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Spatiotemporal variability in fire foci detection in the state of Pará, Brazil

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ABSTRACT

In the current climate change scenario, the adoption of actions aimed at reducing wildland fires and, consequently, greenhouse gas emissions is urgent. The use of environmental satellites to trace wildland fires is an essential instrument in the development of fire prevention strategies. The objectives of this study were to (a) analyze the spatiotemporal variability in fire foci detection in the state of Pará, Brazil; (b) identify the main differences between data from AQUA and Suomi-NPP (S-NPP) satellites; and (c) determine the variables responsible for changes in fire detection at municipal level. Mean annual detection of fire foci was of 43,488 by AQUA based on data from 2003-2023, and of 156,038 by S-NPP from 2012-2023. During the overlap period, S-NPP detected 4.5 times more foci than AQUA. Despite the difference, both datasets were significantly correlated. Most fire foci were detected in August, September and November. São Félix do Xingu and Altamira were the municipalities with the highest number of detections, while Bajaru and Concórdia do Pará registered higher fire foci density. Of the 144 municipalities, 89 were classified as having extreme fire incidence. Deforested area was the variable that presented the highest correlation with municipal fire density, followed by pasture area, rainfall, urbanized area, forest area, agricultural area and demographic density. The results of this study could be used as basis for the development of public policies aiming at the reduction of wildland fire occurrence in Pará.

KEYWORDS: Amazon rainforest; wildland fires; remote sensing; nature conservation

Variabilidade espacial e temporal na detecção de focos de queima no estado do Pará, Brasil

RESUMO

No cenário atual de mudanças climáticas, é urgente adotar medidas que visem a diminuição da queima da vegetação e, consequentemente, da emissão de gases do efeito estufa. O uso de satélites ambientais para a detecção de focos de queima é uma ferramenta fundamental para o desenvolvimento de estratégias de prevenção ao fogo. Este estudo objetivou (a) analisar a variação no registro de focos de queima no estado do Pará, Brasil; (b) identificar as principais diferenças entre os dados dos satélites AQUA e S-NPP; e (c) identificar as variáveis correlacionadas com o registro de focos a nível municipal. A média anual de focos detectados foi de 43.488 com AQUA para o período 2003-2023, e de 156.038 com S-NPP para 2012-2023. Durante o período de sobreposição, S-NPP detectou 4,5 vezes mais focos que AQUA. Apesar da diferença, ambos os dados se correlacionaram significativamente. A maioria dos focos foi detectada em agosto, setembro e novembro. São Félix do Xingu e Altamira foram os municípios com maior número de detecções, enquanto Bajaru e Concórdia do Pará apresentaram maior densidade de focos de queima. Dos 144 municípios, 89 foram classificados como tendo incidência extrema de fogo. Desmatamento foi a variável com a maior correlação com a densidade de focos, seguida por área de pastagem, precipitação pluviométrica, área urbanizada, área florestal, área agrícola e densidade demográfica. Os resultados obtidos podem ser utilizados para o delineamento de políticas públicas que visem a redução da ocorrência de queima da vegetação no estado.

PALAVRAS-CHAVE: floresta amazônica; incêndios florestais; sensoriamento remoto; conservação da natureza

INTRODUCTION

Wildland fires are responsible for several environmental impacts, which are amplified by the effects of global warming (Gajendiran *et al.* 2023). To date, 2023 has been the warmest year since global temperature records started in 1850, with an increase of 1.18°C above the 20th-century average (NOAA 2024). Over the period 1997-2014, modeled global fire carbon dioxide (CO_2) emissions were estimated at a mean value of 2.8 billion tCO_2 year^{-1} (Arora and Melton 2018). In 2021, for example, Brazil's emissions totaled approximately 2.5 billion tCO_2, of which about 50% were owed to changes in land use and land cover (LULC) (SEEG 2024). Pará is one

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of the Brazilian states with the highest rate of LULC change, mainly due to the deforestation of the Amazon rainforest, contributing substantially to the emission of greenhouse gases (GHG). In 2021, LULC in Pará contributed with 475 million tCO_2, about 19% of the total carbon dioxide emissions of Brazil (SEEG 2024).

The replacement of vast areas of forest with pyrophytic grasslands is one of the most negative ecological impacts of fires in tropical rainforests, turning a dense evergreen forest into an impoverished environment populated by a few fire-resistant tree species and a ground cover of weedy grasses (Nasi *et al*. 2002). By 2050, 10% to 47% of Amazonian forests will be exposed to compounding disturbances that may trigger a tipping point, inducing large-scale collapse, unexpected ecosystem transitions and potentially exacerbate regional climate change (Flores *et al.* 2024). The Amazon rainforest acts as a carbon sink and holds an amount of carbon equivalent to 15–20 years of global CO_2 emissions (150 to 200 billion tons of carbon) (Flores *et al.* 2024). Its degradation and the resulting release of GHG could threaten the survival of numerous species and decisively contribute to the process of global warming.

The use of satellites to detect wildland fires is an important tool for monitoring burning vegetation, especially in remote areas. The Brazilian *Centro de Previsão de Tempo e Estudos Climáticos* (CPTEC), at *Instituto Nacional de Pesquisas Espaciais* (INPE), generates and provides information on the occurrence of wildland fires based on environmental satellite data. Although receiving images from ten satellites that have optical sensors operating in the thermal-average range of 4μm (NOAA-18, NOAA-19, METOP-B, METOP-C, TERRA, AQUA, Suomi-NPP, NOAA-20, GOES-13 and MSG-3), the images generated during the afternoon passage of the AQUA satellite (MODIS sensor), processed by the "Collection 6" algorithm, has been used as reference by INPE since 2002. These images 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 2023). Since the AQUA satellite has far exceeded its expected lifespan and will stop working in the near future, it becomes necessary to integrate and adjust the AQUA data with the data from the next reference satellite, which, according to INPE (2023), will be the Suomi (VIIRS sensor, afternoon passage).

Given that AQUA and Suomi (S-NPP) have similar overpass times and both observe the earth two times during the day (morning and afternoon), sampling of the diurnal fire cycle is similar in both (INPE 2023). Nevertheless, compared to the 1-km MODIS bands for fire detection, the VIIRS higher spatial resolution (375 m) enables the detection of smaller fires, as well as improved mapping of large fire perimeters (Li *et al*. 2018). VIIRS also applies onboard aggregation processing to compensate for pixel footprint enlargement with distance from nadir, which strongly affects its fire detection data (Cao *et al.* 2013).

