Assessment of land restoration from optical satellite image time-series

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Abstract

Ecosystem conservation and restoration is recognized by the international community as a key strategy for human well-being as well as our planet's health. Assessing the efficiency of actions implemented in this context is essential, as their application on the ground may prove challenging. In the present paper, we present a methodology for characterising vegetation regeneration. This methodology has been developed and tested at the scale of the Sao Paulo state. It is based on two successive steps. Firstly, annual land cover maps are produced with breakpoints detection and Random Forest classification. This process is performed on biophysical variables derived from more than 10 000 optical images (2016 – 2021 included) and 4774 reference data. Secondly, we applied an expert-based rules algorithm to derive land regeneration map from annual land cover time series. The distinction is made between natural and anthropogenic regeneration. The accuracy assessment shows an overall accuracy of more than 80% for both the annual land cover maps and the regeneration map.

1. Introduction

1.1 Context

Natural ecosystems play a critical role in maintaining sustainable living conditions on Earth for people and wildlife (IPBES, 2019). However, natural resources have been largely and globally damaged due to deforestation practices, intensive farming and overgrazing. This global land degradation phenomenon affects over 3 billion people and over 30 percent of Earth's arable land. Every year, it is estimated that 24 billion tons of fertile soil (IPBES, 2018) and 13 million hectares of forests (FAO, 2020) are lost. The scientific community has provided evidence that fostering natural regeneration constitutes an efficient action to restore high quality ecosystems and to mitigate climate change (Chazdon et al., 2020; Crouzeilles et al., 2017).

In response, the international community committed itself to end deforestation and promote natural land restoration. In 2011, a global effort named the *Bonn challenge* was launched with the objective to bring 150 million hectares of degraded and deforested landscapes into restoration by 2020. In 2020, 74 pledgers from 61 countries, 8 states and 5 associations were restoring 210 million hectares of degraded and deforested lands (Flasbarth, 2020). Based on these preliminary results, the objective was revised to 350 million hectares by 2030, during the UN Decade of Ecological Restoration (2021–2030; https://www.decadeonrestoration.org/). However, going beyond these positive figures, it is essential to estimate how effective rehabilitation efforts are around the world, since implementation on the ground may prove challenging (Frietsch et al., 2023).

To do so, nine principles were proposed. Among them, one consists of "planning and undertaking monitoring, evaluation, and adaptive management throughout the lifetime of the restoration project or program" (Science Task Force for the UN Decade on Ecosystem Restoration, 2021). This aspect is even more important considering the long-term nature of natural land regeneration (Holl and Cairns, 2002).

1.2 Related work

Restoration is a key component of ecosystem resilience. In the field of Ecology, resilience corresponds to the capacity of an ecosystem to deal with disturbances and recover under restoration processes. A disturbance is defined as "any relatively discrete event in time that disrupts an ecosystem, community, or population structure and changes resource pools, substrate availability, or the physical environment" (Pickett and White, 1985). Disturbances should be large and rare enough to significantly differ from the normal variability of the ecosystem. Restoration is defined as actions aimed at promoting the natural or anthropogenic regeneration of vegetation cover after deforestation and achieving full restoration is a long-term process that takes several years or decades.

In this paper, we focus on monitoring areas concerned by a forest-landscape restoration (FLR) process after being impacted by human activity or disasters and leading to deforestation (Chazdon et al., 2017). In the FLR context, the term "under restoration" corresponds to any measures, anthropogenic or natural, consisting of stopping and gradually reversing degradation into regeneration (Dave et al., 2019). Anthropogenic and natural regeneration differ particularly from successive stages from bare soil to full natural land recovery. On one hand, anthropogenic regeneration corresponds to renewal or regrowth of natural ecosystem that has been influenced by human activities. Whereas natural regeneration corresponds to natural recovery of an ecosystem without human interventions.

Earth observation (EO) data has been proven efficient in monitoring ecosystem restoration, since relying solely on ground data can be challenging (Frietsch et al., 2023). Nevertheless, its full potential in planning and monitoring ecological restoration across different levels, from individual trees to whole landscapes, is yet to be fully explored (Harrison et al., 2021).

1.3 Problem statement

Measuring changes in ecosystems resilience to disturbances is an important field of application for EO data. In their review, Bathiany et al. (2024) provide recommendations to remote sensing experts on EO data requirements and processing methods to accurately estimate ecosystems' recovery rate following disturbances.

Looking for a restoration assessment method applicable everywhere and continuously throughout time requires the consideration of methods that look for trends in EO data time-series, taking into account permanent fluctuations related to natural ecosystem variability. These methods require long time-series, at least enough to cover the recovery period after a single disturbance and separate seasonal changes from long-term change. With respect to this particular requirement, producing such time-series implies the use of data coming from multiple satellites. Consequently, this would require data processing with an adapted method to provide (as much as possible) a dataset that is homogeneous as well as consistent in space and time. In that context, methods that apply inversion of radiative transfer model on raw reflectance are well suited.

