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Supplementary appendix

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Supplement to: Xu R, Ye T, Huang W, et al. Global, regional, and national mortality burden attributable to air pollution from landscape fires: a health impact assessment study. *Lancet* 2024; published online Nov 27. https://doi.org/10.1016/S0140-6736(24)02251-7.

Supplementary Material

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1. Supplementary methods and results

1.1 Data collection

1.1.1 Daily mortality data

We obtained the data on all individual deaths (date and cause of death) in Australia during 2009-2019 from the Australian Cause of Death Unit Record File (COD URF)[1], in New Zealand between 2000-2018 from the New Zealand Ministry of Health[2], in Brazil between 2000-2019 from the Brazil Mortality Information System (Sistema de Informação sobre Mortalidade, SIM)[3], in Canada between 2000-2015 from the Vital Statistics Deaths Database of Statistics Canada[4] and in Chile between 2000-2015 from the Chilean Ministry of Health Epidemiology Department[5]. For a time-series analysis, we aggregated the individual death data at location and daily level based on the administrative boundary with a proper area size for each country (Statistical Area Level 3 [SA3] for Australia [n = 342], territorial authority [TA] for New Zealand [n = 66], immediate region for Brazil [n = 510] , second-level administrative divisions [regions or districts within the provinces and territories] for Canada [n = 288]) and municipalities for Chile [n = 326]).

We also obtained daily mortality data for each city from the Multi-Country Multi-City (MCC) Collaborative Research Network database. The MCC network is a continuously expanding international network that collects daily mortality counts from relevant authorities of multiple countries globally. The details of MCC dataset have been described in our previous works.[6,7] For each city MCC network, daily counts of all-cause mortality were collected and non-external causes (International Classification of Diseases [ICD], 9th Revision codes 0–799 or ICD-10 codes A0–R99) mortality were alternatively collected when all-cause mortality was unavailable. Additionally, mortality counts were collected specifically for cardiovascular (ICD-10 codes I00–I99) and respiratory (ICD-10 codes J00–J99) causes. At the time of our analyses, the MCC database has all-cause mortality or non-external mortality data from 794 communities from 43 countries. MCC cities in Australia, New Zealand, Brazil, Canada and Chile were not included to avoid duplication.

We also collected all-cause mortality data of 32 health and demographic surveillance systems (HDSS) sites from the International Network for the Demographic Evaluation of Populations and their Health (INDEPTH) Network. The INDEPTH Network provides daily all-cause mortality counts data during 2000-2016 in 32 HDSS sites in Africa and Asia that were not overlapped with the MCC database and other data sources mentioned above. The health data were representative of the whole population in each HDSS site, and more information had been presented by previous publications. [8,9]

Consequently, the integrated global dataset covers 2271 communities from 59 countries or territories. Among these 2271 communities, the all-cause mortality data in 139 locations (6.1%) was represented by non-external mortality.

After performing time-series analyses for each community, we further removed communities with very low death counts (<12 deaths per year, i.e., < 1 death per month) that generated rather unstable effect estimates. Therefore, a total of 2267 communities were finally included in the second-stage meta-analyses for all-cause mortality.

The global distributions of those communtieis were presented in **Figure 1.** The definitions and basic characteristics (median area sizes and populations) of communties from different data sources were presented in **Table S2**. The summary statistics of death counts, study periods and exposue levels of the 2267 communities by country/territory were presented in **Table S3.** For cardiovascular and respiratory mortality analyses, some communities where the time-series regression failed to fit were also excluded, their final included numbers of communities were shown in **Table S7**.

1.1.2 Annual mortality data

The GBD 2019 directly provided estimates of cardiovascular deaths as a whole, but this was not the case for respiratory deaths. In this study, we calculated the respiratory deaths by summing up the deaths from chronic respiratory diseases and lower and upper respiratory infections estimated by GBD 2019.[10,11]

1.1.3 Socio-demographic data

Country- or territory-specific annual Socio-Demographic Index (SDI) and population data were sourced from GBD 2019.[11] The SDI is an integrated index of country-specific social and economic development that combines information on the economy, education, and fertility rate.[11] The included countries and territories were classified as 6 GBD super regions, and then 21 GBD regions following the geographical hierarchy of GBD 2019.[10] We also classified countries or territories as low-income, lower-middle income, upper-middle income, and high-income countries according to World Bank 2019 criteria.[12]

We obtained annual population counts from 2000 to 2019 for each 1km×1km grid from the WorldPop project.[13] These population data were then aggregated to 0.25° × 0.25° spatial resolution to match the daily LFS air pollution and weather data, which are used in the calculation of population-weighted average exposures.

1.1.4 Daily weather data

We calculated daily mean (according to location-specific local time zone) ambient temperature and relative humidity from hourly data obtained from the European Centre for

Medium-Range Weather Forecasts Reanalysis v5 (ERA5) at a 0.25° × 0.25° spatial resolution, as described previously.[14]

1.1.5 Population-weighted average exposure

For each of the 2267 communities with daily death data, we calculated population-weighted average daily LFS $PM_{2.5}$, LFS O_3, ambient temperature, and relative humidity. by averaging the exposure of all 0.25° × 0.25° grids within the community boundaries, weighted by grid-specific population counts multiplying by the proportions (0-100%) of the grid's area size intersecting with the community. Following the same approach, we also calculated population-weighted average LFS $PM_{2.5}$ and O_3 at both daily and yearly time scales for each country or territory.

1.2 Two stage-time series analyses

1.2.1 Main model analyses

We quantified the exposure-response (E-R) relationships for the short-term mortality impacts of LFS $PM_{2.5}$ or LFS O_3 using a widely used two-stage time-series analytical framework. [15-18] In the first stage, quasi-Poisson regressions with a distributed lag model were used to estimate the community-specific associations between daily deaths and daily LFS $PM_{2.5}$ or LFS O_3 with the equation below:

$$\text{Log}\ (Y_{it}) = \alpha + \text{cb}(\text{LFS\_AP}_{it}) + \text{ns}(\text{date}_{it}, \text{df} = 7 \times \text{Years}_i) + \text{ns}(\text{Tmean\_lag07}_{it}, \text{df} = 4) + \text{ns}(\text{RH\_lag07}_{it}, \text{df} = 4) + \text{DOW}_{it} + \delta\text{Holiday}_{it} + \varepsilon_{it} \quad (1)$$

where Y_{it} represented the daily death counts (all-cause deaths, or cardiovascular deaths, or respiratory deaths) in community i on day t. α was the intercept; γ and δ were coefficients; ε_{it} was the residual error. $\text{ns}(\text{date}_{it}, \text{df} = 7 \times \text{Years}_i)$ meant that the date was modelled as a nature cubic spline with 7 degrees of freedom (df) per year (Years_i was the number years of death data for community i), to adjust for long-term trends and seasonal variations. Similarly, we modelled the 8-day (lag07, current day and previous 7 days) moving average of daily mean temperature (Tmean_lag07_{it}) and daily mean relative humidity (RH_lag07_{it}) using a natural cubic spline with 4 df to adjust for their potential non-linear impacts on mortality.[16] DOW_{it} referred to categorical day of week (Monday to Sunday) to adjust for death variations within a week. Holiday_{it} was a binary variable (public holiday or not) to adjust for potential impacts of public holidays on deaths.

$\text{cb}(\text{LFS\_AP}_{it})$ was a two-dimensional (exposure-response dimension and lag-response dimension) cross-basis function to model the lagged associations of daily mean LFS $PM_{2.5}$ (or LFS O_3, evaluated separately using single-pollutant model) with death outcomes. According to our preliminary analyses and previous studies,[15,16] the impacts of daily LFS $PM_{2.5}$ and O_3 on daily death were generally linear and lasted to up to 2 days following exposure. Therefore, we used a linear function for the exposure-response dimension, and an unconstrained function at the lag-response dimension along $0-2$ lag days.[17]

The E-R relationships or effect estimates were then presented as cumulative relative risks (RR) with 95% confidence intervals [CI] of all-cause deaths (or cardiovascular and respiratory deaths) over lag0-2 days following exposure to each 10 μg/m^3 increases in daily LFS $PM_{2.5}$ (or daily LFS O_3).

In the second stage, we pooled the community-specific effect estimates for all communities, using a random-effect meta-analysis with maximum likelihood estimation.[19] This provided a global average estimation of RRs (95% CI) for short-term mortality impacts of LFS air pollution (**Table S7)**, which were used for short-term mortality burden assessment. The country- or territory-specific RRs(95%CI) were presented in **Table S8**.

1.2.2 Linear model versus non-linear models

We compared community-specific quasi-Bayesian information criterion (qBIC, i.e., BIC adapted for quasi models used in the first stage time-series analyses) values of linear models (main model) with non-linear models. In the non-linear models, we used natural cubic splines with 2 to 4 degrees of freedom(df) in the exposure-response dimension of the $\mathrm{cb}(\mathrm{LFS\_AP}_{it})$, and the lag-response dimension was the same as the main model's. We found that in >96% of the included communities (>99% communities for all-cause death analyses), qBIC values of non-linear models were larger than linear models (**Table S4**), suggesting that the time-series models were better fitted in linear models than non-linear models in the majority of communities.

1.2.3 Detection of interaction effects

To detect the potential interaction effects between LFS $PM_{2.5}$ and O_3, we put LFS $PM_{2.5}$ and O_3 (moving average over the current day and previous two days) and their interaction term (LFS $PM_{2.5}$ ×LFS O_3) into the first-stage time-series model, then we tested whether the interaction term was statistically significant (*p-value* for the interaction term <0.05) for each community. The results showed that the interaction terms were not statistically significant in 92.5% of included communities for analyses of all-cause death, and in >94% of communities for analyses of cardiovascular and respiratory death (**Table S5**).

1.2.4 Detection of residual confounding

We used a method developed by Flanders et al to detect the potential residual confounding of our time-series analyses by introducing a negative control exposure.[20] In the first-stage time-series analyses, we run a residual confounding detection model with the equation below:

$$\mathrm{Log}\ (Y_{it}) = \alpha + \beta_1 \times \mathrm{Main\_model\_prediction}_{it} + \beta_2 \times \mathrm{LFS\_AP}_{i\ t+1} + \varepsilon_{it} \quad (2)$$

where $\text{Main\_model\_prediction}_{it}$ refers to the daily death counts (all-cause or cardiovascular, respiratory deaths depending on the outcome) on day t in the community i predicted by the main model presented in Equation (1); the $\text{LFS\_AP}_{i\,t+1}$ refers to LFS $PM_{2.5}$ (or LFS O_3) level one day after (t+1) current day t. The LFS $PM_{2.5}$ (or LFS O_3) on one day after the death clearly cannot cause the death, but if there are omitted time-varying confounders or residual confounding that are correlated with the LFS air pollution on the day of death, they are likely also correlated with the pollutant on the following day (given only 1-day difference).[21] Based on this reasonable assumption, as we have adjusted for $\text{Main\_model\_prediction}_{it}$ in Equation (2), the significance of residual confounding of the main model can then be indicated by the statistical significance of β_2. In other words, if there were significant residual confoundings, the daily death would show significant associations with LFS $PM_{2.5}$ (or LFS O_3) one day after the death after controlling for variations explained by our main model.

Similar as our main model, we pooled the community-specific β_2 estimates for all communities, using a random-effect meta-analysis with maximum likelihood estimation.[19] Then we presented it as the global average RRs [i.e., $\exp(\beta_2)$] with *p*-values and 95% CIs (**Table S6)**, indicating short-term mortality impacts of LFS air pollution on the next day. The results showed that the daily all-cause, cardiovascular and respiratory death did not show significant associations (all *p*-values > 0.195) with LFS $PM_{2.5}$ (or LFS O_3) on one day after the death after controlling for variations explained by our main models, suggesting that the residual confounding of our main models tended to be minimal.

1.2.5 Comparison with non-fire and all-source $PM_{2.5}$ and O_3

We defined non-fire $PM_{2.5}$ (or O_3) as the difference between all-source $PM_{2.5}$ (or O_3) and LFS $PM_{2.5}$ (or O_3). By replacing the exposure variable Equation (1) as non-fire and all-source

$PM_{2.5}$ and O_3 (each evaluated separately) while keeping all other two-stage time-series model settings unchanged, we also quantified the short-term mortality impacts of non-fire and all-source $PM_{2.5}$ and O_3 in a comparable manner. We tested the differences between their effect estimates and those for LFS $PM_{2.5}$ and O_3 using fixed-effect meta-regressions.[22-24] The results showed that the effect estimates of non-fire and all-source $PM_{2.5}$ and O_3 were generally smaller than those of LFS $PM_{2.5}$ and O_3, particularly for all-cause mortality (p-values for difference < 0.05) (**Table S9, Figure S1**).

To the best of our knowledge, this is by far the largest study that directly compared short-term mortality impacts of LFS $PM_{2.5}$ and O_3 with all-source and non-fire $PM_{2.5}$ and O_3 , based on the same design and dataset (i.e., ensuring comparability). The potential reasons for the enhanced short-term mortality impacts of LFS $PM_{2.5}$ and O_3 have been discussed in detail previously.[15,16,25]

1.2.6 Model with adjustment for non-fire $PM_{2.5}$ and O_3

We did not adjust for non-fire $PM_{2.5}$ and O_3 in our main model because they were not likely to be confounders (factors being able to affect both the exposure and outcome) when assessing the mortality impacts of LFS $PM_{2.5}$ and O_3. By definition, non-fire $PM_{2.5}$ and O_3 were caused by other emissions (e.g., traffic, industry, sand dust) independent of landscape fires. Therefore, non-fire $PM_{2.5}$ and O_3 tend to be uncorrelated with LFS $PM_{2.5}$ and O_3, which is also supported by our observational data (**Figure S2**, r=0.20 for LFS $PM_{2.5}$ versus non-fire $PM_{2.5}$, r=0.01 for LFS O_3 versus non-fire O_3).

To test the robustness of our main model, we further adjusted for non-fire $PM_{2.5}$ and O_3 in the main model. Specifically, the non-fire $PM_{2.5}$ and O_3 were put in the first-stage time-series model in Equation (1) using the same cross-basiss function and parameters for LFS $PM_{2.5}$ and O_3. Then, same as our main model, we get pooled global average effect estimates for LFS $PM_{2.5}$ and O_3 with adjustment for non-fire $PM_{2.5}$ and O_3. We tested the differences between the pooled effect estimates from non-fire adjustment models and our main models using fixed-effect meta-regressions.[22-24]

As shown in **Table S10** and **Figure S3**, after adjustment for non-fire $PM_{2.5}$ and O_3, the short-term mortality impacts of LFS $PM_{2.5}$ and O_3 on all-cause mortality attenuated slightly, but the differences between non-fire adjustment models and main models were all not statistically significant (all *p*-values for difference > 0.05).

1.2.7 Two-pollutant versus single-pollutant models

In our main model, we evaluated associations for LFS $PM_{2.5}$ or LFS O_3 separately using single-pollutant models due to collinearity issues caused by their high correlation with each other, with an overall Pearson correlation coefficient r=0.61 (**Figure S2)**, and the r >0.80 in 536 (23.6%) communities.

To address the concern that our single pollutant model may neglect the overlapping short-term mortality impacts of LFS $PM_{2.5}$ and O_3, we further conducted two-pollutant model analyses by putting both $\mathrm{cb}(\mathrm{LFS\_PM2.5}_{it})$ and $\mathrm{cb}(\mathrm{LFS\_O3}_{it})$ in the first-stage time series regressions.

As the collinearity between LFS $PM_{2.5}$ and LFS O_3 can make the effect estimates unreliable and difficult to interpret, we diagnosed community-specific collinearity with the adjusted generalized standard error inflation factor (aGSIF) produced by the *vif* function in *car* R package. We defined a serious collinearity as the aGSIF for either $\mathrm{cb}(\mathrm{LFS\_PM2.5}_{it})$ or $\mathrm{cb}(\mathrm{LFS\_O3}_{it})$ in the two-pollutant models being above 2.2 (i.e., $\sqrt{5}$). [26]

Then, in the second-stage meta-analyses, after removing those communities with a serious multi-collinearity (about 11-15% of communities removed, global representativeness reduced compared with our main model), we pooled effect estimates of remaining communities for LFS $PM_{2.5}$ and LFS O_3 from both single- and two-pollutant models. We tested the differences between the pooled effect estimates from single and two-pollutant models using fixed-effect meta-regressions.[22-24] The results showed that the differences in effect estimates from single and two-pollutant models were generally small and all statistically non-significant (all *p*-values for difference>0.18) (**Table S11, Figure S4**).

1.3 Sensitivity analyses of mortality burden assessment

1.3.1 Sensitivity analysis 1: using short-term E-R relationships from the two-pollutant models

To further test the robustness of our main approach based on single pollutant models, we conducted a sensitivity analysis by replacing the short-term E-R relationships for LFS $PM_{2.5}$ and O_3 from the single pollutant model with the ones from the two-pollutant models (i.e., RR in **Table S11**) in the calculation of short-term mortality burdens.

1.3.2 Sensitivity analysis 2: using short-term E-R relationships from non-fire adjustment models

We conducted a sensitivity analysis by replacing the short-term E-R relationships for LFS $PM_{2.5}$ and O_3 from the main model with those from the non-fire adjustment models (i.e., RR in **Table S10**) in calculating short-term mortality burdens.

1.3.3 Sensitivity analysis 3: using hypothetical long-term E-R relationships assuming enhanced long-term mortality impacts of LFS $PM_{2.5}$ and O_3

In our main analyses, we have to use the E-R relationships for the long-term mortality impacts of all-source $PM_{2.5}$ and O_3,[27,28] due to the limited availability of evidence specifically for LFS $PM_{2.5}$ and O_3.[29,30] This practical approach assumes that the long-term mortality impacts of LFS $PM_{2.5}$ and O_3 are the same as all-source $PM_{2.5}$ and O_3, respectively. However, this assumption may not hold, given the differences in chemical components, toxicity, accompanying exposures (e.g., high ambient temperatures often come together with wildfires), and exposure patterns (acute high exposure versus chronic moderate or low exposure) between LFS and other-sourced (e.g., traffic, industry, household) air pollution. Generally, existing evidence on chemical components and toxicity of LFS $PM_{2.5}$ suggests that the LFS $PM_{2.5}$ tends to have stronger mortality impacts than all-source $PM_{2.5}$, and high temperatures accompanying wildfires also tend to exacerbate the mortality impacts of $PM_{2.5}$ and O_3.[25,31] Our analyses on the short-term mortality impacts (**Figure S1, Table S9**) also support that the mortality impacts of LFS $PM_{2.5}$ and O_3 tend to be stronger than all-source $PM_{2.5}$ and O_3, thus our long-term mortality burden was likely to be underestimated. We cannot accurately quantify this potential underestimation until the evidence for long-term mortality impacts of LFS $PM_{2.5}$ and O_3 becomes available.

Here, we introduced another assumption that can help give a potentially reasonable estimation of the bias caused by our practical approach. We assumed that the degrees of enhancement in mortality impacts of LFS $PM_{2.5}$ and O_3 compared with all-source $PM_{2.5}$ and O_3 were the same for the short-term and long-term mortality impacts. Then we estimated the hypothetical E-R relationships for long-term mortality impacts of LFS $PM_{2.5}$ and O_3 using the equation below:[32]

$$\beta_{\text{long\_LFS}} = \beta_{\text{long\_all\_source}} \times \frac{\beta_{\text{short\_LFS}}}{\beta_{\text{short\_all\_source}}} \quad (3)$$

where $\beta_{\text{long\_LFS}}$ refers to the Beta value, i.e., log(RR) for the long-term impacts of LFS $PM_{2.5}$ (or O_3) on all-cause (or cardiovascular/respiratory) mortality; $\beta_{\text{long\_all\_source}}$ represents the Beta value for long-term impacts of all-source $PM_{2.5}$ (or O_3) on all-cause (or cardiovascular/respiratory) mortality as presented in **Table S12**; the $\beta_{\text{short\_LFS}}$ and $\beta_{\text{short\_all\_source}}$ represents corresponding Beta values for the short-term mortality impacts of LFS and all-source $PM_{2.5}$ (or O_3), as presented in **Table S7 and Table S9**, respectively. We used Monte Carlo simulations of 1000 samples to estimate the 95% CI of the $\beta_{\text{long\_LFS}}$. The $\beta_{\text{long\_LFS}}$ and its 95%CIs were then transformed as RR [i.e., exp($\beta_{\text{long\_LFS}}$)] with 95% CI, and were presented in **Figure S5**. As expected, the hypothetical long-term RRs for LFS $PM_{2.5}$ and O_3 were generally higher than those all-source $PM_{2.5}$ and O_3, but their 95%CIs largely overlapped with each other. Then, we conduct a sensitivity analysis by using the hypothetical long-term RRs for LFS $PM_{2.5}$ and O_3 in the long-term mortality burden assessment.

