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Comparison of burned area products for analysis on a regional scale in southwestern Amazonia, Brazil

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Abstract. *Fires have increasingly affected the Amazon Forest, and this process causes a variety of socioenvironmental problems. Monitoring has become important to support both combatting and preventing fire. However, many studies have reported discrepancies in the quantification of forest affected by fires. We analyzed the total burned area detected in the southwest Brazilian Amazon during 2019 and compared four burned-area products. We evaluated the relative performance of these products in estimating total burned area for the year 2019 in both forest and non-forest areas. The products showed maximum decrease of 90.6% in the total burned area associated with the spatial resolution and similarity of burned-area products.*

1. Introduction

The human species is the main agent of nature transformation, offering great interference in ecosystems and causing profound changes in the landscape [Berlinck and Batista 2020], especially when associated with fire. The fire effect on Brazilian territory has increased in recent years [Alencar et al. 2022]. This offers greater susceptibility to new and future events, especially in the Amazon rainforest region where this type of event is naturally rare [Bush et al. 2008]. This scenario can have several consequences for the ecosystem, such as impacts on biodiversity [Mataveli et al. 2021; Mataveli, de Oliveira et al. 2021; Mataveli et al. 2017], economic losses [de Mendonça et al. 2004] and climate change [Aragão et al. 2018; Silva Junior et al. 2019; Carvalho et al. 2021; Aragão et al. 2020].

Amazon rainforest is an important global climate regulator, acting as a provider of environmental services [Fearnside 2008], mainly those associated with carbon stock, being a regulator of rainfall in South America [Leite-Filho et al. 2021]. This forest has suffered a great deal of threat from deforestation and forest degradation propagated by the fire of atrophic origin, which causes humans health problems [Campanharo et al. 2022] and an imbalance of hydrological and carbon cycle [Maraseni et al. 2016; Prentice et al. 2011; Leite-Filho et al. 2021; Shakesby and Doerr 2006]. Therefore, it increases the importance of actions to monitor fire-related activities which can support measures definitions to prevent and mitigate environmental impacts in the Amazon rainforest [Mataveli et al. 2021; de Andrade et al. 2020].

The creation of remote forms of fire mitigation, mainly in forest regions, has allowed the development of several methodological approaches that use remote sensors for the detection and monitoring of burned areas [Anderson et al. 2015; Giglio et al. 2018; Shimabukuro et al. 2015; Penha et al. 2020]. These methodologies have several specificities that can achieve different purposes, scales, and spatial resolutions, showing variation in distribution, time, size, and frequency of the burned area among the results of products [Mouillot et al. 2014; Long et al. 2019].

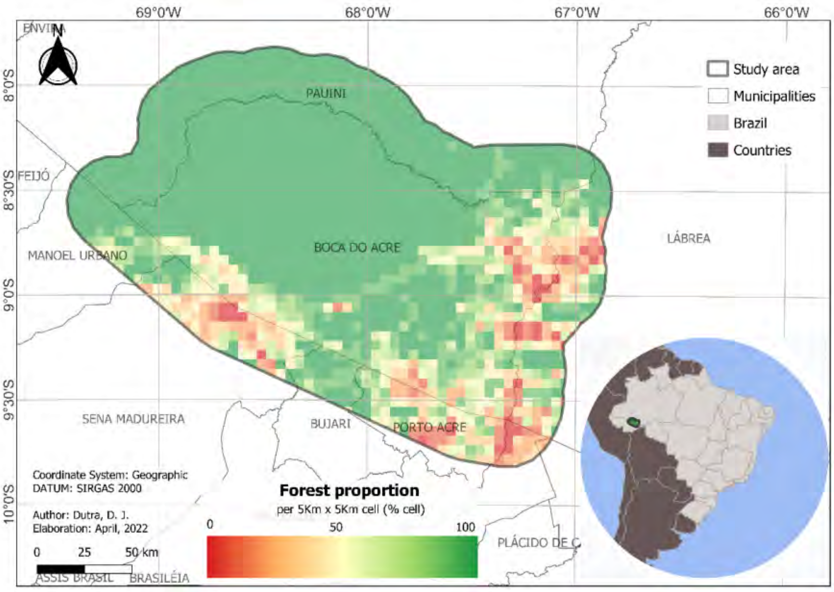
Diversity in mapping creates the need to use a comparison tool among the burned area products, once it allows evaluation of the mapping according to performance [Humber et al. 2019; Padilla et al. 2015], especially when are no field validation points in the region. In this aspect, it is important to understand which comparison between products has several limitations [Pessôa et al. 2020], once it is necessary to assume that all methodologies are providing an approximation of the region conditions [Humber et al. 2019], and should be used as a complementary evaluation to the product validation process [Pessôa et al. 2020]. Thus, due to the presence of these limitations, the comparison analysis aims to consider the disadvantages and advantages of the analysis [Pessôa et al. 2020; Anderson et al. 2015]. Therefore, the processes must carry out with the products according to their specifications, being necessary the balance of this information for the choice of given data [Pessôa et al. 2020; Long et al. 2019; Boschetti et al. 2020; Artés et al. 2019].

