MapBiomas Uruguay

Collection 3

Algorithm Theoretical Basis Document (ATBD)

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General Coordinator
Tasso Azevedo

Country coordinators
Santiago Baeza
Federico Gallego

Uruguay team
Andrea Barbieri
Laura Bruzzone
Sebastián Ramos
Gonzalo Rama
Pablo Baldassini

1 INTRODUCTION

1.1 Scope and content of the document

The objective of this document is to describe the theoretical basis, justification and methods applied to produce annual maps of land use and land cover (LULC) in Uruguay from 1985 to 2024 (Collection 3). The document presents a general description of the satellite image processing, the feature inputs and the process step by step applied to obtain the annual classifications.

1.2 Region of Interest

MapBiomas Uruguay initiative was created to produce LULC annual maps for the Uruguay territory (**Figure 1**). The total mapped area was 17,8 million hectares (Mha)

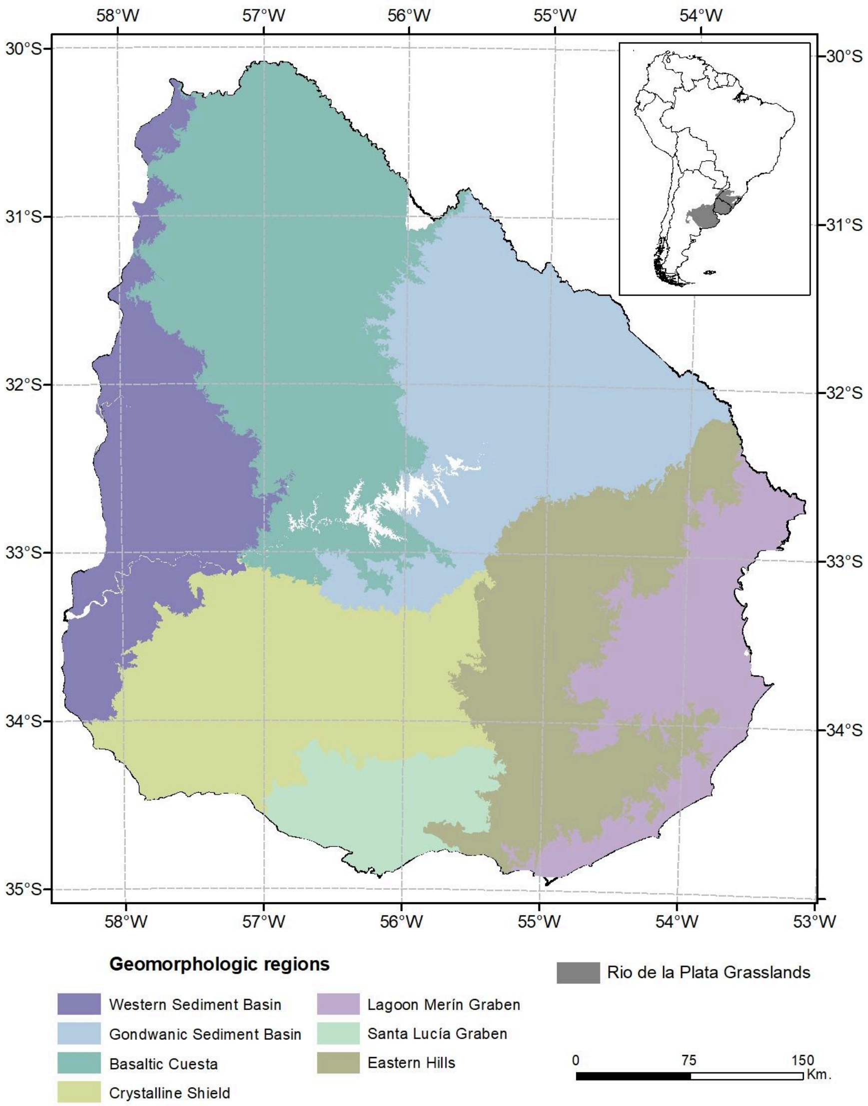

Figure 1. Location of Uruguay within the Rio de la Plata grasslands biome and the regionalisation used in the classifications (Geomorphological regions proposed by Panario et al., 2014).

2 GEOGRAPHICAL UNITS OF CLASSIFICATION

The classification process was carried out in smaller and homogeneous zones spatial units. These units correspond to seven geomorphological regions (Panario et al. 2014) (Figure 1). The purpose of these geographical units of classification was to try to reduce samples and classes confusion and to allow a better balance of samples and results to improve accuracy.

3 REMOTE SENSING DATA

3.1 Landsat Collection

The imagery dataset used in the *MapBiomas Uruguay (LULC),* Collection 3 was obtained from the Landsat sensors Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and the Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS), on board of Landsat 5, Landsat 7 and Landsat 8, respectively. The Landsat imagery collections with 30 m-pixel resolution were accessible via Google Earth Engine and were provided by NASA and USGS. The *MapBiomas Uruguay* Collection 3 used Collection 2, Tier 1 Landsat Surface Reflectance products from USGS, which underwent through radiometric calibration and orthorectification correction based on ground control points and digital elevation model to account for pixel co-registration and correction of displacement errors. A total of 18 scene boundaries were used to cover the entire region, where each of them is totally or partially within the area.

According to the year and the quality of available images, a specific Landsat collection was selected:

- from 1985 to 1999: Landsat 5,
- year 2000: Landsat 5 (Brazil and Uruguay) and Landsat 7 (Argentina),
- years 2001, 2002 and 2012: Landsat 7,
- from 2003 to 2011: Landsat 5,
- from 2013 to 2024: Landsat 8.

3.2 Landsat Mosaics

All Landsat scenes were merged and clipped within standardized spatial units for data processing, hereafter called ‘charts’, based on the grid of the World

International Chart to the Millionth, at the 1:250,000 scale level. A total of 19 charts were used to cover the biome (**Figure 2**). Each chart sets the geographical limits to build up the temporal and spatial Landsat mosaics and to proceed with digital classification procedures. Each geographical classification unit was generated by merging the correspondent mosaic charts.

