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Unprecedented health costs of smoke-related $PM_{2.5}$ from the 2019-20 Australian megafires

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Abstract

In flammable landscapes around the globe longer fire seasons with larger, more severely burnt areas are causing social and economic impacts that are unsustainable. The Australian 2019/20 fire season is emblematic of this trend burning over 8 million ha of predominately *Eucalyptus* forests over a six- month period. We calculated wildfire smoke-related health burden and costs in Australia for the most recent 20 fire seasons and found that the 2019/20 season was a major anomaly in the recent record, with smoke-related health costs of $1.95 billion. These were largely driven by an estimated 429 smoke-related premature deaths in addition to 3230 hospital admissions for cardiovascular and respiratory disorders and 1523 emergency attendances for asthma. This was well above the next highest estimate of $566 million in 2002/3 and more than 9 times the median annual wildfire associated costs for the previous 19 years of $211 million. There are substantial economic costs attributable to wildfire smoke and potential for dramatic increases in this burden as the frequency and intensity of wildfires increases with a hotter climate.

Main text

Landscape fires are an inherent feature of the ecology of many forested landscapes around the world. However, the global trend of longer fire seasons with more extreme fire weather is leading to fires that are historically unusually frequent, severe, and, in some cases, economically destructive fires,[1] a trend that is likely to worsen according to climate projections.[2] For example, the Australian fire season of 2019/20 was globally anomalous given the geographical scale of the fires burning over 8 million ha (Figure 1),[3] driven by prolonged drought and dangerous fire weather,[4] with numerous ignitions from dry lightning storms and a variety of anthropogenic causes.[5] Such extreme fire events are increasingly stressing socio-ecological systems that were already poorly adapted to co-existing fire prone environment.[6] Developing more sustainable flammable landscapes has become an urgent priority for many societies, yet this is extremely difficult to achieve because solutions lie at the intersection of the biophysical and socio-cultural domains.[7] A prime example of this sustainability challenge concerns the health costs from wildfire smoke pollution.

During the 2019-20 fire season the most densely populated regions of Australia, especially those along the eastern seaboard, were affected by extreme air pollution for periods ranging from weeks to months. Fire-smoke is a complex and dynamic mix composed of particulate matter and a range of gases, such as, nitrogen dioxide, carbon monoxide, volatile organic compounds, and polycyclic aromatic hydrocarbons.[8 9] Wildfire smoke is known to cause a substantial health burden given the well-established associations between particulate matter less than 2.5 microns in diameter ($PM_{2.5}$) and admissions to hospital and premature mortality, particularly for cardiovascular and respiratory conditions.[10-15] Health impacts of smoke pollution are not always included in economic assessments of the impacts of wildfires, which generally focus more on the costs of fire-related injuries, infrastructure losses and fire supression.[16-19] Relatively few studies have estimated the health burden and/or associated costs of wildfire smoke exposure.[10 20-25] Standard methods for quantifying the burden of disease attributable to air pollution[26] can also be applied to wildfire smoke.[10 24 27] We aimed to calculate the number of presentations to hospital emergency departments (ED) for asthma, admissions to hospital for cardiorespiratory disorders, and mortality from all causes associated with wildfire smoke attributable air pollution in populated temperate regions of Australia, and compare the total economic costs associated with these outcomes for each fire season (October through March) for a 20-year period from 1 October 2000. For all outcomes we used risk estimates recommended by the World Health Organization,[26] except for asthma ED presentations where we used the risk estimates from a recently published fire-smoke specific meta-analysis.[28]

(Figure 1. About here. Maps of Australia showing (a) geographic area of fires in temperate forest and woodlands during the 2019-2020 fire season; (b) population density (c) location of air monitoring stations; and (d) statistical local areas included in the analysis.)

Our comparisons of the relative burden of fire smoke across two decades in Australia using consistent definitions of the population exposed, attribution of wildfire smoke exposure, health burden and economic valuation, clearly highlighted 2019/20 as an anomalous fire season (see Methods section below for more detail). We found that concentrations of fire-related $PM_{2.5}$ this season were well in excess of any of the previous 19 seasons (see Extended Data Fig. 1 and Fig. 2) and that the smoke-related health costs of the 2019/20 season of $AUD 1.95 billion was unprecedented in magnitude, and more than nine times higher than the median of the previous 19 seasons- of $AUD 211 million (Figure 2). Population exposure to wildfire smoke in the 2019/20 season alone was estimated to be associated with 1523 asthma ED presentations, 2092 admissions to hospital for respiratory conditions, 1138 admissions for cardiovascular disorders and 429 premature deaths (Table 1). By contrast, the next highest estimate of $566 million was in 2002/3, while the lowest smoke-related costs occurred in 2000/1 at $75 million. Impacts were greatest in the state of New South Wales (Figure 3).

Table 1. Estimated number of premature deaths, admissions to hospital for cardiovascular and respiratory disorders, presentations to hospital emergency departments for asthma and associated economic cost for the 2019-2020 wildfire season in Australia.

Outcome	**Number** (95 %CI)	**Costs ($AUD million)** (95% CI)
Premature deaths (all causes)	429 (154 - 712)	1,923 (693 - 3,194)
Hospital admissions - Cardiovascular diseases	1,138 (210 - 2,113)	8.51 (1.57 – 15.8)
Hospital admissions - Respiratory diseases	2,092 (0 - 4,638)	15.83 (0 – 35.1)
Hospital emergency department attendances - Asthma	1,523 (750 - 2,466)	1.12 (0.55 – 1.81)
TOTAL		**1,948 (695 – 3,246)**

Figure 2 and 3.

Figure 2. Cumulative smoke-related health costs for the 20 consecutive fire seasons (1 Oct– 31 March) in Australia

Figure 3. Annual fire season smoke-related health costs by state for the 20 consecutive fire seasons (1 Oct – 31 March).

We acknowledge that the health and economic impact assessments are subject to a range of assumptions and uncertainties. Those at greatest risk of death from short-term smoke exposure are likely to have pre-existing diseases[11] and potentially a shorter life expectancy than the average for others of the same age.[29] Our valuation of the cost of these deaths was based on the value of a statistical life which is based on willingness to pay, and does not take into account underlying health status, age or life expectancy of the individual (see section on Economic Valuation in the Methods). While there is uncertainty about how these factors affect the value ascribed to the premature mortality component of the smoke-related health economic burden, it does not influence the relative difference in economic burden between years. Our estimates are based on a limited range of outcomes for which the air pollution and health risk effect estimates have been well established. They do not include many other well established health outcomes of population exposure to smoke such as increases in symptoms, medication use, primary health care attendances, ambulance callouts, which have all been clearly associated with episodic fire smoke events.[8] Further, they do not capture reduced productivity or the mental health burden which are important contributors to economic impacts of fire disasters.[30-33] Finally, they do not include the premature mortality associated with the contribution of the wildfire smoke to increased annual average air pollution, which is of much greater magnitude than that associated with short-term daily fluctuations in air pollution.[10] For these reasons, the health and economic assessments we present are likely to be an underestimate of the true burden. In the supplementary material, we summarise the approach used to estimate mortality and the economic burden using long-term risk coefficients and years of life lost which produced economic assessments of much greater magnitude (see summary results in Extended Data Fig. 3).

Severe fire smoke impacts on large populations are common in equatorial parts of southeast Asia where tropical deforestation fires are routinely used to convert forested landscapes to primary production,[34] and are increasingly being documented in other forested regions such as North America.[2] An important feature of wildfire-related air pollution is that it is transnational, and in particular, during the 2019/20 fire season, wildfire plumes affected air quality in New Zealand and was observed to travel around the southern hemisphere.[35] Managing wildfire smoke is thus a global policy challenge that requires multiple strategies ranging from global climate stabilisation through to local-scale fuel management. The direct and manifest health impacts of wildfires on large human populations is a powerful reason to motivate improved climate change mitigation and the achievement of sustainable wildfire management.[36]

Methods

We estimated population exposure to bushfire smoke derived particulate matter less than 2.5 microns in diameter ($PM_{2.5}$) using publicly available air quality monitoring data. We then applied the relevant exposure-response coefficients to the baseline incidence rates for each health outcome to calculate the number of cases. Finally, we multiplied the number of cases by the attributed economic value for each outcome included in the analysis and summed these to obtain the estimated economic impact attributable to elevated air pollution from the wildfires. These steps are detailed further below.

Geographic Region

We included all forested Australian regions with ongoing air quality monitoring by government agencies, apart from those located in the northern tropical savannas because these regions have distinct fire regimes that do not coincide with the pattern of severe wildfires during the hotter austral summer months. Our study incorporated over 80 percent of the population of Australia, the majority living along the southern and eastern seaboard.

Exposure attribution

We obtained hourly averages for two size fractions of particulate matter; particulate matter less than 10 micrometres in diameter (PM_{10}) and $PM_{2.5}$ from each air quality monitoring station in the study area and used these to calculate 24-hour averages.[37-43] While our analysis was based on the 24-hour average of $PM_{2.5}$, we used the 24-hour average PM_{10} to interpolate missing values for 24-h average $PM_{2.5}$ for each station as these size fractions of particulate matter are highly correlated. We estimated the $PM_{2.5}/PM_{10}$ ratio for each site-month, region-month and state-month combination to impute missing $PM_{2.5}$ values.[21] This assumption was validated by analysing goodness of fit between observed $PM_{2.5}$ and predicted $PM_{2.5}$ for each station, region and state (see Supplementary Tables 1-9). Population exposure to $PM_{2.5}$ was then estimated at a statistical level 2 (SA2) administrative divisions which have an average population of 10,000 (range 3-25,000) using an inverse distance weighting (IDW) method from each air quality monitoring station.[44] We selected this approach for its simplicity and given that our study region was large with a relatively small number of air quality monitors. Other spatial interpolation methods such as kriging do not perform significantly better compared to IDW, unless a dense and consistent set of observed data is available for the interpolation.[45] We included only SA2s that were less than or equal to 100 km away from any given monitoring station (measured as the distance between the SA2 centroid and the monitoring station location). With this restriction, our study included 1,910 SA2s out of 2,234 (85.5%) and on average about 84% of the population of the selected States.

