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Supplementary appendix

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Supplement to: Chen G, Guo Y, Yue X, et al. Mortality risk attributable to wildfire-related $PM_{2·5}$ pollution: a global time series study in 749 locations . *Lancet Planet Health* 2021; **5:** e579–87.

Supplementary Appendix

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1. Methods

1.1 Estimation of wildfire-related $PM_{2·5}$

Daily concentration of wildfire-related $PM_{2·5}$ was firstly estimated globally using the GEOS-Chem at a spatial resolution of 2° × 2·5°, and then was adjusted and downscaled for study areas at a spatial resolution of 0·25° × 0·25° using ground-level measurements of $PM_{2·5}$ and other predictors.

GEOS-Chem Model development

The 3-D chemical transport model GEOS-Chem version 12·0·0 (http://wiki.seas.harvard.edu/geos-chem/) was used to estimate global fire-induced perturbations in $PM_{2·5}$. The model included a fully coupled O_3-NO_x-hydrocarbon-aerosol chemical mechanisms to simulate atmospheric composition and air quality.[1] The GEOS-Chem model was driven by climate reanalyses from the Modern-Era Retrospective analysis for Research and Applications (MERRA) version 2 at 2° latitude × 2·5° longitude horizontal resolution and 47 vertical layers from surface to 0·01 hPa.[2] Global anthropogenic emissions in GEOS-Chem were from the EDGAR v4·2 inventory (http://edgar.jrc.ec.europa.eu/), with updates of regional inventories.[3] We used biomass burning emissions from Global Fire Emissions Database version 4·1 (GFED v4·1),[4-7] which derived biomass burned based on satellite retrieval of burn area and active fire information.[8] GFED v4·1 considers six land cover types: temperate forests, peat, savanna, deforestation, boreal forest, and agricultural waste. For each land type, fire-induced emissions are estimated as the product of dry matter and species-specific emission factors.[9] By default, GFED v4·1 provides monthly fire emissions. From the year 2003, daily fire emissions become available by multiplying daily scale factors onto the monthly data.[10] Many studies have shown that GEOS-Chem well captured the spatiotemporal variability of global $PM_{2·5}$.[11,12] Following the same protocols as previous studies,[13] daily enhancement of $PM_{2·5}$ by fires in 2000-2016 was estimated as the differences between simulations with and without fire emissions.

Adjustment and downscaling of estimated wildfire-related $PM_{2·5}$

We have improved the exposure assessment for wildfire-related $PM_{2·5}$ by further adjustment and downscaling method, as following steps:

Step 1: The all-source $PM_{2.5}$ were further adjusted using a random forest (RF) model and data on ground measured $PM_{2.5}$ and other spatial and temporal predictors (e.g., meteorological data). Particularly, global meteorological data on temperature, precipitation, barometric pressure, and wind speed have a spatial resolution of 0·25° (≈28km). The following random forest model was developed using ground measured $PM_{2·5}$ data from 6,882 sites in 61 countries (where daily $PM_{2·5}$ were monitored, Figure S1), GEOS-Chem derived all-source $PM_{2·5}$, and meteorological data (0·25° spatial resolution).

$$\mathrm{PM}_{2\cdot5\mathrm{GM}} = F(\mathrm{PM}_{2.5\mathrm{Chem}}, \mathrm{TEMP}, \mathrm{PREC}, \mathrm{BP}, \mathrm{WS}, \mathrm{Month}, \mathrm{DOW}, \mathrm{DOY}, \mathrm{Lon}, \mathrm{Lat})$$

where $PM_{2\cdot5GM}$ is the daily ground measured $PM_{2\cdot5}$ at a monitoring station; $PM_{2\cdot5Chem}$ is the estimated all-source $PM_{2.5}$ by GEOS-Chem. TEMP, PREC, BP and WS are daily ambient temperature, precipitation, barometric pressure, and wind speed, respectively. Month is calendar month. DOW and DOY are day of the week and the year. Lon and Lat are longitude and latitude of a monitoring station. The predictive ability of this daily RF model was examined using a 10-fold cross-validation (CV) method. It showed that the CV R^2 and Root Mean Square Error (RMSE) were 86·5% and 15·1 μg/m³ (Figure S2). The all-source $PM_{2\cdot5}$ was predicted for all grid cells of a 0·25°grid across the world using above random forest model and predictors.

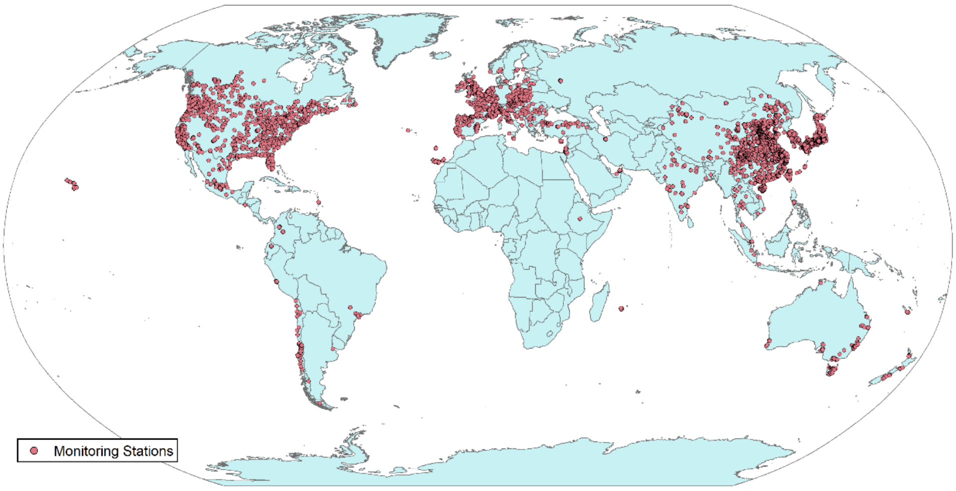

Figure S1. Locations of 6,882 ground monitoring sites used for data validation and adjustment.

