ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Spatial patterns of environmental injustice in social vulnerability and ambient dust levels across Australia

To cite this article: Sylvester Dodzi Nyadanu *et al* 2026 *Environ. Res. Lett.* **21** 064005

IOP Publishing Environ. Res. Lett. 21 (2026) 064005 https://doi.org/10.1088/1748-9326/ae4d5d

ENVIRONMENTAL RESEARCH
LETTERS

Check for updates

OPEN ACCESS

RECEIVED
9 January 2025

REVISED
30 December 2025

ACCEPTED FOR PUBLICATION
4 March 2026

PUBLISHED
17 March 2026

LETTER

Spatial patterns of environmental injustice in social vulnerability and ambient dust levels across Australia

Sylvester Dodzi Nyadanu[1,2,*], **Massimo Vieno**[3], **Siqin Wang**[4,5,6], **Gizachew A Tessema**[1,7,8] **and Gavin Pereira**[1,7,9]

1 Curtin School of Population Health, Curtin University, Perth, Western Australia 6102, Australia
2 Healthy Environments and Lives (HEAL) National Research Network, Canberra, Australia
3 UK Centre for Ecology & Hydrology, Bush Estate, Penicuik, Midlothian EH26 0QB, United Kingdom
4 Spatial Sciences Institute, Dornsife College of Letters, Arts and Sciences, University of Southern California, Los Angeles, CA, United States of America
5 School of Science, RMIT University, Melbourne, Victoria, Australia
6 School of Earth and Environmental Sciences, University of Queensland, Brisbane, Australia
7 enAble Institute, Curtin University, Kent Street, Bentley, Perth, Western Australia 6102, Australia
8 School of Public Health, University of Adelaide, Adelaide, South Australia, Australia
9 WHO Collaborating Centre for Climate Change and Health Impact Assessment, Faculty of Health Science, Curtin University, Bentley, WA, Australia
* Author to whom any correspondence should be addressed.

E-mail: sylvester.nyadanu@curtin.edu.au

Keywords: dust, particulate matter air pollution, vulnerability, climate change, environmental justice

Supplementary material for this article is available online

Abstract

Ambient dust exposure has been associated with several adverse health outcomes. Unlike ambient air pollution, the vulnerability of subpopulations to ambient dust has not yet been explored. As the driest inhabited continent, Australia provides a natural laboratory for studying large-scale dust exposure. This study aimed to examine environmental injustice in the ambient dust of $\leqslant 10\ \mu$m particle size and vulnerability of subpopulations in Australia, which has not been studied previously. A nationwide cross-sectional design was employed by linking a highly spatially resolved census-derived composite measure of social vulnerability index (a wide range of factors measuring susceptibility, and a more complex capacity of individuals and society to cope with hazards and damage) to 2021 annual mean ambient dust concentrations in Australia. Global and local spatial autocorrelations, bivariate spatial correlations, and generalised additive logistic regression with spatial smoothing were applied to investigate geographic variation and the association between social vulnerability and ambient dust at the Australian Census' most precise geographical unit. The results indicated geographical inequalities of social vulnerability and ambient dust exposure, with a positive association and more elevated in urban areas than in rural areas. Those with high social vulnerability were 13% more likely to reside in areas with the highest dust exposure (OR 1.13, 95% CI: 1.03, 1.23). High dust exposure was especially elevated in urban areas (OR 1.74, 95% CI: 1.42, 2.13) and areas with relatively high cultural and minority vulnerability (OR 3.55, 95% CI: 3.20, 3.94) and housing vulnerability (OR 2.63, 95% CI: 2.38, 2.90). Social vulnerability is associated with greater exposure to ambient dust with identified hotspots, particularly in urban areas and communities with elevated cultural and housing vulnerability. These areas could be prioritised for policies and interventions to reduce the health burden of ambient dust, as initial steps to addressing environmental injustice in Australia.

1. Introduction

Dust is present in our environment, including homes, workplaces, communities and public spaces, exposing everyone to at least some level of dust. Dust consists of solid particles ranging in size from less than 1 μm to hundreds of microns in size, released into the air from both natural and anthropogenic sources [1]. Natural sources include soil and sand, sea salt, wildfire smoke, natural disasters, pollen, and spores. Anthropogenic sources include construction, industrial, mining, transportation, and agricultural activities [1, 2]. Ambient dust can remain in the atmosphere for hours to weeks and travel great distances from its sources, depending on particle size and meteorological conditions. Ambient dust is a major contributor to high concentrations of harmful particulate matter air pollution with sizes up to 2.5 μm ($PM_{2.5}$) and 10 μm (PM_{10}) [1–3]. Although there is no biologically tolerated dose, the 2021 World Health Organization air quality guidelines recommend annual concentrations for $PM_{2.5}$ and PM_{10} at $\leqslant 5\ \mu g\ m^{-3}$ and $\leqslant 15\ \mu g\ m^{-3}$, respectively, to minimise the harmful effects of these toxic pollutants [4].

Ambient dust has been associated with several health outcomes, such as all-cause cardiovascular and respiratory mortality and morbidity [2, 5, 6] and exacerbation of infectious disease outbreaks [7]. Ambient dust can adversely affect health through well-documented pathways, such as airway irritation, oxidative stress, systemic inflammation, and impaired immune, respiratory and cardiovascular functions [5–7]. In the context of climate change, which exacerbates dust emissions and health risks, these impacts may be more concerning for socioeconomically and geographically vulnerable subpopulations, particularly vulnerable groups with weaker immune systems [1, 2, 8]. Vulnerability, whether biophysical or social, broadly refers to individuals and populations at greater risk of health outcomes or environmental impacts [9]. Biophysical vulnerability relates to the likelihood of experiencing the impact of environmental exposures due to an individual's biological or physiological conditions, while social vulnerability encompasses the social or geodemographic characteristics of a population, such as age, gender, ethnicity, disability, geographic location, urban-rural disparity, infrastructural and healthcare access, housing, and socioeconomic disadvantage [9, 10]. Since human societies are integrated into complex social-ecological systems, social vulnerability is conceptualised into two dimensions: sensitivity to environmental hazards and the capacity to cope with their effects [11]. From an environmental justice perspective, since the early 1970s, inequalities in environmental exposures (e.g. air pollution or dust exposure) are often driven by disparities in social structure and resource distribution [9, 11–13]. Dust exposure inequalities have reflected the same historical structural inequities central to the environmental justice framework. These inequities are driven by policy decisions, such as residential segregation, discriminatory lending, exclusionary zoning, and siting industrial and transport infrastructure [12–14]. These social structural processes systematically placed racially/ethnically and socioeconomically marginalised communities closer to major anthropogenic dust sources such as construction, industrial land uses, and agriculture, creating persistent inequities in exposure [12–14]. Natural dust provides a broad baseline, but human activity amplifies risks, and anthropogenic sources cluster in marginalised neighbourhoods due to the structural inequities. These communities face disproportionate risks, with environmental justice frameworks highlighting why marginalised groups face higher risks [3, 12–15]. Thus, the mechanism of action is both biological and social stratification, where ambient dust acts as both a pollutant and a proxy for systemic inequality [12–14, 16].

