MAPBIOMAS
COLOMBIA

Appendix - Vegetation Loss and Secondary Vegetation Module

Vegetation Loss and Secondary Vegetation Module Collection 4

Version 1.0



November 2026

MapBiomas Colombia Project Coordination
Adriana Rojas Suárez

Technical Lead, MapBiomas Colombia
Karen Andrea Huertas

Team of Specialists
Luis Medina

Institution
Fundación Gaia Amazonas

Gaia
Amazonas

Calle 70a # 11- 30
Bogotá, Colombia.
(57-1) 772 35 42 / (57-1) 805 37 68
contacto@gaiaamazonas.org
https://www.gaiaamazonas.org

How to cite:
Fundación Gaia Amazonas (2026). Appendix - Vegetation Loss and Secondary Vegetation Module. Vegetation Loss and Secondary Vegetation Module Collection 4

TABLE OF CONTENTS

1. Methodology 3
    1.1. Input data 3
    1.2. Classification Trajectory Analysis 5
        1.2.1. Criteria for Primary Vegetation Loss 5
        1.2.2. Criteria for Secondary Vegetation Regeneration 6
        1.2.3. Temporal Analysis Period 7
        1.2.4. Corrección y continuidad de las trayectorias 7
        1.2.5. Classification Scheme 8
    1.3. Post-processing 10
2. Conclusions 11
3. References 11

LIST OF FIGURES

Figure 1. Comparison between the general map and the grouped classes. 4
Figure 2. Methodological overview of the vegetation loss and secondary vegetation regeneration module. 8

LIST OF TABLES

Table 1. Grouping scheme for the classes in the annual LULC time series. 4
Table 2. Description of the classes mapped in the annual vegetation dynamics time series produced by the method presented. 9

OVERVIEW

This document describes the method applied to generate the annual vegetation loss and secondary vegetation maps using the annual land cover and land use maps from MapBiomas Cobertura Colombia Collection 4. Processing was conducted at the national scale for the 1985–2025 period.

The processing involves grouping the original land cover classes, evaluating temporal classification sequences, and applying filters to reduce spatial and temporal inconsistencies. The resulting output is a series of annual maps distinguishing anthropogenic land cover, primary vegetation, secondary vegetation, and transitions associated with their suppression or recovery.

The procedure was implemented in Google Earth Engine (GEE), a platform that enables the management and processing of satellite image collections through operations on raster data. The algorithm operates on a multiband time series, in which each band represents the classification for a given year. This data structure allows pixel-level trajectories to be evaluated throughout the analysis period and the defined temporal rules to be applied to identify changes.

Although the method and its parameters are applied consistently at the national scale, the code implementation is parameterized by regional units. Consequently, processing is performed for each unit, generating the corresponding outputs while maintaining the same methodological criteria.

