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An alternative approach for mapping burn scars using Landsat imagery, Google Earth Engine, and Deep Learning in the Brazilian Savanna

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ABSTRACT

The Cerrado biome in Brazil is characterized by a mosaic of vegetation types similar to African savanna and has one of the highest levels of biodiversity in the world. Wildfires have historically contributed to shaping the natural vegetation and are now being used in the establishment and management of agricultural systems and pastures. Consequently, the fire regime has been changing over the last few decades and increasingly affecting native vegetation, natural habitats, and ecosystem services in tropical regions. Mapping fire dynamics and spatial distribution are crucial to assess impacts on ecosystems and to define and enforce strategies and measures of fire control and prevention. In this study, we developed an alternative approach for mapping burned areas in the Cerrado biome in Brazil, using Landsat imagery and Deep Learning algorithm, implemented on the Google Earth Engine and on Google Cloud Storage platform. We compared our mapping results with two Burned Area products developed by INPE (30 m resolution) and MODIS MCD64A1 Burned Area Product (500 m resolution). Additionally, we assessed the accuracies of these three mapping products using 2,200 validation points within the study area. By comparing our mapping result with MCD64A1 and INPE burn scar products, we estimated an average agreement of 34% for both. We observed that most mapping disagreements were mainly because of the effects of clouds/shadow conditions that affected the ability for spectral observations, differences in methodologies, and spatial resolution of each remotely sensed datasets used for mapping burned areas. Our validation results indicated an overall accuracy of 97% of our methodological approach for mapping burned areas and, therefore, it can be successfully applied across savanna regions. Our results showed that 202,230 km^2 was affected by fires within the Cerrado biome in 2017, in which 31% overlapped cropping lands (agricultural fields and pastures) and 67% overlapped various types of native vegetation (forest, savanna and grassland). Our proposed methodological approach and its results can be useful to enforce environmental command and control policies and to estimate carbon emissions, analyses interactions between climate and ecological drivers of fire, develop predictive models of fire risk dynamics, and providing spatial information that can help public policies and fire management/prevention actions for the Cerrado conservation.

1. Introduction

The Brazilian Cerrado is the second largest biome in Brazil and one of the most species-rich savannas of the world (Lewinsohn and Prado, 2005; Munhoz and Felfili, 2005). It plays a central role in continental hydrology, by spanning three of the largest watersheds in South America (Strassburg et al., 2017) and it maintains other fundamental ecosystem services such as carbon storage, both below- and above-ground (De Miranda et al., 2014), contributing towards reducing greenhouse gas emissions (Noojipady et al., 2017).

The climate of the Cerrado biome is characterized by strong seasonality and variations, with dry winters and rainy summers. Temperature and precipitation vary greatly across the approximately 2 million square kilometers of the Cerrado, which is also characterized by great variability in soil, nutrient, and water availability (Sano et al., 2019). These factors have contributed to the existence of a large variety of

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distinct vegetation types, including closed-canopy forests, savannas, and grassland formations (De Miranda et al., 2014; Ribeiro and Walter, 1998).

Currently, the Cerrado biome is under threat from increasing anthropogenic pressure, which has led to the accelerated conversion of natural ecosystems into cropping lands, pastures, and infrastructure developments (Alencar et al., 2020). Those land use and land cover changes (LULC) have resulted in several environmental impacts, including loss and fragmentation of natural habitats, increasing the risk of species extinction and affecting the hydrological cycle, biogeochemical processes, and ecosystem functioning (Strassburg et al., 2017).

Fire events are a common and determinant phenomenon in the Cerrado vegetation, which have greatly contributed to the evolution of its flora (Simon et al., 2009). However, rapid regional LULC has been affecting the natural fire regime (size, pattern, frequency, and magnitude) with consequences on native vegetation structure/composition, natural habitats, and ecosystem processes. Those changes in the fire regime contribute to increasing fire frequency and intensity, affecting ecosystem resilience (Miranda et al., 2002).

Spatiotemporal mapping of areas affected by fires may support analysis to better understand the occurrence and frequency of fire events and their impacts on vegetation and provide information for policymakers and firefighters to ensure efficient and organized fire management/prevention actions (Piromal et al., 2008). In this context, remote sensing can be useful for monitoring and mapping the occurrence of fires at regional and global scales, with different spatial, temporal, and spectral resolution (Daldegan et al., 2019; Matricardi et al., 2013; Oliva et al., 2011).

Global burned area products from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor aboard the Terra and Aqua satellites provided by the National Aeronautics and Space Administration (NASA) have been used to estimate global emissions, with a coarse spatial resolution (500 m), in 15 days-based products available for worldwide download (Andela et al., 2017; Chen et al., 2013; Randerson et al., 2012; Zhang et al., 2016). Those products, however, are not suitable for the identification of small burned areas due to their spatial resolution (Giglio et al., 2016). Despite the increasing frequency and intensity of fire events in the Cerrado biome, burned area products and studies conducted using medium and high spatial resolution are limited to local estimations (Alvarado et al., 2017; Daldegan et al., 2019) or simply to a specific year (Long et al., 2018). Automatic mapping for burned areas using medium and high spatial resolutions, cloud computing, and free remotely sensed data is not available and is still a scientific challenge.

By making the long-time series of Landsat imagery freely available, with a nominal 16- day repeat cycle since 1972, the United States Geological Survey (USGS)/NASA initiative has made those satellite data among the most frequently used for monitoring fire scars and impacts (USGS, 2020). However, a major challenge in mapping 30-meter spatial resolution Landsat images is the time required to process those images (Long et al., 2018). The Google Earth Engine (GEE) represents a new generation cloud computing platform that gives access to a vast catalog of satellite imagery, as well as global scale analysis capabilities, allowing efficient geospatial analyses (Gorelick et al., 2017).

More recently, there has been a great effort to automate the process of classification/mapping of specific targets using Deep Learning (Lecun et al., 2015) algorithms, such as the Deep Neural Network (DNN), which includes a learning algorithm based on an artificial neural network (Langford et al., 2019). In this study, we developed a semi-automatic methodological approach for mapping burned areas in the entire Cerrado biome in Brazil using Deep Learning techniques available on Google Cloud computing and Landsat 8 imagery, which consist of eleven spectral bands with a spatial resolution of 30 meters for bands 1-7 and 9, 15 meters for band 8, and 100 meters for bands 10 and 11. We did not use Landsat-7 imagery because of the data gaps observed images acquired after 2003, which would substantially affect the spatial coverage of our analysis. We assessed accuracies and compared our mapping product with existing burn mapping products from NASA and INPE. We also identified the best time of year for mapping burn scars and estimated the total area affected by fire in 2017 in the Cerrado biome.

