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Wildfires and Mortality

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Wildfires and Mortality

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Abstract

Wildfires are becoming more frequent and intense, especially in countries with a large forest coverage like Brazil. Using monthly data for Brazilian municipalities from 2010 to 2019, this research estimates the aggregate effect of wildfires on mortality. It combines satellite fire detections, ERA5 wind and weather data, and land-use data in fixed-effects regressions, with fires measured within 50, 75 and 100 km of each municipality. Fires increase mortality, and the effect falls as distance grows. The effects come mainly from upwind fires, which point to smoke transport as the main channel. Infants, adults aged 45–64 and people aged 65 and over are the most affected. We also document an indirect ecological channel: fires initially reduce reported mosquito-borne disease cases, but the effect reverses to an increase about 16–20 months later as vegetation regrows. These findings show that wildfires harm health both directly and indirectly.

Keywords: Wildfires, smoke, mortality

JEL Q54, I18, C23.

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Introduction

Wildlife is no longer rare or isolated disaster, they have become a recurring and intensifying threat to public health, ecosystems, and economies worldwide. This is particularly true for countries with large forest coverage, such as Brazil, where dense vegetation, seasonal droughts, and widespread land-use burning combine to create conditions in which fires spread rapidly and reach extreme intensity. Beyond the immediate destruction they cause, wildfires release large quantities of smoke and pollutants that travel far beyond their point of origin, exposing populations who may be kilometers away from any visible flame.

A substantial body of literature has documented the health effects of wildfire smoke, establishing clear links between pollutant exposure and adverse respiratory and cardiovascular outcomes. However, this research has largely centered on a single pollutant at a time, such as PM2.5, PM10, SO2, or NO2, and hospitalization rates rather than mortality. This narrow focus leaves two important gaps. First, it understates the full health burden of wildfires, since it does not capture the aggregate effect of the many pollutants released simultaneously during a fire event. Second, it overlooks indirect channels through which wildfires can affect health outcomes, for instance, by altering ecosystems in ways that affect disease vectors, which may partially offset or compound the direct effects of smoke exposure.

This paper addresses these gaps and contributes to the previous literature in three ways. First, we provide a comprehensive analysis of wildfires' effects on mortality across multiple distance thresholds, capturing the aggregate impact of fire exposure rather than isolating a single pollutant. Second, we examine how these effects differ by fire sources, distinguishing forests, farming, and natural formation fires. Third, we present new evidence on an indirect and previously undocumented channel; the effect of wildfires on vector-borne disease transmission. We show that fires initially suppress mosquito populations, temporarily reducing disease cases, but that this effect reverses in the medium term. Throughout, we also examine how mortality effects vary by age, finding that infants, adults aged 45–64, and the elderly are the groups most affected, consistent with their heightened physiological vulnerability to smoke exposure.

Taken together, these findings offer a more complete picture of how wildfire affects population health, not only through the immediate and well-known channel of smoke inhalation, but through the more complex interplay of pollutant transport, land use, and ecological disruption.

Background

Wildfires have become increasingly frequent events in recent years, showing a clear upward trend. Serious events doubled in number during the period from 2003 to 2023, becoming much more intense and aggressive, especially where large carbon deposits are present (Cunningham 2024). These phenomena generate harmful effects on society, the environment, the economy, and ecosystems. The increase in wildfires is one of the direct impacts of climate change, which alters and disrupts rainfall patterns, leading to dry seasons that facilitate conditions for wildfires to occur. The fire season has already become longer for one quarter of the earth, and in the case of Brazil, the fire season increased by more than a month in the last 35 years (NASA Science Editorial Team, 2015).

Wildfire can originate from natural or human causes. Among the natural causes, we can mention lightning hitting trees and generating a combustion that spreads into a larger fire. Human interaction plays a bigger role in the increase in wildfires, such as agricultural practices that rely on burning, camping activities, disposing of residues inadequately, or even reckless behavior. Countries with a higher presence of forest coverage, such as Brazil where around sixty percent of the land is forested, are more endangered by this phenomenon. Brazil is also composed of multiple biomes with unique species of flora and fauna adapted to their environment. The intensity and emissions of fires and smoke vary across biomes depending on the type of organic matter that burns. In areas such as the Amazon rainforest, the abundance of large trees results in the release of greater quantities of smoke than other areas like the Pampa, which is a grassland.

The released smoke contains a wide range of pollutants, including Particulate Matter (PM), Carbon Monoxide (CO), Nitrogen Oxides (NOx) and Volatile Organic Compounds

(VOCs) which can contribute to ground-level Ozone (O3). These pollutants can negatively affect human health through different mechanisms, such as pulmonary irritation and chemical damage, impairment of oxygen use and asphyxiation, inflammation, oxidative stress, and systemic effects that can worsen existing heart and lung conditions and lead to severe health issues, ultimately impacting overall mortality. These negative effects are expected to have a larger impact on children, the elderly, and people with pre-existing health conditions.

Focusing on one of the main pollutants, PM2.5, whose effects are well documented in the field of epidemiology. The main concern with this pollutant is its capacity to remain suspended in the air for extended periods and travel long distances, increasing exposure risks. The WHO recommends a safe annual mean PM2.5 concentration of 5 µg/m3, depending on the context (World Health Organization [WHO], 2021). Its small particles penetrate deep into the lungs and bloodstream (Kim et al., 2014), exacerbating conditions such as asthma, respiratory illnesses, and cardiovascular complications, leading to higher mortality rates (Schwartz, 2000). Vulnerable groups include children under 10 and the elderly, although air pollution affects all genders equally (He et al., 2016). Socio-economic status further shapes health impacts, with low-income populations experiencing greater harm (Yang et al., 2021; Wan & Zhang, 2023). In Brazil, wildfire-related PM2.5 has been associated with significant increases in respiratory and circulatory hospital admissions, particularly in the Amazon dataset (Requia et al., 2021; Morello, 2023). However, the focus has largely been on hospitalizations rather than mortality or broader demographic effects, leaving important gaps in understanding the full health implications of wildfires. Economic losses are also among the negative effects; Pan et al. (2023) found that wildfire emissions significantly degrade air quality and pose serious health and economic risks, estimating that wildfire-related PM2.5 caused around 4,000 premature deaths annually in the U.S., with an economic cost of $36 billion.

