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Impact of the 2022 New Mexico, US wildfires on air quality and health

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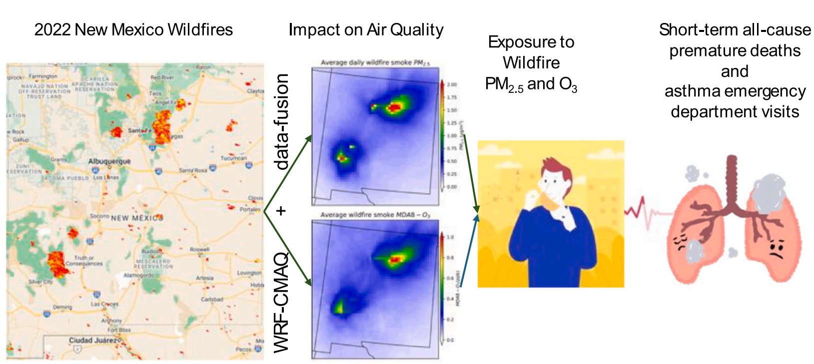
HIGHLIGHTS

- We selected six wildfires that accounted 90 % of the total wildfire burn area in New Mexico in 2022.
- A total of 0.81 million acres of land was burned and 152 thousand tons of fine particulate matter ($PM_{2.5}$) was emitted.
- The 1-h maximum smoke $PM_{2.5}$ and ozone exceeded 120 μg/m^3 and 60 ppb, respectively, near Santa Fe.
- Total 22 short-term premature deaths attributed to wildfire $PM_{2.5}$ and ozone exposure.

GRAPHICAL ABSTRACT



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ABSTRACT

The 2022 wildfires in New Mexico, United States, were unparalleled compared to past wildfires in the state in both their scale and intensity, resulting in poor air quality and a catastrophic loss of habitat and livelihood. Among all wildfires in New Mexico in 2022, six wildfires were selected for our study based on the size of the burn area and their proximity to populated areas. These fires accounted for approximately 90 % of the total burn area in New Mexico in 2022. We used a regional chemical transport model and data-fusion technique to quantify the contribution of these six wildfires (April 6 to August 22) on particulate matter ($PM_{2.5}$: diameter $\leq$ 2.5 μm) and ozone (O_3) concentrations, as well as the associated health impacts from short-term exposure. We estimated that these six wildfires emitted 152 thousand tons of $PM_{2.5}$ and 287 thousand tons of volatile organic compounds to the atmosphere. We estimated that the average daily wildfire smoke $PM_{2.5}$ across New Mexico was 0.3 μg/m^3,

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though 1 h maximum exceeded 120 μg/m^3 near Santa Fe. Average wildfire smoke maximum daily average 8-h O_3 (MDA8-O_3) contribution was 0.2 ppb during the study period over New Mexico. However, over the state 1 h maximum smoke O_3 exceeded 60 ppb in some locations near Santa Fe. Estimated all-cause excess mortality attributable to short term exposure to wildfire $PM_{2.5}$ and MDA8-O_3 from these six wildfires were 18 (95 % Confidence Interval (CI), 15–21) and 4 (95 % CI: 3–6) deaths. Additionally, we estimate that wildfire $PM_{2.5}$ was responsible for 171 (95 %: 124–217) excess cases of asthma emergency department visits. Our findings underscore the impact of wildfires on air quality and human health risks, which are anticipated to intensify with global warming, even as local anthropogenic emissions decline.

1. Introduction

Over the last forty years, the extent of areas burned by wildfires in the United States (US) has approximately quadrupled (Burke et al., 2021). This escalation can be attributed to various contributing factors, notably the accumulation of fuels due to fire suppression practices spanning the past century, as well as a more recent surge in fuel aridity, a trend expected to persist as the climate continues to warm (Burke et al., 2021). The significant rise in wildfire activity has been accompanied by a substantial increase in the number of days of smoky air across the US (O'Dell et al., 2021).

Wildfires contribute 10 to 30 % (yearly to daily) of atmospheric primary fine particulate matter ($PM_{2.5}$) emissions in the US. Increasing emissions from wildfires have caused summertime $PM_{2.5}$ levels to rise in the western US and have exposed millions of people to unhealthy or hazardous $PM_{2.5}$ concentrations (150 to 650 μg/m^3 for 24-h average) (Rooney et al., 2020). Childs et al. (2022) reported that wildfire smoke contributed to an average increase of up to 10 % in ambient $PM_{2.5}$ concentrations in the western US over the last decade. Many locations across the US are exposed to at least one day/year of highly polluted air quality conditions (e.g., $PM_{2.5}$ above 100 μg/m^3) due to wildfire smoke. From August to October 2020, western wildfires contributed 23 % of surface daily $PM_{2.5}$ in the contiguous US (CONUS), with a larger contribution in the West Coast (43 %) and Mountain Regions (42 %) (Li et al., 2021). In California, wildfires contributed an average of over 70 % of total daily $PM_{2.5}$ on days that exceeded federal regulatory standards, compared to an average of 12 % of total daily $PM_{2.5}$ from 2004 to 2020 (Aguilera et al., 2023; Liu et al., 2016). Compared to California, wildfires in New Mexico generally have a lesser impact on air quality, with annual average wildfire smoke $PM_{2.5}$ concentrations ranging from 0 to 5 μg/m3 during 2007–2018 (Zhang et al., 2023). However, during the Hermits Peak and Calf Canyon wildfires in 2022, the average hourly $PM_{2.5}$ concentration in Las Vegas, New Mexico surged to between 100 and 152 μg/m^3 on at least 12 occasions across five different days in April and May (IQAir, 2022).

In the past, there has been a scarcity of studies exploring the influence of wildfires smoke on ozone (O_3) and its impact on public health (Brey et al., 2018; Pratt et al., 2019). However, wildfires also have a substantial impact on regional summertime O_3 concentrations in the western US due to their emissions of O_3 precursors, such as volatile organic compounds (VOCs) and nitrogen oxides (NOx) (Koss et al., 2018; Xu et al., 2021). According to Lu et al. (2016), one-third of summer days surpassing the National Ambient Air Quality Standard (NAAQS) for O_3 in the western US are attributed, in part to wildfires (Lu et al., 2016). Wildfires plumes can travel thousands of kilometers and remain aloft for many days or over a week, causing increased ozone in downwind urban areas, with daily maximum 8-h average O_3 concentrations (MDA8-O_3 and NAAQS is 70 ppb) increasing as much as 5–40 ppb on some days (Hu et al., 2008; Dreessen et al., 2016). O_3 enhancement rises as the plume ages, particularly when additional NOx, e.g., from anthropogenic emissions in urban areas, is added to smoke plumes [NOx (urban) + VOCs (wildfire) + (light and other factors) - > O_3 (urban)] (Jaffe et al., 2020; Jin et al., 2023). The reactive compounds like hydroxyl (OH) emitted and formed due to biomass fires drive O_3 and organic aerosol formation, affecting both air quality and climate (Kumar et al., 2018).

