MapBiomas Trinational Pampa

Collection 1

Version 1.1

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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 the South American Pampa of Argentina, Brazil and Uruguay from 2000 to 2019 of the MapBiomas Collection 1. 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 South American Pampa was created to produce LULC annual maps for the Pampa Region corresponding to Argentina, Brazil and Uruguay territories. Other phytogeographic regions closed or interspersed with Pampa were partially added to allow a better regional delimitation. Thus, a neighbor area of *Espinal* around Pampa bioma as well as the Paraná river Delta located in Argentina were also included (**Figure 1**).

The total mapped area was 1,005,772 km^2, being 807,759 km^2 in the Pampa, 176,745 km^2 in the Espinal and 21,268 km^2 in the Paraná river Delta.

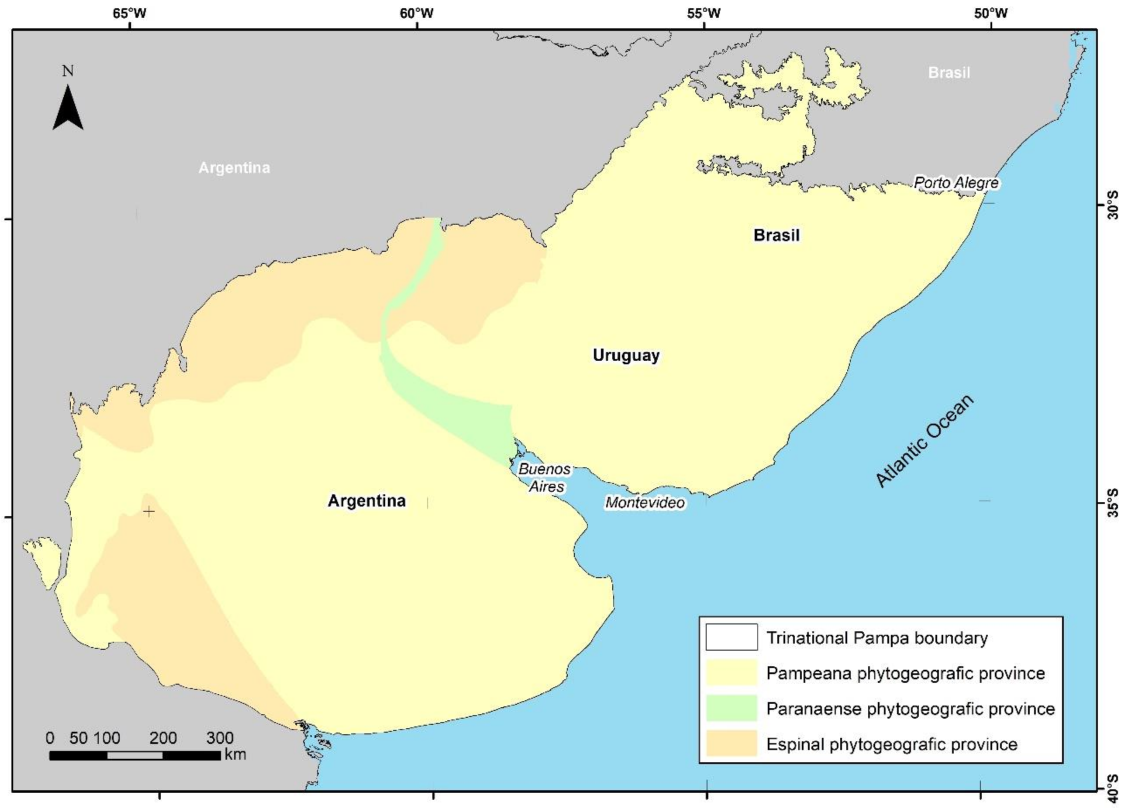

Figure 1 Region of interest mapped in the Trinational Pampa project, including the typical areas of the Pampa, Espinal, and Paraná river Delta.

