

Wildland fire occurrence in the state of Minas Gerais between 2003 and 2020

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ABSTRACT

Wildland fires are responsible for several environmental problems, contributing to climate change as it releases into the atmosphere greenhouse gases. This study had the objective to analyze the spatiotemporal variation of wildland fire occurrence in the state of Minas Gerais, and to determine the main factors affecting fire frequency at municipal level. Data from fire pixels detected by the satellite AQUA between 2003 and 2020, were used for such purposes. A significant downtrend was found in the number of fire pixels recorded over the years. September, October and August were the months, respectively, with the highest fire activity. Approximately 90% of the state area was classified as having high, very high or extreme wildland fire occurrence. The northeast state region stands out for its high fire pixel density, while the south and southeast regions were the ones with less fire activity. The variable that had the biggest influence in the fire pixel density for each municipality was the mean annual rainfall, followed by natural formations area, mean annual temperature and agriculture area. The results obtained should be used by the authorities to develop and apply efficient fire prevention measures seeking to reduce fire occurrence, especially in fire sensitive ecosystems. Keywords: Fire prevention; Fire Pixel; Remote Sensing; Wildfire.

Introduction

When wildland fires occur, whether the fire is controlled or not (wildfire), it releases into the atmosphere greenhouse gases (GHG), such as carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), and others, thus contributing to climate change. In fire sensitive ecosystems, such as in the Atlantic or Amazon Forests, wildland fires are responsible for major environmental impacts that can lead to extinction of rare and endemic species. In fire dependent ecosystems, such as Savannas and the Brazilian Cerrado, fire is a natural element, and the exclusion or increase in fire frequency can also have negative environmental impacts (Soares and Batista 2007; White 2019; White 2020). Due to its effect on air pollution, climate change, biodiversity conservation, wildland fires are responsible for a global environmental imbalance, having great social and economic consequences in short and long term (Caula et al. 2015).

In Brazil, the use of fire in controlled burns is cultural and difficult to replace. Usually, farmers use the fire to clean the fields illegally

without authorization from the responsible environmental agency (White 2018). The lack of inspection results in a large number of control burns that turn into wildfires consuming large areas of vegetation. Also, fire is commonly used in the country to clear forests (Caula et al. 2015; White 2018). Most of the fire pixels detected in the Brazilian's tropical forests in the last decades are due to the use of fire in deforestation for the establishment of new agriculture and pasture areas (White 2018; Junior et al. 2020).

Technological advances have enabled the use of satellite remote sensing to detect and locate fires in real time since 1980s (Caula et al. 2015; Wang, Miao and Peng 2012). Until a few years ago, the satellites equipped with Advanced Very High-Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) sensors were the most effective for this purpose (White 2020). Two new satellites launched in the 2010s (Suomi NPP and NOAA-20) equipped with the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor, are currently the most efficient due to the sensor's greater

resolution capacity (INPE 2021; White 2020). Nevertheless, data from older satellites still in operation, continue to be used to analyze longer term variations in fire occurrence (White 2020; INPE 2021).

The images generated by the satellites are sent to a control center, where they are processed through a detection algorithm that detects fire in vegetation, that can be called as fire foci, fire pixel, active fire pixel, or hotspot (Batista 2004; Wang, Miao and Peng 2012; White 2020; INPE 2021). The current algorithm used by the National Aeronautics and Space Administration (NASA) and by the INPE for images generated by MODIS sensors, such as the one aboard the AQUA satellite, is called “Collection 6” (NASA 2021).

Currently, there are nine satellites in activity that collect fire pixels data in Brazil and are used by the INPE: NOAA-18, NOAA-19, METOP-B, NASA, TERRA, AQUA, NPP-Suomi, NOAA-20, GOES-13 and MSG-3 (INPE 2021). Nevertheless, the images generated by the AQUA satellite have been used as “reference” by the INPE since 2002. Such data are used to compose comparable time data over the years and thus enable trend analysis for the same periods in regions of interest (White 2018; INPE 2021).

The objective of this study is to analyze the spatiotemporal variation of fire pixel detection between 01/01/2003 and 12/31/2020 (totaling 18 years) in the state of Minas Gerais, Brazil, at municipality level, based on data from the AQUA satellite (MODIS). And, to identify the independent variables that had significant influence in fire occurrence. Such research is essential for the design of efficient wildfire prevention measures in order to reduce negative environmental impacts due to fires in the study area.