Emerging literature has demonstrated positive associations between the spatial distribution of ambient air pollution and social vulnerability or vulnerable subpopulations in both high and low-income countries [9, 11, 17–21]. However, to the best of our knowledge, no study has specifically investigated ambient dust exposure in relation to social vulnerability. As the driest inhabited continent and a major source of dust, Australia has been described as a natural laboratory for studying large-scale dust, its sources, transport, and geochemical composition [22], with dust activity varying by a factor of four on decadal timescales [23]. Australia regularly experiences dust storms that impact agriculture, health, and the economy, especially during droughts and periods of low vegetation. For example, the February 2019 inland dust storm event in New South Wales (the most populous state in Australia) resulted in increased air pollution and respiratory hospitalisations and greater than concurrent bushfire events [24]. Bushfires and dust storms were identified as primary sources of $PM_{2.5}$ from 2001 to 2019, with the greatest concentration and health impacts reported in the Northern Territory and among men across all regions [25]. High agricultural dust exposure was also reported among rural workers in Western Australia during harvest [26]. A few Australian studies reported disproportionate ambient air pollution exposure ($PM_{2.5}$, NO_2, and industrial emissions) among lower-income, Indigenous, and ethnic minority communities, especially in urban and industrial areas [19, 27, 28]. However, ambient dust exposure specifically and hotspot areas remained unexamined, leaving a critical gap in Australia's environmental justice literature. Understanding continental-level spatial inequalities in ambient dust exposure and social vulnerability is important to inform policy responses, especially given the potential long-term health impacts on vulnerable subpopulations [2, 5, 6]. Therefore, this study aimed to use a nationwide novel social vulnerability index (SVI) [10] and a novel assessment of ambient dust exposure [29] to examine whether socially vulnerable populations in Australia face higher dust exposure overall and in urban and rural areas. We hypothesised that environmental injustice and structural factors amplify exposure inequalities.

2. Methods

2.1. Study area

Australia is a continent that covers 7.7 million km^2,as the sixth-largest country in the world by area coverage and a population of 25.4 million according to the 2021 census. Australia is highly urbanised, with almost 80% of the population living in cities of the eight states/territories. As a culturally and linguistically diverse country, about 52% of Australian residents were born overseas (29%) or have at least one parent born overseas (22%) [30]. Australia's economy according to the Human Development Index (HDI), ranked 5th in the world in 2021[31]. The country also has extremely variable geology, geochemistry, geomorphological settings, and climatic conditions, with a large part in arid to semi-arid zones defined by little rainfall [22]. The main geographical classification of Australia, as defined by the Australian Bureau of Statistics (ABS), divides Australia into a hierarchy of statistical areas for reporting a broad range of social, demographic, and economic statistics [32]. This comprises six states and two mainland territories, local government areas, Statistical Area Levels 4–1 (SA4 to SA1), and mesh blocks (the smallest geographic areas that form the building blocks for the larger regions). SA1s are the second smallest geographical units, which generally have a population of 200–800 people, and an average of about 400 people, the smallest units in which sensitive census data are released to maintain confidentiality [32]. This study used SA1s as spatial units of analysis (figure 1).

2.2. SVI measurement

We used the nationwide fine-grained measures of SVI data at SA1 spatial units from Wang *et al* [10]. The SVI is an evenly weighted arithmetic (additive) aggregated index derived through a principal composite index of 41 indicators for five themes from the ABS census data and many other data sources. The five themes were Socioeconomic vulnerability, Demographics/Disability vulnerability, Minority and Languages/Cultural vulnerability, Housing vulnerability, and Built environment/Infrastructural vulnerability. The indicators for each theme were summarised in table S1. Out of the 57 523 SA1s in the 2016 census, the index for each theme, the overall SVI, and remoteness (urban and rural) were generated for 55 218 SA1s. The remaining SA1s, with populations of fewer than 50, were excluded as the ABS randomly assigned their populations for data privacy purposes [10]. For SVI overall and within each theme, a higher vulnerability score indicates a greater degree of vulnerability. The SVI and the themes capture structural and social processes in line with the environmental justice framework.

The novel SVI supplements the traditional socioeconomic indexes for areas (SEIFA) derived from census data by ABS [33] by additionally including features of housing, transport, and the built environment that are only partially included in SEIFA. The SVI further innovatively reforged Cutter's framework [34] to involve four-dimensional quantification of the built environment: diversity, design, density, and distance [10]. Comprehensive descriptions of the data sources, principal component analyses procedures in constructing the SVI, and the validation and sensitivity analyses were described in Wang *et al* [10].

2.3. Ambient dust exposure assessment

This study used ambient dust (mainly wind-brown mineral) particles within the PM_{10} size from the new assessment of global and regional budgets, fluxes, and lifetimes of atmospheric reactive species and aerosols [29]. Briefly, the EMEP MSC-W (European Monitoring and Evaluation Programme Meteorological Synthesising Centre—West) open-source atmospheric chemistry transport model version 4.45 was coupled with the WRF (Weather Research and Forecasting) model version 4.2.2 [35] meteorology to undertake a global and regional quantification of the concentrations, deposition, budgets, and lifetimes of atmospheric reactive species and aerosols [29, 36, 37]. The WRF underline meteorology is the fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis of the global climate (ERA5)[38]. The EMEP MSC-W calculates the 3D hourly concentration of pollutants that are then averaged to the annual mean. This included the near-surface concentration of mineral dust to 3 m above the surface. The EMEP MSC-W model calculation was performed using the 2021 meteorological year, with the anthropogenic emissions derived from the EDGAR v6 2018 emissions inventories [39]. Ambient dust is generated online in the model and directly linked with the specific meteorological conditions. The EMEP MSC-W model uses two nested domains: a global domain with a resolution of $1° \times 1°$ and a nested domain covering Australia at a horizontal resolution of $0.11° \times 0.11°$. This study used the 2021 annual average ambient mineral dust concentration ($\mu g\, m^{-3}$) across Australia

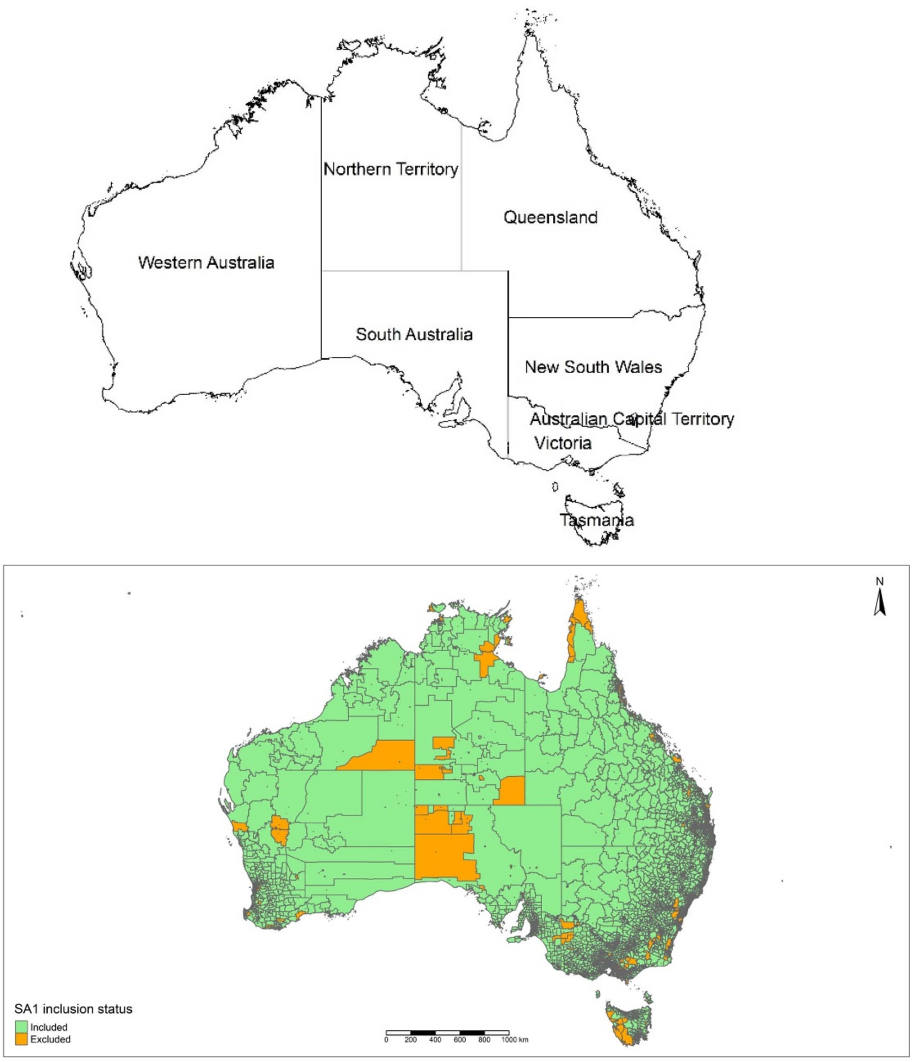

Figure 1. Map of Australia showing the eight states/territories and the included SA1in green ($N = 55\,177$) and excluded SA1 in orange ($N = 2346$) using the 2016 Australian Statistical Geography Standard shapefile (Available at www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.55.001July%202016) *Note:* The Excluded SA1s from the analysis were SA1s with populations of fewer than 50 people randomly assigned by Australian Bureau of Statistics due to the concern of data privacy or SA1s with missing dust concentration.

