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ORIGINAL ARTICLE

Spatiotemporal variation in fire occurrence in the state of Amazonas, Brazil, between 2003 and 2016

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ABSTRACT

Wildland fires can be responsible for negative impacts on the environment, causing damage to the fauna and flora and increasing the release of greenhouse gases. In the state of Amazonas, wildland fires represent a risk for biodiversity conservation, since more than 95% of the state is covered by Amazon rainforest, one of the largest and most biodiverse tropical forests of the world. This study aimed to analyze the spatiotemporal variation of fire occurrence from 2003 to 2016 in the state of Amazonas, based on data from the AQUA satellite processed by the Brazilian National Institute for Space Research, using the "Collection 5" detection algorithm. The correlation between fire incidence versus anthropogenic and climatic variables was also tested. A significant uptrend was observed in the number of hot spots recorded over the years. About 83% of the wildland fires occurred during the months of August, September and October. The variables that correlated significantly with the number of hot spots for each municipality were deforested area, pasture area, agricultural area, municipality area and mean annual rainfall. The municipality with the highest number of hot spots detected was Lábrea, while Careiro da Várzea presented the highest incidence per km^2. The southern and eastern regions of the state were the areas most affected by fire during the analyzed period. The results from this study emphasize the need for implementation of public policies aimed to reduce deforestation and wildland fires in the state, thus ensuring the conservation of the Amazon rainforest and its biodiversity.

KEYWORDS: hot spots; fire prevention; wildfire; remote sensing

Variação espaço-temporal da ocorrência de queimadas e incêndios florestais no estado do Amazonas, Brasil, entre 2003 e 2016

RESUMO

As queimadas controladas e incêndios florestais podem ser responsáveis por impactos negativos ao meio ambiente, ocasionando danos à fauna e flora e contribuindo para a liberação de gases na atmosfera responsáveis pelo efeito estufa. O fogo no Amazonas representa um grande risco para a preservação da biodiversidade, já que mais de 95% da área do estado é recoberta por floresta amazônica, uma das maiores florestas tropicais do mundo. Este trabalho teve por objetivo analisar a variação espaço-temporal dos focos de calor registrados de 2003 a 2016 no estado do Amazonas, com base em dados obtidos através do satélite AQUA e processados pelo INPE, utilizando o algoritmo de detecção "*Collection 5*". Os dados de focos de calor foram correlacionados com variáveis antropogênicas e climáticas. Foi observada uma tendência significativa de alta nos registros de focos de calor ao longo dos anos. Cerca de 83% das detecções ocorreram nos meses de Agosto, Setembro e Outubro. As variáveis área desmatada, área de pastagem, área agrícola, área do município e precipitação média anual apresentaram correlação significativa com o número de focos de calor para cada município. O município com maior registro de focos de calor foi Lábrea, enquanto Careiro da Várzea apresentou a maior incidência por área. Os resultados obtidos ressaltam a necessidade de implementação de políticas públicas que visem a redução do desmatamento e dos incêndios florestais no estado, garantindo a preservação da floresta amazônica e sua biodiversidade.

PALAVRAS-CHAVE: focos de calor; prevenção contra o fogo; incêndios florestais; sensoriamento remoto

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INTRODUCTION

Wildland fires are any non-structure fire that occurs in vegetation or natural fuels and include prescribed (controlled) burns and wildfires (uncontrolled) (NWCG 2017). They can be a major threat to the preservation of biodiversity, causing impact on the fauna and flora, and contributing, indirectly, with environmental degradation (Soares and Batista 2007). Moreover, the smoke often causes respiratory complications and represents, in some locations, a public health issue (Arbex *et al.* 2004; Shlisky *et al.* 2009).

In the state of Amazonas, the use of fire is cultural and difficult to replace (Cabral *et al.* 2013), being generally used in an irregular manner, without authorization from the responsible environmental agency, the Amazonas Environmental Protection Institute (IPAAM). The use of fire, with or without the use of controlled burning techniques, is prohibited in August, September and October in all the state (IPAAM 2010). Between November and June, prescribed burns can be carried out exclusively when authorized by the agency.

The detection of controlled and uncontrolled wildland fire via satellite began in the 1980s (Wang *et al.* 2012). Images generated by the thermal and infrared sensors installed in the satellites are sent to a control center and processed through a detection algorithm (Batista 2004; Wang *et al.* 2012). The use of an efficient algorithm is essential to distinguish fire in vegetation from other heat sources generating a low number of false positives (INPE 2017). It is important to mention that satellite imagery cannot differentiate unmanaged and uncontrolled wildfires from controlled burns (Goldammer and Mutch 2001).