Materials and Methods

Characterization of the study area

Minas Gerais is the fourth largest Brazilian state in size (586,513,993 km²) and the second largest in population (19,597,330) (IBGE 2021). The predominant climate, according to the updated Köppen-Geiger classification (Kottek et al. 2006), is “Aw” (tropical wet and dry, also called humid tropical savanna). However, due to the large territorial extension, several different climates are also found, such “Cfb” (humid temperate climate with moderately hot summer),

“Cwa” (humid temperate climate with dry winter); “Cwb” (humid subtropical with dry winter and temperate summer), and “Bsh” (hot semi-arid climate) (Dubreuil, Fante, Planchon and Neto 2018; Martins, Gonzaga, dos Santos and Reboita 2018).

The Brazilian savanna (Cerrado), is the predominant biome occupying 54% of the Minas Gerais territorial extension. With more than 6,500 plant species, it's a fire dependent biome characterized by the presence of grasses associated with trees and shrubs generally well-spaced (IEFMG 2020). The second largest biome is the Atlantic Forest, representing 40% of the state's area. It is a fire sensitive biome composed of Seasonal Deciduous and Semideciduous Forests, Open and Mixed Forest, Dense Ombrophile Forest, and altitude fields. Usually, fire occurrences are rare in the forests due to the vegetation's high humidity (Fundação SOS Mata Atlântica 2002; IEFMG 2020). The third largest biome is the Caatinga, occurring in 6% of the state's area, and is characterized by thorny plants with dry branches and few leaves in the dry season (GEMG 2021; IEFMG 2020). The “Cerrado” prevails in the west, the Atlantic Forest is located mainly in the eastern portion of the state, and the Caatinga in the north (GEMG 2021; IEFMG 2020; Vasconcelos 2014).

In Minas Gerais, as in the rest of Brazil, the use of fire in farming activities is quite common. Anthropogenic activities are responsible for 99% of wildfires, while only 1% are originated by lightning (Soares and Batista 2007).

Dataset

Data from fire pixels detected by the AQUA satellite and processed with the Collection 6 algorithm, between 01/01/2003 and 31/12/2020 in the state of Minas Gerais, were obtained from the “Programa Queimadas”, a website from the Brazilian National Institute for Space Research (INPE 2021).

The size of the each of the 853 Minas Gerais municipalities was obtained from the IBGE (2021). Their mean annual air temperature and rainfall were obtained through the CLIMATE-DATA (2021) based on climate models and data measured between the years 1982 and 2012. The municipal population and demographic density were based on the last demographic census (IBGE 2011). The municipalities area occupied by natural

formations, agriculture, pasture and agricultural/pasture mosaic from each municipality were obtained from MAPBIOMAS (2021) based on average data from 2003 to 2019.

The municipalities were grouped according to the classification originally proposed by White and White (2016) and updated by White (2020) to identify their frequency of wildland fire occurrence (Table 1).

Wildland fire incidence

Table 1: Frequency of wildland fire occurrence based on fire pixel data from AQUA satellite according to White (2020) classification.

Frequency of wildland fire occurrence	Number of fire pixels detected per year
Very Low	None or one fire pixel for an area $> 600 \text{ km}^2$ (Equivalent to < 0.0017 fire pixel/ km^2).
Low	One fire pixel for an area > 300 and $\leq 600 \text{ km}^2$ (Equivalent to > 0.0033 and ≤ 0.0017 fire pixel/ km^2).
Average	One fire pixel for an area > 150 and $\leq 300 \text{ km}^2$ (Equivalent to > 0.0067 and ≤ 0.0033 fire pixel/ km^2).
High	One fire pixel for an area > 75 and $\leq 150 \text{ km}^2$ (Equivalent to > 0.0133 and ≤ 0.0067 fire pixel/ km^2).
Very High	One fire pixel for an area > 25 and $\leq 75 \text{ km}^2$ (Equivalent to > 0.04 and ≤ 0.0133 fire pixel/ km^2).
Extreme	One fire pixel for an area $\leq 25 \text{ km}^2$ (Equivalent to ≥ 0.04 fire pixel/ km^2).

Statistical analysis

Initially, all the data from fire pixels detected in the state of Minas Gerais were grouped according to months and years, and then, mean values and their respective standard deviations were defined. The Analysis of Variance (ANOVA test) and the Tukey HDS test were used to verify the existence of significant differences between the numbers of fire pixels recorded in different months of the year. The linear trend was used to identify the existence of increase or decrease trend in the number of fire pixels during the evaluated period.