1.3.4 Results of sensitivity analyses

Compared with our main analyses, the point estimates global total all-cause, cardiovascular and respiratory deaths (**Table S18, Figure S13**):

- decreased by 1.8%, 7.4%, and 11.1%, respectively, in sensitivity analysis 1 due to decreases in short-term mortality burden estimates;
- decreased by 5.8%, 4.1% and 1.8%, respectively, in sensitivity analysis 2 due to decreases in short-term mortality burden estimates;
- increased by 20.6%, 28.9% and 12.5%, respectively, in sensitivity analysis 3 due to increases in long-term mortality burden estimates for both LFS $PM_{2.5}$ and O_3.

However, their 95% eCIs largely overlapped with our main estimates, and the long-term trends of the global total AD from 2000 to 2019 almost did not change in all these sensitivity analyses compared with our main analyses). Moreover, the variations of annual (20-year average) AD estimates across 201 countries and territories (i.e., spatial variations) were highly consistent in all the sensitivity analyses compared with our main analyses (all coefficients of determination $R^2 > 0.999$, **panels A-C in Figures S14-16**). The country/territory-specific AD long-term trends (percentage change per year from 2000 to 2019) were also highly consistent in all the sensitivity analyses compared with our main analyses (all $R^2 > 0.998$, **panels D-E in Figures S14-16**). These suggest that the sensitivity analyses by using alternative E-R relationships did not affect the spatial and temporal variations of the attributable mortality burdens.

1.4 Short-term mortality burden based on average versus actual daily death counts

In our short-term mortality burden assessment, we assumed the daily death number was the average daily death counts (i.e., $\frac{\mathrm{Death}_{\mathrm{iy}}}{\mathrm{Day}_{\mathrm{y}}}$) for a given year due to the unavailability of country-specific daily death data, which is an acceptable approach widely used in many studies. [7,33-35] However, this may cause some bias as the daily death counts often show some seasonality (generally higher in cold seasons than in warm seasons but vary by locations[36]). To quantify the actual bias of our approach, we conduct a comparison analysis in the 2267 communities with daily death data available. We calculated the short-term mortality burdens attributable to LFS $PM_{2.5}$ and O_3 of those communities following the similar equations as our main analyses (i.e., taking each community as a country in the main analyses), and the daily death used in calculation has two versions: 1) average daily deaths for a given year, same as the main analyses; 2) actual daily deaths in the time-series data, i.e., benchmark approach. We compared the attributable short-term mortality burdens from these two approaches. The results showed that compared with the benchmark approach, our approach based on average daily deaths caused very small underestimations (bias by -0.42%, -0.56%, and -1.73% for all-cause, cardiovascular and respiratory mortality burdens, respectively) of the short-term mortality burden attributable to LFS $PM_{2.5}$ and O_3 (**Table S19**). Our approach also did not affect the spatial and temporal variations of the short-term attributable burdens, as evidenced by the high consistency ($R^2 > 0.959$) between our approach and the benchmark approach in the community-specific annual AD estimates and temporal AD trends (**Figure S17**).

2. Supplementary discussion

2.1 Proportions of wildfires in global landscape fires

Wildfires refer to uncontrolled or unplanned landscape fires in wildland vegetation.[37,38] However, how many proportions of landscape fires are wildfires remains an unsolved issue, because current techniques of monitoring fire activities across the globe rely on satellite products that cannot tell whether a fire is controlled/planned by humans. We can only give some approximate estimates on this issue based on currently available data, particularly the Global Fire Emissions Database (GFED),[39] and some reasonable assumptions.

According to satellite retrieval of burned areas, land cover type, and active fire information, the GFED estimates fire emissions of six types of fires:1) boreal forest fires; 2) tropical forest fires; 3) savanna, grassland, and shrubland fires; 4) temperate forest fires; 5) peatland fires; 6) agricultural waste burning.[39] Our previous analyses of GFED covering 2000-2019 found that only about 5% of global $PM_{2.5}$ emissions from all these fires were contributed by agricultural waste burning which are not wildfires.[14] Johnston et al extended such analyses to 1998-2022 and generated similar results.[31] For the remaining five types of fires, some of them may also not wildfires, but could be indigenous burning (fire that continues to be used as a cultural practice by indigenous peoples across the globe to manage local environments and maintain connection to the land), prescribed burning (fires deliberately ignited as a management tool to reduce fuel loads or achieve ecological outcomes), and deforestation fires (deliberate application of fire to facilitate conversion of forested landscapes to pasture or cropland) as summarized by Johnston et al. [31] It is difficult to quantify the cotribution of those human controlled/planned fires to the global landscape fires' $PM_{2.5}$ emissions, but given they are human controlled/planned (i.e., low intensity), and usually happen in certain regions (e.g., prescibe fires mostly in high-income countries; deforestation fires mostly in tropical forests in

Amazon and Southeast Asia) or communities (e.g, indigenous fires in indigenous communities), it is reasonable to assume their contribution to global landscape fire $PM_{2.5}$ emission should not be higher than (i.e., <5%.) the contribution by agricultural burning which is common and frequent throughout the world. Under this reasonable assumption, at least 90% of landscape fire $PM_{2.5}$ emissions should be contributed by wildfires globally.

However, it should be noted that the 90% is just a global average rough estimate over 1998-2022, and the actual proportions may vary by location and year. For example, due to climate change, the frequency of extreme wildfires has increased by 2.2-fold from 2003 to 2023,[40] and wildfires tend to keep increasing in the future.[41,42] As a result, the wildfires' proportion in landscape fires tends to be increasing.

2.2 Is there an overlap between short-term and long-term mortality burden?

It is common confusion that the short-term and long-term mortality burdens attributable to air pollution overlap, or the former is a part of the latter. To clarify this issue, we need to understand the definition of attributable fraction:

"The attributable fraction is the excess caseload arising over a risk period due to the presence of exposure as opposed to its absence." (Page 355, Rothman et al. *Modern Epidemiology Third edition*)[43]

In our study, the risk period for the short-term mortality impacts is 0-2 days following daily LFS air pollution exposure; the risk period for the long-term mortality impacts is the follow-up period (i.e., time after baseline year) of the cohort studies where the relative risks were obtained. In cohort studies, the outcome event (i.e., death in our study) does not happen in the baseline year. Therefore, for any given year:

- our estimated short-term attributable mortality burden refers to excess deaths that happened in the current year caused by the daily LFS air pollution in the current year;
- our estimated long-term attributable mortality burden was excess deaths in a future year that tended to be caused by cumulative LFS air pollution exposure in the current year among the population not died in the current year (**baseline population**).

In the equation for calculating long-term mortality burden,

$$\mathrm{AD\_long\_PM_{iy}} = \mathrm{Death_{iy}} \times (1 - \mathrm{RR_{long\_PM}^{-(PWC\_PM_{iy} \div 10)}})$$

the $\mathrm{Death_{iy}}$ ideally should be replaced by the death number of the baseline population in a future year. However, given the population is always changing (e.g., new people born in new years), the ideal future deaths are not observable and not available from death statistics.

The $\mathrm{Death_{iy}}$ (deaths of the current year, $= \mathrm{Population_{iy}} \times \mathrm{Mortalty\_rate_{iy}}$) is the most convenient and practical estimate of the ideal future deaths of the baseline population,[44,45] based on two reasonable assumptions:

1) given the usually small rates of all-cause mortality (usually around 1/1000 [44,45]), for a given year, the whole population (i.e., the $\mathrm{Population_{iy}}$) in the baseline year is a good and convenient approximation of the baseline population (i.e., those not died) mentioned above;

2) the mortality rate of the baseline population in a near future year can be assumed to be the same as the mortality rate (i.e., the $\mathrm{Mortalty\_rate_{iy}}$) of the whole population in the baseline year, given usually small changes in mortality rate within a few years.

Therefore, despite the usage of current year death in calculating long-term mortality burden, it should not be misinterpreted as excess deaths happened in the current year.

In conclusion, the long-term attributable mortality burden should be interpreted as the estimated excess deaths in a future year due to the cumulative LFS air pollution exposure in the current year, which does not overlap with the short-term attributable mortality burden that happened in the current year.

2.3 Strengths of this study compared with previous studies

The present study has several strengths compared with previous studies on the mortality burden of LFS air pollution. [46-58] First, rather than only accounting for the total mortality burdens from LFS $PM_{2.5}$, our study also accounted for cause-specific mortality burdens and those from LFS O_3. We found that the spatiotemporal patterns of cardiovascular mortality burden attributable to LFS air pollution were quite different from the all-cause and respiratory attributable burdens, and LFS O_3 was responsible for 22.4% of the total AD (0.34 million deaths per year). Furthermore, we have provided global, regional, and national estimates of attributable mortality burdens for each year over 2000-2019, which is much more comprehensive and informative than previous studies focusing on certain regions or countries [46-55] or the global total.[56-58]

Our estimated mortality burdens from LFS $PM_{2.5}$ (about 1.19 million deaths per year) were much higher than previous global studies focusing on the total mortality burden from LFS $PM_{2.5}$.[56-58] Johnston et al estimated that 339,000 deaths per year were attributable to LFS $PM_{2.5}$ globally from 1997 to 2006.[56] A more recent study, applying the same exposure-response (E-R) relationship, estimated 677,745 deaths per year attributable to LFS $PM_{2.5}$ during 2016-2019.[57] Notably, the E-R relationship used in these two studies was from early epidemiological studies covering only three locations, and two of them relied on a strong assumption (i.e., 75% of all particles <10 μm were also <2.5 μm, because these two locations only assessed PM_{10} rather than $PM_{2.5}$ exposure) not supported by PM observations during wildfire events.[59] The third global study used the methods and E-R relationships of the GBD 2019 to estimate the long-term mortality burden from LFS $PM_{2.5}$ in 2010-2019 (135,180 attributable deaths per year) and in different future climate change scenarios.[58] The GBD method has the advantage of quantifying disease-specific burdens. However, it can significantly underestimate the total mortality burden of $PM_{2.5}$ as it sums attributable mortality burden from several selected diseases (chronic obstructive pulmonary disease, lung cancer, ischemic heart disease, stroke, lower respiratory tract infection, and type 2 diabetes) while excluding other diseases related to $PM_{2.5}$ exposure.[60]

Compared to previous global studies,[56-58] we have made major advances in both exposure assessment and exposure-mortality relationships, which can explain our difference in estimates. For exposure assessment, our LFS $PM_{2.5}$ and O_3 from chemical transport simulations have been calibrated against observations from thousands of air quality stations across the world using a machine learning approach, while previous global studies used the chemical transport simulations with less comprehensive[56] or in some cases absent empirical validation calibration [57-58]. Johnston et al's modelled annual mean $PM_{2.5}$ combined information from both chemical transport simulations and satellite-based measurements of aerosol optical depth, and their modelled annual $PM_{2.5}$ achieved a R^2=0.38 in validation against annual $PM_{2.5}$ observations of 160 stations in US.[56] In comparison, as shown in our previous validation studies, our calibration approach could substantially improve the accuracy of the exposure estimates, e.g., R^2 against station observed daily $PM_{2.5}$ improved from 0.48 to 0.89 after calibration.

E-R relationships for long-term mortality impacts were sourced from the latest published meta-analyses of cohort studies worldwide,[27,28] representing the best available evidence for global assessment. The E-R relationships for short-term mortality impacts were from meta-analyses from time-series analyses of 2267 communities in 59 countries or territories worldwide, which is also by far the most global representative evidence. This is superior to two previous global studies[56,57] (another global study did not account for the short-term mortality burden[58]) which used evidence based on analyses from only 3 locations. This has also improved from our previous studies based on 749 communities worldwide[15,16] by including more communities, particularly communities in Sub-Saharan Africa, South Asia, Southeast Asia, South America, and Oceania where LFS air pollution was high.

2.4 Limitations of this study

2.4.1 Not accounting for other LFS air pollutants

Our assessment focused on LFS $PM_{2.5}$ and O_3 that can travel far and affect a large population, while did not quantify the mortality burdens from other LFS air pollutants (e.g., carbon monoxide, nitrogen oxides, and sulfur dioxide[25,31], generally confined to fire source areas[61,62]), due to the unavailability of data. Therefore, the total mortality burden attributable to LFS air pollution tended to be slightly underestimated.

2.4.2 Not accounting for interaction effects of LFS $PM_{2.5}$ and O_3

We did not account for the potential interaction effects of LFS $PM_{2.5}$ and O_3 in mortality burden estimation. Although our analyses found generally non-significant interaction effects between LFS $PM_{2.5}$ and O_3 in their short-term mortality impacts (**Table S5**), previous literature found that the long-term mortality impacts of $PM_{2.5}$ and O_3 can be synergistic (i.e., enhance each other), thus our long-term mortality burden estimates tended to be underestimated due to omitting such synergistic impacts.[63]

2.4.3 Using average daily death counts in calculating short-term AD

When calculating short-term AD, the daily death number was represented by average daily death counts for a given year due to the unavailability of country-specific daily death data. Although this approach ignored the seasonality of mortality, our analysis based on daily death data of 2267 communities found that this approach only causes very slight underestimations of (by around 1%) the short-term AD and does not affect its spatial and temporal variations (see section 1.4 and **Table S19, Figure S17**).

2.4.4 Potentially enhanced long-term mortality impacts of LFS $PM_{2.5}$ and O_3

Our estimates of the long-term mortality burdens relied on the assumption that the long-term mortality impacts of LFS $PM_{2.5}$ and O_3 are the same as all-source $PM_{2.5}$ and O_3, respectively. This was a practical approach due to the limited evidence on the long-term mortality impacts of LFS $PM_{2.5}$ and O_3, particularly in regions with high LFS air pollution.[29,30] As detailed in section 1.3, this assumption may not hold. Both our short-term mortality impact assessment (**Table S9, Figure S1**) and existing evidence[25,31] suggest that the mortality impacts of LFS $PM_{2.5}$ and O_3 tend to be enhanced compared with those of all-source $PM_{2.5}$ and O_3, thus our long-term mortality burden was likely to be underestimated. Our sensitivity analysis found that global total all-cause, cardiovascular, and respiratory AD increased by 20.6%, 28.9%, and 12.5%, respectively compared with our main analyses, assuming the degrees of enhancement in mortality impacts of LFS air pollution were the same for long-term and short-term impacts. However, we proved that using alternative long-term E-R relationships did not affect the spatial and temporal variations of our AD estimates (**Figure S16**), thus it would have minimal impacts on our result interpretation and research implications.

2.4.5 Uncertainties in exposure and mortality data

As discussed before,[14] there were some uncertainties in estimating LFS $PM_{2.5}$ and O_3 (e.g., chemical transport model simulations, and machine learning model predictions), and we could not incorporate these uncertainties in our mortality burden estimates. The mortality data from the GBD 2019 also has some limitations, such as relying on model estimates in countries with no death registrations, and uncertainties in disease classifications.[10,11] These limitations of GBD 2019 will be continuously improved in future rounds of GBD, and thus, our estimates could also be updated and improved in the future.

2.4.6 Uncertainties in E-R relationships

Although our time-series daily death data included 2267 communities in 59 countries and territories and represent by far the largest study on short-term mortality impacts of LFS air pollution, many countries remain not covered by the data, including some countries in Africa, Eastern Europe, and Southeast Asia where the attributable mortality burdens were high. The long-term E-R relationships were based on cohort studies predominantly conducted in Western high-income countries and Eastern Asian countries.[27,28] Therefore, both short-term and long-term E-R relationships can be improved further in the future by including health data from those under-examined countries. As there are some uncertainties in extrapolating the existing E-R relationships to these under-examined countries, our AD estimates for these countries may also need to be interpreted with caution, and more localized data and evidence are required to verify or improve our estimates. Besides, although we used linear E-R relationships based on currently available data and evidence, the non-linear impacts (e.g., with thresholds) of LFS air pollution on mortality remain possible in new data and should be continuously explored in future studies.

2.4.7 Not accounting for within-country variations

Our mortality burden assessment was conducted at the country (or territory) level and thus cannot account for within-country variations in the attributable mortality burdens. There are often substantial within-country variations in LFS air pollution exposures, particularly for large countries. For example, our previous study found that the LFS air pollution was much higher in the western US than in other areas of the US, and the increasing trends of LFS air pollution from 2000 to 2019 were also mainly in the western US.[14] Moreover, many studies also found within-country variations in the susceptibility to health impacts of air pollution.[64-67] For example, studies in China and US have found that communities with lower socioeconomic status often show higher susceptibilities to adverse health outcomes of air pollution, which may be explained by poorer health conditions, more limited access to air pollution mitigation measures (e.g., air purifier) and healthcare services in those communities.[64,66,67] The within-country variations in LFS air pollution exposure, susceptibility, population and mortality rates, will lead to substantial within-county variations in mortality burdens from LF air pollution. More studies at finer spatial resolutions are warranted to accurately map the within-county variations and identify the most vulnerable and high-risk communities, which will inform targeted interventions and prevention within each country.

Overall, many further investigations are warranted to fill all data and evidence gaps mentioned above to give more comprehensive and accurate estimates of mortality burdens from LFS air pollution.

3. Supplementary tables and figures

Table S1. STROBE Statement — checklist of items that should be included in reports of observational studies

	Item No	Recommendation	Relevant content in this paper
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	In Title
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	In Summary section.
Introduction			
Background/ rationale	2	Explain the scientific background and rationale for the investigation being reported	In para 1-3, Introduction
Objectives	3	State specific objectives, including any prespecified hypotheses	In para 4, Introduction
Methods			
Study design	4	Present key elements of study design early in the paper	In the Statistical analyses section of Methods, and section 1 of Supplementary Material
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	In Data collection section of the Methods, and section 1.1 of Supplementary Material
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up *Case-control study*—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls *Cross-sectional study*—Give the eligibility criteria, and the sources and methods of selection of participants	In Data collection section of the Methods, and section 1.1 of Supplementary Material
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed *Case-control study*—For matched studies, give matching criteria and the number of controls per case	NA NA
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	In Data collection section of the Methods, and section 1.1 of Supplementary Material
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	In Data collection section of the Methods, and section 1.1 of Supplementary Material
Bias	9	Describe any efforts to address potential sources of bias	In Statistical analyses section of Methods, and section 1.2 of Supplementary Material
Study size	10	Explain how the study size was arrived at	In Data collection section of the Methods, and section 1.1 of Supplementary Material
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	In Statistical analyses section of Methods, and

			section 1.2 of Supplementary Material
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	In Statistical analyses section of Methods, and section 1.2 of Supplementary Material
		(*b*) Describe any methods used to examine subgroups and interactions	In Statistical analyses section of Methods, and section 1.2 of Supplementary Material
		(*c*) Explain how missing data were addressed	In Data collection section of the Methods, and section 1.1 of Supplementary Material
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	NA
		(*e*) Describe any sensitivity analyses	In Statistical analyses section of Methods, and section 1.3&1.4 of Supplementary Material.
Results			
Participants	13	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	NA
		(b) Give reasons for non-participation at each stage	NA
		(c) Consider use of a flow diagram	NA
Descriptive data	14	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	In Table S2-S3, Supplementary Material
		(b) Indicate number of participants with missing data for each variable of interest	NA
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	NA
Outcome data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	NA
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	NA
		Cross-sectional study—Report numbers of outcome events or summary measures	NA
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	NA
		(*b*) Report category boundaries when continuous variables were categorized	NA
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	NA

Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	In Table 1, Figure 1-5 and all tables and figures of Supplementary Material
Discussion			
Key results	18	Summarise key results with reference to study objectives	In para 1, Discussion
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	In two paras before conclusion, Discussion.
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	In para 2-5, Discussion
Generalisability	21	Discuss the generalisability (external validity) of the study results	In para 6, Discussion.
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	In Acknowledgements
Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.			

