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Near Real-Time Fire Detection and Monitoring in the MATOPIBA Region, Brazil

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Abstract: MATOPIBA is an agricultural frontier, where fires are essential for its biodiversity maintenance. However, the increase in its recurrence and intensity, as well as accidental fires can lead to socioeconomic and environmental losses. Due to this dual relationship with fire, near real-time (NRT) fire management is required throughout the region. In this context, we developed, to the best of our knowledge, the first Machine Learning (ML) algorithm based on the GOES-16 ABI sensor able to detect and monitor Active Fires (AF) in NRT in MATOPIBA. To do so, we analyzed the best combination of three ML algorithms and how long it takes to consider a historical time series able to support accurate AF predictions. We used the most accurate combination for the final model (FM) development. The results show that the FM ensures an overall accuracy rate of approximately 80%. The FM potential is remarkable not only for single detections but also for a consecutive sequence of positive predictions. Roughly, the FM achieves an accuracy rate peak after around 20 h of consecutive AF detections, but there is an important trade-off between the accuracy and the time required to assemble more fire indications, which can be decisive for firefighters in real life.

Keywords: active fires; wildfires; time series analysis; machine learning; geotechnologies

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1. Introduction

Fire incidence has the potential to consume and modify large areas of vegetation [1], decrease the surface-to-atmosphere water transfer, increase surface warming [2] and release aerosol and gases that contribute to global climate change [3,4]. In Brazil, fires are also an important source of air pollution with harmful health consequences [5]. It has become a burden for the public health system [6,7], owing to an increase in respiratory diseases during the fire season [8], a period of the year when fires are most likely to occur [9], which takes place mainly during the transition from the dry to wet season.

A staggering number of fires in 2019 and 2020 in different Brazilian biomes revealed the national fire management unpreparedness [9], especially in August, 2019, when fires reached a turning point that was widely covered by the media around the world [10,11]. Different from the Brazilian Amazon and Pantanal biomes, fires in the brazilian tropical savanna, known as Cerrado, can be associated with both human land-use activities and natural drivers [12,13]. It is the easiest and cheapest way to boost fresh grass growth for cattle ranching, as well as to open new agricultural areas [14–16]. At the same time, natural fire ignitions can be caused by lightning [12], making Cerrado an adapted environment for fires. Without this phenomenon, the region would be dominated by grasses, and over time, forest encroachment could cause a biodiversity loss [17]. While human-induced fires are frequent and intense, impacting the biodiversity and aboveground biomass, natural fires are usually rapid, have low intensity and do not spread over large areas. In addition, natural fires occur every 3–6 years, maintaining the regional biodiversity and ecological processes [9]. Thus, Cerrado presents a singular dual relationship with fire: its incidence is necessary for biodiversity preservation [13,18], but the increase in its recurrence and intensity, as well as accidental fires, has the potential to cause negative social, economic and environmental impacts [16,19].

Even though Cerrado is a global biodiversity hotspot, nearly half of its original vegetation has already disappeared, mainly due to advancing agricultural frontiers [20]. Brazil's most recent agricultural frontier is located in northern Cerrado, in a region known as MATOPIBA (an acronym for its location over: Maranhão, Tocantins, Piauí and Bahia states) [21]. Comprehending around 38% of the Cerrado biome, MATOPIBA has experienced almost half of Cerrado's deforestation [22]. Although MATOPIBA is mainly located in Cerrado, it also embraces a small portion of Amazonia and Caatinga biomes, covering an area of approximately 730,000 km^2, which is two times larger than Germany. MATOPIBA presents, at the same time, the largest undisturbed remnants of Cerrado vegetation and a quarter of the Cerrado soybean area [21,23], equally important for environmental and economic issues, respectively. Nonetheless, over the last decade, the combination of climate change and land-use change has severely increased drought conditions in the region, which contribute to a higher fire risk, mainly during the fire season [24], and jeopardize biodiversity and food security.

Given that fire has a dual-character in Cerrado and that it is considered a highly dynamic phenomenon, the use of near real-time (NRT) remote sensing datasets available from geostationary satellites has provided promising results for fire management in this biome [25]. Even though such datasets usually present a trade-off between spatial and temporal resolutions [26], the Advanced Baseline Imager (ABI) onboard the new generation of Geostationary Operational Environmental Satellite-R (GOES-R) Series was designed to overcome it by improving spatial, temporal and radiometric characteristics of the previous GOES Imager [27,28].

Due to the data deluge, high velocity production and Earth surface target diversity [29], the ABI dataset can also be considered big data. While it presents a vast amount of unexplored information, its access, process, and comprehension become impossible by means of traditional methods that rely on hand-made procedures. To overcome this challenge, scientists (from NASA/FIRMS portal [30] and INPE/Fire Monitoring Program [31]) have been developing algorithms and Machine Learning (ML) models using different remote sensing data for fire detection and monitoring, and releasing the results to support fire management.

The Moderate Resolution Imaging Spectroradiometer (MODIS) [32] and the Visible Infrared Imaging Radiometer Suite (VIIRS) [33] present well-designed and already established fire products. Nonetheless, MODIS' temporal resolution, when considering both Aqua and Terra satellites, is four times a day, whereas VIIRS is only twice a day. Even when MODIS and VIIRS data are used together, it does not provide an NRT dataset.

Therefore, to ensure Brazilian biodiversity by means of fire management, we developed, to the best of our knowledge, the first ML algorithm (hereafter, Final Model—FM) able to detect Active Fires (AF) in NRT in MATOPIBA. FM uses GOES-16 ABI imagery and is focused on the Land Use and Land Cover (LULC) of Natural Formation, which is composed of Natural Forest, Savanna Formation, and Grasslands. For the FM development, we first analyzed the performance of three ML algorithms and established how much historical data (expressed in days, hereafter called lag) from before a fire event the FM is required to make accurate AF classifications. Then, the most accurate algorithm and lag were selected for the FM development. In this process, we used MODIS and VIIRS AF products for comparison as reference satellites and filtering purposes and manually mapped BA on Sentinel-2 imagery. This procedure was required in order to have access to the most reliable fire data possible. In addition, its finer spatial resolution data are commonly used for validation processes from coarser-resolution satellites [34].

The novelty of this study is mainly regarding the development of FM and the use of an ultrahigh temporal resolution dataset. In addition, it also complements the literature by comparing ML models for AF detection and monitoring and the comprehension of how much historical data are required to train an ML model to accurately classify AF.

This work aims to: (i) support daily activities of fire monitoring; (ii) understand the FM potential and variables that influence its performance, (iii) characterize MATOPIBA fires based on the FM. Hence, we took the following questions into account:

- What is the overall performance of the FM? Does LULC play an important role in the FM accuracy?
- Does the size of the burned area (BA) influence the FM accuracy? Is the FM influenced by BA found in the surroundings of a central ABI pixel grid?
- What is the FM potential considering a sequence of positive fire indications? What is its agreement with the MODIS and VIIRS datasets?
- Assuming that we have a certain number of consecutive AF detections from the FM, what is the fire reality in the remaining data over MATOPIBA?

2. Data

The dataset used in this paper (described next) is composed of AF products from the reference satellites (MODIS and VIIRS), GOES-16 ABI (Band 7) and the Sentinel-2 (Bands 4, 8A and 12) imagery, and Mapbiomas LULC mapping (Figure 1).