Although there are some studies that assessed the different results of burned area products [Penha et al. 2020; Mataveli et al. 2021; Humber et al. 2019; Anderson et al. 2015; Pessôa et al. 2020], their inter-comparison suggest an heterogeneous performance spatially, which means that a prior evaluation to a site of interest should be carried out before selecting one. Here we assessed four operational burned area products [MAPBIOMAS, MCD64A1, GABAM, and GWIS] for the southwest Brazilian Amazon – a region with an increasingly threat of fires. The specific objectives were: (i) to evaluate the similarities and differences among burned area operational products) in forest and non-forest regions in Boca do Acre region and (ii) to analyze the spatial similarities and differences between the products.

2. Materials and Methods

2.1 Study area

The study area (40,776.75 Km²) includes a buffer of 25 Km in limits of Boca do Acre, which delimits the parts of cities Paiuni (19.42%), Lábrea (5.42%), Acrelândia (1.91%), Senador Guiormard (16.16%), Porto Acre (79.01%), Bujari (28.18%), Sena Madureira (9.58%) and Manoel Urbano (13.68%). Furthermore, the area comprehends indigenous territories of Camicua, Igarapé Capana, Inauini/Teuiní, Boca do Acre, Apurinã, Peneri/Tacaquiri, and Seruini, Mariene, beyond the conservation units of Mapiá-Inauiní National Forest, Purus National Forest, and the Arapixi Extractive Reserve. According to PRODES data from 2019 [Assis et al. 2019], the regions contain 33,335.80 Km² of forest (Figure 1), characterized by dense rain forest (Amazon Forest), mosaics of oligotrophic woody vegetation, and ecotone areas [Barni et al. 2015] with Köppen classification system of Af (equatorial forest climate) [Alvares et al. 2013].



. Figure 1 - Study area located in the Boca do Acre. Forest proportion in a 5 x5 km grid cell, extracted by the Amazon Forest Deforestation Calculation Program (PRODES) forest mask of 2019 used to select burned areas

2.2 Data

We considered three global burned area products (MCD64A1 [Giglio et al. 2018], GABAM [Long et al. 2019], and GWIS [Boschetti et al. 2020]) and one national product (MAPBIOMAS [Arruda et al. 2021]) for the comparative evaluation of burned area detection (Table 1). The choice of products took into account the spatial scale intending to compare products and analyze the influence of increased resolution in burned area detection. For this, we used one product of lower resolution and widely used in the literature (MCD64A1), one product in vectorial format (GWIS) and two products, national (MAPBIOMAS) and global (GABAM), with higher spatial resolution (30 m). The year of 2019 was selected for this analysis.

Table 1 - Specifications of the burned area products.

Name	Developer	Scale	Temporal Scale	Sensor/Data	Spatial resolution	Reference
GABAM	Institute of Remote Sensing and Digital Earth—Chinese Academy of Sciences	Global	1985-2020	Landsat series	30m	(Long et al. 2019)
GWIS	Group on Earth Observations (GEO) and Copernicus Work Programs	Global	2021-2020	MCD64A1, MODIS, Copernicus-Proba-V and Fire CC1	Vector data	(Boschetti et al. 2020)
MAPBIOMAS	MAPBIOMAS	National (Brazil)	2000-2020	Landsat serie	30m	(Arruda et al. 2021; Alencar et al. 2022)
MCD64A1	NASA	Global	2000-present	MODIS (surface reflectance and active fires	500m	(Giglio et al. 2018)

2.3 Analysis

We calculated the total burned area for each product in the vectorial analyses, with separation of class, in the whole study region. For this, the PRODES land cover data from 2019 [Assis et al. 2019] was used to separate the landscape class into forest and non-forest. In the process, we used the SQL command and PyQGIS (gdal library) in QGIS 3.22.6 software (Qgis 2019) and the 'rgeos' package [Bivand and Rundel 2018] in RStudio statistical software [R Core Team 2021].

