Relationship between respiratory diseases and environmental conditions: a time-series analysis in Eastern Amazon

Inter-relações entre doenças respiratórias e condições ambientais: uma análise de séries temporais na Amazônia Oriental

Mauricio do Nascimento Moura[1] , Maria Isabel Vitorino[1] , Glauber Guimarães Cirino da Silva[1] , Valdir Soares de Andrade Filho[2]

ABSTRACT

This study examines the relationship between the time-series analysis of climate, deforestation, wildfire, Aerosol Optical Depth (AOD), and hospital admissions for respiratory diseases in the Eastern Amazon. Through a descriptive study with an ecological approach of an 18-year time-series analysis, we made a statistical analysis of two pre-established periods, namely, the rainy season and the dry season. On a decadal scale, analyzing the signals of climate indices [i.e., the Southern Oscillation Index (SOI) and the Atlantic Meridional Mode (AMM)], the city of Marabá presents correlations between hospital admissions, wildfire, and AOD. This is not observed with the same accuracy in Santarém. On a seasonal scale, our analysis demonstrated how both cities in this research presented an increase in the number of hospital admissions during the dry season: Marabá, 3%; Santarém, 5%. The same season also presented a higher number of fire outbreaks, AOD, and higher temperatures. The AOD monthly analysis showed that the atmosphere of Marabá may be under the influence of other types of aerosols, such as those from mining activities. There is a time lag of approximately 2 months in the records of wildfire in the city. Such lag is not found in Santarém. The linear regression analysis shows that there is a correlation above 64% (Marabá) and 50% (Santarém), which is statistically significant because it proves that the number of hospital admissions for respiratory diseases is dependable on the AOD value. From the cities in the study, Marabá presents the highest incidence of wildfire, with an average of 188.5— the average in Santarém is 68.7—, and therefore the highest AOD value, with an average of 0.66 (Santarém, 0.47), both during the dry season. It is evident that the climate component has a relevant contribution to the increase in the number of hospital admissions, especially during the rainy season, where there are few or no records of wildfires.

Keywords: air pollution; deforestation; wildfire; climate; state of Pará.

RESUMO

Este estudo faz uma análise da inter-relação entre as séries temporais do clima, desmatamento, queimadas, profundidade óptica do aerossol (AOD) e internações hospitalares por doenças respiratórias na Amazônia oriental. Através de um estudo descritivo, com delineamento ecológico de séries temporais de 18 anos de dados, foram feitas análises estatísticas para dois períodos preestabelecidos: chuvoso e seco. Em escala decadal, mediante análise dos sinais dos índices climáticos, índice de oscilação sul (IOS) e o modo meridional do Atlântico (MMA), Marabá apresenta concordância entre internações, focos de queimadas e AOD, o que não se observa com a mesma exatidão para Santarém. Em escala sazonal, nossas análises mostram que os dois municípios estudados nesta pesquisa apresentaram um aumento no número de internações na estação seca, Marabá (3%) e Santarém (5%). A mesma estação também apresentou maior número de queimadas, AOD e alto valor de temperatura. A análise mensal do AOD mostrou que a atmosfera de Marabá pode estar sendo influenciada pela presença de outros tipos de aerossóis, como os emitidos pela atividade mineradora, logo há uma defasagem no tempo de aproximadamente 2 meses em relação às ocorrências de queimadas registradas dentro do município. Santarém não apresentou essa defasagem. A análise de regressão linear mostra que há correlação acima de 64% (Marabá) e 50% (Santarém), sendo estatisticamente significante e comprovando que a taxa de internação por doenças respiratórias depende do valor do AOD. Dos municípios investigados, Marabá é a localidade que apresenta o maior número de incêndios florestais com média de 188.5 (Santarém, 68,7) e, portanto, o maior valor de AOD, com média de 0,66 (Santarém, 0,47), ambos para a estação seca. Fica evidente que a componente climática tem relevante contribuição para o aumento das internações, principalmente na estação chuvosa, onde há pouco ou nenhum registro de focos de incêndio.

Palavras-chave: poluição do ar; desmatamento; queimadas; clima; Pará.

Introduction

Large population clusters are found in urban areas and present multiple physical characteristics in their geoecology, land use and occupation, climate, and social features. When treating a city as an organic space, as somewhere in constant construction and production, it is conceivable to recognize that it promotes an accumulation of social and environmental phenomena that directly influence the population's health and life quality.

Some studies intend to establish a correlation between climate and the increase in air pollution, due to the intensification of wildfire that severely affects the ecological balance and, eventually, human health. Climate variability, such as the Atmosphere–Ocean Dynamics over the Atlantic and the Pacific, influences the modulation of ecological variables (Limberger and Silva, 2016) and, consequently, the combustion of biomass and the continuance of a wildfire.

In recent years, there has been a growing international awareness in controlling forest fires in the Amazon. This is due to climate change and deforestation still at large (Gonçalves et al., 2012). Most diseases are caused by or influenced by environmental factors, including climatic conditions that have increasingly been the subject of epidemiological studies. However, considering the relationship between climate, deforestation, wildfire, and human health, it is evident that studies on this issue are still scarce in Eastern Amazon. The slash-and-burn operation is the greatest issue today. When combined with climate extremes, it can aggravate local human health, especially in cities with a low Human Development Index (HDI) and a weak health-care system (Smith et al., 2014).

Population growth is another issue that may contribute to the increase in air pollution in large urban areas, and it is increasing exponentially. Collectively, people from all over the world utilize an exceedingly large amount of food, water, and raw materials and, thus, produce a lot of pollution, so they tend to be more exposed to the amount of particulate matter produced within the very environment where they live (Miller and Spoolman, 2015).

Studies indicate that the size of the particles that make up the particulate matter, whose diameter may vary from a few nanometers to dozens of micrometers, is directly associated with its potential to cause breathing problems. The smaller the diameter, the greater the effects (Alves et al., 2017).

According to Padilla et al. (2014), socioeconomic factors can also contribute to the effects of particulate matter on human life. Their study demonstrates how populations in precarious living conditions are more vulnerable to breathing problems as they are more exposed to unsanitary environmental conditions. The uneven geographical distribution of living conditions and urban traffic is another key factor to be considered, as differential exposure contributes to the effects of particulate matters, and it can increase the risk of mortality from respiratory diseases (Rodrigues et al., 2019). Other authors such as Forastiere et al. (2007) argue that environmental impacts can significantly contribute to social inequality at a local scale. Therefore, people in precarious living conditions have restricted access to primary health care.

Studies demonstrate how 98% of mortality due to respiratory diseases in children occurs in poor or developing countries (WHO, 2018). In general, children may be more vulnerable when compared with other age groups. Fine Particulate Matter ($PM_{2.5}$) in the atmosphere penetrates more effectively in the lower respiratory tract, bronchi, and pulmonary alveoli of children aged below 10 years and adults aged above 60 years, which can cause genetic changes and the development of tumors (Alves et al., 2015, 2017).

The research on suspended particles from forest fires is still elementary, mainly due to the lack of data on air pollutants. However, remote sensing can offer such data, reading both the Aerosol Optical Depth (AOD) and the Particulate Matter ($PM_{2.5}$), especially in regions with no surface metrology as the Amazon (Andreão and Albuquerque, 2020). Therefore, the AOD is the most appropriate satellite product for estimating the concentrations of $PM_{2.5}$. It is an indicator of aerosols scattering solar radiation in the vertical atmospheric column, which is characterized by wildfire smoke due to the high concentration of organic matter in suspension. In general terms, radiation extinction is measured by reading the scattering and absorption of aerosols in the atmospheric column. Thus, this study intends to foreground the interconnections between the time series of climate, deforestation, wildfire, and hospital admissions for respiratory diseases in the Eastern Amazon.

Methods

The State of Pará, located in the Eastern Amazon (Figure 1), is the study area of this research. From the 144 municipalities distributed throughout the state, we chose the cities of Marabá and Santarém for representing large urban areas, with a considerable population density, industry, and a health-care system for both high and medium complexity procedures. Also, these cities are located along the Arc of Deforestation: Marabá, in the East of the state; and Santarém, in the West, in the region called Lower Amazon.

The environmental and social database available to this study is representative of the period from 2000 to 2017, through a monthly and seasonal scale with the following variables: Aerosol Optical Depth (AOD), The Southern Oscillation Index (SOI), the Atlantic Meridional Mode (AMM), wildfire, deforestation, precipitation, relative humidity, air temperature, and hospital admissions (i.e., a social variable) for respiratory diseases. In the interest of a seasonal analysis, we also arranged the data period to show the rainy season (January–May) and the dry season (June–December).

