

PÂMELA INÊS DE SOUZA CASTRO

**A METHOD FOR MAPPING AND ASSOCIATING BURNED AREAS WITH
AGRICULTURAL PRACTICES WITHIN THE CERRADO MINEIRO**

Dissertation presented to the Graduate Program in
Agriculture and Geospatial Information of the Federal
University of Uberlândia, Monte Carmelo Campus, as part
of the requirements for obtaining the title of MSc. in
Agriculture and Geospatial Information

Advisor

Prof. Dr. João Vitor Meza Bravo

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Prof. Dr. George Deroco Martins

**MONTE CARMELO
MINAS GERAIS - BRASIL
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Dedico
Aos meus pais Welton e Marilza

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BIOGRAPHY

Pâmela Inês de Souza Castro was born in Monte Carmelo, Minas Gerais, Brazil, 1997. She graduated in Surveying and Cartography Engineering from the Federal University of Uberlândia (UFU) - Monte Carmelo Campus, Minas Gerais, Brazil, in December 2020. In March 2021, she entered the Graduate Program in Agriculture and Geospatial Information at the Federal University of Uberlândia - Monte Carmelo Campus, supervised by Prof. Dr. João Vitor Meza Bravo and co-supervised by Prof. Dr. George Deroco Martins. Her research interests include the study of the accuracy of spectral indexes in forest fire detection.

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RESUMO

O incêndio ocorre tanto natural como antropicamente no bioma do Cerrado. Este fenômeno está correlacionado com um conjunto de variáveis tais como hidrológicas, climáticas, topográficas, de uso do solo, e outras. É essencial mapear as áreas queimadas para identificar as principais causas de ajuda no planejamento de ações de prevenção e regulação. No entanto, as cicatrizes de incêndio são normalmente confundidas com os solos expostos, especialmente em regiões geográficas com práticas agrícolas ativas. Por conseguinte, apresentamos aqui um método para mapear áreas queimadas - em regiões geográficas com agricultura ativa - com base na configuração específica do índice espectral e rede neural artificial (RNA). Avaliamos a precisão dos índices espectrais e das técnicas de RNA na identificação de áreas queimadas, ao mesmo tempo que determinamos qual a configuração que permite uma melhor identificação. Além disso, aqui também analisamos a associação de regiões queimadas com práticas agrícolas. Para tal, foram utilizadas imagens de sensores Sentinel-2 para os períodos de escassez de chuva em 2018, 2019, 2020, e 2021; os índices que aplicamos foram NDVI, SAVI, NBR e CSI. O estudo teve duas fases de processamento: a primeira, identificando a melhor configuração para a classificação dos incêndios, e a segunda, classificando e fazendo os mapas de uso e cobertura do solo contendo as cicatrizes do fogo e as culturas. Realizamos duas experiências: a primeira experiência mostrou que o melhor desempenho da RNA na classificação foi utilizar todas as bandas de satélite Sentinel-2 como atributos e os quatro índices no período pós-incêndio. A precisão global e o índice kappa mostraram resultados superiores a 93,7% e 0,92, respectivamente. A segunda experiência mostrou-nos que as cicatrizes do fogo estão localizadas principalmente em áreas de culturas temporárias onde se cultivava soja, cana-de-açúcar, arroz e algodão.

Palavras-chave: Fogos; Índices espectrais; Redes Neurais Artificiais; Agricultura, Cerrado.

¹ Orientador: Prof. Dr. João Vitor Meza Bravo

CASTRO, PÂMELA INÊS DE SOUZA. **A method for mapping and associating burned areas and agricultural practices within the Cerrado Mineiro**. 2023, 40 f. Dissertation (Master in Agriculture and Geospatial Information) – Federal University of Uberlândia, Campus Monte Carmelo, Minas Gerais, Brazil¹.

ABSTRACT

The fire occurs both naturally and anthropically in the Cerrado biome. This phenomenon correlates with variables such as hydrological, climatic, topographical, land use, and others. Therefore, it is essential to map burned areas to identify the leading causes for help in planning actions of prevention and regulation. However, the fire scars are usually confused with bared soils, especially in geographic regions with active agricultural practices. Therefore, here we presented a method to map burned areas - in geographical regions with active agriculture - based on specific spectral index configuration and artificial neural network (ANN). We evaluated the accuracy of spectral indexes and ANN techniques in identifying burned areas while determining which design allows for better identification. In addition, here we also analyzed the association of regions burned with agricultural practices. For this, Sentinel-2 sensor images were used for the periods of rainfall shortage in 2018, 2019, 2020, and 2021; the indexes we applied were NDVI, SAVI, NBR, and CSI. The study had two processing stages: the first one, identifying the best configuration for the classification of the fires, and the second one, classifying the land use and land cover maps containing the fire scars and crops. We have carried out two experiments: the first showed that the best performance of the ANN in classification was using all Sentinel-2 sensor bands and the four indexes in the post-fire period. The overall accuracy and kappa index showed results higher than 93.7% and 0.92, respectively. The second experiment showed us that the fire scars are located mainly in temporary crop areas where soybean, sugarcane, rice, and cotton are cultivated.

Keywords: Fires; Spectral Indexes; Artificial Neural Networks; Agriculture, Cerrado.

¹ Advisor: Prof. Dr. João Vitor Meza Bravo

1. INTRODUCTION

Land use and land cover (LULC) is constantly being modified, especially concerning vegetation cover. When vegetation suffers from any change, there is also modification in ecosystems, which can, within a context of environmental devastation, reduce the resources in the soil, fauna, and flora (FENSHAM et al., 2005; BARRERA; HENRIQUEZ, 2017; BROCKERHOFF et al., 2017). One factor contributing to modifying vegetation cover is forest fires, which can occur through natural or human causes (PEREIRA et al., 2014; PACHECO et al., 2015). Forest fires frequently occur in regions with a dry climate, wind, available dry vegetation, and favorable topographical conditions (KEELEY; SYPHARD, 2019; YU et al., 2021).

With the ever-changing land cover, especially in the context of climate change, forest fires destroy thousands of hectares yearly, threatening the ecological environment and human life (XU et al., 2021). A worrying issue of forest fires is how quickly they spread, making it difficult to contain (MORANDINI; SANTONI; BALBI, 2001). Detecting forest fires and wildfires is gaining more attention in research worldwide (KO; KWAK, 2012; MAHMOUD; REN, 2018).

In the context of this research, it is essential to distinguish what is meant by fires, wildfires, and hotspots. Thus, here it is understood that "hot spots" correspond to the temperatures sensed by the satellite sensors that monitor a given region, and may or may not indicate the presence of fire; "burning" deals with the agricultural or forestry practice, which consists of using fire as a tool to promote agriculture or to modify pasture. In this case, there must be Ibama's authorization, which must be carried out in a controlled way; "fire" corresponds to uncontrolled fire in contact with materials that are prone to combustion and can be caused naturally or anthropically.

In the Brazilian context, the Cerrado biome presented the highest number of hotspots related to fires and wildfires in 2021 ($n = 137,631$) (INPE, 2021). Some research has linked these fires to uncontrolled or unsustainable agricultural practices (GARCIA et al., 2021; PIVELLO et al., 2021). Fire can cause several adverse effects, such as problems related to human health (XU et al., 2020) and climate change at regional and global levels (CLARKE et al., 2022). Thus, the study of fires is critical since there is an ever-increasing need to preserve and recover natural resources such as vegetation (NOLAN et al., 2021; SEDDON et al., 2021; ZITTIS et al., 2022).

The Cerrado biome is the savannah that houses the most extensive biodiversity in the world (FRANÇOSO; BRANDÃO; NOGUEIRA, 2015), occupying 2,036,448 km², equivalent to approximately 23.9% of the Brazilian territory (IBGE, 2004). According to the Ministry of Environment (2018), the Cerrado biome has about 11,627 cataloged native plant species. The

Cerrado biome brings together characteristics conducive to fires and wildfires. The dry period occurs from May to September (EMBRAPA, 2022), and the prevailing climate is seasonal tropical (HORÁK-TERRA et al., 2020). The vegetation predominantly comprises forest, savannah, grassland formations, and terrain with topography ranging from flat to smooth-rounded (GONÇALVES et al., 2022). Remarkably, physiographic characteristics favor agricultural production in this region (LOPES; GUILHERME, 2016; REIS et al., 2021). Here, the focal point is that the Cerrado biome brings together a set of characteristics conducive to spreading fire (RATTER; RIBEIRO; BRIDGEWATER, 1997; SILVA; ASSAD; EVANGELISTA, 2008).