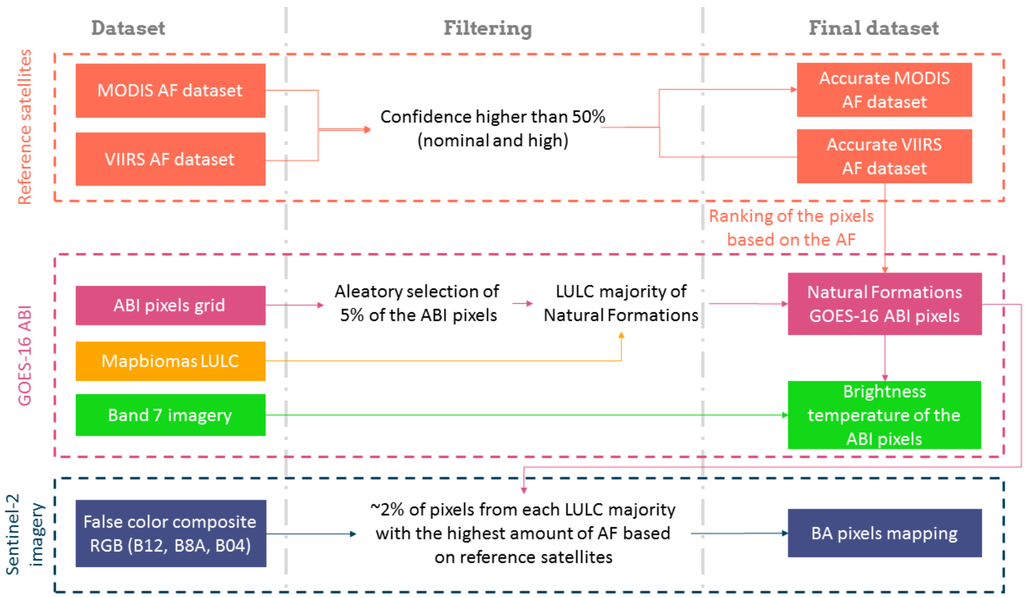

Figure 1. Dataset used and the filtering process of the data. AF: Active Fire; LULC: Land Use and Land Cover.

2.1. Reference Satellites: MODIS and VIIRS Active Fire Data

Remote sensing data have been widely applied to identify AF and to develop fire products for different spatial scales [35,36] that are used by fire monitoring initiatives. Among the products, MODIS and VIIRS are the most prominent and are considered references.

Onboard NASA's Terra and Aqua satellites, the MODIS sensor has provided global fire data for more than a decade. MODIS is already working with Collection 6, which aims to address Collection 5 limitations such as false AF detections. With 1-km spatial resolution, Collection 6 is driven mainly by regional differences and fire sizes.

VIIRS is onboard two different satellites, the Suomi National Polar-orbiting Partnership (S-NPP) and NOAA-20. Its AF products were designed based on the previous MODIS Fire

Thermal Anomalies algorithm in order to support data continuity [37]. VIIRS, with a 375 m spatial resolution, has already been validated by different studies proving to be superior in detecting small AF when compared with MODIS [33,38,39].

The AF datasets, MODIS and VIIRS, were acquired from the Fire Information for Resource Management System (available at https://firms2.modaps.eosdis.nasa.gov/, accessed on 20 November 2020) for August 2019 and filtered for our study area and confidence level, higher than 50% for MODIS, and nominal and high confidence for VIIRS because false alarms are particularly undesirable. The data were used both to indicate the most representative burned ABI Band 7 pixels in order to train the FM model and to assess the FM performance.

2.2. GOES-16 ABI Imagery

GOES-16, launched in November 2016, is the first satellite from the GOES-R Series and is operated by NOAA (National Oceanic and Atmospheric Administration). The ABI sensor, on-board GOES-16, has 16 spectral bands, presenting a nominal spatial resolution of 2 km at nadir, and a full disk image every 10 min over North and South Americas [28,40], which means 144 daily remote sensing imagery acquisitions (≈8 GB).

Among the spectral bands, the ABI Band 7 (3.90 µm) is the most recommended for AF detection because this short wavelength is more sensitive to the hottest part of a pixel [41]. Nonetheless, two of the main limitations of such dataset are that: (i) small fires can be overlooked; and (ii) solar reflectance can influence the ABI Band 7 values [41]. Figure 2 shows an example of the ABI Band 7 on a given day with and without the presence of fire, based on the reference satellites and on the manually mapped BA.

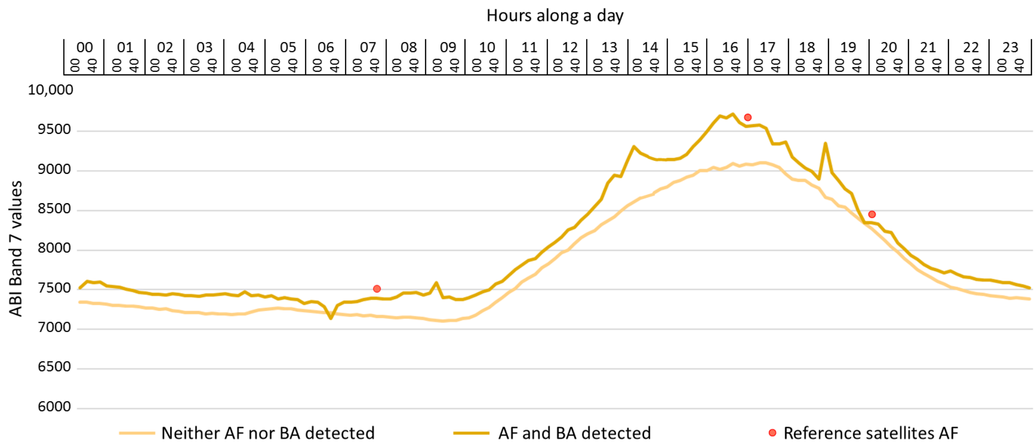

Figure 2. ABI Band 7 values for 2 different pixel locations on a given day with and without the detection of AF and BA. AF: Active Fire; BA: Burned Area.

In this paper, we used the Band 7 imagery ABI pixel grid and brightness temperature for the whole month of August 2019, over MATOPIBA (≈240 GB). Due to such big data, firstly, we randomly selected 5% of the ABI pixel grid to work with. Afterward, we used the 2019 Brazilian Annual LULC Mapping Project (MapBiomas), 4th collection (available at https://mapbiomas.org/, accessed on 10 October 2020), to filter the random grid only for those with a majority of LULC natural formations once it presented the most expressive number of AF throughout August 2019. In addition, the Natural Formation also composes the most representative LULC with 70% of MATOPIBA territory: 16% Natural Forest (NF), 43% Savanna Formation (SF), and 11% Grasslands (Gr). For the selected areas, we extracted brightness temperature from Band 7 imagery for the whole month of August 2019.

2.3. Sentinel-2 Imagery

Based on the reference satellites, we selected 2% of the ABI filtered pixel grid with the highest AF recurrence for the manual BA mapping. In addition, the pixels were equally distributed based on the three LULC natural formations in order to identify areas more prone to fire and, therefore, better support our ML training and modeling.

The BA mapping was performed considering both: (i) the inside of the central ABI pixel grid and (ii) the surroundings of the central pixel, as one of the assumptions of this study is that the presence of BA in the surrounding pixels may influence the brightness temperature of the ABI Band 7 central pixel.

For the BA mapping, we used Sentinel-2 imagery at Sentinel Hub viewer (available at: https://www.sentinel-hub.com/, accessed on 25 January 2022). We also used the false color composite shortwave infrared (SWIR), RGB (B12, B8A, B04), as it enables fire damage mapping [42]. An example of such a process is available in Figure 3.