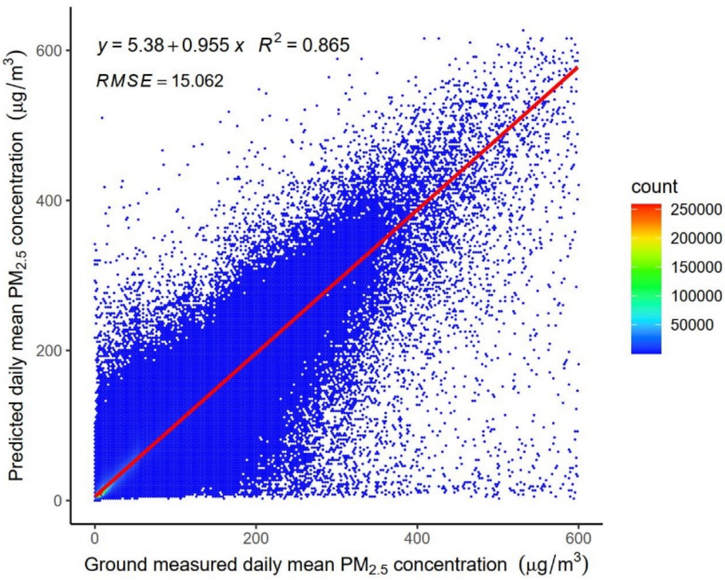

Figure S2. Density scatterplot of 10-fold cross-validation for the daily random forest model.

Note: RMSE, root mean squared prediction error (μg/m³)

Step 2: The daily all-source $PM_{2.5}$ and wildfire-related $PM_{2.5}$ derived from GEOS-Chem were downscaled to a global 0.25°-grid on each day, using the inverse distance weighted (IDW) method. Then, the ratio of downscaled wildfire-related $PM_{2.5}$ to all-source $PM_{2.5}$ derived from GEOS-Chem was calculated for each grid cell on each day.

Step 3: The adjusted wildfire-related $PM_{2.5}$ in each grid cell was derived by multiplying adjusted all-source $PM_{2.5}$ (from step 1) with the ratio of GEOS-Chem derived wildfire-related to all-source $PM_{2.5}$ (from step 2). The level of estimated wildfire-related $PM_{2.5}$ in each city was assigned as the average of all the cell values fell in that city, which was used in the final analyses. The high-resolution data on wildfire-related $PM_{2.5}$ showed a CV R^2 of 86·5% and had a high spatial resolution of 0·25° (≈28km).

1.2 Statistical models

1) Stage 1 - city-specific model

City-specific wildfire $PM_{2·5}$-mortality associations were examined using a time-series Poisson regression as shown:

$$\log(D_{ij}) = \mathrm{PM}_{ij} + \mathrm{ns}(t_j) + \mathrm{ns}(\mathrm{TEMP}_{ij}) + \mathrm{ns}(\mathrm{RH}_{ij})) + \mathrm{dow}_{j,}$$

where $\underline{Dij}$ is the count of deaths in city i on day j; PM_{ij} is the concentrations of wildfire-related $PM_{2.5}$ in the city during lag 0-7 days in city i on day j; t_j is a variable for time with a natural cubic spline (df = 7 per year) on day j to control for the long-term trend and seasonality; TEMP and RH are 7-day moving averages of daily mean temperature and relative humidity in the city with natural cubic splines (df = 4) [8]; and dow_j is a categorical variable for day of week on day j.

3) Stage 2 - Meta-analysis

Coefficients and corresponding covariance matrix of the first stage hospital-specific model were used in the second-stage analysis. A random-effect meta-analysis was conducted with maximum likelihood estimation to pool the hospital-specific results into an overall estimated effect that represents the national level effect.

1.3 Calculation of population attributable fraction

Population attributable fractions in this study was calculated using the following formulas:

$$\mathrm{AN}_i = n * \mathrm{B\_AF}_i$$

$$\mathrm{B\_AF}_i = 1 - \exp\left(-\sum_{l=0}^{L} \beta_{i-l}\right)$$

where: i is the day when deaths occur; AN_i is the number of deaths attributable to acute wildfire-related $PM_{2·5}$ on day i; n is the reported number of deaths; $\mathrm{B\_AF}_i$ is the attributable fraction due to cumulative effects of $PM_{2·5}$ on day $i - l$, with backward approach; l is the lag time; L is the maximum lag time; β_{i-l} is the effect estimate associated with level of wildfire-related $PM_{2.5}$ on day $i-l$. In addition, the upper value and lower value of 95%CI of pooled effect estimates were used to calculate the 95%CI of attributable fraction using the above formulas.

2. Results

Table S1. A summary of study areas, periods and number of deaths in 43 countries/regions included in this study.

Country/region	Study period	Total Mortality		Cardiovascular mortality		Respiratory mortality	
		City (n)	Deaths (n)	City (n)	Deaths (n)	City (n)	Deaths (n)
Argentina	2005-2015	3	686,333	NA	NA	NA	NA
Australia	2000-2009	3	513,527	NA	NA	NA	NA
Brazil	2000-2011	18	2,778,330	NA	NA	NA	NA
Canada	2000-2015	26	2,116,195	26	642,418	26	177,751
Chile	2004-2014	4	325,462	NA	NA	NA	NA
China	2000-2015	15	1,081,700	14	433,839	14	140,017
Colombia	2000-2013	5	843,633	5	237,346	5	88,819
Costa Rica	2000-2016	1	29,120	1	8,783	1	2,467
Czech Republic	2000-2015	4	505,932	4	246,331	4	29,860
Ecuador	2014-2016	2	64,351	2	18,473	2	7,574
Estonia	2000-2015	5	127,135	NA	NA	NA	NA
Finland	2000-2014	1	110,385	1	39,840	1	6,152
France	2000-2014	18	1,639,262	NA	NA	18	101,731
Germany	2000-2015	12	2,120,825	NA	NA	NA	NA
Greece	2001-2010	1	287,969	1	136,194	1	28,771
Guatemala	2009-2016	1	62,715	NA	NA	NA	NA
Iran	2004-2013	1	121,585	1	40,704	1	6,745
Ireland	2000-2007	6	333,088	6	91,232	6	50,077
Italy	2006-2015	18	804,278	NA	NA	NA	NA
Japan	2000-2015	47	18,008,670	47	5,233,495	47	2,750,685
Kuwait	2000-2016	1	73,748	1	35,285	1	5,715
Mexico	2000-2014	10	2,682,202	10	691,353	10	253,922
Moldova	2001-2010	4	59,906	NA	NA	NA	NA
Netherlands	2000-2016	5	338,448	NA	NA	NA	NA
Norway	2000-2016	1	76,577	1	24,518	1	7,548
Panama	2013-2016	1	11,457	1	3,862	1	971
Paraguay	2004-2016	1	39,713	1	12,791	1	3,544
Peru	2008-2014	18	633,137	NA	NA	NA	NA
Philippines	2006-2010	4	274,516	4	87,401	4	31,190
Portugal	2000-2016	5	779,638	5	250,047	5	88,472
Puertorico	2009-2016	1	26,564	NA	NA	NA	NA
Romania	2000-2016	8	697,505	NA	NA	NA	NA

