MAPBIOMAS
ARGENTINA

Loss of vegetation and secondary vegetation

Collection 2 - Version 1

1. Overview

This document describes the method applied to generate the annual maps of loss of vegetation and secondary vegetation regrowth produced using the annual maps of land cover land use (LCLU) provided by MapBiomas Argentina Collection 2. A time series of the dynamics of natural vegetation cover was produced for all Argentina 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 18 classes in the original legend of the MapBiomas Argentina 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 Argentina Collection 2 annual LCLU time series to produce the input dataset for classification trajectory analysis.

Aggregated class	Original classes included	Raster Value
Anthropic	Agriculture, Temporary Crops, Perennial Crops, Pastures, Forest Plantations, Agriculture and pasture mosaic, Urban Area	1
Natural	Closed Forests, Open Forests, Flooded Forests, Closed Shrublands, Open Shrublands, Shrubs and herbaceous Mosaic, Grasslands, Flooded Grasslands, Peatlands, Clean-ice glaciers and perennial snow	2
Not Included	Other Non Vegetated Areas, Rivers, lakes or ocean	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 loss of vegetation 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 loss of vegetation, the persistence criteria were defined within a temporal kernel of four years: a pixel was mapped as a loss of vegetation 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 loss of vegetation, 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.

Beyond the basic regrowth detection rule, additional trajectory rules were applied to correctly handle pixels with more complex classification histories. These include: (i) continuity rules that maintain the Secondary Vegetation class in pixels already classified as Secondary Vegetation in previous years; (ii) a rule that reclassifies short-lived apparent regrowth followed by vegetation loss as Anthropic, to avoid spurious detections caused by classification noise; and (iii) a rule that distinguishes Loss of Secondary Vegetation from Loss of Primary Vegetation when the loss event occurs over a pixel with a prior history of secondary regrowth.

Following the trajectory analysis, two additional global corrections were applied using the cumulative count of years classified as Anthropic for each pixel across the full time series. First, pixels identified as Loss of Primary Vegetation (class 4) but with more than one prior year of Anthropic classification were reclassified as Loss of Secondary Vegetation (class 6), as their history is inconsistent with primary vegetation status. Second, pixels classified as Primary Vegetation (class 2) but with at least one prior year of Anthropic classification were reclassified as Secondary Vegetation (class 3).

Given that the criteria for persistence with respect to loss of vegetation involve a two-year period before conversion to verify consistent changes in class, the commencement of the output loss of vegetation 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 loss of vegetation until 2023 only. To produce loss of vegetation 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. Additionally, because the secondary vegetation detection rule requires confirmation of the Natural class for at least two years after the transition, the final years of the time series (2022 and 2023) cannot be fully confirmed using future observations. To avoid false detections, pixels classified as Secondary Vegetation in 2022 or 2023 that had been classified as Anthropic in 2021 were reclassified as Anthropic, as the absence of a confirmed persistence window renders those transitions unreliable.

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 loss of vegetation in the 1988 output map, because the trajectories do not comply with the persistence criteria for loss of vegetation. 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.

