

Evaluating Classification Models in a Burned Areas' Detection Approach

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Abstract. We present a study to improve automation and accuracy on a Woody Savannah burned areas' classification process through the use of Machine Learning (ML) classification models. The reference method for this is to extract polygons from images through segmentation and identify changes in polygons extracted from images taken from the same area but in different times through manual labeling. However, not all differences correspond to burned areas: there are also deforestation, change in crops, and clouds. Our objective is to identify the changed areas caused by fire. We propose an approach that employs polygons' attributes for classification and evaluation in order to identify changes caused by fire. This paper presents the more relevant classifier models to the problem, highlighting Random Forest and an Ensemble model, that achieved better results. The developed approach is validated over a study area in the Brazilian Woody Savannah against reference data derived from classifications manually done by experts. The results indicate enhancement of the methods used so far, and will eventually be applied to more data from different areas and biomes.

Keywords: Burned areas · Classification models · Remote sensing data

1 Introduction

Woody Savannah (commonly referred to as Cerrado in Brazil) is a biodiversity rich region and one of the most threatened biomes in the country. It occupies around 204 million hectares, 24% of the Brazilian territory, and it is estimated that it lost almost half of its original vegetation cover. Deforestation and vegetation fires are the main reasons for this process. More than 30,000 vegetation fires per year have been recorded in this biome in the last 15 years. Several studies cover the fire-related aspects and their economic, social and environmental impacts [3,6,9,16].

To understand the effects and impacts of fire on the Woody Savannah it is important to regularly monitor fire occurrences and to have accurate data products. The Brazilian National Institute for Space Research (INPE) maintains a

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program of Burns and Forest Fires Monitoring [5] based in Earth Observation satellites. It continually analyzes aspects related to the fire occurrences in vegetation areas in the Woody Savannah biome as well as in the rest of Brazil and part of Latin America. As part of this project, some data products are available, such as daily monitoring of active fires, fire risk prediction and periodic fine particulate matter ($PM_{2.5}$) emission estimates, and, more recently, burned surface's estimation. These products are used, for example, by alert services and for public policy subsidies (e.g. application of the Brazilian Forest Code). They are also used to contribute to the reduction of greenhouse gas emissions targets assumed by the Brazilian Government in the Climate Convention [13].

Using satellite data to define burned areas in a fast, continuous and reliable method is a real challenge. Our reference method extracts polygons that represent changed areas and compare changes between different times. However, some of these polygons are deforestations, crops, and clouds. Then, we currently use a method that employs manual evaluation to classify these polygons in burned and non burned polygons. The last published official result of burned areas estimation in the Woody Savannah, in 2017, was published using this manual evaluation. The results are very good but the work is expensive. Considering the need of more automation in the process our aim is to develop an study to improve automation and accuracy on burned areas' classification process through the use of machine learning (ML) classification models. Since there is no generic model for the problem of classifying burned data in a continuous monitoring with controlled accuracy, we employed the solid expertise acquired by the INPE during the last decades of continuous monitoring. We decided to explore features, classifiers and their combinations to improve our approach.

In this article, we present a classification approach through ML that combines distinct vegetation indexes and related features and it is able to distinguish between burned and non burned areas. The proposed approach is validated over a study area in the Brazilian Woody Savannah against reference data derived from classifications done by experts. The results indicates enhancement on the methods used so far, and will eventually be applied to more data from different areas and biomes.

This paper is organized in the following sections: Sect. 2 shows how remote sensing is used to monitor burned areas. Section 3 explains what data is used for classification of areas of interest into burned and non burned areas and presents INPE's burned areas mapping process with the proposed attributes to improve the classification process. Section 4 presents the experiments for some classification models and discuss the results. Section 5 presents the conclusions and future work.

2 Burned Areas Mapping by Remote Sensing Monitoring

The use of remote sensing images collected in different wavelengths is the most efficient way to monitor fires in places with great territorial extension or areas

of difficult access. Furthermore they frequently provides recent information. In Brazil, for example, it is the most efficient fire monitoring means, with the lowest cost. In recent years, new generations of satellites (e.g. Landsat 8, Sentinel-2 and China–Brazil Earth Resources (CBERS-4)) were developed to provide better resolution images and more precise georeferencing. Features and advances made possible by these new satellites generation may be found in [8].