2 GEOGRAPHICAL UNITS OF CLASSIFICATION

In each country, the classification process was carried out in smaller spatial units. These units correspond to subregional homogeneous regions based on several criteria, nationally defined, including geomorphology, soils, vegetation types and land use patterns.

The study area was divided in 23 homogeneous subregions, nine in Argentina, seven in Brazil and seven in Uruguay (**Figure 2**).

The purpose of these geographical units of classification was an attempt to reduce confusion of samples and classes, to allow a better balance of samples and results, improving accuracy.

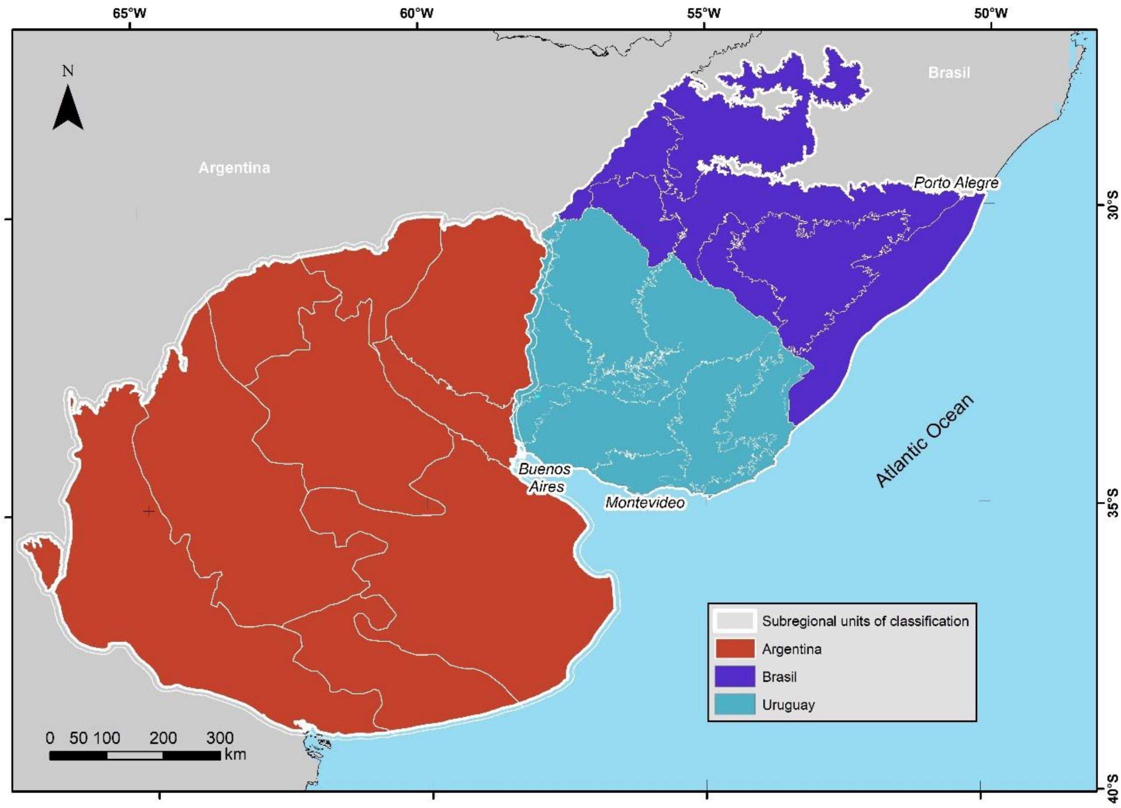

Figure 2. Country defined homogeneous subregions used in the classification process of the South American Pampa.

3 REMOTE SENSING DATA

3.1 Landsat Collection

The imagery dataset used in the *MapBiomas South American Pampa* Collection 1 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-pixel resolution were accessible via Google Earth Engine, and were provided by NASA and USGS. The *MapBiomas South American Pampa* Collection 1 has used Tier 1 from USGS and surface reflectance (SR), 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 71 scenes 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:

- 2000: Landsat 5 (Brazil and Uruguay) and Landsat 7 (Argentina),
- 2001, 2002 and 2012: Landsat 7,
- 2003 to 2011: Landsat 5,
- 2013 to 2019: 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 99 charts were used to cover the biome (**Figure 3**). 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.

