

Wildfire smoke exposure and mortality burden in the USA under climate change

<https://doi.org/10.1038/s41586-025-09611-w>

Received: 23 May 2024

Accepted: 9 September 2025

Published online: 18 September 2025

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Wildfire activity has increased in the USA and is projected to accelerate under future climate change^{1–3}. However, our understanding of the impacts of climate change on wildfire activity, smoke and health outcomes remains highly uncertain because of the difficulty of modelling the causal chain from climate to wildfire to air pollution and health. Here we quantify the mortality burden in the USA due to wildfire smoke fine particulate matter (PM_{2.5}) under climate change. We construct an ensemble of statistical and machine learning models that link climate to wildfire smoke PM_{2.5} and empirically estimate smoke PM_{2.5}–mortality relationships using data on all recorded deaths in the USA. We project that smoke PM_{2.5} could result in 71,420 excess deaths (95% confidence interval: 34,930–98,430) per year by 2050 under a high-warming scenario (shared socioeconomic pathway scenario 3-7.0, SSP3-7.0)—a 73% increase relative to the estimated 2011–2020 average annual excess deaths from smoke. Cumulative excess deaths from smoke PM_{2.5} could reach 1.9 million between 2026 and 2055. We find evidence for mortality impacts of smoke PM_{2.5} that last up to 3 years after exposure. When monetized, climate-driven smoke deaths result in economic damages that exceed existing estimates of climate-driven damages from all other causes combined in the USA^{4,5}. Our research suggests that the health impacts of climate-driven wildfire smoke could be among the most important and costly consequences of a warming climate in the USA.

Wildfire activity has increased substantially over the USA during the past two decades^{3,6}. As a result, air pollution that is associated with wildfire smoke (specifically fine particulate matter, PM_{2.5}) has substantially increased^{7–10}. Given the established impacts of ambient smoke PM_{2.5} exposure on morbidity and mortality^{11–13}, these increases have likely worsened several health outcomes. In many parts of the USA, smoke PM_{2.5} has accounted for over 50% of the annual concentration of PM_{2.5} in extreme smoke years¹⁴, and has led to stagnation or even reversal of the otherwise declining trend in ambient PM_{2.5} over the past two decades due to the Clean Air Act¹⁵.

Mounting evidence has suggested that human-induced climate change is a leading cause for the increased wildfire activity, especially in forested areas in the western USA^{1,2,16–19}, alongside other important causes that include historical fire suppression and the expansion of human activities into forested areas²⁰. A warming climate can influence wildfire activities by altering fuel aridity¹, conditions for fire spread²¹ and lightning ignitions²². For the western USA, many studies have projected increasing wildfire risks under a warming climate primarily due to increasing fuel aridity^{23–25}.

However, the relationship between a warming climate and the resulting increase in wildfire smoke pollution and health impacts remains highly uncertain because of the difficulty of modelling the complex causal chain from climate to wildfire to surface pollution and health effects. Several studies use regression models or land–vegetation–fire models to first project wildfire activity under future climate and then use atmospheric chemical transport models to estimate changes in smoke PM_{2.5} concentrations^{26–28} and associated health outcomes^{29–32}. However, previous projections of future mortality due to climate-driven fire smoke span a wide range of uncertainties, reflecting an important knowledge gap given the large potential impacts. Uncertainties in the previous projections come from three key sources. First, large uncertainties exist in how wildfire emissions respond to climate change³³. Second, modelling wildfire impacts on surface PM_{2.5} often faces large uncertainty in emission inventories and the vertical distribution of emission profiles^{34,35}, resulting in modelled smoke concentrations that sometimes differ by an order of magnitude when compared with surface observations^{36,37}. Third, most previous studies quantify the health impacts of smoke PM_{2.5} by applying existing exposure–response

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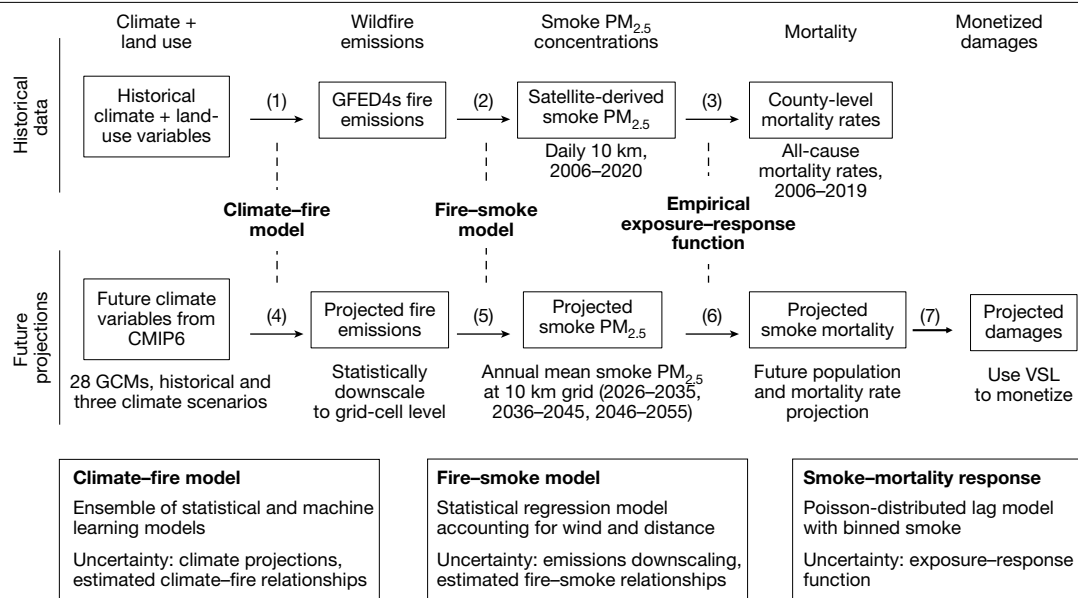


Fig. 1 | Research methodology. Overview of our research methodology. ML, machine learning.

functions derived from total PM_{2.5} exposures, which could fail to capture unique health impacts of smoke PM_{2.5} exposure, such as from smoke-specific chemical composition and toxicity³⁸, or behavioural responses unique to smoke events³⁹.

Owing to these challenges, very few studies to date have projected future smoke PM_{2.5} concentrations using empirically grounded relationships between climate, wildfire and PM_{2.5} (refs. 31,40). To our knowledge, no studies have estimated the future smoke mortality burden accounting for the unique health impacts of smoke PM_{2.5} using exposure–response functions that are specific to smoke pollution exposure. Without this quantification, leading estimates of the societal impact of climate change—many of which are directly used to guide policy—do not incorporate potential mortality impacts due to wildfire smoke PM_{2.5} (refs. 4,41). Detailed projections of future smoke PM_{2.5} exposure and health burden are crucial to inform policies to mitigate and adapt to the negative impacts of climate change and smoke PM_{2.5} on humans.

Here we develop a comprehensive, data-driven approach that addresses the above challenges (Fig. 1). First, we construct an ensemble of statistical and machine learning models that predict wildfire emissions as a function of climate and land use variables over North America (including Mexico and Canada) using observational data from 2001 to 2021. Our ensemble model demonstrates better performance relative to previous statistical models that link meteorological variables to fire emissions or burned areas (Supplementary Fig. 1). One advantage of our data-driven climate–fire model over process-based model projections is its ability to isolate the factors of climate variables from other factors that influence wildfires. We use dry-matter (DM) emissions from the fourth version of the Global Fire Emissions Database with small fires (GFED4s)⁴², which includes fire emissions from agriculture fires and land-use change. However, as most climate-induced increases in fire emissions come from forested areas (Supplementary Table 1), we refer to our estimates as ‘wildfire emissions’ and ‘wildfire smoke PM_{2.5}’ for simplicity and consistency. By modelling changes in wildfire emissions in Canada and Mexico, our approach can also capture important transboundary influences on US smoke PM_{2.5} and human health.

Second, we use surface wildfire smoke PM_{2.5} estimates derived from satellite data and machine learning models⁹ to establish an empirical relationship between wildfire emissions and smoke PM_{2.5} concentrations across the contiguous USA at a 10-km resolution, accounting for variation in wind directions and spatial transport. Our approach

achieves performance comparable to recent machine learning methods for modelling smoke PM_{2.5}, and it enables us to efficiently predict smoke concentrations in one location from changes in wildfire emissions in another (Supplementary Table 6). One key advantage of our approach over previous methods that use process-based models to simulate future smoke PM_{2.5} is that the magnitude of smoke PM_{2.5} is directly constrained by the empirical estimates of smoke PM_{2.5} concentrations; absence of these empirical constraints can render transport-model-based estimates of wildfire smoke unreliable when compared with surface observations^{36,37}. We also designed a stochastic downscaling approach that enables us to characterize the uncertainty in population exposure and mortality related to fire locations, an uncertainty that to our knowledge has not been evaluated in previous projections of smoke PM_{2.5} and mortality burden.

Third, we empirically estimate the effects of annual smoke PM_{2.5} concentrations on annual mortality rates using county-level data from 2006 to 2019 on all recorded deaths in the USA. We estimate exposure–response functions using a Poisson-distributed lag model that allows for nonlinear impacts of smoke PM_{2.5} on mortality rates, consistent with previous papers that examine smoke impacts on mortality and other health outcomes^{39,43}, while flexibly controlling for temperature, precipitation and a broad range of possible spatial and temporal confounds (Methods). We choose to model the mortality response at the annual level to match the temporal resolution of our smoke projections, but test robustness to estimates based on exposure at shorter time scales (for example, the number of extreme smoke days or months in a year). Using a distributed lag model, we also quantify the effects of smoke on mortality years after smoke exposure, given the emerging evidence of potential long-term health impacts of smoke exposure including decline in cognitive functions and cancer survival^{44,45}.

Finally, we combine the empirical relationships between climate, wildfire emissions, smoke PM_{2.5} and mortality rates derived above with bias-corrected climate projections derived from Coupled Model Intercomparison Project Phase 6 (CMIP6) global climate model (GCM) ensembles to generate future projections of smoke PM_{2.5} and mortality burden. We project the annual average smoke PM_{2.5} concentration across the contiguous USA (48 states and the District of Columbia) between 2026 and 2055 under different climate scenarios. We then quantify changes in mortality rates in each county in the contiguous USA between 2050 and the historical period, and the difference across three climate scenarios—SSP1-2.6 (which the IPCC refers to as

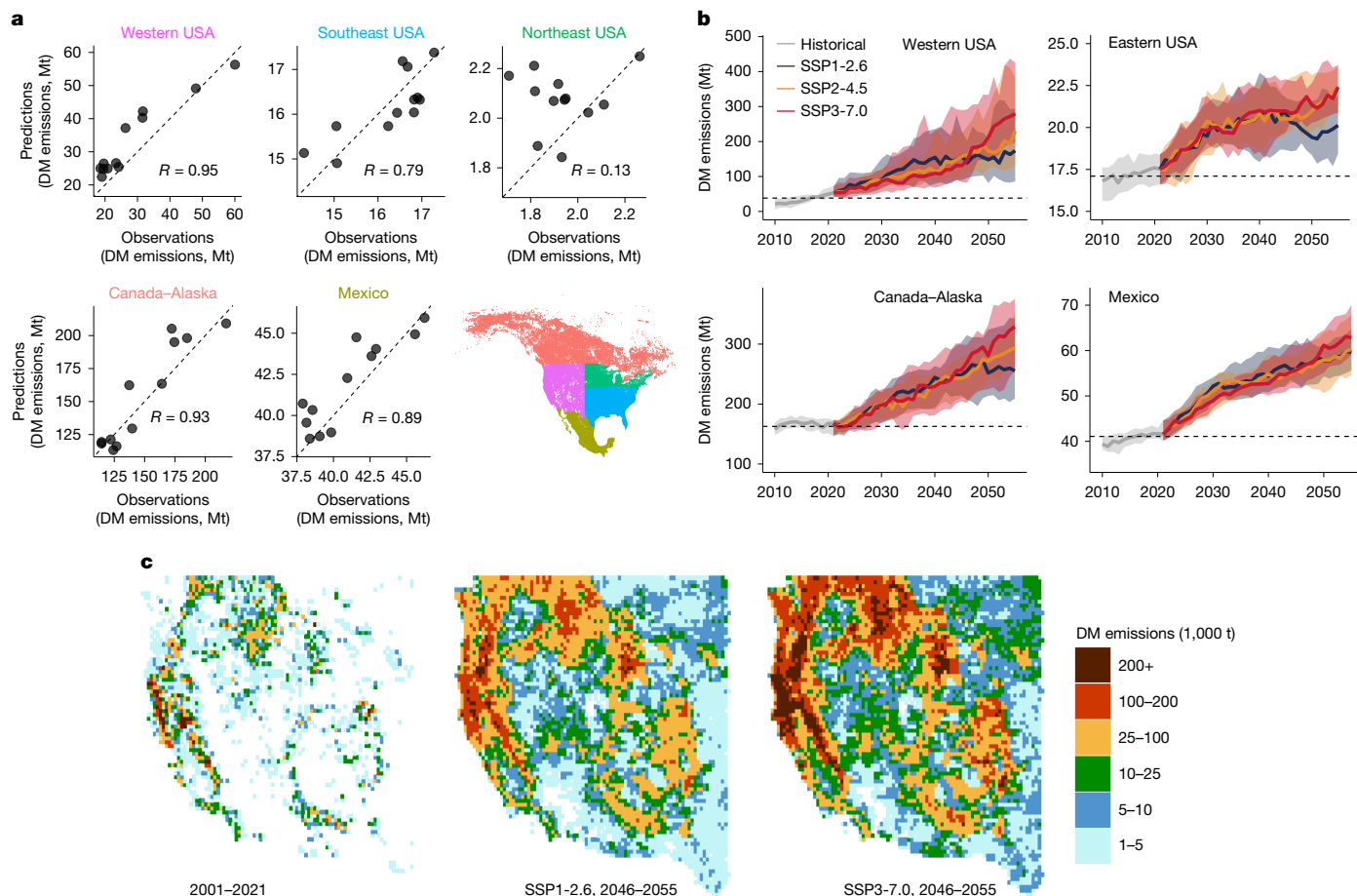


Fig. 2 | Projected wildfire emissions under future climate change scenarios. **a**, The performance of the ensemble climate–fire models. We built separate models to predict wildfire DM emissions for five regions: western USA, southeast USA, northeast USA, Canada–Alaska and Mexico. The plot shows the 10-year moving average of predicted emissions (y axis) against the observed emissions (x axis), aggregated at the regional level. **b**, Projected wildfire emissions under the historical scenarios and three future climate scenarios (SSP1-2.6, SSP2-4.5 and SSP3-7.0). The plot shows the 10-year moving average of wildfire emission projections (median across GCMs). The dashed line represents

the average observed emissions over 2001–2021 for each region. The shaded area represents the 25th and 75th percentiles of the projected emissions across 28 GCMs. For presentation purposes, we aggregate predictions from the northeast USA and southeast USA to calculate the total for eastern USA. **c**, Historical DM emissions for western USA in 2001–2021 from GFED4s (spatial resolution: 0.25°) and projected annual emissions averaged between 2046 and 2055 under the SSP1-2.6 and SSP3-7.0 scenarios. Projected emissions are first stochastically downscaled from regional emissions predictions and then averaged over 40 simulated downscaling estimates.

the low-emissions scenario), SSP2-4.5 (which the IPCC refers to as the intermediate-emissions scenario) and SSP3-7.0 (which the IPCC refers to as the high-emissions scenario). We quantify the uncertainty in the final projected smoke exposure and mortality burden across the different components of our modelling framework. We calculate the monetized health damages using a Value of Statistical Life (VSL) of US\$10.95 million (year 2019 dollars) and compare our mortality estimates with estimates of direct temperature-related mortality burden and aggregate climate damages from previous work^{4,5,46} to contextualize the importance of climate–smoke channels relative to other known climate impacts. As in a large body of existing climate impacts work, our goal is not to project all possible changes in wildfire activity and its impacts in future years, but to isolate the impact of a changing climate on changes in wildfire activity and the resulting effects on air quality and human health.