During the study period we obtained air quality data from 189 different monitoring stations, active at different points in time, with 37 stations active in 2000 and 141 active in 2020 (see Supplementary Table 10). We assessed potential differences in the state-specific study regions and study populations over time, due to changes in the number of monitoring sites through the years, and found only minor differences in the proportion of the population assessed (see Supplementary Table 11). A total of 186 SA2s (~8.3% of all SA2s) had at least one air quality monitoring station at some time during the study period. The average distance between the centroid of each SA2 and the closest monitor was 15.2 km. We defined a fire-smoke affected day as being a day in which the $PM_{2.5}$ was above the 95th percentile of historical values for a given station-month in a location during the study period. We did a sensitivity analysis using days above 90th or 99th percentile of historical values. The excess $PM_{2.5}$ was estimated as the difference between the daily $PM_{2.5}$ for a particular SA2 and the long term historical average $PM_{2.5}$ for that SA2-month combination. Previous work has established that bushfire smoke is the reason for $PM_{2.5}$ concentrations in excess of the 95 percentile in the vast majority of cases,[46] and this approach has been successfully used to identify bushfire smoke affected study days in several previous epidemiological studies.[47-49] The approach is conservative in that days with minor bushfire smoke impacts that do not cause the 95th percentile to be breached will be excluded from the analysis. Additionally, we reviewed air quality annual reports of causes of air quality exceedances for the entire study period and removed 57 dust events during this period.[50]

Health impact calculations

We estimated the number of attributable cases of premature mortality, hospital admissions, and ED attendances for asthma using the following equation:

$$Cases_O = IR_O \times Pop \times \left(e^{\beta_O \times \Delta C} - 1\right)$$

Where

- $Cases_O$: number of estimated cases for outcomes ‘o’

- IR_O: base incidence rate for outcome 'o'
- Pop: estimated exposed population
- β_O: health outcome risk coefficient for outcome 'o'
- ΔC: change in $PM_{2.5}$ concentration

Aggregated and publicly available population and baseline incidence data were obtained from government agencies.[51-57] Health outcomes were classified using the International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification (ICD-10-AM): J00-J99 for respiratory diseases, I00-I90 for cardiovascular disease, and J45 for asthma. We used risk coefficients recommended by the World Health Organization which have been widely used in air pollution health impact assessments [22 24 58 59] for short term (daily) mortality and hospital admissions for cardiovascular and respiratory conditions, as well as a recently published meta-analysis which provided an exposure-response function for fire smoke and asthma ED presentations,[28] an important non-overlapping health outcome (Supplementary Table 12). These coefficients were comparable to coefficients used in other studies of wildfire smoke impacts. [10 27]

During the 2019-20 Australian fire season, some densely populated areas experienced periods when daily concentrations of $PM_{2.5}$ exceeded 1000 μg/m^3, well above usual background concentrations which are generally less than 10 μg/m^3. An important uncertainty in estimating health outcomes is that concentration response relationships for extreme daily $PM_{2.5}$ concentrations, (eg greater than 150 μg/m^3), have not been well characterised. This contrasts with studies of long term exposure to $PM_{2.5}$ for which the shape of the concentration response function across a range of exposures has been derived.[60] Results from a multi-city study of urban air pollution in China suggested that, similar to long term associations, short term mortality associations could be smaller at higher concentrations, although this has not been a consistent observation. [61] Studies of very extreme episodic pollution, such as the severe haze caused by Southeast Asian forest fires in 1998, have provided some evidence of mortality associations persisting at extreme particle concentrations comparable to those in the Australian 2019-20 fire season.[62 63] In our main analysis we dealt with this uncertainty by constraining the maximum daily concentrations of $PM_{2.5}$ to 150 μg/m^3 and present results of sensitivity analyses for different maximum concentrations. This resulted in cost estimates for 2019-20 that were 10% lower than with the unconstrained model for that season but did not appreciably influence effect estimates for other years (Extended Data Fig. 4).

Economic valuation

Unitary health costs used to assess the economic burden are presented in Supplementary Table 13. We valued hospitalisations using a cost of illness method, including the average cost of a hospitalisation obtained from the Independent Hospital Pricing Authority, National Cost Data Collection Report.[64] The costs associated with lost productivity were conservatively represented by lost income only during the average length of hospital stay. Lost income was estimated for adults of working age as the average daily salary using the Average Weekly Earnings and Labour Workforce Statistics published by the Australian Bureau of Statistics.[65] [66] We valued ED presentations using estimates from the Independent Hospital Pricing Authority Emergency Care Costing Report.[67] Mortality was valued using the value of a statistical life (VSL) as recommended by the Office of Best Practice and Regulation.[68] VSL is commonly used to estimate the monetary benefits of reducing the risk of mortality, and is a measure of how much society values the reduced risk of death.[69] It does not take into account underlying health status, age or life expectancy of the individual.[70] While premature mortality associated with short term exposure to air pollution is commonly due to acute exacerbation of pre-existing serious health conditions in older people,[71] this is not always the case, for example the precipitation of severe asthma in young adults.

Risk coefficients are also available for mortality associated with long-term, or annual average exposure to $PM_{2.5}$. These risk coefficients are higher because long-term exposure to air pollution will cause the progression of chronic diseases and thereby increase the pool of people at underlying risk, in addition to causing deterioration in those already at higher risk. Using this approach, it is also possible to calculate the total number of years of life lost and apply the value of a statistical year of life lost. We conducted alternate analyses of the economic impact of premature mortality by calculating the contribution of smoke-related air pollution during the fire season to the annual average air pollution exposure and applying long-term exposure risk coefficients. Studies of long-term exposure to air pollution and mortality are usually set in locations where there are not large fluctuations in exposure to air pollution from year to year and the annual average $PM_{2.5}$ concentration is also likely to be representative of exposures over longer time periods.[72] We note that this is less likely to be the case for wildfire-related air pollution, and the potential influence on estimates of the mortality burden is unknown. A comparison of the results from our primary analysis with results of the economic valuation of the wildfire smoke-related mortality using long term risk coefficients and estimates of years of life lost is shown in Extended Data Fig. 3.

We adjusted all costs to Australian Dollars of 2018 by applying inflation factors from the Reserve Bank of Australia.[73]

The extended data figures also show the results of sensitivity analyses comparing; (1) the influence of selecting the 90th 95th and 99th percentile as a cut point for attributing wildfire smoke pollution (Extended Data Fig. 5), (2) comparing the influence of constraining the maximum daily $PM_{2.5}$ concentrations (Extended Data Fig. 4), and (3) results by each State and Territory included in the study period (Extended Data Fig. 6).

Data availability

The data that support the findings of this study are available on request from the corresponding author on a case-by-case basis. Source Data for Figures are provided as Source Data files.

Code availability

The custom code generated during the current study is available from the corresponding author on a case-by-case basis.

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Author contributions

FJ and DB conceived the paper, FJ drafted the manuscript, NB conducted the analyses, contributed to the design, methods and paper, GM, BJ and AP contributed to methodological approach and paper, GW and DB contributed to the methods, fire data, and writing the paper.

Competing interest declaration

The authors declare they have no competing interests.

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Additional information

Baseline data, sensitivity analyses, individual State and Territory results, and other tables and figures that complement the methods presented, are shown as extended data figures or are presented as supplementary information.

Table Legends

Table 1. Estimated number of premature deaths, admissions to hospital for cardiovascular and respiratory disorders presentations to hospital emergency departments for asthma and associated economic cost for the 2019-2020 wildfire season in Australia.

Figure Captions

Figure 1. Maps of Australia showing (a) geographic area of fires in temperate forest and woodlands during the 2019-2020 fire season; (b) population density (c) location of air monitoring stations; and (d) geographical area included in the analysis based on selected statistical local areas.

