Urban Area - Appendix

Collection 8

Version 1

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1. Overview

This document presents the method developed to map Urban Area (ID 24) and its associated changes in the Collection 8 of MapBiomas. Following the general method of MapBiomas, Urban Area mapping adopts a supervised machine learning classification method applied to Landsat imagery, resulting in annual land cover and land use maps. Main improvements regarding the Collection 8 were the inclusion of Landsat 9 Collection 2 scenes, the use of a smoothing process in the nightlights data in the spatial filter, the update of the Index of Roads and Structures (IRS) (Justiniano et al. 2022) in the spatial filter and the automatic threshold selection for the Random Forest (RF) probability results. A neighborhood approach was adopted to cover areas with few samples, enlarging the processed area.

The mentioned enhancements focused on refining imagery and updating data. By integrating Landsat 9 images, we bolstered classification precision for the time series' final year, resulting in an improved mosaicking process. Adjustments were made to the nighttime layer to mitigate misclassification risks stemming from its spatial resolution. Furthermore, we integrated IRS data from 2022 into our analysis. Notably, this data layer played a pivotal role in the spatial filter processing alongside other criteria. These collective refinements yielded a slight increase in identified urban areas compared to previous iterations of the MapBiomas Collections.

Figure 1 summarizes the main methodological processing steps using Landsat mosaics, Random Forest classification algorithm, and spatial and temporal filters.

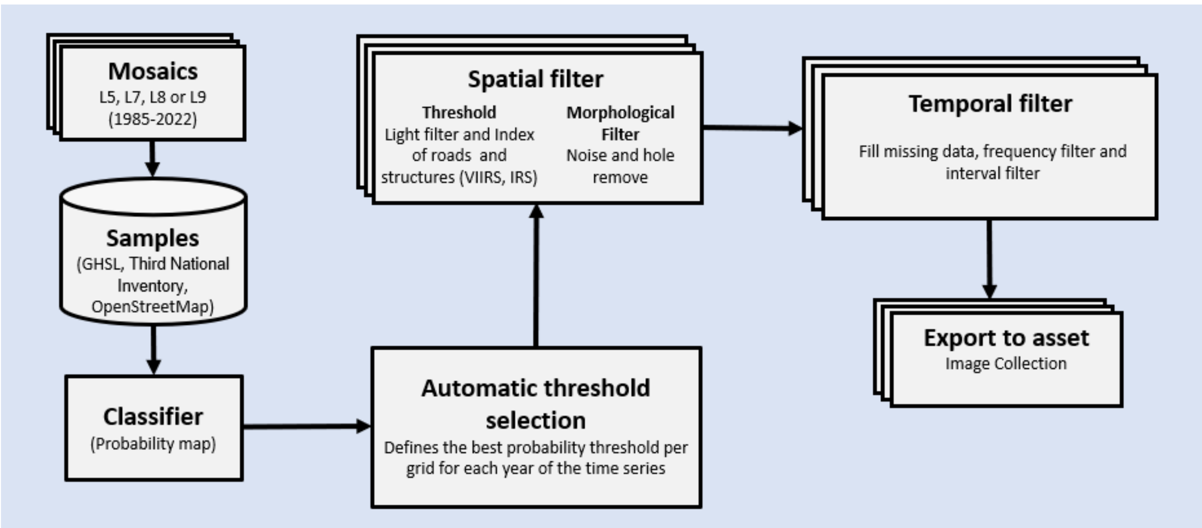


Figure 1. Basic scheme of the production of Urban Area maps in MapBiomas Collection 8.

Since Collection 6, we have adopted as class name the term “Urban/Urbanized Area” (UA) instead of “Urban Infrastructure” in order to cope with the terminology applied in urban studies, such as IBGE (2017). UA are regions with predominance of significant density of buildings, roads and urban related infrastructure. It is worth pointing out that for any external quantitative comparison, it is important that the concepts adopted should be made compatible.

2. Landsat image mosaics

Landsat 5, Landsat 7, Landsat 8 and Landsat 9 imagery were used to create annual mosaics for mapping Urban Area in Collection 8.0, according to Table 1.

Table 1. Landsat imagery used in Urban Area mosaics.

Landsat Collection	Sensor	Collection	Level	Bands [wavelength]
Landsat 5 Level 2, Collection 2, Tier 1 [1]	TM	2	Surface Reflectance	SR_B1: Blue [0.45-0.52 µm] SR_B2: Green [0.52-0.60 µm] SR_B3: Red [0.63-0.69 µm] SR_B4: Near Infrared [0.77-0.90 µm] SR_B5 : Shortwave Infrared 1 [1.55-1.75 µm] SR_B7: Shortwave Infrared 2 [2.08-2.35 µm]
Landsat 5 TM Collection 1 Tier 1 Raw Scenes [2]	TM	2	Raw Images	B4: Near infrared [0.76 - 0.90 µm] B5: Shortwave infrared 1 [1.55 - 1.75 µm] B6: Thermal Infrared 1 (resampled from 60m to 30m) [10.40 - 12.50 µm]
Landsat 7 Level 2, Collection 2, Tier 1 [3]	ETM+	2	Surface Reflectance	SR_B1: Blue [0.45-0.52 µm] SR_B2: Green [0.52-0.60 µm] SR_B3: Red [0.63-0.69 µm] SR_B4: Near Infrared [0.77-0.90 µm] SR_B5 : Shortwave Infrared 1 [1.55-1.75 µm] SR_B7: Shortwave Infrared 2 [2.08-2.35 µm]
Landsat 7 Collection 2 Tier 1 Raw Scenes [4]	ETM+	2	Raw Images	B4: Near Infrared [0.77 - 0.90 µm] B5: Shortwave Infrared 1 [1.55 - 1.75 µm] B6_VCID_1: Low-gain Thermal Infrared 1 (resampled from 60m to 30m) [10.40 - 12.50 µm]
Landsat 8 and 9 Level 2, Collection 2, Tier 1 [5]	OLI / TIRS	2	Surface Reflectance	SR_B2: Blue [0.45 - 0.51 µm] SR_B3: Green [0.53 - 0.59 µm] SR_B4: Red [0.64 - 0.67 µm] SR_B5: Near Infrared [0.85 - 0.88 µm] SR_B6: Shortwave Infrared 1 [1.57 - 1.65 µm] SR_B7: Shortwave Infrared 2 [2.11 - 2.29 µm]
Landsat 8 and 9 Collection 2 Tier 1 Raw Scenes [6]	OLI / TIRS	2	Raw Images	B5: Near infrared [0.85 - 0.88 µm] B6: Shortwave infrared 1 [1.57 - 1.65 µm] B10: Thermal infrared 1 (resampled from 100m to 30m) [10.60 - 11.19 µm]