Empirical link between climate and smoke PM_{2.5}

We considered three different statistical and machine learning frameworks for modelling the climate–fire relationship (Methods). To account for geographical heterogeneity, we estimated each of our frameworks separately by region, resulting in five ensembles of climate–fire models. Our models capture the variability of wildfire

DM emissions at 10-year intervals (to account for fire stochasticity at the annual level; Methods), highlighting their ability to quantify changes in wildfire emissions under different climate conditions (Fig. 2a). When evaluating through cross-validation of temporal blocks (that is, splitting a time series of observations into disjoint sets of training and testing years), our models achieve high prediction performance, especially in the western USA, Canada–Alaska and Mexico, with correlation coefficients of 0.89–0.95 in out-of-sample evaluation. Under these evaluation criteria, our model achieves higher performance relative to other commonly used regression methods such as a log-linear model¹ and machine learning methods²⁴ to model climate impacts on burned area (Supplementary Fig. 1).

Our model performance indicates that climate conditions are not the only factors influencing the variability of wildfire emissions over time. While our models can predict spatially and temporally aggregated emissions effectively, the predictive performance deteriorates when the same model is evaluated at finer temporal and spatial resolutions (Supplementary Tables 3 and 4). Such evaluation results are consistent with previous literature on global linkages between climate variables and burned area⁴⁷. Our findings suggest that, although climate conditions are related to enhanced fire activity in aggregate, whether a fire occurs in a specific location depends on more stochastic factors such

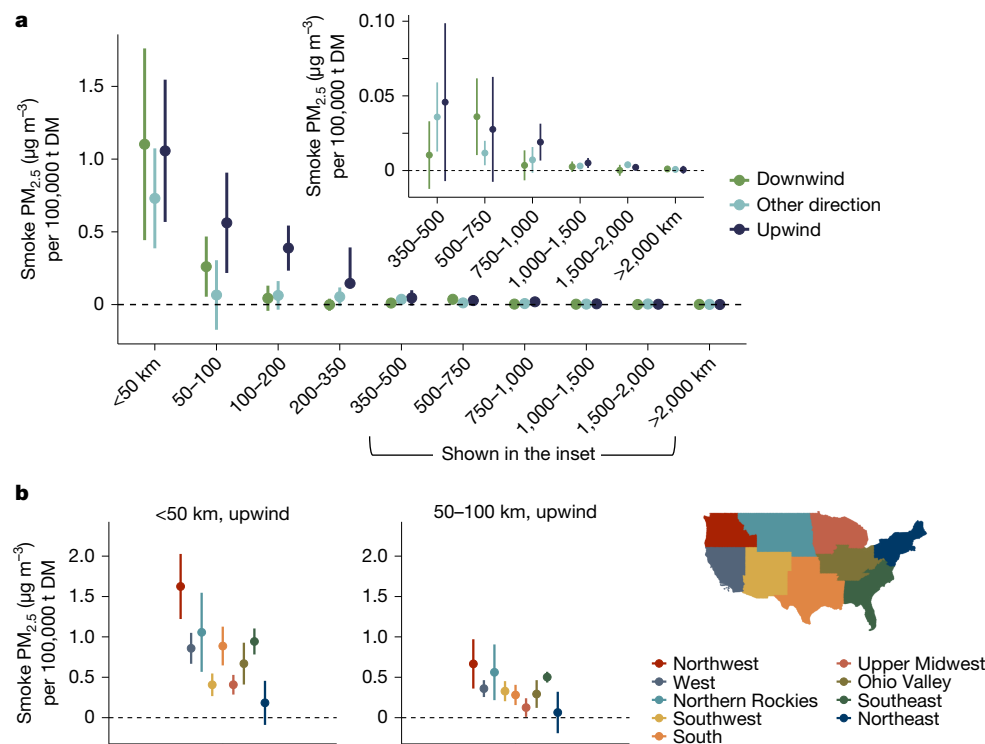


Fig. 3 | Wildfire emissions increase observed smoke $PM_{2.5}$ concentrations in the neighbouring and downwind areas. **a**, Empirically estimated effects of wildfire emissions on smoke $PM_{2.5}$ by distance from emissions and by wind direction. Upwind means that the fire is upwind of the location at which $PM_{2.5}$ is measured. Wildfire emissions are estimated to have larger impacts on smoke $PM_{2.5}$ when the smoke location is closer to the fire (the distance to emissions is shown on the x axis), and when wildfire emissions happen upwind of the smoke locations (wind patterns are shown in colours). The dots show point estimates

for the estimated coefficients, and the whiskers show 95% confidence intervals calculated using a standard two-sided *t*-test. Separate models are estimated for the nine climatic regions in the USA determined by National Centers for Environmental Information (as shown in **b**). The results in the Northern Rockies region are shown in **a**, **b**. Regional heterogeneity in emission impacts on smoke $PM_{2.5}$ across the nine regions in the USA, as measured by the estimated effects of upwind emissions in the <50 km and 50–100 km bins.

as lightning and human ignitions that are very hard to predict. Temporally, our models can capture the decadal average of fire emissions, but are less skilful at predicting fire emissions in individual years, again given the influence of stochastic non-climate factors. Nevertheless, for regions that have historically been large sources of smoke, either for their own region or for other regions—including the western USA, Canada and southeast USA—regional-scale climate–fire models perform reasonably well (achieving region-wide out-of-sample correlation of 0.79–0.95; Fig. 1a). They perform less well in regions such as the northeast USA, where many fires are agricultural or prescribed fires, which are less directly influenced by climate factors. However, fire emissions from northeast USA are much lower compared with other regions (Supplementary Table 1), and local smoke concentrations in northeast USA are more influenced by fires in distant regions (for example, Canada and western USA; Extended Data Fig. 1).

Combining our statistical and machine learning models with future climate projections from CMIP6, we project that wildfire emissions will increase in all of the study regions (Fig. 2b). We focused on the decadal-average wildfire emissions (2026–2035, 2036–2045 and 2046–2055) and used these estimates for the downstream analysis of smoke $PM_{2.5}$ and mortality. The largest increases in wildfire emissions are projected in the western USA, where the model estimates that the annual wildfire emissions will increase by between 262% (SSP1-2.6) and 482% (SSP3-7.0) averaged over 2046–2055 relative to the average emissions during 2011–2020. When compared with 2020, the largest wildfire year for the western USA in our historical sample, projected annual wildfire emissions in 2050 will either reach (as in the case of SSP1-2.6) or exceed (by 36% under SSP2-4.5 or 65% under SSP3-7.0) emissions observed in 2020. This magnitude of increase is largely consistent

with previous estimates of the western USA derived from statistical models and process-based models^{24,28,48}. Consistent with previous literature, we find that decreased soil moisture and increased ambient temperature, especially in the forest areas in the western USA, are the leading contributors to increased wildfire emissions (Supplementary Fig. 2). In the eastern USA, we estimate an increase of wildfire emissions of 19–33%. This projected increase is smaller than in the western USA partly because of the projected increase in precipitation in the eastern USA, which decreases projected emissions (Supplementary Fig. 2), consistent with a previous study that used a process-based climate–fire model²⁸. By 2050, we project an increase in emissions of 45–53% in Mexico and an increase of 48–91% in Canada, relative to average emissions during 2011–2020. Given the large uncertainty in the climate–fire model in the northeast USA, we conduct a sensitivity scenario analysis that uses the historical emissions (instead of projected emissions) in the northeast USA for smoke and mortality projection, and find it has negligible effects on projected smoke $PM_{2.5}$ and mortality because there are low fire emissions in this region (Supplementary Table 5).

To link projected wildfire emissions to smoke $PM_{2.5}$ concentrations, we first stochastically downscale the aggregated projected emissions to the grid cell level (Fig. 2c and Extended Data Fig. 2). The stochastic downscaling method enables us to capture potential fire emissions from grid cells that have not burned before and assess the uncertainty in the downstream smoke and health consequences due to fire locations, given the same regional fire emission predictions (Methods and Extended Data Fig. 3). We then develop an empirical relationship that accounts for wind direction, distance from fire and geographical region between fire emissions and smoke $PM_{2.5}$ concentrations (Fig. 3). Our fire–smoke models achieve comparable performance to previous statistical models

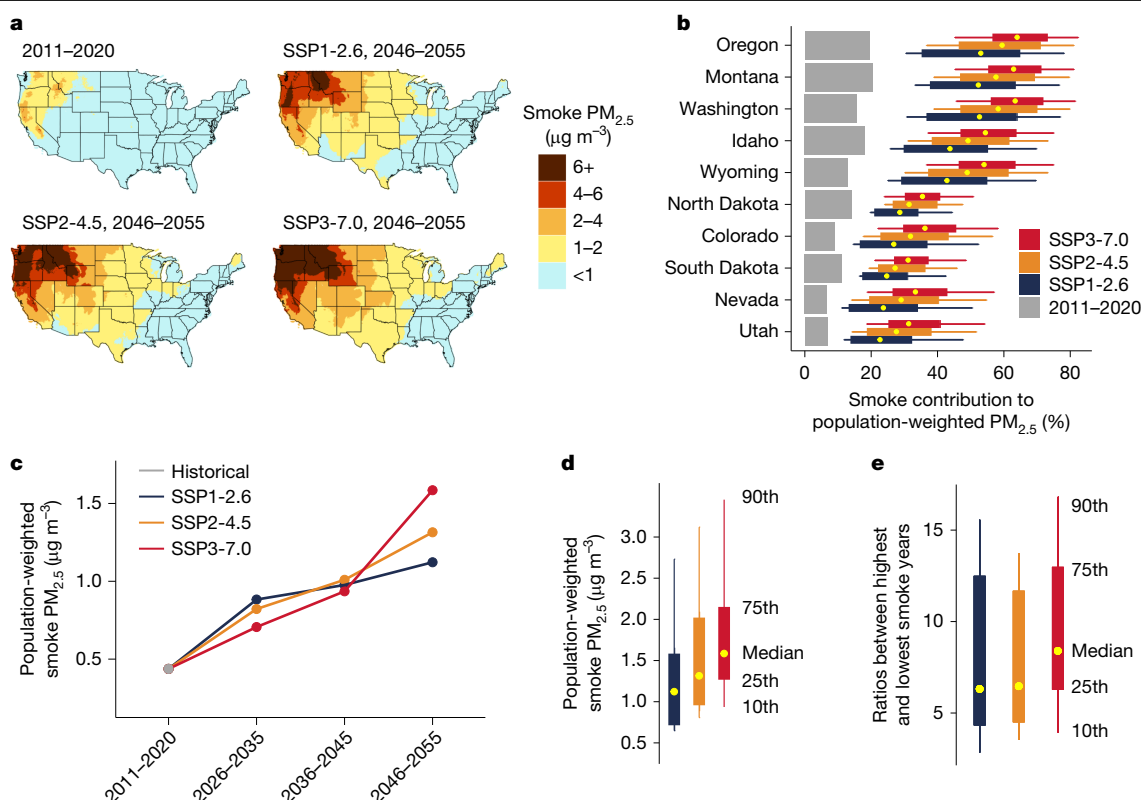


Fig. 4 | Population exposure to wildfire smoke $PM_{2.5}$ increases by two to threefold under future climate scenarios. **a**, The spatial distribution of the annual mean smoke $PM_{2.5}$ concentration in the historical period (2011–2020) and projected annual mean smoke $PM_{2.5}$ concentration under the three climate scenarios in 2046–2055. **b**, The contribution of smoke $PM_{2.5}$ to total population-weighted $PM_{2.5}$ at the state level. Non-smoke $PM_{2.5}$ is calculated as the difference between total $PM_{2.5}$ (derived from ref. 60) and smoke $PM_{2.5}$ in 2016–2020, and is assumed to be constant in the future. The panel lists the top ten states with the highest smoke contribution under the SSP3-7.0 scenario in 2050. The yellow dots show the median, the bars show the 25th and 75th percentiles, and the whiskers show the 10th and 90th percentiles of estimates across 28 GCMs.

that use both fire and non-fire features to predict wildfire smoke $PM_{2.5}$ (Supplementary Table 6 and Supplementary Fig. 3). As shown in Fig. 3a, we find that wildfire emissions increase smoke $PM_{2.5}$ concentrations near an active fire, with the effects gradually decaying as the distance from the fire increases. Nevertheless, we find evidence that wildfire emissions can influence smoke $PM_{2.5}$ in downwind locations up to 1,000 km away. We also find substantial regional heterogeneity in the impacts of DM emissions on wildfire $PM_{2.5}$ (Fig. 3b). For example, we find that one tonne of DM emissions (as estimated in GFED4s fire emissions database) can generate as much as three times surface smoke $PM_{2.5}$ in northwest USA compared with southwest and south USA. Such regional heterogeneity probably reflects a multitude of factors, such as vegetation type, vegetation density and fire intensity (Methods). We validate predictions from our combined climate–fire–smoke model on held-out historical smoke $PM_{2.5}$ estimates at the grid level, finding strong agreement at the national level and in nearly all regions (Supplementary Fig. 4).