Crouzeilles et al. (2019) presented a study to estimate the total amount of "restored forest" in the Brazilian Atlantic Forest between 2011 and 2017. Their approach consists of analysing changes in annual landuse/landcover (LULC) maps derived from satellite images time-series. A set of criteria was defined to identify restored forest. Results of their experiment determine key points necessary while designing a methodology for monitoring ecosystem recovery using EO data: 1) need to define a clear criteria to classify an area as restored (focus on restoration of native forest cover either under natural regeneration or tree planting); 2) use of reliable remote sensing or LULC maps with appropriate space and time resolution and based on standardised approaches to enable the use of multi-sensor images and to monitor restoration commitments at large scale; 3) need to define a robust and locally adaptable criteria to analyse remote sensing images or LULC maps to avoid under/over-estimation of the area undergoing restoration. For example, a forest could be classified as 'restored' if it is observed a minimum of three consecutive years: typically, this number of years of forest persistency should be adapted according to the type of forest and the soil-climate conditions (tropical, temperate, boreal climate) as these factors influence the forest regeneration speed.

The international organisations which involve in nature conservation (such as International Union for Conservation of Nature, United Nations) are actively seeking methods to monitor the progress of restoration efforts in different national and subnational pledges. Under the Bonn Challenge, since 2017, government officials and implementing agencies in pilot countries have worked with IUCN staff to identify appropriate progress indicators (Dave et al., 2018; Dave et al., 2019), the central indicator being "the area under restoration". However, no official guidelines or standard exist so far to measure these indicators and check progress towards the achievement of international restoration pledges.

In this context, the objective of the paper is to propose an accurate and robust methodology applicable everywhere to provide a solution for large-scale monitoring of restored natural land estimates. We look for a cost-effective, automated method for natural land restoration that minimises expertise and supports large processing power requirements. More specifically, we present a methodology to characterise natural land restoration with two successive steps. Firstly, we generate annual LULC maps based on satellite image time series and ground data. The next step is to combine them to track land cover changes over time and identify successive stages of vegetation changes at scale. While developing the methodology, we made sure to work in close collaboration with IUCN, who are engaged in restoration activities and interested in diagnosing natural land regeneration, to better align the capabilities of EO data with user requirements.

2. Study area

The study area in this paper focuses on Sao Paulo state (Brazil, South America) which spans over 250000 km^2. It is composed of two biomes (the Cerrado and the Brazilian Atlantic-Forest) and can be divided into three main parts (Figure 1). The narrow coastal area is bordered by the Serra do Mar mountains: one of the largest continuous primary forests of the state can be found in these mountains. The terrain becomes flatter toward the Paraná River, the most western part of the state. Inland area is mainly comprised of plains, with a large hydrographic network. Here, the vegetation is mainly composed of savannas, remaining dense forest patches, gallery forest and cropland.

Sao Paulo state's economy is one of Brazil's largest. It is driven by various industries including finance, manufacturing and agriculture. Agriculture plays a significant role thanks to its production of sugarcane, orange, coffee, cotton, corn (maize), rice, beans, Indian or Paraguayan tea (maté), potatoes, and bananas. Cattle, hogs, sheep, horses, and goats are also raised.

Figure 1. Location of Sao Paulo state and characterization in terms of biomes defined by (Olson, 2020) in the Terrestrial Ecoregions of the World package. Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS user community.

Due to agricultural expansion and extensive urbanisation, both Cerrado and Brazilian Atlantic-Forest biomes have faced significant deforestation and habitat fragmentation over the years (Calaboni et al., 2018). The Brazilian Atlantic-Forest is the most impacted biome in Brazil. However, there have been concerted efforts by both governmental and non-governmental organisations to preserve and restore these ecosystems. Notably, during the COP 21, Brazil announced the target of restoring 12 million hectares of vegetation by 2030, which will involve important environmental and biodiversity monitoring challenges.

For all these reasons, Sao Paulo state is an ideal study area to test and evaluate the land restoration assessment method described in this paper.

3. Data

3.1 Ground truth

For the purpose of this study, we defined seven LULC classes to describe the Sao Paulo landscape. This nomenclature focuses on vegetation types: 'tropical moist forest', 'dry and secondary forest', 'plantation forest', 'shrubland', 'water', 'artificial', and 'bare soil-low vegetation-cropland'. The reference dataset is composed of 4774 polygons, totalling approximately 35000 ha, labelled with their LULC in 2021. An effort has been made to ensure label repartition evenness.

The dataset has been digitised by computer assisted photo-interpretation based on images from Google Earth Pro version 7.3.3.7786 (2020) and ©OneAtlas Basemap, Airbus DS (based on Airbus Defence & Space satellite constellation imagery). To ensure a good representativeness of the landscape, the study area was divided into 696 tiles of 2048 x 2048 pixels at 10 meters spatial resolution. Digitisation was carried out on 200 tiles randomly selected amongst these. As much as possible, each tile contains 20 to 30 polygons with a balanced number of polygons of each class.

