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The impact of wildfires on air pollution and health across land use categories in Brazil over a 16-year period

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ABSTRACT

Forest fires cause many environmental impacts, including air pollution. Brazil is a very fire-prone region where few studies have investigated the impact of wildfires on air quality and health. We proposed to test two hypotheses in this study: i) the wildfires in Brazil have increased the levels of air pollution and posed a health hazard in 2003–2018, and ii) the magnitude of this phenomenon depends on the type of land use and land cover (e.g., forest area, agricultural area, etc.). Satellite and ensemble models derived data were used as input in our analyses. Wildfire events were retrieved from Fire Information for Resource Management System (FIRMS), provided by NASA; air pollution data from the Copernicus Atmosphere Monitoring Service (CAMS); meteorological variables from the ERA-Interim model; and land use/cover data were derived from pixel-based classification of Landsat satellite images by MapBiomas. We used a framework that infers the "wildfire penalty" by accounting for differences in linear pollutant annual trends (β) between two models to test these hypotheses. The first model was adjusted for Wildfire-related Land Use activities (WLU), considered as an adjusted model. In the second model, defined as an unadjusted model, we removed the wildfire variable (WLU). Both models were controlled by meteorological variables. We used a generalized additive approach to fit these two models. To estimate mortality associated with wildfire penalties, we applied health impact function. Our findings suggest that wildfire events between 2003 and 2018 have increased the levels of air pollution and posed a significant health hazard in Brazil, supporting our first hypothesis. For example, in the Pampa biome, we estimated an annual wildfire penalty of 0.005 μg/m^3 (95%CI: 0.001; 0.009) on $PM_{2.5}$. Our results also confirm the second hypothesis. We observed that the greatest impact of wildfires on $PM_{2.5}$ concentrations occurred in soybean areas in the Amazon biome. During the 16 years of the study period, wildfires originating from soybean areas in the Amazon biome were associated with a total penalty of 0.64 μg/m^3 (95%CI: 0.32; 0.96) on $PM_{2.5}$, causing an estimated 3872 (95%CI: 2560; 5168) excess deaths. Sugarcane crops were also a driver of deforestation-related wildfires in Brazil, mainly in Cerrado and Atlantic Forest biomes. Our findings suggest that between 2003 and 2018, fires originating from sugarcane crops were associated with a total penalty of 0.134 μg/m^3 (95%CI: 0.037; 0.232) on $PM_{2.5}$ in Atlantic Forest biome, resulting in an estimated 7600 (95%CI: 4400; 10,800) excess deaths during the study period, and 0.096 μg/m^3 (95%CI: 0.048; 0.144) on $PM_{2.5}$ in Cerrado biome, resulting in an estimated 1632 (95%CI: 1152; 2112) excess deaths during the study period. Considering that the wildfire penalties observed during our study period may continue to be a challenge in the future, this study should be of interest to policymakers to prepare future strategies related to forest protection, land use management, agricultural activities, environmental health, climate change, and sources of air pollution.

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1. Introduction

The occurrence and extent of wildfires are increasing worldwide. According to the European Space Agency (ESA), 4 million km^2 of vegetation burns worldwide each year (ESA, 2021). Fire–prone regions around the world vary in size. In Europe, about 18,000 km^2 of biomass is burned annually (Youssouf et al., 2014). Africa is a fire-prone region, with about 50% of West African savannas burned each year (Liousse et al., 2010; Tesfaye et al., 2014). In the U.S., about 90,000 km^2 of vegetation is burned annually (Koplitz et al., 2018). In Brazil, according to the National Institute for Spatial Research (INPE), an area of 274,400 km^2 was burned in 2021 (INPE, 2021). Between 2012 and 2017, there were an annual average of 1.4 million active fires in Brazil, representing about 7% of all active fires worldwide (Li et al., 2020).

Wildfires are associated with several environmental impacts, including economic losses (Wang et al., 2021), impacts on water resources (Park et al., 2022), and impacts on air pollution (Kalashnikov et al., 2022; Requia et al., 2019a), which poses serious health hazard (Chen et al., 2021; Requia et al., 2021a, 2021b, 2022). Regarding air pollution, emissions from forest fires can travel considerable distances and affect air quality and human health far from fire sites (Youssouf et al., 2014). Pollutants resulting from biomass burning can travel more than 4,000 km (Rogers et al., 2020). Particulate matter less than 2.5 μm ($PM_{2.5}$) is a major pollutant released by wildfires (McClure and Jaffe, 2018). In the U.S., wildfires accounted for more than 20% of total $PM_{2.5}$ emissions in 2014, according to the National Emissions Inventory (NEI) (EPA, 2014). About 12–16% of global $PM_{2.5}$ emissions from forest fires occur in Brazil (Reddington et al., 2015). In addition, wildfire smoke directly and indirectly affects concentrations of other criteria air pollutants, including carbon monoxide CO (Rogers et al., 2020), nitrogen dioxide (NO_2) (Di Carlo et al., 2015), and tropospheric ozone (O_3) (Di Carlo et al., 2015). In Brazil, for example, biomass burning is a significant source of O_3 precursors, with wildfires contributing between 23 and 41% of total O_3 during pollution events (Targino et al., 2019).

Most previous studies of wildfire impacts on air pollution have focused on specific wildfire events (Grulke et al., 2008; Kalashnikov et al., 2022; Liang et al., 2021) and future pollution scenarios (Liu et al., 2016). However, few studies have focused on national trend analyses of the relationship between air pollution and wildfire with temporal datasets. Our research addresses this gap by quantifying the long-term impacts of wildfires on air quality levels ($PM_{2.5}$, CO, NO_2, and O_3) across land use and land cover categories in Brazil for 16 years (2003–2018). We then estimated the mortality risk associated with the effects of wildfires on air quality. We intended to test two hypotheses in this study: i) forest fires in Brazil have increased air pollution concentrations and posed a severe health hazard and ii) the magnitude of this phenomenon depends on the type of land use and land cover (e.g., forest area, agricultural area, etc.).

Brazil is an important place to test these hypotheses because of the challenging link between Brazilian continental biomes, wildfire occurrence, and land use. In Brazil, there are six distinct biomes (Amazon forest, Cerrado, Atlantic forest, Caatinga, Pampa, and Pantanal) that strongly correlate spatially and temporally with wildfires (Marcia et al., 2013; Santosdos et al., 2020). For example, according to the INPE, the Caatinga region is projected to become warmer and dryer, which may have a significant impact on dust and wildfires. Land use also correlates with wildfire occurrence. From 1990 to 2011, agricultural land in Brazil grew from ~530,000 to ~680,000 km^2, and 60–80% of the deforested land is pasture for beef production (Lapola et al., 2014). It is common practice in Brazil to clear land for agricultural activities, pasture, deforestation, and mining through burning. Our second hypothesis will test whether different origins of fires modify the impact on air quality.

2. Methods

2.1. Data collection

2.1.1. Wildfires

Wildfire events were retrieved from FIRMS – Fire Information for Resource Management System (https://firms.modaps.eosdis.nasa.gov/). These data are provided by the National Aeronautics and Space Administration (NASA) and are based on the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor aboard the Aqua and Terra satellites. The MODIS sensor operates in 36 spectral channels with wavelengths from 0.4 to 14.4 μm, and spatial resolution from 250 to 1,000 m. Together, the Aqua and Terra satellites acquire images of the Earth with a temporal resolution of 1–2 days (NASA, n.d.).