at a spatial resolution of ~10 km ($0.11° \times 0.11°$) [29]. We note that dust concentrations can fluctuate substantially within a year, with short-term spikes during dust storms that were not fully captured by the annual average. With the 2016 boundary files (used for the SVI) from the Australian Statistical Geography Standard, defined by the ABS [40],the mean ambient dust concentration at SA1 levels across Australia was obtained using ArcGIS ArcMap software (version 10.8.1) and the R package *terra*. The SVI and ambient dust concentration datasets were merged, and 41 SAs with missing dust concentrations were excluded. The final analytical sample size was 55 177 SA1s with a total population of 23 331 456 persons (figure 1).

2.4. Statistical analyses

We employed a five-step methodology for exploratory non-spatial and spatial data analyses and estimated the spatial association between SVI and ambient dust exposure. The main analyses and geo-visualisations were performed using R software (version 4.3.3) with packages 'tmap', 'spdep', 'mgcv', and 'forestploter'.

i. Descriptive statistics and choropleth mapping of SVI and ambient dust

Summary statistics were performed to report mean, standard deviations, medians, range, and interquartile range for continuous forms and frequencies and percentages for categorical forms of the ambient dust exposure, SVI, and the individual themes of SVI. SVI and ambient dust distributions were mapped.

ii. Univariate global spatial autocorrelation to determine spatial clustering or dispersion

The commonly used metric of spatial autocorrelation, univariate global Moran's I (a cross-product statistic between a variable and its spatial lag), was used to measure the degree of spatial clustering or dispersion in the geographical distribution of the ambient dust and SVI across the study area. Moran's I range from $+1$ (spatial clustering) to -1 (spatial dispersion) [41, 42].

iii. Univariate local indicator of spatial association (LISA) to identify cluster-outlier locations
A univariate local Moran's I as a LISA was performed to determine the spatial cluster-outlier locations of the ambient dust and SVI. Local Moran's I allowed for the decomposition of global Moran's I into the contribution of each location to identify locations with clustering of *high–high* values (hotspots) which are high ambient dust or SVI areas surrounded by other areas with high values and *low–low* values (coldspots) as areas with low ambient dust or SVI surrounded by other areas with low values of low ambient dust or SVI. Outliers were also detected as *high–low* and *low–high* values for areas with high and low ambient dust or SVI surrounded by other areas with low and high values, respectively [43, 44].

iv. Bivariate Pearson and spatial Lee statistic correlation.
Pearson and Lee's statistics were performed to determine non-spatial and spatial correlations between ambient dust and SVI, respectively. Lee's L statistic is a bivariate association measure that integrates non-spatial bivariate association (Pearson correlation) with a univariate spatial association measure (Moran's I) between ambient dust and SVI [45]. Bivariate local Moran's I spatial associations were also performed. Unlike bivariate local Moran's I, which focuses on cross-location correlation, we used local Lee's L to directly measure co-location correlation, for a more practical and interpretable spatially co-varying association between ambient dust and SVI [45, 46]. For global and local Moran's I and Lee's L statistics correlation, the queen adjacency neighbourhood definition was used so that contiguous polygons (here SA1) sharing at least one border or vertex were considered spatial neighbours [41–44].

v. Spatial generalised additive logistic regression
The ambient dust concentration was treated as a binary dependent variable using the $<$median vs $\geqslant$median (low and high) and tertiles of the SVI score as the independent variable (low, moderate, and high). The low SVI category was used as the reference in the regression models. Ambient dust exposure and social vulnerability were categorised to facilitate comparison and accommodate potential non-linear relationships. Preliminary analyses using continuous variables and generalised additive models (GAMs) with spline-based continuous forms showed that a linear specification did not adequately describe the association. For interpretability, the primary analyses used the categorised specifications, with spline-based continuous models included as a sensitivity analysis. The association between tertile SVI and binary ambient dust was estimated using GAMs logistic regression with thin-plate smoothing splines of the two-dimensional XY coordinates of SA1 as $s(X\text{coord}, Y\text{coord}, bs = \text{‘}tp\text{’})$ and applying the robust estimation of maximum likelihood method to prevent overfitting [47]. The model was fitted as

$$\text{Logit}\left(\text{Dust}_{\text{cat}}\right) = \text{SVI}_{\text{cat}} + s\left(X\text{coord}, Y\text{coord}, bs = \text{‘tp’}\right),$$

where Dust_{cat} denotes the binary ambient dust exposure of SA1, SVI_{cat} is the tertile categories of SVI. Odds ratios (ORs) and 95% confidence intervals (CIs) were reported. An OR above 1 suggests greater odds of the outcome (high ambient dust) while ORs below 1 mean lower odds, and an OR of 1 shows no association between exposure (SVI) and outcome. Precision is indicated by 95% CIs, with narrower CIs being more precise, and intervals excluding 1 suggest a likely association.

Subgroup analyses by remoteness (urban and rural), each SVI theme, and state were also performed. The thematic model included all SVI themes simultaneously in one model for the main analysis, but separately in separate models for sensitivity analyses. A standard (non-spatial) logistic regression was performed as a secondary analysis for all areas and separately for urban and rural areas to identify bias from ignoring spatial structure in the models.

3. Results

The 2021 annual average ambient dust concentration at the SA1 level across Australia ranged from 0.14 to 37.61 $\mu g\ m^{-3}$, with a mean (standard deviation) of 0.67 (0.90) $\mu g\ m^{-3}$ (table S2, figure 2), indicating moderate dust exposure within the global context (figure S1).

The SVI ranged from -30.42 to 69.09 with a mean of -0.01 (2.96). From the choropleth maps, the overall SVI showed spatial variation similar to the ambient dust exposure (figure 2). Univariate global Moran's I indicated positive spatial autocorrelation, which was strong for ambient dust (Moran's $I = 0.95$) and moderate for SVI (Moran's $I = 0.48$). There was a small positive spatial correlation between SVI and ambient dust (Lee's $L = 0.09$). Each SVI theme also showed positive spatial autocorrelation, ranging from global Moran's I of 0.31 (Themes 2: Demographic/Disability vulnerability and Theme 4: Housing vulnerability) to 0.78 (Theme 3: Cultural vulnerability).