1. Methodology

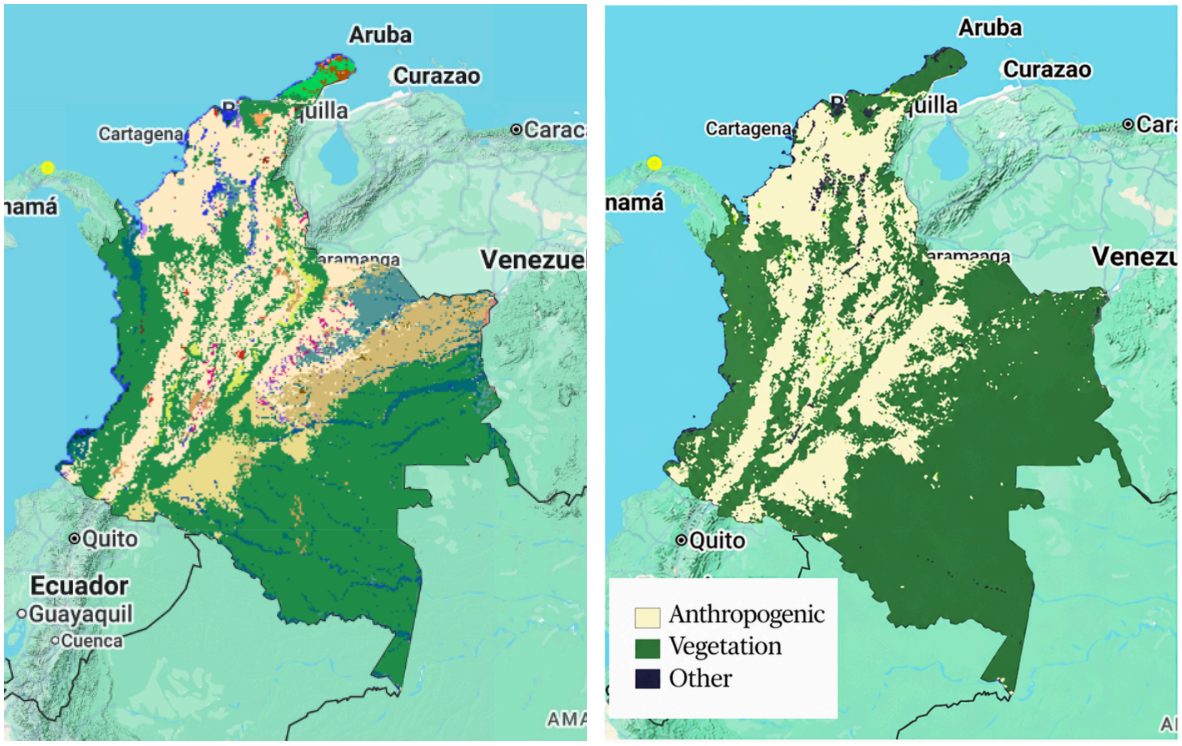
1.1. Input data

The method uses the annual land cover and land use time series from MapBiomas Cobertura Colombia Collection 4 as input data, covering the 1985–2025 period at a spatial resolution of 30 m. The input classes were grouped into Anthropogenic, Natural, and Other categories. The value 0, representing pixels with no data or ignored pixels, was retained separately (Table 1). This grouping allows changes between anthropogenic land uses and natural vegetation to be analyzed, regardless of the specific classes involved.

Before grouping, a temporal filter was applied to the following classes, in this order: Pasture (15), Agriculture (18), Forest plantations (9), Oil palm (35), and Mosaic of agriculture and/or pasture (21). For each class, the years from 2023 to 1986 were processed in descending order. When the class in the year being analyzed differed from both the preceding and the following year's classes, and corresponded to the class being evaluated, it was replaced with the classification of the preceding year. The two neighboring years do not need to have the same classification. This filter was not applied to 1985, 2024, or 2025.

Grouped classes	Individual classes	Raster value
valueAnthropogenic	Forest plantations (9), Oil palm (35), Banana and plantain (74), Mosaic of agriculture and/or pasture (21), Rice (40), Agriculture (18), Pasture (15), Urban infrastructure (24), Mining (30), Aquaculture (31), Solar farms (75).	1
Natural	Forest (3), Mangrove (5), Flooded forest (6), Woody vegetation on sand (49), Natural non-forest flooded formation (11), Herbaceous formation (12), Other natural non-forest formation (13), Herbaceous vegetation on sand (50), Lowland flooded grassland (51), Andean grasslands or shrublands (81), Flooded Andean grasslands or shrublands (82). Includes the aggregated codes 1 and 10 when present.	2
Other	Area without vegetation (22), Beaches, dunes and sandbanks (23), Other area without vegetation (25), Water body (26), Rocky outcrop (29), Hypersaline tidal flat (32), River, lake or ocean (33), Glacier and snow (34), Other natural area without vegetation (68).	7
No data or ignored	Unclassified (0), Not observed (27), and codes not included in the class correspondence.	0

Table 1. Grouping scheme for the classes in the annual LULC time series.



a) Clasificación Colección 4, sin agrupar b) Clases agrupadas

Figure 1. Comparison between the general map and the grouped classes.

