MAPBIOMAS

Deforestation and Secondary Vegetation – Appendix

Collection 10

Version 1

1 Overview

This document describes the method applied to generate the annual maps of deforestation and secondary vegetation regrowth produced using the annual maps of land cover land use (LCLU) provided by MapBiomas Collection 10. A time series of the dynamics of natural vegetation cover was produced for all six Brazilian biomes spanning 1987-2024, by identifying patterns of classification trajectories at the pixel level regarding loss/regrowth of natural vegetation.

2 Method

2.1 Input Dataset

The main goal of this method is to identify events of natural vegetation loss or the regrowth of secondary vegetation after some period of land use, irrespective of the specific vegetation/land-use classes involved. Therefore, the 30 classes in the original legend of the MapBiomas dataset were aggregated into three generic classes: Anthropic, Natural, and Not Included (Table 1). The time series (1985-2024) was used as input data for the trajectory analysis algorithm described in the next section of this document.

Table 1. *Aggregation scheme applied to the MapBiomas Collection 10 annual LCLU time series to produce the input dataset for classification trajectory analysis.*

Aggregated class	*Original classes included*	*Raster Value*
Anthropic	*Pasture, Agriculture (Soybean, Sugar cane, Rice, Cotton, Other Temporary Crops, Coffee, Citrus, Palm Oil, Other Perennial Crops), Forest Plantation, Mosaic of Uses, Urban Area, Mining, Photovoltaic Power Plant*	*1*
Natural	*Forest Formation, Floodable Forest, Savanna Formation, Mangrove, Wooded Sandbank Vegetation, Wetland, Grassland, Hypersaline Tidal Flat, Rocky Outcrop, Herbaceous Sandbank Vegetation*	*2*
Not Included	*Beach, Dune and Sand Spot, Other non Vegetated Areas, River, Lake and Ocean, Aquaculture, Not Observed, Shallow Coral Reef*	*7*

2.2 Classification Trajectory Analysis

Per-pixel classification trajectory analysis was conducted within a moving temporal window while applying persistence criteria to differentiate between noisy class transitions (*e.g.,* toggle caused by mixed pixels; Xie et al., 2020) from transitions consistent with deforestation events and secondary vegetation regrowth events. For a given annual map in the input dataset (with three classes), the algorithm identifies pixels in which there was a change to the previous year and then checks if the classification was persistent before and after the transition. The period a pixel had to present constant classification before and after a class change to be mapped as vegetation loss or regrowth was named persistence criteria. Changes in the input map that agreed with the defined criteria were classified in the respective loss/regrowth category. Changes that did not agree were reverted to reflect no change to the map in the previous year. The resulting output has five classes (Primary Vegetation, Secondary Vegetation, Loss of Primary Vegetation, Loss of Secondary Vegetation and Regrowth), in addition to the original three classes in the input data. In the next iterative step, which will produce the next year's map, the previous steps' output maps are used as a reference for past classification trajectories.

For deforestation, the persistence criteria were defined within a temporal kernel of four years: a pixel was mapped as a deforestation event in year *t* if it persisted as Natural for at least two years before conversion to Anthropic (*i.e.,* Natural in *t*-1 and *t*-2) and persisted as Anthropic for at least one year after the conversion (*i.e.,* Anthropic in *t* and *t*+1).

In contrast with deforestation, the regrowth of secondary vegetation is not a discrete event promptly observable from differences in consecutive annual LCLU maps. Rather, it is a gradual process that spans several years, with its duration controlled by several ecological factors: type and duration of the past land-use regime, abundance of propagules sources (*i.e.,* natural vegetation) in the landscape, climate and topography, among other variables that can vary widely at the biome scale (Aide et al., 2000; Ferreira et al., 2015; Sobrinho et al., 2016; Uriarte et al., 2010). Therefore, we conducted trajectory analysis considering persistent classification as Anthropic for at least two years before the conversion (*i.e.,* Anthropic in *t*-1 and *t*-2) and persistence as Natural for at least two years after the transition (*i.e.,* Natural in *t*, *t*+1 and *t*+2). In the first year of detection of secondary vegetation, it is assigned to the regrowth class and in subsequent years, if it remains, it is called secondary vegetation.