We employed the estimates of the imaging sensor Moderate Resolution Imaging Spectroradiometer (MODIS), presently aboard the Terra and Aqua satellites (Di Nicolantonio et al., 2009; Van Donkelaar et al., 2010), to obtain the AOD data at 550 nm, with a 3-km resolution as the collection 6.0. This includes the models of the optical spectrum for estimating numerous properties of aerosols, including AOD,
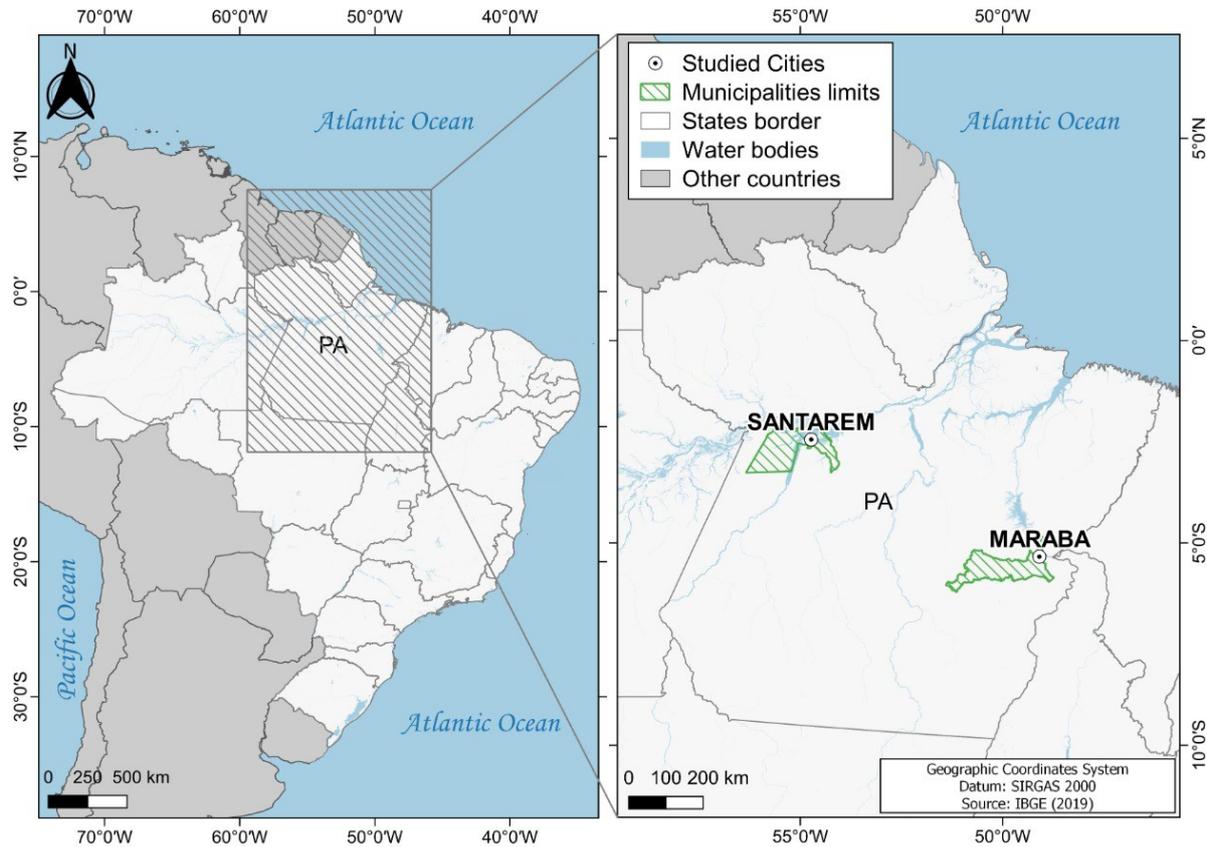
Figure 1 – Map of the study area, with geographic location by country, state, and the cities of Marabá and Santarém, in the State of Pará.

with the product names: MOD04L2-3K and MYD04L2-3K (Lyapustin et al., 2018). The daily AOD data were generated from the average of a morning (10:30 a.m., Satellite Terra) and afternoon (1:30 p.m., Satellite Aqua) reading and then converted into monthly averages for a 40 km² area surrounding the cities in the study.

The data from the AMM and SOI climate indices are available on a monthly time-series analysis at NOAA (2018). These data are available to characterize climatic aspects by demonstrating the ocean–atmosphere oscillations from both the tropical Atlantic and Pacific oceans that modulate precipitation and other atmospheric variables. Such indices indicate climatic conditions by considering the phases of the AMM dipoles, which are as follows: Positive (not favorable conditions for rain) and Negative (favorable conditions for rain); as well as the SOI phases, which are as follows: Negative, for El Niño, and positive, for La Niña (Pereira et al., 2017).

The tropical Atlantic surface waters are cooler (warmer) in the southern hemisphere when the AMM is positive (negative), which affects the rainy season in the Amazon, making it scarcer (abundant). In the tropical Pacific, El Niño (La Niña) incidents tend to decrease (increase) the volume of rainfall at the Western and Eastern ends of the Amazon (Sousa et al., 2018; Kayano et al., 2019).

The annual deforestation rates were obtained through the PRODES webpage (i.e., the Measurement of Deforestation by Remote Sensing), powered by INPE (the National Institute for Space Research), which uses LANDSAT satellite imagery (Montibeller et al., 2020). This is a major instrument for planning public policies in the Amazon.

The INPE also makes available information on hotspots. The data are obtained by remote sensing (see INPE, 2018). This research benefited from the data provided by the reference satellite (i.e., geostationary) using the Advanced Very-High-Resolution Radiometer (AVHRR) sensor, with a late afternoon orbital pass, and the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, with an early afternoon orbital pass, 4- to 5-km resolution, provided by NASA.

The Center for Weather Forecasting and Climate Studies (CPTEC/INPE) publishes the data on Precipitation (PRP) from the Integrated Multi-satellitE Retrievals for GPM (IMERG) product. This technique uses the intercalibrated estimates from surface precipitation analyses and the data from precipitation-relevant satellites (Rozante et al., 2010), resulting in binary files with a 20-km resolution, with a daily pass (accumulated figures for 24 h) here transposed to a monthly time series, covering all South America. In addition, the monthly mean rel-

ative humidity (RH) and air temperature (T), provided by the Brazilian National Institute of Meteorology (INMET) for the conventional surface stations in Marabá and Santarém, in the Eastern Amazon.

For this research, we developed an ecological time-series analysis considering a list of all types of respiratory diseases, with codes from J00 to J99, under the International Statistical Classification of Diseases and Related Health Problems (ICD-10), entrusted to the World Health Organization (WHO). We established a 1–9 age bracket, with both males and females, as it embodies a group that is reasonably vulnerable to respiratory diseases. Aside from climate indices, all other variables in this study were subjected to anomaly detection based on a 6-month moving average for every variable and every city, so that trends, temporal patterns, oscillations, and extreme periods between variables could be identified as closely as possible, over the time-series study.

Monthly anomalies were detected on every variable in this research. All the time series were divided into two decades to detect dominant qualitative trends in the anomaly variability that may have contributed to the increase in the number of hot spots and, consequently, in the number of hospital admissions.

For a better analysis of the AOD series in association with hospital admissions, we examined both the amplitude and the asymmetry of the available dataset through the maximum, the minimum, and the sample median, correspondingly. We developed boxplots to graphically depict these statistics. This type of analysis enables the reader to visualize the distribution of values per time series, and also possible discrepancies in the dataset (Seward and Doane, 2014).

The linear regression model we applied considered the number of hospital admissions as a dependent variable (y) and the AOD as an independent variable (x). The statistics generated by the regression equation also include the calculation of the coefficient of determination (R^2), the coefficient of correlation (r), and the $p < 0.05$, with a confidence interval of 95%.

For an enhanced understanding of our statistical analysis of the linear regression, the hospital admission rate was calculated from the records of monthly admissions of children up to 9 years old, per 1,000 inhabitants, for both cities.

Results and Discussion

Figure 2 demonstrates that the most anthropized areas in the State of Pará overlap the areas with the lowest annual precipitation rates, as in the extreme East of the state where Marabá is located, in the Amazon Arc of Deforestation, and in the West where Santarém is located. In addition, mosaic deforestation reveals that the surroundings of Marabá show higher natural devastation in comparison with Santarém. Therefore, the effects on local rainfall rates would impact both regions as follows: in Marabá, from annual rainfall rate between 1,800 and 2,000 mm; and Santarém, from annual rainfall rate between 2,000 and 2,400 mm. Studies show that areas with considerable rainfall rates are

likely to present higher air quality (Gonçalves et al., 2010), as precipitation cleans the atmosphere, reducing pollution. The opposite is true in areas with limited rainfall rates. Debortoli et al. (2017) concluded that, on a local scale, there is a strong correlation between forest cover and local precipitation, which suggests that large areas of preserved forest enable the viability of higher rainfall rates, in opposite direction to the effects observed on a local scale (Davidson et al., 2012).

Studies suggest that the local contribution of evapotranspiration toward precipitation in the Amazon is in the order of 20-35% (Rocha et al., 2015). Consequently, the expansion of deforestation directly impacts the rainfall rate of a given region, and it is directly related to the increase of wildfire due to land-use change (Seixas and Pinheiro, 2014; Coutinho et al., 2018), mainly in the Arc of Deforestation.

The AMM and SOI climatic indices are imperative for the modulation of rainfall in the Amazon. Figure 3 shows that even with some negative peaks, the signal on the AMM series is predominantly positive over time, which is unfortunate for precipitation because it decreases humidity transport and rises air temperature in the Eastern Amazon (Limberger and Silva, 2016). The SOI series also shows a higher number of positive peaks over time, indicating a higher incidence of La Niña events, which favors precipitation, mainly from 2003 to 2005, 2015, and 2016, when the index was negative.

The first three variables in Figures 4A-4C demonstrate how Marabá has had the stages of approximately 10 years (2000–2009) in which rainfall rates were mostly positive in the first decade (+70.0 ± 60.6 mm), consistent with the first decade of SOI that was correspondingly mainly positive and therefore presented more frequent occurrences of La Niña events, which favored rainfall in the region (Araújo et al., 2013). Nevertheless, air temperature and relative humidity behave contrarily, with temperatures above average and humidity below average during the first decade (+0.6°C ± 0.5°C and -2.9% ± 2.1%). This behavior is also true in the second decade.

It is important to reiterate that the air humidity series in Marabá was contrary to the precipitation series due to the high degree of vegetation degradation in the city, causing the hydrological cycle to change. There is a minimal infiltration and thus increased evaporation, even with positive rainfall anomalies, altering the hydrological cycle in the region (Duarte et al., 2009).

This suggests that Marabá, a city with a highly degraded natural environment, large deforested areas, different soil coverings, and diverse land use activities, presents an imbalance in the behavior of environmental variables, in addition to being influenced by the global climatic fluctuations in comparison with other cities with different natural landscapes. It is in agreement with Pires and Costa (2013), who demonstrated how environmental degradation in the Arc of Deforestation may trigger serious bioclimatic imbalances.

