Risk and burden of hospital admissions associated with wildfire-related $PM_{2·5}$ in Brazil, 2000–15: a nationwide time-series study

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Summary

Background In the context of climate change and deforestation, Brazil is facing more frequent and unprecedented wildfires. Wildfire-related $PM_{2·5}$ is associated with multiple adverse health outcomes; however, the magnitude of these associations in the Brazilian context is unclear. We aimed to estimate the association between daily exposure to wildfire-related $PM_{2·5}$ and cause-specific hospital admission and attributable health burden in the Brazilian population using a nationwide dataset from 2000 to 2015.

Methods In this nationwide time-series analysis, data for daily all-cause, cardiovascular, and respiratory hospital admissions were collected through the Brazilian Unified Health System from 1814 municipalities in Brazil between Jan 1, 2000, and Dec 31, 2015. Daily concentrations of wildfire-related $PM_{2·5}$ were estimated using the 3D chemical transport model GEOS-Chem at a 2·0° latitude by 2·5° longitude resolution. A time-series analysis was fitted using quasi-Poisson regression to quantify municipality-specific effect estimates, which were then pooled at the regional and national levels using random-effects meta-analyses. Analyses were stratified by sex and ten age groups. The attributable fraction and attributable cases of hospital admissions due to wildfire-related $PM_{2·5}$ were also calculated.

Findings At the national level, a 10 μg/m³ increase in wildfire-related $PM_{2·5}$ was associated with a 1·65% (95% CI 1·51–1·80) increase in all-cause hospital admissions, a 5·09% (4·73–5·44) increase in respiratory hospital admissions, and a 1·10% (0·78–1·42) increase in cardiovascular hospital admissions, over 0–1 days after the exposure. The effect estimates for all-cause hospital admission did not vary by sex, but were particularly high in children aged 4 years or younger (4·88% [95% CI 4·47–5·28]), children aged 5–9 years (2·33% [1·77–2·90]), and people aged 80 years and older (3·70% [3·20–4·20]) compared with other age groups. We estimated that 0·53% (95% CI 0·48–0·58) of all-cause hospital admissions were attributable to wildfire-related $PM_{2·5}$, corresponding to 35 cases (95% CI 32–38) per 100 000 residents annually. The attributable rate was greatest for municipalities in the north, south, and central-west regions, and lowest in the northeast region. Results were consistent for all-cause and respiratory diseases across regions, but remained inconsistent for cardiovascular diseases.

Interpretation Short-term exposure to wildfire-related $PM_{2·5}$ was associated with increased risks of all-cause, respiratory, and cardiovascular hospital admissions, particularly among children (0–9 years) and older people (≥80 years). Greater attention should be paid to reducing exposure to wildfire smoke, particularly for the most susceptible populations.

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Introduction

Wildfires are a major natural hazard of great public concern worldwide.[1,2] In California in 2020, the US National Interagency Fire Center reported that 46 148 wildfires burned 8·4 million acres—about 2·1 million more acres than the 10-year average.[3] In Australia in 2019–20, more than 27·2 million acres of bush, forest, and parks were burned[4] with billions of animals killed or displaced, and unprecedented amounts of smoke-related $PM_{2·5}$ produced.[5] The Instituto Nacional de Persquisas Espaciais has monitored and identified 8·3 million acres of burned area in Brazil per complete year since 2003. This monitoring programme uses low (0·3–1·0 km) and medium (10–60 m) spatial resolution satellite images to operationally and automatically estimate the burned surface in Brazil since 1994.

Wildfire activities in Brazil showed a high spatio-temporal variation pattern. Most of the tropical forest fires were from Brazil's Legal Amazon, a region that covers 59% of the Brazilian territory and encompasses nine states,[6] totalling 5 million km². Previous research indicated that the increase in fires in the Amazon since the 1990s was caused by deforestation and forest degradation from human activities[7,8]—eg, mining, logging, and agricultural land use. Fire activities in the Amazon region occur mainly during the dry season (August to November).[9] However, a study from 2016 found that the duration of the dry season is lengthening;[10]

For the **Instituto Nacional de Persquisas Espaciais** see http://www.inpe.br/queimadas

Research in context

Evidence before this study

We searched MEDLINE (via PubMed), Web of Science, and Google Scholar from database inception until Nov 24, 2020, for articles in English. We searched for “wildfire”, “bushfire”, “$PM_{2.5}$”, and health outcome terms (“mortality”, “death”, “morbidity”, “hospitalization”, “hospitalisation”, “hospital admission”, “hospital visit”). A critical review in 2016 included 43 epidemiological studies on the health effects of wildfire smoke exposure, with a quarter of these studies related to $PM_{2.5}$ and five from Brazil. Consistent evidence suggested associations between wildfire smoke exposure and general respiratory health effects; however, whether cardiovascular outcomes are associated with wildfire smoke, and if some populations are more susceptible needs to be further clarified. In Brazil, existing evidence is limited to regions near the location of the fire source during the burning season due to the known consequence of biomass burning and emissions; little is known about the magnitude and scope of its adverse effects on air quality and public health across the nation. The short timescale and small sample size in existing studies might have insufficient statistical power to detect robust evidence for human susceptibility to short-term wildfire-related $PM_{2.5}$ exposure, and a large-scale study at the country level is needed.