We created the grid with approximately 25 Km² (5Km x 5Km) spatial resolution for the matrix analysis of burned area products. In the process, we consider the proportion of burned area inside each product for incorporation of the data in the cell grid. The grid tools and SQL commands in QGIS software were used to run the data in the system.

Regarding the statistical analysis, we executed the non-parametric Kolmogorov–Smirnov two-sample test [Smirnov 1939] to compare the six possible combinations between the burned area products. For this, we executed the process through the 'raster' package [Hijmans 2017] of RStudio software [R Core Team 2021]. We used conditional and repeating structures, in one bootstrap approach, to create 10000 interactions of randomly raffled 10% of the total cells in each execution of the conditional structure. In this process, we considered only cells that presented burning detection by at least one product and realized the randomly raffled with replacement. Finally, we applied the analysis of the mean and standard deviation of the 10,000 p-values resulting from the interactions.

For the spatial analyses, we converted the regular grid in raster format with information of each burned area information to statistical comparison two by two, through to fuzzy numerical method implemented in the "calc reciprocal similarity map" functor [Dinamica EGO Team 2020] of DINAMICA EGO 6 software [Leite-Filho et al. 2020]. The fuzzy method analyses the similarity between pairs of cells in two numerical maps, using the neighborhood (window size of 3 lines and columns) to calculate the similarity of each cell [Dinamica EGO Team 2020]. Furthermore, the value interval of results is between 0 (fully distinct) and 1 (fully identical).

3. Results

We detected the sum of 7167 Km² burned area mapped by the products in the study area, being from 3.69% (264 Km²) in the forest area and 9631% (69.31 Km²) in the non-forest area (Figure 2). In forest areas, GWIS and MCD64A1 detect the most quantity of burned areas, 33.93% (89.57%) and 37.95% (100.19 Km²), respectively. Already in the non-forest areas, GABAM and MAPBIOMAS showed the most quantity of burned areas, 45.07% (3111.18 Km²) and 48.37% (3338.98 Km²), respectively.

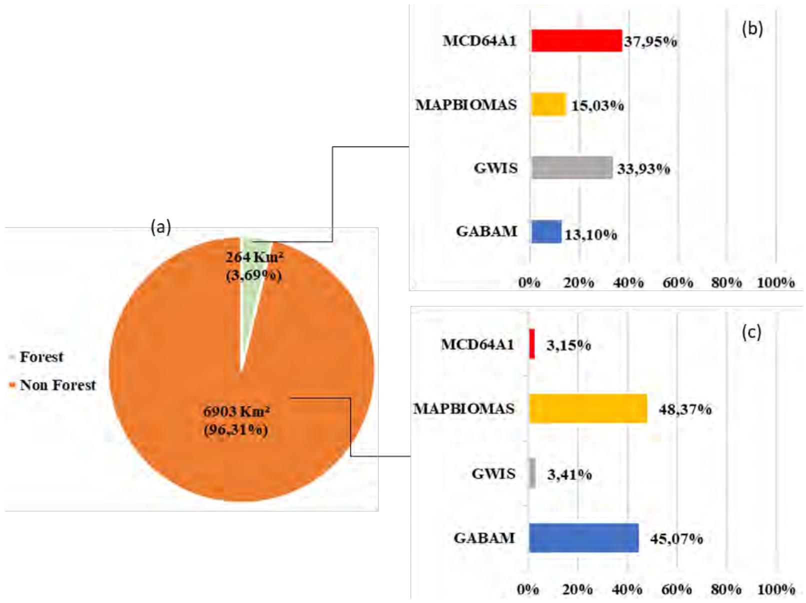


Figure 2 - Contribution of each product in (a) burned areas mapped in (b) forest and (c) non-forest regions

The four products detected different burned areas mapped (Figure 3), with the most significant difference occurring between MAPBIOMAS and MCD64A1, with the second mapping 90.61% (3062 Km²) less burned areas. About the land use class, MAPBIOMAS presents more than 30,43% (3122.33 Km²) of burned in the non-forest area and less than 30,43% (60.33 Km²) of burned in forest area than MCD64A1. The results showed two similarities, between the GWIS/MCD64A1 and GABAM/MAPBIOMAS. MCD64A1 presents 2,46% (8 Km²) less than total burned area in relation to GWIS, but show largest detection in forest class (4.02% - 100.2 Km²) and smaller detection in non-forest class (4.02% - 29.1Km²). MAPBIOMAS showed 6,93% (234 Km²) more than the total burned area concerning GABAM, 8% (228.72 Km²) in non-forest, and 8% (5.27 Km²) less than in forest areas.

