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Anthropogenic climate change contributes to wildfire particulate matter and related mortality in the United States

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Climate change has increased forest fire extent in temperate and boreal North America. Here, we quantified the contribution of anthropogenic climate change to human mortality and economic burden from exposure to wildfire particulate matter at the county and state level across the contiguous US (2006 to 2020) by integrating climate projections, climate-wildfire models, wildfire smoke models, and emission and health impact modeling. Climate change contributed to approximately 15,000 wildfire particulate matter deaths over 15 years with interannual variability ranging from 130 (95% confidence interval: 64, 190) to 5100 (95% confidence interval: 2500, 7500) deaths and a cumulative economic burden of $160 billion. Approximately 34% of the additional deaths attributable to climate change occurred in 2020, costing $58 billion. The economic burden was highest in California, Oregon, and Washington. We suggest that absent abrupt changes in climate trajectories, land management, and population, the indirect impacts of climate change on human-health through wildfire smoke will escalate.

Climate change has driven the observed increase in frequency and intensity of wildfires[1–3], which produce substantial amounts of fine particulate matter (wildfire $PM_{2.5}$). Exposure to $PM_{2.5}$ is a known cause of mortality and cardiovascular disease and is linked to onset and worsening of respiratory conditions[4]. Ongoing trends of increasing wildfire severity align with climate projections and underscore how climate change factors such as earlier snowmelt, intensified heat waves[5,6], and rising vapor pressure deficit[7], have already expanded forest fire extent[8], accelerated daily fire growth rates[9], and enabled more extreme fire events[10].

As climate change exacerbates wildfire risk, $PM_{2.5}$ emissions from wildfires have surged, contributing nearly half of the national annual average $PM_{2.5}$ across the US in recent years[11] and reversing air quality improvements in several regions[12]. Economic and environmental impacts of wildfires on both natural ecosystems and human communities will continue to increase as climate warming intensifies and extreme events become more frequent[13]. Although the connection between anthropogenic $PM_{2.5}$ exposure and mortality is well-documented[14], our understanding of the health impacts of wildfire $PM_{2.5}$ attributable to anthropogenic climate change is limited. With increasing wildfire activity driven by climate change[1], there is a pressing need to quantify the health consequences of subsequent increases in wildfire $PM_{2.5}$ concentrations.

Addressing this need requires attribution, a framework that determines the extent to which human activities, particularly the emissions of greenhouse gases, are responsible for changes in environmental systems. Climate attribution has already been used to link recent high profile fire seasons to climate change. For example, during Black Summer, Australia's 2019–2020 bushfires burned an estimated 24 million hectares; high-risk conditions conducive to widespread burning were at least 30 percent more likely due to climate warming[15]. More recently, the 2023 Canadian forest fires covered seven times the average annual area burned compared to the previous four decades[16,17], and climate change more than doubled the likelihood of extreme fire weather conditions in Eastern and Southwestern Canada[18]. In the western US, observed warming and drying, particularly increased vapor pressure deficit (VPD), correlate with increases in fuel aridity metrics and wildfire burn area (BA). These trends have been linked to anthropogenic climate change in the western

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US and show a doubling of the burn area expected in the absence of climate change[1].

Here, we develop an attribution framework to assess the contribution of anthropogenic climate change-related wildfire $PM_{2.5}$ impacts on human mortality on a county level across the contiguous US (CONUS) (Fig. 1; see "Methods"). Our framework quantifies the effect of climate change on human mortality by comparing observed wildfire $PM_{2.5}$ with that from a counterfactual climate scenario that excludes the direct influence of climate change based on 20 climate models participating in CMIP6[19]. We develop ecoregion-level empirical models of annual burn area (BA) using fire weather index (FWI) and precipitation from ERA5[20] across North America. These models are then forced by observed and counterfactual climates to approximate the climate change contribution to BA at the ecoregion scale annually. We then train a machine learning model to relate monthly mean wildfire $PM_{2.5}$ from published data[11] to observed BA from MODIS (see "Methods") and meteorological variables. Deploying the trained model with historical and counterfactual BA simulations allows us to isolate wildfire $PM_{2.5}$ attributable to climate change. Using an extended shape constrained health impact function and georeferenced data on recorded deaths in the Environmental Benefits Mapping and Analysis Program Community Edition model (Ben-MAP-CE)[21] allows us to estimate mortality from wildfire $PM_{2.5}$ exposure.

Results

Wildfire burn area and wildfire $PM_{2.5}$ attributable to climate change

Observed wildfire burn area. Our longer record of observed wildfire BA (2002–2023) shows temporal variability, with the highest total BA during 2020 across the study area (Fig. 2c, d). We find that approximately 40% of BA occurred in primarily forest lands, and that forest BA significantly increased by 62% ($p = 0.06$) during 2002–2023 while nonforest BA declined by 6%. Results for broader North America are qualitatively similar, albeit forest BA accounted for a majority of the total BA with the highest total BA in 2023 influenced by the historical Canadian fire season (Supplementary Fig. 1).

Climate change contributions to wildfire burn area. We found that the percent of burn area attributable to climate change is stronger in flammability-limited forest lands and ecoregions that exhibit greater sensitivity to FWI (Fig. 2, Supplementary Fig. 2, Supplementary Tables 1, 2). The models showed little predictive skill in the southeastern US where there is more intentional fire that confounds climate-fire relationships (Supplementary Fig. 3). Climate-BA relationships were stronger in the western portions of the CONUS where there is more wildland, similar to prior studies[22,23].

Over the 2006–2020 period of overlap between the available datasets of BA and wildfire $PM_{2.5}$, we estimate that climate change resulted in 39.0% more forest BA and 13.3% more nonforest BA than would have happened in its absence in the CONUS. The weaker influence of climate change on nonforest BA is partially due to heightened importance of antecedent precipitation that augments fine fuel growth and fire potential in fuel-limited fire regimes. Precipitation exhibits limited change under a counterfactual climate scenario.

The highest smoke concentrations are found in the western portion of the country, especially in the states of California, Oregon, Washington, Idaho and Montana (Fig. 3a), where 25 to 60% of the average annual wildfire $PM_{2.5}$ in 2006–2020 can be attributed to climate change (Fig. 3b). Some isolated regions, e.g., rural parts of the Great Plains, show a slight decline, less than $0.25\,\mu g\,m^{-3}$, in average annual wildfire $PM_{2.5}$, based on either a negative relationship between FWI and monthly mean wildfire $PM_{2.5}$ in nonforest areas or intentional agricultural fires as well as prescribed burns. For context, the World Health Organization sets acceptable total $PM_{2.5}$ levels at $5\,\mu g/m^3$ annually and $15\,\mu g/m^3$ for a 24-h period[24]. Over the 2006–2020 analysis period, the climate change contributions to wildfire $PM_{2.5}$ were greater in more recent years (2017, 2018, and 2020) (Fig. 3c).