In Brazil, the Weather and Climate Studies Research Center (CPTEC) of the National Institute for Space Research (INPE) generates and provides information on the occurrence of active fires (hot spots) based on satellite data. Among all images received by INPE from various satellites in operation (NOAA-15, NOAA-18, NOAA-19, METOP-B, NASA, TERRA, AQUA, NPP-Suomi, GOES-13 and MSG-3), those generated by the AQUA satellite and processed with the "Collection 5" algorithm have been used as reference since 2002 to compose comparable interannual time series that enable long-term trend analyses in regions of interest (White and White 2016, INPE 2017; White 2017).

Wildfires in the state of Amazonas represent a huge risk for biodiversity conservation, since more than 95% of the state is covered by the Amazon rainforest, one of the largest tropical forest areas of the world (Primack and Rodrigues 2001; GEA 2017). The exact scope of the problem can only be assessed by satellite data, since local fire statistics in many cases are incomplete or misleading. Therefore, this study aimed to analyze the spatiotemporal variation of fire occurrence in the state of Amazonas using data from the AQUA satellite processed by the "Collection 5" algorithm, for the period from 2003 to 2016. The information obtained can be used by conservation agencies for the improvement of fire prevention and suppression activities, and for the development of public policies focused on wildfire prevention and nature conservation.

MATERIAL AND METHODS

Study area

Amazonas is the largest Brazilian state, occupying a total area of 1,559,149.074 km^2, larger than the size of France, Spain, Sweden and Greece combined (IBGE 2017a). It is located in northern Brazil and is the state with the most preserved and the least deforested portion of Amazon rainforest (SEMA 2017). The climate is equatorial and classified, in most of the state, as "Equatorial rainforest, fully humid" (Af) according to the updated classification of Köppen and Geiger (Kottek *et al.* 2006).

Datasets

The records of hot spots in the state of Amazonas for the period 01/01/2003 to 12/31/2016 were obtained from the INPE Satellite Monitoring Burning Program website, based on data from the AQUA satellite processed through the "Collection 5" algorithm (INPE 2017). The values were quantified for the entire state and grouped by month of occurrence and the municipality in which they were detected.

The following variables that may have a significant influence on the number of hot spots were quantified for each municipality: mean annual temperature; mean annual rainfall; population density; deforested area; agricultural area and pasture area. These variables were chosen due to availability of historical data and because they have been shown to influence with wildland fire occurrence probability (e.g. Oliveira *et al.* 2004; Gonçalves *et al.* 2011; Liu *et al.* 2012; White *et al.* 2016a; White *et al.* 2016b; Suryabhagavan *et al.* 2016; Ajin *et al.* 2016; White and White 2016).

Data on agricultural area was obtained from IBGE (2017b). Data on deforested area was obtained from INPE's "PRODES" project, which performs satellite monitoring of clearcut deforestation in the Amazon and calculates, yearly deforested area in the region (CGOBT 2017). Data on demographic density for each municipality are based on IBGE (2017c). All the variables were quantified annually from 2003 to 2016 for each municipality and had their mean value determined.

Data on pasture area were obtained from project "TerraClass" (CRA 2017; Almeida *et al.* 2016). Data were available for 2004, 2008, 2010, 2012 and 2014. The mean values for each municipality for the period 2003-2016 were extrapolated based on the available data. Mean annual air temperature and rainfall for each municipality were obtained from Climate-Data (2017) based on climate models and data measured between 1982 and 2012. It was assumed that the mean values of temperature and rainfall for each municipality during the period 2003 - 2016 were not statistically different from the average values for 1982 - 2012.

Wildland fire incidence per municipality

The state municipalities were grouped according to the classification proposed by White and White (2016) into five frequency classes based on the number of hot spots per area detected by the AQUA satellite during a period of one year (Table 1).

In order to evaluate wildland fire occurrence over representative long-term time periods of climate variation and land-use change, and to avoid interference of small annual fluctuations, the classification of the frequency of wildfire incidence in each municipality was analyzed in two time periods: 2003-2009 and 2010-2016.

Statistical analysis

Analysis of Variance (ANOVA) and the post-hoc Tukey HDS test were used to test the existence of a significant differences among the number of hot spots recorded in different months of the year. A linear regression was calculated to evaluate the growth trend in number of hot spots throughout the time series. A correlation matrix was constructed with the Pearson (r) correlation coefficients for the several variables analyzed in the study.

Table 1. Frequency of incidence of hot spots detected by the AQUA satellite over one year. The classification follows White and White (2016).

Frequency class	Number of hot spots detected per year
Very Low	None or one hot spot for an area of 601 km^2 or more.
Low	One hot spot for an area between 301-600 km^2.
Average	One hot spot for an area between 151-300 km^2.
High	One hot spot for an area between 76-150 km^2.
Very High	One hot spot for an area of 75 km^2 or less.