Table S2. Definitions and basic characteristics of 2267 included communities from different data sources

Data source	Community definition (official names)	No. of communities	Median (Inter-quartile range)	
			Area size, km^2	Population, 1,000 persons
Australian Bureau of Statistics	Statistical area level 3	315	261 (4123)	619.7 (1142.1)
Brazilian Mortality Information System	Immediate regions	510	6896 (11958)	147.8 (308.3)
VSDD, Statistics Canada	Second-level administrative divisions	287	4111 (15403)	63.6 (157.8)
Chilean Ministry of Health Epidemiology Department	Communes	325	595 (1211)	246.8 (613.3)
New Zealand Ministry of Health	Territorial authorities	63	2625 (5090)	42.6 (92.9)
INDEPTH Network[8]	HDSS sites	32	181 (792)	221.6 (722.8)
MCC Network	Cities	735	732 (1526)	797.3 (1684.0)

Notes: HDSS, health and demographic surveillance systems; INDEPTH, International Network for the Demographic Evaluation of Populations and their Health; IQR, interquartile range; MCC, Multi-Country Multi-City; The included INDEPTH Network covered 32 locations from 16 countries. HDSS sites are defined geographic areas covering specific rural or urban areas in the INDEPTH network. The included MCC Network data covered 735 locations from 40 countries or territories.

Table S3. Summary statistics of the 2267 communities included in the time series analyses

No.	Country/territory	Study period	No. of communities	No. of deaths included			Fire-sourced $PM_{2.5}$		Fire-sourced O_3	
				All-cause	Cardiovascular	Respiratory	min-max	mean±sd	min-max	mean±sd
1	Argentina	2005-2015	3	686333	NA	NA	0.1-50.6	7.8±6.5	0.0-53.8	3.8±3.7
2	Australia	2009-2017	315	1319711	392351	117210	0.0-118.1	1.6±2.5	0.0-66.0	3.2±3.9
3	Bangladesh	2005-2016	1	4797	NA	NA	0.0-75.0	3.8±9.1	0.1-32.6	2.0A±3.0
4	Brazil	2000-2019	510	22661028	6351303	2427663	0.0-70.2	4.8±6.4	0.0-128.5	5.7±7.3
5	Burkina Faso	2000-2015	3	16248	NA	NA	0.0-22.1	1.7±1.8	0.0-46.5	5.3±5.1
6	Canada	2000-2015	287	3810280	1137752	331337	0.0-72.6	1.0±2.2	0.0-41.5	1.4±1.1
7	Chile	2016-2019	325	426646	112958	46777	0.0-208.0	12.7±15.1	0.0-77.8	3.1±4.4
8	China	2000-2015	15	1081700	433839	140016.93	0.0-38.5	1.3±1.8	0.0-33.9	1.8±1.7
9	Colombia	2000-2013	5	843633	237346	88819	0.0-35.4	2.1±2.5	0.0-66.2	7.3±7.7
10	Costa Rica	2000-2017	1	31117	9320	2651	0.1-11.8	2.3±1.6	0.0-22.2	2.2±1.8
11	Czech Republic	2000-2015	4	505932	246331	29860	0.0-37.1	0.5±0.9	0.0-15.6	1.7±1.0
12	Ecuador	2014-2018	2	112264	32833	12989	0.3-19.5	3.6±2.2	0.0-49.2	7.0±6.1
13	Estonia	2000-2018	5	148540	75751	5012	0.0-45.5	0.5±1.5	0.0-15.0	1.6±0.9

14 Ethiopia	2006-2016	6	15037	NA	NA	0.0-37.0	2.5±2.1	0.0-36.4	4.1±3.5
15 Finland	2000-2014	1	110396	39840	6152	0.0-30.7	0.4±1.2	0.0-14.7	1.6±0.9
16 France	2000-2015	22	1820747	NA	109888	0.0-7.9	0.4±0.4	0.0-19.6	1.5±1.0
17 Germany	2000-2015	12	2120825	NA	NA	0.0-37.2	0.3±0.5	0.0-13.9	1.7±1.1
18 Ghana	2000-2014	3	26586	NA	NA	0.1-52.3	4.3±5.4	0.0-58.7	10.5±10.0
19 Greece	2001-2010	1	287969	136194	28771	0.0-9.7	1.2±1.2	0.0-11.1	1.3±1.2
20 Guatemala	2009-2016	1	62715	NA	NA	0.2-23.5	4.1±3.5	0.0-56.5	5.8±8.0
21 India	2009-2016	1	3563	NA	NA	0.0-9.5	0.7±0.9	0.1-4.1	1.3±0.5
22 Iran	2002-2015	2	817913	357680	59394	0.0-24.3	1.4±1.4	0.0-7.7	1.7±0.9
23 Ireland	2000-2007	6	333088	91232	50077	0.0-6.9	0.3±0.3	0.1-7.2	1.4±0.7
24 Israel	2000-2019	1	193727	NA	NA	0.0-12.1	1.3±1.2	0.0-5.2	1.2±0.7
25 Italy	2006-2015	18	804278	NA	NA	0.0-13.9	0.8±1.1	0.0-7.3	1.2±0.8
26 Ivory Coast	2009-2016	1	2815	NA	NA	0.1-35.5	4.4±4.2	1.1-51.5	13.3±9.7
27 Japan	2000-2015	65	8665343	2467625	1308018	0.0-45.0	2.5±2.6	0.0-17.0	1.3±1.2
28 Kenya	2003-2015	2	10859	NA	NA	0.2-34.3	3.4±3.6	0.7-47.5	7.7±7.2
29 Kuwait	2000-2016	1	73748	35285	5715	0.0-14.1	1.1±1.0	0.0-4.4	1.4±0.6
30 Malawi	2003-2016	1	3563	NA	NA	0.1-54.0	11.2±10.4	0.4-57.0	15.2±13.7
31 Mexico	2000-2014	10	2682202	691353	253922	0.0-31.2	2.2±2.6	0.0-59.9	4.1±6.0
32 Moldova	2001-2010	4	59906	NA	NA	0.0-21.5	1.3±1.9	0.0-17.1	1.8±1.3
33 Mozambique	2010-2015	1	4198	NA	NA	0.1-38.0	4.3±5.5	0.1-71.5	7.5±9.4
34 Netherland	2000-2016	5	338448	NA	NA	0.0-14.4	0.3±0.3	0.0-14.1	1.8±1.2
35 New Zealand	2000-2018	63	558365	196476	48470	0.0-19.8	1.2±1.5	0.1-16.3	1.8±1.2
36 Nigeria	2011-2014	1	10223	NA	NA	0.1-9.5	1.3±1.0	0.1-29.5	3.9±3.5
37 Norway	2000-2018	1	85404	23503	7152	0.0-21.9	0.3±0.6	0.0-7.9	1.5±0.8
38 Panama	2013-2016	1	11457	3862	971	0.0-6.7	1.0±0.9	0.2-20.1	2.8±2.4
39 Paraguay	2004-2019	1	48037	15365	4445	0.5-60.7	8.5±7.6	0.0-82.2	10.1±10.3
40 Peru	2008-2014	18	633137	NA	NA	0.1-54.4	6.6±6.0	0.0-86.4	7.6±8.2
41 Philippines	2006-2019	13	821507	296938	118536	0.0-36.0	2.1±1.8	0.0-38.9	1.8±1.9
42 Portugal	2000-2018	6	967490	303179	107939	0.0-41.3	0.8±1.9	0.0-10.4	1.3±0.8
43 Puertorico	2009-2016	1	26564	NA	NA	0.0-5.1	0.5±0.6	0.0-8.4	0.8±0.6
44 Romania	2000-2016	8	697505	NA	NA	0.0-25.2	1.2±1.6	0.0-18.8	1.5±1.1

45	Senegal	2000-2016	3	9245	NA	NA	0.1-44.9	2.7±3.9	0.0-74.1	7.8±8.2
46	South Africa	2000-2016	55	7474222	1110304	943671	0.0-81.4	4.4±6.0	0.0-74.2	5.4±6.4
47	South Korea	2000-2018	36	2681962	610286	202964	0.0-48.1	1.7±2.2	0.0-17.8	1.5±1.3
48	Spain	2000-2014	52	1859279	600992	221208	0.0-36.3	0.6±1.0	0.0-15.3	1.3±0.8
49	Sweden	2000-2016	3	452463	181068	32440	0.0-27.9	0.3±0.6	0.0-11.3	1.7±0.9
50	Switzerland	2000-2013	8	173519	62428	11201	0.0-5.5	0.3±0.3	0.0-8.6	1.5±0.9
51	Taiwan, China	2000-2018	6	1740776	373288	183139	0.0-12.8	1.4±1.2	0.0-17.6	1.2±1.0
52	Tanzania	2000-2014	3	27607	NA	NA	0.1-47.9	8.1±7.4	0.3-60.9	11.9±10.2
53	Thailand	2000-2008	62	1666292	299721	205900	0.0-86.5	5.0±8.9	0.0-75.9	5.6±8.5
54	The Gambia	2000-2015	1	5154	NA	NA	0.1-24.4	2.3±2.8	0.0-63.1	9.3±8.5
55	Uganda	2005-2015	1	5282	NA	NA	0.5-55.1	8.0±6.1	0.7-57.6	10.7±9.1
56	United Kingdom	2000-2016	70	3643041	1183587	528125	0.0-7.9	0.2±0.3	0.0-15.4	1.6±1.0
57	Uruguay	2012-2016	1	153554	NA	NA	0.1-35.4	4.1±3.7	0.1-22.7	2.7±2.5
58	United States	2000-2006	210	8594149	2672728	849506	0.0-88.2	0.7±1.3	0.0-52.3	1.5±1.2
59	Vietnam	2004-2013	3	110584	24433	8970	0.0-43.2	3.2±5.4	0.0-38.1	3.2±4.7
60	**Global**	**2000-2019**	**2267**	**82542973**	**20807151**	**8498909**	**0.0-208.0**	**3.2±6.1**	**0.0-128.5**	**3.5±5.5**

Notes: sd, standard deviation; NA, not applicable, meaning that the data for daily cardiovascular or respiratory deaths were not available. Both $PM_{2.5}$ and O_3 were in μg/m^3

Table S4. quasi-Bayesian information criterion (qBIC) values of non-linear models compared with linear models

Mortality outcome	Exposure	df	Percentage of included communities with qBIC higher than linear model (%)
All-cause	LFS O_3	2	99.5
	LFS O_3	3	99.6
	LFS O_3	4	99.9
	LFS $PM_{2.5}$	2	99.0
	LFS $PM_{2.5}$	3	99.3
	LFS $PM_{2.5}$	4	99.6
Cardiovascular	LFS O_3	2	98.6
	LFS O_3	3	99.0
	LFS O_3	4	99.1
	LFS $PM_{2.5}$	2	99.0
	LFS $PM_{2.5}$	3	98.9
	LFS $PM_{2.5}$	4	98.8
Respiratory	LFS O_3	2	96.2
	LFS O_3	3	97.0
	LFS O_3	4	97.3
	LFS $PM_{2.5}$	2	96.0
	LFS $PM_{2.5}$	3	96.6
	LFS $PM_{2.5}$	4	96.9

Notes: df, degree of freedom of the natural cubic spline fitting the non-linear models

Table S5. The statistical significance of the interaction terms of LFS $PM_{2.5}$ and O_3 in first-stage time-series analyses

	Percentage of included communities (%)	
Mortality outcome	Significant interaction ($P < 0.05$)	Non-significant interaction
All-cause	7.5	92.5
Cardiovascular	5.9	94.1
Respiratory	5.7	94.3

Table S6. Residual confounding detection of the time-series analyses

Exposure	Mortality outcome	RR (95% CI)	Beta	Se	P-value
LFS $PM_{2.5}$ on one day after death	All-cause	1.000396 (0.999798, 1.000995)	0.000396	0.000305	0.195
	Cardiovascular	1.000616 (0.999401, 1.001833)	0.000616	0.000620	0.321
	Respiratory	1.000856 (0.999142, 1.002573)	0.000855	0.000875	0.328
LFS O_3 on one day after death	All-cause	1.000221 (0.999656, 1.000787)	0.000221	0.000288	0.443
	Cardiovascular	1.000498 (0.999353, 1.001645)	0.000498	0.000584	0.394
	Respiratory	1.000778 (0.999140, 1.002419)	0.000778	0.000836	0.352

Notes: The RR refer to relative risks of all-cause, cardiovascular, and respiratory mortality for each 10 μg/m^3 increase in LFS $PM_{2.5}$ or LFS O_3 on one day after death after adjusting for variations explained by our main model

Table S7. The relative risks (RR) for the short-term mortality impacts of landscape fire-sourced (LFS) air pollution based on the main models

Exposure	Mortality outcome	RR (95% confidence interval)	Beta	Se	No. of Communities*
LFS $PM_{2.5}$	All-cause	1.013072 (1.011187, 1.014960)	0.012987	0.000950	2267
	Cardiovascular	1.009011 (1.006107, 1.011923)	0.008970	0.001470	2085
	Respiratory	1.011619 (1.007176, 1.016082)	0.011552	0.002246	1922
LFS O_3	All-cause	1.012878 (1.010929, 1.014830)	0.012795	0.000983	2267
	Cardiovascular	1.012099 (1.009181, 1.015026)	0.012026	0.001473	2082
	Respiratory	1.016632 (1.012027, 1.021258)	0.016495	0.002316	1921

Notes: * refer to the number of communities included in the first-stage time-series analyses; daily LFS O_3 refers to LFS daily maximum 8-hour average O_3. All RR refer to cumulative relative risks of mortality during 0-2 days following exposure associated with each 10 μg/m^3 increase in daily exposure on the current day.

Table S8. Country/territory-specifc relative risks (RR) for the short-term mortality impacts of landscape fire-sourced (LFS) air pollution based on the main models

No.	Country/territory	No. of Comm	RR (95%CI) for LFS $PM_{2.5}$			RR (95%CI) for LFS O_3		
			All-cause	Cardiovascular	Respiratory	All-cause	Cardiovascular	Respiratory
1	Argentina	3	1.015 (0.999, 1.030)	NA	NA	1.026 (1.009, 1.044)	NA	NA
2	Australia	315	1.012 (0.999, 1.027)	0.978 (0.954, 1.002)	1.021 (0.976, 1.069)	1.013 (1.003, 1.024)	0.993 (0.974, 1.013)	1.039 (1.001, 1.079)
3	Bangladesh	1	0.998 (0.933, 1.067)	NA	NA	0.961 (0.790, 1.169)	NA	NA
4	Brazil	510	1.012 (1.010, 1.015)	1.010 (1.006, 1.014)	1.019 (1.012, 1.026)	1.014 (1.011, 1.016)	1.012 (1.008, 1.016)	1.021 (1.015, 1.026)
5	Burkina Faso	3	1.175 (0.849, 1.625)	NA	NA	1.044 (0.932, 1.169)	NA	NA
6	Canada	287	1.000 (0.989, 1.012)	0.988 (0.967, 1.009)	1.011 (0.972, 1.053)	0.988 (0.967, 1.009)	0.960 (0.924, 0.996)	0.958 (0.889, 1.032)
7	Chile	325	1.001 (0.997, 1.005)	1.004 (0.996, 1.013)	0.994 (0.982, 1.007)	1.026 (1.014, 1.039)	1.017 (0.993, 1.043)	1.080 (1.030, 1.133)
8	China	15	1.052 (0.997, 1.111)	1.069 (0.990, 1.154)	1.056 (0.965, 1.156)	1.019 (0.978, 1.063)	1.001 (0.951, 1.054)	1.027 (0.924, 1.141)
9	Colombia	5	1.016 (1.000, 1.033)	1.017 (0.988, 1.047)	1.019 (0.925, 1.123)	1.017 (1.005, 1.028)	1.015 (0.995, 1.035)	1.038 (1.001, 1.076)
10	Costa Rica	1	1.202 (1.072, 1.348)	1.256 (1.019, 1.549)	1.072 (0.719, 1.598)	0.995 (0.867, 1.141)	1.065 (0.831, 1.365)	0.926 (0.576, 1.488)
11	Czech Republic	4	1.057 (1.005, 1.112)	1.045 (0.951, 1.148)	0.916 (0.741, 1.132)	0.924 (0.874, 0.976)	0.923 (0.853, 0.999)	0.888 (0.709, 1.113)
12	Ecuador	2	1.019 (0.965, 1.075)	0.980 (0.907, 1.059)	1.127 (1.002, 1.268)	1.004 (0.982, 1.027)	1.006 (0.965, 1.049)	0.989 (0.932, 1.050)
13	Estonia	5	0.975 (0.923, 1.029)	0.953 (0.881, 1.031)	0.992 (0.759, 1.298)	0.954 (0.790, 1.153)	0.959 (0.834, 1.103)	0.896 (0.530, 1.513)
14	Ethiopia	6	0.871 (0.720, 1.052)	NA	NA	0.930 (0.834, 1.036)	NA	NA
15	Finland	1	0.998 (0.936, 1.064)	1.079 (0.979, 1.189)	0.907 (0.667, 1.235)	1.092 (0.987, 1.208)	1.158 (0.984, 1.362)	1.344 (0.879, 2.055)
16	France	22	1.300 (1.166, 1.448)	NA	1.165 (0.817, 1.661)	0.945 (0.902, 0.990)	NA	0.835 (0.713, 0.978)
17	Germany	12	1.117 (1.063, 1.174)	NA	NA	0.981 (0.953, 1.010)	NA	NA
18	Ghana	3	0.952 (0.789, 1.150)	NA	NA	1.017 (0.928, 1.113)	NA	NA
19	Greece	1	1.064 (1.004, 1.128)	1.123 (1.035, 1.219)	1.100 (0.932, 1.299)	0.969 (0.902, 1.042)	0.985 (0.890, 1.090)	0.970 (0.786, 1.198)
20	Guatemala	1	0.980 (0.934, 1.028)	NA	NA	0.989 (0.963, 1.015)	NA	NA
21	India	1	0.905 (0.498, 1.644)	NA	NA	0.463 (0.134, 1.597)	NA	NA
22	Iran	2	1.039 (1.012, 1.065)	1.042 (1.006, 1.081)	1.089 (0.994, 1.193)	0.928 (0.872, 0.989)	0.900 (0.823, 0.983)	0.878 (0.709, 1.086)
23	Ireland	6	0.896 (0.755, 1.063)	1.026 (0.742, 1.419)	0.637 (0.404, 1.004)	1.120 (1.005, 1.249)	1.187 (0.989, 1.423)	1.248 (0.969, 1.607)
24	Israel	1	0.972 (0.918, 1.029)	NA	NA	1.079 (0.954, 1.219)	NA	NA
25	Italy	18	1.157 (1.076, 1.244)	NA	NA	0.763 (0.712, 0.817)	NA	NA
26	Ivory Coast	1	1.138 (0.918, 1.411)	NA	NA	1.033 (0.907, 1.177)	NA	NA
27	Japan	65	1.013 (1.007, 1.019)	1.014 (1.004, 1.025)	1.009 (0.997, 1.021)	0.967 (0.956, 0.978)	1.002 (0.980, 1.024)	0.920 (0.892, 0.949)

