



Evaluating public exposure to airborne particulates from major incident fires: A back trajectory plume modelling approach

Simon D. Griffiths^{a,*,} Helen M. King^a, Justine Wilkinson^a, Frank J. Kelly^b, Jane A. Entwistle^a, Michael E. Deary^{a,*}

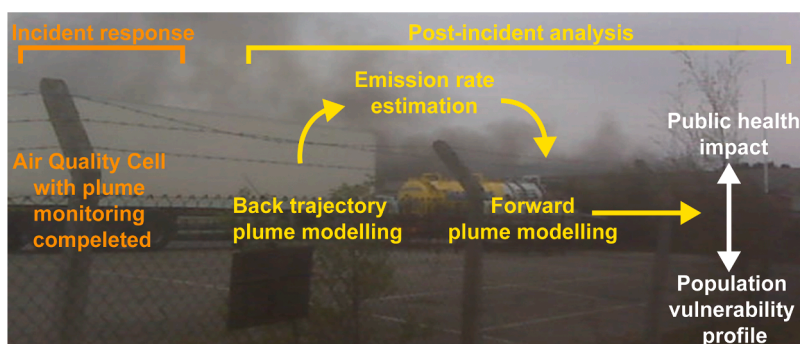
^a Faculty of Engineering and Environment, Department of Geography and Environmental Sciences, University of Northumbria, Ellison Building, Newcastle upon Tyne NE1 8ST, UK

^b Environmental Research Group, School of Public Health, Imperial College London, UK

HIGHLIGHTS

- Urban waste fires pose a significant air pollution risk to nearby populations.
- Novel plume modelling addresses the spatial limitations of air quality monitoring.
- Vulnerability profiles show disadvantaged communities disproportionately impacted.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:

Major incident waste facility fires
PM₁₀, ADMS-STAR back trajectory dispersion model
Population exposure
Environmental justice
Health vulnerabilities

ABSTRACT

Major incident fires at industrial facilities, particularly waste sites, pose a significant risk to public health because of the large amounts of hazardous airborne pollutants released into the ambient environment. Monitoring carried out during these fires is limited in spatial resolution, meaning that the full extent of population exposure is difficult to estimate. In this study, we overcome these limitations by using a novel back-trajectory plume modelling approach, applied to PM₁₀ emission data from a significant tyre fire that occurred in the UK in 2010. This approach allows the calculation of an hourly emission rate that is then used in the forward modelling mode to predict hourly plume concentrations. An analysis of the modelled plume indicated that, as a reasonable worst case, up to 8000 residents in areas adjacent to the fire may have been exposed to PM₁₀ concentrations that are deemed hazardous. Moreover, a vulnerability analysis showed that the exposed population had disproportionately poorer health than the national average, thus raising concerns about environmental justice. This work highlights the need to improve regulatory controls for waste sites located near urban areas and for further research on population exposure and the health impacts of major incident fires.

* Corresponding author.

E-mail address: michael.deary@northumbria.ac.uk (M.E. Deary).

<https://doi.org/10.1016/j.jhazmat.2025.137455>

Received 20 October 2024; Received in revised form 28 January 2025; Accepted 30 January 2025

Available online 1 February 2025

0304-3894/© 2025 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

1. Introduction

1.1. Statement of the problem

Major incident open uncontrolled fires, particularly those occurring at industrial facilities, including waste sites, can cause episodic air pollution incidents that are significant sources of public exposure to particulates and other hazardous airborne pollutants. This results in social, economic, and environmental challenges as well as adverse public health outcomes [1–6]. Across England, Scotland, and Wales, for the period 2009–2018, there were 76 significant major air pollution incidents, which mainly involved uncontrolled open burning of waste materials, including plastics, timber, paper, solvents, and rubber [4]. Emissions from these fires pose acute threats to exposed communities but can also exacerbate existing health disparities and social inequalities. Ground level PM₁₀ concentrations in the thousands of $\mu\text{g m}^{-3}$ have been reported during major incident fires [3], along with high concentrations of additional hazardous air pollutants that exceeded acute health guidelines for many incidents [4].

The evaluation of the health impacts associated with exposure to plumes from major incident fires is challenging and has only recently been reported in the literature in a systematic manner [3,4]. Current approaches are primarily based on monitoring air pollutants at a limited number of locations. For example, the UK's Air Quality in Major Incidents (AQinMI) service typically conducts monitoring at two locations downwind of the emission plume using mobile monitoring teams. Monitoring data are used to establish whether routine public activities can safely continue or if interventions are necessary to protect public health [3,7]. These data also provide valuable evidence for the completion of public health risk assessments [8]. However, the evaluative potential of monitoring is limited in terms of spatial scope (only two monitoring points) and representativeness of locations with respect to public exposure and vulnerability. The challenge is further compounded by practical aspects of monitoring location choice, such as the availability of utilities and considerations concerning the occupational health and safety of the AQinMI monitoring teams. For example, monitoring teams are often kept away from areas with the highest ground level pollutant concentrations due to limitations of personal protective equipment in handling such conditions. As a result of these challenges, the limited spatial resolution of monitoring will be unable to capture the full extent of dispersion of the complex airborne plume, which can spread many kilometres from the point of release [9,6,10]. To address this gap, the current paper develops an innovative dispersion modelling approach that provides a more holistic estimation of public exposure to airborne pollutants from major incident fires. In the following sections we discuss some of the pertinent considerations in carrying out this work.

1.2. Characteristics of major incident fires

Previously, we identified that 80.4 % of major incident fires in the UK over the period 2009–2018 involved waste materials accumulated at resource management sites [4]. Open uncontrolled burning of waste is of growing international concern because of the increasing number of incidents [11,12,10]. The uncontrolled burning of materials, where fuel, temperature, oxygen concentrations, and contact times are unregulated, leads to incomplete combustion, resulting in higher concentrations of particulate matter and volatile organic compounds (VOCs) compared with controlled combustion. Persson and Simonson [13] estimated that every tonne of fuel burned in an uncontrolled fire is equivalent to burning nearly 200 tonnes of fuel in a power station under properly regulated conditions [13,14]. Similarly, the UK Environment Agency [15] estimated that particulate emissions during uncontrolled combustion are 20–400 times higher than those from controlled combustion. Compounding the potential health and environmental impacts further, plume emissions from major incident fires are released close to ground

level, leading to a reduced potential for atmospheric dilution and dispersion [16].

1.3. Public health

1.3.1. Air Quality Cell (AQC) and Air Quality in Major Incidents (AQinMI) service

The AQC and AQinMI are specialist components of the UK's emergency response mechanism that provide multi-agency risk-based public health guidance during the response phase to a significant major air pollution incident [3]. The role of an AQC is to determine whether daily activities can safely continue without requiring a change in public behaviour during the incident [7]. The decision to deploy AQinMI monitoring teams to an incident is made by the AQC. The AQinMI monitoring teams will carry out monitoring of particulates and volatile compounds and return this data to the AQC on an hourly basis. We believe that the AQinMI monitoring service is globally unique, although interest in this function is increasing [17]. A detailed explanation of the function of the AQC and AQinMI is provided in Griffiths et al. [3].

1.3.2. Population vulnerabilities to air pollution from major incident fires

Vulnerability, within the context of air pollution exposure from major fires, is a measure of a population's ability to comprehend, evaluate, and mitigate the consequences of an incident [18]. Vulnerability is a complex construct that is a function of (a) the duration and nature of the exposure [19], and (b) the susceptibility of the exposed individuals, as defined by genetics, race, gender, pre-existing health conditions, and enviro-socio-economic factors [20–23]. Enviro-socio-economic factors arise from physical, social, economic, and environmental conditions external to the individual [24], including educational attainment, economic status, and locations typified by higher pollution levels and poor housing quality [25–28]. Estimating population vulnerabilities, and learning from prior experiences are necessary to design community-resilience policies and practices, including preparation to respond, such as with the AQC and AQinMI processes [29,30].

1.4. Plume modelling

There have been several approaches to modelling emissions from fires and containment failures at industrial facilities. For example, the Hybrid Single Particle Lagrangian Integrated Trajectory (HYSPPLIT) model has been used to reconstruct plume trajectories for a fire at a petrochemical complex in Taiwan [31]. This model has also been used over a much longer transport range to identify the likely source of the elevated concentrations of aerosol-bound PAHs, dioxins, and furans observed in atmospheric samples over Greece following the bombing of industrial facilities in Serbia by NATO during the Kosovo War of 1999 [32]. Operating in forward mode, HYSPPLIT can simulate trajectories taken by plumes from industrial fires, allowing the identification of ambient monitoring locations where detection of the resultant airborne contaminants would be expected. Examples include fires at a fuel storage facility in Santos, Brazil [33], and at a chemical plant in Houston, Texas [23]. Similarly, Leelössy et al. [34] used HYSPPLIT to model the dispersion of a methyl mercaptan plume resulting from an industrial accident in Rouen, France. Other forward plume modelling approaches used in the literature include: Computational Fluid Dynamics (CFD) [35]; Gaussian models such as ADMS-Urban; other Lagrangian models including CALPUFF, SPRAY [36] and NAMES (Numerical Atmospheric Dispersion Modelling Environment) [37]; and Eulerian models [38].

Whilst some of the approaches mentioned above could be used iteratively to match observed downwind monitoring data, to the best of our knowledge none of the models can estimate the source emission rate of fires – a crucial feature for reconstructing plumes and predicting the downwind concentrations through forward modelling. In contrast, ADMS-STAR (Short Term Accidental Releases), a specialist variant of

CERC's ADMS software, is specifically designed to generate back trajectory plumes from hourly monitoring and meteorological data at known locations [39,40]. This Lagrangian puff model has been successfully applied to model the release of a tritium gas tracer and predict the radiological dose under a plume that could result from an accident at a future fusion power plant [41].

1.5. Study overview

In this paper, we report on the novel use of back trajectory plume modelling methodology to characterise the extent and concentration profile of a plume from a typical major incident fire, and its hourly evolution, thus overcoming the limitations of poor spatial monitoring resolution discussed in the preceding sections. Potential health impacts of the plume, including a reasonable worst-case scenario of overall population exposure, are evaluated using a novel spatially-weighted adaptation of the US EPA PM₁₀ AQI categories [42]. The averaged plume is also used to develop a vulnerability profile of exposed populations, highlighting factors that may exacerbate health impacts and weaken community resilience.

The utility of this study extends beyond the immediate application to the study site. The methodology that we develop in this work can be employed to retrospectively analyse population exposure for a range of past AQinMI fires. Such information can be used to inform targeted mitigation strategies for similar existing facilities in urban areas, particularly in relation to vulnerable populations, while also supporting emergency preparedness, enhanced community resilience and improved regulatory control.

2. Methodology

2.1. Selection of typical Major Incident Fire for use in back trajectory modelling

To illustrate the utility of back trajectory modelling for the calculation of wider population exposure to particulate emissions from major incident fires, we required a suitable case study site. The selection was made from UK AQC records obtained from the following sources: (a) the Environment Agency (EA) covering the period April 2009 to March 2016 (England and Wales data were combined for the period April 2009 to March 2013); (b) Natural Resources Wales (NRW) from April 2013 to March 2018; and (c) the Scottish Environmental Protection Agency (SEPA) from April 2009 to January 2018 (known as Airborne Hazard Emergency Response in Scotland).