3.2 Remote sensing dataset

The remote sensing dataset is a dense optical images time series acquired by Sentinel-2 and Landsat satellites. Sentinel-2 is a European mission, aiming to provide systematic global acquisitions of multispectral images. It is comprised of two twin satellites with a 5-day revisit frequency at the Equator. Sentinel-2A was launched on 23 June 2015 and Sentinel-2B followed on 7 March 2017. The Sentinel-2 carries an optical instrument payload that samples 13 spectral bands: four bands at 10 m, six bands at 20 m and three bands at 60 m spatial resolution.

Landsat-8 and Landsat-9 were developed as a collaboration between NASA and the United States Geological Survey (USGS). Considering both satellites, the revisit frequency is 8 days. Landsat-8 was launched on 11 February 2013 and Landsat-9 followed on 27 September 2021. Landsat-8 and Landsat-9 each carry an optical instrument payload that samples 8 spectral bands at 30 m, and a panchromatic band at 15 m.

We collected images between the 1st of June 2015 and the 1st of June 2022. Optical images are sensitive to clouds and cloud shadows. No optical data can be retrieved if weather is cloudy. Considering only images with less than 90% cloud cover, we collected 7401 Sentinel-2 and 3130 Landsat images to cover the Sao Paulo state. Then, we reduced the number of images to be processed ensuring a 95% probability of having one valid observation per pixel and per month.

4. Method

The proposed method to characterise and monitor natural land restoration using satellite images time series relies on two main steps:

- Step 1: Annual LULC processing
- Step 2: Regeneration map based on annual LULC

4.1. Annual LULC maps

A complete processing chain was developed to classify LULC time series (Figure 2) (Coquet and Poilvé, 2019). It was first developed to monitor deforestation over tropical forests. This processing chain is currently being used operationally in the *Starling* service (Airbus Defence & Space, no date) and delivers annual basemaps at large scale.

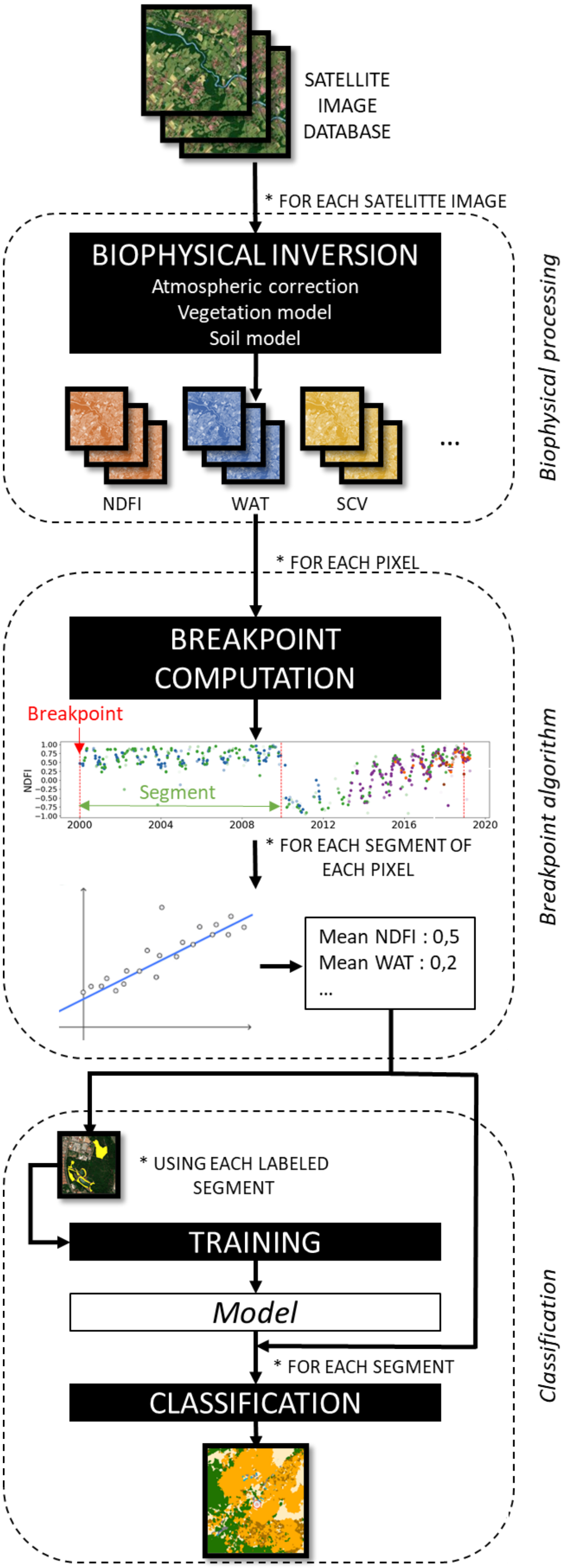

Figure 2. Satellite images time-series processing workflow to produce annual LULC maps.