In the short term, the timing at which smoke exerts negative effects on mortality remains unclear. Vedal and Dutton (2006) examined whether short-term increases in particulate matter (PM) from both PM10 and PM2.5 from wildfire smoke in Denver

were associated with mortality but did not find any clear effect on short-term mortality since no immediate increase in deaths was observed after PM levels spiked. However, Doubleday et al. (2020) tested for an association between exposure to wildfire smoke and non-traumatic mortality in Washington State, USA, finding that smoke increases all-age non-traumatic mortality on the same day and following days as well, suggesting an increase in mortality in the first few days following exposure to wildfire smoke. They employed an analysis of wildfire smoke PM2.5 on a global scale with 749 cities in 43 countries and regions, finding that an increase in the 3-day moving average of wildfire-related PM2.5 increased the probability of all-cause death, cardiovascular death and respiratory death during the period of the study.

Even particles of larger sizes like PM10 can have negative effects on the population, despite being less invasive in the human body since the respiratory system is able to capture more particles before they reach the lungs compared to smaller particles. The WHO recommends a safe annual mean PM10 concentration of 15 μg/m3 (World Health Organization [WHO], 2021). Linares et al. (2017) found that the increase in burned biomass transported by wind to the main areas in Spain has a positive impact on the overall levels of PM10, thus increasing all-cause mortality. Tarín-Carrasco et al. (2021) also tested the effects, but in this case for larger fires of more than 1,000 hectares during the fire season and found some associations between PM10 levels and all-cause mortality and respiratory mortality; however, their method did not allow them to distinguish between normal background levels of pollution and those generated by the fire, since PM10 levels are also endogenous to human activity.

Several studies have analyzed wildfire health effects in various settings. Requia et al. (2021b) documented the heterogeneous impact of wildfires on hospital admissions in the Brazilian Amazon, while Moeltner et al. (2013) examined smoke from areas with varying organic fuel loads. Wildfire effects can differ depending on the vegetation that is burned; for instance, forests have a larger quantity of carbon trapped in the wood than small vegetation areas, and thus the burning of forests releases a larger quantity of pollutant-laden smoke. In addition, the spread and intensity of fires is greater in forests, making them harder to extinguish and enabling them to last for days in a row.

In addition to particulate matter, gaseous pollutants are also present in wildfire smoke and pose a major health risk, including Nitrogen Oxides (NOx), Volatile Organic Compounds (VOC) and Carbon Monoxide (CO). These can travel long distances and, in combination with sunlight or high temperatures, can generate a chemical reaction leading to the formation of Ozone (Verma et al., 2009). Ozone can affect health through cardiovascular and respiratory complications due to irritation of respiratory airways, making the lungs more prone to infections or simply reducing their capacity to capture oxygen. The WHO recommends a safe peak season O3 concentration of 60 µg/m3 and 24-hour CO concentrations of 4 µg/m3 (World Health Organization [WHO], 2021). Earlier literature has found that wildfires increase ozone levels by increasing the levels of VOCs, which in contact with the chemical mixture of the atmosphere, sunlight, or heat generate higher levels of Ozone (Schneider et al., 2024). This increase in Ozone levels has been linked to all-cause and respiratory mortality according to Chen et al. (2024). SO2 also poses a significant threat to human health; the WHO recommends a safe 24-hour threshold of 40 µg/m3 (World Health Organization [WHO], 2021). There has been evidence of wildfires affecting SO2 concentration levels. In Brazil and many developing countries, open fires are the largest source of biomass SO2 emissions, contributing a substantial share of total SO2. Orellano et al. (2021) found that exposure to SO2 is generally positively associated with all-cause and respiratory mortality, with significant results across multicity studies and sensitivity analyses, though short-term exposure did not present significant results. However, this study is focused on overall concentrations rather than wildfire emissions.

So far, we have discussed the negative effects, but there are some ways in which people can protect themselves, such as relocation, air purifiers, staying indoors, and mask use; however, these measures remain limited in developing regions due to economic and infrastructural constraints (Xu et al., 2020). Brazil also lacks a country-level air quality alert system, and despite efforts to increase the monitoring network, only a few large urban centers have monitoring stations. Many people are unaware of pollution increases during fire episodes, reducing their ability to respond or avoid unnecessary exposure.

Several factors might enhance the negative effects of wildfire and smoke; for instance, higher temperatures can facilitate the occurrence of more fires. Smoke impacts on health can be exacerbated by higher temperatures, posing a strain on respiratory and circulatory systems. Shaposhnikov et al. (2014) analyzed day-to-day variations in the number of deaths in relation to air pollution levels and extreme temperature interactions during a disastrous heat wave and wildfire, with approximately 11,000 excess deaths from nonaccidental causes during this period, mainly among those older than 65 years.

Wildfires affect populations not only through smoke exposure but also through a wide range of direct physical effects. Gelaw et al. (2025) found that people fighting fires are also exposed to a wide array of negative effects not only from smoke, but also from direct exposure to the flames. The strongest evidence was linked to increased risk of mental health conditions, including PTSD, stress, anxiety, and depression, as well as a high incidence of injuries, particularly musculoskeletal injuries, burns, and fractures. These negative effects can also extend to the population living close to fire-prone areas, as the probability of direct exposure is much higher.

Beyond their direct effects, wildfires can also influence mortality through ecological pathways. They alter the environment and the natural landscape by destroying forests, killing vegetation, or forcing some species to relocate temporarily. Brazil is a country composed of large areas of forest that can also host several species of animals or insects that pose a threat to the human population. Among them, we may mention vectors of several diseases such as mosquitoes. The three main diseases caused by mosquitoes between 2010 and 2019 were Dengue, Chikungunya, and Zika. Dengue can cause death by leading to bleeding, organ failure, or shock when blood vessels become leaky; Chikungunya can lead to death mainly in older adults or people with chronic illnesses due to severe joint, heart, or organ complications; and Zika can be extremely serious for fetuses, causing Congenital Zika Syndrome (microcephaly) and other birth defects. We hypothesize that wildfires may also affect vector populations by directly eliminating them and destroying their habitat. Since wildfires can negatively affect the mortality rate through direct exposure and smoke, the reduction in

mosquito populations may have a positive effect by lowering mosquito-borne disease cases in the short term. In addition, we also explore the long-term effects on vector-borne disease cases due to changes in the landscape.