Projected smoke $PM_{2.5}$ under future climate

As a result of projected rising wildfire emissions, we find increases in annual smoke $PM_{2.5}$ concentrations throughout the USA in 2050 under all future climate scenarios (Fig. 4a). Under our highest warming scenario (SSP3-7.0), we estimate that the 10-year annual average smoke $PM_{2.5}$ concentration could reach $10 \mu g m^{-3}$ in some regions on the US

West Coast, a level that has been observed only in extreme smoke years such as 2020 (ref. 9). While the most substantial changes in smoke $PM_{2.5}$ happen across the western USA, smoke $PM_{2.5}$ concentrations are also projected to increase in the midwest and northeast USA, largely as a result of projected increases in emissions in the western USA and Canada and subsequent increases in cross-boundary transport of wildfire smoke from these fires. We find large transboundary influences of fire emissions on smoke $PM_{2.5}$ concentrations across regions; for example, 70% of the population-weighted smoke $PM_{2.5}$ in the northeast USA is projected to come from fires in western USA or Canada (Extended Data Fig. 1).

We estimate that smoke $PM_{2.5}$ will account for 14–18% of total population-weighted $PM_{2.5}$ in the USA in 2050, which is around three times its contribution of 5.4% during 2011–2020. These contribution estimates assume that non-smoke $PM_{2.5}$ remains constant—a possibly conservative assumption given recent and ongoing declines in non-smoke $PM_{2.5}$ concentrations¹⁵. We estimate that wildfire smoke will account for at least 15% of total population-weighted $PM_{2.5}$ in 23 states in 2050, including states both in the western USA such as Oregon (with 64% smoke contribution), Washington (63%) and California (24%), as well as states in the south and northeast USA such as Oklahoma (20%) and Maine (18%). Figure 4b shows the smoke contribution in the top 10 states (see Extended Data Table 1 for more states). Under the SSP3-7.0 scenario, average population-weighted smoke

Some states with high smoke concentrations, such as California, are not among the top 10 states with highest smoke contribution due to relatively high non-smoke $PM_{2.5}$ levels. **c**, The predicted population-weighted smoke $PM_{2.5}$ concentrations for the USA in different future decades. **d**, Uncertainty in the population-weighted smoke $PM_{2.5}$ across the 28 GCMs used in the projections; colours match scenarios in **c**. **e**, For each GCM, we calculate the ratio between the highest and lowest projected population-weighted smoke $PM_{2.5}$ during 2046–2055. The panel shows the quantiles of these ratios across the 28 GCMs. For **d** and **e**, the yellow dots show the median, the bars show the 25th and 75th percentiles, and the whiskers show the 10th and 90th percentiles of estimates across 28 GCMs.

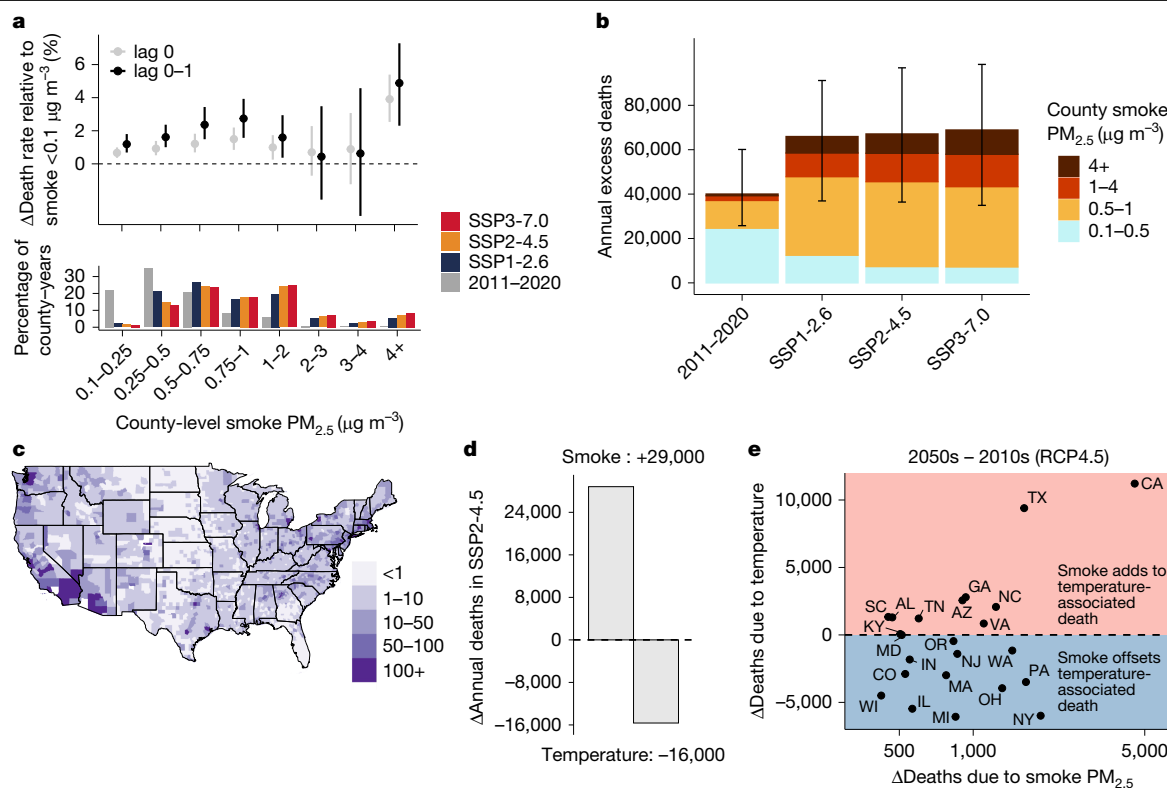


Fig. 5 | Mortality impacts of wildfire smoke $\text{PM}_{2.5}$ and estimated mortality due to smoke $\text{PM}_{2.5}$ under future climate scenarios. **a, Empirically estimated effects of annual smoke $\text{PM}_{2.5}$ concentration on county-level all-age all-cause annual mortality rates, in the year of exposure (lag 0) and in both the year of exposure and the subsequent year (lag 0-1). The dots show the estimated effects of exposure to different annual mean concentrations of smoke $\text{PM}_{2.5}$ (x axis) relative to a year with smoke concentration below $0.1 \mu\text{g m}^{-3}$, and the whiskers show the 95% bootstrapped confidence intervals (500 bootstraps). The histograms at the bottom show the percentage of county-years in each smoke concentration bin over the historical period (2011-2020) and future climate scenarios (2046-2055). **b**, The estimated annual excess deaths due to smoke $\text{PM}_{2.5}$, and contribution to total smoke excess deaths from different smoke concentration bins. The bars show the mean of bootstrapped**

estimates, and the whiskers show the 95% bootstrapped confidence intervals (500 bootstraps). **c**, The county-level projected increases in annual excess deaths due to smoke $\text{PM}_{2.5}$ in 2050; increases are calculated as the differences between the average deaths under SSP2-4.5 scenario over 2046-2055 and the 2011-2020 average. **d**, Increases in USA-wide total annual smoke deaths exceed declines in estimated direct temperature-related deaths in 2050; the latter was estimated previously⁴⁶. Net declines in direct temperature-related deaths are a result of declining cold deaths more than offsetting increasing heat deaths. **e**, Some states experience projected increases in both smoke and direct temperature-related deaths, while others experience offsetting effects. The x axis shows the changes in deaths due to smoke $\text{PM}_{2.5}$ in 2050 (note the log scale), and the y axis shows the changes in deaths due to temperature change. Only the 23 states with >400 smoke-related deaths per year are visualized.

$\text{PM}_{2.5}$ exposure is projected to reach $1.59 \mu\text{g m}^{-3}$, an increase of over 260% relative to the average level between 2011 and 2020 (Fig. 4c), and 1.7× the population-weighted smoke $\text{PM}_{2.5}$ concentration in the historically extreme year of 2020 ($0.90 \mu\text{g m}^{-3}$). The differences across the three climate scenarios are negligible in 2030 and 2040 because there is little difference in projections of the climate variables over this period (Supplementary Fig. 2). However, by 2050, population-weighted smoke $\text{PM}_{2.5}$ is meaningfully smaller in the lower warming scenarios, at $1.12 \mu\text{g m}^{-3}$ under SSP1-2.6 or $1.31 \mu\text{g m}^{-3}$ under SSP2-4.5, averaged across GCMs. Some individual GCMs project much larger or smaller increases (Fig. 4d). These estimates represent decadal averages of annual smoke $\text{PM}_{2.5}$ concentrations, in this case averaged from 2046 to 2055. Given interannual climate variability, projections suggest that average smoke $\text{PM}_{2.5}$ concentrations in individual years could differ substantially, with the highest projected smoke year having roughly 5-10× the concentration of the lowest year (Fig. 4e). Our method likely underestimates the interannual variability, as it does not capture variability in non-climate factors.

Mortality burden due to smoke $\text{PM}_{2.5}$

In recent historical data, we find that exposure to smoke $\text{PM}_{2.5}$ increases all-cause mortality rates even at low annual smoke concentrations

($<1 \mu\text{g m}^{-3}$; Fig. 5a). Compared with a year of minimal smoke $\text{PM}_{2.5}$ (annual mean concentration $<0.1 \mu\text{g m}^{-3}$), we find that a year with annual average smoke $\text{PM}_{2.5}$ of $0.75-1 \mu\text{g m}^{-3}$ increases county-level mortality rate by 1.5% (95% confidence interval (CI): 0.8-2.2%). Years with extreme ambient wildfire smoke concentrations ($>4 \mu\text{g m}^{-3}$) increase annual mortality rates by 3.9% (95% CI: 2.5-5.4%). Wildfire smoke increases mortality rates among both older people and the general population, with similar relative (percentage) impacts across age groups but much larger total deaths for elderly populations (Extended Data Table 2). Our estimated smoke-mortality relationship is similar in shape to previous results estimated using monthly data⁴³. We find strong nonlinear effects of smoke $\text{PM}_{2.5}$ on mortality, and simple linear models cannot meaningfully capture the mortality effects, consistent with previous research^{39,43} (Supplementary Fig. 5). Estimated mortality effects are otherwise largely robust across alternative specifications of the smoke-mortality models, including alternative functional forms, temporal aggregations and bin definitions (Extended Data Fig. 4).

We find that smoke exposure increases mortality rates not only in the year of exposure but also in the following years (Fig. 5a and Extended Data Fig. 5). For example, exposure to annual mean smoke concentrations of $0.75-1 \mu\text{g m}^{-3}$ increases the mortality rate by 1.5% in the same year, but by 2.7% (95% CI: 1.6-3.9%) if we also account for deaths occurring in the following year, and by 5.3% (95% CI: 3.3-7.5%) if we account

for mortality within 3 years of smoke. As wildfires can happen late in the year (for example, many recent extreme fires in California happen in October to December) and smoke exposure could worsen a range of health outcomes that could lead to increases in mortality risk that emerge at longer time scales, the distributed lag model helps to capture more complete health impacts compared with the contemporaneous model (lag 0). We use the cumulative mortality during the smoke year and the following year (lag 0–1) as our conservative main estimate, and report the estimates using alternative lags in Extended Data Fig. 5.

We estimate that annual smoke $\text{PM}_{2.5}$ caused 41,380 excess deaths (95% CI: 25,780–60,110) cumulatively over the smoke year and the subsequent year, averaged over 2011–2020 (Fig. 5b). We find that most of the estimated mortality burden comes from non-accidental deaths, while the accidental mortality rate shows little increase under low smoke conditions but declines in high smoke years (Supplementary Fig. 6), consistent with previous research on accidental emergency department visits in California³⁹. Our estimates are higher than those reported in earlier work that used different epidemiological models in the contiguous USA⁴³, but lower than comparable estimates from a study using California data and exposure–response functions derived from a combination of all-source and wildfire-specific $\text{PM}_{2.5}$ (ref. 49) (Supplementary Table 7).

We estimate that climate-induced increases in smoke $\text{PM}_{2.5}$ will cause an additional 26,500 to 30,040 annual excess deaths by mid-century across the three climate scenarios—an increase of 64–73% over the estimated 41,380 annual deaths due to smoke $\text{PM}_{2.5}$ between 2011–2020. Projected increases in smoke $\text{PM}_{2.5}$ concentrations account for 56% of the estimated increases in smoke-related mortality, with the remaining 44% due to projected changes in demographic patterns (that is, more population in the group aged 65+ years; Supplementary Table 8). Total cumulative deaths attributable to wildfire smoke $\text{PM}_{2.5}$ are estimated to be 1.9 million over 2026–2055, even in the lowest-warming scenario. The geographical distribution of climate-induced smoke deaths reflects a combination of exposure and underlying population density, with large numbers of projected deaths across populous counties in the western USA, as well as in the midwest, northeast and south (Fig. 5c). The top five states that are predicted to experience the largest increases in annual smoke $\text{PM}_{2.5}$ deaths in 2050 under SSP3-7.0 are California (5,060 excess deaths per year relative to 2011–2020), New York (1,810), Washington (1,730), Texas (1,700) and Pennsylvania (1,600). While projected smoke concentrations are highest in the western USA, over half of the smoke mortality comes from eastern states (east of 95° W) because they have higher population densities and damages from low wildfire smoke concentrations (Extended Data Fig. 6 and Extended Data Table 3).

We contextualize the magnitude of these mortality impacts in two ways. First, we compare our estimates to the direct effects of extreme temperatures on mortality, an impact which has been the primary focus of climate change impacts on mortality and which is estimated to be one of the leading economic costs of global climate change^{41,46}. Recent studies find that, by mid-century in the USA, increasing mortality from more frequent extreme heat is likely to be more than offset by declining mortality due to cold weather, with a projected net decrease in annual excess deaths of 15,640 by mid-century in the USA (under the SSP2-4.5 scenario) compared with 2001–2010⁴⁶. Our projected increase in smoke mortality in the same period and scenario is nearly twice the estimated reduction in direct temperature-related deaths (Fig. 5d). However, as shown in Fig. 5e, the size of this offset differs across the USA, with certain states likely to suffer compounded consequences from increases in both smoke-related and heat-related deaths (such as California and Texas) and others experiencing offsetting effects.

As a second comparison, we compare our estimates of climate-induced smoke damages with two previous estimates of aggregated economic damages due to climate change. Using a VSL of US\$10.95 million (year 2019 dollars⁴⁶), we find that the projected increase in

annual excess deaths due to climate-driven wildfire smoke (30,040 deaths under SSP3-7.0) would result in annual damages of US\$608 billion in 2050 (not discounted, in year 2019 dollars; Methods). Under a similar projected warming level of SSP3-7.0 scenario, a previous study⁴ estimated annual damage of 0.4–0.8% of the US gross domestic product (GDP) or US\$166–332 billion (in year 2019 dollars, using annual projected GDP of US\$38.5 trillion from ref. 5), which included damages from temperature-related mortality, agriculture, crime, coastal storms, energy and labour channels. The Framework for Evaluating Damages and Impacts (FrEDI), developed by the US EPA⁵, considered more sectors (including estimated wildfire damages from the western USA³¹) and estimated total annual damages due to climate change of US\$292 billion in 2050. Thus, our estimates suggest that damages from climate-induced smoke-related mortality could substantially exceed damages from all other estimated causes by mid-century in the USA combined.

