Spatial-temporal Analysis of active fire classified by INPE's Fire Risk Model in Brazil using Python language

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Abstract. *The use of programming languages such as Python to analyse geospatial data has simplified the analysis of remote sensing data. In this study, we evaluated the spatial-temporal distribution of active fires detected by MODIS in Aqua Satellite by classes of fire risk, as defined by INPE's Fire Risk model. The study area was the federative units, geographical regions, and biomes in Brazil. The temporal assessment comprised different time seasons and the years from 2015 to 2019. Active fires were higher during winter and spring seasons when also more Critical and High risks were noticed. The same risk was prevalent in Northeastern and Southeastern Brazil, as well as in the Caatinga and Cerrado biomes.*

1. Introduction

Fire in natural environments is the result of a combination of factors, such as vegetation type and climate combined with human actions or natural causes [Fearnside 2006, Phillips et al. 2009]. Therefore, it requires a complex territory-level network to be properly managed. For such endeavors, large databases are necessary to gather information aiming the support of fire monitoring as a way of preventing serious forest fires, especially in fire-prone biomes, such as the Brazilian Cerrado [Schmidt et al. 2016, Tedim et al. 2016].

Fire use can be convenient for anthropological purposes but its abusive use can worsen health problems, due to smoke-carrying combustion products [Souza et al. 2012]. Also, it features a positive feedback relationship with climate change, which can cause harm to fire-prone ecosystems. Lately, these ecosystems have had more contact with fire, especially in the Amazon [Aragão et al. 2018]. Monitoring fire risk is, therefore, necessary for land management over time and within the same year, according to the region under analysis. Considering a continental country like Brazil, with such heterogeneity of vegetation cover, time seasons, land use, and occupation, a complex regional monitoring system is needed [Nogueira et al. 2017].

As consequence, another typical challenge on this issue is dealing with large volumes of data. In Brazil, the National Institute for Space Research (INPE) gathers a database with more than 10 satellites, capable of detecting the occurrence of active fire, generally indicating fire occurrences. Besides, Weather Forecasting and Climate Studies Center – CPTEC/INPE, has implemented fire risk observation and forecasting models, including as variables: vegetation cover, accumulation of days without rain, air temperature, altitude and latitude, and the active fire observation itself [Setzer et al. 2019].

The use of computational languages, such as Python allows the creation and documentation of geospatial data processing architectures. By doing so, the scripts can either be improved in different versions afterward or be easily adapted to other regions of interest [Teodoro and Duarte 2013]. In this sense, such routines related to fire monitoring can be adjusted to allow more input data or even improve time series to perform different analyses and their new results are easily compared to previous ones [Gomes et al. 2017].

Based on the preceding, this work aimed to evaluate active fire occurrence relative to different risk classes, according to the Fire Risk Model developed by INPE's Wildfire Monitoring Program. For this purpose, the analysis was performed across all Brazilian regions, states, and biomes, also considering different seasonality, using programming languages to provide adaptive and replicable processing routines.

2. Material and Methods

The following sections give details on the study area, data, and processing routines chosen for this study. In summary, active fire classified by fire risk were spatially distributed, considering seasonal assessments from 2015 to 2019. Python libraries inserted in the programming routine, which was developed and documented in a Github platform using Jupyter Notebook application, supported all the processing and plotting of main results.

2.1. Study Area

Three Brazilian territory delimitations were considered as spatial analysis unit: Federative Units, or States, Geographical Regions, and Biomes (Figure 1). Either considering the regions or states, the analysis intends to show important results for administrative purposes [Nogueira et al. 2017]. Moreover, important insights can be realized regarding the active fires on the biome delimitation, according to its specific vegetation and other environmental characteristics.

