



Amazonian Biomass Burning Drives Regional Air Pollution and Premature Mortality in South America

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Abstract. Biomass burning is a major source of atmospheric trace gases and aerosols, and Amazonian fires are among its most intense sources globally, with documented impacts on the carbon cycle and regional climate. Long-range transport of Amazonian smoke toward Andean and coastal cities has been reported in individual case studies, but its continental-scale atmospheric footprint, and how it translates into population exposure and health outcomes across South America, remains poorly quantified.

- 5 Here, we address this gap by combining Lagrangian plume tracking, regional chemical transport modeling (WRF-Chem), satellite fire data, and health-impact functions to characterize how Amazonian burning perturbs atmospheric composition across the continent and how that perturbation drives population exposure in major South American cities. We show that Amazonian burning generates a recurrent, continental-scale smoke season during the austral dry season (June-November), with transport corridors carrying fire-derived PM_{2.5} to cities along the Andes, the Pacific coast, southeastern Brazil, and the southern cone.
- 10 This atmospheric perturbation is substantial: WRF-Chem simulations indicate 50-100 $\mu\text{g m}^{-3}$ of added PM_{2.5} across the basin during peak months, translating into an estimated 33,000 (95% CI: 19,700-48,900) excess premature deaths annually across South America. Fire trends reveal strong geographic contrasts linked to land-use dynamics and governance, and countries that have already curbed Amazonian fires show that the tools to reduce this burden exist wherever political will meets social awareness. As climate change reshapes fire regimes and these transport corridors, whether governance and mitigation efforts can
- 15 keep pace with the resulting burden remains an urgent open question.



1 Introduction

The Amazon rainforest is one of the most important ecosystems on Earth and a fundamental component of the South American climate system. As the largest tropical rainforest in the world, it plays a central role in regulating the global carbon cycle, regional hydrology, and atmospheric circulation through carbon storage, evapotranspiration, and moisture recycling (Lovejoy and Nobre, 2018; Gatti et al., 2021). Disturbances to the Amazon therefore have implications that extend far beyond the forest itself.

Over recent decades, deforestation, agricultural expansion, and land-use change have intensified fire activity across the basin (Liévano-Latorre et al., 2021). Amazonian fires are often discussed in terms of ecosystem degradation, carbon emissions, and climate feedbacks, but biomass burning is also a major source of atmospheric pollution: it releases large quantities of particulate matter and trace gases that affect air quality, atmospheric composition, and human health across South America (Lelieveld et al., 2015; McDuffie et al., 2021). Amazonian fires are therefore as much a continental-scale air-quality and public-health issue as a local environmental one.

This burning follows a strong and recurrent seasonal cycle. Active-fire detections from the Visible Infrared Imaging Radiometer Suite (VIIRS) active-fire product — referred to as hotspots in the figures below, a term we use interchangeably with active fires throughout this study (see Sect. 2.1 for the dataset and detection criteria) — show a pronounced intensification during the austral winter and spring (June-August, JJA, and September-November, SON), when burning expands across the southern and eastern Amazon and the broader arc of deforestation (Fig. 1), consistent with previous studies linking dry-season burning to land-use change, agricultural expansion, and climate variability across Amazonia (Aragão et al., 2018; Lovejoy and Nobre, 2018).

As shown in Fig. S1, South America is characterized by the juxtaposition of the Amazon Basin, the Andes, and densely populated urban regions across diverse climatic and topographic settings. Although the Andes act as a barrier to near-surface transport (Casallas et al., 2024), deep convection and large-scale circulation frequently inject smoke into the free troposphere, allowing Amazonian pollutants to travel hundreds to thousands of kilometers from their source (Freitas et al., 2005; Reddington et al., 2015; Aragão et al., 2018). Atmospheric processes within the basin can therefore influence air quality across much of the continent.

Previous studies have documented long-range smoke transport from Amazonian and adjacent biomass-burning regions affecting cities along the Andes, the Pacific coast, southeastern Brazil, and the southern cone (e.g., Gonzalez et al., 2018; Casallas et al., 2022, 2023b). Major urban centers, including Bogotá (Colombia), Quito (Ecuador), Lima (Peru), Cochabamba (Bolivia), São Paulo (Brazil), Santiago (Chile), Buenos Aires (Argentina), and Montevideo (Uruguay), have all been identified as potentially influenced by transported smoke under favorable meteorological conditions (Reddington et al., 2015; González et al., 2026). Yet while individual transport episodes are documented, the cumulative contribution of Amazonian fires to regional PM_{2.5} exposure and public health across South America remains poorly quantified.

This gap matters because so many people live along Amazonian outflow pathways. South America is home to roughly 459 million people across the 14 countries analyzed here (Table 1), and five of its largest urban agglomerations alone (São Paulo,

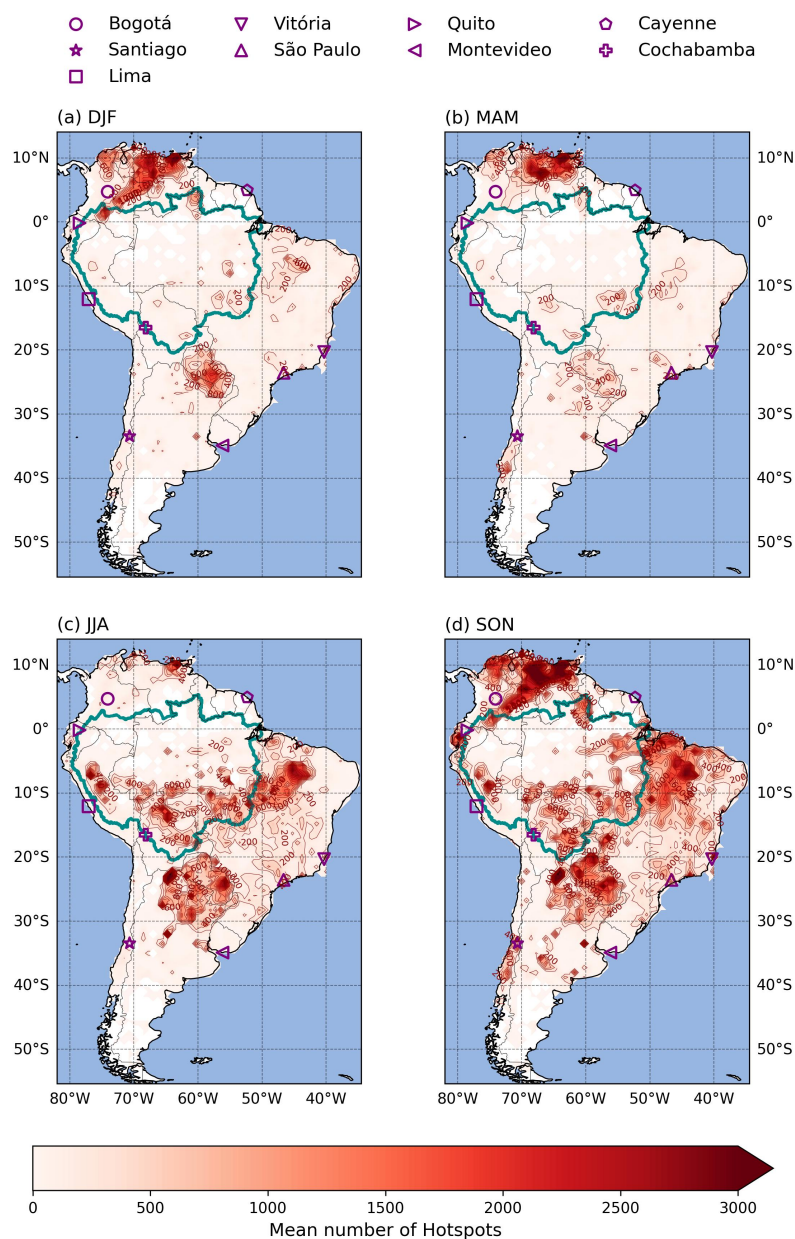


Figure 1. Seasonal mean (2013-2023) distribution of VIIRS fire hotspot detections across South America for (a) December-February (DJF), (b) March-May (MAM), (c) June-August (JJA), and (d) September-November (SON) during the study period (2013-2023). Shaded colors and contours indicate the mean number of hotspot detections. The green contour delineates the biogeographic Amazon Basin, and symbols indicate the urban locations included in the air-quality, transport, and health-impact analyses.



50 ≈ 21.7 million inhabitants; Buenos Aires, ≈ 15.0 million; Bogotá, ≈ 10.6 million; Lima, ≈ 10.4 million; and Santiago, ≈ 6.7 million) together house about 64 million people (United Nations, 2019). $\text{PM}_{2.5}$ exposure is well established to increase risks of cardiovascular and respiratory disease, premature mortality, and a range of chronic conditions (Burnett et al., 2018, 2022; Pozzer et al., 2023). Yet how much Amazonian fires contribute to that exposure, how the contribution varies geographically, and the resulting health burden all remain uncertain.

55 Quantifying the specific contribution of Amazonian fires to urban air pollution is challenging: smoke plumes travel long distances, interact with complex terrain, and mix with emissions from other fires and anthropogenic sources (Artaxo et al., 2013; Casallas et al., 2023a). Traditional fixed-location (Eulerian) approaches struggle to disentangle these overlapping influences, particularly during widespread burning (Freitas et al., 2005). Lagrangian plume-tracking instead follows the transport and evolution of smoke plumes directly (Stohl and Seibert, 2002), enabling source-receptor relationships to be examined across
60 large spatial scales, though plume interactions and source mixing still complicate attribution.

In this study, we combine a Lagrangian plume-tracking framework with regional chemical transport modeling using WRF-Chem (Grell et al., 2005, 2010; Skamarock et al., 2019); the datasets and methods used throughout are described in Sect. 2 below. First, we identify the dominant transport pathways linking smoke plumes from Amazonian fires to major South American cities and characterize their seasonal behavior. Second, we use targeted WRF-Chem sensitivity simulations to isolate the
65 contribution of Amazonian fire emissions to $\text{PM}_{2.5}$ exposure across the continent. Third, we estimate the associated health burden and evaluate how it varies among countries. Finally, we place these results in the context of recent fire trends, protected areas, and land-use governance across the basin.

By linking fire activity in one of Earth's most important ecosystems to air quality, population exposure, and public health across an entire continent, this study positions Amazonian fires as a continental driver of atmospheric pollution and mortality,
70 in addition to their already well-quantified impact on the global carbon cycle.

2 Data and Methods

2.1 CAMS Reanalysis, ACAG, and Active Fires datasets

We utilize the Copernicus Atmosphere Monitoring Service (CAMS) Reanalysis dataset to evaluate atmospheric composition over northern South America. CAMS is a comprehensive global reanalysis of atmospheric constituents produced by the Euro-
75 pean Centre for Medium-Range Weather Forecasts (ECMWF). It integrates satellite retrievals, including aerosol optical depth (AOD), total column carbon monoxide (TCCO), nitrogen dioxide (NO_2), and ozone, into a global data assimilation system using ECMWF's Integrated Forecasting System (IFS) with a coupled aerosol–chemistry model. This framework produces spatially and temporally consistent three-dimensional fields of atmospheric composition from 2003 onward, at a horizontal resolution of approximately 80 km ($0.75^\circ \times 0.75^\circ$) and a 3-hourly temporal frequency (Inness et al., 2019).

80 In this study, we analyze CAMS data for the period 2013–2023 for $\text{PM}_{2.5}$, PM_{10} , and TCCO, consistent with the availability of surface observations and fire activity diagnostics used throughout the analysis. CAMS incorporates aerosol dynamics,



dry and wet deposition, and biomass burning emissions from the Global Fire Assimilation System (GFAS v1.2), along with improved representations of biogenic and anthropogenic emissions (Inness et al., 2019).

Additionally, we utilize version 6 of the Atmospheric Composition Analysis Group (ACAG) dataset (van Donkelaar et al., 2021; Shen et al., 2024), which provides global estimates of ground-level PM_{2.5} concentrations. This dataset is produced by combining satellite-based AOD retrievals, chemical transport model simulations (notably GEOS-Chem), and geographically weighted regression incorporating geophysical and ground-based monitoring data. For this study, we use the monthly product at a spatial resolution of 0.01° for the year 2019.

According to van Donkelaar et al. (2021), the dataset demonstrates strong global performance, with cross-validated R² values of 0.90 and mean absolute error of 3.6 $\mu\text{g m}^{-3}$ when compared against ground observations. However, the authors note higher uncertainties in regions with sparse monitoring data (e.g., parts of Africa, Southeast Asia, and Latin America). Specifically for South America, validation studies (Rodriguez-Villamizar et al., 2022) report acceptable performance in urban areas, with mean biases around 1.7 $\mu\text{g m}^{-3}$ and normalized mean bias below 25% for the largest Colombian cities. Nonetheless, extensive areas (particularly in the Caribbean, the Eastern Plains, and the Amazon Basin) lack monitoring coverage, which introduces additional uncertainty into the interpolated estimates.

Active fire (hotspot) information was obtained from VIIRS aboard the Suomi National Polar-orbiting Partnership (Suomi NPP) satellite for the period January 2013 to December 2023; data from the NOAA-20 and NOAA-21 satellites, which also carry VIIRS sensors, were not used. The VIIRS active fire product identifies thermal anomalies associated with biomass burning using infrared observations from polar-orbiting satellites, providing near-global coverage with a native spatial resolution of approximately 375 m and daily temporal sampling based on one to two satellite overpasses per day, depending on latitude (NASA FIRMS, 2023). For brevity, figure axes, panel annotations, and colorbars throughout this study may label these counts simply as “fires”; this should always be read as shorthand for active fire (hotspot) detections rather than discrete fire events, since a single fire can generate many detections across space and time.