The acquired data include wildfire records from 2003 to 2018 with the following information: i) date of wildfire occurrence; ii) geographic location; iii) Fire Radiative Power (FRP), which is the rate of radiant energy emitted by the fire at the time of observation (expressed in units of power, megawatts, MW), indicating the intensity of the fire event; and iv) confidence level, which assesses the quality of individual fire pixels. We only considered fire events with a confidence level greater than 30%, which covers the "nominal" and "high" confidence classes reported by NASA.

2.1.2. Air pollution

We accessed air pollution data [$PM_{2.5}$ (μg/m^3), NO_2 (ppb), O_3 (ppb), and CO (ppb)] from the Copernicus Atmosphere Monitoring Service (CAMS). This is a reanalysis of the European Centre for Medium-Range Weather Forecasts (ECMWF). The validation for the CAMS global model is reported in prior studies (Inness et al., 2018). Pollution levels were estimated on a daily temporal scale and a 0.125° (about 12.5 km) spatial scale. This air pollution data was modeled worldwide, so we were able to access the data covering entire Brazil from 2003 to 2018.

We aggregated these data by municipality, taking into account the geographic location of the boundaries of each municipality in Brazil. There are 5572 municipalities in Brazil, which are the smallest areas considered by the Brazilian political system. We aggregated the municipalities into the six Brazilian biomes, including Amazon, Caatinga, Cerrado, Atlantic Forest, Pampa, and Pantanal. Figure S1 in the supplementary materials shows the spatial distribution of Brazilian municipalities and biomes.

The validation of $PM_{2.5}$ from CAMS global model is evaluated with ground observations of the Aerosol Robotic Network (AERONET). CAMs estimates in South America have a root mean square error – RMSE (compared with AERONET stations) of 0.268 (Gueymard and Yang, 2020). Studies have shown that AERONET observation sites in South America have significant representativity for AOD measured by Moderate Resolution Imaging Spectroradiometer (MODIS), aboard TERRA and AQUA satellites (Hoelzemann et al., 2009). Note that MODIS is an instrument included in the CAMS model. This association between AERONET data and AOD from MODIS is significant during the biomass burning seasons in South America, which the R^2 for most of the AERONET stations in Brazil was higher than 0.85 (Hoelzemann et al., 2009). The validation of O_3, CO, and NO_2 was made by comparing the reanalysis data with surface measurements from observations from the WMO's Global Atmosphere Watch (GAW) program (Galbally et al., 2013). Their findings suggest that the CAMS data reproduces the monthly mean values and the seasonal variability of the pollutants in a very acceptable way (Galbally et al., 2013) (Inness et al., 2018).

2.1.3. Meteorological variables

Climate data were obtained from satellite remote sensing. These data were derived from the ERA-Interim model (Berrisford et al., 2011; Dee et al., 2011), which consists of a global atmospheric reanalysis from ECMWF. We included as meteorological variables wind speed (m/s), surface air temperature (°C), precipitation (mm), and relative air humidity (%). These climate data were estimated on a daily temporal scale and a 12.5 km by 12.5 km spatial scale. As we did for air pollution data, we aggregated the meteorological data at the municipal level.

2.1.4. Land use and land cover

The land use/cover data were obtained from the Brazilian Annual Land Use and Land Cover Mapping Project – MapBiomas (https://mapbiomas.org/). The data were produced by pixel-based classification of Landsat satellite images, with a resolution of 30 m. We accessed the data with a yearly temporal resolution from 2003 to 2018. Among the several land use/cover classes considered in MapBiomas, we selected those that are related to wildfires, such as: i) Forest, representing forest formation, savanna formation, mangrove, and forest plantation; ii) Non-forest natural formation, representing wetland, grassland, salt flat, and other non-forest formations; iii) Farming, representing pasture, temporary crop, soybean, sugar cane, other temporary crops, perennial crop, and mosaic of agriculture and pasture; and iv) Non-vegetated, representing urban infrastructure, mining, and other non-vegetated areas. The classes provided in the MapBiomas and not considered in our study were rocky outcrop, beach, dune, and water.

2.2. Consolidation of the datasets

We used a spatiotemporal matching process to consolidate the four datasets (wildfire, air pollution, weather, and land use/cover). First, we assigned land use and land cover classes to each wildfire event based on the geographical coordinates and the year of each wildfire event. For example, if a specific wildfire occurred in 2012 at a location classified by the MapBiomas as a soybean crop, we assume that this wildfire occurred due to related activities (e.g., use of fire to clear lands for soybean crop). We defined this procedure as Wildfire-related Land Use activities (WLU). Note that we performed this procedure to investigate the second hypothesis of our study. Changes in climate and land use are associated with the frequency and severity of wildfires (Brando et al., 2020), (Davidson et al., 2012). In addition, land use has different characteristics related to biomass burning, which has instantaneous and long-term effects on the production of atmospheric gases, contributing to global climate change (Chuvieco et al., 2021; Granier et al., 2000; Levine, 1995) and negative effects on human health (Nawaz and Henze, 2020; Sigsgaard et al., 2015).

Then, we considered the FRP values (Fire Radiative Power) to summarize each WLU within the Brazilian municipalities. This process estimates in a better manner the impact of WLU in a given municipality and date, as it considers the frequency of events (WLU) and their respective intensities. First, we summed the WLU records for each municipality and day. Note that this resulted in a sum of wildfire records for each municipality and day stratified by land use activities. For example, on day j at municipality i there was a total number of wildfires at a location with a land-use categorized as u. Second, we calculated the mean value of the FRP for each municipality i and day j. Then, we multiplied the sum of WLU events occurring at each municipality i, on day j, and in a land-use u by the mean value of FRP at the same municipality i on day j. The result of this process generates the $\overline{WLU}$, representing the weighted WLU at municipality i and on date j. Equation (1) describes this process:

$$\overline{WLU}_{i,j,u} = \sum WLU_{i,j,u} \times \left(\frac{\sum FRP_{i,j}}{n_{i,j}}\right) \tag{1}$$

where $\overline{WLU}$ is the weighted WLU at municipality i, on date j, and at a location with land-use categorized as u; WLU is the Wildfire-related Land Use activities at municipality i, on date j, and at a location with land-use categorized as u; FRP is the Fire Radioactive Power at municipality i and on date j; n is the total number of wildfire records at municipality i and on date j.

Finally, we merged the $\overline{WLU}$, air pollution, and weather data by means of a spatio-temporal join based on the date and municipality.

2.3. Statistical analysis

We used a framework proposed by previous studies examining the effects of weather change on air pollution in the United States (Jhun et al., 2015; Requia et al., 2019b) and Spain (Borge et al., 2019). This framework derives "weather penalties" by accounting for differences in β values (linear annual pollution trend) between two models – a model adjusted for the independent variable and a model unadjusted. In our study, this is defined as a "wildfire penalty", where the independent variable is represented by wildfire ($\overline{WLU}$).