Although the SOI had a positive phase in the second decade, the one with more La Niña incidents, the precipitation in Marabá
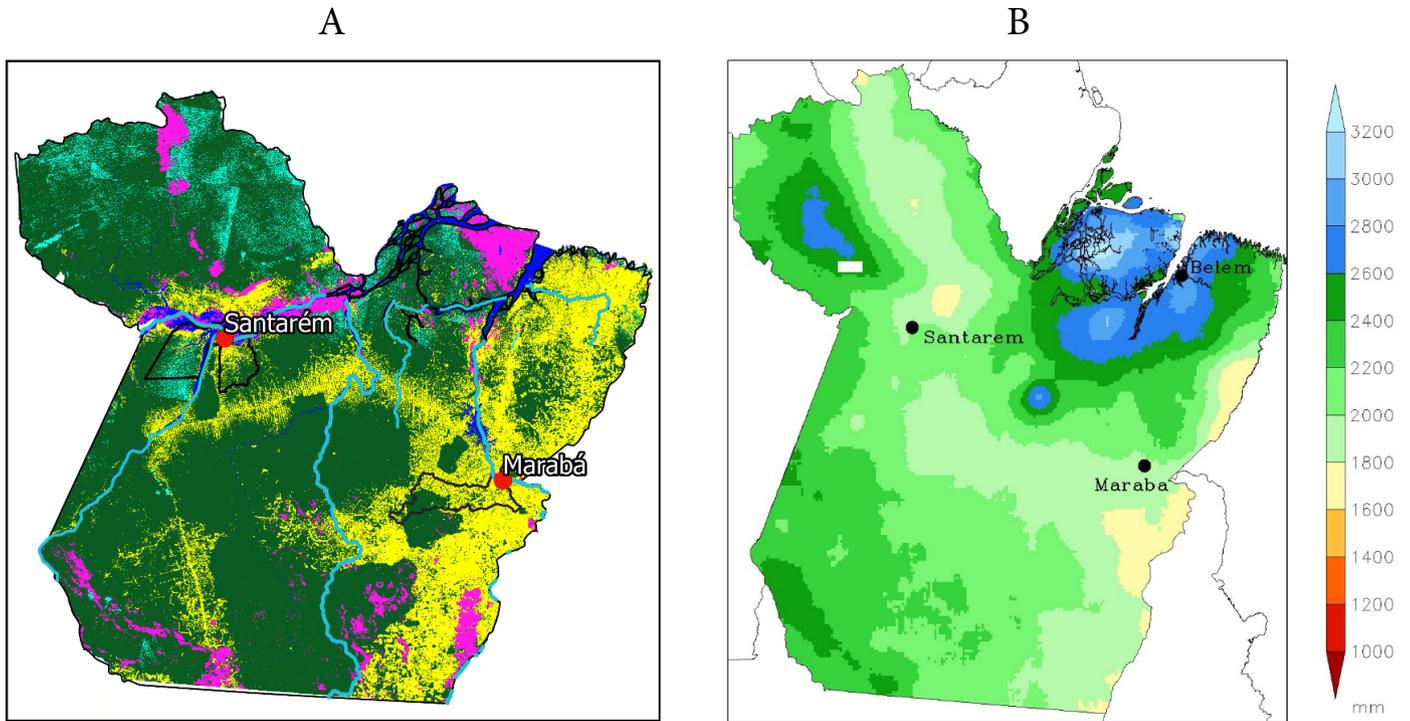
A

B

Figure 2 – Environmental characteristics of the State of Pará, with its hydrography and the location of Marabá and Santarém. (A) Total of deforested areas (in yellow) and anthropized forest areas (in green) from 2000 to 2017 and (B) average climatological for annual precipitation. IMERG, 1981–2017.
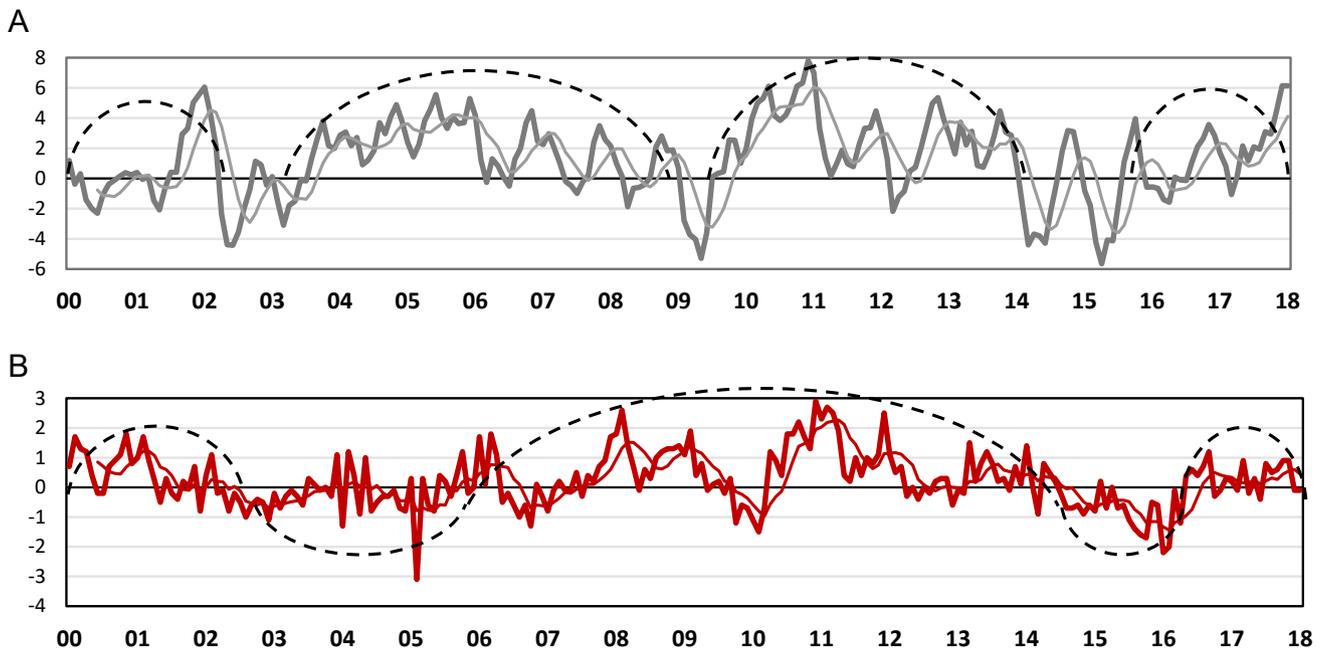

A

B

Figure 3 – Distribution of monthly anomaly values for the 2000–2017 climate indices. (A) AMM (the Atlantic) and (B) SOI (the Pacific). The smoothed line displays the 6-month moving average values, and the dashed line presents the dominant signals for both the positive and the negative phases.

showed a negative phase in the second decade, this time due to the AMM signal that showed mostly positive values throughout the series, particularly in the second decade, which impairs precipitation in the Amazon (De Jesus et al., 2017). Different from the first decade, rainfall was above average, and humidity was below average (-0.6°C ± 0.5°C and -2.5% ± 2.1%).

It is patent that Santarém (Figure 4D-4F), observed in the aforementioned graphs, has rather similar phases in comparison with the SOI series,
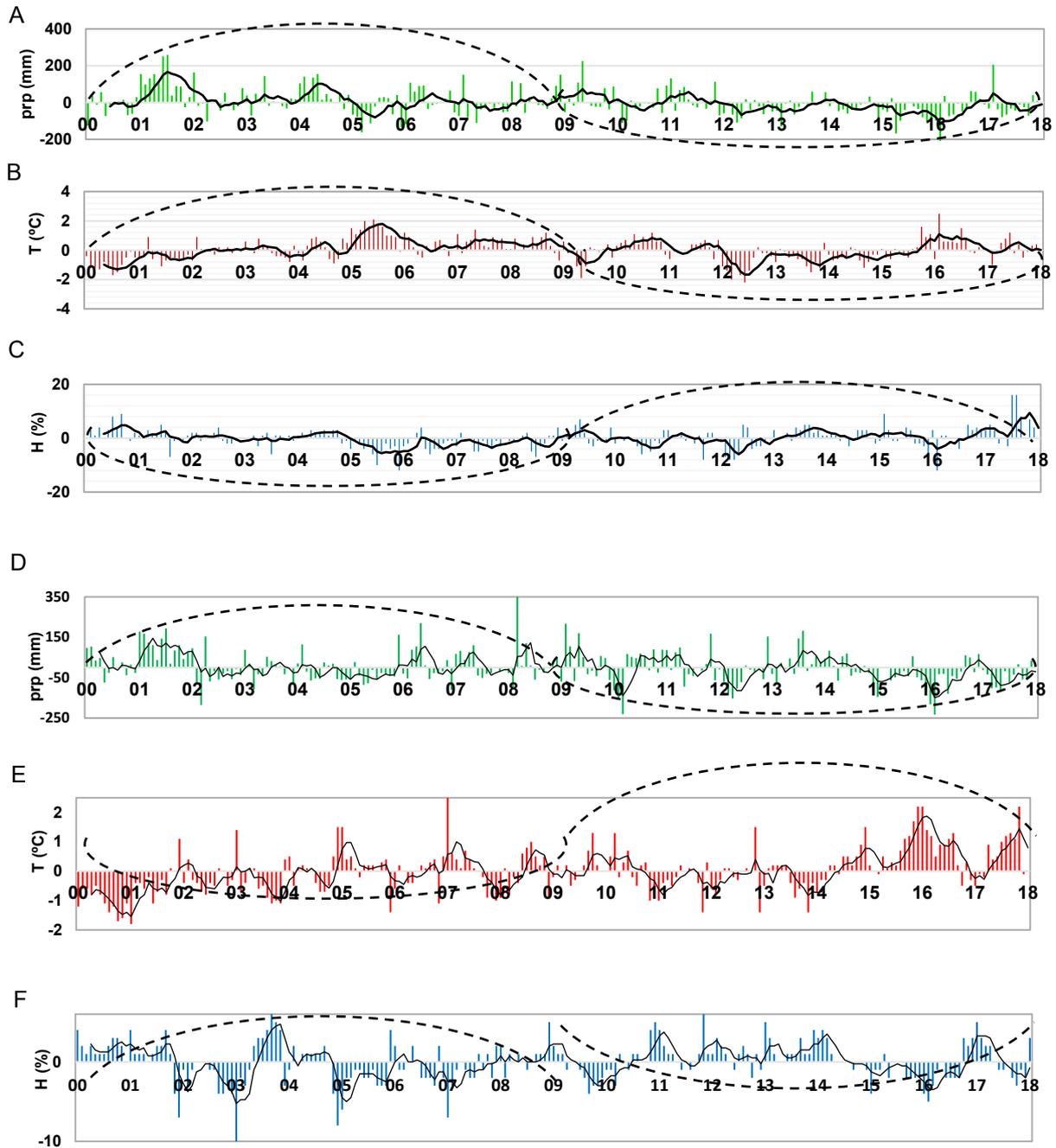

Figure 4 – (A, B, C) Distribution of monthly anomalies values for PRP, T, and RH in Marabá; (D, E, F) PRP, T, and RH in Santarém, both from the 2000–2017 time series. The dashed line presents the dominant signals for both the positive and the negative phases.

with the same variables analyzed for Marabá. As the SOI indicates that the first decade has a higher incidence of La Niña events, that is, it prominently a positive phase (Figure 3B), Santarém also shows a positive phase for rainfall and a negative phase for temperature, with values below average.