Nine independent variables: air temperature; rainfall amount; population; demographic density; size of the municipality area occupied by natural formations; by agricultural fields; by pastures; by mosaic agriculture/pasture; and by urban infrastructure, had their data collected to verify, thought the

Pearson's correlation matrix (r), its influence on the number of fire pixels detected for each municipality. Such variables were chosen due to the availability of data and because they are commonly cited in the literature as having influence on wildland fire occurrence (e.g. Ajin et al. 2016; Soares and Batista 2007; White 2018; White 2019).

Results and discussion

A total of 194,609 fire pixels were detected in the state of Minas Gerais during the period evaluated, which corresponded to an average of 10,812 ($\pm 4,693$) per year. The year with the highest number of fire pixels was 2007 while 2018 had the lowest. The trend line indicates that during the period there was a significant downtrend ($r^2=0.36$; $p<0.05$) (Figure 1).

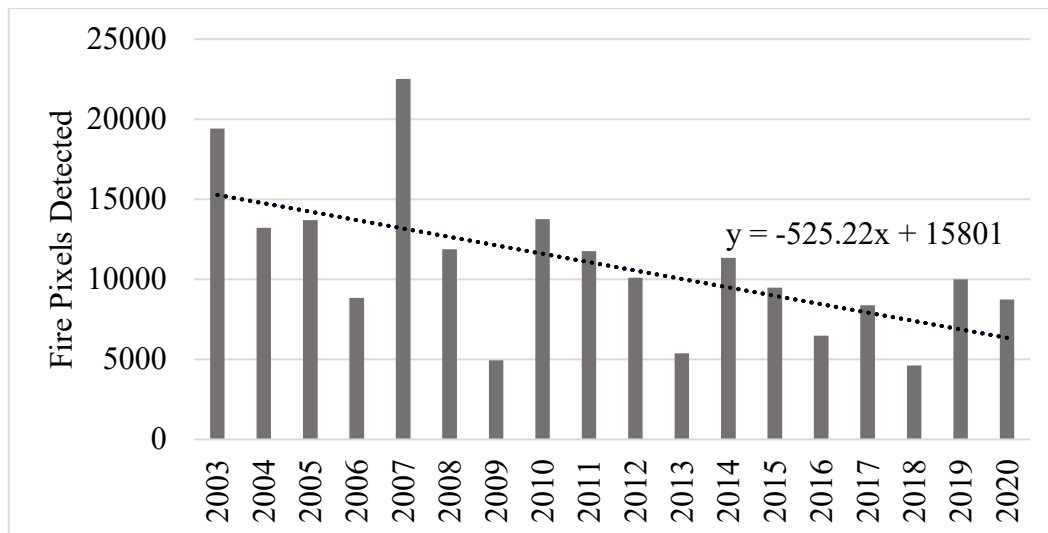


Figure 1: Number of fire pixels detected by the AQUA satellite in the state of Minas Gerais between 2003 and 2020. The line indicates the linear trend for the period evaluated.

The downtrend verified in this study for the state of Minas Gerais, follows the same pattern verified in Brazil, as a whole, for the same period, which also had the highest number of fire pixels in 2007 according to the AQUA satellite (INPE 2021). Interannual variations in fire occurrence are usually associated with meteorological factors, change in land use and occupation or government public policies (Santos et al. 2019). The reduction trend in the rate of deforestation of the primary vegetation in the state of Minas Gerais between 2003 and 2017, as reported by MAPBIOMAS (2021), can partially explain the results.

Regarding the meteorological factors in the South America, the El Niño and La Niña play an important role in changes in the annual rainfall pattern, thus contributing to changes in the wildfire activity (Oliveira-Júnior et al. 2021; White 2019). In most of Brazil, large fires occur in severe droughts years, which in turn are influenced by climate variability caused by the El Niño-Southern Oscillation (ENSO) and the Southern Annular Mode (SAM) (Oliveira-Júnior et al. 2021). The El Niño events in 2003, 2005 and 2007 (Null 2022) could be associated with the high number of fire pixels detected in those years.

However, the 2015, 2016 El Niño events (Null 2022), responsible for a record-breaking warming and extreme drought in the Amazon rainforest (Jiménez-Muñoz et al. 2016), didn't have a big impact on the number of fire pixels detected in those years in Minas Gerais.