2. Material and methods

2.1. Study region

The Brazilian savanna, locally known as Cerrado, encompasses an area of approximately 2 million square kilometers, spatially located between the parallels 2.3^0 S and 24.7^0 S and between the meridians 41.7^0 W and 60.1^0 W (Fig. 1). It is an important biodiversity hotspot due to its high species richness (flora and fauna), the high proportion of endemic species, and the increasing anthropogenic pressure that has impacted more than 70% of its primary vegetation (Klink et al., 2005; Myers et al., 2010). Also, the Cerrado represents the most structurally diverse savanna in the world, consisting of vegetation gradients that range from closed-canopy forests to savanna and grassland formations (Ribeiro and Walter, 1998). Those vegetation mosaics are determined by distinct geomorphological and topographic features, as well as by differences in water and nutrient availability (Silva and Bates, 2002).

The predominant climate in the Cerrado biome is tropical (Aw type according to the Köppen climate classification), characterized by a wet season, from October to March, and an extended dry season from April to September responsible for only 10% of the annual rainfall and the highest fire occurrence (Pereira et al., 2014). The annual precipitation ranges from 800 to 2,000 mm (an average of 1500 mm), while the annual average temperature is 22 °C (Alvares et al., 2013; Bustamante et al., 2012).

Many of the vegetation types in the Cerrado biome are adapted to and partially dependent on fire occurrences. Wildfires ignited by lightning usually burn small patches and are rapidly extinguished by the associated rains. However, the wildfire regime has been rapidly changed in the Cerrado biome in Brazil, increasing its frequency and intensity because of global climate changes and the accelerated anthropogenic land conversion and land management throughout the entire biome. Fires mostly occur during the dry season (May to September) and burn extensive areas of native vegetation, cropping fields, and pastures (Bowman et al., 2020; Pivello, 2011). Although wildfires have strongly shaped the Cerrado's vegetation, changes in the fire regime observed in the last decades have increased environmental impacts, economical losses, air pollution, and emissions of greenhouse gases (Bowman et al., 2020).

2.2. Datasets

We used the Landsat-8 OLI dataset, bands 2 to 7, as orthorectified Surface Reflectance available for downloading and processing on the Google Earth Engine platform. All Landsat images were atmospherically and geometrically corrected and included a cloud cover mask generated by a Function of Mask (FMASK) algorithm available on Google Earth Engine (Zhu and Woodcock, 2014).

Additionally, we used the product MCD64A1 Burned Area Product for 2017, spatial resolution 500 meters, which provides a global monthly burn scar detected by an algorithm that discriminates “fire pixels” representing one or more active fires at the time of those image acquisition (Giglio et al., 2016). The MCD64A1 product is fully available on the Google Earth Engine platform. Finally, we used the fire hotspots and burned area products developed by the National Institute for Space Research (INPE) in Brazil.

The INPE burned area product is based on a semiautomatic algorithm and Landsat images to estimate differences of Normalized Burned Ratio (NBR) among consecutive satellite scenes (Melchiori et al., 2014) to annually map burned areas within the entire Cerrado biome. The INPE fire hotspot product is based on an automatic mapping approach using 1 km x 1 km pixel size and thermal bands of nine satellites, and the

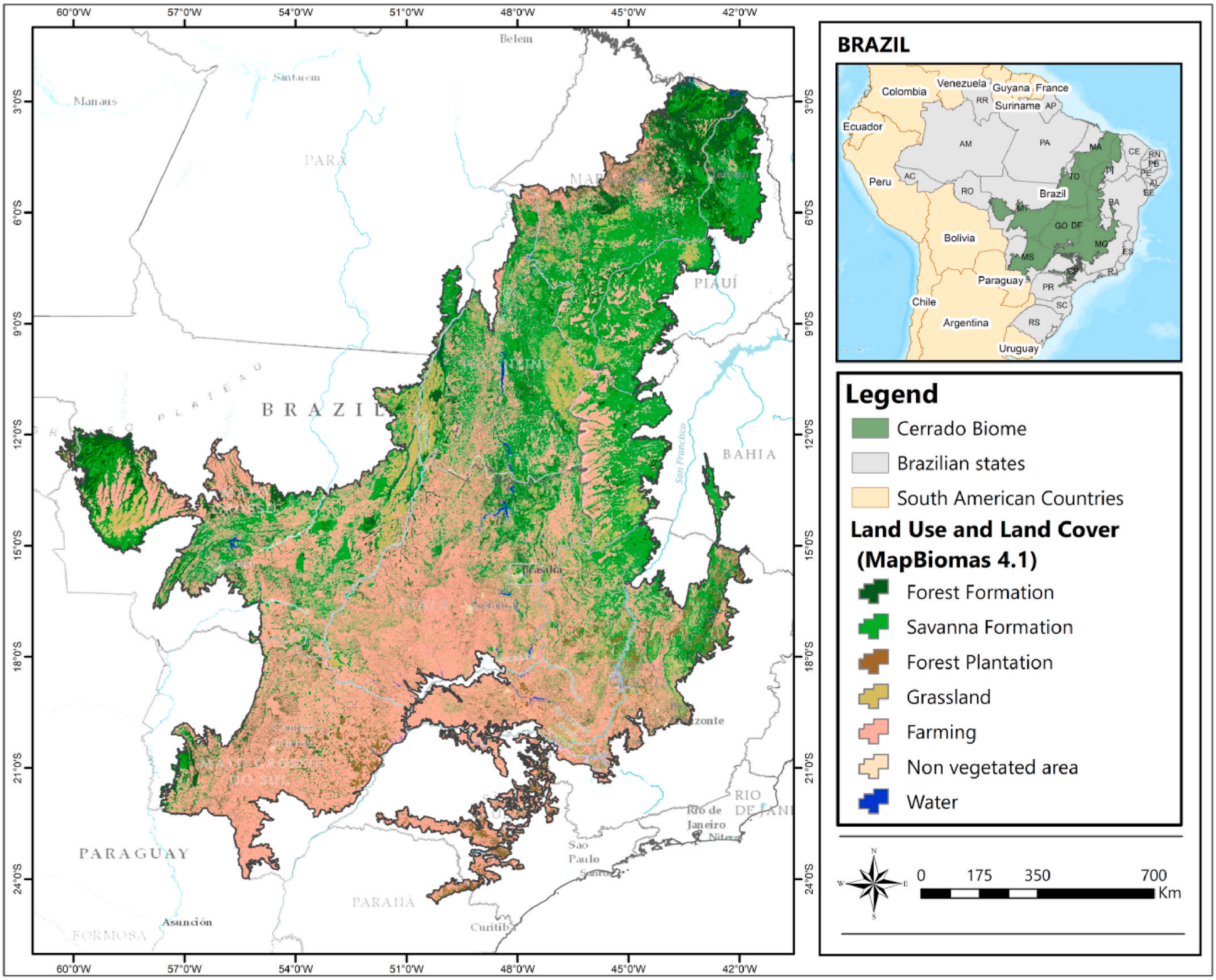

Fig. 1. Study area location that encompasses the entire Cerrado biome in Brazil, a region covered by vegetation types similar to African savanna, and its correspondent land use and land cover classes according to the MapBiomas Collection 4.1 (MapBiomas, 2020).