The selection criteria were as follows:

- 1) an uncontrolled fire in the ambient environment;
- 2) involving the burning of waste materials;
- 3) occurring over an extended period – an AQC can be operational for up to 3 days;
- 4) having a human population downwind and near the point of release;
- 5) having two temporally identical but spatially separated sets of PM₁₀ monitoring data; and,
- 6) having adequate descriptions of monitoring locations to identify spatial coordinates.

Using these criteria, we selected an uncontrolled open fire that consumed between 70,000 and 120,000 waste tyres [43,44] (selection criteria 1 and 2) in the town of Mexborough, South Yorkshire, in June 2010 (UK). At the time of the fire, Mexborough had a population of 15,244 residents [45] (criterion 4). The fire had 25-hours of PM₁₀ monitoring data at two contemporaneous monitoring locations (criterion 5), with detailed monitoring records (criterion 6), and a duration of over

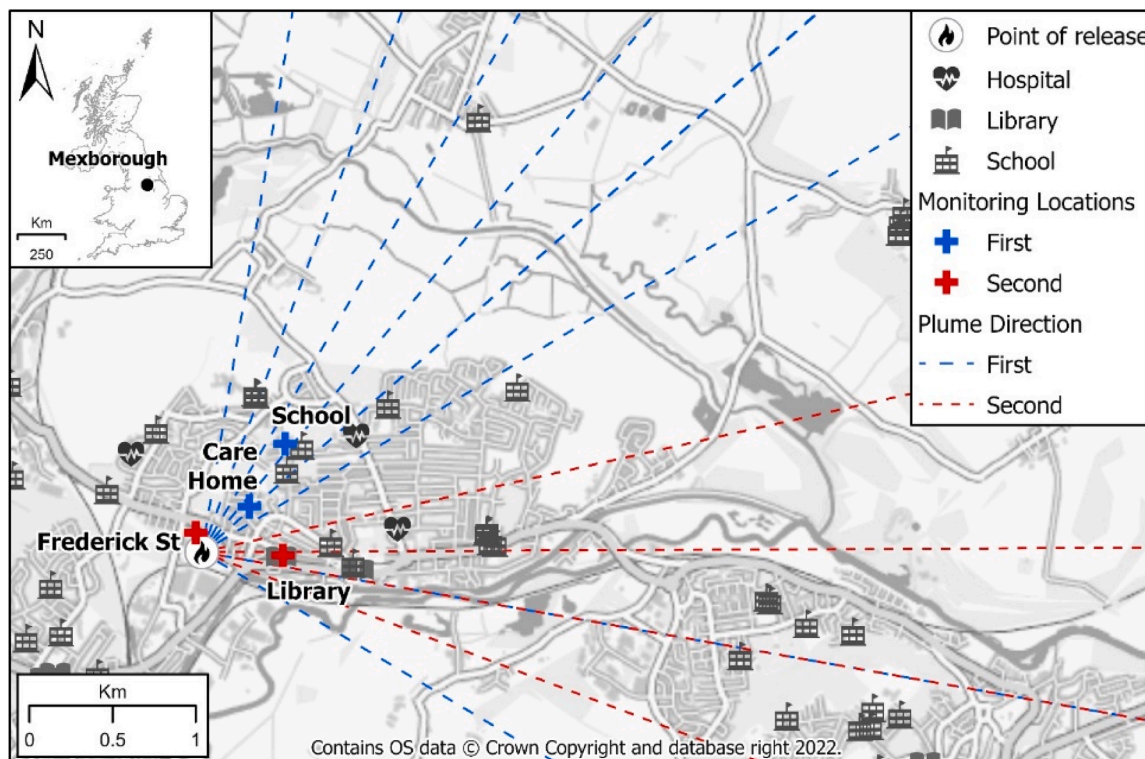


Fig. 1. Point of release and situational context of Mexborough fire incident, including monitoring points, sensitive receptors and wind directions (as reported by the Meteorological Office [46]).

two days (criterion 3). Fig. 1 graphically summarises this incident, showing: (a) the location of the point of the fire; (b) the various wind directions during the monitoring period; (c) the locations of sensitive receptors; and (d) the monitoring locations used by the AQinMI service. The two phases of monitoring were at a residential care home and a school between 18.00 on 28/06/10 and 09.46 on 29/06/10; and at a residential area (Frederick Street) and library car park between 10.32 and 18.56 on 29/06/10.

2.2. PM₁₀ monitoring at the sites

AQinMI monitoring teams reported contemporaneous particulate concentrations measured using an Osiris instrument, which is an indicative laser light scattering instrument for measuring total suspended particulates (TSP), PM₁₀, PM_{2.5}, and PM₁ within the range of 0.4 – 20 µm with a resolution of 0.01 µg m⁻³. A detailed evaluation of Osiris's performance during episodic incidents is available in Griffiths et al. [3]. For the Mexborough data set, 1-min PM₁₀ monitoring data were aggregated to hourly concentrations before being converted from µg m⁻³ to g m⁻³ to comply with the ADMS-STAR input format.

2.3. Modelling hourly back trajectory plumes

Developed by Cambridge Environmental Research Consultants (CERC), ADMS (Advanced Dispersion Modelling System) is a well-established dispersion modelling software package. ADMS is used to model ambient air pollution [47,48,39,49], as well as plumes from point source episodic air pollution events. An example is the prospective modelling of the potential loss of chemical containment at industrial sites storing or processing quantities of chemicals [50]. The current study uses ADMS-STAR, a specialist Lagrangian puff variant of CERC's ADMS software.

ADMS-STAR requires the following data inputs: meteorological data for each hour that the modelling was carried out (wind speed, wind direction, air temperature, cloud cover, and precipitation), surface roughness, emission source details (diameter, temperature, and exit velocity), and the grid references of the source and monitoring locations. The emission rate of particulates (g s⁻¹) from the source can either be directly specified or calculated using a back-trajectory approach that utilises both measured concentrations and meteorological parameters. A waste fire, such as Mexborough, will have a variable emission rate that cannot be specified; therefore, the emission rate for each hour of the fire was back-calculated from concentrations recorded at two monitoring locations using ADMS-STAR.

The model was run without wet deposition or complex terrain because there was no rainfall during the modelling period, and the model area had relatively flat terrain. The modelling was performed within a 25 km × 25 km area and at a resolution of 200 m, though with concentrations also calculated at specific points for sensitive receptors and monitoring points. Meteorological data were obtained from the nearest MIDAS (UK Met Office Integrated Data Archive System) monitoring station [46]. Where data were missing, they were obtained from the next nearest station. Wind speed was converted from knots to m s⁻¹ where 1 knot = 0.5144 m s⁻¹. Both meteorological and OSIRIS monitoring data were standardised to GMT (UTC +0). Model parameters were based on ranges and assumptions used in previous studies on the use of ADMS packages to model fires: emission velocity, 0.1 m s⁻¹ [51] and fire temperature 600 °C [51,52]. The fire diameter 9.77 m was identified from the Fire and Rescue Service's reported area of the pyre.

2.3.1. Model calibration

Back trajectory modelling in ADMS-STAR was used to estimate the hourly PM₁₀ emission rates of the fire (g s⁻¹). The predicted emission rates were used within the model to develop the hourly forward-modelling plume concentrations. To assess the accuracy of the back trajectory model in predicting ground level PM₁₀ concentrations, a

calibration exercise, comparing modelled concentrations against those monitored by the AQinMI service, was conducted.

The monitored results used in the calibration consisted of a pair of 1-hr averaged concentrations corresponding to the two monitoring locations (the school and the residential care home; see Fig. 1 for locations). The back trajectory modelling generates a corresponding pair of predicted results for the two locations, together with the emission rate that is consistent with the measured concentrations at both points. Linear regression was carried out on the 1-hr modelled against 1-hr monitored PM₁₀ concentrations. The emission rates for hours 0300 and 0800 were implausibly high (99 and 154 kg s⁻¹, respectively) compared to the monitoring period average (1.15 kg s⁻¹) and were not included in the calibration or modelling of the plume. The back-calculation of emission rates requires accurate meteorological and concentration data and so the discrepancy for these two time periods is likely to arise from one of these data sources.

In addition to the correlation analysis, FAC2, the fraction of predicted concentrations that fall within a factor of 2 of the observed concentration (i.e. meet the condition of Eq. 1) was calculated. For an urban area, the minimum value of the acceptance criteria for FAC2 is 30 %, whilst for a rural environment the value is 50 % [53,54]

$$0.5 \leq \left(\frac{C_p}{C_o} \right) \leq 2.0 \quad (1)$$

Where, C_p are the modelled 1-hr PM₁₀ model predictions and C_o are the observed 1-hr PM₁₀ concentrations.

2.3.2. Modelled output

PM₁₀ mass concentrations from the 23 individual 1-hour modelled plumes were spatially averaged using ArcGIS Pro to generate a single 23-hour plume of PM₁₀ concentrations.

2.4. Population characteristics

UK Output Areas (OAs) were used to identify demographic characteristics of the exposed population. These represent the smallest geographical units for reporting census and other statistical data on population demographics. For the 2011 UK census, which was used as the nearest census date to the 2010 Mexborough fire, England comprised 171,372 OAs, reflecting populations of between 100 and 625 individuals [55]. The UK's Index of Multiple Deprivation (IMD) was also used in this study to create population vulnerability profiles, though the IMD metric uses Lower Super Output Areas (LSOA) which have a larger spatial footprint than OAs, with England divided into 32,844 areas of between 1000 and 3000 persons [56]. Because of their larger spatial extent, individual LSOAs may partially extend beyond the plume footprint; however, we have included in the analysis all LSOAs intersecting any part of the plume.

It should be noted that population data are based on residents of households and cannot account for the routine daily movements of individuals including travelling into and across the area for work or personal reasons. This is pertinent for the 29th June 2010, where the plume was projected as crossing the main business area of Mexborough and into Conisbrough during daytime hours (Fig. 1).

In addition to using census data for the purposes of estimating exposure, we also used the model to predict PM₁₀ concentrations at specific sensitive receptor locations, including primary schools, libraries, and clinical facilities, and at AQinMI monitoring points.

2.5. Health impact assessment for exposed populations

PM₁₀ concentrations from the 23-hour averaged plume were categorised using the US EPA Air Quality Index (AQI) [42]. This index covers the range of PM₁₀ concentrations appropriate to the magnitude of emissions during AQC incidents, unlike UK and EU ambient standards

[57]. AQIs from ‘moderate’ and above are shown with their cautionary health statements in Table 1. PM₁₀ concentrations > 604 µg m⁻³ are categorised by the US EPA as ‘Beyond the AQI’ although with the same health advice as ‘Hazardous’ [42].

2.6. A reasonable worst-case scenario

For the prediction of population exposure to PM₁₀ emissions from the Mexborough fire, a reasonable worst-case scenario (RWCS) approach was adopted. This is an approach used in resilience planning that constructs an appropriate risk-based scenario that is plausible and challenging, but not the absolute worst case [58]. Thus, rather than categorise an OA that has a footprint within the plume as having the highest AQI that was observed in the OA area, the RWCS is based on a spatially weighted AQI, generated for each exposed OA. Examples of this process is shown in Table 2. Spatial weighting was performed using ArcGIS Pro. Fractional RWCS AQIs (Table 2) were rounded down for further analysis.

In calculating the spatially weighted AQI, we have assumed an equal distribution of population across each OA area but we recognise that, as the plume moves over rural OAs, this assumption becomes less true.

2.7. Vulnerability profile

Vulnerability indicators and the source of that data are presented in Table 3. The profile is determined by assessing the prevalence of each indicator in all English OAs and identifying whether the indicator in each OA exposed to the plume is above or below the English median (50th percentile). Thus, if an indicator occurs at > 50 %, then it is more prevalent than seen across England as a whole.