RESULTS

A total of 96,884 hot spots were detected by the AQUA satellite in the state of Amazonas between 2003 and 2016, resulting in an average of approximately 6,920 per year. The lowest record was in 2008 (2,717), and the highest in 2015 (15,170). The annual records indicate a significant uptrend in the number of hot spots throughout the time series (r^2 = 0.50; $p < 0.01$) (Figure 1).

The month with the highest number of hot spots recorded was September, followed by August, October, November, July, December, January, February, March, June, May and April. About 83% of the hot spots were detected during the months of August, September and October. Less than 1% of the fires detected occurred during the months of April, May and June. The number of hot spots varied significantly among the months of the year (ANOVA, F = 23.36, $p < 0.01$). The Tukey HDS test grouped the months into three groups with significantly different levels of hot spot occurrence (Figure 2).

Hot spots were recorded in all municipalities in the state of Amazonas (Table 2). Lábrea was the municipality with the highest incidence (13,593) and Japurá with the lowest (106).

The municipalities with the highest number of hot spots detected during 2003-2016 presented the largest deforested areas during the same period. Four other independent variables were significantly correlated with the number of hot spots: pasture area, agricultural area, municipality area and mean annual rainfall. Mean annual temperature and demographic density were not significantly correlated with number of hot spots (Table 3).

Apart from Lábrea, eight other municipalities presented a very high incidence of hot spots (Table 4). Proportionally to its area, Careiro da Várzea registered the highest frequency of incidence of hot spots in the state of Amazonas.

In the first seven years of the time series (2003-2009) the predominant wildfire incidence category in the state of

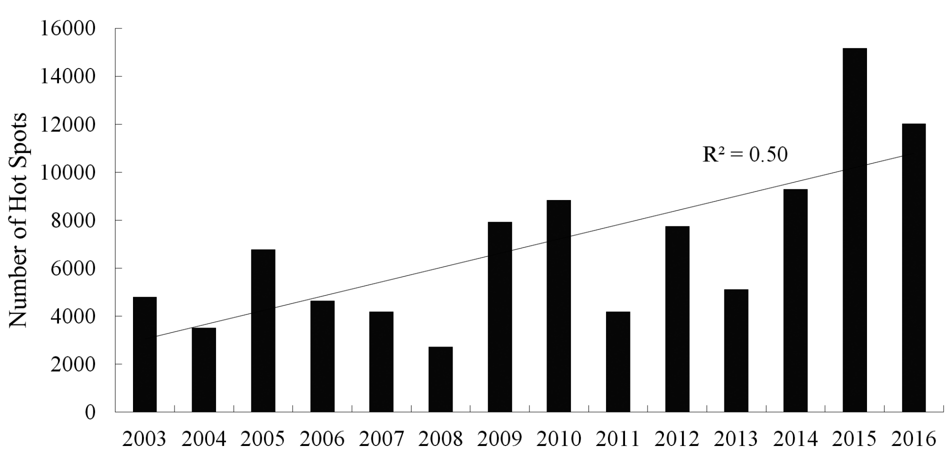

Figure 1. Hot spots detected by the AQUA satellite between 2003 and 2016 in the state of Amazonas, Brazil. The regression line indicates the significant linear upward trend.

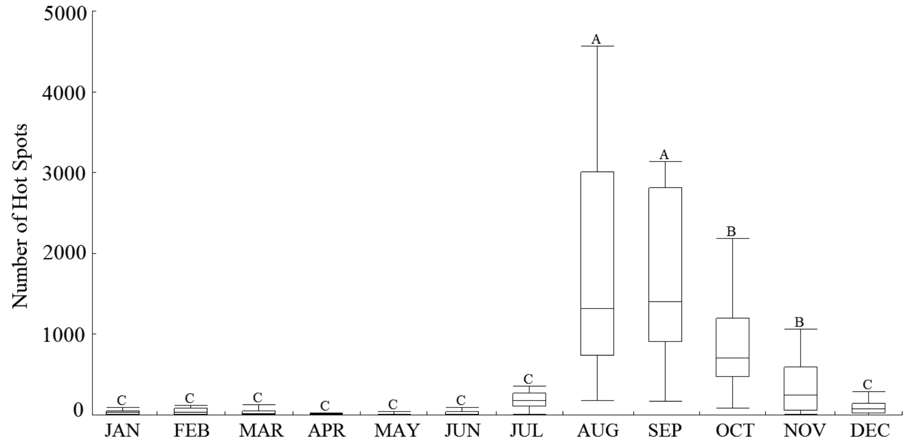

Figure 2. Monthly number of hot spots registered by the AQUA satellite between 2003 and 2016 in the state of Amazonas, Brazil. The line within the box indicates the mean, the box indicates the 25%-75% quartiles, and the bars the 10% and 90% quartiles. Letters above the bars indicate significant differences among means.