AQUA_M-T (Sensor MODIS) as a reference satellite, providing daily data of fire hotspots since 2000, available at http://www.inpe.br/queimadas/bdqueimadas.

In our study, we analyzed the fire hotspots detected in 2017 by the INPE burn area product to determine the fire detection time (months of the year). This analysis allowed us to identify months showing the highest fire frequency within the Cerrado biome, which was subsequently used to define the priority months for mapping burned areas in 2017.

2.3. Cloud computing

We used the Google Earth Engine platform to collect burned and non-burned spectral signatures in Landsat imagery to be used as training areas for the classification model. The training areas and Landsat imagery were exported to Google Cloud Storage and used as input in a Virtual Machine to process the Deep Learning scripts. The Google Earth Engine was also used to collect the validation points and accuracy assessment of the burned areas products used in this analysis.

2.4. Burned area mapping

Deep Neural Network (DNN) is a learning algorithm based on an artificial neural network with multiple hidden layers (Langford et al., 2019). The DNN models use hierarchical data processing, where the input data in each module (called the hidden layer) results in an output that is an input for the next module, connected through weights and biases whose values were learned during the training of the network (Bramhe et al., 2018).

We used Landsat 8 Operational Land Imager (OLI) satellite images and Deep Neural Network models to detect and map burned areas within the Cerrado biome. The image processing and classification followed four steps as follows: (1) collecting spectral training samples of burned and non-burned areas for the entire study area, well distributed in space, (2) training the deep learning models, (3) developing model prediction, and (4) model assessment (validation and concordance analysis). Fig. 2 uses step-by-step bases to show all details of our methodological approach for detecting and mapping burned areas in the Cerrado biome in 2017.

2.4.1. Training samples dataset

The spectral training samples of burned area (BA) and non-burned

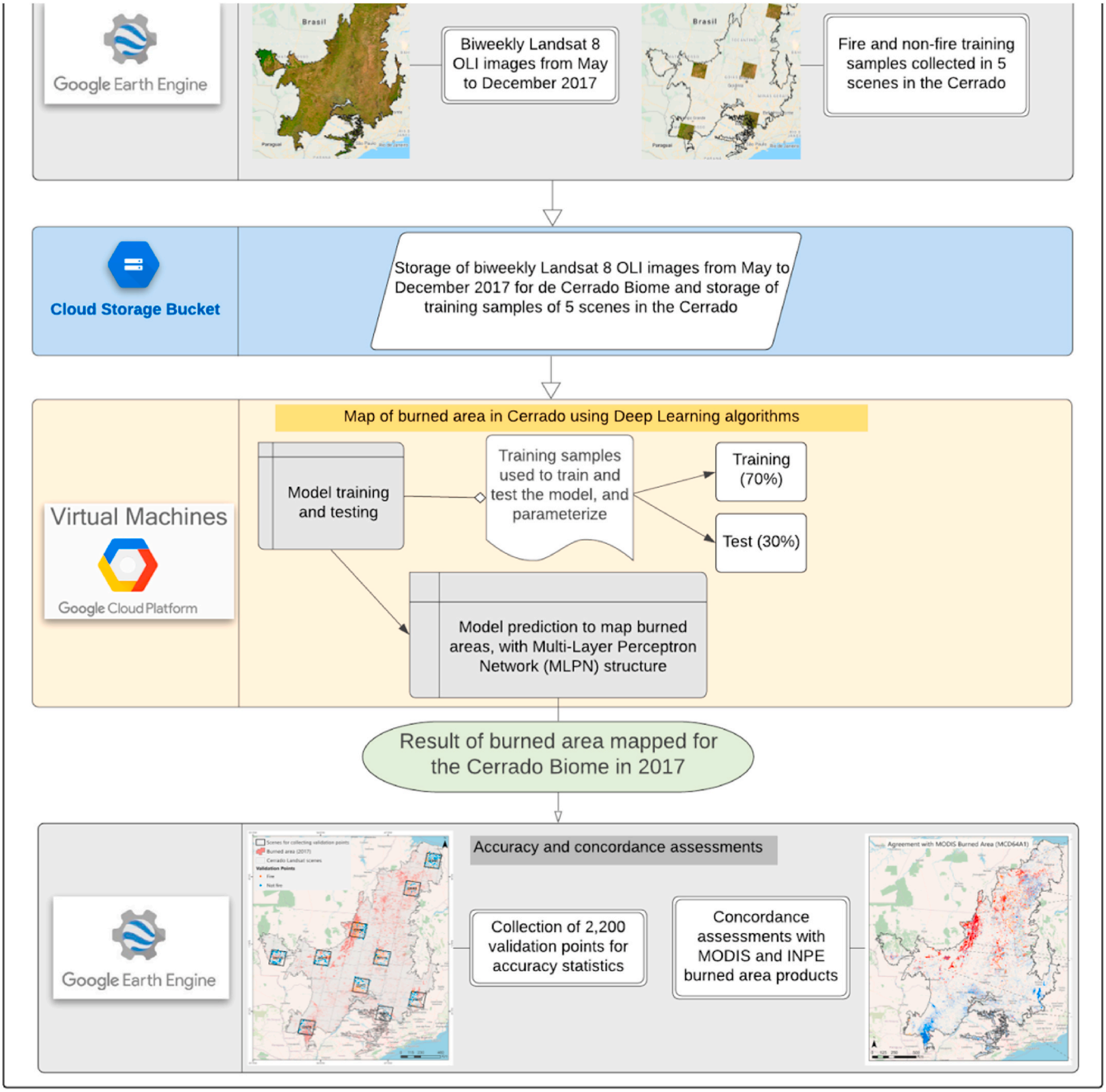

Fig. 2. Methodological approach used for detecting and mapping burned areas in the Cerrado biome using Landsat-8 imagery, deep learning algorithm, and Google Earth Engine and Google Cloud Storage platforms.