Fire detection omission (false negative) happens more frequently with the AQUA (MODIS) data than with the S-NPP (VIIRS) data (Coskuner 2022; White 2022). This happens because the MODIS sensor has coarser spatial resolution than the VIIRS (White 2022). Previous studies showed that MODIS products have high omission errors in large fires due to obscuration by thick smoke (Schroeder and Giglio 2017). Nevertheless, fire omissions can happen with all satellites used to detect wildland fires when fires started and ended during the interval between the satellite passage, due to the presence of dense clouds above the burning area, in cases of surface fire under closed canopy vegetation and fire on mountainsides opposite to the satellite observation path (INPE 2023). Daytime commission (false positive) errors are rare and typically found over bright land surfaces in areas of sun glint, predominantly associated with reflective rooftops on large industrial buildings (Schroeder *et al*. 2014). Usually, commissions account for less than 1.2% of the total fire foci detected in VIIRS sensors and 1% in MODIS sensors (Giglio *et al.* 2016; Schroeder and Giglio 2017; White 2022).

Due to the above limitations in fire detection via satellite, especially in the MODIS sensor, the number of false negatives is much higher than the number of false positives. Therefore, above all in lower resolution sensors, the total number of fire foci detected represents only a percentage of active fire fronts (INPE 2023). In order to accurately describe and understand fire patterns, it is important to understand the main differences between the two reference satellites used by INPE for fire management activities in Brazil. To use the S-NPP data to complement the AQUA time series, which started in 2002, it is necessary to determine whether the data of both satellites are compatible and to establish an adjustment equation.

Of all the 26 Brazilian states, Pará has the highest annual average of fire foci detected since satellite monitoring began in the country in 1998 (INPE 2023). In the Amazon rainforest, the use of fire is intimately related to deforestation, as the trees are first cut and then dried and burned (White 2018). Deforestation data obtained through MAPBIOMAS (2023) from 1987 to 2021, indicate an average area of 630,216 ha of primary vegetation cleared every year in the state. The high rate of deforestation and the large number of fires reveal the inefficiency of the environmental conservation public policies adopted in the state.

This study had as objectives to (a) analyze the space and time variability in fire foci detection in the state of Pará using data from the AQUA (2002-2023) and S-NPP (2012-2023) satellites; (b) identify the main differences of the data obtained from both satellites; and (c) identify the independent variables that have correlation with fire occurrence at municipal level.

MATERIAL AND METHODS

Study area

Pará is the second largest Brazilian state with an area of approximately 1.2 million km². Altamira is the largest of the 144 municipalities of Pará and also the largest of Brazil, with 159,533 km², approximately the same size of the entire state of Ceará. The smallest municipality is Marituba, with an area of 103 km². As of 2020, the total population of the state was estimated as 8.6 million, corresponding to an average population density of 6.9 inhabitants per km² (IBGE 2022).

The predominant climate in most of the state, according to the updated Köppen-Geiger classification, is equatorial monsoon (Am). There are also areas of equatorial savannah with dry winter (Aw) and equatorial rainforest fully humid (Af) (Kottek *et al.* 2006). The average annual precipitation in Pará ranges from 2,000 to 2,500 mm, and the rainfall pattern is well-defined, with a rainy season extending from December to May, and a less rainy season spanning from June to November (Menezes and Fernandes 2016). The average, average maximum, and average minimum temperatures are 26.6 °C, 30.1 °C, and 24.5 °C, respectively (CLIMATE-DATA 2023).

The state's predominant biome is the Amazon, with a small area of savanna in its southeastern portion. According to satellite imagery from 2020, most of the state's territory is covered by natural forests, occupying a total area of 954,635.19 km² (about 76% of the state area), followed by pastures, with a total area of 203,760 km². Both land cover types account for approximately 93% of the state area (MAPBIOMAS 2023) (Figure 1). Integral protection and sustainable use areas occupy 249,400 km², equivalent to 20% of the state's area, while indigenous lands occupy 275,500 km². Both protection categories account for 42% of the state area (FAPESPA 2018). The state's economic profile is basically extractive, with a predominance of the agricultural and forestry sectors, which are characterized by deforestation and biomass burning (Paixão *et al.* 2019).

Data collection

Records of fire foci in the state of Pará were obtained from the Queimadas Program of INPE (http://terrabrasilis.dpi.inpe.br/queimadas/), based on 21 years of data from the AQUA satellite (afternoon passage), from 01 Jan 2003 to 31 Dec 2023, and 12 years of data from the S-NPP satellite, from 01 Jan 2012 to 31 Dec 2023. The values were quantified by municipality, grouped by month and year.