Inside the automatic mapping of burned areas literature, there are few studies applying the new advances of medium resolution data. Liu et al. [9] developed an algorithm to continuous monitoring of annually burned areas using the harmonic model in Landsat time series rather than two image comparisons, as we do. Pereira et al. [16] presents an approach for automatically mapping of burned areas. Their study has good accuracy results in using a One-Class Support Vector Machine (SVM) Trained by Active Fire. Like them, we compare two images, but our work did not process images, it is focused on evaluating polygons attributes generated in a remote sensing extraction data.

There are many recent studies on applying machine learning techniques on distinct research fields. Plazas et al. [19] employed ML classifiers in another problem: the Cacao production classification and had better precision with Random Forest classifier. Some works employ successfully ensemble approaches such as text information retrieval [1] and Polikar [20] that presents details and advantages of using combined classifiers.

In [2] we proposed a semiautomatic approach to classify burned areas through the use of neural networks. Previous results decreased the number of polygons wrongly classified and showed the viability of using Neural Networks in the classification process. Mithal et al. [14] employ machine learning approaches in the problem of burned areas mapping. They present a three-step approach to map burned areas in tropical areas which compares data from two low resolution (500m) successive images from Moderate Resolution Imaging Spectroradiometer (MODIS), feeds it into a proprietary algorithm to classify these data and makes final processing for burned areas. According to the authors, although it has many errors in indicating correct burned areas, it is a promising global approach brings a more comprehensive assessment of tropical fires. The general idea of our whole process is similar and the main difference is that our work is focused on building robust classifiers to evaluate supposed burned polygons to work every two weeks with high reliability for medium resolution images (30 m).

Previous results show the difficulty of choosing one specific model to answer our burn classification problem. To contribute to understanding this problem, our work is related to the effort to develop automated approaches to classify burned areas. We treat this problem by separating it into two parts: one that looks for all the changes that occurred with the suspicion of burning and another that classifies these data. We use the high reliability of finding changes and combine with the comprehensiveness of machine learning techniques to classify burned areas in a continuous and periodical way with high accuracy.

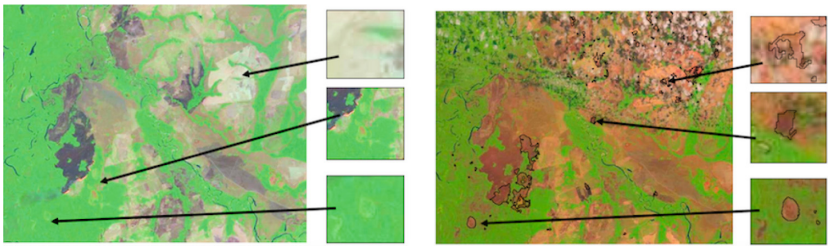
3 Burned Areas Mapping Process at INPE

INPE's monitoring is developed in two independent ways, using different satellite images' resolutions. Low-resolution images (with pixels larger than 300 m) are used to generate daily data products. Medium-resolution images (with pixel' sizes around 30 m) are used for less frequent but more accurate studies. With these distinct views, it is possible to monitor forest fires detected by satellites and to analyze related information, such as estimation of burned area and the prediction of the risk of fire on vegetation. These products can be used to prevent, monitor, combat and create actions to reduce the damage caused by fire, analyze the impacts of burning and estimate the emission of pollutants.

A challenge for monitoring extensive territories is to combine efficiency, quickness and reliability. If it generates a high number of false detections (to classify non burned polygons as burned polygons) it arises, e.g., the risk of waste effort on non-priority areas. If it loses the highest number of burned areas, it arises, for example, the risk of does not know real events. In a reality of fire use culture [18], areas with difficult access, few combat resources and a great number of active fires, it needs to have the smallest error tax as possible, mainly in the burned areas set. Furthermore, to be officially published without manual validation in each polygon, it is at maximum of 5% of false burns error tax.

