FIRE SCARS MAPPING OVER BRAZILIAN AMAZON FOREST BY EXPLOITING SENTINEL-2 DATA AND DEEP LEARNING

Yineth Viviana Camacho-De Angulo [1,2], *Nicolas Cechinel Rosa* [1], *Yady Tatiana Solano-Correa* [2], *Mauro Roisenberg* [1]

[1]Universidade Federal de Santa Catarina, 88040-900, Florianópolis, Brasil.
[2] Universidad Tecnológica de Bolívar, Km 1 Vía Turbaco, 130010 Cartagena, Colombia.

ABSTRACT

Wildfires in the Brazilian Amazon have raised significant concerns owing to the environmental, social, and global impacts associated with these events. They have led to habitat loss for various species and release of substantial amounts of carbon dioxide into the atmosphere. Thereby contributing to climate change and deterioration of air quality due to pollutants emission. The integration of advanced technologies, including high-spatial resolution satellite data and image processing algorithms, enables a more precise and comprehensive understanding of the wildfire scenario. This research introduces a model based on deep learning that can be applied over Sentinel-2 images to reliably detect fire scars with an accuracy above 90% (92% on training data and 82% on validation data). A SpectrumNet convolutional neural network was employed, incorporating features extracted from spectral bands at 10m and 20m.

Index Terms— Deep Learning, Remote Sensing, Semantic Segmentation, Wildfires, Brazilian Amazon.

1. INTRODUCTION

Wildfires and forest fires monitoring through satellite images represents a fundamental tool in environmental management and ecosystem preservation [1, 2, 3]. The use of space technology allows for a comprehensive and efficient approach to detecting, analyzing, and combating fire events in different areas and times, reducing costs and risks by avoiding direct contact with the affected areas [4, 5]. Satellites provide a broad and continuous view of affected areas (before and after the event), enabling the rapid identification of wildfires, even in remote and inaccessible regions [2]. Remote sensing offers near-real-time monitoring, making it invaluable for environmental authorities, conservation organizations, and firefighting teams [6]. The satellites' ability to identify subtle and localized damage contributes to a quick and effective response, minimizing environmental impacts and facilitating the implementation of recovery measures. Additionally, detailed analysis of burned areas provides insights into ignition patterns, fire behavior, and causes, informing long-term prevention strategies. Thus, it plays a crucial role in the sustainable management of ecosystems, contributing to biodiversity conservation and the protection of natural resources. Nevertheless, forest fire detection depends highly on availability of cloud-free images at the moment of the event, and thus the standard is to map fires by detecting the so-called fire scars. Fire scars can be described as the blackened land surface that is left after a fire has burned the vegetation.

In recent years, fire scars detection with remote sensing has been exemplified by several case studies, showcasing advanced technologies' effectiveness in monitoring post-fire landscapes. The application of satellite imagery in regions prone to wildfires, such as Cerrado (Brazil), has enabled the precise identification of fire scars and their spatial extent [7]. Nevertheless, the detection accuracy highly depends on good quality data availability, cloud-free images, temporal resolution, among others. Authors in [7] exploited MODIS data, with a nearly daily temporal resolution, to detect burned areas. While the temporal resolution is useful to guarantee images availability, MODIS spatial resolution is too coarse (500m) to provide a detailed mapping. The use of multi-spectral sensors on satellites such as Landsat, with a better spatial resolution but lower temporal one, with artificial intelligence techniques has allowed the mapping of burned areas in fire-prone regions in Chile, as reported by [8]. In [8] they used a U-Net model to automate and optimize the process of mapping burned areas. Additionally, in the national context, a study has been carried out in Pantanal using PlanetScope images with Deep Learning (DL) segmentation methods, specifically Transformer-based networks [9], obtaining accurate results ($>90\%$) in mapping burned forest areas as reported by the authors. While the above works have successfully detected burned areas, adn therefore fire scars, several constrains exist related to the adecuate combination of tools that allowed the best cost/benefit result. This study presents a simple, yet effective, methodology that can be used to map fire scars by exploiting deep learning and Sentinel-2 images.