Added value of this study

To our knowledge, this study is by far the largest and most comprehensive to evaluate the health effects of wildfire-related $PM_{2.5}$ in Brazil. We included approximately 148 million hospital admissions from 1814 municipalities, covering nearly 80% of the Brazilian population over 16 years and evaluated respiratory, cardiovascular, and all-cause hospital admissions. We found substantial adverse health effects of short-term exposure to wildfire-related $PM_{2.5}$ at a national level, and detected variations in different age groups. The specific subgroups of people who are most susceptible to wildfire $PM_{2.5}$ exposure are children (aged 0–9 years) and older people (aged ≥80 years). People living close to fire sources (eg, the northern region) had a greater attributable fraction, while the estimated attributable cases were much higher in southeastern Brazil due to high population density.

Implications of all the available evidence

The findings of our study suggest that exposure to wildfire-related $PM_{2.5}$ was significantly associated with increased respiratory, cardiovascular, and all-cause hospital admissions with greater effects for respiratory diseases. More attention should be paid to younger children and older people who were particularly susceptible to wildfire $PM_{2.5}$ to raise awareness of the adverse health effects of wildfire smoke and reduce exposure during fire events.

extreme hydrological events (ie, frequent drought in 2005, 2010, and 2015[11]) might also increase the frequency and severity of wildfires in the Amazon.

Although most wildfire events occur in remote and sparsely populated areas, toxic smoke from wildfires can travel great distances, threatening people living thousands of miles away from the fire source.[12] The exact composition of wildfire smoke is complex and depends on many factors including, but not limited to, the type of fire, the type of biomass fuel, the characteristics of the land cover, the rate of fuel consumption, and meteorological conditions.[13] An essential component of the emissions from wildfires that worsens air quality can be attributed to ambient air particles,[14] such as $PM_{2.5}$. For example, during the fire season in 2012, observed surface $PM_{2.5}$ concentrations in the southwestern Amazon region increased from 2 μg/m³ to 30–50 μg/m³ in late August and September, then declined to less than 10 μg/m³ in October.[15] Emerging evidence shows that even short-term exposures to high concentrations of $PM_{2.5}$ from wildfires can trigger adverse health outcomes including coughing, asthma, heart attacks, stroke, decrease in lung function, hospital admissions, and premature death.[16–18] For asthma, a review study summarised that health outcomes related to wildfire $PM_{2.5}$ were more severe than those from typical mixture $PM_{2.5}$.[19]

Compared with the vast literature on the health effects of total $PM_{2.5}$ generally, the health effects of wildfire-related $PM_{2.5}$ are much less thoroughly explored, although they are an important issue in Brazil. In this study, we aimed to estimate the associations between daily exposure to wildfire-related $PM_{2.5}$ and cause-specific hospital admission and attributable health burden in the Brazilian population using a nationwide dataset from 2000 to 2015.

Methods

Data collection

In this nationwide time-series analysis, data for daily counts of hospital admissions for municipalities in Brazil from Jan 1, 2000, to Dec 31, 2015, were obtained from the Brazilian Unified Health System.[20,21] Individual-level information included date of admission, sex, age, and primary diagnosis, among which all-cause admissions, cardiovascular admissions (codes I00 to I99), and respiratory admissions (codes J00 to J99) were extracted according to the tenth revision of the International Classification of Diseases. Additionally, all-cause admissions were divided into ten age groups (0–4, 5–9, 10–19, 20–29, 30–39, 40–49, 50–59, 60–69, 70–79, and ≥80 years) and two sex groups. For analysis, 1814 municipalities (covering >78% of the national population) were included, which had complete data for the 16-year duration. These municipalities were located across five regions of Brazil: the north, northeast, central-west, southeast, and south.

Daily data for temperature and relative humidity in Brazilian municipalities were downloaded from a gridded dataset at a 0·25° latitude by 0·25° longitude horizontal resolution[22] by overlaying the centroid of each municipality. Here, we used daily mean temperature, calculated by the mean of daily maximum and minimum temperatures, to reflect the general thermal characteristics for each day. Data for municipality-specific populations were downloaded from the 2000 Brazilian Census and 2010 Brazilian Census.

Ethical approval was not required for this analysis of anonymous data.

Model development

Based on our previous work,[14] the 3D chemical transport model GEOS-Chem coupled with O_3-NO_x-hydrocarbon-aerosol chemical mechanisms were used to determine the global fire-induced perturbations in $PM_{2·5}$. This model was driven by meteorological reanalysis data from the Modern-Era Retrospective analysis for Research and Applications, version 2, at 2·0° latitude by 2·5° longitude horizontal resolution and 47 vertical layers.[23] Data for global anthropogenic emissions were from the EDGAR, version 4.2 inventory, with emissions provided per main source category. Biogenic emissions are simulated using the Model of Emissions of Gases and Aerosols from Nature.[24] A biomass burning inventory was adopted from the Global Fire Emissions Database (GFED), version 4.1, which captures biomass burned based on satellite retrieval of burn area and active fire information. Briefly, daily $PM_{2·5}$ from wildfire emissions during the study period was estimated as the difference between results obtained under two conditions with or without fire events. This difference generates a ratio applied to adjust the wildfire-related $PM_{2·5}$ as explained in the model validation section. Therefore, time-series datasets of all-source $PM_{2·5}$ and wildfire-related $PM_{2·5}$ during 2000–16 at a 2·0° latitude by 2·5° longitude horizontal resolution were generated.