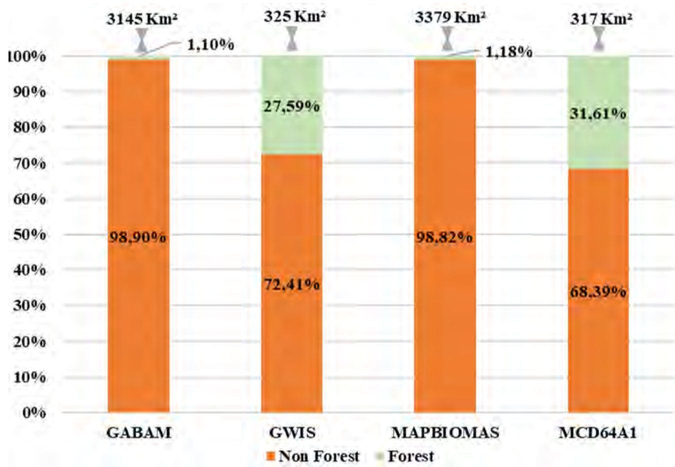


Figure 3- Total burned area mapped by GABAM, GWIS, MAPBIOMAS, and MCD64A1; and percentage of occurrence in forested areas and non-forested regions

The GWIS and MCD64A1 showed non-significant differences at a 95% confidence level ($p > 0.05$), Table 2. In this process, the bootstrap approach resulted in 99.37% of 10000 interactions was non-significant ($p > 0.05$). Other combinations among the burned area products present 100% significant p-values at a 95% confidence level ($p < 0.05$).

Table 2 - Mean and standard deviation of p-values resulted from 10,000 iterations of Kolmogorov- Smirnov two-sample tests, raffling different samples of 10% of the total grid cells of 25 Km².

	GABAM X GWIS	GABAM X MAPBIOMAS	GABAM X MCD64A1	GWIS X MAPBIOMAS	GWIS X MCD64A1	MAPBIOMAS X MCD64A1
Mean	6.97E-05	3.22E-05	1.04E-04	2.40E-08	5.94E-01	3.13E-08
Sd	2.96E-04	6.24E-05	3.8E-04	5.27E-07	2.91E-01	1.67E-07

Regarding the spatial analysis, the four products showed divergence, mainly in the northeast region of the study area that contains the most presence of forest (Figure 4). We identified the spatial resolution influence in the mapping of burned areas because the data with a better spatial resolution (GABAM and MAPBIOMAS) showed a larger registry of areas with smaller burned cell proportions. Among the four products, MAPBIOMAS mapped a greater amount of burned cell proportions between 20% to 50% (Figure 5). Compared with GABAM, with the same spatial resolution, the MAPBIOMAS project identified a greater amount of burned cells that ranged from 59 to 4439 pixels. GWIS and MCD64A1showed values close to the burned cells proportion ranging from 0 to 10 pixels.

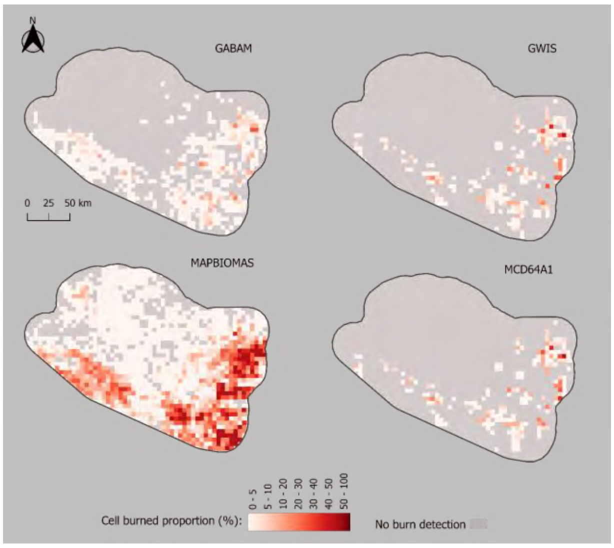


Figure 4 - Burned area spatialization in a 5 km × 5 km regular grid. Each grid cell contains the burned proportion indicated by the color gradient.