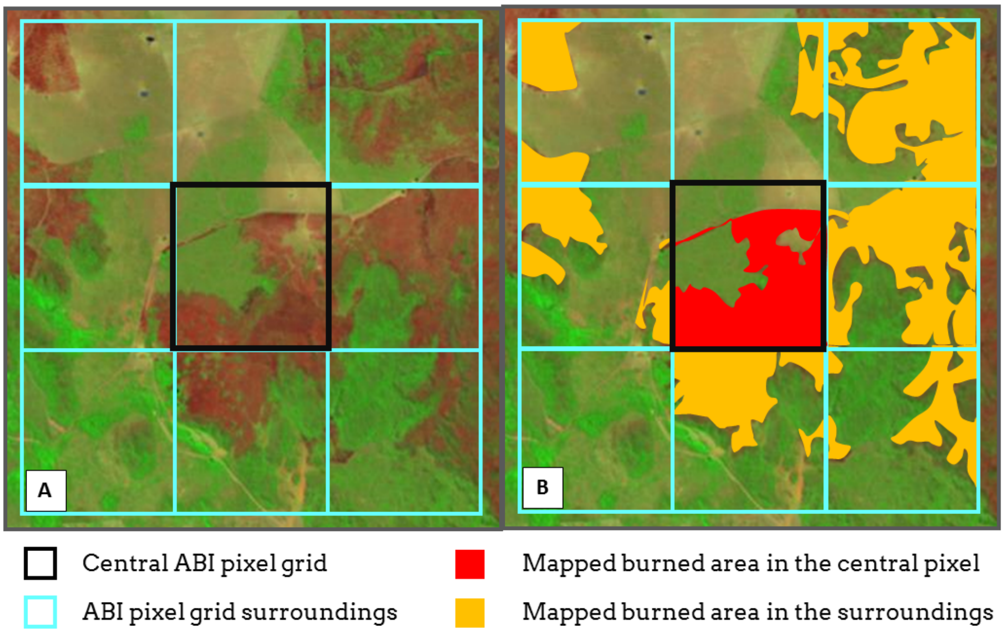

Figure 3. Example of burned area mapping in the central ABI pixel grid and surroundings based on Sentinel-2 imagery. RGB (B12, B8A, B04). (**A**) Remote sensing image without BA mapping. (**B**) Remote sensing image with BA mapping.

Even though Sentinel-2 data does not provide the exact time of a fire occurrence, it is one of the most suitable satellites since it presents a 10–20 m spatial resolution and a five-day revisit time. Due to the satellite temporal resolution, the BA mapping was quantified by the ABI pixel grid and by date and only in cloud and cloud shadow-free areas. The use of such data allowed us to design the FM in a way that it could detect AF, whose impact can be seen on Sentinel-2 imagery by means of burned areas.

3. Methods

The methods were divided into three main sections: data split, data processing and experiments, and FM development (Figure 4).

3.1. Data Split

For the ML processes, we used the areas with BA mapping, equally distributed among the three Natural Formation LULC, where 94 of the brightness temperature pixels were selected for the training (Figure 4(1a)), while 40 pixels were used for the test set (Figure 4(1b)). It was divided once each pixel presented more than 4000 GOES-16 passages due to its ultrahigh temporal resolution. The remaining data pixels (2291) were used for the final inference process (Figure 4(1c)).

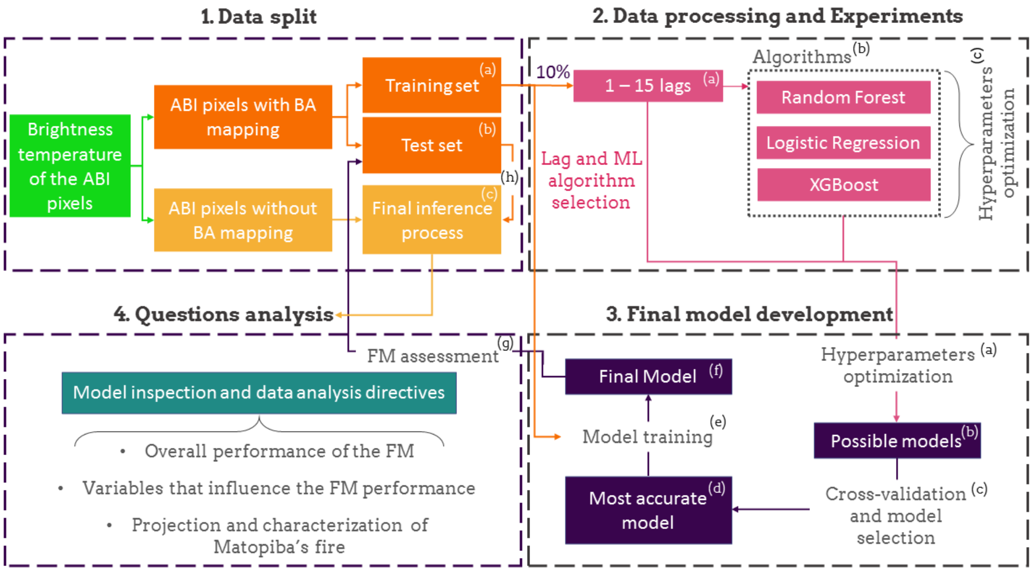

Figure 4. Methods divided into four main steps: data split, data processing and experiments, Final Model (FM) development and questions analysis. XGBoost: Extreme Gradient Boosting; ML: Machine Learning.

3.2. Data Processing and Experiments

The data processing workflow used in this study starts with the identification of how much historical data (lag) the FM requires before a fire event to make accurate AF classifications (Figure 4(2a)). To do so, we applied the data normalization known as standard score (z-score), which requires not only the last brightness temperature but also a historical time series, from which the last brightness temperature can be compared and analyzed, that is, how distant the last value is from the historical time series average. Based on an empirical analysis, the premise here is that the average pixel value is the absence of fire, positive values are related to fires, and negative values, to the presence of clouds. In this paper, the unit of the historical time series lag is a day, where 1 lag represents the last 144 ABI Band 7 passages, and 15 lags represents the last 2160 passages. It is important to highlight that the greater the amount of data, the more computational power is required.

Integrated with the lag analysis, we also conducted experiments with the three different ML algorithms, aiming to identify the most suitable combination for the FM development (Figure 4(2b)). The ML algorithms used in this work were: Random Forest (RF), Logistic Regression (LR) and Extreme Gradient Boosting (XGBoost). The three ML algorithms were selected based on their performance and literature recurrence as techniques for fire management and decision-making processes [43,44].

Because GOES-16 ABI presents such an ultrahigh temporal resolution dataset, for the FM analysis, there were two main hindrances: the necessity to (i) create an approach able to compare datasets with different temporal resolutions (GOES-16 ABI, MODIS/VIIRS and Sentinel-2); (ii) develop ways to support firefighters prioritization planning to maximise the efficiency of the response team. In this manner, for the FM performance assessment, we analyzed not only a single AF detection (naive) but also consecutive AF indications as well.

3.2.1. Algorithms and Hyperparameters Optimization

RF is a tree-based ensemble ML algorithm that combines tree predictors into a 'forest' [45], where the combination of the tree predictors can be used to predict, classify or cluster events. XGBoost is also a tree-based ensemble ML algorithm, but it continuously minimizes bias errors, aiming to produce a new optimized model [46,47].

Finally, LR is an analysis method recommended for binary outcomes, such as the presence or absence of fires. In addition, it also allows the explanatory power analysis of the independent variables (i.e., temperature brightness) on the response variable (i.e., fires) through the analysis of the regression coefficient estimates of those independent variables [48].

By using such ML algorithms, we aimed to develop a model trained by the historical time series in order to correctly identify AF by means of an NRT dataset.

For the experiments, we used 10% of the training set and created a z-score based on a historical time series of 1 to 15 lags. For each lag, we applied each ML algorithm. Due to the number of ML algorithm hyperparameters, we also developed and applied an optimization step for each model, with automatic hyperparameter adjustments running for at least three hours on the computer and with a minimum of 100 attempts per model (Figure 4(2c)). The possibilities of lag and algorithm combinations reached almost 10,000 models.

3.2.2. Lag and Machine Learning Algorithm Selection

Although in [49] RF models were more efficient than LR for forest fire probability mapping, in our study, XGBoost presented an even higher performance. RF and LR hardly achieved an accuracy of 60–70%, whereas XGBoost achieved an accuracy of 70–80% (Figure 5).