First, we applied a general linear regression model with a year trend adjustment to estimate trends of each air pollutant for each biome. Then, we used generalized additive models (GAMs) to examine the wildfire-pollution ($PM_{2.5}$, NO_2, O_3, and CO) relationship for each month. We used two GAM models to estimate long-term trends in daily air pollutants. In the first model, defined as adjusted model, we included $\overline{WLU}$ as an adjustment. In the second model (unadjusted model), we removed the adjustment for $\overline{WLU}$. Both models were controlled by meteorological variables. The adjusted and unadjusted models are described in equations (2) and (3), respectively.

$$Y_{i,j,p,u} = \beta_0 + \beta_{1\ (adjusted)} year_{i,j,p} + \gamma month_{i,j,p} + s_1(temp) + s_2(prec) + s_3(rh) + s_4(ws) + s_5(\overline{WLU_u}) + e_{i,j,p} \tag{2}$$

$$Y_{i,j,p,u} = \beta_0 + \beta_{1\ (unadjusted)} year_{i,j,p} + \gamma month_{i,j,p} + s_1(temp) + s_2(prec) + s_3(rh) + s_4(ws) + e_{i,j,p} \tag{3}$$

where Y is the daily concentration of the pollutant p at municipality i, on date j, and for the land use/cover u; β_0 is the regression intercept; $\beta_{1\ (adjusted)}$ and $\beta_{1(unadjusted)}$ are the regression coefficients representing the linear wildfire-adjusted and unadjusted pollutant trends, respectively, between 2003 and 2018 for a specific biome. Note that year is defined as a calendar year as a number; γ is the vector of coefficient that represents monthly variability of pollutant p at municipality i; and $s$are the smoothing spline function to characterize nonlinear relationships between the daily concentration of pollutant p and covariates, represented by temperature (*temp*), precipitation (*prec*), relative humidity (*rh*), wind speed (*ws*), and $\overline{WLU}$ (only in the adjusted model).

As described in equations (2) and (3), we stratified our analysis for land use and land cover u. For comparison, we applied the same equations without this stratification. This comparison provides additional information referring to the second hypothesis of our study.

We then used the β_{adjusted} and $\beta_{\text{unadjusted}}$ values to quantify past $\overline{WLU}$-related increases ("$\overline{WLU}$ penalty") in $PM_{2.5}$, NO_2, O_3, and CO. We derived the $\overline{WLU}$ penalties (μg/m^3 per year for $PM_{2.5}$ and ppb per year for NO_2, O_3, and CO) for each biome by the differences between $\beta_{\text{unadjusted}}$ and β_{adjusted} ($\beta_{\text{unadjusted}}$- β_{adjusted}). While the effect of $\overline{WLU}$ is included in the unadjusted trends ($\beta_{1\ (unadjusted)}$ in Equation (3)), controlling for $\overline{WLU}$ in model 2 removes the effect of the interannual $\overline{WLU}$ variation on the trends of $PM_{2.5}$, NO_2, O_3, and CO ($\beta_{1\ (unadjusted)}$ in Equation (2)). Therefore, we assumed that any differences between the unadjusted and the $\overline{WLU}$-adjusted trends were entirely due to the effects of long-term WLU changes. A positive penalty ($\beta_{\text{unadjusted}} > \beta_{\text{adjusted}}$) indicates that increases in $PM_{2.5}$, NO_2, O_3, and CO are associated with WLU changes between 2003 and 2018.

Finally, we applied bootstrap analysis to estimate the standard error for each coefficient, including the β_{adjusted}, $\beta_{\text{unadjusted}}$, and $\overline{WLU}$ penalty. We created randomized subsets (defined as pseudo-datasets) of the input dataset accounting for serial correlation structures among the observations of each air pollutants. We created 100 pseudo-datasets and then applied the models described in equations (2) and (3) (adjusted and unadjusted, respectively) to each pseudo-dataset. Finally, we estimated the standard error for each trend (the adjusted and unadjusted trends), and the $\overline{WLU}$ penalty by obtaining the standard deviation from the 100 estimates in the bootstrap analysis.

2.4. Burden of disease assessment

We used the estimates of $\overline{WLU}$ penalty to estimate the effects of $\overline{WLU}$-caused increases in air pollution on mortality (for each biome). For these estimates, we used concentration-response functions from the literature. We assessed health risks associated with non-accidental all-cause mortality for individuals >30 years old. We considered only the pollutants responsible for most air pollution-related deaths (according to the epidemiological literature), including $PM_{2.5}$, O_3, and NO_2.

In the absence of large cohort studies in Brazil, we used relative risks based on the published American Cancer Society – Cancer prevention study II cohort study in the United States (Turner et al., 2016). In this study, the relative risk (RR) of all-cause mortality is reported in relation to each 10-unit increase in average $PM_{2.5}$ (in $\mu g/m^3$) [RR = 1.05 (95% CI:1.03–1.07)], O_3 (in ppb) [RR = 1.02 (95%CI: 1.01–1.04)], and NO_2 (in ppb) [RR = 1.04 (95%CI: 1.03–1.06)]. Considering these RRs, we used the following health effects function:

$$\Delta M_{p,u,b} = \sigma_b \times \left(1 - e^{-\beta_p \times \delta_{p,u,b}}\right) \times Pop_b \tag{4}$$

where M is the mortality impact estimation of $\overline{WLU}$-related increases in the air pollutant p, specifically for the land use and land cover u, in the biome b; σ is the baseline mortality incidence rate of the population within the boundaries of the biome b; β is the mortality risk coefficient based on the literature for the pollutant p; δ is the $\overline{WLU}$ penalty for the air pollutant p, land use and land cover u, in the biome b; and Pop is the exposed population size in the biome b.

Finally, we calculated the uncertainty in our estimates of the mortality impacts by using the multivariate delta method (Alan Agresti, 2012):