Model validation

To validate the all-source $PM_{2·5}$ from GEOS-Chem against monitoring data, the ground measured $PM_{2·5}$ ($PM_{2·5GM}$) was collected from 6882 sites in 61 countries (appendix p 6). Other spatial and temporal variables were included to develop a random forest model:

$$PM_{2·5GM} \sim f(PM_{2·5Chem}, TEMP, PREC, BP, WS, Month, DOW, DOY)$$

in which $PM_{2·5Chem}$ is the estimated all-source $PM_{2·5}$ by GEOS-Chem; TEMP, PREC, BP, and WS are daily ambient temperature, precipitation, barometric pressure, and wind speed, respectively; Month is calendar month; DOW is day of the week and DOY is day of the year. Random forest is a classic and widely used machine learning approach developed from decision trees.[25] The model performance was examined using a ten-fold cross-validation method. It showed that the cross-validation r^2 was 70% and root mean square error was 25·9 μg/m³ (appendix p 6).

The all-source $PM_{2·5}$ derived from GEOS-Chem was adjusted for all municipalities during the study period using the trained random forest model. Then, the adjusted wildfire-related $PM_{2·5}$ was derived by multiplying adjusted all-source $PM_{2·5}$ with the ratio of wildfire-related to all-source $PM_{2·5}$, which could be derived from the GEOS-Chem model for each municipality on each day. Municipality-specific wildfire-related $PM_{2·5}$ for Brazilian municipalities were collected by overlaying the geographical centroid.

For the **2000 Brazilian Census** see http://www.ibge.gov.br/censo/

For the **2010 Brazilian Census** see http://www.censo2010.ibge.gov.br/

Statistical analysis

A two-stage analysis strategy was developed to assess the association between wildfire-related $PM_{2·5}$ and hospital admissions.[26] At the first stage, time-series models were developed to estimate municipality-specific associations. At the second stage, a random-effects meta-analysis was used to pool the effect estimates at the national and regional levels.

For the **EDGAR, version 4.2 inventory** see http://edgar.jrc.ec.europa.eu/

In stage one, a standard quasi-Poisson generalised linear model was applied for each municipality in Brazil:

$$\mathrm{Log}_{(\mu t)} = PM_{(2·5t)} + ns(Temp_t, df=3) + \mathrm{ns}(RH_t, df=3) + \mathrm{ns}(Time_t, \mathrm{df}=7*\mathrm{n}) + \mathrm{DOW}_t + Holidays_t$$

where μ_t is the expected daily count of hospital admissions on day t in a specific municipality. We used natural cubic splines with 3 df for the 21-day moving average of temperature, and the 7-day moving average of relative humidity (*RH*).[27] The seasonality and long-term trends were controlled using a natural cubic spline of time with 7 df per year. DOW_t is a categorical variable to control for day of the week, and $Holidays_t$ is a binary variable to control for public holidays. $PM_{2·5t}$ is a single

See **Online** for appendix

	Number of municipalities	Hospital admissions per year			Daily wildfire-related $PM_{2·5}$ (μg/m³)	
		All-cause	Cardiovascular	Respiratory	Mean (SD)	Range
National	1814	8 974 136	927 470	1 135 900	2·19 (3·76)	0·00–164·18
Region						
North	28	241 409	14 411	26 902	5·43 (9·40)	0·00–122·88
Northeast	662	2 624 159	206 904	342 468	1·37 (2·40)	0·00–113·72
South	374	1 561 562	190 855	237 158	2·44 (3·06)	0·00–148·10
Southeast	622	3 808 808	442 229	427 993	2·14 (3·15)	0·00–136·89
Central-west	128	738 198	13 072	101 379	5·22 (7·78)	0·01–164·18

Table 1: **Distribution of hospital admissions and daily wildfire-related $PM_{2·5}$, 2000-15**