Table 2. List of municipalities of Amazonas state (Brazil) and their number of detected hot spots (HS); mean annual hot spots; area; area divided by mean annual hot spot (HS density); hot spot frequency of incidence; deforested area; agricultural area; population size; demographic density; mean annual temperature and mean annual rainfall. Municipalities are grouped in descending order of mean annual hot spot density. The first column indicates the identification code of each municipality in Figure 3.

Code / Rank	Municipality	HS*	Mean annual HS	Municipality area (km^2)	Mean annual HS density (km^2/HS)	HS frequency of incidence**	Deforested area (km^2)***	Agricultural area (km^2)+	Pasture area (km^2)++	Demographic density (hab/km^2)+++	Mean annual temperature (ºC)++++	Mean annual rainfall (mm)++++
1	Careiro da Várzea	1100	79	2631.1	33.49	Very high	9.1	17.97	3.39	8.74	27.4	2166
2	Boca do Acre	7920	566	22348.9	39.51	Very high	60	6.10	2.84	1.38	25.8	2039
3	Autazes	2599	186	7599.3	40.94	Very high	18	10.91	3.40	4.26	27.1	2230
4	Boa Vista do Ramos	712	51	2586.8	50.86	Very high	0.9	7.71	9.37	5.69	27.3	2249
5	Barreirinha	1469	105	5750.5	54.80	Very high	5.2	90.93	891.83	4.88	27.6	2334
6	Parintins	1471	105	5952.3	56.65	Very high	4	7.83	0.49	18.06	27.8	2257
7	Careiro	1477	106	6091.5	57.74	Very high	4.9	35.35	314.33	5.16	27.2	2171
8	Manaquiri	846	60	3975.8	65.79	Very high	1.2	4.38	2.97	5.36	27.3	2218
9	Lábrea	13593	971	68229.0	70.27	Very high	158	13.96	127.55	0.53	26.4	2318
10	Itacoatiara	1727	123	2906.7	72.08	Very high	13	25.13	0.80	9.90	27	2220
11	Apuí	9979	713	2215.0	76.10	High	92	13.48	10.51	0.35	27.3	2200
12	Alvarães	1049	75	8892.0	78.90	High	3.5	10.75	8.94	2.45	26.9	2261
13	Manicoré	8422	602	54239.9	80.26	High	59	36.16	1180.34	0.95	26.1	2019
14	Urucurituba	493	35	7329.2	82.54	High	0.4	29.46	23.05	5.58	27.3	2309
15	Manacapuru	1221	87	48282.5	84.04	High	5.6	17.18	4.12	11.91	26.6	2550
16	Canutama	4836	345	5911.8	86.33	High	36	6.29	370.98	0.42	26.9	2645
17	Silves	593	42	3748.8	88.50	High	2.2	13.64	45.41	2.35	21.7	2191
18	Iranduba	335	24	29819.6	92.57	High	3.4	23.86	153.51	18.50	26.5	2440
19	Nova Olinda do Norte	807	58	8904.2	97.30	High	3.5	15.57	126.12	5.66	25.4	2170
20	Guajará	1196	85	5608.5	104.23	High	7.4	39.19	12.66	1.60	27.1	2241
21	Novo Aripuanã	5220	373	41191.3	110.47	High	47	20.45	5.34	0.52	26.9	2444
22	Humaitá	3853	275	33071.7	120.17	High	12	16.73	73.01	1.24	26.5	2322
23	Anamá	239	17	2453.9	143.74	High	0.7	28.21	77.94	3.88	27	2251
24	Envira	1168	83	13369.3	160.25	Average	8.5	36.91	2.33	1.27	25.8	2497
25	Rio Preto da Eva	507	36	14105.6	160.52	Average	3.1	20.02	209.45	4.59	27.6	2348
26	Uarini	876	63	25422.2	163.75	Average	3.1	45.45	189.43	1.20	27.1	2975
27	Nhamundá	1201	86	9456.6	164.43	Average	4	11.91	68.81	1.30	27.1	2204
28	Caapiranga	800	57	5813.2	165.49	Average	1.5	21.58	54.37	1.17	27.3	2302
29	Presidente Figueiredo	2131	152	39988.4	167.02	Average	10	92.11	285.50	1.08	27.2	2101
30	Maués	3338	238	10246.2	167.72	Average	16	9.26	9.23	1.30	26.6	3032
31	Tefé	1911	137	23704.4	173.66	Average	5.9	4.99	18.16	2.75	27	2464
32	Eirunepé	873	62	4231.1	253.89	Average	2.6	2.69	0.64	1.97	27	2163
33	Itapiranga	230	16	15831.6	257.55	Average	0.8	4.73	3.03	2.07	25.8	2431

Table 2. Continued.