28 Kenya	2	1.164 (0.887, 1.528)	NA	NA	1.025 (0.933, 1.127)	NA	NA
29 Kuwait	1	1.087 (0.970, 1.219)	1.210 (1.035, 1.415)	0.919 (0.624, 1.352)	0.732 (0.582, 0.921)	0.704 (0.513, 0.967)	0.845 (0.396, 1.803)
30 Malawi	1	0.971 (0.866, 1.088)	NA	NA	0.976 (0.901, 1.059)	NA	NA
31 Mexico	10	1.029 (1.000, 1.060)	1.025 (0.994, 1.057)	1.027 (0.954, 1.104)	1.015 (1.003, 1.026)	1.016 (1.008, 1.024)	1.005 (0.980, 1.032)
32 Moldova	4	1.018 (0.941, 1.101)	NA	NA	1.135 (1.011, 1.275)	NA	NA
33 Mozambique	1	1.258 (0.886, 1.787)	NA	NA	1.097 (0.900, 1.336)	NA	NA
34 Netherland	5	1.024 (0.889, 1.179)	NA	NA	0.958 (0.901, 1.019)	NA	NA
35 New Zealand	63	0.995 (0.965, 1.026)	0.940 (0.897, 0.985)	1.091 (0.991, 1.201)	1.081 (1.017, 1.148)	1.109 (1.004, 1.226)	1.204 (0.970, 1.494)
36 Nigeria	1	0.441 (0.187, 1.040)	NA	NA	0.798 (0.584, 1.091)	NA	NA
37 Norway	1	1.140 (0.961, 1.352)	NA	NA	1.219 (1.021, 1.455)	NA	NA
38 Panama	1	0.992 (0.696, 1.413)	1.150 (0.635, 2.082)	0.537 (0.146, 1.978)	0.978 (0.825, 1.159)	0.873 (0.652, 1.169)	0.435 (0.216, 0.877)
39 Paraguay	1	1.030 (0.999, 1.062)	1.027 (0.975, 1.083)	1.094 (0.997, 1.201)	0.994 (0.978, 1.011)	1.000 (0.971, 1.029)	1.013 (0.963, 1.066)
40 Peru	18	0.995 (0.984, 1.006)	NA	NA	0.999 (0.990, 1.007)	NA	NA
41 Philippines	13	1.037 (1.015, 1.061)	1.009 (0.976, 1.044)	1.013 (0.960, 1.070)	0.992 (0.967, 1.018)	0.983 (0.946, 1.021)	0.936 (0.848, 1.034)
42 Portugal	6	1.035 (0.988, 1.085)	NA	1.023 (0.914, 1.144)	0.924 (0.875, 0.977)	NA	0.937 (0.795, 1.105)
43 Puertorico	1	1.344 (1.017, 1.774)	NA	NA	1.081 (0.776, 1.505)	NA	NA
44 Romania	8	1.063 (1.035, 1.091)	NA	NA	0.953 (0.911, 0.997)	NA	NA
45 Senegal	3	0.770 (0.562, 1.054)	NA	NA	1.032 (0.907, 1.175)	NA	NA
46 South Africa	55	1.003 (0.999, 1.006)	1.001 (0.993, 1.009)	0.994 (0.986, 1.002)	1.014 (1.011, 1.017)	1.016 (1.009, 1.023)	1.012 (1.003, 1.021)
47 South Korea	36	1.014 (1.002, 1.026)	0.994 (0.975, 1.014)	1.013 (0.973, 1.054)	0.973 (0.950, 0.996)	1.012 (0.980, 1.046)	0.933 (0.881, 0.988)
48 Spain	52	1.058 (1.017, 1.101)	1.067 (1.014, 1.123)	0.940 (0.835, 1.058)	0.872 (0.825, 0.922)	0.843 (0.780, 0.911)	0.860 (0.744, 0.995)
49 Sweden	3	0.966 (0.907, 1.030)	0.981 (0.889, 1.082)	0.901 (0.703, 1.155)	1.005 (0.943, 1.072)	0.973 (0.880, 1.076)	1.032 (0.811, 1.312)
50 Switzerland	8	1.054 (0.814, 1.364)	1.306 (0.896, 1.905)	0.675 (0.270, 1.686)	0.930 (0.835, 1.034)	0.856 (0.717, 1.023)	0.783 (0.497, 1.233)
51 Taiwan	6	1.048 (1.028, 1.069)	1.032 (0.992, 1.074)	1.023 (0.967, 1.084)	1.012 (0.985, 1.040)	1.022 (0.969, 1.079)	1.063 (0.987, 1.144)
52 Tanzania	3	1.081 (0.962, 1.215)	NA	NA	1.082 (1.000, 1.172)	NA	NA
53 Thailand	62	1.034 (1.028, 1.039)	1.024 (1.013, 1.036)	1.038 (1.025, 1.051)	1.032 (1.027, 1.037)	1.019 (1.009, 1.030)	1.033 (1.020, 1.047)
54 The Gambia	1	1.029 (0.745, 1.421)	NA	NA	0.991 (0.872, 1.128)	NA	NA
55 UK	1	1.011 (0.935, 1.094)	1.019 (0.915, 1.135)	1.002 (0.817, 1.228)	1.051 (1.029, 1.075)	1.057 (1.019, 1.097)	1.065 (1.006, 1.129)
56 USA	70	1.006 (0.998, 1.015)	1.001 (0.986, 1.016)	1.004 (0.975, 1.034)	1.014 (1.004, 1.025)	1.007 (0.989, 1.025)	1.030 (0.996, 1.065)
57 Uganda	1	0.975 (0.880, 1.079)	NA	NA	0.990 (0.923, 1.062)	NA	NA
58 Uruguay	210	1.023 (1.001, 1.046)	NA	NA	1.047 (1.014, 1.082)	NA	NA

59 Vietnam	3	1.048 (1.019, 1.078)	1.045 (0.993, 1.099)	1.046 (0.960, 1.141)	1.031 (1.000, 1.063)	1.021 (0.967, 1.079)	1.050 (0.957, 1.152)

Notes: NA, not applicable, meaning that the data for daily cardiovascular or respiratory deaths were not available. All RR refer to cumulative relative risks of mortality during 0-2 days following exposure associated with each 10 μg/m^3 increase in daily exposure on the current day. No. of Commun refers to the number of communities included in the first-stage time-series analysis for all-cause mortality.

Table S9. The relative risks (RR) for the short-term mortality impacts of non-fire and all-source $PM_{2.5}$ and O_3 based on the main models

Exposure	Mortality outcome	RR (95% confidence interval)	*P-values* for difference*	Beta	Se	No. of Communities
All-source $PM_{2.5}$	All-cause	1.010146 (1.009271, 1.011022)	**0.006**	0.010095	0.000442	2267
	Cardiovascular	1.006754 (1.005474, 1.008035)	0.150	0.006731	0.000649	2085
	Respiratory	1.010600 (1.008706, 1.012498)	0.680	0.010545	0.000957	1922
All-source O_3	All-cause	1.009855 (1.009349, 1.010362)	**0.003**	0.009807	0.000256	2267
	Cardiovascular	1.008095 (1.007419, 1.008770)	**0.009**	0.008062	0.000342	2082
	Respiratory	1.010169 (1.009156, 1.011183)	**0.007**	0.010118	0.000512	1921
Non-fire $PM_{2.5}$	All-cause	1.008021 (1.007115, 1.008928)	**<0.001**	0.007989	0.000459	2267
	Cardiovascular	1.005478 (1.004147, 1.006810)	**0.027**	0.005463	0.000676	2085
	Respiratory	1.008706 (1.006746, 1.010671)	0.240	0.008669	0.000993	1922
Non-fire O_3	All-cause	1.009917 (1.009386, 1.010448)	**0.004**	0.009868	0.000268	2267
	Cardiovascular	1.008087 (1.007383, 1.008792)	**0.009**	0.008055	0.000357	2082
	Respiratory	1.009993 (1.008938, 1.011048)	**0.006**	0.009943	0.000533	1921

Notes: *P*-values for difference tested the statistical significance of the difference between effect estimates for all-source/non-fire $PM_{2.5}$/O_3 versus LFS $PM_{2.5}$/O_3 in our main model (i.e., those in Table S7). All RR refer to cumulative relative risks of mortality during 0-2 days following exposure associated with each 10 μg/m^3 increase in daily exposure on the current day.

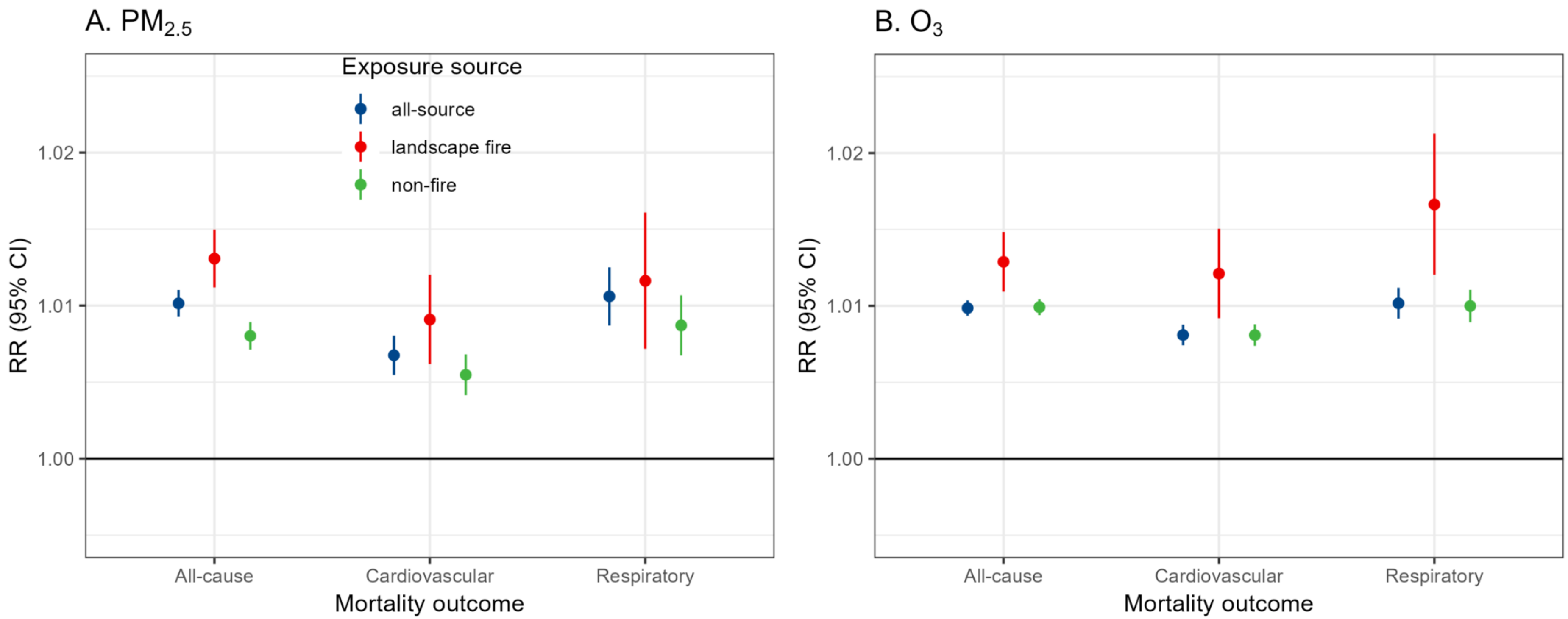

Figure S1. Comparison between all-source, landscape fire-sourced, and non-fire $PM_{2.5}$ and O_3 in the short-term mortality impacts based on our main models

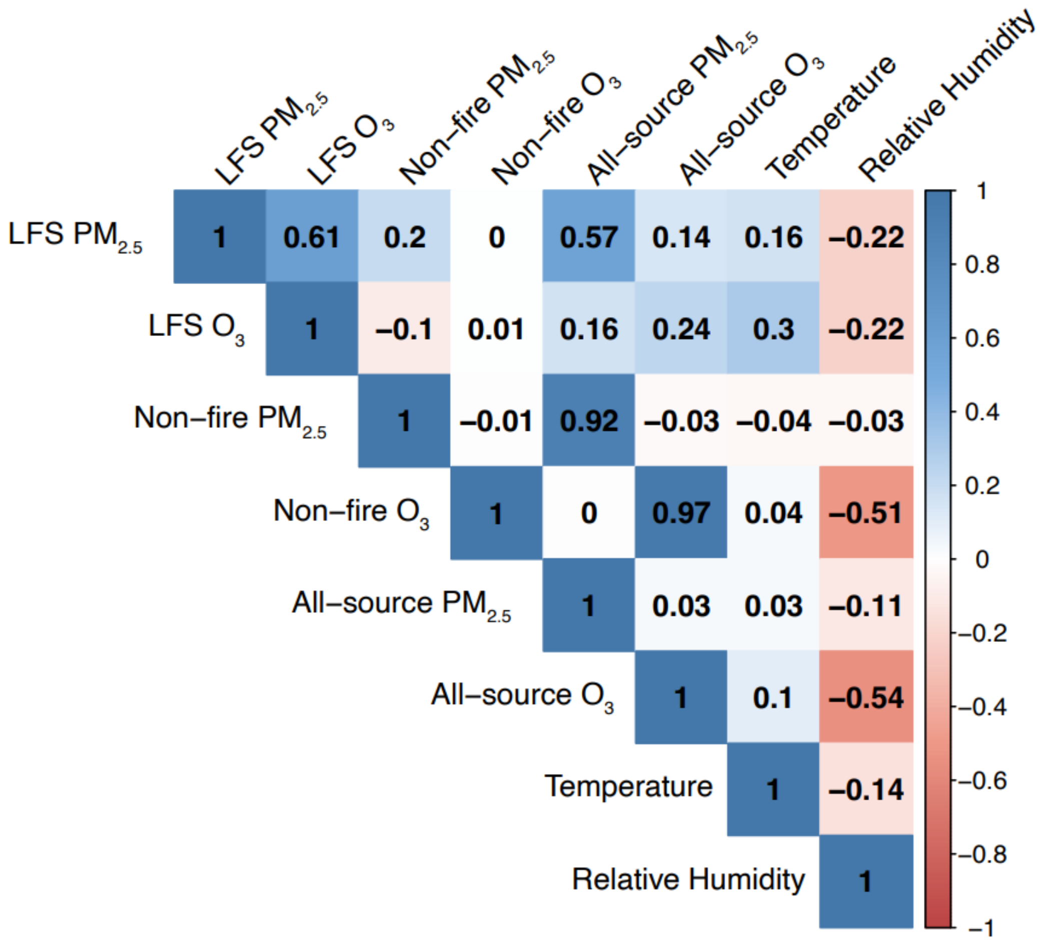

Figure S2. Pearson correlation matrix of daily population-weighted average environmental exposures linked to the daily time-series death data in 2267 coomuties.

Table S10. The relative risks (RR) for the short-term mortality impacts of landscape fire-sourced (LFS) $PM_{2.5}$ and O_3 based on the non-fire adjustment models

Exposure	Mortality outcome	RR (95% confidence interval)	*P-values* for difference*	Beta	Se	No. of Communities
LFS $PM_{2.5}$	All-cause	1.010367 (1.008262, 1.012476)	0.061	0.010314	0.001064	2267
	Cardiovascular	1.005115 (1.001896, 1.008345)	0.079	0.005102	0.001637	2085
	Respiratory	1.009099 (1.004294, 1.013927)	0.451	0.009058	0.002435	1922
LFS O_3	All-cause	1.009824 (1.007315, 1.012338)	0.060	0.009776	0.001269	2267
	Cardiovascular	1.010777 (1.007752, 1.013811)	0.538	0.010719	0.001529	2082
	Respiratory	1.016668 (1.011717, 1.021643)	0.992	0.016530	0.002491	1921

Notes: *P*-values for difference tested the statistical significance of the difference between effect estimates from this model versus those in our main model (i.e., those in Table S7). All RR refer to cumulative relative risks of mortality during 0-2 days following exposure associated with each 10 $\mu g/m^3$ increase in daily exposure on the current day.

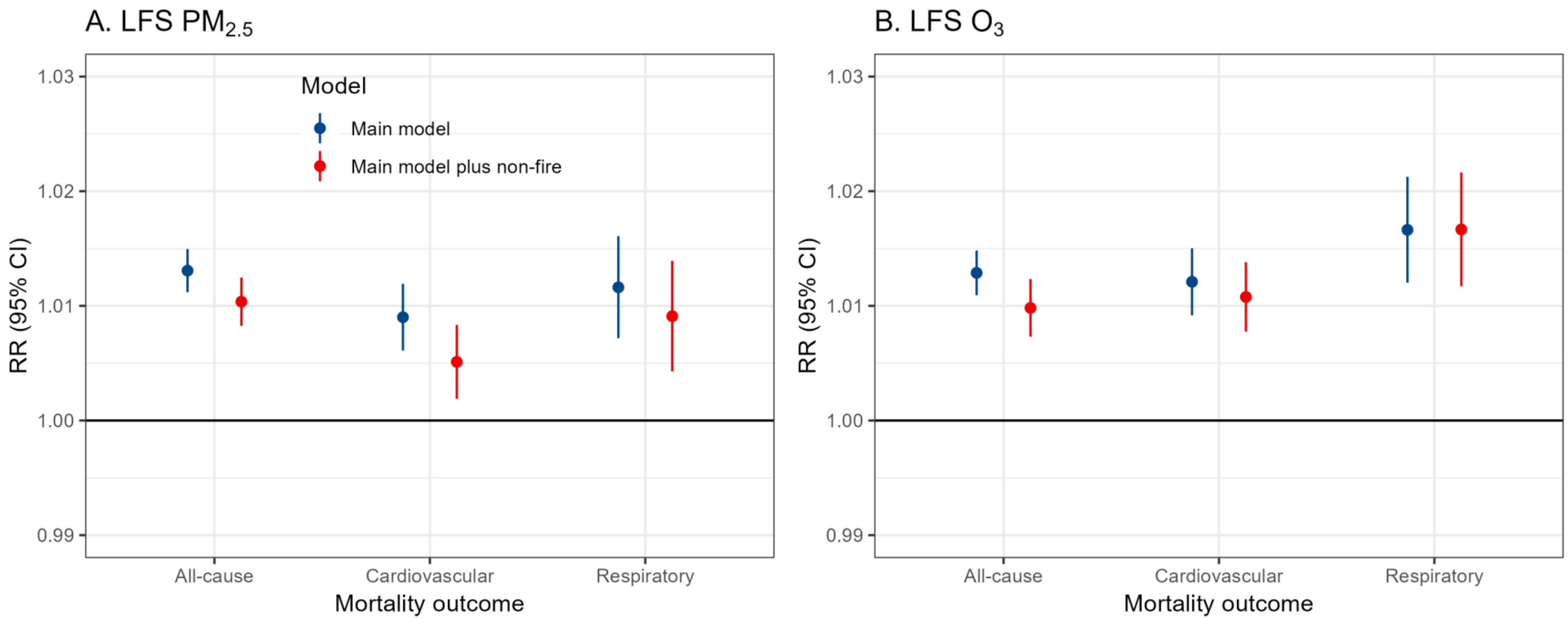

Figure S3. Comparison between models with adjustment for non-fire $PM_{2.5}$ and O_3 and our main models in the short-term mortality impacts of landscape fire-sourced (LFS) $PM_{2.5}$ and O_3

Table S11. Single- versus two-pollutant model in the relative risks (RR) for the short-term mortality impacts of daily landscape fire-sourced (LFS) $PM_{2.5}$ and O_3

Exposure	Mortality outcome	Single- or two-pollutant model	RR (95% confidence interval)	*P-values* for difference	Beta	Se	No. of Communities*
LFS $PM_{2.5}$	All-cause	Single	1.012868 (1.010831, 1.014909)	Reference	0.012786	0.001027	2019
LFS $PM_{2.5}$	All-cause	Two-pollutant	1.013231 (1.011066, 1.015401)	0.811	0.013145	0.001092	2019
LFS $PM_{2.5}$	Cardiovascular	Single	1.006897 (1.003788, 1.010016)	Reference	0.006874	0.001578	1856
LFS $PM_{2.5}$	Cardiovascular	Two-pollutant	1.005453 (1.001939, 1.008979)	0.547	0.005438	0.001786	1856
LFS $PM_{2.5}$	Respiratory	Single	1.009187 (1.003956, 1.014445)	Reference	0.009145	0.002651	1630
LFS $PM_{2.5}$	Respiratory	Two-pollutant	1.003842 (0.998078, 1.009640)	0.180	0.003835	0.002938	1630
LFS O_3	All-cause	Single	1.011630 (1.009183, 1.014082)	Reference	0.011562	0.001235	2019
LFS O_3	All-cause	Two-pollutant	1.011182 (1.008477, 1.013894)	0.810	0.01112	0.001367	2019
LFS O_3	Cardiovascular	Single	1.008044 (1.004326, 1.011775)	Reference	0.008012	0.001885	1856
LFS O_3	Cardiovascular	Two-pollutant	1.006706 (1.002558, 1.010871)	0.638	0.006683	0.002107	1856
LFS O_3	Respiratory	Single	1.012149 (1.004984, 1.019365)	Reference	0.012076	0.003624	1630
LFS O_3	Respiratory	Two-pollutant	1.010652 (1.003213, 1.018145)	0.777	0.010595	0.003769	1630

Notes: * refer to the number of communities included in the first-stage time-series analyses; *P*-values for difference tested the statistical significance of the difference between effect estimates from single- and two-pollutant models. All RR refer to cumulative relative risks of mortality during 0-2 days following exposure associated with each 10 μg/m^3 increase in daily exposure on the current day.