3. Results and discussion

3.1. Summary of measured PM₁₀ concentrations

Before considering the results of the modelling study, it is useful to summarise data for the monitoring that was carried out during the Mexborough fire. The Osiris 1-minute average PM₁₀ mass concentrations for the fire are plotted in Fig. 2 (first monitoring phase at a school and residential care home) and Fig. 3 (second monitoring phase at

Frederick Street and Library car park). The most notable finding was that at a distance of nearly 1 km from the source of the fire, 1-minute averaged PM₁₀ concentrations exceeded the 6527 µg m⁻³ ceiling of the Osiris instrument [3,71]. We have reported similarly high PM₁₀ concentrations for monitoring carried out at other major incident fires [3]. The monitoring data also demonstrated large variations in PM₁₀ concentrations over time, as previously reported [3]. This variability may be due to (a) varying burn conditions, such as temperature and oxygen availability; (b) wind direction changes; or (c) firefighting interventions, for example, the breaking open of a pyre, releasing a larger fraction of particulates.

Table 4 summarises the hourly-averaged PM₁₀ concentrations at AQinMI monitoring locations. Apart from Frederick Street, all locations had hourly mean PM₁₀ concentrations exceeding 1000 µg m⁻³ during the monitoring period, with maximum hourly concentrations of 3000–5400 µg m⁻³. The monitoring period mean concentrations (up to 15hr, at a particular monitoring location, so most appropriately compared to 24-hr guideline values) are well above the US EPA AQI highest category of ‘Hazardous’. In contrast to the other three monitoring locations, the PM₁₀ concentrations for the Frederick Street location, which was part of the second phase of monitoring (Fig. 3), were consistently lower and showed little variability. This is likely because the Frederick Street monitoring location was upwind of the prevailing plume (Fig. 1). Nevertheless, one aspect of the AQC process is to reassure communities that their health is protected, and the Frederick Street site, which is c. 120 m North of the point of release, was chosen to support residents whose homes, very close to the fire, smelt heavily of smoke [44].

3.2. Model validation

3.2.1. Evaluation of hourly emissions rates

Across 25-hours of available monitoring data, the hourly average emission rate calculated by ADMS-STAR for the Mexborough fire was 1.15 kg s⁻¹ (range 0.015–9.33 kg s⁻¹; sd 2.42). Note, however, the emission rates for 0300 and 0800 were unrealistically high (99 and 154 kg s⁻¹, respectively) and these two hours have been excluded from the calibration and plume modelling, leaving 23 of the 25 h sampled.

3.2.2. Calibration of modelled against monitored PM₁₀ results

Fig. 4 shows the results of the calibration exercise performed to assess the accuracy of the back trajectory model in predicting ground level PM₁₀ concentrations resulting from the Mexborough fire. Linear regression analysis of modelled against monitored PM₁₀ concentrations gave the following relationship: modelled = 1.28 (± 0.19) × monitored, where the intercept was set at 0 (r² = 0.66). Therefore, we are confident that the model can predict ground level concentrations of PM₁₀ over a wide range of concentrations (up to 6000 µg m⁻³) with a reasonable goodness of fit (ie ~66 %). Nevertheless, there are potential caveats in the use of this model. Firstly, the predicted concentrations will be most accurate for areas that are closest to the AQinMI monitoring locations, which were chosen to correspond to areas with the highest concentrations and the greatest concern for public health. Second, the r² value indicates that only 66 % of the variance is explained by the modelling and, therefore, there are additional factors that contribute towards the uncertainty of the measurements. This is most likely due to the complex and unpredictable dynamics of uncontrolled burns, local meteorological conditions varying from those recorded at the weather station used in the modelling, and inaccuracies in the monitored data resulting from the ceiling in real-time measured concentrations for the Osiris instrument.

3.2.3. Evaluation of model by FAC2

The hourly results of the FAC2 analysis are presented in Table S1. The FAC2 parameter (Eq. 1) was 63 %, well above both the 30 % and 50 % acceptance criteria proposed by [72] for dispersion modelling in

Table 1
Selected AQI categories adopted to indicate potential health impacts on population affected by the plume [42]. Unhealthy exposures are defined as those within the range ‘unhealthy for sensitive groups’ to ‘beyond the AQI’.

AQI category (Index Value)	PM ₁₀ (µg m ⁻³)	Cautionary Statements
Moderate (51–100)	55 – 154	Unusually sensitive people should consider reducing prolonged or heavy exertion.
Unhealthy for Sensitive Groups (101–150)	155 – 254	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should reduce prolonged or heavy exertion.
Unhealthy (151–200)	255 – 354	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should avoid prolonged or heavy exertion; everyone else should reduce prolonged or heavy exertion.
Very Unhealthy (201–300)	355 – 424	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should avoid all physical activity outdoors. Everyone else should avoid prolonged or heavy exertion.
Hazardous (301–500)	≥ 425 – 604	Everyone should avoid all physical activity outdoors; people with heart or lung disease, older adults, children, and people of lower socioeconomic status should remain indoors and keep activity levels low.
Beyond the AQI (>500)	> 604	

Table 2

Example of calculation of RWCS spatial AQI for five AOs. The weighting factors shown are based on the proportion of the OA area exposed to each AQI category. Numbers in parentheses record the numerical value assigned to each AQI category. RWCS spatial AQI column represents weighted OA. We have included the highest recorded AQI for comparison.

Below (0)	Moderate (2)	Unhealthy for sensitive groups (3)	Unhealthy (4)	Very unhealthy (5)	Hazardous (6)	Beyond AQI (7)	RWCS Spatial AQI for OA	Highest observed AQI for OA
0.50	0.50	0.00	0.00	0.00	0.00	0.00	1.00	2
0.25	0.25	0.25	0.25	0.00	0.00	0.00	2.25	4
0.50	0.50	0.00	0.00	0.00	0.00	0.00	1.00	2
0.33	0.33	0.33	0.00	0.00	0.00	0.00	1.67	3
0.50	0.50	0.00	0.00	0.00	0.00	0.00	1.00	2

Table 3

Datasets identifying population characteristics used for spatial statistical analysis. NOMIS datasets were ranked against all OAs in England, with population counts reflecting those normally resident on the day of the Census 2011. IMD were ranked against all LSOA in England.

Indicator	Description of dataset	Source
NOMIS datasets linked to OAs		
Children (≤16)	Age ranges 0–4, 5–7, 8–9, 10–14, 15 and under 16 combined.	Population normally resident on the day of census 2011
Older adults (≥65)	Age ranges 65–74, 75–84, 84–89, over 90 and over 65 combined.	Age [59]
Gender	Male or female	Gender [60]
Ethnicity	Ethnic group classification reflects the 'Harmonised Concepts and Questions for Social Data Sources Primary Standards'.	Ethnicity [61] Occupation [62]
Indices of Multiple Deprivation (IMD)		
A weighted measure providing a score for each Lower Super Output Areas (LSOA). Scores are generated against 'domains' of deprivation: education, employment, living environment, health, housing and services, income and crime [63].		Ministry of Housing Communities and Local Government [64]
Individual domains of deprivation for IMD [63]		
Education: measures deprivation in educational attainment, skills and training using Key Stage school results, qualifications and the number of school absences reported.		Ministry of Housing Communities and Local Government [65]
Employment: measures the 'involuntary exclusion of the working-age population from work' being based on those receiving benefits		Ministry of Housing Communities and Local Government [66]
Living Environment: deprivation in the 'quality of the local environment' combining two sub-domains: 1) 'indoors', a measure of poor housing condition and 2) 'outdoors', including air quality and a count of road traffic accidents.		Ministry of Housing Communities and Local Government [67]
Health: measures the 'relatively high rates of people who die prematurely or whose quality of life is impaired by poor health or who are disabled'		Ministry of Housing Communities and Local Government [68]
Housing and Services: embraces two sub-domains: 1) 'geographical barriers' which measures accessibility of shops, GPs, schools and Post Offices and 2) 'wider barriers' which includes issues relating to access to affordable housing		Ministry of Housing Communities and Local Government [69]
Income: proportion of the population with income deprivation constructed using income related benefits		Ministry of Housing Communities and Local Government [70]

urban and rural environments respectively.

3.3. Reasonable worst-case scenario of predicted population exposure

3.3.1. Population exposed to PM₁₀ concentrations in unhealthy AQI categories

The 23-hr averaged modelled concentrations of PM₁₀ were categorised according to the US EPA AQI concentration breakpoints for PM₁₀ (Table 1; U.S. Environmental Protection Agency [42]) and are shown in Fig. 5. For context, the UK's 2010 urban ambient PM₁₀ mean concentration was 18.70 µg m⁻³ [73], meaning that the values in

Table 5 ranged from between ten- and a hundred-fold higher.

From the ArcGIS Pro analysis of population and spatially weighted AQI data, Figs. 6 and 7 show, respectively, the proportion of the population in the overall map area and the proportion of the residents of the closest wards to the fire, Mexborough and Conisbrough, that were exposed to AQI categories at 'Unhealthy for Sensitive Groups' and above (24 h). Fig. 6 indicates that 30,023 usual residents may have been exposed to unhealthy AQI categories across the whole plume, with 8119 indicated to have been exposed to the combined 'Hazardous' and 'Above the AQI' spatially weighted AQI. The majority of the latter (7856) were the residents in the two nearest wards, Mexborough and Conisbrough (Fig. 7). It should be caveated that these predictions are based on the modelled emission factors generated by ADMS-STAR.

The health protection guidance given for exposure to concentrations in the AQI 'Hazardous' and 'Beyond AQI' category is to avoid all physical activity outside and for those with heart or lung disease, older adults and children to remain indoors and keep activity levels low [42].

3.4. Modelled concentrations at sensitive receptors

Modelled PM₁₀ concentrations at sensitive receptors, defined as those where children, the elderly, and those in poor health may be present for a significant period, are shown in Table 5. Primary school age children (5–11 years old) were exposed to concentrations ranging from 171 µg m⁻³ (unhealthy for sensitive groups category) to 552 µg m⁻³ (hazardous category). Among secondary school aged children (11–18 years old) concentrations ranged from 203 µg m⁻³ (unhealthy for sensitive groups category) to 1459 µg m⁻³ (beyond the AQI). At the hospital, where many individuals are likely to have pre-existing health conditions, the concentration was 647 µg m⁻³ (beyond the AQI). At a residential care home, the predicted concentration was 1932 µg m⁻³ (beyond the AQI), which is corroborated by the AQInMI monitored data at this site.

The public health advice during the Mexborough fire was for nearby residents to shelter in place but 60 residents self-evacuated, returning to their homes the following day [44].