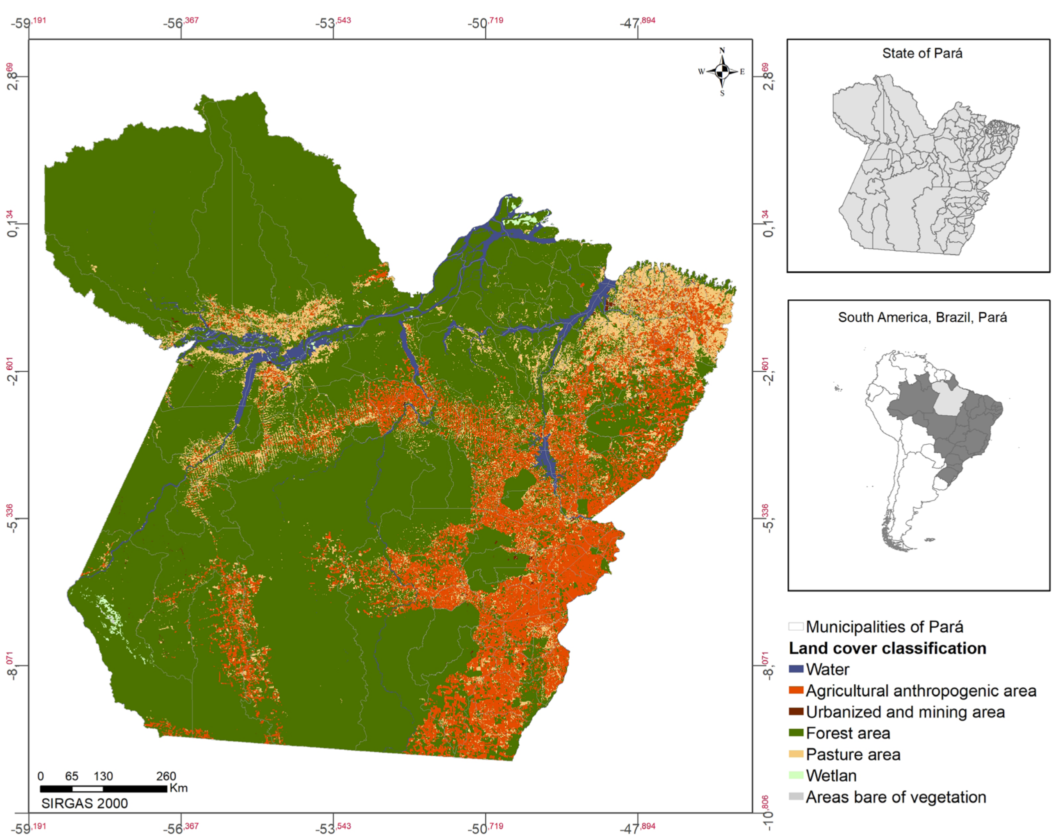

Figure 1. Distribution of land cover types in Pará state (Brazil). The inserts show the location of Pará (light grey) in Brazil (dark grey), and the outlines of the 144 municipalities of Pará. Credit: B. White. Data Source: IBGE (2020).

The following independent variables that may have influenced the number of fire foci were quantified for each municipality: mean annual temperature; mean annual rainfall; population density; mean area of forest (including natural and planted forests, and mangroves); mean area of non-forest natural formations [including wetlands, grasslands, mangrove-terra firme forest transition (*apicum*) and other non-forest formations]; mean urbanized area; mean agriculture area; mean pasture area; mean primary vegetation deforestation area; and mean secondary vegetation deforestation area. These variables were used due to the availability of historical data and due to the fact that previous studies have already indicated that they can influence the probability of fire occurrence (Suryabhagavan *et al*. 2016; White and White 2016; White 2018; White 2020). The areas of forest, non-forest natural formations, urbanization, agriculture, pasture and deforestation were divided by the area of the municipality to avoid the effect of municipality size on wildland fire detection in correlational analyses.

Mean annual temperature and mean annual rainfall were obtained from CLIMATE-DATA (2023), which is based on data from the European Centre for Medium-Range Weather Forecasts (ECMWF) collected from 1991 to 2023. Population density and municipality size were obtained from IBGE (2011, 2022). The means of each land use/cover category were obtained through MAPBIOMAS (2023) based on data from 2003 to 2023. Deforestation data was also obtained from MAPBIOMAS (2023) based on data from 2003 to 2020. The data available from MAPBIOMAS are annual and based on images from the Landsat satellite with 30 m resolution. For each year, a mosaic is created that covers Brazil, representing the behavior of each pixel according to the number of available observations, varying from 0 to 23 observations per year (MAPBIOMAS 2024).

Fire foci incidence classification

The municipalities were grouped according to the classification originally proposed by White and White (2016) and updated by White (2020) into six fire incidence classes, based on the number of fire foci detected per area by the AQUA satellite, afternoon passage, during a period of one year (Table 1).

Data analysis

To verify the existence of significant upward or downward trends in the yearly number of fire foci, and to build an adjustment equation between AQUA and S-NPP data, linear regression analysis was used. To verify the correlation between AQUA and S-NPP satellites, the Pearson's correlation analysis was used between the total number of fire foci detected per year by each satellite in Pará and in each municipality (2012 to 2023).

The influence of all the independent variables on fire foci density per municipality was tested using a Pearson correlation matrix. Only the fire foci density by the AQUA satellite was used due to the greater temporal data availability. The analyzed variables conformed to the requirements for Pearson's correlation analysis (linear relationship, normal distribution, absence of significant outliers and adequate sample size).

The monthly mean values of the number of detected fire foci from 2003 to 2023 were initially compared using ANOVA (data presented normal distribution and homogeneity of variance) folloed by a Tukey-Kramer test for a pairwise comparison of the means. The monthly analysis was also done only using AQUA due to the greater temporal data availability.

RESULTS

A total of 913,249 fire foci were detected by the AQUA satellite from 2003 to 2023, and 1,872,461 were detected by S-NPP from 2012 to 2023, resulting in annual means of 43,488 and 156,038 foci for AQUA and S-NPP, respectively. Fire foci were detected in all 144 municipalities. Marituba had the lowest number and São Félix do Xingu the highest. Proportionally to their area, Bajaru and Concórdia do Pará were the two municipalities with the highest density of fire foci. These results were the same for both satellites during the time periods assessed. The linear regression of the annual number of fire foci over time indicated a significant downtrend from 2003 to 2023 for the AQUA satellite data ($r^2 = 0.45$; $p < 0.01$). Considering only the data for the overlap period (2012-2023), no significant trend was observed for any of the satellites (Figure 2).

Table 1. Classification of hotspot density values detected by the AQUA satellite (afternoon passage) over one year according to White (2020).

Frequency class	Number of hotspots detected per year	Density of hotspots
Very Low	None or one hotspot for an area > 600 km^2	< 0.0017 hotspots km^{-2} $year^{-1}$
Low	One hotspot for an area > 300 and ≤ 600 km^2	> 0.0033 and ≤ 0.0017 hotspots km^{-2} $year^{-1}$
Average	One hotspot for an area > 150 and ≤ 300 km^2	> 0.0067 and ≤ 0.0033 hotspots km^{-2} $year^{-1}$
High	One hotspot for an area > 75 and ≤ 150 km^2	> 0.0133 and ≤ 0.0067 hotspots km^{-2} $year^{-1}$
Very High	One hotspot for an area > 25 and ≤ 75 km^2	> 0.04 and ≤ 0.0133 hotspots km^{-2} $year^{-1}$
Extreme	One hotspot for an area ≤ 25 km^2	≥ 0.04 hotspots km^{-2} $year^{-1}$

During the AQUA and S-NPP overlap period (2012-2023), S-NPP detected 4.5 times more fire foci than AQUA (Table 2). Despite this difference, AQUA and S-NPP yearly fire foci data for the whole state were significantly correlated during their overlap period ($r = 0.95$; $p < 0.001$). Considering the yearly fire foci per municipality, both datasets also were significantly correlated ($r = 0.99$; $p < 0.001$). Due to the significant correlations, it was possible to build an AQUA / S-NPP adjustment equation using linear regression (Figure 3).