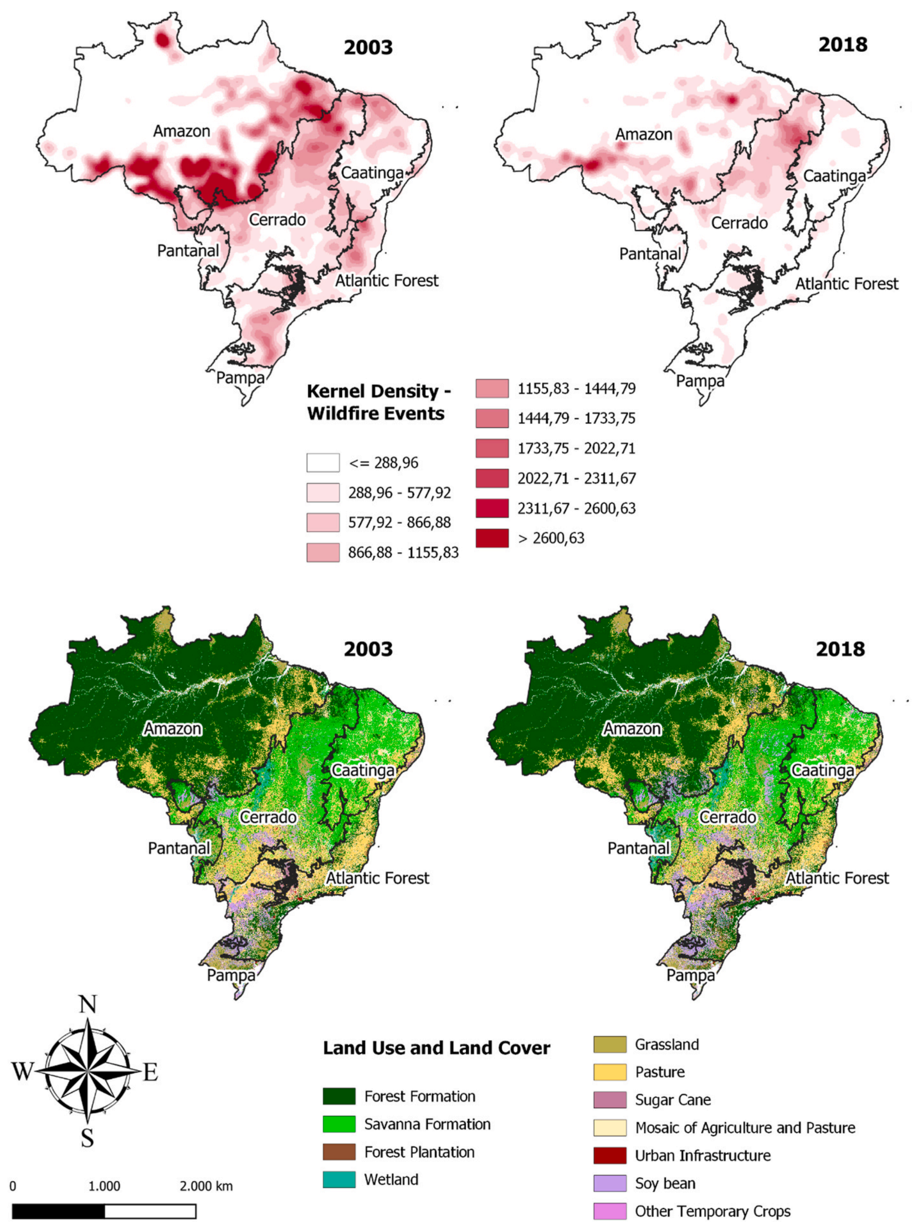

Fig. 1. Kernel density of wildfire events and land use/cover across the Brazilian biomes in 2003 and 2018. Note: the legends for the wildfire distribution were based on the equal interval.

$$Variance = \left[\left(\frac{\partial f}{\partial \beta}\right)^2 \times Variance(\beta)\right] + \left[\left(\frac{\partial f}{\partial \delta}\right)^2 \times Variance(\delta)\right] \tag{5}$$

where, $\frac{\partial f}{\partial}$ represents the partial derivative of equation (4), for either β (from the confidence intervals of the original concentration-response function reference) or δ (from the bootstrapping procedure discussed in the previous section).

3. Results

3.1. Wildfires and air pollution in Brazil between 2003 and 2018

Wildfires varied substantially over space and time in Brazil. In 2003, the highest densities of wildfire events were located across the Amazon and Cerrado biomes borders, mainly in southern Amazonia. Over time, in 2018, the wildfire events expanded to the northern portion of the Cerrado biome bordering the Caatinga. Regarding land use and land cover, sugar cane crops had the highest increase in Brazil between 2003 and 2018. Most of this growth occurred in the Pantanal biome, with an estimated increase of 20 times over the study period. In the other biomes, the highest increases were related to perennial crops (17,325% in Atlantic Forest), rice crops (1332% in Cerrado and 295% in Pampa), soybean crops (605% in Amazon), and other temporary crops (370% in Caatinga). In Fig. 1, we present the spatial density of wildfire events over the Brazilian biomes and land use and land cover categories in 2003 and 2018.

Time series plots of the yearly mean of wildfire records and concentration of air pollutants stratified by biome are presented in Fig. 2. The number of wildfire events in Brazil increased by 4.87% from 2003 to 2018. Overall, a higher number of wildfire events occurred in Pantanal, with a mean of 8 wildfire events per day, followed by Amazonia, with a mean of 6 wildfire events per day (Fig. 2, panel A). For comparison, note that we present in Fig. 2 the variable representing the number of wildfires (Fig. 2, panel A) and the variable representing the weighted wildfires, WLU (Fig. 2, panel B).

For air pollution, the time series indicates a similar temporal pattern for CO and $PM_{2.5}$ in all biomes, with the highest concentrations observed in the Amazon biome, with daily mean concentrations of 257.5 ppb and 28.33 $\mu g/m^3$, respectively, during the study period (Fig. 2, panels C and D). For NO_2, the highest daily mean concentration between 2003 and 2018 was observed in the Atlantic Forest, with a daily mean of 2.17 ppb, and the lowest in the Caatinga, with a daily mean of 0.97 ppb (Fig. 2, panel E). On the other hand, Caatinga was the biome with the highest O_3 concentration, with a daily mean 26.49 ppb concentration during the study period (Fig. 2, panel F). To demonstrate the temporal variation of wildfire and air pollution in Brazil, we present heatmaps based on the daily mean of air pollutant concentrations and wildfire events in each biome stratified per month and year for the study period in Figures S2-S7.

3.2. Impact of wildfires on air pollution and health across land use/cover categories

Our results suggest that $\overline{WLU}$-related impacts on air pollution varied considerably over biomes depending on the air pollutant. Figs. 3–8 show the $\overline{WLU}$ penalties by biomes, land use/cover classes, and air pollutants during the study period, 2003–2018. Table S1 in supplementary materials shows all coefficients (including the unadjusted trends and $\overline{WLU}$-adjusted trends) by biome, land use classes, and air pollutant. Table S2 shows the general linear regression model results with a year trend adjustment. In Figures S8-S13 in supplementary materials, we show the health effects associated with the penalties. Below, we present

Fig. 2. Concentration time series of air pollutants and wildfire events stratified by Brazilian biomes in 2003–2018.
Note 1: Number of Wildfire Events (A); Weighted wildfire (B), CO (C); $PM_{2.5}$ (D); NO_2 (E); and O_3 (F).
Note 2: considering the raw monitored values, we used a smoothed conditional means function to illustrate the temporal variation in these charts.
Note 3: the color bands represent the 95% confidence intervals.

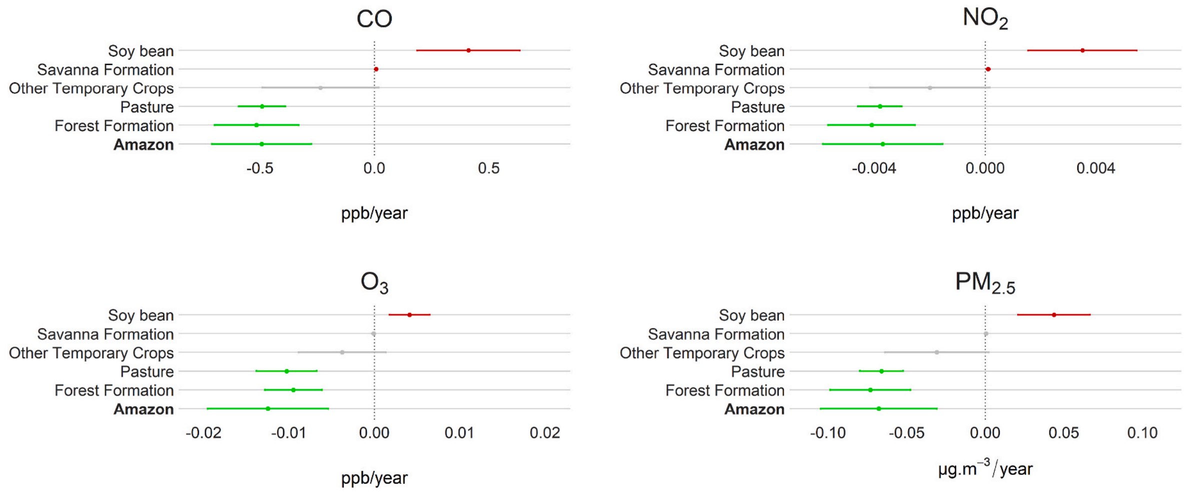

Fig. 3. Wildfire penalties in the Amazon biome in 2003–2018 by land use/cover and air pollutants.
Note 1: Green color represents negative penalties, red color represents positive penalties, and non-significant ones are grey color.
Note 2: The bolded text highlighted on the last row (Amazon) represents the model without stratification for land use and land cover classes.

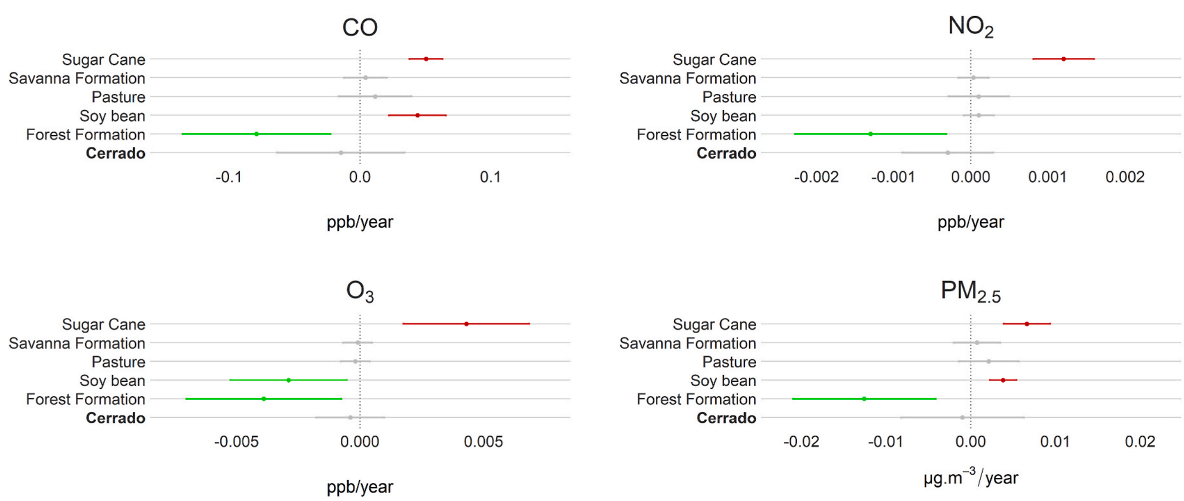

Fig. 4. Wildfire penalties in the Cerrado biome in 2003–2018 by land use/cover and air pollutants.
Note 1: Green color represents negative penalties, red color represents positive penalties, and non-significant ones are grey color.
Note 2: The bolded text highlighted on the last row (Cerrado) represents the model without stratification for land use and land cover classes.

the results for each biome.

3.2.1. *Amazon biome*

Results from the unadjusted model without stratification for land use and land cover classes in the Amazon biome indicate that daily $PM_{2.5}$, O_3, NO_2, and CO concentrations had an annual trend of -0.584 µg/m^3 (95% CI: 0.744; -0.417), -0.099 ppb (95% CI: 0.151; -0.048), -0.029 ppb (95% CI: 0.038; -0.021), and -4.315 ppb (95% CI: 5.455; -3.175), respectively. The corresponding annual wildfire penalties were -0.068 µg/m^3 (95% CI: 0.104; -0.031), -0.013 ppb (95% CI: 0.019; -0.005), -0.004 ppb (95% CI: 0.005; -0.002), and -0.49 ppb (95% CI: 0.71; -0.27), respectively (Table S1).

Different from the unstratified analysis for land use and land cover, in which the wildfire penalties were negative for all pollutants, the subgroup analysis for land use and land cover classes ($\overline{WLU}$ penalties) in the Amazon biome was positive when we accounted for wildfires that occurred within soybean areas. In these areas, we estimated an annual penalty of 0.044 µg/m^3 (95% CI: 0.021; 0.066) for $PM_{2.5}$, 0.004 ppb (95% CI: 0.002; 0.006) for O_3, 0.003 ppb (95% CI: 0.002; 0.004) for NO_2, and 0.409 ppb (95% CI: 0.186; 0.634) for CO (Fig. 3). These $PM_{2.5}$, O_3, and NO_2 penalties were associated with 242 (95% CI: 160; 323), 9 (95% CI: 5; 13), and 16 (95% CI: 10; 21) excess annual deaths from 2003 to 2018, respectively (Figure S8).

Wildfires in areas classified as savanna formation in the Amazon biome was also linked with positive penalties on $PM_{2.5}$, NO_2, and CO with 0.0004 µg/m^3 (95% CI: 0.0002; 0.0009), 0.0001 ppb (95% CI: 0.0353; 0.0001), and 0.0069 ppb (95% CI: 0.0008; 0.0129), respectively. Wildfires from other areas resulted in negative penalties (Fig. 3). As we can see in Fig. 3, note that there were wildfire events only in five types of land use and land cover in the Amazon biome, including forest formation, other temporary crops, pasture, savanna formation, and soybean.

3.2.2. *Cerrado biome*

Considering the analyses without stratification for land use and land cover classes in the Cerrado biome, our results suggest a wildfire penalty of -0.001 µg/m^3 (95% CI: 0.008; 0.006), -0.0004 ppb (95% CI: 0.002; 0.0009), -0.0003 ppb (95% CI: 0.0009; 0.0003), and -0.015 ppb (95% CI: 0.063; 0.034) for $PM_{2.5}$, O_3, NO_2, and CO, respectively (Fig. 4). On the other hand, the analyses stratified by land use and land cover

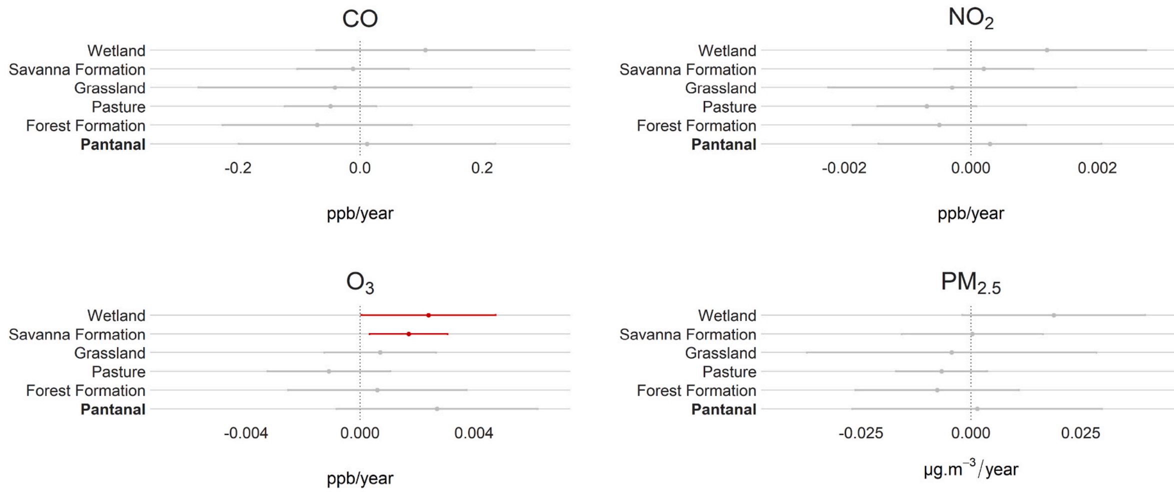

Fig. 5. Wildfire penalties in the Pantanal biome in 2003–2018 by land use/cover and air pollutants.
Note 1: Green color represents negative penalties, red color represents positive penalties, and non-significant ones are grey color.
Note 2: The bolded text highlighted on the last row (Pantanal) represents the model without stratification for land use and land cover classes.