3.5. Analysis of exposure based on population vulnerabilities

3.5.1. Vulnerability indicators for the Mexborough and Conisbrough Wards: socio-economic disparities and environmental justice

A particular concern about major incident fires is that they often involve facilities that are located near urban areas, and can affect populations that are both socioeconomically disadvantaged and which have poorer health metrics compared to national averages [23]. These populations may already be exposed to higher-than-average ambient air pollution concentrations. Therefore, the effect of the very high particulate concentrations arising from an industrial fire, over a limited duration, may have a disproportionate impact on health. Fig. 7 established that 99 % of residents of the Mexborough and Conisbrough Wards were exposed to PM₁₀ concentrations that fell within the 'Unhealthy for sensitive groups' US AQI category and above. Therefore, for these two wards, we were interested to analyse for any indicators of population vulnerability that might exacerbate the health effects of exposure. In

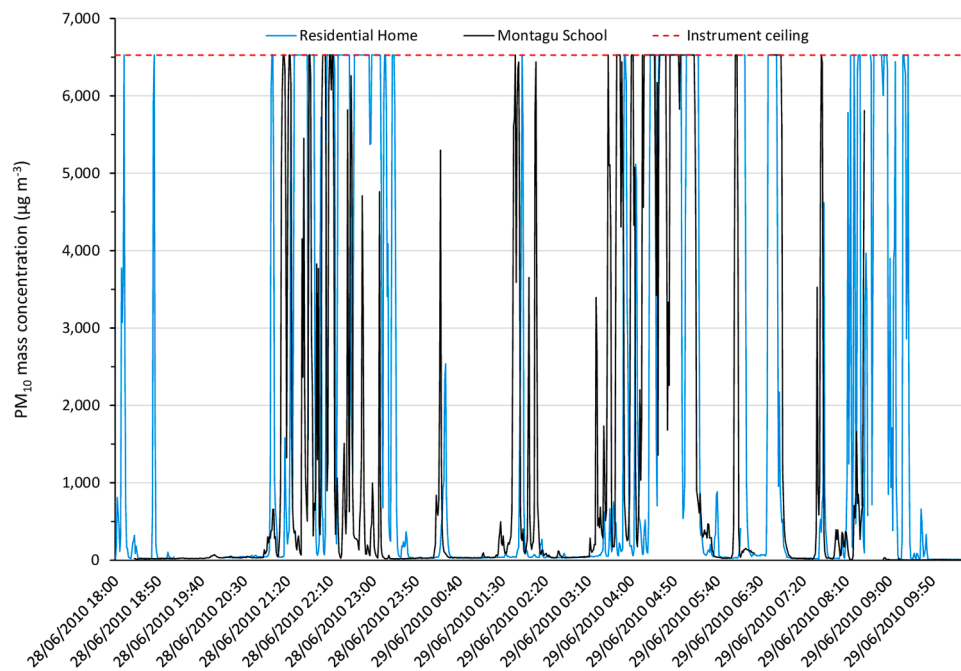


Fig. 2. Variation in 1 min-averaged PM_{10} mass concentrations ($\mu g m^{-3}$) over the duration of the Mexborough fire, as measured by a Turnkey Osiris instrument at two different locations (Residential Care Home and School). Griffiths et al. [3] reported the OSIRIS instrumentation ceiling of $6527 \mu g m^{-3}$.

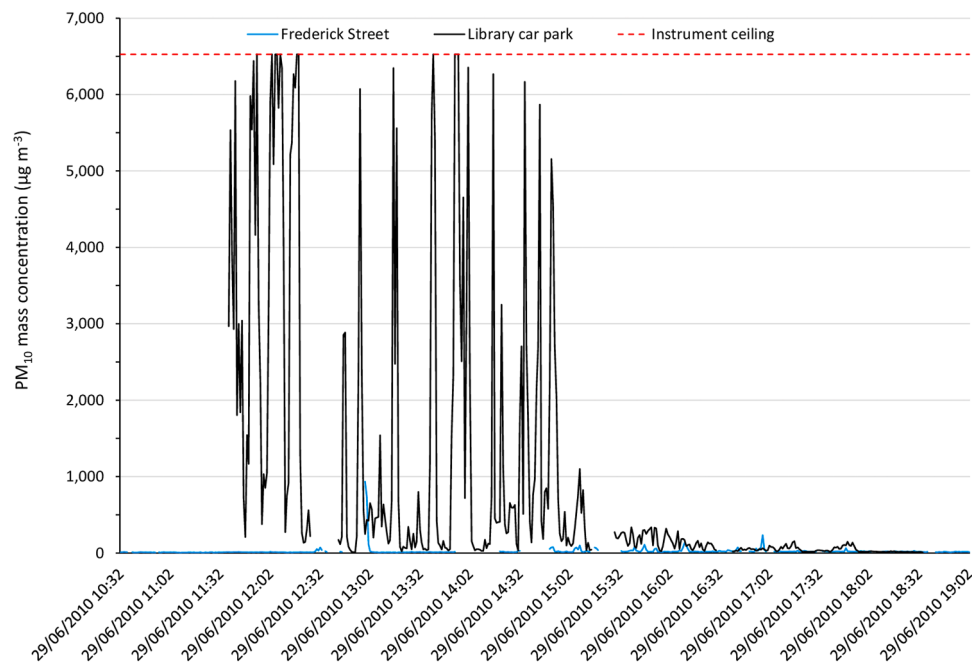


Fig. 3. Variation in 1 min-averaged PM_{10} mass concentrations ($\mu g m^{-3}$) over the duration of the Mexborough fire, as measured by a Turnkey Osiris instrument at two different locations (Frederick Street and Library Carpark). Griffiths et al. [3] reported the OSIRIS ceiling of $6527 \mu g m^{-3}$.

Fig. 8 we present the results of an analysis of the population vulnerability profiles, based on age, ethnicity, health, education and employment for those OAs intersecting with the two wards ($n = 79$). These are compared with the national average, which is, by definition, the 50th percentile. In addition, Fig. 9 shows the Index of Multiple Deprivation (IMD) parameters for LSOAs that intersected the modelled plume for the whole plume and for the Mexborough and Conisbrough wards.

Compared with all English OAs (Fig. 8a to 8f) and LSOAs (Fig. 9), data from the Mexborough and Conisbrough wards exceeds the 50th percentile value across the range of vulnerability characteristics. Thus, it

is evident that those individuals with no or lower-level qualifications (Fig. 8g) and those employed in non-professional roles are over-represented compared with the English median (Fig. 8h). Self-reported health data (Fig. 8f), an indicator of pre-existing medical conditions within the community, shows a greater proportion of the population in the fair, bad, or very bad categories, compared to the national picture. Relative to the national average, the white population is over-represented, while mixed-race, Asian, and Black groups are under-represented. In addition, across a range of IMD metrics, including the overall IMD score, income, employment, health deprivation and

Table 4

Descriptive statistics for hourly PM₁₀ concentrations at three locations used during the AQinMI monitoring of the Mexborough Tyre fire in June 2010.

Statistic	PM ₁₀ mass concentration ($\mu\text{g m}^{-3}$)			
	Residential Care Home	School	Library	Frederick Street
Minimum	9.86	5.6	16.10	9.07
Mean	1477	1115	1103	24.79
Standard deviation	1731	1505	1226	9.34
Median	672	439.4	783.8	24.19
Maximum	5384	5269	3098	37.37
Count of hourly data (n)	15	15	8	8

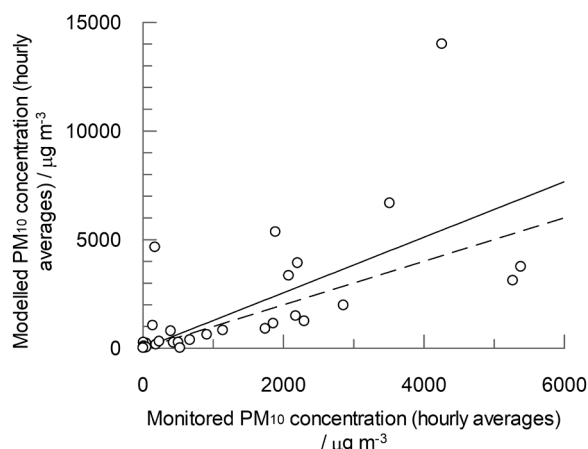


Fig. 4. Relationship between monitored and modelled PM₁₀ mass concentrations. Two modelled hours (0300 and 0800) were removed because of the elevated unrealistic modelled emission rate. The solid line is the best fit to the equation of a straight line with the intercept set at zero and the dashed line is the 1:1 relationship.

education, skills, and training, Fig. 9 shows that the exposed population in the Mexborough and Conisbrough wards were significantly more deprived compared to the national average.

3.5.2. Implications for health

The Mexborough open uncontrolled fire resulted in substantial ground level concentrations of PM₁₀ (Figs. 3 and 4; Table 4), with a significant proportion of this likely to be PM_{2.5} and smaller, which can penetrate deeper into the lungs [74]. The acute and chronic health effects of particulate matter exposure have been well-documented [75–77, 25,78].

As indicated by our RWCS analysis, nearly 8000 residents, along with several sensitive receptors including schools and the local hospital, were exposed to air quality levels categorised as ‘Hazardous’ and ‘Beyond AQL’, indicating significant potential health risks (Table 5). In assessing possible health effects, a pertinent comparable situation might be wildfires, where similar PM₁₀ concentrations are observed [57], although usually with longer burn durations. Moreover, there has been a considerable amount of research on the health effects of wildfire smoke [79,21,80–82], including considerations of the types of susceptibilities that we see in the Mexborough and Conisbrough populations.

In the general population, there is evidence that smoke at the levels observed during wildfires and in the Mexborough fire are associated with acute respiratory [79] and cardiovascular effects [80]. Usually, these effects lead to increased visits to hospital emergency departments or doctors’ surgeries, although the lag period can be up to two weeks [79,83]. Respiratory hospital admissions following the Southern California wildfires of 2003 were mainly for asthma (34 % increase) but also

included acute bronchitis, chronic obstructive pulmonary disease, and pneumonia [83]. To see whether similar health effects were evident during and after the Mexborough event, syndromic surveillance could be used [84,85], though this is beyond the scope of the current study.

For the more susceptible groups in the population, children aged < 16 years are more likely to be affected by chemical exposures, including particulate matter [86,87]. They have developing lungs and immune systems [88], as well as elevated respiratory and metabolic rates which result in proportionately greater contaminated air intake per Kg of body weight compared to adults [47,89,27], which can harm organ development [89,90]. This is exacerbated by children being more physically active compared to adults [91]. Statistically significant associations between wildfire smoke and children’s exposure include nose, eye, and throat irritation, cough, bronchitis, and asthma attacks [82]. Visits to hospital emergency departments also significantly increase, as do hospitalisations for asthma, particularly for children under five years [83,81,82]. Exposure to particulate matter in smoke may also be associated with mental health symptoms in children and adolescents [80, 92]. For Mexborough and Conisbrough, against the English median (50th percentile), the 0–4 and 5–7 years olds are marginally over-represented at 53.0 % and 52.0 % respectively (Fig. 8a). Young adults (18–19, 20–24; 25–29) are overrepresented at 67.4 %, 61.6 % and 54.6 % respectively (Fig. 8c). Moreover, and especially pertinent as it was a weekday, several schools are seen to have been exposed to potentially hazardous AQIs during the fire (Table 5).

Older adults (>65) are more susceptible to the effects of poor air quality [86,21,80,87]. For the older population, a study of the 2003 southern California wildfires by Delfino et al. [83] found that this group was the most affected group for respiratory hospital admissions. The link between health effects in the elderly and exposure to particulate matter may be predominantly due to pre-existing health conditions. Although the population > 65 years old is marginally underrepresented at 49.6 % in the Mexborough and Conisbrough wards (Fig. 8c), there is a greater representation of the 65–74 age group at 50.5 % and of the 85–89 age group at 53.9 %. The residential care home is a vulnerable location for this population, and it is seen that the averaged exposure at this location was 1932 $\mu\text{g m}^{-3}$ (Table 5).