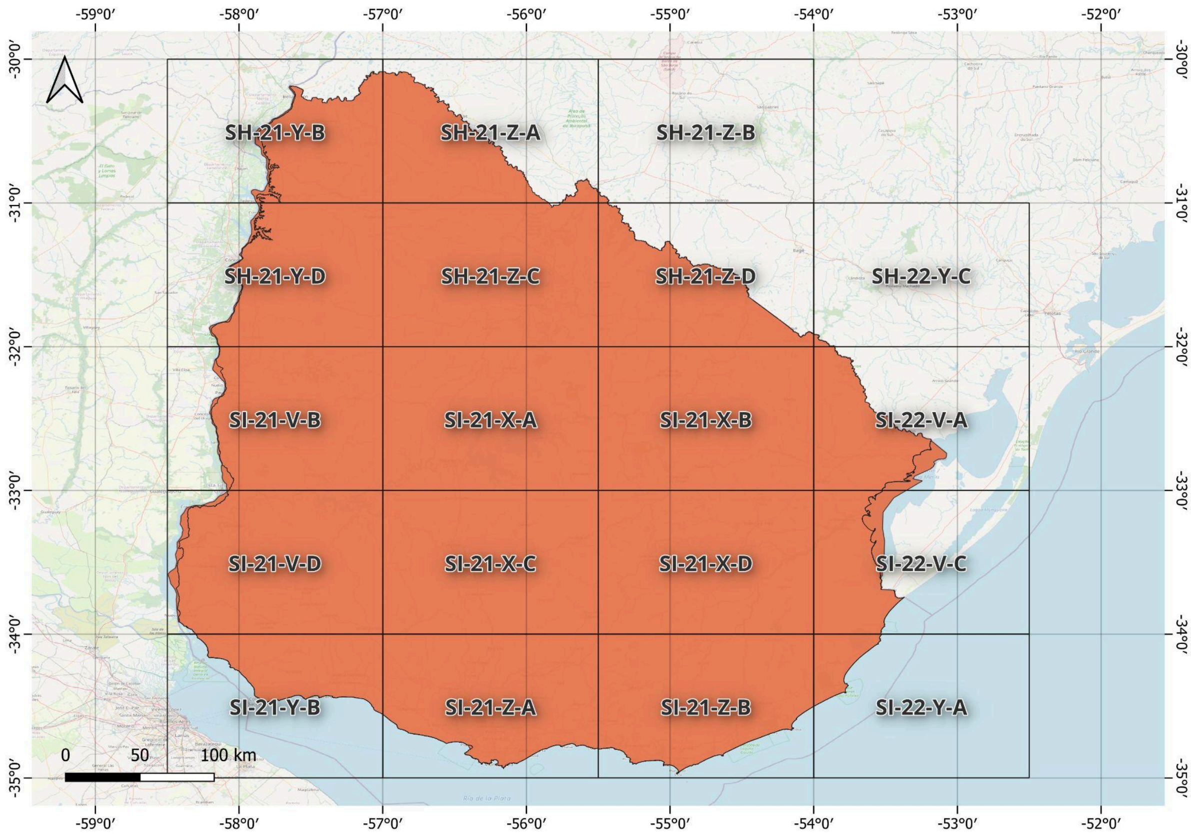

Figure 2. Charts scheme used to build up Landsat mosaics used throughout the classification process.

3.3 Definition of the temporal period

The mosaics were formed by the composition of pixels in each set of images for a certain time period. The periods of the year in which the images are selected vary by country and result from the balance between the probability of maximizing the differences in classes spectral behavior and the availability of cloud-free images. The considered period was from September to November of each year. Nevertheless, for some years this period was adapted (extended one to three months) for each chart according to the availability of cloud-free images. For example, if during the three-months period a cloud free mosaic could not be generated, the period was extended to four, five or six months to get a complete or almost complete mosaic.

For the selection of Landsat scenes a threshold of 90% of cloud cover was applied (i.e., any available scene with up to 90% of cloud cover was accepted). This limit was established based on a visual analysis, after many trials observing the results of the cloud removing/masking algorithm. Time periods were extended for some years and portions of the study area when the availability of cloud-free images was low.

4 CLASSIFICATION

4.1 Overview of methodological process

The methodological procedures of Collection 3 included several steps (**Figure 3**).

The first step was to generate annual Landsat image mosaics based on yearly periods. The second step was to generate a new selection of temporally stable samples derived from the stable areas of the maps of Collection 2. Stable areas were defined in sub-periods of near 10 years-length (1985-1994, 1995-2004, 2005-2014 and 2015-2023). Then, the spectral feature inputs derived from the Landsat bands were extracted and associated to each sample point. Once the samples for each LULC class were selected for each of the subregions, it was possible to adjust the training data set according to its statistical needs. The number of samples for training for each class was defined initially according to the proportion of the area of each class and its variation along the classification period (sample size balance). Additionally, to improve the classification results, complementary samples were generated, defining georeferenced points of different classes by visual interpretation of historical satellite images (high and very high resolution images) and time series of vegetation indices. Based on the adjusted training data set, a supervised classification using the random forest algorithm was run.

Following that, gap, spatial, temporal and frequency filters were applied to remove classification noise and stabilize the classification. The LULC maps of each region were integrated to generate the final map of Collection 3. The MapBiomas Uruguay annual LULC maps were used to derive the transition analysis (with an additional spatial filter application) and statistics. The statistical analysis covered different spatial territories, such as countries, state similar and municipality similar levels of each country, water basin and phytogeographic provinces.

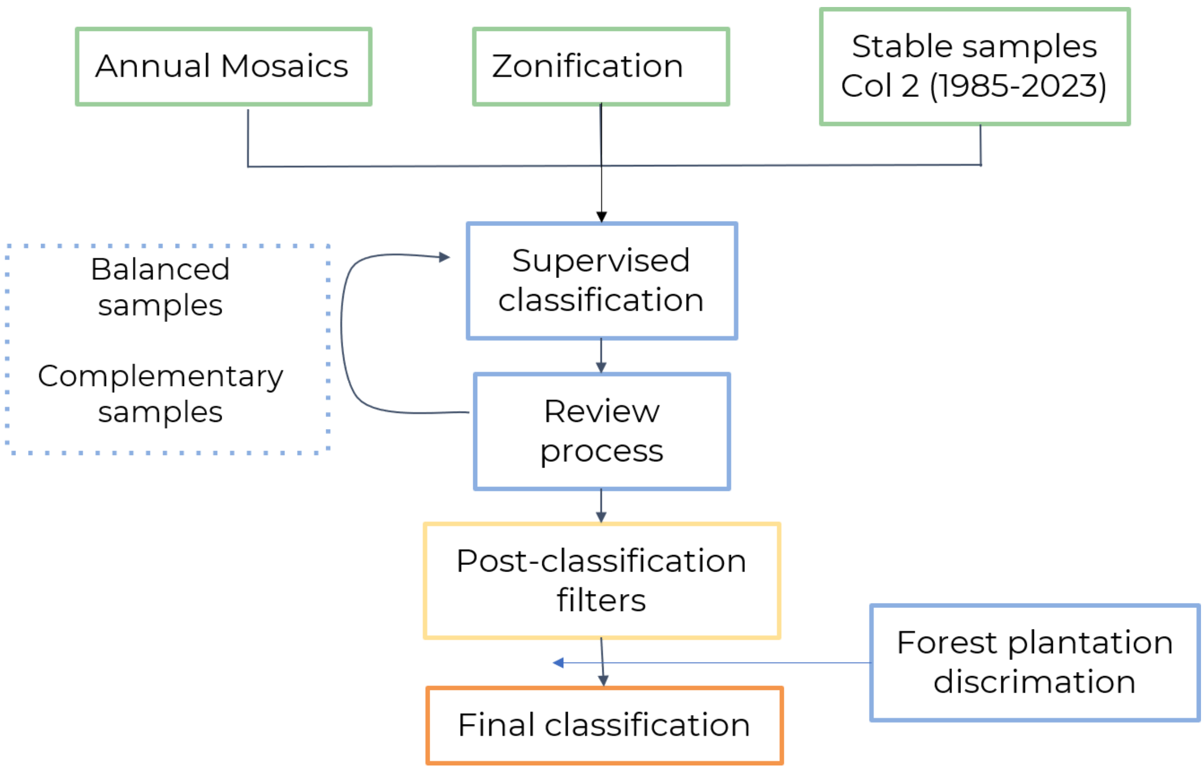

Figure 3. Classification process of Collection 3 in the *MapBiomas Uruguay* for the period 1985-2024

4.2 Map Legend

The classification for the *MapBiomas Uruguay* initiative using Landsat mosaics included eleven land use and land cover (LULC) classes (**Table 1**): Closed forest and closed shrubland (3), Flooded grassland and swampy areas (11), Grassland (12), Pasture (15), Pinus plantation (79), Eucalyptus plantation (80), Other forestry uses (83), Agriculture (18), Non vegetated area (22), River, lake or ocean (33) and Not observed (27). A full description of the legend is described in the document Legend Description.