Specifically, with the growing demand for agricultural land in the Cerrado, management practices occur that, when incorrect, increase the chances of forest fire risk (ARMENTERAS; GONZÁLEZ; RETANA, 2013). For example, a common practice is using fire to clean and prepare pastures for planting, which can result in uncontrolled fire, a significant threat to biodiversity conservation (TAUFIK; SETIAWAN; VAN LANEN, 2015; REID et al. 2016; AMBREY et al., 2017).

Considering the importance of preserving the environment and avoiding continuous degradation, it becomes necessary to identify the regions that suffer from fires more frequently (HUA; SHAO, 2017). For this, information should be collected regarding the locality of fires, aiming to implement strategies to minimize the occurrence of that phenomenon (GOYAL et al., 2020). The research investigations examining the event of forest fires usually observe the precise location of occurrence to obtain accurate information about the ignition point (KWAK et al., 2012). In contrast, field research demands time and resources, making it challenging to get the data for the historical basis of the event, limiting fire prediction (KHARUK et al., 2016; BUI et al., 2016).

One solution to overcome such limitations is using remote sensing methods, making it possible to remotely study the events occurring in a given region with a time series of data available (LIM et al., 2019). In addition, in Brazil, records of forest fires are accessible on online platforms, such as the burning program of the National Institute for Space Research - INPE, which makes the data available for free.

The spectral indexes are one of the tools to distinguish fire-related features in vegetation and regions with bared soil (STROPPIANA et al., 2012). Spectral indexes are mathematical expressions that combine spectral bands to highlight information on the surface (CARNEIRO et al., 2020). Each spectral index can highlight specific information besides discriminating it from other objects on the surface (MAHLEIN et al., 2013). The Normalized Burn Ratio (NBR) is among the most widely used indexes for mapping the severity of forest fires and fire scars (CHEN; LARA; HU, 2020). The

NBR index uses the near-infrared and shortwave infrared bands, having the information concentrated on ash, coal, soil, and surface moisture (BEY; BERSON, 1999). The NDVI index presents information in the red and near-infrared region and is most often used to analyze the vegetative vigor on the earth's surface (ROUSE et al., 1973). The SAVI index was created to minimize soil's effects on vegetation detection, using the red and infrared bands, and the factor L that varies from 0 to 1, according to the type of vegetation cover (HUETE, 1988). Regions with high vegetation cover receive $L = 0$, with moderate vegetation $L = 0.5$ and low vegetation $L = 1$ (HUETE, 1988). The CSI index uses the near-infrared and shortwave infrared bands to detect recently or severely burned areas (SMITH et al., 2007).

Agriculture, especially in those regions with a predominance of temporary crops, can hide the detection of fire scars since these crops have phenological stages (SPANNO et al., 1999; SALAZAR et al., 2006) that modify the spectral response (LIN et al., 2014; FORMAGGIO; SANCHES, 2017; ZENG et al., 2020). Thus, a given temporary crop region, for example, has different spectral responses during the crop cycle since there will be a modification in the physiognomic and physiological structure of the plant (FORMAGGIO; SANCHEZ, 2006).

Because spectral indexes are mathematical expressions that work with reflectance values, it is natural that the detection of phenomena such as fire scars encounters barriers. For example, Santos et al. (2023) indicate that the most significant difficulty lies in confusion with the class "bared soil". Brand and Manandhar (2021) explain that in regions with urban areas or bared soil, there may be confusion with the burning class due to the sensitivity of the indexes in correctly discriminating the land cover information. Filipponi (2019) points out that the confusion occurs due to highly dark pixels, which confuses with areas of bared soil or natural/artificial dark spots. Therefore, it is necessary to fill this knowledge gap using robust tools such as machine learning. According to Maxwell, Warner, and Presa (2018), ML algorithms can work with various data without making previous assumptions regarding their distribution. Machine Learning (ML) seeks to extend computational functions to improve performance automatically through its own experience (MITCHELL et al., 1990). ML is increasingly being used in remote sensing (PAL; MATHER 2003, 2005; PAL; MATHER, 2005; MOUNTRAKIS, IM; OGOLE, 2011; BELGIU; DRĂGUȚ, 2016).

Considering these problems, we answered the following question: What aspects hinder the detection of burned areas when applying spectral indexes to map the occurrence of scars from fires? Thus, the general goal of this work was to use artificial neural networks to identify the configuration with the best performance to classify burned areas, detecting and eliminating the aspects that hinder

the detection of this type of phenomenon. Furthermore, this research analyzed the association between the areas with fire scars and the types of crops in a cerrado region.

2. STUDY AREA

The microregion of Patrocínio is located in the southeast region of Brazil, in the state of Minas Gerais, at the intersection of latitude geographic coordinates ranging from 18°40'44.004 "S to 19°03'58.674 "S, and longitude 47°09'51.546 "W to 46°32'46.413 "W (Figure 1). The study region has an area of approximately 11,986.16 km², which covers eleven municipalities, namely Abadia dos Dourados, Coromandel, Cruzeiro da Fortaleza, Douradoquara, Estrela do Sul, Grupiara, Iraí de Minas, Monte Carmelo, Patrocínio, Romaria, and Serra do Salitre.

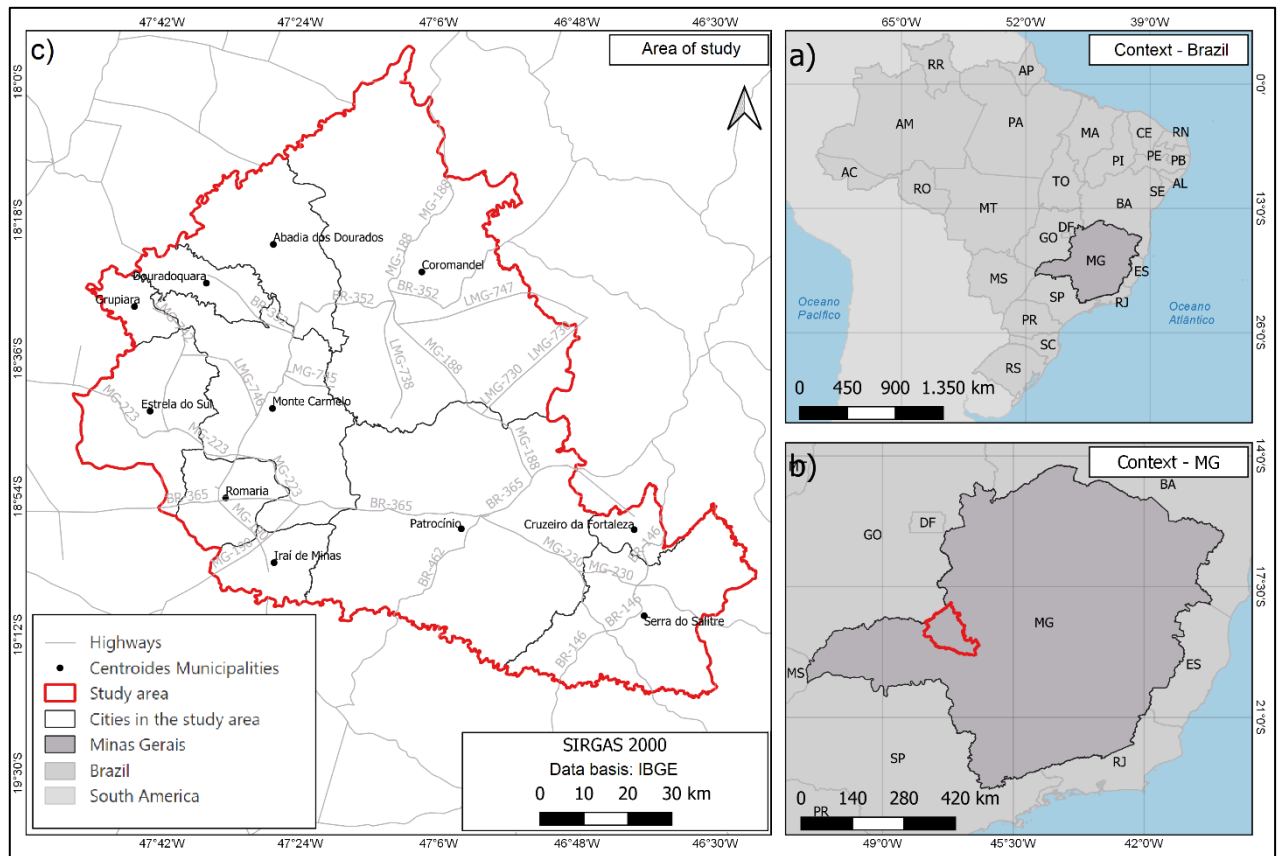


FIGURE 1. The geographic location of the Patrocínio microregion: (a) Brazil, (b) Minas Gerais, and (c) Patrocínio microregion.