	0 - 5	5 to 10	10 to 20	20 to 30	30 to 40	40 to 50	>50
GABAM	443	57	22	3	2	0	0
GWIS	137	42	21	6	5	1	1
MAPBIOMAS	4882	2075	2351	1619	1223	724	59
MCD64A1	128	32	25	8	3	2	1
Total	5590	2206	2419	1636	1233	727	61

Figure 5 - Number of cells in different burned proportion classes

We identified that the similarity index is medium to high (≥0.8) between the burned area products (Figure 6). Considering the whole study area, the results present values from 0.4 to 0.95. In the results, we observed one pattern: lower indexes when MAPBIOMAS is considered in comparisons of areas. These results can be explained for the reason of MAPBIOMAS showed the largest extent of the burned area mapped, which allows identifying areas that other products did not map. From another perspective, the other results present a higher similarity due to the reduced extent mapped, which makes them more likely to be similar during the analysis.

	GABAM	GWIS	MAPBIOMAS	MCD64A1
GABAM	-	0,850	0,525	0,844
GWIS	▲0,850	-	0,488	0,957
MAPBIOMAS	▼0,525	▼ 0,488	-	0,488
MODIS	▲0,844	▲ 0,957	▼ 0,488	-

0,1 0,2 0,3 0,4 0,5 0,6 0,7 0,8 0,9

0 … 1

▼ <0.8 ▲ >= 0.8

Figure 6 - Overall similarity for each burned area product comparison pair, considering the whole area

In spatial scale, we observed similarity in the scale extremities (Figure 7) with values close to 0 and 1. This analysis allows the identification of regions more cohesive, or not, between the burned area products, once the similarity indices only register the general average of the region. We identified that most lower values occurred when MAPBIOMAS is in analysis. In this process, the southeast region showed lower values between 0.7 and 0.9, and the northwest present higher values in this interval. The opposite relationship occurs with the other products, which demonstrate higher values in the southeast direction of the study region.

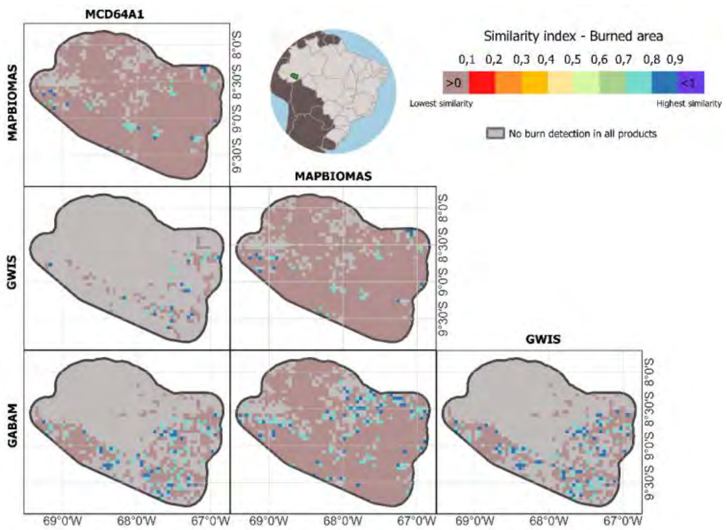


Figure 7 - Similarity maps for each burned area product comparison pair

We observed that MAPBIOMAS registered a low similarity in the region, mainly in the northwest, where the product showed the best performance than another, that identified burned areas in the eastbound and southeast directions. In this analysis, we detected that MCD64A1 and GWIS showed the burned area in the same regions as other products, mainly eastbound (Figure 8b). Different from the registry of GWIS and MCD64A1, GAMBAM presents a lot of burned areas regions in the same regions that

MAPBIOMAS, mainly in the southwest region (Figure 8a). Regarding the scale resolution, the products demonstrated that GWIS and MCD64A1 (lower resolution) concentered the burned registry in some stains distributed in the east and southeast directions near the study area limit. High-resolution products (GABAM and MAPBIOMAS), identified more burned areas in the region, mainly in the forest region (located in the northeast of the study area), and present the same burn in eastbound and southwest the region.