1.2. Classification Trajectory Analysis

A pixel-based classification trajectory analysis was performed using a moving temporal window, applying persistence criteria to distinguish between noisy class transitions (e.g., changes caused by mixed pixels; Xie et al., 2020) and transitions consistent with vegetation loss or secondary vegetation regeneration events.

The algorithm evaluates class sequences using moving temporal windows. The rules consider persistence before and after a transition and update the time series throughout processing. The rules for primary vegetation loss are applied first, followed by those for secondary vegetation regeneration and persistence, and finally those for secondary vegetation loss and last-year exceptions.

- Trajectories that meet the defined rules are identified as primary vegetation loss, secondary vegetation loss, or regeneration events.
- Correction rules are also applied to specific non-persistent trajectories. These rules modify the sequences described in Section 1.2.4. They do not constitute a general reversal of all changes that fail to meet the persistence criteria.

The analysis distinguishes the following vegetation classes and change events:

- Primary vegetation
- Secondary vegetation
- Primary vegetation loss
- Secondary vegetation loss
- Regeneration

The output also includes the Anthropogenic and Other transitions classes, resulting in a total of seven thematic classes, while retaining the value 0 for pixels with no data. The rules are applied to the time series as updated at each processing step.

Trajectory evaluation is performed by comparing bands in the multitemporal image. Operationally, the algorithm identifies the classes present in a consecutive set of years and checks whether their sequence matches any of the predefined patterns. When a rule is met, the value of the band corresponding to the event year or to the years specified by that rule is modified. Therefore, the output is not merely a classification of detected changes, but rather a time series in which certain original classes may be corrected or reclassified during processing.

1.2.1. Criteria for Primary Vegetation Loss

Primary vegetation loss was defined within a four-year time frame. A pixel is classified as primary vegetation loss in year t if it meets the following conditions:

- It was classified as Natural for at least two consecutive years prior to conversion (i.e., Natural in t-1 and t-2).

- It remained classified as Anthropogenic for at least one year after conversion (i.e., Anthropogenic in t and t+1).

In terms of the classification sequence, the trajectory [2, 2, 1, 1] is transformed into [2, 2, 4, 1]. The value 4 represents the year in which primary vegetation loss is identified. The following year retains the Anthropogenic category, confirming that the change does not correspond to an isolated occurrence.

Additionally, the algorithm incorporates rules to correct two trajectories in which an isolated anthropogenic occurrence appears between years classified as natural vegetation. These sequences are [2, 2, 1, 2] and [2, 1, 2, 2], which are transformed into [2, 2, 2, 2]. This prevents a transition without temporal continuity from being identified as vegetation loss.

Therefore, the identification of primary vegetation loss is based on the combination of two conditions: the prior presence of natural vegetation and the subsequent persistence of anthropogenic land cover. This approach helps reduce the occurrence of isolated temporal changes, although it does not imply that all transitions classified as loss have been verified through independent observations.

1.2.2. Criteria for Secondary Vegetation Regeneration

Unlike primary vegetation loss, secondary vegetation regeneration is a gradual process that may extend over several years and depends on multiple ecological factors (such as previous land use, availability of propagule sources, climate, and topography; Aide et al., 2000; Ferreira et al., 2015; Sobrinho et al., 2016; Uriarte et al., 2010).

Therefore, regeneration was defined as a class change that meets the following conditions:

- Persistent classification as Anthropogenic for at least two years prior to the change (t-1 and t-2).
- Persistent classification as Natural for at least three years after the change (t, t+1, and t+2).

The trajectory [1, 1, 2, 2, 2] is transformed into [1, 1, 5, 3, 3]. The value 5 identifies the first year of recovery, while the value 3 represents the following two years of secondary vegetation. Secondary vegetation loss is also identified through the rule [3, 4, 1] → [3, 6, 1], which reclassifies a previously detected loss when it is preceded by secondary vegetation.