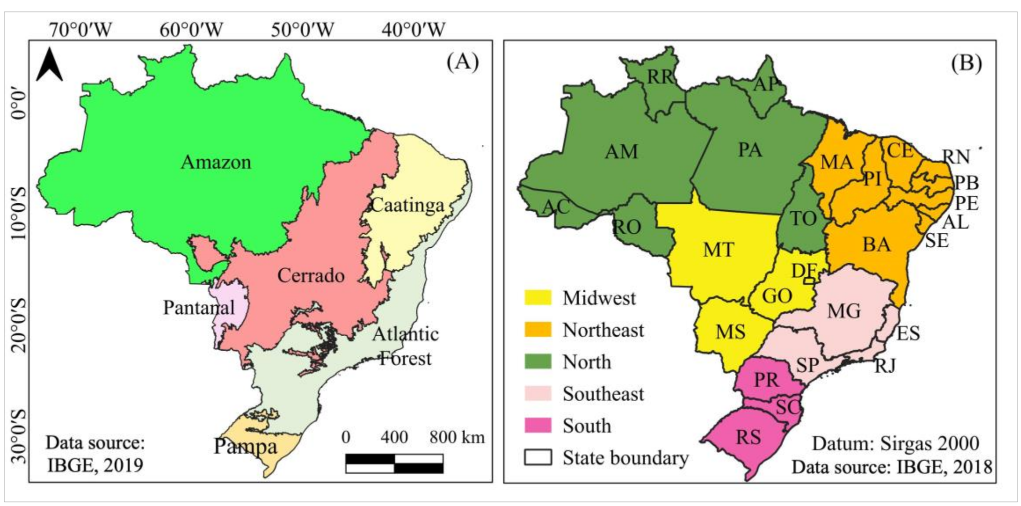

Figure 1. Study area and spatial analysis units: A) Brazilian Biomes B) Geographical Regions and Federative Units (states).

Besides, active fires were also evaluated for different seasons (summer, fall, winter, and spring) from 2015 to 2019. Fundamentally, time assessment may stress the possibilities of different patterns in the monitored events during a defined period.

Identifying these spatial and temporal fire risk patterns are relevant considering the changes in climate the world is facing lately or even the planning of public policies directed to land and environmental administration [Fonseca et al. 2019].

2.2. Database

The database for this study were mainly active fire points (shapefiles) from January 1st to December 31st between 2015 and 2019, available at INPE's Wildfire Monitoring website. Only data from the reference satellite (Aqua afternoon) were selected for this study. The active fire data already bring attributes on date/time, state, biome, and fire risk when registered. Only geographical region delimitation was complemented with data from the Brazilian Institute of Statistics and Geography (IBGE). Season information derived from date/time attribute in terms of days of the year. Summer was defined from December 21st to March 20th; Fall, from March 21st to June 20th; Winter, from June 21st to September 20th, and Spring, from September 21st to December 20th.

2.3. Data processing and analysis

For data processing and analysis, we used the following Python's libraries: Pandas, Geopandas, Numpy, and Matplotlib. The entire sequence of commands was organized into two Jupyter Notebooks and a module, named as riscofogo.py[1]. Some active fires, whose fire risk values were null, were excluded from the analysis. A random 5% sample was selected from active fire data in each a series of routines were applied to consolidate all other necessary information (time seasons and regions) in the same Geodataframe (i.e Geopandas' data organized in table structure including the object geometry as an attribute).

Numpy, Pandas, Geopandas were libraries applied for organizing the data and operating on them. Thus, logic operators to derive time season attributes from date/time and spatial join function were used to include geographical region classes in active fire Geodataframe. Another fundamental process was to define classes for fire risk attributes using logical operators, according to Setzer et al. (2019) classification (Table 1).

Table1. Risk classes according to Fire Risk Values registered in active fire database

Risk classes	Fire Risk Values (RF)
Minimum	$RF < 0,15$
Low	$0,15 < RF \leq 0,40$
Medium	$0,40 < RF \leq 0,70$
High	$0,70 < RF \leq 0,95$
Critical	$RF > 0,95$

Adapted from Setzer et al. (2019)

Pandas' Pivot Table function was applied to summarize the results per season, geographical regions, biomes, and federative units, which were then represented in stack horizontal bars, showing the relative occurrence of active fire in different risk classes. Figures and maps showing active fire distribution in the study area were plotted using Matplotlib. Other details can be found in the Jupyter Notebooks developed for this work.