Wildfire $PM_{2.5}$ mortality and economic burden

Mortality attributable to observed wildfire $PM_{2.5}$. We estimate between 3500 (95% CI 1700 to 5100) to 28,000 (95% CI 14,000 to 42,000) wildfire $PM_{2.5}$ attributable deaths per year between 2006 and 2020, with the largest number of these deaths occurring in 2020 and a cumulative total of 164,000 deaths over the 15 years. The annual average wildfire $PM_{2.5}$ mortality rate was 5.14 deaths per 100,000 population for the CONUS between 2006 and 2020. We estimated the annual economic burden of observed wildfire $PM_{2.5}$ mortality to be between \$31 billion (95% CI 2.6–88) to \$325 billion (95% CI 28–920). For comparison, tropical cyclones result in 1.9–3.1 deaths per 100,000 annually in the US[25] and have caused an average of \$22.8 billion in damages per event.

Climate change contributions to wildfire $PM_{2.5}$ mortality. We estimate climate change contributed to approximately 15,000 wildfire $PM_{2.5}$ deaths between 2006 and 2020 (Table 1, ca. 10% on average), with year-to-year variability ranging from 130 (95% CI 64–190) to 5100 (95% CI 2500 to 7500) deaths, and greater contribution in more recent years commensurate with the growing climate change signal (Figs. 4, 5). The cumulative economic burden of climate change-related wildfire $PM_{2.5}$ mortality was \$160 billion (Table 1), with year-to-year costs ranging from \$1.2 (95% CI 0.1–3.4) to \$58.0 (95% CI 5.0–170) billion. On average, the annual rate of wildfire $PM_{2.5}$ deaths attributable to climate change was 0.45 per 100,000 population between 2006 and 2020, with an average economic burden of \$11 billion annually. Approximately 34% of the additional deaths attributable to climate change over the 15 years of our study occurred in 2020 (Fig. 4).

On a state-level, Western US states experienced the highest annual rates of climate change-related wildfire $PM_{2.5}$ mortality and incurred the highest economic costs between 2006–2020 (Table 2, Supplementary Tables 3–5). In the western states of Oregon, Montana, Idaho, Washington, California, and Nevada, the climate change contribution to total annual wildfire $PM_{2.5}$ mortality averaged across the 15 years was between 19 and 36% (Table 2, Supplementary Table 4). On the county level, the ten counties with the highest annual mortality rates from climate change-related wildfire $PM_{2.5}$ were all in the Western US, dominated by California and Oregon (Table 3, Fig. 5, Supplementary Fig. 4, Supplementary Tables 6, 7). The climate change contributions to total annual wildfire $PM_{2.5}$ mortality exceeded 50% in 12 western US counties in 2020, and ranged from 40 to 63% in 66 counties (Supplementary Tables 6, 7).

Sensitivity analyses using different concentration response functions to estimate the climate change contribution to wildfire $PM_{2.5}$ mortality showed similar direction and magnitude (Supplementary Table 8). Using the Global Exposure Mortality Model (GEMM) concentration response function, we estimate 13,000 climate change-related wildfire $PM_{2.5}$ deaths between 2006 and 2020 in the CONUS, with a total economic burden of \$144 billion. Additionally, we apply the concentration response function from a long-term $PM_{2.5}$ mortality study[26] and estimate 17,000 climate change related wildfire $PM_{2.5}$ deaths, with a total economic valuation of \$186 billion.

Discussion

It is essential to reduce greenhouse gas emissions and associated impacts on natural and human systems. Over the last half-century, climate change has been a substantial driver of increased wildfire burn area in western US forests[27], which has generated additional $PM_{2.5}$ pollution and negatively impacted public health[28]. This is the first study to quantify the annual time-varying impact of climate change on historical wildfire $PM_{2.5}$ mortality on a state and county level across the contiguous US. Using our attribution framework to document this excess mortality, we show that 15,000 of 164,000 wildfire $PM_{2.5}$ related deaths (ca. 10%) from 2006 to 2020 are solely attributable to climate change, corresponding to \$160 billion of economic damages.

Climate change-caused wildfire $PM_{2.5}$ has a distinct spatial pattern, with the highest concentrations, excess mortality, and economic damages in the western US. Climate change accounts for up to 60% of the average annual wildfire $PM_{2.5}$ in portions of California, Oregon, Washington, Idaho, and Montana. The contribution of climate change to excess deaths attributable to wildfire $PM_{2.5}$ also offers a potential area of intervention.

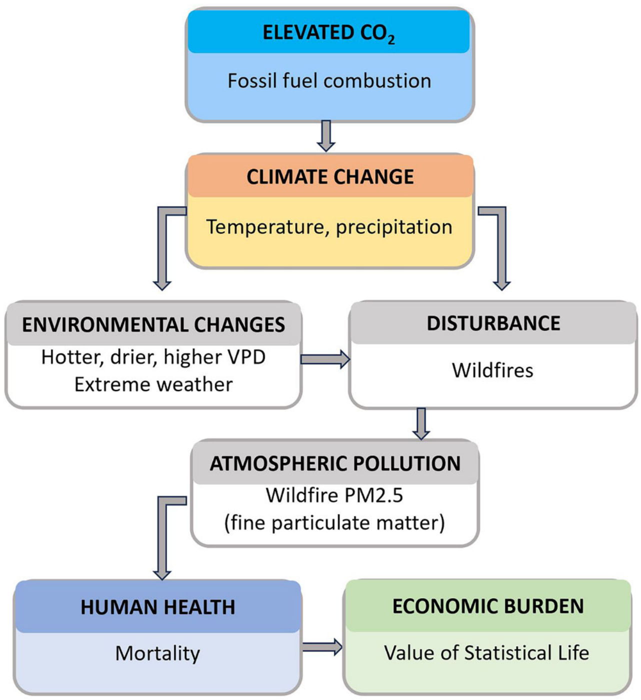


Fig. 1 | Conceptual model of the approach to examine the contribution of anthropogenic climate change to wildfire $PM_{2.5}$ and impacts on human mortality and economic burden. VPD is vapor pressure deficit. The Value of Statistical Life (VSL) is the amount society is willing to pay to reduce the risk of premature mortality for one person, estimated at $11.6 million (USD 2024). This value does not represent the value of an individual's life.