Pre-existing health conditions are known to adversely influence health susceptibility to particulate exposure in populations [79,80]. Data on pre-existing health conditions for populations affected by the Mexborough fire came from self-reported health conditions through the NOMIS dataset and from IMD data, with both measures indicating poorer health than the national average. Those reporting fair, bad and very bad health are significantly above the median with 77.50 %, 87.40 % and 80.15 % respectively (Fig. 8f), though the cause of poor health was not identified in the NOMIS data. However, a proportion of this poor health is likely to be due to respiratory disease because Mexborough has a standardised admission ratio for Chronic Obstructive Pulmonary Disease (COPD) of 231.6, versus 100 for England, i.e. more than twice the national average, with Conisbrough having a ratio of 149.6 [93]. Pre-existing health conditions undermine an individual’s resilience to respond to exposure events, making them more susceptible to the harmful effects of air pollution [26].

Social and economic factors comprise a mixture of external vulnerabilities that are associated with greater negative health effects compared to higher socioeconomic status groups [87]. Susceptibility for populations with lower socioeconomic status arises because of an increased prevalence of pre-existing diseases (Fig. 8f), as well as lack of social capital to be able to make changes to their environment, including access to medical services [86,21,94]. Socioeconomic factors can be quantified using the IMD score which includes a range of weighted characteristics, as shown in Fig. 9. LSOAs impacted by the plume are approximately 25 % above the national median and thus more deprived, which is also reflected in the sub-categories of IMD, particularly income, employment, health deprivation, education, skills, and training. The categories ‘health deprivation’ and ‘education, skills, and training

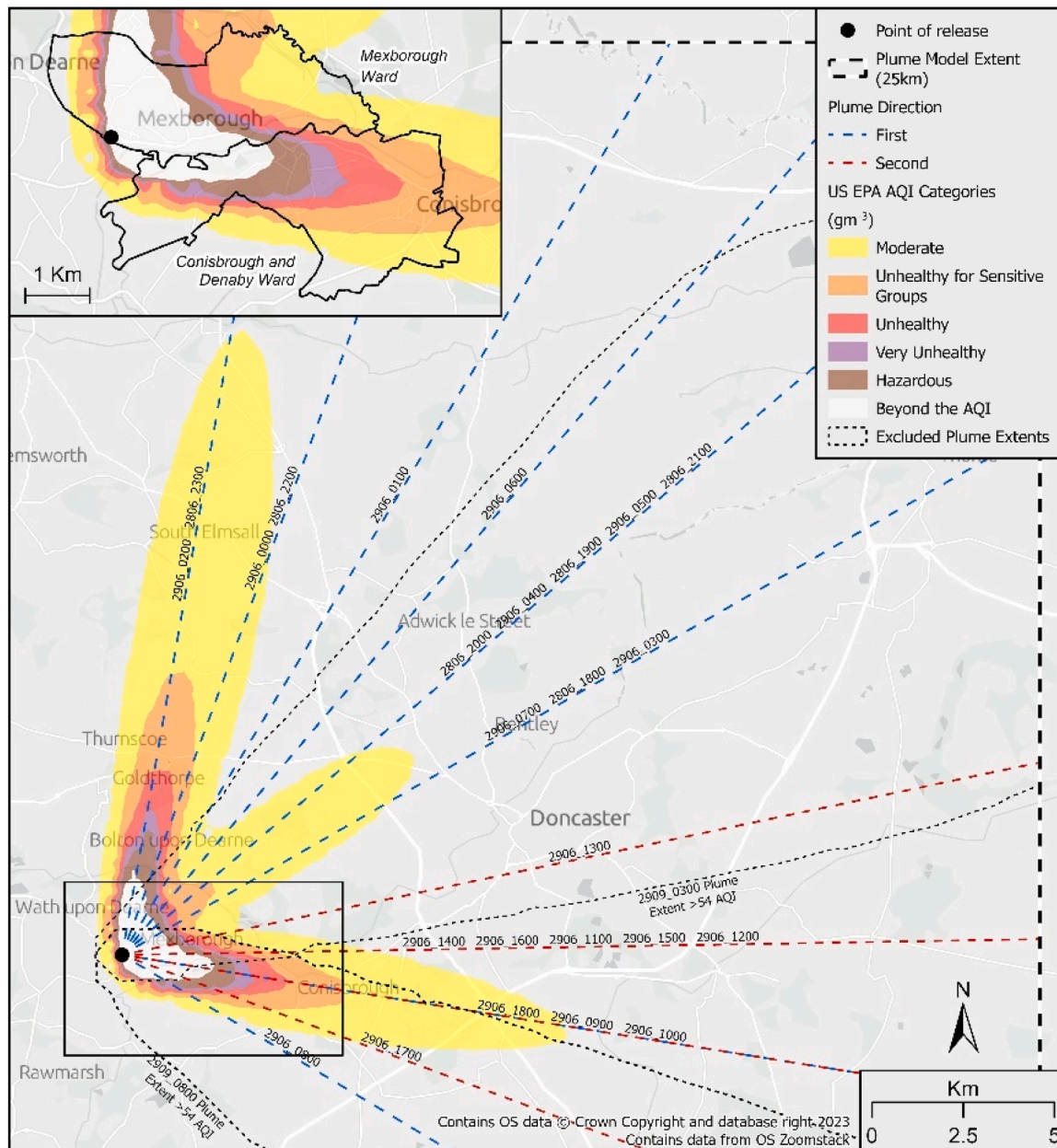


Fig. 5. Extent of modelled plume for 25Km (N) and 25Km (E) from the point of release. Bandings in the plume show the US EPA AQI [42] categories that represent potential health impacts as specified in Table 1. Numbers on the plume direction lines represent the date and time at which these directions were recorded.

attainment' are both in the worst quartile at 35 % and 33 % above the national median, respectively.

The final potential susceptibility factor considered was ethnicity. While it has been reported that populations comprising > 20 % of non-White ethnic backgrounds are exposed to greater air pollution concentrations [95], the study area has a dominant white ethnicity. While spatial associations between poor air quality and ethnicity have been reported [95], it is equally important to recognise confounding factors, such as low socio-economic status, which may be drivers behind reported associations [25,26].

For future work, we intend to characterise population vulnerabilities and exposure profiles for a range of other AQC events including fires involving chemicals, wood, mixed recyclables, and electronic waste. Additionally, we will investigate how factors such as topography, local meteorological conditions, and geographical features influence plume behaviour and population exposure. For more recent AQC incidents, the 2021 Census records are available, which provide much improved data

analysis tools compared to the 2011 dataset. These will be evaluated as a development of our methodology. Further, we intend to investigate actual health impacts of Mexborough and other major incident fires through confirmatory triangulation with the UK Department of Health's syndromic surveillance datasets of 'live' consultations with medical practitioners. Such an analysis was outside the scope of the current study but is important as a further development, given the predicted exposure profile during major fire incidents.

4. Conclusions

The Mexborough fire served as an early test of the (then) newly established AQinMI service. The AQC and AQinMI functions continue to provide monitoring during major fire incidents in the UK and can be considered an exemplar for other countries. Nevertheless, the limited spatial resolution of monitoring carried out during such incidents does not allow a full evaluation of population exposure to be made. In this

Table 5

Modelled 23-hr averaged ground level PM₁₀ concentrations at different categories of sensitive receptor site (Fig. 5), together with the corresponding AQI category (Table 1).

Name	Vulnerable population	Modelled 23-hr PM ₁₀ conc. (µg m ⁻³)	AQI category
Hospital	All ages; Pre-existing health conditions	647	Beyond the AQI
Residential care home	Older population; Pre-existing health conditions	1932	Beyond the AQI
Libraries	All ages	1523	Beyond the AQI
		341	Unhealthy
		196	Unhealthy for Sensitive Groups
Day Nursery	< 5 years old	997	Beyond the AQI
Primary schools	4–11 years old	486	Hazardous
		552	Hazardous
		171	Unhealthy for Sensitive Groups
		552	Hazardous
		341	Unhealthy
Academy and High Schools	11–18 years old	258	Unhealthy
		308	Unhealthy
		274	Unhealthy
		203	Unhealthy for Sensitive Groups
		1459	Beyond the AQI
		1250	Beyond the AQI

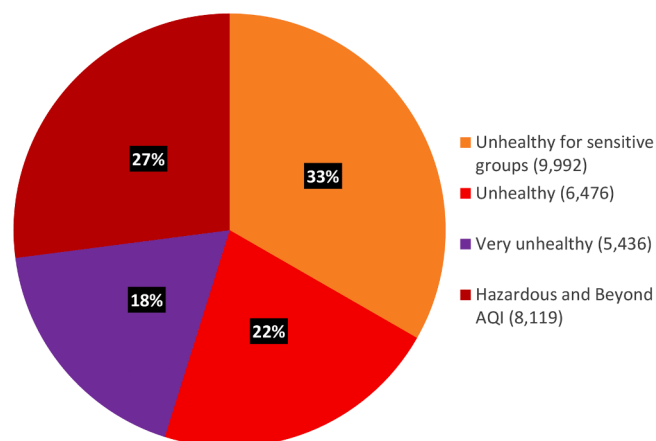


Fig. 6. Distribution of population exposure by spatially weighted AQI across the whole plume shown in Fig. 5. Numbers in parentheses represent the number of usual residents indicated as exposed for each AQI category. Segment colours are as assigned by US EPA for AQIs [42].

paper, we demonstrate the novel application of back trajectory modelling to calculate PM₁₀ emission rates during a major incident fire. Forward modelling is then used to calculate plume concentrations that, combined with spatial analysis in ArcGIS, allows an evaluation of the scale of exposure, and the level of vulnerability of the exposed. Of particular concern in this study was the high prevalence of pre-existing health conditions, which may have led to increased acute and chronic health symptoms during the fire and increased demand for clinical services. If these results were replicated at other AQC fire incidents, we would see that less affluent and socially disadvantaged populations are more commonly exposed to significant major air pollution incident plumes. Such examples highlight the need for policies that evaluate and promote environmental justice by reducing environmental risks equitably across a population [96].

Emergency preparedness relies on the continuous assessment of risks arising from evolving circumstances. The shift from a linear to a circular

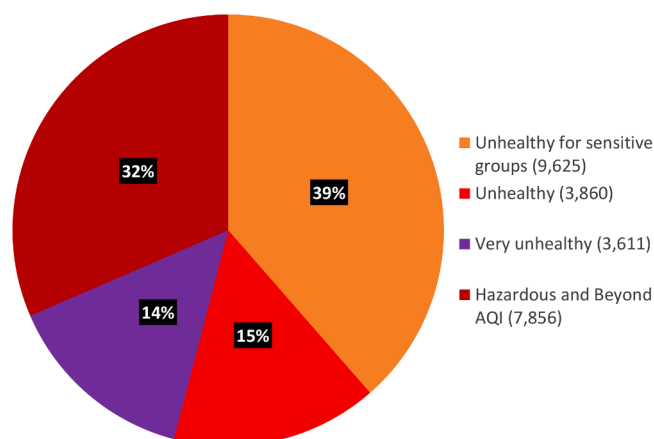


Fig. 7. Distribution by population of AQI exposure by spatially weighted AQI across the Mexborough and Conisbrough Wards only (Fig. 5). Numbers in parentheses represent the number of usual residents indicated as exposed for each AQI category. Segment colours are as assigned by US EPA for AQIs [42].

waste economy has increased risks associated with waste sites located in urban areas, posing greater threats to nearby populations. Mitigating strategies could include evaluating the perceived risk from these sites for inclusion in national and local risk registers, reevaluating the siting of such facilities relative to populations, and implementing stricter regulatory controls at industrial facilities to reduce the risk of fire outbreaks [1].