[1] https://github.com/ser-347/risco-de-fogo

3. Results

We observed more occurrences of active fire in the winter and spring seasons. Notably, there is a pattern that persists for the entire time studied. The Critical risk class showed more active fires in the Midwest and Southeast during winter and the Northeast during spring (Figure 2). There are also considerable active fires in the Minimum risk class, mainly in the Amazon and Pampa biomes. Likewise, in the summer, states such as Pará (PA), Mato Grosso (MT), Rondônia (RO), and Tocantins (TO), which are in the Arc of Deforestation, presented a substantial number of active fires with Minimum risk.

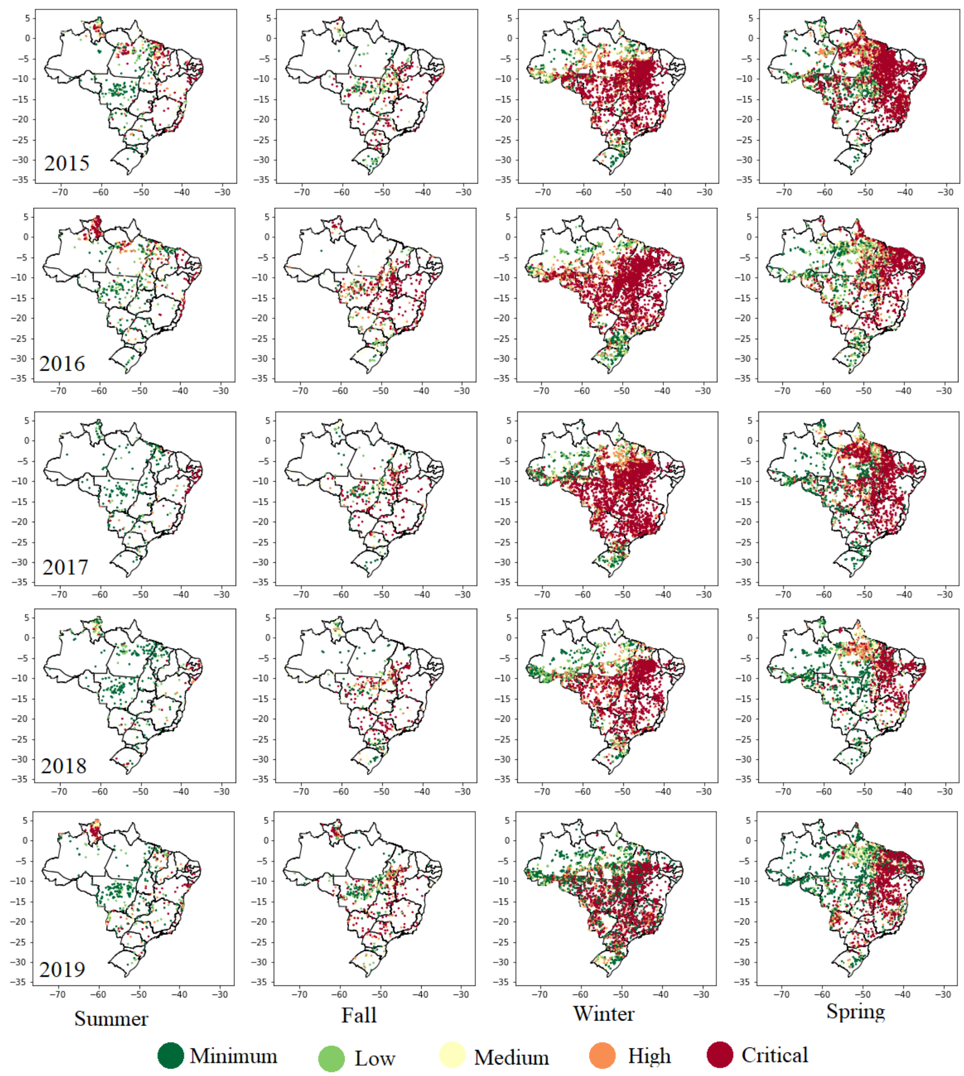

Figure 2. Spatial distribution of active fire in Brazil per fire risk classes from 2015 to 2019 and in different seasons.