Figure 2. Cumulative smoke-related health costs for the 20 consecutive fire seasons (1 Oct– 31 March) in Australia

Figure 3. Annual fire season smoke-related health costs by state for the 20 consecutive fire seasons (1 Oct – 31 March)

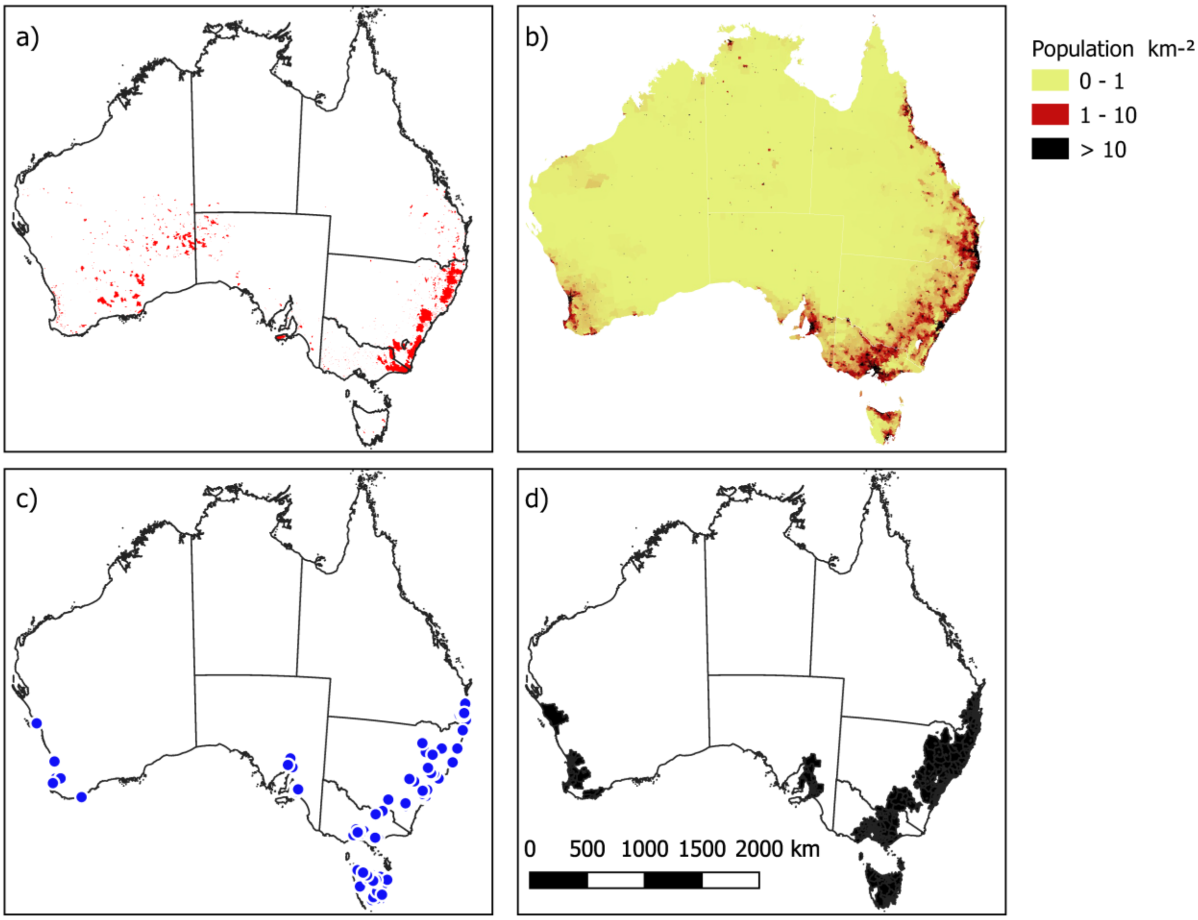


Figure 1. Maps of Australia showing (a) geographic area of fires in temperate forest and woodlands during the 2019-2020 fire season; (b) population density (c) location of air monitoring stations; and (d) geographical area included in the analysis based on selected statistical local areas.

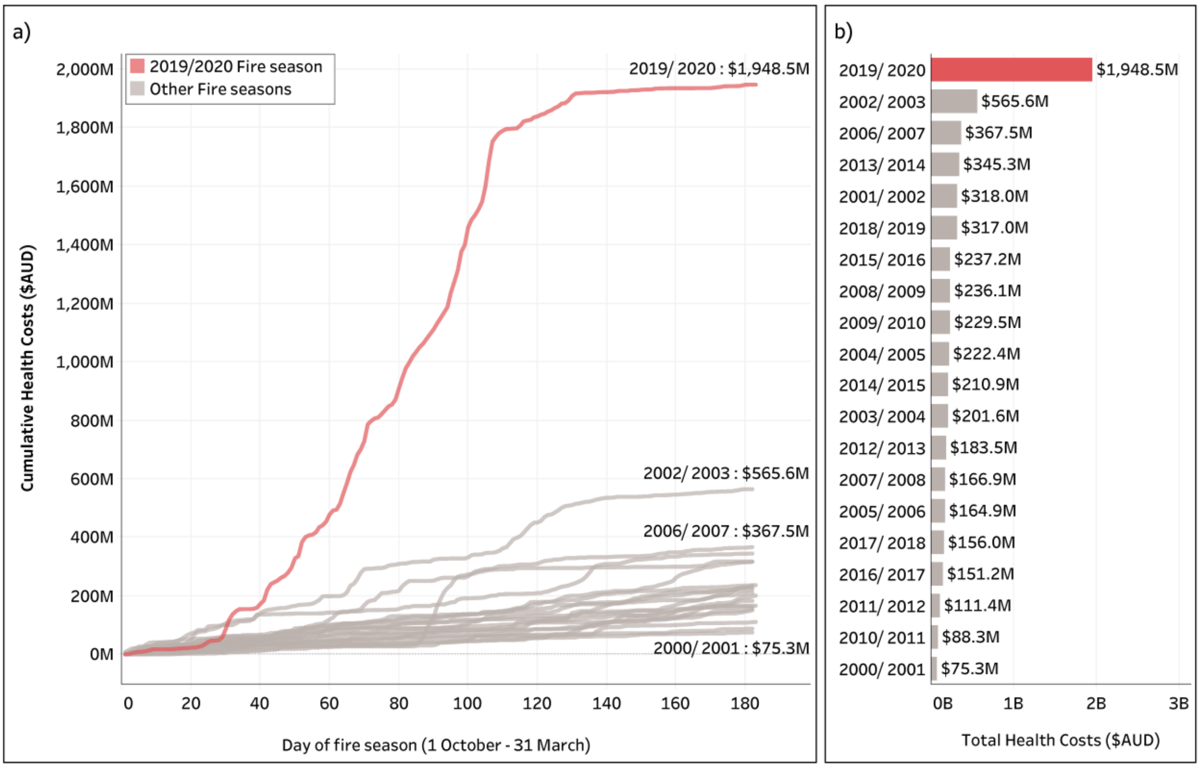


Figure 2 Cumulative smoke-related health costs for the 20 consecutive fire seasons (1 Oct–31 March) in Australia by a) day of fire season and b) total