Environmental implication

The exposure of populations to hazardous air pollution from major industrial fires has significant environmental and public health implications. We utilise a novel dispersion modelling approach, together with real-world monitoring data, to estimate population exposure to PM₁₀ during a major fire in the UK. Our results show that several thousand individuals from the local population, many from socio-economically disadvantaged backgrounds, were exposed to dangerous levels of PM₁₀. The study will be of benefit to environment agencies and environmental/public health departments across the world, as they develop their own strategies and responses to these types on incident.

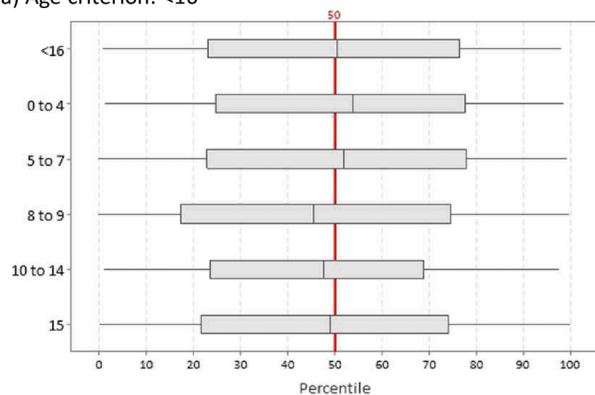
Funding

We are grateful to Northumbria University for supporting this research.

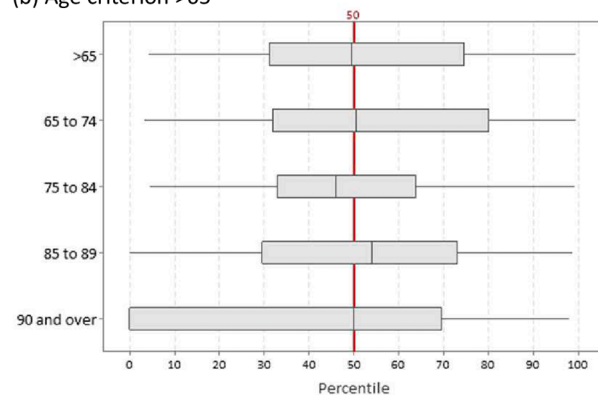
CRediT authorship contribution statement

Griffiths Simon D.: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **King Helen M.:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Entwistle Jane A.:** Writing – review & editing, Supervision, Resources, Investigation, Conceptualization. **Deary Michael E.:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Wilkinson Justine:** Writing – review & editing, Software, Methodology, Investigation. **Kelly Frank J.:** Writing – review & editing, Supervision, Conceptualization.

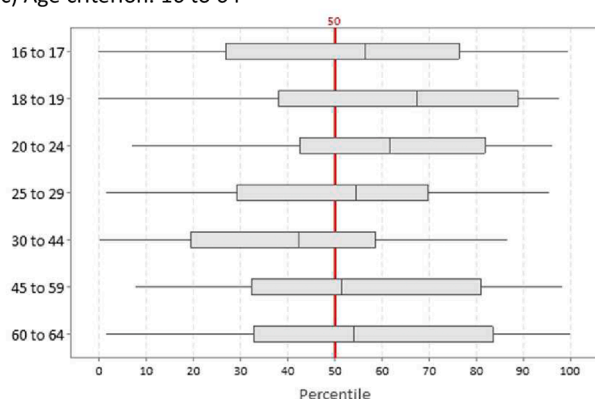
(a) Age criterion: <16



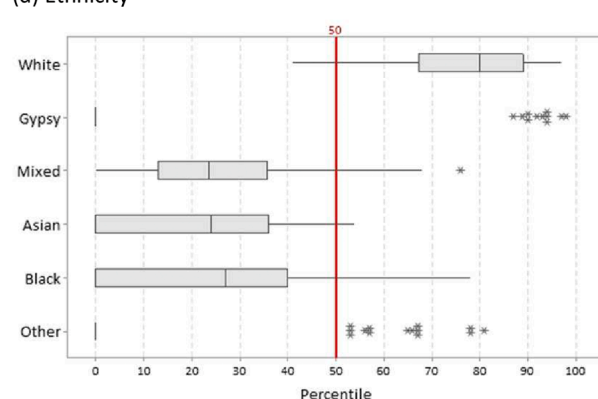
(b) Age criterion >65



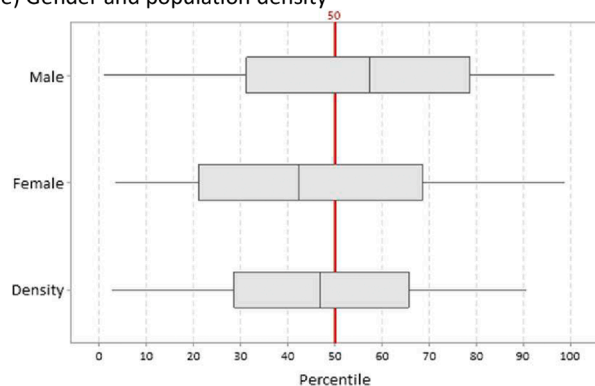
(c) Age criterion: 16 to 64



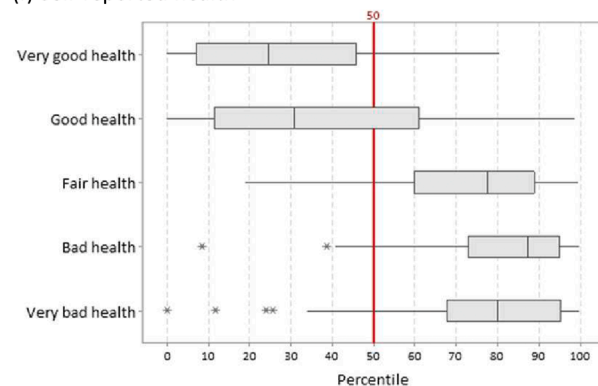
(d) Ethnicity



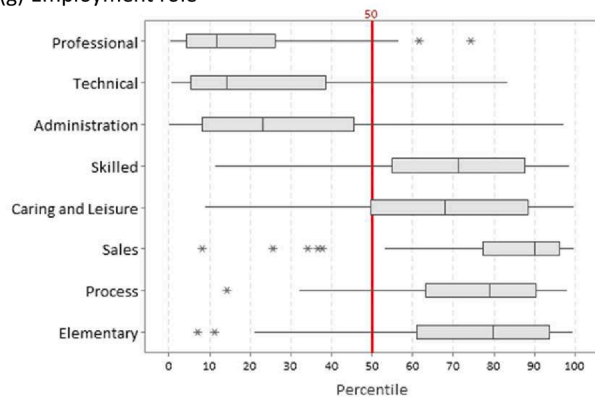
(e) Gender and population density



(f) Self-reported health



(g) Employment role



(h) Highest qualification

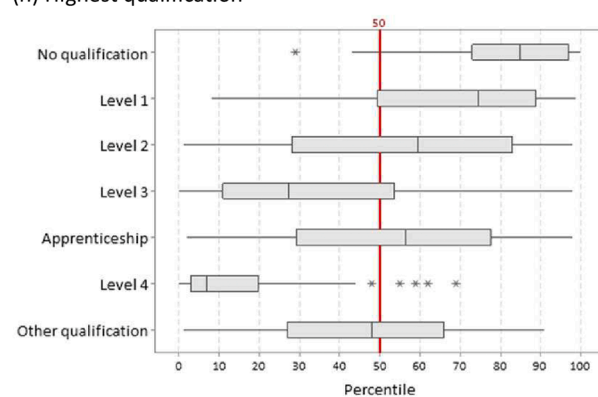


Fig. 8. Box-and-whisker plots of vulnerability indicators for people exposed to PM₁₀ in the Mexborough and Conisbrough Wards.

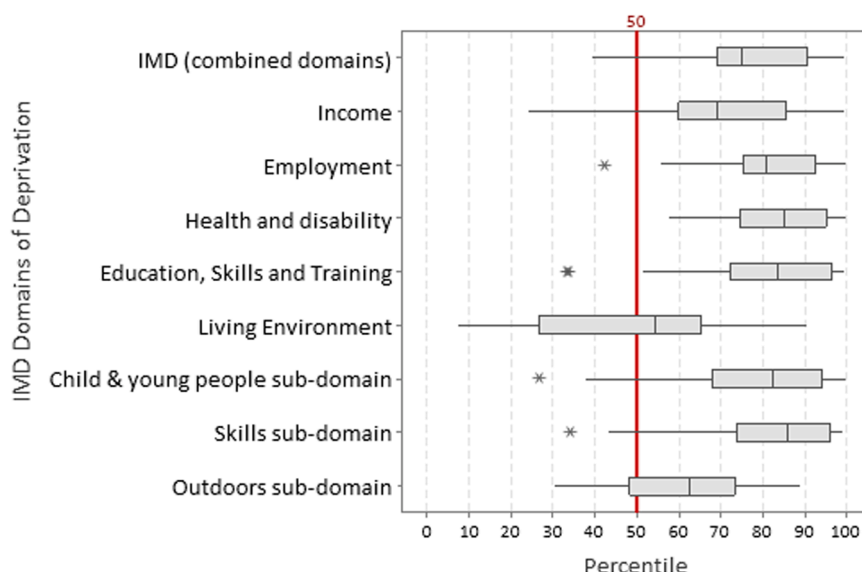


Fig. 9. Index of Multiple Deprivation (IMD) based on LSOAs exposed to the plume. The 50th percentile value is shown, and values greater than this indicates poorer deprivation scores. As well as the overall IMD, other domains and sub-domains of deprivation are shown.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Simon Griffiths reports financial support was provided by Northumbria University. Simon Griffiths reports a relationship with Northumbria University that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work uses the data collected contemporaneously during AQinMI events. It was shared by the Environment Agency, the Scottish Environmental Protection Agency and Natural Resources Wales. We are grateful for their support. We also gratefully acknowledge Northumbria University for financially supporting this work.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.jhazmat.2025.137455](https://doi.org/10.1016/j.jhazmat.2025.137455).

Data availability

Data will be made available on request.