Extensive research on wildfires has identified the negative health effects of wildfire smoke and wildfires across specific outcome settings. Most studies, however, focus on one pollutant such as PM2.5, PM10, SO2, and NO2. This approach leaves out the overall aggregate negative effect produced by fires both directly and indirectly. We contribute to the literature by providing a comprehensive analysis of wildfires' effects on mortality, accounting for multiple channels beyond single pollutants and capturing a wide range of direct and indirect impacts. We also measure the effects of wildfires under different settings using wind direction and fire source data. In addition, we present new evidence on the short- and medium-term impacts of wildfires on the transmission of vector-borne diseases, which has not been addressed in previous literature.

Data

Fire data

For the wildfire data, we relied on MODIS Collection 6 from NASA's Fire Information for Resource Management System (FIRMS). This dataset reports thermal anomaly detections from the Terra and Aqua satellites, with a spatial resolution of approximately 1 km^2 and records including location, date, and time of observation. We used the monthly frequency of fires from 2010 to 2019 as our main independent variable. MODIS can detect fires as small as 15 m^2 and up to 1,000 m^2.

A key challenge is the potential overidentification of fire occurrences: large or long-lasting fires may be detected multiple times (by different satellites or on consecutive days), leading to multiple counts of the same underlying fire. To address this, we applied a spatial threshold of 1 km, if multiple detections fell within this radius on the same or subsequent days, we collapsed them into a single fire event. This procedure provides a conservative measure of fire frequency, effectively capturing the lower bound of fire incidence while minimizing bias from duplicate detections.

Each detected fire was then assigned to the centroid of the corresponding municipality. We aggregated these to obtain the monthly frequency of fires within radii of 50 km, 75 km, and 100 km of each centroid.

Since the pollutants can also be transported across space, we incorporated wind information to capture pollution exposure more accurately. Using hourly ERA5 data from Copernicus, we calculated the daily average wind direction at 10 km x 10 km grid resolution. We then applied inverse distance weighting to the four nearest wind observations around each fire and matched this to the bearing of each municipality centroid. This approach allowed us to identify upwind fires (those located within a 90° sector relative to the wind direction at the municipality centroid) and non-upwind fires (those located within the remaining 270° sector).

To conclude, we employed land-use data from MapBiomas to classify areas into three main categories: forest, lower vegetation, and agricultural land. Combining this data with the fire and wind data enabled us to estimate the marginal effects of fires by land-use type, distinguishing between upwind and downwind exposures.

Mortality data

For the mortality data, we used the monthly mortality rate per 100,000 inhabitants. The municipality counts are linked to the location of residence of the deceased. The data was obtained from the Brazilian Mortality Information System (SIM) from the Brazilian Ministry of Health. We also separate into gender specific mortality and different age groups for the heterogeneity analysis.

Weather data

We employed the mean monthly average temperature, humidity and wind speed using the ERA5 product from the European Space Agency Copernicus. The satellite data is composed of a grid level of 10 km x 10 km. We took the average daily observations of each weather-related variable and aggregated it to a monthly level. Then we identified the four closest observations to each municipality centroid and used the inverse distance weighting to calculate the variables of each municipality centroid.

Mosquito reported cases data

According to previous research, mosquitoes can move at least 800 meters in 6 days in Brazil (Honório et al., 2003) and can transmit several diseases such as dengue, chikungunya, or malaria. A new dengue case can appear within 1 km of another case within a few days. Females can live for 2 to 4 weeks under favorable conditions, and the larval phase lasts about 4–14 days. We delimited the range of hotspots from 4 km up to 24 km from each municipality centroid. The outcome variable is the number of monthly reported cases by municipality, provided by the Brazilian Ministry of Health, expressed as a rate per 100,000 inhabitants.

Methodology

Our analysis starts by comparing the effects of wildfires on the overall mortality rate per municipality. First, we employed a least squares regression with fixed effects as follows in equation (1).

$$Mort_{it} = \beta_1 Fires_{it} + X_{it}\gamma + \tau_t + \pi_i + \epsilon_{it} \ (1)$$

Where $Mort$ is the monthly mortality rate per 100,000 inhabitants. $Fires_{it}$ are the number of fires within a month according to the distance threshold of 50 km, 75 km or 100 km. X_{it} is our set of covariates include monthly average temperature, humidity, precipitation, wind speed, and GDP per capita of the municipality, to account for the economic capacity of inhabitants. Individuals with higher income are expected to have access to better health care and thus face a lower likelihood of mortality. τ_t and π_i are our sets of time-varying and time-invariant fixed effects. In addition, we distinguish fires by source, such as forest, farmland, or natural formation area, to capture the separate effects that different fuel loads can have on the mortality rate. The equation is presented below, where k denotes the fire source.

$$Mort_{it} = \beta_1 Fires_{ikt} + X_{it}\gamma + \tau_t + \pi_i + \epsilon_{it} (2)$$

With Equations (1) and (2) we can identify the overall effect of wildfires on mortality. However, if we want to isolate the effects of the smoke from the direct effects of the

fire, we can make Equation (1) more restrictive by adding the wind direction relative to the wildfire and the municipality centroid in the following way.

$$Mort_{it} = \beta_1 UpWindFires_{it} + \beta_2 NonUpwindFires_{it} + X_{it}\gamma + \tau_t + \pi_i + \epsilon_{it} (3)$$

Here we differentiate between upwind fires (within 90 degrees relative to the wind direction) and fires that are not upwind (the remaining 270 degrees). In this way, we can capture the direct and indirect effects of wildfires by isolating the contribution of smoke from the direct damage generated by the fires. In addition, we can differentiate such effects by using a more detailed version of Equation (2), where we use an identification of the source of wildfires, such as forest, non-forest natural formations, and farming areas. Equation (4) follows, where k denotes the source of the fires.