2. STUDY AREA AND DATA

The study area for this research is the Brazilian Amazon forest located in the northern part of Brazil, in the states of: Acre, Amazonas, Amapá, Maranhão, Mato Groso, Pará, Roraima, Rondonia and Tocantins (see Fig.1) [10]. The Brazilian Amazon forest, often referred to as the Amazon Rainforest or Amazonia, is a vast and ecologically diverse region considered as the largest rainforest in the world because of its crucial role in producing oxygen and regulating the global climate [11]. It is one of the most biodiverse places on Earth, hosting an estimated 390 billion individual trees representing around 16,000 different species [12].

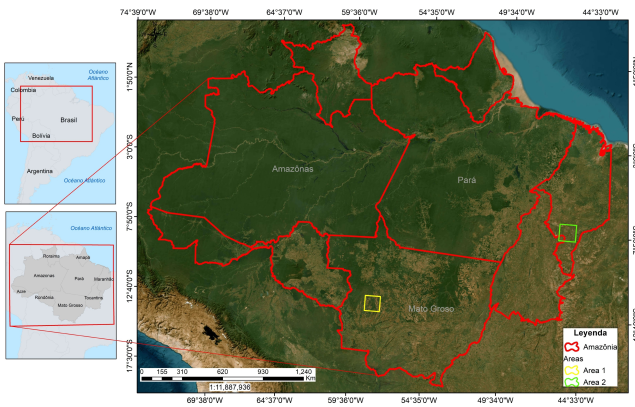

Fig. 1. Brazilian Amazon forest location: studied areas area highlighted in green and yellow squares.

The Amazon Rainforest faces significant threats, including deforestation, illegal logging, agricultural expansion (especially cattle ranching and soy cultivation), and infrastructure development [13]. Balancing economic development and conservation in the region is a major challenge. Debates surround issues such as dam construction, mining, and the expansion of agricultural activities. There are ongoing controversies related to government policies, land rights, and the enforcement of environmental regulations [14]. To add on top of these problems, forest fires are an additional issue that requires attention and remains a major challenge, even with the continuous efforts to control and monitor the area.

Considering the location of the Amazon forest, it is clear that using satellite images to detect real times forest fires is challenging. This is due to the high presence of clouds that limits the availability of usable optical data for the analysis. Thus, detecting fire scars is an alternative that helps in the correct mapping and quantification of areas affected by forest fires. In this study, two Sentinel-2 (S2) L2A cloud free tiles (21LUF and 23MLM), acquired on August 2019, were selected. Based on these images, and by making use of a false color composition (B11, B8A and B4) and photointerpretation, a total of three classes were defined for the detection: (1) older fires scars, (2) newer fire scars and (3) crops. Spectral bands at 10m and 20m were used for the analysis, and those at 20m were re-scaled to 10m by means of a bi-cubic interpolation. Authors are aware that this is not the best strategy to follow, but the methodology performed well and we decided to keep the method as simple as possible.

3. METHODOLOGICAL WORKFLOW FOR FIRE SCARS DETECTION

In order to detect the fire scars in the Brazilian Amazon forest, it is important to consider the challenge imposed by the fact that forest fires can occurred at different moments, even over the same area. This means that, while a forest fire, and therefore a fire scar, might exist in a given day, others can be present that correspond to fires occurred a couple of days or weeks before than the most recent one. In fact, this is one of the greatest challenges faced, since this means that we will have two different classes of fire scars: older and newer ones. On top of this, crops pose another challenge, since their high vegetation content means that they can be also affected by the fires. In order to reduce confusion in the detection, three classes were defined: (1) older fires scars, (2) newer fire scars and (3) crops. The strategy to help the classification process was that of training and classifying the image with the three mentioned classes, but the final fire scars map fuses the two types of fire scars into a single class, and removes the crops from it. It means that the final map shows a single class, i.e., fire scars. The proposed methodology for detecting fire scars is shown in Fig.2.

