding and following it. In 3-year sequences, there is only one possible central or intermediate year. In 4- or 5-year sequences, there are two or three possible central positions. This rule modifies classification values for the years 1986 to 2024.

First-Year Rules (FYR). Applied only to the first year of the time series. This rule modifies classification values for the year 1985.

Last-Year Rules (LYR). Applied to the last year of the classification. This rule modifies the classification values for the year 2022.

Thus, temporal filters reduce information gaps and temporal inconsistencies or changes that are not possible or are not permitted.

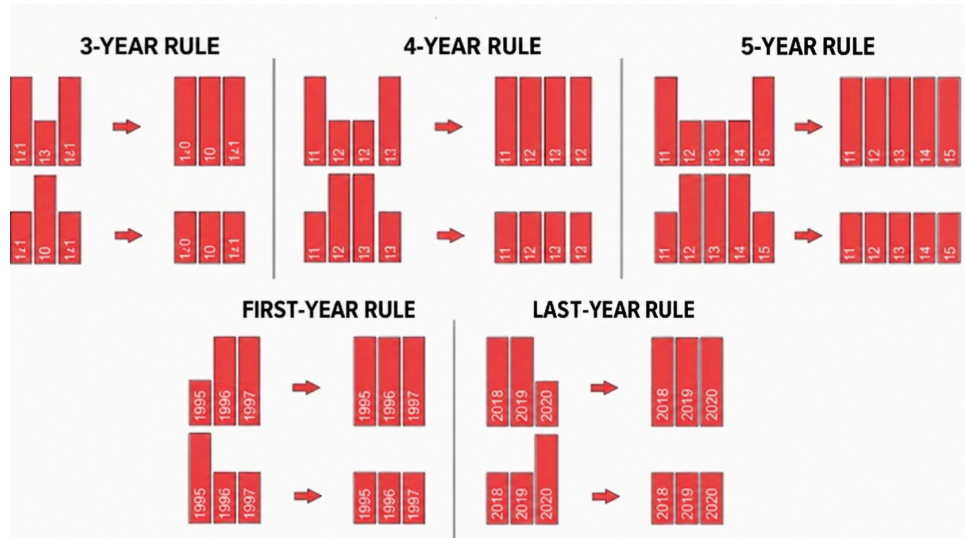


Figure 7: Effect of the temporal filter. Prepared by MapBiomias.

6.3. Adjusted Frequency Filter

This filter considers the occurrence of the class throughout the time series in order to normalize the historical trajectory of the class. Given that urban infrastructure exhibits an incremental and expanding trend throughout the time series, two filters (first year and last year) were applied to regulate the consistent increase of urban pixels and avoid anomalous fluctuations from one year to the next.

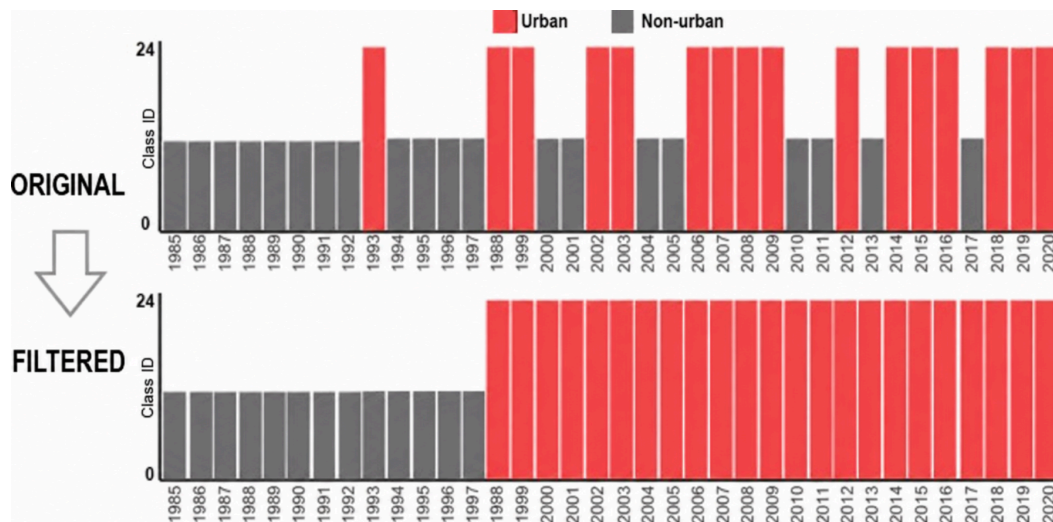


Figure 8: Functional scheme of the frequency filter. Prepared by MapBiomias.

6.4. Spatial Filter

The final filter in the post-classification sequence was the spatial filter based on the "connectedPixelCount" function in Google Earth Engine. This function identifies connected pixels (neighbors) that share the same value using a moving window. Only pixels that do not share a connection with a predefined number of identical neighbors are considered isolated pixels.