Table 1. Land cover and land use classes considered for digital classification of Landsat mosaics for the MapBiomas Uruguay initiative - Collection 3.

Legend class of Collection 3	Numeric ID	Color
1.1. Forest formation	3	
2.1. Wetland	11	
2.2. Grassland	12	
3.1. Pasture	15	
3.2. Agriculture	19	
3.3.1. Pinus plantation	79	
3.3.2. Eucalyptus plantation	80	
3.3.2. Other forestry uses	83	
4. Non vegetated area	22	
5.1. River, lake or ocean	33	
6. Not observed	27	

4.3 Annual Mosaics

The total available bands of the MapBiomas Uruguay feature space is composed of 93 input variables, including the original Landsat bands, fractional and textural information derived from these bands (**Table 2**). Reducers were used to generate temporal features such as:

- Median: median of the pixel values of the best mapping period defined by each country.
- Median_dry: median of the quartile of pixels with the lowest NDVI values.
- Median_wet: median of the quartile of pixels with the highest NDVI values.
- Amplitude: amplitude of variation of the index considering all the images of each year.
- stdDev: standard deviation of all pixel values of all images of each year.
- Min: lower annual value of the pixels of each band.

Table 2. List of the variables included in the feature space used in the classification processes of the MapBiomas Uruguay Initiative Collection 3 (1985-2024).

D	riable	Va	Description	tatistics	range	Temporal	acronym	Script	Group
	2	Evi	Enhanced Vegetation Index 2	mplitude	months	mosaic	p	evi2_am	Spectral index
		Gv	Green vegetation fraction	mplitude	months	mosaic		gv_amp	Spectral Mixture Modeling
	fi	Nd	Normalized Difference Fraction Index	mplitude	months	mosaic		ndfi_amp	Spectral Mixture Modeling
	vi	Nd	Normalized Difference Vegetation Index	mplitude	months	mosaic	p	ndvi_am	Spectral index
	wi	Nd	Normalized Difference Water Index	mplitude	months	mosaic	p	ndwi_am	Water Index
	l	Soi	Soil fraction	mplitude	months	mosaic		soil_amp	Spectral Mixture Modeling
	efi	W	Woodland ecosystem fraction index	mplitude	months	mosaic	p	wefi_am	Fraction index
	ue	Bl	Landsat band	edian	months	mosaic	dian	blue_me	Landsat band
	ue dry	Bl	Landsat band	edian	quartile	year -first	dian_dry	blue_me	Landsat band
	ue wet	Bl	Landsat band	edian	quartile	year – fourth	dian_wet	blue_me	Landsat band
0		Cai	Cellulose Absorption Index	edian	months	mosaic	an	cai_medi	Spectral index
		Cai	Cellulose Absorption			year -first		cai_medi	Spectral index

D	riable	Va		Description	tatistics	range	Temporal	acronym	Script		Group
1	dry		Index		edian	quartile		an_dry			
2	oud	Cl		Cloud fraction	edian	months	mosaic	edian	cloud_m	Modeling	Spectral Mixture
3	2	Evi	Index 2	Enhanced Vegetation	edian	months	mosaic	dian	evi2_me		Spectral index
4	2 dry	Evi	Index 2	Enhanced Vegetation	edian	quartile	year -first	dian_dry	evi2_me		Spectral index
5	2 wet	Evi	Index 2	Enhanced Vegetation	edian	quartile	year – fourth	dian_wet	evi2_me		Spectral index
6	vi	Gc		(nir/green − 1)	edian	months	mosaic	ian	gcvi_med		Spectral index
7	vi dry	Gc		(nir/green − 1)	edian	quartile	year -first	ian_dry	gcvi_med		Spectral index
8	vi wet	Gc		(nir/green − 1)	edian	quartile	year – fourth	ian_wet	gcvi_med		Spectral index
9	een	Gr		Landsat band	edian	months	mosaic	edian	green_m		Landsat band
0	een dry	Gr		Landsat band	edian	quartile	year -first	edian_dry	green_m		Landsat band
1	een wet	Gr		Landsat band	edian	quartile	year – fourth	edian_wet	green_m		Landsat band
2		Gv	fraction	Green vegetation	edian	months	mosaic	an	gv_medi	Modeling	Spectral Mixture
		Gv		GV / (100 - shade)			mosaic		gvs_medi		Spectral Mixture

D	Va riable	Description	tatistics	Temporal range	Script acronym	Group
3	s		edian	months	an	Modeling
4	Gv s dry	GV / (100 - shade)	edian	year -first quartile	gvs_medi an_dry	Spectral Mixture Modeling
5	Gv s wet	GV / (100 - shade)	edian	year – fourth quartile	gvs_medi an_wet	Spectral Mixture Modeling
6	Ha llcover	Hall cover vegetation index	edian	mosaic months	hallcover _median	Spectral index
7	Nd fi	Normalized Difference Fraction Index	edian	mosaic months	ndfi_me dian	Spectral Mixture Modeling
8	Nd fi dry	Normalized Difference Fraction Index	edian	year -first quartile	ndfi_me dian_dry	Spectral Mixture Modeling
9	Nd fi wet	Normalized Difference Fraction Index	edian	year – fourth quartile	ndfi_me dian_wet	Spectral Mixture Modeling
0	Nd vi	Normalized Difference Vegetation Index	edian	mosaic months	ndvi_me dian	Spectral index
1	Nd vi dry	Normalized Difference Vegetation Index	edian	year -first quartile	ndvi_me dian_dry	Spectral index
2	Nd vi wet	Normalized Difference Vegetation Index	edian	year – fourth quartile	ndvi_me dian_wet	Spectral index
3	Nd wi	Normalized Difference Water Index	edian	mosaic months	ndwi_me dian	Water Index
4	Nd wi dry	Normalized Difference Water Index	edian	year -first quartile	ndwi_me dian_dry	Water Index
	Nd	Normalized Difference		year – fourth	ndwi_me	Water Index