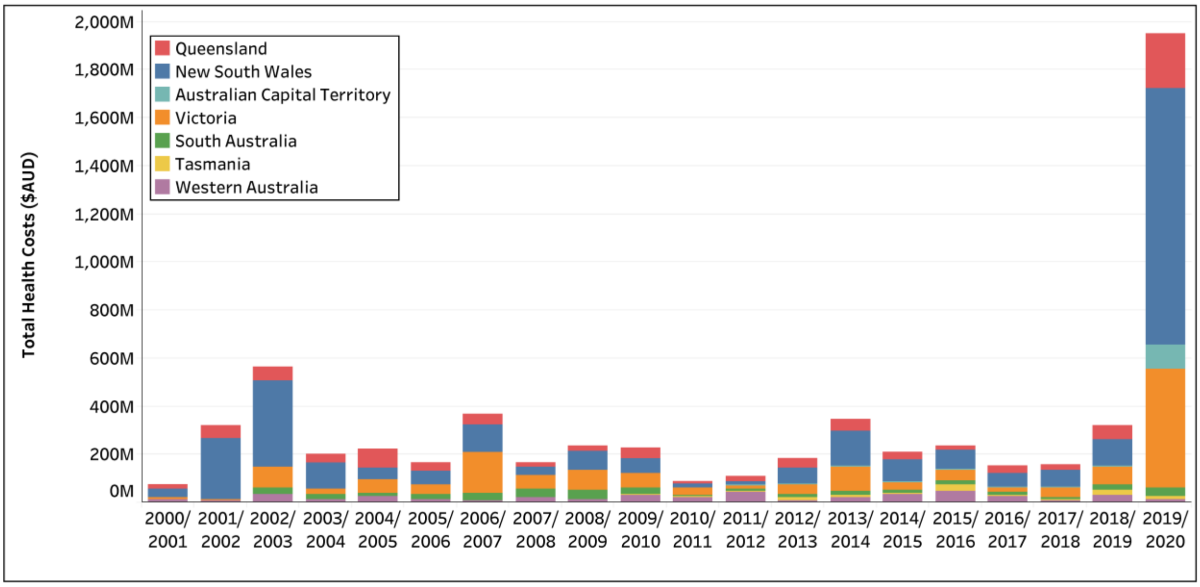
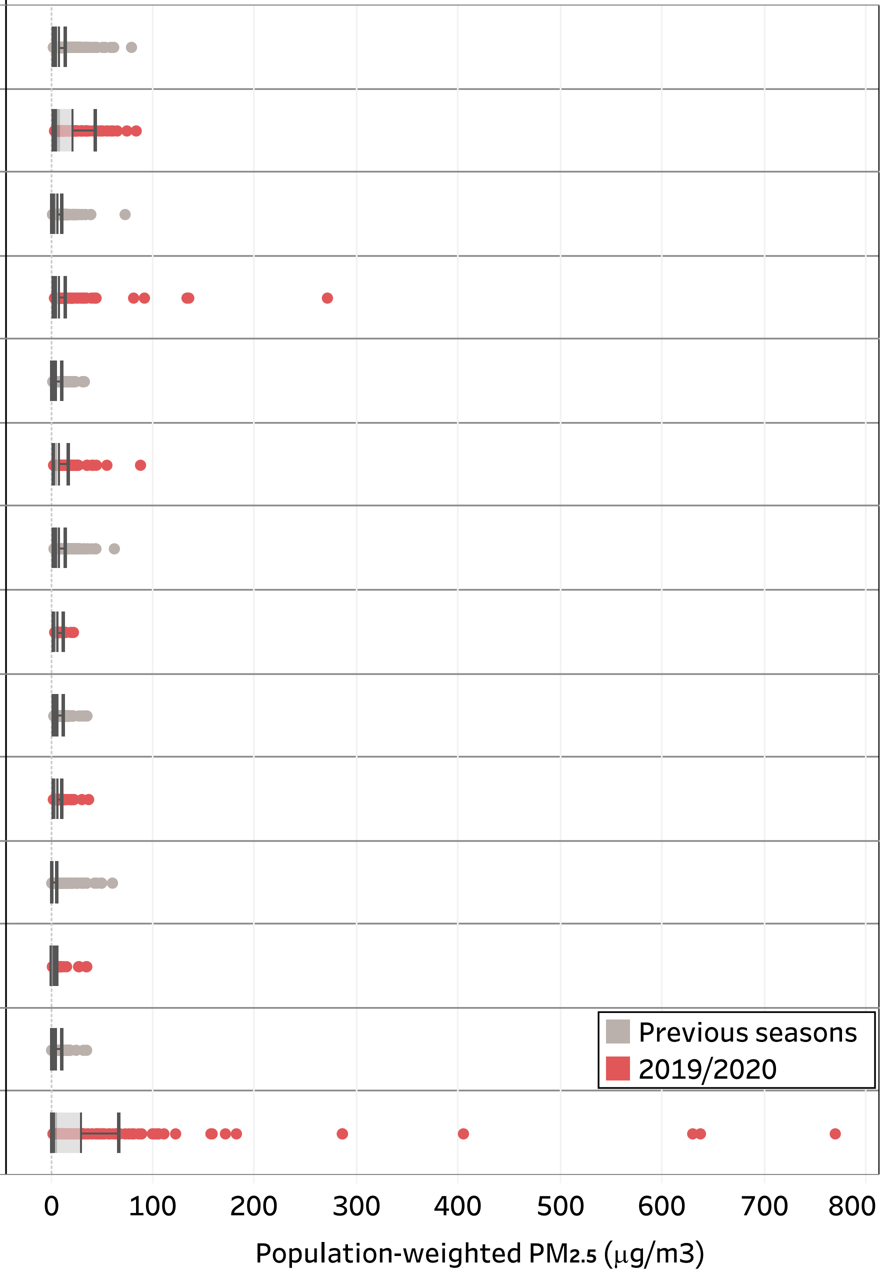
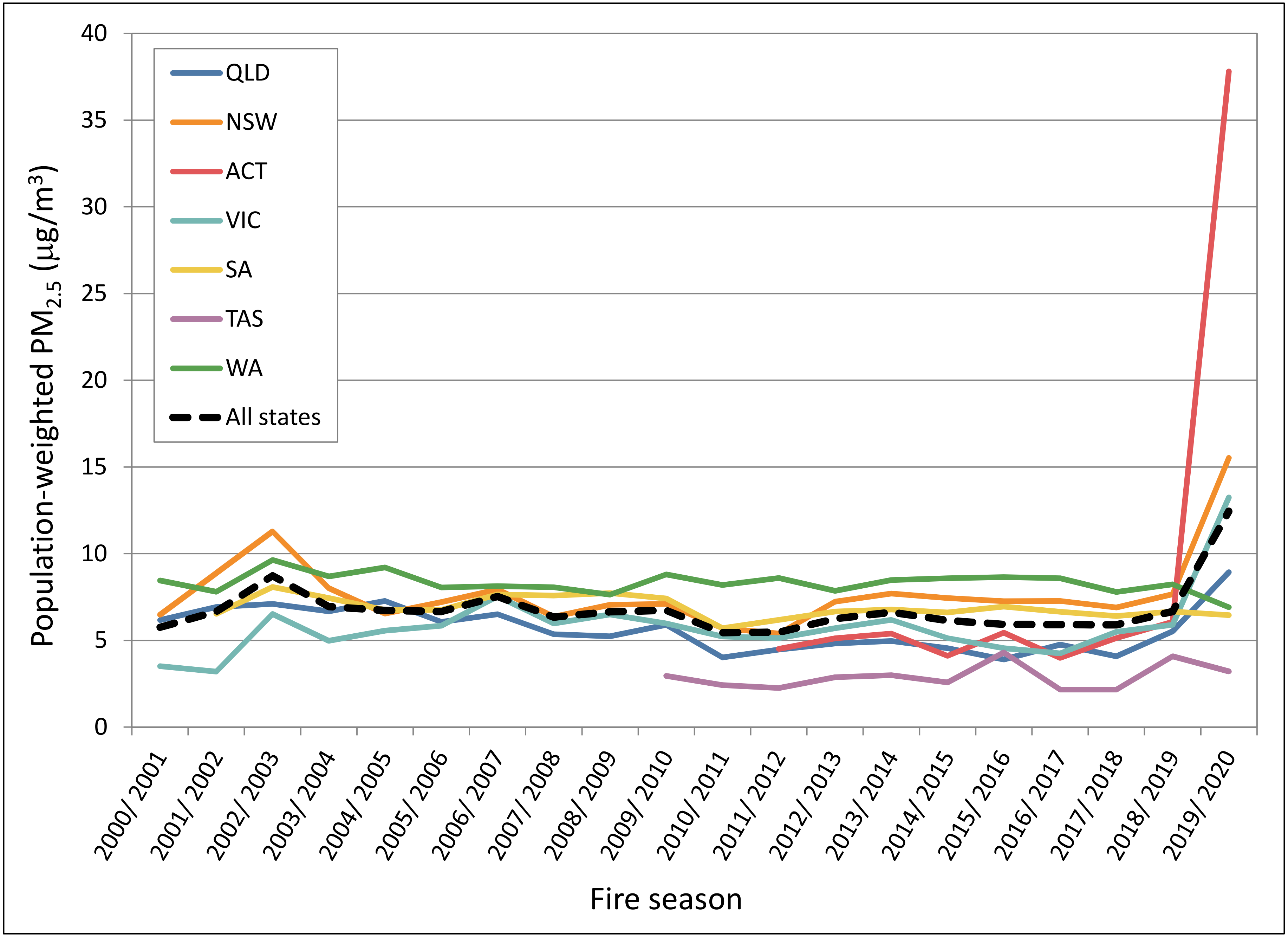


Figure 3. Annual fire season smoke-related health costs by state for the 20 consecutive fire seasons (1 Oct – 31 March)

State (Population)	Fire season	Min	Mean	Median	Max	SD
New South Wales (7,988,241)	Previous seasons	1.6	7.3	6.5	78.3	4.1
	2019/2020	2.8	15.5	9.7	83.0	14.7
Victoria (6,460,675)	Previous seasons	0.8	5.4	4.9	72.1	3.1
	2019/2020	2.7	13.2	6.3	270.6	28.4
Queensland (5,011,216)	Previous seasons	1.2	5.5	5.1	32.1	2.5
	2019/2020	1.9	8.9	5.4	87.2	9.9
Western Australia (2,595,192)	Previous seasons	2.3	8.4	7.7	61.5	3.2
	2019/2020	3.1	6.9	6.5	21.4	2.9
South Australia (1,736,422)	Previous seasons	2.2	6.9	6.5	34.7	2.6
	2019/2020	1.6	6.5	5.3	36.3	4.6
Tasmania (528,201)	Previous seasons	0.2	2.9	2.2	59.6	3.7
	2019/2020	0.8	3.3	2.0	34.5	4.6
Australian Capital Territory (420,960)	Previous seasons	0.7	5.1	4.7	34.3	2.8
	2019/2020	1.3	37.8	6.1	769.0	97.9



Extended Data Figure 1 - Population-weighted daily PM2.5 statistic (ug/m3) by State for the 2019/2020 fire season and the median of the previous 19 fire seasons



Extended Data Figure 2 - Median population-weighted PM2.5 (ug/m3) by fire season for each state and all states combined

Fire season (1 Oct – 31 March)	Premature mortality - Short-term exposure risk coefficient** Number	Cost based on value of a statistical life (AUD Mil)	Premature mortality - Long-term exposure risk coefficient Number	Cost based on value of a statistical life (AUD Mil)	Years of Life lost (YLL) Number	Cost based on value of a statistical life year (AUD Mil)
2000-2001	17	74.5	79	352.4	1,124	218.4
2001-2002	70	314.7	321	1,440.3	4,548	884.1
2002-2003	125	559.9	587	2,633.2	8,163	1,586.8
2003-2004	44	199.5	210	941.5	2,891	561.9
2004-2005	49	220.0	234	1,049.9	3,241	630.0
2005-2006	36	163.2	172	770.8	2,335	453.8
2006-2007	81	363.6	382	1,711.8	5,116	994.6
2007-2008	37	165.2	176	789.3	2,337	454.3
2008-2009	52	233.6	247	1,107.2	3,254	632.6
2009-2010	51	227.0	240	1,074.9	3,191	620.4
2010-2011	19	87.4	93	415.8	1,219	236.9
2011-2012	25	110.2	116	519.9	1,556	302.4
2012-2013	40	181.4	190	853.6	2,456	477.5
2013-2014	76	341.4	358	1,607.8	4,629	899.9
2014-2015	46	208.5	220	986.9	2,859	555.7
2015-2016	52	234.6	249	1,115.3	3,195	621.1
2016-2017	33	149.5	158	709.0	2,031	394.8
2017-2019	34	154.0	160	718.6	2,037	395.9
2018-2019	70	313.0	331	1,483.4	4,206	817.7
2019-2020	429	1,923.0	2,148	9,634.6	26,998	5,248.4

Note:
* Results for mortality only, excluding hospital-related costs.
** Primary analysis for the main paper.