South Africa	2000-2013	52	7,443,918	52	1,110,304	52	943,671
South Korea	2000-2016	36	2,362,545	36	542,146	36	166,046
Spain	2000-2014	52	1,859,279	52	600,992	52	221,208
Sweden	2000-2016	3	452,463	3	181,068	3	32,440
Switzerland	2000-2013	8	173,519	8	62,428	8	11,201
Taiwan	2000-2014	3	907,141	3	199,305	3	93,464
Thailand	2000-2008	62	1,666,292	62	299,721	62	205,900
UK	2000-2016	70	3,642,897	70	1,183,375	70	528,080
USA	2000-2006	210	8,594,149	210	2,672,728	210	849,506
Uruguay	2012-2016	1	153,554	NA	NA	NA	NA
Vietnam	2009-2013	2	108,173	2	24,433	2	8,970
In total	2000-2016	749	65,617,836	629	15,110,412	647	6,842,497

Table S2. Results for test of heterogeneity of effect estimates across cities

Lag days	All-cause mortality		Cardiovascular mortality		Respiratory mortality	
	I^2	Cochran Q P	I^2	Cochran Q P	I^2	Cochran Q P
0	50%	<0·01	6%	0·13	0%	0·49
1	41%	<0·01	10%	0·03	5%	0·19
2	37%	<0·01	6%	0·13	18%	<0·01
3	22%	<0·01	0%	0·58	11%	0·02
4	13%	<0·01	6%	0·14	3%	0·29
5	14%	<0·01	6%	0·12	5%	0·19
6	18%	<0·01	2%	0·38	14%	<0·01
7	13%	<0·01	0%	0·78	14%	<0·01
0-2	43%	<0·01	8%	0·07	6%	0·15

Table S3. A summary of estimated daily wildfire-related $PM_{2·5}$ (μg/m³) in 43 countries/regions during 2000–2016

Country/region	Wildfire-related $PM_{2·5}$ (μg/m³)			
	Min	Mean	Median	Max
Argentina	0·02	1·31	0·70	44·29
Australia	<0·01	0·91	0·31	46·48
Brazil	<0·01	2·66	0·64	114·82
Canada	<0·01	1·38	0·19	152·84
Chile	<0·01	0·65	0·35	10·32
China	<0·01	1·26	0·47	65·78
Colombia	<0·01	1·39	0·45	77·03
Costa Rica	0·02	0·26	0·55	5·25
Czech Republic	<0·01	0·44	0·29	37·31
Ecuador	0·03	1·12	0·49	28·60
Estonia	<0·01	0·49	0·14	65·69
Finland	<0·01	0·22	0·09	30·69
France	<0·01	0·35	0·25	6·74
Germany	<0·01	0·41	0·32	26·60
Greece	<0·01	0·88	0·57	14·51
Guatemala	<0·01	2·53	0·88	144·53
Iran	<0·01	0·49	0·36	6·41
Ireland	<0·01	0·18	0·12	8·10

Italy	<0·01	0·67	0·50	10·91
Japan	<0·01	1·94	1·03	47·80
Kuwait	<0·01	0·53	0·44	4·49
Mexico	<0·01	0·98	0·51	28·23
Moldova	<0·01	0·88	0·39	26·14
Netherlands	<0·01	0·45	0·33	19·86
Norway	<0·01	0·17	0·08	23·47
Panama	<0·01	0·34	0·32	5·05
Paraguay	0·04	4·36	1·27	155·30
Peru	<0·01	1·94	0·48	73·07
Philippines	<0·01	0·79	0·37	23·30
Portugal	<0·01	0·67	0·25	47·83
Puerto Rico	<0·01	0·25	0·12	3·46
Romania	<0·01	0·94	0·48	30·53
South Africa	<0·01	1·34	0·45	28·63
South Korea	<0·01	2·02	0·69	84·39
Spain	<0·01	0·45	0·24	30·07
Sweden	<0·01	0·20	0·08	26·24
Switzerland	0·02	0·44	0·37	4·94
Taiwan	<0·01	0·79	0·55	10·43
Thailand	<0·01	4·28	0·48	164·30
UK	<0·01	0·23	0·15	14·37

USA	<0·01	1·10	0·35	92·85
Uruguay	<0·01	0·73	0·44	44·62
Vietnam	<0·01	3·70	0·57	178·34

Table S4. Relative risks of mortality associated with exposure to wildfire-related $PM_{2.5}$ during lag 0-2 in WHO regions and by different GDP levels.

Factor	Total mortality	Cardiovascular mortality	Respiratory mortality
	RR (95%CI)	RR (95%CI)	RR (95%CI)
WHO Region			
Australia	1.002 (0.991, 1.012)	NA	NA
Central America	1.001 (0.993, 1.010)	1.001 (0.990, 1.011)	1.002 (0.974, 1.030)
Central Europe	1.141 (1.085, 1.201)	1.071 (0.964, 1.189)	1.047 (0.833, 1.316)
East Asia	1.025 (1.020, 1.030)	1.021 (1.012, 1.030)	1.033 (1.024, 1.043)
Middle-East Asia	1.076 (1.006, 1.151)	1.155 (1.049, 1.272)	1.121 (0.811, 1.551)
North America	1.005 (0.997, 1.013)	1.008 (0.995, 1.022)	1.027 (1.001, 1.053)
North Europe	1.002 (0.978, 1.027)	1.062 (1.011, 1.115)	1.010 (0.890, 1.147)
South-East Asia	1.017 (1.013, 1.020)	1.011 (1.005, 1.017)	1.016 (1.008, 1.023)
South Africa	1.018 (1.011, 1.024)	1.016 (1.005, 1.027)	1.008 (0.995, 1.021)
South America	1.010 (0.999, 1.021)	1.025 (1.004, 1.047)	1.051 (1.019, 1.084)
South Europe	1.086 (1.058, 1.116)	1.088 (1.040, 1.139)	1.005 (0.936, 1.078)
GDP level (US$)			
<10000	1.016 (1.012, 1.019)	1.012 (1.007, 1.017)	1.014 (1.007, 1.020)
10000-20000	1.030 (1.018, 1.042)	1.019 (1.000, 1.039)	0.991 (0.957, 1.026)
20000-30000	0.998 (0.993, 1.004)	1.009 (0.976, 1.042)	1.002 (0.953, 1.053)
>30000	1.028 (1.023, 1.033)	1.025 (1.017, 1.033)	1.037 (1.028, 1.047)