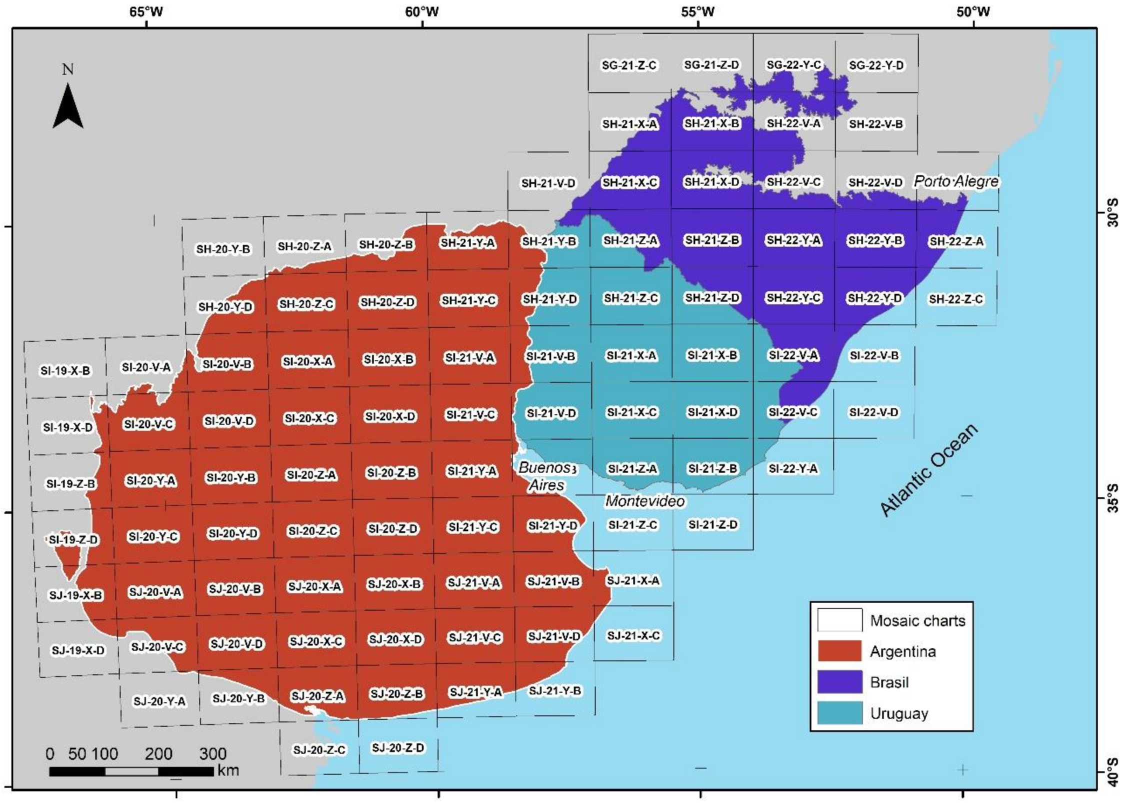

Figure 3 Charts scheme used to build up Landsat mosaics used throughout the classification process.

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. In Uruguay and Brazil, the considered period was from September to November of each year while in Argentina from May to July.