4.1.1 Biophysical processing: First, each satellite image within the time-series is computed by a tool called Overland, developed by Airbus Defence & Space (Poilvé, 2010). The tool focuses on image processing and enables a complete characterisation of the elements which comprise a natural landscape, vegetation in particular, regardless of the conditions of acquisition. Moreover, by performing a homogenisation of the sensors, we minimise their effects to produce data that is independent from the sensor used to collect it. Our interest here lies in collecting information coming from different sensor sources that, once converted into biophysical variables, can be merged and compared. We do so through the inversion of reflectance models (SAIL/PROSPECT for modelling response of vegetation and LOWTRAN/MODTRAN for atmospheric modelling). Effects of topographic conditions are also taken into account using a Digital Elevation Model, here Shuttle Radar Topography Mission (SRTM) at 90 m spatial resolution (Jarvis et al., 2008). The result consists of a time-series of various biophysical variables which help characterise ground cover or vegetation: Brown Cover Fraction, Green Cover Fraction, Soil Cover Fraction, Leaf Chlorophyll Content, Fraction of Absorbed Photosynthetically Active Radiation, Leaf Area Index, Leaf Water Content, Vegetation Brown Ratio and Canopy Shadow Factor Normalised that characterises the mean roughness of vegetation canopy (green plus brown) through a shade factor. The Normalised Difference Water Index (McFeeters, 1996) and the Normalised Difference Fraction Index (NDFI) (Souza et al., 2005) are also derived.

4.1.2 Breakpoint algorithm: A breakpoint detection algorithm (Bai and Perron, 2003) is applied on the NDFI to check whether change in vegetation has occurred during the entire time-series. NDFI is preferred due to its robustness and sensitivity to canopy cover. Breakpoints split the time-series into homogeneous segments. To reduce the amount of data, a compression is performed. On each segment, biophysical variables are fitted against a linear model and a multitude of features are computed such as median, quartiles, regression coefficients and residuals. We obtain a time-series composed of segments associated with their statistics on every biophysical variable. Working with an extensive number of observations (i.e., segments) that follow the same trend produces a classification that is more robust to the variability between each observation.

4.1.3 Classification: The purpose of the classification is to assign a land-use class for each segment of the time-series and for each pixel. First, labels were retrieved from the 4774 polygons of the ground truth dataset of LULC observed over the study area. Classification samples are segments intersecting ground truth date and spatial location, associated with its label. Second, learning models are performed on segments with the Random Forest algorithm. To produce annual LULC maps, we retrieved the label of the segment covering the first day of the year for every pixel and every year, with a 0.5 ha minimum mapping unit.

4.2. Regeneration map

The aim is to detect regeneration occurring during a given period and sustained in a reference year. We defined a nomenclature of three natural land regeneration types: ‘anthropogenic regeneration’, ‘natural regeneration’ and ‘no regeneration’.

An expert-based system was developed to build a regeneration map from annual LULC maps. First, to address the uncertainty of the annual LULC maps, LULC objects too small or with low confidence were removed and re-labeled with the label of surrounding higher confidence polygons. Then, LULC classes were aggregated into three superclasses. ‘Natural vegetation’ superclass includes ‘tropical moist forest’, ‘dry and secondary forest’ and ‘shrubland’. ‘Forest plantation’ superclass remains unchanged. All other classes (‘water’, ‘artificial’, ‘bare soil-low vegetation-cropland’) are included in ‘All other LULC’ superclass. Finally, a decision rule algorithm relying on temporal LULC sequences and based on a conversion table (Table 1) is run.

<table>
<tr><th rowspan="2">FROM</th><th colspan="3">TO</th></tr>
<tr><th>Natural vegetation</th><th>Forest plantation</th><th>All other LULC</th></tr>
<tr><td>Natural vegetation</td><td rowspan="2">No regeneration</td><td rowspan="2">No regeneration</td><td rowspan="3">No regeneration</td></tr>
<tr><td>Forest plantation</td></tr>
<tr><td>All other LULC</td><td>Natural regeneration</td><td>Anthropogenic regeneration</td></tr>
</table>

Table 1. Conversion table defining regeneration classes according LULC superclasses change

A regeneration process can have various stages. The restored area can be bare soil, then developed into low vegetation and finally shrubland. So, to detect a regeneration process, we are looking for a significant change, from all other LULC to natural vegetation (for natural regeneration), or from all other LULC to forest plantation (for anthropogenic regeneration). As recommended by Crouzeilles et al. (2019), we decided to use a criterion to ensure the persistence of the regeneration: the site has to be classified as natural vegetation or forest plantation for at least three consecutive years.