The spatial correlation between the SVI themes and ambient dust exposure from global Lee's L statistic ranged from -0.03 (Theme 1: Socioeconomic vulnerability and Theme 3: Cultural vulnerability) to 0.16 (Theme 5: Infrastructural vulnerability) (table S3). Local Moran's I identified 18 241 (33%) SA1s as

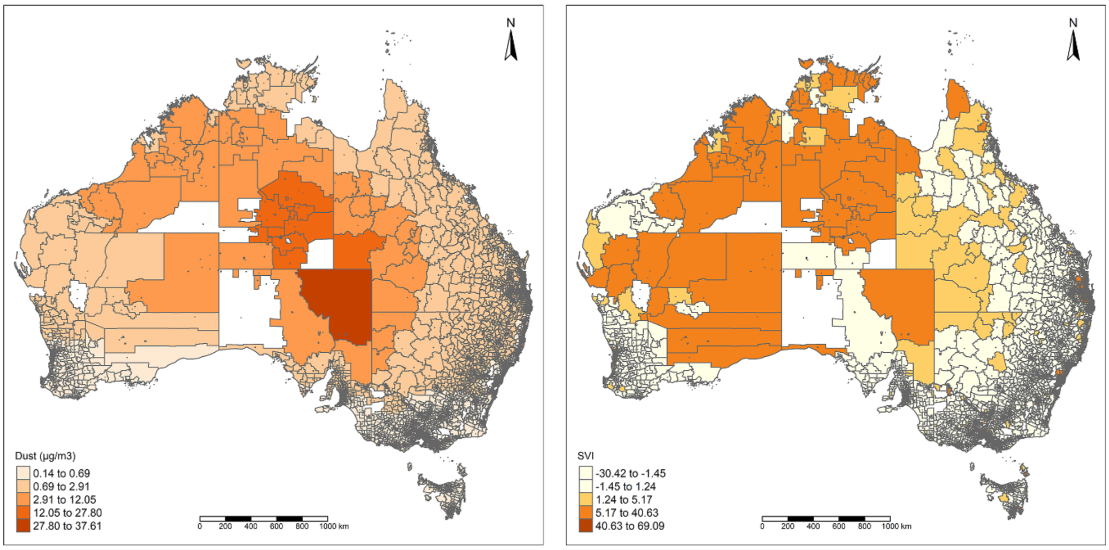

Figure 2. Spatial distribution of ambient dust exposure and social vulnerability index (SVI) across the included SA1 in Australia ($n = 55\,177$). Note: missing values were the SA1s excluded from the analysis due to populations of fewer than 50 people or missing dust concentrations.

hotspots (high–high) and 36 680 (67%) SA1s as coldspots (low–low) for ambient dust, and 17 300 (31%) and 24 732 (45%) SA1s as hotspots and coldspots, respectively, for SVI (figure 3).

Within each state/territory, the greatest percentage of hotspot areas was found in the Australian Capital Territory for ambient dust (60%) and in New South Wales for SVI (35%) (figure S2). The bivariate local Lee's L choropleth map showed areas with spatial positive and negative correlations between ambient dust and SVI at the same location, with 5769 (10.5%) SA1s showing co-location positive correlations of high ambient dust and high SVI across Australia (figure 4) and variations within each state/-territory (figure S3). The ambient dust and SVI also exhibited cross-location correlations, as indicated by the bivariate local Moran's I (figure S4).

For high and low ambient dust exposure across the three categories of SVI, a relatively larger number of areas with high ambient exposure fell within the high SVI category (10 195 SA1; 36%). The distribution of ambient dust exposure levels by remoteness indicated that most urban areas had high ambient dust exposure, while most rural areas had moderate ambient dust exposure levels. There were also slight variations in ambient dust exposure levels within the categories of the SVI themes (table 1). Relative to the low SVI, higher odds of high ambient dust exposure were found in both moderate and high SVI categories and were more elevated in the high SVI category (OR = 1.13, 95% CI:1.03, 1.23) than in the moderate SVI category (OR = 1.03, 95% CI: 0.94, 1.13). The ORs of high ambient dust for the high relative to low SVI category were greater for urban areas (OR = 1.74, 95% CI: 1.42, 2.13) than rural areas (OR = 1.11, 95% CI: 0.90, 1.37). For the SVI themes, there were lower odds of high ambient dust in both moderate and high SVI categories compared to the low SVI category for Theme 1 (Socioeconomic vulnerability), Theme 2 (Demographic/Disability vulnerability), and Theme 5 (Infrastructural vulnerability). The lowest odds of high ambient dust exposure was 0.54 (95% CI: 0.49, 0.60) in the high SVI category for Theme 1 (Socioeconomic vulnerability). However, Theme 3 (Cultural vulnerability) and Theme 4 (Housing vulnerability) showed very strong odds of high ambient dust exposure in both moderate and high SVI categories relative to the low SVI category. The SVI theme with the strongest odds of high ambient dust exposure was Theme 3 (Cultural vulnerability), which was more than three times stronger in the high SVI category relative to the low SVI category (OR = 3.55, 95% CI: 3.20, 3.94) (figure 5, table S4). For each state/territory, high ambient dust showed greater odds in the high SVI category in Western Australia, Northern Territory, New South Wales (both moderate and high SVI categories), Australian Capital Territory, and Tasmania. The most elevated odds of high ambient dust was found in Tasmania (OR = 5.03, 95% CI: 1.22, 20.7). In New South Wales, the odds of high ambient dust were greater in the moderate (OR = 1.29, 95% CI: 1.18, 1.42) than the high SVI category (OR = 1.23, 95% CI: 1.12, 1.35) (table S5).

Results of the non-spatial model showed consistent directions of effect with the main analysis for SVI overall and by remoteness. However, the effect estimates were biased with overestimation in non-spatial models compared to the main analyses that integrated spatial components as smoothing

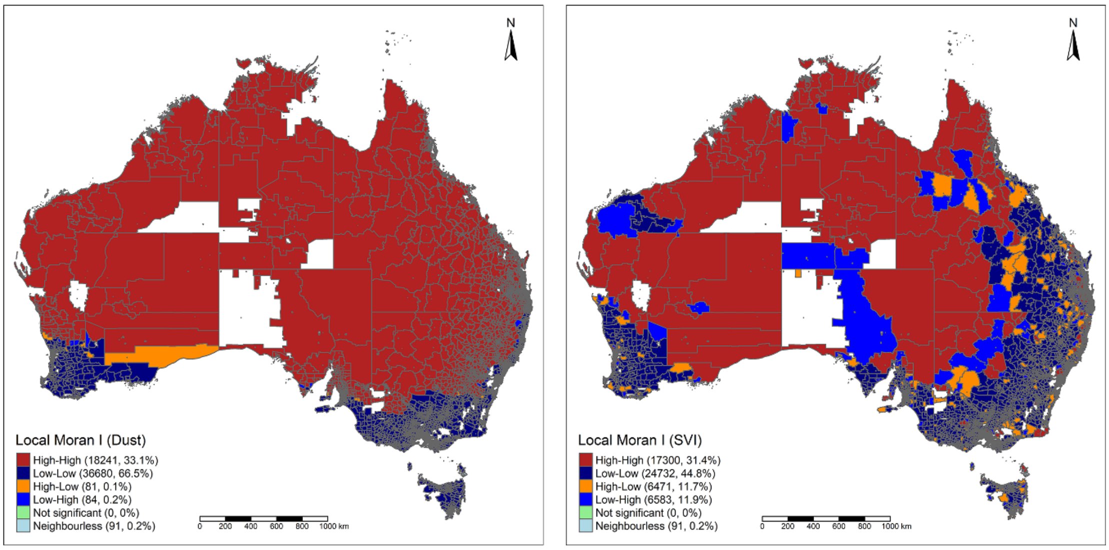

Figure 3. Univariate local Moran's index cluster map showing hotspots (high–high) and cold spots (low–low), and outlier areas (low–high and high–low) of ambient dust exposure and social vulnerability index (SVI) in Australia. Neighbourless refers to spatial units (statistical areal level 1) with no neighbours under the queen adjacency contiguity.