Extended Data Figure 3 - Evaluating the magnitude and value of premature mortality using risk coefficients for short term exposure, long term exposure, and calculating the years of life lost *

Season	Item	Outcome	Maximum $PM_{2.5}$ *50*	*100*	*150**	*200*	*300*	*No limit*
2019/2020	Cases	All-cause Mortality ST	358	411	429	441	458	476
		Cardiovascular hospital admissions	953	1,092	1,138	1,171	1,212	1,252
		Respiratory hospital admissions	1,736	2,001	2,092	2,160	2,253	2,366
		Emergency Department attendances for asthma	1,171	1,413	1,523	1,627	1,819	2,724
	Costs	**Total ($AUD mil)**	**1,628.1**	**1,867.8**	**1,948.5**	**2,006.4**	**2,081.6**	**2,163.2**
Median of previous 19 seasons	Cases	All-cause Mortality ST	46	46	46	46	46	46
		Cardiovascular hospital admissions	105	105	105	105	105	105
		Respiratory hospital admissions	195	195	196	196	196	196
		Emergency Department attendances for asthma	110	110	110	110	110	110
	Costs	**Total ($AUD mil)**	**210.7**	**210.8**	**210.9**	**210.9**	**210.9**	**210.9**
		Cost ratio - 2019/20 vs. median of previous 19 seasons	**7.7**	**8.9**	**9.2**	**9.5**	**9.9**	**10.3**

Note: * Main analysis

Extended Data Figure 4 - Sensitivity analysis showing the influence of constraining the maximum daily PM2.5 concentrations on the total estimated number of cases and health related costs for the 2019-20 fire season and the fire season median for the previous 19 fire seasons (Costs presented in AUD Mil)

Fire season (1 October – 31 March)	Total cost- All days with $PM_{2.5}$ greater than mean background	Total cost including days in which $PM_{2.5}$ >90th centile	Total cost including days in which $PM_{2.5}$ >95th centile (main analysis)	Total cost including days in which $PM_{2.5}$ >99th centile
2000-2001	161.2	121.6	75.3	29.0
2001-2002	419.2	364.9	318.0	238.0
2002-2003	690.2	641.8	565.6	321.7
2003-2004	334.2	284.0	201.6	93.0
2004-2005	317.3	283.7	222.4	80.8
2005-2006	265.6	221.2	164.9	24.9
2006-2007	487.4	444.1	367.5	161.6
2007-2008	253.2	223.3	166.9	63.8
2008-2009	317.6	286.1	236.1	107.9
2009-2010	319.9	282.7	229.5	115.3
2010-2011	147.7	117.0	88.3	37.5
2011-2012	167.0	142.5	111.4	63.0
2012-2013	278.1	246.7	183.5	60.8
2013-2014	424.7	401.6	345.3	186.7
2014-2015	289.7	258.9	210.9	82.7
2015-2016	301.8	286.2	237.2	90.2
2016-2017	230.3	207.3	151.3	68.9
2017-2019	230.3	197.3	156.0	52.0
2018-2019	395.7	367.6	317.0	167.2
2019-2020	2,013.5	1,996.6	1,948.5	1,595.3

Extended Data Figure 5 - Sensitivity analysis showing the influence of selecting different cut-points for identifying a wildfire smoke affected day, on the total estimated health related costs by fire season. (Costs presented in AUD Mil)

Fire season (1 Oct – 31 March)	Queens-land ($AUD Mil)	New South Wales (AUD Mil)	Australian Capital Territory* (AUD Mil)	Victoria (AUD Mil)	South Australia ** (AUD Mil)	Tasmania *** (AUD Mil)	Western Australia (AUD Mil)
2000-2001	18.46	36.46		6.91			13.5
2001-2002	49.51	255.96		1.21			11.31
2002-2003	59.6	355.88		89.31	26.59		34.24
2003-2004	34.93	107.83		24.47	19.4		14.93
2004-2005	79.2	48.34		55.44	11.53		27.9
2005-2006	32.82	55.9		42.32	21.58		12.32
2006-2007	45.82	113.57		170.01	28.74		9.35
2007-2008	17.97	35.26		57.73	35.12		20.8
2008-2009	23.28	77.89		83.66	38.19		13.09
2009-2010	46.59	59.6		62.84	26.77	3.06	30.66
2010-2011	7.5	18.53		33.19	3.99	4.41	20.71
2011-2012	24.22	14.15		15.11	8.83	2.7	46.41
2012-2013	41.16	63.59	0.53	42.83	15.7	9.45	10.24
2013-2014	47.49	144.99	3.14	102.51	18.25	7.59	21.36
2014-2015	30.31	93.5	1.56	34.25	10.99	4.11	36.18
2015-2016	19.91	78.79	1.01	45.87	19.28	26.17	46.19
2016-2017	30.38	56.65	0.62	18.34	13.61	1.8	29.84
2017-2019	21.22	69.84	0.48	42.51	7.84	3.11	10.94
2018-2019	55.72	107.57	2.35	75.86	21.14	21.93	32.45
2019-2020	224.15	1,070.09	98.19	492.95	35.84	13.73	13.52

Note:
* Air quality data not available prior to 2011
** Air quality data not available prior to 2001
***Air quality data not available prior to 2009

Extended Data Figure 6 - Costs for each fire season by State and Territory of Australia based on days during the wildfire season in which PM2.5 > 95th percentile (Main Analysis)

Supplementary Information for

Health costs of bushfire-related $PM_{2.5}$ from the 2019-20 Australian megafires – Supplementary material

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1. Supplementary Methods

Alternative economic evaluations of wildfire smoke related mortality based on long term health risk estimates to calculate the attributable number of premature deaths and years of life lost.

Approach

(a) **The number of premature deaths using long term exposure risk coefficients.** We applied the same modelling approach as described in the main text, but instead using long term health risk coefficient for all-cause mortality, for people aged 30 years or more. We used a RR= 1.062 (95% CI, 1.040 – 1.083) as recommended by the WHO.[1] This approach captures the contribution of wildfire smoke to annual average air pollution. We multiplied the value of a statistical life (VSL) by the total estimated premature deaths.

(b) **Year of life lost.** We estimated the number of years of life lost (YLL) using the following equation:

$$YLL = \sum_{ag} Cases_{deaths_{ag}} \times LE_{ag}$$

Where YLL is the estimated years of life lost, $Cases_{deaths_{ag}}$ is the estimated number of deaths on a particular age group 'ag' using the long-term health risk coefficient, and LE_{ag} is the life expectancy in years for age group 'ag'. We used the 2016-2018 life tables by State from the Australian Bureau of Statistics, [2] and estimated life expectancy by 5 year age groups using the following equation:

$$LE_{ag,s} = \frac{\sum_a LE_{a,s} \times Pop_{a,s}}{\sum_a Pop_{a,s}}$$

Where $LE_{ag,s}$ is the life expectancy in years for a person of state 's' and age group 'ag', $LE_{a,s}$ is the life expectancy in years of a person of state 's' and age 'a' and $Pop_{a,s}$ is the total population for state 's' and age 'a'.

In this analysis we used the value of a statistical life year (VSLY) and multiplied it by the estimated number of YLLs.

For the VSL and VSLY we used values recommended by the Office of Best Practice and Regulation.[3] Both estimates (VSL and VSLY) are a representation of how much society values risk reductions that would sum up to one life (VSL) or one year of life (VSLY). All values were adjusted to reflect the value of Australian Dollars of 2018 by applying inflation factors from the Reserve Bank of Australia.[4] VSL and VSLY values in 2018 $AUD were of $AUD 4,486,062 per statistical life and $AUD 194,396 per statistical life year, respectively.

2. Supplementary Tables

Supplementary Table 1. Correlation statistics for $PM_{2.5}$ observed vs. predicted for Queensland – Station Level

Region	Station	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
Gladstone	Barney Point	0.72	187	0.020020952	36.0	1.05764E-85	87.4%	87.4%	90.4%
	Boat Creek	1.05	2,785	0.012715570	82.4	0	70.9%	70.9%	74.6%
	Boyne Island	1.18	2,950	0.014382962	82.3	0	69.7%	69.6%	77.2%
	Clinton	0.98	3,110	0.010612399	92.4	0	73.3%	73.3%	74.8%
	Fishermans Landing	0.41	919	0.008883203	46.2	9.6322E-242	69.9%	69.9%	82.2%
	Mobile: Mt Larcom	0.88	73	0.034784934	25.4	1.05315E-37	90.0%	89.8%	81.2%
	South Gladstone	1.09	2,717	0.011899673	91.6	0	75.5%	75.5%	77.7%
	Targinie	1.14	2,277	0.015984414	71.0	0	68.9%	68.9%	75.2%
South East Queensland	Arundel	0.99	431	0.016603679	59.7	2.8505E-210	89.2%	89.2%	83.8%
	Brisbane CBD	0.95	100	0.014799934	64.3	1.438E-82	97.7%	97.6%	89.6%
	Cannon Hill	0.97	2,084	0.008810176	110.5	0	85.4%	85.4%	80.5%
	Dinmore	0.79	160	0.024552935	32.2	1.8204E-71	86.7%	86.6%	76.4%
	Jondaryan	0.54	776	0.015205558	35.2	5.3522E-163	61.5%	61.5%	60.2%
	Luscombe	1.10	222	0.028203324	38.9	9.2975E-101	87.2%	87.2%	79.9%
	Lutwyche	0.97	397	0.014047140	69.1	3.8615E-223	92.3%	92.3%	88.9%
	Lytton	0.82	1,857	0.012493261	66.0	0	70.1%	70.1%	67.9%
	Rocklea	0.76	4,968	0.005822179	130.7	0	77.5%	77.5%	75.8%
	South Brisbane	0.72	3,415	0.007820479	92.4	0	71.4%	71.4%	71.7%
	Southport	1.05	423	0.023805455	44.1	3.7099E-160	82.2%	82.1%	84.2%
	Springwood	0.87	5,146	0.006689898	130.1	0	76.7%	76.7%	76.1%
	Woolloongabba	0.75	2,676	0.008358726	89.9	0	75.1%	75.1%	74.3%
	Wynnum	0.69	3,455	0.008114844	84.6	0	67.5%	67.5%	70.7%
	Wynnum West	0.91	1,579	0.015255696	59.6	0	69.2%	69.2%	68.7%
South West Queensland	Condamine	0.95	280	0.025653957	37.1	5.4215E-110	83.2%	83.1%	82.9%
	Hopeland	0.75	658	0.017977803	41.7	1.1478E-186	72.6%	72.5%	75.6%
	Miles Airport	0.63	732	0.011588196	54.5	7.932E-260	80.3%	80.2%	85.3%
Toowoomba	North Toowoomba	0.96	1,531	0.006756602	141.8	0	92.9%	92.9%	84.5%
Townsville	North Ward	1.07	374	0.017102750	62.6	6.0823E-200	91.3%	91.3%	87.5%