In general, the relative air humidity in Santarém remained below average in the first decade, although a balance (+2.0% ± 1.5% and -2.4% ± 2.1%) between positive and negative values is observed (Figure 4F). Considering the meteorological variables, it is understood from this analysis that Santarém reacts well to the modulations of large-scale climate mechanisms. Despite the increase in deforestation (2016-2019) in the past 4 years, the annual deforested area rate is on a downward trend (INPE, 2020) since the beginning of the time series in 2000. It is the result of a change in public policies, the creation of conservation units, extensive improvements in the Forest Code, and the involvement of civil society and NGOs. These efforts managed to contain the expansion of deforestation for over two decades (Bistene and Guimarães, 2019), allowing Santarém to preserve a considerable part of its natural features. Despite an increasing trend in deforestation in the past 8 years, Bandeira Castelo et al. (2020) considered that The Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm), which is currently in its fourth phase, has shown satisfactory results in terms of reducing deforestation in the State of Pará, including Santarém.

Unlike the trends in climate variables observed in Figure 4, Figure 5 shows that for other environmental variables the city of Marabá displays the same anomalies for the two long periods of the series, with concordant phases. Deforestation and hotspots indicate agreement with the two periods, with mostly positive values in the first decade and negative values in the second, supporting the hypothesis that the increase of wildfire is mostly a consequence of unbridled deforestation, which considerably increases the chances for wildfire, as demonstrated by Fearnside (2005). According to Rivero et al. (2009), several factors lead to intense forest clearing and, subsequently, to wildfire. For the authors, agriculture and livestock activities are the two driving factors because they require low capital and less soil preparation. This is a context of scarce economic alternatives, low educational standards, and a lack of technology. These factors, in association with the rooted cultural values carried by rural workmen, enable the process of deforestation and wildfire to extend throughout the Amazon rainforest.

Even with an apparent decrease in the incidence of wildfires in the Amazon over the decade we studied, the number of hotspots in Marabá is still dramatic and always worsens during the second semester, at the peak of the dry season (Figure 5). According to Fearnside (2006), when there is a fire in the forest, it takes trees, increases fuel loads, and dries the forest understory, elevating the risk of future wildfire and the complete degradation of the forest. Analyzing Figure 5C, it is possible to state that the AOD time series also illustrates how Marabá has a phase with the above-average values in most months of the first decade, and a negative phase in the second decade.

Regarding hospital admissions, we illustrated in Figure 5D that Marabá experienced a positive phase in the first decade (2000-2009), followed by a negative phase in the second decade (2010-2018), which is in agreement with the deforestation time-series analysis, hot spots analysis, and AOD.

Unlike the wildfire time series, the AOD series presents peaks of positive anomalies in the second decade, even without peaks of forest fires, which can be explained by the number of aerosols coming from remote regions to Marabá *via* wind flow, as demonstrated by Kaufman et al. (1998): particles in suspension seek trajectories, *via* wind flow, of several kilometers in the atmosphere, and can reach remote regions.

This is evidence that the number of hospital admissions in Marabá followed the increase in air pollution caused by wildfire aerosols, a consequence of large-scale deforestation, not only in Marabá but also in the entire Arc of Deforestation. Barcellos et al. (2019) introduced the research that determined the impact of wildfires and particulate matter in the health of children living in the Arc of Deforestation, where the city of Marabá is located. This research analyzed samples in the course of 1 year and concluded that the number of hospital admissions doubled in areas with excessive incidence of hotspots.

In the decadal analysis, most years of the entire deforestation time series show values below average for the period (59 km²), especially in the second decade, in agreement with the AOD time series and the number of hospital admissions in the same period.

The analysis of the same variables culminated in different results in Santarém: the number of hospital admissions for respiratory diseases shows a predominantly positive phase in the first decade (+12.7 ± 12.3) and a predominantly negative phase in the second (-10.3 ± 8.9), regardless the positive anomalies at some points, mainly in 2013.

The same trend was observed in the historical series of deforestation and AOD. However, the wildfire time series does not present the same behavior: a few fire outbreaks in the first decade, and most months within the average.

The decadal analysis confirmed that the city of Marabá is more affected by local wildfires and forest fire from neighboring cities, as observed by comparing the analysis of decadal phases and by considering the historical series of wildfire and hospital admissions, which made apparent that deforestation and wildfire modulate both the optical depth time series and the number of hospital admissions. The analyses of decadal phases are not the same in Santarém, mainly concerning the number of fire outbreaks, i.e., a low rate for the region.

Therefore, the number of hospital admissions may be influenced by the variation of temperature and humidity in the city (Table 1), which may increase the hospital admission records for respiratory diseases due to fungal pollution of indoor environments, accelerating the emergence of diseases such as asthma, as explained by Rosa et al. (2008).

Andrade Filho et al. (2013), years later, when performing a seasonal analysis of a series of hospital admissions, found that high
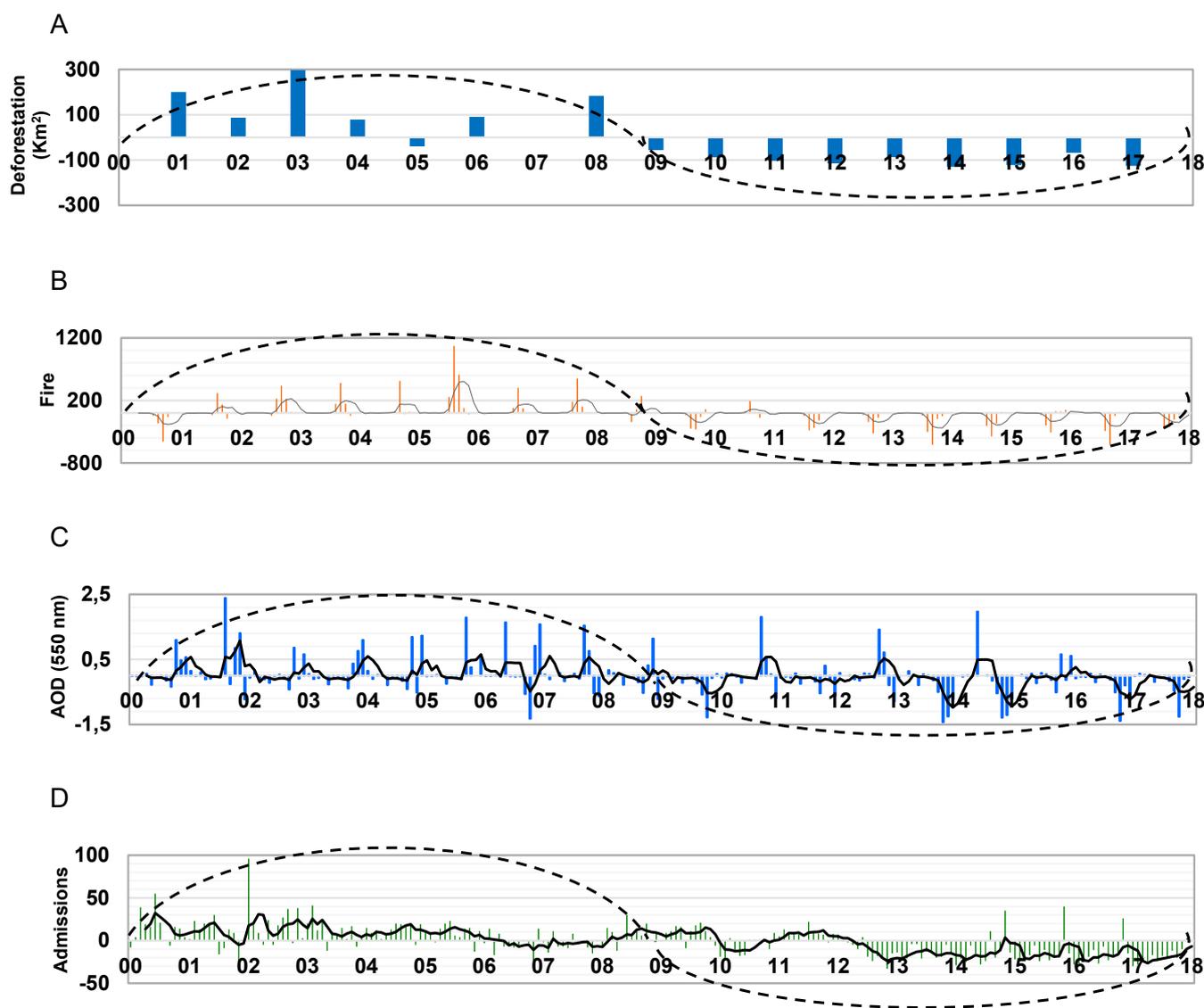
Figure 5 – Distribution of monthly anomalies values for the socio-environmental variables of Marabá from 2000 to 2017: (A) deforestation, (B) fire, (C) AOD, (D) admissions. The dashed line presents the dominant signals for both the positive and the negative phases. The continuous line presents the 6-month moving average.

humidity can influence the number of admissions for respiratory diseases. These results were later confirmed by Smith et al. (2014) when they demonstrated how the peak of hospital admissions of children occurs during the peak of the rainy season due to excessive humidity.