Fire detections were initially retrieved as point observations characterized by acquisition time and geographic coordinates; only detections flagged as vegetation fires were retained, excluding those labeled as volcanoes, other static land sources, or offshore activity. To facilitate direct comparison with gridded air quality fields, individual fire detections were mapped to the nearest grid cell of the CAMS spatial grid using geographic proximity. Daily hotspot counts were then computed by aggregating the number of fire detections within each grid cell for each day (Quishpe-Vásquez et al., 2024). This procedure yields a gridded daily fire activity dataset at the same spatial resolution as the CAMS reanalysis, allowing consistent analyses of the relationship between biomass burning and atmospheric composition.

2.2 Air quality stations and quality control

Surface air-quality observations were used to characterize urban particulate matter concentrations and to evaluate the performance of CAMS, ACAG, and WRF-Chem. Cities were selected based on three criteria: (i) population exceeding one million inhabitants or regional relevance, (ii) the existence of an operational surface air-quality monitoring network, and (iii) open access to data covering a substantial fraction of the study period (2013-2023). Based on these criteria, nine cities were included:



Bogotá (Colombia), Quito (Ecuador), Lima (Peru), São Paulo and Vitória (Brazil), Santiago (Chile), Montevideo (Uruguay), Cayenne (French Guiana), and Cochabamba (Bolivia). The geographic distribution of the cities is shown in Fig. S1.

Hourly measurements were obtained directly from the official environmental agencies or national monitoring platforms of each city. The analysis focuses on particulate matter, using $PM_{2.5}$ for all cities except Cochabamba, where only PM_{10} observations were available consistently over the study period. The study period spans 2013-2023 where possible, although data availability varies by city (e.g., Montevideo from 2014 onward, São Paulo from 2015-2022).

A quality-control procedure was applied to all hourly observations prior to analysis. Outliers were identified using Chauvenet's criterion, which has proven effective for detecting extreme deviations in environmental time series while preserving the statistical integrity of the data (Lishu et al., 2015). To assess robustness, results were compared against other standard approaches (interquartile range, median absolute deviation, and level-shift detection) using the Anomaly Detection Toolkit (Zhao et al., 2020). Differences among methods were minimal, with discrepancies in detected outliers below 2.5%.

Following quality control, hourly concentrations were aggregated across stations within each city to produce a single representative urban time series per pollutant. Only background, urban, and suburban stations were used; traffic- and industrial-influenced stations were excluded to ensure consistency with the spatial representativeness of the gridded model products. Stations were required to meet a minimum data completeness threshold of 75% on an annual basis to be included (Singh et al., 2021).

Daily mean concentrations were calculated using 24-hour averages for $PM_{2.5}$ and PM_{10} . These daily values were subsequently aggregated to monthly and annual means for comparison with CAMS, ACAG, and WRF-Chem outputs and for use in seasonal and inter-annual analyses. Sensitivity tests including traffic and industrial stations did not materially affect the results, particularly in the model evaluation and plume attribution analyses, and therefore do not alter the conclusions presented here.

2.3 Mortality and Population Datasets

Mortality data for South America in 2020 were obtained from the Global Burden of Disease (GBD) (GBD 2019 Risk Factors Collaborators, 2020). We extracted annual death counts by country and 5-year age groups for deaths by non-communicable diseases (NCD) and also lower respiratory infections (LRI). These death counts were distributed onto a grid via use of gridded population data for 2020 from the NASA Socioeconomic Data and Applications Center (SEDAC) (Center for International Earth Science Information Network - CIESIN - Columbia University, 2016).

For a small number of overseas territories without independent entries in the GBD database (e.g., French Guiana and other French, British, and Dutch Caribbean and South American territories), baseline NCD and LRI mortality rates were assumed to match those of their administering country (France, the United Kingdom, the Netherlands, etc.). This assumption may not accurately reflect the true baseline health conditions of these territories and represents an additional source of uncertainty in the country-level mortality estimates for the affected locations.



2.4 Lagrangian Tracking of Pollution Plumes

The method begins by applying a threshold to the pollutant field, identifying regions where concentrations exceed a predefined limit. For PM, this threshold corresponds to the 90th percentile of the pollutant's spatiotemporal distribution. These thresholds were refined based on previous studies and empirical testing to best capture major pollution episodes (Casallas et al., 2024).

The resulting binary mask is processed using a Euclidean distance transform, which highlights the central regions of high-concentration anomalies. From this field, we extract local maxima using a spatial-temporal footprint that defines the expected size and duration of relevant events. These maxima serve as markers for a 3D watershed segmentation performed using the scikit-image library (Virtanen et al., 2020). Each segmented region is assigned a unique label and is treated as an individual plume.

Once initial labels are assigned, the algorithm evaluates object evolution across time steps (3-hourly for CAMS). Continuity is assessed based on spatial overlap and proximity: if a region at time $t + 1$ overlaps significantly ($>50\%$) with a labeled object from time t , it retains the same label; otherwise, a new label is assigned (Casallas et al., 2025). This approach allows the method to track the full lifecycle of pollution plumes, from formation through transport and dissipation. The tracker outputs a labeled 3D field where each integer label corresponds to a distinct pollution object, enabling robust trajectory analysis.

To focus specifically on pollution plumes originating from biomass burning within the Amazon, we apply a post-processing filtering step to the labeled objects. For each identified plume, we:

1. Determine the time of its initial appearance.
2. Extract its spatial extent at onset (i.e., the first timestamp when the object is detected).
3. Assess the percentage of its area that overlaps with a predefined Amazon Basin (green outline in Fig. S1).

An object is retained only if at least 50% of its initial extent lies within the Amazon region. This geographic constraint ensures that only plumes with a clear Amazonian origin are included in the analysis. All other plumes are excluded by setting their object labels to zero in the dataset. The resulting filtered dataset is then used in subsequent analyses, such as quantifying long-range pollutant transport and evaluating fire-related impacts on urban air quality across South America. It is important to note that this method has been validated in previous studies (Casallas et al., 2024; Quishpe-Vásquez et al., 2024; González et al., 2026), demonstrating its reliability and adaptability across pollutants, datasets, and spatial domains. It provides a robust, reproducible framework for quantifying the influence of specific emission sources (e.g., Amazonian fires) on regional air quality.

2.5 City-level diagnostics of fire-related pollution plume impacts

To quantify the contribution of long-range pollution transport to urban air quality degradation across South America, we developed a diagnostic framework that links Lagrangian-tracked pollution plumes to observed peaks in ground-level concentrations. For each city, a reference point was defined using the geographic coordinates of air quality monitoring stations (see Table S1). Using the plume labels from the Lagrangian tracker, we identified objects that passed over the city grid point within a 3-day



window centered on locally observed peaks in $PM_{2.5}$ or PM_{10} concentrations. This approach ensures that modeled plume arrivals from CAMS are temporally aligned with real-world pollution episodes, reinforcing the interpretation that fire-related transport events are captured correctly.

To retain only meaningful events, we applied a combination of spatial, temporal, and observational filters. Specifically, we required that: (i) the plume span more than three grid cells, ensuring physical significance; (ii) it persist for at least four consecutive time steps (12 hours in CAMS), indicating temporal coherence; and (iii) its arrival coincide with a significant ground-based PM peak, confirming its impact on local air quality. When all criteria were met, the plume was considered to have reached the city. Its unique identifier and time of arrival were recorded. This method was systematically applied across all cities and seasons, resulting in a robust city-season-object dataset for analyzing the characteristics and frequency of fire-driven pollution episodes.

To further assess the linkage between fire activity and pollution variability, grid-point Pearson correlation coefficients were computed between daily fire hotspot counts and daily plume-masked concentrations of each pollutant. Correlations were calculated along the time dimension using seasonal subsets (DJF, MAM, JJA, and SON), with missing values excluded. Statistical significance was evaluated using the corresponding Pearson test p-values, and only correlations significant at the 95% confidence level were emphasized in the analysis. This correlation-based approach provides an independent line of evidence linking fire activity to plume-driven pollution variability.

As an internal consistency and quality-control check, we also examined correlations between plume objects of TCCO and those of $PM_{2.5}$ and PM_{10} . TCCO is a well-established tracer of biomass burning emissions and is co-emitted with particulate matter during combustion processes (e.g., Meo et al., 2021). Therefore, strong positive correlations between TCCO plumes and particulate plumes are expected if the detected objects genuinely represent fire-related pollution. The presence of such correlations provides an important sanity check on the plume identification and tracking framework, confirming that the extracted objects are physically consistent with biomass burning emissions rather than spurious features driven solely by meteorology or background variability (Bela et al., 2022; Yurganov and Rakitin, 2022).

To assess the characteristics of the pollution plumes, we calculated the distance and direction between each plume's origin and the city it reached. The plume origin was estimated using the centroid of the object at the first time step it appeared. Distances were computed using geodesic methods (WGS84 ellipsoid), and the bearing angle was used to classify plumes into one of eight cardinal directions (Casallas et al., 2024). All diagnostic information was compiled into city-season matrices for comparative analysis. A distance matrix captured the average origin-to-destination length of the plumes, while directional frequency matrices summarized the proportion of events arriving from each compass sector across the four meteorological seasons. These data products formed the basis for evaluating both spatial and temporal variability in regional pollution contributions.

This methodological framework not only enables robust linkage between observed air quality episodes and upwind emission sources but also provides a quantitative basis to assess the reach and recurrence of fire-related pollution events. The robustness of the analysis was further supported by sensitivity tests on plume detection thresholds, which showed consistent qualitative results under alternative parameter settings.



2.6 Estimation of Fire-Attributable Pollution Using Baseline Method

To approximate the contribution of fire-related emissions to air pollution levels, we apply a baseline-based approach inspired by methods used in previous epidemiological and exposure studies (Johnston et al., 2012; Cusworth et al., 2018). In this framework, baseline pollution levels represent the minimum pollution expected in the absence of fire events. By comparing observed pollution levels against this baseline, we estimate the fire-related pollution enhancement.

In our analysis, the baseline is computed from the daily-mean surface observations at the study cities ($PM_{2.5}$, and PM_{10} in Cochabamba), for the years with available station records (2018 to 2023), whereas the concentrations during plume arrival are taken from the CAMS $PM_{2.5}$ and PM_{10} fields used for the plume identification. For each city and year, the station time series is processed to compute weekly averages (Sunday to Saturday). These weekly values are then sorted in ascending order to identify the least polluted weeks of the year, under the assumption that these represent periods with little to no influence from fire emissions.

We compute a set of baseline values by averaging the lowest weekly concentrations (M), where M ranges from 1 to 4. This results in four alternative baseline estimates per city-year (Fig. S2). The fire-related contribution is then approximated as the difference between the CAMS pollution values at plume arrival and the selected station-based baseline.

After evaluating the different baseline strategies, we chose to proceed with baseline $M=2$, as in Cusworth et al. (2018). However, we note that the overall results and trends are robust across all values of M tested. This method is applied uniformly across cities, using $PM_{2.5}$ for most locations, and PM_{10} in Cochabamba, Bolivia, due to local data availability and monitoring standards. Because the baseline is station-based and the plume values come from CAMS, the resulting enhancement also includes any systematic difference between CAMS and the stations (evaluated in the Supplement), and it is available only for 2018–2023.

2.7 Simulation Setup and Experiments

We employed the WRF-Chem model, Version 4.2 (Skamarock et al., 2019), with its integrated chemistry module (Grell et al., 2005, 2010, 2011). The model configuration consisted of a single domain, using a 30-second time step and producing hourly outputs. The domain extended from $84^{\circ}W$ to $64^{\circ}W$ and from $5^{\circ}S$ to $14^{\circ}N$, with a horizontal resolution of 9 km (Fig. S1). Simulations were performed for the entire year 2020, since it is the year with the largest amount of fire events (Fig. S3). This year was therefore selected to assess the influence of biomass burning and its associated health impacts.

The chemical and physical configurations followed previous studies (Kumar et al., 2016; Gonzalez et al., 2018). The second-generation Regional Acid Deposition Model (RADM2) gas-phase chemistry scheme (Stockwell et al., 1990, 1997) was implemented together with the Goddard Chemistry Aerosol Radiation and Transport (GO-CART) aerosol scheme, using boundary conditions described by Chin et al. (2000) and Ginoux et al. (2001). Secondary organic aerosol formation was represented by the Secondary Organic Aerosol Model (SORGAM) volatility basis set parameterization (Ahmadov et al., 2012). Gas-phase chemistry followed Wang et al. (2015), while photolysis processes were modeled according to Madronich (1987).



245 Regarding the physical parameterizations, the microphysics was represented using the Thompson-Eidhammer scheme (mp_physics = 28) (Thompson et al., 2008; Thompson and Eidhammer, 2014; Iversen et al., 2021). The Rapid Radiative Transfer Model for General Circulation Models (RRTMG) scheme was applied for both longwave and shortwave radiation (Mlawer et al., 1997; Iacono et al., 2008). The surface layer processes followed Monin-Obukhov similarity theory (Monin and Obukhov, 1954), while the planetary boundary layer (PBL) dynamics were simulated using the Yonsei University (YSU) scheme (Hong and
 250 Pan, 1996; Hong et al., 2006), chosen for its robust performance in complex mountainous terrain (Potvin et al., 2020). Surface fluxes were computed using the turbulent kinetic energy (TKE) approach (Skamarock et al., 2019) due to its correct representation of convective core sizes (Casallas et al., 2025), and convective processes were represented through the Grell 3D ensemble cumulus parameterization (Grell and Dévényi, 2002).