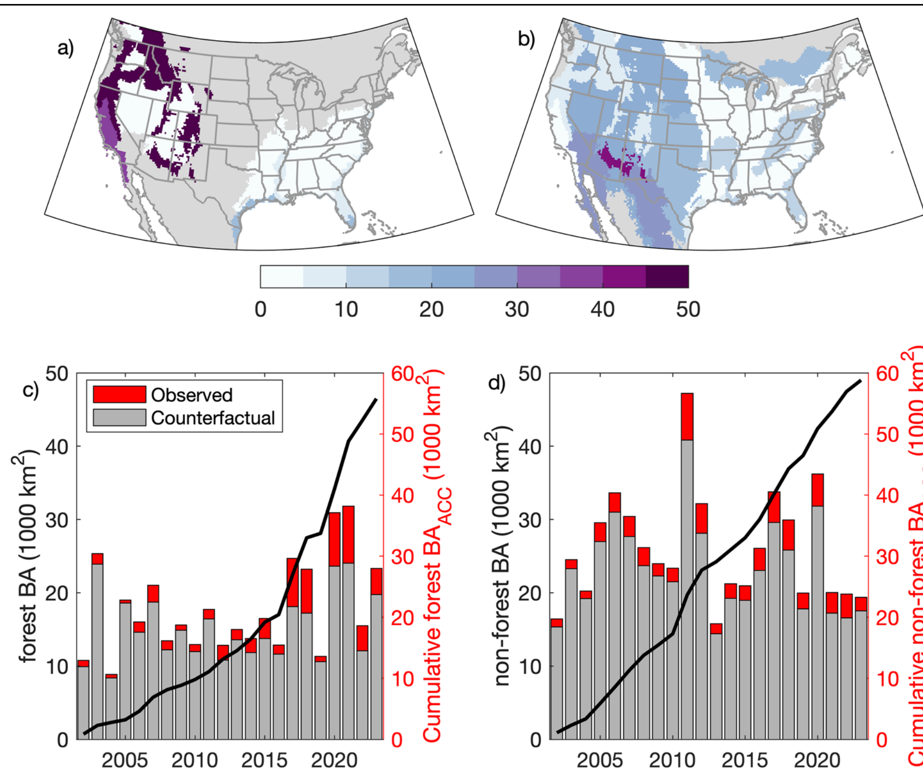
Mitigating climate change could reduce wildfire $PM_{2.5}$ mortality with sizable economic benefits. In a scenario without climate change contributing to wildfire $PM_{2.5}$, the mortality reductions in the Western US would approach those seen with the influenza vaccine, one of the most important public health interventions[29], though eliminating all global greenhouse emissions is not as simple as developing a vaccine.

Understanding contributions of climate change to wildfire mortality and its economic burden at the scale of higher-level administrative divisions —counties across the CONUS—can identify hotspots of compounded health risks and guide policies to protect disproportionately affected communities. At the county-level, we find the ten most impacted counties—located in California (4 of 10 counties), Idaho (1), Oregon (4), and Montana (1)—exhibited climate change-caused wildfire $PM_{2.5}$ excess mortality rates ranging from 9.8 to 17.1 per 100,000 people. For comparison, the second most leading cause of mortality in the US is cancer (malignant neoplasms) with mortality rates of 17.5 (2021) and 18.5 (2022) per 100,000 US standard population[30].

In addition to a clear spatial pattern, we find a trend of worsening climate change-caused wildfire $PM_{2.5}$ impacts in recent years. Across our 15-year record of excess mortality, the record 2020 fire season saw the highest mortality and economic burden, with 5100 deaths from climate change-caused wildfire $PM_{2.5}$ and a $58 billion associated cost. The record fire year 2020 also marked the beginning of the COVID-19 pandemic. Prior studies have shown long-term $PM_{2.5}$ exposure was associated with higher COVID-19 mortality rates[31]. The recent trend of more adversarial public health outcomes is expected to continue across the CONUS under multiple future scenarios. For instance, one study[32] projected 1300 additional deaths by 2050 under a stabilized climate scenario and 1600 under a fossil-fuel intensive scenario. Additionally, another study[33] estimated that a 50% increase in wildfire $PM_{2.5}$ levels could result in 9–20 additional deaths per 100,000 adults aged 65 and older annually.

In the only comparable study[28] to our knowledge, the authors show approximately −6% to 35% of wildfire $PM_{2.5}$ deaths between 2000 and 2010 in the CONUS were attributable to climate change, depending on the global fire–vegetation model used. In that global study, regions were at the continent or subcontinent level, rather than the state and county level we report

Fig. 2 | Spatial and temporal distribution of forest and nonforest burn area and percent attributed to anthropogenic climate change from 2002 through 2023. Cumulative percentage of (**a**) forest and (**b**) nonforest burn area from 2002 to 2023 attributed to anthropogenic climate change (ACC), defined as the percent difference of observed burned area relative to counterfactual. Models with insufficient burn area for a given vegetation type are not shaded. Time series of observed (red) and counterfactual (gray) annual (**c**) forest and (**d**) nonforest burn area summed over ecoregions that intersected the CONUS. The black line shows the cumulative burn area during the study period attributable to ACC.



