Semiautomatic AI-based remote sensing classification to deliver an EU Landmark 2020 deforestation map for the Brazilian Amazon and Cerrado biomes

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1. Introduction

Since the late 1980s deforestation in the Brazilian Amazon has been monitored by PRODES (The Brazilian Deforestation Monitoring Program by Satellite) in an annual basis, using mostly Landsat images and now Sentinel images. The minimum area adopted to calculated annual rates is 6,25 ha, but additional data is currently available containing polygons up to 1 ha. In complement, DETER (Near Real-Time Deforestation Detection System) monitors the region in a daily basis with a minimum area mapped of 3 ha. Initially in 2004 DETER adopted 250 m resolution using MODIS data, and after 2016 resolution was improved to ~ 60 m thanks to WFI and AWFI sensors on board of CBERS 4, CBERS 4A and Amazonia-1 satellites.

The competence and long term expertise of INPE (The National Institute for Space Research) in mapping deforestation is worldwide recognized, and it has been crucial in dampening deforestation rates more than four times within 2004-2010 (Câmara, 2011, Messias, 2021). Despite denial of PRODES deforestation rates by some Brazilian governments in the past, not by chance, in 2007 an article in Science stated that PRODES was “the envy of the world” (Kintisch, 2007). Official deforestation data from PRODES and DETER have been consolidated also as referenced data to run zero deforestation and market regulation policies. Key policies implemented adopting PRODES as the ground truth for deforestation mapping are the Soy Moratorium and the Zero-Deforestation Cattle Agreements (Gibbs et al., 2015, Skidmore et al., 2021), both now extended to Cerrado biome where cattle ranchers are voluntarily engaging certified markets stamping free from deforestation products, so they can keep governmental subsidies.

In this context, on May 31st 2023 the European Parliament and the Concil of the European Union deliberated the new Regulation (EU) 2023/1115 on deforestation-free products (http://data.europa.eu/eli/reg/2023/1115/oj), which is expected to bring down greenhouse gas emissions and biodiversity loss. As the abovementioned Brazilian policies, this new EU Regulation shall demand a fine and trustful Landmark map of deforestation to every country that trades commodities within EU countries. In the case of Brazil, after dispute opinions among delegates from EU and the Brazilian Ministry of Agriculture, Livestock and Food Supply (MAPA) regarding why JRC maps (https://www.wri.org/initiatives/global-forest-watch) had been chosen instead of PRODES maps, an overall agreement was set. They decided that a Landmark deforestation map of Brazil, based on PRODES would be chosen, but required INPE to fulfil the observable deforested patterns that may occurs outside PRODES calendar up until December 2020.

2. Challenges and AI-based approaches

In order to deliver the EU Landmark 2020 deforestation map, initially for the Brazilian Amazon and Cerrado biomes, INPE´s team invested on AI based approaches adopting two different strategies which are described below. The biggest challenges to build the EU Landmark 2020 deforestation map based on artificial intelligence (AI) to Brazilian Amazon and Cerrado biomes are mostly two: 1) The non-observable areas outside the monitoring calendar (i.e January-June and October-December), when deforestation still occurs but is hardly seen through cloudiness; 2) The georeferenced alignment between the >30-year PRODES historical series build upon Landsat series (30 m) and the AI classification maps based on Sentinel images with 10 m of spatial resolution. In the latter, the main issues were bordering pixels of PRODES mask that did not exactly match the new borders of Sentinel AI classification maps. We then assumed that total deforestation figures based on the new classified images AI-based would ramp figures compared to previous deforestation rates already published.

2.1 Non-supervised approach and time series

First we adopted a method developed by Silva et al., (2022), based on two unsupervised clustering algorithms: SOM and agglomerative hierarchical clustering. The Self-Organizing Map (SOM) is an unsupervised learning method based on competitive learning that reduces a high-dimensional feature input space to a low-dimensional feature output space. A dataset can be mapped and represented by a set of neurons by using weight vectors. After that a hierarchical clustering is used with the help of binary trees called dendrograms, which supports the decision whether clusters should be merged or split. The spectral bands and indexes of Sentinel time series adopted in the first tests where B04, B8A, B11, NDVI, NBR, NDWI, MNDWI and a texture image based on the average of B8A. Sentinel data was retrieved from the Brazil Data Cube (BDC). In this method there are no need for sampling classes.