A challenge in understanding the broader impact of changing wildfire activity on air quality is the difficulty of accurately linking fire activity to pollutant exposures in distant population centers (Johnson et al., 2020). Satellite-based smoke exposure measurements are increasingly available and are appealing because plume monitoring intuitively links source and receptor regions. Such data, however, cannot yet be used on their own to accurately estimate smoke density nor to separate surface-level smoke from smoke higher in the atmospheric column, and thus they are difficult to use with existing exposure–health response relationships (Brey et al., 2018; O'Dell et al., 2019). Further, such observations do not include ground-level ozone. Chemical Transport Models (CTMs) like the Community Multiscale Air Quality Modeling System (CMAQ), which directly models the movement and evolution of wildfires emissions, offer an alternate approach for linking pollution to specific fire activity. Generating accurate exposure estimates from CTMs requires surmounting several major uncertainties in the pathway between source and receptor. Data fusion (DF) statistical models, which integrate observations with CTM simulations, can reduce the exposure uncertainty (Huang et al., 2019).

Wildfires smoke is known to cause a substantial health burden given the well-established associations between $PM_{2.5}$ and hospital admissions and premature mortality, particularly for cardiovascular and respiratory conditions (Clarke et al., 2023; Liu et al., 2015; Reid et al., 2016; Schollaert et al., 2023; Ye et al., 2022). Despite this, economic assessments of wildfires impact often omit the health consequences of smoke pollution. These assessments typically concentrate on expenses related to fire-induced injuries, infrastructure damage, and fire suppression. Only a limited number of studies have endeavored to estimate the mortality and morbidity burden resulting from wildfires smoke exposure (Burke et al., 2021; Cascio, 2018; Johnston et al., 2020). However, conventional methods for determining the disease burden attributable to air pollution can be extended to evaluate the impacts of wildfires smoke on public health (Ford et al., 2018; Neumann et al., 2021; O'Dell et al., 2021).

In New Mexico, the average size of wildfires has grown, and the total acreage burned in 2010–2019 was nearly double that burned in the previous decade. Furthermore, wildfires exceeding 1000 acres in size have been observed with greater frequency since the 1980s (MTBS, 2023). The state's two largest fires on record in 2022, the Calf Canyon/Hermits Peak Fire and the Black Fire, burned areas that were 15 % and 9 % larger, respectively, compared to the previously recorded largest wildfire, the Whitewater–Baldy Complex in 2012 (Johnston, 2023).

Given the historical size of the 2022 wildfires in New Mexico and the overall trend toward larger wildfires in the western US, there is a compelling need to comprehensively assess the impacts of the 2022 wildfires in New Mexico on air quality. Thus, our objective was to assess the effects of these wildfires on both regional and local $PM_{2.5}$ and MDA8-O_3 levels across the state. Additionally, to provide a comprehensive context, we utilized a standard health impact assessment approach to estimate the excess deaths attributable to the heightened levels of $PM_{2.5}$ and MDA8-O_3 resulting from the wildfires.