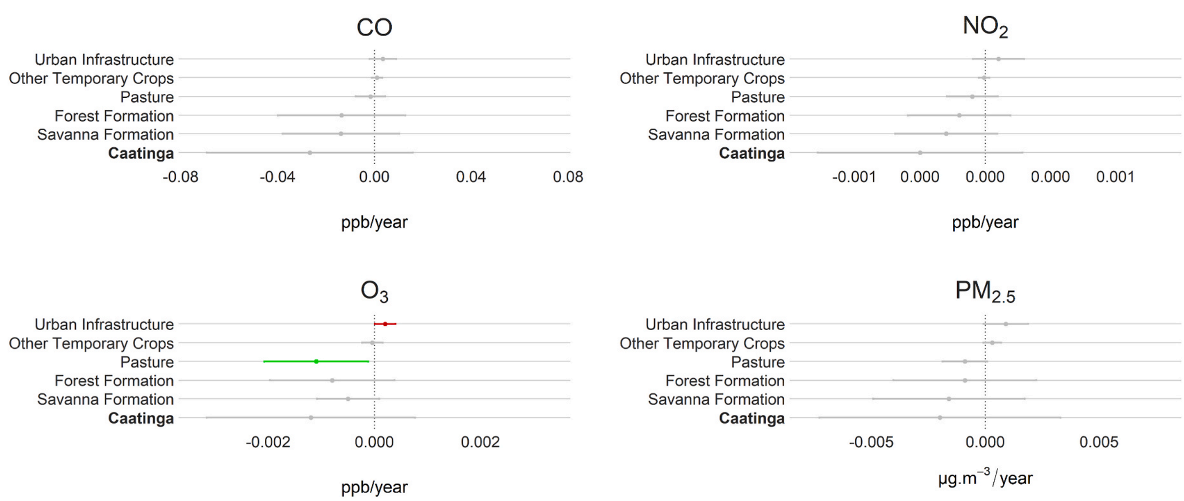

Fig. 6. Wildfire penalties in the Caatinga biome in 2003–2018 by land use/cover and air pollutants.
Note 1: Green color represents negative penalties, red color represents positive penalties, and non-significant ones are grey color.
Note 2: The bolded text highlighted on the last row (Caatinga) represents the model without stratification for land use and land cover classes.

indicate positive penalties on all pollutants when we accounted for wildfires from sugar cane areas. Wildfires occurring in these areas within the Cerrado biome were associated with a penalty of 0.007 $\mu g/m^3$ (95% CI: 0.004; 0.009), 0.004 ppb (95% CI: 0.002; 0.007), 0.001 ppb (95% CI: 0.001; 0.002), and 0.05 ppb (95% CI: 0.04; 0.06) for $PM_{2.5}$, O_3, NO_2, and CO, respectively (Fig. 4). These wildfire-related sugar cane penalties were associated with 102 (95% CI: 72; 132), 27 (95% CI: 14; 39), and 15 (95% CI: 11; 19) excess annual deaths for $PM_{2.5}$, O_3, and NO_2, respectively (Figure S11).

In the Cerrado biome, we also estimated statistically significant positive penalties for $PM_{2.5}$ [0.004 $\mu g/m^3$ (95% CI: 0.002; 0.005] and CO [0.04 ppb (95% CI: 0.02; 0.06)] in soybean areas (Fig. 4).

3.2.3. Pantanal biome

In the Pantanal biome, the unstratified analyses for land use and land cover in the model without weather and wildfire changes (adjusted model), $PM_{2.5}$, O_3, NO_2, and CO concentrations would have changed by -0.33µg/m3 (95% CI: 0.47; -0.19), 0.26 ppb (95% CI: 0.15; 0.38), -0.0027 ppb (95% CI: 0.009; 0.004), and -4.40 ppb (95% CI: 5.44; -3.37), respectively (Table S1). This reflects an annual wildfire penalty of 0.0014 $\mu g/m^3$ (95% CI: 0.027; 0.030) on $PM_{2.5}$, 0.0027 (95% CI: 0.0008; 0.0062) on O_3, 0.0003 ppb (95% CI: 0.0014; 0.0021) on NO_2, and 0.011 ppb (95% CI: 0.19; 0.22) on CO (Fig. 5).

The sub-group analysis for land use and land cover classes indicated statistically significant positive penalties only for O_3 in wetland areas, with a penalty of 0.002 ppb (95%CI: 0.00005; 0.005) and in savanna formation, with a penalty of 0.002 ppb (95%CI: 0.001; 0.004) (Fig. 5).

3.2.4. Caatinga biome

Penalties from the models without stratification for land use and land cover classes in the Caatinga biome were slightly negative for all pollutants (Fig. 6). In contrast, fires in urban infrastructure had slightly positive penalties on all pollutants, but statistically significant only for O_3, with a penalty of 0.0002 ppb (95% CI: 0.000004; 0.000396) (Fig. 6). There was also a positive penalty only on $PM_{2.5}$ associated with wildfire events in areas classified as other temporary crops, with a penalty of 0.0003 $\mu g/m^3$ (95% CI: 0.00009; 0.00069) (Fig. 6), reflecting in 4 (95% CI: 3; 5) excess annual death (Figure S10).