In XGBoost lag accuracy, lags 12 and 13 had the best results. Although lag 12 presented the greatest number of accurate models, 70–80%, we selected lag 13 as it presented more accurate models than those of lag 12—around 80%. In other words, using lag 13 means that for every new piece of ABI data, the spectral distance from the mean of the last 13 days is analyzed in standard deviation units in order to confirm if it is above or below the local pattern, where positive z-score values are generally related to fires and negative z-score values to clouds.

Once the algorithm XGBoost and lag 13 were selected, the FM was developed and applied to the whole dataset in order to answer the proposed questions.

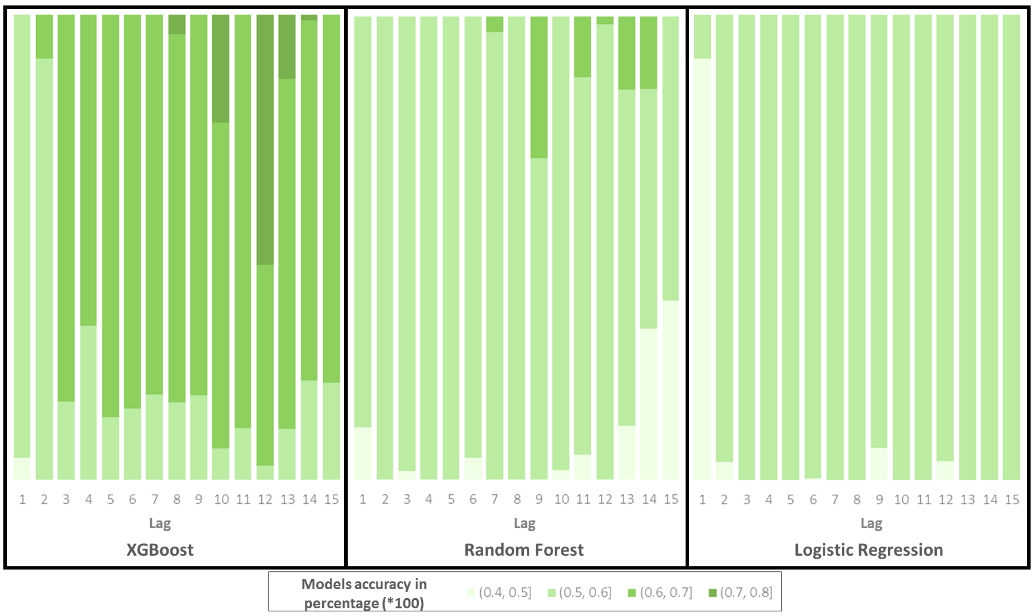

Figure 5. Lag comparison over 15 days and overall Machine Learning models performance.

3.3. Final Model Development and Assessment

For the FM, we aimed to optimize its hyperparameters until its saturation by means of 25% of the training data (Figure 4(3a)). This process generated about 2150 models (Figure 4(3b)). Afterward, 75% of the remaining training data and the test set were used to assess the models in a process known as cross-validation (Figure 4(3c)).

The most accurate model was then selected (Figure 4(3d)) and trained based on the training set (Figure 4(3e)), which resulted in the FM (Figure 4(3f)). We then assessed the FM with the test set (Figure 4(3g)) and applied it to the pixels without BA mapping for the inference process (Figure 4(3h)). Due to the temporal resolution difference of the GOES ABI dataset (10 min), reference satellites (12 h) and the BA mapping (5 days), we assessed the FM accuracy in the test set considering both: a single indication of AF and a certain sequence of AF. The consecutive AF indications mean a more persistent fire over time. For fire management, it is important to comprehend the presence of fire throughout the territory (single detection). Nonetheless, it is also essential to understand how persistent a fire is in order to direct efforts to where it is most needed (sequence of consecutive AF detection). In addition, it is vital to highlight that as a consequence of the used dataset, only fires whose BA impact can be seen on Sentinel-2 false color composition can be detected by the FM.

For both single and sequential AF detections, the analysis was conducted from 14 to 31 August 2019. As lag 13 was selected, the first 13 days of August were only used to compose the historical data required for the z-score. The accuracy analysis for the single detection process aimed to identify, based on the previous 13 days' z-score, if the brightness temperature found on the 14th day would present a fire or not. The same was performed for the consecutive AF detections; however, we considered a certain number of consecutive AF indications as a prediction.

Evaluating FM performance is a complex task because all of the data used have different temporal resolutions. In this manner, for the overall FM performance analysis by LULC and BA mapping, we only considered the dataset on the days with BA mapping. In addition, for the FM performance evaluation considering a consecutive sequence of AF indications, we analyzed the previous days of a BA mapping in order to identify the presence of AF indication from FM and the reference satellites.

4. Results

4.1. Overall Performance of the FM

The FM applied to the test set resulted in an accuracy rate of 78.9% (Table 1). In our analysis, the probability of an FM being right when it points out an AF detection is around 87%, and when it indicates a non-fire, around 70%.

In order to understand if LULC plays an important role in the FM performance, we also analyzed the FM for each LULC natural formation (Table 1). We observed that the percentage of fire prevalence among the classes varies up to 50%. Nonetheless, the overall accuracy rate ranged between 70% and almost 90%, which indicates that the FM performance is versatile among the three natural formations.

Furthermore, to explore the weaknesses and strengths in specific situations, it is important to take into account the rate of FM accuracy in detecting AF when there is fire (sensitivity) and not detecting AF when fire is absent (specificity). In this manner, it is possible to have greater clarity on the FM classifications interpretability and the required further improvements in the FM.

The FM performance in the different LULC can be grouped into two: (i) NF, with high sensitivity (more than 90%) and low specificity (58.9%); and (ii) SF and Gr, with low sensitivity (58% and 54%, respectively) and high specificity (72% and 77%, respectively). In NF, the FM has a tendency to identify practically all the AF activities; however, it can indicate more AF than there really are, whereas in SF and Gr, we have the opposite process. Even though the FM presents such specificities, its performance in any LULC presents an overall accuracy rate higher than 70%, which means that the FM classifications will be right in at least 70% of the cases.

Compared with NF and Gr, SF presents higher false positives ($\approx$11%). Such result could be related to (i) the high heterogeneity of the physiognomies presented in this natural formation that embraces areas with defined tree and shrub-herbaceous stratum, and (ii) the absence of BA on the Sentinel-2 imagery due to the fast grassland vegetation recovery. Finally, Gr presented the highest true negatives and the lowest false positive among the natural formations, probably due to the predominance of herbaceous-shrub species.

Table 1. Overall and Land Use and Land Cover (LULC) final model prediction assessment metrics. NF: Natural Forest; SF: Savanna Formation; Gr: Grassland; BA: Burned Area. True positives, false positives, false negatives and true negatives. Results in absolute numbers and percentage.

Metrics	Overall FM Assessment	FM Assessment by LULC NF	SF	Gr
True positives (real: fire, predicted: fire)	6607 (40.60%)	3906 (82.09%)	1691 (24.98%)	1010 (21.28%)
False negatives (real: fire, predicted: non-fire)	2468 (15.17%)	419 (08.81%)	1190 (17.58%)	859 (18.10%)
False positives (real: non-fire, predicted: fire)	971 (05.96%)	178 (03.74%)	763 (11.27%)	30 (00.63%)
True negatives (real: non-fire, predicted: non-fire)	6228 (38.27%)	255 (05.36%)	3125 (46.17%)	2848 (60.00%)
Fire prevalence on test data	55.8%	90.9%	42.6%	39.4%
Accuracy rate	78.9%	87.5%	71.1%	81.3%
Sensitivity	72.8%	90.3%	58.7%	54.0%
Specificity	86.5%	58.9%	80.4%	99.0%
Positive Predictive Value	87.2%	95.6%	68.9%	97.1%
Negative Predictive Value	71.6%	37.8%	72.4%	76.8%

4.2. FM Performance Regarding Burned Areas Mapping

The size of the BA does not influence the FM accuracy (Table 2a). Actually, smaller BAs (0.01–0.1 km^2) presented about 10% higher true positives than those of bigger BAs (>1.0 km^2), which can be explained by the following reasons: (i) most of the BA data are smaller than 1.0 km^2, and as a consequence, there is a great number of representative samples of smaller BA proportions within the pixels to train the models; (ii) fires of different proportions may present different z-score patterns, and due to the great number of small BA samples (<1.0 km^2), the FM is probably more focused on this dimension of fire. In other words, the FM can be more accurate at predicting AF at the beginning of the fire phenomenon; (iii) larger BAs (>1.0 km^2) can be generated by means of fire of small proportions burning for a longer period of time, which would not necessarily sensitize the FM.