We also calculated the anomalies for the same socio-environmental variables in Santarém, namely, deforestation, wildfire, AOD, and hospital admissions (Figure 6). Unlike Marabá, phases were not so coincident over the time-series period, thus showing a higher data variability.

Table 1 shows that hospital records for respiratory diseases in Marabá. The average number of children hospitalized during the rainy season is 32 (±15.4) and during the dry season is 33 (±11.4), i.e., a 3% increase in hospitalizations from one season to the other. In Santarém, the average is 45.8 (±12.1) during the rainy season and 49.2 (±16.5) during the dry seasons, i.e., an increase of 5%.

The AOD value draws a growing trend following the increase of wildfire and temperature, with a significant rise during the dry season. In Marabá, there is a higher variation from one season to an-

Table 1 – Seasonal descriptive statistical analysis of the study variables for the two cities surveyed, with emphasis on the most relevant values in bold.

Marabá	Average (SD)	Min	P25	P50	P75	Max
Rainy season						
Hospital admissions < 9 years old	32 (15.4)	8.0	18.0	33.0	45.0	61.0
Temperature (°C)	32.4 (0.6)	31.2	32.1	32.6	32.7	33.8
Humidity (%)	80 (2.4)	73.0	79.0	81.0	81	84.0
AOD (550 nm)	0.28 (0.03)	0.24	0.27	0.28	0.29	0.33
Wildfire	0.7 (0.8)	0.0				2.8
Dry season						
Hospital admissions < 9 years old	**33 (11.4)**	15.0	18.0	32.0	**44**	**50.0**
Temperature (°C)	**34.4 (0.7)**	33.3	34.0	34.5	**34.9**	**35.5**
Humidity (%)	**68 (4.2)**	65.0	65.0	67.0	**69.8**	**82.0**
AOD (550 nm)	**0.66 (0.69)**	0.21	0.27	0.35	**0.79**	**2.9**
Wildfire	**188.5 (166.0)**	45.9	155	346	**484**	**475.1**
Santarém						
Rainy season						
Hospital admissions < 9 years old	45.8 (12.1)	19.4	26.0	43.0	57.0	61.4
Temperature (°C)	30.2 (0.4)	29.6	29.9	30.1	30.4	31.2
Humidity (%)	90 (1.0)	89.0	90.0	91.0	91.0	92.0
AOD (550 nm)	0.29 (0.03)	0.25	0.28	0.29	0.31	0.35
Wildfire	6.0 (8.0)	0.0				27.6
Dry season						
Hospital admissions < 9 years old	**49.2 (16.5)**	16.9	29.0	39.0	**53.0**	**78.0**
Temperature (°C)	**32.7 (0.7)**	31.2	32.3	32.5	**32.5**	**34.1**
Humidity (%)	**83 (2.1)**	80.0	81.0	83.0	**84.0**	**88.0**
AOD (550 nm)	**0.47 (0.48)**	0.31	0.32	0.35	**0.39**	**2.39**
Wildfire	**68.7 (25.3)**	8.9	73	87	**114**	**111.0**

SD: standard deviation; P: percentile; MAX: maximum value; MIN: minimum value (2000-2017); AOD: Aerosol Optical Depth.

other (0.38), whereas Santarém experiences a lower variation (0.18). The AOD value is an indication that the local atmosphere is polluted, as it estimates the concentration of aerosols in the atmospheric column by the scattering of solar radiation (Paixão, 2011). Other studies also indicate an increase in both the AOD and wildfires in locations with high atmospheric pollution (Rocha and Yamasoe, 2013).

Regarding temperature and humidity, Marabá presented higher temperatures, mainly during the dry season, with an average of 34.4°C (±0.7), and also presented a less humid atmosphere, with an average of 68% (±4.2) during the dry season, with a 12% amplitude from one season to another. Santarém was more humid, with an average of 83% (±2.1) during the dry season, however, with a much smaller amplitude, only 7%, from one season to another.

The AOD monthly variability shows coherence between Marabá and Santarém with maximum values during dry season fires (Figure 7).

Both cities have a higher AOD value in the second semester, every year. Marabá presents the higher magnitude throughout the time series, especially in 2005 and 2015, years in which extreme climate incidents took place, such as the severe and prolonged droughts in the Amazon (Zeng et al., 2008; Jiménez-Muñoz et al., 2016), whereas the AOD value reached 2.0, which is a trace of areas with a higher incidence of fire outbreaks.

Figure 8A shows the relationship between the AOD averages and the number of hospital admissions for respiratory diseases in Marabá during the dry seasons (June-December). In the time-series analysis, there is a noticeable decrease in hospital admissions (i.e., the continuous line) as the AOD value (i.e., dashed line) decreases. From 2010, it is possible to verify that the AOD value falls sharply, reaching the average value of 0.60 nm during the dry season in 2017. These results are consistent with the anomaly values in the time-series analysis in Figure 5, where Marabá (from 2009 to 2010) recorded the values below the average for deforestation and wildfire.
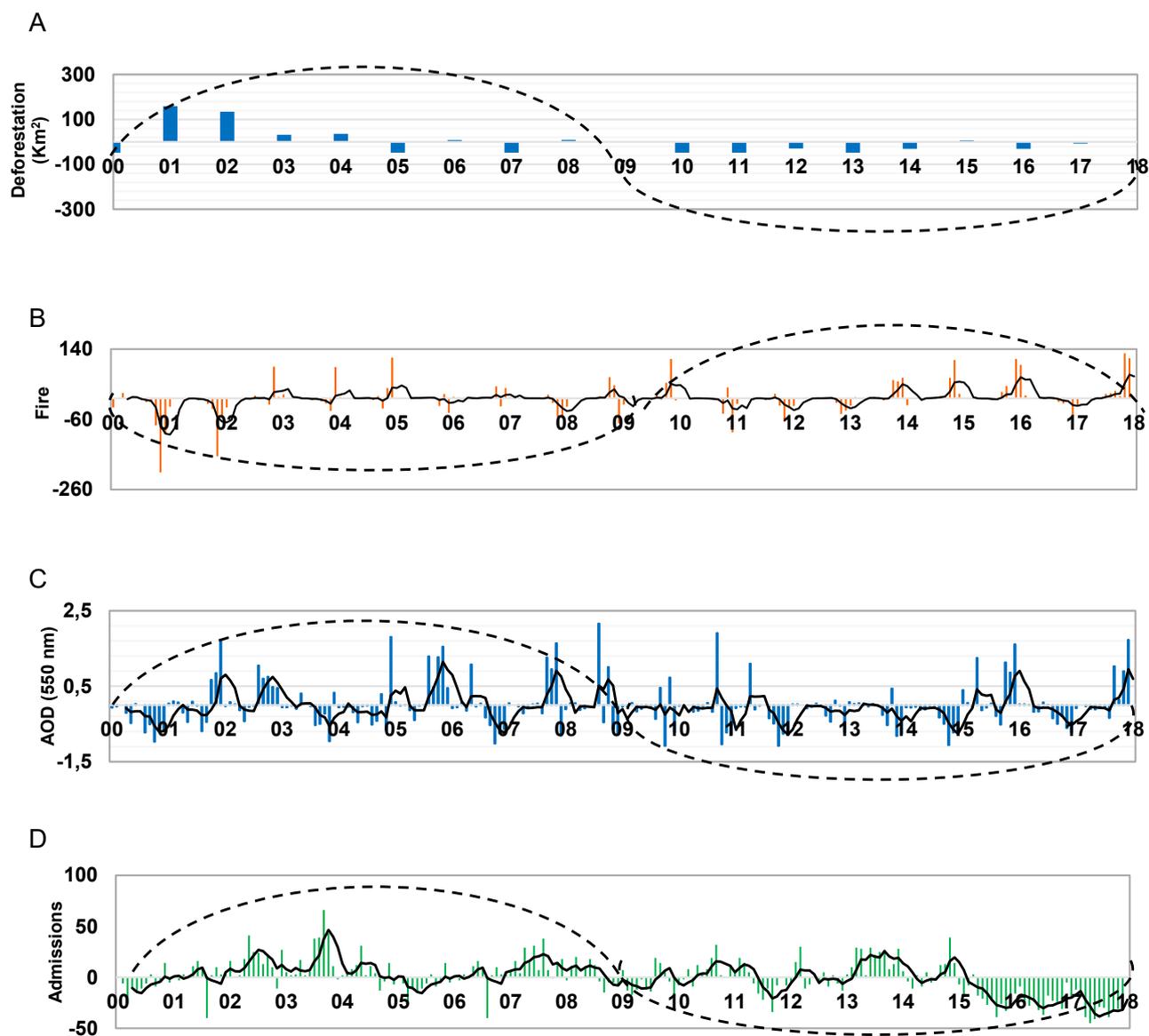
Figure 6 – Distribution of monthly anomalies values for the socio-environmental variables of Santarém from 2000 to 2017: (A) deforestation, (B) fire, (C) AOD, (D) admissions. The dashed line presents the dominant signals for both the positive and the negative phases. The continuous line presents the 6-month moving average.

The linear regression model (Figure 8B) shows a good performance, with a correlation of 64% and confidence interval of 95%, proving that the number of respiratory disease cases in children under 9 years old is dependable on the value of AOD in the atmosphere of Marabá. These results are compatible with those shown by Smith et al. (2014) where they demonstrate the substantial increase in the number of hospitalized children in cities highly exposed to forest fires, located in the Arc of Deforestation, where Marabá is located. According to this study, in 2005, when the Amazon suffered from a severe and prolonged drought, the AOD was responsible for the high incidence of respiratory diseases in Marabá and Santarém. It proves how harmful it is to exposure vulnerable groups to air that has been polluted by wildfire.