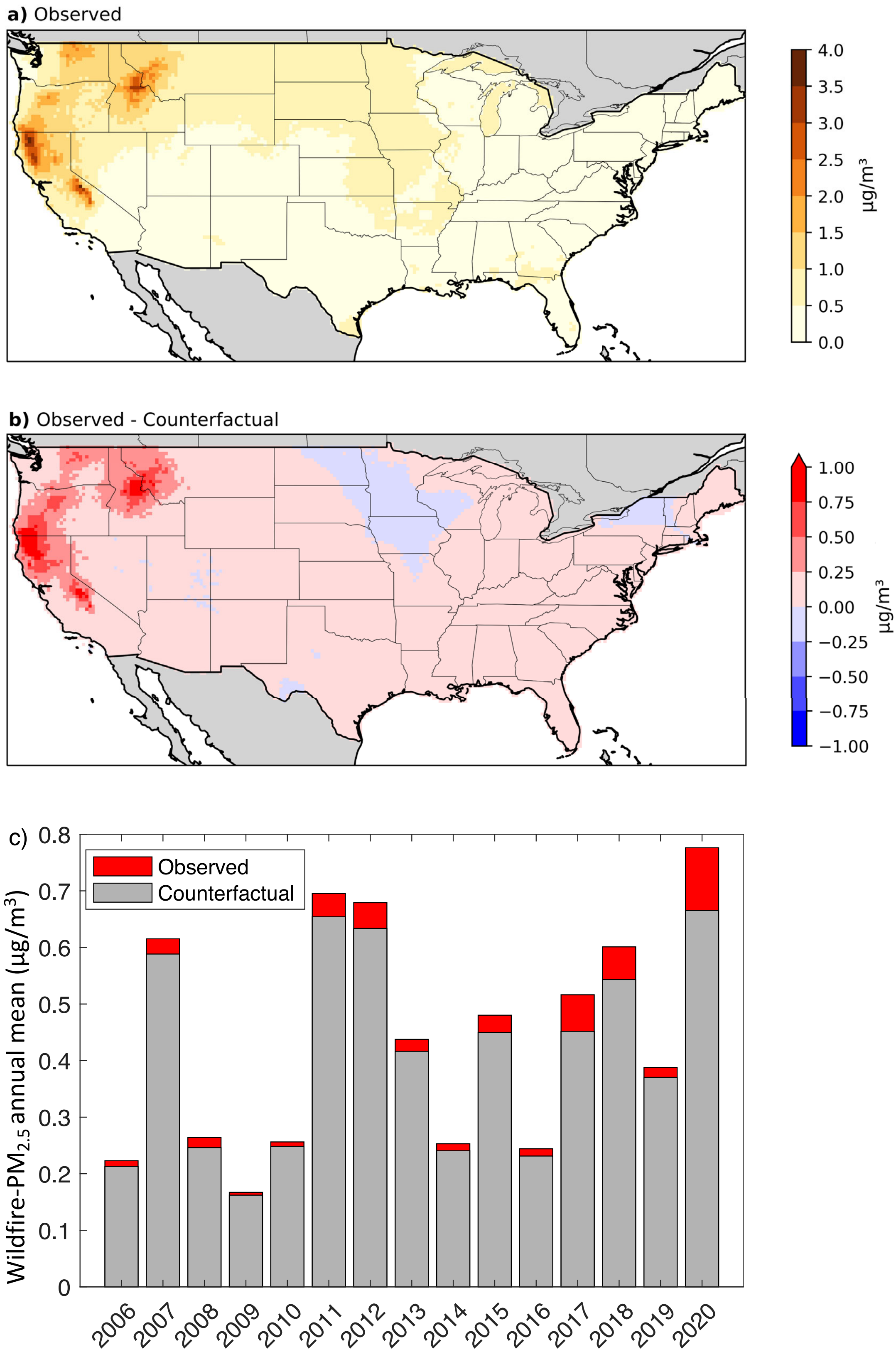


Fig. 3 | Spatial and temporal distribution of the impact of climate change on annual mean wildfire $PM_{2.5}$ concentrations in the contiguous United States. **a** The observed annual average wildfire $PM_{2.5}$ between 2006 and 2020. **b** Annual mean wildfire $PM_{2.5}$ attributable to climate change between 2006 and 2020. This is calculated by taking the difference between the counterfactual and the observed concentrations. Positive values indicate where increased smoke levels are caused by climate change. **c** Annual time series of population-weighted observed wildfire $PM_{2.5}$ (red) and counterfactual wildfire $PM_{2.5}$ (gray) between 2006 and 2020 for the CONUS.

Table 1 | Annual climate change contribution to wildfire $PM_{2.5}$ mortality and the associated economic burden

Year	Climate change related wildfire $PM_{2.5}$ mortality (95% CI)	Total economic burden in billions USD 2024 (95% CI)
2006	180 (88, 260)	1.6 (0.13, 4.5)
2007	600 (300, 890)	5.5 (0.47, 16)
2008	650 (330, 960)	6.2 (0.53, 18)
2009	130 (64, 190)	1.2 (0.1, 3.4)
2010	150 (74, 220)	1.4 (0.12, 4)
2011	780 (390, 1200)	7.8 (0.67, 22)
2012	720 (360, 1100)	7.3 (0.62, 21)
2013	520 (260, 770)	5.4 (0.46, 15)
2014	340 (170, 510)	3.6 (0.31, 10)
2015	710 (360, 1100)	7.5 (0.64, 21)
2016	420 (210, 620)	4.4 (0.38, 13)
2017	1800 (920, 2700)	20 (1.7, 57)
2018	2200 (1100, 3300)	24 (2.1, 70)
2019	480 (240, 710)	5.4 (0.47, 15)
2020	5100 (2500, 7500)	58 (5, 170)
Total	15,000 deaths	$160 billion

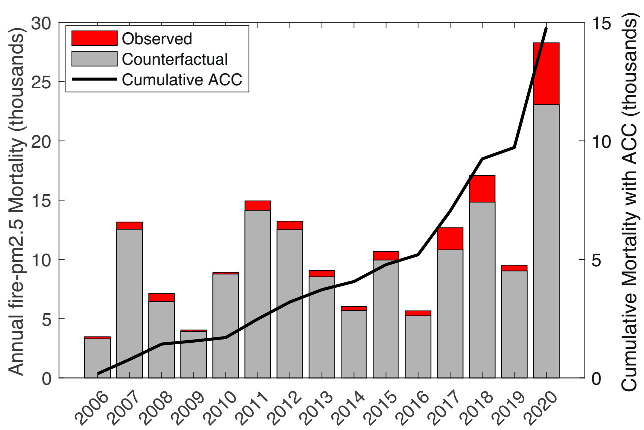


Fig. 4 | Increasing climate change contributions to wildfire $PM_{2.5}$ mortality for CONUS between 2006 and 2020. Annual observed wildfire $PM_{2.5}$ mortality with the counterfactual wildfire PM2.5 mortality shown in gray and red representing the climate change wildfire $PM_{2.5}$ mortality. The solid black line is the cumulative contribution of climate change to wildfire $PM_{2.5}$ deaths between 2006 and 2020 for the CONUS.

here. The 10% we find using our attribution framework is within the range described by another study[28] across their three global fire–vegetation models. However, the wide range in model-specific outcomes highlights the well-documented difficulties of fire–vegetation models in reproducing observed trends in BA and the divergence in historical burn area products[28,34]. Our approach, which uses observed BA, wildfire $PM_{2.5}$ and climate alongside a counterfactual provides increased credibility with observed impacts.