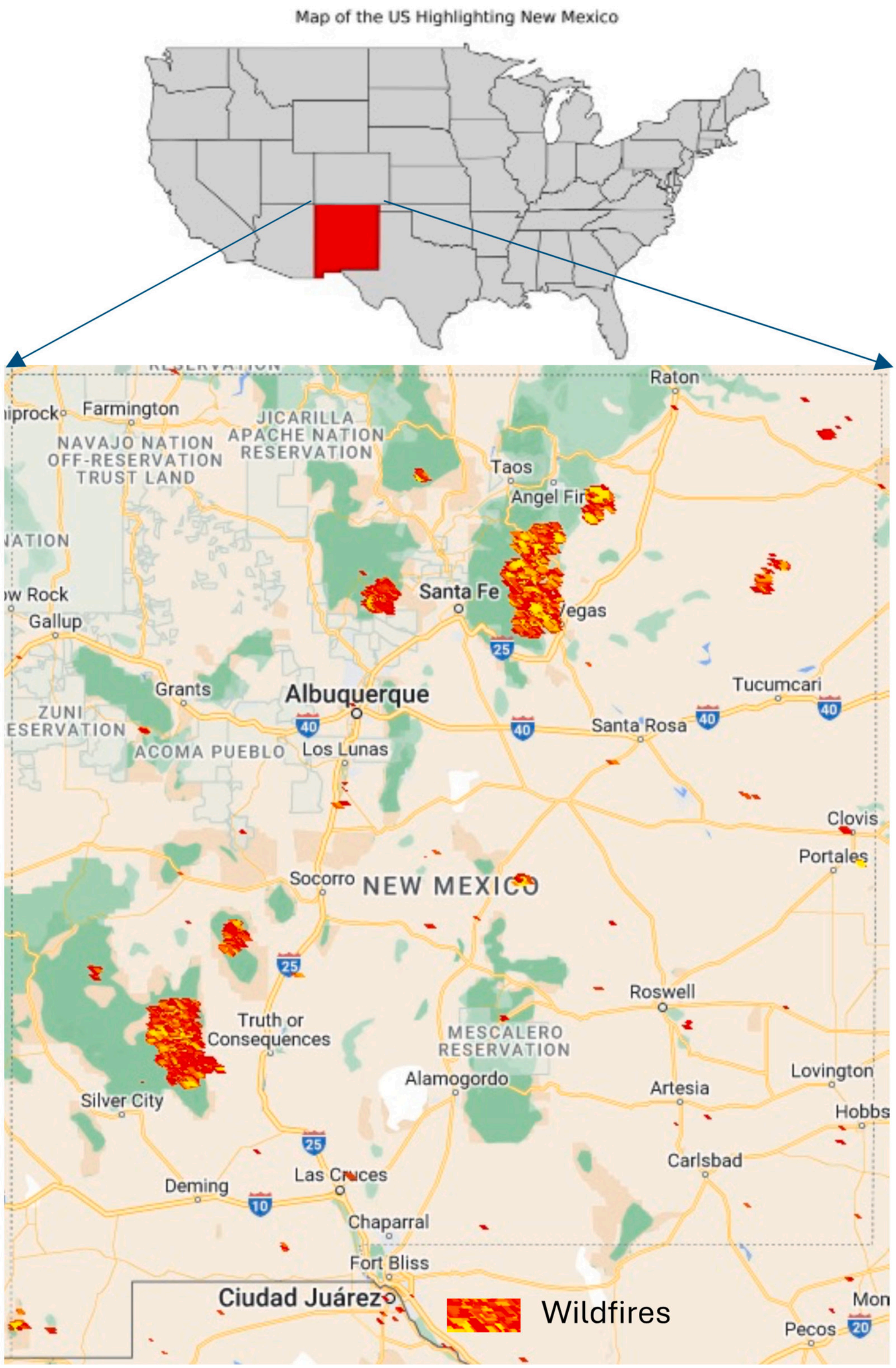

Fig. 1. The wildfire perimeters shown here represent the total area burned for each fire from April 6 to August 22, 2022, within our study domain in New Mexico, US. We presented the total number of fires detected during the study period by the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Aqua and Terra satellites, as well as the Visible Infrared Imaging Radiometer Suite (VIIRS).

2. Methods

In 2022, New Mexico experienced 748 wildfires. In this study, we selected six of these based on the size of the burn area and their proximity to populated areas (Fig. 1). These six wildfires accounted for 811,000 acres of the burned area, approximately 90 % of the total burn area in New Mexico in 2022. These include the Calf Canyon/Hermits Peak Fire, Black Fire, Cerro Pelado, Cooks Peak Fire, Bear Trap, and Big Hole fires. The duration of these wildfires spanned from April 6 to August 22, 2022. Here, we designed a multistage modeling framework to quantify daily wildfires smoke $PM_{2.5}$, MDA8-O_3 and NO_2 concentrations: (a) daily wildfire burn areas are identified for each wildfire to estimate three-dimensional wildfire emissions using the BlueSky emission inventory framework; (b) wildfires emission impacts on air quality are calculated using the CMAQ (spatial resolution of $12 \times 12\ km^2$); (c) in the data-fusion step, we integrated CMAQ $PM_{2.5}$, MDA8-O_3 and NO_2 with daily observations at US Environmental Protection Agency (USEPA) air quality monitoring network data to generate an "adjusted wildfire impact"; and finally, (d) wildfire-specific $PM_{2.5}$ and MDA8-O_3 were used to estimate the short-term health impact on a population of 2.1 million in New Mexico in 2022, employing concentration-response functions (Fig. S1).

2.1. Wildfire emissions

The BlueSky smoke modeling framework integrates various models that characterize critical aspects of fire behavior including fire location, size, and type, and is used to characterize hourly emissions originating from wildfires (Larkin et al., 2009). Additionally, it incorporates models for fuel-related parameters such as fuel type, amount, consumption, speciated emissions, emissions dispersion, and emissions trajectories (AirFire Research Team, 2024). BlueSky utilizes data from the Weather Research and Forecasting (WRF) model to characterize smoke dispersion. Fuel load data are also essential inputs for BlueSky. For default values, BlueSky uses fuel types from the fuel characteristic classification system (FCCS), which has extensive data and maps on wildland fuels throughout the United States. We used every day burn area of the six wildfires as an input, along with gridded three-dimensional weather parameters in the BlueSky framework to estimate three-dimensional hourly wildfire emissions for CMAQ. Details about the overall modeling framework, the component models, and how they are linked together are described in Larkin et al. (2009) and its use in past studies (Li et al., 2023, Michael et al., 2023).

2.2. CMAQ model configuration

We simulated hourly $PM_{2.5}$ and O_3 concentration during the wildfire period (April 6 to August 22, 2022) in New Mexico using WRF coupled with Community Multiscale Air Quality Modeling System (CMAQ) (version 5.4). CMAQ is an atmospheric chemical transport model, contains state-of-the-art parameterizations of atmospheric processes affecting the transport, transformation, and deposition of pollutant species at three-dimensional grid cells throughout the modeling domains. Emissions include anthropogenic emissions based on the National Emission Inventory (NEI) (USEPA, 2023), and wildfire emissions described above. Hourly emissions were prepared using the Sparse Matrix Operator Kernel Emissions (SMOKE) model (version 4.7). The SMOKE processing system is an advanced tool designed for air quality modeling that processes emissions data into formats suitable for CMAQ (Camilleri et al., 2023). SMOKE can process large datasets to deliver high-resolution emissions data tailored for specific modeling needs, thereby playing a critical role in air quality management and policymaking (Arter et al., 2021). Emissions from the 2016 NEI inventories were processed using the USEPA 2016v1 platform (USEPA, 2021). Through SMOKE programs, we allocated the sectorized anthropogenic mobile, point, and area emissions into hourly speciated gridded emission rates fields as CMAQ-ready inputs, while biogenic (BEIS), lightning NOx and windblown dust emissions were calculated interactively within CMAQ.

The modeling domain covers New Mexico and surrounding states at a 12 km × 12 km horizontal resolution, with 35 vertical levels extending up to 50 hPa. Contributions of wildfires between April 6 to August 22, 2022, were calculated by simulating two scenarios: a baseline simulation (s) with all emissions ($CMAQ^s_{all}$) and a second simulation in which wildfire emissions were not included ($CMAQ^s_{no-WF}$). This allowed us to quantify the impact from the wildfires (WF):

$$\Delta CMAQ^s_{WF}(x,t) = CMAQ^s_{all}(x,t) - CMAQ^s_{no-WF}(x,t) \tag{1}$$

where $\Delta CMAQ^s_{WF}$ is the simulated concentration associated with wildfire emissions, and x and t indicate variation in space and time, respectively.