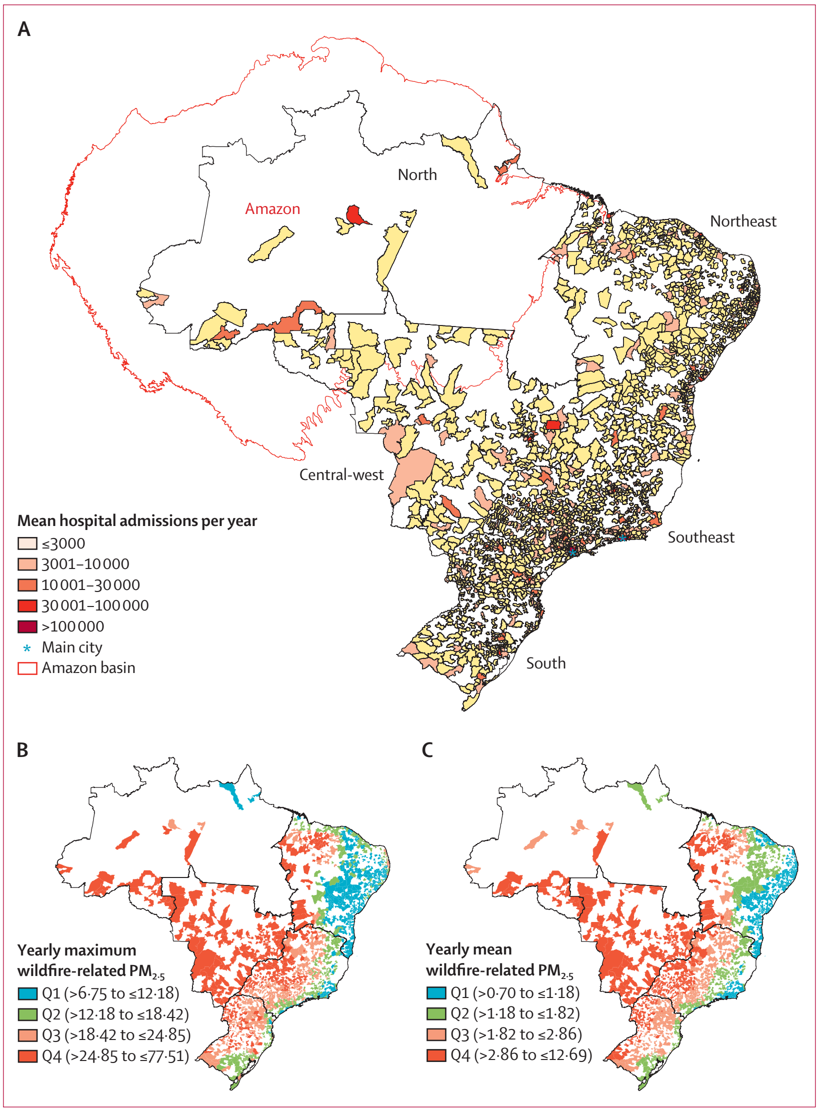

Figure 1: **Regional differences in hospital admissions and wildfire-related $PM_{2·5}$ concentrations across Brazil**
Five regions in Brazil and hospital admissions per year (A), four groups by quartile (Q1 to Q4, from low to high) based on yearly maximum wildfire-related $PM_{2·5}$ in μg/m³ (B), and yearly mean wildfire-related $PM_{2·5}$ in μg/m³ (C). Q=quartile.

lag variable (ie, $PM_{2·5}$[0], $PM_{2·5}$[1], $PM_{2·5}$[2], $PM_{2·5}$[3], $PM_{2·5}$[4], $PM_{2·5}$[5], $PM_{2·5}$[6], and $PM_{2·5}$[7]) to calculate the lagged effect of wildfire-related $PM_{2·5}$ on different single lag days; a moving average (ie, $PM_{2·5}$[0–1], $PM_{2·5}$[0–2], $PM_{2·5}$[0–3], $PM_{2·5}$[0–4], $PM_{2·5}$[0–5], $PM_{2·5}$[0–6], and $PM_{2·5}$[0–7]) was then used to calculate the cumulative effect of wildfire-related $PM_{2·5}$ over lag days.

In stage two, the municipality-specific estimates were pooled at the regional and national levels using a random-effects meta-analysis with maximum likelihood estimation. The lagged effects and cumulative effects of wildfire-related $PM_{2·5}$ on hospital admissions were described as the percentage change in the estimated risk of hospital admissions and corresponding 95% CIs per 10 μg/m³ increase in $PM_{2·5}$ concentration. Analyses were stratified by sex and age category (0–4, 5–9, 10–19, 20–29, 30–39, 40–49, 50–59, 60–69, 70–79, and ≥80 years) for all-cause hospital admissions. Cause-specific hospital admissions were reclassified into three age categories (0–9, 10–59, and ≥60 years) for respiratory diseases and two age categories (0–59 and ≥60 years) for cardiovascular diseases. Between-group differences were tested using random-effects meta-regression[28] with categorical predictors of region, sex, and age.

For each municipality, the number of hospital admissions attributed to wildfire-related $PM_{2·5}$ was calculated using previously published methods,[29] with empirical CIs estimated through Monte Carlo simulation (5000 random samples):

$$DAN_{it}=\left[1-\exp\left(-\sum_{K=0}^{K}\beta_{t-k}\right)\right]\times n_{it}$$

where k was lag day and K was maximum lag day. β_{t-k} is the pooled effect estimate calculated with a backward approach on day t–k. n_{it} is the reported daily hospital admission counts on day t in municipality i. The number of attributable hospital admissions for each municipality was calculated by summing DAN_{it} every day during 2000–15, which were then summed to obtain the total attributable cases of hospital admissions at the national and regional levels. The corresponding attributable fractions were calculated by dividing the total attributable number of hospital admissions by the total number of hospital admissions during the study period.

Sensitivity analyses were done to examine the robustness of the results. We changed the maximum lag of wildfire-related $PM_{2·5}$ from 0–1 to 0–5 days. We also tested the df of meteorological variables (3–7 df).