Meteorological boundary conditions were obtained from the Global Forecast System (GFS) (Research Data Archive at the
 255 National Center for Atmospheric Research. Computational and Information Systems Laboratory, 2015) at a 0.25° resolution, with 40 vertical levels and 6-hour temporal intervals. Chemical initial and boundary conditions employed the global anthropogenic emissions inventory developed by Antezana Lopez et al. (2025), provided at 1 km² resolution on an annual basis (see their Figure 6 for details). Biogenic emissions were taken from the Model of Emissions of Gases and Aerosols from Nature (MEGAN) v2.1 inventory (Guenther et al., 2012), available at a 0.5° spatial resolution. Fire emissions were incorporated from
 260 the Fire Inventory from NCAR (FINN) v2 database, which provides daily data at a 1 km² resolution (Wiedinmyer et al., 2011; Pfister et al., 2011).

To quantify the contribution of biomass burning to ambient particulate matter concentrations (PM_{2.5}, and PM₁₀ for Cochabamba, Bolivia) and their associated health impacts, three numerical simulations were performed. First, a control simulation was conducted using the full FINN dataset, in which all fire emissions were included. This simulation served as the baseline, providing
 265 annual average pollutant concentrations representative of current conditions (Chowdhury et al., 2022). Next, a sensitivity experiment was carried out in which all fire emissions occurring within the official Amazon Basin (Fig. S1, green outline) were removed from the FINN dataset. The model was then integrated for one full year, allowing direct comparison with the control simulation to quantify the specific contribution of Amazonian fires to air pollutant levels and the resulting health burden.

It is important to note that the Amazon Basin boundary represents an administrative and ecological delineation rather than
 270 a strict atmospheric one. At the model resolution of 9 km, individual grid cells frequently span both Amazonian and non-Amazonian land cover, and emissions originating near the basin margins can be rapidly transported across the boundary by prevailing winds. As a result, fire emissions occurring just outside the formal basin limits may still influence air quality within the Amazon, and vice versa. To ensure physical consistency, emissions from grid cells intersecting the Amazon boundary were therefore treated as part of the Amazon fire category, acknowledging an inherent but unavoidable uncertainty associated with
 275 boundary effects and spatial discretization.

A third simulation was performed in which all fire emissions across South America were excluded. This experiment was designed to estimate the total contribution of continental-scale fires to PM concentrations and to assess the corresponding health impacts attributable to biomass burning throughout the region.



2.8 Evaluation metrics and model-data comparison design

PM_{2.5} concentrations from the ACAG and CAMS reanalysis datasets, and from the WRF-Chem simulation described above, were evaluated against the ground-based station observations described in Sect. 2.2. For most cities, the comparison focused on PM_{2.5}; for Cochabamba, Bolivia, where ground-based PM_{2.5} observations were unavailable, PM₁₀ was used instead and the evaluation was limited to the CAMS dataset.

Dataset and model performance were evaluated using six statistical indicators – mean bias (MB), index of agreement (IOA), normalized mean bias (NMB), Spearman correlation coefficient (Rho – ρ), factor of two (FAC2), and root mean square error (RMSE) – along with three categorical parameters: Hit Rate (HIT), False Alarm Rate (FAR), and Proportion of Correctness (POC) (see Celis et al. (2022) for details on these evaluation metrics). Results were compared against benchmarks for MB, NMB, and RMSE established in previous research (Boylan and Russell, 2006; Emery et al., 2017; Guevara-Luna et al., 2020), and, following standard practice in regional air-quality evaluation studies, acceptable performance was interpreted as ρ above 0.5 (Mogollón-Sotelo et al., 2021), FAC2 values exceeding 50%, and NMB within ± 30 -50%, recognizing that stricter thresholds are difficult to achieve for reanalysis products at coarse resolution over complex urban environments.

The comparison used daily and monthly data for CAMS and monthly and annual averages for ACAG. The ACAG dataset was evaluated for 2020 (results are similar for 2023), enabling direct comparison with the WRF-Chem simulations; the CAMS dataset was assessed for both 2020 and 2023, and only 2023 is shown given the similarity of outcomes and its more recent conditions.

For the WRF-Chem simulation, simulated monthly and annual mean PM_{2.5} concentrations were compared against the same ground-based observations, using the same statistical indicators described above. WRF-Chem was additionally evaluated against the ACAG dataset, which provides a long-term, observation-constrained estimate of PM_{2.5} exposure with associated uncertainty; to ensure consistency between products, the higher-resolution ACAG field was conservatively remapped onto the coarser WRF-Chem grid (Bony et al., 2020). MB, NMB, and RMSE were calculated for both annual and monthly averages, and the categorical metrics (HIT, FAR, POC) were computed at hourly resolution to evaluate the model's ability to capture short-term variations and pollution events.

2.9 Estimating Excess Mortality

We estimated the mortality attributable to PM_{2.5} for each disease and age group at every grid cell in the region ($M(d, a)_{x, y}$) following the standard methodology described in Pozzer et al. (2023):

$$M(d, a)_{x, y} = \left(\frac{deaths(d, a)}{POP(a)} \right) \cdot pop(a)_{x, y} \cdot AF(d, a)_{x, y}, \quad (1)$$

where d and a denote disease type and age class, respectively, while x and y represent location. The variable *deaths* corresponds to the number of deaths recorded in a specific geographic location, *POP* is the total population of the country to which that location belongs, $pop_{x, y}$ is the population within each grid cell, and $AF_{x, y}$ represents the attributable fraction for that grid cell, which quantifies the proportion of deaths attributable to air pollution exposure.



The exposure map (i.e. the pollution concentration in the region) has been obtained from public available dataset, which combines remote sensed observations and numerical model results (van Donkelaar et al., 2021). Gridded population data were taken from SEDAC (Center for International Earth Science Information Network - CIESIN - Columbia University, 2016). The attributable fraction values ($AF_{x,y}$) were calculated using the FUSION exposure-response function (Burnett et al., 2022),
 315 which provides estimates for so-called all-cause mortality associated with NCD and LRI. For LRI, two age groups were considered: individuals under five years and those aged 25 years and older. For NCD, only populations aged 25 years and older were included. The FUSION exposure response function uses a counterfactual range of $0-5.4 \mu g m^{-3}$, which defines a 95% confidence interval in AF , which in turn defines the 95% confidence interval in the mortality estimate M .

Country-level mortality was derived by summing the grid-level mortality values ($M_{x,y}$) within each country. Scenario-
 320 specific mortality results were then estimated by ratioing the scenario's modelled $PM_{2.5}$ field with that of the reference scenario, and scaling the reference mortality by this ratio.

2.10 Trend analysis of Amazon Fires and the Role of Protected Areas

To provide context for the atmospheric and health impacts identified in this study, we analyzed recent patterns of fire occurrence across the Amazon Basin and evaluated the potential role of protected areas (PAs) in reducing fire activity. Although
 325 the primary objective of protected areas is the conservation of ecosystems and biodiversity, they may also contribute to limiting anthropogenic fire occurrence by restricting land-use conversion, agricultural expansion, and other activities commonly associated with biomass burning (Cabrera et al., 2024).

Fire occurrence was characterized using hotspot detections from the VIIRS sensor available through NASA's Fire Information for Resource Management System (FIRMS) for the period 2013-2023. Analyses were restricted to the biogeographic Amazon as defined by the Amazon Network of Georeferenced Socio-Environmental Information (RAISG) dataset (Red Amazónica de Información Socioambiental Georreferenciada, 2024) and were conducted separately for each Amazonian country. Annual hotspot counts were used to calculate linear trends in fire occurrence over the study period. To ensure data quality, only hotspot detections with a confidence level greater than 80% and brightness temperatures exceeding 360 K were retained. Spatial trends in fire occurrence were assessed by aggregating hotspot detections into a hexagonal grid (hexbin) and estimating linear temporal trends in annual hotspot counts for each grid cell. Independently, country-level trends were computed by summing all
 335 hotspot detections within each country's Amazonian territory for each year and fitting a linear regression to the resulting annual national totals. Because the country-level trend aggregates counts across hundreds of grid cells, its slope is one to two orders of magnitude larger than the per-hexagon slopes shown in the spatial trend map; the two quantities describe trends at different spatial aggregation levels (grid-cell versus national total) and are not directly comparable in magnitude despite sharing the
 340 same units.

To evaluate the role of PAs, hotspot detections were overlaid with the RAISG protected-area database (Red Amazónica de Información Socioambiental Georreferenciada, 2024). Hotspot density (hotspots per km^2) was calculated separately for PA and non-PAs and compared through time for each country. This analysis allowed us to assess differences in fire occurrence



between protected and surrounding landscapes and to explore how land-use management and governance may influence fire
 345 activity across the Amazon Basin.

3 Results

3.1 Validation of atmospheric datasets and the WRF-Chem simulation against ground-based observations

At the daily scale (Fig. S4), CAMS captures a substantial fraction of the observed day-to-day variability in PM across most cities: correlation coefficients generally exceed 0.6 and reach values above 0.8 in several locations, and HIT rates are con-
 350 sistently high. RMSE and mean bias remain elevated in some cities, particularly those affected by strong local emissions or complex terrain, reflecting the limited ability of a global reanalysis to resolve fine-scale urban processes, and false alarm ratios are moderate, indicating that CAMS occasionally overestimates pollution events during stagnant conditions. At the monthly scale (Fig. S5), performance improves markedly: RMSE decreases and IOA, FAC2, and correlations increase relative to the daily evaluation, confirming that CAMS reliably reproduces the seasonal cycle and inter-monthly variability of PM concen-
 355 trations, with NMB generally falling within accepted benchmark ranges for long-term exposure analyses. For Cochabamba, Bolivia, the daily PM_{10} evaluation (Fig. S6) shows correlations comparable to those obtained for $PM_{2.5}$ elsewhere, though with larger absolute errors reflecting the broader size range and additional non-combustion sources influencing PM_{10} ; the model nonetheless captures the timing and persistence of elevated pollution periods. Overall, CAMS performs best at monthly and seasonal time scales, consistent with previous regional evaluations (Casallas et al., 2022; González et al., 2026) of CAMS in
 360 data-sparse environments, and this level of skill supports its use for diagnosing long-range transport and fire-related pollution impacts in this study.

ACAG reproduces the observed seasonal cycle of $PM_{2.5}$ with good fidelity at the monthly scale (Fig. S7): correlation coefficients are generally high, FAC2 values typically exceed the benchmark, and IOA values indicate robust agreement, though ACAG does not capture short-lived pollution extremes associated with episodic events. At the annual scale (Fig. S8),
 365 ACAG exhibits its strongest performance, with very high correlations, low RMSE, and small mean biases across most cities, consistent with the product's design objective of long-term accuracy and spatial consistency over high-frequency resolution. Performance varies somewhat by location, with slightly larger biases in cities with complex terrain or strong local emission gradients, but ACAG consistently meets or exceeds benchmark criteria for long-term $PM_{2.5}$ assessment (Boylan and Russell, 2006; Emery et al., 2017; Mogollón-Sotelo et al., 2021), supporting its use for estimating chronic exposure and associated
 370 health impacts.

WRF-Chem reproduces the broad seasonal evolution and inter-monthly variability seen in ACAG across most cities at the monthly scale (Fig. S9), with agreement strongest during dry seasons and some discrepancies during transition seasons likely reflecting differences in emission inventories and aerosol chemistry; correlations nonetheless remain robust. Against surface observations at the monthly scale (Fig. S10), the model captures the observed seasonal cycle well, with elevated concentrations
 375 during dry or stagnant periods and lower values during wet seasons; biases remain within ranges commonly reported for



regional chemical transport models at similar resolution, though errors are larger in complex urban environments and regions with strong local sources not fully resolved at the model grid scale.

At the annual scale (Fig. S11), agreement with both station observations and ACAG improves relative to the monthly and daily evaluations, reflecting the dominance of long-term emission patterns and climatological transport processes; WRF-Chem reproduces the intercity gradients and relative magnitudes seen in ACAG, with several cities falling between ACAG estimates and station observations, indicating a physically consistent representation that balances observational constraints with process-based simulation. Overall, WRF-Chem performs best at monthly to annual time scales, where regional emissions and large-scale transport dominate the signal; while some uncertainty remains at finer temporal scales, this level of skill supports its application for isolating biomass-burning contributions and quantifying associated health impacts across South American cities.

3.2 Amazonian burning defines the continental smoke season

With the CAMS and ACAG datasets and the WRF-Chem simulation validated against independent observations (Sect. 3.1), we turn to the continental-scale patterns of fire activity and pollution transport that these datasets reveal. Building on the seasonal fire cycle established in the Introduction (Fig. 1), we find a continental-scale imprint of Amazonian fires on regional air quality using the Lagrangian plume analysis: consistent patterns across $PM_{2.5}$, PM_{10} , and TCCO (Figs. 2, S12, and S13) closely track these same fire hotspot distributions, with enhancements extending from the Amazon toward major population centers across the Andes, the Pacific coast, southeastern Brazil, and the Southern Cone during JJA and SON (Freitas et al., 2005; Artaxo et al., 2013), while DJF-MAM plume signatures are weaker and more spatially confined, consistent with reduced fire activity (Artaxo et al., 2013; Armenteras et al., 2019).

Importantly, the strongest plume signatures are not restricted to the interior Amazon but frequently coincide with the broader fire corridor surrounding the basin, particularly along its southern and eastern margins. This spatial pattern suggests that Amazonian and non-Amazonian fire regions operate as an interconnected atmospheric system, motivating the source-attribution analyses presented in subsequent sections.

Interannual variability further supports this interpretation. Although the intensity and spatial extent of burning vary substantially from year to year (Fig. S3), annual plume composites closely track these fluctuations (Figs. S14-S16). Years characterized by more extensive burning generally exhibit stronger and more widespread particulate matter enhancements, particularly along transport pathways affecting western, southeastern, and southern South America. While meteorological variability modulates the magnitude of these responses, the dominant transport corridors remain remarkably consistent between years, in agreement with previous studies describing recurrent circulation pathways for Amazonian smoke transport (Freitas et al., 2005; Aragão et al., 2018; Mendez-Espinosa et al., 2019). As an independent consistency check, the multi-year composite of $PM_{2.5}$ and PM_{10} from all tracked plume events closely overlaps with the major fire regions identified by VIIRS, both within the Amazon Basin and across South America (Fig. S17), supporting the interpretation that the tracked events represent transported biomass-burning emissions rather than unrelated atmospheric variability.