Table 2b shows that when there is a larger BA mapping in the surroundings (>1.0 km^2), the FM result presents a higher false negative in the central pixel. In addition, BA mapping in the surroundings larger than 0.1 km^2 already negatively affects the true positive values in the central pixel.

Table 2. Final model prediction accuracy considering burned areas. F: Fire; NF: Non Fire.

(a)		FM Accuracy According to BA Mapping in the Central Pixel (km^2)							
		0–0.01		**0.01–0.1**		**0.1–1.0**		**>1.0**	
	Classification	**F**	**NF**	**F**	**NF**	**F**	**NF**	**F**	**NF**
BA Mapping	**F**	0.00%	0.00%	77.10%	22.90%	71.20%	28.80%	67.80%	32.20%
	NF	13.50%	86.50%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

(b)		FM Accuracy According to BA Mapping in the Sorroundings (km^2)							
		0–0.01		**0.01–0.1**		**0.1–1.0**		**>1.0**	
	Classification	**F**	**NF**	**F**	**NF**	**F**	**NF**	**F**	**NF**
BA Mapping	**F**	0.00%	4.00%	82.00%	10.00%	31.00%	13.00%	47.00%	28.00%
	NF	12.00%	84.00%	0.00%	8.00%	9.00%	47.00%	4.00%	21.00%

4.3. What Is the FM Potential When Considering a Consecutive Sequence of Positive Predictions?

Aiming to explore ABI temporal resolution of 10 min and to support firefighters in NRT detections, we analyzed the FM accuracy considering a single detection (naive) and a sequence of 15 and 125 consecutive AF detections (Figure 6). While the accuracy rate of the naive approach is 56.6%, 15 consecutive AF detections (after 2.5 h) is 67.3%, and 125 (after ≈20 h) achieves an accuracy peak of 73.4%. From then on, the increase in consecutive AF detections does not improve fire detection performance. Such a fact can also be associated with the low number of samples with more than 20 h of consecutive fire indications.

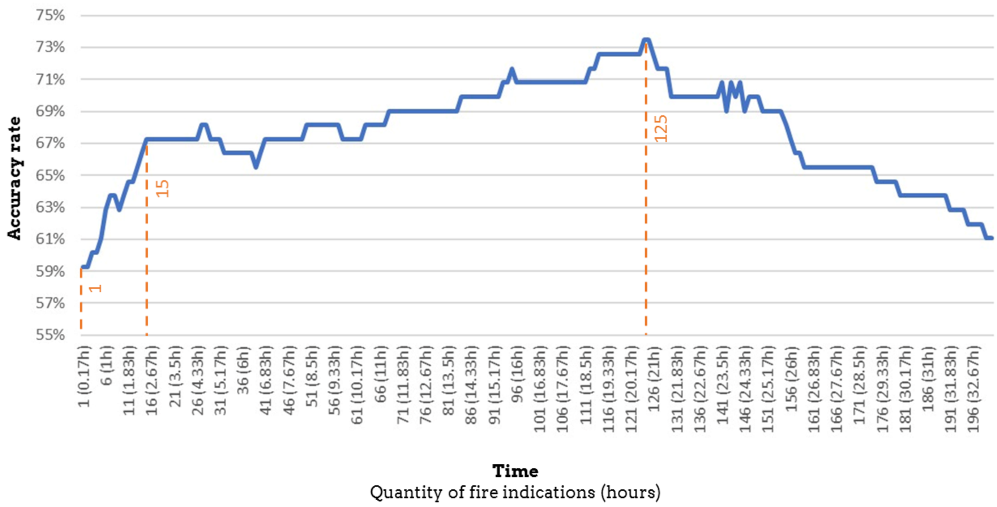

Figure 6. FM consecutive AF prediction assessment metrics.

Comparatively, the results show that with the increase in consecutive AF detections, there are slightly lower true positives, around 6%, but significantly higher true negatives, more than 20% (Table 3). Moreover, it also presents lower false positive cases, from ≈39% of the naive approach to ≈16% of the 125 consecutive AF. Roughly, until the 125 consecutive AF detections, more detections result in better overall accuracy metrics, but the time required to identify more fire indications can be decisive for firefighters in real life. Furthermore, fires with a shorter lifetime are more likely to be unseen when a longer consecutive AF detection approach is considered.

The accuracy rate of the reference satellites is almost 71% and roughly half of the fires are correctly detected. In addition, reference satellites rarely commit false positives, less than 3%, yet their true positives are lower than those of the FM. In comparison with the reference satellites, in the three presented approaches, FM has a higher sensitivity and a lower specificity. In addition, the 125 consecutive AF detection has a higher accuracy rate. However, it is noteworthy that due to our methodology, the reference satellites have an advantage, as the data were already filtered, and low confidence detections were removed.

According to the BA manual mapping, almost 50% of the 125 consecutive AF detections from the FM and the reference satellites are correct and in agreement, and almost 5% are incorrectly classified by both (Table 4). The main difference is regarding the errors. While the 125 consecutive AF detections approach sees more fires than there are (false positives is almost 16%), the reference satellites are more restrictive and point to fewer fires than there really are (false negative is 23%), probably due to the filtering process of high confidence AF from the reference satellites. In this context, the FM can be considered an important improvement over the reference satellites, not because it is more accurate, but because it presents a high agreement with traditional methods, not to mention its ultrahigh temporal resolution of 10 min, which could be integrated with the already consolidated reference data in order to provide NRT fire detection in the MATOPIBA region.

Table 3. Reference satellites (MODIS and VIIRS) and Final Model (FM) prediction assessment metrics by 1 (naive), 15 and 125 consecutive Active Fire (AF) detections. Results in absolute numbers and percentage.

Metrics	Reference Satellites	Consecutive AF Detection Naive	15	125
True positives (real: fire, predicted: fire)	32 (28.32%)	58 (51.33%)	56 (49.56%)	51 (45.13%)
False negatives (real: fire, predicted: non-fire)	30 (26.55%)	4 (3.54%)	6 (5.31%)	11 (9.73%)
False positives (real: non-fire, predicted: fire)	3 (2.65%)	45 (39.82%)	31 (27.43%)	19 (16.82%)
True negatives (real: non-fire, predicted: non-fire)	48 (42.48%)	6 (5.31%)	20 (17.70%)	32 (28.32%)
Fire prevalence on test data	55.76%	55.76%	55.76%	55.76%
Accuracy rate	70.80%	56.64%	67.26%	73.45%
Sensitivity	51.61%	93.55%	90.32%	82.26%
Specificity	94.12%	11.76%	39.22%	62.75%
Positive Predictive Value	91.43%	56.31%	64.37%	72.86%
Negative Predictive Value	61.54%	60.00%	76.92%	74.42%

Table 4. Agreement between the Final Model (FM) and the reference satellites (MODIS and VIIRS). True Positive (TP); True Negative (TN); False Positive (FP); False Negatives (FN).