Supplementary Table 2. Correlation statistics for $PM_{2.5}$ observed vs. predicted for New South Wales – Station Level

Region	Station	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
Bushfire Emergency - Coffs Harbour	Coffs Harbour	1.12	150	0.039435384	28.3	7.05776E-62	84.3%	84.2%	88.3%
Bushfire Emergency - Lismore	Lismore	0.83	128	0.038888770	21.3	9.21075E-44	78.1%	78.0%	80.6%
Bushfire Emergency - Port Macquarie	PORT MACQUARIE	1.27	149	0.040681425	31.3	4.66068E-67	86.8%	86.8%	91.6%
Central Coast	WYONG	1.08	2,738	0.009212734	117.2	0	83.4%	83.4%	82.0%
Central tablelands	BATHURST	1.03	1,453	0.017474581	58.8	0	70.5%	70.4%	78.0%
	ORANGE	1.17	459	0.024279199	48.1	3.1616E-181	83.5%	83.4%	89.6%
Illawarra	ALBION PARK STH	0.96	1,868	0.008327684	114.7	0	87.6%	87.6%	80.4%
	KEMBLA GRANGE	0.96	1,852	0.009521455	100.4	0	84.5%	84.5%	76.2%
	WOLLONGONG	0.91	7,275	0.004992157	181.3	0	81.9%	81.9%	78.9%
Lower Hunter	BERESFIELD	0.65	6,953	0.005203162	124.3	0	69.0%	69.0%	70.7%
	NEWCASTLE	1.04	2,305	0.008786489	117.9	0	85.8%	85.8%	77.0%
	WALLSEND	0.69	6,929	0.004280717	161.5	0	79.0%	79.0%	85.3%
Newcastle local	CARRINGTON	1.00	2,082	0.008225840	121.3	0	87.6%	87.6%	77.4%
	MAYFIELD	1.02	2,086	0.008454967	120.7	0	87.5%	87.5%	79.6%
	STOCKTON	0.96	1,989	0.008851741	108.8	0	85.6%	85.6%	69.5%
Northern Tablelands	ARMIDALE	1.19	741	0.020705816	57.5	2.0407E-275	81.7%	81.7%	87.8%
North-west slopes	GUNNEDAH	0.80	859	0.015911706	50.4	1.3831E-258	74.7%	74.7%	71.9%
	NARRABRI	0.67	867	0.017574942	37.9	3.6298E-186	62.4%	62.4%	65.1%
	TAMWORTH	0.84	1,495	0.013302406	62.9	0	72.6%	72.6%	72.4%
Research Monitoring	KATOOMBA	1.22	373	0.008919892	137.3	0	98.1%	98.1%	99.0%
Roadside Monitoring	BRADFIELD HIGHWAY	1.22	189	0.025531580	47.6	7.2587E-107	92.3%	92.3%	94.6%
South-west slopes	ALBURY	1.37	1,155	0.017471070	78.3	0	84.2%	84.1%	91.9%
	WAGGA WAGGA NTH	0.89	3,139	0.017272366	51.4	0	45.7%	45.7%	47.3%
Sydney central-east	CHULLORA	0.73	6,163	0.005785487	126.9	0	72.3%	72.3%	67.2%
	COOK AND PHILLIP	1.20	206	0.021401780	56.1	2.5021E-126	93.9%	93.9%	95.5%
	EARLWOOD	0.74	7,174	0.005657906	130.8	0	70.4%	70.4%	65.9%
	MACQUARIE PARK	1.10	985	0.014825968	74.5	0	84.9%	84.9%	84.9%
	RANDWICK	1.11	1,100	0.016284893	68.0	0	80.8%	80.8%	79.2%
	ROZELLE	1.08	1,751	0.009206086	117.9	0	88.8%	88.8%	85.4%
Sydney north-west	PARRAMATTA NORTH	1.06	2,215	0.007826153	135.0	0	89.2%	89.2%	85.2%
	PROSPECT	1.02	1,945	0.009162862	110.8	0	86.3%	86.3%	81.3%
	RICHMOND	0.67	6,975	0.006844086	98.3	0	58.1%	58.1%	60.8%
	ROUSE HILL	1.08	332	0.032320744	33.4	6.9154E-108	77.1%	77.0%	81.2%
	ST MARYS	1.04	1,415	0.011914573	87.7	0	84.5%	84.5%	83.2%
Sydney south-west	BARGO	1.18	1,231	0.018398014	64.3	0	77.1%	77.1%	84.0%

Region	Station	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
	BRINGELLY	1.03	1,378	0.012773309	81.0	0	82.7%	82.6%	81.9%
	CAMDEN	1.11	2,729	0.009758223	113.4	0	82.5%	82.5%	83.1%
	CAMPBELLTOWN WEST	0.99	1,660	0.010209621	96.6	0	84.9%	84.9%	80.6%
	LIVERPOOL	0.80	6,950	0.005072381	157.0	0	78.0%	78.0%	75.8%
	OAKDALE	1.13	1,232	0.014407036	78.6	0	83.4%	83.4%	89.0%
Upper Hunter	CAMBERWELL	0.75	3,175	0.007338525	102.7	0	76.9%	76.8%	57.8%
	MUSWELLBROOK	0.90	3,408	0.006363797	142.0	0	85.5%	85.5%	71.0%
	SINGLETON	0.88	3,413	0.007293563	120.8	0	81.0%	81.0%	63.3%

Supplementary Table 3. Correlation statistics for $PM_{2.5}$ observed vs. predicted for Australian Capital Territory – Station Level

Region	Station	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
ACT	Civic	1.39	1,724	0.007467727	185.7	0	95.2%	95.2%	97.8%
	Florey	1.36	2,156	0.007082270	192.7	0	94.5%	94.5%	97.6%
	Monash	1.59	2,459	0.009153640	174.2	0	92.5%	92.5%	97.3%

Supplementary Table 4. Correlation statistics for $PM_{2.5}$ observed vs. predicted for Victoria – Station Level

Region	Station	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
EAST	Alphington	1.10	1,945	0.011188256	98.2	0	83.2%	83.2%	79.6%
	Dandenong	1.72	1,078	0.042416026	40.5	1.3041E-218	60.4%	60.3%	82.4%
	Mooroolbark	1.16	906	0.017940003	64.8	0	82.3%	82.2%	86.1%
GEELONG	Geelong South	0.90	1,221	0.017029603	53.0	0	69.7%	69.7%	66.1%
LATROBE V2	Traralgon	1.12	1,933	0.009680247	115.4	0	87.3%	87.3%	85.6%
WEST	Brooklyn	1.14	676	0.033740798	33.8	1.4625E-147	62.9%	62.9%	72.0%
	Footscray	1.06	1,630	0.011427202	93.2	0	84.2%	84.2%	83.2%

Supplementary Table 5. Correlation statistics for $PM_{2.5}$ observed vs. predicted for South Australia – Station Level

Region	Station	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
North Western Adelaide	Le Fevre 1	0.90	1,406	0.007916836	113.1	0	90.1%	90.1%	68.1%
	Le Fevre 2	0.90	2,332	0.006885891	130.9	0	88.0%	88.0%	63.0%
South Australia	Port Augusta	0.40	981	0.009908809	40.9	6.9394E-214	63.0%	63.0%	75.3%
	Sellicks Beach	0.67	211	0.020531112	32.8	1.27675E-84	83.7%	83.6%	70.2%
Western Adelaide	Netley	0.81	6,357	0.004074759	199.3	0	86.2%	86.2%	57.7%
Northern Adelaide	Elizabeth	0.77	1,150	0.011697575	65.4	0	78.8%	78.8%	49.1%
Adelaide CBD	CBD	0.94	1,839	0.006691172	140.0	0	91.4%	91.4%	69.5%

Supplementary Table 6. Correlation statistics for $PM_{2.5}$ observed vs. predicted for Tasmania – Station Level

Region	Station	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
Break O'Day	FI	1.05	2,515	0.013176641	80.0	0	71.8%	71.8%	68.0%
	SH	1.18	2,702	0.017663491	66.9	0	62.4%	62.3%	72.0%
Burnie	ER	1.63	2,496	0.019033728	85.5	0	74.5%	74.5%	90.2%
Central Coast	WU	1.29	380	0.024688071	52.1	7.4933E-175	87.7%	87.7%	92.6%
Circular Head	ST	1.29	2,457	0.018279383	70.8	0	67.1%	67.1%	78.8%
Clarence	MT	1.17	1,576	0.013444431	87.0	0	82.8%	82.7%	84.0%
Dervent Valley	BE	1.05	952	0.016902367	62.1	0	80.2%	80.2%	75.1%
Derwent Valley	GR	1.19	2,409	0.010499874	113.4	0	84.2%	84.2%	86.1%
	NN	1.08	1,946	0.004292969	251.9	0	97.0%	97.0%	97.4%
Devonport	DT	1.32	1,477	0.016208499	81.1	0	81.7%	81.7%	88.1%
Dorset	DE	0.90	2,836	0.010782245	83.5	0	71.1%	71.1%	64.3%
	SC	1.36	2,664	0.015851505	85.7	0	73.4%	73.4%	82.0%
George Town	GB	1.23	2,364	0.014349734	86.0	0	75.8%	75.8%	82.3%
Glamorgan/Spring Bay	TR	1.22	391	0.022255673	55.0	1.0207E-185	88.6%	88.5%	91.2%
Glenorchy	GO	1.27	591	0.013920490	90.9	0	93.3%	93.3%	95.9%
Hobart	CG	1.03	874	0.015037966	68.2	0	84.2%	84.2%	79.8%
	HT	1.10	2,757	0.006878267	160.2	0	90.3%	90.3%	90.9%
Huon Valley	CY	1.96	548	0.021082593	92.9	0	94.0%	94.0%	99.0%
	GV	1.31	2,908	0.012270273	106.6	0	79.6%	79.6%	86.6%
	HV	1.19	2,788	0.009684990	123.3	0	84.5%	84.5%	87.6%
	JB	1.81	2,407	0.026180178	69.0	0	66.4%	66.4%	86.8%
Kentish	SF	1.35	2,435	0.014388509	93.5	0	78.2%	78.2%	85.7%
Latrobe	LT	1.10	401	0.013222996	83.3	8.1964E-255	94.5%	94.5%	94.9%
Launceston	LD	1.18	2,753	0.011665616	101.4	0	78.9%	78.9%	81.4%
	SL	1.18	2,690	0.009845420	120.2	0	84.3%	84.3%	87.2%
	TI	1.31	392	0.020721015	63.2	2.7859E-207	91.1%	91.1%	95.3%
Meander Valley	CA	0.98	995	0.016003649	61.4	0	79.1%	79.1%	71.9%
	DL	1.10	1,061	0.007048594	155.6	0	95.8%	95.8%	96.0%
	HA	1.21	1,749	0.007059954	172.1	0	94.4%	94.4%	95.9%
	WE	1.16	409	0.015173143	76.1	2.8397E-243	93.4%	93.4%	94.2%
Northern Midlands	CT	1.14	1,890	0.010309393	111.0	0	86.7%	86.7%	87.4%
	LF	1.16	1,759	0.006233343	186.3	0	95.2%	95.2%	96.1%
	PE	1.23	1,609	0.007400391	165.9	0	94.5%	94.5%	96.1%
Sorell	BC	1.07	1,177	0.015727677	68.0	0	79.7%	79.7%	75.1%
Southern Midlands	OL	1.13	599	0.010640389	106.2	0	95.0%	95.0%	95.2%
Waratah/Wynyard	WY	1.16	404	0.018093619	64.1	1.9132E-213	91.1%	91.0%	92.2%
West Coast	QT	1.15	418	0.015525475	73.8	1.4215E-241	92.9%	92.9%	94.0%
West Tamar	EX	1.45	2,690	0.014502594	99.9	0	78.8%	78.8%	89.2%

Supplementary Table 7. Correlation statistics for $PM_{2.5}$ observed vs. predicted for Western Australia – Station Level

Region	Station	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
Western Australia	Bunbury	1.03	7,175	0.003652726	281.8	0	91.7%	91.7%	84.3%
	Caversham	0.96	4,863	0.003699435	259.7	0	93.3%	93.3%	78.9%
	Duncraig	0.98	7,122	0.002838214	346.8	0	94.4%	94.4%	80.0%
	South Lake	0.97	4,981	0.003714317	261.7	0	93.2%	93.2%	77.2%
	Kalgoorlie	0.97	64	0.041783300	23.3	1.13938E-32	89.6%	89.4%	68.5%

Supplementary Table 8. Correlation statistics for $PM_{2.5}$ observed vs. predicted for all States – Regional level

State	Region	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
Queensland	Gladstone	0.75	15,018	0.004982511	149.9	0	59.9%	59.9%	67.4%
	South East Queensland	0.78	27,689	0.002750769	283.8	0	74.4%	74.4%	73.9%
	South West Queensland	0.68	1,670	0.009225765	74.0	0	76.7%	76.6%	81.0%
	Toowoomba	0.96	1,531	0.006756602	141.8	0	92.9%	92.9%	84.5%
	Townsville	1.07	374	0.017102750	62.6	6.0823E-200	91.3%	91.3%	87.5%
New South Wales	Bushfire Emergency - Coffs Harbour	1.12	150	0.039435384	28.3	7.05776E-62	84.3%	84.2%	88.3%
	Bushfire Emergency - Lismore	0.83	128	0.038888770	21.3	9.21075E-44	78.1%	78.0%	80.6%
	Bushfire Emergency - Port Macquarie	1.27	149	0.040681425	31.3	4.66068E-67	86.8%	86.8%	91.6%
	Central Coast	1.08	2,738	0.009212734	117.2	0	83.4%	83.4%	82.0%
	Central tablelands	1.11	1,912	0.013508740	82.1	0	77.9%	77.9%	85.5%
	Illawarra	0.92	10,995	0.003943345	233.8	0	83.3%	83.3%	78.5%
	Lower Hunter	0.70	16,187	0.003238758	216.2	0	74.3%	74.3%	77.1%
	Newcastle local	0.99	6,157	0.004933900	200.6	0	86.7%	86.7%	75.6%
	Northern Tablelands	1.19	741	0.020705816	57.5	2.0407E-275	81.7%	81.7%	87.8%
	North-west slopes	0.79	3,221	0.008905433	89.1	0	71.1%	71.1%	71.0%
	Research Monitoring	1.22	373	0.008919892	137.3	0	98.1%	98.1%	99.0%
	Roadside Monitoring	1.22	189	0.025531580	47.6	7.2587E-107	92.3%	92.3%	94.6%
	South-west slopes	1.06	4,294	0.013450594	79.0	0	59.3%	59.3%	68.4%
	Sydney central-east	0.81	17,379	0.003684713	220.6	0	73.7%	73.7%	68.0%
	Sydney north-west	0.83	12,882	0.004821801	172.6	0	69.8%	69.8%	68.0%
	Sydney south-west	0.94	15,180	0.004013596	234.9	0	78.4%	78.4%	77.9%
	Upper Hunter	0.85	9,996	0.004074265	208.0	0	81.2%	81.2%	64.2%
Australian Capital Territory	ACT	1.44	6,339	0.004794357	301.1	0	93.5%	93.5%	97.1%
Victoria	EAST	1.20	3,929	0.011459049	104.4	0	73.5%	73.5%	77.8%
	GEELONG	0.90	1,221	0.017029603	53.0	0	69.7%	69.7%	66.1%
	LATROBE V2	1.12	1,933	0.009680247	115.4	0	87.3%	87.3%	85.6%
	WEST	1.09	2,306	0.013538603	80.8	0	73.9%	73.9%	76.6%
South Australia	North Western Adelaide	0.90	3,738	0.005208450	172.6	0	88.9%	88.8%	65.1%
	South Australia	0.41	1,192	0.009088571	45.6	2.4212E-263	63.6%	63.5%	75.1%
	Western Adelaide	0.81	6,357	0.004074759	199.3	0	86.2%	86.2%	57.7%
	Northern Adelaide	0.77	1,150	0.011697575	65.4	0	78.8%	78.8%	49.1%
	Adelaide CBD	0.94	1,839	0.006691172	140.0	0	91.4%	91.4%	69.5%
Tasmania	Break O'Day	1.11	5,217	0.010874891	102.0	0	66.6%	66.6%	70.4%
	Burnie	1.63	2,496	0.019033728	85.5	0	74.5%	74.5%	90.2%

State	Region	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
	Central Coast	1.29	380	0.024688071	52.1	7.4933E-175	87.7%	87.7%	92.6%
	Circular Head	1.29	2,457	0.018279383	70.8	0	67.1%	67.1%	78.8%
	Clarence	1.17	1,576	0.013444431	87.0	0	82.8%	82.7%	84.0%
	Dervent Valley	1.05	952	0.016902367	62.1	0	80.2%	80.2%	75.1%
	Derwent Valley	1.09	4,355	0.003691308	295.9	0	95.3%	95.3%	96.3%
	Devonport	1.32	1,477	0.016208499	81.1	0	81.7%	81.7%	88.1%
	Dorset	1.08	5,500	0.009668536	111.8	0	69.5%	69.5%	70.8%
	George Town	1.23	2,364	0.014349734	86.0	0	75.8%	75.8%	82.3%
	Glamorgan/Spring Bay	1.22	391	0.022255673	55.0	1.0207E-185	88.6%	88.5%	91.2%
	Glenorchy	1.27	591	0.013920490	90.9	0	93.3%	93.3%	95.9%
	Hobart	1.09	3,631	0.006184146	176.7	0	89.6%	89.6%	90.0%
	Huon Valley	1.32	8,651	0.007322619	180.9	0	79.1%	79.1%	86.8%
	Kentish	1.35	2,435	0.014388509	93.5	0	78.2%	78.2%	85.7%
	Latrobe	1.10	401	0.013222996	83.3	8.1964E-255	94.5%	94.5%	94.9%
	Launceston	1.19	5,835	0.007071781	168.4	0	82.9%	82.9%	86.1%
	Meander Valley	1.17	4,214	0.004648554	252.6	0	93.8%	93.8%	95.3%
	Northern Midlands	1.18	5,258	0.004175881	283.4	0	93.9%	93.9%	95.4%
	Sorell	1.07	1,177	0.015727677	68.0	0	79.7%	79.7%	75.1%
	Southern Midlands	1.13	599	0.010640389	106.2	0	95.0%	95.0%	95.2%
	Waratah/Wynyard	1.16	404	0.018093619	64.1	1.9132E-213	91.1%	91.0%	92.2%
	West Coast	1.15	418	0.015525475	73.8	1.4215E-241	92.9%	92.9%	94.0%
	West Tamar	1.45	2,690	0.014502594	99.9	0	78.8%	78.8%	89.2%
Western Australia	Western Australia	0.99	24,359	0.001747846	567.2	0	93.0%	93.0%	81.0%

Supplementary Table 9. Correlation statistics for $PM_{2.5}$ observed vs. predicted for all States - State Level

State	Estimate	Observations (N)	Standard Error	t-value	p-value	R^2	Adjusted R	Correlation
Queensland	0.77	46,282	0.002399759	320.6	0	69.0%	69.0%	71.1%
New South Wales	0.91	102,671	0.001589195	573.4	0	76.2%	76.2%	77.4%
Australian Capital Territory	1.44	6,339	0.004794357	301.1	0	93.5%	93.5%	97.1%
Victoria	1.11	9,389	0.006583850	168.7	0	75.2%	75.2%	76.3%
South Australia	0.75	14,276	0.003104388	241.1	0	80.3%	80.3%	59.4%
Tasmania	1.21	63,469	0.002113611	573.7	0	83.8%	83.8%	88.6%
Western Australia	0.99	24,359	0.001747846	567.2	0	93.0%	93.0%	81.0%

3. Air quality (AQ) monitoring stations data availability

Supplementary Table 10. Number of AQ monitoring stations with data available for each State and Year

Year	Queensland	New South Wales	Australian Capital Territory	Victoria	South Australia	Tasmania	Western Australia	All analysed States
2000	10	13		11			4	37
2001	13	14		12	1		4	43
2002	12	15		14	2		4	46
2003	15	16		14	3		4	51
2004	17	19		13	4		4	56
2005	18	19		13	5		4	58
2006	16	19		14	6		7	61
2007	17	20		13	7		7	63
2008	19	20		12	7		8	65
2009	23	21		13	7		9	72
2010	20	23		15	6	17	9	89
2011	23	36		14	7	19	9	107
2012	23	40	2	14	7	21	9	115
2013	21	39	2	14	9	27	9	120
2014	25	42	3	15	10	25	9	128
2015	28	42	3	17	10	24	9	133
2016	32	42	3	18	11	28	9	143
2017	23	45	3	19	12	33	9	144
2018	15	46	3	19	11	34	8	136
2019	12	54	3	21	11	35	10	146
2020	12	54	3	19	11	35	7	141
Any year between 2000 - 2020	**45**	**55**	**3**	**26**	**12**	**38**	**11**	**189**

4. Proportion of exposed population

Supplementary Table 11. Percentage of exposed population (and total state population) captured by IDW method and availability of AQ monitoring stations for each State and Year

Year	Queensland	New South Wales	Australian Capital Territory	Victoria	South Australia	Tasmania	Western Australia	All analysed States
2000(*)	78.4%(3,571,469)	80.9%(6,530,349)	0.0%(321,538)	86.3%(4,763,615)	0.0%(1,503,461)	0.0%(473,668)	84.0%(1,906,274)	72.4%(19,070,374)
2001	81.3%(3,571,469)	82.0%(6,530,349)	0.0%(321,538)	86.3%(4,763,615)	82.6%(1,503,461)	0.0%(473,668)	84.0%(1,906,274)	79.8%(19,070,374)
2002	81.4%(3,653,123)	82.0%(6,580,807)	0.0%(324,627)	86.8%(4,817,774)	82.7%(1,511,567)	0.0%(474,152)	84.1%(1,928,512)	80.0%(19,290,562)
2003	83.0%(3,743,121)	82.0%(6,620,715)	0.0%(327,357)	91.0%(4,873,809)	88.6%(1,520,399)	0.0%(478,534)	84.2%(1,952,741)	81.8%(19,516,676)
2004	83.3%(3,829,970)	82.2%(6,650,735)	0.0%(328,940)	87.0%(4,927,149)	88.9%(1,528,189)	0.0%(483,178)	84.4%(1,979,542)	81.0%(19,727,703)
2005	83.4%(3,918,494)	82.9%(6,693,206)	0.0%(331,399)	87.1%(4,989,246)	89.0%(1,538,804)	0.0%(486,202)	84.6%(2,011,207)	81.3%(19,968,558)
2006	83.5%(4,007,992)	82.9%(6,742,690)	0.0%(335,170)	91.2%(5,061,266)	89.1%(1,552,529)	0.0%(489,302)	86.8%(2,050,581)	82.6%(20,239,530)
2007	83.5%(4,111,018)	83.1%(6,834,156)	0.0%(342,644)	91.3%(5,153,522)	89.4%(1,570,619)	0.0%(493,262)	87.0%(2,106,139)	82.7%(20,611,360)
2008	83.6%(4,219,505)	83.2%(6,943,461)	0.0%(348,368)	87.6%(5,256,375)	89.5%(1,588,665)	0.0%(498,568)	87.4%(2,171,700)	81.9%(21,026,642)
2009	84.3%(4,328,771)	83.3%(7,053,755)	0.0%(354,785)	87.8%(5,371,934)	89.6%(1,608,902)	0.0%(504,353)	89.6%(2,240,250)	82.4%(21,462,750)
2010	84.3%(4,404,744)	83.5%(7,144,292)	0.0%(361,766)	87.9%(5,461,101)	89.7%(1,627,322)	100.0%(508,847)	89.6%(2,290,845)	84.9%(21,798,917)
2011	83.8%(4,476,778)	85.1%(7,218,529)	0.0%(367,985)	88.0%(5,537,817)	89.8%(1,639,614)	100.0%(511,483)	89.7%(2,353,409)	85.3%(22,105,615)
2012	83.9%(4,569,863)	85.4%(7,308,205)	100.0%(376,564)	88.2%(5,653,429)	89.8%(1,656,711)	100.0%(511,848)	89.8%(2,426,846)	87.2%(22,503,466)
2013	84.0%(4,654,521)	85.5%(7,409,082)	100.0%(383,652)	88.3%(5,775,808)	89.9%(1,671,661)	100.0%(512,520)	90.0%(2,492,951)	87.3%(22,900,195)
2014	85.7%(4,724,417)	85.6%(7,517,195)	100.0%(389,406)	88.5%(5,901,970)	89.9%(1,687,673)	100.0%(513,839)	90.2%(2,523,100)	87.7%(23,257,600)
2015	86.2%(4,784,367)	85.8%(7,627,418)	100.0%(396,690)	88.6%(6,032,968)	90.0%(1,701,843)	100.0%(515,396)	90.5%(2,544,267)	88.0%(23,602,949)
2016	86.5%(4,848,877)	85.9%(7,739,274)	100.0%(403,468)	92.4%(6,179,249)	90.1%(1,713,054)	100.0%(517,588)	90.7%(2,558,951)	89.1%(23,960,461)
2017	84.5%(4,929,152)	86.5%(7,861,674)	100.0%(411,667)	92.5%(6,321,648)	90.1%(1,723,671)	100.0%(522,152)	90.9%(2,575,452)	88.9%(24,345,416)
2018	82.9%(5,011,216)	87.1%(7,988,241)	100.0%(420,960)	92.6%(6,460,675)	90.2%(1,736,422)	100.0%(528,201)	91.0%(2,595,192)	88.8%(24,740,907)
2019(*)	73.6%(5,011,216)	94.6%(7,988,241)	100.0%(420,960)	92.8%(6,460,675)	90.2%(1,736,422)	100.0%(528,201)	91.0%(2,595,192)	89.4%(24,740,907)
2020(*)	73.6%(5,011,216)	94.6%(7,988,241)	100.0%(420,960)	92.8%(6,460,675)	90.2%(1,736,422)	100.0%(528,201)	91.0%(2,595,192)	89.4%(24,740,907)

(*): Population of 2000 assumed same as that of 2001. Population of 2019 and 2020 assumed same as that of 2018.

Annual exposed total population proportion for each state remained similar over time for all states (range of state specific variation from 0% to 14%) apart from the Australian Capital Territory and Tasmania which had no exposure data prior to 2012 and 2010 respectively and then 100% coverage after then. South Australia had no exposure data prior to 2001.

Supplementary Table 12. Exposure-response functions used to calculate the attributable health burden

Outcome	**Cause**	**Age group**	**Exposure**	**Beta (*)**	**Standard Error**	**RR per 10 ($\mu g/m^3$) (95% Confidence Interval)**
Premature Mortality	All-cause	All	24h $PM_{2.5}$	0.001222	0.000393	1.0123[1] (1.0045-1.0201)
Hospital Admissions	Cardiovascular	All	24h $PM_{2.5}$	0.000906	0.000377	1.0091[1] (1.0017 – 1.0166)
	Respiratory	All	24h $PM_{2.5}$	0.001882	0.001051	1.019[1] (0.9982 – 1.0402)
ED visits	Asthma	All	24h $PM_{2.5}$	0.00639	0.001344	1.066[5] (1.038 – 1.094)

(*) Beta estimated as follows: $\beta = {\ln(RR)}/{\Delta C} = {\ln(RR)}/{10}$

Supplementary Table 13. Unitary health costs used to assess the economic burden

Outcome	Value ($AUD)	Period of value	Inflation[4]	Value 2018 ($AUD)
Cardiovascular hospital admissions	7,193[6]	2015-2016	3.9%	7,473
Respiratory hospital admissions	7,280[6]	2015-2016	3.9%	7,564
ED asthma visits	705[7]	2015-2016	3.9%	732
Premature mortality	4,200,000[3]	2014	6.8%	4,486,062

5. References

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