Note: RRs (95%CI) were associated with per 10 $\mu g/m^3$ increase in moving average of wildfire-related $PM_{2.5}$ during lag 0-2 days

Table S5. Population attributable fraction of annual mortality due to exposure to wildfire-related $PM_{2 \cdot 5}$ during lag 0-2 days by different WHO regions and GDP levels

Factor	All-cause mortality	Cardiovascular mortality	Respiratory mortality
	PAF(%) (95%CI)	PAF(%) (95%CI)	PAF(%) (95%CI)
Region			
Australia	0.88 (0.70, 1.07)	NA	NA
Central America	1.73 (1.35, 2.10)	1.66 (1.30, 2.02)	1.75 (1.37, 2.13)
Central Europe	0.16 (0.12, 0.19)	0.14 (0.11, 0.17)	0.12 (0.09, 0.15)
East Asia	0.62 (0.49, 0.76)	0.61 (0.48, 0.75)	0.61 (0.47, 0.74)
Middle-East Asia	0.35 (0.27, 0.42)	0.35 (0.27, 0.42)	0.31 (0.24, 0.37)
North America	0.27 (0.21, 0.33)	0.26 (0.21, 0.32)	0.26 (0.20, 0.32)
North Europe	0.09 (0.07, 0.12)	0.09 (0.07, 0.11)	0.08 (0.07, 0.10)
South Africa	0.99 (0.78, 1.21)	1.00 (0.78, 1.21)	1.10 (0.86, 1.34)
South America	0.87 (0.68, 1.06)	1.01 (0.79, 1.22)	1.00 (0.78, 1.22)
South Europe	0.25 (0.20, 0.31)	0.23 (0.18, 0.28)	0.22 (0.17, 0.27)
South-East Asia	1.63 (1.29, 1.97)	1.55 (1.22, 1.88)	1.77 (1.39, 2.13)
GDP level (US$)			
<10,000	1.14 (0.89, 1.38)	1.16 (0.91, 1.41)	1.27 (1.00, 1.55)
10,000-20,000	0.38 (0.30, 0.46)	0.33 (0.25, 0.4)	0.34 (0.27, 0.42)
20,000-30,000	0.38 (0.30, 0.46)	0.26 (0.20, 0.32)	0.23 (0.18, 0.29)
>30,000	0.38 (0.29, 0.46)	0.39 (0.3, 0.47)	0.42 (0.33, 0.51)

Note: PAFs were calculated using the pooled global-level risk estimates.

Table S6. Population attributable number of annual deaths due exposure to wildfire-related $PM_{2.5}$ during lag 0-2 days in 43 countries/regions

Country/region	All-cause mortality	Cardiovascular mortality	Respiratory mortality
	AN (n) (95%CI)	AN (n) (95%CI)	AN (n) (95%CI)
Argentina	478 (373, 582)	NA	NA
Australia	483 (380, 583)	NA	NA
Brazil	1,610 (1,258, 1,960)	NA	NA
Canada	440 (343, 536)	132 (103, 161)	35 (27, 43)
Chile	190 (148, 232)	NA	NA
China	1,289 (1,006, 1,571)	527 (412, 643)	166 (130, 202)
Colombia	585 (457, 713)	164 (128, 200)	60 (47, 74)
Costa Rica	16 (13, 20)	5 (4, 6)	1 (1, 2)
Czech Republic	43 (34, 53)	21 (16, 25)	2 (2, 3)
Ecuador	210 (164, 256)	58 (45, 71)	25 (19, 30)
Estonia	13 (10, 16)	NA	NA
Finland	11 (8, 13)	4 (3, 5)	1 (0, 1)
France	127 (99, 155)	NA	8 (6, 9)
Germany	172 (134, 210)	NA	NA
Greece	95 (74, 116)	44 (35, 54)	10 (8, 12)
Guatemala	238 (187, 289)	NA	NA
Iran	41 (32, 50)	14 (11, 17)	2 (1, 2)
Ireland	36 (28, 44)	10 (8, 12)	5 (4, 6)
Italy	254 (198, 310)	NA	NA
Japan	7,062 (5,509, 8,610)	1,990 (1,553, 2,426)	1,045 (815, 1,274)
Kuwait	16 (13, 20)	8 (6, 9)	1 (1, 1)
Mexico	3,078 (2,409, 3,740)	778 (609, 946)	300 (235, 364)
Moldova	16 (13, 20)	NA	NA
Netherlands	25 (19, 31)	NA	NA
Norway	4 (3, 5)	1 (1, 2)	0 (0, 0)
Panama	11 (8, 13)	4 (3, 4)	1 (1, 1)
Paraguay	64 (50, 78)	21 (16, 25)	6 (5, 7)
Peru	1,454 (1,136, 1,770)	NA	NA
Philippines	436 (341, 532)	140 (110, 171)	48 (38, 59)
Portugal	127 (99, 155)	38 (29, 46)	14 (11, 17)
Puertorico	9 (7, 11)	NA	NA
Romania	142 (111, 174)	NA	NA
South Africa	5,278 (4,126, 6,425)	790 (618, 962)	740 (579, 901)
South Korea	733 (572, 893)	168 (131, 204)	51 (40, 62)
Spain	234 (182, 286)	74 (58, 91)	27 (21, 32)
Sweden	26 (20, 32)	10 (8, 13)	2 (1, 2)
Switzerland	19 (15, 23)	7 (5, 8)	1 (1, 1)
Taiwan	348 (271, 425)	75 (59, 92)	36 (28, 44)
Thailand	4,291 (3,386, 5,175)	809 (638, 975)	558 (440, 672)
UK	188 (147, 230)	60 (47, 74)	26 (20, 32)

USA	3,193 (2,490, 3,896)	978 (763, 1,193)	310 (241, 378)
Uruguay	156 (122, 190)	NA	NA
Vietnam	266 (207, 323)	63 (49, 76)	22 (17, 26)

Note: Attributable numbers of deaths were calculated using the pooled global-level risk estimates.