2.2 Supervised approach: Segmentation and SMM

The second experimental approach adopts image segmentation based on the Simple Non-Iterative Clustering (SNIC) segmentation method (Achanta and Süsstrunk, 2017). After SNIC it is applied Random Forest machine learning algorithm in Google Earth Engine. The innovation here is the adoption of fraction images generated by a Spectral Mixture Model (SMM) using Sentinel B03, B04 and B08 bands at 10 m resolution. As input to SNIC both the Soil fraction image resulting from SSM and the NDVI index were adopted. The method was run to two ecoregions in the Amazon using a mosaic of Sentinel images with tiles ranging from June 1st to 15th July 2021. In this method the samples to Random Forest are retrieved on Soil fraction image and NDVI, using the clusters resulting from SNIC segmentation. Thus final classification is performed at the clusters level and not at the pixel level.

Figure 1. Tiles classified in the Brazilian Amazon and Cerrado biomes using the non-supervised approach.

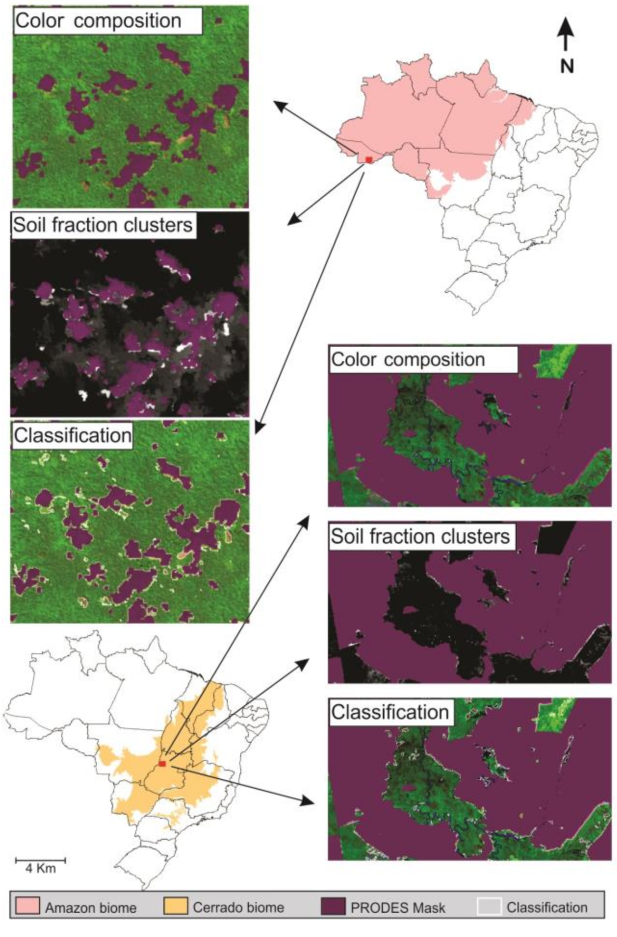

Figure 2. Tiles classified in the Brazilian Amazon biome using the supervised approach using SNIC and SSM.

3. Main outcomes

Regarding the non-supervised classification approach (Figure 1) it has been able to detect deforestation from non-deforested areas in both biomes with a visual accuracy close to PRODES´s. In Cerrado biome, secondary vegetation detection has shown significant results. This method was successful within the period not covered by PRODES 2020 calendar, due to temporal series of Sentinel images in data cubes previously treated for cloud removal. However, the final output still requires some final auditing in order to match with PRODES mask from previous years. Despite that, it decreases considerably the time spent by interpreters and auditors in delivering the final EU Landmark 2020 deforestation map.

Regarding the supervised classification approach the SNIC segmentation method was very efficient in separating detailed features between deforested and non-deforested areas (Figure 2). This is likely because SNIC considers not only the distance of pixel values, but also the spatial distance and texture. Another advantage of such method is the short processing time when compared to K-means algorithm for example. The SSM method has shown remarkable results in classifying deforested borders and small polygons of deforestation seen in Sentinel images of 10 m resolution, that were outside PRODES 2020 mask. The hypothesis of a possible boom in small deforested areas in the Amazon when using Sentinel images was not corroborated in the tests performed. This was because the total deforested area was balance between the rough trace of borders resulting from visual interpretation and Landsat images compensate the fine trace of SNIC-SMM method using Sentinel images.

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