All data analyses were done using R software. The mvmeta package[25] was used to fit the meta-analysis and meta-regression. p values of less than 0·05 (two-sided) were considered as statistically significant.

Role of the funding source
The funders of the study had no role in study design, data collection, data analysis, data interpretation, or writing of the report.

Results
During the study period, there were 143 586 178 hospital admissions (85 374 535 [59·5%] girls or women), among which 14 839 526 were cardiovascular admissions and 18 174 392 were respiratory admissions. The daily mean wildfire-related $PM_{2·5}$ of the 1814 municipalities was 2·19 μg/m³ (SD 3·76 [range 0·00–164·18]) between 2000 and 2015, varying across regions (table 1). Municipalities in the north region had the highest daily mean wildfire-related $PM_{2·5}$ concentration, followed by the central-west, while municipalities in northeast Brazil had the lowest concentrations. When dividing municipalities into

four groups (Q1 to Q4) according to the quartiles of $PM_{2·5}$ concentrations, a conspicuous parallel banding distribution could be seen and the annual maximum and mean wildfire-related $PM_{2·5}$ declined from west to east (figure 1).

Figure 2 shows the pooled associations between wildfire-related $PM_{2·5}$ (with a 10 μg/m³ increase) and hospital admissions on a single lag day and over moving average lag days. At a national level, the estimated risks of hospital admission were highest during the first day of exposure and declined thereafter, with positive associations on lag 0, 1, and 2 days for all-cause hospital admissions. Positive associations were observed on lag 0 and 1 day for cardiovascular admissions. For respiratory disease admissions, the health effects of wildfire-related $PM_{2·5}$ had a positive correlation on lag 0, 1, 2, and 3 days and were consistently stronger (higher relative risks) than all-cause and cardiovascular admissions on each single lag day. Generally, lag 0–1 day average exposure had the highest effect estimates for all the groups. Therefore, we chose the 0–1 day moving average to calculate the cumulative effects of wildfire-related $PM_{2·5}$.

The increased cumulative relative risks over 0–1 lag days for all-cause hospital admissions associated with a 10 μg/m³ increase in wildfire-related $PM_{2·5}$ was 1·65% (95% CI 1·51–1·80) at the national level, varying from 2·50 (2·24–2·74) in the south to 0·58 (0·20–0·96) in the northeast (figure 3). Despite the geographical difference in the cumulative effect estimates, the associations between respiratory hospital admission and wildfire-related $PM_{2·5}$ showed stronger effects across the five Brazilian regions. For respiratory admissions, the estimated risk of hospital admission increased by 5·09% (95% CI 4·73–5·44) per 10 μg/m³ increase in wildfire-related $PM_{2·5}$ over lag 0–1 days, ranging from the lowest in the northeast (2·18% [95% CI 1·22–3·14]) to the highest in the southeast (6·59% [5·98–7·20]; figure 3). For cardiovascular admissions, the estimated risk of hospital admission increased by 1·10% (95% CI 0·78–1·42) per 10 μg/m³ increase in wildfire-related $PM_{2·5}$ over lag 0–1 days at the national level. Regionally, there was a significant positive association in the south (2·36% [95% CI 1·70–3·04]) and southeast (1·03% [0·49–1·56]).

Stratified analyses by sex and age group are shown in figure 4. Generally, there were no significant differences (p=0·20) on the basis of sex in the associations between wildfire-related $PM_{2·5}$ exposure and hospital admissions. However, an age difference was apparent: the estimated percentage increase in relative risk was highest in children aged 0–4 years (4·88% [95% CI 4·47–5·28]), followed by people aged 80 years and older (3·70% [3·20–4·20]), and children aged 5–9 years (2·33% [1·77–2·90]). The effect estimate was lowest in adults aged 30–39 years (0·83 [95% CI 0·44–1·23]). Overall, estimates for all age groups indicated positive associations between wildfire-related $PM_{2·5}$ and all-cause hospital admissions during lag 0–1 days.

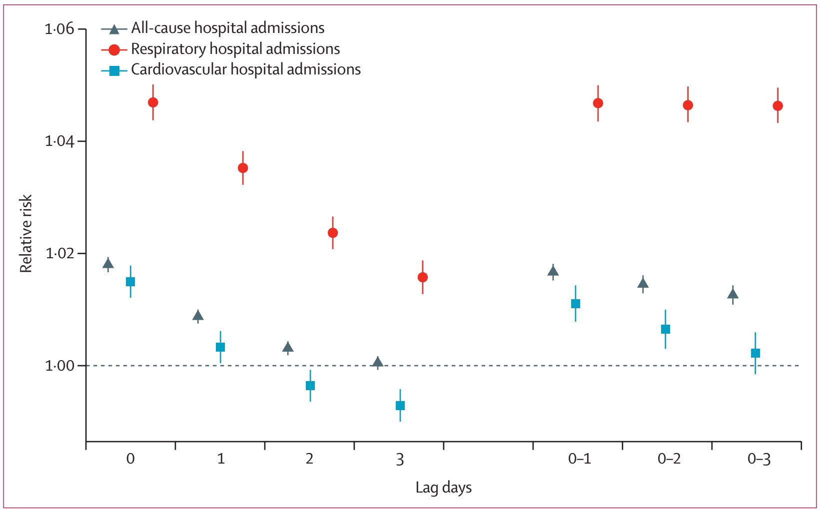

Figure 2: **Pooled relative risks of all-cause, cardiovascular, and respiratory hospital admission associated with a 10 μg/m³ increase in wildfire-related $PM_{2·5}$ at single lag 0–3 days and moving average over 0–1, 0–2, and 0–3 days**
Error bars are 95% CIs.