Table S7. Population attributable number of annual deaths due to exposure to wildfire-related $PM_{2\cdot5}$ during lag 0-2 days in WHO regions and in regions with different GDP levels

Factor	All-cause mortality	Cardiovascular mortality	Respiratory mortality
	AN (n) (95%CI)	AN (n) (95%CI)	AN (n) (95%CI)
Region			
Australia	483 (380, 583)	782 (612, 950)	
Central America	3,336 (2,612, 4,053)	27 (21, 33)	301 (235, 365)
Central Europe	520 (405, 634)	2,685 (2,095, 3,273)	11 (9, 14)
East Asia	9,085 (7,088, 11,074)	21 (17, 26)	1,262 (985, 1,539)
Middle-East Asia	57 (45, 70)	1,110 (865, 1,354)	3 (2, 4)
North America	3,633 (2,833, 4,432)	86 (67, 105)	345 (269, 421)
North Europe	304 (237, 371)	790 (618, 962)	34 (26, 41)
South Africa	5,278 (4,126, 6,425)	248 (193, 301)	740 (579, 901)
South America	4,764 (3,721, 5,801)	156 (122, 191)	93 (72, 113)
South Europe	710 (554, 866)	1,087 (855, 1,314)	50 (39, 62)
South-East Asia	5,342 (4,205, 6,455)	782 (612, 950)	663 (522, 801)
GDP level US$			
<10,000	19,495 (15,269, 23,677)	3,369 (2,639, 4,090)	1,928 (1,511, 2,340)
10,000-20,000	1,855 (1,447, 2,262)	380 (296, 463)	130 (102, 159)
20,000-30,000	1,080 (846, 1,311)	196 (153, 239)	52 (40, 63)
>30,000	11,081 (8,642, 13,513)	3,049 (2,378, 3,718)	1,392 (1,086, 1,697)

Note: Attributable numbers of deaths were calculated using the pooled global-level risk estimates.

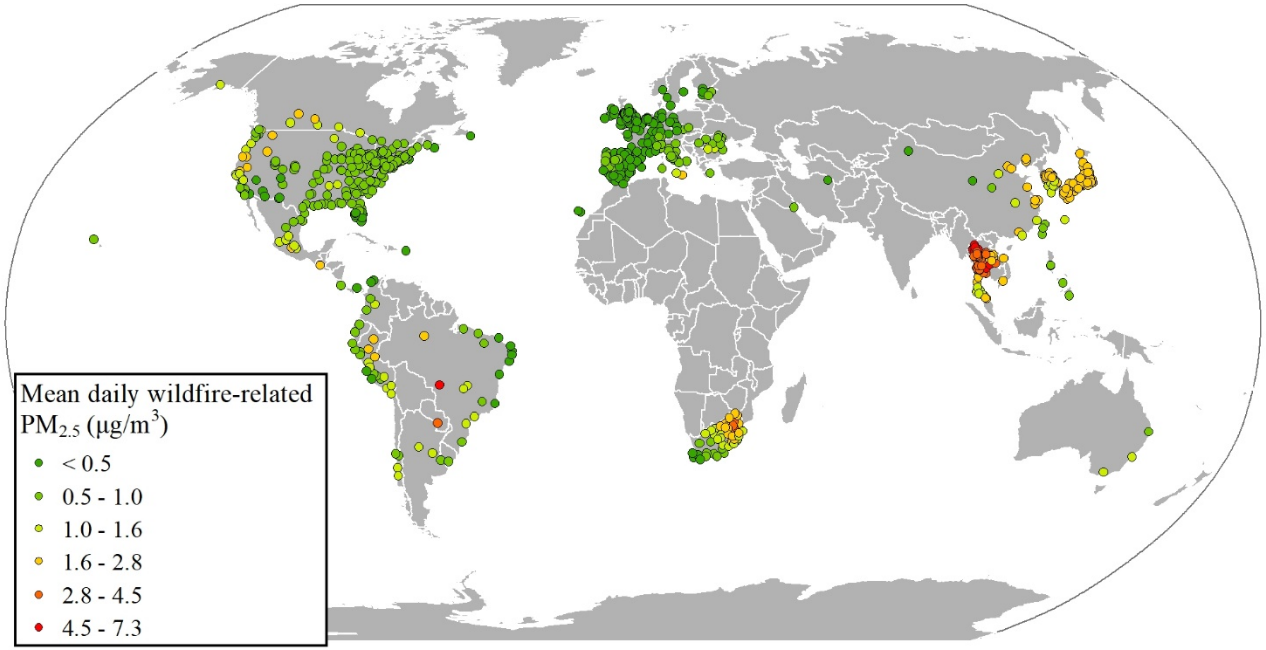

Figure S3. Mean levels of estimated daily wildfire-related $PM_{2 \cdot 5}$ in study locations during 2000–2016

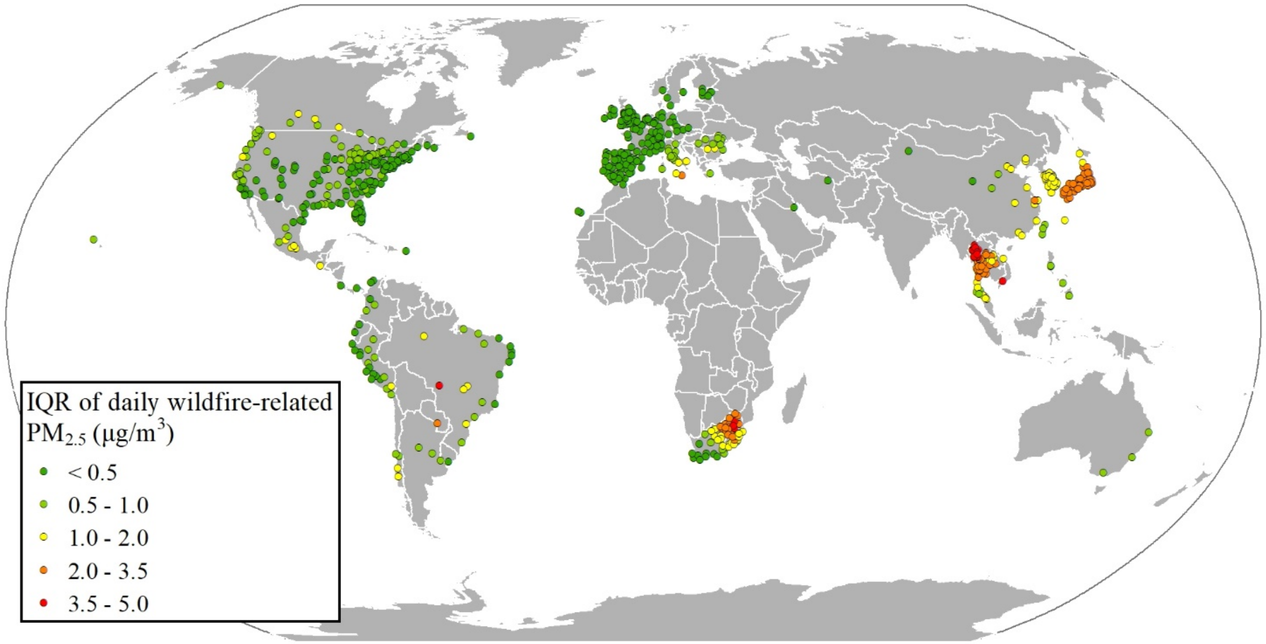

Figure S4. The interquartile range (IQR) of estimated daily wildfire-related $PM_{2.5}$ in study locations during 2000–2016

Sensitivity analyses were performed to examine the potential confounding effects of $PM_{2.5}$ from other sources and to compare the results using adjusted and unadjusted wildfire-related $PM_{2.5}$. For all-cause mortality, the results were pooled at 265 cities where ground monitoring data of $PM_{2.5}$ were available, and for other causes, the results were pooled at 240 cities.