Therefore, despite the total annual rainfall and its distribution over a year have already been proven to have a significant effect on annual fire activity (White and Ribeiro, 2011), not always the wettest and driest years have less or more fire activity, respectively, since several other factors play a key role in fire ignition and propagation (Santos et al. 2019; White and Ribeiro 2011). Also, it is important to take into consideration, when analyzing meteorological parameters and its influence on fire activity, that climate trend analysis should, preferably, apply data series longer than 30 years, since normal climate is usually defined by three decades.

Through the analysis of the seasonal variation in fire pixel detection, it was found that, during the time period assessed, September and October were the months with the highest record, followed by August and July, respectively. Based on the Tukey HDS tests, there was no significant difference in the frequency of fire pixels in the remaining months (Figure 2).

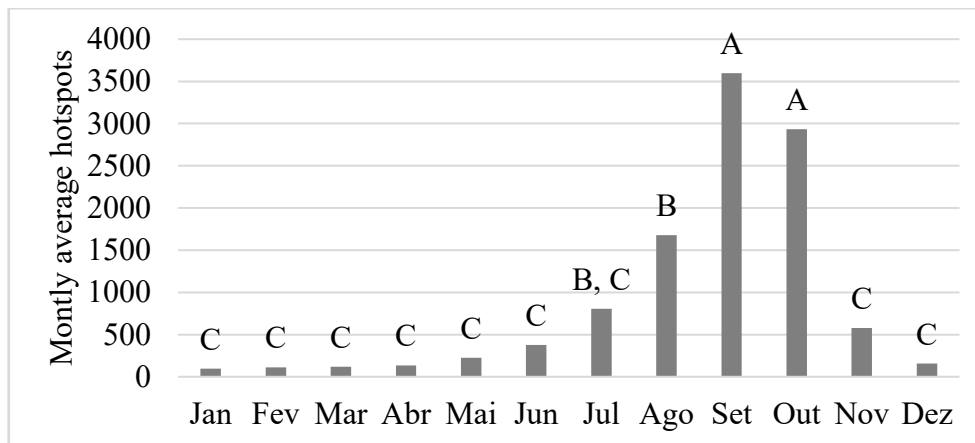


Figure 2: Monthly average number of fire pixels detected by the AQUA satellite in the state of Minas Gerais between 2003 and 2020. Different letters indicate a significant difference between months according to the Tukey HDS test.

The seasonal pattern verified in the state of Minas Gerais follows the national pattern. According to White (2019), September is the month in which Brazil has the highest record of fire pixels, followed by August and October, respectively. This happens because in Minas Gerais, as in most of Brazil, winter is dry while summer is rainy (Mendonça and Danni-Oliveira 2017). Due to the low rainfall during the winter, the vegetation becomes drier and more prone to burn in late winter and early spring (Soares and Batista 2007). Despite the direct effect of the precipitation in the fire activity, usually the months with higher wildland fire occurrence aren't the driest ones. This occurs due to a delay in the effect of the rainfall in the vegetation moisture since, if there is a large amount of moisture accumulated in the forest, it will take some time to dry, just as the dry vegetation will not recover its moisture immediately after short rainfall events (White and Ribeiro 2011). This

statement is true for the state of Minas Gerais, since the driest months are July and August (Santos et al. 2019), being the rainfall increase in the months of September and October, compared to the months above mentioned, not sufficient to reverse the flammability state of the vegetation.

During the time assessed, the municipality with the highest number of fire pixels detected was Paracatu (3,785). Proportionally to the municipalities size, the five with the highest density of fire pixels were Patrocínio; Mário Campos; João Monlevade; Divisa Alegre; and Comercinho, respectively. The five with the lowest density were Tocos do Moji; Conceição dos Ouros; Piranguçu; Estiva; and Patrocínio do Muriaé, respectively. Using the classification proposed by White (2020), 48 municipalities were classified in the "Extreme" class of wildland fire incidence, 343 in the "Very High", 265 in the "High", 98 in the "Medium", 33 in the "Low" and 16 in the "Very Low" (Figure 3).