This recurrent smoke season provides the basis for examining how these pathways affect individual cities and for quantifying the specific contribution of Amazonian fires to particulate matter exposure across South America.

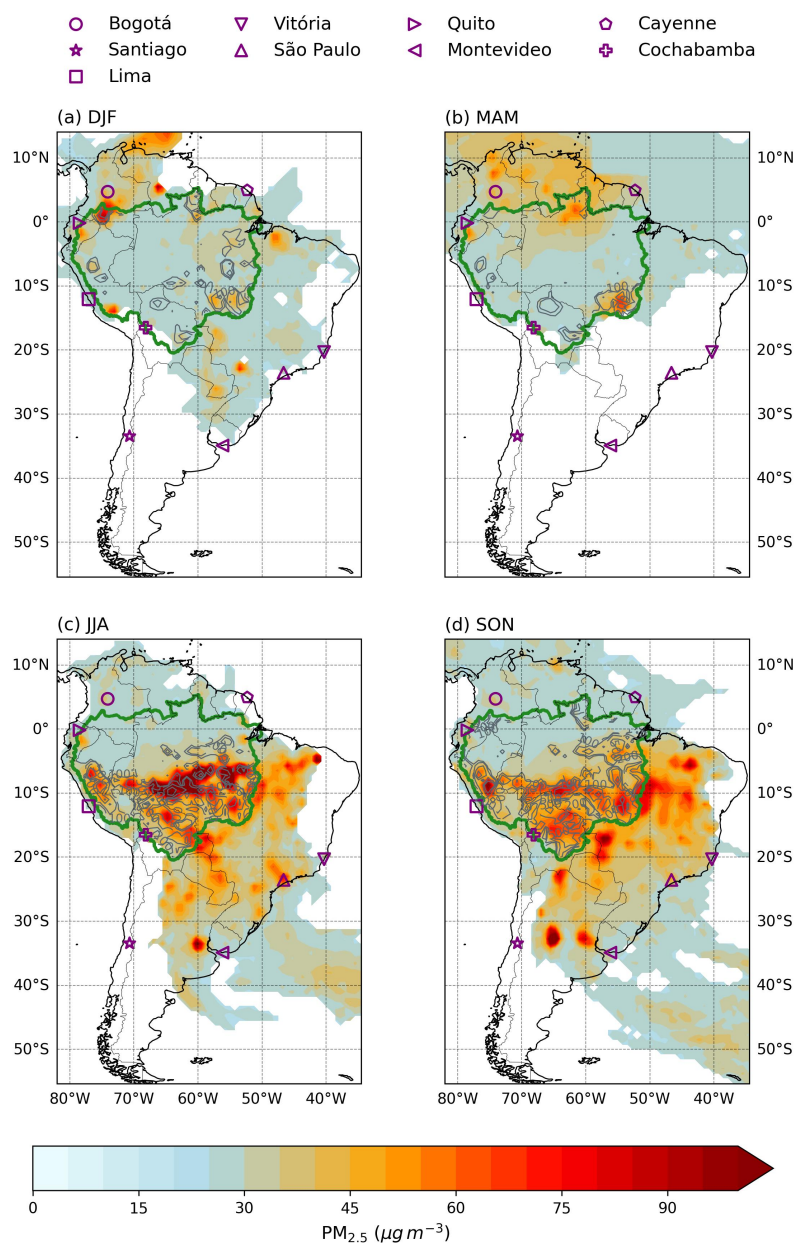


Figure 2. Seasonal multi-year mean (2013–2023) of $PM_{2.5}$ concentrations associated with Amazon-origin smoke plumes identified using the Lagrangian plume-tracking methodology. Shaded areas show the multi-year seasonal mean $PM_{2.5}$ concentrations linked to tracked plumes, while grey contours represent the seasonal mean fire hotspot distribution derived from VIIRS observations. Panels show (a) DJF, (b) MAM, (c) JJA, and (d) SON. The green outline denotes the biogeographic Amazon, and symbols (legend at top) mark the cities analyzed in this study.



410 3.3 Amazonian smoke reaches major South American population centers

3.3.1 Identifying continental-scale transport corridors

Amazonian fires connect to the rest of South America through a small set of coherent transport corridors that switch on with the fire season itself. Correlations between plume-associated $PM_{2.5}$ and fire hotspots (Fig. 3), derived from the Lagrangian plume framework, shift from weak and spatially fragmented relationships during DJF and MAM to coherent and statistically
 415 significant transport corridors during JJA and SON. During the peak fire season, positive correlations extend across large portions of the Amazon Basin and its surrounding fire belt, indicating a strong coupling between biomass-burning activity and downwind particulate pollution. Negative correlations occur only sporadically and never reach statistical significance. This is physically expected: fire emissions can only add particulate matter to the atmosphere, not remove it, so a genuine negative relationship would require an independent process suppressing pollution precisely where and when fires are most active, for
 420 which we find no evidence. The total absence of significant negative correlations therefore supports rather than undermines the coupling identified here.

These transport corridors connect Amazonian source regions with major population centers across northern, western, south-eastern, and southern South America. Particularly strong correlations emerge along pathways influencing Bogotá, Quito, São Paulo, Vitória, Montevideo, Santiago, and Cochabamba (city-selection criteria are described in Sect. 2.2). For Bogotá, the
 425 strongest associations are linked to fires occurring in southern Colombia, especially within the Caquetá-Guaviare deforestation frontier, rather than to the northern Amazon more broadly (Celis et al., 2023; Armenteras et al., 2019; Liévano-Latorre et al., 2021). Surface observations corroborate this picture, though the magnitude of the seasonal signal varies among cities (Figs. S18-S19): cities directly connected to Amazonian outflow pathways show stronger seasonal $PM_{2.5}$ increases, whereas coastal and high-elevation locations are more influenced by local meteorology and non-fire sources (Gonzalez et al., 2018;
 430 Casallas et al., 2023b). Bogotá is again the clearest exception, with a distinct DJF maximum consistent with the Caquetá-Guaviare burning identified above rather than the broader Amazon-wide fire peak.

These transport pathways are further confirmed by the same hotspot-correlation analysis applied to PM_{10} and TCCO, and by cross-correlating TCCO with particulate matter as an additional combustion tracer (Figs. S20–S23). While PM_{10} correlations are generally weaker because of the shorter atmospheric lifetime of coarse particles (Andreae, 2019), the spatial structures
 435 remain remarkably consistent with those obtained for $PM_{2.5}$. TCCO exhibits the strongest and most spatially extensive correlations with fire activity, reflecting its long atmospheric lifetime and efficient transport (Gaubert et al., 2016; Andreae, 2019). The close agreement among hotspots, particulate matter, and TCCO demonstrates that the identified transport corridors represent persistent pathways for biomass-burning emissions across the continent rather than isolated pollution episodes (Artaxo et al., 2013; Yurganov and Rakitin, 2022; Bela et al., 2022).

440 3.3.2 Urban impacts of long-range smoke transport

Statistics on plume frequency and directions (Fig. 4) reveal clear regional differences in the source regions influencing South American cities. Northern Andean cities such as Bogotá and Quito are primarily connected to fires occurring along the north-

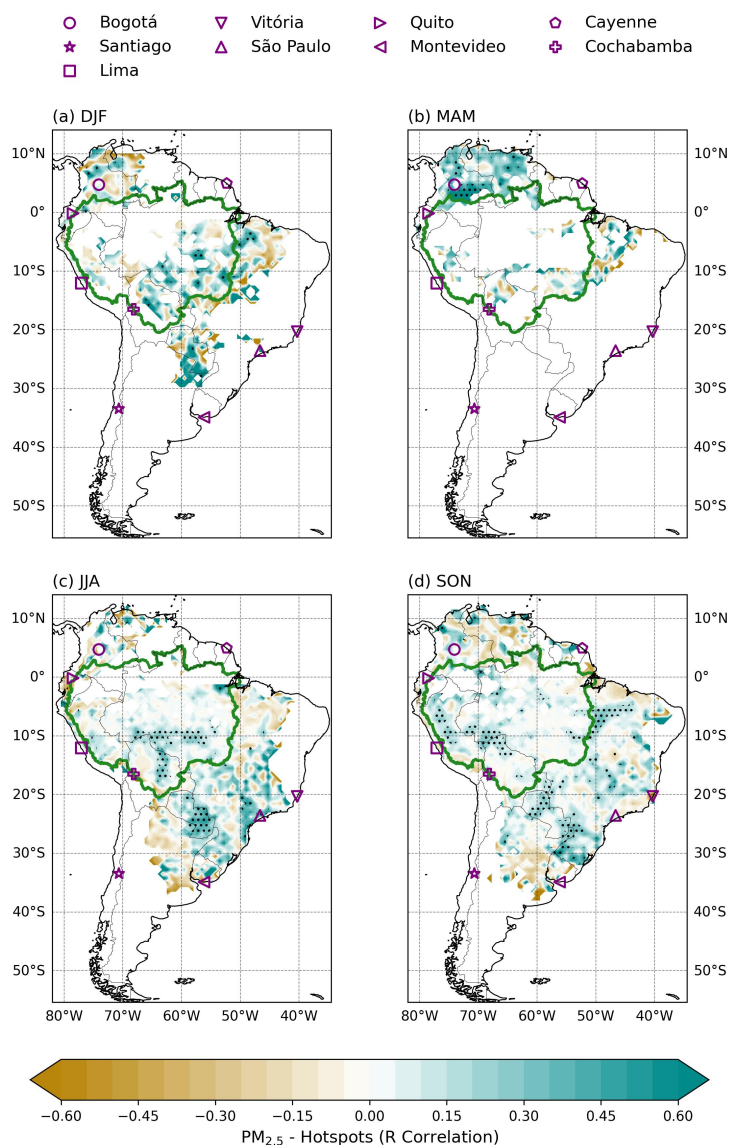


Figure 3. Seasonal Pearson correlation coefficients between daily fire hotspot counts and daily plume-masked $PM_{2.5}$ concentrations, computed independently at each grid point over the 2013–2023 record for (a) DJF, (b) MAM, (c) JJA, and (d) SON. Stippling denotes statistically significant correlations ($p < 0.05$). The green contour outlines the biogeographic Amazon Basin, and symbols indicate the urban locations analyzed in this study.



western Amazon frontier, particularly in southern Colombia and adjacent western Amazonian regions. In contrast, Lima is influenced predominantly by transport originating east of the Andes, while southern cities including São Paulo, Vitória, Montevideo, and Cochabamba are linked to longer transport pathways extending from the southern and eastern Amazon and central Brazil (Reddington et al., 2015).

The directional distribution of plume arrivals provides additional insight into these source-receptor relationships. Bogotá exhibits a clear dominance of SE–S sector arrivals, indicating plume origins in Caquetá and the southwestern Colombian Amazon, where deforestation-driven fires are particularly active (Celis et al., 2023). This pattern is consistent with prevailing easterly and southeasterly flow across the Amazon-Andes transition, which efficiently channels smoke toward the northern Andes (Longo et al., 2010; Andreae, 2019). Quito shows a similar prevalence of SE-sector arrivals, pointing to source regions located east of the Andes in the western Amazon lowlands.

Lima displays a predominance of NE–E sector arrivals during JJA and SON, indicating frequent transport across the Andes from western Brazil and the Peruvian Amazon (Reddington et al., 2015). Further south, São Paulo experiences its strongest activity during SON, with plume origins concentrated in the NW sector, consistent with transport from central-western Brazil and the southern Amazon fire belt (Requia et al., 2021). Montevideo exhibits fewer events overall, but the predominance of northern-sector arrivals suggests occasional long-range transport from interior Brazil and subtropical South America during favorable circulation conditions.

The remaining cities reflect more localized expressions of these broader transport regimes. Cayenne receives relatively few events, primarily associated with plume origins over the Amazonian interior to the south and southwest, consistent with the export of smoke toward the Atlantic coast under easterly flow (Artaxo et al., 2013). Cochabamba exhibits only a limited number of plume detections, but the dominance of easterly-sector origins indicates a direct connection with fire activity in the Bolivian Amazon and adjacent lowland regions. These directional patterns confirm that Amazonian smoke reaches urban centers through distinct but physically coherent transport pathways: persistent source-receptor relationships rather than random pollution episodes.

Transport-distance distributions further demonstrate the continental scale of these connections (Fig. S24). While northern Andean cities are often affected by sources located several hundred kilometers away, plume pathways reaching Lima, São Paulo, and Montevideo frequently extend more than 2000 km from their origin (Longo et al., 2010; Andreae, 2019; González et al., 2026). These long transport distances become particularly common during JJA and SON, when enhanced easterly flow and reduced wet scavenging favor sustained smoke transport across South America (Freitas et al., 2005, 2020; Thornhill et al., 2018).

The air-quality consequences of these transport events are quantified using lead-lag composites centered on plume arrival (Fig. 5). The temporal extent shown for each city reflects the duration of the events contributing to its composite rather than a fixed averaging window: where a small number of unusually long-lived plumes are present (e.g., Bogotá), the composite extends across more days than in cities where events cluster within a shorter, more typical duration.