Given that the criteria for persistence with respect to deforestation involve a two-year period before conversion to verify consistent changes in class, the commencement of the output deforestation time series is established as 1987. This choice is due to the fact that the years 1985 and 1986 in the input dataset do not possess two years of prior information, rendering them ineligible for inclusion in the analysis. Additionally, as 2024 is the last year in the input dataset, the methodology described above is used to map deforestation until 2023 only. To produce deforestation in 2024, we adopted as criteria the persistence as natural in 2021, 2022 and 2023 and we used a spatial filter (1 ha to 3 ha, depending on the biome) to remove noises (see details in the 2.4 topic). For secondary vegetation regrowth, the initial year is 1986 and the final year in the output time series was 2022. In 2023 and 2024 there is only secondary vegetation occurrence and loss.

Pixels showing class changes between Natural and Anthropic (or *vice versa*) but not following the defined rules were reclassified to correctly represent land-cover/land-use in the next step of the iterative algorithm (*i.e.,* when analyzing the next year in the series). For example: when analyzing the 1988 input LCLU map, pixels originally classified as Natural in 1987, Anthropic in 1988, and then as Natural again in 1989 were not identified as deforestation in the 1988 output map, because the trajectories do not comply with the persistence criteria for deforestation. Rather, pixels with land-use change trajectories that did not follow the persistence criteria were reclassified to match the classification in the previous year, so that the information available for the next step of the trajectory analysis (1989 in this example) indicates stability until there is a change that follows the persistence criteria.

An overview of the processes through which information in the MapBiomas annual LCLU time series is used to map vegetation loss or regrowth is given in Figure 1. The seven classes representing vegetation dynamics or stability -- that derive from the trajectory analysis of the original input dataset with three classes – are explained in detail in the next session.

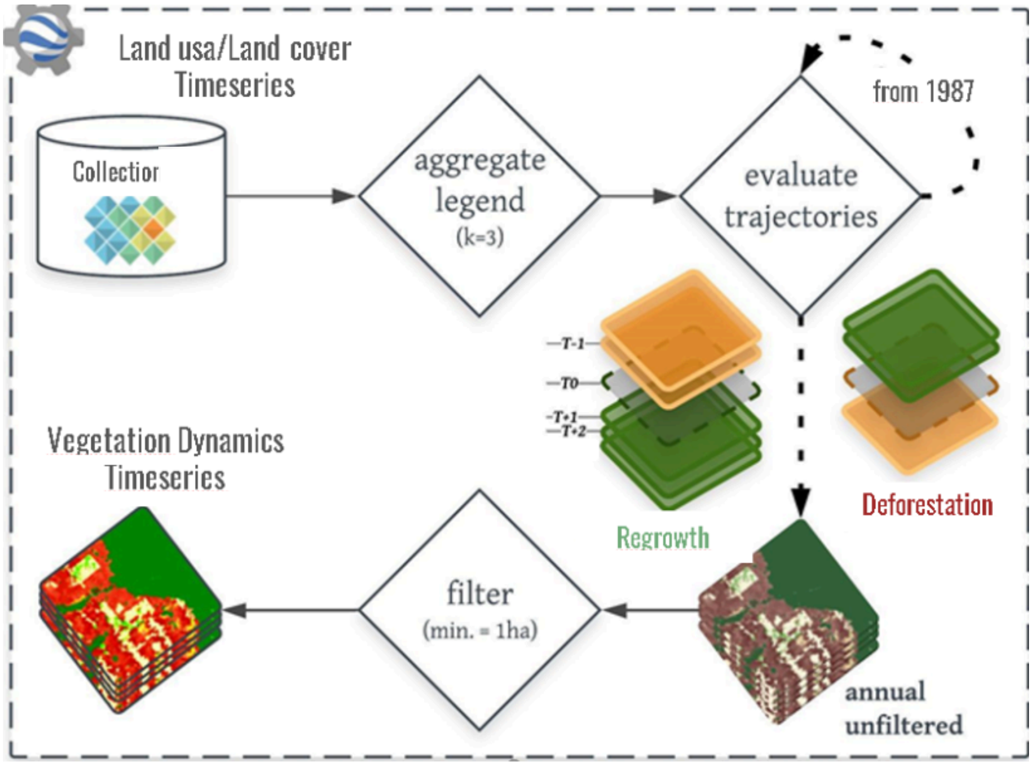

Figure 1. *Overview of the steps needed to map vegetation dynamics using a LCLU annual time series as input, following the presented method. The first step is aggregating 29 LCLU classes in the original datasets into three classes. In the second step, pixels in the resulting aggregated annual time series have their trajectory analyzed to identify changes consistent with the defined persistence criteria. For a pixel to be identified as Regrowth, it has to be classified as Natural in the current year of analysis (tile with dashed green border; T0), in (at least) the following two years (green tiles; T+1 and T+2) and also be classified as Anthropic in the two years immediately before the year of analysis (yellow tiles, T -1 and T -2). For a pixel to be identified as Deforestation (*i.e. *Loss of Primary Vegetation or Loss of Secondary Vegetation) it has to be classified as Anthropic in the current year of analysis (tile with dashed yellow border; T0), in the following year (yellow tile; T+1) and also be classified as Natural (Primary vegetation or Secondary Vegetation) in the two years immediately before*