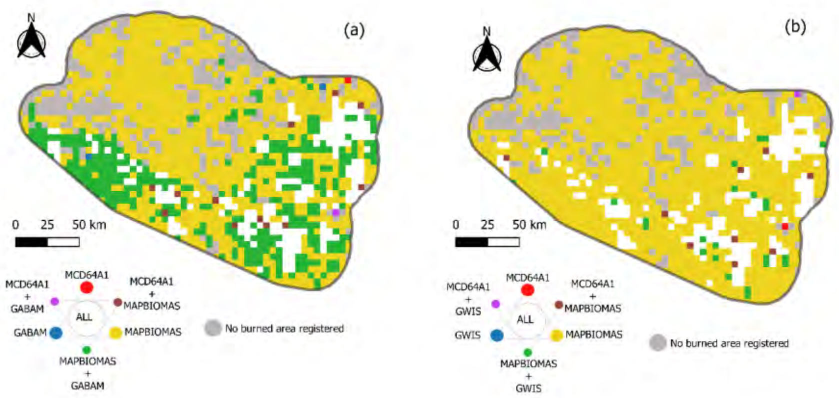


Figure 8 - Confusion maps considering (a) GABAM, MCD64A1 and MPBIOMAS burned area products, and (b) GWIS, MCD64A1, and MPBIOMAS burned area products.

4. Discussions

Results showed the importance of users understanding the product characteristics of the burned area to choose the most appropriate for their analyses, because each burned area product can have a significant impact on the final result in studies on different scales, mainly on regional scales. This is due to the characteristics and some specifications that affect performances regionally of the final product of the burned area, such as daily temporal resolution, spatial resolution, and climactic conditions [Pessôa et al. 2020].

Regarding the mapping of burned areas, we identified two similar groups: GWIS/MCD64A1 and GABAM/MAPBIOMAS. Although the MCD64A1 product showed 2.46% to 90.61% less total burned area compared to all products analyses, this product registered the most burned forest, with the rate of 10.51% to 65.47% more than other products. Although some studies demonstrate that MODIS data can underestimate burned area by approximately 25% regarding Landsat data [Morton et al. 2011; Roy and Boschetti 2009; Pessôa et al. 2020], we identified, on a regional scale, that MAPBIOMAS and GABAM (Landsat data) generally underestimated burned scars, mainly in forest regions, when compared to MCD64A1 and GWIS (MODIS data). However, underestimation of burned area in products that use MODIS data as reference was identified in non-forest regions, once MAPBIOMAS and GABAM data registered an increase of 92.95% to 93.50% in the burned area mapping compared to MCD64A1 and GWIS. These differences can be associated with the spatial resolution of data sources [Long et al. 2019].

We observed such as characteristics of mapping can be delimited by different quantitate of burned area in regional scales. The temporal resolution of MODIS data (used for

MCD64A1 and GWIS), allows for greater data acquisition and less interference from clouds [Alonso-Canas and Chuvieco 2015; Pessôa et al. 2020] once the resolution is monthly with the possibility to know the date of burn [Bush et al. 2008]. Thus, the frequency of MODIS data (500 m spatial resolution), which allows daily information, identifies the burned time elapsed speed and vegetation regeneration after the fire, being important factors for monitoring tropical regions, once the higher temporal frequency minimizes cloud cover and climatic conditions. Therefore, this product has been widely used in burned area detection across the globe [Giglio et al. 2018; Justice et al. 2002]. The temporal resolution of LANDSAT data (used for GABAM and MAPBIOMAS) is of 16 days with a higher spatial resolution in the optical spectrum (30 m). The increase in resolution along with the long time series of Landsat data allows one to trace historical trends in fire dynamics [Meddens et al. 2018] and improve the boundaries definition of the burned area because avoid a pixels mixture among burned and unburned patches [Long et al. 2019; Arruda et al. 2021].

The increase of resolution in analyses, such as GABAM and MAPBIOMAS, allows better mapping of active fire pixels and the identification of small burned area scars. However, we identified that this process can be overestimated when using national-scale products (MAPBIOMAS). The results demonstrate that MAPBIOMAS registered 11,02 times higher small burned area proportions when compared to a global product with the same resolution in a grid of 25 km². According to GABAM developers [Long et al. 2019; Pessôa et al. 2020], the overestimated values in the use of Landsat data can be associated with temporal resolution and cloud contamination [Long et al. 2019], which can become a limitation in tropical regions, where cloud cover is persistent and the vegetation recovery is quick. Regarding the MAPBIOMAS data, the developers recommend making some adjustments to the algorithm before applying multitemporal analysis in regions other than the Cerrado, which demonstrates that this data still needs to be studied in tropical regions [Arruda et al. 2021].