Code / Rank	Municipality	HS*	Mean annual HS	Municipality area (km^2)	Mean annual HS density (km^2/HS)	HS frequency of incidence**	Deforested area (km^2)***	Agricultural area (km^2)+	Pasture area (km^2)++	Demographic density (hab/km^2)+++	Mean annual temperature (ºC)++++	Mean annual rainfall (mm)++++
34	Tabatinga	163	12	11401.1	277.00	Average	1.2	16.79	12.37	15.94	27.4	2145
35	Manaus	543	39	3225.1	293.95	Average	3.7	45.03	1952.51	158.97	25.9	2748
36	Ipixuna	608	43	10741.0	312.37	Low	5	153.04	63.21	1.57	27.3	2105
37	São Sebastião do Uatumã	430	31	13565.9	349.71	Low	2.8	20.04	28.38	0.97	25.8	2491
38	Anori	211	15	5795.3	384.52	Low	0.7	23.51	64.76	2.72	26.9	2391
39	Borba	1285	92	44251.2	482.11	Low	5.2	120.42	468.04	0.81	27.1	2023
40	Amaturá	124	9	4758.8	537.28	Low	0.5	11.99	1.83	2.01	25.6	2896
41	Beruri	429	31	17251.2	562.98	Low	1.9	77.84	102.47	0.89	25.8	2039
42	Coari	1407	101	57921.6	576.33	Low	2.8	22.75	72.43	1.36	26.3	2290
43	Pauini	924	66	43263.4	655.51	Very low	6.3	30.62	32.10	0.42	25.8	2359
44	Santo Antônio do Içá	253	18	12307.8	681.06	Very low	1	5.74	7.60	2.31	25.7	3261
45	Tonantins	123	9	6432.6	732.17	Very low	0.7	24.15	247.81	2.87	25.7	3033
46	Carauari	474	34	25767.3	761.06	Very low	1.1	48.61	199.52	1.03	26.2	2587
47	Codajás	340	24	18711.6	770.48	Very low	1.4	16.01	62.05	1.18	26.7	2654
48	Benjamin Constant	141	10	8793.4	873.10	Very low	0.8	79.06	100.73	3.70	25.8	2751
49	Fonte Boa	174	12	12110.9	974.44	Very low	0.9	27.50	49.64	2.18	25.6	2750
50	Urucará	303	22	27904.9	1289.34	Very low	1.6	7.18	3.97	0.67	27.4	2089
51	Tapauá	959	69	89324.3	1304.00	Very low	3.1	8.05	2.03	0.21	25.6	2460
52	Maraã	181	13	16910.4	1307.99	Very low	1.5	25.48	6.25	1.11	26.1	2857
53	Itamarati	252	18	25275.9	1404.22	Very low	1.7	11.75	3.40	0.32	25.8	2530
54	São Paulo de Olivença	193	14	122475.7	1432.34	Very low	1	6.38	48.16	1.63	26.8	2339
55	Barcelos	1123	80	19745.8	1526.86	Very low	1.5	15.49	50.43	0.23	25.6	2717
56	São Gabriel da Cachoeira	861	62	37771.2	1775.36	Very low	3.6	5.78	5.74	0.36	24.2	2504
57	Juruá	151	11	109184.9	1798.71	Very low	1.5	22.63	28.80	0.53	26.4	2909
58	Novo Airão	292	21	19400.4	1810.95	Very low	1	103.30	7.22	0.36	26.2	2937
59	Jutaí	283	20	69551.9	3440.73	Very low	1.9	10.34	2.87	0.29	25.6	2957
60	Santa Isabel do Rio Negro	205	15	62846.2	4291.94	Very low	1.3	39.10	0.76	0.26	26.8	2497
61	Atalaia do Norte	154	11	55791.5	6941.36	Very low	1.5	22.35	53.24	0.19	25.7	3101
62	Japurá	106	8	76355.0	7368.69	Very low	0.9	14.72	13.92	0.14	25.8	2709

* Accumulated between 2003 and 2016 (Source: INPE 2017)
** According to White and White (2016)
*** Annual mean from 2003 to 2016 (Source: PRODES 2017)
+ Annual mean from 2003 to 2016 (Source: IBGE 2017b)
++ Annual mean from data of the years 2004, 2008, 2010, 2012 and 2014 (Source: CRA 2017)
+++ Annual mean from 2003 to 2016 (Source: IBGE 2017c)
++++ Average value based on data from 1982 to 2012 (Source: Climate-Data 2017)

Table 3. Matrix of Pearson correlation coefficients (r) between all variables (dependent and independent) used in this study based on the mean value for each municipality of Amazonas state (Brazil). Significant correlations are marked in bold.