The microregion of Patrocínio is known for its agro-industrial activities (OLIVEIRA; MATOS, 2009). The main crops are corn, sugarcane, soybeans, coffee, plus animal husbandry

(SANTANA et al., 2020). According to Franco and Rodrigues (2019), agriculture is the main economic activity in this geographic region because of the uneven relief, favorable hydroclimatic conditions, and fertile soils. These conditions save expenses with soil correction inputs and enable agricultural machinery to maximize the productive potential at lower costs (CAMPOS et al., 2012; OLIVEIRA et al., 2013).

The study area was chosen because it is located in the Cerrado of Minas Gerais, which has several characteristics prone to the occurrence of fires, supporting the hypothesis under test here in this article. In addition, its economic importance and potential for supplying natural resources place this area in the study priorities of the research being developed in the region.

According to data from the National Institute of Meteorology - INMET, the period of scarce rainfall in the region starts around April/May, and continues until September/October. Figure 2 shows the rainfall record in the years of study, data which helped us define the period of interest and data collection.

Figure 3 presents the graph of the fire spots registres per month, in each year. Figure 4 shows the distribution of fire spots, and Figure 5 illustrates the occurrence of fires per km² in the municipalities of the Patrocínio microregion for 2018, 2019, 2020, and 2021 (dry months). On average, the dry months in the region range from April to October.