The five-year rule allows the first year of a recovery trajectory to be identified when there is prior persistence of anthropogenic land cover and subsequent continuity of natural vegetation. Assigning the value 5 to the first year of recovery makes it possible to distinguish the onset of the process from the following years, which are represented by the value 3.

Additionally, the code applies four-year rules aimed at maintaining the continuity of secondary vegetation and resolving specific trajectories involving changes between secondary vegetation, natural vegetation, and loss events. These rules allow the classification of consecutive years to be adjusted when the observed sequence matches one of the patterns defined in the algorithm.

1.2.3. Temporal Analysis Period

The output time series covers 1985–2025. Events requiring two years of prior information can be identified from 1987 onward. The years 1985 and 1986 are retained as part of the time series but do not have the historical information required to apply these detection criteria.

- Last year available in the input data: 2025.
- Last year with vegetation loss confirmed through the standard temporal window: 2024.
- To identify vegetation loss in 2025, an exceptional rule was applied: three consecutive years of primary or secondary vegetation in 2022, 2023, and 2024, followed by anthropogenic land use in 2025. These events do not have subsequent confirmation. The spatial filter described in Section 1.3 was also applied.
- Last year with regeneration events identified using the five-year window: 2023.
- No new regeneration events are identified in 2024 and 2025 using this window. End-of-series adjustments are applied to secondary vegetation trajectories that lack sufficient confirmation.

For the end-of-series adjustments, if 2023 remains classified as Anthropogenic, the Secondary Vegetation assignments for 2024 and 2025 are replaced with Anthropogenic. Additionally, if 2024 remains classified as Secondary Vegetation and 2025 as Anthropogenic, the latter is reclassified as Secondary Vegetation when the transition has not previously been identified as a vegetation loss event.

1.2.4. Corrección y continuidad de las trayectorias

The primary vegetation loss rules correct two non-persistent sequences: [2, 2, 1, 2] and [2, 1, 2, 2] are converted into [2, 2, 2, 2]. In these sequences, 1 represents Anthropogenic and 2 represents natural vegetation before its differentiation into primary or secondary vegetation.

For example, a four-year trajectory with the following classes is corrected using the first of these rules:

- Natural vegetation in 1986 and 1987.
- Anthropogenic in 1988.
- Natural vegetation in 1989.

In this case, the 1988 classification is replaced with Natural vegetation. Additional four-year rules are applied to maintain secondary vegetation continuity: [5, 3, 3, 2] becomes [5, 3, 3, 3]; [3, 2, 2, 2] becomes [3, 3, 3, 3]; [3, 2, 2, 4] and [3, 3, 2, 4] become [3, 3, 3, 6]; [3, 3, 2, 2] and [3, 3, 3, 2] become [3, 3, 3, 3]. The sequence [1, 2, 2, 4] is converted into [1, 1, 1, 1]. The values correspond to the classes listed in Table 2.

These corrections help maintain the temporal consistency of specific trajectories and prevent isolated or inconsistent changes from generating events that do not meet the defined criteria.

However, the rules do not constitute a general persistence filter applied to all classes. Their scope is limited to the sequences explicitly defined in the algorithm parameters.

An overview of the processes through which the annual land use and land cover (LULC) time series from MapBiomas Cobertura Colombia Collection 4 is used to map vegetation loss or regeneration is presented in Figure 2. The seven classes representing vegetation dynamics or stability, derived from the trajectory analysis applied to the original three-class dataset, are explained in detail in the following section..