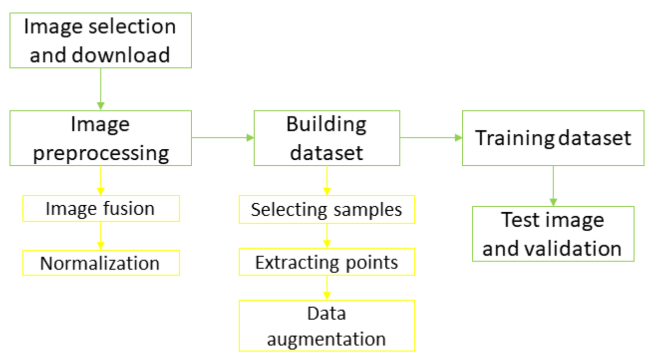

Fig. 2. General blockscheme of the proposed methodology.

3.1. Data collection and labeling

The method starts by accessing the satellite images to be used: two multispectral S2 image tiles (21LUF and 23MLM) were selected and downloaded from Copernicus Data Space Ecosystem (https://dataspace.copernicus.eu/), and were acquired on August 2019. The original images have different spatial resolutions, and only those acquired at 10m and 20m were considered for the analysis. All the bands are interpolated to 10m spatial resolution and normalized w.r.t. the other tile in order to guarantee homogeneity in the analysis. A total of 10272 samples were selected with photointerpretation for the three different classes, with 4067 samples for older fire scars, 3203 for newer fire scars and 3002 for crops. With the images composed of 10 bands, the automatic extraction of points was carried out by class, and data augmentation was applied to balance the number of samples of the three classes and to prevent over-fitting of the model.

3.2. Model training and inference

The next step is that of performing the classification of the three classes: (1) older fires scars, (2) newer fire scars and (3) crops. To do so, a Convolutional Neural Network (CNN) is used, more specifically a Depthwise separable convolution Architecture - SpectrumNet model [15]. The main objective of applying this network is to take advantage of information from all the spectral bands in the images, since these are multispectral images. This architecture does a spatial convolution channels apart and then follows up with a depth convolution. To train this network, a dataset must be built. . Finally, the SpectrumNet network was trained for detection of fire scars and in the final stage, the trained model was used to detect only fire scars on a test image. The accuracy of the parameters used in the model was validated using the Intersection over Union (IoU) metric.

4. PRELIMINARY RESULTS

With the dataset built, the SpectrumNet network was selected, which is a neural network focused on multi-band images, based on the MobileNet and SqueezeNet networks. The network was trained with 80% of the data and validated with the other 20%, obtaining the best model with a combination of parameters: $Batchsize = 2, Numberofepochs = 50, Learningrate = 0.001, seed = 60, imagesize = 5, splitofdataset = 0,2$, which gave an accuracy value of 92% for training and 82% for validation. A preliminary result of the detected fire scars can be seen in Fig.3 shows the plot of the results obtained for training loss and accuracy on dataset and the Fig.4 shows the fire scars classification. It is important to recall (as indicated in the methodology section) that only one class is highlighted (in green) that indicates the areas were fire scars have occurred, independently of the period in which they happened. The result shows an example over a smaller portion of the entire studied area. The background image is a false color composition of the S2 one, with B11, B8A and B4 for RGB channels, respectively. In that false color composition fire scars appear in a light purple color. It can be seen that the method mis-detected some of the areas, and this is happening in fact due to the complexity of the studied problem. Yet, most of the affected areas are detected (82% of accuracy). The preliminary results considered only a small portion of the entire studied areas due to computational processing constrains and space limitations. Yet, the results are representative of the entire studied area.