2.3. Data integration method

Simulation results from CMAQ have potential errors related to uncertainties in estimated emissions values, meteorological parameter data, and physical/chemical transport processes; hence, these simulated results differ from the results of field measurements. To reduce the model biases and error in the current study, we calibrated daily average and hourly maximum $PM_{2.5}$ and MDA8-O_3 results simulated by CMAQ using a data fusion (DF) approach (Friberg et al., 2016). For DF and model evaluation, we obtained ground measurements of ambient daily observations for $PM_{2.5}$ and MDA8-O_3 concentrations from the U.S. Environmental Protection Agency's (USEPA) air quality system and used them as reference measurements. Eq. (2) reflects the regression model applied to produce optimized fused concentration fields $C^{DF}_{all}(x,t)$ by computing a weighted average with the weight depending on the spatial autocorrelation of observations and the correlation between observations and CMAQ simulations (Friberg et al., 2016):

$$\mathrm{C^{DF}_{all}(x,t)} = \left[\mathrm{W(x,t)} \times \left(\frac{\mathrm{OBS_m(t)}}{\overline{\mathrm{OBS_m}}}\right)_{\mathrm{krig}} \times \overline{\mathrm{FC(x)}}\right] + \left[(1-\mathrm{W(x,t)}) \times \mathrm{CMAQ^s_{all}(x,t)} \times \left(\frac{\overline{\mathrm{FC(x)}}}{\overline{\mathrm{CMAQ^s_{all}(x)}}}\right) \times \beta^{(t)}_{\mathrm{season}}\right] \tag{2}$$

where,

$$\overline{\mathrm{FC(x)}} = \alpha_{\mathrm{year}} \times \overline{\mathrm{CMAQ^s_{all}(x)}}^{\beta}$$

$$\beta_{season}(t) = e^{A \times \cos\left[\frac{2\pi}{365.25}(t - t_{max})\right]}$$

The resulting product $C^{DF}_{all}(x,t)$ is a new fused-field that captures the temporal variations in local observations, as well as spatial variability in CMAQ simulations. Here, OBS_m represents daily observations at each monitor (m), overbar indicates temporal averaging (annual), β is a parameter derived for all years, α_{year} is a regression parameter derived for each year and W is an average weighting factor for the study period. β_{season} is the seasonal correction function that was modeled as a smooth trigonometric function with two fitted parameters, amplitude (A) and day of peak correction (t_{max}).

The ratio of fused $PM_{2.5}$ and MDA8-O_3 fields, and CMAQ-simulated $PM_{2.5}$ and MDA8-O_3, were multiplied by wildfire-contributed $PM_{2.5}$ and MDA8-O_3 from CMAQ for each day and each grid cell to generate an 'adjusted wildfire impact' ($\Delta C^{DF}_{WF}(x,t)$) as follows (Huang et al., 2019):

$$\Delta C^{DF}_{WF}(x,t) = \Delta CMAQ^s_{WF}(x,t) \times \left[C^{DF}_{all}(x,t) / CMAQ^s_{all}(x,t)\right] \tag{3}$$

A similar data integration approach using CMAQ-simulated data with aerosol optical depth (AOD), meteorological data, land-use data, and Hazard Mapping System (HMS) smoke plume height information has been previously used (Burke et al., 2021; Shaddick et al., 2018; Zhang et al., 2023).

2.4. Estimates of short-term health impacts

In this study, we estimated all-cause short-term premature deaths attributed to smoke $PM_{2.5}$ and MDA8-O_3 exposure, as well as asthma emergency department visit (AEDV) morbidity attributed to smoke $PM_{2.5}$, using concentration-response functions (CRFs) describing the relative risk dependency on the pollutant abundance by age and disease (Lou et al., 2023):

$$\Delta HI_{WF}(t) = \sum \left\{ \left[1 - e^{-CRF\times\overline{\Delta C}^{DF}_{WF}(x,t)}\right] \times B_0(t) \times Pop\left(x,t\right)\right\} \qquad (4)$$

where $\Delta HI_{WF}(t)$ is the cause-specific excess health impact due to wildfire smoke $PM_{2.5}$ and MDA8-O_3 exposure during the study period t; $\overline{\Delta C}^{DF}_{WF}(x,t)$ is the grid-level average air pollution contributed by wildfires, obtained from Eq. (3); $B_0(t)$ is the cause-specific baseline incidence rates provided in New Mexico and $Pop(x,t)$ is the gridded exposed population.

For all-cause mortality we used the CRFs recommended by Chen et al. (2021) for $PM_{2.5}$ (derived for wildfire-$PM_{2.5}$) and Bell et al. (2005) for O_3 (derived from outdoor O_3). For $PM_{2.5}$, we used a CRF recommended by Zanobetti and Schwartz (2009) as a sensitivity analysis. For AEDV we used a CRF from Stowell et al. (2019) derived for wildfire smoke exposure. Baseline rates for all-cause mortality for the age group ≥25 years was obtained from the Global Burden of Disease (GBD) results tool (GBD, 2019), and baseline rates for AEDV was collected from New Mexico Department of Health report (NMDOH, 2021). We obtained the spatial distribution of the population in 2020 with a resolution of 1 km from the Gridded Population of the World (GPW) datasets (WorldPop, 2023) and re-gridded it to our 12 km model resolution. The ratios of ≥25 years old over the entire population was derived from the New Mexico state's age structure data (USCB, 2023).

3. Results

The six selected wildfires burned a total of 0.81 million acres of forest land in 2022 in New Mexico, in which Calf Canyon/Hermits Peak Fire and Black Fire burned over 0.34 and 0.32 million acres of land, respectively. We estimated that these wildfires emitted 152 thousand tons of $PM_{2.5}$, 287 thousand tons of VOCs, 997 thousand tons of carbon monoxide (CO), and 9 thousand tons of NOx. The details of each wildfire emission are reported in Supplementary Material.

3.1. Assessing model performance

We compared the simulated daily $PM_{2.5}$ and MDA8-O_3 concentrations in CMAQ and data-fusion field with observational data, available from the EPA's Air Quality System (AQS), between April 6 and August 22, 2022. Evaluation of CMAQ indicated that the model generally underestimated $PM_{2.5}$ by ~20 % (NME: 47 % and NMB: −16 %) and overestimated MDA8-O_3 by ~16 % (NME: 21 % and NMB: −18 %) throughout the study period. This could be due to biases in emissions, model chemistry, and/or rapid artificial dilution of $PM_{2.5}$. Significant correlations between data-fusion concentration and observations were found for both $PM_{2.5}$ and MDA8-O_3 with the R^2 estimated at 0.59 (RMSE: 2.76 μg/m^3; NME: 22 %; NMB: −1 %) and 0.58 (RMSE: 6.0 ppb; NME: 10 %; NMB: −2 %), respectively (Fig. 2). R^2 calculated at a monitor level was over 0.82 for $PM_{2.5}$ (Fig. S4) and 0.85 for MDA8-O_3 (Fig. S5). Overall, good performance supports the analysis of the effects of emission changes from different sources on ambient air quality. This performance is above the performance of benchmark CTM-based $PM_{2.5}$ data generation (Table S4) (Emery et al., 2017).