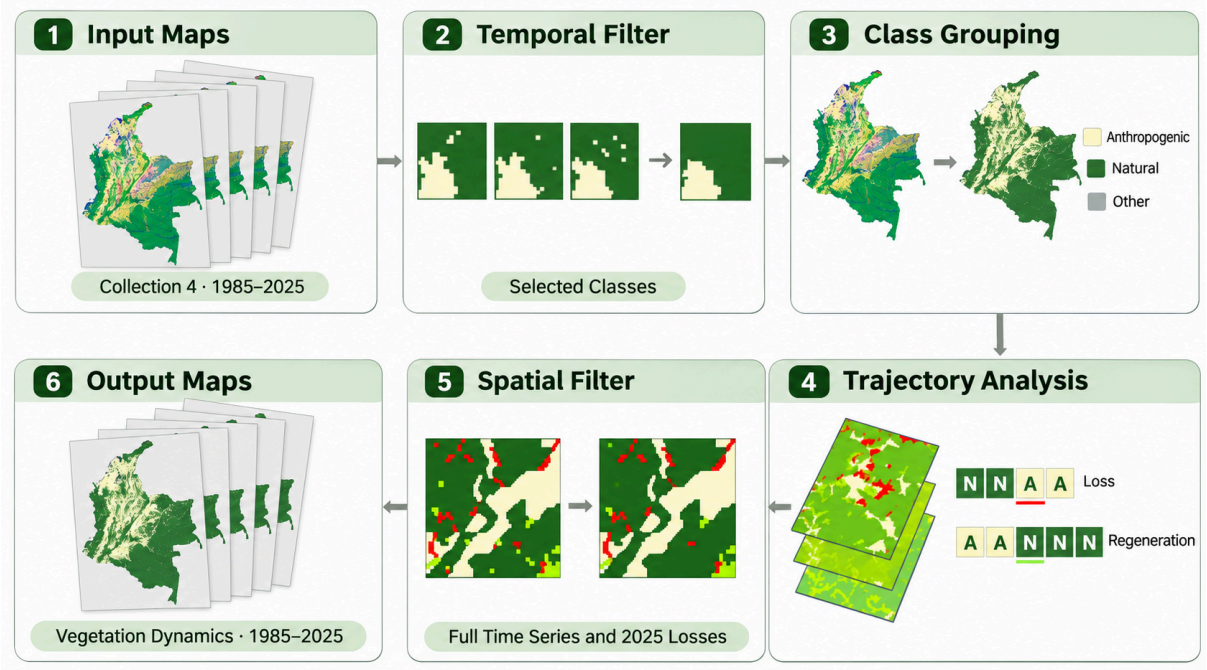


Figure 2. Methodological overview of the vegetation loss and secondary vegetation regeneration module.

1.2.5. Classification Scheme

The final annual maps contain seven thematic classes, which may represent either a land cover state or a change event (Table 2). The value 0 identifies pixels with no data and is retained separately from these classes.

The distinction between primary and secondary vegetation incorporates the cumulative anthropogenic history of each pixel in the grouped time series, following the initial temporal filter. Pixels that retain a value of 2 and have at least one anthropogenic year up to the year being analyzed are reclassified as secondary vegetation. Events with a value of 4 are reclassified as secondary vegetation loss when the cumulative count of anthropogenic years is greater than one, including the event year.

CLASS NAME	CLASS DESCRIPTION	RULE	RASTER VALUE
Anthropogenic	Areas classified as anthropogenic land use after the temporal rules are applied.	Grouped class 1 that was not assigned to a loss or regeneration event.	1
Primary vegetation	Natural vegetation with no observed anthropogenic history up to the year being analyzed.	Class 2 that remains after applying the rules and has no accumulated anthropogenic years up to the year being analyzed.	2
Secondary vegetation	Vegetation with an observed anthropogenic history in the time series.	Continuity following regeneration, four-year rules, or reclassification of class 2 based on accumulated anthropogenic history.	3
Primary vegetation loss	Change from primary vegetation to anthropogenic land use in the year being analyzed.	[2, 2, 1, 1] → [2, 2, 4, 1]. For 2025: [2, 2, 2, 1] → [2, 2, 2, 4]. The adjustment based on anthropogenic history is then applied.	4
Regeneration	First year of natural vegetation recovery following persistent anthropogenic land use.	[1, 1, 2, 2, 2] → [1, 1, 5, 3, 3]: two anthropogenic years followed by three natural vegetation years, including the event year.	5
Secondary vegetation loss	Change from secondary vegetation to anthropogenic land use in the year being analyzed.	Secondary vegetation continuity and loss rules, and reclassification of class 4 events based on anthropogenic history. For 2025: [3, 3, 3, 1] → [3, 3, 3, 6].	6
Other transition	Land cover classes grouped as Other and occurrences excluded by the spatial filters.	Grouped class 7 or reclassification of classes 3, 4, 5, and 6 according to the spatial thresholds.	7