This regeneration detection algorithm was tested over the Sao Paulo state study area for the period 2016-2021. Taking into account these characteristics, we specified below the information needed to interpret the results:

- If a regeneration was in place before the reference year (2021) but was damaged (for example, tree cuts in 2020), it will be a ‘no-regeneration’. This regeneration is not taken into account because there is no more regeneration at the reference year.
- Only significant changes happening during the monitored period will be detected. For example, a regeneration process started in 2000, with already matured vegetation (so no significant change during 2016-2021), will be identified as ‘no-regeneration’.
- Regeneration process has started less than three years before the reference date (2021), i.e. after 2019, will not be detected (the persistence criterion is not reached).
- Forest plantations with fast-growing trees and established before 2016 will be detected as ‘anthropogenic regeneration’ if the cut between two rotations happens during the monitoring period 2016-2021.

Lastly, for each object in the reference year’s map, the type of natural land regeneration it belongs to is retrieved at a 10 m pixel scale.

4.3. Validation

The objective is to evaluate the accuracy of both annual LULC maps and the regeneration map. A comprehensive validation, through space and time was performed. We used a stratified random sampling protocol (Olofsson et al., 2014) facilitating sufficient statistical representation of each class of the map. A stratification is a partitioning of the study area. The classes determined from the maps were used as strata. A random sampling was performed within each stratum. According to Cochran's sample size formula (Cochran, 1977, eq. 5.25), a sample size of 900 assessment units was recommended for both annual LULC maps and regeneration map. Sections 4.3.1 and 4.3.2 below show allocation made for each assessed map.

The labelling of the selected samples was performed by computer-assisted photo-interpretation of optical imagery time-series (using Google Earth Pro version 7.3.3.7786 (2020) and ©OneAtlas Basemap, Airbus DS images).

Following the good practices recommendations from Olofsson et al. (2014), for annual LULC, we reported the error matrix in terms of estimated area proportion using the Eq. (4) of Olofsson et al. (2014). The large disproportion between regeneration map classes forces us to report the regeneration matrix in terms of sample counts.

4.3.1 Annual LULC maps: For each annual LULC map, we evaluated the accuracy of the three superclasses used as input in the regeneration detection algorithm: ‘natural vegetation’, ‘forest plantation’ and ‘All other LULC’. Nine hundred samples were selected per year. The initial allocation of sample units within each stratum was made proportionally to the stratum’s area. This choice was done because we wanted to evaluate the overall accuracy of the map. Table 2 shows the allocation after the points’ photo-interpretation. Some points have been removed for lack of usable data or re-labelled due to errors. This explains why the sample distribution has changed.

	2016	2017	2018	2019	2020	2021
Natural vegetation	271	274	274	266	274	275
Forest plantation	74	73	71	67	75	75
All other LULC	555	551	555	564	551	548

Table 2. Number of samples allocated by stratum for annual LULC map accuracy assessment after photo-interpretation

4.3.2 Regeneration map: In the regeneration map, the ‘no-regeneration’ class covers over 99 % of the study site. Thus, proportional allocation would not have been adequate. For this reason, we selected 800 samples within the ‘no-regeneration’ class, 100 samples from the ‘natural regeneration’ class and 100 samples from the ‘anthropogenic regeneration’ class. To label the samples, we used the rules defined for the regeneration detection algorithm (see section 4.2).

5. Results

5.1. Annual LULC maps

Classification algorithm was applied to retrieve annual LULC maps from 2016 to 2021 (Figure 3) with the seven classes’ nomenclature, focusing on Sao Paulo State vegetation types.

Assessment was performed on the three superclasses used in the regeneration map process, as well as on the seven initial classes, allowing to analyse intra-superclasses errors. Global precision metrics (overall accuracy and F-score) are good to very good. The overall accuracy is higher than 90% for every year and the F-score is higher than 0.80 for all superclasses and every year (Table 3).

	2016	2017	2018	2019	2020	2021
Overall accuracy	91.7	93.6	91.8	94.9	93.5	93.4
F-score						
Natural vegetation	0.88	0.91	0.88	0.93	0.91	0.91
Forest plantation	0.81	0.85	0.86	0.87	0.82	0.85
All other LULC	0.95	0.96	0.95	0.97	0.96	0.96

Table 3. Global precision metrics of LULC maps (grouped in superclasses)

Accuracy remains stable over the years. We could expect better results for 2021 as the reference data is from 2021. But the homogenisation of sensors in Overland allows us to obtain satisfactory results on the whole time series. Results are better for ‘natural vegetation’ than for ‘forest plantation’.

Errors (omission or commission) are mostly due to vegetation composition and distribution characteristics. In open areas, dominated by herbaceous cover with sparse trees, differentiating cropland, low vegetation (included in the superclass ‘All other LULC’) and ‘shrubland’ is challenging. In closed areas mainly composed of trees with variable heights and more or less sparsely distributed, this is the ‘forest plantation’ that are confused with ‘shrubland’.

5.2. Regeneration map

Regeneration map for the period 2016-2021 is produced over Sao Paulo state (Figure 4).

Using 2016 as the first year of monitoring and a threshold of three years to consider an area under restoration, the total area under restoration in 2021 is estimated to 188884 ha, with respectively 65% and 35% of natural and anthropogenic regeneration.