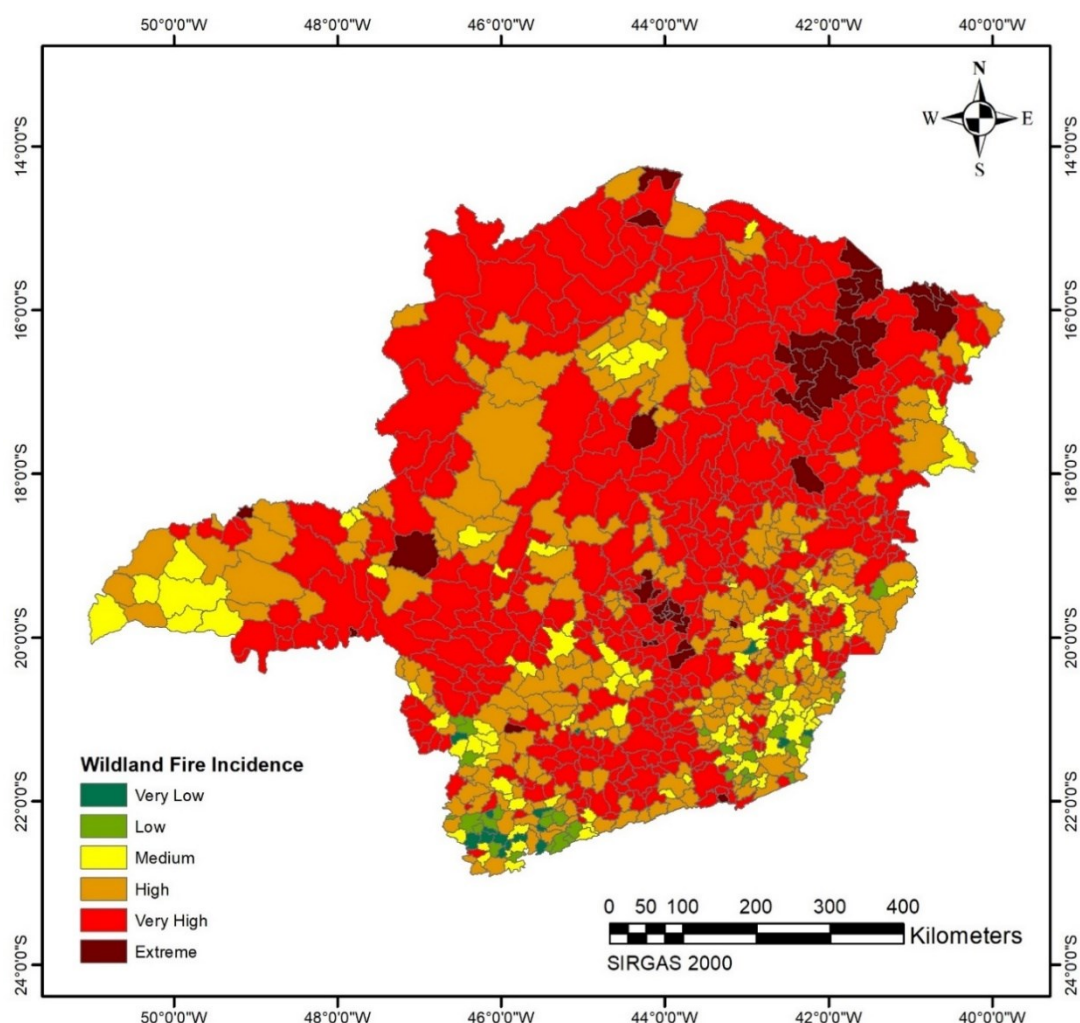


Figure 3: Wildland fire incidence in the municipalities of the state of Minas Gerais (Brazil), based on the mean annual number of fire pixels from 2003 to 2020 detected by the AQUA satellite. The categorization is based on the White (2020) classification.

Through the observation of the developed map, it is noticed that most of the state (approximately 90% of its area) was classified as having high, very high or extreme wildland fire occurrence. These findings highlight the need to implement fire prevention activities. The municipalities from the northeast state region, more specifically, the north area of the Jequitinhonha and the northeast of the Norte de Minas mesoregions, stand out for their high incidence of fire pixels during the analyzed period. The central region of the Metropolitana de Belo Horizonte mesoregion also presented

several municipalities with high fire pixel density. The south and southeast portions of the state, especially the Sul/Sudeste de Minas and Zona da Mata mesoregions, had the least fire activity. These findings are in agreement with Santos et al. (2019) that the northeast and northwest Minas Gerais regions have the highest wildland fire occurrence. However, it is also important to underline the high fire pixel occurrence in the state's center region.