area (NBA) were collected in 5 Landsat scenes within the Cerrado biome (Fig. 2) by considering the great spectral variability among burned and non-burned pixels and by observed differences of the Normalized Burned Ratio (NBR) (Key and Benson, 2006) from pre-fire and post-fire images (Fig. 3), in which just the pixels in the NBR mask (greater than 0.25) was considered. The delta NBR fire scars were conservative in terms of the burned area since they captured only areas affected by fire in consecutive images, which increased our chances of collecting training samples in burned areas only. The training samples were collected using MODIS Burned Area as an indicator of fire occurrences, where areas of burn scars were hand digitized as polygons into vector layer using a drawing tool available on Google Earth Engine and only pixels masked out with the delta NBR were used as samples of burned areas. Hand digitizing was done along the periphery of visible fire scars on each Landsat scene used for collecting the spectral training samples. We considered the greatest variability of burned areas and samples to select the training samples, which represented different land use and land cover types and different sizes and shapes of the burned areas. Similarly, training samples of non-burned areas were also collected by sampling different land use and land cover types and the greatest landscape variability.

The Normalized Burned Ratio (NBR) is defined as:

$$NBR = \frac{\rho_{SWIRL} - \rho_{NIR}}{\rho_{SWIRL} - \rho_{NIR}} \quad (1)$$

Where ρSWIRL is the Short Wave Infrared Short surface reflectance,

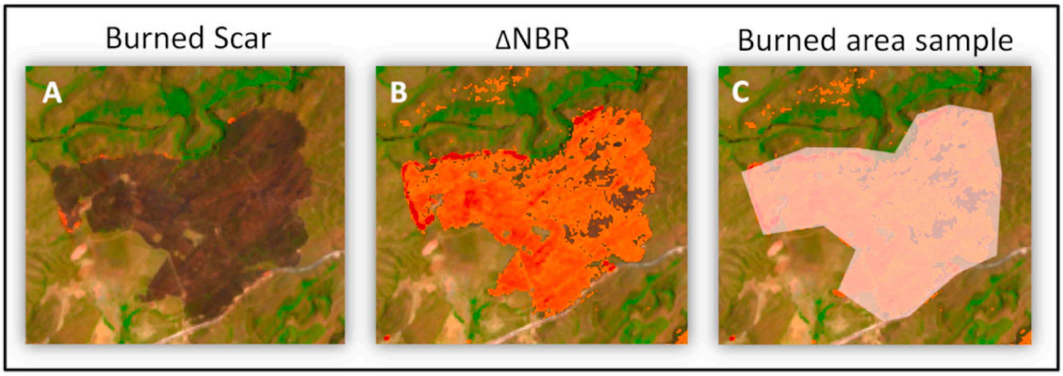

Fig. 3. Examples of: (a) a burn scar observed on a Landsat scene, (b) burn scar detected by applying a mask with Normalized Burn Ratio, and (c) hand digitized polygon used to train the model classification, where only pixels masked out (burned pixels) detected using the delta NBR image were sampled.

band 6 for Landsat 8 OLI sensor, and ρNIR is the Near-Infrared surface reflectance, band 5 for Landsat 8 OLI sensor.

The samples of burned area (BA) and non-burned area (NBA), as well as the Landsat images were exported from Google Earth Engine platform to Google Cloud Storage.

2.4.2. Model building and testing

We used Multi-Layer Perceptron Network (MLPN) structure in our approach, which consists of several layers of interconnected computational units, where each node (neuron) in one layer is connected to a node in the next layer. The layers are divided into three layers: input, hidden, and output layers (Eastman, 2009).

The algorithm includes two steps: training and prediction. In the training phase, the following parameters where defined, based on tests: the learning rate (0.001), the batch size (1,000), the number of interactions (7,000), and the inputs for classification were the spectral data acquired from the training samples of spectral bands defined based on the burned and non-burned areas. The following Lansat-8 spectral bands were used for the classification model of burned areas: red (RED - 0.65 μm), near-infrared (NIR - 0.86 μm), and shortwave infrared (SWIR 1 - 1.6 μm and SWIR 2 - 2.2 μm). In addition to those selected spectral bands, Landsat bands 2 to 7, NDVI (Normalized Difference Vegetation Index), NBR, and delta NBR (Difference Normalizes Burned Index) were tested. The Landsat spectral bands were chosen because of their sensitiveness to fire events. The input of the training data was split into two sets; 70% of the samples were used for training and 30% for testing, to estimate the ability of the DNN algorithm to map burned areas in the study area. In this step, an accuracy is generated for each algorithm applied, however, it is biased because it uses the same sample sets to test the model. So, an additional accuracy assessment using those validation points was conducted in our analysis.

2.4.3. Model prediction

The burned area classification was applied using Landsat images and the training samples for the entire study area and period (May to December 2017). A spatial filter was applied to remove noises (misclassified isolated pixels) and to fill small empty gaps: areas smaller than or equal to 1.4 ha (16 pixels) were removed, and empty gaps smaller than or equal to 5.8 ha (64 pixels) were filled in as burned areas. The asymmetry between spatial filters was adopted to be more conservative by removing more isolated pixels than those added by filling empty gaps within burned and unburned areas.

Since deep learning methods require a powerful computational processing, we conducted our analysis using graphics processing units (GPUs) and specialized hardware components for running parallel arithmetic operations (Goodfellow et al., 2016). The access to GPUs in a virtual machine environment was implemented on the Google Cloud Platform (https://console.cloud.google.com), a suite of cloud computing services provided by Google.

Finally, the burned areas were obtained by combining the fire mapping of individual Landsat images in 2017. The final burned area map was downloaded to a local workstation to proceed with assessment of the concordance with the INPE and MCD64A1 products.

2.4.4. Accuracy and concordance assessments

The concordance assessment was conducted by comparing (cross-tabulation) the fire scars detected using our classification approach with the burn scars product provided by INPE. We also compared our dataset with the MODIS Burned Area product (MCD64A1) by resampling the 500 m to 30 m spatial resolution.

A map-to-map analysis was conducted by overlapping our dataset with those two products: (1) the Cerrado burned area map and (2) the comparison maps (MCD64A1 and INPE burn scars). The cross-tabulation of Burned and Non-Burned classes resulted in a congruence map and a concordance graph.