		Reference Satellites			
		TP	**FN**	**FP**	**TN**
125 consecutive AF detections	**TP**	22.10%	23.00%	0.00%	0.00%
	FN	6.20%	3.50%	0.00%	0.00%
	FP	0.00%	0.00%	0.90%	15.90%
	TN	0.00%	0.00%	1.90%	26.50%

4.4. Fire Reality in the Remaining Data over MATOPIBA

We applied the FM consecutive AF detections to the remaining 5% of the dataset in MATOPIBA territory throughout August, 2019. Thus, the fire prediction varied according to the selected FM approach. If we considered the naive approach, we would have more than 26,000 AF. For the 5 consecutive AF detections, it would represent more than 4200, and for the 125 consecutive AF, 1042 detections (Figure 7).

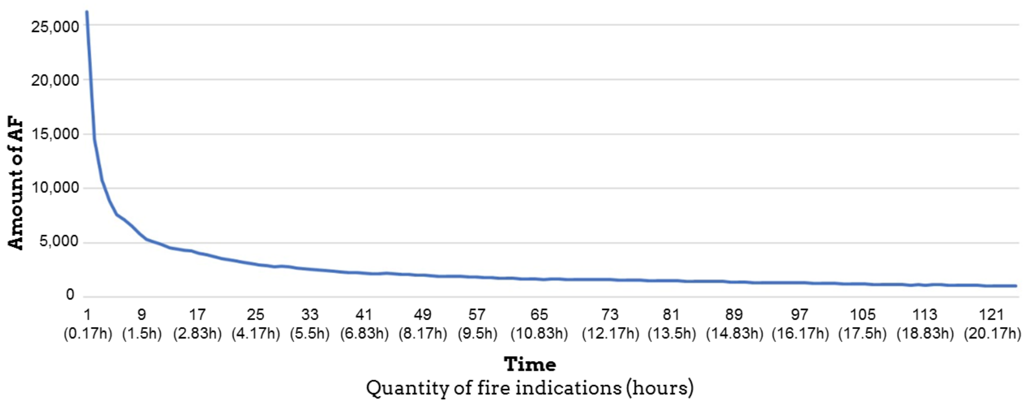

Figure 7. Number of active fires detected according to the number of consecutive AF indicated by the FM.

For the same area and time interval, according to the confusion matrix from the reference satellites, the total number of AF would reach 1209. Comparing the fire prediction based on the reference satellites and the 125 consecutive AF detections, the difference between the results was only 167 AF in more than 2400 of the analyzed pixels. Although fire characteristics (quantity, velocity and persistence) can be a hindrance when comparing AF of different sources and temporal resolutions, both aforementioned approaches presented similar results.

5. Discussion

As presented in Table 1, FM proved to be versatile among the three analyzed natural formations, NF, SF, and Gr, but with specificities in each one of them. Although the overall accuracy rate of FM is high, the FM single detection accuracy can be negatively influenced by BA greater than 1 km^2 in the central pixel and in its surroundings. Consequently, the greatest potential of this approach is when the fire is in its initial phase. In addition, considering that the fire intensity needs to be high enough to sensitize the ABI sensor, and the human-induced fires are frequent and intense [9], most of the FMs potential is also regarding this kind of fire.

Because fire is a dynamic phenomenon, NRT datasets are the most recommended for AF studies. However, ultrahigh temporal resolution data such as GOES-16 ABI is thus far poorly explored in this field. The authors of [50] proposed an approach based on object detection methods to map AF in the Brazilian Pantanal biome. For that, the authors used deep learning (a subset of ML-based on neural networks) and CBERS 4A (China Brazil Earth Resources Satellite) imagery. After extensive experiments and the generation of 150 models, the study achieved a high precision, more than 80%. Nonetheless, CBERS 4A presents a spatial resolution of 55 m and a five-day revisit time. A similar approach was also developed by [51], where deep learning techniques were used for active fire detection. The final model achieved a precision of more than 87%; however, the authors used the Landsat-8 imagery, with a revisit time of 16 days. Considering that different sensors present idiosyncrasies, we can also notice an opportunity to harmonize multi-sensors for AF studies.

Understanding fire behavior is essential for fire management. As resources are scarce, and proper allocation of firefighters is essential for firefighting success, a more refined AF detection and monitoring is imperative. Because of that, we developed the FM consecutive AF. It presented a higher accuracy, reaching its peak after around 20 h (125 consecutive AF). Even though there is an important trade-off between the consecutive AF and time, the 125 consecutive AF presented a number of true positives almost as accurate as those of the reference satellites. Therefore, incorporating the perception of consecutive AF detection, for instance, at INPE's Fire Monitoring Program, is vital for proper firefighting and management. Such an approach could provide not only a single AF detection but also a better comprehension of the NRT fire characteristics, including persistence and direction. Moreover, different AF sources could also be integrated to boost the confidence of one another.

In this study, the FM was developed based on the XGBoost ML model and also considering the z-score of the last 13 days. However, once it is implemented to support fire management, retraining the FM is recommended throughout the year due to the seasonal variability. Furthermore, since a pixel is the smallest unit of analysis, the FM could also be trained for other biomes. As such, not only MATOPIBA but also other areas could benefit from the FM predictions. Further studies are needed to improve the FM in order to reduce weaknesses, such as the false positives found in SF. Finally, the FM could also be improved by using a fire prediction confidence rate instead of the binary prediction (true or false). Additionally, the integration of the FM with other models, for instance, the integration of FM results with the fuel load dynamics and fire spread probability [52], could also better guide firefighters in allocating resources efficiently where they are most needed.

The combination of factors such as the removal of natural vegetation and the inadequate soil management by means of recurrent human-induced fires has already been proven to contribute to soil degradation in MATOPIBA [53]. Because of such impacts, different laws and initiatives have been developed in order to protect natural tropical biomes. In Brazil, the "Zero Fire" policy aimed to ban fires. However, the advance of science in the 1970s resulted in changes in fire management discussions, and from the 2000s on, it became more evident that such policy was inefficient in protecting fire-dependent biomes, including Cerrado [9]. Hence, other more updated strategies have been created, such as the Law for Protection of Native Vegetation (Law 12.651/2012) and the Brazilian Integrated Fire Management Policy Bill (PL 11.276), which include in their regulation the use of fire for ecological purposes.

Although some initiatives already exist, there is a lack of studies in areas with high fire frequency in Cerrado, as already indicated by [54], and little can be achieved without deeper knowledge about fire behavior in the region. Consequently, the NRT dataset and ML approaches, such as the FM, are crucial in supporting fire management.

MATOPIBA may lose approximately 120,000 km^2 of natural formations to anthropogenic uses before 2050 [53]. That being the case, fire management and new agricultural practices in MATOPIBA are fundamental not only to preserving local biodiversity but also to guaranteeing food security and avoiding its associated impacts on the national economy. However, contrary to what is needed, environmental management and research have suffered budget cuts by the Brazilian government in recent years [20].

To avoid further impacts, it is of utmost importance to have financial support for infrastructure as well as human resources for environmental monitoring and research development, where techniques with cutting-edge technology, such as the FM, can be developed and applied for better national fire management. While budgets are scarce, the integration among share- and stakeholders is inefficient, and public policies remain only on paper, and the fire phenomenon persists as an open issue in Brazil.

6. Conclusions

In this study, we developed FM, the first ML algorithm able to detect AF in NRT in the MATOPIBA region. In addition, FM can also be considered a major improvement over the reference satellites for a couple of reasons: the FM is versatile and can be used not only considering a single detection but also consecutive AF detections while retaining a high overall accuracy rate. Such process is able to support an expanded comprehension of fire behavior (e.g., duration and direction) and prioritize daily activities of firefighters. In regions so extensive as MATOPIBA and with low resources for environmental management, such prioritization is essential.

Although further advances and studies are required, FM and the reference satellites could even be integrated, providing an even more accurate AF detection and monitoring in the region; for instance, those fires that are already burning and were also detected by VIIRS/MODIS should have a priority.

Finally, because consistent fire policies are urged for Cerrado conservation [55], and objective regulations require a better comprehension of the fire scenario, FM can be an important tool for providing detailed information about the fire behavior in the region.