	Hot Spots	Municipality area	Pasture area	Population density	Deforested area	Agricultural area	Rainfall	Temperature
Hot Spots	1.00	**0.27***	**0.92****	-0.08	**0.96****	**0.46****	**-0.26***	0.06
Municipality area		1.00	0.18	-0.16	**0.26***	0.03	0.15	-0.13
Pasture area			1.00	-0.04	**0.95****	**0.29***	**-0.26***	0.00
Population density				1.00	-0.06	0.02	-0.16	0.19
Deforested area					1.00	**0.34***	-0.20	0.01
Agricultural area						1.00	-0.16	0.23
Rainfall							1.00	**-0.29***
Temperature								1.00

Note: The source of the data for each variable are described in Table 2.
* Significant at $p < 0.05$
** Significant at $p < 0.01$

Amazonas was Very Low (in 26 municipalities, representing 63.71% of the state area). In the latter seven years of the time series (2010-2016) only 15 municipalities (47.97% of the state area) had a Very Low incidence frequency. The Very High category, on the other hand, rose from 3 to 18 municipalities from the first to the second period, reflecting the increase of wildland fire activity in the state during the last years (Table 4). The southern and eastern regions of the state showed the highest fire incidence in both periods (Figure 3).

Table 4. Number of municipalities and percentage of the total state area for each of five wildland fire incidence classes for the two study periods. Fire incidence classification according to White and White (2016).

Wildland Fire Incidence	Number of municipalities (% of total area)	
	2003-2009	2010-2016
Very High	3 (5.93%)	18 (16.83%)
High	12 (11.86%)	12 (16.03%)
Average	13 (12.13%)	8 (4.49%)
Low	8 (6.38%)	9 (14.68%)
Very Low	26 (63.71%)	15 (47.97%)