Discussion

While the effects of climate change on wildfire smoke and human health have become an emerging research topic, these effects are rarely incorporated into estimates of the societal cost of climate change. In this study, we estimate that climate-induced smoke $\text{PM}_{2.5}$ could lead to 26,500–30,040 additional excess deaths in the USA per year by 2050 relative to 2011–2020, a decade that already saw surging population smoke exposure and health damages relative to previous decades. We find that the monetized damage from these estimated climate-induced smoke deaths exceeds existing quantified climate damages from all other sectors in the USA combined.

Our work builds on a large and emerging literature that studies the impacts of climate change on wildfire smoke and associated health impacts. We contribute to this literature by quantifying the full causal chain linking climate to health through wildfires (climate change–wildfire–air pollution–mortality), and by propagating uncertainty from each step to understand uncertainty in likely health impacts (Extended Data Fig. 7). Our resulting mortality impacts are greater than previous estimates of wildfire smoke mortality under climate change^{30,31,50}, largely because the smoke-specific $\text{PM}_{2.5}$ –mortality relationship that we estimate suggests higher mortality than all-source $\text{PM}_{2.5}$ –mortality relationships used in past work (Supplementary Table 9).

Given our annual-level projections of wildfire smoke, our estimated impacts of smoke on mortality were necessarily conducted at the annual level. We find substantial mortality impacts from relatively low ($<1 \mu\text{g m}^{-3}$) annual increases in smoke $\text{PM}_{2.5}$ concentrations. These modest county–year smoke $\text{PM}_{2.5}$ increments arise primarily from episodic events of which the daily means often exceed 50 or even $100 \mu\text{g m}^{-3}$. Previous evidence suggests that increases in all-source $\text{PM}_{2.5}$ of this magnitude are associated with roughly a 5–10% rise in daily mortality⁵¹, an effect that amplifies rather than dissipates in the weeks after exposure, implying a persistent increase in annual mortality. In a sensitivity analysis, we show that using cumulative short-term daily or monthly extremes to estimate mortality impacts yields similar estimates to using annual averages (Extended Data Fig. 4). Furthermore, the increases in smoke $\text{PM}_{2.5}$ that we study represent additions to background concentrations, for example, shifts in total $\text{PM}_{2.5}$ from roughly $8 \mu\text{g m}^{-3}$ to $9 \mu\text{g m}^{-3}$. In this range, large cohort studies report positive mortality associations of similar magnitudes to our estimates⁵². Owing to the mortality effects that we find at low annual smoke concentrations, we project large mortality burdens not only in heavy smoke regions but also in populous regions with low smoke concentrations (such as the eastern USA). Similarly, we estimate substantial mortality increases even under the low warming scenario (SSP1-2.6) due to projected increases in low-level annual smoke concentration.

The goal of our paper is to estimate the causal impacts of different climate futures on wildfire smoke and mortality. Doing so necessarily

requires isolating the impact of climate from the large number of other factors that affect wildfire and smoke. We did not attempt to model the many non-climate factors that contribute to wildfires, including the location of energy infrastructure, housing development and fire-suppression efforts. If these factors change substantially in the future, then our estimates could understate or overstate future emissions, smoke and mortality. For example, if expansion of housing near wildland vegetation continues²⁰, the effects of a warming climate on wildfire emissions could be larger given more human ignitions, particularly as population growth in the wildland–urban interface has been most rapid in areas where the vegetation is most vulnerable to wildfire⁵³. Previous studies have found that projected land use change (for example, shifts in vegetation type) and land management policies could substantially increase or decrease future wildfire and smoke levels^{30,54}, which point to a policy opportunity as well as a key knowledge gap in projecting future smoke impacts. Alternatively, large increases in wildfire activity could be self-limiting, as fires regulate the amount and availability of fuel load for future combustion. Existing work suggests that this feedback is probably modest by the mid-century in the western USA when the baseline burning probability is still relatively low⁴⁸, but constraining this feedback empirically is a critical area for future work. Finally, our paper does not account for potential indirect effects of climate on wildfire through channels such as climate's influence on vegetation productivity or lightning-related ignitions. One previous study has suggested that vegetation overall would increase under higher warming levels in the USA, which could lead to higher wildfire emissions and smoke²⁴. Yet quantifying the influence of climate–vegetation–fire dynamics remains an important future question for projecting smoke and health damages.

Our projection analysis quantifies the key uncertainties in climate–wildfire–smoke–mortality estimations (Extended Data Fig. 7). We find that uncertainty from the smoke–mortality exposure–response function is the largest source of uncertainty in our mortality estimates. Uncertainty in other components, particularly climate projections and climate–fire models, contributes substantially to the uncertainty of projected smoke PM_{2.5}; however, differences in projected smoke are partially masked by our binned exposure–response function. Related to the interpretation of our exposure–response function, we note first that, because smoke PM_{2.5} is a complex mixture of gases and particles^{38,55}, the exposure–response relationships that we estimate probably capture the integrated mortality impacts of this mixture, not necessarily of PM_{2.5} from wildfires alone. Second, we find important lagged impacts of smoke exposure on mortality up to 3 years after the smoke exposure. Estimating the long-term health impacts of smoke exposure is challenging because extreme smoke pollution events have only emerged in recent years. Given the presence of toxic components in smoke that are known to be carcinogenic, investigating the long-term effects of smoke exposure on mortality is an important future research area. While our analysis does not project cause-specific deaths from smoke PM_{2.5}, previous studies found that cardiovascular, cancer, mental health, and endocrine diseases are among the leading causes of smoke-related mortality and therefore warrant future study^{43,56,57}. Finally, by focusing on mortality alone, our estimated health damages exclude short- and long-term non-fatal health impacts from smoke PM_{2.5}, including morbidity, worsened mental health, and potential long-run cancer risks associated with the carcinogenic constituents of wildfire smoke.

Given that substantial damages are present even under aggressive climate change mitigation scenarios, our findings point to the urgent need for adaptation to wildfire smoke if damages are to be avoided. Adaptation could occur at many points along the wildfire–smoke–mortality chain. Increased fuel management, such as prescribed burning, could reduce the likelihood of extreme wildfire activity during adverse climate conditions, but will create smoke of its own^{54,58}. Adaptation could also target the relationship between smoke and adverse health outcomes. This could include better informing individuals of,

and protecting them from, smoke pollution, as current reliance on individuals to self-protect appears highly inadequate and inequitable⁵⁹. Our projected mortality burden does not attempt to explicitly model these adaptations that have yet to occur, given the limited empirical evidence on the effectiveness of specific actions and the speed and scale with which they could be adopted. Thus, our estimates represent the likely outcome under a 'business as usual' scenario that assumes that future adaptations reflect those that have already occurred. Understanding what interventions work to lower fire risk and reduce the health burden of wildfire smoke, and how they can be cost effectively scaled, is a critical research priority.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at <https://doi.org/10.1038/s41586-025-09611-w>.

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Methods

Wildfire and smoke PM_{2.5} datasets

We use annual and monthly fire emissions from the GFED4s from 2001–2021, with a spatial resolution of 0.25×0.25 degrees⁴². We use the estimated DM emissions as our primary variable for the emissions. DM emissions capture the amount of biomass being consumed in the burning process. We choose DM emissions as the proxy for overall fire emissions (rather than individual emissions species such as black carbon or NO_x) because of uncertainty in the emission factors used in GFED4s. GFED4s include fire emissions from agriculture fires and land-use change as well. However, as wildfire emissions from forested areas dominate in western USA and Canada where we project the largest increase in fire emissions, we refer to our estimates as wildfire emissions and wildfire smoke for simplicity and consistency.

For smoke PM_{2.5}, we use gridded daily wildfire smoke PM_{2.5} predictions for the contiguous USA at a 10-km resolution from 2006 to 2020 derived from ref. 9. This dataset specifically estimates the ambient PM_{2.5} concentration due to wildfire smoke influence by constructing a machine learning model that uses smoke plume data, remotely sensed variables and meteorological variables to predict the anomalous increases in surface PM_{2.5} measured by air quality monitors during wildfire smoke events. To estimate contributions of smoke PM_{2.5} to total PM_{2.5}, we use the total PM_{2.5} estimates from ref. 60, which combines satellite retrievals of aerosol optical depth, chemical transport modelling and ground-based measurements to estimate monthly total ambient PM_{2.5} concentrations. While estimates of smoke and total PM_{2.5} come from two separate models and may therefore not be compatible in certain time–location, our analysis only uses the 2016–2020 average of smoke PM_{2.5} and total PM_{2.5} to estimate the non-smoke PM_{2.5} for each grid cell. The 5-year mean smoke PM_{2.5} exceeds total PM_{2.5} in only one grid cell by a small margin. For this grid cell, the non-smoke PM_{2.5} is assumed to be zero. We then use the 5-year mean non-smoke PM_{2.5} to estimate the wildfire contributions to total PM_{2.5} in future scenarios, assuming the non-smoke PM_{2.5} remains constant. This calculation provides likely conservative estimates of wildfire contribution to future PM_{2.5} given recent and ongoing declines in non-smoke PM_{2.5} concentrations.

Climate and meteorological datasets

We use climate and land-use variables to predict wildfire DM emissions. The climate variables include 2-m air temperature, precipitation, relative humidity, soil moisture (of the topsoil layer), vapour pressure deficit, 10-m wind speed and runoff (sum of surface and subsurface). The selection of these variables is consistent with previous studies²⁴. Our models do not include fire weather index and fuel moisture (as used previously⁶¹) because they are unavailable in future projections. However, given that fuel moisture and fire weather index are closely related to the meteorological variables included in our model, our flexible statistical and machine learning model likely captures the additional information from fire weather index or fuel moisture. We use variables derived from the North American Regional Reanalysis (NARR)⁶², with the exception of soil moisture. Soil moisture is derived from the VIC land-surface model of phase 2 of the North American Land Data Assimilation System (NLDAS-2)⁶³ and is available only in the contiguous USA. While soil moisture data are available from NARR for Canada and Mexico, we do not use them because of their uncertainty and bias relative to NLDAS-2, which assimilates high-quality in situ precipitation data for the land surface modelling in the USA⁶⁴. In a sensitivity analysis, we show that including NARR soil moisture in the climate–fire models in Canada and Mexico has limited influence on model performance (Supplementary Table 10), probably because other correlated features (such as vapour pressure deficit and runoff) are already incorporated. The native spatial resolution is 32 km for NARR variables and 0.125° for NLDAS-2 variables. Land-use variables are derived from the North American Land Change Monitoring System (NALCMS) for the year

2015 (ref. 65). Specifically, we use three land-use variables which each represents the percentage of area in three categories: cropland, forest and grassland. The native resolution of land-use variables is 30 m. The land-use variables are held constant across time in both the historical and future periods.

For future climate change scenarios, we use the projected climate variables from the CMIP6. We examine three primary climate-forcing scenarios featured by the IPCC, which are constructed as pairs between the Shared Socio-economic Pathways (SSPs) and the Representative Concentration Pathways. We use SSP1-2.6 (which the IPCC refers to as the low-emissions scenario), SSP2-4.5 (which the IPCC refers to as the intermediate scenario) and SSP3-7.0 (which the IPCC refers to as the high scenario). We use projections from 28 GCMs that include the selected variables that cover the study region (Supplementary Table 11). We correct the biases in projected climate variables against the reanalysis data of the corresponding variables from 2001–2014 at the monthly level. Following the practice of IPCC, we select only one ensemble realization for each model—we use the first ensemble variant of each model (r1i1p1f1) when possible.

Predicting wildfire emissions

We construct an ensemble of statistical and machine learning models to predict wildfire emissions using climate and land-use variables. The climate–fire models are developed using data at the annual or monthly scale and various spatial resolutions between 2001 to 2021 to predict DM emissions derived from GFED4s emission inventory. We build separate models for each of the five regions (western USA, southeastern USA, northeastern USA, Canada–Alaska and Mexico) to capture the regionally heterogeneous relationships between climate, land-use type and wildfire emissions. For each region, we construct six different models as potential model candidates: linear regression model, linear regression model with log outcomes, least absolute shrinkage and selection operator (LASSO) models, LASSO models with log outcomes, two-layer neural network (NN) model, and NN models with log outcomes. These six algorithms are selected to cover a possible range of model candidates with varying desired characteristics—including simple models that are commonly used in previous studies (for example, the linear and log-linear regression models), models that are easy to interpret (such as the linear regression and LASSO models) and more flexible machine learning models that are used in previous studies (such as the NN model).

For the spatial scale of the climate–fire models, we develop separate models to predict emissions aggregated at four different spatial scales. We aggregate the outcome variables and input features at four spatial scales: the grid scale (0.25° , 26,956 cells in total), the North America level-3 ecoregion scale (177 regions in total), the North America level-2 ecoregion scale (51 regions in total) and the regional scale (5 regions in total). Supplementary Fig. 7 shows the level-2 and level-3 ecoregions considered in our models. We construct models at these aggregated scales because the fire occurrence and resulting emissions at local scales are often stochastic as a result of varying and hard-to-predict non-climate factors, including where and when human and natural ignitions occur and how much suppression effort is applied. Thus, to better capture the predictable components of the climate–wildfire relationship, we create models to predict aggregated annual emissions. We then select the spatial resolution that optimizes model performance for each model type (as described below), allowing the optimal spatial resolution to differ across different model types and regions (model performances across spatial scales are shown in Supplementary Table 4).

For the temporal scale of the climate–fire models, we develop three classes of climate–fire models to predict fire emissions at the monthly or annual scale. The first set of models uses monthly mean meteorological variables to predict monthly fire emissions (denoted as ‘monthly’ in Supplementary Table 2). The second set of models uses

annual mean meteorological variables to predict annual fire emissions (denoted as ‘annual (mean)’ in Supplementary Table 2). The third set of models uses both the annual mean meteorological variables as well as extreme conditions to capture the potential influences of extreme weather conditions on fire emissions in addition to the average conditions (denoted as ‘annual (extreme)’ in Supplementary Table 2). For each meteorological variable, we include two additional variables for the extreme conditions. For example for temperature, we include ‘temperature-low’, which calculates the fraction of area in a region that falls below a low-temperature threshold (2.5th percentile of historical values) and ‘temperature-high’ which calculates the fraction of area in a region that exceeds a high-temperature threshold (97.5th percentile). Despite the different temporal resolutions, all models are first aggregated to the annual scale for model evaluation.