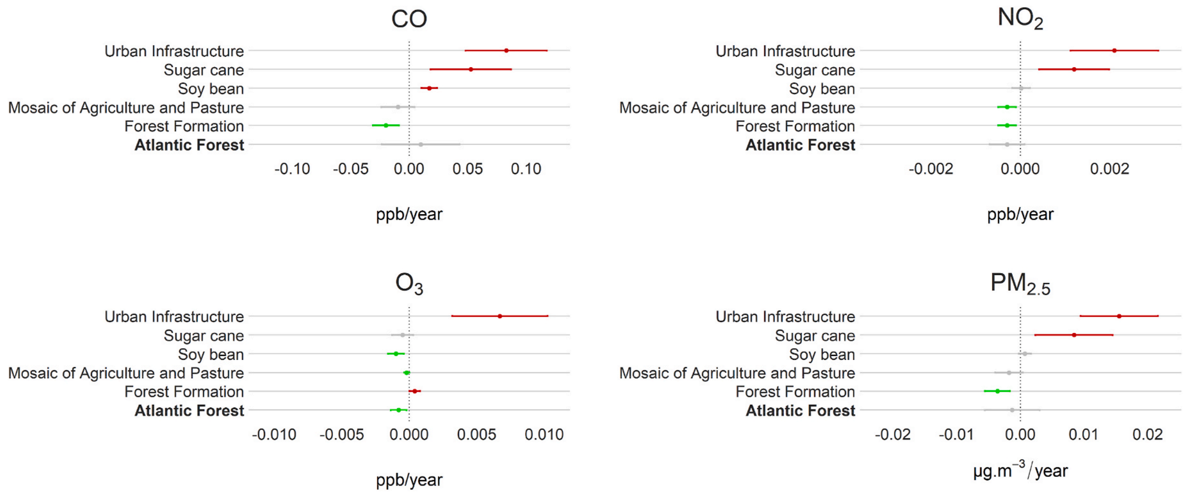

Fig. 7. Wildfire penalties in the Atlantic Forest biome in 2003–2018 by land use/cover and air pollutant.
Note 1: Green color represents negative penalties, red color represents positive penalties, and non-significant ones are grey color.
Note 2: The bolded text highlighted on the last row (Atlantic Forest) represents the model without stratification for land use and land cover classes.

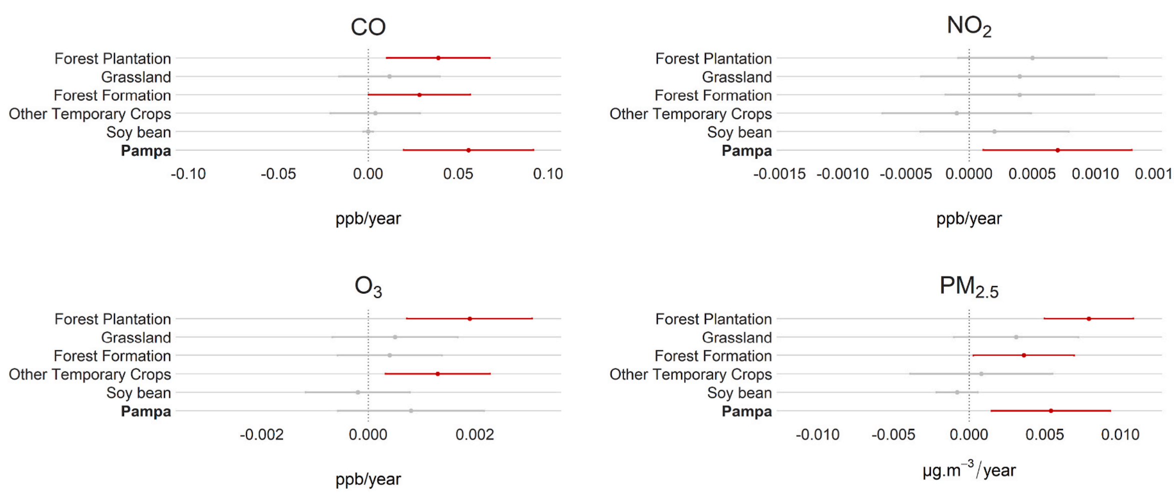

Fig. 8. Wildfire penalties in the Pampa biome in 2003–2018 by land use/cover and air pollutant.
Note 1: Green color represents negative penalties, red color represents positive penalties, and non-significant ones are grey color.
Note 2: The bolded text highlighted on the last row (Pampa) represents the model without stratification for land use and land cover classes.

3.2.5. Atlantic Forest biome

Wildfire penalties from the analyzes without stratification for land use and land cover classes in the Atlantic Forest biome were statistically significant only for O_3, for which there was a negative penalty of -0.0008 ppb (95% CI: 0.0014; -0.0002) (Fig. 7). However, fires in urban infrastructure had slightly positive penalties on all pollutants. $\overline{WLU}$ penalties were also statistically positive in sugar cane areas within the Atlantic Forest biome (similar to Cerrado biome), except for O_3, with a penalty of 0.0084 μg/m^3 (95% CI: 0.0023; 0.0145) on $PM_{2.5}$, 0.0012 ppb (95% CI: 0.0004; 0.0020) on NO_2, and 0.05 ppb (95% CI: 0.018; 0.087) on CO (Fig. 7). These wildfire-related sugar cane penalties in the Atlantic Forest were associated with 475 (95% CI: 275; 675) and 54 (95% CI: 33; 75) excess annual deaths for $PM_{2.5}$ and NO_2, respectively (Figure S9). Specifically, for $PM_{2.5}$, our wildfire-adjusted model (wildfire from sugar cane areas) of this pollutant trends showed that without wildfire-related sugar cane area changes, $PM_{2.5}$ would have decreased by 0.16 μg/m^3 (95% CI: 0.21; -0.09) per year.

3.2.6. Pampa biome

Our findings from the models without stratification for land use and land cover classes in the Pampa biome showed an annual wildfire penalty of 0.005 μg/m^3 (95% CI: 0.001; 0.009) on $PM_{2.5}$, 0.0008 (95% CI: 0.0005; 0.0021) on O_3, 0.0007 ppb (95% CI: 0.0001; 0.0012) on NO_2, and 0.05 ppb (95% CI: 0.02; 0.09) on CO (Fig. 8).

The sub-group analysis for land use and land cover classes indicates significantly positive penalties in areas classified as forest plantation, except for NO_2, with 0.0079 μg/m^3 (95% CI: 0.0049; 0.0108) on $PM_{2.5}$, 0.0019 ppb (95% CI: 0.0007; 0.0031) on O_3, 0.0005 ppb (95% CI: 0.00008; 0.00108) on NO_2, and 0.04 ppb (95% CI: 0.01; 0.07) on CO (Fig. 8). Penalties were also statistically positive when we accounted for wildfire events in areas classified as forest formation for $PM_{2.5}$ and CO, with a penalty of 0.0036 μg/m^3 (95% CI: 0.0003; 0.007) and 0.028 ppb (95% CI: 0.00008; 0.056), respectively (Fig. 8).

4. Discussion

Our findings suggest that wildfire events between 2003 and 2018 have increased the levels of air pollution and posed a significant public health hazard in Brazil, supporting our first hypothesis - the forest fires in Brazil have increased the levels of air pollution and posed health. These results agree with previous studies performed in other regions, including the U.S.A (Burke et al., 2021; Jaffe et al., 2020; Requia et al., 2019a) and Europe (Knorr et al., 2016).

Given that our statistical approach takes into account the impact of interannual weather variation on air pollution trends, our findings can also be discussed in terms of the relationship between air pollution and weather. Previous studies have found a positive correlation between temperature and air pollution (Kalisa et al., 2018; Liu et al., 2020), while other studies suggest a negative correlation between wind speed and some air pollutants, including O_3 (Banta et al., 1998). Temperature and relative humidity are important determinants of $PM_{2.5}$ and O_3 trends (Jayamurugan et al., 2013). To facilitate this analysis, we used a GAM model (adjusted only for year and month) to estimate the weather trends over the study period. The results are shown in Figure S14 in supplementary materials. From these results, considering the temperature variation, for example, we estimated an increase in temperature in all biomes. The highest increase occurred in Cerrado, where the temperature increased by approximately 1.12 °C during the 16 years, 2003–2018 (Figure S14). As we showed in Fig. 1, a substantial number of wildfire events expanded to the northern portion of the Cerrado biome during the study period. Cerrado was the biome with the most land use and land cover classes identified with positive wildfire penalties. For example, for $PM_{2.5}$, CO, and NO_2, four land use and land cover classes had positive penalties, including sugar cane, savanna formation, pasture, and soybean (Fig. 4). Our results suggest that the impacts of $\overline{WLU}$-related increases in air pollution estimated in our study may also be influenced by weather conditions.