$$Mort_{it} = \beta_1 UpWindFires_{ikt} + \beta_2 NonUpwindFires_{ikt} + X_{it}\gamma + \tau_t + \pi_i + \epsilon_{it} (4)$$

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Mortality rate	34,320	50.948	12.066	11.628	262.146
Mortality rate 0-4	34,320	24.163	17.232	0	218.241
Mortality rate 5-14	34,320	3.469	5.816	0	238.365
Mortality rate 15-24	34,320	12.152	8.51	0	277.25
Mortality rate 25-44	34,320	17.228	6.803	0	193.727
Mortality rate 45-64	34,320	62.697	16.464	0	243.662
Mortality rate 65	34,320	367.041	75.29	48.544	955.215
Mosquito rate	34,320	17.639	114.272	0	4260.937
Temperature	34,320	22.94	3.564	8.378	32.307
Humidity	34,320	74.701	9.532	27.442	92.501
Precipitation	34,320	3.909	3.241	0	31.707
Wind Speed	34,320	3.393	2.166	.76	9.718
GDP per capita	34,320	30689	20908	3608	232761
Fires 50 km	34,320	14.891	28.871	0	432
Fires 75 km	34,320	32.753	61.217	0	1016
Fires 100 km	34,320	55.468	102.24	0	1643
Forest 50 km	34320	5.24	14.766	0	348
Forest 75 km	34,320	11.382	31.415	0	788
Forest 100 km	34,320	18.949	51.874	0	1226
Farming 50 km	34,320	8.834	17.328	0	236
Farming 75 km	34,320	19.513	36.069	0	523
Farming 100 km	34,320	33.203	59.709	0	875
Natural Formation 50 km	34,320	0.816	5.331	0	276

Natural Formation 75 km	34,320	1.859	9.559	0	367
Natural Formation 100 km	34,320	3.316	15.023	0	437
Fires Upwind 50 km	34,320	3.982	8.321	0	143
Fires non-upwind 50 km	34,320	10.908	21.995	0	359
Fires Upwind 75 km	34,320	8.669	17.091	0	254
Fires non-upwind 75 km	34,320	24.084	46.822	0	762
Fires Upwind 100 km	34,320	14.738	28.229	0	419
Fires non-upwind 100 km	34,320	40.729	78.04	0	1295

Results

Wildfires on Mortality

Table 2. Wildfires on Mortality

	50 km radius	75 km radius	100 km radius
	(1)	(2)	(3)
	Mortality	Mortality	Mortality
Fires	0.00778***	0.00422***	0.00290***
	(0.00150)	(0.000728)	(0.000444)
N	34320	34320	34320
R-sq	0.726	0.726	0.726

Note: All equations outcomes are the monthly mortality rate per 100.000 inhabitants. All equations employ monthly average temperature, humidity, precipitation, wind speed, and GDP per capita as controls. Municipal, monthly and yearly fixed effects are employed. Robust standard errors are employed. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 2 shows the effects of wildfires on the mortality rate within different distance radii from the municipality centroid following equation (1). For the overall mortality rate, fires within the smallest radius of 50 km have larger effects on mortality, increasing the mortality rate per 100,000 inhabitants by 0.00778 per fire within the month. The effect is reduced to 0.00422 at 75 km and 0.00290 at 100 km. Statistical significance remains consistent across all ranges for all outcomes.

Wildfires by Source

Table 3 presents the results when using fires divided by source into three groups: forests, farming areas, and natural formations as it is expressed in equation (2). Forest fires are those occurring in forested areas, farming fires are those in areas dedicated to agriculture and cattle pasture, and natural formation fires occur in areas without dense forests or tree vegetation. Forest fires show no statistically significant effect on mortality at any of the three ranges. Fires in farming areas, however, significantly increase mortality across all thresholds, with coefficients of 0.0123 at 50 km, 0.00715 at 75 km, and 0.00498 at 100 km. Fires in natural formation areas do not show a

significant effect within 50 km, but become significant at the larger ranges, with coefficients of 0.0118 at 75 km and 0.0123 at 100 km.

Table 3. Wildfires by Source

	50 km radius (1) Mortality	75 km radius (4) Mortality	100 km radius (7) Mortality
Forest Fires	0.00195	0.000266	-0.000434
	(0.00364)	(0.00178)	(0.00119)
Farm Fires	0.0123***	0.00715***	0.00498***
	(0.00351)	(0.00181)	(0.00110)
Natural Formation Fires	0.0144	0.0118**	0.0123***
	(0.0108)	(0.00588)	(0.00407)
N	34320	34320	34320
R-sq	0.726	0.726	0.726
F	39.64	39.00	39.03

Note: All equations outcomes are the monthly mortality rate per 100.000 inhabitants. All equations employ monthly average temperature, humidity, precipitation, wind speed, and GDP per capita as controls. Municipal, monthly and yearly fixed effects are employed. Robust standard errors are employed. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Wildfires with Wind Direction

Table 4 presents the effects of wildfires with the distinction between upwind and non-upwind fires as expressed in equation (3). Upwind fires are those located within a 90-degree angle relative to the wind direction and the municipality centroid at the date of the fire was detected. If this condition is not met, the fire is categorized as a non-upwind fire. Upwind fires account for most of the effects of wildfires, with coefficients of 0.0180 at 50 km, 0.0102 at 75 km, and 0.00879 at 100 km, all remaining statistically significant. Non-upwind fires, by contrast, are not statistically significant at any distance. This suggests that the main channel is the transport of pollutants from the fires to the municipality centroid.