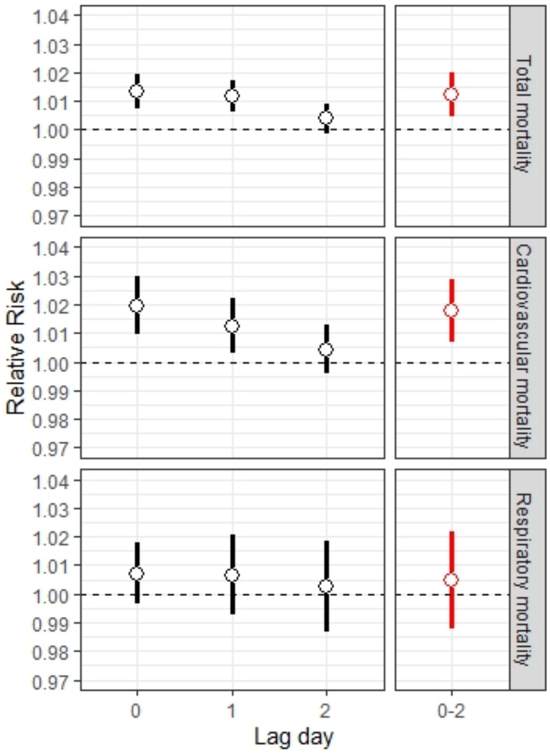

Figure S5. Pooled relative risks and 95% confidence intervals of mortality associated per 10 μg/m³ increase in wildfire-related $PM_{2.5}$ in selected cities during lag 0–2 days controlling for $PM_{2.5}$ from non-wildfire sources.

Note: The results were pooled at 265 cities where ground monitoring data of $PM_{2.5}$ were available, and for other causes, the results were pooled at 240 cities)

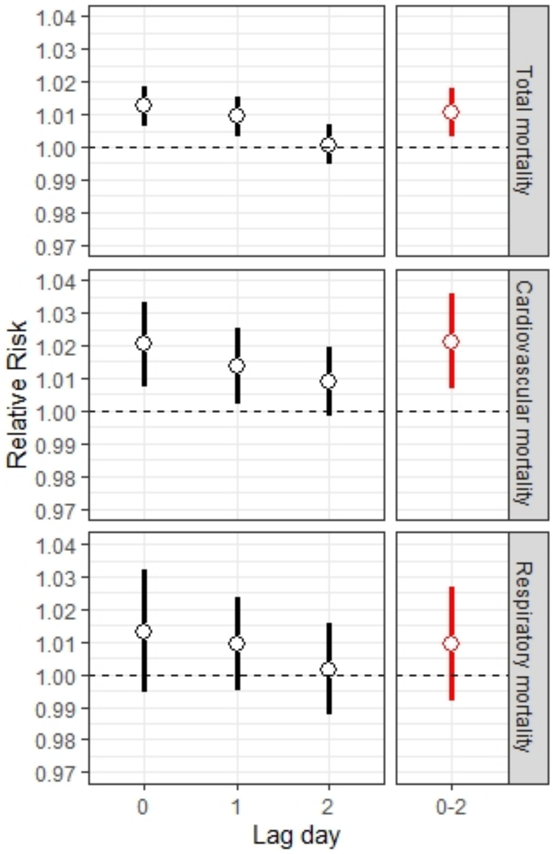

Figure S6. Pooled relative risks and 95% confidence intervals of mortality associated per 10 μg/m^3 increase in wildfire-related $PM_{2\cdot5}$ in selected cities during lag 0–2 days only considering wildfire-related $PM_{2\cdot5}$.

Note: The results were pooled at the same cities as those in Figure S4 where ground monitoring data of $PM_{2\cdot5}$ were available (265 cities for all-cause mortality and 240 cities for other causes).

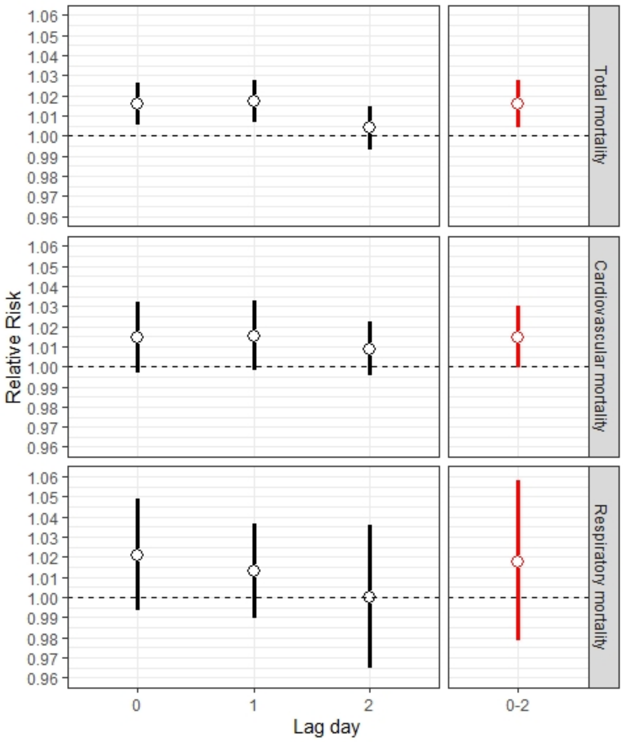

Figure S7. Pooled relative risks and 95% confidence intervals of mortality associated per 10 μg/m^3 increase in wildfire-related $PM_{2\cdot5}$ in selected cities during lag 0–2 days using unadjusted data of estimated wildfire-related $PM_{2\cdot5}$.

Note: The results were pooled at the same cities as those in Figures S4-S5 where ground monitoring data of $PM_{2\cdot5}$ were available (265 cities for all-cause mortality and 240 cities for other causes).