Table 2. Total, mean and standard deviation of the yearly number of fire foci detected in Pará state (Brazil) by the AQUA and S-NPP satellites. AQUA data are shown for its total active period and for its overlap period with S-NPP.

	AQUA		S-NPP
Period	2003-2023 (21 years)	2012-2023 (12 years)	2012-2023 (12 years)
Total	913,249	416,315	1,872,461
Mean ± standard deviation	43,488 ± 15,653	34,693 ± 8,910	156,038 ± 42,867

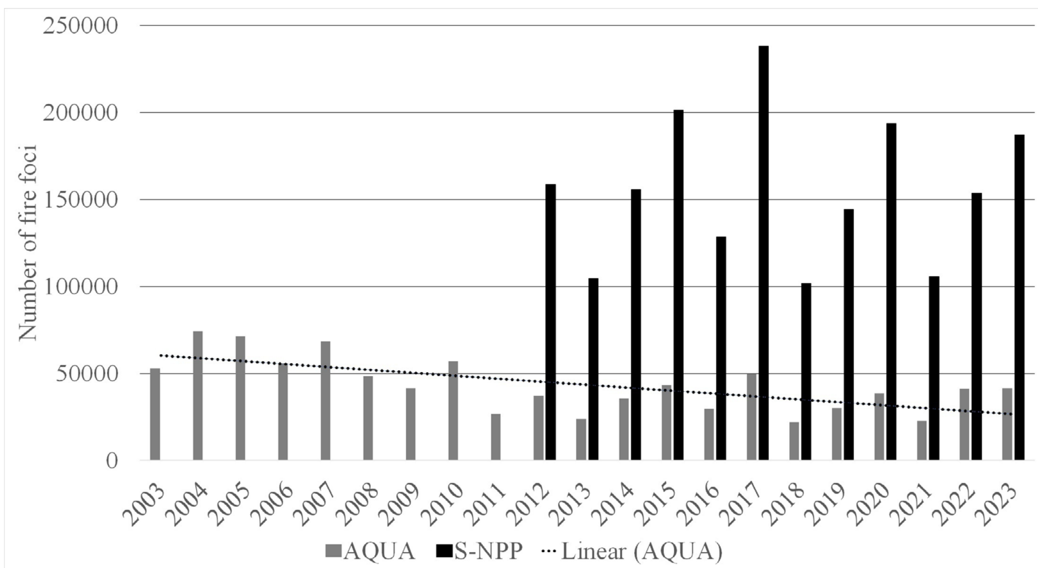

Figure 2. Yearly number of fire foci detected in Pará state (Brazil) by the AQUA (2003-2023) and S-NPP (2012-2023) satellites. The dashed line indicates the regression line of AQUA detections over time, indicating a significant downward trend over the period 2003-2023.

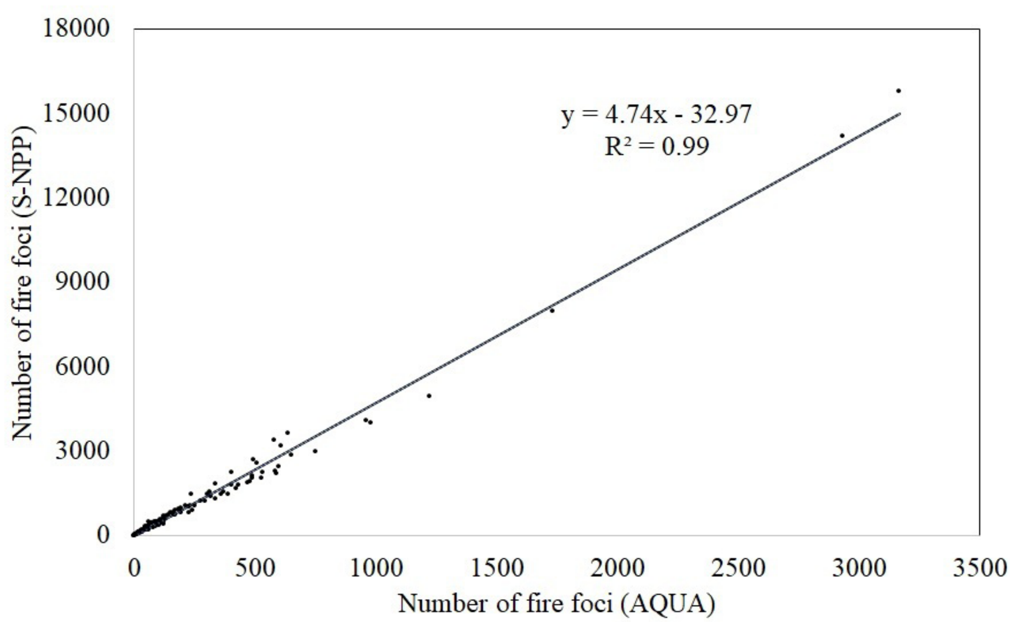

Figure 3. Linear regression between the total number of fire foci detected in 144 municipalities of Pará state (Brazil) by the AQUA and S-NPP satellites during 2012-2023. The solid line indicates the line of best fit.

Classifying the total number of fire foci according to the months of the year in which they were registered and using the ANOVA test, there was a significant variation among the months ($F = 44.03$; $p < 0.001$). The Tukey-Kramer test grouped the monthly means into five groups, with the highest numbers of fire foci in August, September and November (Figure 4).

Using the AQUA data to classify the wildland fire incidence intensity according to White (2020), 89 municipalities were classified as having extreme incidence of wildland fires, 41 had very high incidence, six high, four medium, three low, and one very low (Table 3). The majority of municipalities with the highest densities of fire foci are located in the eastern portion of the state, while those with the lowest densities are located mainly in the north and northwest (Figure 5).