Table 4. Wildfires with Wind Direction

	50 km radius (1) Mortality	75 km radius (2) Mortality	100 km radius (3) Mortality
Upwind Fires	0.0180** (0.00736)	0.0102*** (0.00390)	0.00879*** (0.00257)
No Upwind Fires	0.00411 (0.00297)	0.00226 (0.00153)	0.000980 (0.000942)
N	34320	34320	34320
R-sq	0.726	0.726	0.726

Note: All equations outcomes are the monthly mortality rate per 100.000 inhabitants. All equations employ monthly average temperature, humidity, precipitation, wind speed, and GDP per capita as controls. Municipal, monthly and yearly fixed effects are employed. Robust standard errors are employed. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Wildfires by Source with Wind Direction

Table 5 presents fires by source, including the wind direction relative to the fire location and the municipality centroid, across the three distance ranges as it is expressed in equation (4). Using this distinction, we can separate the direct impacts of the fires from the impacts generated by fire smoke transported over distances on the mortality rate. Forest fires show no statistically significant effect on mortality, whether upwind or non-upwind, at any of the three ranges. Farming fires display a shifting pattern across distances: at 50 km, only non-upwind farming fires are significant, with a coefficient of 0.0113; at 75 km, the pattern reverses and upwind farming fires become significant instead, with a coefficient of 0.0130; at 100 km, both upwind (0.0120) and effects remain concentrated on the upwind channel. Natural formation fires are not significant at 50 km in either direction, but non-upwind natural formation fires become significant at 100 km, with a coefficient of 0.0122. Overall, these results suggest that the transport of pollutants via wind plays a more prominent role for farming and natural formation fires as the distance from the source increases, while forest fires do not generate a detectable mortality effect at any of the ranges

considered. Fires, suggesting that exposure in certain occupational settings plays a role in the increase in mortality.

Table 5. Wildfires by Source with Wind Direction

	50 km radius	75 km radius	100 km radius
	(1)	(2)	(3)
	Mortality	Mortality	Mortality
Forest Upwind	0.0162	0.00456	0.00235
	(0.0161)	(0.00885)	(0.00696)
Forest No-Upwind	-0.00189	-0.000680	-0.000819
	(0.00487)	(0.00270)	(0.00198)
Farming Upwind	0.0141	0.0130*	0.0120**
	(0.0128)	(0.00762)	(0.00558)
Farming No-Upwind	0.0113*	0.00474	0.00211
	(0.00597)	(0.00355)	(0.00246)
Nat For Upwind	0.0309	0.00958	0.0130
	(0.0323)	(0.0144)	(0.0126)
Nat For No-Upwind	0.00907	0.0127	0.0122**
	(0.0174)	(0.00857)	(0.00546)
N	34320	34320	34320
R-sq	0.726	0.726	0.726
F	29.35	29.47	30.32

Note: All equations outcomes are the monthly mortality rate per 100.000 inhabitants. All equations employ monthly average temperature, humidity, precipitation, wind speed, and GDP per capita as controls. Municipal, monthly and yearly fixed effects are employed. Robust standard errors are employed. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Heterogeneity

We continue with the heterogeneity analysis by age. We divided the mortality rate per 100,000 inhabitants into six different age groups and measured the effects of fires near the municipality centroid within 50 km, 75 km, and 100 km. Table 6 presents the effects on the overall mortality rate by age. Fires affect the mortality rate among infants, with

a coefficient of 0.00817 at 50 km decreasing to 0.0034 at 100 km. The second affected group is those aged 45 to 64 years, which shows a greater impact than infants, ranging from 0.012 at 50 km down to 0.004 at 100 km. Finally, the 65 and older group shows the largest influence, as expected, since the elderly are the most sensitive to variations in pollution levels and to other indirect impacts of fires. The impact ranges from 0.059 at 50 km down to 0.019 at 100 km. All findings remain statistically significant across all ranges in the affected groups.

Table 6. Age Heterogeneity

Panel A. 50 km radius						
	(1)	(2)	(3)	(4)	(5)	(6)
	0-4	5-14	15-24	25-44	45-64	65+
Fires	0.00817**	-0.000448	0.000225	0.000197	0.0126***	0.0590***
	(0.00387)	(0.00100)	(0.00166)	(0.00151)	(0.00359)	(0.0160)
N	34320	34320	34320	34320	34320	34320
R-sq	0.116	0.437	0.342	0.301	0.351	0.356
Panel B. 75 km radius						
	(7)	(8)	(9)	(10)	(11)	(12)
	0-4	5-14	15-24	25-44	45-64	65+
Fires 75 km	0.00470**	-0.000272	0.000271	0.000199	0.00631***	0.0309***
	(0.00188)	(0.000487)	(0.000810)	(0.000731)	(0.00176)	(0.00793)
N	34320	34320	34320	34320	34320	34320
R-sq	0.116	0.437	0.342	0.301	0.351	0.356
Panel C. 100 km radius						
	(13)	(14)	(15)	(16)	(17)	(18)
	0-4	5-14	15-24	25-44	45-64	65+
Fires 100 km	0.00346***	-0.000122	0.000186	0.000253	0.00400***	0.0192***
	(0.00116)	(0.000298)	(0.000496)	(0.000448)	(0.00109)	(0.00491)
N	34320	34320	34320	34320	34320	34320
R-sq	0.116	0.437	0.342	0.301	0.351	0.356

Note: All equations outcomes are the monthly mortality rate per 100.000 inhabitants. All equations employ monthly average temperature, humidity, precipitation, wind speed, and GDP per capita as controls. Municipal, monthly and yearly fixed effects are employed. Robust standard errors are employed. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 7 presents the effects of fires within the same range on the mortality rate by age group for females. The groups affected by fires are those aged 45–64 and 65 and older. The impact is 0.0104 for the 45–64 group and 0.0526 for the 65 and older group at the 50 km range, decreasing to 0.00375 for the 45–64 group and 0.0178 for the 65 and older group at 100 km. This effect may be attributable to pollutant exposure, since these age groups are more prone to respiratory and cardiovascular problems.