We also assessed the accuracies of our dataset and those two products: MODIS Burned Area (MCD64A1) and the INPE burn scar. We used 2,200 validation points (2,000 for non-burned areas and 200 for burned areas) randomly distributed within the ten Landsat scenes (Fig. S1) in the Cerrado biome. We previously defined the number of validation points (burned and unburned) based on the proportion of burned (10%) and unburned areas (90%) compared to the entire Cerrado biome. The ten Landsat scenes used to assess the burn mapping accuracy covered the greatest representativeness of the study region, which included protected areas, private lands with different land uses, transitional zones among Cerrado and other biomes in Brazil, and areas of fire hotspots and high morphoclimatic variability. The sampling points were individually checked and used as input data for the confusion matrices and to estimate accuracy levels of the three burned area products.

3. Results

3.1. Optimal period of burn scar mapping

The fire hotspot data analysis provided by INPE (http://www.inpe.br/queimadas/bdqueimadas) indicates that most of the fire events in the Cerrado biome occurred between May and December, showing a peak in September 2017 (Fig. 4). Based on it, we focused our mapping analysis of burn scars on the period between May and December, which comprised 98% of fire hotspots detected in 2017 by INPE.

3.2. Burned areas in 2017

The individual images acquired between May and December 2017 were automatically classified using our previously described methodological approach that uses Landsat-8 imagery. The resulting maps were

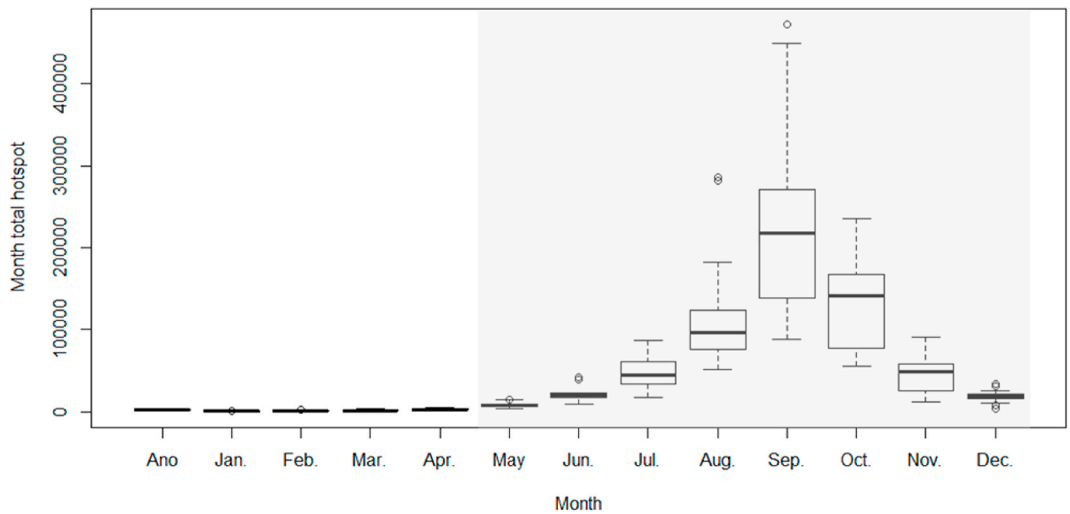

Fig. 4. Seasonal pattern of fire events occurred within the Cerrado biome in 2017 available on the fire hotspot dataset provided by the INPE platform. In each box, the central mark is the median, the edges of the boxplot are the 25th and 75th percentiles and the whiskers delimitate the extreme values (maximum and minimum). Black circles represent outliers (values outside the limits defined by the whiskers). The gray area represents the study period (May to December).

aggregated in a final map including all of the burned areas detected within the Cerrado biome (Fig. 5), a total of 202,230 km^2 burn scars, which corresponds to 10% of the entire biome (approximately 2 million square kilometers) in 2017. The final map of burned areas was overlapped with land use and land cover map provided by MapBiomas (2020) to identify classes of land use and land cover affected by fire in 2017.

We observed that burned areas may occur throughout the study region with some burned clusters spatially located in the west and south of the Cerrado biome. Tocantins was the most affected State by fires in the study region, immediately followed by the states of Mato Grosso and Maranhão (Supplementary Materials—Table S1). We also observed that 39% and 10% of the indigenous lands and protected areas, respectively, were burned in 2017 (Fig. 5). Furthermore, we estimated that 31% and 67% of the total burned area was in farming lands and various types of native vegetation, respectively (Supplementary Materials— Fig. S2). Prescribed fires are commonly used as an alternative to farming and land management in the study region and they eventually propagate into the native Cerrado vegetation (Miranda et al., 2010).

3.3. Concordance assessment/validation

Comparing our mapping results with the INPE burn scars and MODIS Burned Area (MCD64A1) resulted in a spatial map of agreement (Fig. 6 and Fig. 7). We estimated 34% of agreement between our mapping product and the MODIS (MCD64A1) product.

Most of the agreements between our mapping approach to detect burned areas and MCD64A1 product were observed in the north and western part of the Cerrado biome. The major mapping disagreements between these burned areas products were observed in the southern part of the study area. It is likely that the coarse spatial resolution of the MDC64A1 product did not allow it to detect small-burned scars in the southern study region (Rodrigues et al., 2019), which indicates that our methodological approach is an important matter for mapping fires in the Cerrado biome. The total burned area (202,230 km^2) detected in 2017 using our methodological approach was 57% higher than the total burned areas detected using the MDC64A1 product (128,945 km^2) in the Cerrado biome.

The total burned areas detected (202,230 km^2) using our proposed alternative methodological approach was 115% greater than the total of burned areas detected by the INPE product (93,868 km^2). This indicates a low agreement (34%) between those two products, given that 58% was detected only by our product and 8% by the INPE product only. Overall, we were able to detect more burned areas (fires greater than 0,1 ha) than the MCD64A1 and INPE products using our mapping approach, likely due to the higher spatial resolution provided by the Landsat imagery compared to those used to generate the MODIS (fires greater than 25 ha) and INPE products.

Since mapping accuracy may vary significantly in space, we assessed accuracies of the three mapping products using a set of 2,200 sample validation points. We estimated overall accuracies of 97%, 95%, and 94% for our mapping product, MCD64A1 product, and INPE burn scar product, respectively (Tables 1–3).