The INPE's burned areas mapping process finds which areas have changed in a comparison of two different acquisition moments. An algorithm [12] automatically defines areas that have changed from the previous image with high reliability in detect changed areas. The changes detected are caused by many factors and some of them are burns. This is our interest set: changed areas caused by fire. Thus, a further evaluation process is essential to classify burned and non burned areas. The aim of this study is to develop an automatic approach to separate this changed areas set with reliability at around 95%.

Figure 1(a) illustrates a composition of RGB colors of an image fragment on September 24th. Three areas are highlighted. An area with clowns, an area with forest cover and a burning area with visible active fires. Figure 1(b) shows a similar fragment on October 10th, next Landsat's passage. The black lines in the image highlight the polygons detected with changed areas.



(a) September 24th (b) October 10th

Fig. 1. Fragments of an example RGB composition in two consecutive dates

3.1 Data

The INPE's Fire Monitoring Program uses images from Landsat satellites. The Landsat Program [23] stands out among Earth observation satellites that provide medium resolution orbital images of the same area every 16 days since the 1980s. It provides environmental data with all corrections processed, such as spectral band values and spectral vegetation indexes.

Landsat imagery is separated by path and row. The red parallelogram in Fig. 2, the study area of this work, illustrates a fragment of an image position of path 220 and row 065, part of the Woody Savannah biome in the states of Maranhão and Piauí, in Brazilian territory. Light gray highlights indicate Woody Savannah delimitation and dark gray indicates protected areas. Each single pixel in the image corresponds to a square cell of 30 m × 30 m on the terrain and each complete image represents a coverage area of 18,500 × 18,500 ha.

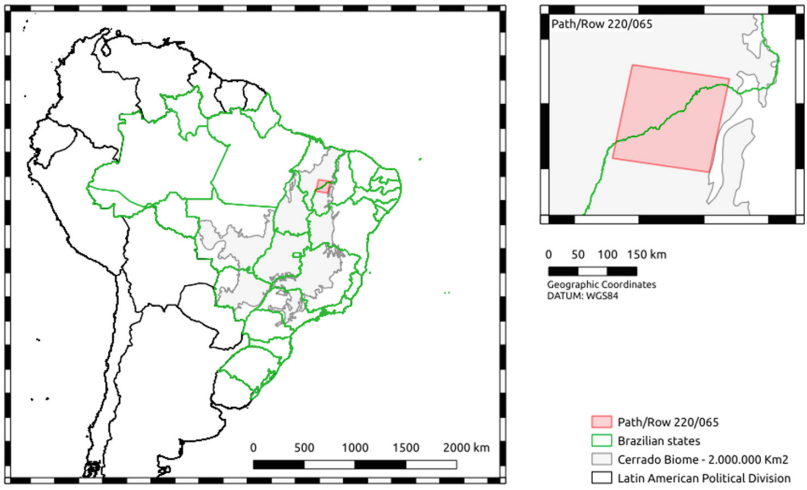


Fig. 2. Fragment of Brazilian territory illustrating Woody Savannah biome and highlighting Landsat 220_065 path/row

Our approach is based on comparing images from the same orbit-point to different dates, with the standard difference being a 16-day. The ones that present interference like noise or many clouds are discarded and an image prior to this one is used, with 32, 48 or at most 64 days difference. At intervals greater than this, the vegetation recovers and it is not possible to detect the changes. The whole images set is composed of 18 images of the 220_065 path/row of the years 2017 and 2018, with data ranging from April to October. The resulting database is composed of polygons extracted by the burned areas mapping algorithm [12].

The Woody Savannah has two well defined seasons: rainy and dry. Figure 3 illustrates the average monthly percentage of clouds for the available images in these two years. This value is generated by Landsat Programs and indicates the

area occupied by clouds in the each image. From November to March it's a rainy season and images frequently contain high clouds percentage. In these months, the use of successive images is low and the number of real burnings is small. From May to August it's a dry season with low rainy level and small clouds percentage. April is considered a transition between the rainy to the dry season and, September and October are transitions between dry and rainy season.