[1] https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LT05_C01_T1
[2] https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LT05_C02_T1_L2
[3] https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LE07_C02_T1_L2
[4] https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LE07_C02_T1

[5] https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C02_T1_L2 and https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC09_C02_T1_L2
[6] https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C02_T1 and https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC09_C02_T1

Mosaics were created following these steps:

1. Filtering Landsat Collections scenes by date (year-by-year, from 1985 to 2022) and bounds (Brazilian territory).
2. Masking pixels of clouds and cloud shadows in all scenes, using pixel quality attributes generated by the CFMASK[1] algorithm. For scenes of Landsat Collection 2 (surface reflectance of Landsat 5, 7, 8 and 9 and raw scenes of Landsat 5, 7, 8 and 9), pixel quality is in QA_PIXEL band.
3. Scaling surface reflectance values to 0 to 1, using values of scale (-0,2) and offset (0.0000275) informed in collections' bands description in each reference page.
4. Calculating selected spectral indexes and fractions from spectral mixture analysis for each scene (Table 2).
5. Applying an appropriate reducer to each band/index to obtain one pixel value per year (Table 2).
6. Calculating reduced indexes difference to capture intra-annual changes (Table 2).
7. Compositing all bands and indexes to obtain one mosaic per year.

Table 2. List, description, reducer, and script acronym used in Urban Area mosaic.

Band / Index / Fraction	Description	Reducer	Script acronym
BLUE	Landsat band	median	BLUE_median
GREEN	Landsat band	median	GREEN_median
RED	Landsat band	median	RED_median
NIR	Landsat band	median	NIR_median
SWIR1	Landsat band	median	SWIR1_median
SWIR2	Landsat band	median	SWIR2_median
NDVI	Normalized Difference Vegetation Index	median	NDVI_median
EVI1	Enhanced Vegetation Index 1	median	EVI_median
EVI1	Enhanced Vegetation Index percentiles	10th percentile, 90th percentile	EVI_p10 EVI_p90
EVI1	Enhanced Vegetation Index percentiles difference	difference	EVI_dif9010

[1] CFMask is a multi-pass algorithm that uses decision trees to prospectively label pixels in the scene; it then validates or discards those labels according to scene-wide statistics. It also creates a cloud shadow mask by iteratively estimating cloud heights and projecting them onto the ground. Reference: https://www.usgs.gov/core-science-systems/nli/landsat/cfmask-algorithm.

Band / Index / Fraction	Description	Reducer	Script acronym
EVI2	Enhanced Vegetation Index 2	median	EVI_median
EVI2	Enhanced Vegetation Index percentiles	10th percentile, 90th percentile	EVI2_p10 EVI2_p90
EVI2	Enhanced Vegetation Index percentiles difference	difference	EVI2_dif9010
MNDWI	Modified Normalized Difference Water Index	median	MNDWI_median
NDWI	Normalized Difference Water Index	median	NDWI_median
NDBI	Normalized Difference Built-Up Index	median	NDBI_median
NBR	Normalized Burn Ratio	median	NBR_median
NDRI	Normalized Difference Road Index	median	NDRI_median
BAI	Bare Soil Area Index	median	BAI_median
UI	Urban Index	median	UI_median
NDUI	Normalized Difference Urban Index	median	NDUI_median
BSI	Bare-Soil Index	median	BSI_median
BU	Built-up Index	median	BU_median
GV	Green Vegetation Fraction	median	GV_median
NPV	Non Photosynthetic Vegetation Fraction	median	NPV_median
SOIL	Soil Fraction	median	SOIL_median
CLOUD	Cloud Fraction	median	CLOUD_median
SHADE	Shade Fraction	median	SHADE_median
GVS	Green Vegetation + Soil Fraction	median	GVS_median
NDFI	Normalized Difference Fraction Index	median	NDFI_median
SUBS	Substrate Fraction	median	SUBS_median
VEG	Vegetation Fraction	median	VEG_median
DARK	Dark Fraction	median	DARK_median
EBBI	Enhanced Built-Up and Bareness Index	median	EBBI_median
EBBI	Enhanced Built-Up and Bareness Index percentiles	25th percentile, 90th percentile	EBBI_p25 EBBI_p90
EBBI	Enhanced Built-Up and Bareness Index percentiles difference	difference	EBBI_dif7525
EBBI	Positive part of the Enhanced Built-Up and Bareness Index	median	EBBIsNeg_median
EBBI	Positive part of the Enhanced Built-Up and Bareness Index percentiles	25th percentile, 90th percentile	EBBIsNeg_p25 EBBIsNeg_p75
EBBI	Positive part of the Enhanced Built-Up and Bareness Index percentiles difference	difference	EBBIsNeg_dif7525

3. Classification

3.1. Classification algorithm

The Random Forest algorithm implemented in Google Earth Engine (smileRandomForest) was applied to map Urban Area in MapBiomas Collection 8 using training datasets of points in urban areas and points in non-urban areas.

To reduce computational cost, the automatic classification was performed only in “search areas”, defined by polygons where urban areas were likely to be found. A uniform hexagonal polygon grid was created over Brazilian territory and intersected with urban census tracts (IBGE, 2021)[2], totalizing a search area of 226.005.594 ha, covering 27% of the Brazilian territory.

Materials used in urban areas (like in roofs, pavements, and others) in Brazil usually are spatially and temporally highly diverse. In time, diversity is related to the urbanization process itself: streets in Humaitá, Amazonas State, for instance, were more sparse and predominantly unpaved in 1985, whereas today they are paved in a denser urban environment. Furthermore, roofs and pavements have distinct spectral behavior depending on their materials, colors, aging and coating (such as algae, lichen, dirt, dust, rubber tire marks, etc.) (HEROLD et al., 2004).

To cope with the diversity of urban cover types, different random forest classifiers were built. We divided Brazil territory into 558 tiles that correspond to charts with a scale of 1:250.000, derived from the International Map of the World (IMW). Tiles with no hexagon search area were discarded, resulting in 522 valid tiles. Then, a specific classifier was trained to each of these tiles of each year of the 38 years of the Collection 8.0.

Random Forest parameters were set to 500 trees and 20 minimum leaf populations. The classification result is an image assigning to each pixel the probability of being urban.