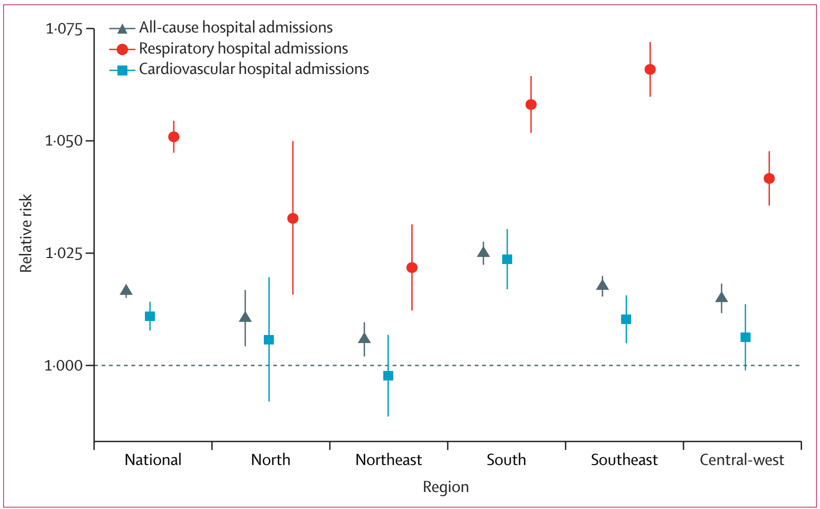

Figure 3: **Pooled relative risks of all-cause, cardiovascular, and respiratory hospital admission associated with a 10 μg/m³ increase in wildfire-related $PM_{2·5}$ by region over a 0–1 day moving average**
Error bars are 95% CIs.

Table 2 shows the attributable fractions and cases of hospital admission attributable to wildfire-related $PM_{2·5}$ during the 16-year study duration. An estimated 766 091 (95% CI 692 740–839 301) cases in total could be related to wildfire-related $PM_{2·5}$ exposure over lag 0–1 days. This number accounted for 0·53% (95% CI 0·48–0·58) of the total hospital admissions, equating to 35 cases (95% CI 32–38) per 100 000 residents per year nationwide. Geographically, higher estimates of attributable fractions and attributable rate were found in the north, south, and central-west regions, whereas municipalities in the northeast had the lowest attributable rate. Of all age groups, the highest attributable rates of hospital admission due to wildfire-related $PM_{2·5}$ were

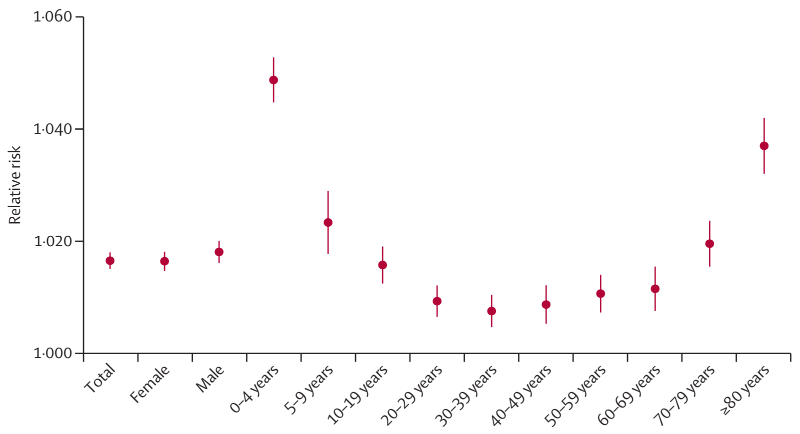

Figure 4: **Pooled relative risks of all-cause hospital admission associated with a 10 μg/m³ increase in wildfire-related $PM_{2·5}$ stratified by sex and age group over a 0–1 day moving average**
Error bars are 95% CIs.