While this study focuses on the impact of climate change on wildfire $PM_{2.5}$ mortality, we also present overall wildfire $PM_{2.5}$ mortality and associated economic burden in agreement with the current knowledge base. Our estimate of 11,000 annual deaths (range: 3500–28,000) from wildfire $PM_{2.5}$ exposure is consistent with a study[35] that reported an average of 11,415 deaths from 2007 to 2020. Other studies report similar ranges (4080–28,000)[36] and (8700–32,000)[37], with variations due to differing methodologies. Similarly, our estimated economic burden of $95 billion (2024 USD) between 2008 and 2012 aligns with the $110.2 to 188.5 billion (USD 2024) range reported across the same timeframe[37], with differences driven by year-to-year variability and regional wildfire activity.

Methodologically, our approach introduces several innovations, including the explicit attribution of wildfire $PM_{2.5}$ mortality to climate change by using BA linked to climate change, a dynamic annual time series rather than static or long-term windows[28]., and the ability to analyze across multiple spatial scales from pixels to counties, and states. It also aligns with established methodologies for health impact assessments[21,37,38]. However, limitations warrant further investigation. Earth System Models (ESMs) coupled with climate simulations could provide an alternative method for quantifying the BA response to climate change. Such approaches can capture some of the indirect influence of climate change on BA including increased biomass due to carbon dioxide fertilization and fire-fuel feedbacks[1] that are not in the empirical approach used here. However, simulations of BA from ESMs massively overestimate fire extent across the US partly due to the lack of scalable fire management[39]. There are uncertainties in each analytical step from ACC to BA to $PM_{2.5}$ to mortality. Our confidence intervals focus on our primary outcome, wildfire $PM_{2.5}$ mortality. We include confidence intervals to account for uncertainties related to our primary outcome, wildfire $PM_{2.5}$ mortality. For this exercise, we argue that a ground-truth empirical approach that uses observed BA and $PM_{2.5}$ likely better represents reality.

We used a concentration-response function for long-term ambient $PM_{2.5}$ mortality as a surrogate for wildfire $PM_{2.5}$ mortality. This assumes similar health effects from long-term wildfire $PM_{2.5}$ exposure and long-term ambient $PM_{2.5}$ exposure, even though wildfire $PM_{2.5}$ concentrations are highly variable, particularly during wildfire season[40], unlike ambient $PM_{2.5}$ concentrations that are typically stable across time. Only a few studies conducted to date have attempted to examine the relationship between longer duration smoke exposures (i.e., across years) and mortality. A methodology that captures the dynamic smoke exposure's frequency, intensity, and duration has yet to be elucidated. While some evidence shows that short-term (daily) exposures to wildfire $PM_{2.5}$ may have more severe health impacts (e.g., respiratory-related outcomes) than ambient $PM_{2.5}$[40,41], this epidemiologic and toxicologic literature is not robust. Few studies have examined annual wildfire $PM_{2.5}$ exposure and mortality and only two studies modeled long-term exposure and premature death[35,42]. This means that health impact assessments for wildfire smoke use concentration response functions for ambient $PM_{2.5}$ and mortality, which assumes that $PM_{2.5}$-related health effects are unchanged across different exposure patterns. Our $PM_{2.5}$ estimates are based on a 2.5° grid across the continental US, with transboundary smoke and smoke transport from Canada factored in only when within a 500 km neighborhood (see "Methods"). Given evidence that Canadian smoke impacts $PM_{2.5}$ levels in the western US[43], our estimates of wildfire $PM_{2.5}$ exposure and mortality are likely conservative. Avenues for future improvement of smoke modeling include higher resolution models, explicitly accounting for out-of-sample smoke (e.g., Canadian wildfires in 2023), and incorporating more complex atmospheric transport and smoke dispersion models.

A key message of the most recent Intergovernmental Panel on Climate Change assessment, a central document of climate science and policy, highlights how more frequent and intense extreme events have led and will continue to lead to "damages to nature and people, beyond natural climate variability"[44]. Here we show that, had we eliminated the climate change contribution to wildfire $PM_{2.5}$ between 2006 and 2020, there likely would have been 10% less mortality due to wildfire $PM_{2.5}$ nationally, with even greater reductions of 30–50% in some western states and counties, while also saving billions of dollars from avoided mortality. Without efforts to address climate change, the increasing burn area and wildfire $PM_{2.5}$ trends will continue as there is strong evidence that climate warming will continue to increase[45]. By mid-century, projections of climate-driven wildfire $PM_{2.5}$ across the CONUS indicate at least a 50% increase in mortality from smoke relative to 2011–2020 with annual damages of $244 billion[46]. A study on