Due to the large number of municipalities present in the state (853), only those 48 classified with extreme fire incidence are described below (Table 3).

Table 3: List of the 48 municipalities of Minas Gerais (Brazil) with the highest fire pixel density during 2003-2020 according to data from the AQUA satellite processed by the Collection 6 algorithm. The municipalities are listed in decreasing order of fire pixel density. Also, is presented the respective municipalities data from: mean annual number of fire pixels (FP); mean annual temperature; mean annual

rainfall; agriculture area; mosaic agriculture/pasture area; pasture area; urban infrastructure area; natural formations area; population; and demographic density.

Munic.	Mean annual FP	Mean annual FP/km² (Density)	Mean annual temp. (°C)	Mean annual rainfall (mm)	Agric. area (ha)	Mosaic area (ha)	Pasture area (ha)	Urban Infra. area (ha)	Natural Form. area (ha)	Pop	Domog. density
Patrocínio	55	0.504	21.2	1408	35680	0	147658	3253	92582	82471	28.69
Mário Campos	4	0.112	20.8	1315	12	1459	404	278	1323	13192	374.82
João Monlevade	10	0.097	20.4	1299	9	512	2067	2221	4901	73610	742.35
Divisa Alegre	11	0.094	21.1	638	0	420	1185	448	9692	5884	49.95
Comercinho	56	0.086	23.1	882	0	5113	14632	45	44751	8298	12.67
Itinga	134	0.081	24.4	714	0	6489	43691	361	113196	14407	8.73
Jenipapo de Minas	23	0.080	23.4	603	1	972	9765	300	17347	7116	25.02
Vespasiano	5	0.077	21.6	1039	2	0	2940	2177	1963	104527	1467.62
Sarzedo	5	0.076	20.3	1315	12	1775	808	1110	2319	25814	415.46
Águas Vermelhas	93	0.074	21.3	637	0	5585	21759	8771	88627	12722	10
Mata Verde	17	0.073	21.3	1014	0	2265	9465	50	10972	7874	34.61
Confins	3	0.072	21.4	1039	3	0	2129	510	1535	5936	140
Ribeirão das Neves	10	0.065	21.6	1039	1	0	5692	4928	4901	296317	1905.07
Bandeira	31	0.065	22.2	899	0	3992	20326	7	24032	4987	10
Itaobim	44	0.064	23.4	653	0	2775	20605	532	42872	21001	30.93
Coronel Murta	51	0.062	23.8	855	5	3564	23216	968	52923	9117	11.18
Araçuaí	137	0.061	24.4	633	2	8383	63930	877	148197	36013	16.10
Divisópolis	34	0.060	20.7	781	0	4668	12430	480	39692	8974	15.66
Medina	85	0.059	22.1	845	0	9385	27312	263	102813	21026	14.64
Curral de Dentro	33	0.058	21.6	830	18	2613	11304	4282	38600	6913	12.17
São José da Lapa	3	0.056	21.1	1039	3	0	2138	940	1651	19799	413.08
Rubelita	59	0.053	23.5	855	8	7254	34123	4124	65250	7772	7.00
Santa Cruz de Salinas	31	0.053	21.6	830	12	4880	19775	3473	30613	4397	7.46
São Joaquim de Bicas	4	0.053	21.1	1315	81	1535	2074	842	2512	25537	356.88
Ninheira	58	0.052	21.5	671	0	5402	27872	6086	70483	9815	8.86
Francisco Badaró	24	0.052	23.8	603	1	879	26584	40	18458	10248	22.21
Delta	5	0.051	23.6	1368	5797	2667	663	176	749	8089	78.66
São João das Missões	34	0.050	25.3	784	153	1399	15571	29	50171	11715	17.27
Virgem da Lapa	44	0.050	23.5	821	7	1071	45878	2258	37204	13619	15.67