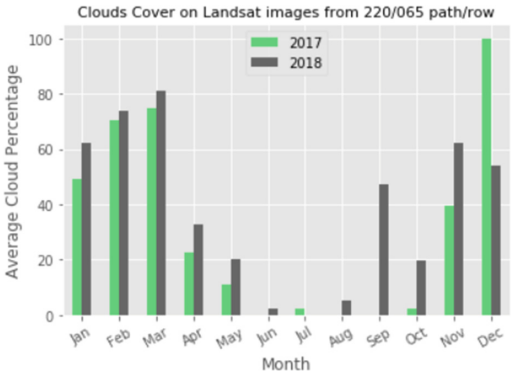


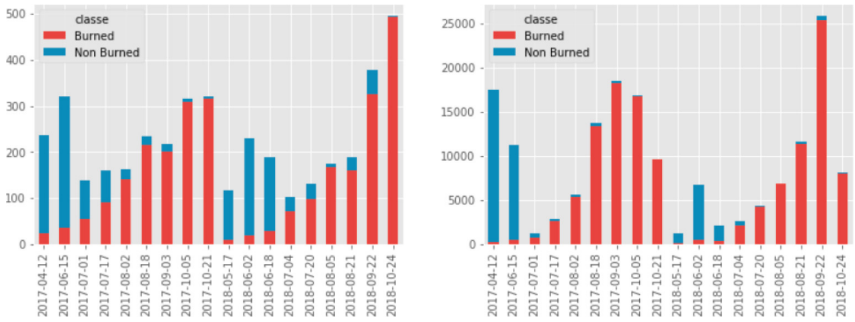
Fig. 3. Average cloud coverage per month per year

This work analyzes a region within a 10 km buffer along an existing transmission line inside 220_065 path/row. In this region the fires can reach transmission lines and generate large scale impacts such as power outages. This area is part of two years validated database derived from field observations and manual interpretation of medium-resolution images. The study area contains 4112 polygons add up around 166,679.46 ha. It corresponds at around 1543 soccer fields. Inside them, 2753 corresponds to confirmed burned polygons totaling 126,381.69 ha and 1359 areas changed due to other factors, which we call non burned polygons and sum 40,297.77 ha. Each polygon is associated with a set of attributes. Figure 4 illustrates the number of polygons and the area occupied by changed areas by month in each year.

In this study, b4 is an anagram to data from Landsat band 4, b5 corresponds to data from Landsat band 5 and so on. As each original Landsat image contains the reflectance spectra for each pixel in a digital image, the polygons are composed by a set of pixels. The set of attributes of each polygon is composed by the average of each Landsat band from b2 to b7 and other vegetation indexes.

3.2 Preprocessing

The first step to apply the machine learning approach to classify burned data is to understand the knowledge database: data and their set of attributes. The strategy is to have a small set of relevant attributes to reduce the volume of analyzed data and the processing time while maintaining a low error rate.



(a) Number of polygons by date (b) Area of polygons by date

Fig. 4. Distribution of burned and non burned areas (number of polygons and occupied area)

The knowledge database is composed by area characteristics, spectral bands values, and spectral vegetation indexes. Each polygon inside this set was manually evaluated by expert and is classified in burned and non burned polygons. Figure 5 shows an overview of spectral bands data from b2 to b7 through the boxplot charts. It allow us a general idea on the differentiation of burned and non burned data sets. Except for b7, the sets are symmetric. The graphs have some outliers, common to the process data. They should not be discarded to avoid some tendency results. We highlight bands b4, b5 and b6 as the best differentiators among burned and non burned datasets.