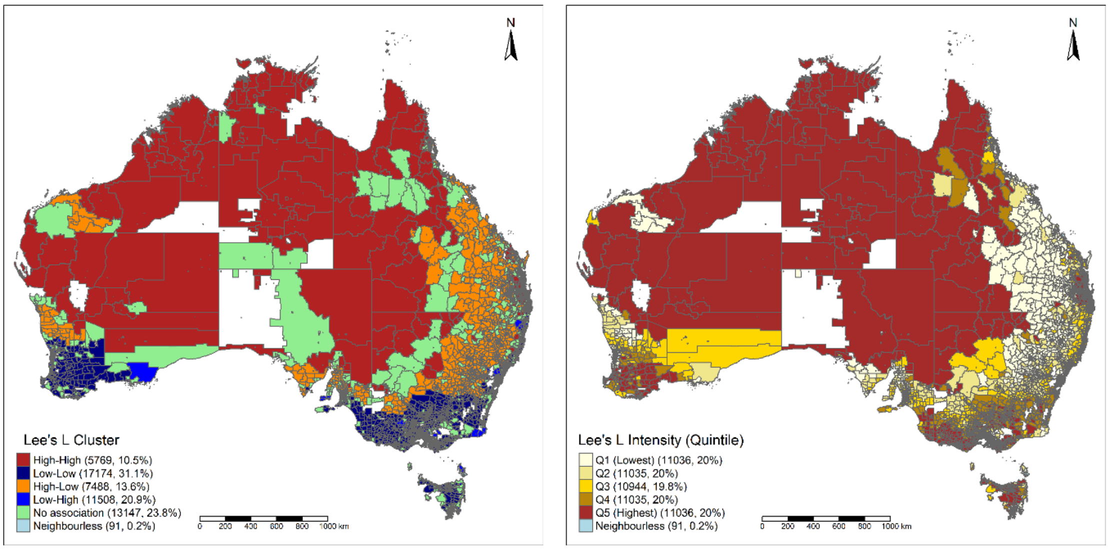

Figure 4. Bivariate local Lee's L cluster map (same-location correlation) showing areas with both high dust and SVI (high–high), both low dust and SVI (low–low), high dust and low SVI (high–low), low dust and high SVI (low–high), and no association between dust and SVI. The right map is the quintile classification of local Lee's L intensity. Neighbourless refers to spatial units (statistical areal level 1) with no neighbours under the queen adjacency contiguity. SVI, social vulnerability index.

splines of the SA1 centroids (table S6). Although the effect estimates showed only modest attenuation, analyses of SVI themes in separate individual models were also consistent with the main analysis, which included all five SVI themes together in a single model (table S7). The spline-based continuous forms with predicted dust at SVI percentiles and differences from the minimum predicted dust showed a non-linear relationship (table S8).

4. Discussion

4.1. Main findings and interpretations

In this study, we analysed the spatial association between ambient dust exposure and vulnerable subpopulations in Australia using nationwide fine-grained SVI [10] and a novel assessment of ambient dust exposure [29]. The results indicated geographical distributions and a positive association

Subgroup	Low Dust (n,%)	High Dust (n,%)	OR (95% CI)
SVI (overall)			
Moderate	9,121 (34)	9,271 (33)	1.03 (0.94 to 1.13)
High	8,197 (31)	10,195 (36)	1.13 (1.03 to 1.23)
Urban			
Moderate	6,570 (33)	4,779 (31)	1.33 (1.10 to 1.60)
High	6,088 (31)	6,022 (39)	1.74 (1.42 to 2.13)
Rural			
Moderate	2,551 (37)	4,492 (34)	0.91 (0.74 to 1.12)
High	2,109 (30)	4,173 (32)	1.11 (0.90 to 1.37)
Socioeconomic vulnerability			
Moderate	9,154 (34)	9,238 (32)	0.59 (0.53 to 0.64)
High	8,851 (33)	9,541 (34)	0.54 (0.59 to 0.60)
Demographic/disability vulnerability			
Moderate	9,668 (36)	8,724 (31)	0.63 (0.58 to 0.70)
High	9,163 (34)	9,229 (32)	0.59 (0.54 to 0.65)
Cultural vulnerability			
Moderate	9,196 (34)	9,196 (32)	2.80 (2.52 to 3.12)
High	10,085 (38)	8,307 (29)	3.55 (3.20 to 3.94)
Housing vulnerability			
Moderate	9,405 (35)	8,987 (32)	1.80 (1.64 to 1.98)
High	7,882 (29)	10,510 (37)	2.63 (2.38 to 2.90)
Infrastructural vulnerability			
Moderate	8,367 (31)	10,025 (35)	0.92 (0.82 to 1.02)
High	7,617 (28)	10,775 (38)	0.80 (0.72 to 0.89)

Subgroup:Low category was used as reference.

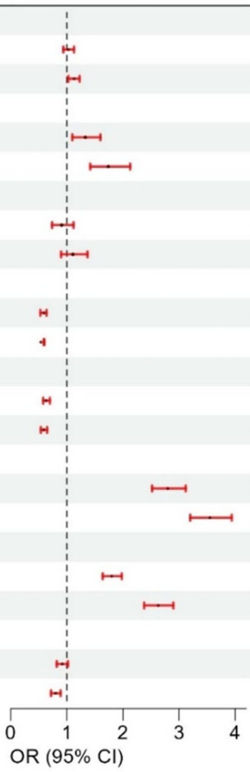

Figure 5. The odds of high ambient dust exposure with SVI overall and by remoteness (urban and rural), and for each SVI theme, using the low category as the reference. Note: SVI, social vulnerability index; OR, odds ratio; CI, confidence interval. The higher the vulnerability for both SVI overall and each subgroup, the greater the degree of vulnerability. Tertiles were used to define the Low, Moderate, and High categories of SVI and each subgroup. Binary dust exposure: Low (0) is $<$median dust and High (1) is $\geqslant$median.

between SVI and ambient dust exposure with hotspot locations. For specific SVI themes, negative associations were found between ambient dust exposure and SVI for Theme 1 (Socioeconomic vulnerability), Theme 2 (Demographics/Disability vulnerability) and Theme 5 (Infrastructural vulnerability), but positive associations were found for Theme 3 (Cultural vulnerability) and Theme 4 (Housing vulnerability). Cultural vulnerability, which was defined by minority groups and those with limited English proficiency, experienced the strongest exposure to ambient dust. Our results also showed that associations were stronger in the high than in the moderate SVI category, relative to the low SVI category across all instances.

Although there are no known studies specifically on ambient dust and social vulnerability or vulnerable subpopulations, our results were consistent with the previous studies in Australia [19, 27, 28], other countries [9, 17, 18, 48–51] and globally [11, 21] showing positive associations between the spatial distribution of SVI or selected vulnerable population indicators and ambient air pollution. The few Australian studies that investigated the associations between SEIFA and other census-derived specific variables for SES with NO_2 in urban areas [27], $PM_{2.5}$ and NO_2 in both urban and rural areas [19], and with sites and emissions from industrial pollution sources [28] also found that lower-income, Indigenous, and ethnic minority communities were disproportionately affected. The positive associations of high ambient dust exposure with SVI in urban and rural areas suggest the pervasiveness of the disparities across the country, as observed in previous findings for SEIFA indexes with $PM_{2.5}$ and NO_2 in Australia [19]. That previous study found consistent overall associations between rural and urban areas in Australia [19], but we found urban-rural disparity as the ambient dust-SVI association was stronger in urban than rural areas, as reported in previous studies on air pollution and SVI in the United States [52, 53], Korea [54] and a 2024 global study based on 2000–2019 data [21]. The higher ambient dust exposure and a stronger positive association in urban areas than rural areas could be due to comparatively more vegetation in rural areas than urban areas, characterised by higher populations, higher temperatures from the urban heat island effect, and roads [54]. Ambient dust from anthropogenic sources, such as building construction and industrial activities in urban areas, tends to be higher than that from agricultural activities predominant in rural areas.

Table 1. Distribution of ambient dust exposure levels by social characteristics in Australia (N= 55 177 SA1s).