D	Va riable	Description	tatistics	Temporal range	Script acronym	Group
5	wi wet	Water Index	edian	quartile	dian_wet	
6	Ne ar Infrared (NIR)	Landsat band	edian	mosaic months	nir_medi an	Landsat band
7	Ne ar Infrared (NIR) dry	Landsat band	edian	year -first quartile	nir_medi an_dry	Landsat band
8	Ne ar Infrared (NIR) wet	Landsat band	edian	year – fourth quartile	nir_medi an_wet	Landsat band
9	Np v	Non-photosynthetic vegetation fraction	edian	mosaic months	npv_med ian	Spectral Mixture Modeling
0	Pri	Photochemical reflectance index	edian	mosaic months	pri_medi an	Spectral index
1	Pri dry	Photochemical reflectance index	edian	year -first quartile	pri_medi an_dry	Spectral index
2	Pri wet	Photochemical reflectance index	edian	year – fourth quartile	pri_medi an_wet	Spectral index
3	Re d	Landsat band	edian	mosaic months	red_med ian	Landsat band
4	Re d dry	Landsat band	edian	year -first quartile	red_med ian_dry	Landsat band
5	Re d wet	Landsat band	edian	year – fourth quartile	red_med ian_wet	Landsat band
6	Sa vi	Soil-adjusted Vegetation Index	edian	mosaic months	savi_med ian	Spectral index

D	Va riable	Description	tatistics	range	Temporal	acronym	Script	Group
7	Sa vi dry	Soil-adjusted Vegetation Index	edian	quartile	year -first	ian_dry	savi_med	Spectral index
8	Sa vi wet	Soil-adjusted Vegetation Index	edian	quartile	year – fourth	ian_wet	savi_med	Spectral index
9	Sef i	Savanna Ecosystem Fraction Index	edian	months	mosaic	ian	sefi_med	Fraction index
0	Sef i dry	Savanna Ecosystem Fraction Index	edian	quartile	year -first	ian_dry	sefi_med	Fraction index
1	Sh ade	Shade fraction	edian	months	mosaic	edian	shade_m	Spectral Mixture Modeling
2	Soi l	Soil fraction	edian	months	mosaic	ian	soil_med	Spectral Mixture Modeling
3	Sh ortwave Infrared (SWIR) 1	Landsat band	edian	months	mosaic	edian	swir1_m	Landsat band
4	Sh ortwave Infrared (SWIR) 1 dry	Landsat band	edian	quartile	year -first	edian_dry	swir1_m	Landsat band
5	Sh ortwave Infrared (SWIR) 1 wet	Landsat band	edian	quartile	year – fourth	edian_wet	swir1_m	Landsat band
6	Sh ortwave Infrared (SWIR) 2	Landsat band	edian	months	mosaic	edian	swir2_m	Landsat band
7	Sh ortwave Infrared	Landsat band	edian	quartile	year -first	edian_dry	swir2_m	Landsat band

D	Va riable	Description	tatistics	Temporal range	Script acronym	Group
	(SWIR) 2 dry					
8	Sh ortwave Infrared (SWIR) 2 wet	Landsat band	edian	year – fourth quartile	swir2_m edian_wet	Landsat band
9	W efi	Woodland ecosystem fraction index	edian	mosaic months	wefi_me dian	Fraction index
0	W efi wet	Woodland ecosystem fraction index	edian	year – fourth quartile	wefi_me dian_wet	Fraction index
1	Bl ue min	Landsat band	inimum	mosaic months	blue_min	Landsat band
2	Gr een min	Landsat band	inimum	mosaic months	green_mi n	Landsat band
3	Ne ar Infrared (NIR) min	Landsat band	inimum	mosaic months	nir_min	Landsat band
4	Re d min	Landsat band	inimum	mosaic months	red_min	Landsat band
5	Sh ortwave Infrared (SWIR) 1	Landsat band	inimum	mosaic months	swir1_mi n	Landsat band
6	Sh ortwave Infrared (SWIR) 2	Landsat band	inimum	mosaic months	swir2_mi n	Landsat band
7	Bl ue	Landsat band	tandard deviation	mosaic months	blue_std Dev	Landsat band

D	Va riable	Description	tatistics	range	Temporal	acronym	Script	Group
8	Cai Index	Cellulose Absorption	edian	months	mosaic	ev	cai_stdD	Spectral index
9	Cl oud	Cloud fraction	tandard deviation	months	mosaic	dDev	cloud_st	Spectral Mixture Modeling
0	Evi 2 Index 2	Enhanced Vegetation	tandard deviation	months	mosaic	Dev	evi2_std	Spectral index
1	Gc vi	(nir/green − 1)	tandard deviation	months	mosaic	Dev	gcvi_std	Spectral index
2	Gr een	Landsat band	tandard deviation	months	mosaic	dDev	green_st	Landsat band
3	Gv fraction	Green vegetation	tandard deviation	months	mosaic	v	gv_stdDe	Spectral Mixture Modeling
4	Gv s	GV / (100 - shade)	tandard deviation	months	mosaic	ev	gvs_stdD	Spectral Mixture Modeling
5	Ha llcover index)	Hall cover vegetation	tandard deviation	months	mosaic	_stdDev	hallcover	Spectral index
6	Nd fi Fraction Index	Normalized Difference	tandard deviation	months	mosaic	Dev	ndfi_std	Spectral Mixture Modeling
	Nd	Normalized Difference			mosaic		ndvi_std	Spectral index

D	Va riable	Description	tatistics	range	Temporal	acronym	Script	Group
7	vi	Vegetation Index	tandard deviation	months		Dev		
8	Nd wi	Normalized Difference Water Index	tandard deviation	months	mosaic	Dev	ndwi_std	Water Index
9	Ne ar Infrared (NIR)	Landsat band	tandard deviation	months	mosaic	ev	nir_stdD	Landsat band
0	Re d	Landsat band	tandard deviation	months	mosaic	ev	red_stdD	Landsat band
1	Sa vi	Soil-adjusted Vegetation Index	tandard deviation	months	mosaic	ev	savi_stdD	Spectral index
2	Sef i	Savanna Ecosystem Fraction Index	tandard deviation	months	mosaic	ev	sefi_stdD	Fraction index
3	Sh ade	Shade fraction	tandard deviation	months	mosaic	dDev	shade_st	Spectral Mixture Modeling
4	Soi l	soil fraction	tandard deviation	months	mosaic	ev	soil_stdD	Spectral Mixture Modeling
5	Sh ortwave Infrared (SWIR) 1	Landsat band	tandard deviation	months	mosaic	dDev	swir1_st	Landsat band
	Sh	Landsat band			mosaic		swir2_st	Landsat band

D	Va riable	Description	tatistics	Temporal range	Script acronym	Group
6	ortwave Infrared (SWIR) 2		tandard deviation	months	dDev	
7	W efi	Woodland ecosystem fraction index	tandard deviation	mosaic months	wefi_std Dev	Fraction index
8	Slo pe	Terrain slope	dentity	Permanent	slope	Geomorphomet ric
9	Gr een Texture	Texture from Landsat band	ean	mosaic months	green_m edian_texture	
0	Lat itude	Geographical coordinate		Permanent	Latitude	Geographic
1	Lo ngitude	Geographical coordinate		Permanent	Longitud e	Geographic
2	Nd vi_3years	Normalized Difference Vegetation Index	mplitude	Last 3 years mosaic months	ndvi_am p_3y	Spectral index

4.4 Classification algorithm, training samples and parameters

Classification was performed subregion by subregion, year by year, using the Random Forest algorithm (Breiman, 2001) available in Google Earth Engine, running 100 iterations (random forest trees).