3.2. Training Samples

Training samples were obtained from OpenStreetMap database (OpenStreetMap, 2018) combined with nightlight images (NOAA), land cover and land use maps from the Third National Inventory (MCTI, 2015) and built-up maps of the Global Human Settlement Layer (GHSL), provided by Joint Research Center (JRC) (Corbane et al., 2019).

[2] Census tracts are classified according to their situation. To build the search areas, we considered tracts in the following situations: (1) urban area with high density of buildings, (2) urban area with low density of buildings and (3) urban nucleus.

Firstly, a preliminary urban mask was built based on pathways from OpenStreetMap database, representing all roads, streets, sidewalks, and unknown roads already registered by OpenStreetMap users. Pathways within the urban patches or conglomerates of specific categories (residential, service, path, and living street) were selected. Then, pathways outside urban area were removed using a nightlight image (Figure 2). For specific years, pathways were also filtered by existing data: built-up surfaces maps of the Global Human Settlement Layer (GHSL) for 1985, and urban area mappings of the Third National Inventory (MCTI, 2015), for 1994, 2002, and 2010. Then these filtered pathways were transformed into areas applying a buffer of approximately 100 meters to each one of them.

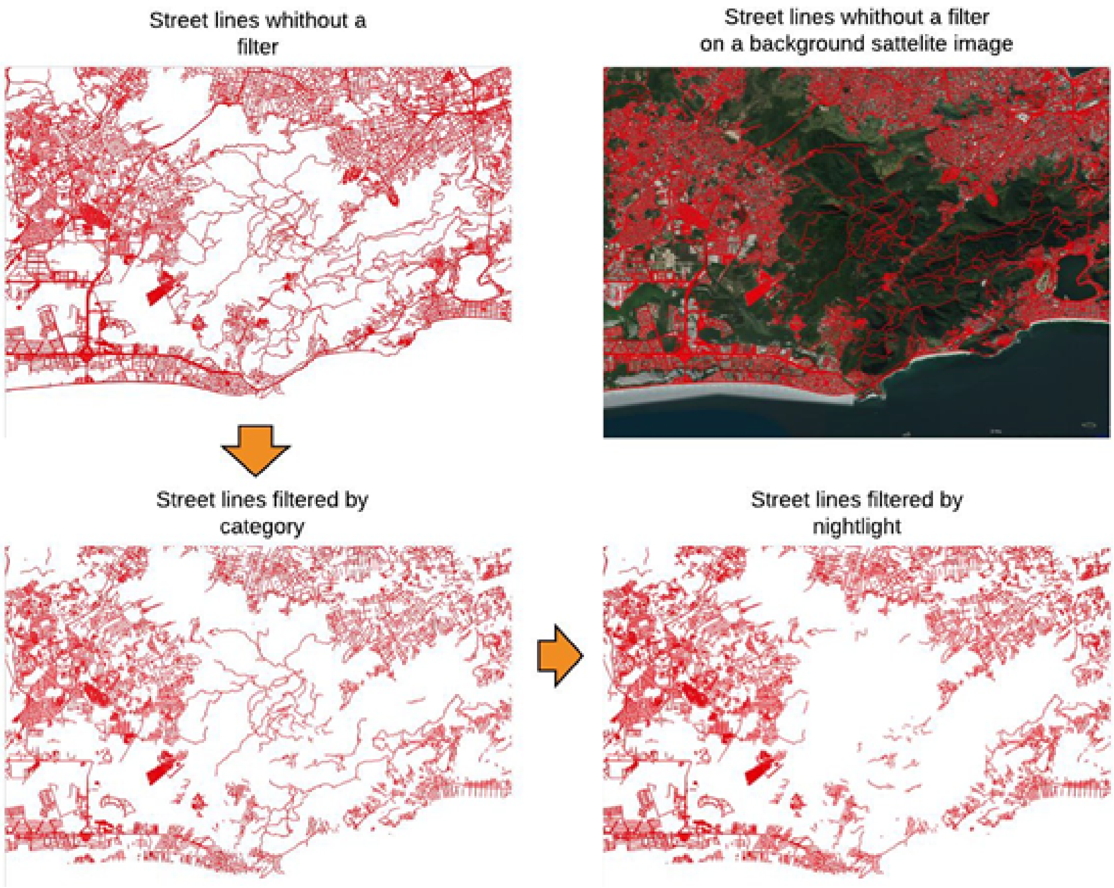


Figure 2. Example of filters used on the vector layer of OpenstreetMap in Rio de Janeiro - RJ Brazil.

Secondly, an explorative classification of urban area using indexes of normalized difference of vegetation and water (NDVI and NDWI) was produced to mask water and vegetation (Figure 3).

The final urban mask was obtained by the intersection of the preliminary mask, derived from OpenStreetMaps polylines and filtered by ancillary data, with the explorative classification (Figures 4 and 5). And the symmetrical difference of the final urban mask is the final non-urban mask.

Random points were generated within the search area of each of the 522 tiles. Then PostGIS was used to label points using the final urban and non-urban masks (Figure 6), generating a dataset of urban and non-urban samples for the years of 1985, 1994, 2002, 2010 and 2018 (these dates coincide with urban mapping reference data available).

Figure 3. Explorative classification results for Rio de Janeiro - RJ, Brazil.