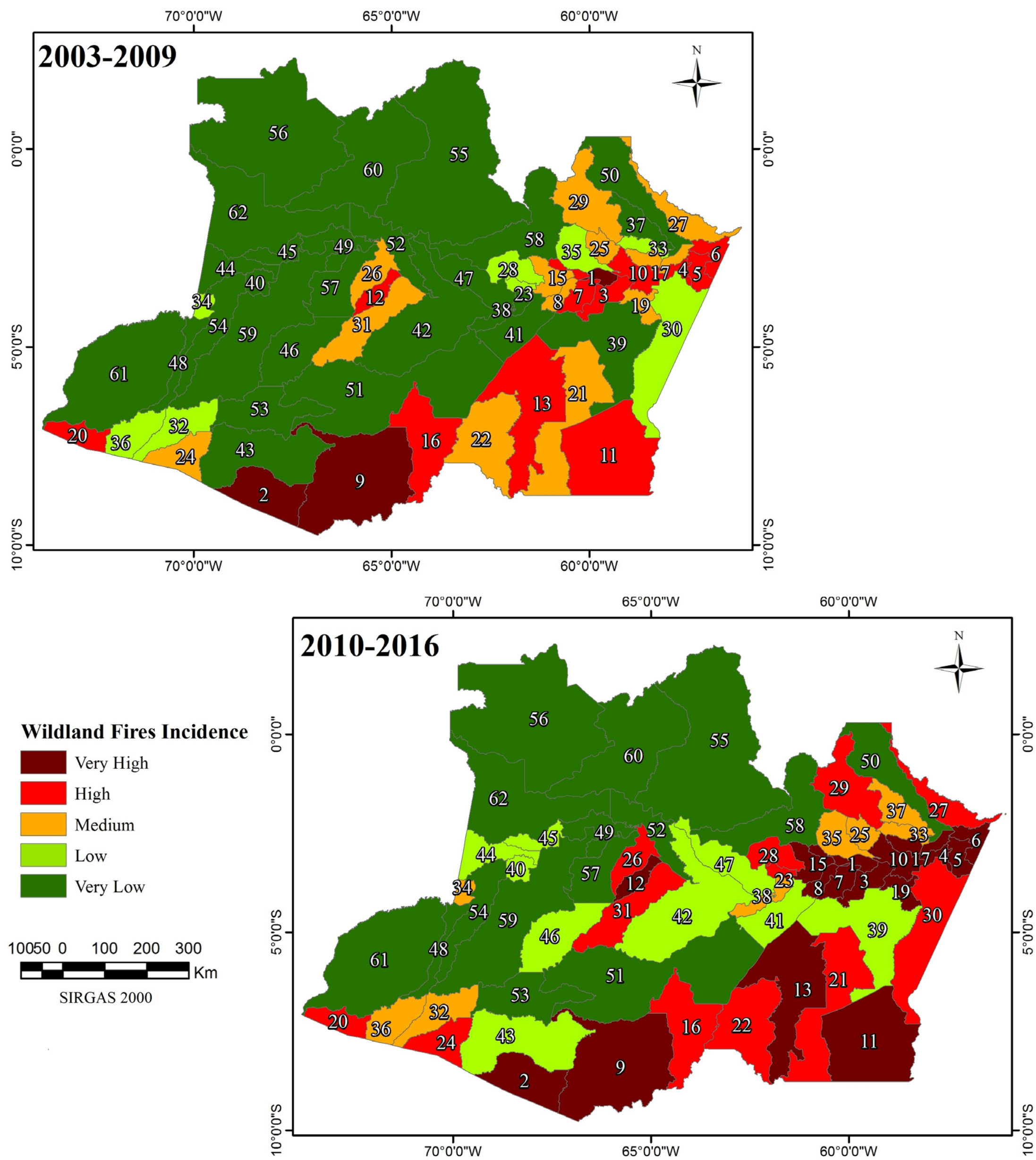

Figure 3. Wildland fire incidence in the municipalities of the state of Amazonas (Brazil) based on the classification proposed by White and White (2016). The first image is based on the mean annual number of hot spots in the period 2003-2009. The second is based on the mean annual number of hot spots in the period 2010-2016. Municipalities are indicated by numbers with correspondence in Table 2. This figure is in color in the electronic version.

DISCUSSION

Although the use of satellites for detecting wildland fires has the advantage of wide range and access to remote areas, resolution limitations of satellites equipped with Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, as in AQUA, prevent the detection of small wildland fires with front line width below 30 m (INPE 2017). Additionally, satellite-based fire detection may also be restricted when fires started and ended during the interval between the satellite passage, by the presence of dense clouds above the burning area, surface fire under closed canopy vegetation, and fire on mountainsides opposite to the satellite observation path (Setzer *et al.* 1992; Pereira *et al.* 2012; INPE 2017). Therefore, the number of wildland fires recorded in this study is likely underestimated.

The highest number of hot spots in the months of August and September follows the pattern observed in most of South America (Bella *et al.* 2006; White 2017). All South American countries below the equator, with the exception of Chile, present higher fire activity from August to November (White 2017). Vasconcelos *et al.* (2013) also estimated that 99% to 95% of the wildland fires in the Amazonas state occur from July to March with peaks in August, September and October.

The predominant climate in Amazonas is equatorial, differing in some aspects from the predominant tropical climates in Brazil (Mendonça and Danni-Oliveira 2007), with temperatures in winter usually higher than in summer, and a very small intra-annual variation. In most of the state, the hottest months are August, September and October (Mendonça and Danni-Oliveira 2007; Climate-Data 2017). In all municipalities annual rainfall is rarely below 2,000 mm, however, during winter, mainly in August and September, monthly precipitation may fall below 50 mm in some municipalities (Mendonça and Danni-Oliveira 2007; Climate-Data 2017). Due to low rainfall and high temperatures during this period, the fuel load becomes drier and, therefore, susceptible to burning.

The interannual changes in wildland fire occurrence observed in this study are mostly due to human behavior and are probably linked with climate variations caused by global warming and by the El Niño and La Nina phenomenons (Victoria *et al.* 1998; Jiménez-Muñoz 2016; White 2017). During the last century global warming was responsible for an increase of 0.56 ºC in the mean temperature in the Brazilian Amazon (Victoria *et al.* 1998). New climate models predict a reduction in rainfall in the Amazon Basin due to changes in sea surface temperature due to global warming (Harris *et al.* 2008; Dai 2013). The increase in temperature and reduction in rainfall cause a decrease in vegetation moisture content, the most important component that affects the ignition probability and fire behavior (White *et al.* 2016b).

The El Niño–Southern Oscillation (ENSO) alters rainfall patterns and intensifies drought in some South American regions. Recent studies proved the relation between ENSO and interannual fire activity (Page *et al.* 2008; Chen *et al.* 2011; Jiménez-Muñoz *et al.* 2016). The 2015-2016 ENSO was responsible for record-braking high temperatures and extreme drought in the Amazon region (Jiménez-Muñoz *et al.* 2016). These extreme temperatures and droughts were likely the main factors responsible for the highest incidence of hot spots in 2015 and 2016. On the other hand, La Niña consists of a basinwide cooling of the tropical Pacific Ocean, and thus the cold phase of ENSO, causing an increase in rainfall in some South American regions (Trenberth 1997). The strong La Niña events during 2007 and 2011 (Null 2016) are likely responsible for the reduction of hot spot detection during these years.