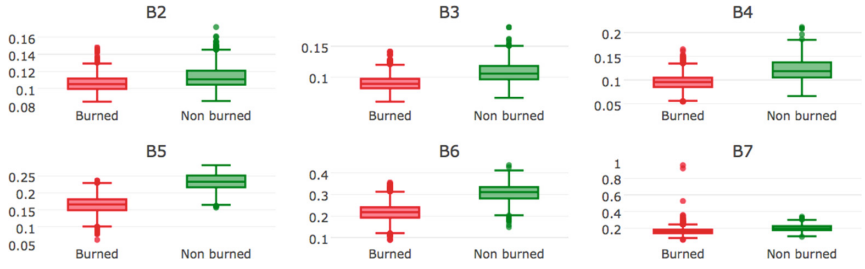


Fig. 5. Boxplot charts of spectral bands b2, b3, b4, b5, b6 and b7

Based on the best differentiators of bands (b4, b5, and b6), we tested spectral vegetation indexes that used at least one of these indexes. We used: Normalized Difference Vegetation Index (NDVI) [21], Normalized Burn Ratio (NBR) [7], Mid-Infrared Burn Index (MIRBI) [22], Normalized Difference Water Index (NDWI) [11], Burn Area Index (BAI) [4], Char Soil Index (CSI) [10], and Global Environment Monitoring Index (GEMI) [17]. A summary of the vegetation indexes applied in this approach can be found in Table 1.

Table 1. Description of relevant spectral vegetation indexes

Index	Description	Example
Area	Polygon area in hectares (ha)	263021.807
NDVI	(b5 − b4) / (b5 + b4)	0.178
NBR	(b5 − b7) / (b5 + b7)	0.073
dif_NDVI	NDVI(actual) − NDVI(previous)	0.274
dif_NBR	NBR(actual) − NBR(previous)	0.543
MIRBI	(10 * b7) − (9.8 * b6) + 2	0.178
NDWI	(b3 − b6) / (b3 + b6)	0.073
BAI	(1/((pow((0.1 − b4),2)) + (pow((0.06 − b5),2))))	0.067
CSI	b2/b6	0.056
GEMI	(n * (1 − 0.25 * n) * (b5 − 0.125) / (1 − b5)) where n is	0.274
	n = (2 * (pow(b7,2) − pow(b5,2)) + 1.5 * b7 + 0.5 * b5)/(b7 + b5 + 0.5)	
GEMIL	Apply b6 in the place of b7 on GEMI index definition	0.543

Each index brings a different combination of bands and highlights some specific characteristics of the vegetation cover change. We verified the most relevant ones for our classification process and present here the smallest set able to characterize our burned data. We also made a change in the GEMI index, calling it GEMIL, since instead of using b5 and b7, it uses b5 and b6 data, which is spectrally close and better differentiated our target set. Figure 6 shows the boxplot graph of some indexes: NDVI, difference between NDVI in two distinct dates (dif_NDVI), difference between NBR in two distinct dates (dif_NBR), NDWI, GEMI and GEMIL vegetation indexes. The outliers are present in our process and it can be observed in all charts. We highlight the NDWI, GEMI and GEMIL indexes.