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References

1. Bond, W.J.; Woodward, F.I.; Midgley, G.F. The global distribution of ecosystems in a world without fire. *New Phytol.* **2005**, *165*, 525–538. [CrossRef] [PubMed]
2. Ivo, I.O.; Biudes, M.S.; Vourlitis, G.L.; Gomes, N.; Martim, C.C. Effect of fires on biophysical parameters, energy balance and evapotranspiration in a protected area in the Brazilian Cerrado. *Remote. Sens. Appl. Soc. Environ.* **2020**, *19*, 100342. [CrossRef]
3. Lashof, D. The contribution of biomass burning to global warming: An integrated assessment. In *Global Biomass Burning: Atmospheric, Climatic, and Biospheric Implications*; Levine, J., Ed.; Massachusetts Institute of Technology Press: Williamsburg, VA, USA, 1991; pp. 441–444.
4. Van der Werf, G.R.; Randerson, J.T.; Giglio, L.; Collatz, G.; Mu, M.; Kasibhatla, P.S.; Morton, D.C.; DeFries, R.; Jin, Y.V.; van Leeuwen, T.T. Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009). *Atmos. Chem. Phys.* **2010**, *10*, 11707–11735. [CrossRef]
5. Silva, P.R.D.S.; Ignotti, E.; de Oliveira, B.F.A.; Junger, W.L.; Morais, F.; Artaxo, P.; Hacon, S. High risk of respiratory diseases in children in the fire period in Western Amazon. *Rev. Saude Publica* **2016**, *50*, 1–11. [CrossRef]
6. Uriarte, M.; Yackulic, C.B.; Cooper, T.; Flynn, D.; Cortes, M.; Crk, T.; Cullman, G.; McGinty, M.; Sircely, J. Expansion of sugarcane production in São Paulo, Brazil: Implications for fire occurrence and respiratory health. *Agric. Ecosyst. Environ.* **2009**, *132*, 48–56. [CrossRef]
7. Aragão, L.E.O.C.; Silva Junior, C.H.L.; Anderson, L.O. *O Desafio do Brasil Para Conter o Desmatamento e as Queimadas na Amazônia Durante a Pandemia por COVID-19 em 2020: Implicações Ambientais, Sociais e sua Governança*; SEI/INPE: São José dos Campos, Brazil, 2020; Volume 1, p. 34. [CrossRef]
8. Machado-Silva, F.; Libonati, R.; de Lima, T.F.M.; Peixoto, R.B.; de Almeida França, J.R.; Magalhães, M.d.A.F.M.; Santos, F.L.M.; Rodrigues, J.A.; DaCamara, C.C. Drought and fires influence the respiratory diseases hospitalizations in the Amazon. *Ecol. Indic.* **2020**, *109*, 105817. [CrossRef]
9. Pivello, V.R.; Vieira, I.; Christianini, A.V.; Ribeiro, D.B.; da Silva Menezes, L.; Berlinck, C.N.; Melo, F.P.; Marengo, J.A.; Tornquist, C.G.; Tomas, W.M.; et al. Understanding Brazil's catastrophic fires: Causes, consequences and policy needed to prevent future tragedies. *Perspect. Ecol. Conserv.* **2021**, *19*, 233–255. [CrossRef]
10. Alencar, A.; Moutinho, P.; Arruda, V.; Silvério, D. The Amazon in Flames: Fire and Deforestation in 2019—And What's to Come in 2020. 2020. Available online: https://ipam.org.br/wp-content/uploads/2020/04/NT3-Fire-2019.pdf (accessed on 3 February 2022).
11. Bencherif, H.; Bègue, N.; Kirsch Pinheiro, D.; Du Preez, D.J.; Cadet, J.M.; da Silva Lopes, F.J.; Shikwambana, L.; Landulfo, E.; Vescovini, T.; Labuschagne, C.; et al. Investigating the Long-Range Transport of Aerosol Plumes Following the Amazon Fires (August 2019): A Multi-Instrumental Approach from Ground-Based and Satellite Observations. *Remote. Sens.* **2020**, *12*, 3846. [CrossRef]
12. Ramos-Neto, M.B.; Pivello, V.R. Lightning fires in a Brazilian savanna National Park: Rethinking management strategies. *Environ. Manag.* **2000**, *26*, 675–684. [CrossRef]
13. Fidelis, A. Is fire always the "bad guy"? *Flora* **2020**, *268*, 151611. [CrossRef]
14. Miranda, H.S.; Bustamante, M.M.; Miranda, A.C.; Oliveira, P.; Marquis, R. The fire factor. In *The Cerrados of Brazil: Ecology and Natural History of a Neotropical Savanna*; Columbia University Press: New York, NY, USA, 2002; pp. 51–68.
15. Klink, C.A.; Machado, R.B. A conservação do Cerrado brasileiro. *Megadiversidade* **2005**, *1*, 147–155.
16. Pivello, V.R. The use of fire in the Cerrado and Amazonian rainforests of Brazil: past and present. *Fire Ecol.* **2011**, *7*, 24–39. [CrossRef]
17. Abreu, R.C.; Hoffmann, W.A.; Vasconcelos, H.L.; Pilon, N.A.; Rossatto, D.R.; Durigan, G. The biodiversity cost of carbon sequestration in tropical savanna. *Sci. Adv.* **2017**, *3*, e1701284. [CrossRef]
18. Fidelis, A.; Alvarado, S.T.; Barradas, A.C.S.; Pivello, V.R. The Year 2017: Megafires and Management in the Cerrado. *Fire* **2018**, *1*, 49. [CrossRef]
19. Miranda, H.; Neto, W.; Neves, B. Caracterização das queimadas de Cerrado. In *Efeitos do Regime do Fogo Sobre a Estrutura de Comunidades de Cerrado: Resultados do Projeto Fogo*; Miranda, H.S., Ed.; IBAMA: Brasília, Brazil, 2010; pp. 23–33.
20. Schmidt, I.B.; Eloy, L. Fire regime in the Brazilian Savanna: Recent changes, policy and management. *Flora* **2020**, *268*, 151613. [CrossRef]