The results for sensitivity analyses showing in Figures S6-S11 were pooled results in all cities using adjusted wildfire-related $PM_{2\cdot5}$ (749 cities for all-cause mortality, and 629 and 647 cities for cardiovascular and respiratory mortality)

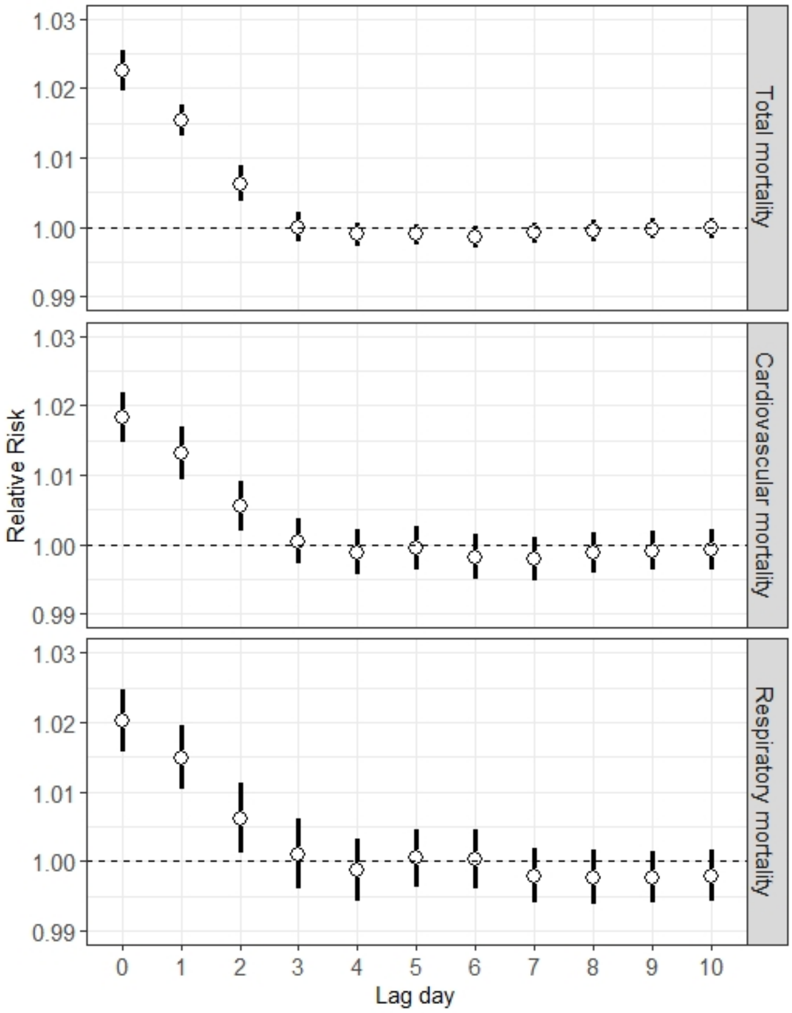

Figure S8. Pooled relative risks and 95% confidence intervals of mortality associated per 10 μg/m^3 increase in wildfire-related $PM_{2\cdot5}$ during lag 0–10 days.

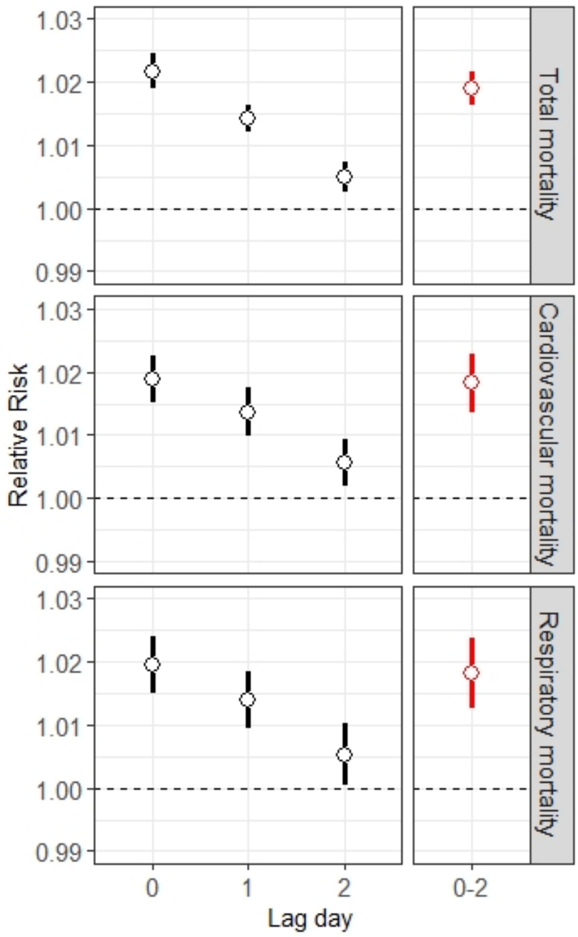

Figure S9. Pooled relative risks and 95% confidence intervals of mortality associated per 10 μg/m^3 increase in wildfire-related $PM_{2 \cdot 5}$ during lag 0–2 days using 3 degrees of freedom for meteorological variables.

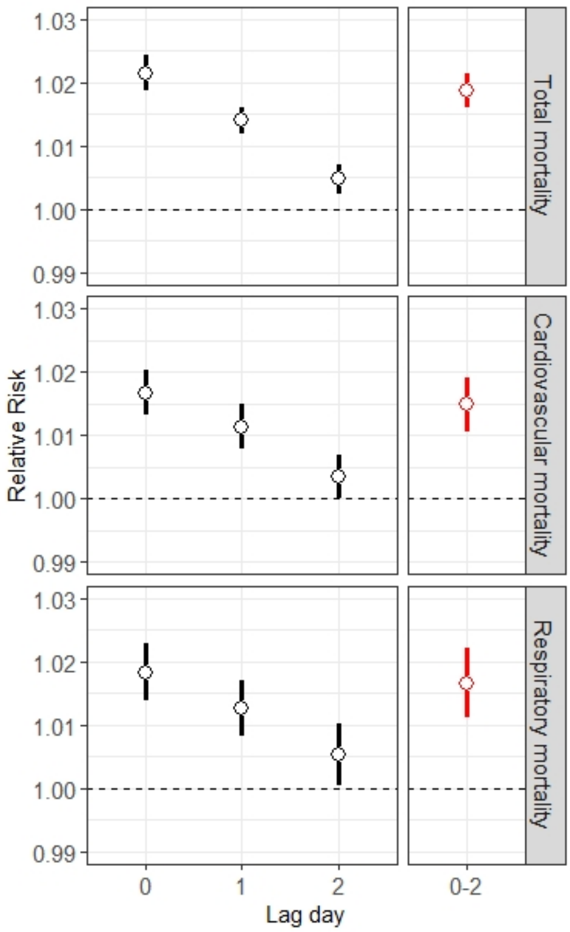

Figure S10. Pooled relative risks and 95% confidence intervals of mortality associated per 10 μg/m^3 increase in wildfire-related $PM_{2 \cdot 5}$ during lag 0–2 days using 5 degrees of freedom for meteorological variables.