In the case of MapBiomias Amazonia, the minimum mapping unit was defined as 0.5 ha

(approximately 5 pixels). Consequently, at least five connected pixels were required to meet the minimum connectivity criterion. Thus, the spatial filter smooths local differences by removing isolated or edge pixels smaller than 0.5 ha, increasing the spatial consistency of the class.

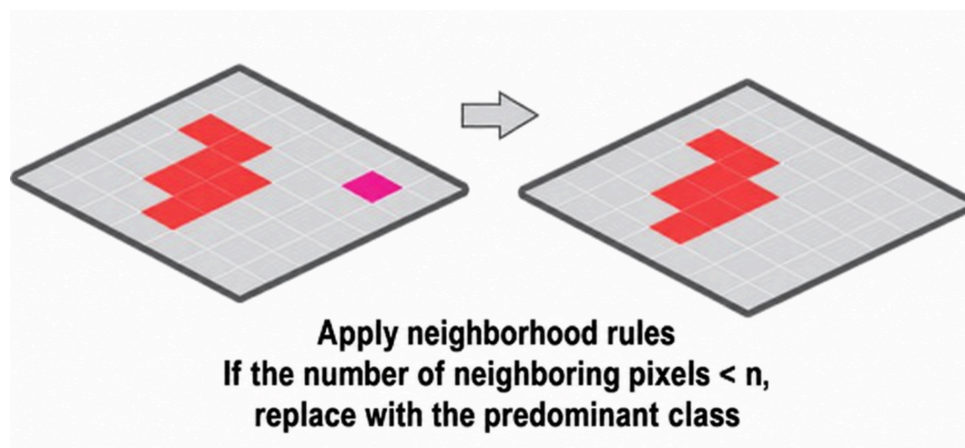


Figure 9: Functional scheme of the spatial filter. Prepared by MapBiomias.