To evaluate the model performance, we use nested leave-one-out temporal cross-validation. Specifically, we divide our data into 21 temporal folds, each including one year of data and, for each holdout fold, we train the model using the remaining 20 folds of data with hyperparameters selected using an inner-loop fivefold cross-validation within the training data. We then obtained out-of-sample predictions for the holdout fold and repeat this process to obtain out-of-sample predictions for the entire time period. As we focus on projecting the future wildfire emissions over a 10-year period (that is, decadal averages) under future climate scenarios, we therefore evaluate the performance of our models on similar 10-year intervals. We compute the moving averages of predicted and observed emissions over 10-year moving windows. We compute two metrics and use them as the basis for evaluating the performance of each model: (1) the root mean squared error (r.m.s.e.) between predictions and observations; and (2) the prediction biases of the highest-emitting 10-year period. The first metric enables us to assess the model performance across years with different climate conditions to detect differences between current and future climate scenarios. The second metric enables us to assess the model performance under extreme smoke conditions that are more likely to occur under future climate. We not only select models with the best performance for each region (that is, lowest bias and r.m.s.e.) but also keep models with similar performance (defined as when $\text{r.m.s.e.}/\text{mean} + |\text{Bias}|$ is within 4% of the best model for each region) given their future projections could be different despite similar performances during the historical period. We used 4% as the threshold in our main analysis, and find that the projected emissions remain largely similar across alternative threshold values (Supplementary Fig. 8). To obtain the final model used for future projections, we create an ensemble model, which combines the predictions from the selected base models with the corresponding optimal spatial resolution. The selected models and their performances can be found in Supplementary Table 2. In a sensitivity analysis, we also re-estimate the selected linear models after removing the linear trend in wildfire emissions and meteorological variables to reduce the possibility of spurious correlation due to trends in non-climate factors of wildfires (Supplementary Fig. 9).

Quantifying wildfire impacts on smoke PM_{2.5}

To estimate smoke PM_{2.5} concentrations associated with future wildfire emissions, we fit spatially explicit statistical models that estimate the empirical relationship between ambient smoke PM_{2.5} concentrations from a previous study⁹ and wildfire emissions derived from GFED4s. The fire–smoke models are developed using data at monthly and 10 km grid level across the contiguous USA (48 states and the District of Columbia), accounting for variation in wind directions and atmospheric transport. This approach enables us to efficiently predict smoke concentration in one location from changes in wildfire emissions in another. Despite using estimated DM emissions from GFED4s as an input, our estimates of smoke PM_{2.5} concentrations strongly predict the variations in the empirical estimates of surface smoke PM_{2.5} concentrations, and are

therefore directly constrained by surface PM_{2.5} measurement during wildfire episodes.

Specifically, we use the following regression equation to empirically quantify how historical smoke PM_{2.5} in a given 10 km grid cell is affected by emissions in different directions and distances from that grid cell:

$$\text{Smoke}_{iym} = \sum_{d,w} \beta_{dw} \text{Emis}_{dw,iym} + \gamma W_{iym} + \eta y + \psi_m + \theta_i + \varepsilon_{iym} \quad (1)$$

where Smoke_{iym} denotes smoke PM_{2.5} at grid cell i , year y , and month-of-year m . $\text{Emis}_{dw,iym}$ denotes the wildfire DM emissions that in the distance bin d and wind direction w ($w \in \{\text{upwind, other, downwind}\}$) of the smoke location i on month-of-year m and year y . In our main specification, we estimate the impacts of wildfire DM emissions at different distances from the smoke location: <50 km, 50–100 km, 100–200 km, 200–350 km, 350–500 km, 500–750 km, 750–1,000 km, 1,000–1,500 km, 1,500–2,000 km > 2,000 km. W_{iym} is the meteorological variables at the grid cell i (temperature, wind, RH and precipitation). We include these meteorological variables to capture potential meteorological variability that could directly influence ambient PM_{2.5} concentrations. Our main specification includes linear year trends (ηy) and month-of-year fixed effects (ψ_m) to capture the long-term trend and seasonality of smoke PM_{2.5} concentration and grid-level fixed effects (θ_i) to control for the time-invariant unobserved factors at the grid cell location. ε_{iym} represents the error term.

To better capture the atmospheric transport of smoke PM_{2.5}, we divide the wildfire emissions (from a given distance bin) into three categories depending on wind direction and the location of fires. Following similar methods to those described previously^{66,67}, wildfire emissions are classified into upwind or downwind depending on whether the wildfire location is at the upwind or downwind direction of the smoke grid cell. We combine daily emissions with daily wind direction to calculate the daily emissions from each wind direction and further aggregate to the monthly level. We acknowledge that extreme wildfire smoke conditions can alter meteorological conditions (for example, surface wind and boundary layer height) during smoke events and can substantially influence smoke PM_{2.5} concentrations⁶⁸. Our model, which uses monthly aggregated meteorological variables, is designed to capture the average relationship between fire emissions and downwind smoke PM_{2.5} concentrations, and therefore does not explicitly account for this feedback. Improved modelling of this feedback could further improve our smoke PM_{2.5} estimates during particularly extreme events.

We use leave-one-out temporal cross-validation to quantify the performance of our fire–smoke model and compare it to similar methods. We split the 15 years of data (2006–2020) into training and test sets by years and evaluate the model performance against the hold-out test set. Our model performance is comparable to two previous models that estimate smoke PM_{2.5} concentrations using fire and non-fire features (Supplementary Table 6). Our model aims to quantify the causal relationship between fire emissions and smoke PM_{2.5} concentrations, while the other two models only aim to predict wildfire smoke PM_{2.5} concentrations^{9,10}. Thus, the other two models used many more features than our model. Furthermore, our model predicts the wildfire smoke estimates generated in ref. 9 because these data provide full spatial and temporal coverage for our study period, while the other two models predict surface PM_{2.5} concentrations measured only at monitor locations. Nevertheless, the comparable performance further justifies the usage of our fire–smoke model in the downstream analysis.

Many previous studies have demonstrated that wildfire emission factors (for example, mass of organic carbon particles emitted from burning one kg fuel) strongly depend on the combustion conditions (for example, the combustion completeness) and the underlying fuel type among many other factors^{69–72}. As many of these characteristics (for example, the combustion efficiency of different fires) are not available at the national scale, we use a data-driven approach and estimate

different models/equations for the nine US climate regions determined by National Centers for Environmental Information (see Fig. 3 for region definitions), which allows the relationship between emissions and surface smoke $PM_{2.5}$ to differ by region. The resulting regional estimates therefore implicitly account for heterogeneity in the vegetation fuel types, fire intensities and topographies for different locations. For example, previous studies have shown that smouldering fires often have higher $PM_{2.5}$ emission factors compared with flaming fires as a result of incomplete combustion⁷¹, which might partly explain the relatively high emissions factors in the southeast USA in our estimates as smouldering fires are more common there because of high humidity⁷³.

Projecting wildfire and smoke $PM_{2.5}$ under future climate

We combine our ensemble of statistical and machine learning models with climate projections from ensembles of GCMs to project the wildfire emissions and smoke $PM_{2.5}$ under future climate scenarios. Consistent with the optimal spatial resolutions selected for each region, we predict the annual wildfire DM emissions at different spatial resolutions from 2001–2055.

We statistically downscale the predicted regional emissions (regional, level-2 and level-3 ecoregions) to the grid cell level (0.25°) using a stochastic downscaling approach (illustrated in Extended Data Fig. 3). In this approach, we first estimate the maximum possible DM emissions in each grid cell (that is, DM emissions if all burnable areas in the grid cell burn). We calculate ‘burnable’ areas from each grid as the area that falls into the following land classes: forest, shrubland, grassland and cropland. For each grid cell, the maximum possible emissions is calculated using the burnable areas and the average ratio between the burned area and DM emissions in the historical period for that grid cell. Second, we estimate fire emission for each grid cell using a random draw from a gamma distribution while ensuring the grid cell level emission is below the upper limit (that is, the maximum possible emissions). For each grid cell, the gamma distribution has the following parameter {shape = 1 and scale = $0.1 \times$ maximum possible DM}, which is designed to capture the long-tail distribution of fire emissions. Third, we add the predicted emissions across grid cells and compare with the predicted regional emissions (that is, the emission target). If the aggregated emission is below the emission target, we repeat the second step until the aggregated emission exceeds the emission target. Finally, when the aggregated emission is above the emission target, we randomly drop subregions within the region until the aggregated emissions reach the projected emission targets. This final step is designed to capture the scenarios that different subregions will burn in different years. Our stochastic downscaling method enables us to capture potential fire emissions from grid cells that have not burned before, and assess the uncertainty in the downstream smoke and health consequences due to fire locations, given the same regional fire emission predictions (uncertainty is shown as emission downscaling in Extended Data Fig. 7).

We then combine the downscaled predicted DM emissions at GFED4s grid cell level (0.25°) with the empirical relationship that we established between smoke $PM_{2.5}$ and DM emissions to calculate predicted smoke $PM_{2.5}$ in each smoke grid cell (resolution of 10 km). We further calculate the difference between the estimated smoke in any future year and the average estimated smoke between 2011–2020. The difference is then added to the average observed smoke $PM_{2.5}$ concentration between 2011 and 2020 to obtain the final smoke predictions for each grid cell in the future years. In our main analysis, we hold the wind direction and meteorological conditions constant at the average conditions in the historical period for smoke projections. Our main estimates thus only capture the influences of climate change on smoke $PM_{2.5}$ through changes in wildfire emissions, rather than potential influences of meteorology on smoke $PM_{2.5}$ concentration directly (for example, through changes in pollution transport). In a sensitivity analysis, we also estimate the smoke $PM_{2.5}$ under future meteorological conditions (projected monthly temperature, relative humidity, wind speed and

precipitation derived from CMIP6) using the derived historical relationship between these meteorological variables and smoke $PM_{2.5}$ concentration, conditioned on wildfire emissions. We find that smoke $PM_{2.5}$ concentrations remain largely similar across all regions, and slightly increase in the eastern USA as a result of direct influence from meteorological conditions under future climate (Supplementary Fig. 10). These results are largely consistent with previous studies that found an increase in summer $PM_{2.5}$ in the eastern USA^{74,75}. We acknowledge that our sensitivity analysis only considers the potential effects of future climate change on pollution transport and dispersion through local meteorological conditions, without accounting for climate-induced changes in large-scale circulation patterns with potentially important implications for surface air quality^{76–78}.

Impacts of smoke $PM_{2.5}$ on mortality

We calculate all-cause mortality associated with wildfire smoke exposure historically and under future climate scenarios using an exposure–response function empirically derived from 2006–2019 county-level data. We combine county-level population-weighted annual smoke $PM_{2.5}$, derived from ref. 9, with county-level all-cause mortality rates by different age groups. We obtain individual-level multiple cause of death mortality data from the National Center for Health Statistics to calculate age-standardized mortality rates for all ages, those under 65 years of age and those 65 years and older⁷⁹. County-level mortality rates were age-standardized using the direct method and 5-year bins (0–4, 5–9, ..., 85 and over) based on the 2000 US Census Standard Population. Monthly mortality rates were standardized per 100,000 population. We separately estimate impacts for the all-age group, those 65 years and older, and those under 65 years of age (Extended Data Table 2).

In our main analysis, we estimate a Poisson-distributed lag model in which we allow nonlinear impacts of annual smoke $PM_{2.5}$ on mortality rates at the county–year level. We also allow smoke $PM_{2.5}$ to influence mortality both in the smoke year and the following years:

$$D_{csy} = \exp \left(\sum_{\text{bin } i} \sum_{\text{lag } l} \beta_i^l \text{smokeBIN}_{cs,y-l}^i + \gamma W_{csy} + \eta_{sy} + \theta_c + \varepsilon_{csy} \right) \quad (2)$$

where D_{csy} denotes the age-adjusted all-cause mortality rates in county c , state s , and year y . $\text{smokeBIN}_{cs,y-l}^i$ is a dummy variable for whether annual population-weighted smoke $PM_{2.5}$ in county c , state s and year $y-l$ falls into the range of bin i (0–0.1, 0.1–0.25, 0.25–0.5, 0.5–0.75, 0.75–1, 1–2, 2–3, 3–4, $>4 \mu\text{g m}^{-3}$; 0–0.1 is the reference category). The main coefficients of interest are the β_i^l values, which estimate the effects of a year with annual smoke concentration of bin i on mortality rates l years after the smoke. The reference category included <0.1 because only 4 county–year observations had exactly zero ambient wildfire smoke. W_{csy} denotes a flexible control of temperature (the number of days that fall in different temperature bins) and linear and quadratic terms of annual population-weighted precipitation. η_{sy} denotes a vector of state–year fixed effects (that is, separate intercepts for each year in each state) that accounts for all factors that differ across states in a given year (for example, California 2018 versus Oregon 2018) as well as all factors that differ within states across years (for example, California 2017 versus California 2018). θ_c denotes a set of county-level fixed effects that accounts for any county-specific time-invariant factors that could be correlated with both smoke exposure and mortality. In essence, we identify the effect of wildfire smoke on mortality using within-county variation over time, after accounting for any factors that trend over time within that county’s state, and for any correlation between smoke variation and variation in temperature and precipitation. As temporal variation in wildfire smoke exposure is largely a function of idiosyncratic factors such as where a given fire starts and which way the wind blows, our estimates have a plausibly causal interpretation. The coefficients are estimated using weighted Poisson regression

models with the `feglm` function from the R package `fixest`. The estimations are weighted by county-level population counts to enable estimates of population-averaged effects, as well as to reduce statistical uncertainty. The uncertainty of the coefficients is estimated using the assumptions of a quasi-Poisson model to account for the potential overdispersion of the outcome variable. $\varepsilon_{c,y}$ represents the error terms.

We use a distributed lag model to capture the potential effects of smoke $PM_{2.5}$ on mortality both in the smoke year and the subsequent years. This is both because wildfires can happen late in the year (for example, many recent extreme fires in California happen in October to December), and also because smoke exposure could worsen a range of health outcomes that could lead to increases in mortality risk that emerge at longer time scales. We estimate how results change across different lag periods (lag 0, lag 0–1, ..., lag 0–4). We only estimate lags up to four years because the number of observations in the highest smoke bins, which nearly all occurred in very recent years, drops very quickly with longer lags, resulting in unstable coefficient estimates for the highest smoke bin. We report results from lag 0–1 model in the main text as a conservative estimate compared with longer lags, which is also consistent with previous literature that quantifies the cumulative impacts of total $PM_{2.5}$ on hospitalizations with 1-year lag⁸⁰. Estimates of other lags are reported in Extended Data Fig. 5.