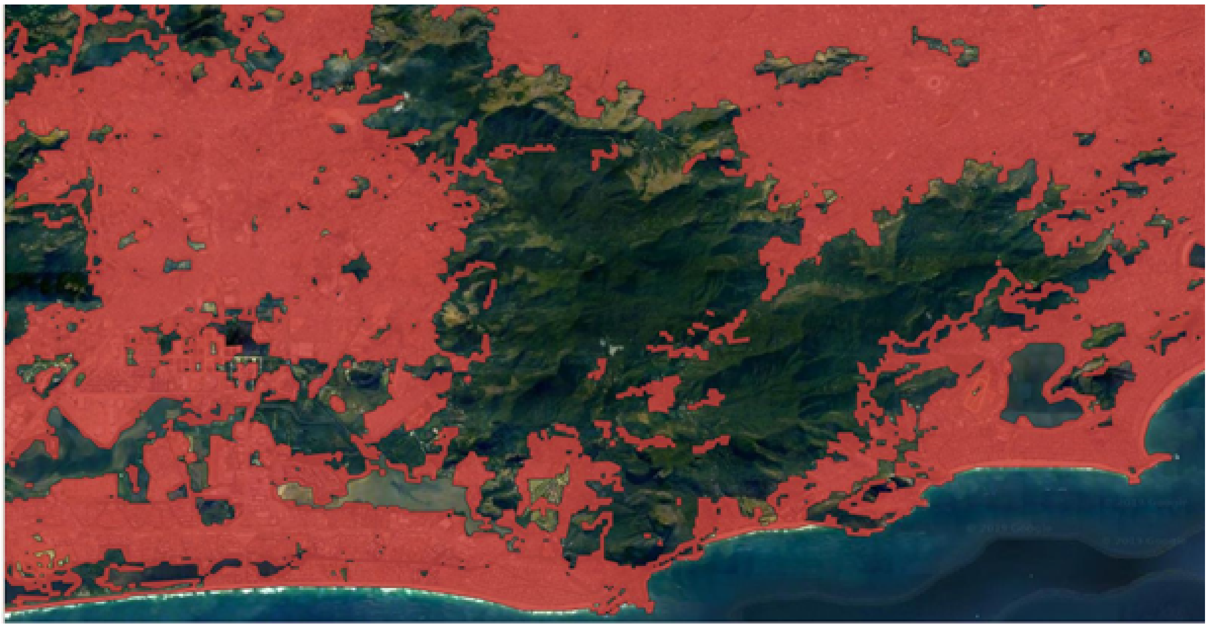
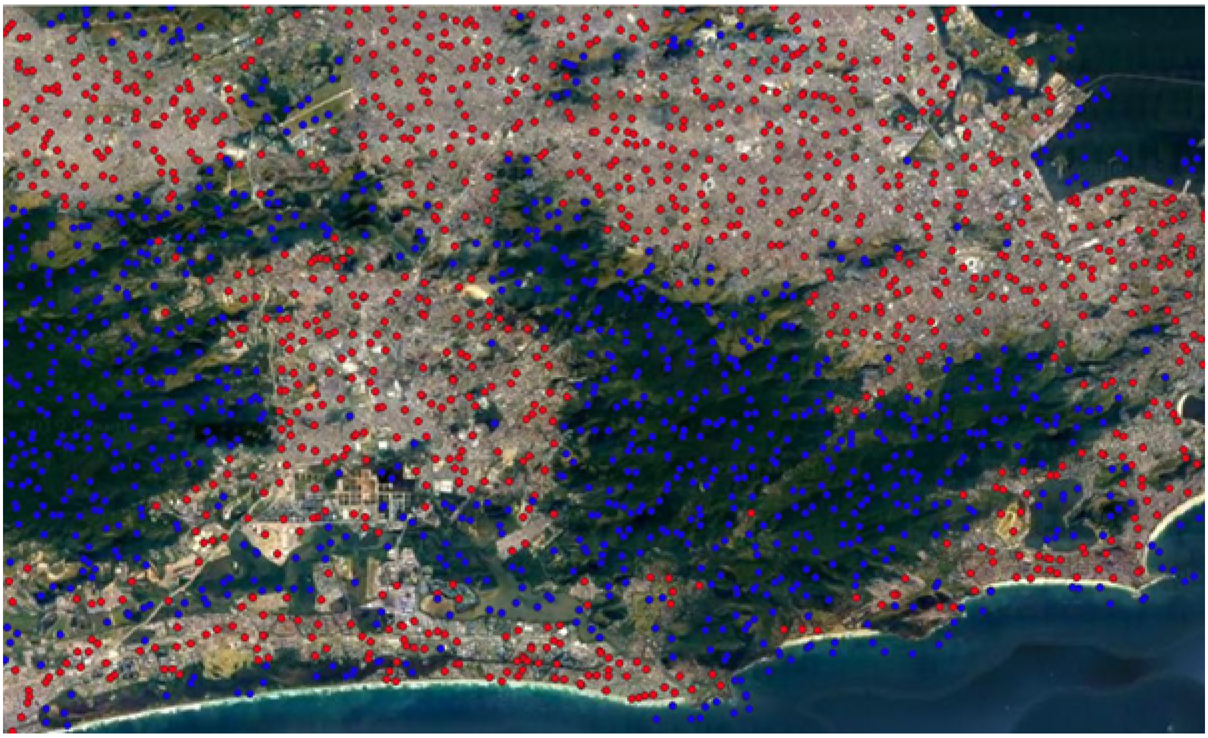


Figure 4. Final urban mask for Rio de Janeiro- RJ, Brazil.

Figure 5. Final non-urban mask (orange color) for Rio de Janeiro - RJ, Brazil.

Figure 6. Random points divided by urban area (red) and non-urban area (blue).



To balance the sample dataset, points were generated in each of the 522 tiles observing the extension of urban area and non-urban area, according to the final urban mask. Considering the entire Brazil, In the early years of the time series, this balance was 1 sample of urban area to 2.6 samples of non-urban area. In the final years, it was 1 to 2.

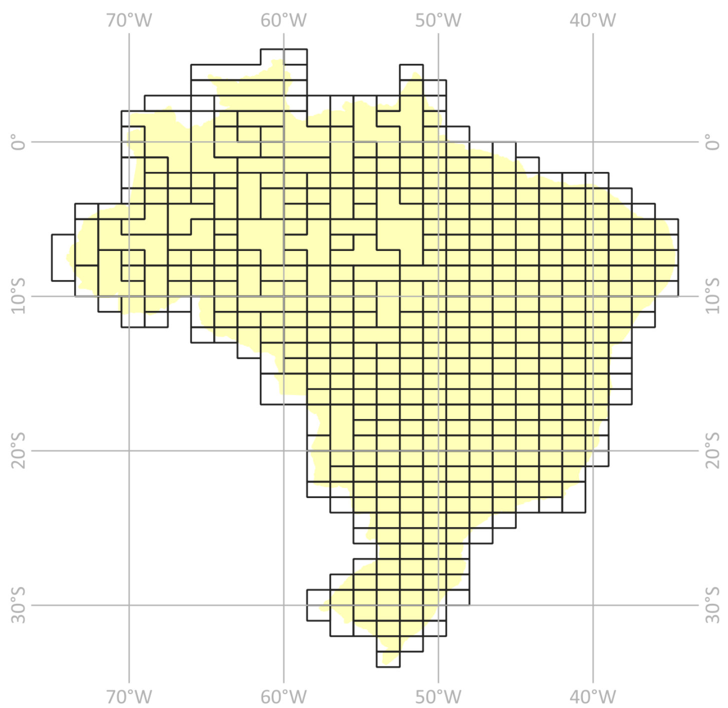
3.3. Feature space

The feature space that characterizes Urban Area for MapBiomas Collection 8.0 is the dataset of urban and non-urban points trained with 43 variables from Landsat image mosaics (summarized in Table 1, Section 2), calculated for each tile.