Table 7. Female Age Heterogeneity

Panel A. 50 km radius						
	(1)	(2)	(3)	(4)	(5)	(6)
	0-4	5-14	15-24	25-44	45-64	65+
Fires	0.00210	0.000967	0.00223	0.000704	0.0104**	0.0526***
	(0.00480)	(0.000914)	(0.00156)	(0.00148)	(0.00421)	(0.0199)
N	34320	34320	34320	34320	34320	34320
R-sq	0.073	0.033	0.029	0.087	0.215	0.244
Panel B. 75 km radius						
	(7)	(8)	(9)	(10)	(11)	(12)
	0-4	5-14	15-24	25-44	45-64	65+
Fires 75 km	0.00108	0.000368	0.000946	0.000530	0.00577***	0.0282***
	(0.00234)	(0.000426)	(0.000727)	(0.000712)	(0.00205)	(0.00971)
N	34320	34320	34320	34320	34320	34320
R-sq	0.073	0.033	0.029	0.087	0.215	0.244
Panel C. 100 km radius						
	(13)	(14)	(15)	(16)	(17)	(18)
	0-4	5-14	15-24	25-44	45-64	65+
Fires 100 km	0.00105	0.000202	0.000462	0.000393	0.00375***	0.0178***
	(0.00142)	(0.000258)	(0.000430)	(0.000434)	(0.00126)	(0.00599)
N	34320	34320	34320	34320	34320	34320
R-sq	0.073	0.033	0.029	0.087	0.215	0.244

Note: All equations outcomes are the monthly mortality rate per 100.000 inhabitants. All equations employ monthly average temperature, humidity, precipitation, wind speed, and GDP per capita as controls. Municipal, monthly and yearly fixed effects are employed. Robust standard errors are employed. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 8 presents the effects of fires within the same range on the mortality rate by age for males. The effects of fires on males are like those on females, with the same age groups being affected. For males in the 45–64 group, the coefficient is 0.0164 at 50 km, decreasing to 0.00473 at 100 km. For the 65 and older group, the effect is similar, starting at 0.0702 at 50 km and decreasing to 0.0219 at 100 km. All affected groups remain statistically significant across all ranges.

Table 8. Male Age Heterogeneity

Panel A. 50 km radius						
	(1)	(2)	(3)	(4)	(5)	(6)
	0-4	5-14	15-24	25-44	45-64	65+
Fires	0.00300	-0.00104	-0.00142	-0.000290	0.0164***	0.0702***
	(0.00522)	(0.00101)	(0.00294)	(0.00260)	(0.00612)	(0.0236)
N	34320	34320	34320	34320	34320	34320
R-sq	0.088	0.048	0.372	0.305	0.248	0.254
Panel B. 75 km radius						
	(7)	(8)	(9)	(10)	(11)	(12)
	0-4	5-14	15-24	25-44	45-64	65+
Fires 75 km	0.00137	-0.000638	-0.000093	-0.000119	0.00748**	0.0361***
	(0.00251)	(0.000498)	(0.00147)	(0.00126)	(0.00301)	(0.0119)
N	34320	34320	34320	34320	34320	34320
R-sq	0.088	0.048	0.372	0.305	0.248	0.254
Panel C. 100 km radius						
	(13)	(14)	(15)	(16)	(17)	(18)
	0-4	5-14	15-24	25-44	45-64	65+
Fires 100 km	0.00128	-0.000363	0.000129	0.000121	0.00473**	0.0219***
	(0.00155)	(0.000305)	(0.000911)	(0.000782)	(0.00186)	(0.00741)
N	34320	34320	34320	34320	34320	34320
R-sq	0.088	0.048	0.372	0.305	0.248	0.254

Note: All equations outcomes are the monthly mortality rate per 100.000 inhabitants. All equations employ monthly average temperature, humidity, precipitation, wind speed, and GDP per capita as controls. Municipal, monthly and yearly fixed effects are employed. Robust standard errors are employed. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Mosquito cases

In this section we analyze an indirect effect of wildfires: their impact on the mosquito population. We use reported cases of vector-borne diseases as a proxy for mosquito population. We consider fires at a shorter distance than in the previous section, since mosquitoes travel much shorter distances than the 50 km lower bound used previously. Since mosquitoes can travel around 1 kilometer per week and have an average lifespan of four weeks, we selected fires within 4 kilometers from the municipality centroid as the lower bound for the analysis. Some epidemiological studies have found dengue cases occurring more than 1 km from the nearest case. We measure the aggregate of the main mosquito-borne diseases affecting the Brazilian population, namely Dengue, Chikungunya, and Zika, for each municipality, weighted by population density and expressed as a rate per 100,000 inhabitants.

Table 9 presents the results of a regression measuring the effects of wildfires on the rate of reported mosquito cases per 100,000 inhabitants. Across all specifications, wildfires consistently reduce the mosquito case rate. Column (1) shows that hotspots within 4 km of the municipality centroid decrease the mosquito case rate by 1.417, while column (2) shows the largest single-point effect at 5 km (−1.550). When fires are grouped into bins, column (3) shows a decrease of 1.283 for the 4–6 km bin and 0.875 for the 7–9 km bin, while column (4) shows a decrease of 1.125 for the 5 km bin and 0.988 for the 5–8 km bin. The destruction of the mosquito population, the forced displacement of food sources, the destruction of habitat, and reduced rainfall accumulation can alter the number of mosquitoes over a short period, such as one month. Vector-borne diseases have a large impact on the Brazilian health system. Several outbreaks of dengue, Zika, and chikungunya have been reported between 2010 and 2019. Therefore, fires may have a short-term effect on mortality by reducing mosquito-borne disease cases, which positively impacts health by reducing the number of mosquito cases that have such negative health outcomes for Brazilians.