While we observe historical data on daily smoke $PM_{2.5}$ concentrations and monthly mortality rates, we estimate the exposure–response functions at the annual level to be consistent with our smoke concentration projections at the annual level. This approach deviates from previous studies estimating health impacts from wildfire smoke which focus primarily on sub-annual exposures, but it allows for a direct application of the estimated response functions to annual smoke projections. It also has the advantage of allowing us to capture the net effect of either behavioural dynamics in response to short-term variation, as has been observed in related settings³⁹ or displacement of mortality that would otherwise occurred but was hastened as a result of short-term exposure—a common concern in climate impact studies⁸¹.

To assess the sensitivity of our results to multiple assumptions, we estimate several alternative specifications of the Poisson model. We estimate a model that additionally includes year 2020, a model that follows similar specification from⁴³—a monthly model with alternative bin specifications and 12-month moving average of smoke $PM_{2.5}$ concentration, a model that calculates the number of months or the number of days in a year that falls in different smoke bins to represent different temporal aggregations. While we cannot calculate the impact on projected mortality under future scenarios using these subannual measures of wildfire smoke $PM_{2.5}$ given the resolution of the wildfire smoke projections, we instead compare between estimated historical excess deaths during 2011–2020, calculated as the difference between predicted deaths at observed smoke levels relative to what would have occurred absent any smoke. We find largely similar results across the alternative model specifications (Extended Data Fig. 4).

To evaluate the influence of functional forms of the exposure–response function, we estimate alternative response functions using a linear model and a spline model in which wildfire smoke concentrations were treated as a continuous exposure, and calculate how different functional forms influence the estimates of projected annual excess deaths (Supplementary Fig. 5). We find that linear models fail to capture meaningful impacts of both low-level and high-level smoke exposure, which highlights the importance of accounting for the nonlinear influence of smoke $PM_{2.5}$ on mortality (Supplementary Fig. 11). We find that the mortality estimates from the spline model are slightly higher than the bin model estimates, possibly as a result of the extrapolated higher mortality effects at high smoke concentrations that are beyond the historical levels (while the binned exposure–response functions treat all years with annual mean smoke above $4 \mu g m^{-3}$ as the same—that is, it estimates the same mortality effects if annual mean smoke is 4.1, 15 or $25 \mu g m^{-3}$). We use the bin model estimates as our main results

for a conservative estimate of smoke-related mortality. For comparison, we also estimate the mortality burden using previously reported exposure–response functions derived from all-source total $PM_{2.5}$ ^{82–85} (Extended Data Fig. 4). While the full mortality data that we used for the analysis are restricted (but can be accessed by application to the National Center for Health Statistics), we replicate our smoke–mortality results with publicly available mortality data (derived from the CDC WONDER⁸⁶). These data include 2,374 counties with complete data in all years for all age groups, and additional counties with data in some years, as compared to the full (restricted) data which cover 3,077 counties in every year. We find that the estimated exposure–response function between smoke and mortality remain highly similar when using the public mortality data (Supplementary Fig. 12). The public mortality data are included in the data repository (Data availability).

Estimating the mortality burden and monetized damages

We calculate the changes in county-level premature mortality due to smoke $PM_{2.5}$ changes according to the approach described previously^{49,87}:

$$\Delta \text{Mortality}_{c,y} = \text{pop}_c \times D_c \times \text{PAF}_{c,y} \quad (3)$$

where $\Delta \text{Mortality}_{c,y}$ estimates the changes in premature mortality at county c and year y due to smoke $PM_{2.5}$, pop_c denotes the population at county c , D_c denotes the baseline mortality rate at county c , and $\text{PAF}_{c,y}$ is the population attributable fraction (PAF) associated with changes in smoke $PM_{2.5}$ concentrations and is further defined by (given our binned exposure dose–response function)

$$\text{PAF}_{c,y} = \exp \left(\sum_i \beta_i \times \text{smokeBIN}_{c,y}^i \right) - 1 \quad (4)$$

where β_i is our estimated cumulative mortality effects for smoke bin i . When the distributed lag model has lag > 0 , we first calculate $\beta_i = \sum_{\text{lag}=1} \beta_i^{\text{lag}}$, which represents the cumulative mortality effects from smoke exposure in the same year and years after. $\text{smokeBIN}_{c,y}^i$ is a dummy variable for whether annual population-weighted smoke $PM_{2.5}$ in county c and year y falls into smoke bins i .

To calculate smoke attributable deaths in the historical and future scenarios, we use our age-specific exposure–response functions (separate relations for those above 65 and those below 65). For the historical scenario, we use the county-level population data for the year 2019. We use the county-level average death rate between 2006 to 2019 as the baseline mortality rate. For projections of future mortality burden, we use the future population projections for different age groups and projected changes in baseline mortality rate within each age group from the US Census⁸⁸. We acknowledge that our projected mortality burden does not account for potential migration that could be driven by extreme wildfire smoke. Recent evidence suggests that wildfire smoke may have a role in decisions to move, yet the largest effects come from rare and highly destructive fires that destroy substantial housing structures^{89,90}.

As one way to contextualize the magnitude of the estimated deaths from climate-induced smoke $PM_{2.5}$, we compare our estimates against the estimated mortality impacts due to non-optimal temperature in the USA under climate change from an earlier analysis⁴⁶. In the analysis, the authors⁴⁶ first estimated the effects of non-optimal temperature on mortality in a global econometric analysis, and then quantified the net changes in mortality (from changes in heat and cold conditions) under future climate scenarios in each county.

We monetize our estimated mortality impacts using a VSL of US\$10.95 million (year 2019 dollars), as recommended by the US EPA⁹¹ and used in previous studies⁴⁶. For future scenarios, we adjust VSL values using the projected economic growth of 2% and income elasticity of one, following a similar method from ref. 46. VSL is a widely used measure based on individuals' willingness to pay to reduce mortality risk, and

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therefore our estimates reflect societal valuation of avoided deaths, not direct healthcare costs or expenditures. As VSL is widely used in cost–benefit analysis related to climate change, it offers us a way to compare the magnitude of climate-induced mortality to prior estimates that do not account for smoke damages. We compare the economic cost associated with mortality from climate-induced smoke with two prior estimates of aggregate economic damage due to climate change. A previous study⁴ empirically calculated the effects of climate change on a variety of economic damages from temperature-related mortality, agriculture, crime, coastal storms, energy, and labour channels⁴. The FrEDI, developed by US EPA⁵, considered 21 sectors (including estimated wildfire damages from western USA). The wildfire health damages considered in FrEDI only accounted for effects of wildfire in the western USA and used an empirical climate–fire relationship derived from historical data before 2013 which did not include recent extreme wildfire years³¹. We use the default parameters and results from FrEDI in the year of 2050.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Data needed to replicate results and main text figures are available in a public repository at Zenodo⁹² (<https://doi.org/10.5281/zenodo.16855665>), except for county-level mortality data for low-population counties, which were obtained through application to the National Center for Health Statistics. Although we cannot share the full mortality data that we used in the analysis, we released a dataset that allows replication of our smoke–mortality model using public mortality data derived from CDC WONDER.

Code availability

R code to replicate results and main text figures is available at Zenodo⁹² (<https://doi.org/10.5281/zenodo.16855665>).

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Acknowledgements We thank A. Wilson for helping process mortality data; Y. Ma and K. Chen for sharing their smoke mortality estimates for comparison; A. van Donkelaar for helping with dataset of total PM_{2.5} concentrations; seminar participants at Stanford University, Harvard University and the Brookhaven National Laboratory for comments; and the Keck Foundation for funding. M.Q. acknowledges the support from the planetary health fellowship at Stanford's Center for Innovation in Global Health, and Minghua Zhang faculty career catalyst award from Stony Brook University. M.L.C. was supported by an Environmental Fellowship at the Harvard University Center for the Environment. R.J. acknowledges support for this work from NIH grant R01HD104835 and the Ruth L. Kirschstein National Research Service Award grant 5T32HS026128-07. N.S.D. acknowledges support from Stanford University. Some of the computing for this project was performed on the Stanford Sherlock cluster, and we thank Stanford University and the Stanford Research Computing Center for providing computational resources and support that contributed to these research results. NCEP North American Regional Reanalysis (NARR) data were provided by the NOAA PSL from their website (<https://psl.noaa.gov>).

Author contributions M.Q. and M.B. designed the study. M.Q. led the smoke projection modelling with inputs from all of the authors. M.Q., J.L. and R.J. led the statistical and machine learning modelling of fire emissions. M.Q., S.H.-N., C.F.G. and M.L.C. led the health impacts analysis. M.Q. and M.B. led the writing of the manuscript. M.Q., J.L., C.F.G., R.J., M.K., M.L.C., J.W., Y.X., M.L., M.V.K., S.H.-N., N.S.D. and M.B. contributed to interpretation of results and reviewed the manuscripts.

Competing interests The authors declare no competing interests.

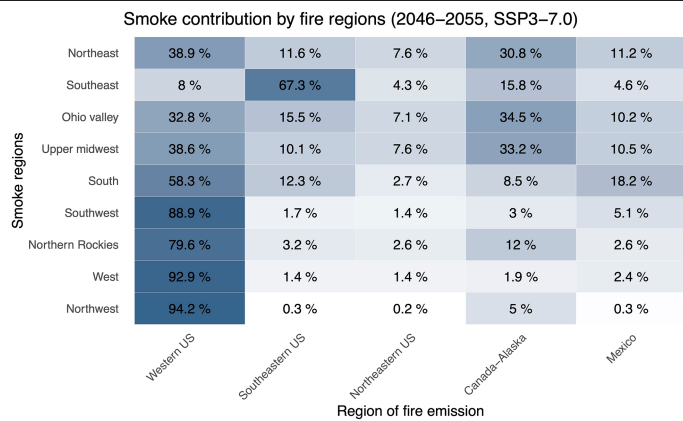
Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s41586-025-09611-w>.

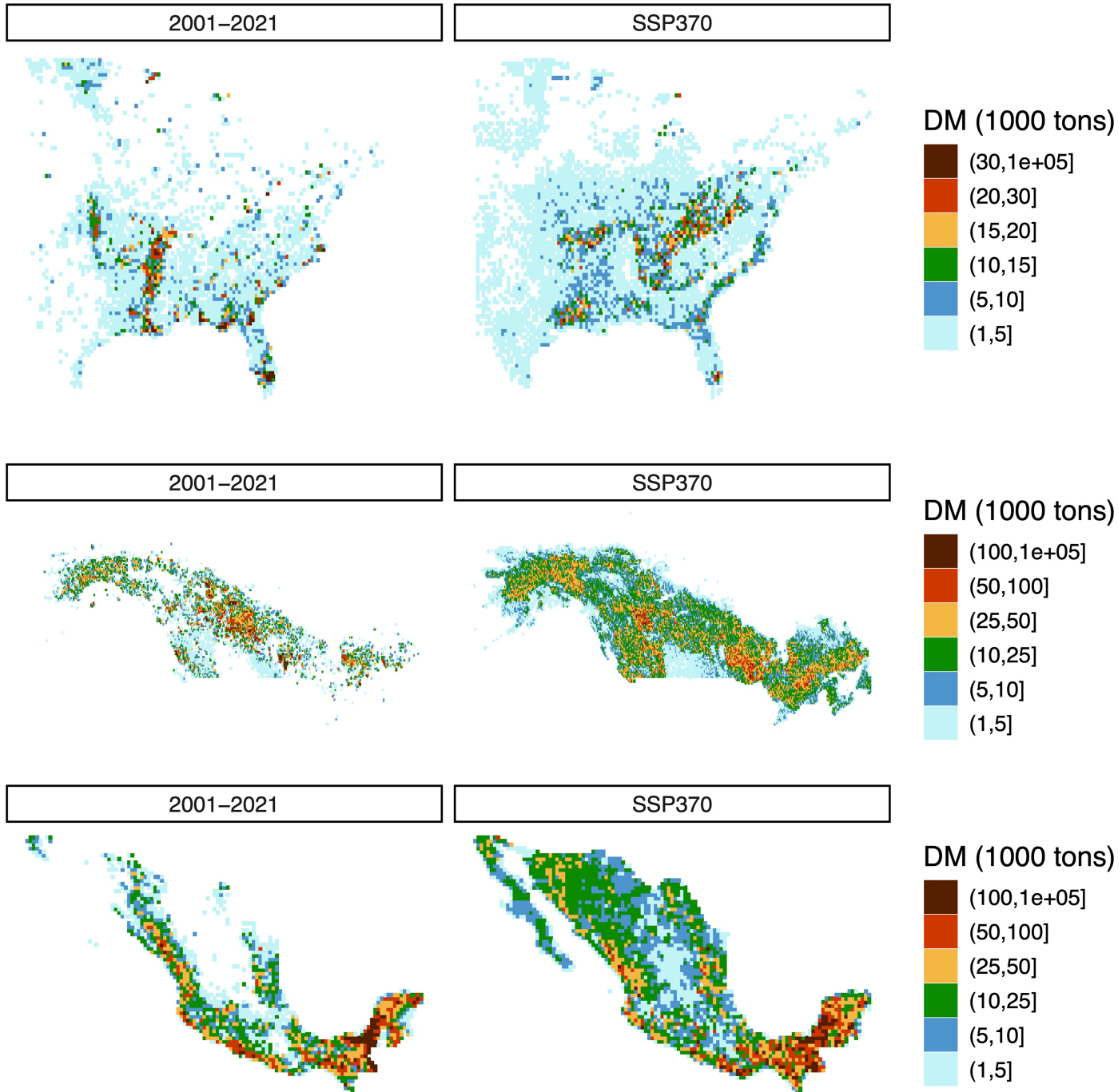
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Peer review information Nature thanks Joan Casey, Lulu Chen, Gaige Kerr, Scott Weichenath, Xiao Wu and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. Peer reviewer reports are available.