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 1 included several steps (**Figure 4**). The first step was to generate annual Landsat image mosaics based on yearly periods. The second step was to establish the spectral feature inputs derived from the Landsat bands to run the random forest classification. The acquisition of training samples started with the generation of polygons of each class by visual interpretation of historical satellite images and time series of vegetation indices. After a preliminary classification, a new selection of temporally stable samples was derived from the stable areas of the maps. Once the samples of each LULC class were selected for each of the subregions, it was possible to adjust the training data set according to its statistical needs, including complementary samples. Based on the adjusted training data set, the random forest classifier was run. Following that, gap, spatial and temporal filters were applied to remove classification noise and stabilize the classification. The LULC maps of each subregion were integrated to generate the final map of Collection 1. The MapBiomas annual LULC maps were used to derive the transition analysis (with spatial filter application) and statistics. The statistical analysis covered different spatial categories, such as subregion, state similar and municipality similar levels of each country

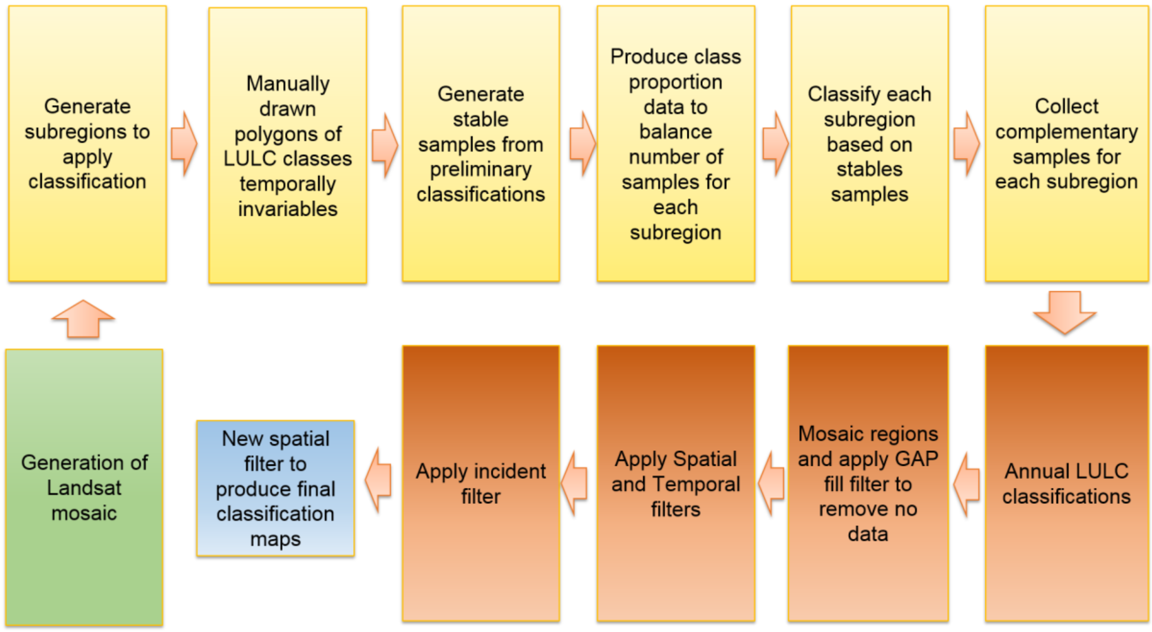

Figure 4. Classification process of Collection 1 in the *MapBiomas South American Pampa.*

4.2 Classification scheme

The digital classification of the Landsat mosaics for the *MapBiomas South American Pampa* included nine land use and land cover (LULC) classes (**Table 1**): Forest Formation (3), Savanna Formation (4), Forest plantation (9), Wetland (11), Grassland (12), Farming (14), Non Vegetated Area (22), River, Lake and Ocean (33) and Non Observed (27).

Table 1 Land cover and land use classes considered for digital classification of Landsat mosaics for the South American Pampa - Collection 15.

Legend class of Collection 5	Numeric ID	Color
1.1.1. Forest Formation	3	
1.1.2. Savanna Formation	4	
1.2. Forest Plantation	9	
2.1. Wetland	11	
2.2. Grassland	12	
3 Farming	14	
4. Non-Vegetated Area	22	
5. River, Lake and Ocean	33	
6. Non Observed	27	

4.3 Feature space

The total available bands of the MapBiomas feature space is composed of 107 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 main variables included in the feature space used in the classification of the South American Pampa Landsat image mosaics in the MapBiomas Collection 1 (2000-2019).