We observed that omission errors were high for all products (24.5%, 22.5%, and 29.9% for our mapping approach, MCD64A1, and INPE's product, respectively) to map burned areas (Tables 1–3). All products tested in this analysis showed low omission errors (lower than 3.8%) to detect unburned areas. However, our methodological approach showed the lowest commission errors for mapping both burned and unburned areas (3.2% and 1.5%, respectively) while the MCD64A1 and INPE's product showed 34.5% and 38%, respectively, of commission errors to detect burned areas. It indicates that our approach was more conservative and accurate to detect burned scars in the Cerrado biome.

The results of the automatic/visual comparison indicate a good overall accuracy of the algorithm, which includes omission and commission errors smaller than 20% by considering those 40 comparison areas as a whole. The highest omission errors have been observed when the burned areas have low contrast with the unburned background, sometimes related to the burned signal disappearance considering the low temporal effective resolution as a consequence of the platform and clouds, and some errors identified as omissions that are related to dating issues (areas detected, but later than the validation period considered). As for commission errors, the most critical classification error was observed in croplands. This land cover type includes a variety of cropping types and planting times, where farmers may adopt prescribed fires as an alternative of land management, which makes difficult to discriminate burned and unburned areas using automatic classification.

4. Discussion

The study intended to develop an alternative approach to detect burned areas in the Brazilian Savanna (Cerrado biome). Our proposed approach was based on a semi-automated technique, medium spatial resolution remotely sensed data, and deep learning algorithm

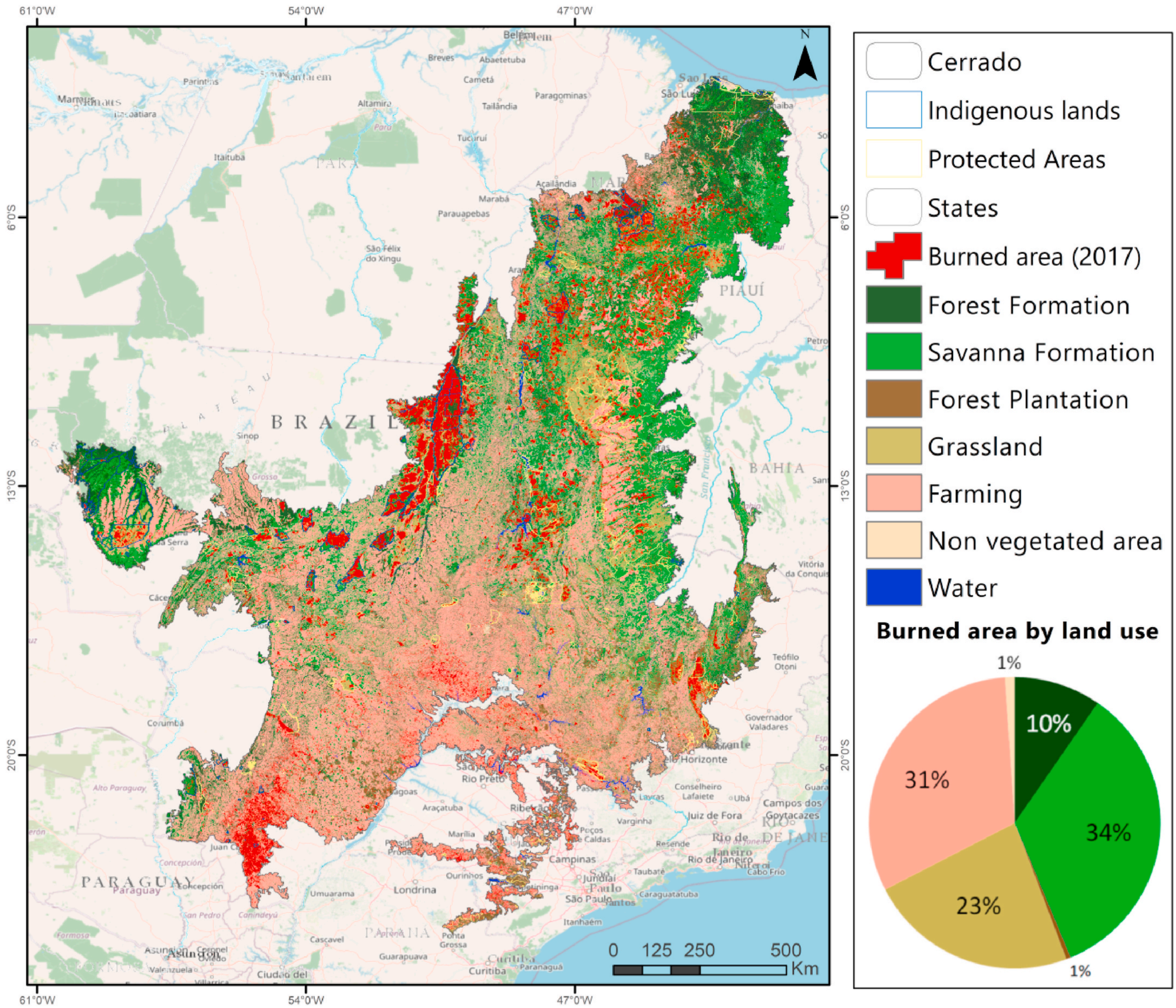

Fig. 5. Spatial distribution of burned areas in 2017 within the Cerrado biome overlapped with land use and land cover classes mapped by the MapBiomas project, collection 4.1.

implemented on the Google Cloud Platform. Also, the Google Earth Engine (GEE) platform was used to implement our study by providing Landsat-8 imagery and access to acquire training samples and geospatial analyses.

It took 7 hours of computing processing to achieve our final burn scar map for the Cerrado biome in 2017 with 97% of overall accuracy. The total of burned areas mapped (202,230 km^2) in the study area in 2017 corroborates the fact that the fire phenomenon is strongly present in Brazilian Cerrado.

We observed that by using Landsat imagery as input data in our mapping approach can contribute to improve those long-term temporal series of burned areas in tropical regions, based on free access remotely sensed datasets available on the GEE platform. However, the number of valid observations is a limiting factor for detecting areas impacted by fire, since Landsat temporal resolution is relatively low (16 days), and vegetation recovery after fire events may create temporal data gaps and decrease accuracy of mapping fire scars. We also observed that omission errors for mapping fire scars in savannas may occur due to the rapid vegetation recovery following fire events. It might be a possible reason of those burned areas detected by the MCD64A1 product using MODIS daily images that were not detected using our classification approach based on Lansdat imagery of 16-days temporal resolution. Some differences observed along the edges of burn scars detected by the MCD64A1 product are due to its spatial resolutions (Pereira et al., 2017).