According to the Pearson correlation matrix, deforestation was the variable with the highest correlation with fire foci

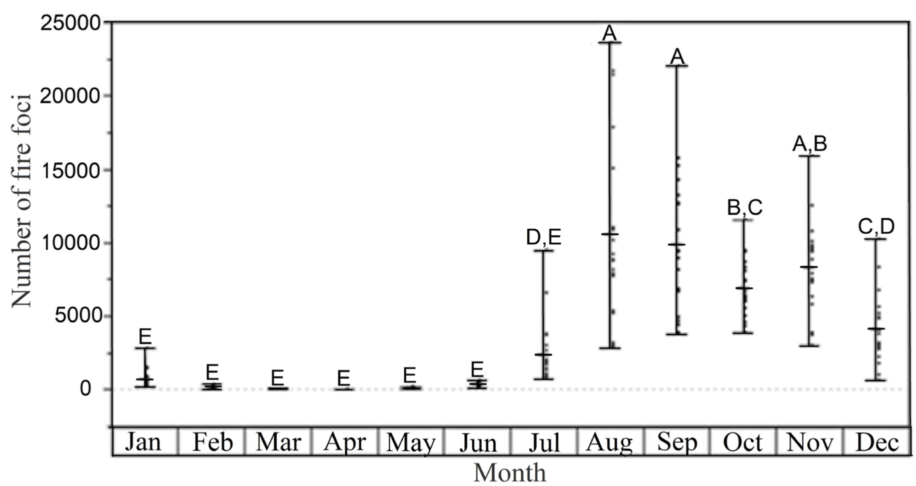

Figure 4. Monthly numbers of fire foci detected by the AQUA satellite in each year of the period 2003-2023. Vertical bars indicate the monthly range, and the horizonal mid-line the mean. Different letters indicate significative difference between the mean monthly values according to a Tukey-Kramer test.

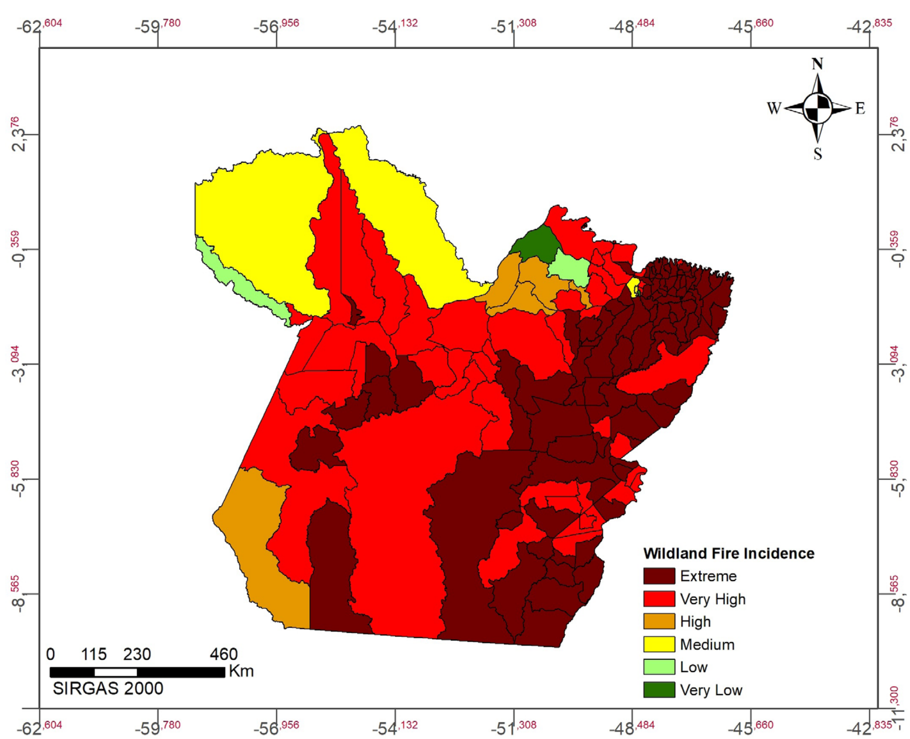

Figure 5. Classification of the 144 municipalities of Pará state (Brazil) according to their fire foci density (White 2020), based on the number of wildland fires detected by the AQUA satellite (afternoon passage) in the period 2003-2023.

Table 3. Municipalities of Pará state (Brazil) ranked according to density of fire foci (FF) from 2003 to 2023 according to data from AQUA satellite, afternoon passage. Values for number FF are the mean ± standard deviation. Classification of fire foci density according to White (2020).