the year of analysis (green tiles; T-1 and T-2). The process is carried on iteratively, starting by the 1987 map (1985 and 1986 input maps used to check persistence criteria) and the result is an annual time series mapping seven classes, which can represent either a type of land cover or a class change event: Primary Vegetation (cover), Secondary Vegetation (cover), Anthropic (cover), Regrowth (change), Loss of Primary Vegetation (change) and Loss of Secondary Vegetation (change). Post-processing of the annual time series that results from the trajectory analysis involved of a spatial filter that removes small isolated patches of pixels.

2.3 Classification Scheme

The final annual maps produced through trajectory analysis contain seven classes, which can represent either a type of land cover or a class change event: Primary Vegetation (cover), Secondary Vegetation (cover), Anthropic (cover), Regrowth (change), Loss of Primary Vegetation (change) and Loss of Secondary Vegetation (change). The definition of these classes and the persistence rules related to each are shown in Table 2.

Table 2. *Description of the classes mapped in the annual vegetation dynamics time series produced by the presented method.*

Class Name	**Class Description**	**Rule Description**	**Raster value**
Anthropic	Pixels classified as Anthropic in the input data and that did not show any change in the year analyzed	NA	1
Primary vegetation	Natural areas from the beginning of the series (1985) to the year analyzed	NA	2
Secondary vegetation	Areas with a history of Anthropic use followed by a change to the Natural class in the year prior to the year analyzed	Classified as Natural in the year analyzed and as Regrowth or as Secondary Vegetation in the previous year	3
Loss of Primary Vegetation	Areas with change from Primary vegetation to Anthropic vegetation in the year analyzed	Classified as Primary Vegetation at least two years before the year analyzed and classified as Anthropic in the year analyzed and the following year	4
Regrowth	Areas with a history of Anthropic use followed by change to the Natural class in the year analyzed	Classified as Anthropic at least two years before the year analyzed and classified as Natural for at least two years after the change	5
Loss of secondary vegetation	Areas with change from Secondary vegetation to Anthropic in the year analyzed	Classified as Secondary Vegetation at least two years before the year analyzed and classified as Anthropic in the year analyzed and the following year	6

Other	Areas classified as Not included in input data	NA	7

2.4 Post-processing

Different options of post-processing filters were tested and the specialists in each biome chose those that best suit the characteristics of the deforestation and regeneration processes in each case. Therefore, two types of filters were used, applying different parameters to each biome. In the first type (hereafter time series filter), all pixels with vegetation regrowth throughout the time series (*i.e.,* classified as Regrowth at least once) were accumulated into a single layer and the same was done to vegetation loss. Patches (*i.e.,* connected pixels of the same class) containing less than a biome-specific threshold of pixels within each mask were removed. Such pixels were reclassified to the “other” class. The second filter (hereafter 2024 filter) removed areas below a biome-specific threshold in 2024 only. The biome's specific thresholds for each filter are presented in Table 3.

Table 3: *Biome-specific area (in hectares) thresholds for the two types of applied post-processing filters (see the text for a description of each filter).*

Biome	Accumulated time series filter	2024 filter
Amazon	2	2
Atlantic Forest	1	1
Caatinga	1	1
Cerrado	3	3
Pampa	3	3
Pantanal	1	3

3 Concluding remarks

The method presented here conceptualizes categories of vegetation dynamics based on per-pixel LCLU classification trajectories, which demands some premises to be adopted. For example, any natural vegetation mapped at the beginning of the input time series is regarded as Primary Vegetation until its experiments change, even though some of those areas of natural vegetation cover in Brazil had already been used before 1985. Additionally, the mapping of Secondary Vegetation following the presented method is unable to inform about the quality of the developing vegetation and, therefore, can represent contrasting ecological processes, such as regeneration, restoration, or biological invasion (*e.g.,* Damasceno et al., 2018; Fernandes et al., 2016; Pinheiro & Durigan, 2009).

Even though the quality of the produced maps is tightly linked to the accuracy of the input dataset (MapBiomas), a validation protocol is being produced to allow per biome quality assessment of the vegetation dynamics classification. The main goal is to reduce uncertainties and eliminate bias when estimating area and accuracy metrics for vegetation dynamic classes that are not prevalent in the territory.

4 References

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