Similar to the analysis in Figure 8, Figure 9 shows the average behavior of two variables, namely, AOD and number of hospital admissions in Santarém during the dry seasons of the time-series analysis. Unlike Marabá, the city of Santarém did not present a sharp drop in the number of hospitalizations for respiratory diseases, remaining from 0.80 to 1.40, with similar behavior for the AOD value.
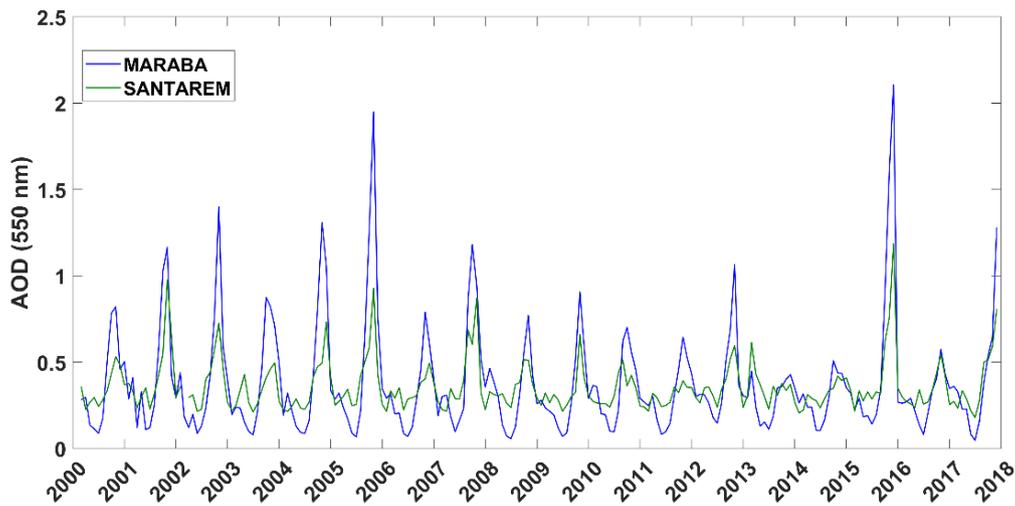
Figure 7 – Variability of monthly values for Aerosol Optical Depth (AOD), based on the MODIS data for Marabá (in blue) and Santarém (in green), from 2000 to 2017.
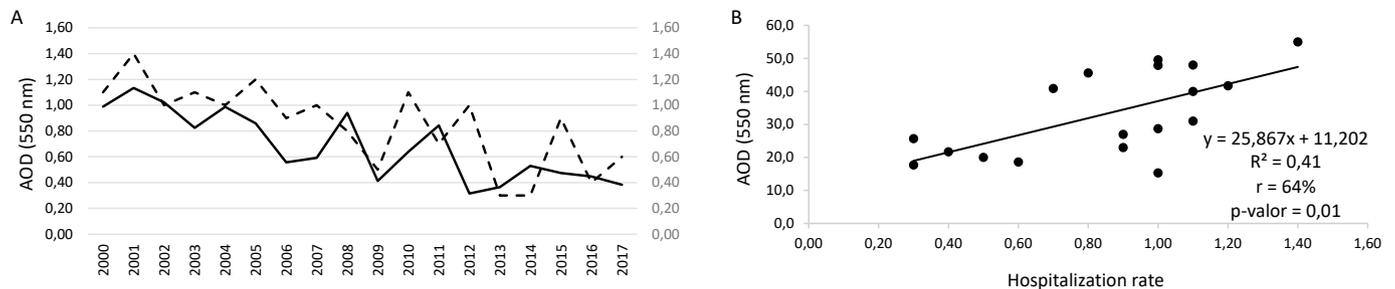

Figure 8 – Correlation between AOD and the number of hospital admissions of children under 9 years of age in Marabá per 1000 inhabitants. (A) Average variability of AOD (dashed line) and the number of hospital admissions (continuous line) during the dry season in every year of the time-series analysis and (B) linear regression model between AOD and hospitalization rate, with p < 0.05 for the average during the dry season in every year of the time-series analysis.

However, the linear regression model (Figure 9B) shows a degree of dependence between these two variables, with a 50% statistical correlation and a 95% confidence interval.

The time-series analysis made in Santarém shows how wildfire pollution (embodied in the AOD) can modulate the number of hospital admissions for respiratory diseases. However, despite having a lower annual wildfire rate in comparison with Marabá, the city of Santarém does not show a downward trend for the AOD variability during dry season fires. This can be explained by the increase of pastures in large properties, the deficient structure of land agencies, and the land documentation along highway BR-163 (from the city of Cuiabá to Santarém). This context facilitates the migration of large and medium landowners to the region in search for better work (Coy and Klingler, 2014; Souza et al., 2017), enabling other sources of pollution. The research of Bandeira Castelo et al. (2020) supports these arguments by showing that in over a decade the deforestation has increased in the Lower Amazon region, Western Pará, where Santarém is located. It was considered a very low level and now it is a moderate level of deforestation. This is according to the research carried out within the city itself, with help from INPE and Brazilian Institute of Geography and Statistics (IBGE).

The monthly analysis in Figure 10 shows Marabá as the city that burns the most forest biomass, reaching an average of 10,000 fire outbreaks in September. In general, for the two cities in the time-series

408

analysis, the highest number of fire outbreaks and the maximum AOD value occur in the second semester, i.e., from September to November.

The boxplot statistical analysis shows that Marabá has a higher amplitude of AOD in comparison with Santarém, as evident in the difference between maximum and minimum values (0.5-2.0) for each month, by the interquartile range (box size), and the median value (1.0) in November.

This demonstrates how Marabá presents a higher data variability, while Santarém, in addition to showing less amplitude, also does not reach maximum values comparable to Marabá, for both wildfire and AOD.

In Figure 10, it is possible to observe that the joint analysis of the monthly average of the number of fire outbreaks in association with the

AOD shows a time lag between the maximum peaks of wildfire and the AOD. In the case of Marabá, the time lag reaches 2 months, with the highest number of fire outbreaks in September, followed by the highest AOD value in November. Santarém does not present a lag concerning these two variables, with peaks in November of both wildfire and AOD.

The time lag can be explained by the presence of other types of aerosols emitted through the mining process that remain in the atmosphere even after the peak of forest fire in the region of Marabá. This massive presence of ore aerosols in the atmosphere, as presented in Barroso et al. (2021), corroborates the presence of particulate matter in the form of sulfides, sulfates, silicates, and carbonates, all above the
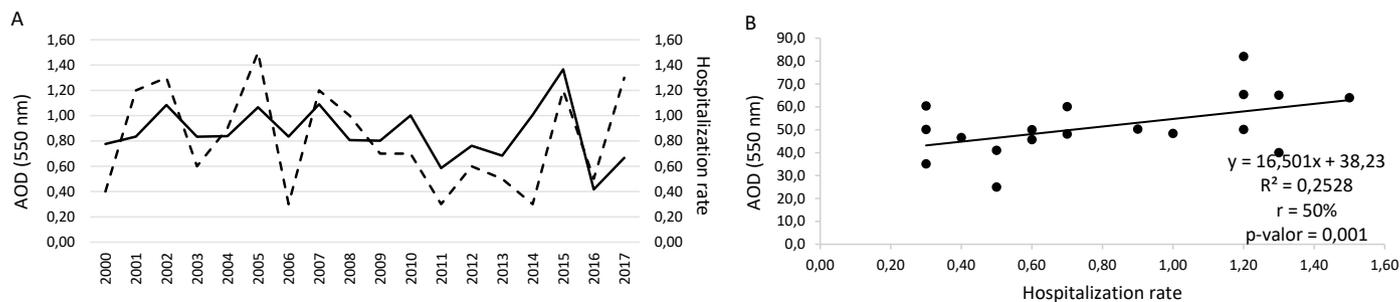

Figure 9 – Correlation between AOD and the number of hospital admissions of children under 9 years of age in Santarém per 1,000 inhabitants. (A) Average variability of AOD (dashed line) and the number of hospital admissions (continuous line) during the dry season in every year of the time-series analysis and (B) linear regression model between AOD and hospitalization rate, with p < 0.05 for the average during the dry season in every year of the time-series analysis.
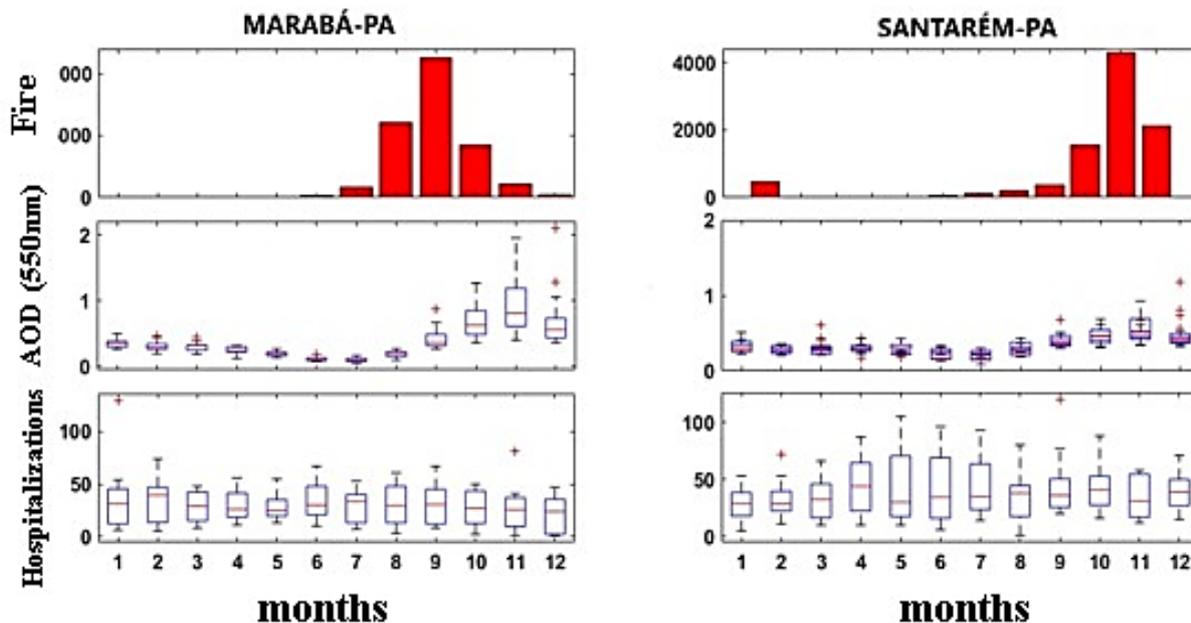

Figure 10 – Statistical information presented by histograms and boxplot of the monthly average of wildfire, AOD, and hospital admissions in Marabá and Santarém from 2000 to 2017.

established guidelines for the regions of intense mining. The authors concluded that there is a strong correlation between the aerosol suspended in the atmosphere and the ore found in the contaminated soil. It is noteworthy that large companies operating in Marabá measure the surface particulate matter, but the results were not provided to assist in this study. Another factor that can contribute to this gap between wildfire peaks and AOD is the transport of aerosols from remote regions with a high incidence of forest fire. In this case, Marabá can suffer the influence of neighboring cities, as confirmed by Nascimento and Medeiros (2012). The study was carried out in the State of Mato Grosso, where large amounts of aerosols can reach kilometers following the wind flow, significantly affecting remote regions, including the number of hospital admissions. However, it is necessary to take into account the maximum number of hospitalizations in Santarém during May, at the end of the rainy season, where there are fewer records of fire outbreaks. The number of hospitalizations can be caused by other factors, such as the climatic conditions that also lead to hospital admission (Andrade Filho et al., 2013; Silva et al., 2013).