Training samples for each subregion were defined following a strategy of using random pixels for which the land use and land cover remained the same (stable samples) along the maps of Collection 3 over different subperiods: 1985-1994, 1995-2004, 2005-2014 and 2015-2024, named as “stable samples”.

The identification of stable areas consist in extracting random pixels or “stable samples” based on a criterion of minimum temporal frequency aiming to ensure confidence to use them as training areas. Each pixel should be classified with the same LULC class throughout each sampling subperiod (1985-1994, 1995-2004, 2005-2014 and 2015-2024). A layer of pixels with a stable classification for each subperiod was then generated. From the resulting layer of stable samples, a subset of 2,000 samples for each subregion was randomly generated for each class for each subperiod. It is important to clarify that not all of these samples were necessarily used in the classification process for each year.

In addition, a classical procedure to detect outliers was implemented. For each year, and within each training class, we searched for outliers in all variables. An outlier was defined as any value of a specific variable lower or higher than 1.5 times the interquartile range (the first quartile value subtracted from the third quartile value) considering all values of this variable within a specific class of a particular year. Samples containing values considered outliers for some variables were not discarded a priori, but fixed by replacing those values with the 5th percentile or the 95th percentile, whenever they were lower or higher than the thresholds considered, respectively. Finally, we disregarded only those samples containing simultaneously more than 20 variables of the feature space with values considered as outliers.

4.4.1 Sample size balance

We generated a fixed number of samples for each class, subregion and subperiod for classification. However we used in the classification process only a random subset based on the class area proportion within each subregion, considering each year to be classified. To do this, we previously adjusted linear simple functions to estimate the area of each class for each year from 1985 to 2024, based on the annual class area observed along the Collection 2 dataset. These functions were used to estimate, for each year, the proportion of each class to train the classifier. Then, these annual proportions for each class were set to extract a subset of the available samples for the correspondent classification in each year. Whenever the classification resulted in overestimation or underestimation of the class after comparing with supplemental information (e.g.: Collection 3 maps, independent crop type maps, etc.) this proportion was adjusted changing the bias (intercept of linear regression model) accordingly. Notwithstanding the above, a minimum number of 50 to 100 samples per class was set for each region and year, to ensure the correct detection of the less frequent categories.

4.4.2 Complementary samples

The need for adding complementary samples was evaluated by visual inspection of the output of a preliminary classification, with both Landsat and high-resolution images available in Google Earth Engine and time series of vegetation indices, and also by comparing with the Collection 2 classification. Complementary sample collection was also done manually using points in Google Earth Engine Code Editor. All the false-color images of the 40 years (1985-2024) Landsat mosaics and the vegetation index time series were checked at the selected point. Based on the knowledge of each subregion, the samples for different classes were collected. Complementary samples previously generated for Collection 2 were also added in some regions to improve the classification when necessary.

4.4.5 Final classification

The final classification was performed for all subregions and years combining stable and complementary samples. For some years, the classification output resulted in anomalous results for some classes. Then, it was necessary to improve the classification through a new sample size balance and a specific set of complementary samples.

4.4.6 Post-classification

The results of the final classification were improved through a sequence of filters, to correct missing data, “salt-and-pepper” classification errors and, specially, cases of misclassification. Temporal filters were done with the aim to generate a more stable classification pattern over time, avoiding unexpected class variation during short times.

4.4.6.1. Gap fill filter

A filter to fill no-data pixels (“gaps”) was applied. Because theoretically the no-data values are not allowed, they are replaced by the temporally nearest valid classification. In this procedure, if no “future” valid position was available, then the no-data value was replaced by its previous valid class. Therefore, gaps should only exist if a given pixel has been permanently classified as no-data throughout the entire temporal domain.

4.4.6.2. Spatial filter

The spatial filter avoids unwanted modifications to the edges of the pixel groups, a spatial filter was built based on the "connectedPixelCount" function. Native to the Google Earth Engine platform, this function locates connected components (neighbors) that share the same pixel value. Thus, only pixels that did not share connections to a predefined number of identical neighbors were considered isolated. In this filter, at least six connected pixels were needed to reach the minimum connection value. Consequently, the minimum mapping unit is directly affected by the spatial filter applied, and it was defined as 6 pixels (~0,5 ha).

4.4.6.3. Temporal filters

The temporal filters use the information from the year before and after to identify and correct a pixel misclassification, considered as cases of invalid transitions. In a first step, the filter looks for specific cover classes (3, 11, 12, 33) that are not this class in 1985 and were kept unchanged in 1986 and 1987 and then corrects the 1985’s value to avoid any regeneration in the first year. In a second step, the filter looks at a pixel value in 2024 that for example is not 11 (wetland) but is equal to 11 in 2022 and 2023. The value in 2024 is then converted to 11 to avoid any regeneration in the last year. The third process looks in a 3-year moving window to correct any value that changed in the middle year and returns to the same class next year.

A temporal filter with a slightly different approach was applied to solve problems in forestry classification. To correct the problems related to the years with forestation cutting, interrupting a continuous series of years classified as forestry we used a special six-year spatial filter. The rule of application checks whether two years before and two years after the class was forestation, if this is true it shifts the classification of the two middle years to silviculture.

4.4.6.4. Frequency filter

To correct classification problems associated with some classes in specific regions, frequency filters were applied to use the temporal information available for each pixel to correct cases of false positives. The general logic of the frequency filter is to search for each pixel a specific combination of classes throughout the 40 years producing a subset of pixels considered eligible for correction. Then the filter detects and overwrites only those years where cases of false positives are present using a fixed class value, that usually is the mode of classifications detected along the temporal range. This type of filter was used with parsimony to solve very well delimited cases.

4.4.6.5. Specific filters

Additional specific filters were generated to remove unexpected classification changes that remained after applying previous standard filters. In general, these filters that we applied work with frequency and incidence. Frequency is the number of years a class occurs in a pixel. The incidence is the number of times that a pixel classification changes along the entire series of years. The application of these filters was limited to fix problems of false transitions between specific classes.

We also used a filter that eliminates problems related to the shadows of the mountains. These filters use characteristics of the relief, in addition to the frequency to be applied. It corrects false positives of water and wetland in shaded slopes in regions with wavy relief. The filter selects all pixels classified as water at least in one year but in less than 37 years (<95%), or as wetland at least in one year but in less than 35 years (<90%), whenever occurring in areas of cliffs and slopes, established by a combination of slope data (SRTM derived) with HAND (Height Above the Nearest Drainage) database, to define places where it is not expected the presence of water or wetland. In such cases, both classes were replaced by the class corresponding to the pixel mode.