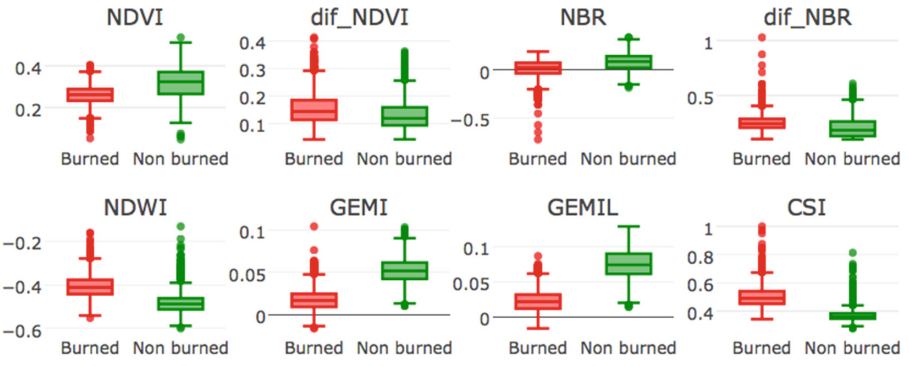


Fig. 6. Boxplot charts of vegetation indexes

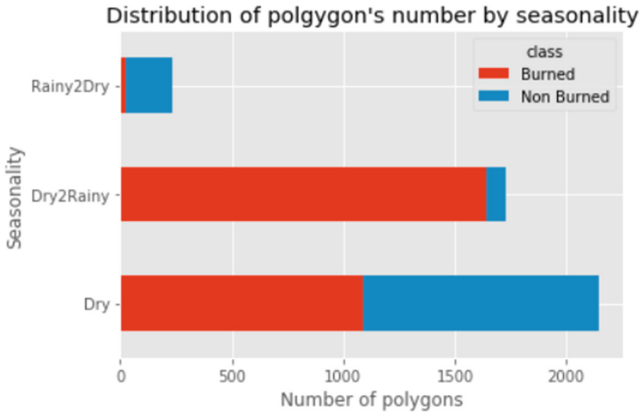


Fig. 7. Seasonality of Burned and Non burned polygons

The rains seasonality was added to database based on the month acquisition image. The spectral response of a burned area and its recovery are influenced by the season in which it occurs. For example, fire that strikes vegetation in the transition from a rainy season to a dry season brings a different spectral response to the fire that strikes vegetation in a dry season. The result, illustrated in Fig. 7, is a set of four binary attributes: Rainy(that doesn't contain polygons in this study case), Dry, Rainy2Dry, and Dry2Rainy that describes the seasonality.

Attributes area, MIRBI and, BAI were processed arithmetic operations, such as the application of log operation with subsequent division by 10, to decrease the range of attributes values. Figure 8 shows the original set and the resulting data set after fit processing. The processed data preserves the original distribution characteristics, decreases the outliers effect and allows a better interpretation of the set.

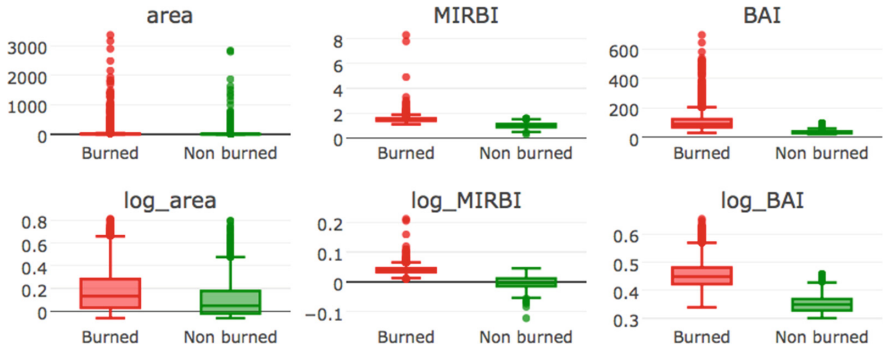


Fig. 8. Boxplot of original and processed attributes area, MIRBI and BAI

4 Classification Experiments

To explore the effectiveness we started by a cross-validation test with 30% of the whole set. After this experiment, we created another validation test that simulates a real aim process of using recent knowledge dataset to predict the classification to a posterior data. We used the whole 2017 year to build a knowledge database and to predict the whole 2018 dataset.

We recovered the dataset available in early November to build our knowledge base and run experiments from that release. However, as work is in operation and with continuous development, as advances are made within the group's research, some advances are introduced into the system. For example, improvements in the data offered by the satellites and also in clouds and smoke masks. In addition, because the data is used by real users and input from other information systems, some omission or detection errors are reported. In this way, the data is reprocessed, re-evaluated and sometimes the official results are updated in the official system and made available to the user.

4.1 Classification Models

We performed experiments at Scikit-learn environment [15]. The training sets are the same for all models and the result is the average of the values in these 10 tests. Individual cross-validations results and parameters are detailed to each algorithm in the next subsections.

K-Nearest Neighbors (kNN): A kNN is a data classification algorithm that employs the influence of the majority of labeled nearest neighbors to perform the classification. It determines what group a data point is in by looking at the data points around it. The best parameters used in the experiments are: 3 neighbors, Euclidean metric and Distance weight.