References

- [1] Deary, M.E., Griffiths, S.D., 2024. The impact of air pollution from industrial fires in urban settings: monitoring, modelling, health, and environmental justice perspectives. *Environments* 11 (7), 157. <https://doi.org/10.3390/environments11070157>.
- [2] Gorzelnik T. Air Pollution Caused by Fires at Waste Storage Sites: Analysis of Selected Episodes in Poland. Extended Abstracts From 4th International Conference on Sustainable Energy and Environmental Development 2023.
- [3] Griffiths, S.D., Chappell, P., Entwistle, J.A., Kelly, F.J., Deary, M.E., 2018. A study of particulate emissions during 23 major industrial fires: implications for human health. *Environ Int* 112, 310–323. <https://doi.org/10.1016/j.envint.2017.12.018>.
- [4] Griffiths, S.D., Entwistle, J.A., Kelly, F.J., Deary, M.E., 2022. Characterising the ground level concentrations of harmful organic and inorganic substances released during major industrial fires, and implications for human health. *Environ Int* 162, 107152. <https://doi.org/10.1016/j.envint.2022.107152>.
- [5] Mikalsen, R.F., Lönnermark, A., Glansberg, K., McNamee, M., Storesund, K., 2021. Fires in waste facilities: challenges and solutions from a Scandinavian perspective. *Fire Saf J* 120. <https://doi.org/10.1016/j.firesaf.2020.103023>.
- [6] Oleniacz, R., Drzewiecki, W., Gorzelnik, T., Grzesik, K., Kozakiewicz, R., Kowalewski, Z., et al., 2023. Assessment of the impact of waste fires on air quality and atmospheric aerosol optical depth: a case study in Poland. *Energy Rep* 9, 16–38. <https://doi.org/10.1016/j.egy.2023.03.087>.
- [7] McParland, A., Paranthaman, K., 2012. Burton Latimer – an air quality cell case study. *Chem Hazards Poisons Rep* 13–15.
- [8] Duarte-Davidson, R., Amlöt, R., Idahosa Taylor, E., Desel, H., Settimi, L., Buscema, P.M., et al., 2018. Chemical Health Threats: Assessing and Alerting. Royal Society of Chemistry, Cambridge, United Kingdom. <https://doi.org/10.1039/9781782623687>.
- [9] Lemieux, P.M., Lutes, C.C., Santoian, D.A., 2004. Emissions of organic air toxics from open burning: a comprehensive review. *Prog Energy Combust Sci* 30 (1), 1–32. <https://doi.org/10.1016/j.pecs.2003.08.001>.
- [10] University of Technology Sydney, 2016. In: Department of Environment (AU) (Ed.), *Waste Fires in Australia: Cause for Concern?*. Institute for Sustainable Futures, New South Wales.
- [11] Ibrahim, M.A., Alriksson, S., Kaczala, F., Hogland, W., 2013. Fires at storage sites of organic materials, waste fuels and recyclables. *Waste Manag Res* 31 (9), 937–945. <https://doi.org/10.1177/0734242X13487581>.
- [12] National Fire Chiefs Council, 2019. Waste Management and Recycling Fires. (<http://www.cfca.org.uk/17512>). (accessed 12th July 2019 2019).
- [13] Persson, B., Simonson, M., 1998. Fire emissions into the atmosphere. *Fire Technol* 34 (3), 266–279. <https://doi.org/10.1023/a:1015350024118>.
- [14] Stec, A.A., 2017. Fire toxicity – the elephant in the room? *Fire Saf J* 91, 79–90. <https://doi.org/10.1016/j.firesaf.2017.05.003>.
- [15] Environment Agency, 2009. Review of emission factors for incident fires. In: *National Air Quality Modelling & Assessment Unit* (Ed.). Environment Agency, Bristol.
- [16] Lemieux, P.M., 2002. Emission of organic air toxics from open burning. In: *National Risk Management Research Laboratory* (Ed.). United States Environmental Protection Agency, Washington DC.
- [17] UNEP, 2024. Wasted Air: Impact of Landfill Fires on Air Pollution and People's Health in Serbia. Air Pollution Series. United Nations Environment Programme, Belgrade, Serbia.
- [18] Tahmid, M., Dey, S., Syeda, S.R., 2020. Mapping human vulnerability and risk due to chemical accidents. *J Loss Prev Process Ind* 68, 104289. <https://doi.org/10.1016/j.jlp.2020.104289>.
- [19] Wakefield, J.C., 2010. In: Agency, H.P. (Ed.), *A Toxicological Review of the Products of Combustion*. Health Protection Agency.
- [20] Chas-Amil, M.-L., Nogueira-Moure, E., Prestemon, J.P., Touza, J., 2022. Spatial patterns of social vulnerability in relation to wildfire risk and wildland-urban interface presence. *Landsc Urban Plan* 228. <https://doi.org/10.1016/j.landurbplan.2022.104577>.
- [21] D'Evelyn, S.M., Jung, J., Alvarado, E., Baumgartner, J., Caligiuri, P., Hagmann, R. K., et al., 2022. Wildfire, smoke exposure, human health, and environmental justice need to be integrated into forest restoration and management. *Curr Environ Health Rep* 9 (3), 366–385. <https://doi.org/10.1007/s40572-022-00355-7>.
- [22] Diderichsen, F., Hallqvist, J., Whitehead, M., 2019. Differential vulnerability and susceptibility: how to make use of recent development in our understanding of mediation and interaction to tackle health inequalities. *Int J Epidemiol* 48 (1), 268–274. <https://doi.org/10.1093/ije/dyy167>.

- [23] Goldman, G.T., Desikan, A., Morse, R., Kalman, C., MacKinney, T., Cohan, D.S., et al., 2022. Assessment of air pollution impacts and monitoring data limitations of a spring 2019 chemical facility fire. *Environ Justice* 15 (6), 362–372. <https://doi.org/10.1089/env.2021.0030>.
- [24] Fakhrudin, B., Kirsch-Wood, J., Niyogi, D., Guoqing, L., Murray, V., Frolova, N., 2022. Harnessing risk-informed data for disaster and climate resilience. *Prog Disaster Sci* 16, 100254. <https://doi.org/10.1016/j.pdisas.2022.100254>.
- [25] Bell, M.L., Zanobetti, A., Dominici, F., 2013. 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* 178 (6), 865–876. <https://doi.org/10.1093/aje/kwt090>.
- [26] Makri, A., Stilianakis, N.I., 2008. Vulnerability to air pollution health effects. *Int J Hyg Environ Health* 211 (3–4), 326–336. <https://doi.org/10.1016/j.ijheh.2007.06.005>.
- [27] Morris, G., Saunders, P., 2017. *The Environment in Health and Well-Being*. Oxford University Press.
- [28] Riggs, D.W., Yeager, R.A., Bhatnagar, A., 2018. Defining the human envirome: an omics approach for assessing the environmental risk of cardiovascular disease. *Circ Res* 122 (9), 1259–1275. <https://doi.org/10.1161/circresaha.117.31230>.
- [29] Heo, S., Kim, M., Yu, H., Lee, W.-K., Sohn, J.R., Jung, S.-Y., et al., 2018. Chemical accident hazard assessment by spatial analysis of chemical factories and accident records in South Korea. *Int J Disaster Risk Reduct* 27, 37–47. <https://doi.org/10.1016/j.ijdrr.2017.09.016>.
- [30] World Health Organisation, 2009. *Manual for the Public Health Management of Chemical Incidents*. World Health Organisation, Geneva.
- [31] Shie, R.-H., Chan, C.-C., 2013. Tracking hazardous air pollutants from a refinery fire by applying on-line and off-line air monitoring and back trajectory modeling. *J Hazard Mater* 261, 72–82. <https://doi.org/10.1016/j.jhazmat.2013.07.017>.
- [32] Vukmirović, Z.B., Unkasević, M., Lazić, L., Tosić, I., 2001. Regional air pollution caused by a simultaneous destruction of major industrial sources in a war zone. The case of April Serbia in 1999. *Atmos Environ* 35 (15), 2773–2782. [https://doi.org/10.1016/S1352-2310\(00\)00530-6](https://doi.org/10.1016/S1352-2310(00)00530-6).
- [33] da Silva, D.O., Arôxa, B.H., Klausner, V., Bastos, E.Jd.B., Prestes, A., Pacini, A.A., 2020. Report of particulate matter emissions during the 2015 fire at fuel tanks in Santos, Brazil, 1178622120971251. *Air Soil Water Res* 13. <https://doi.org/10.1177/1178622120971251>.
- [34] Leelösy, A., Ludányi, E.L., Kohlmann, M., Lagzi, I., Meszaros, R., 2013. Comparison of two Lagrangian dispersion models: a case study for the chemical accident in Rouen, January 21–22, 2013. *Időjárás* 117, 435–450.
- [35] Efthimiou, G., Andronopoulos, S., Tavares, R., Bartzis, J., 2017. CFD-RANS prediction of the dispersion of a hazardous airborne material released during a real accident in an industrial environment. *J Loss Prev Process Ind* 46, 23–36. <https://doi.org/10.1016/j.jlp.2017.01.015>.
- [36] Tagliaferri, F., Invernizzi, M., Capelli, L., 2022. A sensitivity analysis applied to SPRAY and CALPUFF models when simulating dispersion from industrial fires. *Atmos Pollut Res* 13 (1), 101249. <https://doi.org/10.1016/j.apr.2021.101249>.
- [37] Smethurst, H., Witham, C., Robins, A., Murray, V., 2012. An exceptional case of long range odorant transport. *J Wind Eng Ind Aerodyn* 103, 60–72. <https://doi.org/10.1016/j.jweia.2012.03.006>.
- [38] Johnson, A.L., Gao, C.X., Dennekamp, M., Williamson, G.J., Brown, D., Carroll, M. T., et al., 2019. Associations between respiratory health outcomes and coal mine fire PM_{2.5} smoke exposure: a cross-sectional study. *Int J Environ Res Public Health* 16 (21), 4262. <https://doi.org/10.3390/ijerph16214262>.
- [39] Harvey, E., 2008. The development of a puff dispersion model for use in modelling short term accidental releases, based on the ADMS 4 model: ADMS-STAR2. *Hrvat Meteor Cas* 43 (43/1), 135–139.
- [40] US Department of Agriculture, 2006. ADMS-STAR Development: A Short Range Emergency Response Atmospheric Dispersion Model. (<https://www.nal.usda.gov/research-tools/food-safety-research-projects/adms-star-development-short-range-emergency-response>). (accessed 28th June 2022).
- [41] Lukacs, M., Williams, L., 2021. A sensitivity analysis of the factors that influence the hazard potential of fusion power plants. *Fusion Eng Des* 164, 112183. <https://doi.org/10.1016/j.fusengdes.2020.112183>.
- [42] U.S. Environmental Protection Agency, 2018. In: Standards, O.o.A.Q.Pa (Ed.), Technical Assistance Document for the Reporting of Daily Air Quality – the Air Quality Index (AQI). U.S. Environmental Protection Agency, Research Triangle Park, NC.
- [43] BBC, 2010. Mxborough Tyre Fire Residents Return Home. (<https://www.bbc.co.uk/news/10460976>). (accessed 12th April 2021).
- [44] Izon-Cooper, L., 2010. Tyre fire, Mxborough, Doncaster. *Chem Hazards Poisons Rep* (18), 9–11.
- [45] Office for National Statistics, 2011. Mxborough Built-up area sub division, Local Area Report. (<https://www.nomisweb.co.uk/reports/localarea?compare=E35000697#section.6.0>).
- [46] Meteorological Office, 2019. Met Office MIDAS Open: UK Land Surface Stations Data (1853-current). Centre for Environmental Data Analysis. (<http://catalogue.ceda.ac.uk/uuid/dbd451271eb04662beade68da43546e1>).
- [47] Crabbe, H., Mitsakou, C., Doutsis, A., Iqbal, N., Fletcher, T., Leonardi, G.S., 2021. Developing an air pollution exposure surveillance system in England; a new national vulnerability indicator. *ISEE Conf Abstr* 2021 (1). <https://doi.org/10.1289/isee.2021.0-LT-009>.
- [48] Dédélé, A., Miškinytė, A., 2015. The statistical evaluation and comparison of ADMS-Urban model for the prediction of nitrogen dioxide with air quality monitoring network. *Environ Monit Assess* 187 (9), 1–12. <https://doi.org/10.1007/s10661-015-4810-1>.
- [49] Righi, S., Lualli, P., Pollini, E., 2009. Statistical and diagnostic evaluation of the ADMS-Urban model compared with an urban air quality monitoring network. *Atmos Environ* 43 (25), 3850–3857. <https://doi.org/10.1016/j.atmosenv.2009.05.016>.
- [50] Carruthers, D.J., McKeown, A.M., Hall, D.J., Porter, S., 1999. Validation of ADMS against wind tunnel data of dispersion from chemical warehouse fires. *Atmos Environ* 33 (12), 1937–1953. [https://doi.org/10.1016/S1352-2310\(98\)00168-X](https://doi.org/10.1016/S1352-2310(98)00168-X).
- [51] Ladd C.Approaches to Fire Modelling with ADMS Cambridge Environmental Research Consultants Edinburgh ADMS 5 User Group Meeting2018.
- [52] Zhao, B., Kruppa, J., 2004. Structural behaviour of an open car park under real fire scenarios. *Fire Mater* 28 (2–4), 269–280. <https://doi.org/10.1002/fam.867>.
- [53] Deary, M.E., Upipatanakul, S., 2014. Evaluation of the performance of ADMS in predicting the dispersion of sulfur dioxide from a complex source in Southeast Asia: implications for health impact assessments. *Air Qual Atmos Health* 7 (3), 381–399. <https://doi.org/10.1007/s11869-013-0225-8>.
- [54] Hanna, S., Chang, J., 2012. Acceptance criteria for urban dispersion model evaluation. *Meteorol Atmos Phys* 116 (3), 133–146. <https://doi.org/10.1007/s00703-011-0177-1>.
- [55] Office of National Statistics, 2016. Output Area (OA). (<https://webarchive.nationalarchives.gov.uk/ukgwa/20160107193025/http://www.ons.gov.uk/ons/guide-met-hod/geography/beginner-s-guide/census/output-area-oas/index.html>). (accessed 30th September 2022).
- [56] Office for National Statistics, no date. Census 2021 Geographies. (<https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeographies/census2021geographies>).
- [57] Deary, M.E., Griffiths, S.D., 2021. A novel approach to the development of 1-hour threshold concentrations for exposure to particulate matter during episodic air pollution events. *J Hazard Mater* 418, 126334. <https://doi.org/10.1016/j.jhazmat.2021.126334>.
- [58] Cabinet Office, 2020. Reasonable Worst Case Scenario for borders at the end of the transition period on 31 December 2020.
- [59] NOMIS, 2014. Age by single year, Census 2011. Office for National Statistics. (<https://www.nomisweb.co.uk/census/2011/qs103uk>).
- [60] NOMIS, 2014. Sex, Census 2011. Office for National Statistics. (<https://www.nomisweb.co.uk/census/2011/qs104uk>).
- [61] NOMIS Ethnic Group, Census 2011. Office for National Statistics 2014. (<https://www.nomisweb.co.uk/census/2011/ks201uk>).
- [62] NOMIS Employment Status (Workplace population). Office for National Statistics (<https://www.nomisweb.co.uk/census/2011/wp601we>).
- [63] The Area Based Analysis Unit, Of.N.S., 2009. Understanding patterns of deprivation. *Reg Trends* 41 (1), 93–114. <https://doi.org/10.1057/rt.2009.7>.
- [64] Ministry of Housing Communities and Local Government, 2013a. Index of Multiple Deprivation Score, 2010. (<https://opendatacommunities.org/resource?uri=http%3A%2F%2Fopendatacommunities.org%2Fdat%2Fsocietal-wellbeing%2Fdeprivation%2Fimd-score-2010>).
- [65] Ministry of Housing Communities and Local Government, 2013b. Indices of Multiple Deprivation 2010, Education Score. (<https://opendatacommunities.org/resource?uri=http%3A%2F%2Fopendatacommunities.org%2Fdat%2Fsocietal-wellbeing%2Fdeprivation%2Fimd-education-score-2010>).
- [66] Ministry of Housing Communities and Local Government, 2013c. Indices of Multiple Deprivation 2010, Employment Score. (<https://opendatacommunities.org/resource?uri=http%3A%2F%2Fopendatacommunities.org%2Fdat%2Fsocietal-wellbeing%2Fdeprivation%2Fimd-employment-score-2010>).
- [67] Ministry of Housing Communities and Local Government, 2013d. Indices of Multiple Deprivation 2010, Environment Score. (<https://opendatacommunities.org/resource?uri=http%3A%2F%2Fopendatacommunities.org%2Fdat%2Fsocietal-wellbeing%2Fdeprivation%2Fimd-environment-score-2010>).
- [68] Ministry of Housing Communities and Local Government, 2013e. Indices of Multiple Deprivation 2010, Health Score. (<https://opendatacommunities.org/resource?uri=http%3A%2F%2Fopendatacommunities.org%2Fdat%2Fsocietal-wellbeing%2Fdeprivation%2Fimd-health-score-2010>).
- [69] Ministry of Housing Communities and Local Government, 2013f. Indices of Multiple Deprivation 2010, Housing Score. (<https://opendatacommunities.org/resource?uri=http%3A%2F%2Fopendatacommunities.org%2Fdat%2Fsocietal-wellbeing%2Fdeprivation%2Fimd-housing-score-2010>).
- [70] Ministry of Housing Communities and Local Government, 2013g. Indices of Multiple Deprivation 2010, Income Score. (<https://opendatacommunities.org/resource?uri=http%3A%2F%2Fopendatacommunities.org%2Fdat%2Fsocietal-wellbeing%2Fdeprivation%2Fimd-income-score-2010>).
- [71] Turnkey Instruments Limited, 2014. Topas & Osiris Environmental Monitor Training Manual.
- [72] Hanna, S., Chang, J., 2012. Acceptance criteria for urban dispersion model evaluation. *Meteorol Atmos Phys* 116 (3), 133–146.
- [73] DEFRA, 2023. Fig. 5: Annual Mean Concentrations of PM₁₀ in the UK, 1992 to 2022. (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1153248/Table05.csv/preview). (accessed 16th October 2023).
- [74] Brown, J.S., Gordon, T., Price, O., Asgharian, B., 2013. Thoracic and respirable particle definitions for human health risk assessment. *Part Fibre Toxicol* 10, 12. <https://doi.org/10.1186/1743-8977-10-12>.
- [75] Aguilera, R., Corringham, T., Gershunov, A., Benmarhnia, T., 2021. Wildfire smoke impacts respiratory health more than fine particles from other sources: observational evidence from Southern California. *Nat Commun* 12 (1), 1493. <https://doi.org/10.1038/s41467-021-21708-0>.