Our results also confirm our second hypothesis, that the variation of the impact of wildfires on air pollution and health in Brazil varies across land use and land cover among the biomes. In other words, the type of land use and land cover on which wildfire occurs plays a significant role in the impact of wildfire on air quality and health. We found that the most significant impacts occurred in soybean areas in the Amazon biome, particularly the effects of wildfire on $PM_{2.5}$ concentrations. This impact on $PM_{2.5}$ in the Amazon biome was ten times greater than that in the Cerrado, the second largest impacted biome. The conversion of forests to produce commodities may explain part of these results. The production of commodities was historically responsible for the deforestation of the Amazon Forest, where there was a substantial expansion of the soybean area during the study period. In 2003, there were 0.65 million hectares of soybean area in the Amazon biome. In 2018, this cropped area increased to 4.56 million hectares (MapBiomas Project, 2022). In the Cerrado biome, soybean areas have also increased substantially between 2000 (5,699,918 ha) and 2019 (16, 782, 120 ha) (Song et al., 2021). Both in the Amazon region and in Cerrado, soybean crops have been a driver of deforestation-related fires (Nepstad et al., 2014; Oliveira et al., 2020). Agreements and strategies have been widely applied to reduce deforestation in the Amazon, such as the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (Girão et al., 2017) and the Soy Moratorium (Gibbs et al., 2015), but there is no regulation for the Cerrado area (da Silva Junior et al., 2020). Both biomes are critical for the implementation of effective public policies to prevent and combat wildfires.

Besides soybean, sugarcane crops have also been a driver of deforestation-related fires in Brazil, mainly in Cerrado and Atlantic Forest. These findings may be related to the large production of ethanol in Brazil. Ethanol is a biofuel produced from sugarcane, and Brazil is the world's largest producer of this culture, with a cultivated area of 8.73 million hectares (CONAB, 2018). Sugarcane crops have been shown to advance over pastures and agricultural areas in Brazil (Adami et al., 2012; Sparovek et al., 2008). Ethanol production had substantial growth in Brazil between 2003 and 2008, because of the use of flex-fuel vehicles (Moraes and Bacchi, 2014). Ethanol produced from sugarcane is considered more sustainable than other fuels (e.g., gasoline) in energy balance, greenhouse gas (GHG) savings, fuel efficiency, and water footprint (Bordonal et al., 2018). However, despite the environmental benefits of ethanol, sugarcane crops are associated with an impactful activity – fires. Ethanol production includes the burning of sugarcane crops before manual harvesting. This produces negative impacts on the atmosphere and human health (Tsao et al., 2011). The emission of air pollutants from burning sugarcane in Brazil is related to respiratory diseases (Arbex et al., 2007; Cançado et al., 2006; Ramos et al., 2019; Silveira et al., 2013). The practice of burning sugarcane crops has been gradually eliminated by mechanized harvesting, in which there are no burning of agricultural residues (Aguiar et al., 2011; Bordonal et al., 2018). However, even with the elimination of this practice, there is evidence that emissions of air pollutants continue to increase since sugarcane growing areas continue to grow and fires are the main life cycle of emissions (Tsao et al., 2011).

Note that we stratified the analyses by biome. This approach was based on the relationship between the Brazilian biomes and environmental conditions, including wildfire occurrence, air quality, and weather variability in Brazil. Each biome has contiguous vegetation type clusters, similar geoclimatic conditions, and common records of change (IBGE, 2004). The biomes can be categorized according to biomass fire occurrence (Hardesty et al., 2005). These include fire-dependent/influenced biomes such as the Cerrado, Pantanal, and Pampa, as they are susceptible and resilient to fire; fire-sensitive biomes such as the Atlantic Forest and Amazon, which have no natural adaptive mechanisms to the presence of fire; and fire-independent biomes such as the Caatinga, which are vulnerable to fire due to insufficient biomass or climatic conditions (Pivello, 2011).

Our study has some limitations. First, wildfire, air pollution, weather, and land use/cover variables were either derived from satellite remote sensing or models that use satellite data (specifically, air pollution variable). This may lead to some measurement errors. Second, we considered only four weather parameters (temperature, precipitation, relative humidity, and wind speed). We suggest that other additional climate factors (e.g., cloud cover, wind direction, and atmospheric mixing height) may be highly correlated with the variables we included in our analyses. Third, we only focused on annual trends. Further studies could look at the short-term effect of wildfires. Fourth, the lag effect is important in the interrelationship between weather, wildfire, and air pollution. Given that this was not accounted for in our study, we suggest this analysis in further studies. Another limitation is related to the health analysis, which has an important source of uncertainty, including that the estimates of the RR reported by epidemiological studies (in the health effects function, we used RR suggested by the literature) were highly variable with wide confidence intervals, and the baseline population data varied during our study period, and this was not accounted in our analysis. We also must consider that the RR values are from US studies because there are no large cohort studies in Brazil. This may lead to the possibility of underestimation or overestimation in our analyses. Another limitation is that we accounted for long-term effects by considering annual trends. The literature shows that wildfires are expected to emit pollutants in a short-time period (hours to a few days) and consequently our estimates may represent the secondary effect of wildfires, as the primary effect occurs within a short time. However, we highlight that previous studies have considered long-term exposure to wildfire (Matz et al., 2020). Finally, our methods have a stochastic nature, which cannot indicate causal descriptions for our findings.

5. Conclusion

Our findings suggest that wildfire events over the 16-years study period (2003–2018) increased the ambient concentration of most air pollutants in Brazil. The type of land use and land cover where the wildfire is occurring is suggested to be an important driver of the magnitude of the wildfire penalty. Given that the wildfire penalties observed in our study period may continue to be a challenge in the future, this study should be of interest to policymakers to prepare future strategies related to land use management, agricultural activities, environmental health, climate change, and air pollution sources.

Example of the main implication of our findings for policymakers is related to the emission controls used to improve air quality. Our findings suggest that further policies to reduce emissions in Brazil should consider the changes in wildfire events and the land use activities. If current trends continue, greater emissions reductions will be needed to meet the same air quality standards in the face of wildfire penalties.

Credit author statement

Igor Cobelo Ferreira: Data curation, Data analysis, Writing- Original draft preparation. **Francisco Jablinski Castelhano:** Data curation, Writing- Reviewing and Editing, **Rafael Borge:** Methodology, Health analysis and Writing- Reviewing and Editing. **Henrique L Roig:** Writing- Reviewing and Editing. **Matthew Adams:** Writing- Reviewing and Editing. **Heresh Amini:** Writing- Reviewing and Editing. **Petros Koutrakis:** Methodology, Writing- Reviewing and Editing, **Weeberb J. Requia**: Conceptualization, Methodology, Software, Data curation, Writing- Original draft preparation, Funding acquisition, Resources.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Weeberb J. Requia reports financial support was provided by National Council for Scientific and Technological Development.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2023.115522.

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