Table 9. Wildfires and Mosquito Cases

	(1)	(2)	(3)	(4)

	Mosquito	Mosquito rate	Mosquito	Mosquito
Hotspot 4 km	-1.417**			
	(0.695)			
Hotspot 5 km		-1.550***		
		(0.516)		
Hotspot bin 4-6km			-1.283**	
			(0.569)	
Hotspot bin 7-9km			-0.875**	
			(0.429)	
Hotspot bin 5km				-1.125**
				(0.549)
Hotspot bin 5<-8km				-0.988*
				(0.484)
N	34320	34320	34320	34320
R-sq	0.118	0.118	0.118	0.118

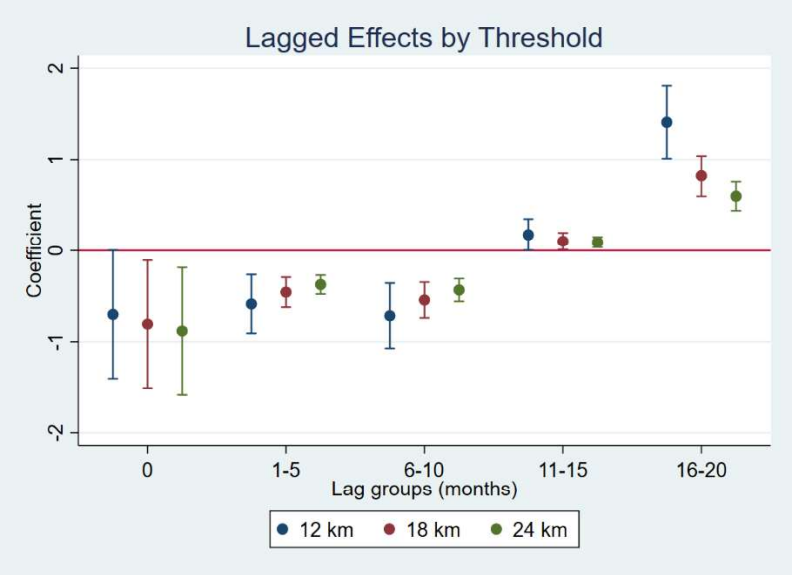
Note: All equations outcomes are the monthly mortality rate per 100.000 inhabitants. All equations employ monthly average temperature, humidity, precipitation, wind speed. Municipal, monthly and yearly fixed effects are employed. Robust standard errors are employed. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

We now analyze the effects of wildfires on mosquito cases over a longer period. To do this, we include a set of lag variables in addition to our contemporaneous wildfire observations. This approach allows us to measure not only the direct effects of wildfires on mosquito populations but also the indirect effects generated through environmental alterations. After a fire, vegetation is destroyed, and soil composition changes, leaving an ash layer that reduces water absorption. While forests may take several years to fully recover after a large wildfire, a 20-month window is sufficient for vegetation to regrow and create favorable conditions for mosquito reproduction.

Figure 1 presents the lagged effects of wildfires on the vector-borne disease rate per 100,000 inhabitants across three distance thresholds (12 km, 18 km, and 24 km), with lag groups in 5-month intervals capturing long-term dynamics. Across all thresholds, we observe a consistently negative effect from the current month through the 6–10-month lag group, reflecting the immediate destruction of mosquito populations and

breeding habitats. Coefficients are approximately −0.75 to −1.0 at lag 0 and remain negative through the 6–10-month window. From the 11–15-month lag group onward, the effect shifts upward toward zero and turns clearly positive in the 16–20-month window, with coefficients reaching approximately 1.4 at 12 km, 0.8 at 18 km, and 0.65 at 24 km. This reversal is consistent across all three thresholds, suggesting a robust pattern of initial suppression followed by mosquito population recovery and growth. This increase in cases may be caused by changes in land composition following a fire. The ash layer generates a barrier that prevents water from being absorbed by the soil, creating a more favorable environment for larvae to develop. As the mosquito population grows, mosquitoes may search for food close to human settlements, increasing reported cases as an indirect impact of wildfires.

Figure 1. Wildfires and Mosquito Cases



We also analyze the effects of wildfires on mosquito cases by separating fires according to their source. Figure 2 presents the lagged effects by fire source — farming, forest, and natural formation fires — across the same three distance thresholds (12 km, 18 km, and 24 km).

For farming fires, the pattern broadly mirrors the aggregate result. Coefficients are negative from lag 0 through the 6–10-month window across all thresholds, with the most pronounced decreases in the early months. From the 11–15-month period onward, the effect moves toward zero and turns positive by the 16–20-month window,

where coefficients reach approximately 1.9 at 12 km, 1.3 at 18 km, and 1.1 at 24 km. These effects are likely driven by the recovery of pasture areas, which comprise about 60% of farming land, while agriculture accounts for only 20%. Cattle pastures in Brazil are open, and the natural recovery process allows small vegetation to regrow. The ash layer left by the fires initially prevents rainwater absorption, but the recovering vegetation eventually creates favorable conditions for mosquito reproduction. Importantly, cattle typically remain present after farming fires, providing a continuous source of blood for mosquitoes, which may explain why the eventual rebound in mosquito cases is particularly pronounced in these areas.

