Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Interaction Effects of $PM_{2.5}$ and High Temperatures on the Respiratory Health of Vulnerable Age Groups in the Brazilian Amazon.

LUCAS de Oliveira do COUTO

lucas.oliv.couto@gmail.com

Fundação Oswaldo Cruz https://orcid.org/0000-0002-3758-3567

Rochelle Schneider

European Space Agency https://orcid.org/0000-0002-2905-0154

Ludmilla Viana Jacobson

Universidade Federal Fluminense https://orcid.org/0000-0002-6698-4431

André Reynaldo Santos Périssé

Fundação Oswaldo Cruz

Sandra Hacon

Fundação Oswaldo Cruz https://orcid.org/0000-0002-8222-0992

Research Article

Keywords: Legal Amazon, PM2.5, Respiratory diseases, Vulnerable age groups, DLNM.

Posted Date: September 9th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10973377/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Abstract

In the Legal Amazon, wildfire smoke raises $PM_{2.5}$ concentrations for months. Hot weather and air pollution may aggravate respiratory diseases in vulnerable age groups in this region. The objective was to assess the effects of the interaction between $PM_{2.5}$ and heat on hospitalizations for respiratory diseases in children and adolescents (1-19 years) and on respiratory mortality in older adults (≥60 years). We conducted an ecological study with monthly data from 2009 to 2019, applying hierarchical Bayesian models integrated with distributed lag non-linear models (0-2 months lag) to estimate the delayed effects of this interaction. A positive and significant association was observed, with an immediate response in both groups. At lag 0, mortality increased by 2.5% and hospitalizations by 2.7% for each 10 μg/m³ increase in $PM_{2.5}$ under high-temperature conditions in the Amazon. These findings indicate an important risk to respiratory health in the region and reinforce the urgency of reducing biomass burning, strengthening air-quality surveillance, and increasing the resilience of the health system and the population to the current impacts of climate and air pollution.

INTRODUCTION

Air pollution represents a significant risk factor for global health, the World Health Organization (WHO) estimates that nearly the entire global population (99%) lives in areas where air quality falls outside the standards suggested by the agency (World Health Organization, 2024). Among the wide range of pollutants suspended in the atmosphere, fine particulate matter ($PM_{2.5}$), defined as a mixture in suspension of solid and liquid particles in the atmosphere with an aerodynamic diameter smaller than 2.5 μm, holds a significant toxic potential, ranking among the top 10 global risk factors for diseases (1). It can remain suspended and dispersed over long distances depending on atmospheric and weather conditions (2, 3). In the Brazilian Amazon, forest fires are a major source of $PM_{2.5}$, especially during the dry season with approximately 1.68 tons of $PM_{2.5}$ released into the atmosphere annually between 2010 and 2019 due to these fires (4).

Fine particles matter is a key pollutant from a respiratory health perspective. It can be deposited throughout the respiratory tract, in small airways and alveoli. People with preexisting respiratory conditions, such as asthma and chronic obstructive pulmonary disease, and cardiovascular conditions, are specially affected (5, 6).

Besides its individual effects, the literature has also found consistent evidence of interaction effects between air pollutants and hot weather. Episodes of high $PM_{2.5}$ concentrations and hot temperatures can contribute to increases in hospital emergency room visits for respiratory diseases, as well as an increase in hospital admissions due to Chronic Obstructive Pulmonary Disease (COPD) exacerbations, especially in the elderly (7, 8). Children and adolescents are also affected, hot temperatures and high air pollutant concentrations can increase asthma related ED visits and hospitalizations for acute bronchiolitis related disease (9, 10). Hot weather can also strengthen the impact of air pollution on respiratory mortality, such COPD complications, especially in older adults (11–13).

Respiratory diseases (RD) are among the leading causes of hospitalizations and deaths in Brazil, representing the second largest cause of hospital admissions and the fourth leading cause of death in the country. Between 2009 and 2019, the BA recorded more than 2.2 million hospitalizations due to respiratory diseases, of which 41.6% (840,731) are individuals aged 1 to 19 years. In this age group, pneumonia (461,958 cases) and asthma (141,317 cases) represent 71% of the causes of hospitalizations. Over the same period, the region recorded more than 119,000 deaths due to respiratory diseases, of which 73.7% (87,657) are elderly, 83.3% of elderly death are due to pneumonia (39,420 cases) and chronic lower respiratory tract diseases (33,705 cases) (14, 15).

Elderly individuals, children, and adolescents are considered very vulnerable populations to the adverse effects of air pollution and extreme temperatures. In the elderly, the presence of comorbidities, a diminished immune response, and reduced thermoregulation capabilities expose them to a higher risk of health complications (16). On the other hand, children and adolescents, whose immune and respiratory systems are still developing, also face significant risks. This age group tends to spend more time outdoors, increasing their exposure to pollutants and elevated temperatures (17).

In this study, we focus on the interaction effects between $PM_{2.5}$ and high temperatures exposure to assess their impact on respiratory health in two vulnerable age groups in the Brazilian Amazon. We investigate the lagged influence of these environmental factors on hospital admissions for respiratory diseases among children and adolescents aged 1 to 19 years and on mortality from respiratory diseases among the elderly aged 60 and over.

METHOD

In Brazil, the Amazon region is defined by two geographical boundaries: the Amazon biome and the Brazilian Legal Amazon. Our analyses were conducted in the Brazilian Legal Amazon (BA), hereafter referred to as the Brazilian Amazon. The BA covers an area of 5,015,146.01 km², 59% of Brazil's territory, comprises 772 municipalities across nine states and includes a large and environmentally heterogeneous territory with more than 27 million inhabitants, 13% of Brazil's total population. Of this total, more than 9 million are children and adolescents, and over 2.7 million are elderly, together making up 42% of the region's population (14).