Juvenília	53	0.050	25.9	749	298	1932	24795	95	78645	5708	5.36
Francisco Dumont	78	0.049	23.3	842	64	0	50043	15213	91443	4863	3.09
Araçaí	9	0.049	22.5	1194	11	0	11851	424	6450	2243	12
Água Boa	63	0.048	22.5	1129	0	15315	48624	667	67303	15195	12
Berizal	23	0.047	21.8	644	0	2632	12588	1525	31978	4370	8.94
Prudente de Moraes	6	0.046	21.5	1279	8	0	7933	467	3920	9573	77.08
Almenara	104	0.045	23.0	864	0	19136	85992	722	121754	38775	17
Pedro Leopoldo	13	0.045	21.4	1039	5	0	15979	1877	11203	58740	200.51
Santa Luzia	11	0.045	21.5	1023	4	201	8719	3334	11172	202942	862.38
Sabará	14	0.045	20.5	1258	5	5873	4411	2319	16847	126269	417.87
Araporã	13	0.044	25.0	1123	11745	6661	4109	229	2426	6144	21
Josenópolis	24	0.044	22.5	929	5	0	9095	12260	32759	4566	8.43
Lagoa Santa	10	0.044	21.8	1039	6	0	11356	2033	9214	52520	229.08
Itabirito	23	0.043	19.3	1590	26	14548	6685	2555	21946	45449	83.76
Rio Acima	10	0.042	19.7	1258	6	6854	882	240	11813	9090	39.55
Simão Pereira	6	0.041	21.1	1347	0	2217	7586	31	3597	2537	18.70
Campo do Meio	11	0.041	21.0	1364	374	1832	14655	626	5568	11476	41.67
Sete Lagoas	22	0.040	21.5	1279	102	0	30121	6258	16830	214152	398.32
Chapada do Norte	33	0.040	23.1	728	4	1403	26631	1128	53510	15189	18.28

Font: Mean annual FP (INPE 2021); mean annual temperature and rainfall (CLIMATE-DATA 2021); population and demographic density (IBGE 2011); areas of agriculture, mosaic, pasture, urban infrastructure and natural formation (MAPBIOMAS 2021).

The Pearson's correlation matrix (r) indicated that the independent variable that had the biggest influence in the fire pixel density for each municipality was the mean annual rainfall. The variables that presented a significant correlation with the municipal fire pixel density

were: natural formations area, mean annual temperature and agriculture area also. The pasture area, urban infrastructure area, population, demographic density, and mosaic agriculture/pasture area, showed no significant correlation with the fire pixel density (Table 2).

Table 2: Matrix of Pearson correlation coefficients (r) between all variables (dependents and independent) used in this study. Note: * - Significant at 0,05%; ** - Significant at 0,01%

	HS density	Mean annual temp.	Mean annual rainfall	Natural form. area	Pop.	Demog . density	Agric. area	Mosaic area	Pasture area	Urban infra. area
HS density	1.00	0.10*	-0.21**	0.14**	0.06	0.00	0.07*	-0.04	0.06	0.04
Mean annual temperature	.	1.00	-0.65**	0.33**	0.00	-0.03	0.18**	-0.21**	0.37**	0.10*
Mean annual rainfall	.	.	1.00	-0.28**	0.00	0.03	0.04	0.18**	-0.16**	-0.09*
Natural form. area	.	.	.	1.00	0.05	-0.02	0.35**	-0.05	0.58**	0.52* *

Pop.	.	.	.	.	1.00	0.09*	0.11*	0.09*	0.11*	0.18*
Demog. density	.	.	.	.	.	1.00	-0.01	0.06	0.00	0.00
Agriculture area	.	.	.	.	.	.	1.00	0.05	0.54**	0.16*
Mosaic area	.	.	.	.	.	.	.	1.00	0.09*	-0.05
Pasture area	.	.	.	.	.	.	.	.	1.00	0.39*
Urban infrastructur e area	.	.	.	.	.	.	.	.	.	1.00

Note: * Significant at $p < 0.05$; ** Significant at $p < 0.01$.

Based on the analysis of the correlation matrix, the mean annual rainfall amount was the main independent variable appointed to have effect on the municipalities fire pixel density. That happens because the rain increases the vegetation (fuel) moisture content, making it harder, i.e., requiring a greater amount of heat energy, to ignite. Therefore, places with drier vegetation should be more prone to burn (Silva Junior et al. 2022; White 2018).

Municipality area occupied by natural formations presented the second highest correlation with fire pixel density. Such findings show that the municipalities with bigger natural formation areas, whether forests, savannas, or grasslands, have burned, during the time assessed, even more than municipalities with larger areas of agriculture and pastures. This is worrisome, since burns in natural vegetations are commonly associated with deforestation (White 2018). The degradation of natural forests and others vegetations with the use of fire is responsible for the increase in greenhouse gas emissions, mainly due to deforestation and to the decline on soil organic carbon (Silva Junior et al. 2022). Burns of wildland areas also represents a critical factor in the biodiversity conservation, causing severe habitat loss, reducing the population of wild animals and, in some cases, being responsible for the extinction of endemic fire sensitive species (Lugo 1988).