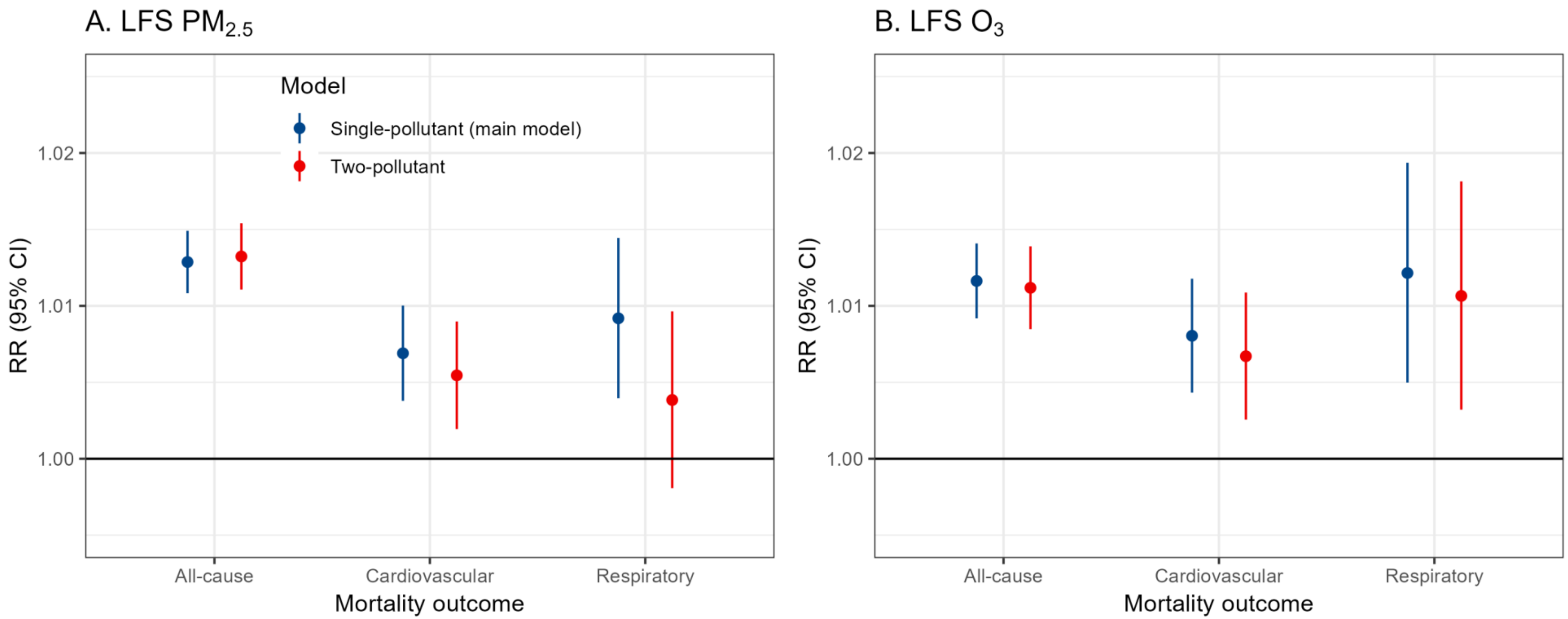

Figure S4. Comparison between single- and two-pollutant models in the short-term mortality impacts of landscape fire-sourced (LFS) $PM_{2.5}$ and O_3

Table S12. The relative risks (RR) for the long-term mortality impacts of all-source $PM_{2.5}$ and O_3 based on published meta-analyses

Exposure	Mortality outcome	RR (95% confidence interval)	Beta	Se	No. of cohort studies*
All-source $PM_{2.5}$	All-cause	1.080000 (1.060000, 1.090000)	0.076961	0.007120	25
	Cardiovascular	1.110000 (1.090000, 1.140000)	0.104360	0.011441	21
	Respiratory	1.100000 (1.030000, 1.180000)	0.095310	0.034683	17
All-source O_3	All-cause	1.008234 (1.005298, 1.011163)	0.008200	0.001484	23
	Cardiovascular	1.011163 (1.002357, 1.020497)	0.011101	0.004575	15
	Respiratory	1.014670 (1.005886, 1.023402)	0.014564	0.004404	16

* refer to the number of cohort studies included in the meta-analyses analyses; annual average O_3 refers to annual mean of daily maximum 8-hour average O_3. RR for $PM_{2.5}$ were from Chen et al,[27] and RR for O_3 were from Sun et al.[28] The RR refer to relative risks of all-cause, cardiovascular, and respiratory mortality for each 10 μg/m^3 increase in annual average $PM_{2.5}$ and O_3.

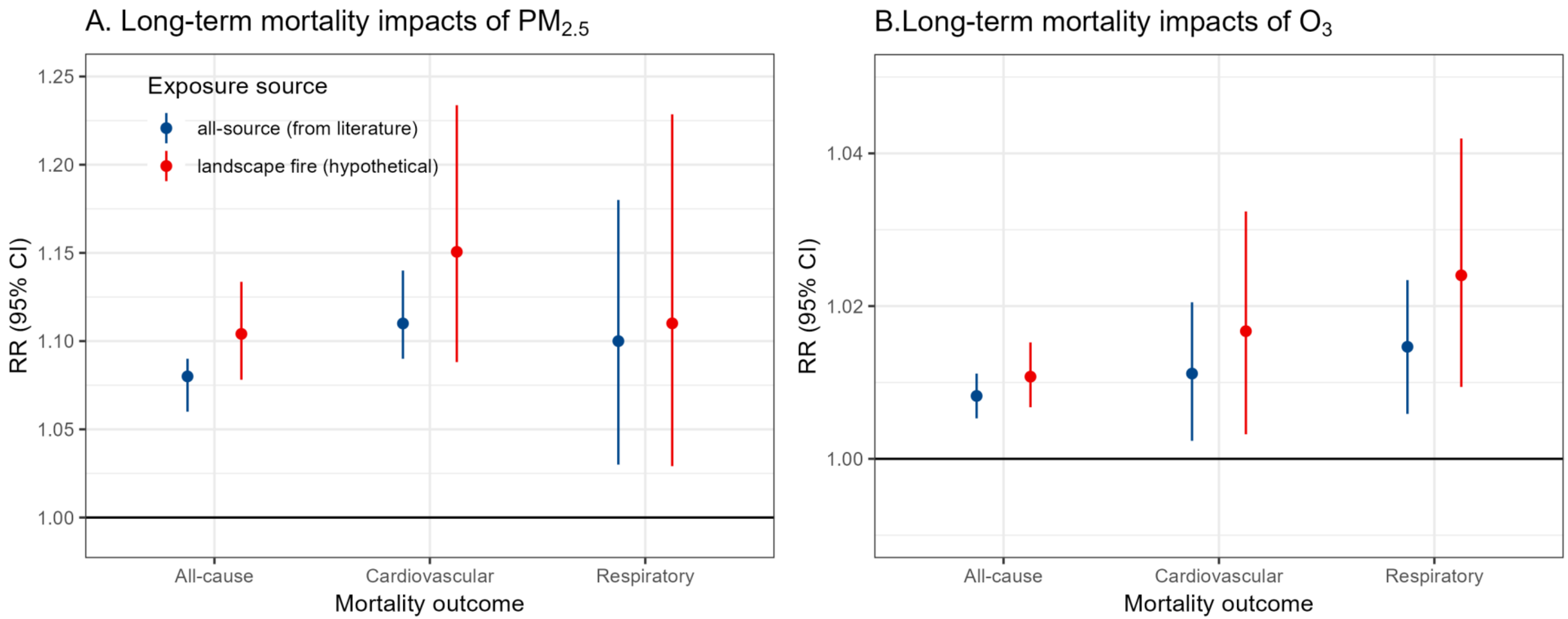

Figure S5. Hypothetical relative risks (RR) for the long-term mortality impacts of LFS $PM_{2.5}$ and O_3 compared with those for all-source $PM_{2.5}$ and O_3

Table S13. Global annual average fractions of deaths attributable to landscape fire air pollution during 2000-2019 by GBD super regions, GBD regions, World Bank income groups, and SDI levels

Subgroup	All-cause death		Cardiovascular death		Respiratory death	
	Annual AF (95% eCI), %	Change per year (%)	Annual AF (95% eCI), %	Change per year (%)	Annual AF (95% eCI), %	Change per year (%)
Global	2.90 (2.35, 3.44)	-0.55*	2.80 (2.04, 3.56)	0.26	3.48 (1.35, 5.56)	-0.22
GBD super regions and regions						
Central Europe, Eastern Europe, and Central Asia	2.00 (1.63, 2.38)	-0.56	2.50 (1.82, 3.17)	-0.53	2.41 (0.92, 3.89)	-0.52
Central Asia	2.02 (1.64, 2.40)	-0.17	2.45 (1.78, 3.11)	-0.23	2.42 (0.92, 3.90)	0.31
Central Europe	1.10 (0.89, 1.30)	0.01	1.37 (1.00, 1.75)	0.09	1.35 (0.55, 2.14)	-0.22
Eastern Europe	2.40 (1.95, 2.84)	-0.55	2.94 (2.14, 3.73)	-0.56	3.02 (1.14, 4.88)	-0.37
High-income	1.52 (1.24, 1.80)	-0.40	1.73 (1.26, 2.20)	-0.14	2.11 (0.81, 3.37)	-0.42
Australasia	2.21 (1.80, 2.61)	-0.97	2.66 (1.94, 3.39)	-0.99	2.75 (1.12, 4.36)	-0.96
High-income Asia Pacific	2.52 (2.05, 2.99)	-1.79*	3.18 (2.30, 4.04)	-1.79*	3.21 (1.16, 5.23)	-1.80*
High-income North America	0.99 (0.81, 1.17)	2.08**	1.19 (0.87, 1.51)	2.16**	1.24 (0.50, 1.98)	2.05**
Southern Latin America	9.09 (7.40, 10.75)	-2.08***	11.19 (8.18, 14.15)	-2.06***	10.93 (3.99, 17.50)	-2.29***
Western Europe	0.64 (0.53, 0.76)	0.35	0.76 (0.55, 0.96)	0.46	0.78 (0.35, 1.20)	0.38
Latin America and Caribbean	4.05 (3.29, 4.81)	-0.51	4.76 (3.47, 6.05)	-0.63	5.35 (2.13, 8.48)	-0.57
Andean Latin America	6.88 (5.54, 8.21)	0.19	8.20 (5.93, 10.47)	0.32	8.81 (3.46, 13.97)	0.02
Caribbean	1.06 (0.86, 1.26)	-1.31	1.24 (0.90, 1.59)	-1.11	1.33 (0.53, 2.13)	-1.35
Central Latin America	3.49 (2.84, 4.14)	0.71	4.09 (2.98, 5.20)	0.75	4.48 (1.87, 7.06)	0.59
Tropical Latin America	4.74 (3.86, 5.61)	-1.51*	5.78 (4.22, 7.33)	-1.50*	5.82 (2.28, 9.28)	-1.52*
North Africa and Middle East	1.58 (1.27, 1.88)	0.52	1.86 (1.35, 2.38)	0.93*	1.99 (0.74, 3.23)	0.30
South Asia	1.52 (1.23, 1.81)	0.80	1.90 (1.38, 2.43)	0.80	1.90 (0.71, 3.08)	0.84
Southeast Asia, East Asia, and Oceania	2.58 (2.09, 3.07)	0.73	2.93 (2.13, 3.73)	0.79	2.98 (1.14, 4.78)	1.16
East Asia	1.50 (1.21, 1.78)	-0.09	1.83 (1.33, 2.32)	-0.09	1.86 (0.73, 2.99)	-0.04
Oceania	4.63 (3.67, 5.57)	0.47	5.13 (3.69, 6.59)	0.76	6.22 (2.28, 10.07)	0.42
Southeast Asia	5.24 (4.24, 6.23)	1.30	6.42 (4.67, 8.16)	1.48	6.36 (2.38, 10.22)	1.06
Sub-Saharan Africa	7.27 (5.88, 8.65)	-1.02***	8.80 (6.37, 11.20)	-0.74**	8.78 (3.51, 13.85)	-0.92***
Central Sub-Saharan Africa	17.82 (14.43, 21.15)	-0.52**	21.13 (15.37, 26.78)	-0.46**	22.16 (8.60, 34.83)	-0.48**
Eastern Sub-Saharan Africa	7.32 (5.92, 8.70)	-1.01**	8.60 (6.24, 10.94)	-0.85**	8.70 (3.41, 13.80)	-0.80**

Southern Sub-Saharan Africa	5.93 (4.78, 7.07)	-2.32***	6.83 (4.97, 8.67)	-2.07**	7.36 (2.88, 11.70)	-1.78**
Western Sub-Saharan Africa	4.68 (3.78, 5.58)	-0.84**	5.63 (4.05, 7.22)	-0.80*	5.80 (2.43, 9.13)	-0.79**
World Bank income groups						
Low Income	7.04 (5.69, 8.37)	-0.90***	6.93 (5.03, 8.82)	-0.51*	8.25 (3.23, 13.07)	-0.63**
Lower Middle Income	3.03 (2.45, 3.60)	-0.02	3.32 (2.41, 4.23)	0.78	3.45 (1.33, 5.52)	-0.15
Upper Middle Income	2.43 (1.97, 2.89)	-0.37	2.68 (1.95, 3.41)	-0.60	2.89 (1.12, 4.62)	0.59
High Income	1.22 (0.99, 1.44)	0.12	1.38 (1.01, 1.76)	0.35	1.61 (0.63, 2.58)	-0.05
SDI levels						
Low SDI	5.78 (4.67, 6.88)	-1.05***	5.82 (4.21, 7.41)	-0.64**	6.92 (2.72, 10.97)	-0.71***
Low-middle SDI	2.64 (2.14, 3.14)	0.87*	3.29 (2.39, 4.18)	0.87	2.94 (1.13, 4.72)	0.73
Middle SDI	2.07 (1.67, 2.46)	-0.39	2.28 (1.66, 2.89)	-0.48	2.47 (0.95, 3.96)	0.55
High-middle SDI	1.95 (1.58, 2.31)	-0.55	2.43 (1.77, 3.08)	-0.52	2.34 (0.89, 3.76)	-0.71
High SDI	1.15 (0.94, 1.36)	0.21	1.31 (0.95, 1.67)	0.47	1.52 (0.60, 2.44)	0.11

Notes: AF, attributable fraction; SDI, socio-demographic index. CI, confidence interval. From row 3 to 28, those in bold text were GBD super regions, and those in plain text were GBD regions. * P for trend < 0.05; ** P for trend < 0.01; *** P for trend < 0.001

Table S14. Global annual average mortality rates attributable to landscape fire air pollution during 2000-2019 by GBD super regions, GBD regions, World Bank income groups, and SDI levels

Subgroup	All-cause death		Cardiovascular death		Respiratory death	
	Annual AMR (95% eCI), 1/100,000	Change per year (%)	Annual AMR (95% eCI), 1/100,000	Change per year (%)	Annual AMR (95% eCI), 1/100,000	Change per year (%)
Global	22.08 (17.88, 26.24)	-1.29***	6.43 (4.67, 8.17)	0.44	3.12 (1.21, 4.97)	-1.37***
GBD super regions and regions						
Central Europe, Eastern Europe, and Central Asia	23.96 (19.46, 28.42)	-1.33*	16.56 (12.06, 21.02)	-1.40*	1.41 (0.54, 2.26)	-1.97**
Central Asia	15.48 (12.56, 18.39)	-1.34*	9.57 (6.96, 12.15)	-1.33*	1.54 (0.58, 2.48)	-2.45***
Central Europe	12.28 (9.99, 14.56)	0.50	7.88 (5.74, 10.01)	0.19	0.79 (0.32, 1.25)	0.55
Eastern Europe	33.68 (27.35, 39.93)	-1.61*	24.04 (17.52, 30.52)	-1.58	1.70 (0.64, 2.74)	-2.55**
High-income	12.90 (10.51, 15.26)	-0.02	4.85 (3.53, 6.15)	-0.68	1.78 (0.69, 2.85)	0.53
Australasia	14.80 (12.08, 17.50)	-0.92	5.95 (4.33, 7.57)	-2.26	1.58 (0.64, 2.51)	-0.26
High-income Asia Pacific	19.89 (16.14, 23.59)	-0.17	6.71 (4.87, 8.55)	-0.86	2.90 (1.04, 4.73)	0.33
High-income North America	8.17 (6.65, 9.66)	2.27***	3.31 (2.41, 4.21)	1.37*	1.02 (0.41, 1.63)	2.72***
Southern Latin America	65.29 (53.16, 77.20)	-1.85***	23.74 (17.35, 30.01)	-2.44***	10.54 (3.85, 16.87)	-0.78*
Western Europe	5.93 (4.86, 6.99)	0.45	2.46 (1.79, 3.12)	-0.33	0.65 (0.30, 1.00)	0.98
Latin America and Caribbean	23.12 (18.79, 27.42)	0.09	6.96 (5.07, 8.84)	0.35	3.10 (1.24, 4.93)	0.19
Andean Latin America	35.21 (28.35, 42.00)	0.09	7.93 (5.73, 10.12)	1.31*	6.47 (2.54, 10.25)	-0.27
Caribbean	8.37 (6.76, 9.97)	-0.72	2.94 (2.13, 3.76)	0.09	0.90 (0.36, 1.44)	-1.10
Central Latin America	17.66 (14.36, 20.94)	1.71*	4.87 (3.54, 6.18)	2.60***	2.02 (0.84, 3.18)	1.35
Tropical Latin America	29.06 (23.69, 34.39)	-1.07	9.89 (7.22, 12.54)	-1.14	3.88 (1.52, 6.18)	-0.36
North Africa and Middle East	8.44 (6.79, 10.08)	-0.10	3.79 (2.74, 4.84)	1.18**	0.88 (0.33, 1.43)	-1.37***
South Asia	10.87 (8.80, 12.93)	-0.41	3.07 (2.23, 3.91)	2.01***	2.11 (0.79, 3.42)	-0.08
Southeast Asia, East Asia, and Oceania	17.59 (14.22, 20.93)	1.04	7.36 (5.35, 9.35)	2.50**	2.77 (1.06, 4.45)	-0.54
East Asia	10.44 (8.45, 12.43)	0.40	5.00 (3.64, 6.37)	1.75*	1.88 (0.73, 3.02)	-2.03*
Oceania	35.31 (28.04, 42.53)	0.17	9.23 (6.63, 11.84)	1.29**	8.62 (3.16, 13.95)	-0.54
Southeast Asia	33.75 (27.29, 40.15)	1.18	12.75 (9.28, 16.19)	2.89**	4.73 (1.77, 7.61)	0.52
Sub-Saharan Africa	71.50 (57.81, 85.01)	-4.48***	8.67 (6.28, 11.04)	-1.61***	9.62 (3.84, 15.18)	-4.26***
Central Sub-Saharan Africa	171.78 (139.06, 203.90)	-4.35***	22.44 (16.32, 28.45)	-1.36***	23.63 (9.17, 37.14)	-4.65***
Eastern Sub-Saharan Africa	65.51 (52.98, 77.87)	-5.03***	7.58 (5.49, 9.64)	-1.30***	8.13 (3.19, 12.89)	-4.53***