Datasets comprising both urban and non-urban samples were employed, based on the assumption that once a point was classified as urban, it retained this designation in the subsequent years. Accordingly, images spanning from 1985 to 1993 were utilized to construct the 1985 dataset, thereby yielding a distinct feature space for each year and tile. Similarly, images spanning from 1994 to 2002 were utilized for the 1994 dataset; images from 2003 to 2009 for the 2003 dataset; images from 2010 to 2017 for the 2010 dataset; and images from 2018 to 2021 for the 2018 dataset. These intervals were arbitrarily defined in order to take into account the differences in Landsat mosaics and cover the whole dataset. It constitutes one of the limitations of the classification process.

A neighborhood approach was adopted in tiles without feature space due to the lack of urban samples or lack of cloud-free data. In these cases, the nearest tile with a feature space was used, resulting in 421 tiles with feature spaces for each year (Figure 7).

Figure 7. Feature space's tiles.



4. Spatial and Temporal Filters

The spatial and temporal filters were configured to improve the classification considering the diversity of materials and features of the urbanized areas of several Brazilian municipalities, from 1985 to 2022. These procedures resulted in a binary raster which indicated urban and non-urban areas.

4.1 Spatial Filter

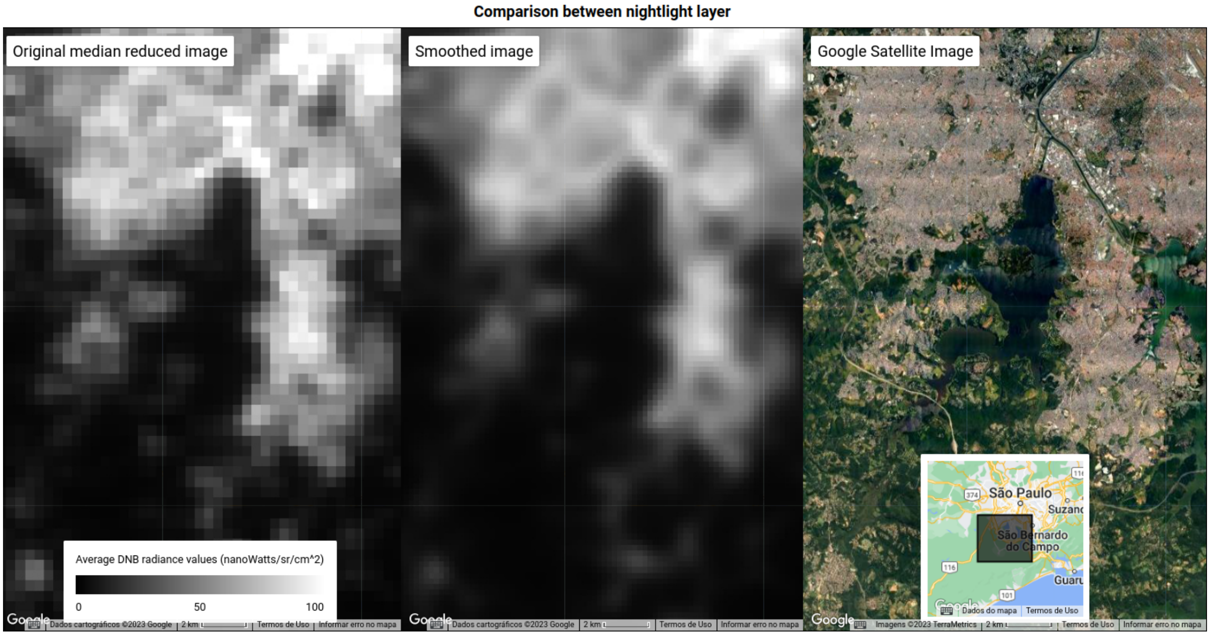
From one perspective, the classifier exhibits a tendency to assign elevated UA (Urban Area) probability values to regions beyond urban confines, encompassing mining, sand deposits, rural structures, and various other features. Conversely, the classifier assigns diminished probability values to pixels within the urban framework that contain trees and public squares. Adding to the complexity, adopting uniform probability thresholds for pixel assignment to UA zones would inevitably result in inaccuracies, given the unique traits of different cities. To counter this, the thresholds for defining UA regions were established within the spatial filter code, where they harmonize with supplementary data and contextual factors.. This was done considering the layers presented in Table 3.

Table 3. Layers and thresholds for the spatial filter.

Layer	Description	Threshold criteria	Why use?
IRS	Defines urban limits according to roads and infrastructure density. Quantitative layer.	Values greater than or equal to 500 (JUSTINIANO et al., 2022).	Provides a general mask layer identifying where urban area must be.
VIIRS	Defines general regions where urban areas can be found according to night light values. Quantitative layer.	Greater than or equal 1.	
Census tracts	Defines urban limits according to census criteria and official organism. Qualitative layer.	Tracts with urban characterization (types 1, 2 and 3) (IBGE, 2020).	
Subnormal settlements	Defines regions where there are human populations with specific vulnerabilities around urban area. Qualitative layer.	All the regions were considered.	
UA (probability)	Defines urban area according to the RF algorithm through time series. Quantitative layer.	Defined using 'best threshold algorithm'.	Provides the urban classification

Additionally, as part of the enhancements introduced in Collection 8, adjustments were made to the nightlight layer (VIIRS) in order to prevent misclassification of UA. This was achieved through the reprojection of the original image resolution, coupled with a pixel neighborhood erosion, as depicted in the figure 8.

Figure 8. VIIRS smoothed image.



Considering that UA has higher population and light emission at night, raster files of the satellite Visible Infrared Imaging Radiometer Suite (VIIRS), on board the Suomi NNP satellite Day Night Band were used. The threshold value of the VIIRS bands and the annual values of UA probability were established through an algorithm that calculates the best threshold for each grid per year of the time series (see urban area GitHub[3]).

The result of applying filters based on threshold values per year is a raster with values zero and one, where the latter value is associated with the urban area. In this raster, it was possible to observe the occurrence of isolated pixels or small clusters of pixels with different values than those in the surrounding area. In the urban area, small clusters of isolated pixels with a value of zero would be associated with squares, boulevards, water, trees, and other urban elements. In the non-urban area, isolated pixels with one value may be related to agricultural structures, summer homes, and other non-urban structures.