	Attributable fraction	Attributable cases during 2000–15	Annual attributable rate (per 100 000 population)
National	0·53% (0·48–0·58)	766 091 (692 740–839 301)	35 (32–38)
Cause-specific			
Respiratory	1·66% (1·54–1·78)	302437 (280726–324055)	14 (13–15)
Cardiovascular	0·37% (0·25–0·49)	55 170 (38 005–72 264)	3 (2–3)
Region			
North	0·70% (0·23–1·15)	26 848 (8965–44 368)	42 (14–70)
Northeast	0·12% (0·04–0·20)	50 326 (14 705–85 824)	8 (2–14)
South	0·86% (0·76–0·96)	215 142 (190 094–240 130)	62 (55–69)
Southeast	0·53% (0·45–0·60)	321 455 (275 846–366 958)	30 (26–34)
Central-west	1·04% (0·79–1·28)	122 809 (93 811–151 577)	71 (54–88)
Sex			
Female	0·51% (0·45–0·57)	432 806 (382 657–482 843)	37 (32–41)
Male	0·57% (0·50–0·64)	331 961 (290 721–373 091)	29 (25–32)
Age, years			
0–4	1·51% (1·38–1·63)	254 044 (232 574–275 408)	145 (133–157)
5–9	0·80% (0·60–0·99)	41 124 (30 948–51 223)	22 (17–28)
10–19	0·51% (0·40–0·62)	77 380 (60 344–94 341)	18 (14–22)
20–29	0·30% (0·21–0·39)	83 794 (57 965–109 530)	20 (14–26)
30–39	0·25% (0·13–0·36)	47 930 (25 689–70 073)	13 (7–19)
40–49	0·31% (0·18–0·43)	45 843 (27 385–64 217)	15 (9–21)
50–59	0·38% (0·25–0·50)	52 097 (34 921–69 195)	24 (16–32)
60–69	0·41% (0·25–0·56)	46 786 (29 215–64 262)	75 (64–86)*
70–79	0·67% (0·53–0·81)	64 906 (51 010–78 731)	75 (64–86)*
≥80	1·21% (1·04–1·37)	79 630 (68 731–90 465)	75 (64–86)*

Data are as indicated with 95% CIs. *Due to the grouping limitation of the 2000 and 2010 Brazilian Census datasets, the three older age groups (60–69, 70–79, and ≥80 years) were grouped into ≥60 years when calculating attributable rates.

Table 2: **Attributable fractions and hospital admissions associated with wildfire-related $PM_{2·5}$ over lag 0–1 days in the 1814 Brazilian municipalities by region, sex, and age, 2000–15**

observed in children aged 4 years or younger, corresponding to 145 cases (95% CI 133–157) per 100 000 residents per year.

Our findings were robust to the sensitivity analyses when changing the dfs for temperature and relative humidity (appendix p 1).

Discussion

In this study, the association between wildfire-related $PM_{2·5}$ and hospital admissions was assessed across five regions in Brazil during 2000–15, based on a nationwide dataset covering 1814 municipalities and approximately 80% of the national population. We found substantial adverse health effects for both cardiovascular and respiratory diseases with stronger effect estimates for respiratory hospital admissions. 766 091 (95% CI 692 740–839 301) all-cause hospital admissions were estimated to be attributable to $PM_{2·5}$ exposure from wildfire smoke during 2000–15.

Overall, we found no significant differences in health estimates by sex. However, a significant difference was observed by age group. Similar to findings in a systematic review,[30] children and the older population in Brazil were more susceptible to wildfire-related $PM_{2·5}$ exposure, possibly due to a higher sensitivity to environmental hazards as a result of having either immature or ageing cardiorespiratory systems. Geographical variation in the relationship between wildfire-related $PM_{2·5}$ and health has been found. Individuals in the north and central-west regions had lower susceptibility to wildfire-related $PM_{2·5}$, than those in the south, although they had higher attributable health burdens mainly due to higher exposures. This finding might be explained by the fact that northern Brazil has a smaller proportion of the population who are aged older than 60 years than other regions that are more affected by wildfire-related $PM_{2·5}$ (appendix p 2). By contrast, the higher attributable health burden in north and central-west areas could be explained by the geographical proximity to fire sources, the unique patterns of topography, and atmospheric transportation of wildfire smoke. The north and central-west regions are close to the Amazon rainforest, a substantial source region of biomass burning emissions, aggravating the local attributable hospital admissions burden during the fire season. Regional estimations of attributable cases and fractions for all-cause hospital admission divided up into Q1 to Q4 could provide additional evidence (figure 1, appendix p 3). The exception was in the southeastern region where the municipalities of São Paulo and Rio de Janeiro are located; although a lower attributable fraction was estimated, the attributable cases were highest due to the vast number of hospital admissions in this region.

Due to differences in the methods used—including the choice of study period and spatial domain, fire emissions inventories, simulations of fire air pollution, health outcomes, and concentration–response functions—straightforward comparisons with other studies are challenging. A 2020 study mapped the effect of forest fires on paediatric health in the 100 most affected municipalities in northern Brazil.[31] The results suggested that the risk of hospital admission for respiratory problems was 36% higher for children living near fire spots than others, which was consistent with our investigations. A study in California estimated that the relative risk for respiratory hospital admissions and emergency department visits associated with a 10 μg/m³ increase in $PM_{2·5}$ was 1·035 (95% CI 1·023–1·046) during an intense wildfire event in 2008.[32] Studies from the past 5 years in Brazil have attempted to assess the consequence of premature deaths attributable to fire emissions. Nawaz and colleagues found that during the fire season (July to September) of 2019, 4966 (95% CI 2427–8340) premature deaths were attributable to fire emissions making up 10% (95% CI 5–17) of all $PM_{2·5}$-related premature deaths in Brazil.[33] During the dry season (August to October) in 2012, Butt and colleagues estimated that vegetation fires contributed 80% of mean surface $PM_{2·5}$ in the western Amazon region. Thus, the prevention of vegetation fires would avert 16 800 (95% CI 16 300–17 400) premature deaths across South America, with 26% of the avoided health burden located within the Amazon Basin.[34] Reddington and colleagues simulated the effect of deforestation rates on air quality and human health between 2001 and 2012, showing that reductions in fires associated with deforestation would decrease mean surface particulate matter concentrations by 30% during the dry season (August to October) in Bolivia and southwest Brazil, preventing around 400–1700 premature adult deaths annually.[35]