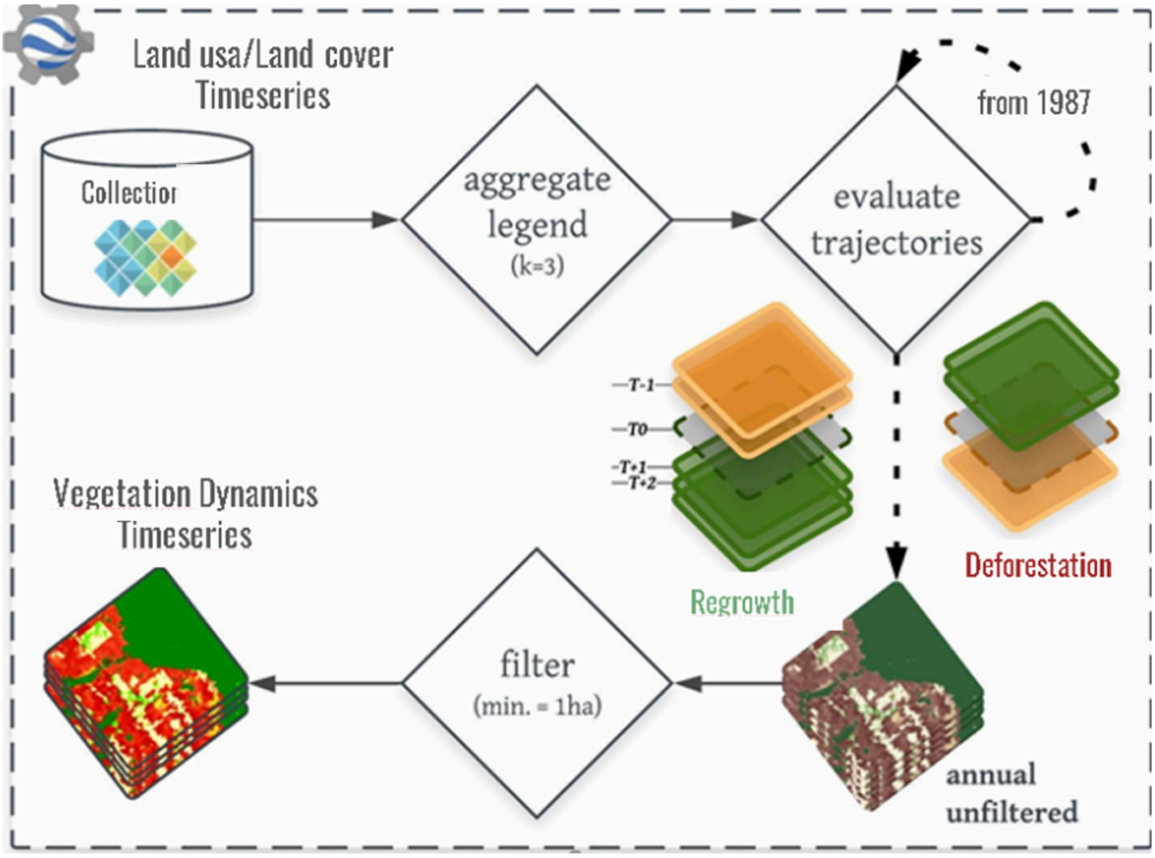

Figure 1. *- Overview of the steps needed to map vegetation dynamics using a LCLU annual time series as input, following the presented method. The first step is aggregating 18 LCLU classes in the original datasets into three classes. In the second step, pixels in the resulting aggregated annual time 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 loss of vegetation (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

Post-processing spatial filters were applied to the output of the trajectory analysis to remove small isolated patches of pixels that are likely to represent classification noise rather than real vegetation dynamics events.

Two types of filters were applied. The first filter (hereafter *time series filter*) operates on the full temporal extent of the output. All pixels classified as a vegetation loss event (Loss of Primary Vegetation, class 4; or Loss of Secondary Vegetation, class 6) at least once across the time series were accumulated into a single binary mask, and the same was done independently for secondary vegetation pixels (Secondary Vegetation, class 3; and Regrowth, class 5). For each mask, spatially connected groups of pixels (patches) were identified using 8-connectivity. Patches containing fewer than 12 pixels (equivalent to approximately 1 hectare, given a pixel area of 900 m^2 at 30 m resolution) were removed, and the corresponding pixels were reclassified to class 7 (Other). This threshold was applied uniformly across all of Argentina, in contrast with the MapBiomas Brazil approach where thresholds vary by biome.

The second filter (hereafter *last-year filter*) was applied exclusively to the year 2024, for which no post-event confirmation year is available. For this year, a stricter area threshold of 34 pixels (approximately 3 hectares) was used for vegetation loss patches, to compensate for the higher noise expected in the absence of temporal confirmation. As with the time series filter, pixels in patches below this threshold were reclassified to class 7 (Other).

3. Concluding remarks

The method presented here conceptualizes categories of vegetation dynamics based on per-pixel LCLU classification trajectories done by the team of Brazil and adapted to the legend and context of Argentina (MapBiomas, 2025), 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 Argentina 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).

4. References

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