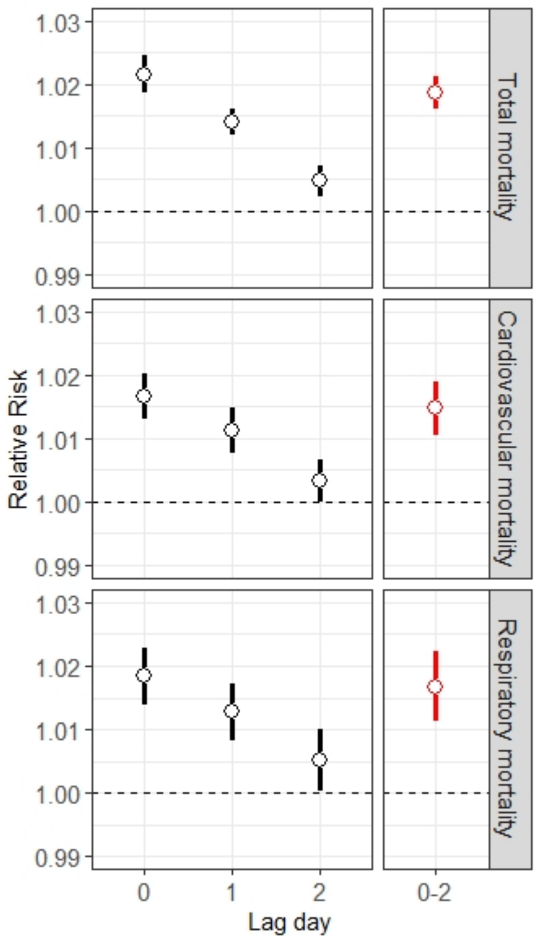

Figure S11. Pooled relative risks and 95% confidence intervals of mortality associated per 10 μg/m³ increase in wildfire-related PM2·5 during lag 0–2 days using 6 degrees of freedom for meteorological variables.

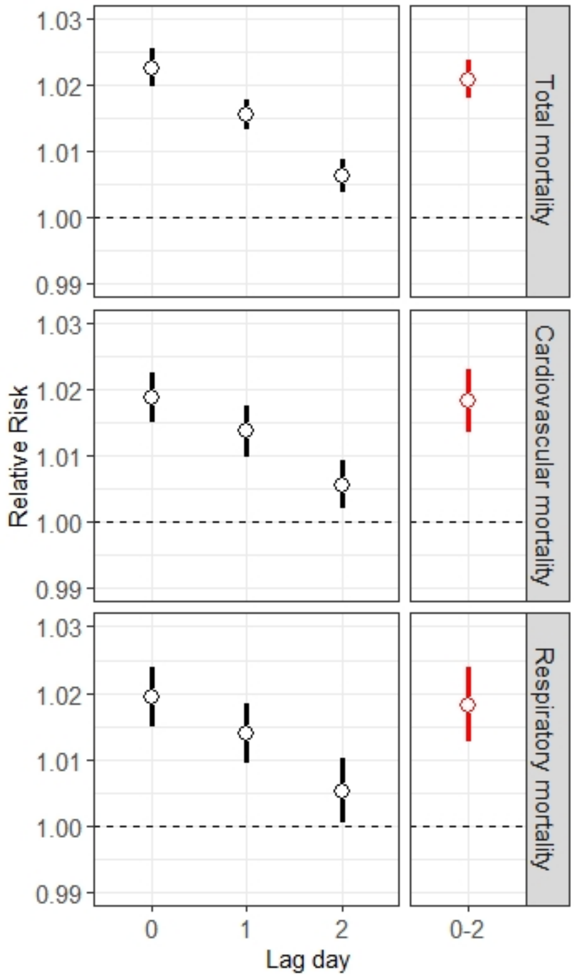

Figure S12. Pooled relative risks and 95% confidence intervals of mortality associated per 10 μg/m³ increase in wildfire-related $PM_{2\cdot5}$ during lag 0–2 days considering 10-day lag effects of meteorological variables.

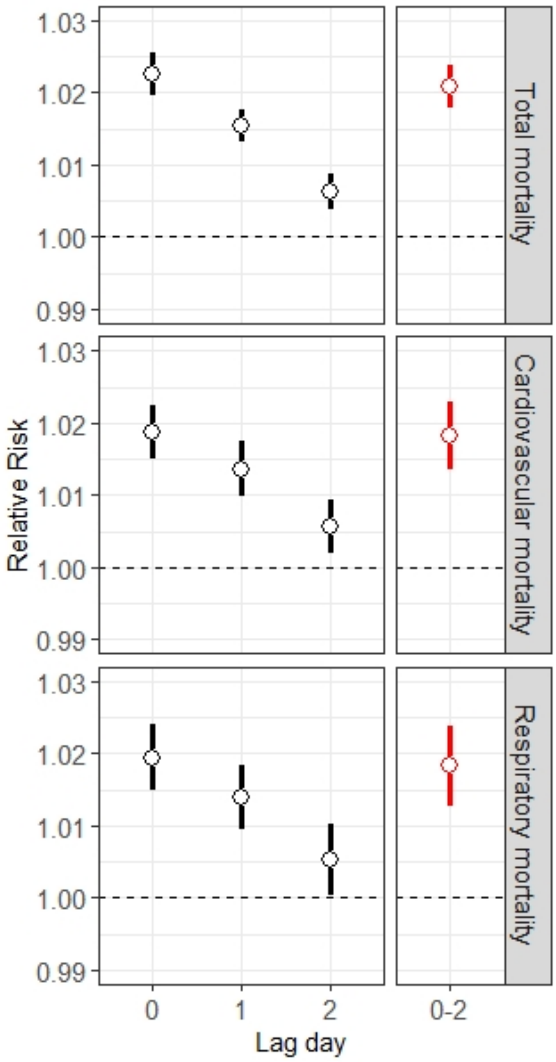

Figure S13. Pooled relative risks and 95% confidence intervals of mortality associated per 10 μg/m^3 increase in wildfire-related $PM_{2·5}$ during lag 0–2 days only controlling ambient temperature.

3. References

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