Overestimation of MAPBIOMAS data may be associated with the application of the Deep Neural Network (DNN) methodology which according to the density of training samples per Landsat WRS-2 path/row map created for developers, the study region is located in the scene where there was an intermediate separation of samples [Alencar et al. 2022]. Since the DNN uses pattern recognition to execute the algorithm [Safi and Bouroumi 2013; Langford et al. 2019], the low number of samples from the region may have helped in the overestimated result and reinforces the issues that in tropical regions adjustments are necessary for the product algorithm [Arruda et al. 2021]. In addition, we identified that comparisons made between MCD64A1 and GABAM data showed differences on a regional scale when compared with the results of analyzes carried out by MAPBIOMAS developers on a regional scale [Alencar et al. 2022], these issues may be associated with a form of data validation, once we used fuzzy analysis and the developers selected 10,000 random points with analysis of proportions and convergence of burned area. Furthermore, we were unable to verify whether the study region was within the sample of random points that were created by MAPBIOMAS developers for product comparison with the MCD64A1 and GABAM. The MAPBIOMAS product has great potential for fire mapping in the study region, but still needs improvements to avoid omission and commission errors, such as increasing the number of classification regions, increasing the number of bands and spectral indices in the DNN model, and separating models to classify burned areas in native vegetation from burned areas in pastures and crop fields [Alencar et al. 2022]. Therefore, the use of images with lower resolution for mapping burned areas can be useful, once these products have a higher temporal frequency and less cloud cover influence [Giglio et al. 2018].

Regarding, the lower resolution products, such as MCD64A1 and GWIS, studies demonstrate the unable to adequately detect small fires (<100 ha) [Rodrigues et al. 2019], which can cause the burned area underestimation [Giglio et al. 2018; Justice et al. 2002], as we identified in our results. Despite the MCD64A1 presenting a significantly better detection of small burns (<100 ha) than older versions [Pessôa et al. 2020; Justice et al. 2002; Chuvieco et al. 2018], we registered the underestimated to 89.9% to 90.61% burned area than the highest resolution products (30m). Therefore, GABAM and MAPBIOMAS detect better small burned areas, showing recorded small burn proportions (associated with small burned patches) in the grid of 5 Km × 5 Km.

We observed that results demonstrate different patterns when compared, with similarities that can cross-validate each other through a spatial pattern. Furthermore, we identified the potential of MAPBIOMAS product for mapping the burned area, requiring future adjustments as described by the developers [Arruda et al. 2021], for tropical regions, such as the Amazon rainforest. Thus, in the absence of a national product that doesn't require adjustment in the algorithm, the global products still prove to be reliable for operationalization and analysis of socio-environmental loss related to tropical forest fire [Barlow et al. 2020].

5. Conclusions

The comparison among the products allowed us to analyze the influence of spatial resolution in burned area analysis on the regional scale. Accounting for the magnitude of difference, GWIS and MCD64A1 are the most similar products, because identified a smaller difference in the burned area compared to other products. Furthermore, the products that stand out the most are MAPBIOMAS and MCD64A1 due to a difference of 90,62% between the burned area mappings. Regarding the land use, we observed that the products with higher resolution (GABAM and MAPBIOMAS) shower smaller differences in burned area mapping rate than the products with lower resolution (GWIS and MCD64A1). On the regional scale, we identified that spatial resolution influences in burned are, once that the higher resolution maps the contribution of small burned polygons, which creates a greater number of cells with smaller burn proportions in the study region. This difference can be observed in products with the same origin (Landsat 8), where the MAPIOMAS identified a greater amount of burned area than GABAM, and registered more small burned polygons. Despite the greater mapping of the burned area, MAPBIOMAS may be registering a greater interference of clatter and contribution of small polygons, which would make a more detailed field analysis necessary to differentiate clatters of small scars in the burned area. Thus, between comparisons on a regional scale, the data from GABAM, GWIS, and MCD64A1 were more similar for mapping the burned area in the study region, even with differences in spatial resolutions.

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