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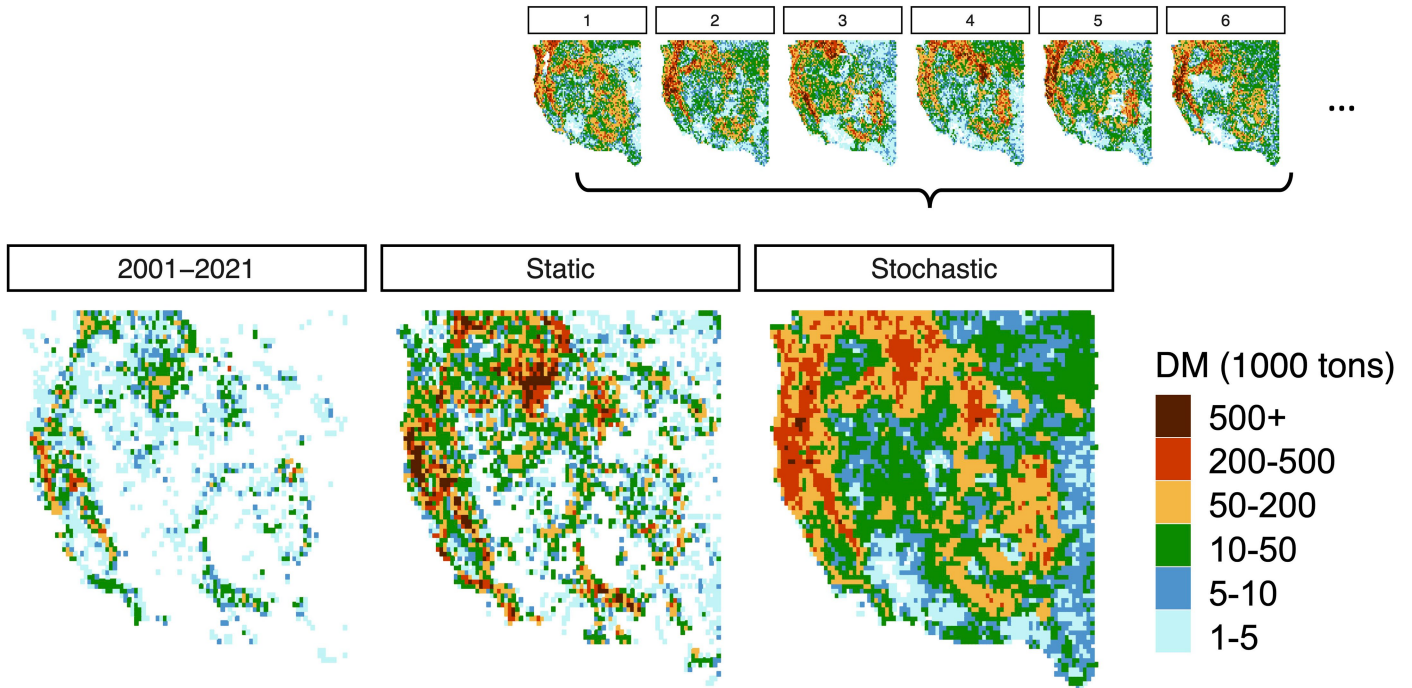
Extended Data Fig. 1 | Future smoke contribution from different fire regions. Source-receptor matrix of the contributions from fire emissions from the five source regions (x-axis) to population-weighted smoke $PM_{2.5}$ concentrations in nine receptor regions across the contiguous US (y-axis). The plot shows the contributions in 2046–2055 averaged over all GCMS under the SSP3-7.0 scenario.



Extended Data Fig. 2 | Historical and projected dry matter (DM) emissions. Historical annual average emissions in 2001–2021 and projected annual emissions (2046–2055) under the SSP3-7.0 scenario in the eastern US (top),

Canada and Alaska (middle), and Mexico (bottom). Projected emissions are first stochastically downscaled from regional emissions predictions and then averaged over 40 simulated downscaling estimates.

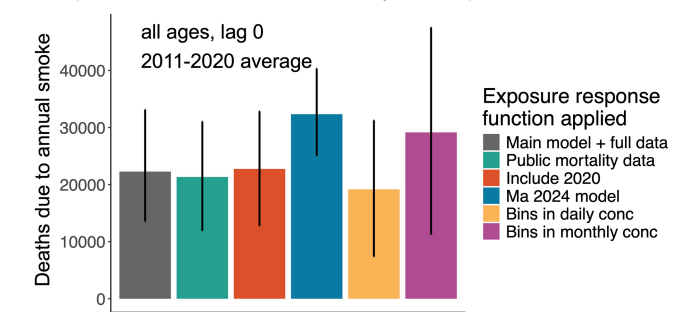
Different downscaling estimates



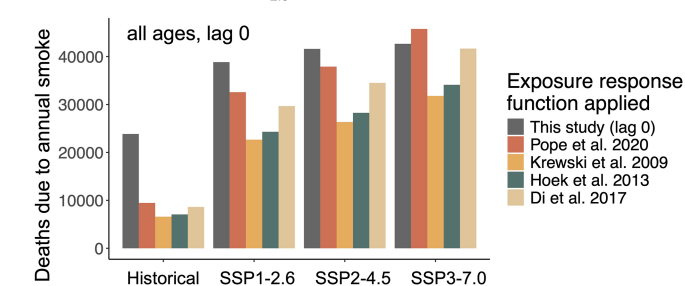
Extended Data Fig. 3 | Illustration of the stochastic downscaling approach using the western US as an example. Historical annual average emissions in 2001–2021 from GFED4s, and projected annual emissions averaged between 2046–2055 under the SSP3-7.0 scenario at the grid level. The “static” panel shows the results derived from the static downscaling method, which applies a common ratio to the historical emission pattern to match the future projected

emissions. The “stochastic” panel shows our main stochastic downscaling method, which generates the same total emissions as the static method regionally but allows for the possibility that grids that have never burned could burn. Projected emissions are first stochastically downscaled from regional emissions predictions and then averaged over 40 simulated downscaling estimates (six are shown here for the illustration purpose).

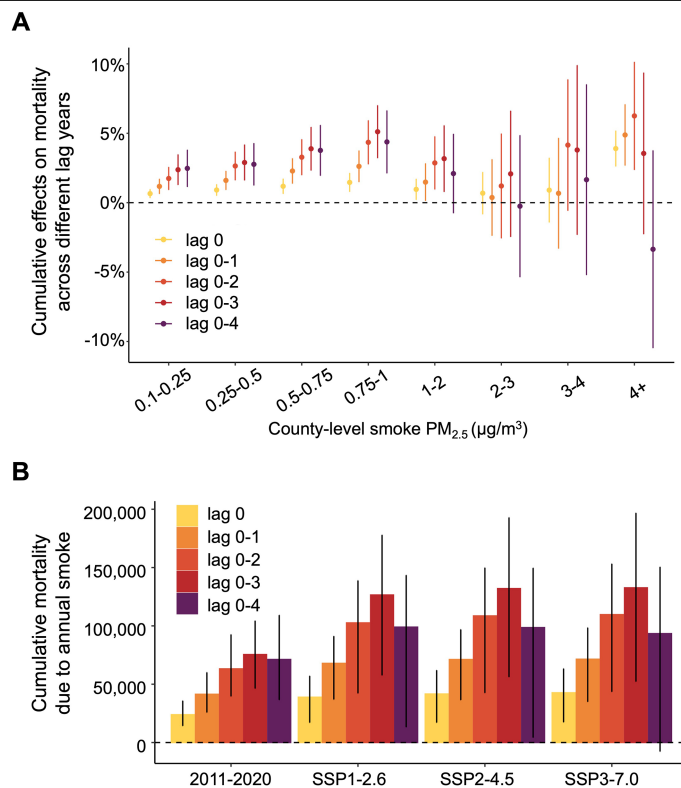
A compared to alternative smoke-mortality model specifications



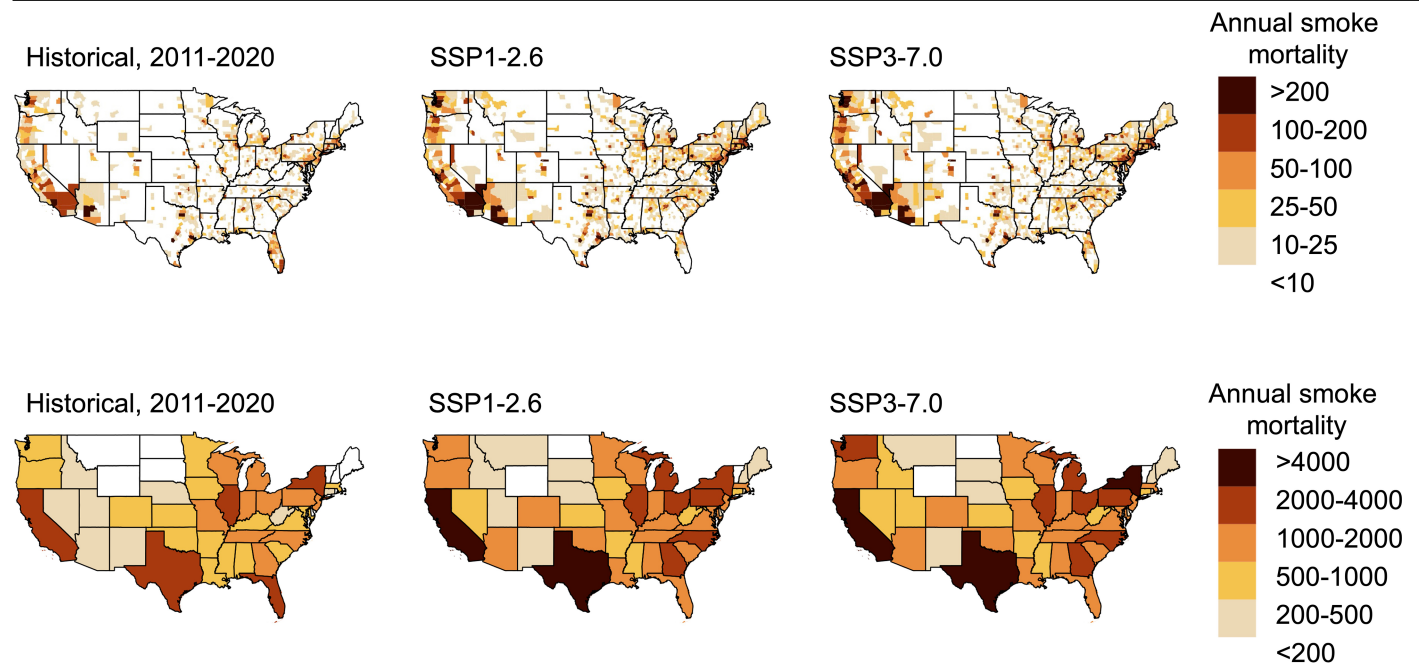
B compared to all-source PM_{2.5} exposure response functions



Extended Data Fig. 4 | Estimated annual excess deaths due to smoke PM_{2.5} using alternative exposure-response functions. Panel A: results estimated using alternative smoke-mortality models (averaged over 2011–2020). In addition to our main model (grey bar), we estimate a model that uses the public mortality data from CDC WONDER, a model that additionally includes year 2020 in the regressions, a model that follows similar specification from Ma et al., 2024 (i.e. a monthly model with alternative bin specifications and 12-month moving average of smoke PM_{2.5} concentration), and models which calculates the number of months or the number of days in a year that fall in different smoke bins to represent different temporal aggregations. The bars show mean values of bootstrapped estimates, and the whiskers show bootstrapped 95% confidence intervals (500 bootstraps). Panel B: results estimated using published exposure-response functions that link total PM_{2.5} to mortality. Note the results here are estimated using lag 0 model and all-ages group, to match earlier work.

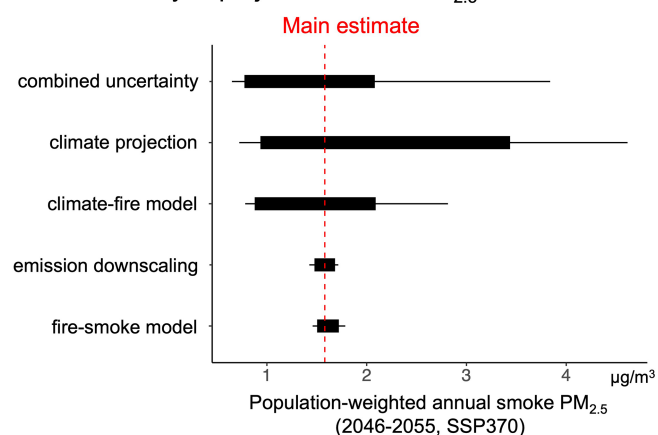


Extended Data Fig. 5 | Cumulative effects of smoke on mortality across different lag years. Panel A: aggregated coefficients for each smoke bin across different lag years, representing the cumulative effects of smoke exposure on mortality in the same year and subsequent years. Panel B: estimated mortality due to annual smoke $PM_{2.5}$ under historical (2011–2020) and future scenarios (2046–2055). The plot shows the same-year mortality due to smoke (in the case of lag 0), and cumulative mortality (lag 0-1,...,lag 0-4). The bars show mean values of bootstrapped estimates, and the whiskers show bootstrapped 95% confidence intervals (500 bootstraps). We report results from “lag 0-1” model as our main estimates.

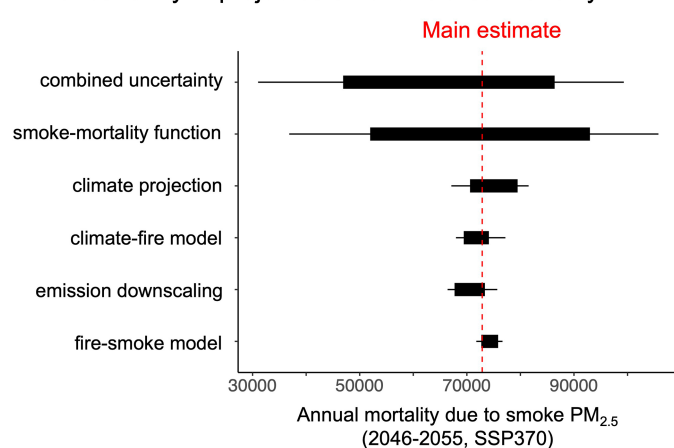


Extended Data Fig. 6 | Estimated excess deaths due to smoke $PM_{2.5}$ under the historical, SSP1-2.6, and SSP3-7.0 scenarios due to annual smoke exposure (lag 0-1). The top panels show estimates at the county level. The bottom panels show estimates at the state level.

A uncertainty in projected smoke $\text{PM}_{2.5}$



B uncertainty in projected smoke-related mortality



Extended Data Fig. 7 | Uncertainty in projected annual smoke $\text{PM}_{2.5}$ concentration (Panel A) and mortality (Panel B). The red dashed line shows the main estimate. The solid bar shows the 10th and 90th percentile, and the black line shows the 2.5th and 97.5th percentile. Uncertainty from “climate projection” is calculated using the percentiles of 28 GCMs. Uncertainty from “climate-fire model” and “fire-smoke model” is calculated using bootstrap procedures performed on the climate-fire and fire-smoke models. Uncertainty from “emission downscaling” shows the range of smoke and mortality estimated across 40 different downscaling estimates. Uncertainty from “smoke-mortality function” is calculated using bootstrap procedures performed on the smoke-mortality response functions. The combined uncertainty is quantified using a Monte-Carlo simulation approach, where we randomly sample 500 combinations of GCMs, climate-fire models, downscaling estimates, and fire-smoke models, and smoke-mortality functions.