Considering the absolute number of active fires, the Amazon biome exhibited more active fires in the Critical than in the Minimum class between 2015 and 2017, but this pattern reversed from 2018 onwards. In 2019, there was a peak of 1,900 active fires in the Minimum risk class for the Amazon, reaching about twice the amount of Critical risk active fires for the same year in the same biome. In contrast, although active fires were classified as Minimum risk increased, Critical risk class was dominant in the Cerrado (Figure 3).

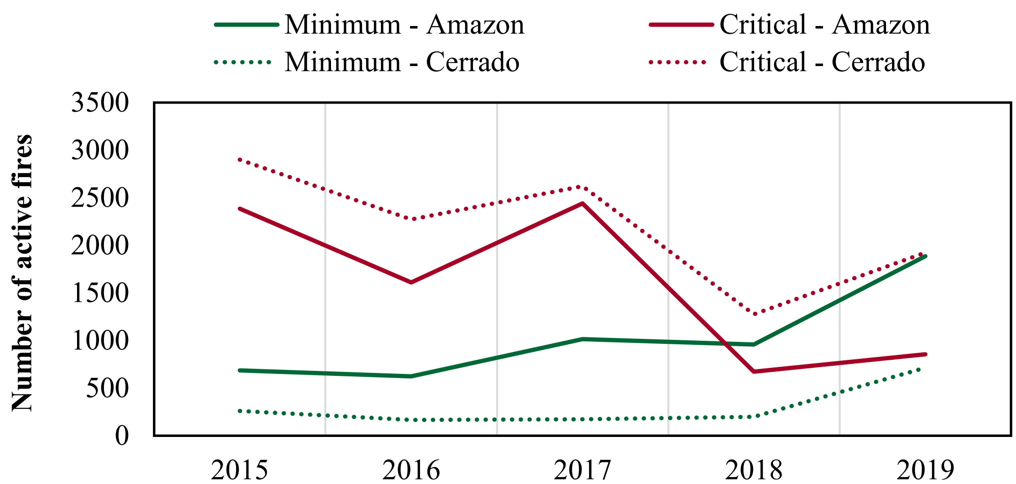

Figure 3. Number of active fires classified as Minimum and Critical fire risk for the Amazônia and Cerrado biomes between 2015 and 2019.

The mean relative occurrence of active fire by seasons, regions, biomes, and states are shown in Figure 4. The model was more accurate during the winter and spring seasons, followed by fall and summer when more active fires were detected at Minimum risk locations (Figure 4.A). Regarding Brazilian administrative regions (Figure 4.B), Northeast and Southeast presented about 80% of active fire classified as Critical risk, whereas North and South less than 40%. Midwest showed almost 60% of active fire in the Critical risk region.

Given the Brazilian biomes (Figure 4.C), the patterns are somewhat related to those observed among geographical regions. The Caatinga biome (located mainly in northeastern Brazil) presented a greater relative occurrence of active fire in Critical risk areas (about 90%), followed by the Cerrado (about 80%). The opposite took place in the Pampa biome, which is found in southern Brazil, followed by the Amazon, showing less than 40% of active fires classified as Critical risk.

Finally, with concerns to the Brazilian States (Figure 4.D), they are somehow linked to the results presented in the geographic regions (Figure 4.B). For instance, states like the Rio Grande do Norte (RN), Sergipe (SE), and Piauí (PI), which are located in the Northeast, and São Paulo (SP), Rio de Janeiro (RJ), and Minas Gerais (MG), in the Southeast, were among those with the greater relative occurrence of active fire classified as a Critical risk. Conversely, Acre (AC), Amazonas (AM) from the North or the Rio Grande do Sul (RS) and Santa Catarina (SC) from the South showed the greater occurrence of active fire classified as Minimum risk.