Although meteorological and climatic parameters play a key role in the wildland fire occurrence in the state of Amazonas, human behavior is responsible for 99% of ignition sources, since only 1% of wildfires in Brazil originate from a natural source, that is lightning (Soares and Batista 2007). Therefore, it is essential to analyze human activities in order to understand better fire occurrence.

Land use is one of the most important variables in determining wildland fire risk. While tropical forests have a low fire risk, agricultural fields and pastures are generally defined as high risk (e.g. Gonçalves *et al.* 2011; Suryabhagavan *et al.* 2016; Ajin *et al.* 2016; White *et al.* 2016a). In this study, the municipalities with larger deforested areas, pasture areas and agricultural areas had a higher number of hot spots, which was probably related to deforestation for agricultural and livestock expansion (DeFries *et al.* 2008) and the constant use of fire for land clearing. The large fires related to deforestation are easily detected through remote sensing. Small controlled burns, used for clearing pastures and agricultural areas from weeds and shrubs, can be detected by satellites usually when the frontline is wider than 30 m (INPE 2017).

Although deforestation rates in the Brazilian Amazon have declined from 2004 to 2014 (CRA 2017), the number of hot spots detected during this period increased. This happens because fire continues to be used after deforestation as a tool for cleaning pastures and agricultural fields (Chen *et al.* 2011). Therefore, it is important to consider accumulated deforestation rates and data on land use change when analyzing wildland fire occurrence.

Deforestation of the Amazon may be responsible for an increase in the temperatures and decrease in rainfall throughout the region (Fisch *et al.* 1997; Alves *et al.* 1999; Cohen *et al.* 2007; Correia *et al.* 2008; Araujo and Ponte 2016; Sumila 2016). This indirect impact, allied with the effects of global warming, increases the rate of climate change over the Amazon region, leaving it drier and, consequently, more prone to burning. The change in the climate, combined with land cover change, is likely the reason why fire has become a devastating force in Amazonia in recent years. The expectations for the next years are not good, as the native forest continues to be cleared and global warming effects increase in the region (Dai 2013; Vasconcelos *et al*. 2013).

The significant correlation of the number of hot spots with the mean annual amount of rainfall was expected, since vegetation moisture content increases with rainfall, making it more difficult to burn (Schroeder and Buck 1970; Soares and Batista 2007; White and Ribeiro 2011; White and White 2016). Although air temperature is also pointed out by several authors as an important factor that positively influence fire occurrence through the drying of the fuel load (e.g. Schroeder and Buck 1970; Soares and Batista 2007; White *et al*. 2016b), the variation of average annual air temperature among the municipalities was very low and was not significantly correlated with fire occurrence.

Despite the absence of a significant correlation between the number of hot spots and demographic density, the latter variable is constantly cited in the literature as a main factor that positively affects wildland fire incidence (e.g. Oliveira *et al*. 2004; Liu *et al*. 2012; White *et al*. 2016a; Suryabhagavan *et al*. 2016; Ajin *et al*. 2016). Since anthropic activities are responsible for 99% of wildfires that occur in Brazil (Soares and Batista 2007), and fires in Amazonas state are mainly initiated by humans (Vasconcelos *et al.* 2013), 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 pastures, agricultural fields and forest areas (White and White 2016).

The map indicating the wildland fire incidence in the municipalities of the state of Amazonas can be an important visual tool to assess the future risk of wildland fire occurrence. In both periods assessed, the municipalities most affected by fire were located in the south and east of the state, confirming that data from past fires can be used to predict areas with higher risk of future fires (White and White 2016). Besides using fire occurrence history, other thematic maps of the road system, land use, rainfall distribution, among other aspects, can be integrated using Geographic Information Systems (GIS), allowing a better interpretation of the factors responsible for wildland fire occurrence (Chuvieco and Salas 1996; Díaz-Delgado *et al*. 2004; White and White 2016; White *et al*. 2016a).

CONCLUSIONS

The incidence of hot spots in the state of Amazonas increased significantly from 2003 to 2016. The expectation that numbers will continue to grow imposes the urgent need for the implementation of public policies aimed to reduce wildland fires in the region, thus ensuring the conservation of the Amazon rainforest and its biodiversity. These public policies should be applied mainly in the southern and eastern municipalities of the state, since deforestation and fire occurrence were more intense in these regions over the study period. The prevention and combat of wildfires should be carried out with greater effort from early August to late October, since more than 80% of the hot spots were detected during this period of the year. If the Amazon rainforest continues to be replaced by croplands and, mainly, cattle ranching, and no measures are taken to reduce the use of fire as a management tool, the number of wildland fires in the region will continue to grow, increasing the release of carbon dioxide into the atmosphere and putting at risk global climate stability.

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