Then, visually, according to the nature of the regeneration, the polygons present a specific pattern and spatial distribution. ‘Natural regeneration’ polygons are small and fragmented which makes sense as we look for hotspots of natural regeneration developed within a period of 3 years. They are predominantly located in Serra do Mar mountains, near the remaining primary forest. Anthropogenic regeneration polygons are larger and, logically, with geometric shapes since man-made. They are mostly located in the center of the Sao Paulo state, nearby forest plantations which were already in place at the beginning of the study period in 2016.

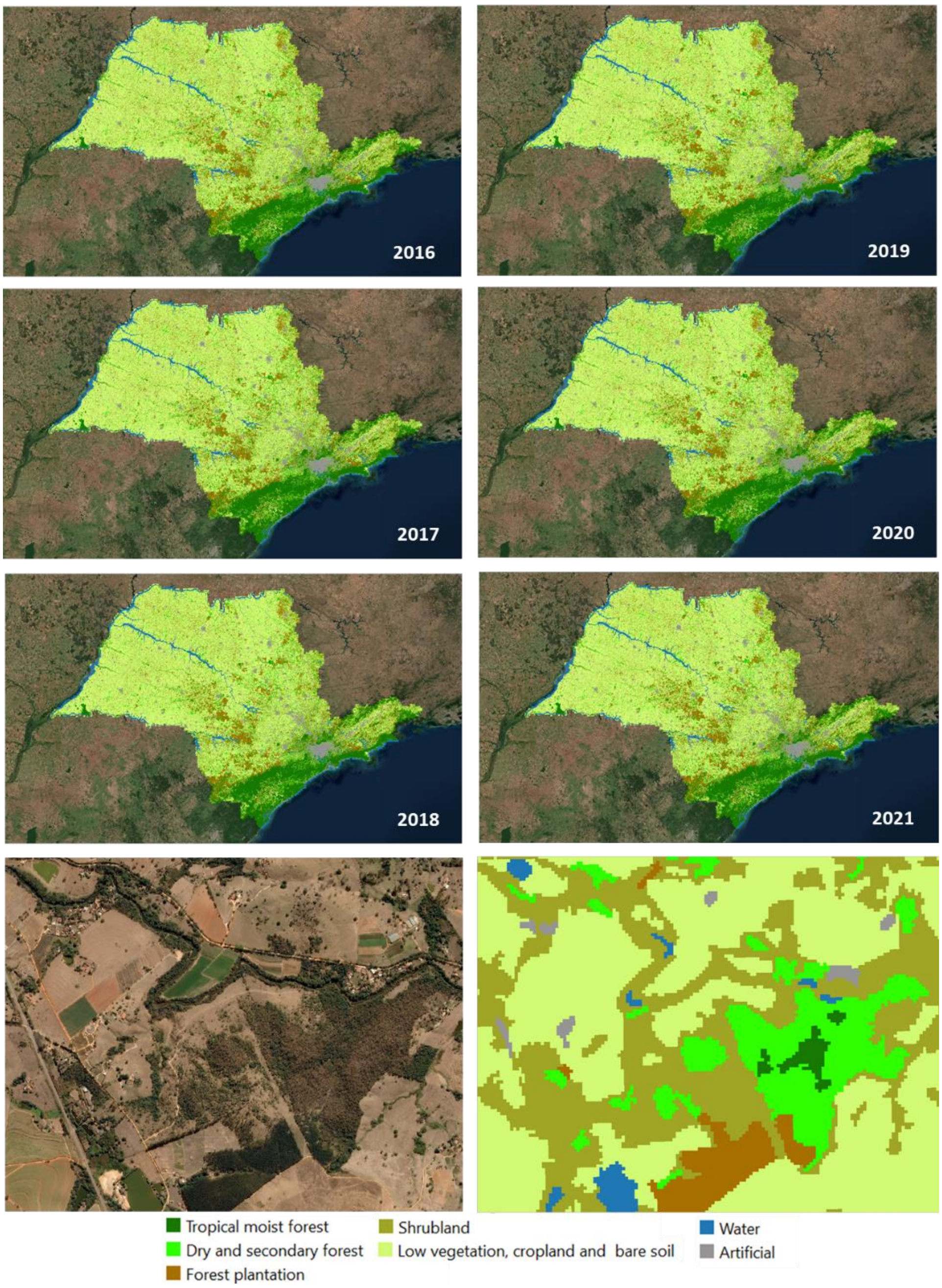

Figure 3. At the top: LULC maps over Sao Paulo state for 2016-2021 – At the bottom: 2021 LULC maps over a zoom area (21°53'59.45"S, 46°51'36.32"O) on the right with corresponding Pléiades imagery from 05/09/2020 on the left.

An accuracy assessment was conducted on 1000 points over the three regeneration classes: anthropogenic regeneration, natural regeneration and no regeneration. Overall accuracy is good, reaching 0.91. Table 4 shows the F-score of each class.