ID	Variable	Description	Statistics	Temporal range	Script acronym	Group
0	Evi 2	Enhanced Vegetation Index 2	amplitude	mosaic months	'amp_evi2'	Spectral index
1	Gv	Green vegetation fraction	amplitude	mosaic months	'amp_gv'	Spectral Mixture Modeling
2	Ndfi	Normalized Difference Fraction Index	amplitude	mosaic months	'amp_ndfi'	Spectral Mixture Modeling
3	Ndvi	Normalized Difference Vegetation Index	amplitude	mosaic months	'amp_ndvi'	Spectral index
4	Ndwi	Normalized Difference Water Index	amplitude	mosaic months	'amp_ndwi'	Water Index
5	Npv	Non-photosynthetic vegetation fraction	amplitude	mosaic months	'amp_npv'	Spectral Mixture Modeling
6	Sefi	Savanna Ecosystem Fraction Index	amplitude	mosaic months	'amp_sefi'	Fraction index
7	Soil	soil fraction	amplitude	mosaic months	'amp_soil'	Spectral Mixture Modeling
10	Blue dry	Landsat band	median	year -first quartile values	'median_blue_dry'	Landsat band
11	Blue wet	Landsat band	median	year – fourth quartile	'median_blue_wet'	Landsat band
15	Cloud	Cloud fraction	median	mosaic months	'median_cloud'	Spectral Mixture Modeling
16	Evi 2	Enhanced Vegetation Index 2	median	mosaic months	'median_evi2'	Spectral index
17	Evi 2 dry	Enhanced Vegetation Index 2	median	year -first quartile values	'median_evi2_dry'	Spectral index
18	Evi 2 wet	Enhanced Vegetation Index 2	median	year – fourth quartile values	'median_evi2_wet'	Spectral index
19	Fns	((gv + shade) − soil)/((gv + shade) + soil)	median	mosaic months	'median_fns'	Fraction index
20	Fns dry	((gv + shade) − soil)/((gv + shade) + soil)	median	year -first quartile values	'median_fns_dry'	Fraction index
21	Fns wet	((gv + shade) − soil)/((gv + shade) + soil)	median	year – fourth quartile values	'median_fns_wet'	Fraction index
22	Gcvi	(nir/green − 1)	median	mosaic months	'median_gcvi'	Spectral index
24	Gcvi wet	(nir/green − 1)	median	year -first quartile values	'median_gcvi_wet'	Spectral index
27	Green wet	Landsat band	median	year -first quartile values	'median_green_wet'	Landsat band
31	Gvs wet	GV / (100 - shade)	median	year -first quartile values	'median_gvs_wet'	Spectral Mixture Modeling
32	Hallcover	(−red ∗ 0.017 − nir ∗ 0.007 − swir2 ∗ 0.079 + 5.22)	median	mosaic months	'median_hallcover'	Spectral index
34	Ndfi wet	Normalized Difference Fraction Index	median	year – fourth quartile	'median_ndfi_wet'	Spectral Mixture Modeling
36	Ndvi	Normalized Difference Vegetation Index	median	mosaic months	'median_ndvi'	Spectral index