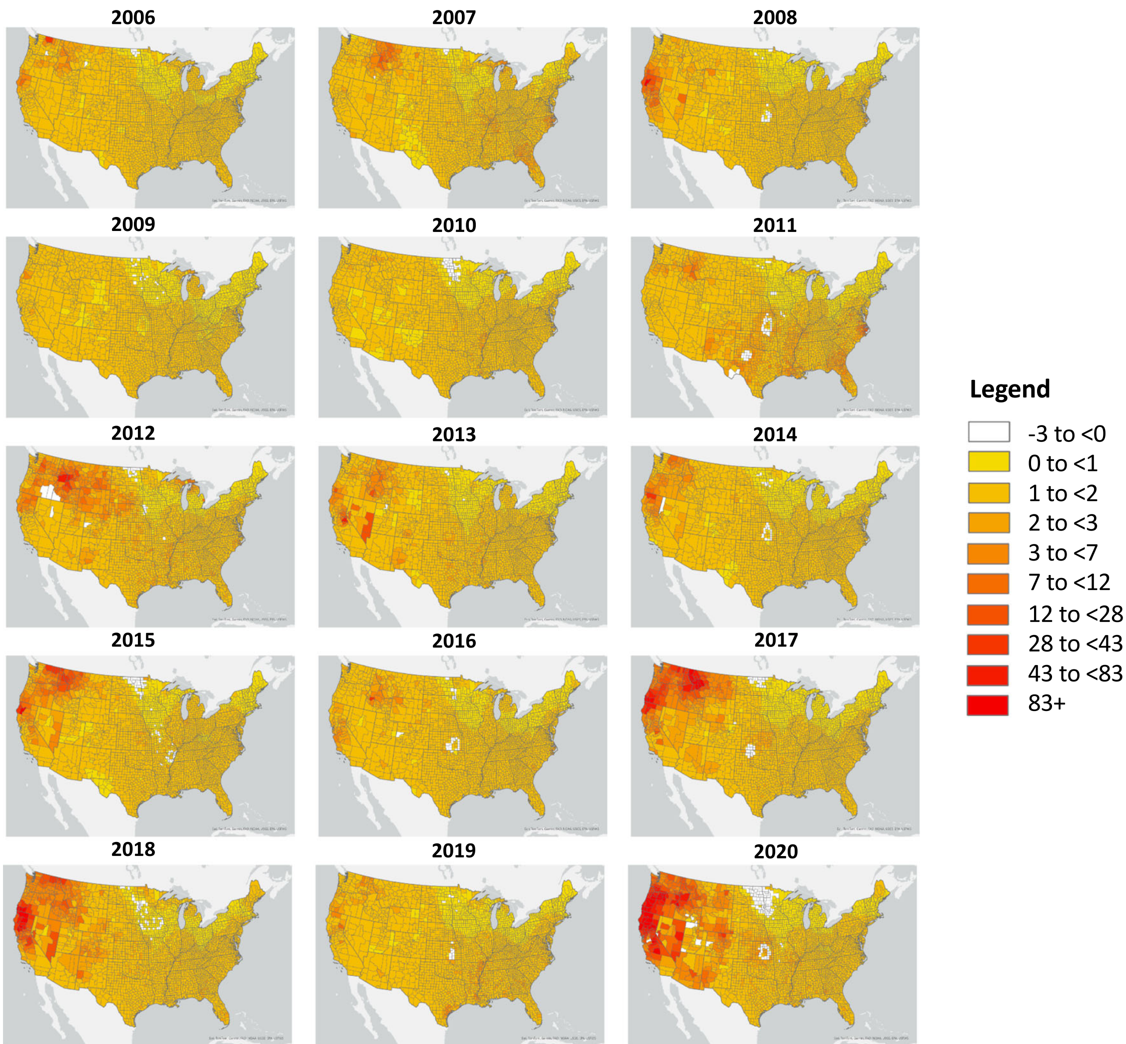


Fig. 5 | County level mortality attributed to climate change related wildfire $PM_{2.5}$ in the CONUS was highest in western counties between 2006 and 2020. Units are annual average mortality per 100,000 population.

economic impacts across the US found that the greatest direct cost for global mean surface temperature changes larger than 2.5 °C is the burden of excess mortality, with sizable but smaller contributions from changes in labor supply, energy demand, and agricultural production[47]. This highlights the substantial impacts on nature that result in human deaths from failure to reduce greenhouse gas emissions. It is imperative to understand the consequences of climate change on wildfire $PM_{2.5}$ and human health, and to focus on reducing the economic burden on communities.

Methods

Wildfire burn area attributable to climate change

The monthly burn area from MODIS (MCD64A1) was used from 2002 to 2023. We disaggregated burn area (BA) in forest and woodland areas (tree cover >20%) from the nonforest areas (tree cover <20%), as there are different climate-fire relationships and emission factors per vegetation type[48,49]. Though there are higher resolution fire data (e.g., MTBS[50]), we opted to use MODIS data as these provide wall-to-wall coverage in the US and Canada from a single consistent source. However, MODIS does not distinguish between wildfires and other types of biomass burning. Hence, in parts of the central and eastern US much of the BA is due to prescribed fire or agricultural burning rather than wildfire, thus likely confounding climate-fire relationships[51].

The Fire Weather Index (FWI) is an indicator of potential fire intensity calculated from meteorological data that accounts for the fuel dryness and short-term fire weather. Two climate predictors are used based on past studies that show that interannual variability in macroscale BA is influenced by both antecedent fine-fuel build-up in the prior year and fire weather conditions during the fire season[23]. First, we used antecedent precipitation from January-August during the prior year as a proxy for fuel biomass accumulation to account for moisture that influences vegetation productivity during the previous growing season[22]. Secondly, rather than apply a fixed seasonal window for contemporary fire weather, we calculate the annual maximum of 90-day average FWI for each pixel[52]. We chose a 90-day window for average FWI that is flexible across years and ecoregions rather than a prescribed window (e.g., Jun–Sep) as temporally varying windows have higher correlative power to burned area[48] and they account for the geographic variations in core fire season across the study region. Daily meteorological data were sourced from ERA5 at a 0.25° horizontal resolution. FWI was calculated using daily maximum temperature, daily minimum relative humidity, daily accumulated precipitation, and daily mean wind speed per prior analyses[23].

Counterfactual climate data were developed using a simple approach that removes the first-order influence of monthly temperature, precipitation, humidity, and winds from the observed record[1,53]. This approach preserves the temporal variability of the observed record, but removes a low-pass filtered signal from climate models. While climate variability may change due to anthropogenic forcing[54], we focus on the stronger, more robust, and direct influence of climate change on means.

Table 2 | Top 10 states for climate change contribution to annual wildfire $PM_{2.5}$ attributable mortality averaged across 2006 to 2020 and the state level economic valuation

Rank	State	Annual average mortality rate related to climate change wildfire $PM_{2.5}$ (per 100,000 population)	Annual average mortality related to climate change wildfire $PM_{2.5}$	Climate change contribution to total wildfire $PM_{2.5}$ mortality (%)	Average annual economic burden (in millions USD 2024)
1	Oregon	4.9	130	36	1600
2	Montana	3.9	26	23	300
3	Idaho	2.7	27	21	310
4	Washington	2.2	100	27	1200
5	California	1.4	350	25	4100
6	Nevada	1.0	19	19	220
7	Wyoming	0.9	3.4	12	39
8	Colorado	0.6	22	13	260
9	Louisiana	0.4	12	6.5	130
10	Arkansas	0.4	7.3	4.1	80

Table 3 | Counties with highest average annual climate change related wildfire $PM_{2.5}$ mortality rates per 100,000 population and the average associated economic burden for the county between 2006 and 2020

Rank	State	County	Average annual mortality from climate change related wildfire $PM_{2.5}$ (per 100,000 population)	Average annual mortality from climate change related wildfire $PM_{2.5}$	Average annual economic burden (millions USD 2024)
1	California	Trinity	17	1.8	18.7
2	Oregon	Josephine	17	11	116
3	California	Siskiyou	13	4.2	45.4
4	Oregon	Jackson	13	20	216
5	Oregon	Curry	12	2.1	23
6	Oregon	Douglas	12	9.3	103
7	California	Shasta	11	14	156
8	California	Del Norte	11	2.1	23.2
9	Idaho	Idaho	10	1.2	12.9
10	Montana	Ravalli	9.8	3.0	31.2

Counties with larger populations have higher burdens.