Spatial filters also perform morphological operations that eliminate groups of up to 60 pixels with zero values in UA and assign them a one value. Conversely, in non-urbanized areas, groups with less than 5 pixels with a value of one are eliminated, giving zero value.

[3] https://github.com/mapbiomas-brazil/urban-infrastructure/tree/mapbiomas80

4.2 Temporal filter

Temporal filters (TF) were applied as rules to check classification consistency over time, observing the conceptual aspects delimited to the mapped category. For this purpose, the sequence of filters indicated and described in Table 4 was developed. General rules for middle years (GR), and specific rules for the first years (FYR) and last years (LYR) were determined for each TF. The temporal consistency was established according to results obtained by pixel in a ranging between 3 and 5 years (kernel) for the immediately previous TF results.

Table 4. Descriptions of TFs used.

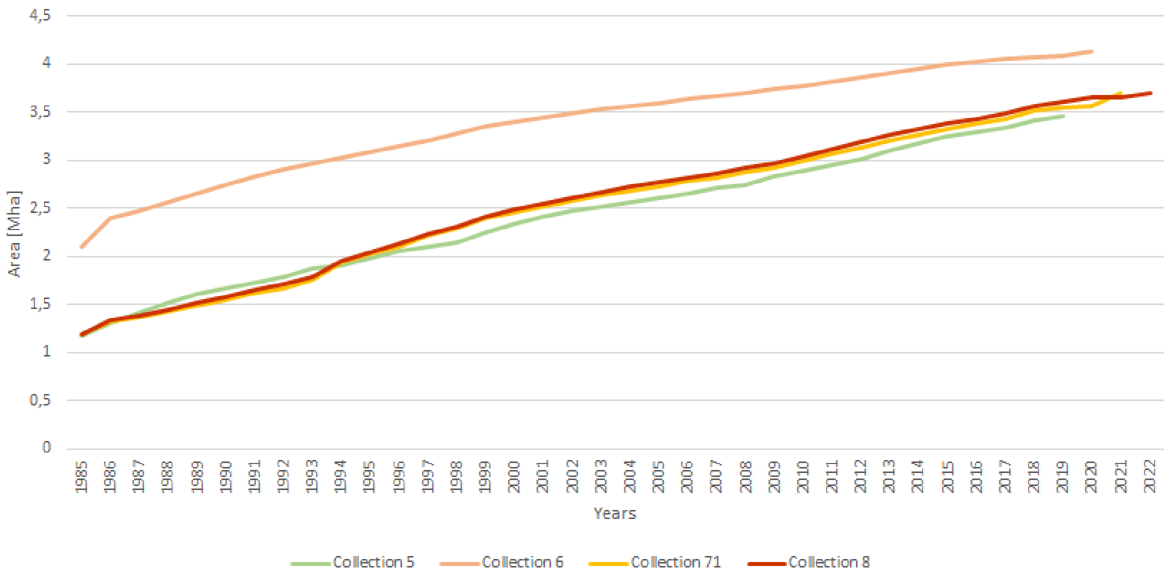
TF	Scope	Type	Years	Kernel						Conditionals
				i-2	i-1	i	i+1	i+2	i+3	
1	It acts on the pixels that were classified as ‘UA’ in the SF results and sets the mask for the filters up to TF3.	FYR	1985 and 1986			x	x	x		If the pixel under analysis is classified as ‘UA’ within two or more years of the kernel, then the ‘UA’ is assigned to the TF2.
		GR	1987 to 2019	x	x	x	x	x		If the pixel under analysis is classified as ‘UA’ within three or more years of the interval, then the ‘UA’ is assigned to the TF2.
		LYR	2021 to 2022	x	x	x				If the pixel under analysis is classified as ‘UA’ within two or more years of the interval, then the ‘UA’ is assigned to the TF2.
2	It acts on pixels that have been validated as ‘UA’ in the TF1 results.	GR	1985 to 2018			x	x	x	x	If the pixel under analysis is classified as ‘UA’ within two or more years of the range, then the ‘UA’ is assigned to the TF3.
		LYR	2018 and 2020	x	x	x	x			If the pixel is classified as ‘UA’ within two or more years of the range, then the ‘UA’ is assigned to the TF3.
		LYR	2022	x	x	x				If the pixel is classified as ‘UA’ within two or more years of the range, then the ‘UA’ is assigned to the TF3.
3	Extends the filter mask and acts on pixels not classified as urban in TF2.	FYR	1985			x				The results obtained for TF2 are assumed.
		GR	1986 to 2020		x	x	x			If the pixel is classified as ‘UA’ for i-1 and i+1, then ‘UA’ is assigned.
		LYR	2022		x	x				If the pixel is rated 'UA' for i-1, then 'UA' is assigned.
4	Area Consolidation Filter.	FYR	1985			x	x			If a pixel under analysis is rated 'UA' for i and not rated for i+1, then it becomes non-urban.
		FYR	1986			x				The results obtained for TF3 are assumed.
		GR	1986 to 2022			x	x			If a pixel under analysis is classified as 'UA' for i, then for i+1 it will also be UA.

FYR = firsts years rules; GR = general rule; LYR = lasts years rules.