Mean annual temperature also presented a significative correlation with the fire pixel density, meaning that the municipalities with higher temperatures presented higher wildland fire occurrence per area. In the absence of rainfall, the fuel moisture content fluctuates through the exchange of water vapor between the fuel and the environment (adsorption or

desorption). Higher temperatures contribute with the drying of the vegetation, mostly of the dead leaves and fine branches located in the litter, leaving it more prone to burn. The moisture content of the fine and dead fuels is one of the main variables used in wildfire risk assessment (White 2019). Warming can further enhance drought severity from precipitation deficit through an increase in potential evapotranspiration (Jiménez-Muñoz et al. 2016).

The size of the municipalities agriculture areas presented the lowest significative correlation with the fire pixel density. These results also suggest that control burns are still commonly used in agricultural activities. According to Agência Minas (2021), Minas Gerais had 854,2 thousand hectares of sugar cane plantations in 2020, number that has been increasing in the last years, and should continue to increase in the further years. This size represents about 30% of the total agricultural area of the state and should explain the correlation between municipality agricultural area and fire pixel density, since, the pre-harvest burning is a very common practice, being areas of sugar cane plantations already related to places with high fire pixels detection (França et al. 2012; Oliveira-Júnior et al. 2020).

The variables population, demographic density, mosaic agriculture/pasture area, pasture area and urban infrastructure area did not present significant correlation with the municipality fire pixel density. The pasture fields are usually cited in the literature as areas with higher occurrence of wildland fires, since ranches commonly use the fire to clean the fields and stimulate the growth of grasses. White (2018), for example, in an analysis carried out in the state of Amazonas, affirm that cattle rising, associated with the deforestation process, are the main variables affecting the

occurrence of wildland fires in the state of Amazonas. But, different from what is happening in the Amazonia state, in Minas Gerais the annual rate of deforestation has been decreasing over the last years and no new pasture areas had been created. In fact, the pasture area for the entire state had reduced from approximately 27,5 million of hectares in 2003 to 23,7 in 2019 (MAPBIOMAS, 2021). Taking those factors in consideration may be the key to understand why the municipalities pasture area did not significantly affect their fire pixel density.

Population and demographic density are also usually used as variables that affect the wildfire risk of occurrence (e.g. Soares and Batista 2007; Oliveira et al. 2004; Oliveira-Júnior et al. 2020) but in studies done in the states of Sergipe (White and White 2016) and Amazonas (White, 2018), no correlation between population and demographic density versus the number of fire pixels detected were found. Since anthropic activities are responsible for 99% of wildfires that occur in Brazil (Soares and Batista 2007), it could be expected that more densely populated municipalities would be more prone to burnings. However, larger populations are usually concentrated in urbanized areas with lower density of vegetated areas susceptible to burn, thus affecting the correlation that would be expected between both variables (White and White 2016).

Conclusions

Despite the reduction in the number of fire pixels detected in the state of Minas Gerais over the last years, wildland fire occurrence in most of the state is still elevated, thus justifying the need to develop and apply new and efficient fire prevention actions that should reduce negative environmental impacts caused by fire. The fire prevention activities should be applied, above all, in the months of September and October and in the 48 municipalities that were classified with Extreme wildland fire incidence.

The independent variable that had the influence in the fire pixel density for each municipality were, in decreasing order of significance, the mean annual rainfall, natural formations area, mean annual temperature and agriculture area. The positive correlation between natural formation areas and fire pixel density, suggest that the natural vegetation areas are being

constantly burned, even more than agricultural or pasture areas, putting at risk endemic species with low distribution and sensitive to fire.

Although the wildland fires in agriculture fields do not endanger wildlife as the fires in natural formations, they still release into the atmosphere greenhouse gases and can contribute with the soil degradation. Therefore, municipalities with large agriculture areas should encourage the farmers to use alternative techniques to the use of fire.

Continuity of the analysis of the dependent and independent variables used in this study is recommended to better understand the factors affecting the spatiotemporal changes in wildland fire occurrence in the long term.

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