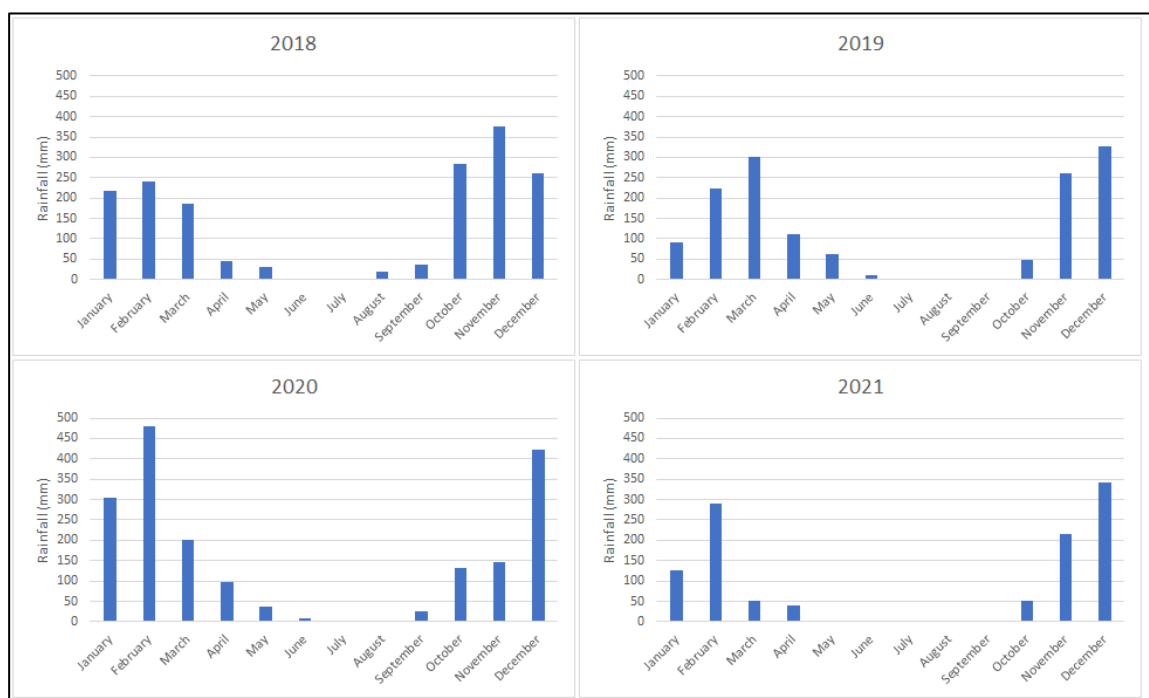


FIGURE 2. Rainfall over the years in the study area

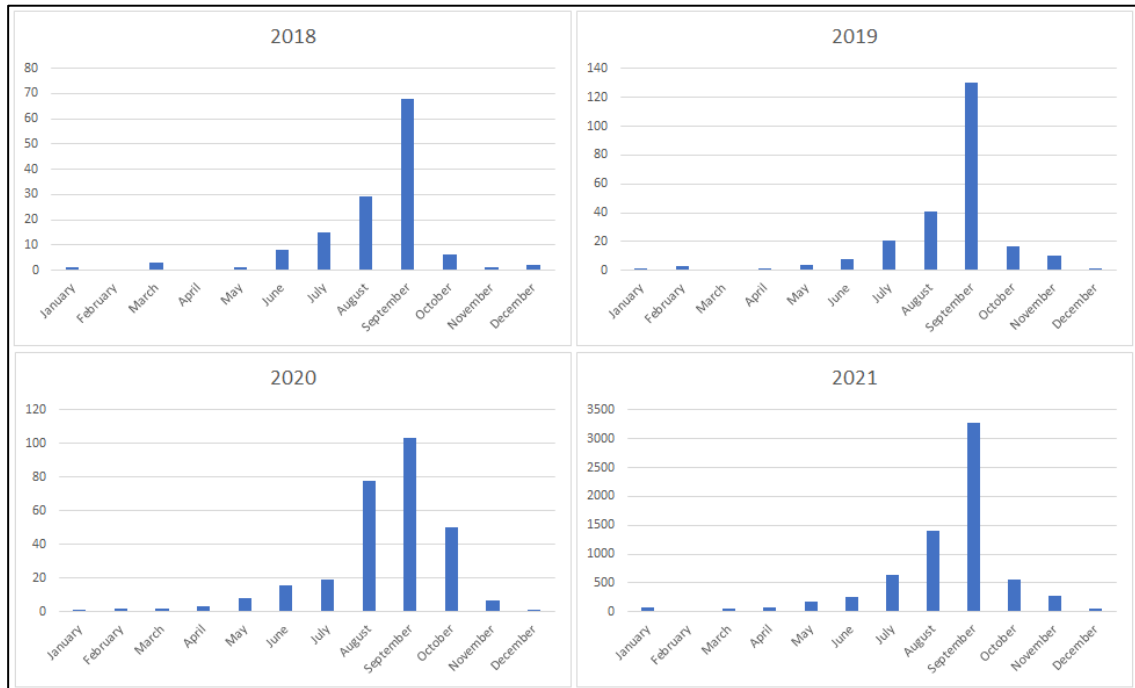


FIGURE 3. Fire spots distribution over the study area

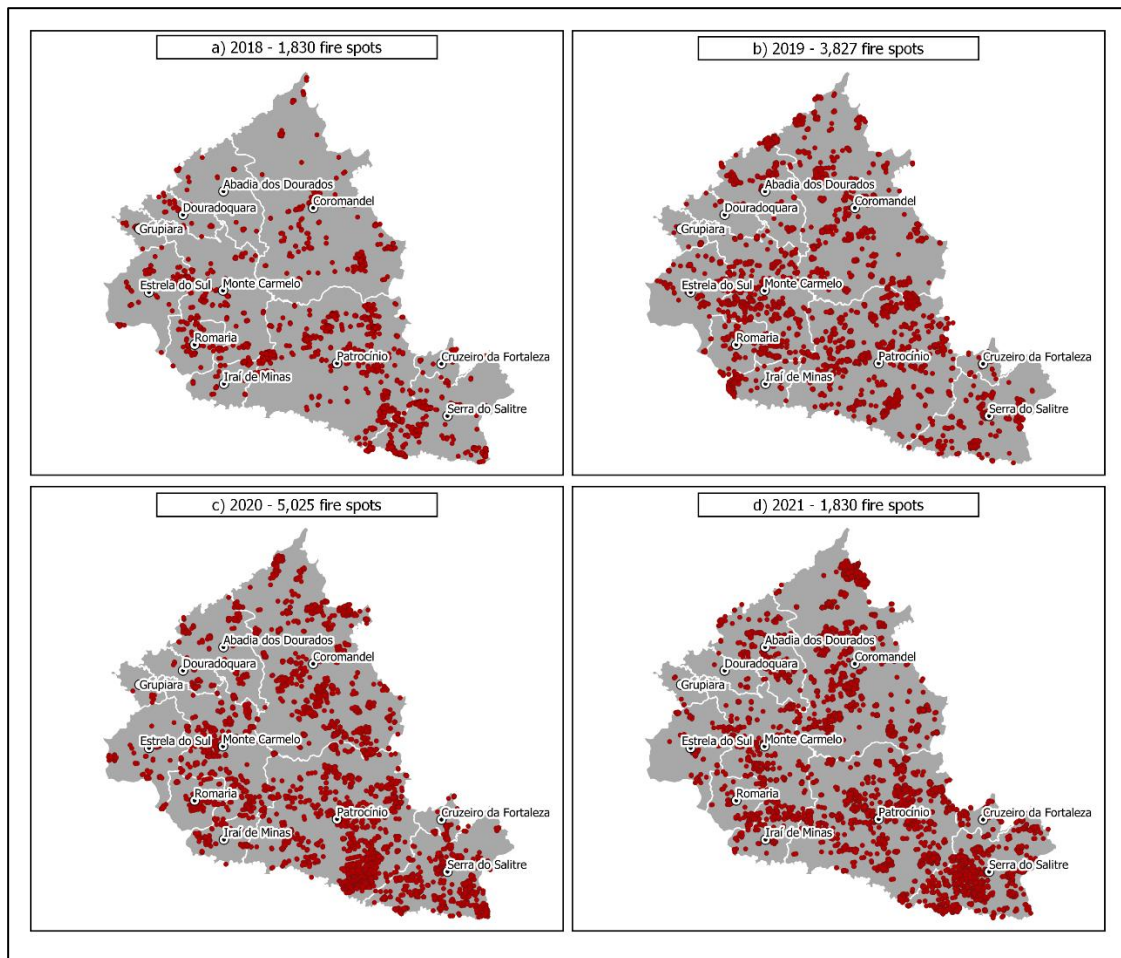


FIGURE 4. Fire spots in (a) 2018, (b) 2019, (c) 2020, (d) 2021

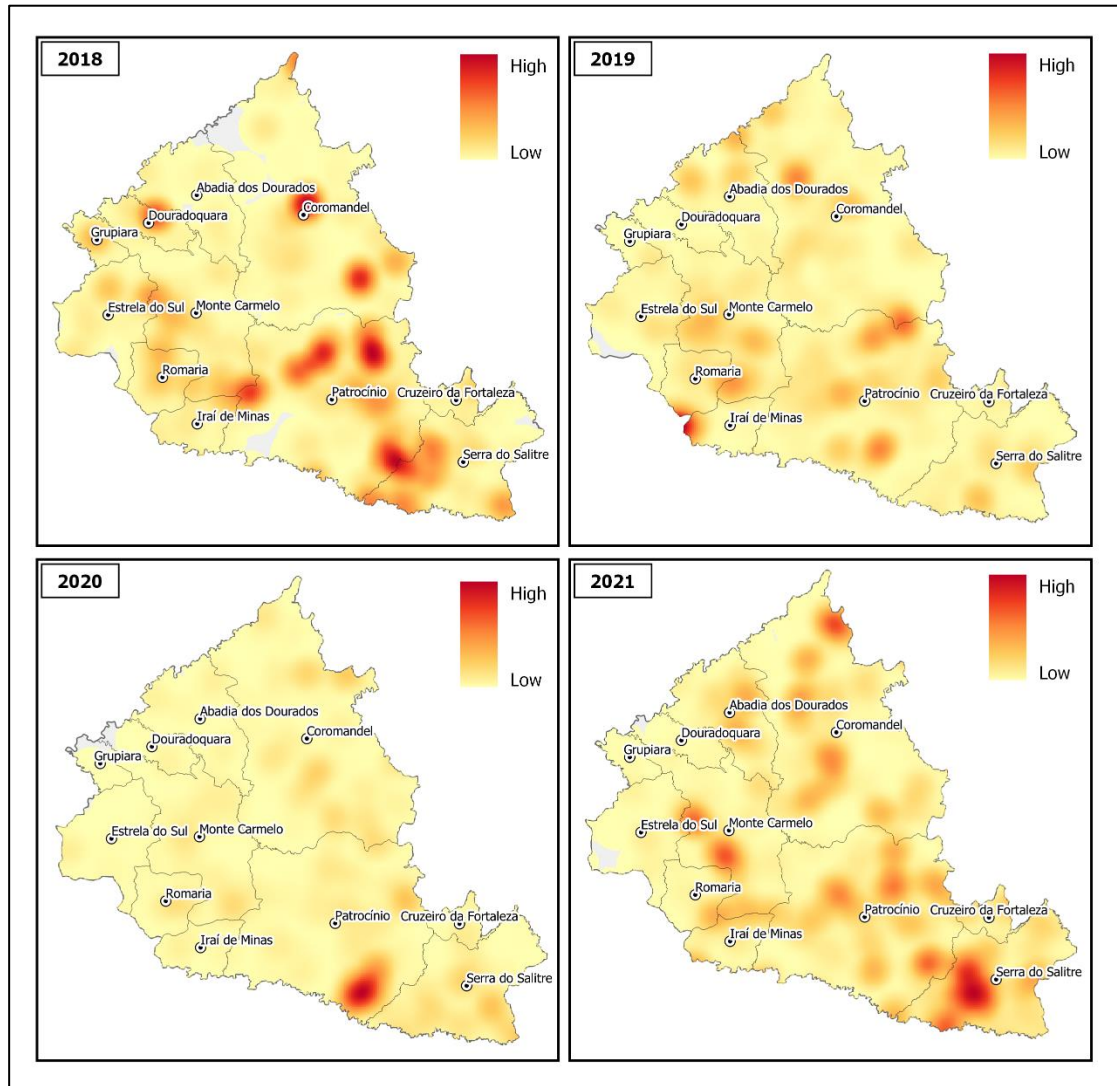


FIGURE 5. Heatmap by municipalities in (a) 2018, (b) 2019, (c) 2020, (d) 2021.

3. MATERIAL AND METHODS

This research was proposed and executed according to the flow described in Figure 6.

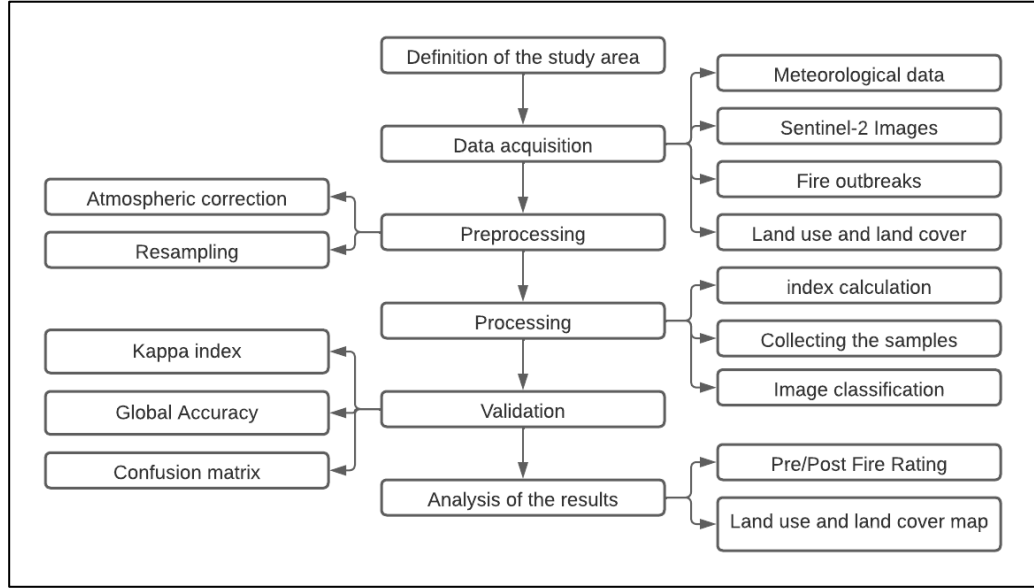


FIGURE 6. Research execution steps.

We divided the research into two experiments. The objective of experiment 1 was to evaluate the band's relationship configuration that must allow the best detection of burned areas in the image classification process. The aim of experiment 2 was, based on experiment 1, to analyze the association of agricultural practices with the occurrence of fire spots. Thus, in the following items, we describe each procedure in detail.

3.1 Data acquisition and pre-processing

Free images from the Sentinel-2 satellite were acquired through the United States Geological Survey (USGS) website. The sensor attached to the Sentinel-2 satellite has a spectral resolution of 13 bands, radiometric resolution of 12 bits, a temporal resolution of 5 days, and spatial resolution of 10 meters for the bands B02 (490 nm), B03 (560 nm), B04 (665 nm) and B08 (842 nm); 20 meters for bands B05 (705 nm), B06 (740 nm), B07 (783 nm), B08A (865 nm), B11 (1610 nm) and B12 (2190 nm); and 60 meters for bands B01 (443 nm), B09 (940 nm) and B10 (1375 nm).