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

Therefore, the Secondary Vegetation class includes both the continuity following a confirmed regeneration event and pixels reclassified based on their anthropogenic history. The Other Transition class comprises land cover classes grouped as Other and pixels reclassified during spatial filtering.

1.3. Post-processing

Two spatial filters were applied using parameters common to the entire national territory: one filter for occurrences accumulated throughout the time series and an additional filter for 2025 loss events. In both cases, groups of pixels connected by their sides or diagonals were evaluated using eight-neighbor connectivity.

For the first filter, two masks were constructed: one containing pixels that exhibited primary or secondary vegetation loss (classes 4 and 6) in any year, and another containing pixels that exhibited secondary vegetation or regeneration (classes 3 and 5) in any year. Occurrences of these classes belonging to groups of five pixels or fewer in their respective masks were reclassified as Other Transition (value 7). Group size is evaluated using the accumulated mask and not based on the patches from each year separately.

Connected groups are identified using the connectedPixelCount function, which calculates the number of pixels belonging to the same spatial group according to the defined connectivity criterion. In this case, eight-neighbor connectivity considers both pixels sharing a side and those in diagonal positions as contiguous. This configuration allows the spatial continuity of the occurrences identified in the masks to be evaluated.

The use of accumulated masks means that the general filter does not evaluate the size of each event independently for each year. Instead, it considers the spatial distribution of pixels that exhibited any of the selected categories at any point in the time series. Consequently, a pixel may be part of a connected group due to its spatial relationship with occurrences recorded in different years. This characteristic should be considered when interpreting the sizes of the retained groups, as they do not necessarily represent the extent of an individual loss or regeneration event.

The second filter was applied exclusively to primary and secondary vegetation loss events in 2025, using a mask for that year. Events that remained after the first filter and belonged to groups of 34 pixels or fewer in the 2025 loss mask were reclassified as Other Transition. This filter was not applied to the secondary vegetation or regeneration classes.

At a nominal spatial resolution of 30 m, five pixels correspond to approximately 0.45 ha and 34 pixels to 3.06 ha. Since groups equal to or smaller than these values are excluded, the minimum retained group sizes are six pixels (approximately 0.54 ha) for the time series filter and 35 pixels (approximately 3.15 ha) for the 2025 loss filter. These values correspond to the national configuration used.

The spatial filters are intended to reduce the representation of isolated occurrences or small groups that may be associated with classification inconsistencies. However, the size of a pixel group is not, in itself, a measure of thematic accuracy. The removal of small groups may exclude both classification errors and actual events of limited extent. Therefore, the spatial thresholds should be understood as operational criteria for product selection rather than as validation of the detections.

2. Conclusions

The method presented here conceptualizes vegetation dynamics categories based on pixel-level land use and land cover (LULC) classification trajectories, which requires adopting certain assumptions. For example, all natural vegetation mapped at the beginning of the time series (1985) is considered Primary Vegetation until a change occurs, even though some of these areas may have been altered before 1985. Likewise, the identification of Secondary Vegetation using this method cannot determine the quality of the developing vegetation and may therefore represent contrasting ecological processes, such as natural regeneration, active restoration, or even biological invasion (e.g., secondary forests vs. invasive grasses).

The interpretation of the results depends on the quality of the input land use and land cover time series and the persistence rules adopted. Applying common parameters allows the national processing to be described consistently, although trajectories may represent different processes depending on the conditions of each ecosystem. Assessing the accuracy of vegetation dynamics classes requires independent validation.