The BA experiences two well defined seasons: the rainy season, which occurs between December and May, and the dry season, between June and November. The climate in the region is generally describe as humid and warm, with an average temperature of 25.7°C and humidity of 88% during the rainy season, and 26.4°C and 77.2% during the dry season, but in certain regions, at south of BA, the temperature can go up to 30°C and humidity got down to 35% in the dry season (18, 19). As mentioned before, fires are the major source of PM in tropical regions, and in BA the majority of these fires occur during the dry season, from June to November mainly started by human actions. From May to June, the number of fires typically increases by about 150%. August and September are critical months for fires in the BA,

compared to May, the fires occurrence increases more than 1,500%. These two months usually concentrate about 54.6% of the fires occurring in a year (20).

Data Source and Collection

Health and Population Data

Monthly data on hospital admissions and mortality from respiratory diseases were obtained from Information Technology Department of the Public Health Care System (DATASUS) through the Brazilian Unified Health System's hospital information system (SIH-SUS) and the mortality information system (SIM-SUS). The data were compiled considering the individuals' place of residence, the month of occurrence, and the cause of hospital admission and death, according to the International Classification of Diseases, 10th Revision - Diseases of the Respiratory System, Chapter X (14).

Additionally, data on the number of health establishments, in each municipality within the BA region, and annual municipal population estimates stratified by age group for the period between 2009 and 2019 were also obtained from DATASUS (14).

The data collection and organization were carried out using the R environment, version 4.1.3 (21).

Environmental Data

The estimates for the average monthly concentration of $PM_{2.5}$ between 2009 and 2019 were obtained from Van Donkelaar et al. (2021) work, available through the Atmospheric Composition Analysis Group at Washington University, at <Atmospheric Composition Analysis Group>. The data is available on a global scale with a spatial resolution of approximately 0.01° (~ 1 km) in "NetCDF" format. This dataset, covers a period from 1998–2022, integrates Aerosol Optical Depth (AOD) from various satellites sensors (MODIS, MISR, SeaWIFS, and VIIRS) and the GEOS-Chem chemical transport model, calibrated with ground observations using Geographically Weighted Regression (GWR), to provide comprehensive geophysical estimates of $PM_{2.5}$ (22). For the municipalities of the BA, the estimates were filtered using the QGIS software (23).

Monthly average temperature, relative humidity and total precipitation data for each municipality in the BA, covering the period from 2009 to 2019, were obtained from the Integrated Environmental Information System for Health (SISAM) – INPE, responsible for, preprocessing, standardize, and made the data available (18).

Both databases have been applied in health studies before (24–27).

Statistical Analysis.

We applied a Bayesian hierarchical model to examine the delayed interaction effects of $PM_{2.5}$ concentration and high temperatures, defined at the 90th percentile, on hospital admissions and mortality, both related to RD. We work on two distinct models, one for hospital admissions of children and adolescents, and another for mortality of the elderly.

While traditional Bayesian approaches, such as Markov Chain Monte Carlo (MCMC), are widely used for their flexibility in modeling complex systems, they are often computationally intensive and present convergence issues, particularly when dealing with complex models. To overcome these limitations, we employed the Integrated Nested Laplace Approximation (INLA), a more efficient alternative to MCMC, which provides fast and accurate approximations of the posterior distributions. This allows us to estimate the lagged relative risk of RD hospital admissions and mortality, significantly faster without compromising accuracy (28).

The response variables for each model were assumed to follow a negative binomial distribution, chosen to account for potential overdispersion in the count data for RD related hospital admissions (y_{mt}^{ha-dar}) among children and adolescents and RD related death (y_{mt}^{de-dar}) among the elderly. Let:

$$y_{mt} \mid \mu_{mt}, \kappa \sim NegBin(\mu_{mt}, \kappa)$$

where y_{mt} represents the number of RD related hospital admissions or death in municipality *m* at time *t*, μ_{mt} is the expected number of cases, and *Kappa* (κ) is the dispersion parameter, which adjusts the variance to account for overdispersion.

To ensure that the estimates were appropriately adjusted for population size across municipalities over time, a logarithmic offset for the exposed population was included in the model, such that:

$$log(\mu_{mt}) = log(pop_{mt}) + log(Ra_{mt})$$

here, pop_{mt} represents the annual population of municipality *m* at time *t*, standardized per 100,000 inhabitants, and Ra_{mt} is the estimated rate of hospital admissions or death.

We modeled residual spatial variation in both outcomes using the BYM2 specification (a reparameterization of the Besag–York–Mollié model), which combines a spatially structured component capturing correlation between neighboring municipalities defined by an adjacency graph and an unstructured component that captures municipality specific heterogeneity (28, 29). Temporal random effects were included to capture smooth variation over time, modeled as a second order random walk (RW2) for hospitalizations and a first order random walk (RW1) for deaths, based on model performance. For each random effect, a Penalized Complexity (PC) prior with parameters $\sigma_0 = 0.5$ and $\alpha = 0.01$ was assigned, favoring a simpler model unless the data provide evidence of greater variability (29, 30).

To assess the exposure-lag-response association between $PM_{2.5}$ and health outcomes, we used a Distributed Lag Non-Linear Model (DLNM). We defined a cross-basis for $PM_{2.5}$ with a linear function for the exposure response (fun="lin"), based on the assumption that the risk of hospitalization and death increases proportionally with the elevation in $PM_{2.5}$ concentration. For the lag structure (fun="ns"), we applied a natural spline. We considered a lag period ranging from zero to two months to capture possible influences from fires, which typically peak around August and September (31). We also based this lag period on Mebrahtu et al. (32) findings, who reported significant lagged effects of $PM_{2.5}$ on emergency visits for respiratory issues, with risks peaking around 76 days after exposure.