Rank	Municipality	Number of FF		Density (FF km^{-2} year^{-1})	Classification
		Mean	Standard deviation		
1	Bujaru	223.05	93	0.2242	Extreme
2	Concórdia do Pará	144.90	61	0.2068	Extreme
3	São Domingos do Capim	307.33	134	0.1822	Extreme
4	Acará	692.71	189	0.1595	Extreme
5	Mocajuba	129.05	38	0.1481	Extreme
6	Garrafão do Norte	209.81	148	0.1305	Extreme
7	São Miguel do Guamá	132.57	65	0.1211	Extreme
8	Cametá	337.67	104	0.1096	Extreme
9	Moju	951.57	307	0.1046	Extreme
10	Irituia	143.90	83	0.1039	Extreme
11	Nova Esperança do Piriá	279.76	149	0.0996	Extreme
12	Aurora do Pará	180.33	88	0.0995	Extreme
13	Santa Maria das Barreiras	986.67	740	0.0955	Extreme
14	Bonito	55.14	27	0.0939	Extreme
15	Cachoeira do Piriá	221.81	94	0.0917	Extreme
16	Pacajá	1076.38	289	0.0910	Extreme
17	Santana do Araguaia	1038.33	996	0.0896	Extreme
18	Abaetetuba	143.14	50	0.0889	Extreme
19	Marapanim	71.10	29	0.0884	Extreme
20	Eldorado do Carajás	258.71	236	0.0875	Extreme
21	Bannach	251.81	243	0.0852	Extreme
22	Placas	605.10	224	0.0844	Extreme
23	São Francisco do Pará	39.00	26	0.0813	Extreme
24	Terra Alta	16.67	11	0.0813	Extreme
25	Magalhães Barata	26.19	10	0.0808	Extreme
26	Santa Maria do Pará	36.86	23	0.0805	Extreme
27	Mojuí dos Campos	398.90	167	0.0800	Extreme
28	Capitão Poço	231.48	162	0.0798	Extreme
29	Tucumã	197.76	145	0.0787	Extreme
30	Itupiranga	612.19	443	0.0777	Extreme
31	Ourém	43.48	26	0.0774	Extreme
32	São João da Ponta	14.86	9	0.0758	Extreme
33	Tailândia	328.90	144	0.0742	Extreme
34	Conceição do Araguaia	427.38	276	0.0733	Extreme
35	Igarapé-Açu	57.62	37	0.0733	Extreme
36	São João do Araguaia	93.29	70	0.0729	Extreme
37	Rurópolis	506.38	190	0.0721	Extreme
38	Novo Repartimento	1089.62	652	0.0708	Extreme
39	Maracanã	55.52	16	0.0687	Extreme
40	Cumaru do Norte	1165.52	1160	0.0682	Extreme
41	Marabá	1032.00	821	0.0682	Extreme
42	Curuá	96.10	41	0.0671	Extreme
43	Pau D'Arco	111.38	50	0.0666	Extreme
44	Inhangapi	31.48	16	0.0666	Extreme
45	Primavera	17.05	6	0.0659	Extreme
46	Castanhal	67.62	41	0.0657	Extreme
47	Augusto Corrêa	70.95	33	0.0645	Extreme
48	Tomé-Açu	330.90	119	0.0643	Extreme
49	Abel Figueiredo	38.86	19	0.0633	Extreme
50	Oeiras do Pará	243.48	98	0.0632	Extreme
51	Bragança	134.00	48	0.0631	Extreme
52	Santarém Novo	14.14	7	0.0616	Extreme
53	Uruará	652.67	241	0.0605	Extreme
54	São Félix do Xingu	5067.24	3440	0.0602	Extreme
55	Nova Ipixuna	92.90	69	0.0594	Extreme
56	Floresta do Araguaia	200.52	103	0.0582	Extreme
57	Igarapé-Miri	115.90	35	0.0580	Extreme
58	Ulianópolis	289.10	157	0.0568	Extreme
59	Nova Timboteua	27.81	17	0.0568	Extreme
60	Baião	213.43	67	0.0568	Extreme
61	Novo Progresso	2161.19	1090	0.0566	Extreme
62	Rondon do Pará	462.10	221	0.0560	Extreme
63	Barcarena	72.86	32	0.0556	Extreme
64	Peixe-Boi	24.95	11	0.0554	Extreme
65	Ipixuna do Pará	288.05	108	0.0552	Extreme
66	São Caetano de Odivelas	25.62	16	0.0552	Extreme
67	Dom Eliseu	285.43	164	0.0542	Extreme
68	São João de Pirabas	35.81	13	0.0536	Extreme
69	Curuçá	36.05	14	0.0533	Extreme
70	Mãe do Rio	24.90	16	0.0531	Extreme
71	Breu Branco	203.90	138	0.0517	Extreme
72	Salvaterra	47.00	13	0.0512	Extreme
73	Santa Luzia do Pará	68.76	27	0.0511	Extreme
74	Tracuateua	42.00	19	0.0484	Extreme
75	Capanema	28.38	14	0.0457	Extreme
76	Vigia	18.33	11	0.0457	Extreme
77	Santo Antônio do Tauá	23.62	14	0.0439	Extreme
78	Viseu	216.81	88	0.0436	Extreme
79	Anapu	517.86	175	0.0435	Extreme
80	Trairão	515.86	200	0.0430	Extreme
81	São Domingos do Araguaia	59.52	52	0.0427	Extreme
82	Santa Izabel do Pará	30.19	19	0.0421	Extreme
83	Tucuruí	87.67	32	0.0421	Extreme
84	Água Azul do Norte	295.10	239	0.0415	Extreme
85	Medicilândia	339.76	102	0.0411	Extreme
86	Quatipuru	12.29	7	0.0406	Extreme
87	Goianésia do Pará	282.86	140	0.0403	Extreme
88	Redenção	153.67	113	0.0402	Extreme
89	Piçarra	133.05	128	0.0402	Extreme
90	Rio Maria	154.29	98	0.0375	Very high
91	Bom Jesus do Tocantins	102.90	50	0.0365	Very high
92	São Geraldo do Araguaia	111.90	101	0.0353	Very high
93	Prainha	518.71	179	0.0351	Very high
94	Portel	882.10	409	0.0347	Very high

Table 3. Continued.

Rank	Municipality	Number of FF		Density (FF km^{-2} year^{-1})	Classification
		Mean	Standard deviation		
95	Brasil Novo	216.38	130	0.0340	Very high
96	Paragominas	651.19	307	0.0337	Very high
97	Brejo Grande do Araguaia	42.76	31	0.0332	Very high
98	Jacundá	65.52	49	0.0326	Very high
99	Curionópolis	76.19	52	0.0322	Very high
100	Terra Santa	60.48	30	0.0319	Very high
101	Santa Cruz do Arari	33.71	26	0.0313	Very high
102	Colares	11.71	7	0.0305	Very high
103	Salinópolis	6.86	4	0.0303	Very high
104	Santarém	517.86	177	0.0289	Very high
105	Juruti	236.57	87	0.0285	Very high
106	Vitória do Xingu	83.24	69	0.0269	Very high
107	Xinguara	100.10	71	0.0265	Very high
108	Cachoeira do Arari	81.00	25	0.0261	Very high
109	Óbidos	722.86	268	0.0258	Very high
110	Belterra	113.43	45	0.0258	Very high
111	Canaã dos Carajás	80.86	55	0.0257	Very high
112	Curralinho	92.19	34	0.0255	Very high
113	Porto de Moz	440.10	211	0.0253	Very high
114	Aveiro	426.81	142	0.0250	Very high
115	Monte Alegre	451.95	143	0.0249	Very high
116	Senador José Porfírio	352.48	151	0.0244	Very high
117	Palestina do Pará	22.95	20	0.0233	Very high
118	Itaituba	1421.95	416	0.0229	Very high
119	Ourilândia do Norte	303.48	207	0.0211	Very high
120	Parauapebas	144.57	95	0.0210	Very high
121	Alenquer	477.29	184	0.0202	Very high
122	Santa Bárbara do Pará	5.52	4	0.0199	Very high
123	Ponta de Pedras	66.24	22	0.0197	Very high
124	Altamira	3084.24	1157	0.0193	Very high
125	Muaná	71.48	26	0.0190	Very high
126	Sapucaia	23.67	17	0.0182	Very high
127	Bagre	77.90	38	0.0177	Very high
128	Benevides	2.76	2	0.0147	Very high
129	Limoeiro do Ajuru	20.62	13	0.0138	Very high
130	Soure	38.48	21	0.0135	Very high
131	Chaves	166.62	94	0.0133	High
132	Breves	119.67	39	0.0125	High
133	São Sebastião da Boa Vista	20.29	12	0.0124	High
134	Jacareacanga	636.10	209	0.0119	High
135	Gurupá	90.90	45	0.0106	High
136	Melgaço	56.43	23	0.0083	High
137	Belém	5.29	4	0.0050	Average
138	Almeirim	362.67	152	0.0050	Average
139	Ananindeua	0.86	1	0.0045	Average
140	Oriximiná	447.10	145	0.0042	Average
141	Faro	35.43	15	0.0030	Low
142	Anajás	16.90	17	0.0024	Low
143	Marituba	0.19	0	0.0018	Low
144	Afuá	10.76	11	0.0013	Very low