ID	Variable	Description	Statistics	Temporal range	Script acronym	Group
37	Ndvi dry	Normalized Difference Vegetation Index	median	year -first quartile values	'median_ndvi_dry'	Spectral index
39	Ndwi	Normalized Difference Water Index	median	mosaic months	'median_ndwi'	Water Index
40	Ndwi dry	Normalized Difference Water Index	median	year -first quartile values	'median_ndwi_dry'	Water Index
41	Ndwi wet	Normalized Difference Water Index	median	year – fourth quartile	'median_ndwi_wet'	Water Index
43	Near Infrared (NIR) dry	Landsat band	median	year -first quartile values	'median_nir_dry'	Landsat band
45	Npv	Non-photosynthetic vegetation fraction	median	mosaic months	'median_npv'	Spectral Mixture Modeling
47	Pri dry	(blue − green)/(blue + green)	median	year -first quartile values	'median_pri_dry'	Spectral index
48	Pri wet	(blue − green)/(blue + green)	median	year – fourth quartile	'median_pri_wet'	Spectral index
49	Red	Landsat band	median	mosaic months	'median_red'	Landsat band
50	Red dry	Landsat band	median	year -first quartile values	'median_red_dry'	Landsat band
51	Red wet	Landsat band	median	year – fourth quartile	'median_red_wet'	Landsat band
52	Savi	Soil-adjusted Vegetation Index	median	mosaic months	'median_savi'	Spectral index
53	Savi dry	Soil-adjusted Vegetation Index	median	year -first quartile values	'median_savi_dry'	Spectral index
55	Sefi	Savanna Ecosystem Fraction Index	median	mosaic months	'median_sefi'	Fraction index
56	Sefi dry	Savanna Ecosystem Fraction Index	median	year -first quartile values	'median_sefi dry'	Fraction index
57	Sefi wet	Savanna Ecosystem Fraction Index	median	year – fourth quartile	'median_sefi wet'	Fraction index
63	Shortwave Infrared (SWIR) 2	Landsat band	median	mosaic months	'median_swir2'	Landsat band
64	Shortwave Infrared (SWIR) 2 dry	Landsat band	median	year -first quartile values	'median_swir2_dry'	Landsat band
65	Shortwave Infrared (SWIR) 2 wet	Landsat band	median	year – fourth quartile	'median_swir2_wet'	Landsat band
68	Wefi dry	((gv + npv) − (soil + shade))/ ((gv + npv) + (soil + shade))	median	year -first quartile values	'median_wefi_dry'	Fraction index
70	Blue min	Landsat band	minimum	mosaic months	'min_blue'	Landsat band
71	Green min	Landsat band	minimum	mosaic months	'min_green'	Landsat band
73	Red min	Landsat band	minimum	mosaic months	'min_red'	Landsat band
74	Shortwave Infrared (SWIR)	Landsat band	minimum	mosaic months	'min_swir1'	Landsat band

ID	Variable	Description	Statistics	Temporal range	Script acronym	Group
75	1 Shortwave Infrared (SWIR) 2	Landsat band	minimum	mosaic months	'min_swir2'	Landsat band
76	Temperature	Landsat band	minimum	mosaic months	'min_temp'	Landsat band
77	Blue	Landsat band	standard deviation	mosaic months	'stdDev_blue'	Landsat band
79	Cloud	Cloud fraction	standard deviation	mosaic months	'stdDev_cloud’	Spectral Mixture Modeling
82	Gcvi	(nir/green − 1)	standard deviation	mosaic months	'stdDev_gcvi'	Spectral index
86	Hallcover	(−red ∗ 0.017 − nir ∗ 0.007 − swir2 ∗ 0.079 + 5.22)	standard deviation	mosaic months	' stdDev_hallcover'	Spectral index
88	Ndvi	Normalized Difference Vegetation Index	standard deviation	mosaic months	'stdDev_ndvi'	Spectral index
92	Pri	(blue − green)/(blue + green)	standard deviation	mosaic months	'stdDev_pri'	Spectral index
93	Red	Landsat band	standard deviation	mosaic months	'stdDev_red'	Landsat band
94	Savi	Soil-adjusted Vegetation Index	standard deviation	mosaic months	'stdDev_savi'	Spectral index
95	Sefi	Savanna Ecosystem Fraction Index	standard deviation	mosaic months	'stdDev_sefi'	Fraction index
97	Soil	soil fraction	standard deviation	mosaic months	'stdDev_soil'	Spectral Mixture Modeling
98	Shortwave Infrared (SWIR) 1	Landsat band	standard deviation	mosaic months	'stdDev_swir1'	Landsat band
100	Temperature	Landsat band	standard deviation	mosaic months	'stdDev_temp'	Landsat band
102	Slope	Slope	-	Permanent	'slope'	Geomorphometric
105	Latitude	Geographical coordinate	-	Permanent	'latitude'	Geographic
106	Ndvi_3anos	Normalized Difference Vegetation Index	amplitude	mosaic months	'amp_ndvi_3anos'	Spectral index