Temporal and spatial filters are part of the product definition and modify the original input classes. Their application does not, by itself, allow error reduction to be quantified. In particular, 2025 loss events should be interpreted considering the absence of subsequent observations and the additional spatial threshold applied.

Additionally, the identification of primary and secondary vegetation depends on the classification history available since 1985. For this reason, the Primary Vegetation category does not necessarily represent vegetation without historical human intervention, but rather areas with no anthropogenic history identified within the analysis period. Similarly, the Secondary Vegetation category should not be interpreted as a direct estimate of the age or successional stage of the land cover.

Finally, the method provides a homogeneous spatial and temporal representation of vegetation loss and recovery dynamics based on the MapBiomas Cobertura Colombia land use and land cover time series. Its main scope is to identify trajectories consistent with the established criteria and organize their results into comparable categories across the national territory. However, the ecological interpretation of these categories requires consideration of the limitations of the input data, the specific conditions of each ecosystem, and the uncertainty inherent in satellite-based classification processes.

3. References

Aide, T. M., Zimmerman, J. K., Pascarella, J. B., Rivera, L., & Marcano-Vega, H. (2000). Forest Regeneration in a Chronosequence of Tropical Abandoned Pastures: Implications for Restoration Ecology. Restoration Ecology, 8(4), 328–338. https://doi.org/10.1046/j.1526-100x.2000.80048.x

Damasceno, G., Souza, L., Pivello, V. R., Gorgone-Barbosa, E., Giroldo, P. Z., & Fidelis, A. (2018). Impact of invasive grasses on Cerrado under natural regeneration. BiologicalInvasions, 20(12), 3621–3629. https://doi.org/10.1007/s10530-018-1800-6

Fernandes, G. W., Coelho, M. S., Machado, R. B., Ferreira, M. E., Aguiar, L. M. de S., Dirzo, R.,Scariot, A., & Lopes, C. R. (2016). Afforestation of savannas: an impending ecological disaster. Natureza & Conservação, 14(2), 146–151 https://doi.org/10.1016/j.ncon.2016.08.002

Ferreira, M. C., Walter, B. M. T., & Vieira, D. L. M. (2015). Topsoil translocation for Brazilian savanna restoration: propagation of herbs, shrubs, and trees. Restoration Ecology, 23(6), 723–728. https://doi.org/10.1111/rec.12252

Pinheiro, E. D. S., & Durigan, G. (2009). Dinâmica espaço-temporal (1962-2006) das

fitofisionomias em unidade de conservação do Cerrado no sudeste do Brasil. Revista Brasileira de Botânica, 32(3), 441–454.

https://doi.org/10.1590/S0100-84042009000300005

Rosa, M. R., Brancalion, P. H. S., Crouzeilles, R., Tambosi, L. R., Piffer, P. R., Lenti, F. E. B., Hirota, M., Santiami, E., & Metzger, J. P. (2021). Hidden destruction of older forests

threatens Brazil's Atlantic Forest and challenges restoration programs. Science

Advances, 7(4). https://doi.org/10.1126/sciadv.abc4547

Sobrinho, M. S., Tabarelli, M., Machado, I. C., Sfair, J. C., Bruna, E. M., & Lopes, A. V. (2016).Land use, fallow period and the recovery of a Caatinga forest. Biotropica, 48(5),586–597. https://doi.org/10.1111/btp.12334

Uriarte, M., Schneider, L., & Rudel, T. K. (2010). Land Transitions in the Tropics: Going Beyond the Case Studies. Biotropica, 42(1), 1–2. https://doi.org/10.1111/j.1744-7429.2009.00580.x

Xie, Z., Pontius, R. G., Huang, J., & Nitivattananon, V. (2020). Enhanced intensity analysis to quantify categorical change and to identify suspicious land transitions: A case study of Nanchang, China. Remote Sensing, 12(20), 1–16. https://doi.org/10.3390/rs12203323https://doi.org/10.3390/rs12203323