5. Comparison between Collections

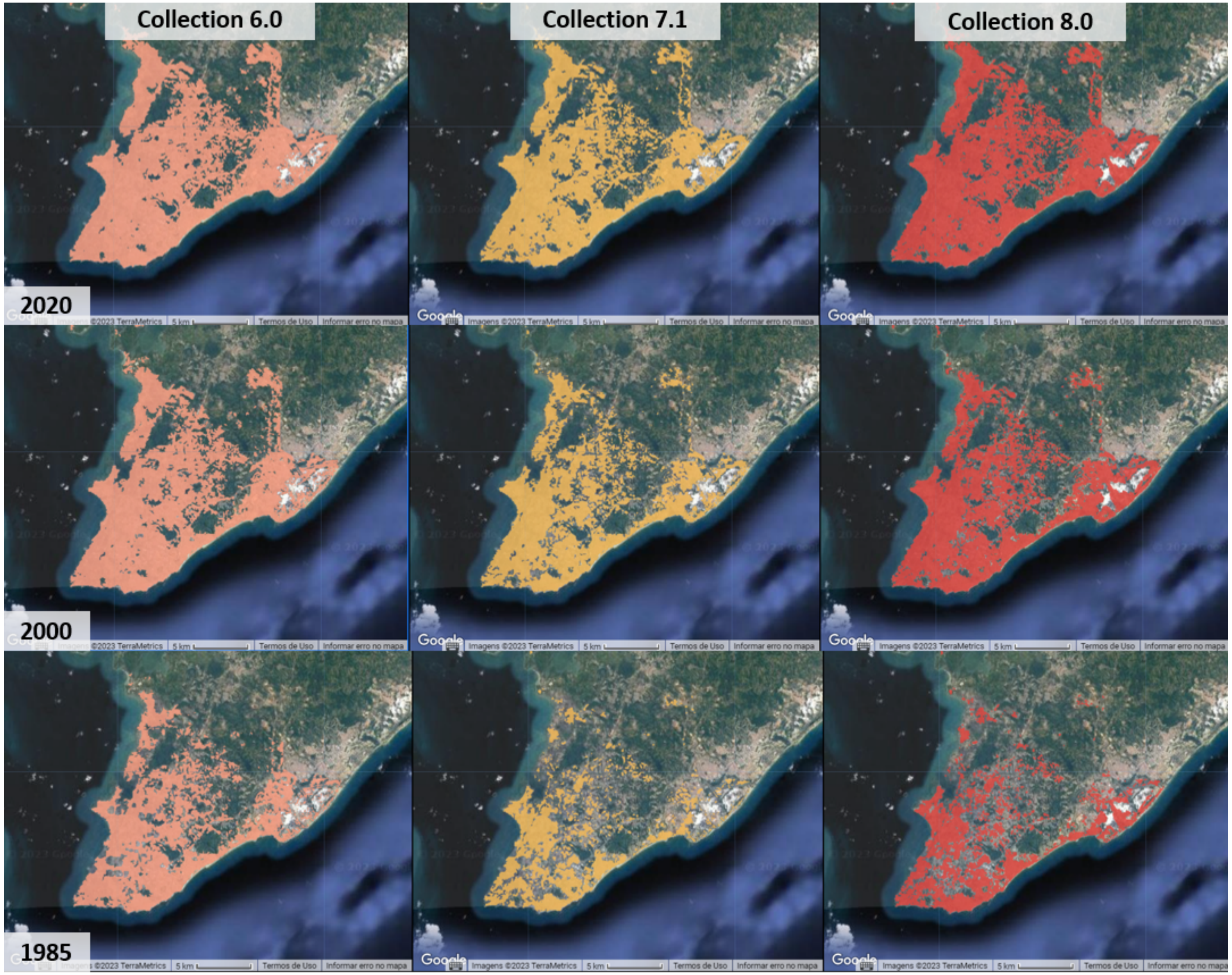
This section presents visual examples that offer a comparative view between the current Collection and its predecessors. As shown in Figure 9, the criteria embraced in this collection exhibit a greater inclusivity (excluding the Collection 6 results) in classification across temporal dimensions. This evolution has fostered a more consistent and harmonized process, aligned with the underlying conceptual framework. However, this refinement has led to an increase in omission errors, a topic further presented upon in the subsequent section.

Figure 9. Comparison between growth of urbanized areas for Collections.



As an example, the Salvador municipality presents significant challenges with regard to remote sensing mapping, mainly due to the frequent presence of cloud cover. The rugged topography and high atmospheric humidity contribute to the formation of clouds that often obscure the view of land surfaces captured by satellites. Figure 10 shows the evolution of the mapping of these areas over the last three collections, where it is possible to notice the reduction of commission errors, especially when compared to Collection 6

Figure 10. Example of visual comparison considering Salvador (BA).



6. Validation strategies

6.1 Performance

The validation analysis was performed using point samples collected by the Laboratory of Image Processing and Geoprocessing (LAPIG), University of Goiás-GO, Brazil. According to the reference data, (i) the samples of UA that were correctly classified are the True Positive; (ii) the samples of UA that were classified as not UA are the False Negative; and the samples of UA that were not classified as UA are the False Positive.

The comparison of accuracy results between Collection 6.0, Collection 7.0 and Collection 8.0 are shown in Figure 11 and Figure 12. The first shows that commission errors in the last collections were smaller than in the previous. The omission errors, however, were larger and more concentrated in the first 15 years of the time series.

Figure 11. Omission (Producer's accuracy).

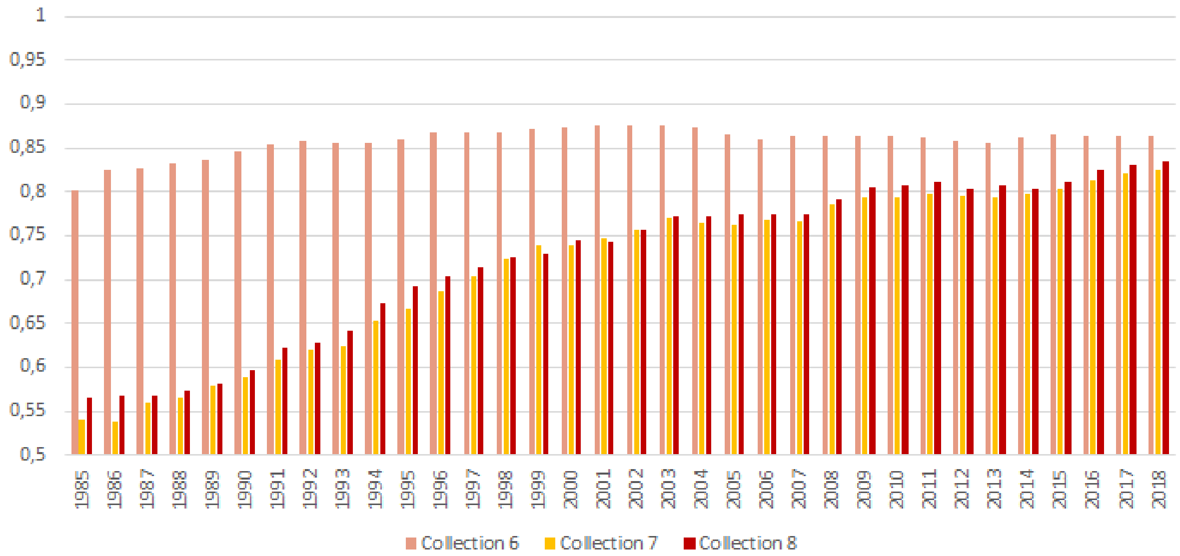
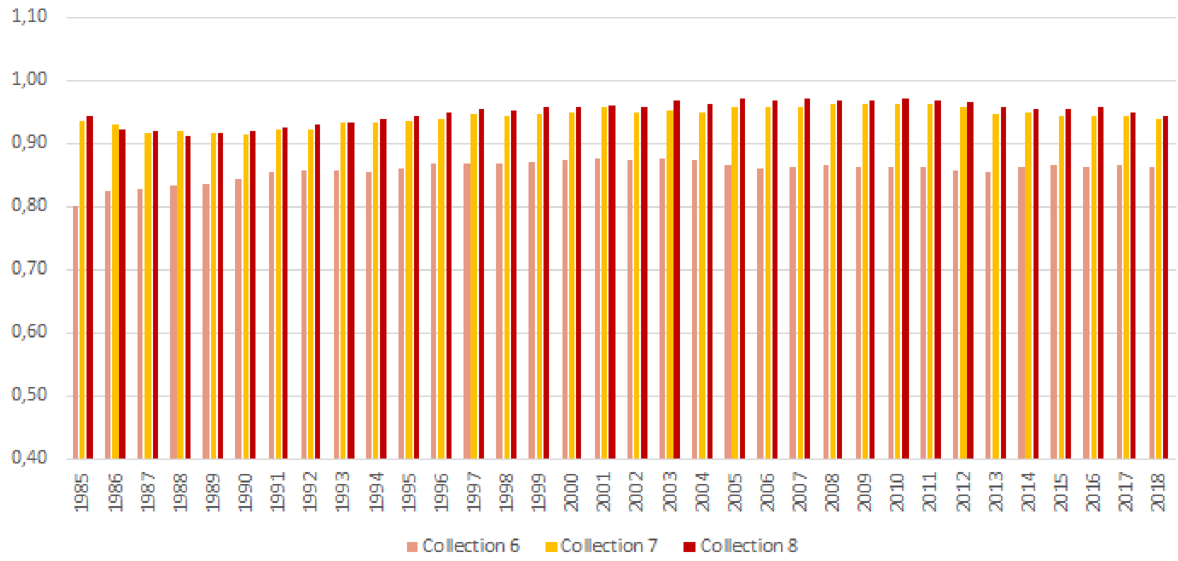