Variable[a]	Low ambient dust exposure[b] (N = 26 747 SA1s), n (%)	High ambient dust exposure[b] (N = 28 430 SA1s), n (%)
SVI (Overall)		
Low	9,429 (35)	8,964 (32)
Moderate	9,121 (34)	9,271 (33)
High	8,197 (31)	10,195 (36)
Remoteness		
Urban		
Low	7,140 (36)	4,535 (30)
Moderate	6570 (33)	4779 (31)
High	6088 (31)	6022 (39)
Rural		
Low	2289 (33)	4429 (34)
Moderate	2551 (37)	4492 (34)
High	2109 (30)	4173 (32)
Themes		
Theme 1 (Socioeconomic vulnerability)		
Low	8742 (33)	9651 (34)
Moderate	9154 (34)	9238 (32)
High	8851 (33)	9541 (34)
Theme 2 (Demographic/disability vulnerability)		
Low	7916 (30)	10 477 (37)
Moderate	9668 (36)	8724 (31)
High	9163 (34)	9229 (32)
Theme 3 (Cultural vulnerability)		
Low	7466 (28)	10,927 (38)
Moderate	9196 (34)	9196 (32)
High	10 085 (38)	8307 (29)
Theme 4 (Housing vulnerability)		
Low	9460 (35)	8933 (31)
Moderate	9405 (35)	8987 (32)
High	7882 (29)	10 510 (37)
Theme 5 (Infrastructural vulnerability)		
Low	10 763 (40)	7630 (27)
Moderate	8367 (31)	10 025 (35)
High	7617 (28)	10 775 (38)

Note: SVI, Social Vulnerability Index.

[a] For both SVI overall and thematic vulnerabilities, the higher the vulnerability score the greater the degree of vulnerability. Low, Moderate, and High categories of SVI and individual themes were defined using tertiles.

[b] Binary dust: Low is $<$median dust and High is $\geqslant$median dust exposure.

For specific SVI themes, positive associations between ambient dust and Theme 3 (Cultural vulnerability) and Theme 4 (Housing vulnerability) were consistent with similar previous findings that Indigenous and ethnic minorities are more likely to be exposed to higher concentrations of ambient air pollution [19, 27, 28]. These subpopulations are also more likely to reside in rented and substandard houses or areas with poor housing characteristics in peri-urban centres [10, 55], prone to ambient dust infiltration, making them more vulnerable to ambient dust exposure. Data on dust infiltration, outdoor occupations, and place-time activity patterns would be needed for a more accurate assessment of vulnerability. Moreover, the negative association between ambient dust and Theme 5 (Infrastructure vulnerability) suggests that a highly built environment offers protection from ambient dust exposure. Surprisingly, the negative associations between ambient dust exposure and SVI for Theme 1 (Socioeconomic vulnerability) and Theme 2 (Demographics/Disability vulnerability) indicated areas with high levels of poor SES and high percentages of older adults and children and those not in labour force and needing childcare, and disabled individuals experienced low ambient dust exposure. While these unexpected results deserve further investigation, it could be that these vulnerable subpopulations were more prevalent in rural or peri-urban areas where ambient dust exposure was low.

Given the observed spatial autocorrelations for both ambient dust and SVI, the consistent but over-estimated effect estimates from the non-spatial models are explainable by biases from not accounting for the spatial autocorrelation or spatial effect, leading to more false-positive findings in the non-spatial models [54, 56]. Thus, accounting for spatial autocorrelation or location is important and should be considered in environmental justice studies [54, 56].

Our findings support the proposition of environmental injustice, where certain groups and locations of the subpopulations are at a higher risk of ambient dust exposure [3, 12–15, 57, 58]. Urban areas and communities experiencing cultural, ethnic/racial minority, or housing vulnerability were disproportionately exposed to ambient dust. These inequities reflect policy decisions and broader social structural processes, such as residential segregation, discriminatory lending, and inequitable land use, that place marginalised groups closer to major anthropogenic sources of dust and other co-occurring environmental hazards, such as toxic chemicals, air pollution, and extreme climate change-related events (e.g. heatwaves, bushfires, natural disasters) [3, 12–15]. Although ambient dust is mainly natural, human activities such as land clearing, construction, industrial and transport infrastructure, and reduced vegetation can intensify emissions, and urbanisation may further concentrate exposure. Similar to previous studies on ambient air pollution and SVI indicators [9, 17–19, 27, 28, 48–54], we did not assess whether these associations translate to adverse health outcomes. Nonetheless, the findings are very relevant to public health interventions and policymaking for the reason that ambient dust is predominantly particulate matter ($PM_{10-2.5}$ and PM_{10}) by mass, and recent systematic reviews and meta-analyses found that high concentrations of $PM_{10-2.5}$ and PM_{10} during dust storm events were associated with several health effects and mortality [5–7]. Recent scoping reviews have also documented that SVI indicators relate to the health impacts of climate change and predict disaster response, and health outcomes [59, 60].

The vulnerable subpopulations are more susceptible to negative health outcomes directly or from environmental exposures, including ambient dust exposure through social stratification and underlying determinants of health inequalities, consistent with environmental justice frameworks [5, 16, 19, 57, 61]. Therefore, any policy decisions and interventions targeted to make even small differences in reducing environmental injustice could benefit the entire population, with potentially larger benefits for high-risk subpopulations [57, 62]. Although ambient dust cannot be completely controlled, targeted mitigation and adaptation strategies are required, which could include sustainable land management (e.g. soil conservation, reforestation, and sustainable agriculture to reduce desertification) and climate resilience. Infrastructural and public health policies are also required to withstand extreme weather events, reduce dust generation or emissions (e.g. road maintenance, dust suppression at industrial and construction sites), and protect air quality. Health monitoring, early dust warning systems, and provision of healthcare support during extreme dust storm events, especially for vulnerable subpopulations, are also critical. Areas identified as hotspots with high vulnerability and high ambient dust exposure could be targeted for interventions.

Our key findings provide far-reaching policy implications for vulnerable subpopulations by taking into account health, environment, geographical location, and social vulnerability dimensions. Future corresponding public health and environmental health studies to demonstrate and quantify disproportionate health effects of ambient environmental exposures, including ambient dust exposure in vulnerable subpopulations, are recommended [19, 57]. Moreover, individual-level assessment of the ambient dust exposure will be more helpful. Recent scoping reviews have indicated that, despite the contextuality of SVI, using limited social vulnerability indicators, mostly restricted to sociodemographic and socioeconomic variables, may not adequately capture the SVI metric for public health and environmental justice assessments required for appropriate interventions and policy making, including climate adaptation planning [59, 60]. Therefore, detailed information on housing characteristics and additional inclusion of different data sources on the built environment as used by the US Centres of Disease Control and Prevention to construct SVI [34], especially the '4D' quantification of the built environment (diversity, design, density, and distance) by Wang *et al* [10] to construct the SVI used in our study could be considered in future studies.

By linking social vulnerability to ambient dust exposure, this study highlights how environmental hazards intersect with structural inequities, underscoring the need for equity-focused interventions. This study also provides a generalisable framework for identifying ambient dust-vulnerability associations and hotspots that can be updated as data and modelling tools advance to inform future environmental justice assessments and related climate adaptation planning strategies.

4.2. Strengths and limitations

To the best of our knowledge, this is the first study to specifically examine ambient dust and SVI in Australia and among the first globally. The SVI metric additionally included detailed information on housing, transport, and the built environment, together with four-dimensional quantification of the built environment [10], providing another strength of this study. The ambient dust concentration was obtained from a new assessment of global and regional budgets, fluxes, and lifetimes of atmospheric reactive species and aerosols [29]. The analytical frameworks were robust, including global and local univariate and bivariate spatial autocorrelations and correlations, and spatial smoothing GAMs at the fine-grained spatial units as SA1.

Similar to the previous studies [9, 17–19, 27, 28, 48–54], this is a cross-sectional study to investigate correlation, but not causation, which is usual with this topic because of the inability to randomise dust exposure in observational research. The annual average ambient dust concentration may contribute to understanding overall long-term exposure, but it is not well-suited for capturing acute dust events such as episodic dust storms and peaks from anthropogenic activities and seasonal variability in dust emissions. Although one of the smallest geographical units in Australia (SA1) was reported in this study, ecological fallacy cannot be ruled out, as the findings from SA1-level analysis may be different from individual-level analysis. More temporally and spatially refined data on ambient dust exposure and SVI at the individual level would allow more precise quantification of environmental justice in ambient dust exposure and SVI. Finally, this study did not examine the composition of the ambient dust.