The data about fires within the study area were obtained from the INPE website. We searched for the dry season interval for each year of interest. The dry period was established by the rainfall data from the stations located in the region, ranging from April to October among the study years. The pre-fire images are used to see what was in the region before the dry season. Thus, based on the definition of the dry spells, the images for 2018, 2019, 2020, and 2021 were acquired, as shown in Table 1.

TABLE 1. Date of the images for the dry spells of 2018, 2019, 2020, and 2021.

Year/Period	2018	2019	2020	2021
Pre-fire	05/05	04/20	05/29	04/24
Post-fire	09/27	10/17	10/01	09/06

Considering the presence of particles in the atmosphere, such as water, nitrogen, oxygen, and aerosols, it was necessary to perform the atmospheric correction, aiming to reduce the influence of particles on the image (GAO *et al.*, 2009). The atmospheric correction of the images was performed using the Semi-Automatic Classification Plugin (SCP) in the QGIS software. Congedo (2016) states that the SCP plugin performs atmospheric correction using the Dark Object Subtraction (DOS) method. The DOS method estimates atmospheric intervention based on the satellite image's digital numbers (DNs). According to Chavez (1988), shaded regions should present low DN's; however, due to atmospheric scattering, they deliver high DN's values and thus, these pixels are used as a correction parameter. Chavez (1988) states that the analysis is done by choosing the shortest wavelength band. From the study of the frequency histogram of the DN's, the value of the darkest pixel is identified. Thus, the correction is made uniformly, subtracting the scattering value of the entire scene (CHAVEZ, 1988).

In addition, all the Sentinel-2 satellite bands were resampled to spatial resolution of 10 meters, and this procedure was performed by SNAP software. The resampling was performed by the nearest neighbor method (NNM), which uses the gray level values closest to the inverse mapping (PARKER; KENYON; TROXEL, 1983).

3.2 Mosaic generation

Due to the size of the study area, it was necessary to use six scenes to compose its limits, being acquired the scenes KHE, KKA, KKV, KLU and KLV. The mosaic was made for each year, in the pre-fire period and in the post-fire period. The cloud filter was 30% in the choice of images.

3.3 Mapping fire scars

For the mapping of the fire scars, the indexes present in Table 2 were used, being the bands used: NIR (near infrared), SWIR2 (shortwave infrared) and R (red).

TABLE 2. Spectral indexes used for identification of fire scars

Spectral Indexes	Acronym	Formula	Reference
<i>Normalized Burn Ratio</i>	NBR	$(\text{NIR} - \text{SWIR2})/(\text{NIR} + \text{SWIR2})$	KEY; BERSON 1999
<i>Normalized Difference Vegetation Index</i>	NDVI	$(\text{NIR} - \text{R})/(\text{NIR} + \text{R})$	ROUSE <i>et al.</i> 1973
<i>Soil Adjusted Vegetation Index</i>	SAVI	$(1 + L) * [(\text{NIR} - \text{R})/(\text{NIR} + \text{R} + L)]$, where $L = 1$	HUETE 1988
<i>Char Soil Index</i>	CSI	$\text{NIR}/\text{SWIR2}$	SMITH <i>et al.</i> 2007

3.4 First experiment – bands and indexes evaluation

In the first experiment, we evaluated the band configuration that allows better detection of burned areas in the image classification process. Thus, six tests were used each year (2018, 2019, 2020, and 2021), divided into two groups: post-fire period and variation between pre-fire and post-fire. In the analysis of the method of the post-fire period and the variation between pre-fire and post-fire, the classification performance was tested: (I) with the use of all bands of the Sentinel-2 sensor and the four indexes; (II) only with the NBR index, and (III) only with the CSI index. The pre- and post-fire period variation is the modifications that occurred in the land cover during the dry season, composed by a mathematical operation of subtraction of pre- and post.

For this experiment, Region of Interest (ROI) samples were collected for the classes of fires scars, bare soil, native vegetation, reforestation, water, and crops. The other classes were acquired only by visual analysis. The fire samples were identified using INPE fire spots data and visual analysis on the Sentinel-2 satellite's true color composition (RGB). After collection, the vector files were used in the Envi software, which extracted the surface reflectance values for each pixel, band, and index, which were exported in ASCII format, as shown in Figure 7.

ID	X	Y	Map X	Map Y	Lat	Lon	B1
1	8274	608	247538.99	8093970.00	-17.225312	-47.374082	1
2	8273	609	247528.99	8093960.00	-17.225401	-47.374177	9
3	8274	609	247538.99	8093960.00	-17.225403	-47.374083	5
4	8275	609	247548.99	8093960.00	-17.225404	-47.373989	5
5	8276	609	247558.99	8093960.00	-17.225405	-47.373895	7
6	8278	610	247578.99	8093950.00	-17.225497	-47.373708	8
7	8272	610	247518.99	8093950.00	-17.225491	-47.374272	9
8	8273	610	247528.99	8093950.00	-17.225492	-47.374178	9
9	8274	610	247538.99	8093950.00	-17.225493	-47.374084	5
10	8275	610	247548.99	8093950.00	-17.225494	-47.373990	5
11	8276	610	247558.99	8093950.00	-17.225495	-47.373896	7
12	8277	610	247568.99	8093950.00	-17.225496	-47.373802	7
13	8279	610	247588.99	8093950.00	-17.225498	-47.373614	8
14	8281	611	247608.99	8093940.00	-17.225591	-47.373427	6
15	8272	611	247518.99	8093940.00	-17.225581	-47.374273	9
16	8273	611	247528.99	8093940.00	-17.225582	-47.374179	9
17	8274	611	247538.99	8093940.00	-17.225583	-47.374085	11
18	8275	611	247548.99	8093940.00	-17.225584	-47.373991	11
19	8276	611	247558.99	8093940.00	-17.225585	-47.373897	6
20	8277	611	247568.99	8093940.00	-17.225587	-47.373803	6

FIGURE 7. Example of part of the training data in ASCII file.

The first column represents pixel identification. Columns two through seven represent the coordinate information for each pixel, both in Cartesian coordinates and geographic coordinates. The surface reflectance values for each band and pixel are located from column eight to the last one.

The samples were divided into two groups, 80% for training and 20% for validation, according to Figure 8. Thus, the Attribute - Relation File Format (ARFF), the standard used by the WEKA software, was generated, as shown in Figure 9.