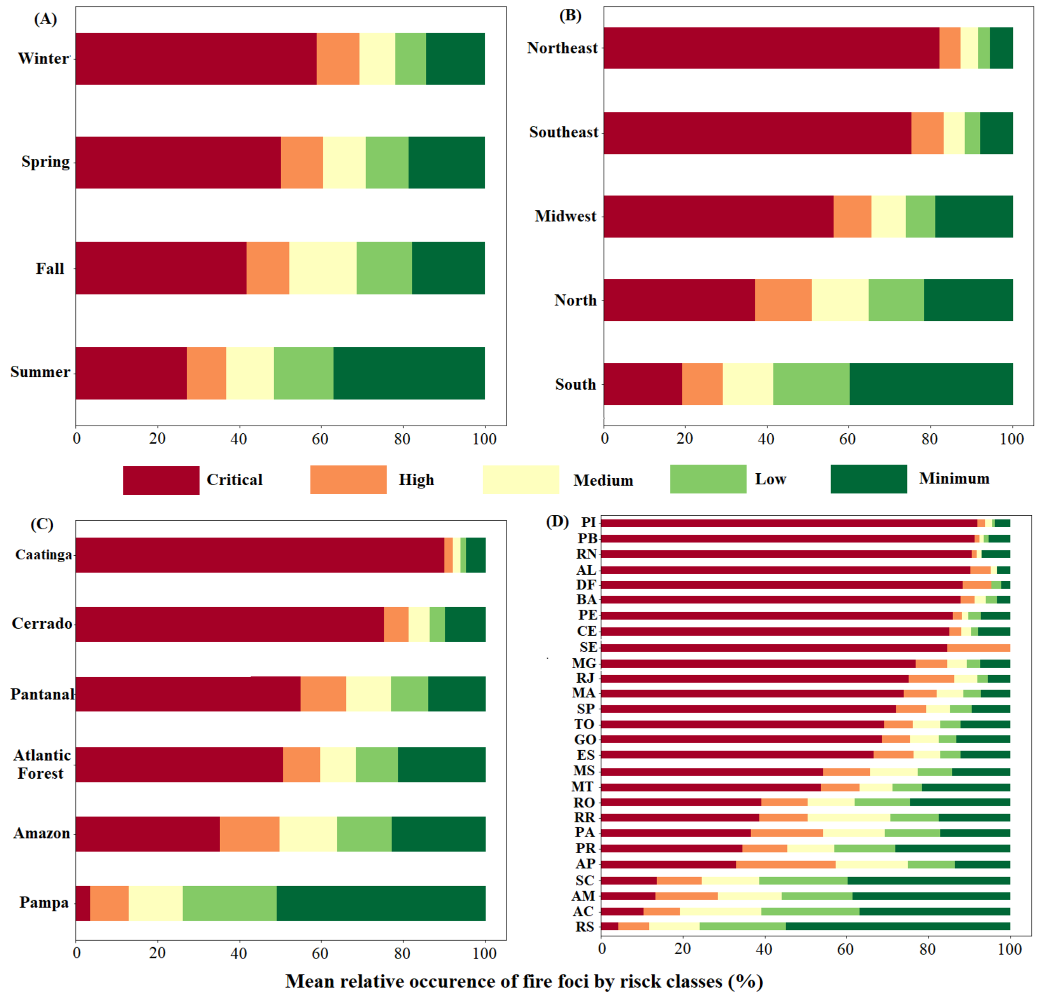

Figure 4. Mean relative occurrence of active fire by fire risk classes in different seasons (A), regions (B), biomes (C), and states (D). The bars were arranged in descending Critical risk order.

4. Discussion

Python libraries used in this study enabled active fire analysis in different states, biomes, regions, and seasons in Brazil from 2015 to 2020. By documenting and making the routines available in an open source platform, however, one could easily reproduce them in other analysis units (e.g. municipal level) and/or time span.

A possible limitation to consider before replicating this analysis is the spatial resolution of the model. Its input variables are typically in kilometric-scale, which may restrict local studies depending on the size of the study area. However, taking advantage of current open source culture and the popularization of geoinformatics, new modeling of fire risk with local variables (generated from finer spatial resolution) is encouraged. Once developed, its architecture could be shared, so other researchers could either test it, by applying variables from their research area or contribute to its processing efficiency [Teodoro and Duarte 2013].