Southern Sub-Saharan Africa	74.12 (59.78, 88.33)	-4.92***	10.57 (7.69, 13.42)	-2.40***	8.14 (3.19, 12.93)	-3.52***
Western Sub-Saharan Africa	47.63 (38.47, 56.71)	-3.89***	5.33 (3.83, 6.83)	-1.99***	7.26 (3.04, 11.43)	-3.98***
World Bank income groups						
Low Income	63.98 (51.71, 76.08)	-3.97***	8.47 (6.14, 10.77)	-0.89***	8.83 (3.46, 13.99)	-3.70***
Lower Middle Income	22.51 (18.20, 26.77)	-1.38***	6.11 (4.43, 7.77)	1.40**	3.39 (1.31, 5.42)	-1.48***
Upper Middle Income	17.28 (14.01, 20.53)	-0.34	7.41 (5.39, 9.41)	0.04	2.34 (0.91, 3.75)	-0.85
High Income	10.28 (8.37, 12.16)	0.41	3.96 (2.88, 5.03)	-0.24	1.27 (0.50, 2.03)	0.82
SDI levels						
Low SDI	50.22 (40.58, 59.74)	-3.96***	7.30 (5.29, 9.30)	-1.03***	7.17 (2.82, 11.37)	-3.88***
Low-middle SDI	17.25 (13.98, 20.50)	0.33	5.81 (4.23, 7.39)	2.05***	2.56 (0.98, 4.10)	0.32
Middle SDI	14.43 (11.68, 17.16)	-0.06	5.98 (4.35, 7.61)	1.03	2.32 (0.90, 3.72)	-1.16*
High-middle SDI	21.66 (17.60, 25.67)	-1.20*	13.71 (9.99, 17.40)	-1.53*	1.42 (0.54, 2.28)	-1.19**
High SDI	9.68 (7.89, 11.45)	0.60	3.60 (2.62, 4.58)	-0.11	1.27 (0.50, 2.03)	1.04

Notes: AMR, attributable mortality rate; SDI, socio-demographic index. CI, confidence interval. From row 3 to 28, those in bold text were GBD super regions, and those in plain text were GBD regions. * P for trend < 0.05; ** P for trend < 0.01; *** P for trend < 0.001

Table S15. Annual average attributable deaths (AD) by different types of landscape fire air pollutant and the short- or long-term mortality impacts

	Annual AD (95% eCI)	Proportion(%)
All-cause AD		
long O_3	110295 (71250, 148995)	7.2
long $PM_{2.5}$	1015289 (834516, 1193389)	66.2
short O_3	232943 (191403, 274541)	15.2
short $PM_{2.5}$	174012 (143662, 204400)	11.4
Cardiovascular AD		
long O_3	36044 (6951, 64819)	8.1
long $PM_{2.5}$	332322 (262147, 401362)	74.5
short O_3	47833 (35096, 60973)	10.7
short $PM_{2.5}$	29894 (20056, 40071)	6.7
Respiratory AD		
long O_3	22229 (9081, 35221)	10.3
long $PM_{2.5}$	142313 (41612, 238748)	65.8
short O_3	33998 (22989, 45627)	15.7
short $PM_{2.5}$	17777 (10399, 25654)	8.2

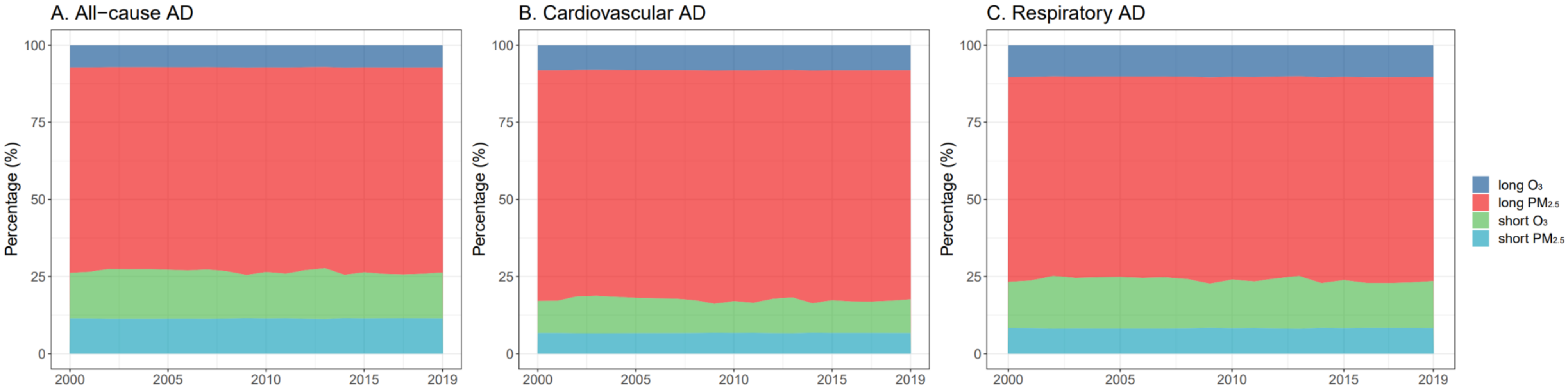

Figure S6. Annual global attributable deaths (AD) by different types of landscape fire air pollutant and the short- or long-term mortality impacts from 2000 to 2019.

Table S16. The long-term trends of global and regional AD estimates and their contributors from 2000 to 2019

	Percentage change per year, %				
Cause/Region	AD	Population	Mortality rate	LFS $PM_{2.5}$	LFS O_3
All-cause death					
Global	-0.08	1.22***	-0.74***	0.43*	0.03
GBD super regions					
High-income	0.59*	0.61***	0.38***	-0.42	-0.58
Central Europe, Eastern Europe, and Central Asia	-1.28**	0.05**	-0.77***	0.24	-0.83
Latin America and Caribbean	1.31***	1.22***	0.60***	-0.32	-0.60
North Africa and Middle East	1.77***	1.87***	-0.62***	1.29*	-0.73
South Asia	1.23	1.65***	-1.20***	0.40	-0.60
Southeast Asia, East Asia, and Oceania	1.70**	0.66***	0.30***	1.24*	-0.45
Sub-Saharan Africa	-1.88***	2.72***	-3.50***	-0.93***	-0.61***
Cardiovascular death					
Global	1.67***	1.22***	0.18***	0.43*	0.03
GBD super regions					
High-income	-0.07	0.61***	-0.55***	-0.42	-0.58
Central Europe, Eastern Europe, and Central Asia	-1.36**	0.05**	-0.88***	0.24	-0.83
Latin America and Caribbean	1.57***	1.22***	0.99***	-0.32	-0.60
North Africa and Middle East	3.07***	1.87***	0.24***	1.29*	-0.73
South Asia	3.70***	1.65***	1.20***	0.40	-0.60
Southeast Asia, East Asia, and Oceania	3.17***	0.66***	1.69***	1.24*	-0.45
Sub-Saharan Africa	1.07***	2.72***	-0.87***	-0.93***	-0.61***
Respiratory death					
Global	-0.17	1.22***	-1.16***	0.43*	0.03
GBD super regions					
High-income	1.15***	0.61***	0.96***	-0.42	-0.58
Central Europe, Eastern Europe, and Central Asia	-1.92***	0.05**	-1.45***	0.24	-0.83

Latin America and Caribbean	1.41***	1.22***	0.76***	-0.32	-0.60
North Africa and Middle East	0.48	1.87***	-1.66***	1.29*	-0.73
South Asia	1.57**	1.65***	-0.91***	0.40	-0.60
Southeast Asia, East Asia, and Oceania	0.12	0.66***	-1.67***	1.24*	-0.45
Sub-Saharan Africa	-1.65***	2.72***	-3.36***	-0.93***	-0.61***

Notes: AD, attributable deaths. CI, confidence interval. Trends for AD and its four contributors (population, mortality rates, LFS $PM_{2.5}$, and LFS O_3) were calculated using linear regression, with log-transformed annual metrics as the dependent variable and year as the predictor. * *P* for trend < 0.10, ** *P* for trend < 0.05, *** *P* for trend < 0.01

Table S17. The percentage change of global and regional AD estimates and their contributors from 2013 to 2014

Cause/Region	Percentage change (2014 versus 2013), %				
	AD	Population	Mortality rate	LFS $PM_{2.5}$	LFS O_3
All-cause death					
Global	24.07	1.16	-0.52	30.18	6.45
GBD super regions					
High-income	9.26	0.53	0.47	17.05	16.73
Central Europe, Eastern Europe, and Central Asia	55.36	0.21	0.08	35.43	14.95
Latin America and Caribbean	4.08	1.16	0.53	-1.78	1.63
North Africa and Middle East	34.60	1.62	1.60	39.69	-1.82
South Asia	40.15	1.49	-1.59	46.21	5.30
Southeast Asia, East Asia, and Oceania	69.88	0.61	0.40	49.99	23.18
Sub-Saharan Africa	-4.02	2.65	-3.12	-1.55	-8.38
Cardiovascular death					
Global	39.85	1.16	0.21	30.18	6.45
GBD super regions					
High-income	6.69	0.53	-0.13	17.05	16.73
Central Europe, Eastern Europe, and Central Asia	56.73	0.21	-0.64	35.43	14.95
Latin America and Caribbean	7.05	1.16	1.11	-1.78	1.63
North Africa and Middle East	34.62	1.62	0.71	39.69	-1.82
South Asia	44.16	1.49	0.46	46.21	5.30
Southeast Asia, East Asia, and Oceania	73.23	0.61	1.34	49.99	23.18
Sub-Saharan Africa	-1.10	2.65	-0.52	-1.55	-8.38
Respiratory death					
Global	23.35	1.16	-0.57	30.18	6.45
GBD super regions					
High-income	9.31	0.53	0.86	17.05	16.73
Central Europe, Eastern Europe, and Central Asia	49.43	0.21	0.48	35.43	14.95

Latin America and Caribbean	5.62	1.16	0.87	-1.78	1.63
North Africa and Middle East	31.08	1.62	-0.89	39.69	-1.82
South Asia	43.40	1.49	0.04	46.21	5.30
Southeast Asia, East Asia, and Oceania	62.39	0.61	-1.39	49.99	23.18
Sub-Saharan Africa	-3.81	2.65	-2.65	-1.55	-8.38

Notes: AD, attributable deaths.

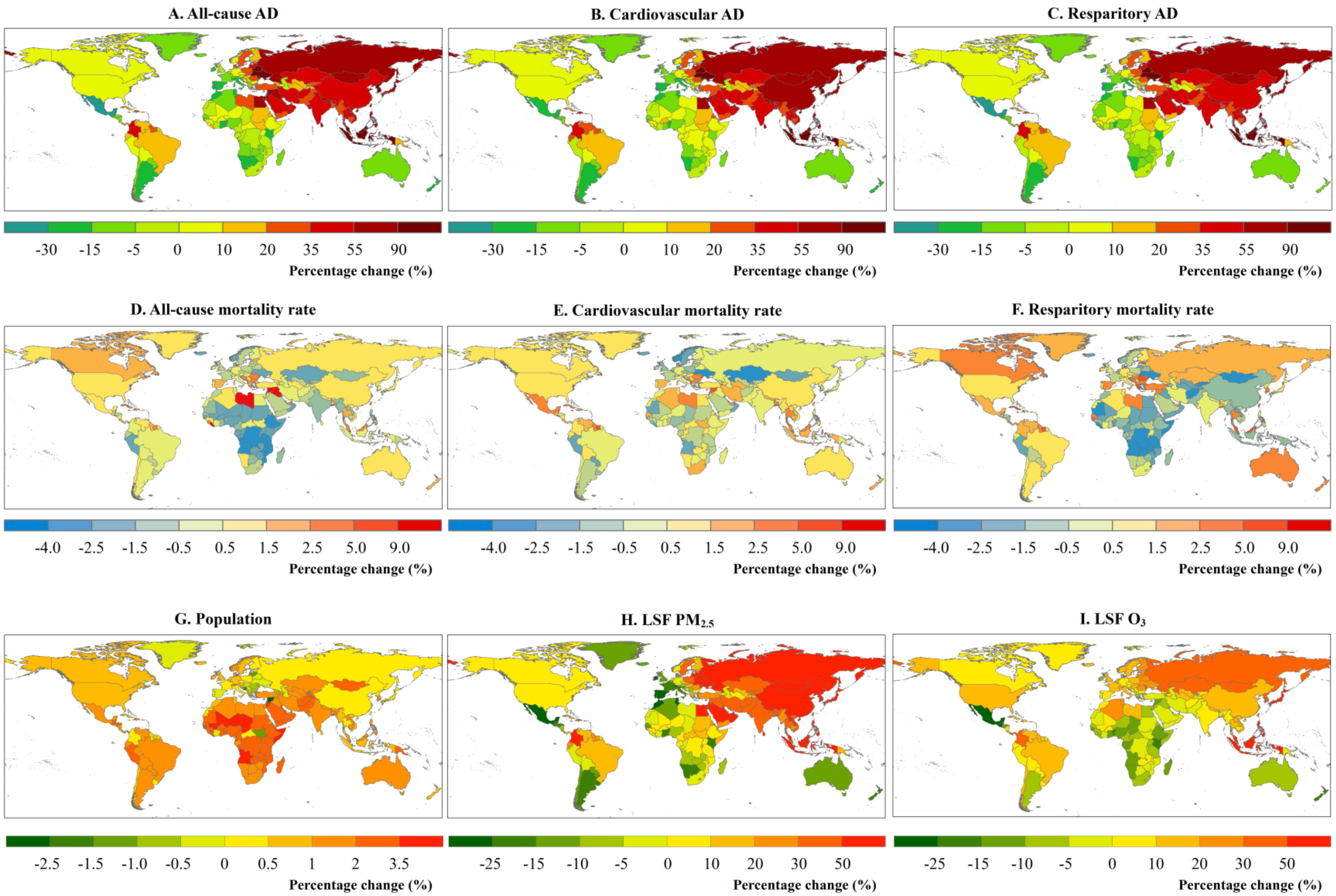

Figure S7. The percentage change of AD estimates and their contributors from 2013 to 2014 across 201 countries and territories.

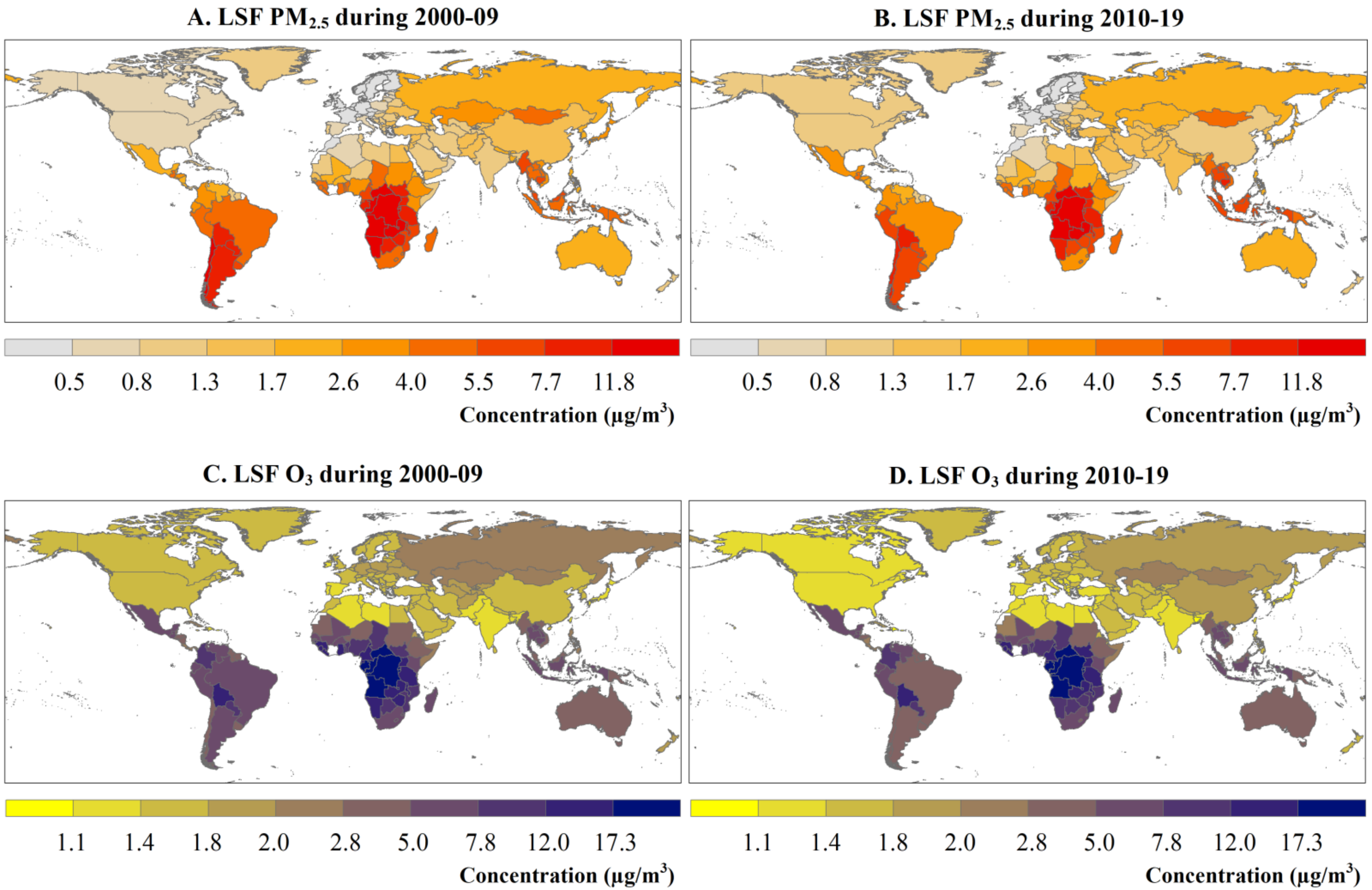

Figure S8. Population-weighted average LFS $PM_{2.5}$ and O_3 concentrations across 201 countries and territories.