To evaluate the interaction between temperature and $PM_{2.5}$ on the risk of hospital admissions and mortality from respiratory diseases, we included an interaction term following Gasparrini et al. (33). Specifically, the interaction was defined by multiplying the $PM_{2.5}$ cross-basis matrix by a temperature indicator variable. This indicator captures how much the observed temperature in a given month and municipality deviates from a heat threshold, defined as the 90th percentile of the monthly temperature distribution in BA. The indicator variable (Temp.Ind) was defined as:

$$Temp.Ind_{t,m} = Temperature_{t,m} - P_{90}Temperature$$

By centering the temperature variable at the heat threshold, the main effects (crossbasis variables) can be interpreted as representing the exposure-lag-response relationship at this reference temperature. As described in previous studies, this approach allows to capture how the health impacts of $PM_{2.5}$ vary depending on deviations from the heat threshold, also, it ensures that the model remains interpretable under different scenarios without altering its overall structure (Gasparrini *et al.*, 2015; Lowe *et al.*, 2021; Stafoggia *et al.*, 2023; VanderWeele; Knol, 2014) (34, 33, 35).

In addition, we adjusted the models for temperature as a non-linear term using a natural spline (ns, df = 8), as well as total monthly precipitation, health establishments per 100 inhabitants, and a categorical influenza-season indicator (Table S1).

The final model was selected through the comparison of models with increasing complexity and a reference base model, using the Deviance Information Criterion (DIC) and the mean log score as fit metrics. These same metrics were also applied to select the structure of the random effects, their priors, and the crossbasis for $PM_{2.5}$. The DIC assesses model precision by weighing its complexity, and the mean log score estimates the predictive capacity of the model by removing and evaluating one data point at a time. In both cases, lower values indicate a better fit of the model to the data (28, 29). We selected as final models those with a less complex structure and good fit metrics. The performance metrics and model variables are presented in Table 1S in the Supplementary Material.

All analyses were conducted using the INLA package for Bayesian modeling and DLNM for risk estimation (36, 31, 21). The risk estimates, made through the crosspred function of the DLNM package, were centered at 0 micrograms of $PM_{2.5}$ and presented as non-cumulative effects.

RESULT

A statistical summary is provided in Table 1, detailing the evaluated outcomes and environmental characteristics of BA. Between 2009 and 2019, more than 836,000 hospital admissions for respiratory diseases were recorded among children and adolescents, with an average of 6,300 monthly admissions. In the same period, over 87,600 deaths from respiratory diseases were reported among elderly, with a monthly average of 664 deaths. Table 2S presents summary statistics specifically for August to October, dry season months when air pollution usually peaks. These months accounted for 37% of hospitalizations among children and adolescents and 40.7% of deaths among the elderly (Fig. 1S).

The average monthly concentration of $PM_{2.5}$ was 20 μg/m^3 (min 2 μg/ m^3; max 135 μg/m^3), and the average monthly temperature was 26°C, with a minimum of 17°C and a maximum of 32°C. Figure 2S in the supplementary material presents boxplots of $PM_{2.5}$ and temperature distributions aggregated across the BA. Table 3S summarizes pollution, temperature and health statistics by state. Additionally, map 2S illustrates the spatial distribution of $PM_{2.5}$ concentrations in all municipalities during August to November.

The models for children and adolescents' hospitalization without the interaction term between $PM_{2.5}$ and high temperature (90th percentile) did detect a significant increase in risk at lag zero (Fig. 3S-A, left). However, when the interaction between these two variables was included, a significant increase in hospitalization risk emerged, not only at lags 0, but also at lag 1 (Fig. 3S-A, right).

Figure 1 (A–D) illustrates the lagged effects of $PM_{2.5}$ exposure under high temperature conditions on hospitalization risk across lags 0 to 2. Figure 1A presents a contour plot depicting non-cumulative risk estimates from the interaction model across different $PM_{2.5}$ concentrations and lag months. Additionally, Figs. 1B - D further detail these effects at lags 0 to 2, along with their corresponding credibility intervals.

Those figures illustrate significant effects observables in the same month of exposure (lag 0). Considering the mean monthly $PM_{2.5}$ concentration in the BA (20 μg/m³), the estimated relative risk (RR) at lag 0 is 1.05 (1.03–1.08), whereas at lag 2, it decreases to 1.02 (0.99–1.05). Also, the risk estimates increased as concentration rise, for a 40 μg/m³ $PM_{2.5}$ average concentration, the estimated RR at lag 0 is 1.11(1.06–1.16), and at lag 2, it increases to 1.03 (0.97–1.10). A numerical summary of risk variation across different $PM_{2.5}$ concentrations is available in Table 4S of the supplementary material. Figure 3A presents the lagged percentage change in hospitalization risk per 10 μg/m³ increase in $PM_{2.5}$, indicating a 2.7% (1.4% – 3.9%) increase at lag 0, and a 0.9% (-0.7% – 2.4%) at lag 02.

These results indicate that $PM_{2.5}$ exposure during warmer months has a significant effect on respiratory disease hospitalizations, manifesting in the same month of exposure and persisting up to one month (lags 0 to 1), with the highest risks observed in the same month of exposure (lag 0).

Unlike what was observed for hospitalizations, models for elderly mortality without the interaction term between $PM_{2.5}$ and high temperature (90th percentile) detected risk increases very similar to the interaction model, with a 2.3% increase in death risk per 10 μg/m³ increase in $PM_{2.5}$ at lag 0 (Fig. 3S-B, left). When the interaction between these two variables was included, the death risk per 10 μg/m³ increase in $PM_{2.5}$ rose to 2.5% at lag 0 (Fig. 3S-B, right).

Figure 2 (A–D) illustrates the lagged effects of $PM_{2.5}$ exposure under high-temperature conditions on mortality risk across lags 0 to 2. Figure 2A presents a contour plot depicting non-cumulative risk estimates from the interaction model across different $PM_{2.5}$ concentrations and lag months. Figures 2B–D further detail these effects at lags (0, to 2, along with their corresponding credibility intervals.