Figure 12. Commission (User's accuracy).



6.2 Reference Maps

MapBiomas Collection 8.0 were compared to two urban area maps: (1) the World Settlement Footprint (WSF) produced by Deutsches Zentrum für Luftund Raumfahrt (DLR) (MARCONCINI et al., 2020) and (2) Brazil Urbanized Areas produced by IBGE, Instituto Brasileiro de Geografia e Estatística (IBGE, 2022).

WSF is a 10m resolution binary mask outlining the extent of human settlements globally derived by means of 2014-2015 multitemporal Landsat-8 and Sentinel-1 imagery, using different classification schemes based on Support Vector Machines. It is available at Earth Engine Data Catalog[4].

Brazil Urbanized Areas is a visual interpretation of urban features, identified according to the elements of specific shape (geometry of objects) and pattern (spatial arrangement). It is based on Sentinel 2 imagery, with spatial resolution of 10m. It is available in shapefile format at IBGE's website[5].

Quantitative analysis (Table 5) shows that MapBiomas Collection 8.0 is compatible with WSF, for 2015, despite the different spatial resolution of the two maps (30m and 10m, respectively). The comparison with IBGE's 2019 data points to an underestimation of MapBiomas Collection 8.0 urban area. The underestimation is reported in MapBiomas accuracy assessment. Worth to note that the interpretation method and higher resolution of IBGE's data improve the mapping of low-density areas, which are not completely mapped by MapBiomas.

[4] https://developers.google.com/earth-engine/datasets/catalog/DLR_WSF_WSF2015_v1

[5] https://www.ibge.gov.br/geociencias/cartas-e-mapas/redes-geograficas/15789-areas-urbanizadas.html?=&t=acesso-ao-produto

Table 5. Quantitative analysis with reference data.

Region	State	Urban Area in 2015 (in ha)		MapBiomas Collection 8.0 in relation to WSF 2015	Urban Area in 2019 (in ha)		MapBiomas Collection 8.0 in relation to IBGE 2019
		MapBiomas Collection 8.0	WSF 2015		MapBiomas Collection 8.0	IBGE 2019	
Norte	Rondônia	47.862	40.222	19%	49.901	59.520	-16%
	Acre	23.102	15.462	49%	15.754	25.380	-38%
	Amazonas	40.125	37.811	6%	48.026	77.925	-38%
	Roraima	15.725	10.437	51%	16.150	26.181	-38%
	Pará	116.610	108.799	7%	123.055	206.217	-40%
	Amapá	40.610	32.799	24%	13.123	17.603	-25%
	Tocantins	49.529	38.743	28%	52.131	63.882	-18%
Nordeste	Maranhão	98.236	98.088	0%	105.770	187.240	-44%
	Piauí	56.695	51.974	9%	63.253	112.714	-44%
	Ceará	107.109	121.810	-12%	118.588	211.352	-44%
	Rio Grande do Norte	44.885	44.352	1%	50.463	100.088	-50%
	Paraíba	45.228	46.668	-3%	53.247	83.218	-36%
	Pernambuco	89.689	89.354	0%	103.545	175.755	-41%
	Alagoas	46.012	45.678	1%	36.740	71.265	-48%
	Sergipe	22.194	28.877	-23%	26.083	56.044	-53%
	Bahia	174.942	174.369	0%	196.765	345.110	-43%
Sudeste	Minas Gerais	370.864	384.356	-4%	395.205	567.443	-30%
	Espírito Santo	58.500	59.247	-1%	61.233	84.683	-28%
	Rio de Janeiro	209.574	226.448	-7%	216.140	314.771	-31%
	São Paulo	705.256	723.426	-3%	740.500	962.026	-23%
Sul	Paraná	250.939	261.311	-4%	268.448	373.872	-28%
	Santa Catarina	173.387	180.364	-4%	185.296	295.119	-37%
	Rio Grande do Sul	222.217	248.607	-11%	233.673	407.517	-43%
Centro-oeste	Mato Grosso do Sul	71.577	67.612	6%	75.572	95.304	-21%
	Mato Grosso	111.628	90.979	23%	118.622	146.920	-19%
	Goiás	178.353	161.408	10%	188.639	224.282	-16%
	Distrito Federal	55.286	50.445	10%	57.195	62.283	-8%
BRAZIL		3.426.133	3.439.646	0%	3.613.119	5.353.717	-33%

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