Across all cities, pollutant concentrations increase systematically prior to plume arrival, peak near lag zero, and remain elevated for several days afterward. This behavior is consistent with the passage of coherent smoke-laden air masses rather

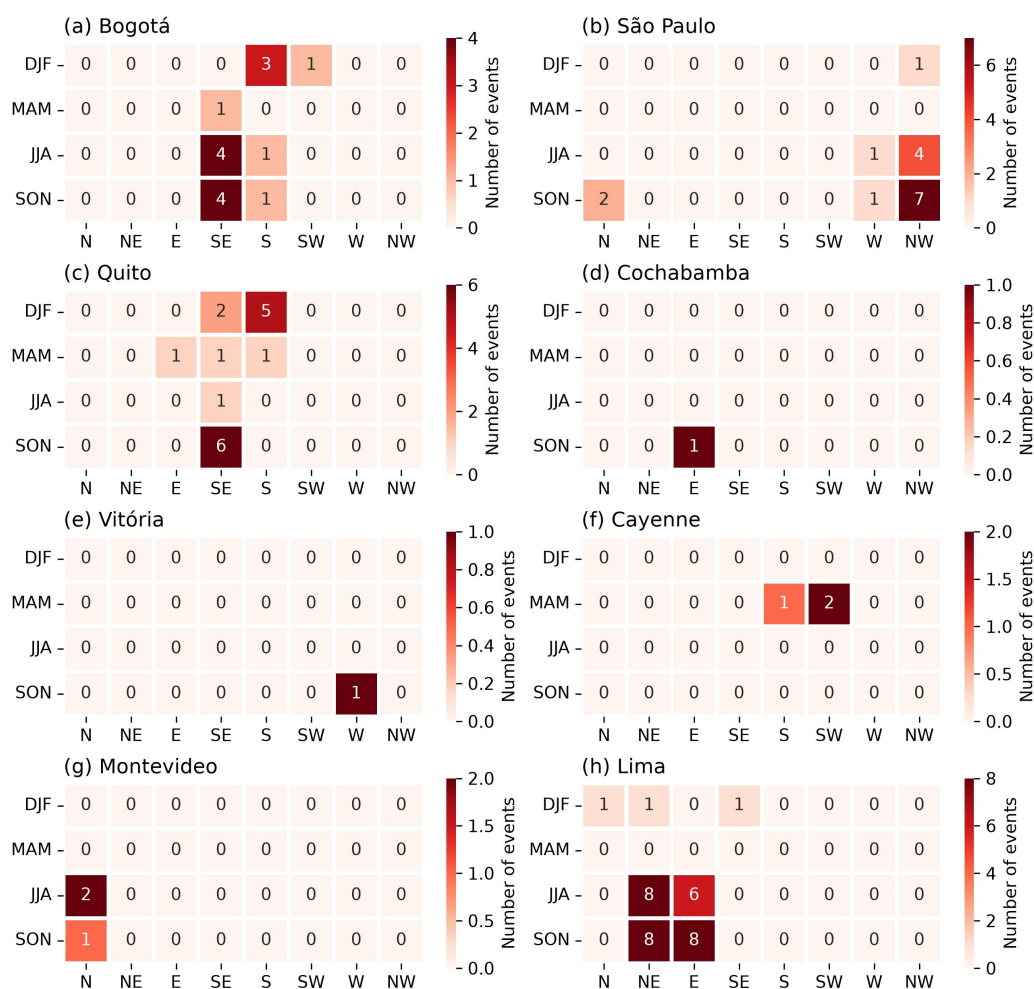


Figure 4. Seasonal multi-year mean (2013-2023) number of Amazon-origin plume arrivals at the study cities as a function of arrival direction. Each panel corresponds to one city: (a) Bogotá, (b) São Paulo, (c) Quito, (d) Cochabamba, (e) Vitória, (f) Cayenne, (g) Montevideo, and (h) Lima. Within each panel, the heatmap shows the average number of plume events identified by the Lagrangian tracking framework per year over the 2013-2023 record for each season (rows: DJF, MAM, JJA, and SON) and directional sector (columns: N, NE, E, SE, S, SW, W, and NW). Values are multi-year means of the number of plume arrivals in each season and sector; each tracked plume is assigned once, to the sector that contains its onset location as seen from the city.



than short-lived pollution spikes (Freitas et al., 2005; Longo et al., 2010). Northern and western cities experience the most frequent smoke-related enhancements, whereas southern cities experience fewer but often equally intense episodes. During
 480 JJA and SON, mean $PM_{2.5}$ enhancements commonly reach several tens of $\mu g\ m^{-3}$, demonstrating that transported smoke can substantially degrade urban air quality even at distances of thousands of kilometers from the source region (Requia et al., 2021; Pozzer et al., 2023; González et al., 2026).

Across northern cities (Bogotá, Quito, and Lima), $PM_{2.5}$ concentrations exhibit a coherent increase approaching plume arrival, with a clear maximum at or shortly after lag 0. Mean enhancements reach several tens of $\mu g\ m^{-3}$ during JJA and
 485 SON, indicating that plume passage is consistently associated with substantial degradation of surface air quality (Requia et al., 2021; Pozzer et al., 2023). Southern cities (São Paulo and Montevideo) experience fewer plume events, but the composites still show pronounced mean increases when transport occurs, demonstrating that long-range smoke incursions, although episodic, have strong impacts when they reach these regions (Reddington et al., 2015). In Cochabamba, SON composites reveal marked PM_{10} enhancements centered on plume arrival, reflecting the combined influence of transported biomass-burning aerosols and
 490 coarse-mode particle processes in the central Andes (González et al., 2026).

The persistence of elevated concentrations for one to several days following plume arrival indicates the sustained influence of smoke-laden air masses rather than instantaneous pollution spikes, consistent with slow plume dispersion and boundary-layer entrainment (Freitas et al., 2005; Longo et al., 2010). Composite responses are strongest during JJA-SON, when enhanced fire activity coincides with more efficient long-range transport, and considerably weaker during DJF-MAM owing to reduced
 495 burning and stronger atmospheric removal processes (Aragão et al., 2018; González et al., 2026). Together, these results demonstrate that long-range smoke transport is not an exceptional occurrence but a recurring feature of the South American atmosphere, linking Amazonian fires to persistent air-quality degradation across geographically diverse urban environments.

3.3.3 Amazonian fires as a recurrent component of urban exposure

Amazonian smoke is a persistent, not episodic, contributor to urban particulate matter exposure across the study cities (Fig. 6),
 500 which quantifies CAMS $PM_{2.5}/PM_{10}$ enhancements above a station-based baseline following the baseline approach of Cusworth et al. (2018) (Sect. 2.6).

Building on the frequency-intensity contrast identified above, Bogotá and Lima register positive background contributions in most JJA-SON seasons, and Quito mainly in SON, the most consistent pattern among the study cities (Reddington et al., 2015; Butt et al., 2020). Cities in southeastern and southern South America contribute less consistently across seasons, yet individual
 505 events can still match or exceed the magnitude seen further north, underscoring the efficiency of long-range transport under favorable circulation conditions (Longo et al., 2010; Andreae, 2019).

Cochabamba exhibits a distinct response characterized by episodic but intense PM_{10} enhancements, likely reflecting the combined effects of transported smoke and topographic confinement within the central Andes (Cordova et al., 2016; Casallas et al., 2023b). Across all cities, fire-related contributions are concentrated mostly during JJA and SON, with only occasional
 510 DJF and MAM events (e.g., Bogotá in 2022), reinforcing the dominant role of the dry-season fire regime in shaping continental air-quality patterns (Andreae, 2019).

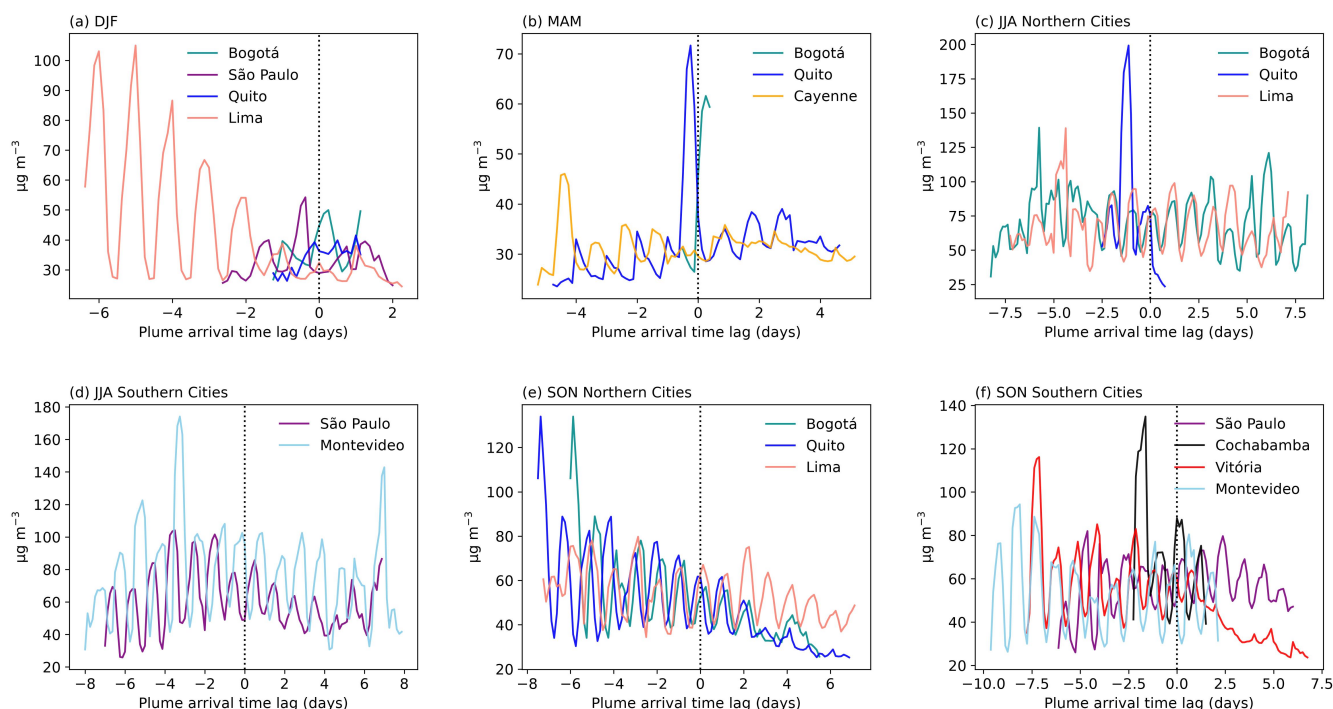


Figure 5. Composite evolution of particulate matter concentrations, derived from CAMS PM_{2.5}/PM₁₀ fields using the Lagrangian plume-tracking methodology, relative to the arrival of Amazon-origin smoke plumes at the study cities. Time series are centered on plume arrival (lag = 0), with negative values representing days before arrival and positive values representing days after arrival. Panels are arranged in two rows of three. Top row: (a) DJF (Bogotá, São Paulo, Quito, and Lima), (b) MAM (Bogotá, Quito, and Cayenne), and (c) JJA for northern cities (Bogotá, Quito, and Lima). Bottom row: (d) JJA for southern cities (São Paulo and Montevideo), (e) SON for northern cities (Bogotá, Quito, and Lima), and (f) SON for southern cities (São Paulo, Cochabamba, Vitória, and Montevideo). All panels show PM_{2.5} concentrations except for Cochabamba in panel (f), where PM₁₀ observations were used due to data availability.

Amazonian biomass burning exerts a measurable, and in some locations dominant, influence on particulate pollution across South American cities, but the plume-based attribution framework should be interpreted as an indicator of relative fire influence rather than a fully resolved source-apportionment method. Contributions may be affected by source mixing with non-Amazonian fires, anthropogenic emissions, meteorological variability, and occasional long-range aerosol intrusions such as Saharan dust outbreaks (Stohl and Seibert, 2002; Freitas et al., 2005; Longo et al., 2010; Cusworth et al., 2018; Yu et al., 2015; Prospero and Mayol-Bracero, 2013). Additional uncertainty arises from the representation of plume structure in the CAMS reanalysis and from the difference in spatial representativeness between gridded CAMS values and point-station baselines (Inness et al., 2019). Consequently, these diagnostics are most robust for identifying seasonal behavior, dominant transport pathways, and the relative importance of Amazonian smoke within the regional air-quality system. To more directly isolate the Amazonian fire signal, we next employ WRF-Chem sensitivity simulations in which Amazonian fire emissions are selec-



tively removed, enabling a physically based quantification of fire-attributable particulate matter and associated health impacts (Chowdhury et al., 2022).

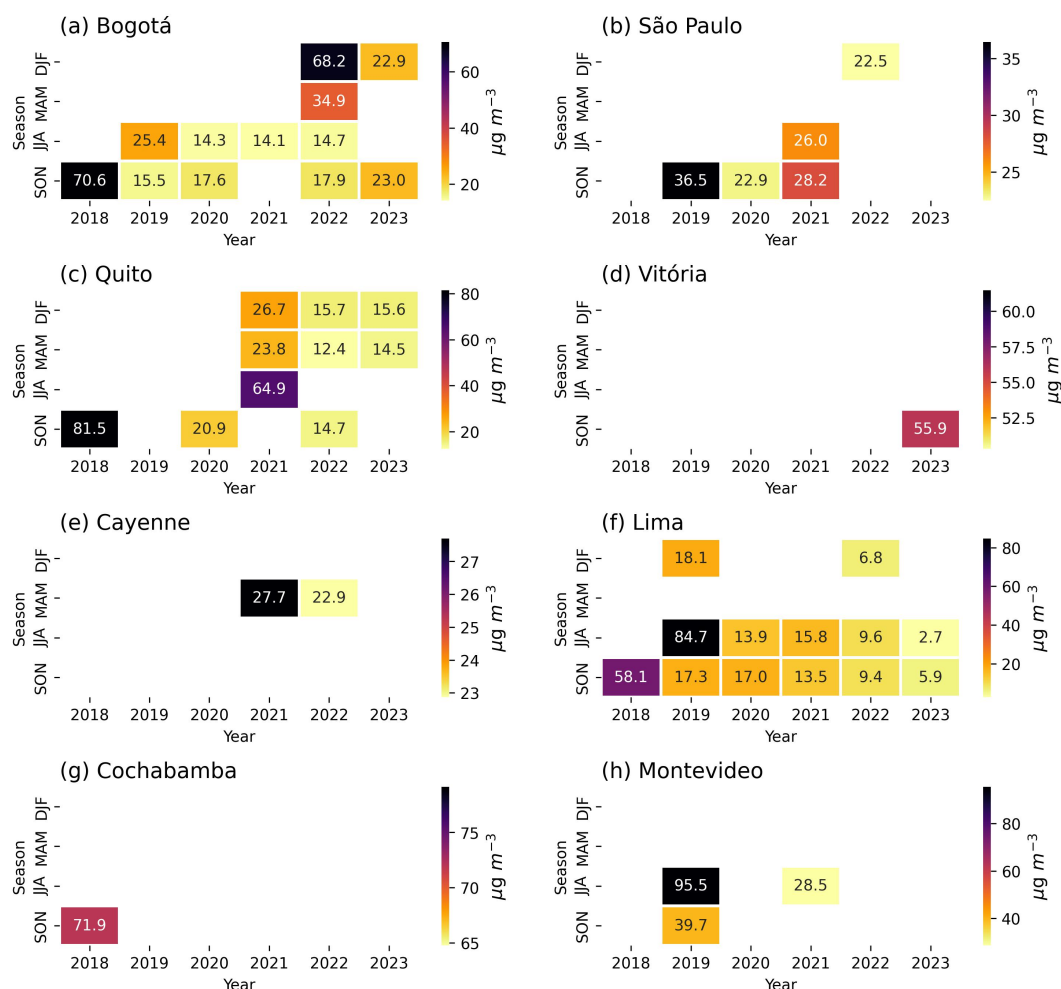


Figure 6. Seasonal contribution of Amazon-origin smoke plumes, derived from CAMS $\text{PM}_{2.5}/\text{PM}_{10}$ fields, to background particulate matter concentrations, following the methodology of Cusworth et al. (2018). Values represent the plume-related enhancement above the baseline concentration ($\mu\text{g m}^{-3}$), calculated for each city, season, and year in which plume events were identified. Each panel corresponds to one city: (a) Bogotá, (b) São Paulo, (c) Quito, (d) Vitória, (e) Cayenne, (f) Lima, (g) Cochabamba, and (h) Montevideo. Within each panel, rows indicate season (DJF, MAM, JJA, and SON) and columns indicate year (2018-2023); blank cells denote seasons without identified plume events. All values correspond to $\text{PM}_{2.5}$, except for Cochabamba, where CAMS PM_{10} and PM_{10} observations were used due to data availability.



3.4 Amazonian fires are a major contributor to regional $PM_{2.5}$ exposure

525 WRF-Chem sensitivity simulations confirm that Amazonian fires are a major, physically-resolved source of regional $PM_{2.5}$ pollution, not merely a statistical correlate of it. For the year 2020, we selectively removed fire emissions originating within the Amazon Basin (full simulation setup and experimental design in Sect. 2.7) and compared the result against the baseline scenario, isolating the fraction of $PM_{2.5}$ attributable to Amazonian biomass burning and distinguishing it from the contribution of fires occurring elsewhere in South America.

530 The annual mean $PM_{2.5}$ distribution (Fig. 7a) exhibits pronounced pollution maxima across the southern and eastern Amazon, extending toward the Andean foothills, central Brazil, and southeastern South America (Aragão et al., 2018; Butt et al., 2020), coinciding with the major fire corridors identified in the hotspot and plume analyses, as expected since both diagnostics reflect the same underlying fire distribution.

When the Amazonian contribution is isolated (Fig. 7b), elevated $PM_{2.5}$ concentrations emerge across the principal burn-
 535 ing regions of the basin, including southern Pará, Mato Grosso, Rondônia, northern Bolivia, and the western Amazon (van Marle et al., 2017). Strong contributions are also evident along the Colombian Amazon frontier, particularly in Caquetá and neighboring departments, consistent with the transport pathways previously identified as influencing Bogotá and the northern Andes (Bolaño-Díaz et al., 2022). Beyond the source regions themselves, Amazonian fire emissions contribute substantially to $PM_{2.5}$ exposure along major urban corridors extending toward Bogotá, Quito, Lima, Cochabamba, São Paulo, and Montevideo
 540 (Longo et al., 2010; Peralta et al., 2023; González et al., 2026). The modeled patterns closely align with the transport diagnostics presented in Sect. 3.2, providing independent confirmation that long-range smoke transport translates into measurable surface air-quality impacts.

Because the Amazon Basin boundary is an administrative and ecological delineation rather than a strict atmospheric one (Sect. 2.7), a residual $PM_{2.5}$ anomaly persists along the southern and southeastern margins of the basin, extending into adjacent
 545 regions of central Brazil and northern Bolivia (Fig. 7b). Although these areas lie partially outside the formal basin boundary, the remaining enhancement reflects the spatial smoothing intrinsic to finite grid resolution, rather than a failure of the fire-removal experiment itself. While this introduces some uncertainty in the exact spatial attribution of fire impacts near the basin edge, additional sensitivity tests indicate that the effect on basin-wide results is limited. Specifically, when an alternative experiment was conducted for August (the month with the highest fire activity) in which fire emissions from boundary-adjacent regions
 550 were excluded, the resulting change in domain-averaged $PM_{2.5}$ concentrations was less than 5% across the Amazon Basin (not shown), with larger differences confined only to grid cells immediately adjacent to the boundary. Given that the primary objective of this study is to assess fire contributions at regional and basin-wide scales, rather than to resolve fine-scale gradients at the basin margins, we retain the original configuration and explicitly acknowledge the associated uncertainty as a manageable limitation of the modeling framework.

555 The broader contribution from all South American fires (Fig. 7c) reveals an important regional contrast. While Amazonian fires dominate fire-attributable $PM_{2.5}$ across much of northern and western South America, additional contributions emerge from central and southeastern Brazil, the Gran Chaco, and agricultural regions south of the basin (Rudke et al., 2025; Baumann

et al., 2026), as well as from the Llanos/Orinoquía savannas of Colombia and Venezuela in the north. These non-Amazonian sources substantially reinforce particulate pollution in southeastern and southern cities such as São Paulo, Vitória, and Montevideo, and across northern South America, helping explain why these locations experience some of the largest pollution episodes despite fewer direct plume arrivals from the Amazon in the Lagrangian analysis (Reddington et al., 2015; van Marle et al., 2017; Butt et al., 2020; González et al., 2026).

These source-region enhancements are not directly comparable in magnitude to the downwind urban enhancements shown in Fig. 5, since the latter are measured at the study cities rather than within the Amazon Basin itself; the two are complementary lines of evidence, both indicating that Amazonian fires drive substantial $PM_{2.5}$ increases at their respective locations.

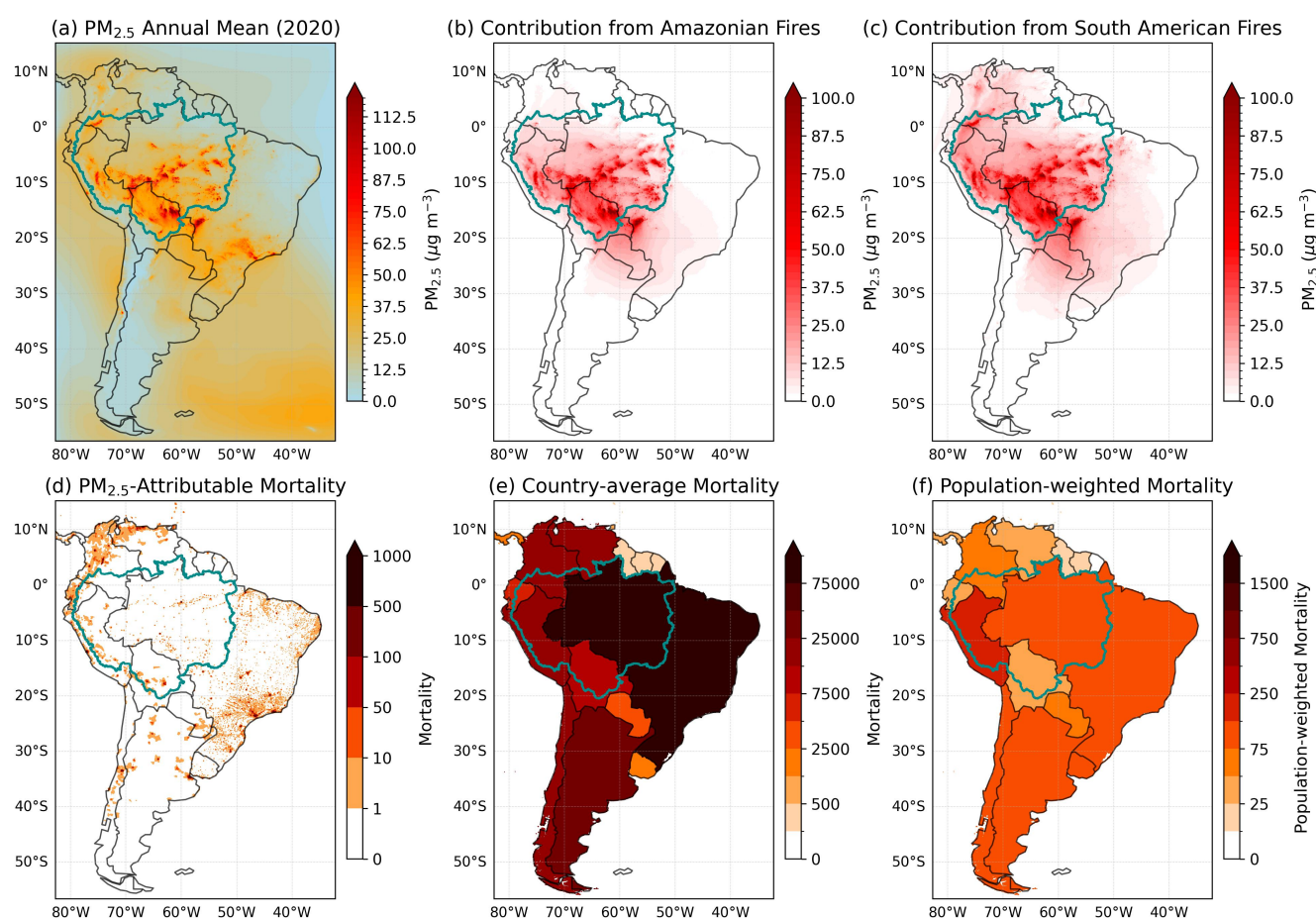


Figure 7. WRF-Chem simulations of annual mean $PM_{2.5}$ concentrations and fire-related contributions for 2020. Top row: (a) annual mean $PM_{2.5}$ concentration from the baseline simulation, and $PM_{2.5}$ contribution attributable to (b) Amazonian fires and (c) all South American fires. Bottom row: mortality due to $PM_{2.5}$ exposure in the baseline reference scenario for the year 2020, shown as (d) gridcell-level mortality (deaths), (e) country-level mortality (deaths), and (f) country-level, population-weighted mortality (deaths per 100,000 population). The green contour delineates the biogeographic Amazon Basin.



The monthly evolution of fire-attributable $PM_{2.5}$ (Figs. S25–S26) further demonstrates the strong seasonality of these impacts. Contributions remain relatively weak from January through June, reflecting reduced fire activity and less favorable transport conditions (van Marle et al., 2017; Aragão et al., 2018). Beginning in July, $PM_{2.5}$ enhancements intensify rapidly across the basin and expand toward downwind regions, reaching their maximum extent during August–October when widespread burning coincides with sustained continental-scale transport (Andreae, 2019; Butt et al., 2020). During this period, Amazonian fires alone generate $PM_{2.5}$ enhancements exceeding $50\text{--}100\ \mu\text{g m}^{-3}$ across large portions of the basin and produce substantial anomalies extending into western and southern South America.

This seasonal progression mirrors the evolution of hotspot density, plume frequency, and observed pollution peaks described in Sect. 3.2, providing a physically consistent picture across independent observational and modeling frameworks, while interactions with other regional fire sources broaden and intensify impacts in the southern urban corridor (Reddington et al., 2015; Butt et al., 2020; McDuffie et al., 2021).

3.5 Amazonian fires impose a substantial public-health burden

Amazonian fires translate into a substantial public-health burden across South America. We estimated $PM_{2.5}$ -attributable mortality for 2020 under three scenarios: a baseline reference simulation, a simulation excluding Amazonian fire emissions, and a simulation excluding all South American fire emissions, using a state-of-the-art exposure-response function (Burnett et al., 2022) (further methodological details in Sect. 2.9).

The baseline mortality burden associated with $PM_{2.5}$ exposure is shown in Fig. 7d–f. Mortality is concentrated in densely populated regions of South America, particularly Brazil, reflecting the combined effects of population density and elevated $PM_{2.5}$ concentrations. While absolute mortality is highest in heavily populated countries, population-weighted mortality highlights a different pattern, with countries such as Peru and Uruguay exhibiting disproportionately large health burdens relative to population size. Normalizing by population further highlights this pattern: $PM_{2.5}$ -attributable mortality per capita (Fig. S27) shows that fire-related health risk is not simply proportional to population size, but reflects each country’s exposure to Amazonian and regional smoke.

Relative mortality reductions are particularly pronounced in countries closely connected to Amazonian smoke transport pathways. In the no-Amazon-fires scenario (Fig. 8a), Bolivia exhibits the largest reduction, with mortality decreasing by approximately 65%, while Peru and Paraguay also experience substantial benefits. Similar patterns emerge in the no-South-America-fires scenario (Fig. 8b), although the benefits extend more broadly across northern and southeastern South America as additional fire sources are removed. These results indicate that Amazonian fires are a dominant contributor to population exposure in several countries located near the basin and along major smoke transport corridors. On the other side, removing wildfires from all of South America produces substantial health benefits reaching all the way to South America’s northern-most countries, such as Colombia and Venezuela.

Absolute mortality reductions reveal a complementary perspective (Fig. 8c–d). Because of its large population, Brazil experiences the greatest reduction in premature mortality, with approximately 14,000 deaths avoided in the no-Amazon-fires scenario and nearly 21,000 deaths avoided when all South American fire emissions are removed. Colombia also exhibits sub-

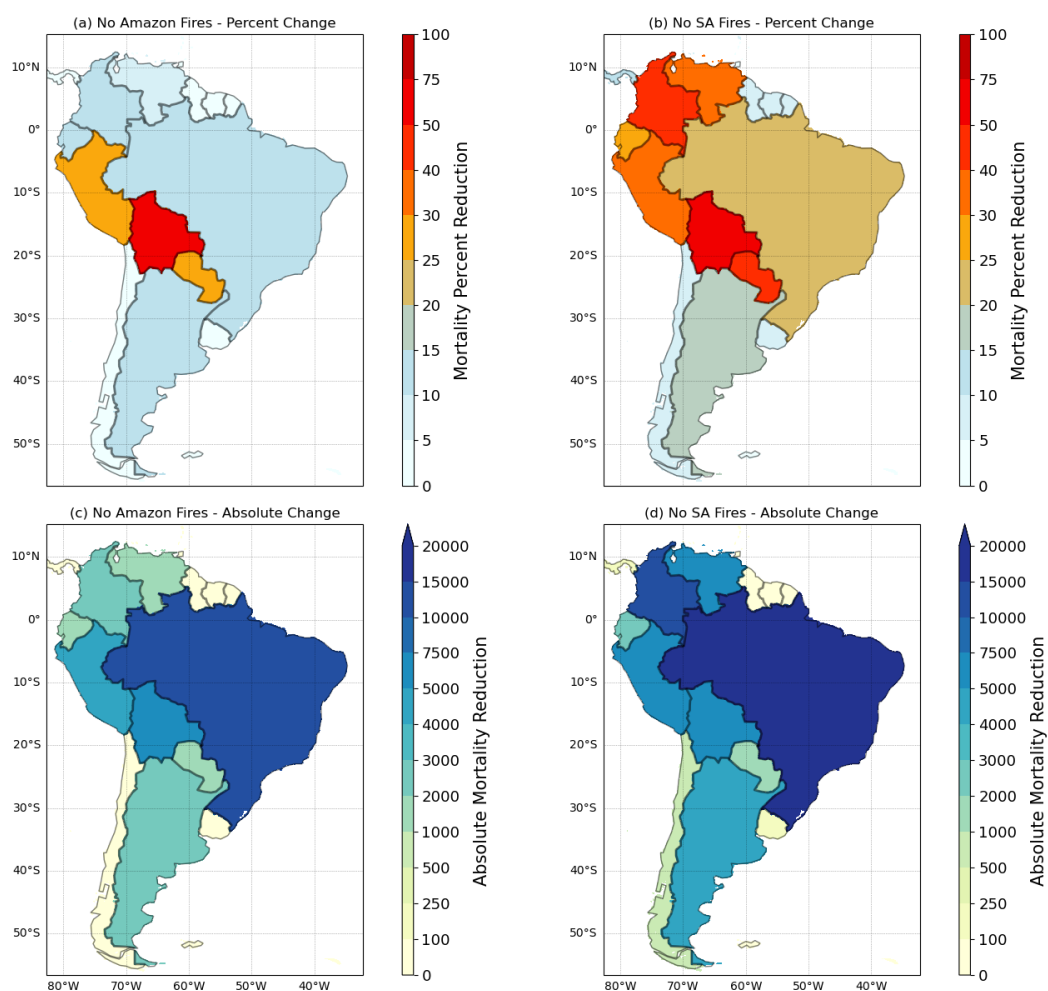


Figure 8. (a) Mortality percent reductions, relative to the baseline scenario, at the country-level for the no-Amazon-fires scenario and (b) the no-South-America-fires scenario. (c) Absolute reductions in mortality, relative to the baseline scenario, at the country-level for the no-Amazon-fires scenario and (d) the no-South-America-fires scenario.



Table 1. Tabulated country-level mortality estimates for the baseline scenario, as well as the no-Amazon-fires (No Am. Fires) and no-SA-fires scenarios, with 95% confidence intervals given in parentheses.

Country	Pop.	Baseline	No Am. Fires	No SA Fires
Argentina	45,217,392	25,743 (13,796-40,709)	23,052 (12,314-36,523)	21,007 (11,210-33,304)
Bolivia	11,909,656	9,751 (6,264-13,613)	3,441 (2,214-4,798)	2,739 (1,764-3,815)
Brazil	216,078,992	92,090 (48,388-147,272)	78,638 (40,602-127,019)	71,342 (36,683-115,502)
Chile	20,710,210	10,950 (6,499-16,252)	10,850 (6,440-16,103)	10,223 (6,076-15,160)
Colombia	63,171,940	24,842 (15,084-36,285)	22,218 (13,501-32,436)	14,822 (9,001-21,647)
Ecuador	17,650,678	7,326 (4,297-10,959)	6,249 (3,675-9,332)	5,200 (3,066-7,752)
French Guiana	355,773	216 (109-352)	215 (109-352)	196 (99-321)
Guyana	730,689	387 (208-611)	387 (208-611)	362 (194-572)
Panama	3,944,666	1,539 (840-2,406)	1,508 (823-2,358)	1,318 (720-2,058)
Paraguay	7,539,376	4,063 (2,471-5,931)	2,917 (1,776-4,256)	2,402 (1,463-3,503)
Peru	35,367,652	15,502 (9,320-22,816)	11,224 (6,753-16,512)	10,184 (6,125-14,984)
Suriname	623,337	301 (163-474)	301 (163-474)	281 (152-442)
Uruguay	3,123,572	2,052 (989-3,435)	1,968 (952-3,289)	1,886 (914-3,150)
Venezuela	32,079,418	19,192 (11,560-28,209)	17,936 (10,792-26,380)	12,113 (7,283-17,830)
South America	458,503,350	213,953 (119,987-329,323)	180,903 (100,319-280,442)	154,075 (84,750-240,041)

stantial benefits when all regional fires are excluded ($\approx 10,000$ deaths reduction), reflecting the influence of both Amazonian and non-Amazonian fire sources. In contrast, countries such as Chile show relatively small reductions, consistent with their weaker atmospheric connectivity to the principal fire regions and the partial barrier effect imposed by the Andes Mountains.

Country-level mortality estimates and associated uncertainties are summarized in Table 1. Across South America, removing Amazonian fire emissions reduces the estimated $PM_{2.5}$ mortality burden from 213,953 (95% CI: 119,987-329,323) to 180,903 (95% CI: 100,319-280,442) premature deaths, corresponding to approximately 33,000 avoided deaths annually. Notably, this represents a large fraction of the total mortality reduction obtained when all South American fire emissions are removed, demonstrating that Amazonian fires account for the majority of the fire-related health burden across the continent.

This absolute geography is spatially consistent with the relative patterns described above: Brazil's large population drives its dominant contribution in absolute terms, even as the strongest relative benefits remain concentrated in Bolivia, Peru, and Paraguay. Taken together, these findings indicate that Amazonian biomass burning is not merely a localized environmental problem but a major regional determinant of air-quality-related health risk across multiple countries.

The estimated mortality burden attributable to Amazonian fires places biomass burning among the most important air-pollution sources affecting public health in South America. Previous studies have identified biomass burning as a major contributor to $PM_{2.5}$ exposure and mortality across the Amazon Basin, central Brazil, the Colombian Amazon and Orinoquía, and portions of the southern cone (Reddington et al., 2015; Requia et al., 2021; Chowdhury et al., 2022; González et al., 2026). Our results enlarge this perspective by showing that Amazonian fires alone are associated with more than 33,000 premature



deaths annually across South America, emphasizing that the consequences of Amazonian burning extend far beyond the source regions themselves. While global assessments identify residential energy use, transportation, industry, and agriculture as the dominant contributors to ambient $\text{PM}_{2.5}$ mortality worldwide (Burnett et al., 2018; McDuffie et al., 2021; Pozzer et al., 2023), our findings indicate that Amazonian biomass burning represents a substantial and potentially avoidable component of the regional health burden. Reducing fire activity across the basin would therefore constitute not only an environmental and climate mitigation strategy, but also a major public-health intervention with benefits extending across national boundaries.

3.6 Fire governance determines future air-quality and health outcomes

3.6.1 Divergent fire trends across the Amazon Basin

Fig. 9 reveals substantial spatial and temporal heterogeneity in fire activity across Amazonian countries during 2013–2023, combining a per-hexagon trend map (panel a) with time series of each country’s annual active-fire-detection total (panels b–i); the two are not directly comparable in magnitude, as the latter sums many hexagons per country (for details of the trend calculation, see Sect. 2.10). Significant positive trends are concentrated primarily in the southern Amazon, with Bolivia showing the strongest national-level increase and central Brazil showing significant hexagon-level clusters despite a more modest, only marginally significant national trend (owing to strong interannual variability). Northern portions of the basin exhibit weaker or non-significant changes. These contrasting trends indicate that fire occurrence is not evolving uniformly across the basin but is strongly influenced by regional differences in land-use change, economic development, and environmental governance.

Among all countries, Bolivia exhibits the strongest and most statistically significant increase in fire activity, with a national annual total rising by 21,407 active fire detections year^{-1} ($p < 0.001$). This increase coincides with rapid forest loss, agricultural expansion, and the continued use of fire-based land-clearing practices such as *chaqueo* (the clearing and burning of woody vegetation to prepare land for agricultural use) (Tejada et al., 2016; McKay et al., 2022; OXFAM, 2024; Lantes, 2024; Tierra, 2024; FAO, 2025; He et al., 2025). Brazil also exhibits an overall increase in fire occurrence (20,451 active fire detections year^{-1}), although with greater interannual variability and weaker statistical significance ($p = 0.063$). The pronounced fire activity observed during 2019–2022 is consistent with periods of intensified deforestation and reduced environmental enforcement, whereas more recent declines suggest that strengthened governance and monitoring can substantially influence fire occurrence (Ferrante and Fearnside, 2019; Pessôa et al., 2020; Gatti et al., 2023).

This pattern should be read against a longer governance history that predates our study period: Brazil’s command-and-control enforcement program (PPCDAm), launched in 2004 and backed by near-real-time satellite deforestation monitoring, drove an approximately 80% reduction in Amazon deforestation between 2004 and 2012 (Nunes et al., 2024), well before the 2013–2023 window analyzed here. The increase we observe therefore does not reflect an absence of effective governance tools, but rather their weakening after 2012, when enforcement actions and penalties fell sharply (Nunes et al., 2024). If anything, Brazil’s earlier experience is the clearest demonstration in the basin that sustained political will and monitoring capacity can rapidly and substantially reduce fire and deforestation activity, a precedent other Amazonian countries with rising fire trends, such as Bolivia and Ecuador, could draw on.