A filter to smooth abrupt transitions between the first and the second year (1985 - 1986) and the last and penultimate years (2022-2024) was applied It has been observed in previous collections, that the last year of the series registered an unexpected increase in the area of anthropic classes and a decrease of natural classes, most likely corresponding to an artifact resulting from the set of applied filters. To alleviate the problem, a filter was developed to smooth this abrupt transition, avoiding all transitions from natural areas to anthropic areas, and vice versa, in patches equal to or smaller than 2 hectares. In these cases, the corresponding pixels from the last year receive the same classification as the penultimate year as well as pixels from the first year receive the same classification as the second year.

Exceptionally, the spatial effect of some filters was limited to a set of polygons, in such a way as not to modify the entire zone classification. Similarly, in some cases, filters were applied only for specific years. Examples of these filters include: a grassland filter that unifies wet and dry years, taking into account the coverage of that place and not the rainfall of a particular year. Or a rice filter that corrects sites classified as wet grasslands, only for certain years, as long as it has been previously classified as agriculture.

4.4.7 Discrimination Between Pasture and Agriculture

In much of the study region (Uruguay, southern Brazil, and 3 regions of Argentina), previous collections jointly classified annual crops and perennial pastures into a single category (Class 21: agriculture or pasture), In MapBiomas Uruguay collection 2, this category was separated into its main components—annual crops and perennial pastures—using a methodology different from the one previously described. The inputs and methodology used are detailed below.

4.4.7.1 Imagery

To separate Class 21 (agriculture-pasture as a single class) into agricultural crops and pastures for the entire temporal series (1985–2024), satellite images from Landsat 5, 7, 8, and 9 were used. To harmonize measurements across sensors, the Landsat image collections were harmonized following the approach proposed by Roy et al. (2016).

From the harmonized image collection, quarterly and annual composites were generated:

A) Quarterly composites:

- Median of reflective bands (B, G, R, NIR, SWIR1, SWIR2).
- Median of various spectral indices (NDVI, GNDVI, NDMI, NBR).

B) Annual composites (corresponding to an agricultural year: July–June):

- Median, maximum, minimum, standard deviation, and day of the year for reflective bands (B, G, R, NIR, SWIR1, SWIR2).
- Median, maximum, minimum, standard deviation, and day of the year for spectral indices (NDVI, GNDVI, NDMI, NBR).

A total of 81 bands of information were considered for the classification process.

4.4.7.2 Classification

A mask of Class 21 was applied for each year within the study period, and only the pixels within this mask were classified. A supervised approach using the Random Forest classifier was employed for the classification. Ground truth data were used for three climatically contrasting years: 2015, 2016, and 2020 (Figure 4). This data allowed the training of a generic classifier that accounts for climatic variability and was applied to each year in the temporal series.

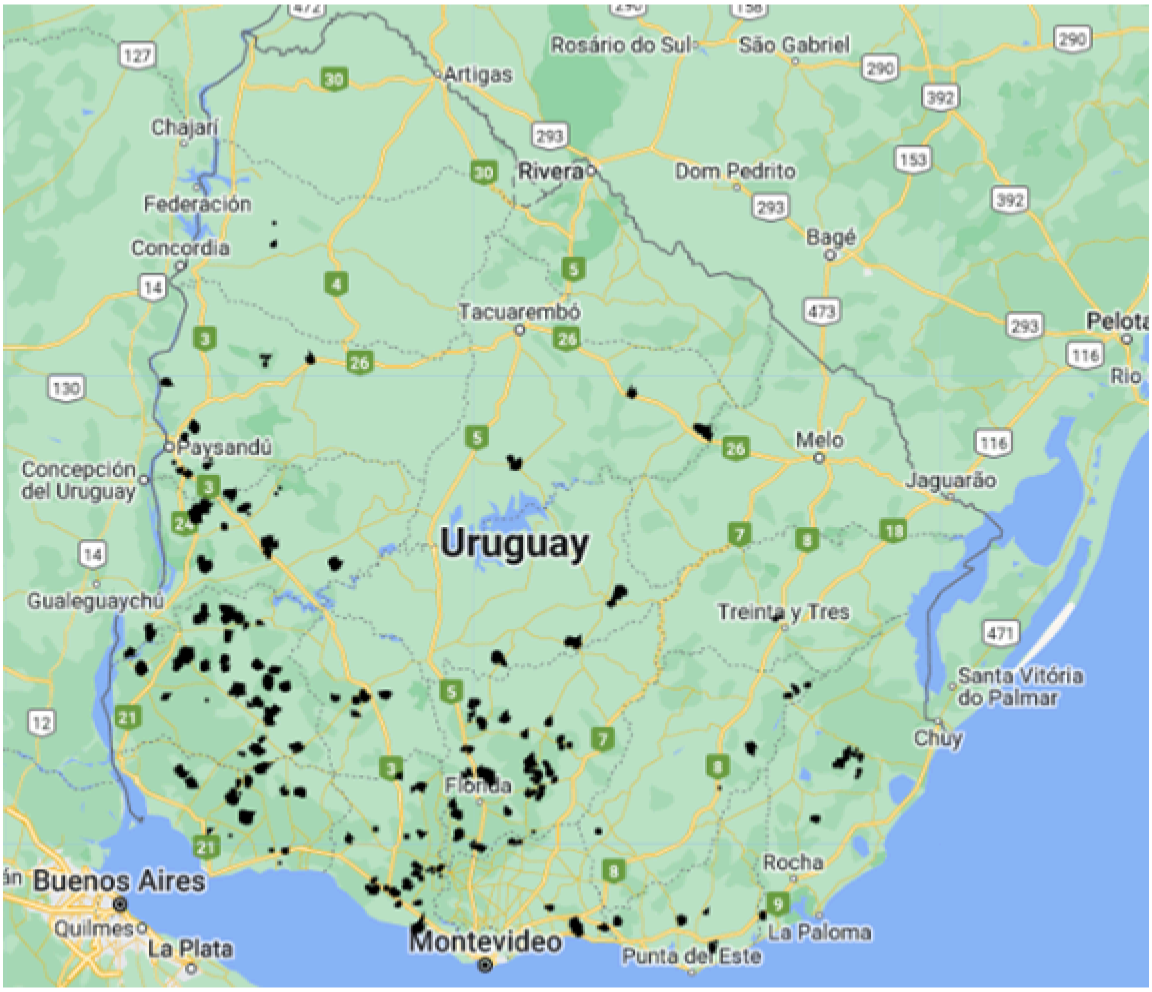

Figure 4: distribution of training samples

4.4.7.3 Post-processing

Post-processing involved applying a modal spatial filter (3x3 window) and a temporal filter (3 years) exclusively for pastures. The purpose of the temporal filter was to eliminate pastures lasting less than one year, a scenario that is agronomically unlikely since pastures generally have a lifespan of 3 to 4 years.

The generated map was then integrated with the original map, resulting in an updated cartography that separates Class 21 into annual crops and perennial pastures (Figure 5). From collection 3 onwards, the Agriculture and Pastures categories were incorporated into the general workflow (see Figure 3). The training samples used for classification come from stable samples from previous collections.