Random Forests (RF): This model consists of an ensemble of simple trees, which are used to determine the final outcome. Each simple tree employs a set of decision rules to separate the classes and, the ensemble votes for the most popular class. RF is a robust algorithm that minimizes the errors in specific trees. We consider 24 trees in the forest and 5 as the minimum number of instances in leaves.

Neural Networks (NN): A multilayer perceptron (MLP) algorithm with back propagation that automatically learns the structure of data by example and is trained to separate classes. It was done with the following parameters: 100 neurons per hidden layer, rectified linear unit function as the activation function, 300 as the maximum number of iterations and 0,00010 as the penalty (regularization term) parameter.

Support Vector Machines (SVM): A SVM is a discriminative classifier that employs the best hyperplane to separate two target classes in the space. The parameters used to set the experiments are: Cost: 100; Regression loss epsilon: 0,5; kernel Linear; Numerical tolerance: 0,01 and Iteration limit: 1000.

Ensemble of Classification Models (ST): It consists of an ensemble of Random Forest and Neural Networks previous trained models into a single meta-model. We used a Stacking [24] algorithm to combine our better two distinct paradigms with a Logistic Regression model to minimize individual error rates.

4.2 Experiment 1: Test the the Whole Dataset

The dataset is composed by 4112 polygons that correspond to more than 160,000 ha. The cross-validation algorithm separated 70% to training dataset and 30% to test dataset. Then, 2878 were used to train and 1234 were used to test the models. This test was done 10 times, the result is the average of the values and the training set is the same on the five tested models.

To compare resulting details, we combined the individual confusion matrix in a side by side way that can be seen in Table 2. In the rest of this work we use the acronym B to indicate the number of burned areas and NB to indicate the number of non burned areas.

Table 2. Average cross-validation confusion matrix of each classifier model

		Predictions									
		kNN		SVM		RF		NN		ST	
		B	NB	B	NB	B	NB	B	NB	B	NB
Reference	B	823	8	818	13	823	8	821	10	825	6
	NB	8	395	23	380	3	400	12	391	4	399

The average errors set have similar results with small values, both in false positives or false burns (NB polygons classified as B polygons) and false negatives or lost burns (B polygons classifieds as NB polygons). Specifically, SVM presents a higher number of lost burns and the smallest number of false burns. ST and RF presents the small error sets, but the results are statistically similar.

The statistical metric accuracy is the proportion of correctly classified examples in relation to the total number of samples classified. Overall accuracies are larger than 0.96 and they are statistically similar. SVM accuracy is 0.97, NN accuracy is 0.98 and kNN, RF and ST accuracies are 0.99. These high accuracies results indicates the viability of our dataset and our approach to classify burned data.

4.3 Experiment 2: Using the 2017 Dataset to Classify the 2018 Dataset

In this experiment, 2105 areas belong to the 2017 year and 2007 areas belong to the 2018 year. The training set (data from the 2017 year) is composed by 1370 burned polygons, 637 non burned polygons and it is the same on the five tested models. The set is not balanced, but it represents the real dataset and it is important to deal with this characteristic of class imbalance. Table 3 presents the individual resulting confusion matrix to each model.

Table 3. Individual resulting confusion matrix of each classifier model

		Predictions									
		kNN		SVM		RF		NN		ST	
		B	NB	B	NB	B	NB	B	NB	B	NB
Reference	B	1353	17	1356	14	1339	31	1355	18	1351	19
	NB	34	603	65	572	14	623	35	602	23	613

As results in the first experiment, SVM classifier presents the larger number of false burns (NB polygons classified as B polygons). kNN and NN have similar quantity of false burns and RF and ST presented the better results. Inside lost burns (B polygons classified as NB polygons), RF presented the larger values. Other classifiers presented similar results.

Our set is not balanced, neither in the number of polygons nor in the total extension. It is important to check F1, precision and recall metrics to best overview and understand our results. Table 4 presents statistics evaluation metrics accuracy, precision, recall and F1 calculated for each model. The precision is the proportion of true positives among instances classified as positive. In our case, e.g., the number of confirmed B polygons inside all predicted B polygons. Recall is the proportion of recovered true positives among all positive instances in the data. In our case, e.g., the number of recovered B polygons inside all real B polygons. F1 is a weighted harmonic mean to detach a balance between precision and recall.