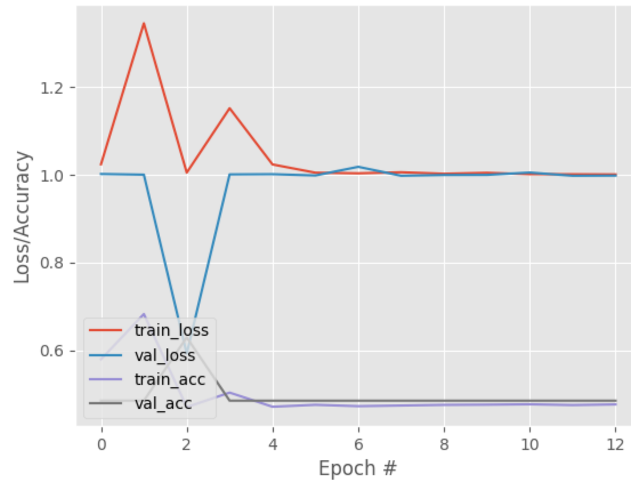

Fig. 3. Training loss and accurancy on dataset

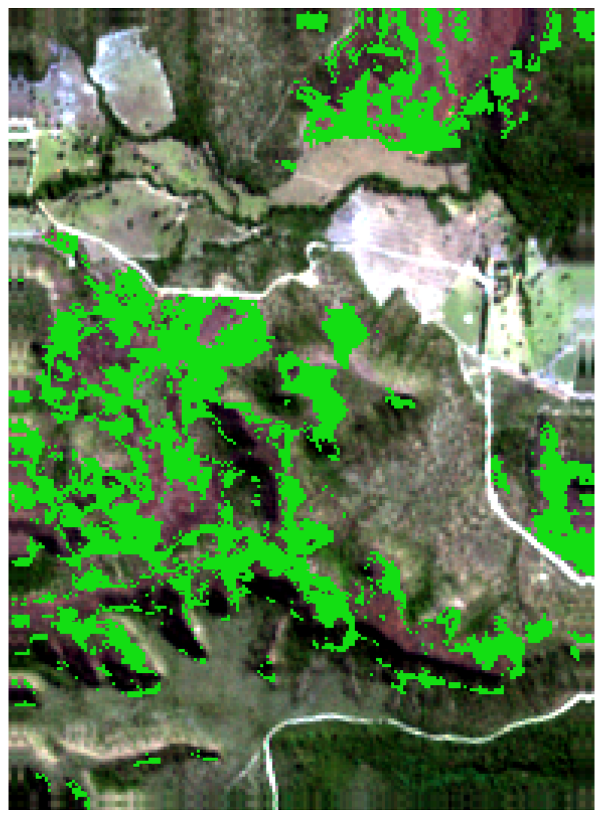

Fig. 4. Fire scars detection: Fire scares highlighted in green over a false color composition image (B11, B8A, B4)

5. CONCLUSIONS

A methodology for detection and mapping of fire scars in the Brazilian Amazon forest has been presented. This method leverages Sentinel-2 (S2) satellite images and Convolutional Neural Networks (CNNs) to effectively identify fire scars.

Additionally, it introduces a strategic approach to classification to enhance detection accuracy. The strategy consists on separating among older and newer fire scars, that appear to be different classes at first glance, but correspond to the same one. The final result fuses the two types of fire scars into a single one, allowing to quantify the actual extension of forest fires, and separates errors introduced by crops present in the area. The proposed method is simple, yet effective (82% accuracy). For future work, it would considered integrating data from other sources, such as radar imagery or meteorological data, and be valuable to investigate additional features such as radiometric indices (explored in literature), and compare to simpler architectures or machine learning approaches to determine the most effective and robust in terms of computational time and accuracy.

6. ACKNOWLEDGMENTS

This research was performed with support from the Ministry of Science Technology and Innovation, MINCIENCIAS, in Colombia, through the announcement No. 933 of 2023 for national doctoral programs with a territorial, ethnic and gender focus in the context of the Mission-Oriented Policy, and the project "4D Integrated Quantitative Characterization of Reservoirs" (Contract No. FEESC/PETROBRAS/4600671602)

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