Once again, a significant effect is observed at lag 0, the same month of exposure, and persists until lag 1, but only at very high concentrations. The dose response relationship remains linear, with the risk increasing proportionally to $PM_{2.5}$ concentration. And like hospital admissions, where the highest risks occurred at the same month of exposure, mortality risk peaks at lag 0 but the decline in risk estimates over time, is more pronounce, we can observe non-significant risk estimates already at lag 1 under lower concentrations. Once again if we consider the mean monthly $PM_{2.5}$ concentration in the BA (20 μg/m³), the estimated RR at lag 0 is 1.05 (1.02–1.08), whereas at lag 2, it decreases to 0.99 (0.96–1.03). Figure 3B displays the lagged percentage change in mortality risk per 10 μg/m³ increase in $PM_{2.5}$, indicating a 2.5% (0.9%–4.1%) increase at lag 0, and a 1.0% (0.1%-2.0%) at lag 02.

We can understand that, in warmer months, exposure to $PM_{2.5}$ also has a significant and immediate effect on elderlies mortality, with the greatest effects observed in the same month of exposure (lag 0) and, to a lesser extent, one month after exposure.

DISCUSSION

The present study aimed to investigate the lagged interaction effects between $PM_{2.5}$ and high temperature exposure on hospitalizations in children and adolescents, as well as mortality in the elderly. Our analyses focused on monthly data and considered the lagged effects spanning a period of 0 to 2 months.

Our findings are consistent with previous evidence on the effects of $PM_{2.5}$ and heat on respiratory outcomes, while extending the literature in the Brazilian Amazon by jointly examining hospitalizations in children and adolescents and mortality in older adults, with emphasis on their interaction effects (25, 37, 38).

The lagged structure of the associations differed by outcome. Among children and adolescents, hospitalizations were associated with $PM_{2.5}$ exposure in the same month and up to one month later. This pattern suggests that exposure may trigger inflammatory responses or increase susceptibility to

respiratory complications over time. A similar delayed pattern was reported by Mebrahtu et al. (32), indicating that $PM_{2.5}$ effects are not restricted to the immediate period after exposure. Although limited, evidence also indicates that monthly variations in air pollutants influence hospitalization, In South Brazil, Castañeda et al. (39), found that a 10 μg/m³ increase in monthly PM_{10} was associated with higher respiratory hospitalizations across all ages, with the strongest effects in young adults (16–59 years, IRR: 2.04, 95% CI: 1.97–2.12). Also, in China, Ju et al. (40) observed a 3.1% increase in all cause hospitalizations per 10 μg/m³ of PM_{10}.

In contrast, mortality among older adults was more strongly associated with $PM_{2.5}$ exposure in the same month, with weaker effects thereafter. This more immediate pattern may reflect age-related physiological vulnerability, including reduced immune response and greater susceptibility to respiratory complications (16). Previous studies using monthly data have also reported increased mortality associated with $PM_{2.5}$ exposure in older populations, in Chile, Busch et al. (24) reported a 1.7% increase (95% CI: 1.1–2.4%) in all-cause mortality per 10 μg/m³ of monthly $PM_{2.5}$ in individuals aged 75 or older. A nationwide study in the U.S. similarly found a 1.6% increase in respiratory mortality per 10 μg/m³ of monthly $PM_{2.5}$ (41).

These lagged patterns are likely influenced by the seasonal overlap between high temperatures and peak fire activity in the Brazilian Amazon. During the dry season, hotter and drier conditions favor forest fires and increase $PM_{2.5}$ concentrations, which may amplify respiratory risks in vulnerable age groups (4, 42).

Evidence suggests that these climatic conditions in BA are becoming increasingly favorable for fires. The dry season in the Amazon has lengthened by about one month since the 1970s, and projections indicate further increases in temperature and reductions in rainfall, which will likely extend drought periods and further elevate fire risks (43–45). As these conditions worsen, we can expect the associated health risks to intensify, particularly for vulnerable groups such as children, adolescents, and the elderly, who are already being affected, as our, and previous, results show.

Addressing air pollution and climate-related health risks in the Brazilian Amazon requires coordinated action to reduce deforestation and fires, strengthen health services (46). Increasing air quality surveillance and warning systems throughout the BA region is essential in this process. The use of multiple surveillance methods is an important strategy to cover Amazon vast area, such as via satellite monitoring systems and low cost air quality monitors (47, 48). Community communication is also vital, in association with the warning systems, it can provide timely alerts about critical air pollution days or weather related events and offer guidance on the best ways to protect against extreme heat and air pollution (49). This is particularly important for the elderly, children, adolescents, and their caregivers, as well as individuals with respiratory conditions, pregnant women, and outdoor workers.

This study has two main limitations. First, the use of aggregated monthly data, which tends to smooth out the behavior of the analyzed data, making it impossible to capture acute events and weekly variations in the models. However, the use of aggregated data allows us to capture long term effects and

observe how these effects vary across different seasons (50, 51). Our results show that the use of aggregated monthly data has revealed expected risk patterns for the region, consistent with a significant portion of the literature presented previously. Second, the environmental exposures were based on modeled data rather than ground monitoring, which is less precise but necessary in the Brazilian Amazon because of its vast territory and limited monitoring network. Even so, these data capture the seasonal variation in $PM_{2.5}$ and temperature and have been used in previous health studies including evaluations of the $PM_{2.5}$ effects on mortality, early childhood growth impairment risk and stillbirth (17, 24, 26, 52–55).

CONCLUSION

In this study, we explored the interaction effect of $PM_{2.5}$ exposure and high temperatures on the respiratory health of two vulnerable populations in the Brazilian Amazon. We identified a positive and significant association between $PM_{2.5}$ concentrations and health outcomes during hot months, consistent with existing literature.

The results indicate that both age groups are vulnerable to heat and air pollution, with children and adolescents also experience impact a month after the exposure suggesting that, in this group, $PM_{2.5}$ exposure may trigger physiological responses that develop over time, potentially due to delayed inflammatory processes or increased susceptibility to secondary infections.

This work adds to the existing body of evidence on the impacts of air pollution on respiratory health among the most vulnerable age groups of the Brazilian Amazon, particularly during warmer periods. It underscores the need for immediate actions to significantly reduce forest fires in the region and to expand air quality surveillance and communication to the population. Furthermore, it is crucial to ensure the continuous expansion and adaptation of healthcare services in the region, enhancing their capacity to serve the population effectively during climatic and air pollution extremes.

References

1. Bu X, Xie Z, Liu J, Wei L, Wang X, Chen M et al (2021) Global PM2.5-attributable health burden from 1990 to 2017: Estimates from the Global Burden of disease study 2017. Environ Res junho de 197:111123. 10.1016/j.envres.2021.111123
2. Amaral SS, Costa MAM, Soares Neto TG, Costa MP, Dias FF, Anselmo E et al (2019) CO2, CO, hydrocarbon gases and PM2.5 emissions on dry season by deforestation fires in the Brazilian Amazonia. Environ Pollut junho de 249:311–320. 10.1016/j.envpol.2019.03.023
3. Zender-Świercz E, Galiszewska B, Telejko M, Starzomska M (2024) The effect of temperature and humidity of air on the concentration of particulate matter - PM2.5 and PM10. Atmospheric Res dezembro de 312:107733. 10.1016/j.atmosres.2024.107733

4. Prist PR, Sangermano F, Bailey A, Bugni V, Villalobos-Segura MDC, Pimiento-Quiroga N et al (2023) Protecting Brazilian Amazon Indigenous territories reduces atmospheric particulates and avoids associated health impacts and costs. Commun Earth Environ 6 de abril de 4(1):34. 10.1038/s43247-023-00704-w
5. Thangavel P, Park D, Lee YC (2022) Recent Insights into Particulate Matter (PM2.5)-Mediated Toxicity in Humans: An Overview. Int J Environ Res Public Health 19 de junho de 19(12):7511. 10.3390/ijerph19127511
6. Mo S, Hu J, Yu C, Bao J, Shi Z, Zhou P et al (2023) Short-term effects of fine particulate matter constituents on myocardial infarction death. J Environ Sci novembro de 133:60–69. 10.1016/j.jes.2022.07.019
7. Ding PH, Wang GS, Guo YL, Chang SC, Wan GH (2017) Urban air pollution and meteorological factors affect emergency department visits of elderly patients with chronic obstructive pulmonary disease in Taiwan. Environ Pollut maio de 224:751–758. 10.1016/j.envpol.2016.12.035
8. Zhang Y, Wang S, Fan X, Ye X (2018) Temperature modulation of the health effects of particulate matter in Beijing, China. Environ Sci Pollut Res abril de 25(11):10857–10866. 10.1007/s11356-018-1256-3
9. Leung SY, Lau SYF, Kwok KL, Mohammad KN, Chan PKS, Chong KC (2021) Short-term association among meteorological variation, outdoor air pollution and acute bronchiolitis in children in a subtropical setting. Thorax abril de 76(4):360–369. 10.1136/thoraxjnl-2020-215488
10. Mohr LB, Luo S, Mathias E, Tobing R, Homan S, Sterling D (2008) Influence of Season and Temperature on the Relationship of Elemental Carbon Air Pollution to Pediatric Asthma Emergency Room Visits. J Asthma janeiro de 45(10):936–943. 10.1080/02770900802404082
11. Kim SE, Lim YH, Kim H (2015) Temperature modifies the association between particulate air pollution and mortality: A multi-city study in South Korea. Sci Total Environ agosto de 524–525:376–383. 10.1016/j.scitotenv.2015.03.137
12. Tian L, Liang F, Guo Q, Chen S, Xiao S, Wu Z et al (2018) The effects of interaction between particulate matter and temperature on mortality in Beijing, China. Environ Sci Process Impacts 20(2):395–405. 10.1039/C7EM00414A
13. Ma Y, Zhou L, Chen K (2020) Burden of cause-specific mortality attributable to heat and cold: A multicity time-series study in Jiangsu Province, China. Environ Int novembro de 144:105994. 10.1016/j.envint.2020.105994
14. Brasil - Ministério da Saúde (2025) Departamento de Informática do SUS - Tabnet [Internet]. Disponível em: https://datasus.saude.gov.br/informacoes-de-saude-tabnet/
15. Couto LDOD, Jacobson LDSV, Périssé ARS, Hacon SDS (2024) Identifying high occurrence areas of hospitalization and mortality from respiratory diseases in the Brazilian Legal Amazon: a space-time analysis. Cad Saúde Pública 40(11):e00148023. 10.1590/0102-311xen148023
16. Chen S, Dong H, Li M, Huang L, Lin G, Liu Q et al (2022) Interactive Effects Between Temperature and $PM_{2.5}$ on Mortality: A Study of Varying Coefficient Distributed Lag Model — Guangzhou, Guangdong

Province, China, 2013–2020. China CDC Wkly 4(26):570–576. 10.46234/ccdcw2022.124

17. Clarke K, Rivas AC, Milletich S, Sabo-Attwood T, Coker ES (2022) Prenatal Exposure to Ambient PM2.5 and Early Childhood Growth Impairment Risk in East Africa. Toxics 18 de novembro de 10(11):705. 10.3390/toxics10110705
18. Instituto Nacional de Pesquisas Espaciais. Programa Queimadas do INPE [Internet] (2022) SISAM - Sistema de Informações Ambientais Integrado a Saúde. Disponível em: https://dataserver-coids.inpe.br/queimadas/queimadas/sisam/
19. Schneider R, Arima E, Veríssimo A, Barreto P, Souza CM (2000) Amazônia Sustentável: Limitantes e Oportunidades para o Desenvolvimento Rural [Internet]. 10.13140/RG.2.1.3667.0889
20. Instituto Nacional de Pesquisas Espaciais. Programa Queimadas do INPE [Governamental] [Internet] (2023) [citado 1 de abril de 2023]. TerraBrasilis. Disponível em: https://terrabrasilis.dpi.inpe.br/queimadas/portal/
21. R Core Team. R: A language and environment for statistical computing [Internet]. Vienna, Austria (2024) Disponível em: https://www.R-project.org/
22. Van Donkelaar A, Hammer MS, Bindle L, Brauer M, Brook JR, Garay MJ et al (2021) Monthly Global Estimates of Fine Particulate Matter and Their Uncertainty. Environ Sci Technol 16 de novembro de 55(22):15287–15300. 10.1021/acs.est.1c05309
23. qgis (2022) Qgis software
24. Busch P, Rocha P, Lee KJ, Cifuentes LA, Tai XH (2024) Short-term exposure to fine particulate pollution and elderly mortality in Chile. Commun Earth Environ 28 de agosto de 5(1):469. 10.1038/s43247-024-01634-x
25. Do Carmo CN, Alves MB, Hacon SDS (2013) Impact of biomass burning and weather conditions on children's health in a city of Western Amazon region. Air Qual Atmos Health junho de 6(2):517–525. 10.1007/s11869-012-0191-6
26. Larson PS, Espira L, Glenn BE, Larson MC, Crowe CS, Jang S et al (2022) Long-Term PM2.5 Exposure Is Associated with Symptoms of Acute Respiratory Infections among Children under Five Years of Age in Kenya, 2014. Int J Environ Res Public Health 22 de fevereiro de 19(5):2525. 10.3390/ijerph19052525
27. Requia WJ, Amini H, Mukherjee R, Gold DR, Schwartz JD (2021) Health impacts of wildfire-related air pollution in Brazil: a nationwide study of more than 2 million hospital admissions between 2008 and 2018. Nat Commun 12 de novembro de 12(1):6555. 10.1038/s41467-021-26822-7
28. Moraga P (2020) Geospatial health data: modeling and visualization with R-INLA and Shiny. CRC Press/Taylor & Francis Group, Boca Raton, p 274
29. Gomez-Rubio V (2020) Bayesian Inference with INLA. CRC Press LLC, Milton, p 1
30. Simpson D, Rue H, Riebler A, Martins TG, Sørbye SH (2017) Penalising Model Component Complexity: A Principled, Practical Approach to Constructing Priors. Stat Sci 1 de fevereiro de 32(1). 10.1214/16-STS576

31. Gasparrini A, Armstrong B, Kenward MG (2010) Distributed lag non-linear models. Stat Med 20 de setembro de 29(21):2224–2234. 10.1002/sim.3940
32. Mebrahtu TF, Santorelli G, Yang TC, Wright J, Tate J, McEachan RR (2023) The effects of exposure to NO2, PM2.5 and PM10 on health service attendances with respiratory illnesses: A time-series analysis. Environ Pollut setembro de 333:122123. 10.1016/j.envpol.2023.122123
33. Gasparrini A, Guo Y, Hashizume M, Kinney PL, Petkova EP, Lavigne E et al (2015) Temporal Variation in Heat–Mortality Associations: A Multicountry Study. Environ Health Perspect novembro de 123(11):1200–1207. 10.1289/ehp.1409070
34. VanderWeele TJ, Knol MJ (2014) A Tutorial on Interaction. Epidemiol Methods. 1 de janeiro de. ;3(1). 10.1515/em-2013-0005
35. Lowe R, Lee SA, O'Reilly KM, Brady OJ, Bastos L, Carrasco-Escobar G et al (2021) Combined effects of hydrometeorological hazards and urbanisation on dengue risk in Brazil: a spatiotemporal modelling study. Lancet Planet Health abril de 5(4):e209–e219. 10.1016/S2542-5196(20)30292-8
36. Rue H, Martino S, Chopin N (2009) Approximate Bayesian Inference for Latent Gaussian models by using Integrated Nested Laplace Approximations. J R Stat Soc Ser B Stat Methodol 1 de abril de 71(2):319–392. 10.1111/j.1467-9868.2008.00700.x
37. Zhou L, Wang Y, Wang Q, Ding Z, Jin H, Zhang T et al (2023) The interactive effects of extreme temperatures and PM2.5 pollution on mortalities in Jiangsu Province, China. Sci Rep 10 de junho de 13(1):9479. 10.1038/s41598-023-36635-x
38. Fernandes T, Hacon SDS, Novais JWZ, Sguarezi SB, Da Silva CJ, Alcântara LCS et al Poluição do ar e efeitos na saúde de crianças na Amazônia paraense: uma análise bibliométrica. Res Soc Dev. 25 de fevereiro de 2019;8(4):e4984907. 10.33448/rsd-v8i4.907
39. Agudelo-Castañeda DM, Calesso Teixeira E, Alves L, Fernández-Niño JA, Rodríguez-Villamizar LA (2019) Monthly-Term Associations Between Air Pollutants and Respiratory Morbidity in South Brazil 2013–2016: A Multi-City, Time-Series Analysis. Int J Environ Res Public Health 9 de outubro de 16(20):3787. 10.3390/ijerph16203787
40. Ju X, Yimaer W, Du Z, Wang X, Cai H, Chen S et al (2023) The impact of monthly air pollution exposure and its interaction with individual factors: Insight from a large cohort study of comprehensive hospitalizations in Guangzhou area. Front Public Health 21 de março de 11:1137196. 10.3389/fpubh.2023.1137196
41. Rau A, Abadi A, Fiecas MB, Gwon Y, Bell JE, Berman JD (2023) Nationwide assessment of ambient monthly fine particulate matter ($PM_{2.5}$) and the associations with total, cardiovascular and respiratory mortality in the United States. Environ Res Health 1 de junho de 1(2):025001. 10.1088/2752-5309/ac9b7e
42. Instituto Nacional de Pesquisas Espaciais. Monitoramento do Desmatamento da Floresta Amazônica Brasileira por Satélite [Internet] (2024) Disponível em: https://queimadas.dgi.inpe.br/queimadas/bdqueimadas

43. Marengo JA, Tomasella J, Alves LM, Soares WR, Rodriguez DA (2011) The drought of 2010 in the context of historical droughts in the Amazon region: DROUGHT AMAZON 2010. Geophys Res Lett junho de 38(12). n/a-n/a 10.1029/2011GL047436
44. Marengo JA, Tomasella J, Soares WR, Alves LM, Nobre CA (2012) Extreme climatic events in the Amazon basin: Climatological and hydrological context of recent floods. Theor Appl Climatol janeiro de 107(1–2):73–85. 10.1007/s00704-011-0465-1
45. Espinoza JC, Marengo JA, Ronchail J, Carpio JM, Flores LN, Guyot JL (2014) The extreme 2014 flood in south-western Amazon basin: the role of tropical-subtropical South Atlantic SST gradient. Environ Res Lett 1 de dezembro de 9(12):124007. 10.1088/1748-9326/9/12/124007
46. Moulin CSA Deforestation between capacity building and policy dismantling: a socio-legal interpretation of the Action Plan for Prevention and Control of Deforestation in the Brazilian Amazon, 2004–2022 [Doutorado Direto em Filosofia e Teoria Geral do Direito] [Internet]. [São Paulo]: Universidade de São Paulo; 2024 [citado 20 de maio de 2024]. Disponível em: https://www.teses.usp.br/teses/disponiveis/2/2139/tde-15042024-155853/ doi:10.11606/T.2.2024.tde-15042024-155853
47. Chu Y, Liu Y, Li X, Liu Z, Lu H, Lu Y et al (2016) A Review on Predicting Ground PM2.5 Concentration Using Satellite Aerosol Optical Depth. Atmos 14 de outubro de 7(10):129. 10.3390/atmos7100129
48. Oliveira IND, Oliveira BFAD, Silveira IHD, Machado LMG, Villardi JWR, Ignotti E (2023) Air pollution from forest burning as environmental risk for millions of inhabitants of the Brazilian Amazon: an exposure indicator for human health. Cad Saúde Pública 39(6):e00131422. 10.1590/0102-311xen131422
49. Urrutia-Pereira M, Varanda Rizzo L, José Chong-Neto H, Solé D (2021) Impact of exposure to smoke from biomass burning in the Amazon rain forest on human health. J Bras Pneumol 31 de outubro de e20210219. 10.36416/1806-3756/e20210219
50. Busch P (2024) Short-term exposure to fine particulate pollution and elderly mortality in Chile
51. Millstein J, Gilliland F, Berhane K, Gauderman WJ, McConnell R, Avol E et al (2004) Effects of Ambient Air Pollutants on Asthma Medication Use and Wheezing among Fourth-Grade School Children from 12 Southern California Communities Enrolled in The Children's Health Study. Arch Environ Health Int J outubro de 59(10):505–514. 10.1080/00039890409605166
52. Boing AF, deSouza P, Boing AC, Kim R, Subramanian SV (2022) Air Pollution, Socioeconomic Status, and Age-Specific Mortality Risk in the United States. JAMA Netw Open 24 de maio de 5(5):e2213540. 10.1001/jamanetworkopen.2022.13540
53. Li T, Zhang Y, Wang J, Xu D, Yin Z, Chen H et al (2018) All-cause mortality risk associated with long-term exposure to ambient PM2·5 in China: a cohort study. Lancet Public Health outubro de 3(10):e470–e477. 10.1016/S2468-2667(18)30144-0
54. Rodriguez-Villamizar LA, Belalcazar-Ceron LC, Castillo MP, Sanchez ER, Herrera V, Agudelo-Castañeda DM Avoidable mortality due to long-term exposure to PM2.5 in Colombia 2014–2019.

Environ Health. 24 de dezembro de 2022;21(1):137. 10.1186/s12940-022-00947-8

55. Xue T, Tong M, Li J, Wang R, Guan T, Li J et al (2022) Estimation of stillbirths attributable to ambient fine particles in 137 countries. Nat Commun 29 de novembro de 13(1):6950. 10.1038/s41467-022-34250-4

Figures

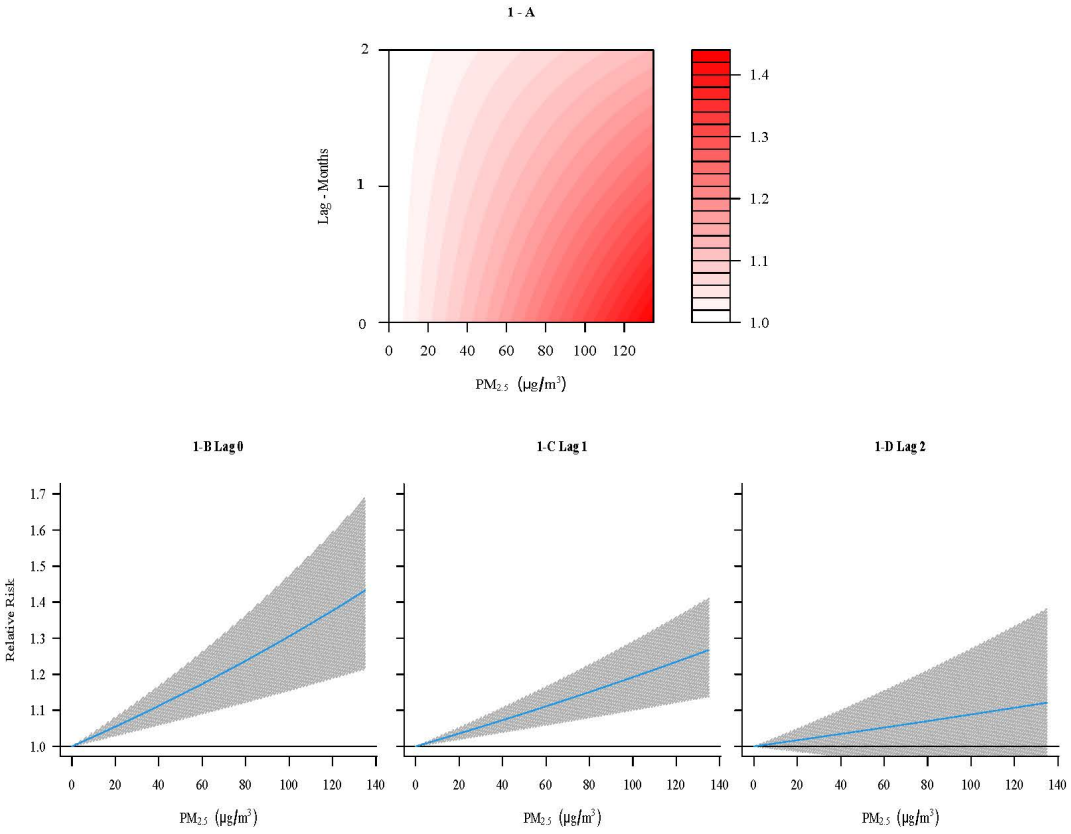


Figure 1

Figure 1 A - D: Lagged effects of $PM_{2.5}$ exposure under high temperature conditions on the risk of hospitalization for respiratory diseases in children and adolescents.

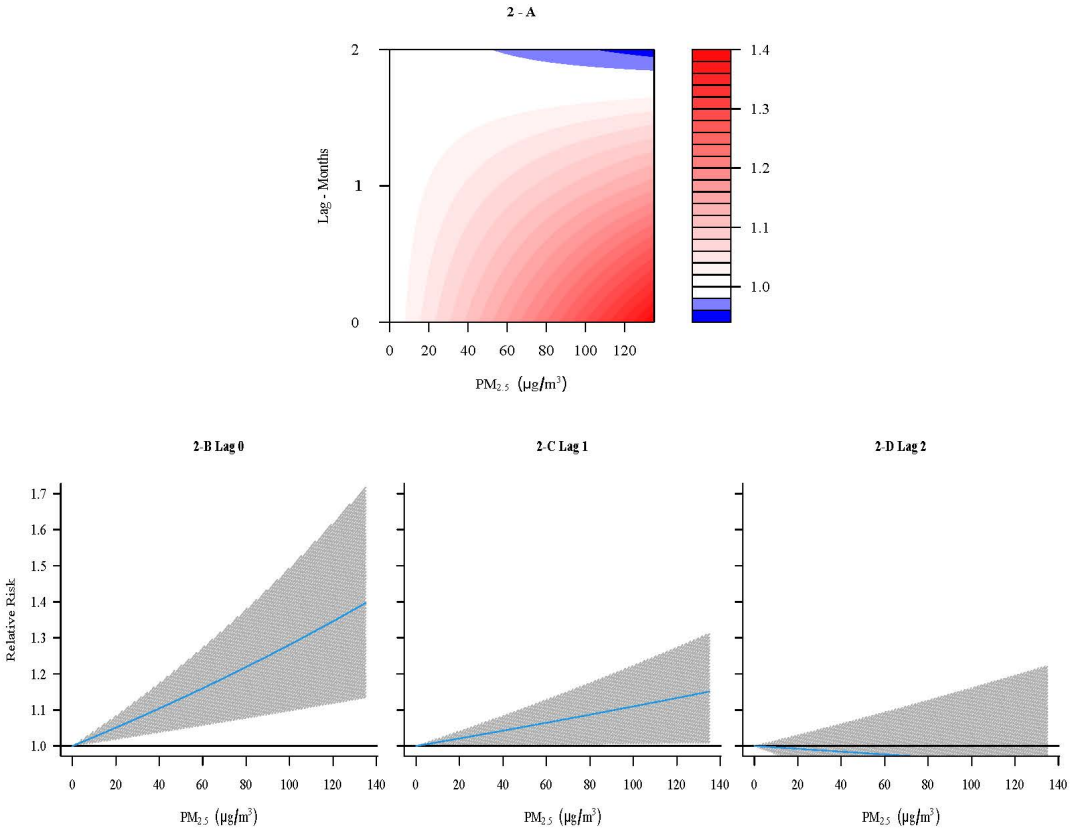


Figure 2

Figure 2 A - D: Lagged effects of $PM_{2.5}$ exposure under high temperature conditions on the risk of mortality for respiratory diseases in elderlies.

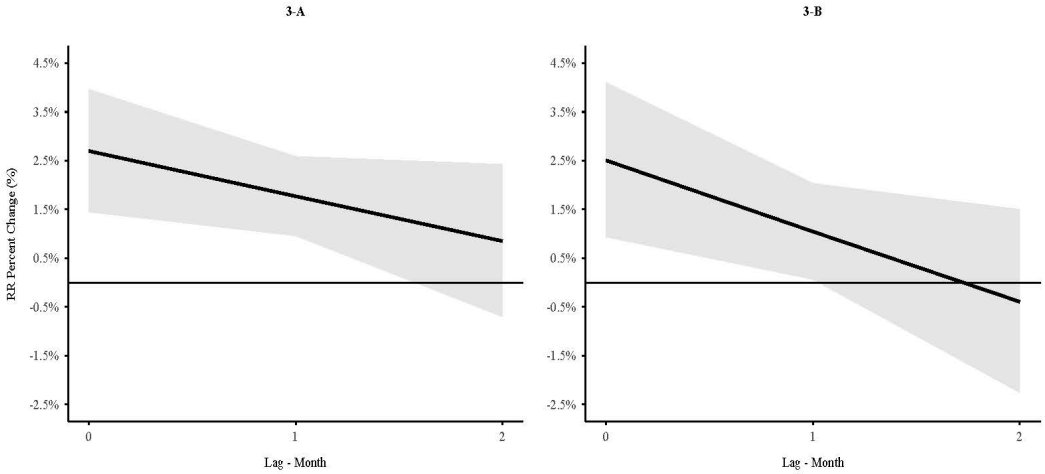


Figure 3

Figure 3: Lagged percentage change in hospitalization and mortality risk per 10 μg/m³ increase in $PM_{2.5}$ under high temperature conditions. A: Percentage change in hospitalization risk for children and

adolescents; B: Percentage change in mortality risk for the elderly.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- 01.2supplementarymaterialvok.docx