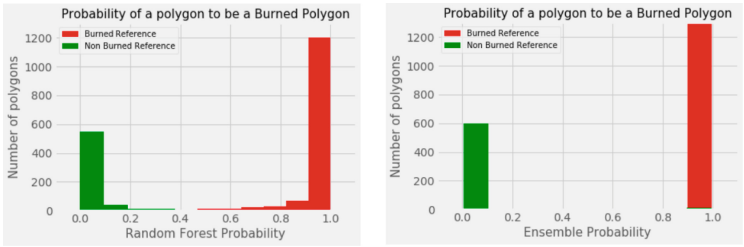
As previous tests, in this experiment overall metrics are greater than 0.95. The accuracies are greater than 0.96 and the F1 values indicates the models deals well with this uneven class distribution. The error set size is very small, both in lost burns and false burns. SVM presents a higher number of lost burns and the smallest number of false burns, but the difference is numerically very small. Better results were obtained by RF, NN and ST and experiments showed that the classifier models are suitable for classifying burned polygons.

Given the above goods results, we chose two classifiers to inspect another result of some classifiers model, the probability of the observed object to be part of a specific class. Some family of classifiers, as RF, NN and ST, use this value (that ranges from 0 to 1) to divide their results into the classes, employing

Table 4. Evaluation results considering the average over classes

Classifier	Accuracy	Precision	Recall	F1
kNN	0.97	0.98	0.99	0.98
SVM	0.96	0.95	0.99	0.97
RF	0.98	0.99	0.98	0.98
NN	0.97	0.97	0.99	0.98
ST	0.98	0.98	0.98	0.98

0.5 value as the division limit. In our case, we inspected the probability of each object to be similar to the set of burned data. The aim was to verify if the errors (lost burns and false burns) are accumulated in the mean values to deal with doubt values and to decrease the error set. Figure 9 illustrates the probabilities distributions of RF and ST models.



(a) Random Forest model (b) Ensemble model

Fig. 9. Probability resulting distribution in RF and ST models (Color figure online)

Figure 9(a) presents distribution probability of RF model and Fig. 9(b) presents distribution probability of ST model. In red, real B polygons are represented and in green, real NB polygons are represented. Both sets have the majority of results concentrated smaller than 0.1 and greater than 0.9. RF resulting data is a few more spread out than ST resulting data. The set of errors is very small and it not is possible to observe if resulting data presents classification errors closer to the center of the set (0.5) than the ST. This study continues with other areas to increase the reliability of the approach.

The errors and doubts will be evaluated by experts in a posterior moment. We know the expert validation is a error susceptible and a highly expensive process. However, it is important an expert to solve the doubts because he uses knowledge to verify the specific data and the round area to better understand the indication. Therefore, we will use this reevaluated data to insert data into knowledge base to build a more robust approach.

5 Conclusions and Future Work

We developed a more generic and automated model to classify burned data that is robust enough to deal with previously unknown data. We proposed a small and more complete set of features to build a knowledge base to be used in a machine learning approach to classify burned and non burned areas.

We used our previous approach [2] to evolving from three months model to a more accurate model. Since there is no complete model that describes whether it is burned, we proposed more relevant features. After this we studied distinct classifiers using a labeled dataset that is the real classifications made by experts. As each different algorithm creates a different model, we have analyzed various types of classifiers to explore the performance of each one. We chose an Ensemble model to combine better characteristics of Random Forest and Neural Network models. These tests present precision and recall near the value of 0.95.

We are working on testing the adaptability of this model to other areas or the need to develop other local area specific knowledge base. Preliminary results show that is possible to use this knowledge approach to classify distinct areas and to create a more automatic process of burning mapping using a machine learning approach. Another future step of this work is to develop a reliable process able to classify data every image generated by satellites.

As part of a work in progress we continue the searches of new configurations and new attributes that can enrich the model. For future work, we suggest the incorporation of other fire-related data products such as fire risk and soil use to generate models that can more accurately distinguish burned areas.

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