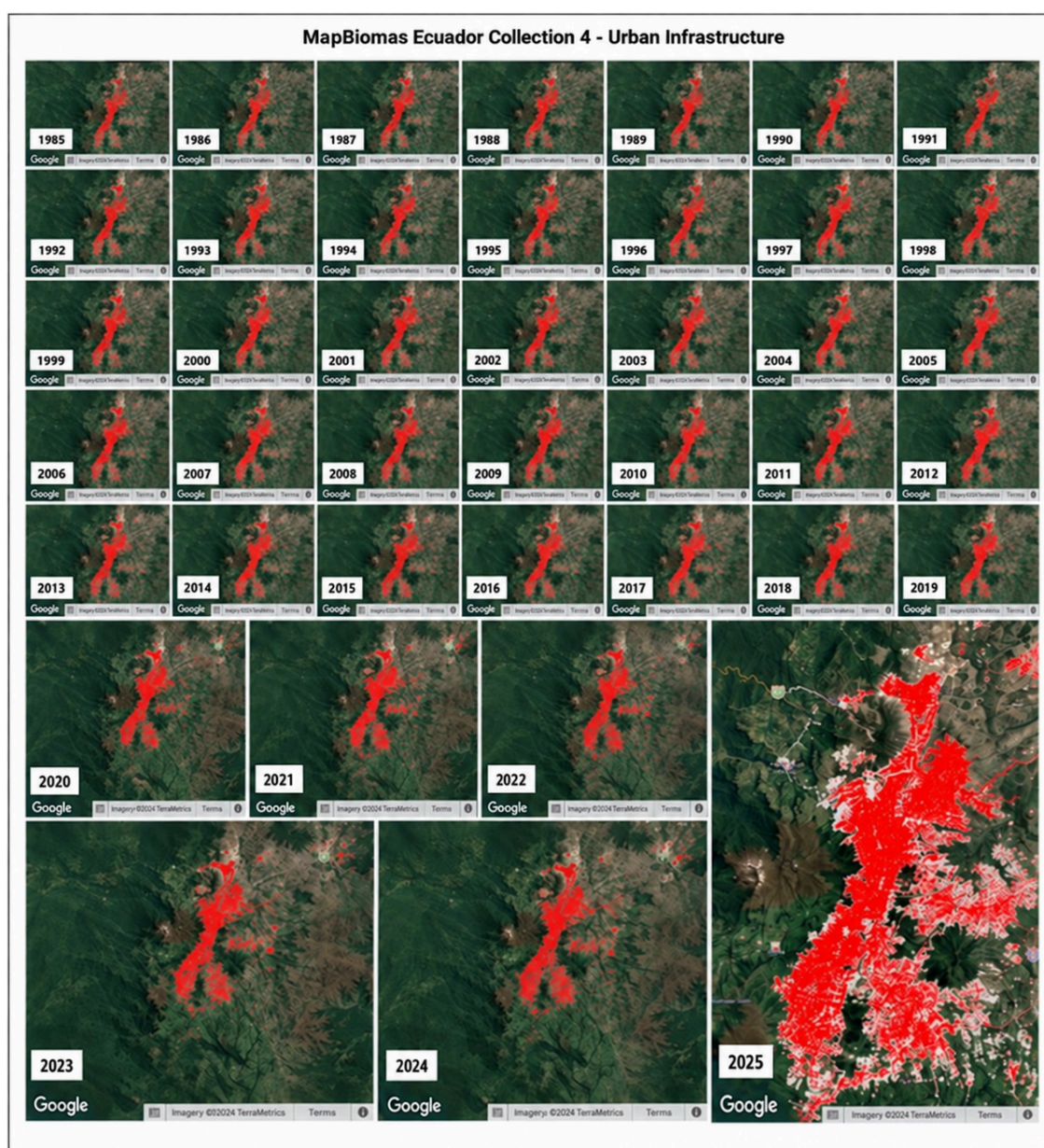


Figure 10. Multitemporal Urban Infrastructure classification, Collection 4.0 – 1985 to 2025 (Quito, Ecuador case).

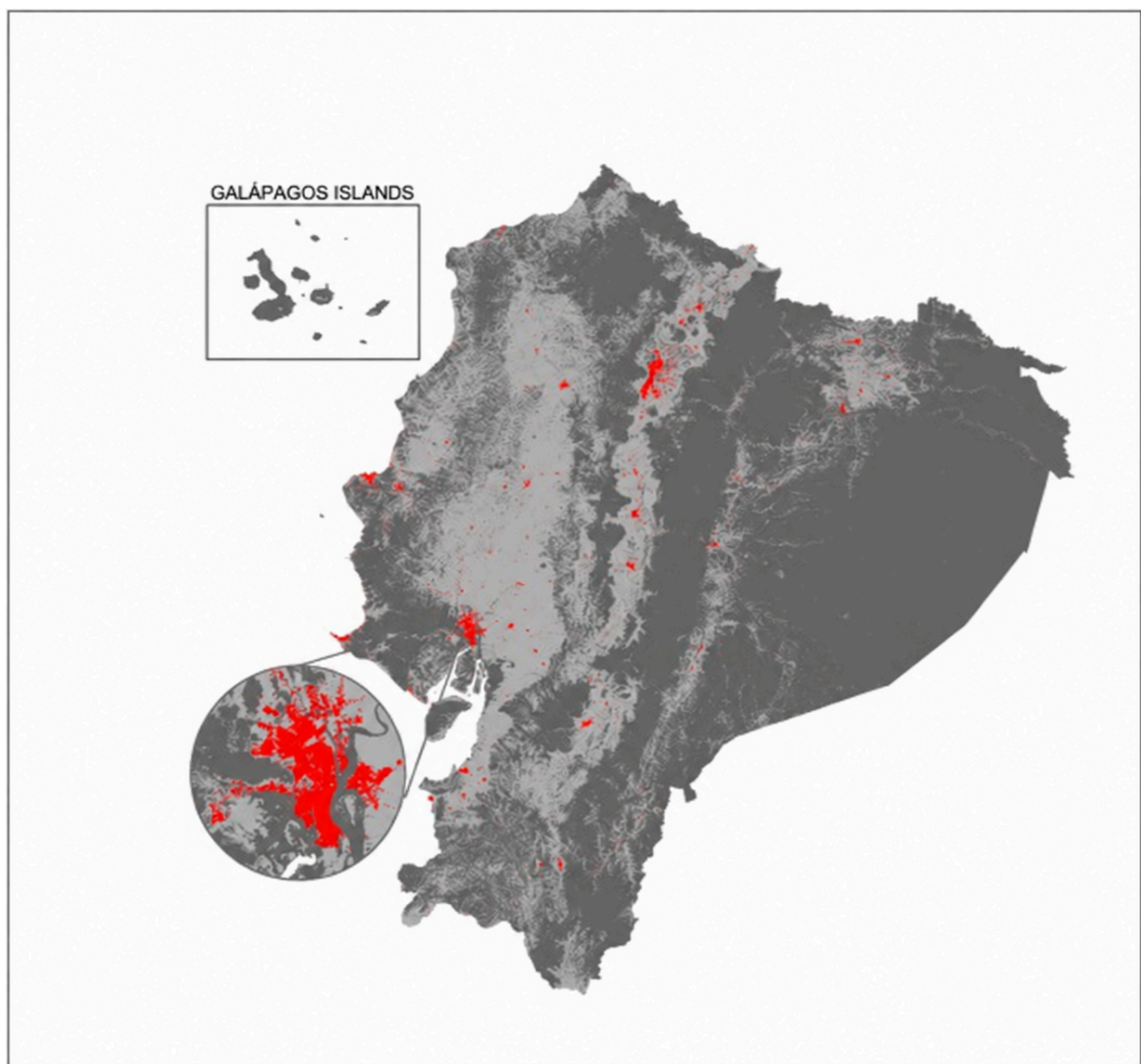


Figure 11: 2025 urban infrastructure map. Prepared by EcoCiencia.

7. Reference

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