Although existing evidence supporting worse effects of wildfire smoke exposure on respiratory and cardiovascular health is scarce in Brazil, there are studies from the past 5 years suggesting that the chemical composition of biomass burning aerosols might be the culprit in explaining a differential toxicity compared with that of urban aerosols.[36] Wildfire particulate matter has a stronger effect on the risk of asthma-related events than urban particulate matter, but the effect regarding the risk of cardiovascular events could be similar to that of urban particulate matter.[37] In addition, the frequency and magnitude distribution of $PM_{2·5}$ concentration from wildfire sources differs from that of non-fire $PM_{2·5}$. The time-series pattern of wildfire-related $PM_{2·5}$ is mostly zero with occasional high peaks for short periods during dry seasons. Due to these characteristics, exposure to wildfire-related $PM_{2·5}$ is less predictable but valuable.

To the best of our knowledge, this study is the first nationwide evaluation of the short-term effects of wildfire-related $PM_{2·5}$ in Brazil. We sought to enhance the exposure estimates for population with use of the modelled air pollution data due to the poor distribution and scarcity of monitoring stations in Brazil. The model captured the temporal and spatial trends of $PM_{2·5}$ and particularly focused on separation of smoke $PM_{2·5}$ from other sources. Another strength of this study is that we provided evidence for cause-specific age and sex stratified outcomes. Results for cardiovascular effects remain inconsistent, but several studies have reported associations for specific cardiovascular mortality and morbidity in southern Europe,[38] and in the Brazilian Amazon.[39] Additionally, this study involved the application of a standard two-stage analytical approach on an available dataset that included more than three-quarters of the Brazilian population. Our findings are very likely to be representative of the general Brazilian population.[40]

The major limitation of our study is that the results are heavily dependent on the models used to assess exposure to wildfire-related $PM_{2·5}$. Although the exposure simulation was done at a 2·0° latitude by 2·5° longitude resolution, the overall accuracy of the GEOS-Chem model in capturing the major characteristics of wildfire-related $PM_{2·5}$ distribution has been validated by ground monitoring data at 6882 sites with a high r^2 of 70% (appendix p 6). There are errors in using exposure data at a coarse resolution. However, this error is mainly of the Berkson type (ie, statistically not correlated with the observed variable).[41,42] This bias does not substantially interfere with effect estimates for the association between exposure and response, but does lose precision—ie, make the CIs wider. Previous studies compared the health effects of $PM_{2·5}$ at a coarse resolution modelled by GEOS-Chem with models at finer resolutions, showing that coarse resolutions tend to slightly underestimate the effect estimates.[43] The regional biases in model performance and prediction accuracy, and the effect of exposure measurement error on the results obtained in this study need further investigation. Additionally, we cannot run sensitivity analyses regarding the biomass burning emissions. Compared with other emission inventories (eg, Fire INventory from NCAR [FINN] at around 1 km² horizontal resolution), GFED, version 4.1 inventory, has a coarse spatial resolution. A 2021 study using both GFED and FINN, version 1.5, showed similar spatial pattern and seasonality of fire-induced $PM_{2·5}$ in the Amazon region, although the magnitude using GFED is slightly lower than that with FINN.[44]

In conclusion, exposure to wildfire-related $PM_{2·5}$ was associated with an increased risk of all-cause, respiratory, and cardiovascular hospital admissions in Brazil. Children aged 0–9 years and adults aged 80 years and older were more susceptible to wildfire-related $PM_{2·5}$ than other age groups. As fires and their emissions remain a persistent problem in Brazil, a quantification of the health effects associated with wildfire smoke should provide an additional perspective when considering public health protection policy.

Contributors

YG and SL conceived, designed, and supervised the study, and developed the statistical methods. TY analysed the data and wrote the paper. YG, SL, and TY led the drafting of the manuscript, interpretation of the results, and verification of the underlying data. YG and XY did the exposure assessment of wildfire-related $PM_{2·5}$. GC, QZ, RX, XY, and MSZSC prepared the database and did the quality assurance. All authors reviewed and edited the paper. All authors had full access to all the data in the study and had final responsibility for the decision to submit for publication after obtaining approval from all coauthors.

Declaration of interests

We declare no competing interests.

Data sharing

The authors do not have permission to directly share the health outcome data, which were obtained from the Brazilian Unified Health System. Census data can be downloaded from the 2000 Brazilian Census and 2010 Brazilian Census. For other data, researchers who are interested should contact the corresponding authors with their study protocol and plan.

For the **2000 Brazilian Census** see http://www.ibge.gov.br/censo/

For the **2010 Brazilian Census** see http://www.censo2010.ibge.gov.br/

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