density in the Pará municipalities, followed by pasture area, rainfall, urbanized area, forest area, agricultural area and demographic density. Temperature and natural vegetation area did not correlate significantly with fire foci density. The results thus indicate that the municipalities with a higher proportion of deforested, pasture and agricultural area had higher density of fire foci, while those with higher mean annual rainfall, higher proportion of urbanized or forested area, and with higher population density, had lower fire foci density (Table 4).

DISCUSSION

The results of this study indicate that wildland fires occur with high incidence in most municipalities of the Brazilian Amazonian state of Pará, releasing GHG into the atmosphere, likely contributing to global warming. Natural wildfires are rare events in the Amazon rainforest due to the forest high humidity (Ribeiro et al. 2021). Despite 76% of the state's area being covered by natural forests (MAPBIOMAS 2023), fires occur frequently on the frontiers of agricultural expansion, where slash-and-burn farming methods are used to convert rainforests into agricultural land (Cochrane 2003; White 2018; Ribeiro et al. 2021).

The yearly number of fire foci recorded by AQUA from 2003 to 2023 showed a significant downward trend, but there was no significant trend when considering only the period 2012-2023. During the decade spanning from 2004 to 2013, the Brazilian government implemented policies to combat illegal deforestation through the combination of monitoring and enforcement, supply chain interventions, and the expansion of protected areas, which reduced the deforestation rate in the Brazilian Amazon by around 70% (Brando *et al.* 2020). However, over the last decade, the pressures imposed by cattle ranching and agricultural expansion, as well as the relaxation of governmental policies, have increased deforestation in some regions of the Amazon, preventing the continued decrease in wildfires and, in some areas, caused them to rise again (Abreu et al. 2022; White 2018).

The comparison of detected fire foci between the AQUA and S-NPP satellites shows that the VIIRS sensor detects more fire foci than the MODIS sensor. The sensitivity of the sensors depends on factors such as geographic area analyzed, the intensity of the fires, cloud condition and timing of satellite overpass (Waigl et al. 2017; Fu et al. 2020). For example, in a study in Punjab (India), the S-NPP/AQUA ratio was 6.5 (Vadrevu and Lasko 2018). All over South America, until 2021, S-NPP detected 5.13 times more fire foci than AQUA (White 2022). However, despite these differences, all studies found in the literature concluded that the data of both satellites are significantly correlated (e.g., Waigl et al. 2017; Vadrevu and Lasko 2018; Fu et al. 2020).

Table 4. Pearson correlation matrix of all variables potentially related to fire foci density in the municipalities of Pará state (Brazil). Correlation coefficients in bold are significant at p < 0.001; those underlined are significant at p < 0.05.

	Forest area	Natural formation area	Pasture area	Agricultural area	Urbanized area	Deforested area	Mean annual temperature	Annual rainfall	Population density	Fire foci density
Forest area	1.00	-0.27	**-0.73**	0.05	-0.07	-0.22	-0.05	0.28	-0.07	-0.19
Natural formation area		1.00	**-0.30**	-0.10	-0.06	**-0.31**	0.11	0.28	-0.06	-0.14
Pasture are			1.00	0.01	-0.12	**0.52**	-0.15	**-0.60**	-0.13	**0.36**
Agricultural area				1.00	-0.02	0.27	0.03	-0.05	-0.04	0.17
Urbanized area					1.00	-0.16	0.06	0.17	**0.93**	-0.20
Deforested area						1.00	-0.10	**-0.36**	-0.16	**0.77**
Mean annual temperature							1.00	0.23	0.07	-0.10
Annual rainfall								1.00	0.11	**-0.29**
Population density									1.00	-0.17
Fire foci density										1.00

In larger states or municipalities with high detection rates of fire foci, linear regression equation could be used to convert S-NPP to AQUA data or vice-versa (White 2022). Therefore, when the AQUA satellite stops providing data, it will be possible to continue the time series started in 2002 using S-NPP data. Yet, in small areas with low fire foci detection rates, the data conversion may not be feasible due to limited data availability to build a mathematical model with an acceptable level of significance. Also, location errors can occur in satellite fire detection, mostly affecting data from small locations, with a location error average of 400 m ± 3 km for MODIS and other sensors with lower resolution, while the VIIRS maximum error in accuracy is 400 m (INPE 2023).

The differences between AQUA and S-NPP are owed to variation in the spectral bands of both satellites and, mostly, in their spatial resolution. AQUA and S-NPP have similar spectral bands covering visible and infrared wavelengths, but they differ slightly in width, sensitivity, and position within the electromagnetic spectrum, affecting fire detection capability (Schroeder and Giglio 2017). Discrepancies in fire foci detection between the two satellites can arise from these combined factors, the more relevant aspect being the differences in spatial resolution, as they affect the capability of detection of smaller or less intense fires. The results highlight the importance of considering spectral and spatial characteristics when analyzing fire data from different satellite sources.