Conclusions

The research aimed to demonstrate the importance of environmental protection, considering how locations with very different natural characteristics respond to climatic oscillations and anthropic actions toward the environment.

The decadal analysis of time series indicates the advance of deforestation as the primary cause of forest fire and, consequently, the cause of atmospheric pollution that aggravates the emergence of respiratory diseases.

The climatic oscillations presented by the indices of SOI (the Pacific) and AMM (the Atlantic) modulate the environmental variables that, in turn, modulate social variables, including human health. However, local natural features are essential in this modulation process, as evident in different decadal phase signals between Marabá and Santarém, cities from the regions of different natural features.

It appears that wildfire contributes significantly to increase the number of hospital admissions, as the regression analysis showed a statistically meaningful association between hospitalization rates and the AOD in both cities, but with a stronger correlation in Marabá, above 60%. In other words, during the dry season, the greater the number of fire outbreaks, the greater the number of hospital admission of 9-year-old children for respiratory diseases.

From the two cities in the study, we concluded that Marabá presents the highest number of forest fires, a more polluted and drier atmosphere, and also the highest AOD value, the main indicator of aerosol in the local atmosphere. This consideration is evident through the monthly statistical analysis, although it presents a time lag between the peaks of wildfire and AOD, exposing the presence of other types of aerosols, such as from ore mining, an activity developed by large mining companies operating in the Southeastern region of Pará.

The seasonal analysis with descriptive statistics allows us to state that both Santarém and Marabá show an increase in the number of hospital admissions for respiratory diseases, 3% and 5%, respectively, during the dry season in contrast to the rainy season. In the second semester, this growth occurs in conjunction with the increase in the number of fires and the value of AOD.

This study expresses the importance of government actions to mitigate public health problems and improve the quality of life of its population, facing climate change and the destruction of the forest by illegal deforestation, especially in the Arc of Deforestation in the Legal Amazon, amid a scenario of increased forest fires in the last 2 years and with an increasing trend for the upcoming years.

If synergistic and planned actions are taken to minimize environmental problems, the expenses of health treatment will decrease, especially in the most vulnerable regions. A more in-depth analysis of the $PM_{2.5}$ in the atmosphere of these cities will be presented in an upcoming study.

Contribution of authors:

Moura, M.: Conceptualization, Data curation, Formal analysis, Research, Programs, Visualization, Writing — original draft, Writing — review and editing. Vitorino, I.: Conceptualization, Formal analysis, Research, Methodology, Programs, Supervision, Visualization, Writing — review and editing. Cirino, G.: Conceptualization, Programs, Supervision, Visualization, Writing — review and editing. Andrade, V.: Research, Formal analysis, Writing — review and editing.

References

Alves, N.; Brito, J.; Caumo, S.; Arana, A.; Hacon, S.; Artaxo, P.; Hillamo, R.; Teinilä, K.; Medeiros, S.R.B.; Vasconcellos, C., 2015. Biomass burning in the Amazon region: aerosol source apportionment and associated health risk assessment. Atmospheric Environment, v. 120, 277-285. http://dx.doi.org/10.1016/j.atmosenv.2015.08.059.

Alves, N.; Vessoni, A.; Quinet, A.; Fortunato, R.; Kajitani, G.; Peixoto, M.; Hacon, S.; Artaxo, P.; Saldiva, P.; Menck, C.F.M.; Medeiros, S., 2017. Biomass burning in the Amazon region causes DNA damage and cell death in human lung cells. Scientific Reports, v. 7, (1), 10937. https://doi.org/10.1038/s41598-017-11024-3.

Andrade Filho, V.; Artaxo, P.; Hacon, S.; Carmo, C.; Cirino, G., 2013. Aerossóis de queimadas e doenças respiratórias em crianças, Manaus, Brasil. Revista de Saúde Pública, v. 47, (2), 239-247. https://doi.org/10.1590/S0034-8910.2013047004011.

Andreão, W.; Albuquerque, T., 2020. Fine particles as a public health indicator in Brazil: from monitoring to modeling. Air Quality, Atmosphere & Health, v. 13, 1453-1463. https://doi.org/10.1007/s11869-020-00899-3.

Araújo, R.; Andreoli, R.; Candido, L.; Kayano, M.; Souza, R., 2013. A influência do evento El Niño-Oscilação Sul e Atlântico Equatorial na precipitação sobre as regiões norte e nordeste da América do Sul. Acta Amazônica, v. 43, (4), 469-480. http://dx.doi.org/10.1590/S0044-59672013000400009.

Bandeira Castelo, T.; Adami, M.; Nascimento dos Santos, R., 2020. Fronteira agrícola e a política de priorização dos municípios no combate ao desmatamento no estado do Pará, Amazônia. Estudos, Sociedade e Agricultura, v. 28, (2), 434-457. http://dx.doi.org/10.36920/esa-v28n2-8.

Barcellos, C.; Xavier, D.; Hacon, S.; Artaxo, P.; Gracie, R.; Magalhães, M.; Matos, V.; Monteiro, A.M.; Feitosa, P., 2019. Queimadas na Amazônia e seus impactos na saúde: A incidência de doenças respiratórias no sul da Amazônia aumentou significativamente nos últimos meses. In: Observatório de Clima e Saúde, Instituto de Comunicação e Informação Científica e Tecnológica em Saúde (ICICT), Fundação Oswaldo Cruz (Fiocruz) (Eds.), 3º Informe Técnico do Observatório de Clima e Saúde (Accessed Feb, 2020) at: https://climaesaude.icict.fiocruz.br/sites/climaesaude.icict.fiocruz.br/files/informe_observatorio_queimadas.pdf.

Barroso, A.; Mogo, S.; Silva, M.; Cachorro, V.; Frutos, Á., 2021. Morphology, mineralogy, and chemistry of atmospheric aerosols nearby an active mining area: aljustrel mine (SW Portugal). Atmosphere, v. 12, (3), 333. https://doi.org/10.3390/atmos12030333.

Bistene, M.; Guimarães, J., 2019. Desmatamento, população e desenvolvimento econômico no oeste do Pará nos eixos das Rodovias Santarém-Cuiabá e Transamazônica. Natural Resources, v. 9, (2), 19-35. https://doi.org/10.6008/CBPC2237-9290.2019.002.0003.

Coutinho, C.; Rocha, E.; Lima, A.; Ribeiro, H.; Gutierrez, L.; Barbosa, A.; Paes, G.K.A.A.; Bispo, C.J.C.; Tavares, P., 2018. Variabilidade climática da precipitação na bacia amazônica brasileira. Revista Brasileira de Climatologia, v. 22, (14), 476-500. http://dx.doi.org/10.5380/abclima.v22i0.46074.

Coy, M.; Kingler, M., 2014. Frentes pioneiras em transformação: o eixo da BR-163 e os desafios socioambientais. Territórios e Fronteiras, v. 7, 1-26. http://dx.doi.org/10.22228/rt-f.v7i0.282.

Davidson, E.; Araújo, A.; Artaxo, P.; Balch, J.; Brown, I.F.; Bustamante, M.M.C.; Coe, M.T.; DeFries, R.S.; Keller, M.; Longo, M.; Munger, J.W.; Schroeder, W.; Soares-Filho, B.S.; Souza, C.M.; Wofsy, S.C., 2012. The Amazon basin in transition. Nature, v. 481, (7381), 321-328. http://dx.doi.org/10.1038/nature10717.

Debortoli, N.; Dubreuil, V.; Hirota, M.; Rodrigues Filho, S.; Lindoso, D.; Nabucet, J., 2017. Detecting deforestation impacts in Southern Amazonia rainfall using rain gauges. International Journal of Climatology, v. 37, (6), 2889-2900. https://doi.org/10.1002/joc.4886.

De Jesus, L.; Vitorino, M.I.; Silva Santos, M., 2017. Modulação climática da precipitação na produção de caranguejo do estuário paraense. Revista Brasileira de Geografia Física, v. 10, (4), 993-1001. http://dx.doi.org/10.26848/rbgf.v10.4.p993-1001.

Di Nicolantonio, W.; Cacciari, A.; Tomasi, C., 2009. Particulate matter at surface: Northern Italy monitoring based on satellite remote sensing, meteorological fields, and in-situ samplings. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, v. 2, (4), 284-292. https://doi.org/10.1109/JSTARS.2009.2033948.

Duarte, C.; Souza, S.; Galvíncio, J.; Melo, I., 2009. Detecção de mudanças na cobertura vegetal da bacia hidrográfica do rio Tapacurá–PE através da análise por componentes principais. In: Simpósio Brasileiro de Sensoriamento Remoto, 2009, Natal. Anais, 5765-5772 (Accessed Feb, 2020) at: http://marte.sid.inpe.br/col/dpi.inpe.br/.