The INPE and MCD64A1 products are based on different sensor methodologies than applied in our mapping approach, which may explain the lower agreement among those products. The MCD64A1 product uses active fire as auxiliary data to make cumulative maps that are used in the collection of burned and unburned samples applied in a hybrid algorithm with dynamic thresholds generated from the NBR2 (Normalized Burn Ratio) spectral index and a measure of temporal and spatial texture (Giglio et al., 2016). A previous study concluded that uncertainties in Burned Area using MCD64A1 in the Cerrado are most significant over the southern portion, possibly due to land-use dynamics associated with pasture and croplands that use fire for land clearing and crop residue burning (Rodrigues et al., 2019).

The second comparison data (the INPE product) is based on differences in NBR of consecutive scenes, which may explain some omission

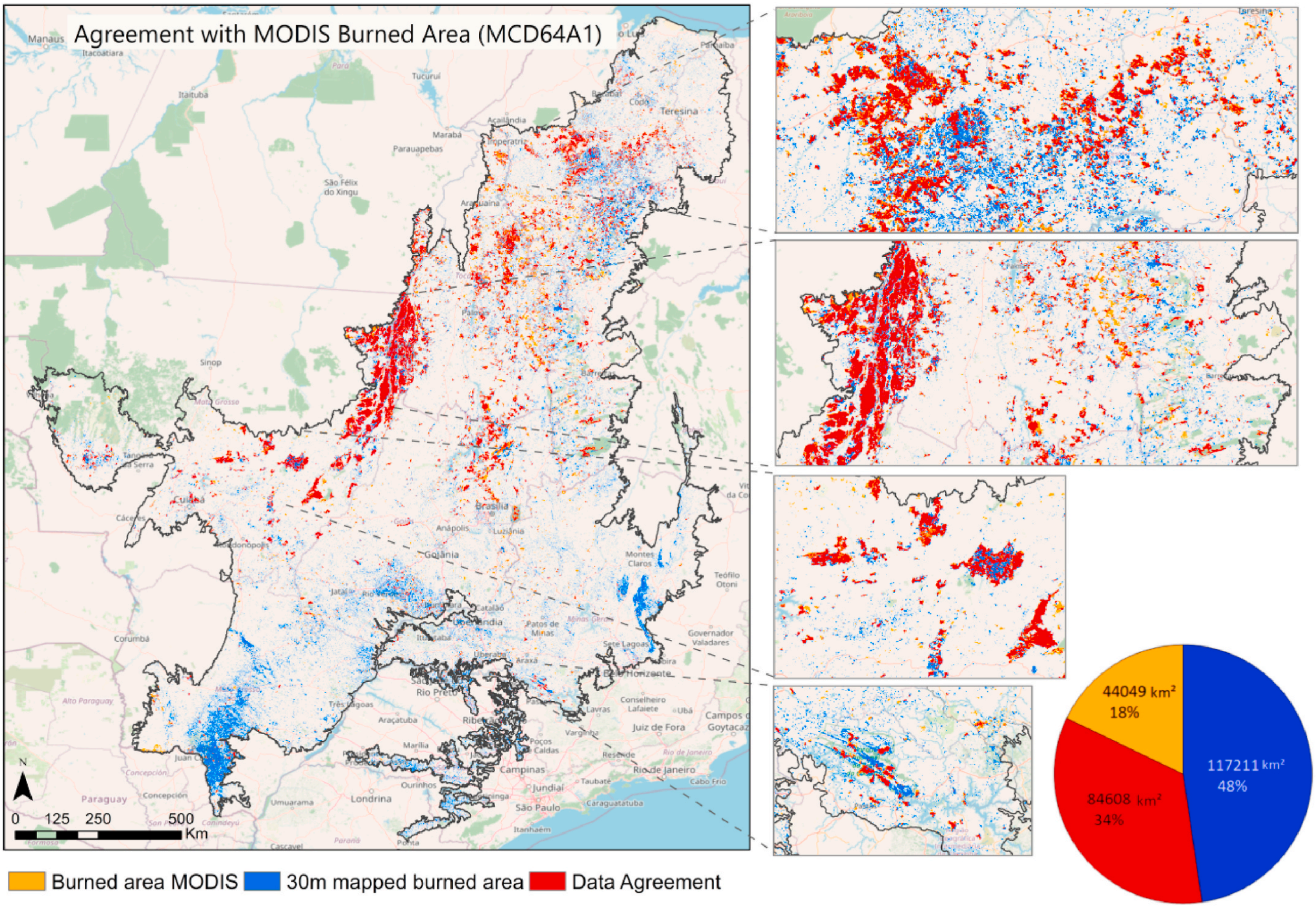

Fig. 6. Spatial distribution of burned areas mapped in this analysis and those burned areas mapped using the MCD64A1 product, used as comparison data in this analysis. Orange represents burned areas detected by MCD64A1; blue indicates burned areas detected by the alternative methodological approach proposed in this study; and red represents the burned areas detected by both mapping products (agreement between orange and blue). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

errors in detecting burned areas because of Landsat data gaps due to cloud contamination. Also, cropping lands may be a source of classification error in the INPE product because of shades and several cropping types and time observed in the study region (Melchiori et al., 2014).

Fire events are geographically small and uncommon on Landsat imagery, which makes finding a dataset for mapping validation even more challenging (Goodwin and Collett, 2014). Nevertheless, we achieved a high overall accuracy (97%) in mapping burn scars in the entire Cerrado biome in 2017 using our semi-automated approach. We believe that our methodological approach can be broadly applied to map burned areas in tropical regions since we achieved high accuracy in a very diverse landscape and extensive region as the Cerrado biome in Brazil. However, we would recommend proceeding some adjustments in our algorithm before applying it for multitemporal analysis and other regions.

5. Conclusions

Our alternative approach, based on a semi-automated technique, remotely sensed data, and deep learning algorithm available on Google Cloud Storage and Computing, allowed us to map burn scars in the Cerrado biome in Brazil with high overall accuracy (97%). We achieved these results because of the geometrically corrected and preprocessed Landsat data available on Google Earth Engine Platform and the capacity of Deep Learning techniques to differentiate spectral signatures of burned and unburned areas in the study area.

The high accuracy achieved by our mapping approach demonstrates that deep learning algorithms can be successfully applied to the remote sensing field using large remote sensing datasets and extensions, requiring low time and labor demand. Our proposed mapping approach created new perspectives on fire scar detection by producing a technique that is accurate, promising, and replicable to other regions.