Despite the intrinsic relationship between deforestation and fire foci, other factors also play a key role in wildland fire incidence. The concentration of fire foci in August and September follows the pattern observed in most of South America (White 2019). All South American countries below the equator, with the exception of Chile, have the highest number of fire foci detection between August and November, due to the low amount of rainfall during winter in the southern hemisphere, which leaves the vegetation drier and easier to burn (White 2019).

The pattern shown in this study agrees with other studies on fire occurrence in Pará (e.g., Cordeiro *et al.* 2022; Santos *et al.* 2022). Determining which municipalities have higher fire occurrence is essential to establish prioritary sites for fire surveillance and other fire prevention policies (White 2018; White 2019). The fact that 89 of the 144 municipalities (accounting for about 35% of the state's area) were classified as being at extreme risk of fire incidence, represents an enormous threat to the conservation of Pará's natural ecosystems. In comparison, based on data from 2003 to 2016, no municipality of the neighboring state of Amazonas was in the extreme fire risk class (White 2018). The high frequency of wildland fires in Pará leaves the vegetation even drier and more prone to burn, creating a vicious cycle that contributes to global warming (Moritz 2012). For each 1 ºC increase in global temperature, a total of 53 ± 17 gigatons of CO_2 will be released into the atmosphere, most of these emissions coming from the collapse of tropical forests (Cox et al. 2013).

The correlation matrix showed that the density of fire foci was higher in municipalities with a higher proportion of deforested area or area occupied by pasture or agriculture. Land use is one of the most important variables in determining wildland fire risk (Soares and Batista 2007; White 2018). In the state of Amazonas, the municipalities with the largest areas of deforestation, pasture or agriculture also had a higher density of fire foci (White 2018). The correlation between deforestation, agriculture and cattle ranching versus wildland fire occurrence has also been shown in other studies (e.g., Silvestrini *et al.* 2011; Caúla *et al.* 2015; White 2018; Brando *et al.* 2020; White 2020; Reis 2021; Teodoro *et al.* 2022). This link exists because the clearing of humid forests generally starts by cutting down the vegetation, since the standing forest is too humid to burn, followed by burning and clearing a few weeks later, when the vegetation lost enough humidity, to establish a new agricultural or livestock area (Brando *et al.* 2020). After deforestation, the new agricultural or cattle ranching areas often undergo regular controlled burning which, when not managed properly, can start wildfires.

In Brazil, the use of controlled burning in farming activities is cultural and difficult to replace (Cabral *et al.* 2013). Despite the advantages of this technique, such as a short-term increase in soil nutrients, removal of unwanted vegetation, and faster grass regrowth; in the long term, repeated burns can leave the soil poorer in nutrients and more acid, affecting the sustainability of farming activities (Heringer *et al.* 2002). In Pará, most of the deforested areas are used for cattle ranching (Skidmore *et al.* 2021). This is reinforced in this study, as deforest areas had a higher correlation with pastures than with agricultural areas. Besides the use of burning in farming activities, in the last years mining extraction increased in the Amazon region and is also directly related to the expansion of fires (Filho *et al.* 2022), increasing the degradation of the Amazon biome.

The correlation matrix also showed that the municipalities with higher rainfall, forested area, urbanization and population density presented lower fire foci density. The negative correlation between rainfall and fire foci was already expected, as vegetation moisture content increases with rainfall. Larger and densely populated cities usually have less vegetated areas, consequently there is a lower probability of wildland fire occurrence (White and White 2016). The municipalities that presented the highest percentage of its areas covered with forests also presented less fire foci density, since the Amazon forest, especially in well conserved areas, is more resistant to natural and human-induced fires compared to deforested areas (Nepstad et al. 1999).

Due to the environmental impacts of climate change, implementing effective measures to reduce wildland fire occurrences is essential for minimizing associated greenhouse gas emissions. Rising global temperatures lead to drier conditions, prolonged droughts, and an increase in the frequency and intensity of heatwaves, making vegetation drier and more susceptible to igniting and sustaining fires (Bowman et al 2011). Additionally, climate change has intensified El Niño-Southern Oscillation (ENSO) events, which are also associated with an increase in fire occurrence (Teodoro et al. 2022).

To minimize the occurrence of wildland fires in Pará, it is essential to enforce legal penalties for illegal burnings as mandated by law, and to consistently implement environmental education activities. Knowledge about the importance of the forest for climate regulation, for the conservation of biodiversity and even for the long-term sustainability of farming in the Amazon is fundamental. While coercive measures may have some positive effect, only through education the situation can change in the long term, promoting sustainable practices and the preservation of natural resources (Monroe et al. 2020). The creation of new conservation units and the delimitation and consolidation of indigenous lands also contribute to preserve native forests and prevent human-induced wildfires as, in general, such sites have less fire occurrence than non-protected areas (Silva Junior *et al.* 2022). In this context, it is strategic to create new conservation units near agricultural frontier areas, to prevent further expansion.

CONCLUSIONS

Despite the number of fire foci in the state of Pará exhibited a declining trend from 2003 to 2023, in the last decade this decline has plateaued. As a result, Pará remains as one of the Brazilian states with the highest wildland fire incidence. During the overlap years of AQUA and S-NPP satellite data (2012-2023), S-NPP detected 4.5 times more fire foci than AQUA, yet the data from both satellites were significantly correlated. The highest fire foci detection occurred in August, September, and November, highlighting the need for fire prevention and mitigation efforts, mostly during these months. The majority of municipalities in Pará, particularly those situated in the eastern portion of the state, exhibited an extremely high incidence of fire foci. The significant correlation between fire foci density and deforestation, pasture and agricultural areas indicates that, after deforestation, new farmlands continue to be burned regularly. The results of this study underscore the urgency of implementing public policies aimed at reducing wildland fire occurrence in the state. Measures such as increasing the number of protected areas, enhancing protection of indigenous lands, intensifying inspections and fines by environmental agencies, and implementing environmental education initiatives could yield positive outcomes, particularly when targeted at municipalities most vulnerable to fires. Only by applying these measures it will be possible to conserve the Amazon forest to minimize the effects of global warming.

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