The data-fusion method performance was evaluated using a comprehensive 10-fold, 10 % data withholding cross-validation analysis. During the study period, observations were recorded at 20 monitors. The number of withheld data points was 941 for $PM_{2.5}$ and, correspondingly, 3240 for MDA8-O_3. The cross-validation results across all monitors indicate that MDA8-O_3 (R^2 = 0.54, MB = −2.0 ppb, RMSE = 4.52 ppb, NME = 9 %, NMB = -4 %) performed better compared to daily $PM_{2.5}$ (R^2 = 0.51, RMSE = 3.6 μg/m^3, NME = 32 %, NMB = −17 %), and the results meet all the criteria and goals at all stages of cross-validation (Table S4) (Emery et al., 2017).

3.2. Impacts of wildfires on air quality

We observed wide spatial variability in wildfire-specific 24 h-average $PM_{2.5}$ estimates across New Mexico counties in 2022 (Fig. S3). The average contribution of wildfire smoke to daily $PM_{2.5}$ concentration across New Mexico from the six fires was 0.31 ± 0.24 μg/m^3 (values averaged across all days in the study period), though in some locations the impact was as high as 1.21 μg/m^3, which is a major fraction given the average ambient $PM_{2.5}$ concentrations are low in New Mexico (~5 μg/m^3). During the study period, wildfires contributed >10 % to the daily averaged ambient $PM_{2.5}$ concentrations on 22 % of the study days. Moreover, the highest daily maximum contribution of smoke exceeded 20 % of the daily ambient $PM_{2.5}$ concentration across the New Mexico domain during the study period. Daily average wildfire $PM_{2.5}$ exceeded 50 μg/m^3 in some locations in New Mexico and 1 h-max wildfire smoke $PM_{2.5}$ exceeded 120 μg/m^3 in some grid cells near the Santa Fe region (Fig. 3).

The average wildfire MDA8-O_3 across New Mexico was 0.18 ± 0.29 ppb, which is approximately 0.34 % of ambient MDA8-O_3 during the study period in New Mexico. Counties near Santa Fe, like Mora, San Miguel, and Los Alamos experienced over 0.50 ppb wildfire MDA8-O_3

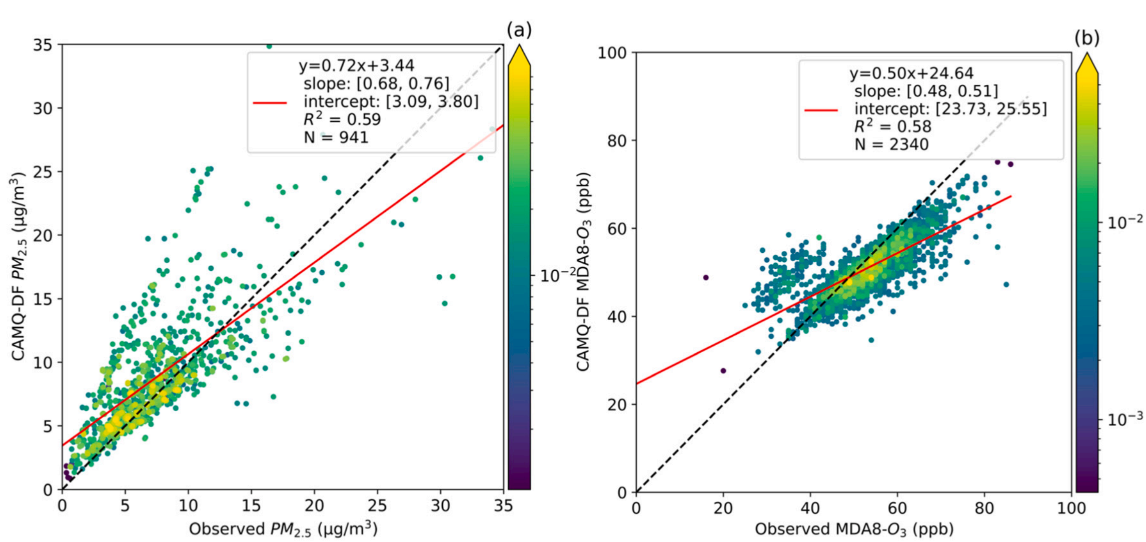

Fig. 2. Density scatterplots of model performance of daily observed and CMAQ-DF pollutant (a) $PM_{2.5}$ and (b) MDA8-O_3. The dotted line shows 1:1.

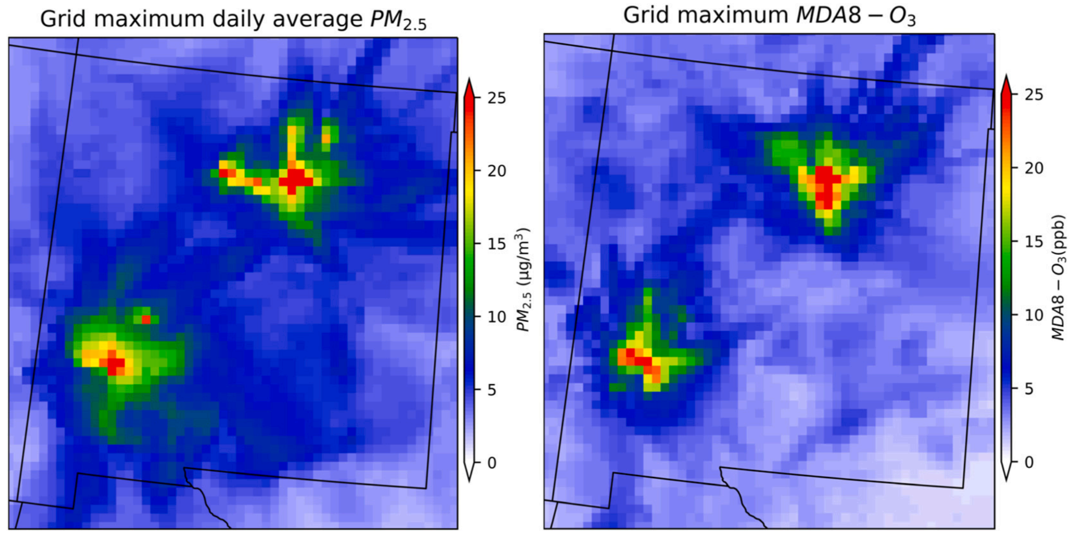

Fig. 3. Grid maximum daily average $PM_{2.5}$ concentration (μg/m^3) (left) and MDA8-O_3 concentrations (ppb) (right) from the studied fires from April 6 to August 22, 2022.

during the study period (1 % of ambient MDA8-O_3). (Fig. S2). Daily wildfire MDA8-O_3 exceeded 35 ppb in some regions in New Mexico; however, 1 h-max smoke O_3 exceeded over 60 ppb in some grids near the Santa Fe region (Fig. 4). The build-up of O_3 due to photochemical reactions takes several hours, and as a result, the highest levels of photo-oxidants can be expected some distance downwind of the sources.