5. Conclusion

This national study identified spatial variability with several identified hotspot areas and positive associations between SVI and ambient dust exposure, particularly elevated in the urban areas. For SVI themes, strong positive associations were found in Cultural and Housing vulnerabilities. Interestingly, we observed negative associations for Socioeconomic, Demographic/Disability, and Infrastructural vulnerabilities. Targeted ambient dust or air pollution reductions are essential to provide all people and areas with a level of protection from environmental exposures to mitigate the environmental injustice of ambient dust and other co-occurring environmental hazards. Further studies should examine the composition and duration of the ambient dust and SVI and the corresponding health outcomes to guide preventative public health measures and policy decisions.

Acknowledgment

MV was in part supported by the Natural Environment Research Council as part of the NC-International programme (number NE/X006247/1) delivering National Capability, and the South Asian Nitrogen Hub funded by the UK Global Challenges Research Fund of UKRI administered by the Natural Environment Research Council (number NE/S009019/1). GP was supported with funding from the National Health and Medical Research Council Project (number 1099655) and Investigator Grants (number 1173991). GAT was supported with funding from the National Health and Medical Research Council Investigator Grant (number 1195716).

Data availability statement

The processed area-level dataset generated during this study is publicly available at Zenodo https://doi.org/10.5281/zenodo.18811539.

The source Social Vulnerability Index (SVI) data and further information are available at the Harvard China Data Lab project page (https://projects.iq.harvard.edu/chinadatalab/AU_vulnerability) and from Wang *et al* [10].

The chemical transport model code used to generate the 2021 EMEP-WRF ambient mineral dust used in this study is publicly available at https://github.com/metno/emep-ctm.

Geographic boundaries were based on the 2016 Australian Statistical Geography Standard (ASGS) shapefiles provided by the Australian Bureau of Statistics (Catalogue No. 1270.0.55.001, July 2016 release), which are publicly accessible from the ABS website (www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.55.001July%202016).

No individual-level data were used or generated in this study.

Supplementary data 1 available at https://doi.org/10.1088/1748-9326/ae4d5d/data1.

Conflict of interest

The authors declare no competing interests.

Ethical approval

Not applicable.

Author contributions

Sylvester Dodzi Nyadanu 0000-0002-6233-0262
Conceptualization (lead), Data curation (lead), Formal analysis (lead), Methodology (lead), Project administration (lead), Visualization (lead), Writing – original draft (lead), Writing – review & editing (lead)

Massimo Vieno 0000-0001-7741-9377
Methodology (supporting), Writing – review & editing (supporting)

Siqin Wang 0000-0002-1809-7088
Methodology (supporting), Writing – review & editing (supporting)

Gizachew A Tessema 0000-0002-4784-8151
Writing – review & editing (supporting)

Gavin Pereira 0000-0003-3740-8117
Conceptualization (supporting), Methodology (supporting), Supervision (lead), Writing – review & editing (supporting)

References

[1] Di Biagio C, Banks J R and Gaetani M 2022 7.11—dust atmospheric transport over long distances *Treatise on Geomorphology* 2nd edn, ed J F Shroder (Academic) pp 259–300

[2] Lian L, Huang J, Chen S, Du S, Zhang L and Yang J 2025 A comprehensive review of dust events: characteristics, climate feedbacks, and public health risks *Curr. Poll. Rep.* **11** 18

[3] Prospero J M, Ginoux P, Torres O, Nicholson S E and Gill T E 2002 Environmental characterization of global sources of atmospheric soil dust identified with the nimbus 7 Total Ozone Mapping Spectrometer (TOMS) absorbing aerosol product *Rev. Geophys.* **40** 2–1

[4] World Health Organization 2021 *WHO Global Air Quality Guidelines: Particulate Matter (PM2. 5 And PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide* (World Health Organization)

[5] Pouri N, Karimi B, Kolivand A and Mirhoseini S H 2024 Ambient dust pollution with all-cause, cardiovascular and respiratory mortality: a systematic review and meta-analysis *Sci. Total Environ.* **912** 168945

[6] Sadeghimoghaddam A, Khankeh H, Norozi M, Fateh S and Farrokhi M 2021 Investigating the effects of dust storms on morbidity and mortality due to cardiovascular and respiratory diseases: a systematic review *J. Educ. Health Promot.* **10** 191

[7] Vergadi E, Rouva G, Angeli M and Galanakis E 2022 Infectious diseases associated with desert dust outbreaks: a systematic review *Int. J. Environ. Res. Public Health* **19** 6907

[8] Carlson C J 2024 After millions of preventable deaths, climate change must be treated like a health emergency *Nat. Med.* **30** 622

[9] Clarke K, Ash K, Coker E S, Sabo-Attwood T and Bainomugisha E 2022 A social vulnerability index for air pollution and its spatially varying relationship to PM2.5 in Uganda *Atmos* **13** 1169

[10] Wang S, Zhang M, Huang X, Hu T, Sun Q C, Corcoran J and Liu Y 2022 Urban-rural disparity of social vulnerability to natural hazards in Australia *Sci. Rep.* **12** 13665

[11] Yang X, Geng L and Zhou K 2021 The construction and examination of social vulnerability and its effects on PM2.5 globally: combining spatial econometric modeling and geographically weighted regression *Environ. Sci. Pollut. Res.* **28** 26732–46

[12] Justice UCoCCfR 1987 Toxic wastes and race in the United States: a national report on the racial and socio-economic characteristics of communities with hazardous waste sites (Public Data Access)

[13] Brulle R J and Pellow D N 2006 Environmental justice: human health and environmental inequalities *Ann. Rev. Public Health* **27** 2006):103–124

[14] Agyeman J, Schlosberg D, Craven L and Matthews C 2016 Trends and directions in environmental justice: from inequity to everyday life, community, and just sustainabilities *Annu. Rev. Environ. Resour.* **41** 321–340

[15] Xu Z 2013 Airborne particles in outdoor air: atmospheric dust *Fundamentals of Air Cleaning Technology and Its Application in Cleanrooms* vol 14 (Springer) pp 47–132

[16] Riley A R 2020 Advancing the study of health inequality: fundamental causes as systems of exposure *SSM Popul. Health* **10** 100555

[17] Zwickl K, Miklin X and Naqvi A 2024 Sociodemographic disparities in ambient particulate matter exposure in Austria *Ecol. Econ.* **224** 108180

[18] Fecht D, Fischer P, Fortunato L, Hoek G, de Hoogh K, Marra M, Kruize H, Vienneau D, Beelen R and Hansell A 2015 Associations between air pollution and socioeconomic characteristics, ethnicity and age profile of neighbourhoods in England and the Netherlands *Environ. pollut.* **198** 201–10

[19] Cooper N, Green D and Knibbs L D 2019 Inequalities in exposure to the air pollutants PM2.5 and NO2 in Australia *Environ. Res. Lett.* **14** 115005

[20] Woodward H, Oxley T, Holland M, Mehlig D and ApSimon H 2024 Assessing PM2.5 exposure bias towards deprived areas in England using a new indicator *Environ. Adv.* **16** 100529

[21] Yu W, Ye T, Chen Z, Xu R, Song J, Li S and Guo Y 2024 Global analysis reveals region-specific air pollution exposure inequalities *One Earth* **7** 2063–71

[22] De Deckker P 2019 An evaluation of Australia as a major source of dust *Earth Sci. Rev.* **194** 536–67

[23] Evans S, Ginoux P, Malyshev S and Shevliakova E 2016 Climate-vegetation interaction and amplification of Australian dust variability *Geophys. Res. Lett.* **43** 11–823