Our results indicated to be coherent to other studies [Nogueira et al. 2017]. More than 80% relative occurrence of fire in Critical or High-risk areas from Cerrado and Caatinga, for instance, maybe explained by many days of drought and available biomass as fire fuel in those biomes, which are important parameters for the fire risk model [Setzer et al. 2019]. Fire is commonly used as a technique for deforestation and pasture management in the Midwest [Schmidt and Eloy 2020] and in the North and Northeast regions, to where agricultural frontiers are expanding [Aragão 2018, Silva 2020].

On the other hand, in the Amazon or Pampa active fires were majorly classified as Minimum to Medium risk. According to the model's parameters, Lower risks may be associated to regions with dense forest vegetation and frequent rainfall as commonly seen in the Amazon, or Lower mean temperatures, as typically noticed in the Pampa [Setzer et al. 2019]. Perhaps, considering the current shift in political scenario [Fonseca et al. 2019, Amigo 2020] and agricultural expansion in the Amazon biome, other parameters should be considered for future modeling, such as areas threatened by deforestation, as they have been increasingly associated with fire events [Silvério et al. 2019].

Between 2015 and 2019, INPE's database recorded more than 19,000 active fires spread in the Amazon. Even though 2017 had the largest absolute number (5,336 active fires), 2019 had the highest percentage of active fires from deforested areas (~34%) [Silvério et al. 2019]. This pattern has changed over the past years and mainly after the current Brazilian government's antienvironmental agenda [Escobar 2019]. Therefore, despite important Brazilian monitoring programs such as the Real-Time Deforestation Detection System (DETER) and the Program for Monitoring Deforestation of the Amazon by Satellite (PRODES), and the Wildfire Monitoring program itself, more stakeholders, including politicians, are needed to mitigate this problem.

Finally, even though uncertainties may be expected in fire risk modeling, the ongoing active fire monitoring is necessary to support the environmental agenda in Brazil. Since 2004, Brazilian policies have played an important role to reduce deforestation and carbon emissions and thus helping improve air quality and human health [Reddington et al. 2015, Wiedinmyer 2015, Oliveira 2020]. However, as stated before, this scenario has changed over the past four years, when decision-makers have been favoring agricultural expansion over natural areas, besides dismantling environmental laws [Fonseca et al. 2019, Take action to stop the Amazon burning 2019, Amigo 2020]. Consequently, respiratory problems may be aggravated by the constant burning of vegetation at large distances due to particulate transport through the atmosphere [Aragão et al. 2020].

5. Conclusions

In this study we demonstrated how using programming language, like Python, may be useful for visualizing and analyzing geospatial data in time and space. Our focus was on active fire and risk distribution exploratory analysis throughout Brazilian states, regions, and biomes from 2015 to 2019 and in different seasons. Thus, it could be noted how fire risk and possible occurrence behave differently across the study area and time considered in the assessment.

Programming language contributed to the spatial-temporal analysis of active fire by risk classes and allowed documentation of every processing routine to adapt or update it in the future, whenever needed. Python's libraries like Pandas, Geopandas, Numpy, and Matplotlib were useful for processing and analyzing data, as well as presenting the results.

In addition, using GitHub as an open source development platform to host codes like the ones developed on these analyses may allow developers to share and adapt different versions of processing routines.

Active fires classified as High and Critical fire risk is more frequent during winter and spring. Regarding space, the same was verified in the Northeast and Southeast regions, as well as in the Caatinga and Cerrado biomes. In the Amazon we identified an interesting pattern of a greater relative register of active fires classified as Critical fire risk until 2017, which reversed from 2018 onwards, indicating a greater likelihood of fire occurrence in less fire-prone regions in the last years.

Lastly, although this study used different geographical limits in the analysis, fire negative effects are usually boundaryless. This implies that, in addition to all the monitoring work being carried out through satellite products, more actions should be taken by the government and other agencies to curb fire and activities associated with it, which might be challenging by itself, considering the climate change scenario.

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