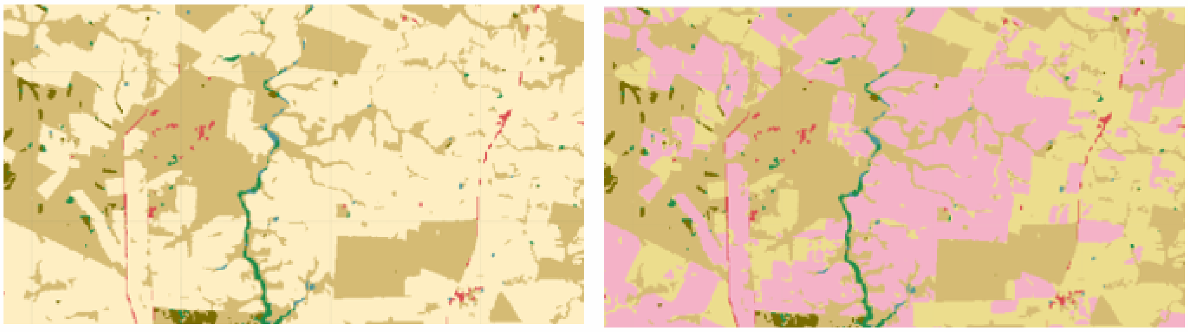

Figure 5: Illustrative image of the separation of Class 21 into agriculture (green) and pasture (yellow), along with the integration into the original map.

4.4.8 Discrimination Between Forest Plantations

In Collection 3 of MapBiomas Uruguay, a relevant methodological improvement was introduced: the disaggregation of Class 9, originally representing *forest plantations* as a single category, into three distinct classes. From this version onwards, pine plantations, eucalyptus plantations, and other forest plantations are mapped separately. This enhancement allows for a more detailed and accurate characterization of the extent and composition of forest plantations across the national territory.

4.4.8.1 Imagery

To differentiate Class 9 (forest plantations) into the category's eucalyptus, pinus, and other forest plantations throughout the temporal series (1985–2024), satellite imagery from Landsat 5, 7, 8, and 9 was used. To ensure consistency across sensors, Landsat collections were harmonized following the approach proposed by Roy et al. (2016).

For each year, spectral bands (B2, B3, B4, B5, B6, B7) and several vegetation and water indices were calculated, specifically the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Modified Soil-Adjusted Vegetation Index (MSAVI), Normalized Difference Water Index (NDWI), and Normalized Burn Ratio (NBR).

To enhance class separability, temporal statistical metrics—median, maximum, minimum, and standard deviation—were calculated for each spectral band and index to summarize intra-annual spectral variability. These metrics were then aggregated into a multi-band annual composite stack. In addition, topographic variables, specifically slope and the digital elevation model (DEM) derived from the Shuttle Radar Topography Mission (SRTM), were incorporated to account for terrain-related spectral variability.

4.4.8.2 Classification

Forest plantation classes were mapped using a supervised pixel-based classification based on the Random Forest algorithm (Breiman, 2001). The classification was constrained to areas identified as forest by the annual MapBiomas forest cover layers for each year of the study period, within which the three plantation categories were discriminated.

A single classification model was developed and trained using satellite data from 2020 and subsequently applied to the entire temporal series. The year 2020 was chosen because it was the most recent year with species-disaggregated cartographic reference data available at the time of the study (DGF-MGAP, 2021).

Training samples were generated using a stratified random sampling approach to ensure adequate representation across the spectral variability of all target classes. In total, 205 samples of eucalyptus plantations, 177 samples of pine plantations, and 110 samples of other forest plantation classes were collected (Figure 6).

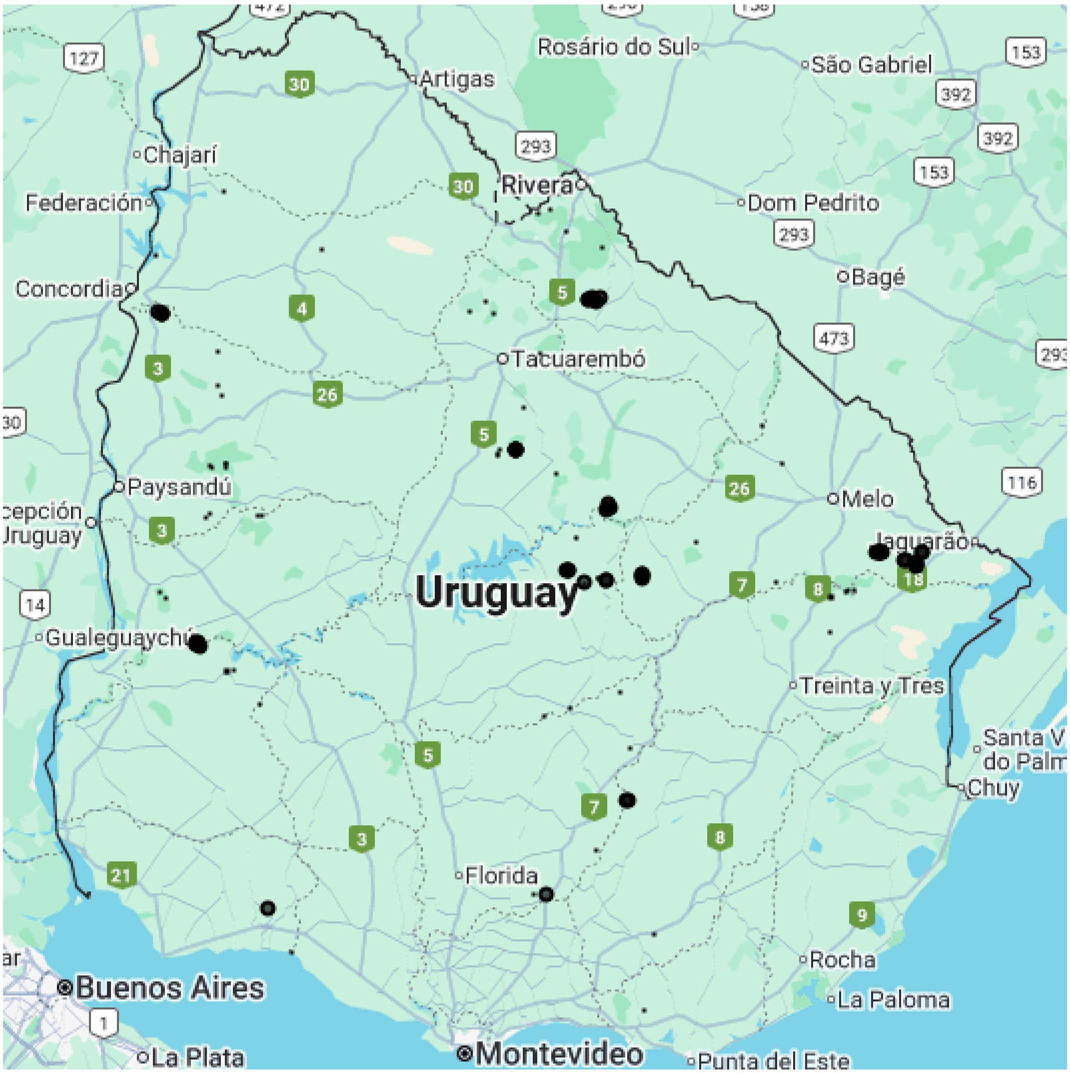

Figure 6: distribution of eucalyptus, pines and other forest plantations training samples.