21. Miranda, E.E.; Magalhães, L.A.; Carvalho, C.A. Nota Técnica: Proposta de Delimitação Territorial do MATOPIBA. 2014. Available online: https://www.infoteca.cnptia.embrapa.br/infoteca/handle/doc/1037313 (accessed on 5 November 2021).
22. INPE, Instituto Nacional de Pesquisas Espaciais. TerraBrasilis, PRODES (Desmatamento). 2022. Available online: http://terrabrasilis.dpi.inpe.br/ (accessed on 22 February 2022).
23. Soterroni, A.C.; Ramos, F.M.; Mosnier, A.; Fargione, J.; Andrade, P.R.; Baumgarten, L.; Pirker, J.; Obersteiner, M.; Kraxner, F.; Câmara, G.; et al. Expanding the Soy Moratorium to Brazil's Cerrado. *Sci. Adv.* **2019**, *5*, eaav7336. [CrossRef]
24. Marengo, J.A.; Jimenez, J.C.; Espinoza, J.C.; Cunha, A.P.; Aragão, L.E. Increased Climate Pressure on the New Agricultural Frontier in the Eastern Amazonia-Cerrado Transition Zone. *Sci. Rep.* **2021**, *12*, 457. [CrossRef]
25. Pletsch, M.A.; Körting, T.S.; Morita, F.C.; Morelli, F.; Bittencourt, O.; Victorino, P.S. Using GOES-16 Time Series to characterize near real-time active fires in Cerrado. In Proceedings of the GEOINFO, São José dos Campos, Brazil, 12 November 2019; pp. 66–76.
26. Wooster, M.J.; Roberts, G.J.; Giglio, L.; Roy, D.P.; Freeborn, P.H.; Boschetti, L.; Justice, C.; Ichoku, C.; Schroeder, W.; Davies, D.; et al. Satellite remote sensing of active fires: History and current status, applications and future requirements. *Remote. Sens. Environ.* **2021**, *267*, 112694. [CrossRef]
27. Schmit, T.J.; Gunshor, M.M.; Menzel, W.P.; Gurka, J.J.; Li, J.; Bachmeier, A.S. Introducing the next-generation Advanced Baseline Imager on GOES-R. *Bull. Am. Meteorol. Soc.* **2005**, *86*, 1079–1096. [CrossRef]
28. Schmit, T.J.; Griffith, P.; Gunshor, M.M.; Daniels, J.M.; Goodman, S.J.; Lebair, W.J. A closer look at the ABI on the GOES-R series. *Bull. Am. Meteorol. Soc.* **2017**, *98*, 681–698. [CrossRef]
29. Laney, D. 3D data management: Controlling data volume, velocity and variety. *Meta Group Res. Note* **2001**, *6*, 1. [CrossRef]
30. NASA, National Aeronautics and Space Administration. FIRMS—Fire Information for Resource Management System. 2021. Available online: https://firms.modaps.eosdis.nasa.gov/ (accessed on 10 November 2021).
31. INPE, Instituto Nacional de Pesquisas Espaciais. Programa Queimadas. 2021. Available online: https://queimadas.dgi.inpe.br/queimadas/portal/ (accessed on 10 November 2021).
32. Giglio, L.; Schroeder, W.; Justice, C.O. The collection 6 MODIS active fire detection algorithm and fire products. *Remote. Sens. Environ.* **2016**, *178*, 31–41.
33. Schroeder, W.; Oliva, P.; Giglio, L.; Csiszar, I.A. The New VIIRS 375m active fire detection data product: Algorithm description and initial assessment. *Remote. Sens. Environ.* **2014**, *143*, 85–96. [CrossRef] [PubMed]
34. Li, F.; Zhang, X.; Kondragunta, S.; Schmidt, C.C.; Holmes, C.D. A preliminary evaluation of GOES-16 active fire product using Landsat-8 and VIIRS active fire data, and ground-based prescribed fire records. *Remote. Sens. Environ.* **2020**, *237*, 111600. [CrossRef]
35. Justice, C.; Giglio, L.; Korontzi, S.; Owens, J.; Morisette, J.; Roy, D.; Descloitres, J.; Alleaume, S.; Petitcolin, F.; Kaufman, Y. The MODIS fire products. *Remote. Sens. Environ.* **2002**, *83*, 244–262. [CrossRef]
36. Schroeder, W.; Oliva, P.; Giglio, L.; Quayle, B.; Lorenz, E.; Morelli, F. Active fire detection using Landsat-8/OLI data. *Remote. Sens. Environ.* **2016**, *185*, 210–220. [CrossRef]
37. Schroeder, W.; Giglio, L. *NASA VIIRS Land Science Investigator Processing System (SIPS) Visible Infrared Imaging Radiometer Suite (VIIRS) 375 m & 750 m Active Fire Products: Product User's Guide Version 1.4*; NASA: Washington, DC, USA, 2018. [CrossRef]
38. Cao, C.; Xiong, J.; Blonski, S.; Liu, Q.; Uprety, S.; Shao, X.; Bai, Y.; Weng, F. Suomi NPP VIIRS sensor data record verification, validation, and long-term performance monitoring. *J. Geophys. Res. Atmos.* **2013**, *118*, 11–664.
39. Csiszar, I.; Schroeder, W.; Giglio, L.; Ellicott, E.; Vadrevu, K.P.; Justice, C.O.; Wind, B. Active fires from the Suomi NPP Visible Infrared Imaging Radiometer Suite: Product status and first evaluation results. *J. Geophys. Res. Atmos.* **2014**, *119*, 803–816. [CrossRef]
40. Schmit, T.; Lindstrom, S.; Gerth, J.; Gunshor, M. Applications of the 16 spectral bands on the Advanced Baseline Imager (ABI). *J. Oper. Meteorol.* **2018**, *6*, 33–46. [CrossRef]
41. NOAA and NASA Geostationary Operational Environamental Satellite—R Series. Quick Guide: ABI Band 7. 2021. Available online: https://www.goes-r.gov/exit.html?http://cimss.ssec.wisc.edu/goes/OCLOFactSheetPDFs/ABIQuickGuide_Band07.pdf (accessed on 9 December 2021). [CrossRef]
42. Sentinel Hub. KSWIR—Short Wave Infrared RGB Composite. 2021. Available online: https://custom-scripts.sentinel-hub.com/sentinel-2/swir-rgb/ (accessed on 25 November 2021).
43. Jain, P.; Coogan, S.C.; Subramanian, S.G.; Crowley, M.; Taylor, S.; Flannigan, M.D. A review of machine learning applications in wildfire science and management. *Environ. Rev.* **2020**, *28*, 478–505.
44. Bot, K.; Borges, J.G. A Systematic Review of Applications of Machine Learning Techniques for Wildfire Management Decision Support. *Inventions* **2022**, *7*, 15. [CrossRef]
45. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
46. Friedman, J.H. Greedy function approximation: A gradient boosting machine. *Ann. Stat.* **2001**, *29*, 1189–1232. [CrossRef]
47. Ampomah, E.K.; Qin, Z.; Nyame, G. Evaluation of tree-based ensemble machine learning models in predicting stock price direction of movement. *Information* **2020**, *11*, 332. [CrossRef]
48. Legendre, P.; Legendre, L. Numerical Ecology. In *Developments in Environmental Modelling*, 2nd ed.; Elsevier: Amsterdam, The Netherlands, 1998; Volume 20. [CrossRef]

49. Milanović, S.; Marković, N.; Pamučar, D.; Gigović, L.; Kostić, P.; Milanović, S.D. Forest fire probability mapping in eastern Serbia: Logistic regression versus random forest method. *Forests* **2021**, *12*, 5.
50. Higa, L.; Marcato Junior, J.; Rodrigues, T.; Zamboni, P.; Silva, R.; Almeida, L.; Liesenberg, V.; Roque, F.; Libonati, R.; Gonçalves, W.N.; et al. Active Fire Mapping on Brazilian Pantanal Based on Deep Learning and CBERS 04A Imagery. *Remote. Sens.* **2022**, *14*, 688. [CrossRef]
51. de Almeida Pereira, G.H.; Fusioka, A.M.; Nassu, B.T.; Minetto, R. Active fire detection in Landsat-8 imagery: A large-scale dataset and a deep-learning study. *ISPRS J. Photogramm. Remote. Sens.* **2021**, *178*, 171–186. [CrossRef]
52. Oliveira, U.; Soares-Filho, B.; de Souza Costa, W.L.; Gomes, L.; Bustamante, M.; Miranda, H. Modeling fuel loads dynamics and fire spread probability in the Brazilian Cerrado. *For. Ecol. Manag.* **2021**, *482*, 118889. [CrossRef]
53. Vieira, R.M.D.S.P.; Tomasella, J.; Barbosa, A.A.; Polizel, S.P.; Ometto, J.P.H.B.; Santos, F.C.; da Cruz Ferreira, Y.; de Toledo, P.M. Land degradation mapping in the MATOPIBA region (Brazil) using remote sensing data and decision-tree analysis. *Sci. Total. Environ.* **2021**, *782*, 146900. [CrossRef]
54. Arruda, F.V.D.; Sousa, D.G.D.; Teresa, F.B.; Prado, V.H.M.D.; Cunha, H.F.D.; Izzo, T.J. Trends and gaps of the scientific literature about the effects of fire on Brazilian Cerrado. *Biota Neotrop.* **2018**, *18*, 1–6. [CrossRef]
55. Durigan, G.; Ratter, J.A. The need for a consistent fire policy for Cerrado conservation. *J. Appl. Ecol.* **2016**, *53*, 11–15. [CrossRef]