	F-score
No regeneration	0.95
Natural regeneration	0.49
Anthropogenic regeneration	0.88

Table 4. F-score for each class of regeneration map

F-score is very good for ‘no regeneration’ class. For ‘anthropogenic regeneration’, F-score is good meaning, that even over a short monitoring period, six years in this landscape could be enough to observe changes due to anthropogenic regeneration activities, especially for fast growing trees, such as eucalyptus. The remaining errors stem from the problem of accuracy in the classification of young forest plantations in the basemaps. In some areas, they are not consistently assigned to the same class within the monitoring period. For example, they may be wrongly classified as cropland or low vegetation at the beginning of the monitoring period and well identified at the end. In that case, these areas are wrongly classified as ‘anthropogenic regeneration’.

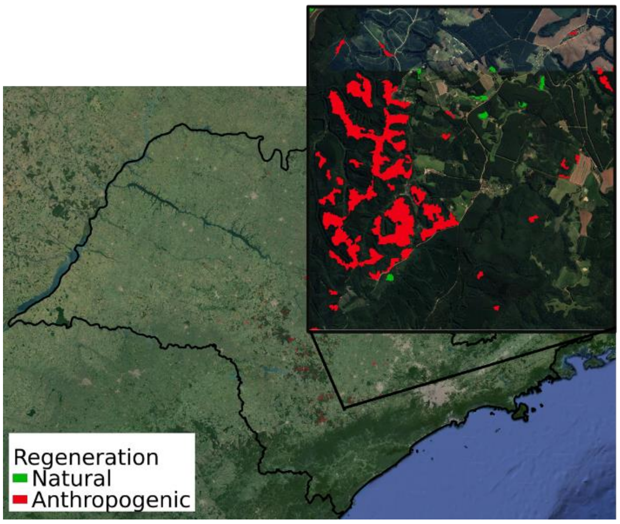

Figure 4. Regeneration map for the period 2016-2021 over Sao Paulo state (Brazil).

Detection of 'natural regeneration' is less accurate with these areas largely over-estimated. There are two main reasons. Firstly, the regeneration detection algorithm is pixel-based. So, it is very sensitive to consistency in time of the geometric accuracy of annual basemaps. For example, in urban areas located next to forest edges, all forest pixels, wrongly classified as urban between 2016 and 2018 because of geometric error, are wrongly assigned to 'natural regeneration' in the regeneration map. Secondly, it is a consequence of classification errors between shrubland and cropland-low vegetation in the annual basemaps. For a given pixel, if the misclassification is not consistent in time, then there is a high risk for this pixel to be wrongly classified as 'natural regeneration'.

Finally, we compare the spatial distribution of the regeneration classes obtained in the frame of our study with those from César et al. (2021). Results are consistent and they both led to the two same main conclusions. Figure 5 shows the map of natural regeneration rate, anthropogenic regeneration rate and sugarcane plantation rate on a 10-km x 10 km square grid made from our regeneration map. 1) There is a negative correlation between the location of sugarcane plantation and areas under restoration. The more the sugarcane plantation density is, the less is the area under restoration. This is mostly explained by the sugarcane practices. Sugarcane in Brazil is intensively conducted to ensure high productivity. Numerous phytosanitary treatments spread by aeroplanes are applied during the crop growth. After harvesting, fire is usually used to burn crop residue and is frequently uncontrolled. Both practices directly damaged land around sugarcane plantations, including land under regeneration. 2) Areas under 'natural regeneration' are preferentially located near the primary forest of Serra do Mar.

6. Discussion

Results obtained over the Sao Paulo state are satisfactory. They demonstrate the effectiveness of the methodology developed and presented in this paper for providing an operational solution for assessing and monitoring restorated natural land at a large scale. Nevertheless, the analysis also highlights improvements and evolutions required to be able to reach a higher accuracy in regeneration detection and better fit with users' needs.