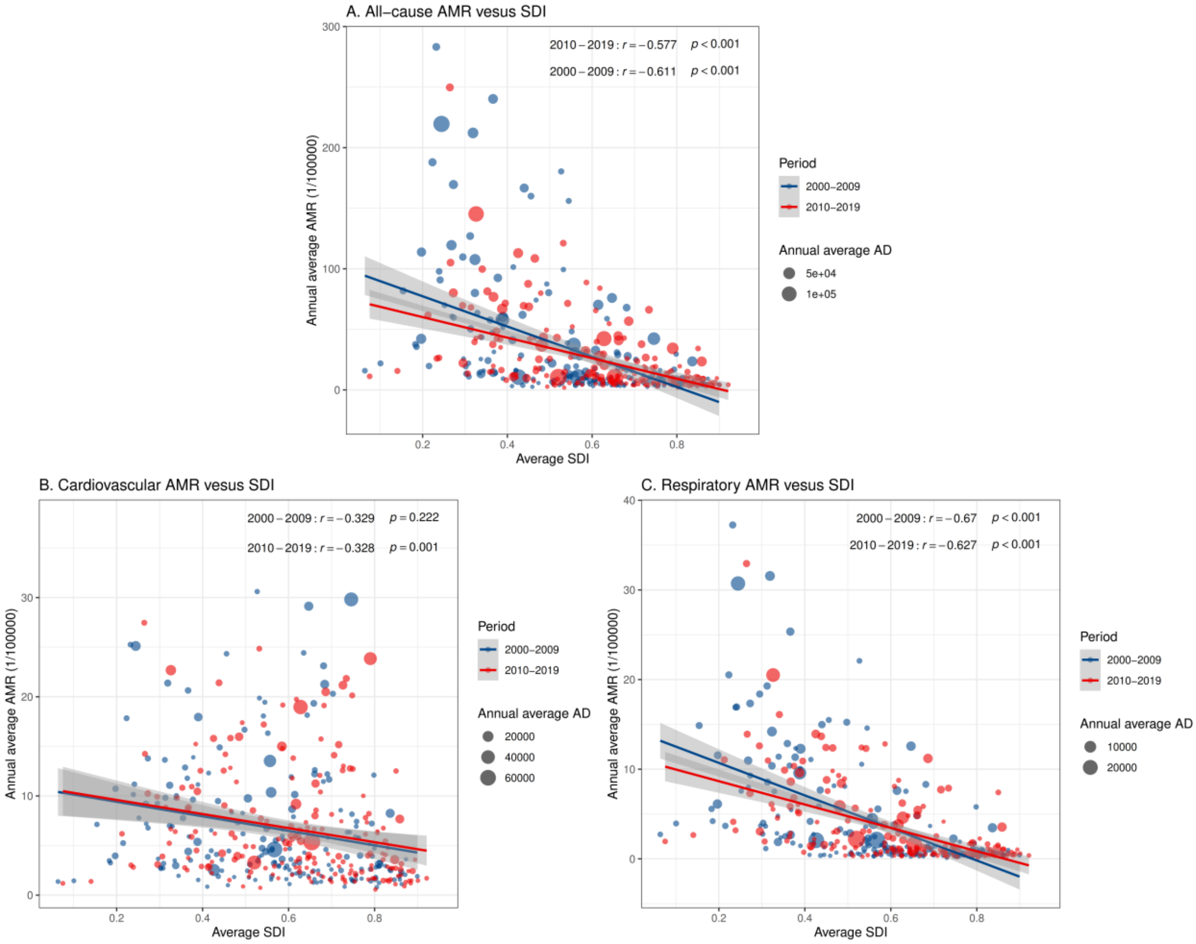

Figure S9. Associations of country- or territory-level attributable mortality rates (AMR) with socio-demographic index (SDI) by period.

Notes: each dot represents one country or territory. r refers to Spearman correlation coefficient.

Low income | Lower middle income | Upper middle income | High income

A. Annual attributables deaths (AD)

Leading countries 2000-09	AD (95% eCI)	Leading countries 2010-19	AD (95% eCI)	Change per year (%)
1 China	61269 (44589, 77924)	1 China	74834 (54360, 95281)	2.3*
2 Russian Federation	43817 (31935, 55591)	2 Indonesia	47533 (34613, 60300)	4.6**
3 Indonesia	30576 (22289, 38800)	3 India	43132 (31323, 54906)	4.2***
4 India	28381 (20640, 36112)	4 Russian Federation	34833 (25364, 44225)	-2.5**
5 Brazil	19195 (14014, 24319)	5 Brazil	19086 (13927, 24207)	0.0
6 Democratic Republic of the Congo	14688 (10717, 18559)	6 Democratic Republic of the Congo	17678 (12847, 22430)	1.7***
7 Argentina	11265 (8236, 14233)	7 Viet Nam	13965 (10142, 17751)	5.2***
8 Japan	10699 (7765, 13614)	8 United States of America	11430 (8317, 14545)	2.2**
9 Ukraine	10206 (7443, 12949)	9 Japan	9910 (7170, 12634)	-0.7
10 United States of America	9160 (6679, 11644)	10 Ukraine	9584 (6975, 12178)	0.6
12 Viet Nam	8243 (5990, 10483)	11 Argentina	8850 (6459, 11206)	-2.1***

B. Annual attributable fractions (AF), %

Leading countries 2000-09	AF (95% eCI)	Leading countries 2010-19	AF (95% eCI)	Change per year (%)
1 Angola	22.25 (16.24, 28.11)	1 Democratic Republic of the Congo	21.91 (15.92, 27.80)	-0.3
2 Democratic Republic of the Congo	22.23 (16.22, 28.09)	2 Central African Republic	20.37 (14.63, 26.09)	0.5
3 Zambia	20.71 (15.13, 26.14)	3 Congo	18.92 (13.67, 24.13)	0.5*
4 Central African Republic	19.04 (13.68, 24.39)	4 Angola	18.57 (13.51, 23.55)	-1.7***
5 Namibia	18.15 (13.23, 22.96)	5 Zambia	16.14 (11.73, 20.48)	-2.3***
6 Congo	17.71 (12.84, 22.53)	6 Burundi	15.44 (11.15, 19.72)	-0.8**
7 Burundi	16.35 (11.86, 20.79)	7 Rwanda	14.51 (10.51, 18.49)	-0.7
8 Chile	15.66 (11.47, 19.76)	8 Chile	13.98 (10.22, 17.66)	-0.9**
9 Rwanda	15.10 (10.96, 19.19)	9 South Sudan	13.74 (9.85, 17.63)	0.6
10 Bolivia (Plurinational State of)	14.53 (10.51, 18.52)	10 Gabon	13.61 (9.85, 17.36)	0.7*
14 South Sudan	12.81 (9.22, 16.41)	11 Bolivia (Plurinational State of)	13.44 (9.68, 17.19)	-0.7
16 Gabon	12.45 (9.01, 15.87)	14 Namibia	12.60 (9.14, 16.03)	-3.7***

C. Annual attributable mortality rates (AMR), 1/100000

Leading countries 2000-09	AMR (95% eCI)	Leading countries 2010-19	AMR (95% eCI)	Change per year (%)
1 Namibia	30.60 (22.30, 38.71)	1 Central African Republic	27.46 (19.72, 35.17)	0.6
2 Russian Federation	29.81 (21.73, 37.82)	2 Congo	24.84 (17.95, 31.70)	0.0
3 Argentina	29.13 (21.30, 36.80)	3 Russian Federation	23.84 (17.36, 30.27)	-2.4**
4 Central African Republic	25.26 (18.15, 32.36)	4 Democratic Republic of the Congo	22.67 (16.48, 28.77)	-1.2***
5 Democratic Republic of the Congo	25.12 (18.33, 31.74)	5 Chile	21.84 (15.96, 27.58)	-0.4
6 Uruguay	24.42 (17.82, 30.94)	6 Cambodia	21.40 (15.59, 27.11)	4.5***
7 Congo	24.33 (17.65, 30.96)	7 Ukraine	21.16 (15.40, 26.89)	1.2
8 Chile	23.12 (16.92, 29.16)	8 Argentina	20.49 (14.96, 25.95)	-3.1***
9 Angola	21.38 (15.60, 27.00)	9 Bulgaria	20.14 (14.63, 25.61)	-0.2
10 Ukraine	21.26 (15.50, 26.97)	10 Gabon	19.74 (14.29, 25.18)	-0.2
12 Bulgaria	20.30 (14.80, 25.77)	11 Namibia	19.16 (13.90, 24.37)	-4.7***
13 Gabon	19.86 (14.38, 25.32)	18 Angola	15.80 (11.49, 20.03)	-2.9***
27 Cambodia	12.87 (9.37, 16.32)	19 Uruguay	15.74 (11.46, 19.99)	-3.9***

Figure S10. Top 10 countries or territories with greatest total cardiovascular deaths, fractions of cardiovascular deaths, and cardiovascular mortality rates attributable to landscape fire air pollution during the first and second decades of 2000-2019.

Notes: * indicates the P for long-term trend < 0.05; ** P <0.01; *** P<0.001.

Low income | Lower middle income | Upper middle income | High income

A. Annual attributables deaths (AD)

Leading countries 2000-09	AD (95% eCI)	Leading countries 2010-19	AD (95% eCI)	Change per year (%)
1 China	27870 (10903, 44701)	1 India	28716 (10737, 46517)	2.2**
2 India	23270 (8907, 37524)	2 China	22952 (8978, 36805)	-1.7*
3 Democratic Republic of the Congo	17961 (6963, 28220)	3 Democratic Republic of the Congo	15986 (6191, 25136)	-1.4***
4 Nigeria	13589 (5758, 21325)	4 Indonesia	11512 (4342, 18402)	1.5
5 Indonesia	10079 (3883, 16090)	5 Nigeria	11176 (4737, 17549)	-1.9***
6 Brazil	7271 (2842, 11577)	6 Brazil	7940 (3106, 12669)	0.9
7 Myanmar	5940 (2187, 9586)	7 United Republic of Tanzania	4854 (1931, 7671)	-1.4**
8 Angola	5585 (2151, 8771)	8 Argentina	4837 (1773, 7771)	0.3
9 United Republic of Tanzania	5508 (2184, 8693)	9 Japan	4583 (1644, 7476)	0.1
10 Argentina	4863 (1788, 7764)	10 Myanmar	4436 (1625, 7166)	-2.2*
12 Japan	4500 (1602, 7342)	13 Angola	3609 (1430, 5648)	-4.2***

B. Annual attributable fractions (AF), %

Leading countries 2000-09	AF (95% eCI)	Leading countries 2010-19	AF (95% eCI)	Change per year (%)
1 Democratic Republic of the Congo	23.04 (8.93, 36.21)	1 Democratic Republic of the Congo	22.72 (8.80, 35.73)	-0.3
2 Angola	22.93 (8.83, 36.01)	2 Central African Republic	20.96 (8.00, 33.14)	0.5
3 Zambia	21.12 (8.19, 33.02)	3 Congo	19.75 (8.03, 30.84)	0.5*
4 Central African Republic	19.70 (7.51, 31.21)	4 Angola	19.42 (7.69, 30.39)	-1.7***
5 Congo	18.53 (7.50, 29.05)	5 Zambia	16.99 (6.66, 26.66)	-2.3***
6 Namibia	18.44 (6.96, 29.14)	6 Burundi	16.13 (6.30, 25.57)	-0.8**
7 Burundi	16.98 (6.63, 26.86)	7 Rwanda	15.20 (6.18, 23.83)	-0.7
8 Rwanda	15.80 (6.38, 24.78)	8 Gabon	14.23 (5.81, 22.35)	0.6*
9 Chile	15.57 (5.57, 24.83)	9 South Sudan	14.01 (5.28, 22.39)	0.6
10 Bolivia (Plurinational State of)	14.88 (5.86, 23.37)	10 Chile	13.87 (4.94, 22.22)	-0.9**
14 South Sudan	13.12 (4.93, 21.00)	11 Bolivia (Plurinational State of)	13.84 (5.42, 21.82)	-0.7
15 Gabon	13.09 (5.44, 20.50)	13 Namibia	13.03 (4.97, 20.73)	-3.7***

C. Annual attributable mortality rates (AMR), 1/100000

Leading countries 2000-09	AMR (95% eCI)	Leading countries 2010-19	AMR (95% eCI)	Change per year (%)
1 Central African Republic	37.24 (14.19, 59.00)	1 Central African Republic	32.94 (12.57, 52.08)	-1.4***
2 Angola	31.56 (12.15, 49.56)	2 Democratic Republic of the Congo	20.50 (7.94, 32.24)	-4.2***
3 Democratic Republic of the Congo	30.72 (11.91, 48.26)	3 South Sudan	16.10 (6.06, 25.73)	-1.5**
4 Zambia	25.35 (9.83, 39.63)	4 Angola	13.93 (5.52, 21.80)	-7.8***
5 Namibia	22.09 (8.34, 34.91)	5 Burundi	13.91 (5.43, 22.05)	-4.2***
6 Burundi	20.52 (8.02, 32.47)	6 Cambodia	13.67 (5.11, 21.74)	0.1
7 Rwanda	19.28 (7.79, 30.25)	7 Namibia	12.82 (4.89, 20.40)	-5.5***
8 South Sudan	18.38 (6.91, 29.43)	8 Guinea	12.60 (5.29, 19.82)	-3.0***
9 Malawi	17.33 (6.80, 27.34)	9 Congo	12.42 (5.05, 19.40)	-2.3***
10 Guinea	16.94 (7.14, 26.59)	10 Zimbabwe	12.42 (4.90, 19.65)	-1.8*
12 Congo	15.49 (6.27, 24.28)	11 Zambia	12.37 (4.85, 19.41)	-7.0***
14 Zimbabwe	14.97 (5.83, 23.65)	16 Rwanda	10.91 (4.44, 17.11)	-5.6***

Figure S11. Top 10 countries or territories with greatest total respiratory deaths, fractions of respiratory deaths, and respiratory mortality rates attributable to landscape fire air pollution during the first and second decades of 2000-2019.

Notes: * indicates the P for long-term trend < 0.05; ** P <0.01; *** P<0.001.

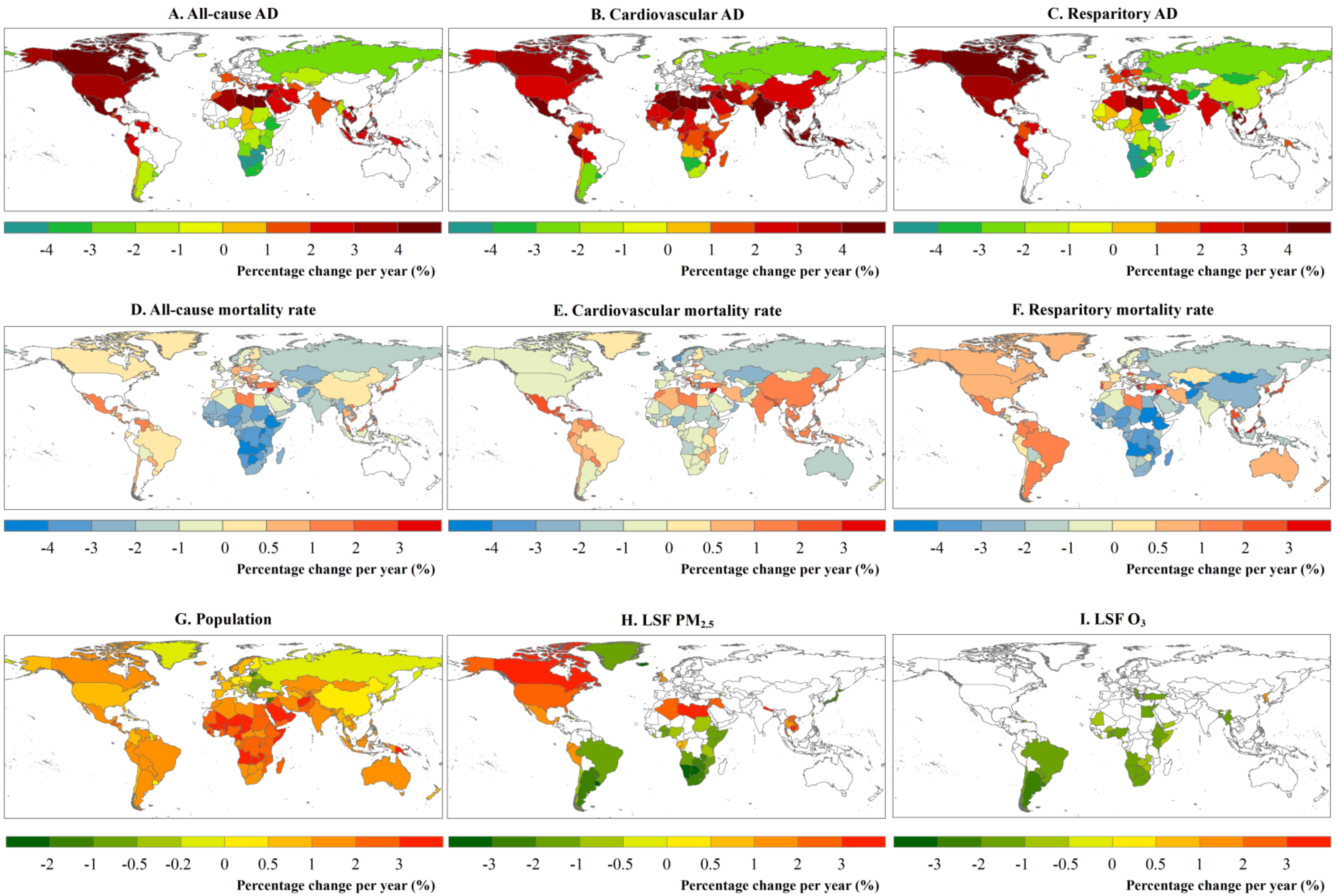

Figure S12. The long-term trends of AD estimates and their contributors from 2000 to 2019 across 201 countries and territories. Notes: those in white color refer to *p*-values for trends > 0.10, i.e., the long trends did not even reach borderline statistical significance.