Our approach follows previous work in developing counterfactuals that adjust for first-order influence of climate change. We suggest that potential change in climate variability is a topic for future work. We examined the climate change signal using twenty climate models participating in CMIP6 (Table S1) for the historical (1850–2014) and future (SSP2-45, 2015–2100) forcing. Specifically, we calculate a low-pass filtered signal for the 20-model mean for each location and month to the pre-industrial baseline (1850–1900). These low-pass climate change signals were subtracted from the observed (2000–2023) data to get a single counterfactual void of the first-order climate change influence following prior studies[1]. These data are then used to calculate a counterfactual FWI and precipitation.

All climate and BA data were aggregated to EPA level II ecoregions, i.e. assemblages of common vegetation and climate[55]. We conducted the BA modeling at ecoregion scales as such regions are large enough to capture top-down climate drivers of BA as seen in prior studies[22,56].

Separate empirical models were developed for each ecoregion for annual forest BA and annual nonforest BA. These models take the simple log-linear approach used in prior studies[22] (Eq. (1)):

$$BA(t) = \alpha + \beta FWI(t)_{90d} + \gamma P(t-1) + \varepsilon$$

where FWI is the maximum 90-day mean FWI during the year, P is the January-September year precipitation from the previous year, and ε represents an error term. The error term ε is randomly pulled from the residual of observed minus modeled without the error term and is incorporated to account for stochastic factors not included in the simple model[27]. Notably, this term is needed to account for underestimates in BA given the log-linear framework and stochastic factors not included in the model. We use these models to simulate both observed and counterfactual BA. For the latter, we substitute the observed FWI and P for counterfactual versions. Ecoregions that recorded <1 km^2 BA for ≥ 25% of years were not modeled due to insufficient burn area and their counterfactuals were set to observed BA. Except for small ecoregions in southern Mexico, ecoregions that were left unchanged had extremely low rates of annual burned fraction (<0.00001% yr^{-1}). Unchanged ecoregions accounted for <3% of BA in forests and <2% of BA in nonforests across North America during 2002–2023.

Lastly, we use results from these models to produce counterfactual BA estimates for forest and nonforest lands at a 0.25° spatial resolution (23.5 by 23.5 km) and monthly scale. We first calculate the ratio of modeled counterfactual to modeled observed data from equation 1 for each year, separately for forest and nonforest BA by ecoregion. We spatially and temporally disaggregate counterfactual BA for each ecoregion by multiplying this ratio by the MODIS BA observations. This approach thereby preserves the spatial and temporal variability in BA between observed and counterfactual simulations, however, it does not capture any shifts in BA seasonality.

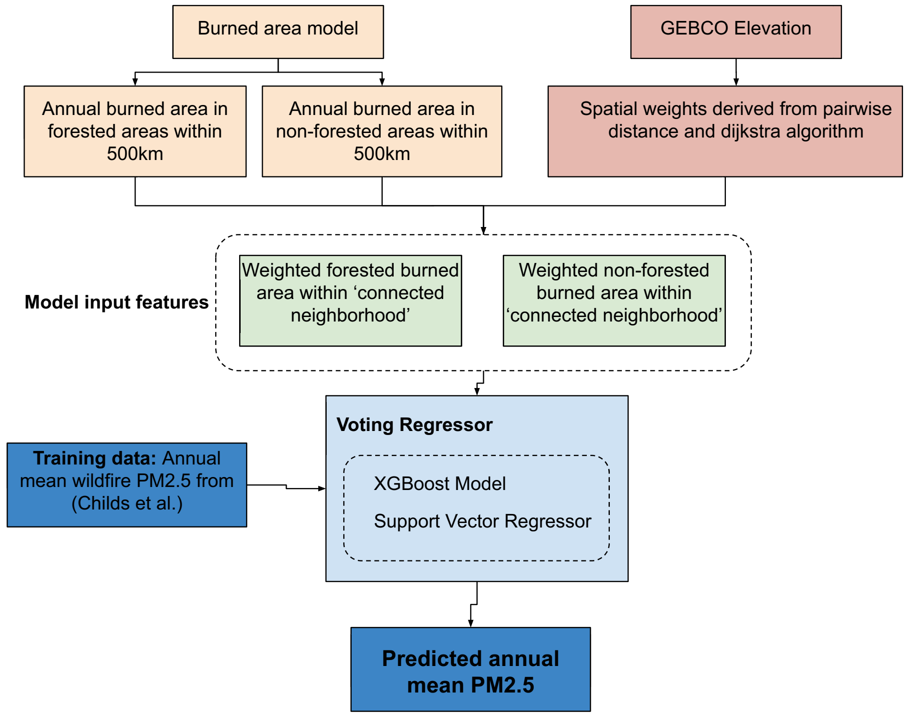


Fig. 6 | Schematic of statistical smoke estimation approach. A combined machine learning model is trained to predict annual mean wildfire $PM_{2.5}$ at a location as a function of forested and nonforested burn area within some neighborhood. The model is trained on observed data to predict smoke during the counterfactual scenario.

Wildfire $PM_{2.5}$ attributable to climate change

Annual mean $PM_{2.5}$ concentrations are estimated using a machine learning approach that incorporates a basic model of atmospheric flow and varying sources of wildfire smoke. The model is trained using published daily data[11]. aggregated into annual averages on a 2.5° grid (277.5 by 277.5 km). Once trained, the model is applied to the real and counterfactual burn area datasets, one grid location at a time, to obtain gridded smoke estimates. The proportional difference between these two datasets (observed and counterfactual) is then obtained and used to scale the observed data during this period to determine the final counterfactual estimate. See (Fig. 6) for a schematic of the model described in this section.