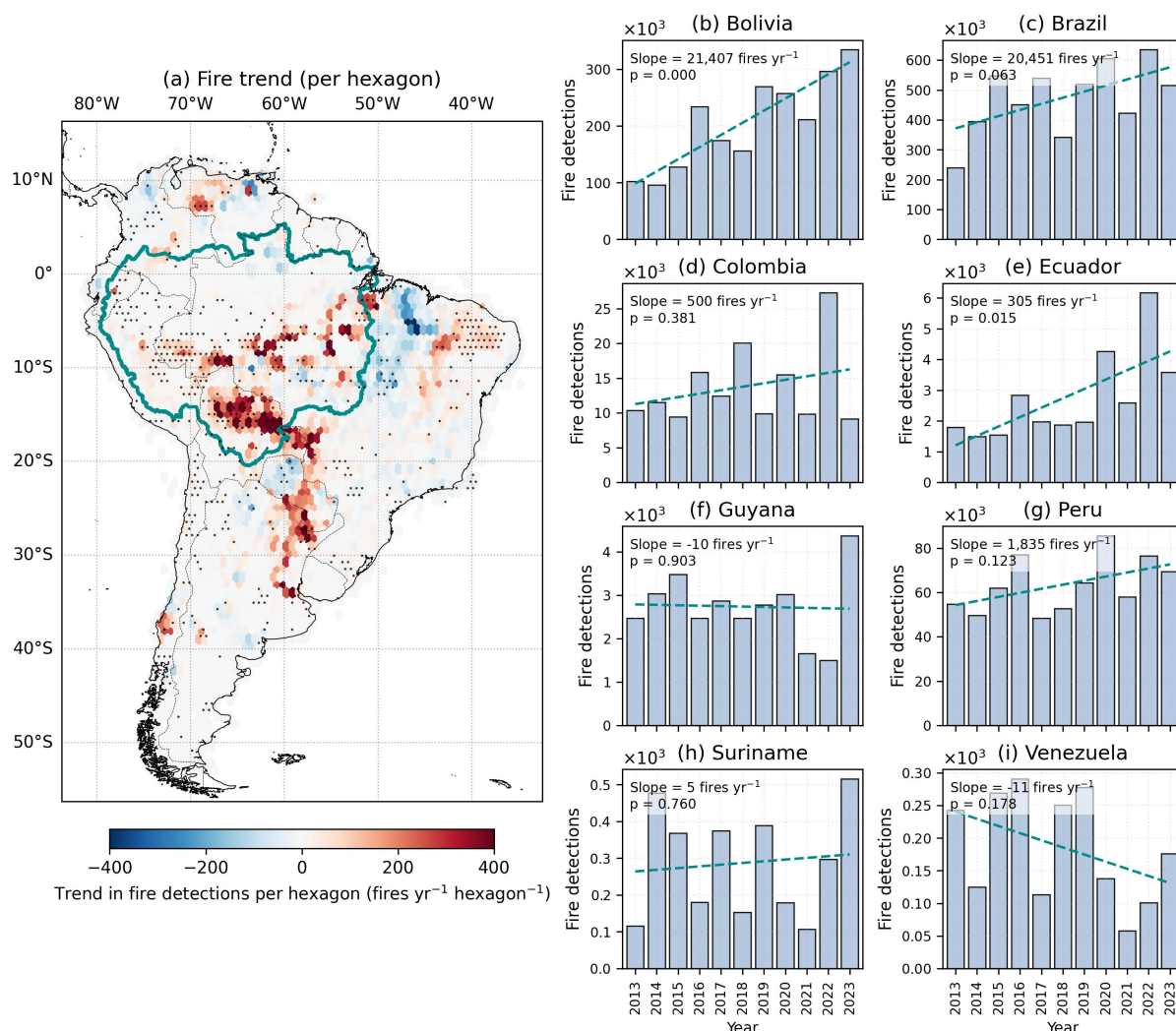


Figure 9. (a) Spatial distribution of the linear trend in annual active fire detections per hexagon (fire detections year⁻¹ hexagon⁻¹) across South America for the period between 2013 and 2023. The green outline marks the Amazon region, and black dots indicate locations where trends are statistically significant ($p < 0.05$). (b–i) Time series of annual active fire detections within the Amazon for selected countries: (b) Bolivia, (c) Brazil, (d) Colombia, (e) Ecuador, (f) Guyana, (g) Peru, (h) Suriname, and (i) Venezuela. Bars represent yearly country-wide totals (in $\times 10^3$ detections), and dashed lines show the linear regression trend of each national annual total. The slope (fire detections year⁻¹, summed across all hexagons within the country) and corresponding p-value are indicated in each panel; because this is a spatially aggregated national total rather than a per-hexagon value, its magnitude is not directly comparable to the per-hexagon trend shown in (a). Note that active fire detections do not correspond one-to-one with individual fire events: a single large or long-lived fire can generate many detections across space and time.



650 Other Amazonian countries display more moderate but still important patterns over the 2013-2023 period. Ecuador shows a statistically significant positive trend, likely reflecting the combined influence of deforestation, infrastructure expansion, mining, and hydrocarbon development, all of which contribute to forest fragmentation and increased fire susceptibility (Aragão et al., 2018; Kleemann et al., 2022; Monitoring of the Andean Amazon Project (MAAP), 2024). Colombia, Peru, and Suriname exhibit positive but non-significant trends, indicating substantial interannual variability superimposed on a gradual increase in
655 fire occurrence across the amazon basin in these countries. In Colombia, particular attention should be given to the Caquetá-Guaviare frontier, which represents one of the most influential fire corridors identified in this study and a major source region affecting air quality in Bogotá and the northern Andes (Celis et al., 2023; Red Amazónica de Información Socioambiental Georreferenciada, 2024; González et al., 2026).

3.6.2 Protected areas and the mitigation of fire emissions

660 Because most Amazonian fires are directly or indirectly associated with human activities, including agricultural expansion, deforestation, infrastructure development, and extractive industries, protected areas are widely used as a mechanism for limiting future emissions (Aragão et al., 2018; Silva Junior et al., 2020; Red Amazónica de Información Socioambiental Georreferenciada, 2024), and the comparison between protected and non-protected areas (Fig. S28) broadly supports this: in most countries (Bolivia, Brazil, Colombia, Peru, Venezuela, and Guyana), hotspot densities remain consistently lower within protected areas
665 than in surrounding landscapes, even under substantial land-use pressure (Cabrera et al., 2024). The contrast is particularly evident in Bolivia and Brazil, where hotspot densities increase through time both inside and outside protected areas, but remain systematically higher in non-protected regions (Tejada et al., 2016; Ferrante and Fearnside, 2019; Gatti et al., 2023; He et al., 2025), indicating that protected status reduces fire activity substantially without eliminating it.

This reduction is not automatic, however: formal legal protection translates into lower fire activity only where it is actively
670 enforced. Colombia's Tinigua National Natural Park illustrates the alternative outcome: despite decades of legal protection, it has been extensively deforested and burned as armed groups, cattle ranching, and coca cultivation expanded into the park amid weak state presence (Armenteras et al., 2019; Liévano-Latorre et al., 2021). Colombian law, for instance, imposes strict prohibitions within protected areas on pouring toxic substances, tree cutting or burning, waste disposal, explosives, and mining, cattle, agricultural, industrial, or tourism activities, under penalty of sanction (República de Colombia, 1977); but as Tinigua
675 shows, enforcing these prohibitions depends on political will and continuous state presence, which are often absent in remote or contested regions. The overall pattern across the basin is therefore geographically heterogeneous, reflecting differences in enforcement capacity as much as in formal protected-area status.

Important exceptions nevertheless emerge. In Ecuador and, to a lesser extent, Suriname, protected areas exhibit hotspot densities comparable to or greater than those observed outside protected regions. In Ecuador, this pattern likely reflects the
680 location of many protected areas within Andean and piedmont regions affected by infrastructure expansion, mining, hydrocarbon development, and forest fragmentation (Lessmann et al., 2016; Rivera-Parra et al., 2020; Kleemann et al., 2022). These cases illustrate that legal protection alone is insufficient when broader land-use pressures remain active within or adjacent to protected landscapes.



These effects extend beyond ecosystem conservation: where protected areas suppress fire activity, they also reduce down-
 stream smoke exposure and health impacts across South America. Future air-quality and health outcomes will therefore depend
 as much on governance effectiveness in the fire source regions identified here as on climatic variability.

El Niño conditions appear to amplify fire-favorable conditions across the basin, as the 2015-2016 fire season illustrated
 within our study period, though too few El Niño events occur in 2013-2023 to quantify this relationship statistically. The
 clearest test of this risk arrived just beyond our analysis window, during the record 2024 fire season, which drove the most
 extensive fire-related forest degradation in the Amazon in over two decades (Bourgoin et al., 2025): even Brazil, which had
 achieved some of the basin's strongest sustained reductions in fire activity, saw burning spike beyond what its governance
 and monitoring systems could contain. This suggests that political will, social awareness, and monitoring capacity, while
 necessary, may not be sufficient once climate variability crosses a certain threshold (Requia, 2024); raising an urgent question
 for the extreme events likely still ahead: what must change, and whether it can change fast enough.

4 Conclusions

The Amazon rainforest is a global carbon reservoir, biodiversity hotspot, and regulator of regional climate. This work shows
 it is also a key regulator of air quality across South America. Amazonian biomass burning drives a recurrent, continental-
 scale smoke season, peaking during JJA–SON, when fire hotspots, plume evolution, particulate matter, and combustion tracers
 converge to degrade air quality across large parts of the continent. Smoke produced within the basin routinely travels hundreds
 to thousands of kilometres beyond its source.

This effective transport links Amazonian fire regions to major urban centers across the northern Andes, the Pacific coast,
 southeastern Brazil, and the southern cone. Plumes reaching cities such as Lima, São Paulo, and Montevideo often travel
 more than 2,000 km, with elevated concentrations persisting for days after arrival: long-range smoke transport is a recurring
 feature of the South American atmosphere, not an exceptional event. The pattern is not universal, however. Bogotá's particulate
 matter maxima track subregional burning along the Caquetá–Guaviare frontier more closely than the Amazon-wide fire peak,
 underscoring that effective air-quality management must address both basin-wide seasonality and city-specific source areas.

Numerical sensitivity simulations confirm Amazonian fires as a major contributor to $PM_{2.5}$ exposure continent-wide, remain-
 ing the dominant fire-related source across much of northern and western South America even where other regional sources
 locally amplify pollution. During the fire-season peak (August–October), Amazonian fires alone raise $PM_{2.5}$ by 50–100 μg
 m^{-3} across large portions of the basin, with anomalies extending into western and southern South America: among the most
 significant seasonal air-quality impacts identified anywhere on the continent.

Removing Amazonian fire emissions would prevent an estimated 33,000 (95% CI: 19,700–48,900) premature deaths annually
 across South America, about 15% of the region's total $PM_{2.5}$ mortality burden and the majority of its fire-related share. Brazil
 bears the largest absolute burden (14,000–21,000 avoided deaths, depending on scenario) and Colombia gains $\approx 10,000$ avoided
 deaths once all regional fires are removed, while Bolivia shows the largest relative reduction ($\approx 65\%$). Amazonian fires are
 therefore not merely a localized environmental problem but a major determinant of regional public health, and reducing fire



activity would be effective both a climate mitigation strategy and a public-health intervention, with benefits extending well beyond national boundaries.

720 Fire trends vary substantially among Amazonian countries: the strongest increases occur where forest conversion and agricultural expansion are most pronounced, while lower fire occurrence is identified in protected-area, although this status alone does not guarantee lower hotspot density. Bolivia shows the strongest, most significant upward trend, driven by agricultural expansion and *chaqueo*; Ecuador's increase reflects deforestation, mining, and hydrocarbon development, and in Ecuador and Suriname hotspot densities inside protected areas rival those outside, showing that legal protection cannot substitute for enforcement capacity. Fire-mitigation policy therefore cannot rely on a single continental strategy; it must be tailored to each country's specific drivers.

730 These results extend a body of prior work that documented individual episodes of Amazonian smoke reaching Andean and coastal cities (Gonzalez et al., 2018; Casallas et al., 2022, 2023b; Reddington et al., 2015) into a systematic, multi-year, continental-scale characterization of the underlying atmospheric transport and its public-health consequences. The magnitude of Amazonian fire-attributable $PM_{2.5}$ found here is consistent with previous regional evaluations of CAMS and WRF-Chem in data-sparse South American settings (Casallas et al., 2022; González et al., 2026), and the mortality burden, estimated using the FUSION exposure-response function (Burnett et al., 2022) within the Global Burden of Disease framework (GBD 2019 Risk Factors Collaborators, 2020; Pozzer et al., 2023), situates Amazonian fires among the leading regional sources of $PM_{2.5}$ -attributable mortality identified for South America to date.

735 Several caveats should be considered when interpreting these results. The Lagrangian plume-tracking framework quantifies the relative influence of Amazonian fires on urban air quality but is not a fully resolved source-apportionment method, and contributions may be affected by source mixing with non-Amazonian fires, anthropogenic emissions, and long-range aerosol intrusions (Sect. 3.3). The WRF-Chem sensitivity experiments were performed for a single year (2020); although fire trends and transport pathways are consistent across the wider study period, year-to-year meteorological variability, including strong El Niño years, could alter the magnitude, though not the basic pattern, of the estimated health burden. The Amazon Basin boundary used to isolate fire contributions is an administrative and ecological delineation rather than a strict atmospheric one, introducing some uncertainty in fire attribution near the basin margins (Sect. 2.7). Mortality estimates further inherit the uncertainty of the underlying exposure-response function and rely on 2020 population and disease-burden data, which may not fully capture demographic change or health-system differences across the region. These limitations affect the precision of country- and city-level estimates but not the basic conclusion that Amazonian fires are a major, recurrent driver of regional $PM_{2.5}$ exposure.

750 For atmospheric science, these results demonstrate that a single, geographically concentrated source region can generate a recurrent, basin-to-continental-scale perturbation to regional air quality, with transport efficient enough to measurably alter $PM_{2.5}$ and CO burdens thousands of kilometres from the source. As climate change alters precipitation, drought frequency, and El Niño dynamics across Amazonia, this source-receptor relationship implies that continental-scale smoke exposure, and the associated health burden, may itself become an increasingly climate-sensitive quantity, with direct relevance for regional climate and air-quality projections.



These impacts are not inevitable: much of the pollution and mortality burden traces to human-driven land-use practices that can be reduced through targeted fire prevention and governance. A small number of source regions offer the greatest potential for impact: the Caquetá–Guaviare frontier in Colombia (affecting Bogotá and the northern Andes), the Bolivian lowlands (driving the largest relative mortality reductions), and Brazil’s southern and eastern arc of deforestation (driving the largest absolute burden). Prioritizing enforcement in these corridors offers a practical, evidence-based entry point for regional air-quality and public-health policy.

Beyond climate, water, and biodiversity, the Amazon shapes the air breathed by millions across South America; protecting it is therefore a public-health strategy. We hope the source-receptor relationships identified here offer a first step toward more targeted, evidence-based, international fire policy across the region.

Author contributions. AC: Conceptualization, Data curation, Methodology, Software, Validation, Formal analysis, Investigation, Visualization, Writing - original draft. TM: Data curation, Methodology, Validation, Writing - original draft. BS and AP: Data curation, Methodology, Software, Validation, Formal analysis, Visualization, Writing - original draft. CJ: Data curation, Methodology, Software, Validation, Formal analysis, Visualization, Writing - original draft. FA-L: Data curation, Software, Writing - original draft. EAL-B, CP, RA, LD, and SH: Methodology, Formal analysis, Writing - original draft. LCB: Methodology, Formal analysis, Validation, Writing - original draft.

Competing interests. At least one of the (co-)authors is a member of the editorial board of Atmospheric Chemistry and Physics.

Code and data availability. All data sources used in this study, including satellite fire detections, atmospheric reanalysis and remote-sensing PM_{2.5} products, ground-based air-quality observations, and population and mortality datasets, are described in the Data and Methods section. WRF-Chem simulation output generated for this study is available at (Pozzer and Casallas García, 2026). Code used to process satellite fire detections, track and analyze pollution plumes, run and evaluate the WRF-Chem simulations, and estimate PM_{2.5}-attributable mortality is available at <https://github.com/Casicus94/Amazon-Fires-air-quality-code>.

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