4.4.8.3 Post-processing

Given the pixel-based classification and the long temporal span of the dataset, several post-classification spatial and temporal filters were applied to improve consistency and reduce noise. The correction process included gap filling, spatial filtering, and temporal filtering steps.

Gap filling:

A gap-fill filter was applied to ensure temporal continuity at the pixel level. In many cases, the annual MapBiomas masks identifying woody classes (e.g., native forest and forest plantations) were not continuous in time, and some pixels intermittently appeared as non-forest (e.g., grassland). Pixels classified at least once as *forest* *plantation* or *native forest* during the time series were assigned the non-forest class for all corresponding years to maintain temporal coherence.

Spatial filtering:

To reduce edge noise and small misclassified patches, a mode filter (3×3 moving window) was applied, reassigning each pixel to the majority class of its neighborhood. Additionally, a connected pixel filter based on the connectedPixelCount function (native to Google Earth Engine) was implemented to remove isolated pixels and very small patches. Only areas with at least 111 connected pixels (≈10 ha) were retained, defining the minimum mapping unit. This spatial filter was applied exclusively to pixels classified as *forest plantation* at least once, or as *native forest* for fewer than 10 years in the series.

Temporal filtering:

Temporal filters were applied to correct implausible class transitions.

1. The first filter corrected early-year inconsistencies (1985) by checking class continuity in 1986 and 1987.

2. The second filter corrected the final year (2024) using information from 2022 and 2023, while avoiding removal of harvest-related non-vegetated states.

3. The third and fourth filters corrected short-term reversions between forest plantation classes within 3- to 6-year moving windows, replacing intermediate inconsistencies with stable class values before and after the transition.

4. The fifth filter addressed confusion between *forest plantation* subclasses, which commonly occurs in early growth stages. In this step, the class present at the end of the plantation cycle was propagated backward to correct the initial years, using a moving window of up to 13 years.

Together, these post-classification procedures minimized temporal noise, removed spurious transitions, and improved the overall thematic consistency of the forest plantation maps (Figure 7), without discarding legitimate transitions such as harvests or land-use changes.

Figure 7: Illustrative image of the separation of Class 9 into eucalyptus, pinus and other forest plantations.

5 VALIDATION STRATEGIES

Validation was performed for the classifications of the years 1986, 1991, 1996, 2001, 2006, 2012, 2018 and 2022 following the good practices recommendations proposed by Olofsson et al. (2014) for area and error estimation. The accuracy assessment was designed for the entire Río de la Plata grassland biome and included a total of 2,330 samples.2,330 randomly selected samples. The number of samples for each class was proportional to the area of each class obtained from Collection 1 for the year 2010. Independent samples were raffled and class classified by visual interpretation of Landsat images, very high resolution images from Google Earth and time series of vegetation indices. Two interpreters evaluated each of the sample points generated from the stratified random design. In those sample points where discordance in class classification was detected among interpreters, a third interpreter defined the final class assignment. When a final class could not be defined by the three interpreters (e.g. three different class assignments), a final class was agreed by a team of interpreters. More details of the validation methodology are described in Baeza et al. (2022).

For collection 3, validation results showed an overall accuracy of 87% for 1986, 88 % for 1991, 89 % for 1996, 90 % for 2001, 85 % for 2006, 88 % for 2012, 84 % for 2018 and 85% for 2022 (Figure 8). In all cases, most of the associated errors were location mismatches rather than quantity mismatches (see Pontius and Milloes, 2011), allowing for more precise area estimates (global accuracy + location mismatch): 91%, 93% and 90% for the years 1986, 2001 and 2018, respectively. A complete classification accuracy analysis comparing the different MapBiomas collections can be found here.

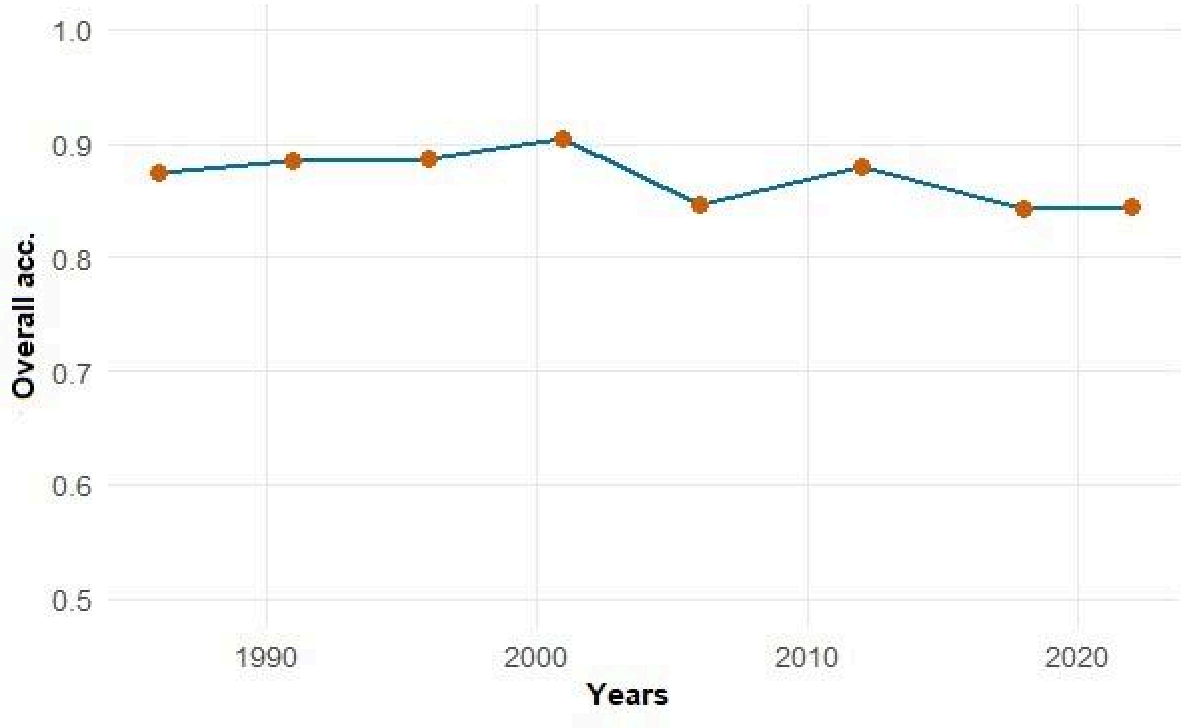

Figure 8: Overall accuracy for the MapBiomas Uruguay initiative maps in the 8 year analyzed.

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