A weighted sum of annual burn area within a reachable neighborhood is used as model input in each grid cell. The burn area in forested and nonforested areas is treated as independent inputs. Elevation data by GEBCO[57] are used with a shortest path algorithm to determine dynamically reasonable regions from which smoke may propagate (for example, deep valleys may influence the horizontal flow of wildfire smoke). These neighborhoods are described by the spatial weights which are calculated using a two-step process:

1. **Distance weighting**. Weights decrease with distance, using a 2-dimensional Gaussian curve. This means that wildfires at greater distances contribute less to local smoke concentrations. The Gaussian function takes the form (Equation 2):

$$e^{-D^2/2\sigma^2}$$

Where D is distance in km and is the standard deviation (i.e., the parameter which controls the width of the Gaussian surface). An iterative validation of the model showed that D = 300 km provides good RMSE and correlations across the analysis domain.

2. **Connected regions**. A second set of pairwise distances is calculated using the Dijkstra shortest path algorithm[58]. To apply the algorithm, the gridded locations are converted into a mathematical network, where the centers of cells are nodes and edges are constructed by connecting 8 neighboring nodes. The edges are assigned weights according to the distance between their corresponding nodes. Nodes are not connected where some elevation difference is exceeded. The algorithm is applied three times, each for elevation differences of 500 m, 1000 m and 1500 m and the three resulting distance arrays are then averaged to obtain the final weights (Supplementary Fig. 5).

Two machine learning algorithms are combined using a voting regressor: XGBoost and Support Vector Regression. The XGBoost algorithm (gradient boosting) obtains monotonic and non-linear relationships between the inputs and annual mean wildfire smoke. Incorporating support vector regression into the framework allows for a smoother output and improved extrapolation/interpolation in the regions of the parameter space lacking observations. The model is trained to make predictions generalized to the whole study grid by concatenating input data before training. Hyperparameters for both models are calibrated using a random search with 5000 iterations and a fivefold cross validation to minimize the root mean square error. Validation shows a correlation of 74% between observed and modeled (out-of-sample) $PM_{2.5}$ values.

The smoke model performs well, is computationally quick to run, and incorporates a simple atmospheric flow model. However, there is scope for improvement. A more complex smoke propagation and dispersion model may better model more complex seasonally changing flows. For this study, we investigated the use of local wind vectors from a reanalysis dataset but found no improvement in the model output. However, using a fully dynamic numerical model such as HYSPLIT to determine neighborhood weights could provide better results, at the cost of computational resources. A more complex atmospheric model could also allow the model to better represent wildfire effects from further afield, beyond the 500 km box used in this study. We found expanding this box in our model is detrimental to the output, likely due to the aggregated complexity of the flow over these distances.

Although not explicitly included in this model, the transport of wildfire smoke can be sensitive to the injection height plume, which is impacted by burn temperature and vegetation characteristics. By separating burned area by forested and nonforested, some of this difference will be captured in a statistical sense. However, future versions of this model should include more variability in vegetation characteristics and a more explicit inclusion of injection height.

Wildfire $PM_{2.5}$ impacts on human mortality and economic burden

To estimate the contribution of climate change to annual wildfire smoke-related mortality and the economic valuation, we use the US Environmental Protection Agency's Environmental Benefits Mapping and Analysis Program (BenMAP-CE)[21] that incorporates a health impact function derived from epidemiologic literature, baseline demographic and health data, and the Value of Statistical Life (VSL).

For human health impacts, we quantify the number of wildfire $PM_{2.5}$ related deaths using:

$$\Delta Y = \left(1 - e^{-\beta * \Delta PM2.5_{ij}}\right) * Yo_j * Pop_{ij}$$

where ΔY is the change in mortality attributable to the contribution of climate change to wildfire $PM_{2.5}$, β is the risk coefficient, $\Delta\ PM_{2.5ij}$ is the difference between the counterfactual (without climate change) and the observed concentrations for annual mean wildfire $PM_{2.5}$ in county i in year j (2006, 2007,…,2020), Yo_j is the baseline mortality rate in year j, and Pop_{ij} is the number of residents in county i in year j. Baseline rates for county level all-cause mortality are obtained from the Centers for Disease Control Wonder database.

A limited number of epidemiologic studies have attempted to examine longer duration wildfire smoke exposure and mortality. It is well recognized that longer duration smoke exposures are spatially and temporally dynamic, varying in intensity, frequency, and duration[40] within and across years. Because of the small evidence base of studies examining longer duration smoke exposures and overall uncertainties in the relationship with mortality, within this analysis, we assume the relationships between annual ambient $PM_{2.5}$ and wildfire $PM_{2.5}$ exposure and mortality are similar. This assumption is based on the well documented relationship between long term (i.e., annual average) ambient $PM_{2.5}$ exposure and mortality[14,59]. Therefore, we selected a published pooled risk estimate for long term ambient $PM_{2.5}$ mortality[60]. to represent the relationship between wildfire $PM_{2.5}$ and mortality and derive our concentration response function. The study used a random effects pooling technique to combine hazard ratios from 8 US, Canadian, and European cohorts that included adults 65 years and older. We use the study's concentration response function[60] derived for ages 65+ reflects a similar response function for our study population that includes ages 25–99. Our use of this study conforms to the 2024 US Scientific Advisory Board recommendation to use a single probabilistic mortality estimate based on pooled risk estimates with associated uncertainty ranges.

We estimated economic valuation using the Value of Statistical Life (VSL), a valuation function based on 26 published studies and used by economists, the US EPA in Regulatory Impact Analyses, and US Congress for policy analyses. VSL is the amount society is willing to pay to reduce the risk of premature mortality for one person, estimated at $11.6 million (USD 2024). This value does not represent the value of an individual's life. We apply a 3% discount rate similar to prior health impact assessments[37]. Discount rates are used in cost benefit analyses to account for economic benefits that occur over multiple years and reflect the social concept that a health benefit today is more valuable than a health benefit in the future. The estimated dollar value of wildfire related impacts account for mortality alone. This estimate does not account for morbidity impacts associated with exposure to fine particles, which include an array of chronic effects like cerebrovascular events, and acute effects like aggravated asthma. Thus, our dollar value is likely underestimated.

Data availability

Data generated during and/or analyzed during the current study (data and script for running climate-burn area model, and $PM_{2.5}$) are available in the Woodwell Climate Risk repository at https://github.com/WoodwellRisk/law_comm-e-e. Data for mortality are available here: https://doi.org/10.7910/DVN/OFAVXL and https://doi.org/10.7910/DVN/UPLVOI.

Code availability

BenMAP-CE code is available here: https://www.epa.gov/benmap/benmap-40.

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Competing interests

The authors declare no competing interests.

Additional information

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