Extended Data Table 1 | Estimated past and future population-weighted average smoke PM_{2.5}, and smoke contribution to total PM_{2.5} (i.e. smoke PM_{2.5}/total PM_{2.5}) at the state level

State	Smoke PM _{2.5} µg/m ³	Total PM _{2.5} µg/m ³	Smoke percent	State	Smoke PM _{2.5} µg/m ³	Total PM _{2.5} µg/m ³	Smoke percent	Scenario
Oregon	1.3	6.6	20%	California	0.6	10.5	6%	2011-2020
	5.4	10.1	53%		1.9	11.3	17%	SSP1-2.6
	7.0	11.7	59%		2.5	11.9	21%	SSP2-4.5
	8.4	13.2	64%		3.0	12.5	24%	SSP3-7.0
Washington	0.9	6.0	16%	Kansas	0.7	7.3	9%	2011-2020
	4.9	9.4	53%		1.5	7.8	19%	SSP1-2.6
	6.2	10.7	58%		1.7	8.0	21%	SSP2-4.5
	7.7	12.2	63%		2.0	8.2	24%	SSP3-7.0
Montana	1.3	6.4	20%	Nebraska	0.7	7.4	9%	2011-2020
	5.5	10.5	52%		1.3	7.5	17%	SSP1-2.6
	6.8	11.8	58%		1.5	7.7	19%	SSP2-4.5
	8.5	13.5	63%		1.7	7.9	22%	SSP3-7.0
Idaho	1.3	7.1	18%	Oklahoma	0.6	7.8	8%	2011-2020
	4.3	9.9	44%		1.2	8.0	15%	SSP1-2.6
	5.4	11.0	49%		1.4	8.1	17%	SSP2-4.5
	6.7	12.3	54%		1.7	8.4	20%	SSP3-7.0
Wyoming	0.7	5.4	13%	Minnesota	0.6	6.6	9%	2011-2020
	3.3	7.8	43%		1.1	6.8	16%	SSP1-2.6
	4.3	8.7	49%		1.2	6.9	18%	SSP2-4.5
	5.2	9.7	54%		1.4	7.1	20%	SSP3-7.0
Colorado	0.5	6.1	9%	Iowa	0.6	7.8	8%	2011-2020
	2.0	7.5	27%		1.1	7.8	14%	SSP1-2.6
	2.6	8.0	32%		1.2	7.9	16%	SSP2-4.5
	3.1	8.6	36%		1.4	8.1	18%	SSP3-7.0
North Dakota	0.7	5.3	14%	Maine	0.2	5.2	4%	2011-2020
	1.8	6.1	29%		0.8	5.3	15%	SSP1-2.6
	2.0	6.4	31%		0.9	5.4	16%	SSP2-4.5
	2.4	6.7	35%		1.0	5.5	18%	SSP3-7.0
Nevada	0.5	7.0	7%	New Hampshire	0.2	6.0	4%	2011-2020
	2.0	8.5	24%		0.8	5.9	14%	SSP1-2.6
	2.6	9.1	29%		0.9	6.0	15%	SSP2-4.5
	3.2	9.7	33%		1.0	6.1	16%	SSP3-7.0
Utah	0.5	6.9	7%	Vermont	0.2	5.5	4%	2011-2020
	1.7	7.7	23%		0.7	5.5	13%	SSP1-2.6
	2.3	8.2	28%		0.8	5.5	14%	SSP2-4.5
	2.7	8.6	31%		0.9	5.6	16%	SSP3-7.0
South Dakota	0.7	6.1	11%	Texas	0.5	8.3	6%	2011-2020
	1.6	6.6	25%		1.0	8.4	11%	SSP1-2.6
	1.8	6.8	27%		1.1	8.5	13%	SSP2-4.5
	2.2	7.2	31%		1.3	8.8	15%	SSP3-7.0
New Mexico	0.3	5.4	6%	Arkansas	0.6	8.2	7%	2011-2020
	1.2	6.0	21%		1.0	7.9	12%	SSP1-2.6
	1.5	6.3	24%		1.1	8.1	14%	SSP2-4.5
	1.9	6.6	28%		1.3	8.2	15%	SSP3-7.0
				Wisconsin	0.5	7.4	7%	2011-2020
					0.9	7.3	13%	SSP1-2.6
					1.0	7.4	14%	SSP2-4.5
					1.1	7.5	15%	SSP3-7.0

Total PM_{2.5} is calculated as the sum of smoke and non-smoke PM_{2.5} concentrations. Non-smoke PM_{2.5} is assumed to be the same as the average non-smoke PM_{2.5} between 2016–2020, calculated as the difference between total PM_{2.5} (derived from van Donkelaar et al., 2021) from and smoke PM_{2.5} (derived from Childs et al., 2022). Only states with >15% smoke contributions under SSP3-7.0 scenario are listed.

Extended Data Table 2 | Empirically estimated exposure-response function of smoke PM_{2.5} on mortality rate across three age groups (all ages, 65 and up, under 65)

Age group	Annual smoke ($\mu\text{g}/\text{m}^3$)	Relative change in mortality rate (from Poisson model)		Mortality per 100k people (from OLS model)	
		lag 0	lag 0-1	lag 0	lag 0-1
all ages	(0.1,0.25]	0.7% (0.4%, 1.0%)	1.2% (0.7%, 1.8%)	3.9 (1.9, 6.1)	7.6 (4.4, 11.2)
	(0.25,0.5]	0.9% (0.5%, 1.4%)	1.6% (1.0%, 2.4%)	5.5 (3.1, 7.9)	10.2 (6.8, 14.3)
	(0.5,0.75]	1.2% (0.7%, 1.8%)	2.4% (1.5%, 3.4%)	6.9 (3.4, 10.7)	14.4 (9.0, 20.3)
	(0.75,1]	1.5% (0.8%, 2.2%)	2.7% (1.6%, 3.9%)	9.4 (4.7, 13.9)	18.0 (10.7, 26.2)
	(1,2]	1.0% (0.3%, 1.7%)	1.6% (0.4%, 2.9%)	5.9 (1.2, 11.0)	10.4 (2.3, 18.8)
	(2,3]	0.7% (-0.7%, 2.3%)	0.4% (-2.2%, 3.5%)	4.4 (-4.4, 12.9)	3.1 (-10.0, 18.3)
	(3,4]	0.9% (-1.2%, 3.1%)	0.6% (-3.1%, 4.6%)	5.6 (-5.7, 18.0)	3.4 (-16.1, 25.7)
	>4	3.9% (2.5%, 5.4%)	4.9% (2.3%, 7.3%)	23.6 (14.7, 32.7)	26.9 (11.9, 40.3)
65 and up	(0.1,0.25]	0.5% (0.2%, 0.8%)	0.8% (0.3%, 1.4%)	15.6 (4.1, 27.5)	26.9 (7.9, 45.3)
	(0.25,0.5]	0.7% (0.3%, 1.1%)	1.0% (0.4%, 1.7%)	20.3 (5.5, 35.9)	33.7 (10.1, 56.5)
	(0.5,0.75]	0.7% (0.2%, 1.3%)	1.6% (0.7%, 2.5%)	18.1 (-4.8, 39.7)	48.1 (15.0, 81.1)
	(0.75,1]	1.1% (0.5%, 1.8%)	2.0% (1.0%, 3.1%)	38.2 (13.7, 65.5)	71.3 (36.0, 116.4)
	(1,2]	0.9% (0.2%, 1.6%)	1.3% (0.2%, 2.4%)	29.2 (1.0, 55.3)	50.4 (8.4, 92.0)
	(2,3]	0.6% (-0.7%, 2.0%)	0.3% (-2.0%, 3.0%)	21.5 (-24.6, 70.9)	11.9 (-62.1, 99.3)
	(3,4]	0.7% (-1.2%, 2.6%)	0.5% (-2.7%, 3.9%)	22.8 (-45.4, 87.4)	8.9 (-90.9, 104.9)
	>4	3.6% (2.1%, 5.2%)	4.2% (1.4%, 6.5%)	126.4 (66.6, 188.6)	129.5 (23.7, 210.4)
under 65	(0.1,0.25]	1.1% (0.5%, 1.7%)	2.2% (1.3%, 3.2%)	2.2 (1.0, 3.5)	4.8 (3.1, 6.7)
	(0.25,0.5]	1.7% (1.0%, 2.4%)	3.2% (2.0%, 4.5%)	3.4 (2.0, 4.9)	6.8 (4.5, 9.7)
	(0.5,0.75]	2.5% (1.5%, 3.5%)	4.4% (2.7%, 6.3%)	5.3 (3.3, 7.4)	9.5 (6.4, 13.4)
	(0.75,1]	2.4% (1.2%, 3.7%)	4.6% (2.3%, 7.1%)	5.2 (2.6, 7.6)	10.3 (5.3, 14.6)
	(1,2]	1.4% (0.0%, 2.8%)	2.3% (0.0%, 4.9%)	2.6 (-0.3, 5.7)	4.6 (-0.4, 9.3)
	(2,3]	0.9% (-1.3%, 3.4%)	0.8% (-3.4%, 5.5%)	1.9 (-2.1, 6.1)	1.9 (-5.2, 9.6)
	(3,4]	1.2% (-2.1%, 4.7%)	0.8% (-5.1%, 7.0%)	3.1 (-2.9, 9.2)	2.7 (-8.5, 14.3)
	>4	4.5% (1.8%, 7.2%)	6.1% (0.8%, 11.0%)	8.7 (3.8, 14.4)	12.0 (2.3, 22.6)

The table shows coefficient estimates of the effects of exposure to different annual mean concentration of smoke PM_{2.5} relative to a year with smoke concentration <0.1 $\mu\text{g}/\text{m}^3$. Left columns show estimates from a Poisson model, right columns ("Mortality per 100k people") are calculated using an ordinary least squares model that estimates smoke PM_{2.5} influences on the absolute mortality rates. Values in the parenthesis represent bootstrapped 95% confidence intervals (500 bootstraps, sampling counties with replacement). The table reports results from the lag 0 and lag 0-1 models.

Extended Data Table 3 | Estimated annual excess deaths due to exposure to wildfire smoke by state

State	Historical	SSP1-2.6	SSP2-4.5	SSP3-7.0	State	Historical	SSP1-2.6	SSP2-4.5	SSP3-7.0
California	2856	6724	7407	7920	Maryland	683	1143	1195	1185
Texas	3540	5224	5153	5241	Minnesota	898	1189	1177	1168
New York	2207	3810	4090	4019	Louisiana	789	1052	1098	1105
Pennsylvania	1703	3094	3343	3302	Oklahoma	829	1090	1013	1052
Ohio	1829	3162	3142	3049	Arkansas	653	855	826	832
Illinois	2161	2768	2726	2731	Connecticut	432	771	817	800
Washington	812	1999	2255	2541	Iowa	605	815	785	783
North Carolina	1252	2290	2490	2535	Mississippi	528	708	771	774
Michigan	1760	2516	2607	2519	Nevada	288	584	659	733
Georgia	1290	2072	2223	2246	Kansas	562	689	653	669
Virginia	819	1795	1924	1942	Idaho	210	457	520	594
New Jersey	1076	1814	1938	1898	West Virginia	264	567	598	586
Oregon	664	1341	1495	1673	Utah	231	462	488	519
Missouri	1257	1660	1652	1651	New Mexico	215	424	478	495
Florida	2088	1120	1430	1649	Nebraska	358	457	428	449
Indiana	1122	1678	1674	1623	Montana	177	361	404	441
Tennessee	1041	1556	1640	1623	Maine	170	361	376	364
Massachusetts	756	1441	1532	1506	New Hampshire	150	314	321	313
Arizona	450	1248	1354	1454	Rhode Island	130	244	259	257
Wisconsin	1009	1419	1431	1391	Delaware	128	205	219	220
Alabama	853	1216	1322	1333	South Dakota	151	210	206	217
South Carolina	757	1127	1208	1231	Wyoming	78	140	157	178
Kentucky	747	1202	1251	1226	North Dakota	127	156	146	158
Colorado	584	1043	1112	1197	Vermont	70	142	153	150
					D.C.	89	128	133	132

For the historical period, the table shows average annual excess deaths due to smoke PM_{2.5} exposure during 2011–2020. For future climate scenarios, the table shows annual excess deaths associated with 10-year average smoke PM_{2.5} exposure during 2046–2055 (median across 28 GCMs). The table shows estimated results using the lag 0-1 model.

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☒	☐ Estimates of effect sizes (e.g. Cohen's <i>d</i> , Pearson's <i>r</i>), indicating how they were calculated

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Software and code

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Data collection	Data sources are detailed in the manuscript and supplementary information and are publicly available except for the mortality data. Individual-level multiple cause of death mortality data is derived from the National Center for Health Statistics to calculate age-standardized mortality rates for all ages, those under 65 years of age, and those 65 years and older.
Data analysis	Data analysis are performed using open source programming language R (version 4.4.1). Analysis procedure is described fully in the manuscript and the original code is made public in a community repository. https://doi.org/10.5281/zenodo.16855664

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Data and code to replicate results and figures in the main text is publicly available at <https://doi.org/10.5281/zenodo.16855664>, except for county-level mortality data for low-population counties, which are not publicly available and were obtained through application to the National Center for Health Statistics. We note that while the mortality data we used in the analysis is restricted (and thus cannot be shared), we released a dataset that allows replication of our smoke-mortality model using public mortality data derived from CDC WONDER.

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Ecological, evolutionary & environmental sciences study design

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Study description	The study quantifies the concentrations of wildfire smoke fine particulate matter (PM2.5) and the associated mortality burden in the US under future climate scenarios. The study first estimates relationships between climate variables and smoke PM2.5 concentration, and the relationship between smoke PM2.5 and mortality using historical data. The study then projects future smoke PM2.5 level and mortality from 2026-2055 using climate projections from Coupled Model Intercomparison Project Phase 6.
Research sample	The research sample consists of all locations in the North America for fire modeling, all locations in the contiguous US for smoke PM2.5 modeling, and all counties in the contiguous US for estimating the smoke-mortality response functions.
Sampling strategy	No sample size calculations were performed.
Data collection	Research team collected data on fire, smoke, and climate variables from public sources (documented in the manuscript). Individual-level multiple cause of death mortality data is derived from the National Center for Health Statistics to calculate age-standardized mortality rates for all ages, those under 65 years of age, and those 65 years and older. Only aggregated data at the county level are used in this analysis.
Timing and spatial scale	We use the county-level mortality data from January 2006 to December 2019.
Data exclusions	No data was excluded in the analysis.
Reproducibility	As the study is an observational study, the reproducibility is assessed through data validation and various robustness checks. Extensive sensitivity analyses are performed to assess the robustness of our findings to alternative model specifications and choices. Code scripts and data is also available for replicate our main findings.
Randomization	This study did not use experimental procedures that involve randomization.
Blinding	This study did not use experimental procedures that involve direct comparisons between the treatment and control group, and thus the blinding does not apply.
Did the study involve field work?	☐ Yes ☒ No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Human research participants
☒	☐ Clinical data
☒	☐ Dual use research of concern

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging