



Research article

Perceptions of air quality and concern for health in relation to long-term air pollution exposure, bushfires, and COVID-19 lockdown: A before-and-after study



Alec T. Cobbold^{a,*}, Melanie A. Crane^a, Luke D. Knibbs^{b,c}, Ivan C. Hanigan^{d,e}, Stephen P. Greaves^f, Chris E. Rissel^{a,g}

^a Sydney School of Public Health, Charles Perkins Centre, The University of Sydney, Sydney, NSW 2006, Australia

^b Sydney School of Public Health, The University of Sydney, Sydney, NSW 2006, Australia

^c Public Health Unit, Sydney Local Health District, Camperdown, NSW 2050, Australia

^d University Centre for Rural Health, School of Public Health, The University of Sydney, Sydney, NSW 2006, Australia

^e Centre for Air Pollution, Energy and Health Research (CAR), Sydney, NSW 2006, Australia

^f Institute of Transport and Logistics Studies, The University of Sydney Business School, The University of Sydney, Sydney, NSW 2006, Australia

^g College of Medicine and Public Health, Flinders University, Royal Darwin Hospital, Tiwi, NT 0810, Australia

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ABSTRACT

Background: Air pollution is a major health burden and the leading environmental risk factor for non-communicable diseases worldwide. People's perceptions and concerns about air pollution are important as they may predict protective behaviour or support for climate change mitigation policies.

Methods: This repeat cross-sectional study uses survey data collected from participants in Sydney, Australia in September–November 2019 ($n = 1,647$) and October–December 2020 ($n = 1,458$), before and after the devastating 2019/2020 bushfires and first COVID-19 lockdown restrictions in Sydney in 2020. Participants' perceptions of air quality and concerns for health in relation to air quality were modeled against estimates of annual average NO_2 and $\text{PM}_{2.5}$ concentrations in their neighbourhood.

Results: Participants in suburbs with higher estimated air pollution concentrations generally perceived poorer air quality and were more concerned for health in relation to air quality. A $5 \mu\text{g}/\text{m}^3$ increase in NO_2 was associated with perceived poorer air quality (OR 1.32, 95%CI 1.18–1.47). A $1 \mu\text{g}/\text{m}^3$ increase in estimated $\text{PM}_{2.5}$ was associated with perceived poorer air quality (OR 1.37, 95%CI 1.24–1.52) and greater concern for health (OR 1.18, 95%CI 1.05–1.32). Air quality was perceived as better in 2020 than in 2019 in both NO_2 and $\text{PM}_{2.5}$ models ($p < 0.001$). Air quality concern increased in 2020 in both models.

Discussion: This study provides the first Australian data on the association between estimated air quality exposure and air quality perceptions and concerns, contributing new evidence to inform public health approaches that increase awareness for air pollution and reduce the health burden.

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1. Introduction

Outdoor (ambient) air pollution is a major public health priority and the leading environmental risk factor for non-communicable disease (NCD) worldwide [1]. Ambient air pollution comprises many sources, and pollutants with well-characterised health effects include fine airborne particulate matter ($<2.5 \mu\text{m}$ aerodynamic diameter, $\text{PM}_{2.5}$) and nitrogen dioxide (NO_2). It is estimated that 4.2 million premature deaths worldwide were attributable to $\text{PM}_{2.5}$ in 2015 [2]. Exposure to $\text{PM}_{2.5}$ impacts morbidity outcomes including

cardiovascular and respiratory disease and decreased life expectancy [2], as well as risk of birth defects [3], preterm birth, low birth weight and still-birth [4], reduced neurocognitive performance in children and accelerated cognitive decline in old age [5], and increased psychological distress [6]. NO_2 is associated with childhood asthma [7], and there is accumulating evidence that the impact of NO_2 on mortality may be as great as $\text{PM}_{2.5}$ [8]. $\text{PM}_{2.5}$ can be both natural and anthropogenic in origin, with major anthropogenic sources including emissions from motor vehicles, wood-heaters, industry, and burning of fossil fuels. In Australian cities, the major sources of NO_2 are on-road vehicle emissions and burning of fossil fuels.

Given its spatial variability, air quality is a pertinent environmental justice issue, where more disadvantaged groups bear a

* Corresponding author.

E-mail address: alec.cobbold@sydney.edu.au (A.T. Cobbold).

disproportionate burden of environmental health risks [9]. Studies in Australia have shown that at a country level, neighborhoods and communities with greater socio-economic disadvantage and higher Indigenous Australian population are exposed to greater NO₂ and PM_{2.5} concentrations [10,11], and greater density of industrial sites [12]. Elderly populations and those with lower educational attainment also are exposed to greater air pollution [11,12]. These populations are more vulnerable to the health impacts from air pollution, with greater mortality for elderly individuals [13] and greater hospitalization rates for Indigenous Australians [14] relating to air pollution exposure.

Transitioning away from fossil fuels to transform cities for sustainability and safeguard human health from climate change also can lead to substantial change improvements in air quality [15–17]. In some circumstances, individuals can be agents for these changes, either individually or collectively, but to do so they must first be aware of the health risks of air pollution. People's health and risk perceptions are important as they may predict future behavior changes [18], as heightened risk appraisals and feelings of vulnerability tend to motivate positive changes to health behaviors [19,20]. This is notable when personal interventions to minimize the health burden from air pollution involve behavioral changes, including reducing personal emission of air pollutants by encouraging active and public transport, and limiting exposure to pollution by avoiding areas or times with excessive air pollution levels [21,22]. These behaviors rely on adequate perceptions of where and when air quality is poor, as well as a proper understanding of the health risks posed by air pollution. Knowledge of the extent to which people are aware of the air pollution around them and how it affects their health will better inform public health practitioners and policy makers. Better understanding can improve effective communication of the health risks; implementation of interventions that limit exposure to air pollution; and encourage behavioral and system change to improve air quality.

Several studies have identified associations between objective air quality measurements and people's perceptions of or concerns for air quality [23], specifically, perceived poorer air quality or health concerns in relation to air quality associated with objective increases in exposure to NO₂ [24,25] and PM_{2.5} [26–28]. Most identified studies investigating associations between measures of air pollution and air quality perception or concern are from China, Europe and the USA

[23], countries and regions with comparatively high average NO₂ and PM_{2.5} levels. While air pollution levels in Sydney are relatively low compared to similarly-sized 'global' cities, low concentrations of PM_{2.5} and NO₂ may still be associated with mortality and morbidity, and emerging evidence suggests at a steeper dose-response curve than at higher concentrations [29]. Air pollution is a ubiquitous exposure and there is no evidence of a safe lower threshold for exposure to PM_{2.5} [30]. The aims of this study are:

- (1) to examine associations between estimated (objective) air pollution levels and people's (subjective) air quality perceptions and concerns; and,
- (2) to examine the sensitivity of these perceptions and concerns in relation to the 2019–2020 bushfires and COVID-19 pandemic, significant events in Sydney that might have influenced people's air quality perceptions and concerns.

2. Methods

2.1. Study design and sample

This study uses a repeat cross-sectional design using survey responses collected as part of the Sydney Travel and Health Study (STAHS), an ongoing study of Sydney residents, their health and travel behaviors, and perceptions of the built environment. Participants were first surveyed in September–November 2019 largely before the 2019–2020 bushfires, with a second wave in October–December 2020, after COVID-19 restrictions had begun lifting in Sydney. The 2019–2020 Australian bushfires, dubbed the *Black Summer* fires, burned from October 2020 until February 2021, although Sydney was only affected from November 2020, causing widespread destruction of natural habitats, an estimated 400 deaths, and 4000 hospitalizations [31]. Shortly after, Australians were struck by a second public health emergency with the spread of COVID-19 in March 2020, and unprecedented restrictions to social, economic and travel activities. However, measured improvements in air quality were recorded in Australia [32] and elsewhere in the world during the pandemic [33,34]. Fig. 1 shows the average daily NO₂ and PM_{2.5}

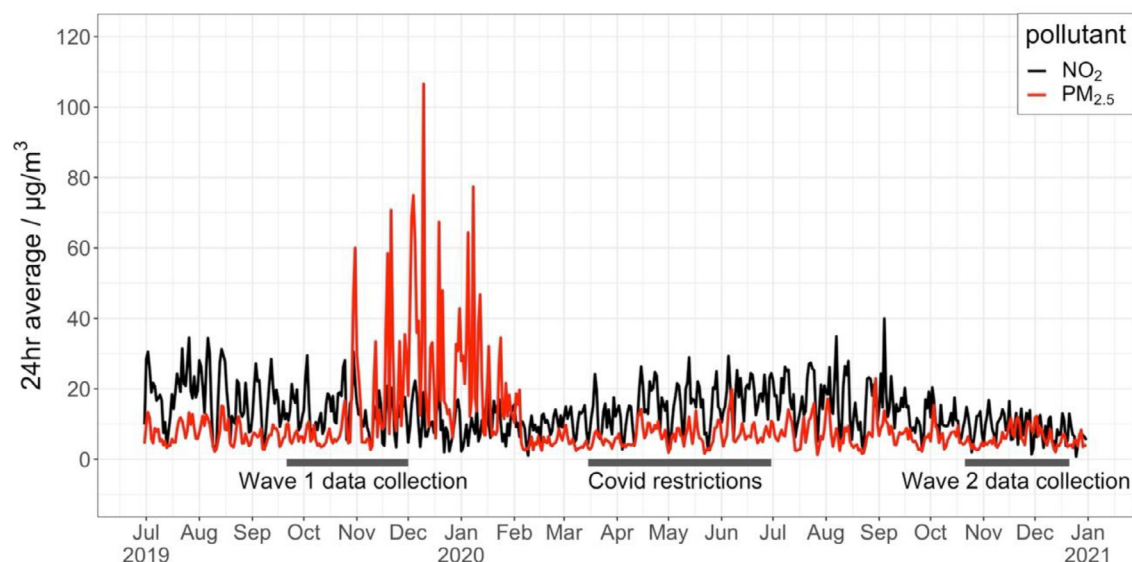


Fig. 1. 24-h average air quality measurements averaged across Sydney's air quality monitoring stations, and timeline of study data collection waves and major Covid restrictions in New South Wales, indicating the peak elevations during the 2019–20 bushfire period (Oct 2019 – Feb 2020). Air quality monitoring data source: NSW Government, Department of Planning and Environment <https://www.dpie.nsw.gov.au/air-quality/air-quality-data-services/data-download-facility>.

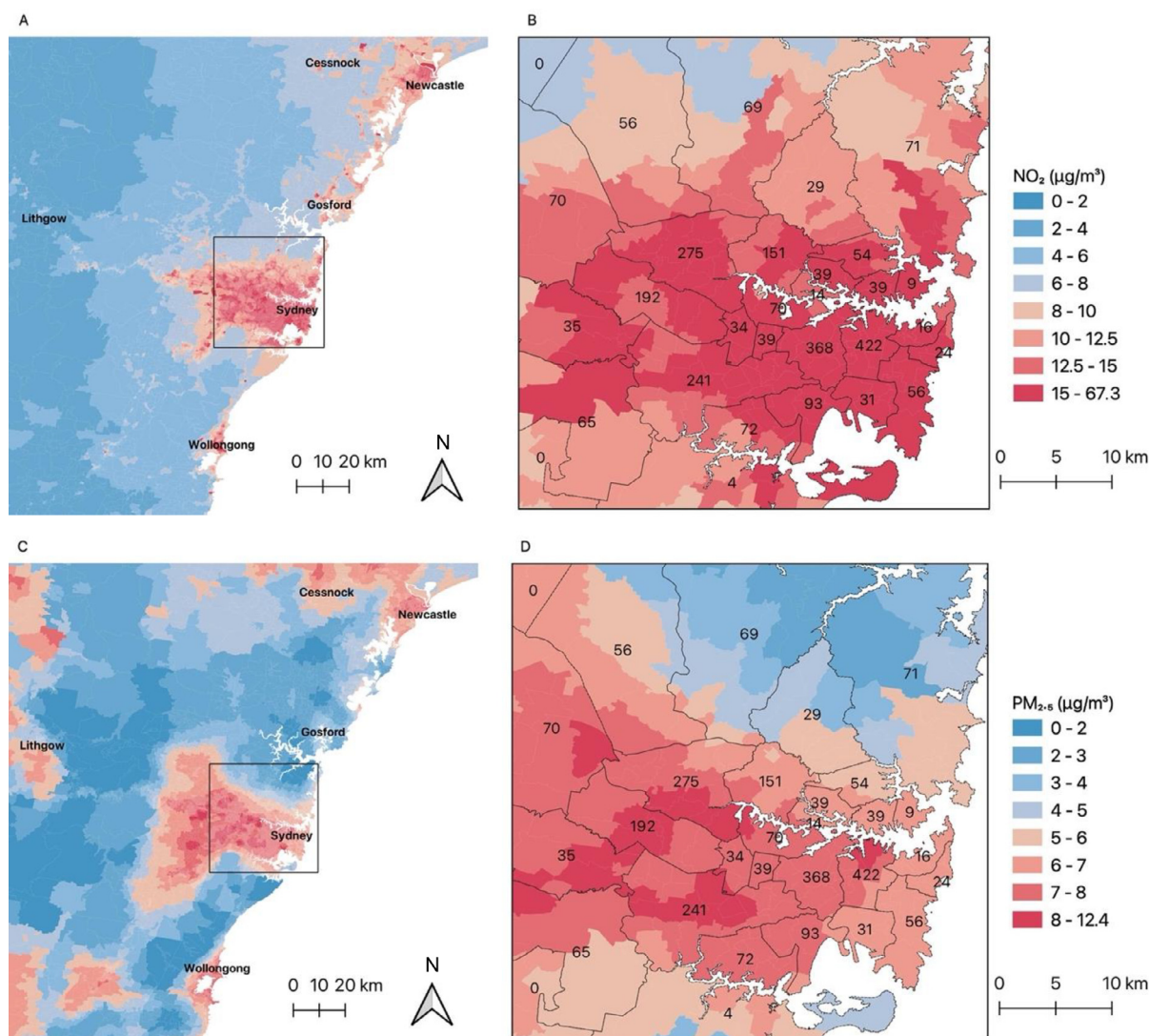


Fig. 2. Map of study area and surrounds with estimated annual average concentrations of NO₂ (A) and PM_{2.5} (C) by mesh-block; and aggregated by postal area code (population weighted) with number of surveyed participants by Local Government Area for NO₂ (B) and PM_{2.5} (D).

concentrations aggregated across 18 monitoring stations within the study area, with data collection periods and major Covid restrictions in New South Wales (NSW) overlayed on the timeline. The period between October 2019 and February 2020 clearly indicates a dramatic increase in daily exposure to PM_{2.5} across Sydney during the 2019–2020 bushfires.

Most participants were recruited through a survey panel, with additional participants recruited through email and social media platforms. Participants needed to be aged between 18 and 70 years-old and residing in Greater Sydney (Fig. 2) to be eligible for the study. The survey was administered through an online questionnaire, which took 15 minutes to complete.

2.2. Variables

2.2.1. Air quality perceptions and concerns for health

Participants were asked two items relating to air quality perceptions and concerns for health: 'How would you rate the overall air quality of your neighborhood?', with responses on a four-point scale as either 'completely unacceptable', 'somewhat unacceptable', 'somewhat acceptable', or 'completely acceptable' (hereafter *air quality perception*); and 'To what extent do you think air quality affects your health and wellbeing?', with responses on a three-point scale as either

'very much', 'a little', or 'not at all' (hereafter *air quality concern*). These variables were analysed as binary outcomes in our models, with air quality perception treated as 'completely acceptable' or 'less than completely acceptable', and air quality concern as 'not at all or a little' or 'very much'. As our interest was to investigate greater concern for air quality a sensitivity analysis was performed to test the alternate reference category for air quality concern ('not at all' vs 'a little or very much') but it generated a poorer model fit (Tables S3A and S3B).

2.2.2. Socio-demographic and health characteristics

Sociodemographic characteristics considered for inclusion in analysis were age, gender, education level, household income, and having children in the household. Health characteristics considered were self-reported quality of life, sufficient physical activity for health, body-mass index (BMI), wheezing, and asthma diagnosis. Quality of life was assessed using the World Health Organization's (WHO) abbreviated quality of life assessment tool (WHOQoL-BREF) [35], measured using a 5-point Likert scale and considered as a binary variable in analysis; 'less than good', 'good or very good'. Physical activity was assessed using the Active-Australia Survey [36], which asks participants to record total minutes of walking, and moderate-vigorous physical exercise in the previous week. Sufficient physical activity was considered as ≥ 150 mins of physical activity across at least 5

sessions in a week. BMI was calculated from participants' recorded height and weight. Participants were asked to record whether they had ever been diagnosed with asthma or had experienced wheezing or whistling in their chest in the past 4 weeks [37].

2.2.3. Objective air quality data

Estimates of annual mean outdoor NO₂ and PM_{2.5} were acquired from satellite-based land-use regression (LUR) models, of which the development and validation is described elsewhere [38–41]. These predictions were made at meshblock centroids, the smallest spatial census unit, of which there were 50,563 in the study area (median size: 0.023 km², median usual resident population (URP): 80). For analysis, meshblock air quality estimations were aggregated as the postal area code (POA) mean, weighted by meshblock URP from the 2016 census, then linked to participant survey responses. Predictions were made for 2015 for NO₂, and 2018 for PM_{2.5}. This was the most recent of available data, however annual mean pollution concentrations are robust estimates that are buffered against transient changes, and we have previously shown negligible year-to-year variability in mesh block estimations [41,42]. LUR models can provide high spatial resolution predictions of background annual average air pollutant exposure, and are accurate in extending air quality readings to unmeasured sites, especially in urban areas [43,44]. For analysis, NO₂ was scaled to a 5 µg/m³ increase for interpretability and comparability with other studies, while PM_{2.5} was scaled to a 1 µg/m³ increase, using respective interquartile ranges of meshblock exposure estimations across our study area.

2.3. Analysis

Descriptive statistics were first used to describe the sample's sociodemographic and health characteristics and tested for consistency across both waves with Pearson's chi-squared tests. Mixed effects linear regression models were first used to examine association between sociodemographic and health characteristics with annual mean air quality predictions (Table S1). Mixed effects logistic regression models were then used to examine associations between sociodemographic and health characteristics with the air quality perception and air quality concern survey items (Table S2). Variables

were selected for analysis as covariates in the final models if they had *p*-values less than 0.2 for association with either the air quality perception or concern outcome, or if their inclusion had been decided *a priori*. Body-mass index was removed from the final model. It was decided *a priori* to include sufficient physical activity as a covariate, given previous evidence of association with air quality concern [24].

Mixed effects logistic regression models were used to examine association between estimated annual average air quality and participants' air quality perceptions and concerns, adjusted for sociodemographic and health characteristics, and wave (year). In all models, participants were clustered as a random effect to account for individuals who participated in both 2019 and 2020 waves (*n* = 557). For each question, predicted air quality was included as either NO₂ or PM_{2.5} in separate models, due to correlation between exposure to either pollutant. In answering the first research question, predicted air quality measures were considered the explanatory variable and all other variables as covariates. In answering the second research question, wave (year) was considered the explanatory variable and predicted air quality measures as covariates, along with other variables, to adjust for background differences in neighbourhood exposure. A sensitivity analysis was performed to test whether people's air quality perceptions were associated with air quality concern, and whether air quality perception should be included as covariate in the air quality concern model. Air quality perception was insignificant (Table S3A and S3B) and not included in the final model. All analysis was performed with R (version 4.0.2) and QGIS (version 3.14) software.

3. Results

3.1. Participant characteristics

A total of 2578 participants were surveyed across two waves: 1647 participants provided complete responses for analysis in 2019, and 1458 in 2020 of which 557 were returning participants from 2019. The sociodemographic and health characteristics of participants were similar across waves and only significantly different in asthma diagnosis (Table 1), indicating that the sample of participants was largely consistent across both waves. The study sample was

Table 1
Socio-demographic and health characteristics of sample.

Variable <i>n</i> (%)		2019 <i>n</i> = 1647	2020 <i>n</i> = 1458	<i>p</i> -value ^{<i>a</i>}
Sociodemographic characteristics				
Gender	Female	862 (52.3%)	743 (51%)	0.465
	Male	785 (47.7%)	715 (49%)	
Age	18 – 34 years	573 (34.8%)	475 (32.6%)	0.069
	35 – 55 years	785 (47.7%)	681 (46.7%)	
	>55 years	289 (17.5%)	302 (20.7%)	
Children in household	No	1041 (63.2%)	877 (60.2%)	0.087
	Yes	606 (36.8%)	581 (39.8%)	
Highest level of education attained	Less than tertiary	601 (36.5%)	543 (37.2%)	0.692
	Tertiary or higher	1046 (63.5%)	915 (62.8%)	
Household income (\$A)	Less than \$40k	237 (14.4%)	204 (14%)	0.265
	\$40k – \$100k	765 (46.4%)	719 (49.3%)	
	\$100k or more	645 (39.2%)	535 (36.7%)	
Health characteristics				
Sufficient physical activity for health	No	446 (27.1%)	432 (29.6%)	0.125
	Yes	1201 (72.9%)	1026 (70.4%)	
Quality of life	Less than good	421 (25.6%)	413 (28.3%)	0.09
	Good or very good	1226 (74.4%)	1045 (71.7%)	
Wheezing or whistling in chest	No	1355 (82.3%)	1186 (81.3%)	0.534
	Yes	292 (17.7%)	272 (18.7%)	
Ever diagnosed with asthma	No	1332 (80.9%)	1133 (77.7%)	0.033
	Yes	315 (19.1%)	325 (22.3%)	
Body-mass index ^{<i>b</i>}	Underweight / normal	750 (45.5%)	659 (45.2%)	0.542
	Overweight / obese	680 (41.3%)	568 (39%)	

^a *p*-value from Pearson's chi-squared test.

^b Body-mass index not included in models for analysis.

mostly from inner Sydney suburbs, as well as the Canterbury-Bankstown, Cumberland, and Parramatta local government areas.

3.2. Air pollution exposure levels

Fig. 2 presents estimates of average annual concentrations of NO₂ from 2015 and PM_{2.5} from 2018 at both meshblock and POA resolution for the study area. Across the Greater Sydney study area, the mean modelled annual concentrations were 14.9 µg/m³ for NO₂ in 2015, and 6.8 µg/m³ for PM_{2.5} in 2018, weighted by meshblock URP. NO₂ concentrations were highest around built-up areas and major roads. Modeled PM_{2.5} concentrations in 2018 were highest in the central business district and some western suburbs. In univariate analysis, estimated NO₂ levels were higher for males, participants attaining tertiary education, higher income households, those with better quality of life, those attaining sufficient physical activity, as well as those experiencing wheezing and diagnosed with asthma. PM_{2.5} levels were negatively associated with older age, household income, education, and quality of life, and positively associated with participants experiencing wheezing (Table S1).

3.3. Air quality perception

In both 2019 and 2020, most participants perceived air quality as 'somewhat acceptable' (2019 54.2%; 2020 52.3%) or 'completely acceptable' (2019 31.6%; 2020 39.1%) (Fig. 3A). For this reason, the outcome variable for the air quality perception question was categorised as completely acceptable and less than completely acceptable. Table 2 presents the adjusted odds ratios (aORs) of an individual perceiving air quality as less than 'completely acceptable', adjusted for sociodemographic and health characteristics, and predicted NO₂ and PM_{2.5} levels separately. Estimated NO₂ and PM_{2.5} concentrations in participants' neighborhood were both associated with perceived air quality. A 5 µg/m³ increase in NO₂ concentration was associated with 32% greater odds of rating air quality as 'less than completely acceptable' (aOR 1.32, 95%CI 1.18–1.47, $p < 0.001$). A 1 µg/m³ increase in PM_{2.5} concentration was associated with 37% greater odds of rating air quality as 'less than completely acceptable' (aOR 1.37, 95%CI 1.24

–1.52, $p < 0.001$). Participants in 2020 had reduced odds of perceiving less than completely acceptable air quality compared to participants in 2019 ($p < 0.001$ in both models). Males and participants with at least good quality of life perceived better air quality in both models, while participants with greater household income perceived better air quality, but only in the NO₂ model. Participants aged 35–55-years perceived worse air quality than the 18–34-years reference group, but there was no difference for the >55-years participants (Table 2).

3.4. Air quality concern for health

In both 2019 and 2020, most participants responded that air quality affects their health and wellbeing 'a little' (2019 50.5%; 2020 48.5%) (Fig. 3B). Table 3 presents the adjusted odds ratios of an individual reporting high air quality concern. The following interpretations consider adjustment for all other variables in the models. Estimated air quality was associated with concern that air quality affects health. A 1 µg/m³ increase in PM_{2.5} concentration in a participant's POA was associated with 18% greater odds of being very concerned for air quality (aOR 1.18, 95%CI 1.05–1.32, $p = 0.005$). A 5 µg/m³ increase in NO₂ concentration was associated with 12% greater odds of being very concerned (aOR 1.12, 95% CI 0.99–1.25, $p = 0.065$), although this result was marginally insignificant at the 95% confidence interval limit. In the NO₂ model, participants in 2020 had 32% greater odds of air quality concern compared with 2019 (aOR 1.32, 95%CI 1.08–1.61, $p = 0.007$). In the PM_{2.5} model, participants in 2020 had 31% greater odds of air quality concern than in 2019 (aOR 1.31, 95%CI 1.07–1.6, $p = 0.008$). Household income was negatively associated with air quality concern in both the NO₂ and PM_{2.5} models. Being sufficiently physical active for health, experiencing wheezing, and diagnosis with asthma were all positively associated with greater concern for health in both models (Table 3).

4. Discussion

This study investigated associations between estimated annual average air pollution levels with people's perceptions of air quality and concerns for health in relation to air quality, and whether these

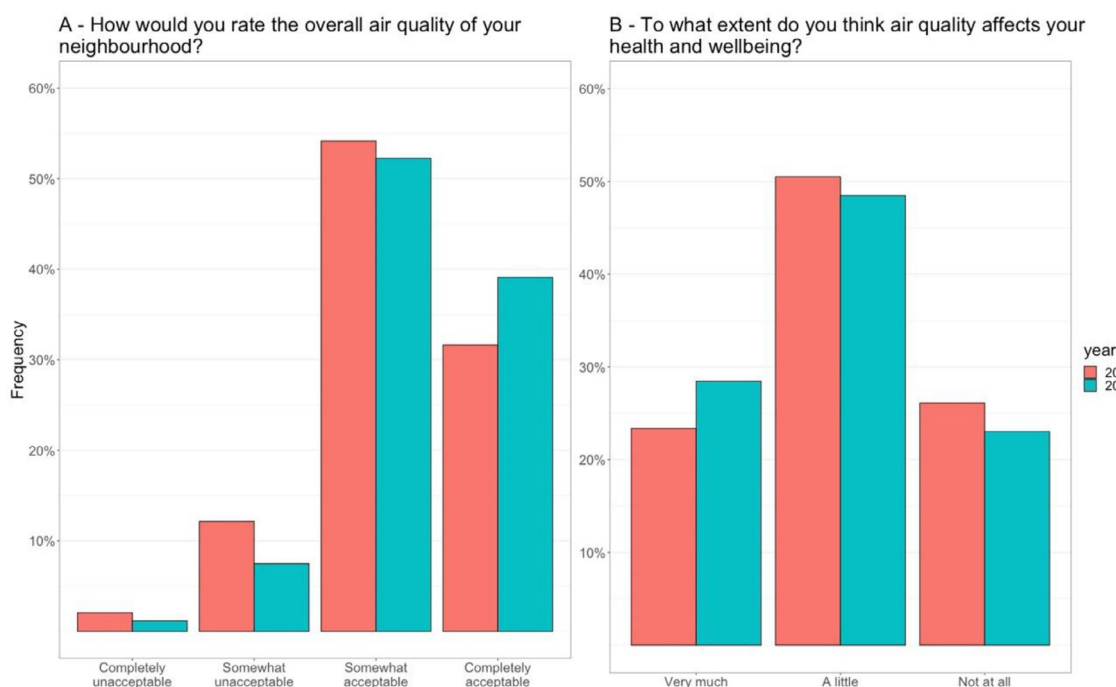


Fig. 3. Frequency of responses to survey items about perceived air quality (A) and concern that air quality affects health and wellbeing (B).

Table 2

Adjusted odds ratios and confidence intervals for two models with outcome as perceiving air quality as less than 'completely acceptable'. Estimated annual average NO₂ and PM_{2.5} concentrations are included separately in the two models. Results are adjusted for all other variables in the model.

Predictors		NO ₂ model (5 $\mu\text{g}/\text{m}^3$)		PM _{2.5} model (1 $\mu\text{g}/\text{m}^3$)	
		aOR (95% CI)	p-value	aOR (95% CI)	p-value
Year	2019	ref		ref	
	2020	0.65 (0.54 – 0.79)	<0.001	0.65 (0.54 – 0.78)	<0.001
Predicted annual average air quality	$\mu\text{g}/\text{m}^3$	1.32 (1.18 – 1.47)	<0.001	1.37 (1.24 – 1.52)	<0.001
Sociodemographic characteristics					
Gender	Female	ref		ref	
	Male	0.62 (0.51 – 0.76)	<0.001	0.62 (0.51 – 0.76)	<0.001
Age (years)	18 – 34 years	ref		ref	
	35 – 55 years	1.44 (1.15 – 1.80)	0.002	1.52 (1.21 – 1.91)	<0.001
	>55 years	0.91 (0.69 – 1.21)	0.535	0.95 (0.71 – 1.26)	0.711
Children in household	No	ref		ref	
	Yes	0.82 (0.66 – 1.01)	0.062	0.86 (0.70 – 1.07)	0.178
Highest level of education attained	Less than tertiary	ref		ref	
	Tertiary or higher	0.91 (0.73 – 1.12)	0.366	0.85 (0.69 – 1.05)	0.131
Household income (\$A)	\$20k	0.96 (0.93 – 1.00)	0.049	0.97 (0.94 – 1.01)	0.190
Health characteristics					
Quality of life	Less than good	ref		ref	
	Good or very good	0.42 (0.33 – 0.53)	<0.001	0.43 (0.34 – 0.55)	<0.001
Sufficient physical activity for health	No	ref		ref	
	Yes	1.15 (0.92 – 1.43)	0.221	1.21 (0.97 – 1.50)	0.097
Wheezing in past week?	No	ref		ref	
	Yes	1.04 (0.79 – 1.38)	0.778	1.05 (0.79 – 1.38)	0.747
Diagnosed with asthma?	No	ref		ref	
	Yes	0.86 (0.66 – 1.12)	0.271	0.92 (0.71 – 1.19)	0.509

aOR = Adjusted odds ratio, 95% CI = 95% confidence interval.

Income and predicted exposure to air pollution included as continuous variables.

perceptions were sensitive to change in relation to significant air pollution related events in Sydney between 2019 and 2020. Our results suggest that in neighborhoods with higher predicted air pollution concentrations, perceived air quality was worse, and people were more concerned that air quality affected their health and wellbeing. Sydneysiders generally perceived air quality as acceptable but were concerned that air quality affects their health and wellbeing at least a little. In both the NO₂ and PM_{2.5} models, exposure to increasing air pollution concentrations predicted poorer perception of

neighborhood air quality, and in the PM_{2.5} model greater exposure was associated with greater concern that air quality affects health and wellbeing. These results support a number of previous studies that have identified worse air quality perceptions or concerns with increasing NO₂ [24,25] and PM_{2.5} levels [23,26–28]. Between 2019 and 2020, we found a contrasting shift in air quality perceptions and concern for health in relation to air quality, with people in 2020 perceiving better air quality, but more concerned that air quality affects their health and wellbeing.

Table 3

Adjusted odds ratios and confidence intervals for two models with outcome being "very much" concerned that air quality affects health and wellbeing. Estimated annual average NO₂ and PM_{2.5} concentrations are included separately in the two models. Results are adjusted for all other variables in the model.

Predictors		NO ₂ model (5 $\mu\text{g}/\text{m}^3$)		PM _{2.5} model (1 $\mu\text{g}/\text{m}^3$)	
		aOR (95% CI)	p-value	aOR (95% CI)	p-value
Year	2019	ref		ref	
	2020	1.32 (1.08 – 1.61)	0.007	1.31 (1.07 – 1.60)	0.008
Predicted annual average air quality	$\mu\text{g}/\text{m}^3$	1.12 (0.99 – 1.25)	0.065	1.18 (1.05 – 1.32)	0.005
Sociodemographic characteristics					
Gender	Female	ref			
	Male	1.22 (0.99 – 1.50)	0.065	1.22 (0.99 – 1.50)	0.065
Age	18 – 34 years	ref			
	35 – 55 years	0.92 (0.73 – 1.16)	0.461	0.94 (0.75 – 1.19)	0.624
	>55 years	0.55 (0.39 – 0.76)	<0.001	0.56 (0.40 – 0.79)	0.001
Children in household	No	ref			
	Yes	2.22 (1.75 – 2.83)	<0.001	2.17 (1.70 – 2.75)	<0.001
Highest level of education attained	Less than tertiary	ref			
	Tertiary or higher	1.26 (1.01 – 1.59)	0.045	1.29 (1.03 – 1.63)	0.028
Household income (\$A)	\$20k	0.9 (0.86 – 0.94)	<0.001	0.9 (0.86 – 0.94)	<0.001
Health characteristics					
Quality of life	Less than good	ref			
	Good or very good	0.99 (0.78 – 1.25)	0.905	1.01 (0.79 – 1.28)	0.966
Sufficient physical activity for health	No	ref			
	Yes	1.44 (1.13 – 1.84)	0.003	1.47 (1.15 – 1.88)	0.002
Wheezing in past week	No	ref			
	Yes	2.92 (2.16 – 3.93)	<0.001	2.92 (2.16 – 3.94)	<0.001
Diagnosed with asthma	No	ref			
	Yes	1.64 (1.24 – 2.15)	<0.001	1.68 (1.28 – 2.21)	<0.001

aOR = Adjusted odds ratio, 95% CI = 95% confidence interval.

Predicted air quality and household income included as continuous variables.

Several sociodemographic characteristics were associated with air quality perceptions and concerns in our models. Males perceived better air quality than females, supporting findings from some previous studies [27], although others have shown females to perceive better air quality [45] and males to be more concerned for air quality [24]. Our models did not show any significant effect from gender in relation to air quality concern. The 35–55-years age group in our sample perceived worse air quality than the reference 18–34-years group, while the >55-years age group were less concerned for health and wellbeing from air quality than 18–34-year-olds. Older individuals are more vulnerable to the health impacts from air pollution, yet in our sample are the least concerned for health in relation to air quality. Education level was not associated with air quality perception; however participants who had attained at least a tertiary education had greater odds of being very concerned for air quality. Previous research has also noted the association between education level and poorer perceptions of air quality [46]. This suggests that health education about the impacts of air quality is needed to improve public understanding, both in instances of adverse conditions such as bushfires, but also during 'regular' conditions when air quality remains a health risk but receives less attention. Previous studies have shown similar associations between income and air quality perceptions [46], and while in our sample participants with greater household income were exposed to greater predicted NO₂ annual averages (Table S1), they also perceived better air quality in the NO₂-adjusted model, and were less concerned for air quality in both models. Evidence of reduced psychological distress in higher income individuals [47], as well as affluent areas generally having greater access to green space [48] which might give a sense of a healthier environment, could explain these lower concerns in our study. Participants with children in the household had greater health concern in relation to air quality, in line with previous findings [6,24], possibly as parents would be concerned with the impact of air pollution on the children's health as well as their own.

Some health characteristics were also associated with air quality perceptions and concerns in our models. Participants with better quality of life were associated with perceiving better air quality in both models. As expected, participants experiencing wheezing or diagnosed with asthma had greater odds of being very concerned that air quality affects health or wellbeing, although there were no differences in air quality perceptions for either group. People with asthma and chronic respiratory diseases have greater vulnerability to air quality and have previously been shown to experience greater annoyance and distress [6,49]; and it is likely this cohort is more aware of the risks of air pollution due to their vulnerability. People who were sufficiently physically active for health were more concerned for health in relation to air quality, a result that agrees with previous findings [24]. It is possible that as physically active individuals might inhale more air pollution while exercising, they would be more concerned. Overall, our results suggest that people with greater vulnerability to the effects of air pollution might be more aware of the health risks and therefore more concerned for air quality. However, given that participants with less education may not be as highly concerned about air quality, public communication and education efforts need to be made to increase awareness of the health risks posed by air pollution, especially to cohorts that are vulnerable to air pollution, but also to the wider population who may be less familiar with air pollution as a health risk.

This study's before-and-after design provided a unique opportunity to explore the sensitivity of air quality perceptions and concerns following the 2019–2020 bushfires and restrictions in response to the COVID-19 pandemic, events that might have had significant impacts on people's air quality perceptions and health concerns. Our results show a contrasting shift between 2019 and 2020, with people generally perceiving better air quality in 2020, but having greater health concern in relation to air quality. We suggest that events

during and preceding the study might have had some effect on people's perceptions and concerns. The 2019–2020 *Black Summer* bushfires received widespread media coverage as Sydney was severely affected by bushfire smoke on several occasions between November 2020 and February 2021 [50], and people's awareness of air quality is likely to have increased during this time. One study showed an increase in online searches for "air quality" and "PM_{2.5}" in Sydney concurrent with significant increases in PM_{2.5} concentration from bushfire smoke [51]. Participants might have perceived improved air quality during data collection in late-2020 compared with at the height of the bushfire period, especially as it is suggested that people tend to recall events by their peaks or endpoints [52].

Soon after the bushfires had been extinguished, the spread of COVID-19 in Australia by mid-March 2020 resulted in vast restrictions to daily life. It is possible that people's perceptions of air quality may have been influenced by reductions in road traffic and industrial activity at the height of the lockdowns due to the COVID-19 restrictions. Measured decreases in air pollution at the height of lockdowns were recorded in Australia [32] and worldwide [33,34], following lockdown restrictions, with media reporting on these improvements at the time [50]. Data from an international survey of air quality perception during the lockdown in May 2020 suggested that Australians ($n = 387$) believed that air pollution levels had decreased compared to before lockdown [53], although this data uses recall-based changes in perception. Nevertheless, our results showed that air quality concern for health and wellbeing was greater in 2020 than in 2019, although this effect was marginal in the PM_{2.5} model. This might be an example of negativity bias, whereby personal experience during and following the 2019/20 bushfires, and further engagement with the climate crisis during a year of upheaval might have motivated concern for health impacts from air quality, even as perceptions of air quality have improved [54]. The bushfires especially are likely to have increased air quality concerns for many Australians. While these changes in perceptions and concerns are unrelated to our exposure data, which are background levels from 2015 for NO₂ and 2018 for PM_{2.5}, these results do suggest that air quality perceptions and concerns are sensitive to observed changes in air quality, or possibly media reporting of air quality.

This study adds to the literature exploring associations between objective air quality measures and subjective air quality perceptions and concerns and is the first such paper in an Australian context, with a unique repeat cross-sectional design on either side of the 2019–2020 bushfires and the first COVID-19 lockdowns. Nevertheless, there are some limitations to our study. The sample is a convenience sample taken largely from a marketing recruitment panel, and perhaps not representative of all Sydneysiders. Additionally, the smallest spatial variable available in our survey was the participant's POA, which meant we had to aggregate mesh-block air pollution concentrations to POA for analysis, reducing some resolution of estimated air pollutant exposure. The most recently available estimations were from 2015 for NO₂ and 2018 for PM_{2.5}, while our survey data was collected in 2019 and 2020. Previous findings have shown negligible year-to-year variation in estimated meshblock NO₂ and PM_{2.5} concentrations [41,42]; nevertheless these estimates only provided background levels of air quality in our models, isolated from changes due to the bushfires or COVID-19 restrictions. While perceptions of air quality in relation to long term background exposure to air pollution were of interest to our first research question, as long term exposure might be more relevant than short term exposure from a health perspective, it is suggested that people tend to recall events either by their peaks or endpoints rather than summations across a year [52]. Using higher temporal resolution air quality measures in addition to estimated annual averages could provide further insight into people's perceptions and concerns.

Given there is no 'safe' threshold for air pollution exposure, more needs to be done to commit to improving air quality by reducing

emissions and encouraging awareness of air quality. Air quality and climate change are inextricably linked, and Australians are reporting climate change as greater concern than the COVID-19 pandemic [55]. Cutting fossil fuel use and greenhouse gas emissions, as part of Australia's response to the climate crisis, likely will have several co-benefits for urban air quality and human health [56]. In Australia, the transport sector is responsible for 17% of greenhouse gas emissions. Reductions in air pollution during the first COVID-19 lockdowns showed that moving away from private vehicle use will have positive effects on air quality [32], and encouraging use of sustainable transport modes in Sydney, especially active travel, has the potential to reduce air pollution from vehicle emissions and provide immediate public health co-benefits through increased physical activity [57]. But while individual decisions are effective in limiting personal emission of air pollutants and exposure to health risks, action is needed at a federal, state, and local government level to disinvest from fossil fuels and commit to responding to the climate crisis.

5. Conclusion

This study shows that Sydney residents are concerned that air quality affects their health and wellbeing. People's perceptions and concerns are important as they influence their behaviors and decisions, and health promoters must continue to understand these to effectively communicate risks and develop policies that safeguard human health by limiting exposure to air pollutants and respond to the climate crisis by urgently transitioning away from fossil fuels. Air quality remains a public health issue in Australia even outside of transient bushfire periods, given that low levels of air pollutants are still associated with morbidity and mortality. Public education efforts should focus efforts on the most vulnerable groups, including those with respiratory conditions, the elderly, parents with small children, pregnant women, and the more poorly educated. Building awareness of the risks that air pollution poses to themselves, and their families, is essential in limiting the morbidity and mortality impacts that air pollution poses.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.joclim.2022.100137](https://doi.org/10.1016/j.joclim.2022.100137).

References

- [1] Murray CJL, et al. Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *Lancet* 2020;396(10258):1223–49.
- [2] Cohen AJ, et al. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *Lancet* 2017;389(10082):1907–18.
- [3] Hansen CA, et al. Ambient air pollution and birth defects in Brisbane, Australia. *PLOS ONE* 2009;4(4):e5408.
- [4] Bekkar B, et al. Association of air pollution and heat exposure with preterm birth, low birth weight, and stillbirth in the US: a systematic review. *JAMA Netw Open* 2020;3(6):e208243–e208243.
- [5] Clifford A, et al. Exposure to air pollution and cognitive functioning across the life course—a systematic literature review. *Environ Res* 2016;147:383–98.
- [6] Sass V, et al. The effects of air pollution on individual psychological distress. *Health Place* 2017;48:72–9.
- [7] Khreis H, et al. Exposure to traffic-related air pollution and risk of development of childhood asthma: a systematic review and meta-analysis. *Environ Int* 2017;100:1–31.
- [8] Faustini A, Rapp R, Forastiere F. Nitrogen dioxide and mortality: review and meta-analysis of long-term studies. *Eur Respir J* 2014;44(3):744.
- [9] Hajat A, Hsia C, O'Neill MS. Socioeconomic disparities and air pollution exposure: a global review. *Curr Environ Health Rep* 2015;2(4):440–50.
- [10] Knibbs LD, Barnett AG. Assessing environmental inequalities in ambient air pollution across urban Australia. *Spat Spatiotemporal Epidemiol* 2015;13:1–6.
- [11] Cooper N, Green D, Knibbs LD. Inequalities in exposure to the air pollutants PM_{2.5} and NO₂ in Australia. *Environ Res Lett* 2019;14(11):115005.
- [12] Chakraborty J, Green D. Australia's first national level quantitative environmental justice assessment of industrial air pollution. *Environ Res Lett* 2014;9(4):044010.
- [13] Bell ML, Zanobetti A, Dominici F. Evidence on vulnerability and susceptibility to health risks associated with short-term exposure to particulate matter: a systematic review and meta-analysis. *Am J Epidemiol* 2013;178(6):865–76.
- [14] Hanigan IC, Johnston FH, Morgan GG. Vegetation fire smoke, indigenous status and cardio-respiratory hospital admissions in Darwin, Australia, 1996–2005: a time-series study. *Environ Health* 2008;7(1):42.
- [15] Landrigan PJ, et al. The Lancet Commission on pollution and health. *Lancet* 2018;391(10119):462–512.
- [16] Whitmee S, et al. Safeguarding human health in the Anthropocene epoch: report of the Rockefeller foundation–lancet commission on planetary health. *Lancet* 2015;386(10007):1973–2028.
- [17] Crane M, et al. Transforming cities for sustainability: a health perspective. *Environ Int* 2021;147:106366.
- [18] Ferrer RA, Klein WMP. Risk perceptions and health behavior. *Curr Opin Psychol* 2015;5:85–9.
- [19] Floyd DL, Prentice-Dunn S, Rogers RW. A meta-analysis of research on protection motivation theory. *J Appl Soc Psychol* 2000;30(2):407–29.
- [20] Sheeran P, Harris PR, Epton T. Does Heightening Risk Appraisals Change People's Intentions and Behavior? A Meta-Analysis of Experimental Studies. *Psychol Bull* 2014;140(2):511–43.
- [21] Carlsten C, et al. Personal strategies to minimise effects of air pollution on respiratory health: advice for providers, patients and the public. *Eur Respir J* 2020;55(6):1902056.
- [22] Laumbach R, Meng Q, Kipen H. What can individuals do to reduce personal health risks from air pollution? *J Thorac Dis* 2015;7(1):96–107.
- [23] Cori L, et al. Risk Perception of Air Pollution: a Systematic Review Focused on Particulate Matter Exposure. *Int J Environ Res Public Health* 2020;17(17).
- [24] Dons E, et al. Concern over health effects of air pollution is associated to NO₂ in seven European cities. *Air Qual Atmos Health* 2018;11(5):591–9.
- [25] Piro FN, et al. A comparison of self reported air pollution problems and GIS-modeled levels of air pollution in people with and without chronic diseases. *Environ Health* 2008;7(1):9.
- [26] Pu S, et al. Spatial distribution of the public's risk perception for air pollution: a nationwide study in China. *Sci Total Environ* 2019;655:454–62.
- [27] Cisneros R, et al. Understanding public views about air quality and air pollution sources in the San Joaquin Valley, California. *J Environ Public Health* 2017;2017:4535142.
- [28] Zakaria MF, et al. Traffic-related Air Pollution (TRAP), air quality perception and respiratory health symptoms of active commuters in a university outdoor environment. *IOP Conf Ser Earth Environ Sci* 2019;228:012017.
- [29] Hanigan IC, et al. All-cause mortality and long-term exposure to low level air pollution in the '45 and up study' cohort, Sydney, Australia, 2006–2015. *Environ Int* 2019;126:762–70.
- [30] Barnett AG. It's safe to say there is no safe level of air pollution. *Aust N Z J Public Health* 2014;38(5):407–8.
- [31] Borchers Arriagada N, et al. Unprecedented smoke-related health burden associated with the 2019–20 bushfires in eastern Australia. *Med J Aust* 2020;213(6):282–3.
- [32] Ryan RG, Silver JD, Schofield R. Air quality and health impact of 2019–20 Black Summer megafires and COVID-19 lockdown in Melbourne and Sydney, Australia. *Environ Pollut* 2021;274:116498.
- [33] Landrigan PJ, Bernstein A, Binagwaho A. COVID-19 and clean air: an opportunity for radical change. *Lancet Planet Health* 2020;4(10):e447–9.
- [34] Muhammad S, Long X, Salman M. COVID-19 pandemic and environmental pollution: a blessing in disguise? *Sci Total Environ* 2020;728:138820.
- [35] Murphy, B., et al. Australian WHOQoL instruments: user's manual and interpretation guide. 2000.
- [36] Australian Institute of Health and Welfare, The Active Australia Survey: a guide and manual for implementation, analysis and reporting. 2003, Canberra: AIHW.
- [37] Australian Centre for Asthma Monitoring. Survey questions for monitoring national asthma indicators. Cat. no. ACM 9. 2007, Australian Institute of Health and Welfare: Canberra.
- [38] Knibbs LD, et al. Modelled yearly NO₂ satellite land use regression data by ABS Mesh-block 2011 for Australia 2012–2015. 2021: downloaded from the Centre for Air pollution, Energy And Health Research <https://cloudstor.aarnet.edu.au/plus/f/5359438859>.
- [39] Knibbs LD, et al. A national satellite-based land-use regression model for air pollution exposure assessment in Australia. *Environ Res* 2014;135:204–11.
- [40] Knibbs LD, et al. Satellite PM_{2.5} data 2015–2018. 2020: retrieved from Centre for Air pollution, energy and health Research. <https://cloudstor.aarnet.edu.au/plus/f/4898720941>.
- [41] Knibbs LD, et al. Satellite-based land-use regression for continental-scale long-term ambient PM_{2.5} exposure assessment in Australia. *Environ Sci Technol* 2018;52(21):12445–55.
- [42] Knibbs LD, et al. Long-term nitrogen dioxide exposure assessment using back-extrapolation of satellite-based land-use regression models for Australia. *Environ Res* 2018;163:16–25.
- [43] Hoek G, et al. A review of land-use regression models to assess spatial variation of outdoor air pollution. *Atmos Environ* 2008;42(33):7561–78.

- [44] Marshall JD, Nethery E, Brauer M. Within-urban variability in ambient air pollution: comparison of estimation methods. *Atmos Environ* 2008;42(6):1359–69.
- [45] Schmitz S, et al. An assessment of perceptions of air quality surrounding the implementation of a traffic-reduction measure in a local urban environment. *Sustain Cities Soc* 2018;41:525–37.
- [46] Kim M, Yi O, Kim H. The role of differences in individual and community attributes in perceived air quality. *Sci Total Environ* 2012;425:20–6.
- [47] Isaacs AN, et al. Lower income levels in australia are strongly associated with elevated psychological distress: implications for healthcare and other policy areas. *Front Psychiatry* 2018;9.
- [48] Astell-Burt T, et al. Do low-income neighbourhoods have the least green space? A cross-sectional study of Australia's most populous cities, 14. *BMC Public Health*; 2014. p. 292.
- [49] Jacquemin B, et al. Annoyance due to air pollution in Europe. *Int J Epidemiol* 2007;36(4):809–20.
- [50] Zhang Y, et al. The 2020 special report of the MJA–Lancet Countdown on health and climate change: lessons learnt from Australia's "Black Summer. *Med J Aust* 2020;213(11):490–2 .e10.
- [51] Brimblecombe P, Lai Y. Subtle Changes or Dramatic Perceptions of Air Pollution in Sydney during COVID-19. *Environments* 2021;8(1).
- [52] Brody SD, Zahran S. Commentary: linking particulate matter and sulphur concentrations to air pollution annoyance: problems of measurement, scale and control. *Int J Epidemiol* 2007;36(4):820–3.
- [53] Lou, B., et al., Air pollution perception in ten countries during the COVID-19 pandemic. *Ambio*, 2021.
- [54] Looi JCL, et al. Fire, disease and fear: effects of the media coverage of 2019–2020 Australian bushfires and novel coronavirus 2019 on population mental health. *Aust N Z J Psychiatry* 2020;54(9):938–9.
- [55] Patrick R, et al. Australians report climate change as a bigger concern than COVID-19. *J Clim Chang Health* 2021;3:100032.
- [56] Beggs PJ, et al. The 2021 report of the MJA – Lancet Countdown on health and climate change: Australia increasingly out on a limb. *Med J Aust* 2021;215(9):390–392.e22.
- [57] Xia T, et al. Traffic-related air pollution and health co-benefits of alternative transport in Adelaide, South Australia. *Environ Int* 2015;74:281–90.