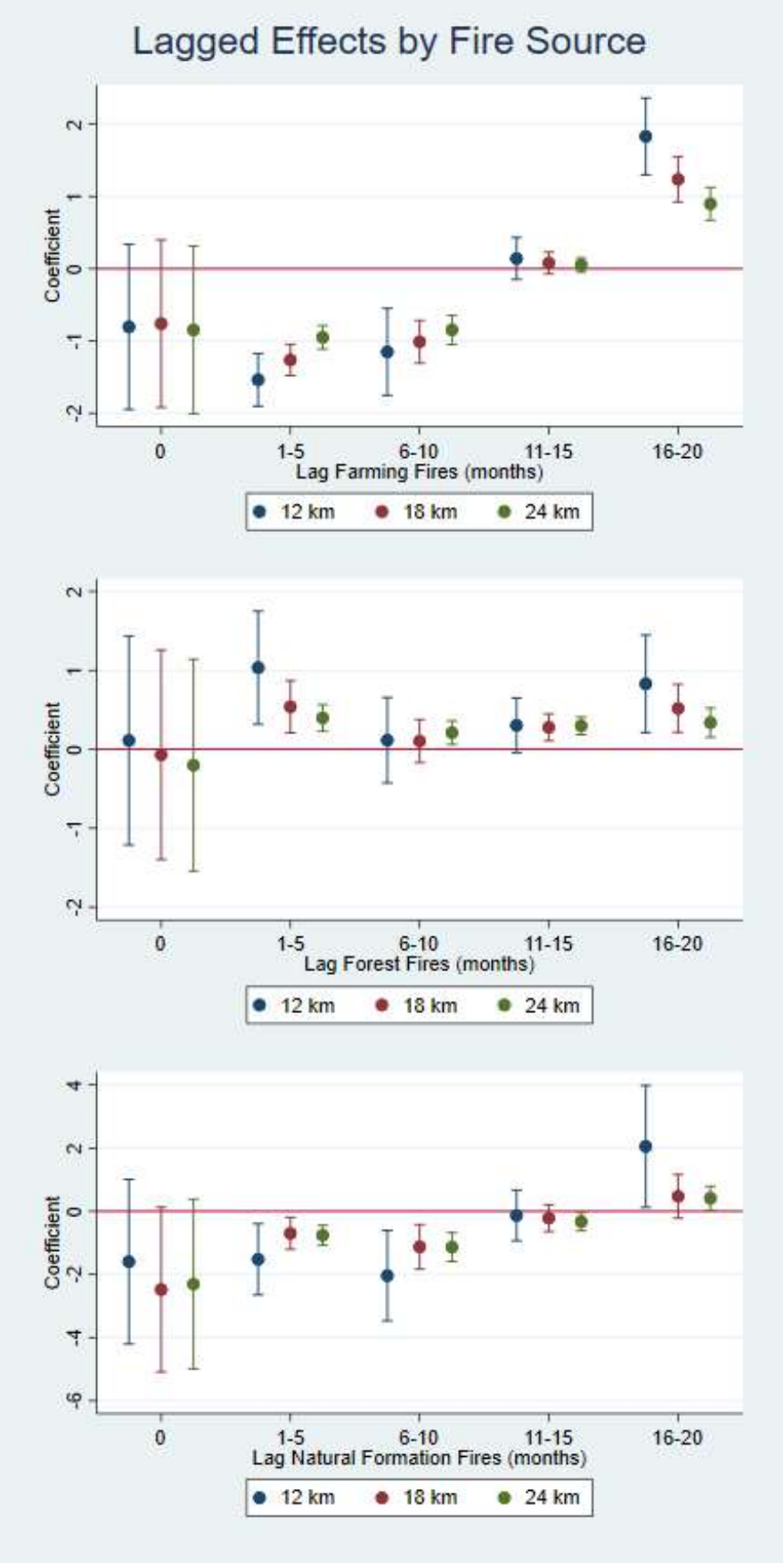
For forest fires, the dynamic is notably different. At the 12 km threshold, coefficients are positive from lag 0, rising to approximately 1.0 in the 1–5-month window before gradually declining toward zero through the 6–15-month period, and rising again modestly at 16–20-months. At 18 km and 24 km, the pattern is more muted and less consistent, with coefficients generally hovering near zero across most lag groups. This initial increase in cases at closer distances is likely due to the ecological characteristics of forest environments: shaded and humid microclimates, along with remaining water bodies, can facilitate mosquito survival and reproduction even after a fire. Additionally, the absence of animals in burned forest areas may force mosquitoes to migrate toward human settlements in search of blood, contributing to the early rise in reported cases. This contrasts with farming areas, where cattle remain available as a blood source, reducing the need for mosquitoes to migrate extensively.

Natural formation fires show a predominantly negative or near-zero effect on mosquito populations across all thresholds and lag groups, with only a modest positive uptick at the 16–20-month window at the 12 km threshold. This pattern is consistent with two factors. First, natural formation environments, such as grasslands and wetlands, are generally less suitable for mosquito larval development due to their limited standing water retention and lower vegetation density. Second, these areas tend to have scarce wildlife and few human settlements, reducing the availability of hosts for mosquitoes. Together, these factors explain the weaker and often statistically

insignificant effects observed in natural formation areas compared to forests or farming zones.

These results highlight how environmental alterations caused by wildfires, combined with vegetation recovery dynamics and the ecological characteristics of different land types, shape mosquito population trends over time.

Figure 2. Wildfires by Source and Mosquito



Conclusion

The frequency and intensity of wildfires in recent years have become a major challenge because of the danger they bring to people's health, the economy, and the environment. Their growing intensity highlights the need for a more comprehensive analysis of their possible impacts, especially on mortality, since this poses a direct threat to vulnerable populations. This is especially true in countries with large forest areas like Brazil, where fires can spread rapidly and reach extreme intensity.

The study shows that fires within 50 km, 75 km, and 100 km from the municipality centroid can have significant effects on the mortality rate of the exposed population. When we consider the wind direction between the fires and the municipalities, we find stronger negative effects for upwind fires. This is consistent with the idea that winds carry pollutants over long distances, from unpopulated areas to populated zones, increasing exposure. Using this approach, we found no gender differences across distance thresholds for upwind fires. The study shows that fires within 50 km, 75 km, and 100 km from the municipality centroid can have significant effects on the mortality rate of the exposed population. When we consider the wind direction between the fires and the municipalities, we find stronger negative effects for upwind fires. This is consistent with the idea that winds carry pollutants over long distances, from unpopulated areas to populated zones, increasing exposure. Farming fires stand out as a particularly relevant source, showing significant effects on mortality regardless of wind direction, and becoming more strongly associated with the upwind channel as distance increases.

Age also plays an important role in vulnerability to wildfires. Infants have lung, circulatory, and immune systems that are still developing, which increases their susceptibility to smoke exposure. Adults over 45 and the elderly are also more vulnerable due to preexisting health conditions, such as respiratory or circulatory diseases, which can worsen when exposed to smoke. These findings highlight the need to prioritize protection for these age groups to reduce the negative effects of wildfires.

When we account for other factors, we also find some effects that are less documented in the literature. Wildfires can temporarily reduce mosquito populations, which lowers the spread of vector-borne diseases and indirectly reduces mortality. However, after several months, especially when the rainy season begins, mosquito numbers rise again. As vegetation regrows and new water pools form, mosquitoes find more suitable breeding sites, leading to population recovery. This can raise the risk of mosquito-related diseases following fires. More research is needed to understand these long-term effects and the environmental changes that occur after wildfires.

Policymakers and public health officials need to combine environmental, social, and health data to develop strategies that address both the direct and indirect effects of wildfires. Our findings show that upwind fires are the most dangerous, that gender and age influence vulnerability, and that ecological feedback such as mosquito population changes can also affect health outcomes. Understanding all these factors together is essential to reducing the health impacts of wildfires in Brazil and other countries.

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