Employing the same methods described above, we observed that the contribution of wildfire smoke to NO_2 levels was low, with the maximum daily average of smoke-related NO_2 being only 0.8 μg/m^3. Additionally, the maximum 1-h peak of smoke NO_2 exceeded 5 μg/m^3, but only over a small region (Fig. 5). High concentrations of pollution from wildfires were observed near the Calf Canyon/Hermits Peak Fire and Black Fire regions.

3.3. Impacts of wildfires smoke on human health

There are approximately 2.1 million people in New Mexico during the study period with average population-weighted exposure to $PM_{2.5}$ and MDA8-O_3 from the six fires of 0.33 μg/m^3 and 0.20 ppb. We calculated that short term exposure to $PM_{2.5}$ during the study period resulted in 18 deaths (95 % CI: 15–21) using the CRF from Chen et al. (2021) and 7 deaths (95 % CI: 5–9) using the CRF from Zanobetti and Schwartz (2009). This represents, between 15 and 6 % of the excess deaths attributed to ambient $PM_{2.5}$ (i.e., 122 deaths). Using all-source-specific concentration-response coefficients, the results showed 2.5 times fewer premature deaths compared to the estimations using wildfire smoke $PM_{2.5}$-specific concentration-response coefficients. For MDA8-O3, we estimated a total of 4 (95 % CI: 3–6) deaths and 171 (95 % CI: 124–217) AEDV (33 % cases among those <17). Wildfires smoke does not only affect local air quality; its impact encompasses vast surrounding areas, thereby influencing the health of populations across these expansive regions. Emissions from the six fires were responsible for an additional 23 (5 %: 20–27), 13 (5 %: 11–15), 10 (5 %: 8–12) premature deaths in Texas, Colorado and Arizona, respectively, using the CRF from Chen et al. (2021).

4. Discussion

This study utilized a multistage modeling framework to estimate the largest wildfires burn impact on air quality and human health in New

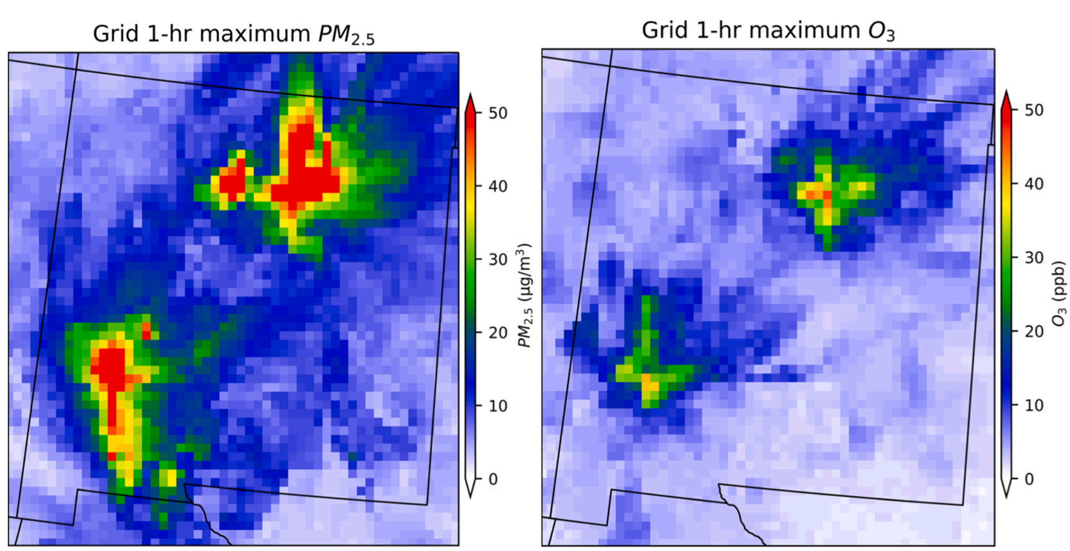

Fig. 4. Grid maximum of 1-h maximum $PM_{2.5}$ concentration (μg/m^3) (left) and 1-h maximum O_3 concentrations (ppb) (right) from the studied fires from April 6 to August 22, 2022.

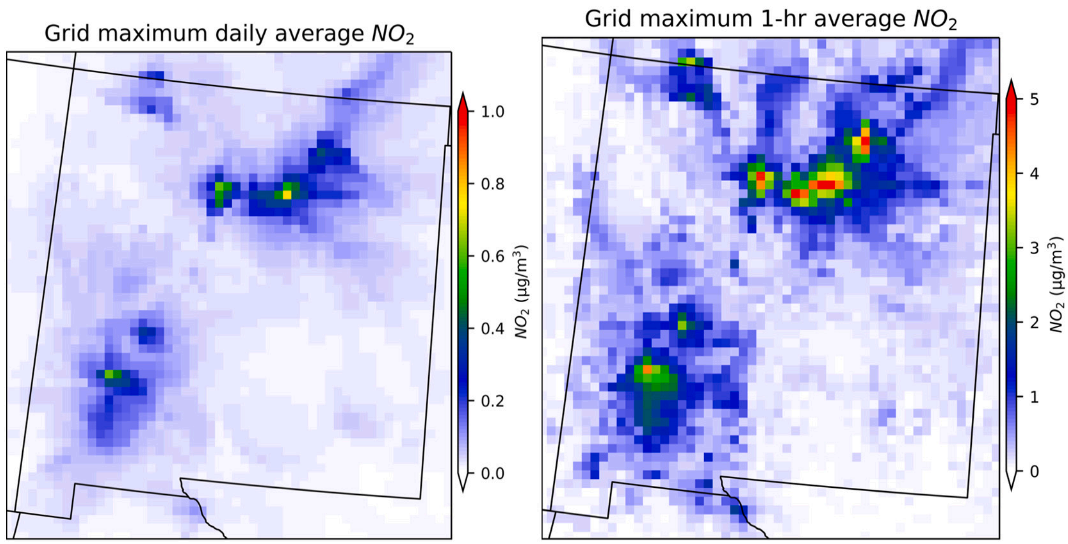

Fig. 5. Grid maximum daily average NO_2 concentration (µg/m^3) (left) and 1-h maximum NO_2 concentrations (ppb) (right) from the studied fires.

Mexico in 2022, providing vital data in an area that is becoming increasingly important as wildfire frequency and intensity grow due to climate change. The BlueSky model framework was used to estimate wildfire emissions because BlueSky has a more advanced fuel classification algorithm (Ottmar et al., 2007) and also contains a comprehensive archive of emission factors for these fuels (Prichard et al., 2020). The data-fusion and the validation of model outputs against observed data enhance the credibility and robustness of the results. This meticulous approach to data handling ensures that the study's findings are well-supported and reliable. By quantifying the health impacts associated with wildfires smoke exposure, the study contributes valuable information to the public health field. However, the major uncertainties involved in this study include wildfire emission estimates, model performance and the assumption of sources-specific pollutant toxicity for health risk assessment.

Emission inventories play a crucial role in various modeling applications aimed at comprehending the impact of emissions on air quality, climate, and human health (Pouliot et al., 2020). Numerous global biomass burning emissions inventories have been developed and updated in recent decades. 'Bottom-up' inventories, like the Global Fire Emissions Database (GFED) and the Fire INventory from NCAR (FINN), rely on satellite data for burned areas and/or active fire detections. They incorporate factors such as fuel loads, combustion completeness, and other emissions factors to estimate fire emissions. On the other hand, 'top-down' inventories, such as the Global Fire Assimilation System (GFAS), Quick Fire Emissions Database (QFED), and Fire Energetics and Emissions Research (FEER), utilize observations of fire radiative power to calculate emissions. Comparisons of different fire emissions inventories have highlighted variability in the results, each with its own set of advantages and disadvantages (Faulstich et al., 2022). A large uncertainty in wildfire emissions inventories has been shown to lead to many-fold differences in wildfire-attributed $PM_{2.5}$ concentrations across the US (> 20 × regional differences in high fire years) when different inventories are used as input to the same CTM (Carter et al., 2020; Koplitz et al., 2018). For instance, Koplitz et al. (2018) found that GFED4's burned area estimates for June 2011 were 40 % higher than those of FINN. However, the average annual wildfires smoke $PM_{2.5}$ in the CONUS was higher in FINN (0.33 µg/m^3) than in GFED4 (0.12 µg/m^3), because of different emission factor used to estimate wildland fire emission. Furthermore, even FINN and GFED4 exhibit dissimilar seasonal patterns (Larkin et al., 2020). Zhang et al. (2014) estimation indicate that for the same region and time period, wildfires smoke emissions of $PM_{2.5}$ differ by factors of 2–4 on an annual basis and by 8–12 for a given fire event across different emission inventories, and that could over/underestimate population exposures and therefore health outcomes. Several bottom-up and top-down fire emission inventories have reported that the black carbon (BC) and organic carbon (OC) emission estimates from the FINN emission inventory lie between those of the highest (i.e., FEER) and lowest (i.e., GFAS) top-down emission inventories, while the GFED bottom-up inventory tends to be biased toward the lower side (Kulkarni et al., 2020). Similar uncertainties were observed in the FINNv1, GFED4s, and GFAS emission inventories for Northern South America, where Ballesteros-González et al. (2020) reported wildfire emissions of 0.06, 0.76, and 0.01 Tg of EC and 0.32, 0.08, and 0.10 Tg of OC, respectively, in February 2018. Wildfires also burn structures that contain treated wood, plastics, paints, hazardous household wastes, vehicles and melt plastic water pipes. All these items release toxic gases and particles that are not considered in the emission inventories (US EPA, 2023). Despite concerted efforts, there remains an urgent need for burn severity and emissions inventories on a scale relevant to actionable management, such as fuel reduction treatments, and over longer temporal periods. Despite concerted efforts, there remains an urgent need for burn severity and emissions inventories on a scale relevant to actionable management, such as fuel reduction treatments, and over longer temporal periods.

Our model performed well, explaining ~72 % and ~ 50 % of the variation in overall $PM_{2.5}$ and MDA8-O_3, respectively, at the study locations. Model performance appears to exceed the benchmark for CTM in the US, however this model performance was achieved after applying our data-fusion approach. Many CTM-based studies are simulated daily variation in $PM_{2.5}$, however, numerous smoke-based CTM studies do not report performance evaluations or are not directly evaluated using the same monitoring stations over time (Pan et al., 2023). Wilkins et al. (2018) used CMAQ to estimate the contribution of wildfires smoke to total $PM_{2.5}$ across the CONUS and estimated that wildfires $PM_{2.5}$ constituted 10.5 % of total $PM_{2.5}$ over 2008–2012 and had an R^2 between 0.37 and 0.42 and NME of42–48 %. A non-CTM based smoke model also shows similar performances over western North America (R^2: 0.44) (Burke et al., 2021). The performance of other smoke-based CTM, such as the WRF-Chem model, was found similar in Indonesia (R^2 = 0.26, NMB = 47 %) (Kiely et al., 2020) and Australia (R^2 = 0.28, NMB = 49 %) (Graham et al., 2021). We also find similar performance for $PM_{2.5}$ without data fusion (R^2 = 0.33, NME: 47 %). The accuracy of CTM is hindered by imperfect characterization of complex fire chemistry, inaccurate height of emissions injections and emission inventories, and rapidly changing local meteorology surrounding fires (Kahn et al., 2008;

Rastigejev et al., 2010). To improve the model performance, data-fusion statistical models, which integrate ground observations with CTM simulations, have proven effective (Huang et al., 2019). For ground-level observed $PM_{2.5}$, the increasing use of low-cost sensors offers a valuable supplement at remote location (Huang et al., 2021). For further improvement of the model performance, Zhang et al. (2023) used random forest (RF) to integrate ground observation from low-cost sensor, multi-angle implementation of atmospheric correction (MAIAC) aerosol optical depth (AOD), Terra and Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) cloud fraction, meteorological data, land use data and Hazard Mapping System (HMS) smoke plume (Zhang et al., 2023).

The mortality in New Mexico state attributable to short-term exposure (spanning a few days to few months) to wildfires $PM_{2.5}$ varies depending on the chosen CRFs for $PM_{2.5}$. Previous studies investigating the health effects of wildfires smoke did not employ an epidemiological study specifically developed for wildfire-related $PM_{2.5}$. Instead, they utilized methods designed for ambient $PM_{2.5}$, implicitly assuming that all $PM_{2.5}$ components are equally toxic. However, Aguilera et al. (2023) reported that exposure to wildfires smoke could lead to a tenfold increase in the risk of respiratory hospitalizations, relative to other $PM_{2.5}$ sources because of high content of BC and OC. Although, there is mixed evidence on the extent to which exposure to wildfires smoke has different health impacts than exposure to other $PM_{2.5}$ sources. There is some evidence that different health endpoints are $PM_{2.5}$ source-specific (Black et al., 2017; DeFlorio-Barker et al., 2019). Lou et al. (2023) also observed a significant difference in the outcomes of short-term all-cause premature deaths when using wildfire-specific and ambient-specific CRFs for $PM_{2.5}$. Krewski et al.'s (2009) study (ambient-$PM_{2.5}$) has been widely used to assess the wildfire $PM_{2.5}$-attributed excess all-cause long-term mortality estimation. Using the same study, we estimated 57 (95 % CI: 38–75) all-cause long-term premature deaths. Using Krewski et al. (2009) study, Pan et al. (2023) reported 13 premature deaths in New Mexico, with an average wildfire $PM_{2.5}$ of 0.13 $\mu g/m^3$ in 2014. Ma et al. (2023) reported that wildfires $PM_{2.5}$ contributed to approximately 1141 all-cause deaths per year in the contiguous US based on a wildfire-specific long-term concentration-response function (CRF). In contrast, O'Dell et al. (2021), Ford et al. (2018) and Pan et al. (2023) reported significantly higher figures for all-cause deaths/year, 6300, 21,000, and 4000, respectively, based on CRFs specific to all sources of $PM_{2.5}$. However, these studies not segregate wildfires from other type of fire like prescribed burning, and agricultural burning. O_3 is a single-species pollutant, and we assume equal toxicity for both ambient O_3 and wildfire-specific O_3. Moreover, there are few epidemiological studies that specifically address the relationship between wildfire-specific O_3 and premature mortality or morbidity (Reid et al., 2019). Therefore, past studies used Bell et al. (2005) to estimate the short-term mortality associated with wildfire-MDA8-O_3 exposure. For instance, Ballesteros-González et al. (2020) reported 83 short-term all-cause deaths linked to high wildfire-O_3 levels (4.3 ppb) during February 2018 in Northern South America. Compounds such as benzenoids and isocyanic acid play a significant role in the toxicity of biomass burning smoke (Chandra and Sinha, 2016). Including these compounds could enhance the accuracy of our health impact assessments.

As wildfire exposure is expected to increase in the future, it is essential to develop strategies that minimize adverse effects to ensure that wildfires do not detrimentally impact air quality and public health. At a minimum, forecasts of wildfire-related pollution must be communicated effectively to vulnerable populations. There is large uncertainty in the emissions inventories, with significant differences in emissions of elemental carbon, organic carbon, $PM_{2.5}$, and gas-phase emissions as well. For a sensitivity analysis, it is important to examine pollution concentrations associated with different wildfire emission inventories to ensure more robust model performance. An increase in horizontal resolution in model grid-spacing may improve model performance; this needs to be examined in future studies (Ye et al., 2022). Despite having some uncertainty, this study – (1) reveals that increased exposure to wildfire smoke raises the risks of premature mortality and asthma exacerbations. These findings highlight the urgent need for targeted public health advisories and emergency response strategies in New Mexico to mitigate these health risks. The exposure data can also aid epidemiological studies to better understand the health outcomes of wildfire smoke; (2) contributes to evidence that climate change intensifies wildfires, significantly affecting air quality and human health. Our empirical data links wildfire smoke to air quality, providing insights to predict future trends and assess climate adaptation strategies; (3) advances understanding of how wildfire smoke impacts air quality and health, emphasizing the need for improved air quality management strategies. The findings advocate for stronger environmental health policies that incorporate wildfire threats in urban and rural planning.

5. Conclusions

This study has quantified the impacts of six major wildfires in New Mexico on daily average $PM_{2.5}$ and maximum daily average 8 h ozone (MDA8-O_3) concentrations and premature mortality. This study additionally presented the spatial distributions of fire-related grid-maximum daily average $PM_{2.5}$ and MDA8-O_3 during the study period. Peak impacts on $PM_{2.5}$ and MDA8-O_3 were as high as 50 $\mu g/m^3$ and 35 ppb, respectively. Daily 1 h-max smoke $PM_{2.5}$ and O_3 frequently exceeded 120 $\mu g/m^3$ and 60 ppb in some grid cells. The wildfires contributed an average of 7 % to the ambient $PM_{2.5}$ levels across New Mexico, with a peak in the daily average impact exceeding 20 % of the ambient $PM_{2.5}$. During the study period in New Mexico, the total estimated short-term all-cause deaths associated with wildfires amounted to 22 cases, comprising 18 deaths related to $PM_{2.5}$ and 4 deaths related to O_3.Wildfires $PM_{2.5}$, was calculated to be responsible for ~170 (95 %: 124–217) asthma emergency department visits. This information is relevant for public health authorities, researchers, urban and regional planners, as well as the general public in New Mexico. The study indicates significant consequences of wildfires, highlighting the need for effective measures to address potential adverse human health outcomes.

CRediT authorship contribution statement

Kamal J. Maji: Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Bonne Ford:** Writing – review & editing, Resources. **Zongrun Li:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Yongtao Hu:** Writing – review & editing, Formal analysis, Data curation. **Leiqiu Hu:** Writing – review & editing, Formal analysis. **Chelsea Eastman Langer:** Writing – review & editing, Resources. **Colin Hawkinson:** Writing – review & editing, Resources. **Srikanth Paladugu:** Writing – review & editing, Resources. **Stephanie Moraga-McHaley:** Writing – review & editing, Resources. **Brian Woods:** Writing – review & editing, Resources. **Melissa Vansickle:** Writing – review & editing, Resources. **Christopher K. Uejio:** Writing – review & editing, Resources. **Courtney Maichak:** Writing – review & editing, Resources. **Olivia Sablan:** Writing – review & editing, Resources. **Sheryl Magzamen:** Writing – review & editing, Resources. **Jeffrey R. Pierce:** Writing – review & editing, Resources. **Armistead G. Russell:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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