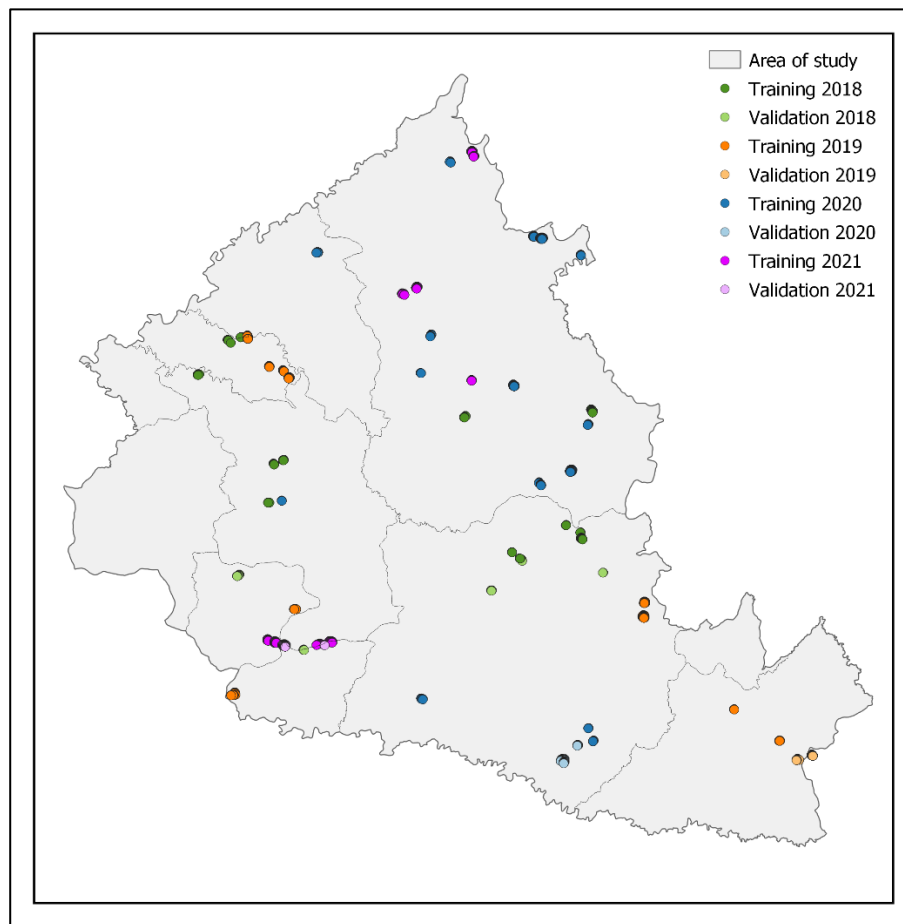


FIGURE 8. The geographical arrangement of the training and validation samples from the four years under study.

```

@relation Amostras
@attribute classe {1,2,3,4,5,6}
@attribute B numeric
@attribute G numeric
@attribute R numeric
@attribute RE1 numeric
@attribute RE2 numeric
@attribute RE3 numeric
@attribute NIR numeric
@attribute RE4 numeric
@attribute SWIR1 numeric
@attribute SWIR2 numeric
@attribute NDVI numeric
@attribute SAVI numeric
@attribute NBR numeric
@attribute CSI numeric
@data
1,48,13,39,16,0,0,0,0,122,119,-1.000,-1.959,-1.000,0.000
1,42,15,38,9,0,0,0,0,123,117,-1.000,-1.954,-1.000,0.000
1,43,18,43,16,0,0,0,0,122,119,-1.000,-1.955,-1.000,0.000
1,39,11,36,16,0,0,0,0,122,119,-1.000,-1.950,-1.000,0.000
1,37,12,32,9,0,0,0,0,123,117,-1.000,-1.947,-1.000,0.000
1,48,18,40,9,0,0,0,0,123,117,-1.000,-1.959,-1.000,0.000
1,52,16,33,31,0,0,0,4,128,126,-1.000,-1.962,-1.000,0.000
1,54,24,48,31,0,0,0,4,128,126,-1.000,-1.964,-1.000,0.000
1,47,21,42,21,0,0,0,0,95,99,-1.000,-1.958,-1.000,0.000
1,45,27,40,26,0,1,18,25,116,108,-0.429,-0.844,-0.714,0.167
1,50,23,42,25,0,0,7,7,112,107,-0.754,-1.483,-0.877,0.065
1,47,17,44,25,0,0,0,7,112,107,-1.000,-1.958,-1.000,0.000
1,43,21,31,22,0,0,3,14,108,106,-0.870,-1.702,-0.945,0.028

```

FIGURE 9. Example ARFF file containing part of the training data.

The ARFF file was defined based on the data presented in the header, as in this specific study, the classes were shown (1: fires scars, 2: exposed soil, 3: native vegetation, 4: reforestation, 5: water, and 6: crops), followed by the data type (numeric, nominal, and dates). The same was done for the validation file. Then, these files were imported into WEKA software, which has metrics capable of analyzing the available data set and estimating the subset with the highest possibility of predicting which class each pixel belongs.

The Multilayer Perceptron (MLP) neural network was used for the classification. As a result of the processing, the overall accuracy was obtained by computing the kappa index, which analyzes the classification according to Table 3, proposed by Landis and Koch (1977). We also used the confusion matrix, which represents the classification quality based on the correlation between the reference and classified information.

TABLE 3. Kappa coefficient values for the classification analysis.

Kappa Coefficient	Quality of Rating
<0.00	Insignificant
0.00 to 0.20	Weak
0.21 to 0.40	Fair
0.41 to 0.60	Moderate
0.61 to 0.80	Strong
0.81 to 1.00	Near Perfect

In addition to these evaluation parameters, the omission error analysis was performed, in which it is possible to verify the percentage of pixels omitted from the classification, as presented in Eq. (1).

$$OE = 100 - \frac{V_n}{\sum_r n} \quad (1)$$

Where, EO: omission error; V: the amount of correctly classified pixels; n: class to be calculated; and r: distribution of reference data. In addition, the inclusion error was analyzed, which analyzes and reports the number of pixels that were wrongly included in each class, as presented in Eq. (2).

$$IE = 100 - \frac{V_n}{\sum_c n} \quad (2)$$

Where, IE: inclusion error; V: the amount of correctly classified pixels; n: class to be calculated; and c: distribution of classified data.

3.5 Second experiment – Scars classification

According to the analysis performed in the first experiment, it was possible to determine the best configuration of the ANN algorithm for classifying burned areas. Thus, the classification was performed using only the images in the post-fire period, together with the use of all bands of the Sentinel-2 satellite and the four indexes we studied.

In this experiment, we used the fire data and the NBR index to refine the samples collected for classification, aiming to improve the computational and classifier performance. Thus, we obtained the pixels and their respective surface reflectance values for the burned areas in ASCII format using the ENVI software. Then, the ARFF file was generated to be exported and classified in the WEKA software. In this file, the pixels should be labeled as unclassified or (?), as shown in Figure 10.

WEKA indicates the class it has classified based on the training data as output. In addition, it presents its prediction error, which means the probability that the pixel has been correctly classified. Figure 11 shows an example output file from the WEKA classification.

```

@relation Amostras
@attribute classe {1,2,3,4,5,6}
@attribute B numeric
@attribute G numeric
@attribute R numeric
@attribute RE1 numeric
@attribute RE2 numeric
@attribute RE3 numeric
@attribute NIR numeric
@attribute RE4 numeric
@attribute SWIR1 numeric
@attribute SWIR2 numeric
@attribute NDVI numeric
@attribute SAVI numeric
@attribute NBR numeric
@attribute CSI numeric
@data
?,44,8,53,1,0,0,0,0,118,210,-1.000,-1.963,-1.000,0.000
?,43,8,51,9,0,0,0,0,120,216,-1.000,-1.962,-1.000,0.000
?,41,9,53,5,0,0,0,0,117,215,-1.000,-1.963,-1.000,0.000
?,40,6,52,5,0,0,0,0,117,215,-1.000,-1.962,-1.000,0.000
?,46,5,50,7,0,0,0,0,116,218,-1.000,-1.961,-1.000,0.000
?,39,6,55,8,0,0,0,0,120,221,-1.000,-1.964,-1.000,0.000
?,48,9,51,9,0,0,0,0,120,216,-1.000,-1.962,-1.000,0.000
?,48,10,56,9,0,0,0,0,120,216,-1.000,-1.965,-1.000,0.000
?,47,13,59,5,0,0,0,0,117,215,-1.000,-1.967,-1.000,0.000
?,43,12,54,5,0,0,0,0,117,215,-1.000,-1.964,-1.000,0.000
?,44,12,53,7,0,0,0,0,116,218,-1.000,-1.963,-1.000,0.000

```

FIGURE 10. Example of an ARFF file to be classified.

inst#	actual	predicted	error	prediction
1	1:?	1:1		1
2	1:?	1:1		0,995
3	1:?	1:1		0,828
4	1:?	1:1		0,992
5	1:?	1:1		0,57
6	1:?	1:1		0,782
7	1:?	1:1		0,49
8	1:?	1:1		0,994
9	1:?	1:1		0,706
10	1:?	1:1		0,801
11	1:?	1:1		1
12	1:?	1:1		0,998
13	1:?	1:1		1
14	1:?	1:1		1

FIGURE 11. Example of the WEKA classification output file.

With the output file in hand, the coordinates referring to each pixel were linked, and then the ArcGIS software was used to transform the ASCII file into a points layer. Later, these data were interpolated using the Geostatistical Wizard tool, interpolating by the kriging method. Then, only the areas understood as burned were extracted for each of the years under study. The burning classes were refined using the point data of fire spots and the NBR index, which allowed the elimination of eventual areas incorrectly classified by WEKA.

To analyze the influence and association of burned areas with the agricultural practices present in the study area, we used the raster data from MapBiomass, where we identified the information on land use and cover, emphasizing temporary and perennial crops. Thus, the land use

and land cover maps were made, allowing an analysis of the presence of fire scars and the type of crops and plantations present near these burned areas.

4. RESULTS AND DISCUSSION

4.1 Results and discussion: First experiment

The machine learning results showed that using all Sentinel-2 satellite bands combined with the NDVI, SAVI, NBR, and CSI indexes was the most effective model in minimizing classification errors. Both the classification of the post-fire period and the variation between the pre-fire and post-fire period presented a kappa index greater than 0.86; therefore, these classifications were considered near perfect.