Table S18. Sensitivity analyses of global annual average all-cause, cardiovascular and respiratory deaths attributable to landscape fire air pollution compared with our main analyses

	All-cause death		**Cardiovascular death**		**Respiratory death**	
Analyses	Annual global AD (95%eCI)	Change per year (%)	Annual global AD (95%eCI)	Change per year (%)	Annual global AD (95%eCI)	Change per year (%)
Main analyses	1532539 (1240831, 1821325)	-0.08	446093 (324250, 567225)	1.67***	216317 (84081, 345250)	-0.17
Sensitivity analysis 1	1505650 (1194950, 1814633)	-0.07	412874 (283506, 541392)	1.69***	192299 (51929, 329400)	-0.14
Sensitivity analysis 2	1443427 (1140421, 1744983)	-0.07	427921 (306147, 548971)	1.67***	212384 (79394, 342164)	-0.17
Sensitivity analysis 3	1848997 (1398627, 2292254)	-0.06	574972 (310699, 833156)	1.68***	243460 (69701, 411050)	-0.16

Notes: AD, attributable deaths; * *P* for trend < 0.05; ** *P* for trend < 0.01; *** *P* for trend < 0.001

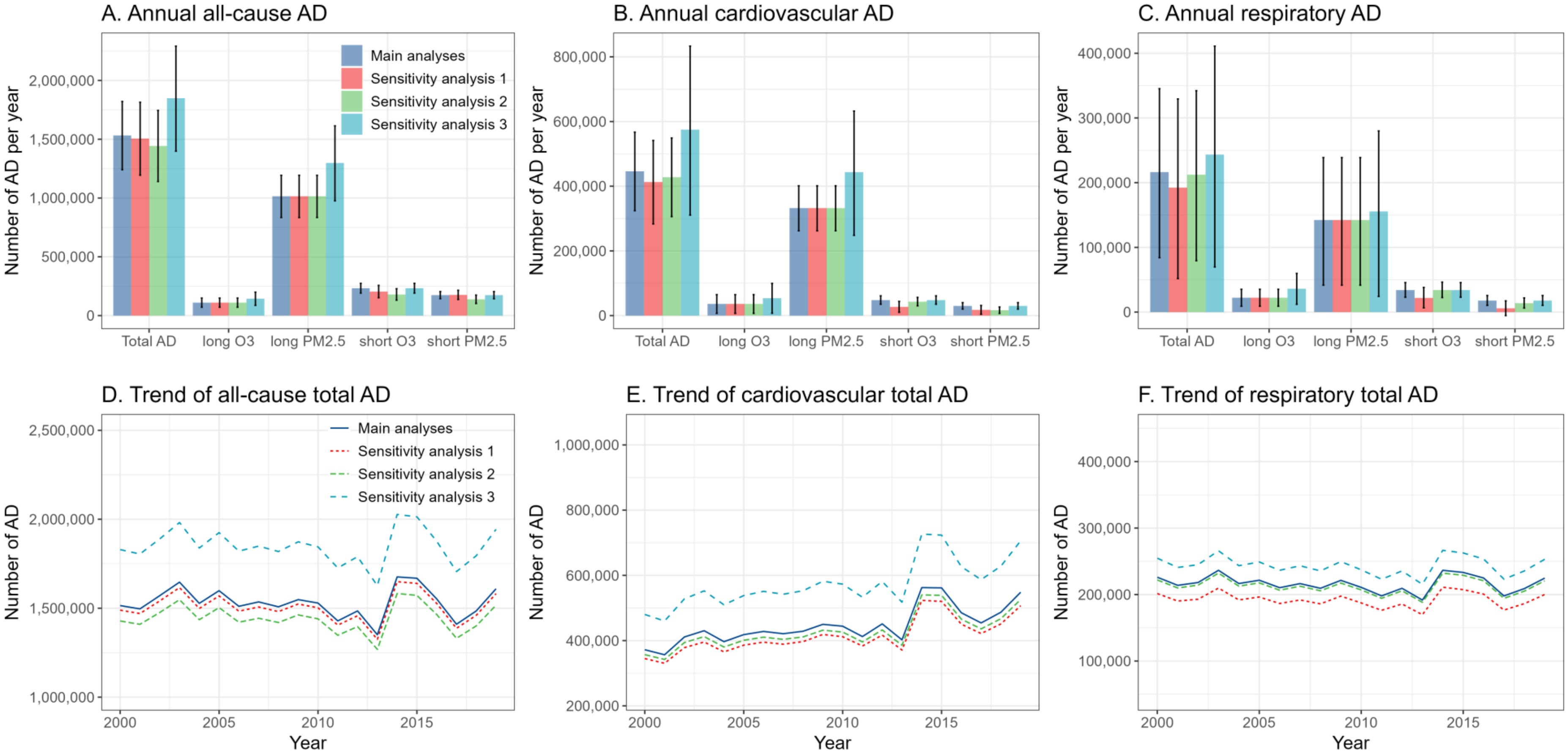

Figure S13. Sensitivity analyses of global annual average total deaths attributable to landscape fire air pollution compared with our main analyses, by cause, type and year

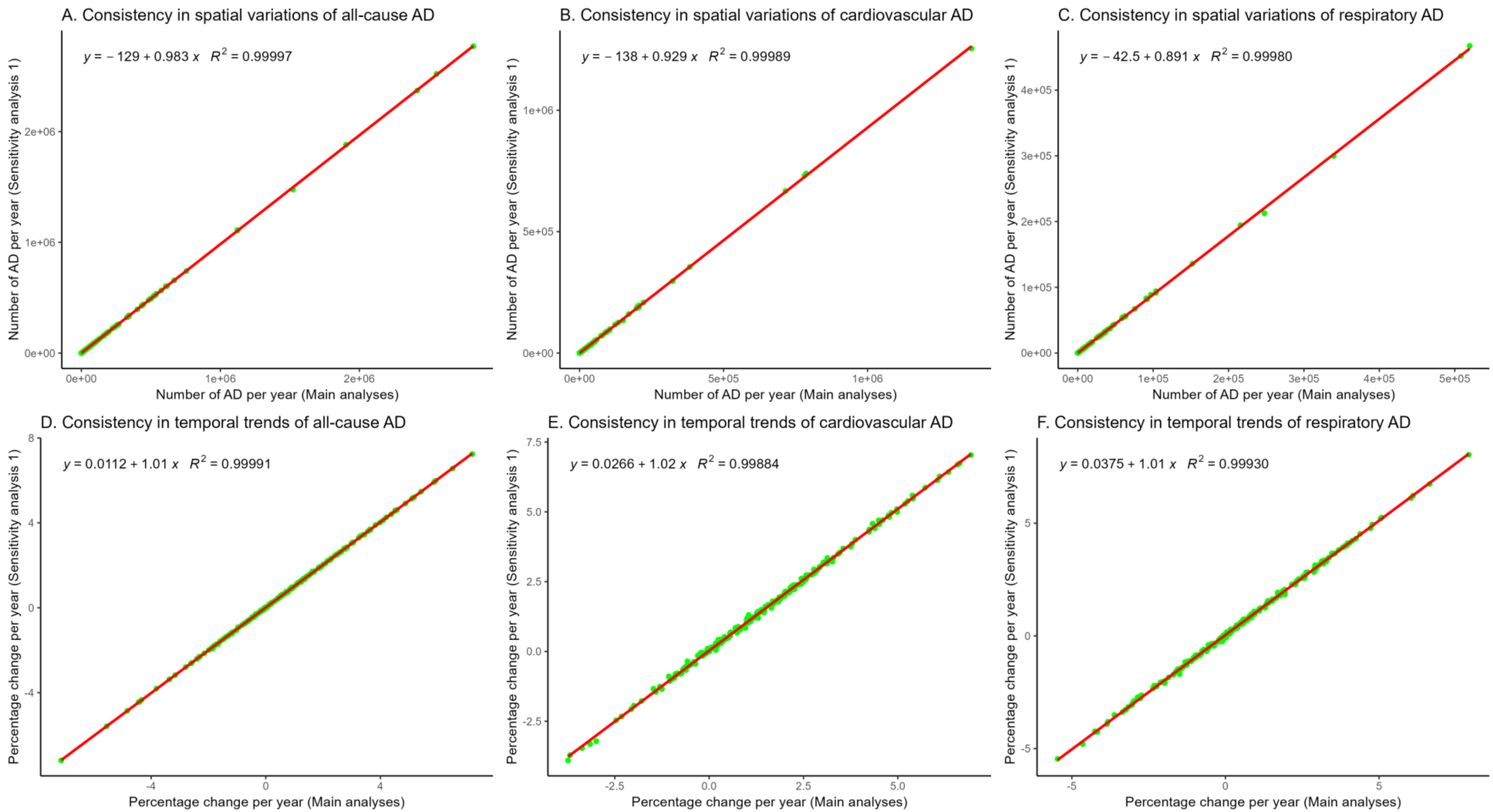

Figure S14. Consistency between sensitivity analysis 1 and main analyses in the spatial variations and temporal trends of attributable deaths (AD).

Notes: each green dot represents one country or territory.

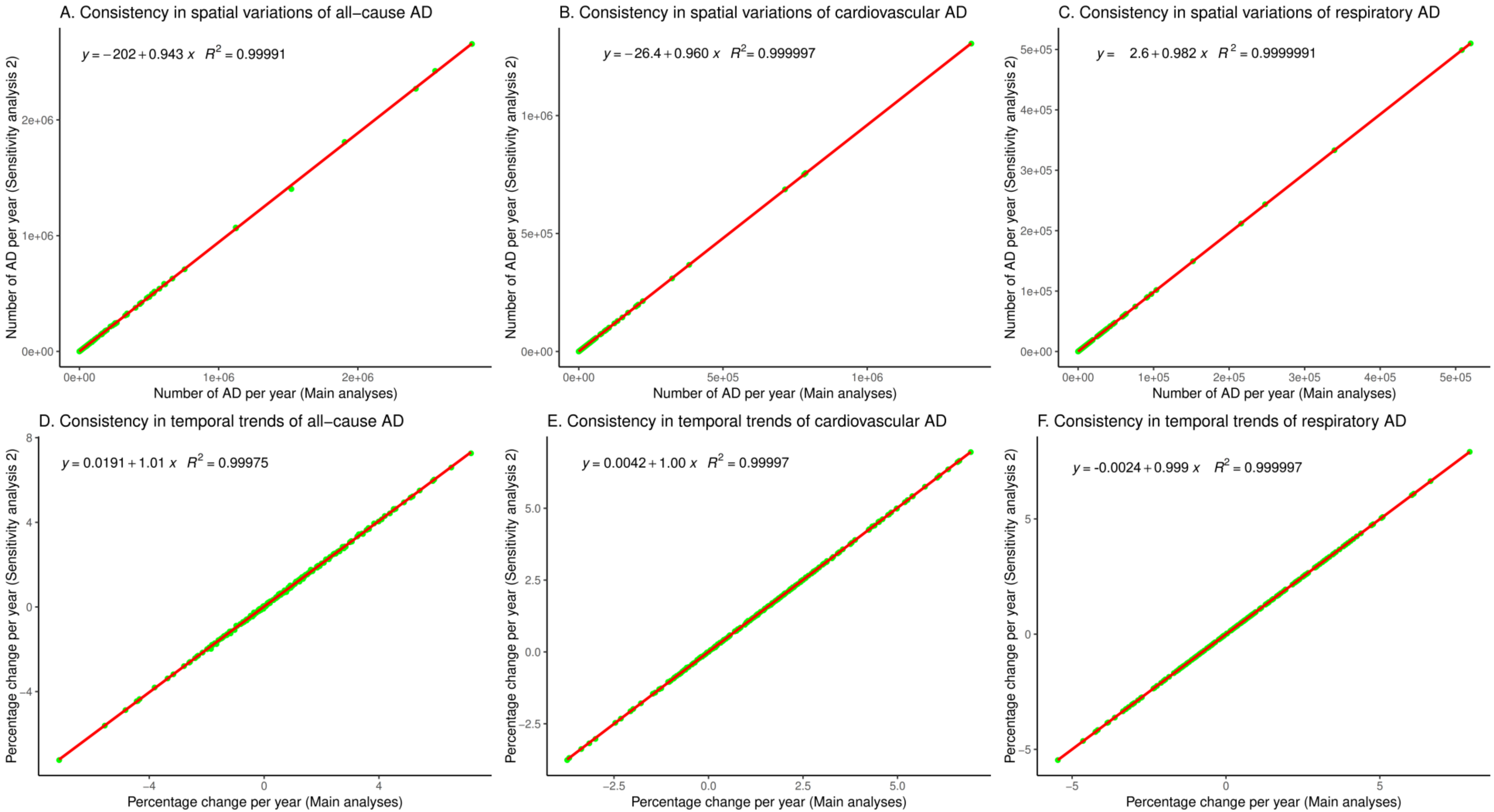

Figure S15. Consistency between sensitivity analysis 2 and main analyses in the spatial variations and temporal trends of attributable deaths (AD).

Notes: each green dot represents one country or territory.

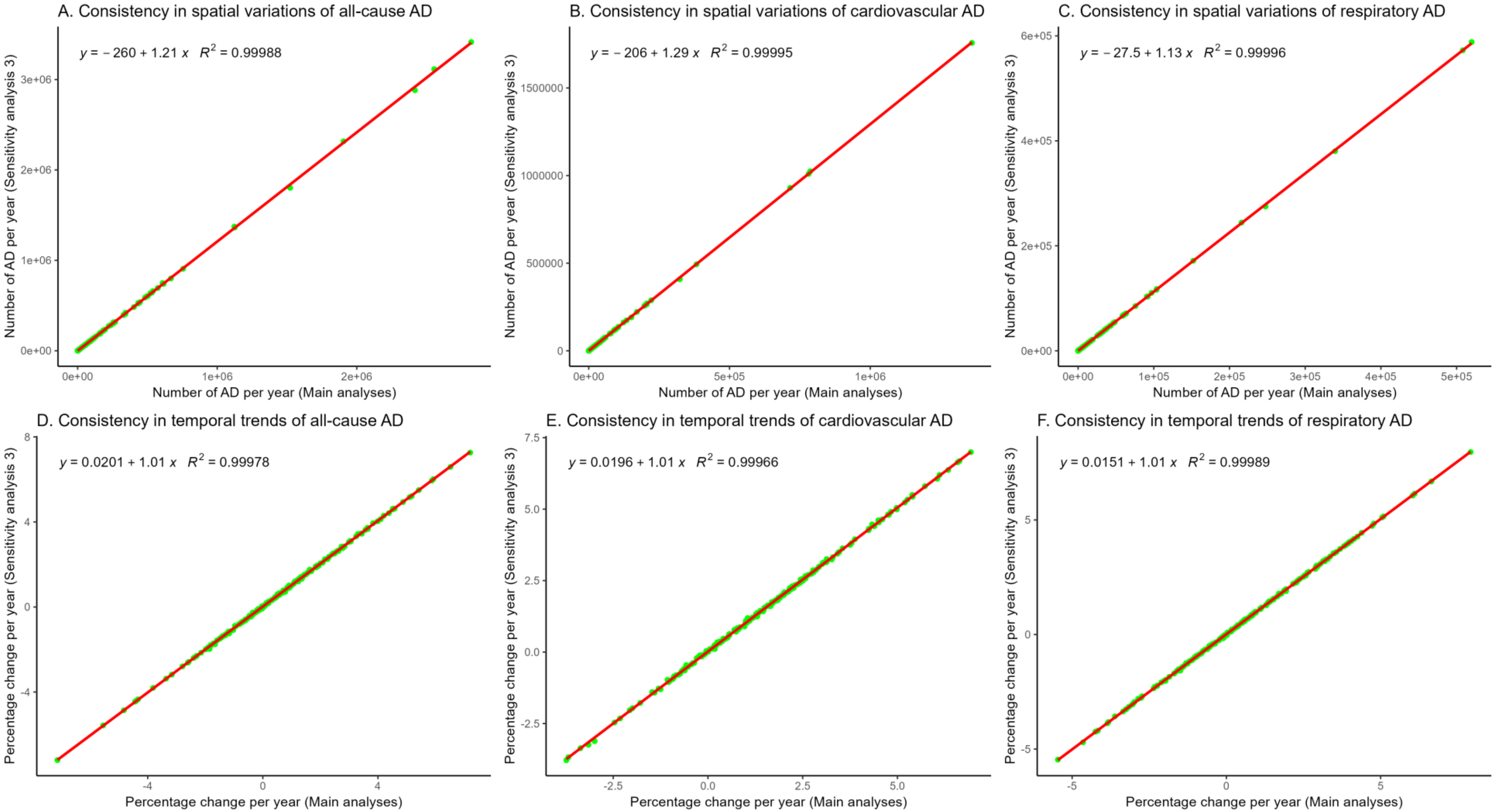

Figure S16. Consistency between sensitivity analysis 3 and main analyses in the spatial variations and temporal trends of attributable deaths (AD).

Notes: each green dot represents one country or territory.

Table S19. Comparing the estimated short-term attributable deaths based on community-specific average daily deaths for each year and actual daily deaths in 2267 communities.

Exposure	Mortality outcome	Total short-term attributable deaths (95% CI)		Percentage difference compared with benchmark (%)	Included communities	
		Our approach	Benchmark approach		No. of Communities*	Total daily deaths
LFS $PM_{2.5}$	All-cause	268160 (230069, 306181)	270562 (232134, 308917)	-0.89	2267	82542973
	Cardiovascular	46067 (31611, 60483)	46564 (31953, 61133)	-1.07	2085	20807151
	Respiratory	26188 (16387, 35945)	27032 (16917, 37100)	-3.12	1922	8498909
LFS O_3	All-cause	320651 (271450, 369756)	320753 (271538, 369870)	-0.03	2267	82542973
	Cardiovascular	72502 (54855, 90101)	72671 (54983, 90309)	-0.23	2085	20807151
	Respiratory	43469 (31612, 55272)	43854 (31893, 55758)	-0.88	1922	8498909
Both LFS $PM_{2.5}$ and LFS O_3	All-cause	588811 (501519, 675937)	591314 (503672, 678788)	-0.42	2267	82542973
	Cardiovascular	118569 (86466, 150584)	119234 (86936, 151442)	-0.56	2085	20807151
	Respiratory	69656 (47999, 91217)	70885 (48810, 92858)	-1.73	1922	8498909

Notes: For each community, our approach used the average daily death for each year to calculate the short-term mortality burden (i.e., the same as our country-specific analyses), while the benchmark approach used the actual daily death in the time-series data.

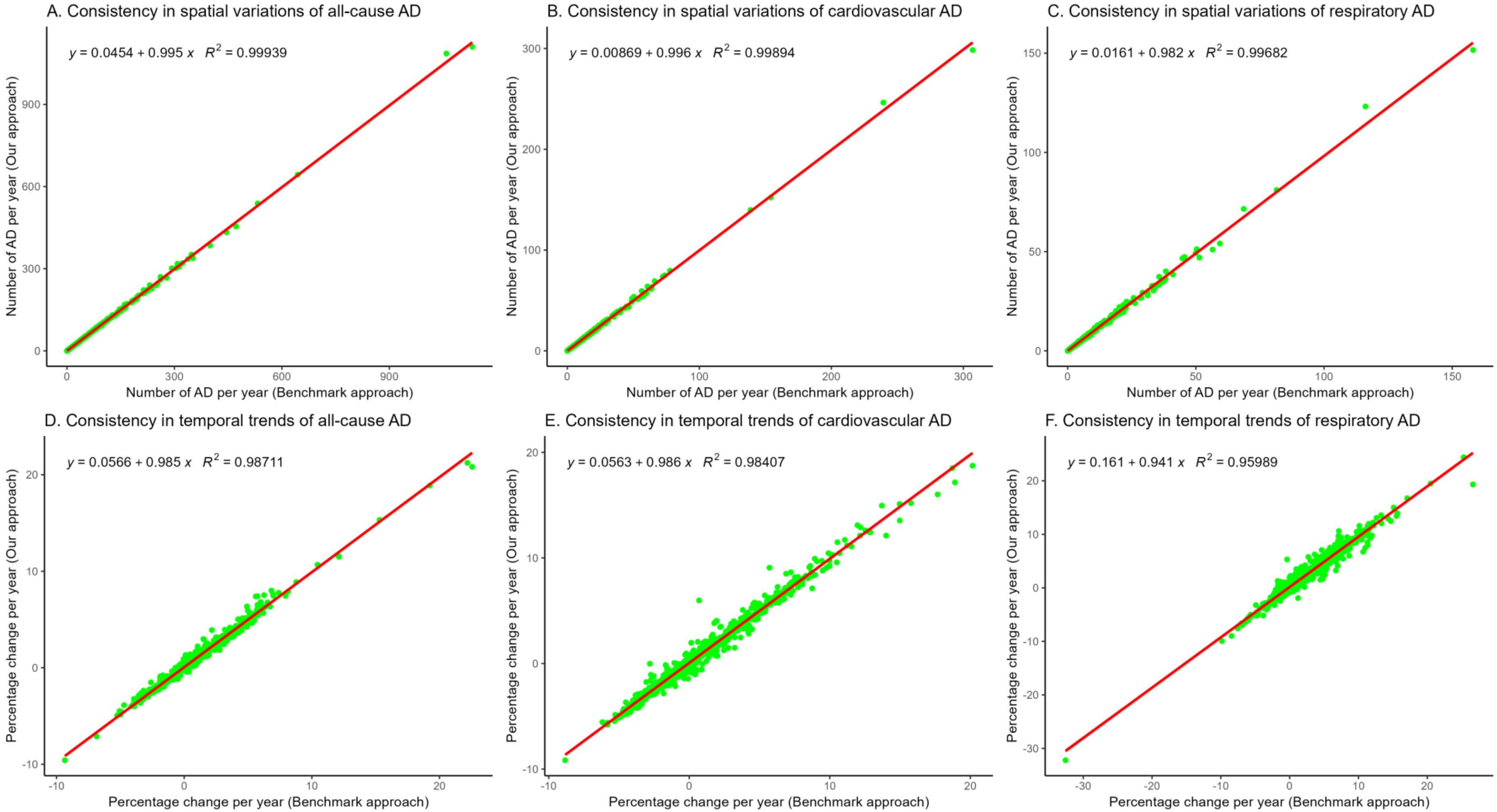

Figure S17. Consistency between our approach and the benchmark approach in the spatial variations and temporal trends of the short-term attributable deaths (AD) in 2267 communities.

Notes: each green dot represents one community, for panels D to F, only communities with at least 10 years of data were included in trend assessment.

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5. Full list of MCC collaborators

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