4.4 Classification algorithm, training samples and parameters

Digital classification was performed region by region, year by year, using the Random Forest algorithm (Breiman, 2001) available in Google Earth Engine, running 40 iterations (random forest trees).

Training samples for each region were defined following a strategy of using random pixels for which the land use and land cover remained the same along a preliminary classification of 20 years, named as “stable samples”. The stable areas were identified through an annual preliminary classification made using random pixels selected from on-screen-digitized polygons obtained by visual interpretation of images and time series of vegetation indices. For this, backdrops of false-color Landsat mosaics for all the 20 years as well as graphs showing the temporal behavior of spectral indices per pixel were used to create a stable LULC class.

4.4.1 Preliminary Classification

From on-screen-digitized polygons, which totalized 4,189 for Argentina and 1,703 for Uruguay, a subset between 200 and 700 pixels per class and per zone were randomly selected from the pixels of the on-screen-digitized polygons (randomly selected too) and used as training areas to classify each of the 20 years with the Random Forest algorithm. A total of 20 yearly preliminary classifications were obtained and the frequency with which a pixel was classified to the same LULC class was calculated to define the temporal stable areas. In Brazil, the results of MapBiomas Brazil collection 4.1 were used to define the temporal stable areas.

4.4.2 Stable Samples

The identification of stable areas to extract random pixels or “stable samples” was based on a criterion of minimum frequency aiming to ensure confidence for use them as training areas. Each pixel should be classified with the same LULC class at least a minimum number of years in the period 2000-2019 to be considered as stable. The thresholds for some classes and each country and subregion were not the same. A layer of pixels with a stable classification along the 20 years was then generated by applying such thresholds. From the resulting layer of stable samples, a subset of 2,000 samples for each subregion were randomly generated for each class based on the class cover percentage. A minimum of 200 samples was used for rare classes that did not reached a land cover at least 10% of the region area.

4.4.3 Complementary samples

The need for complementary samples was evaluated by visual inspection and by comparing the output of the preliminary classification with both Landsat and high-resolution images available in GEE. Complementary sample collection was also done drawing polygons using Google Earth Engine Code Editor. The same concept of stable samples was applied, checking the false-color composites of the Landsat mosaics for all the 20 years during the polygon drawing. Based on the knowledge of each region, polygon samples from each class were collected and the number of random points in these polygons were defined to balance the samples.

4.4.4 Final classification

The final classification was performed for all subregions and years with stable and complementary samples. All years used the same subset of samples, but trained using the specific mosaic of the year being classified.

5 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.

5.1 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.

5.2 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 GEE 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).

5.3 Temporal filter

The temporal filter uses the information from the previous year and the later year to identify and correct a pixel misclassification, considered as cases of invalid transitions. In the first step, the filter looks at any natural cover (3, 4, 11, 12, 33) that is not this class in 2000 and was kept unchanged in 2001 and 2002 and then corrects the 2000's value to avoid any regeneration in the first year. In the second step, the filter looks at a pixel value in 2019 that is not 14 (Farming) but is equal to 14 in 2017 and 2018. The value in 2019 is then converted to 14 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.

5.4 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 20 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 should be used with parsimony to solve very well delimited cases.

6 VALIDATION STRATEGIES

Despite part of visual interpretation samples were separated from training Samples, Collection 1 does not include a description of accuracy analysis. A randomly spatial distributed sampling of independent samples is needed for a full validation process, which is planned for the next collections.

7 REFERENCES

Breiman, L. Random forests. **Machine learning**, v. 45, n. 1, p. 5-32, 2001.