Fearnside, P., 2005. Desmatamento na Amazônia brasileira: história, índices e conseqüências. Megadiversidade, v. 19, (3), 680-688. https://doi.org/10.1111/j.1523-1739.2005.00697.x.

Fearnside, P., 2006. Desmatamento na Amazônia: dinâmica, impactos e controle. Acta amazônica, v. 36, (3), 395-400. http://dx.doi.org/10.1590/S0044-59672006000300018.

Forastiere, F.; Stafoggia, M.; Tasco, C.; Picciotto, S.; Agabiti, N.; Cesaroni, G.; Perucci, C.A., 2007. Socioeconomic status, particulate air pollution, and daily mortality: differential exposure or differential susceptibility. American Journal of Industrial Medicine, v. 50, (3), 208-216. https://doi.org/10.1002/ajim.20368.

Gonçalves, F.; Beheng, K.; Massambani, O.; Vautz, W.; Klockow, D., 2010. Processos de remoção de material particulado atmosférico: uma modelagem numérica de estudo de casos. Revista Brasileira de Meteorologia, v. 25, (4), 437-447. http://dx.doi.org/10.1590/S0102-77862010000400003.

Gonçalves, K.; Castro, H.; Hacon, S., 2012. As queimadas na região amazônica e o adoecimento respiratório. Ciência & Saúde Coletiva, v. 17, (6), 1523-1532. http://dx.doi.org/10.1590/s1413-81232012000600016.

Instituto Nacional de Pesquisas Espaciais (INPE). 2020. Metodologia para o cálculo da taxa anual de desmatamento na Amazônia Legal. INPE, São José dos Campos (Accessed June, 2019) at: http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes.

Instituto Nacional de Pesquisas Espaciais (INPE). 2018. Banco de dados (Accessed Apr, 2019) at: https://queimadas.dgi.inpe.br/queimadas/portal.

Jiménez-Muñoz, J.; Mattar, C.; Barichivich, J.; Santamaría-Artigas, A.; Takahashi, K.; Malhi, Y.; Sobrino, J.A.; Van Der Schrier, G., 2016. Record-breaking warming and extreme drought in the Amazon rainforest during the course of El Niño 2015–2016. Scientific Reports, 6, 33130. http://dx.doi.org/10.1038/srep33130.

Kaufman, Y.; Hobbs, P.; Kirchhoff, V.; Artaxo, P.; Remer, L.; Holben, B.; King, M.D.; Ward, D.E.; Prins, E.M.; Longo, K.M., Mattos, L.F., Nobre, C.A.; Spinhirne, J.D.; Thompson, A.M.; Gleason, J.F.; Christopher, S.A.; Tsay, I., 1998. Smoke, clouds, and radiation-Brazil (SCAR-B) experiment. Journal of Geophysical Research: Atmospheres, v. 103, (D24), 31783-31808. https://doi.org/10.1029/98JD02281.

Kayano, M.; Andreoli, R.; Souza, R., 2019. El niño–southern oscillation related teleconnections over south america under distinct atlantic multidecadal oscillation and pacific interdecadal oscillation backgrounds: La niña. International Journal of Climatology, v. 39, (3), 1359-1372. https://doi.org/10.1002/joc.5886.

Limberger, L.; Silva, M., 2016. Precipitação na bacia amazônica e sua associação à variabilidade da temperatura da superfície dos oceanos Pacífico e Atlântico: uma revisão. GEOUSP Espaço e Tempo (Online), v. 20, (3), 657-675. https://doi.org/10.11606/issn.2179-0892.geousp.2016.105393.

Lyapustin, A.; Wang, Y.; Korkin, S.; Huang, D., 2018. MODIS Collection 6 MAIAC algorithm. Atmospheric Measurement Techniques, v. 11, 5741-5765. https://doi.org/10.5194/amt-11-5741-2018.

Miller, G.; Spoolman, S., 2015. Ciência ambiental. Cengage Learning, São Paulo, 576 pp.

Montibeller, B.; Kmoch, A.; Virro, H.; Mander, Ü.; Uuemaa, E., 2020. Increasing fragmentation of forest cover in Brazil's Legal Amazon from 2001 to 2017. Scientific Reports, v. 10, (1), 5803. https://doi.org/10.1038/s41598-020-62591-x.

411

Nascimento, L.; Medeiros, A., 2012. Admissions due to pneumonia and biomass burning: a spatial approach. Jornal de Pediatria, v. 88, (2), 177-183. http://dx.doi.org/10.2223/JPED.2161.

National Oceanic and Atmospheric Administration (NOAA). 2020. Database. (Accessed July) at: https://psl.noaa.gov/data/climateindices.

Padilla, C.; Kihal-Talantikite, W.; Vieira, V.; Rosselo, P.; Le Nir, G.; Zmirou-Navier, D.; Deguen, S, 2014. Air quality and social deprivation in four French metropolitan areas – A localized spatiotemporal environmental inequality analysis. Environmental Research, v. 134, 315-324. https://doi.org/10.1016/j.envres.2014.07.017.

Paixão, M., 2011. Propriedades ópticas de aerossóis naturais e de queimadas da Amazônia. Mastering dissertation, Instituto de Física, Universidade de São Paulo, São Paulo. Retrieved 2017-08, from www.teses.usp.br.

Pereira, H.; Reboita, M.; Ambrizzi, T., 2017. Características da atmosfera na primavera austral durante o El Niño de 2015/2016. Revista Brasileira de Meteorologia, v. 32, (2), 293-310. https://doi.org/10.1590/0102-77863220011.

Pires, G.; Costa, M., 2013. Deforestation causes different subregional effects on the Amazon bioclimatic equilibrium. Geophysical Research Letters, v. 40, (14), 3618-3623. https://doi.org/10.1002/grl.50570.

Rivero, S.; Almeida, O.; Ávila, S.; Oliveira, W., 2009. Pecuária e desmatamento: uma análise das principais causas diretas do desmatamento na Amazônia. Nova Economia, v. 19, (1), 41-66. https://doi.org/10.1590/S0103-63512009000100003.

Rocha, V.; Correia, F.; Fonseca, P., 2015. Reciclagem de precipitação na Amazônia: Um estudo de revisão. Revista Brasileira de Meteorologia, v. 30, (1), 59-70. https://doi.org/10.1590/0102-778620140049.

Rocha, V.; Yamasoe, M., 2013. Estudo da variabilidade espacial e temporal da profundidade óptica do aerossol obtida com o MODIS sobre a região amazônica. Revista Brasileira de Meteorologia, v. 28, (2), 210-220. https://doi.org/10.1590/S0102-77862013000200010.

Rodrigues, P.; Ignotti, E.; Hacon, S., 2019. Fatores socioeconômicos aumentam os efeitos nocivos da poluição atmosférica e da temperatura na mortalidade. Revista Brasileira de Epidemiologia, v. 22, 523-532. https://doi.org/10.1590/1980-549720190011.

Rosa, A.; Ignotti, E.; Botelho, C.; Castro, H.; Hacon, S., 2008. Doença respiratória e sazonalidade climática em menores de 15 anos em um município da Amazônia brasileira. Jornal de Pediatria, v. 84, (6), 543-9. https://doi.org/10.1590/S0021-75572008000700012.

Rozante, J.; Moreira, D.; Goncalves, L.; Vila, D., 2010. Combining TRMM and surface observations of precipitation: technique and validation over South America. Weather and Forecasting, v. 25, (3), 885-894. https://doi.org/10.1175/2010WAF2222325.1.

Seixas, I.; Pinheiro, E.S., 2014. Sensoriamento remoto aplicado à análise chuva-vegetação na Amazônia Central. GEOUSP Espaço e Tempo (Online), v. 18, (3), 635-649. https://doi.org/10.11606/issn.2179-0892.geousp.2014.90073.

Seward, L.; Doane, D., 2014. Estatística Aplicada à Administração e Economia-4. AMGH, United States, 600 pp.

Silva, A.; Mattos, I.; Ignotti, E.; Hacon, S., 2013. Material particulado originário de queimadas e doenças respiratórias. Revista de Saúde Pública, v. 47, (2), 345-352. https://doi.org/10.1590/S0034-8910.2013047004410.

Smith, L.; Aragão, L.; Sabel, C.; Nakaya, T., 2014. Drought impacts on children's respiratory health in the Brazilian Amazon. Scientific Reports, v. 4, 3726. https://doi.org/10.1038/srep03726.

Sousa, A.; Candido, L.; Andreoli, R., 2018. Variabilidade interanual da precipitação e fluxo de umidade sobre a Amazônia usando o QTCM. Revista Brasileira de Meteorologia, v. 33, (1), 41-56. https://doi.org/10.1590/0102-7786331015.

Souza, A.; Pontes, N.; Adami, M.; Narvaes, S., 2017. A contribuição das estradas e o padrão de desflorestamento e degradação da cobertura florestal no sudoeste paraense. Revista Brasileira de Cartografia, v. 69, (9), 1833-1846 (Accessed June, 2019) at: http://www.seer.ufu.br/index.php/revistabrasileiracartografia/article/view/44089.

Van Donkelaar, A.; Martin, R.; Brauer, M.; Kahn, R.; Levy, R.; Verduzco, C.; Villeneuve, P.J., 2010. Global estimates of ambient fine particulate matter concentrations from satellite-based aerosol optical depth: development and application. Environmental Health Perspectives, v. 118, (6), 847-855. https://dx.doi.org/10.1289%2Fehp.0901623.

World Health Organization (WHO). 2018. Air pollution and child health: prescribing clean air: summary. World Health Organization (Accessed Mar, 2018) at: https://www.who.int/.

Zeng, N.; Yoon, J.; Marengo, J.; Subramaniam, A.; Nobre, C.; Mariotti, A.; Neelin, J., 2008. Causes and impacts of the 2005 Amazon drought. Environmental Research Letters, v. 3, (1), 014002. http://dx.doi.org/10.1088/1748-9326/3/1/014002.