[24] Aragnou E *et al* 2021 Dust transport from Inland Australia and its impact on air quality and health on the Eastern Coast of Australia during the February 2019 dust storm *Atmos* **12** 141

[25] Somboonsin P, Thanyapraneedkul J, Hanigan I C and Canudas-romo V 2025 The burden of air pollution (PM2.5) in subnational Australian life expectancy *Environ. Res.* **285** 122690

[26] Rumchev K, Gilbey S, Mead-Hunter R, Selvey L, Netto K and Mullins B 2019 Agricultural dust exposures and health and safety practices among Western Australian wheatbelt farmers during harvest *Int. J. Environ. Res. Public Health* **16** 5009

[27] Knibbs L D and Barnett A G 2015 Assessing environmental inequalities in ambient air pollution across urban Australia *Spat. Spatio-temporal Epidemiol.* **13** 1–6

[28] Chakraborty J and Green D 2014 Australia's first national level quantitative environmental justice assessment of industrial air pollution *Environ. Res. Lett.* **9** 044010

[29] Ge Y, Vieno M, Stevenson D S, Wind P and Heal M R 2022 A new assessment of global and regional budgets, fluxes, and lifetimes of atmospheric reactive N and S gases and aerosols *Atmos. Chem. Phys.* **22** 8343–68

[30] Australian Bureau of Statistics 2021 Snapshot of Australia *ABS* (available at: www.abs.gov.au/statistics/people/people-and-communities/snapshot-australia/latest-release) (Accessed 3 July 2024)

[31] United Nations Development Programme 2022 Human development report (available at: https://hdr.undp.org/data-center/human-development-index#/indicies/HDI) (Accessed 8 August 2024)

[32] Australian Bureau of Statistics 2021 Australian Statistical Geography Standard (ASGS) edition 3 ABS (available at: www.abs.gov.au/statistics/standards/australian-statistical-geography-standard-asgs-edition-3/jul2021-jun2026) (Accessed 03 July 2024)

[33] Australian Bureau of Statistics 2021 Socio-economic indexes for areas (SEIFA), Australia *Canberra:ABS* (available at: www.abs.gov.au/statistics/people/people-and-communities/socio-economic-indexes-areas-seifa-australia/latest-release) (Accessed 8 October 2024)

[34] Cutter S L, Boruff B J and Shirley W L 2003 Social vulnerability to environmental hazards *Soc. Sci. Q.* **84** 242–61

[35] Skamarock W C, Klemp J B and Dudhia J 2019 A description of the advanced research WRF version 4 *NCAR Technical Notes NCAR/TN-556+STR* vol 145

[36] Ge Y, Heal M R, Stevenson D S, Wind P and Vieno M 2021 Evaluation of global EMEP MSC-W (rv4.34) WRF (v3.9.1.1)

model surface concentrations and wet deposition of reactive N and S with measurements *Geosci. Modell. Dev.* **14** 7021–46

[37] Simpson D *et al* 2012 The EMEP MSC-W chemical transport model—technical description *Atmos. Chem. Phys.* **12** 7825–65

[38] European Centre for Medium-Range Weather Forecast (ECMWF) 2019 ERA5 reanalysis (0.25 degree latitude-longitude grid) (NSF National Center for Atmospheric Research) (Accessed 01 January 2022)

[39] Crippa M, Guizzardi D, Muntean M, Schaaf E, Monforti-Ferrario F, Banja M, Pagani F and Solazzo E 2022 *EDGAR v6.1 Global Air Pollutant Emissions JRC Publications Repository* JRC129555 (available at: https://publications.jrc.ec.europa.eu/repository/handle/JRC129555)

[40] Australian Bureau of Statistics 2016 Australian Statistical Geography Standard (ASGS): main structure and greater capital city statistical areas (Australian Bureau of Statistics) (available at: www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.55.001July%202016?OpenDocument)

[41] Moran P A P 2018 The interpretation of statistical maps *J. R. Stat. Soc. Ser. B Methodol.* **10** 243–51

[42] Cliff A D, Ord J K and Cliff A D 1981 *Spatial Processes: Models & applications/A.D. Cliff & J.K. Ord* (Pion)

[43] Anselin L 1995 Local Indicators of Spatial Association—LISA *Geogr. Anal.* **27** 93–115

[44] Getis A 1999 Spatial statistics *Geographical information systems* vol **1** pp 239–51

[45] Lee S-I 2001 Developing a bivariate spatial association measure: an integration of Pearson's r and Moran's I *J. Geogr. Syst.* **3** 369–85

[46] Kim D, Seo S, Min S, Simoni Z, Kim S and Kim M 2018 A closer look at the bivariate association between ambient air pollution and allergic diseases: the role of spatial analysis *Int. J. Environ. Res. Public Health* **15** 1625

[47] Wood S N 2017 *Generalized Additive Models: An Introduction with R* 2nd edn (Chapman and Hall/CRC)

[48] Ouyang W, Gao B, Cheng H, Hao Z and Wu N 2018 Exposure inequality assessment for PM2.5 and the potential association with environmental health in Beijing *Sci. Total Environ.* **635** 769–78

[49] Li V O, Han Y, Lam J C K, Zhu Y and Bacon-Shone J 2018 Air pollution and environmental injustice: are the socially deprived exposed to more PM2.5 pollution in Hong Kong? *Environ. Sci. Policy* **80** 53–61

[50] Grekousis G, Sunarta I N and Stratoulias D 2024 Tracing vulnerable communities to ambient air pollution exposure: a geodemographic and remote sensing approach *Environ. Res.* **258** 119491

[51] Northeim K and Oppong J R 2023 Mapping health fragility and vulnerability in air pollution–monitoring networks in Dallas–fort worth *Int. J. Environ. Res. Public Health* **20** 1807

[52] Rosofsky A, Levy J I, Zanobetti A, Janulewicz P and Fabian M P 2018 Temporal trends in air pollution exposure inequality in Massachusetts *Environ. Res.* **161** 76–86

[53] Clark L P, Millet D B, Marshall J D and Zhang Y 2014 National patterns in environmental injustice and inequality: outdoor NO2 air pollution in the United States *PLoS One* **9** e94431

[54] Choi G, Heo S and Lee J-T 2016 Assessment of environmental injustice in Korea using synthetic air quality index and multiple indicators of socioeconomic status: a cross-sectional study *J. Air Waste Manage. Assoc.* **66** 28–37

[55] Tao C, Zhang Y, Shindell D and Zhang H 2025 Inequality in air pollution–attributable mortality by income level between and within countries *Proc. Natl Acad. Sci. USA* **122** e2511394122

[56] Jerrett M, Burnett R T, Kanaroglou P, Eyles J, Finkelstein N, Giovis C and Brook J R 2001 A GIS–environmental justice analysis of particulate air pollution in Hamilton, Canada *Environ. Plann. A* **33** 955–73

[57] Maantay J 2002 Mapping environmental injustices: pitfalls and potential of geographic information systems in assessing environmental health and equity *Environ. Health Perspect.* **110** 161–71

[58] Shao S, Liu L and Tian Z 2022 Does the environmental inequality matter? A literature review *Environ. Geochem. Health* **44** 3133–56

[59] Li A, Toll M and Bentley R 2023 Mapping social vulnerability indicators to understand the health impacts of climate change: a scoping review *Lancet Planet Health* **7** e925–e37

[60] Mah J C, Penwarden J L, Pott H, Theou O and Andrew M K 2023 Social vulnerability indices: a scoping review *BMC Public Health* **23** 1253

[61] Phelan J C and Link B G 2015 Is racism a fundamental cause of inequalities in health? *Annu. Rev. Sociol.* **41** 311–330

[62] Deguen S, Amuzu M, Simoncic V and Kihal-Talantikite W 2022 Exposome and social vulnerability: an overview of the literature review *Int. J. Environ. Res. Public Health* **19** 3534