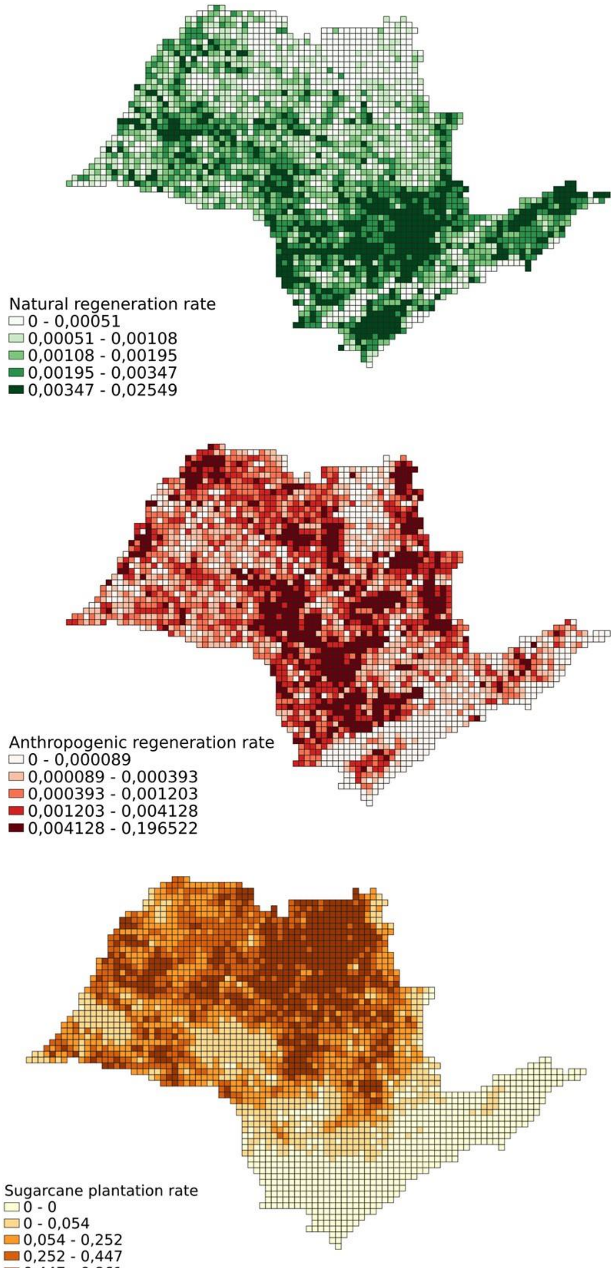

Figure 5. Map of natural regeneration rate, anthropogenic regeneration rate and sugarcane plantation rate on a 10 km x 10 km square grid. Sugarcane plantation rate was derived from the Mapbiomass map (MapBiomas Project - Collection 8.0 of the Annual Land Use Land Cover Maps of Brazil, accessed on May, 30 2024 through the link: https://storage.googleapis.com/mapbiomas-public/initiatives/brasil/collection_8/lclu/coverage/brasil_coverage_2021.tif).

6.1. Evolution to improve the regeneration map quality

6.1.1 Increase length of the satellite images time-series: In the context of this work, we were constrained to measure restoration between 2016 and 2021. Our study case was brought by IUCN, which wanted to monitor restoration activities started in 2014/2015, necessitating the start of our monitoring process in 2016. Moreover, the end of the monitoring is 2021, because the ground truth data were digitised in 2022 over the 2021 year. Assessing restoration over a 6-year period might not be long enough, in some cases, to detect the regeneration process, especially for natural regeneration. It would be better suited to consider a longer monitoring period. It should not be an issue as our processing is sensor agnostic and enables us to produce longer LULC time series.

6.1.2 Reference data: The reference dataset to train the classification algorithm used to produce the annual LULC maps is from 2021. Getting ground truth data from other years of the monitoring period would help improve the accuracy of the annual LULC maps. It is even more important when increasing the length of the satellite images time series. Implementing this new development should not be an issue as the current processing chain enables the use of reference data over the whole time series. With reference data including all possible sensor configurations, the model should be more robust at the temporal level.

6.2. Evolution to improve the regeneration map product

6.2.1 Enrich the regeneration class characterization: Considering annual LULC maps with a more detailed nomenclature than the one used in this paper to produce the regeneration map would enrich the nomenclature of the regeneration map. For example, using the seven initial LULC classes would help distinguish forest regeneration from shrubland regeneration. However, to do so, misclassifications observed between shrubland, forest plantation, cropland and low vegetation must be reduced.

6.2.2 Include an on-going regeneration class: Because we use a persistence criterion which does not allow us to detect regeneration of less than 3 years, we cannot currently capture the ongoing regeneration. It would be possible to flag areas where a change has been observed for less than 3 years as ongoing regeneration if natural vegetation or forest plantation is observed at the reference date.

6.3. Update the regeneration status

In this paper, we focussed on producing a regeneration map to provide, at a given date, an estimate of the areas under restoration, to fit with the most proprietary needs of the users. Nevertheless, there is a strong need to continuously monitor restored areas. The methodology presented here has the ability to compute an annual update of the regeneration status of natural land. However, several aspects of this monitoring process need to be defined including the frequency of the updates and the choice of satellite images time-series such as whether to include the period used to estimate the initial regeneration.

7. Conclusion

Ecosystem restoration is a critical issue that comes with urgent needs of effective monitoring solutions. Through this use case over the whole Sao Paulo state, we demonstrate the capability of the presented methodology to monitor forest landscape restoration through the years. Moreover, this study allows us to validate the processing chain ability to perform well at a large scale.

The methodology meets the recommendation given by Crouzeilles et al. (2019). First, we defined clear criteria to classify an area as restored focusing on restoration of native forest-cover either under natural recovery or tree-planting. Second, we used a reliable methodology to produce annual LULC maps, utilising multi-sensor optical satellite images which is suitable for large scale implementation. Third, the criteria and the nomenclature can be adapted to the local context to avoid under- or over-estimation of the area undergoing restoration.

The next step is to replicate the current processing chain over other areas to validate the methodology across various contexts in order to provide additional references of methodology performance, as well as make it available to the international community on a global scale.

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