We detected a total of 202,230 km^2 in the study area in 2017 throughout the study area with some burned clusters in the west and south of the Cerrado biome. We estimated that 31% and 67% of the total burned area occurred in farming lands and various types of native vegetation, respectively. In our analysis, most burn scars were detected between August and November 2017.

Our mapping approach shows high potential for constructing long time data series of areas affected by fires in tropical regions. A long time series of burned areas can be useful to estimate carbon emissions, environmental impacts, analyze interactions between climate and ecological drivers of fire, and develop predictive models of fire risk dynamics, thus providing spatial information that can aid public policies and fire management/prevention actions for Cerrado conservation.

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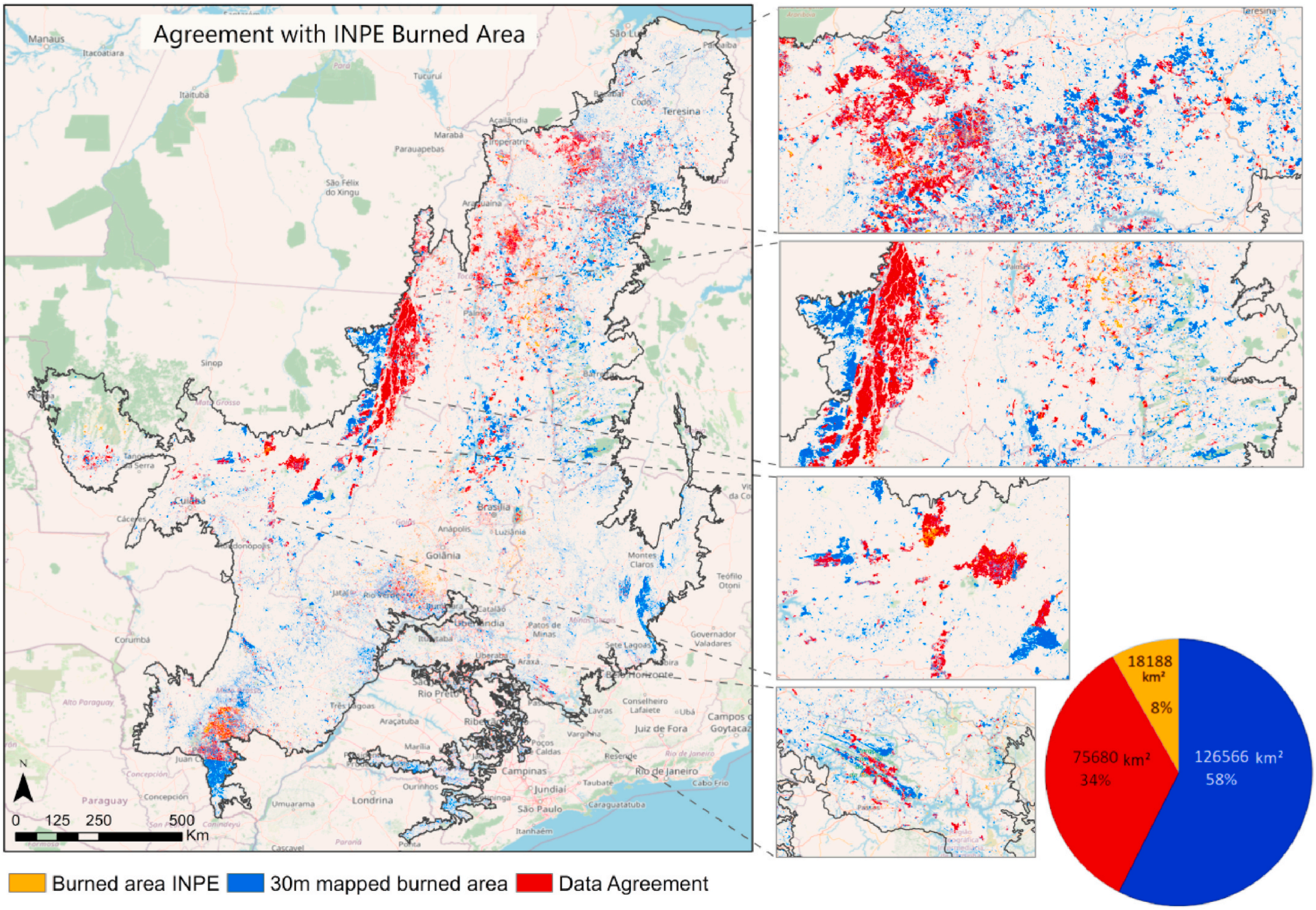

Fig. 7. Spatial distribution of burned areas mapped in this analysis and those burned areas mapped by INPE product used as comparison data in this analysis. Orange represents burned areas detected by INPE; blue represents burned areas detected using the alternative methodological approach proposed in this study; and red represents the agreement between both mapping products (intersected areas of orange and blue colors). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Confusion matrix between reference (sample points) and estimated burned area (30m burn scar mapped in this study).

Estimated (30m burned scar mapped in this study)	Reference			User's accuracy	Total accuracy
	Burned	Nonburned	Total		
Burned	197	3	200	98.5%	
Nonburned	64	1936	2000	96.8%	
Total	261	1939	2200		
Producer's accuracy	75.5%	99.8%			
Total accuracy					97.0%

Table 2
Confusion matrix between reference (sample points) and estimated burned area (MODIS Burned Area MCD64A1).

Estimated (MODIS MDC64A1)	Reference			User's accuracy	Total accuracy
	Burned	Nonburned	Total		
Burned	131	69	200	65.5%	
Nonburned	38	1962	2000	98.1%	
Total	169	2031	2200		
Producer's accuracy	77.5%	96.6%			
Total accuracy					95.1%

Table 3
Confusion matrix between reference (sample points) and estimated burned area (INPE burn scar).

Estimated (INPE)	Reference			User's accuracy	Total accuracy
	Burned	Nonburned	Total		
Burned	124	76	200	62.0%	
Nonburned	53	1947	2000	97.4%	
Total	177	2023	2200		
Producer's accuracy	70.1%	96.2%			
Total accuracy					94.1%

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CRediT authorship contribution statement

Vera L.S. Arruda: Conceptualization, Methodology, Software, Validation, Writing - original draft, Writing - review & editing. **Valderli J. Piontekowski:** Conceptualization, Methodology, Software, Data curation, Visualization, Investigation. **Ane Alencar:** Conceptualization, Methodology, Validation, Writing - original draft, Writing - review &

editing. **Reginaldo S. Pereira:** Writing - original draft, Writing - review & editing. **Eraldo A.T. Matricardi:** Conceptualization, Validation, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2021.100472.

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