TABLE 4. Overall accuracy and kappa index for the tested configurations

Validation	Configuration	Variation between pre-fire and post-fire				Post-fire			
		2018	2019	2020	2021	2018	2019	2020	2021
Kappa	All bands + index	0.974	0.868	0.949	0.981	0.925	0.939	0.998	0.968
	NBR	0.575	0.527	0.622	0.468	0.633	0.581	0.706	0.502
	CSI	0.396	0.468	0.610	0.368	0.497	0.489	0.437	0.255
Global Accuracy (%)	All bands + index	97.876	89.007	95.773	98.432	93.730	94.940	99.841	97.400
	NBR	64.635	60.654	68.511	55.714	69.484	65.119	75.575	58.492
	CSI	49.712	55.734	67.559	47.631	58.095	57.480	53.115	37.936

TABLE 5. Confusion matrix of the classification by neural networks of all Sentinel-2 bands and the NDVI, SAVI, NBR and CSI indexes in the 2018 post-fire period.

Class	1	2	3	4	5	6	Total	Omission (%)
1	836	0	4	0	0	0	840	0.476
2	0	840	0	0	0	0	840	0.000
3	0	0	840	0	0	0	840	0.000
4	74	0	3	763	0	0	840	9.167
5	0	0	0	0	840	0	840	0.000
6	231	0	4	0	0	605	840	27.976
Total	1141	840	851	763	840	605	5040	
Inclusion (%)	26.731	0.000	1.293	0.000	0.000	0.000		

Global Accuracy = 93.7302%; Kappa = 0.925
(1) fires scars; (2) exposed soil; (3) native vegetation; (4) reforestation; (5) water; and (6) crops

TABLE 6. Confusion matrix of the classification by neural networks of all Sentinel-2 bands and the NDVI, SAVI, NBR and CSI indexes in the 2019 post-fire period

Class	1	2	3	4	5	6	Total	Omission (%)
1	836	0	0	0	4	0	840	0.476
2	0	824	0	0	0	16	840	1.905
3	4	0	834	2	0	0	840	0.714
4	82	0	26	727	5	0	840	13.452
5	0	0	0	0	840	0	840	0.000
6	0	108	0	8	0	724	840	13.810
Total	922	932	860	737	849	740	5040	
Inclusion (%)	9.328	11.588	3.023	1.357	1.060	2.162		

Global Accuracy = 94.940%; Kappa = 0.939

(1) fires scars; (2) exposed soil; (3) native vegetation; (4) reforestation; (5) water; and (6) crops

TABLE 7. Confusion matrix of the classification by neural networks of all Sentinel-2 bands and the NDVI, SAVI, NBR and CSI indexes in the post-fire 2020 period

Class	1	2	3	4	5	6	Total	Omission (%)
1	840	0	0	0	0	0	840	0.000
2	0	840	0	0	0	0	840	0.000
3	0	0	839	1	0	0	840	0.119
4	0	0	0	840	0	0	840	0.000
5	0	0	0	0	840	0	840	0.000
6	0	0	7	0	0	833	840	0.833
Total	840	840	846	841	840	833	5040	
Inclusion (%)	0.000	0.000	0.827	0.119	0.000	0.000		

Global Accuracy = 99.841%; Kappa = 0.998

(1) fires scars; (2) exposed soil; (3) native vegetation; (4) reforestation; (5) water; and (6) crops

TABLE 8. confusion matrix of the classification by neural networks of all Sentinel-2 bands and the NDVI, SAVI, NBR and CSI indexes in the post-fire period of 2021

Class	1	2	3	4	5	6	Total	Omission (%)
1	840	0	0	0	0	0	840	0.000
2	0	840	0	0	0	0	840	0.000
3	0	0	709	131	0	0	840	15.595
4	0	0	0	840	0	0	840	0.000
5	0	0	0	0	840	0	840	0.000
6	0	0	0	0	0	840	840	0.000
Total	840	840	709	971	840	840	5040	
Inclusion (%)	0.000	0.000	0.000	13.491	0.000	0.000		

Global Accuracy = 97.400%; Kappa = 0.968

(1) fires scars; (2) exposed soil; (3) native vegetation; (4) reforestation; (5) water; and (6) crops

The best results were obtained in the years 2020 and 2021, having a nominal value of 100% correct classification of the burning class. According to Table 3, the classification of Tables 6 and 7 was considered almost perfect.

Table 5 focuses on the results for 2018, and the inclusion and omission of pixels of the burning class were observed. There was the inclusion of 26.731% of pixels, in which 6.485% were classified as reforestation and 20.245% as crops. The omission presented was 0.476%, in which they were classified in the native vegetation class. Based on the overall accuracy of 97.876% and the kappa index of 0.974, it can be considered that the classification containing all bands of the Sentinel-2 satellite and the four indexes in the post-fire period of the year 2018 presented satisfactory performance, meeting the quality parameter established in Table 3.

Based on Table 6, the pixel inclusion error of approximately 9.328% was observed in the burned class, with about 0.433% being found in the native vegetation class and 8.893% in the reforestation class. The omission error for the burned class was only 0.476%, with these occurring in the water class. According to the overall accuracy of 94.940% and the kappa index of 0.939, the classification of all Sentinel-2 satellite bands and indexes in the 2019 post-fire period showed almost perfect quality, as presented in Table 3.

Engelbrecht et al. (2017), studied forest fires in the Western Cape, South Africa. Images from the Sentinel-1 and Sentinel-2 satellites were used. The authors presented that there was a commission error in the class of fires being associated with vegetation areas. A similar fact occurred in work done by Yang et al. (2016), in which the author associated the use of the normalized difference vegetation index to account for the presence of vegetation in burn mapping. These results are similar to those we found here, indicating that vegetation may have been better identified through NDVI.

Compared to other multispectral sensors, we understand these results occurred since the Sentinel-2 satellite bands present considerably higher accuracy regarding crop biophysical variables (XIE et al., 2019). Furthermore, the spectral indexes NDVI, SAVI, NBR, and CSI possess characteristics capable of highlighting regions of fire scars. Therefore, in addition to the surface reflectance values coming from the sensor bands, they assisted with highlighting the biophysical characteristics of the site (XIE et al., 2019). Thus, the combination of the Sentinel-2 bands and the indexes mentioned above resulted in samples with greater variability of information. This factor probably contributed to the classification performance since each class could be better characterized.

In the step of assigning weights in the backpropagation algorithm of a multilayer perceptron

neural network, when the input classes are well discriminated, the values assigned to the weights tend to converge to their optimum with fewer iterations (HECHT-NIELSEN, 1992). Moreover, since the error propagated between layers will be smaller, the classification performance tends to present more satisfactory results (PAOLA; SCHOWENGERDT, 1995).

Syifa, Panahi and Lee (2020) studied a forest fire in Butte County, California, USA. Using machine learning, the authors used Landsat-8 and Sentinel-2 images to map pre- and post-fire conditions. The results show classifications with overall accuracies greater than 83%, similar to what we found in this research.

In the study by Seydi et al. (2021), the authors evaluated burned areas in Australia using images from the Sentinel-2 satellite and the MODIS sensor. The methodology proposed analyzes the features occurring in the pre- and post-fire period variation. The classification obtained an accuracy higher than 90% and a kappa index above 0.82. These results are compatible with ours, reinforcing that the proposed methodology effectively maps fire scars.

Based on the algorithm used here, it is intended that the post-fire period will make it possible to aid in processing time. Furthermore, according to Engelbrecht et al. (2017), the vegetation of a given region can be removed for causes other than fires, which can cause incorrect classification of burned and unburned areas. Figure 12 shows the neural network structure that performed best in the tests.

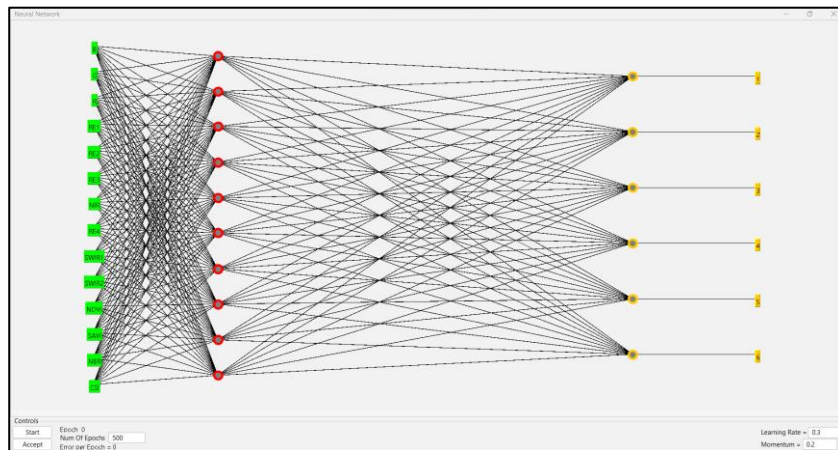


FIGURE 12. The ANN algorithm's structure for the attributes that performed best in classification.

4.2 Results and discussion: Second experiment

The spatial classification of the fire class was obtained using the ANN algorithm, based on the dataset that presented the best performance and allowed showing the fire scars in 2018, 2019,

2020, and 2021. In addition, the types of crops (annual and temporary) were presented to assist in identifying and associating the areas of occurrence of the fire scars and the type of crops located near them. Figure 13 shows the land use and cover map obtained through the classification methodology.

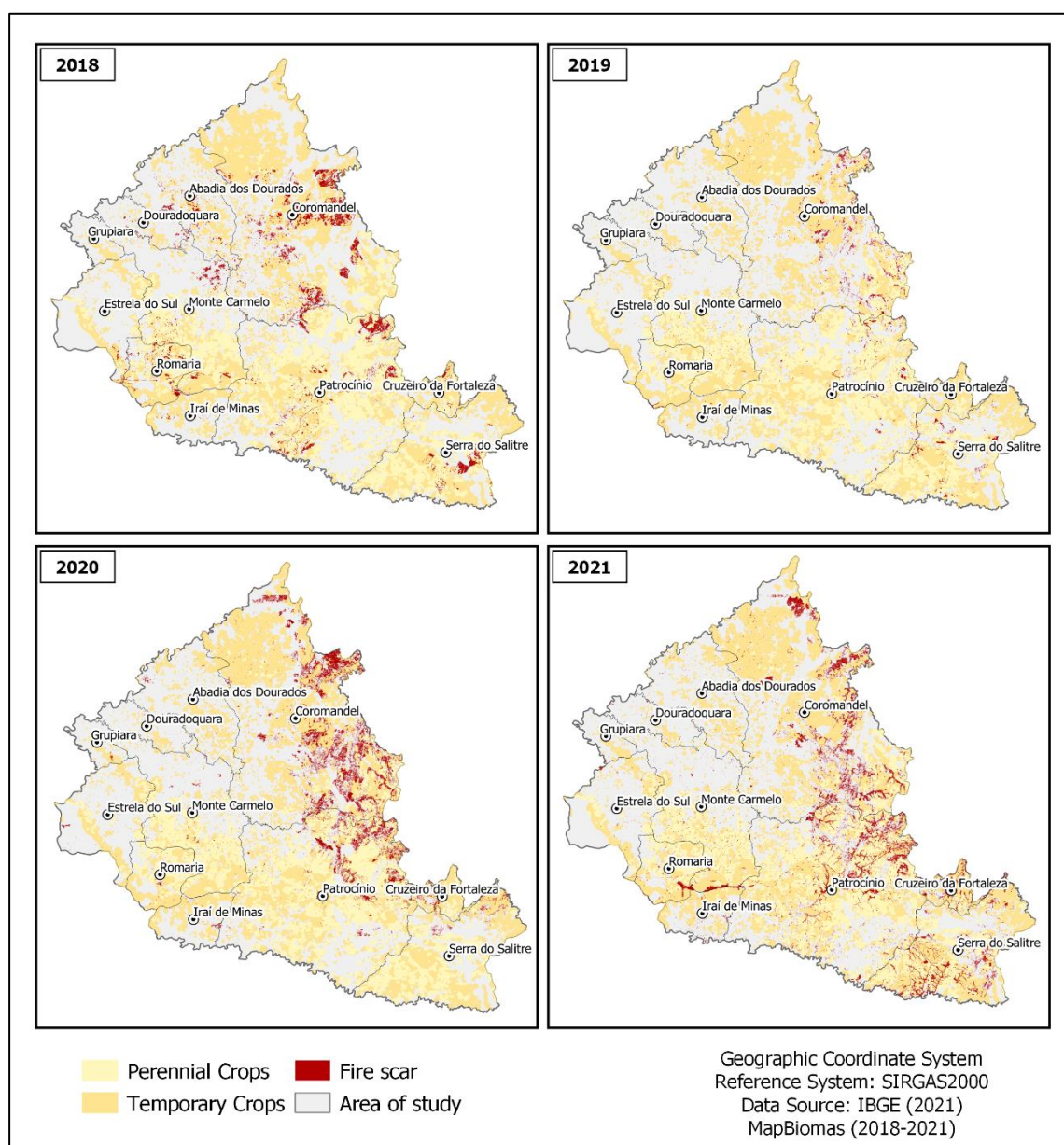


FIGURE 13. Map of fire scars and type of crops in the Patrocínio microregion in 2018, 2019, 2020 and 2021

Based on Figure 13, it was possible to observe that in the four years under study, the fire scars were located near agricultural areas, mainly nearby temporary crops, such as the representative

case of soybeans. Furthermore, it was possible to observe an increase in fire scars between 2020 and 2021. According to MapBiomas (2022), temporary crops consist mainly of soybeans, sugarcane, rice, and cotton.

According to Hebede, Fisher and Jovem (2011), temporary crop plants undergo several stress factors related to environmental conditions, such as high temperature and lack of rain, resulting in moisture deficit. The abovementioned crops present a characteristic of the dehydration process in advanced phenological stages, since the moisture deficit increases throughout the plant's growth, and it is common for them to be dry during the harvest period (KINIRY, 1991). The phenological dynamics of temporary crops and Cerrado's climatic constraints and characteristics, such as lack of rainfall, can be considered contributing factors to the occurrence of fires (DIAO, 2020). In addition, in some cases, the farmers use the burning practice to save costs when cleaning the crops (JAKIMON et al., 2018).

Accordingly, Norsworthy et al. (2020) investigated the effect of soybean post-harvest residues and wind on fire occurrence. The authors pointed out that there is less chance of fire spread in small grain crops since the harvest is close to the soil surface, leaving few residues accessible for burning to occur outside of each bed. Burning residues is legal; however, when done incorrectly, it can cause environmental damage, as presented in the study by Amorim et al. (2021). In addition, the authors associated the burning of waste with soil damage.

In the study by Vargas and Rivera (2021), the authors highlight the importance of planting sugarcane but highlight the dangers that incorrect management can cause, such as burning, which can cause environmental damage and human health. Sugarcane is a crop that requires burning before harvesting in order to facilitate manual harvesting since this action will aid and inhibit the chances of workers being attacked by animals or insects (HOLDER et al., 2017). These findings explain the study region's danger in this research because the fire setting is part of the harvest process, which opens chances for ignition and spread of fire.

According to Phairuang et al. (2019), regions with sugarcane and rice plantations have environmental concerns since, in dry periods, the husks and straws of these crops are more susceptible to burning, which can be an ignition for fires. In the study by Shen et al. (2021), the authors found fire in regions where rice, corn, and cotton were cultivated, with a higher occurrence in the last two crops mentioned. These findings explain what we found in our results.

According to MapBiomas (2022), perennial crops mainly consist of coffee and citrus. As can be seen in Figure 13, the study area had a large coffee plantation site. Locatelli et al. (2011) reinforce that variations in precipitation and temperature can cause the displacement of crops to

areas closer to forests. Arabica coffee, for example, is a crop that requires lower temperatures, varying around 18° to 21°C approximately (ALEGRE, 1959). It can reduce leaf area in regions and seasons of strong wind (CARAMORI et al., 2002). According to Melke and Fetene (2014), when exposed to prolonged dry seasons, Arabica coffee can have its growth and development impaired. According to Martinez et al. (2021), the widespread production of coffee results in many residues, such as bark, dry leaf, and defective beans, which are combustible fire materials. Thus, DaMatta and Ramalho (2006) emphasized the importance of raising awareness about coffee cultivation in forest areas since this practice has the potential to deforest and degrade forests.

5. CONCLUSION

This study presented a method that proved efficient for the ANN classification of burned areas, with the best performances found when all bands of the Sentinel-2 satellite and the four indexes (NDVI, SAVI, NBR and CSI) were used. The first experiment was necessary since it showed results that aim to facilitate future research, such as using images only in the post-fire period. Furthermore, classifications were obtained by the abovementioned method with global accuracy higher than 93.7% and a kappa index higher than 0.92, which qualifies these classifications as "near perfect."

Based on the attributes that presented the best performance in the ANN classification, the land use and land cover maps were generated, making it possible to analyze a higher incidence of fires near temporary crop areas. Although burning is legalized, the agencies responsible and committed to the surveillance of this phenomenon must be attentive to monitoring and investigating the facts.

Based on the land use and land cover maps, it was possible to observe the fixed presence of fire scars in the four years we studied, highlighting the importance of monitoring these areas since burning, when occurring frequently, can bring several environmental problems and human health.

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