- [76] Anderson, J.O., Thundiyil, J.G., Stolbach, A., 2012. Clearing the air: a review of the effects of particulate matter air pollution on human health. *J Med Toxicol* 8 (2), 166–175. <https://doi.org/10.1007/s13181-011-0203-1>.
- [77] Behndig, A.F., Mudway, I.S., Brown, J.L., Stenfors, N., Helleday, R., Duggan, S.T., et al., 2006. Airway antioxidant and inflammatory responses to diesel exhaust exposure in healthy humans. *Eur Respir J* 27 (2), 359–365. <https://doi.org/10.1183/09031936.06.00136904>.
- [78] Crabbe, H., 2012. Risk of respiratory and cardiovascular hospitalisation with exposure to bushfire particulates: new evidence from Darwin, Australia. *Environ Geochem Health* 34 (6), 697–709. <https://doi.org/10.1007/s10653-012-9489-4>.
- [79] Adetona, O., Reinhardt, T.E., Domitrovich, J., Broyles, G., Adetona, A.M., Kleinman, M.T., et al., 2016. Review of the health effects of wildland fire smoke on wildland firefighters and the public. *Inhal Toxicol* 28 (3), 95–139. <https://doi.org/10.3109/08958378.2016.1145771>.
- [80] Hadley, M.B., Henderson, S.B., Brauer, M., Vedanthan, R., 2022. Protecting cardiovascular health from wildfire smoke. *Circulation* 146 (10), 788–801. <https://doi.org/10.1161/CIRCULATIONAHA.121.058058>.
- [81] Henry, S., Ospina, M.B., Dennett, L., Hicks, A., 2021. Assessing the risk of respiratory-related healthcare visits associated with wildfire smoke exposure in children 0–18 years old: a systematic review. *Int J Environ Res Public Health* 18 (16), 8799. <https://doi.org/10.3390/ijerph18168799>.
- [82] Kunzli, N., Avol, E., Wu, J., Gauderman, W.J., Rappaport, E., Millstein, J., et al., 2006. Health effects of the 2003 Southern California wildfires on children. *Am J Respir Crit Care Med* 174 (11), 1221–1228. <https://doi.org/10.1164/rccm.200604-519OC>.
- [83] Delfino, R.J., Brummel, S., Wu, J., Stern, H., Ostro, B., Lipsett, M., et al., 2009. The relationship of respiratory and cardiovascular hospital admissions to the southern California wildfires of 2003. *Occup Environ Med* 66 (3), 189–197. <https://doi.org/10.1136/oem.2008.041376>.
- [84] Johnson, J., Ginsberg, M., French, N., Thelen, B., Koziol, B., 2013. Use of syndromic surveillance information for expanded assessment of wildfire disaster. *Online J Public Health Inf* 5 (1), e95.
- [85] Macklin, Y., Kibble, A., Elliot, A., Smith, G., 2013. Detecting public health impacts associated with air pollution events in the UK using syndromic surveillance. *Online J Public Health Inform* 6 (1). <https://doi.org/10.5210/ajphi.v6i1.5068>.
- [86] Chief Medical Officer, 2017. Annual Report of the Chief Medical Officer 2017, Health Impacts of Air Pollution - what do we know? Department of Health, London.
- [87] Shrestha, R., Flacke, J., Martinez, J., Van Maarseveen, M., 2016. Environmental health related socio-spatial inequalities: identifying “hotspots” of environmental burdens and social vulnerability. *Int J Environ Res Public Health* 13 (7), 691. <https://doi.org/10.3390/ijerph13070691>.
- [88] Dietert, R.R., Etzel, R.A., Chen, D., Halonen, M., Holladay, S.D., Jarabek, A.M., et al., 2000. Workshop to identify critical windows of exposure for children’s health: immune and respiratory systems work group summary. *Environ Health Perspect* 108 (3), 483–490. <https://doi.org/10.1289/ehp.00108s3483>.
- [89] Etzel, R.A., 2020. The special vulnerability of children. *Int J Hyg Environ Health* 227, 113516. <https://doi.org/10.1016/j.ijheh.2020.113516>.
- [90] Brumberg, H.L., Karr, C.J., Bole, A., Ahdoot, S., Balk, S.J., Bernstein, A.S., et al., 2021. Ambient air pollution: health hazards to children. *Pediatrics* 147 (6). <https://doi.org/10.1542/peds.2021-051484>.
- [91] Meng, H., Zhang, X., Xiao, J., Zhang, Y., Lin, W., Li, Z., 2021. A simple physical-activity-based model for managing children’s activities against exposure to air pollutants. *J Environ Manag* 279, 111823. <https://doi.org/10.1016/j.jenvman.2020.111823>.
- [92] Brown, M.R., Agyapong, V., Greenshaw, A.J., Cribben, I., Brett-MacLean, P., Drolet, J., et al., 2019. After the Fort McMurray wildfire there are significant increases in mental health symptoms in grade 7–12 students compared to controls. *BMC Psychiatry* 19, 1–11.
- [93] Office for Health Improvement and Disparities, 2022. Local Health - Small Area Public Health Data, Electoral Wards in Doncaster 2016/17 - 20/21, in: Department of Health (Ed.).
- [94] Lillieul, L., Harrabi, I., 2004. Do socioeconomic conditions reflect a high exposure to air pollution or more sensitive health conditions? *J Epidemiol Community Health* 58 (9), 802–803.
- [95] Fecht, D., Fischer, P., Fortunato, L., Hoek, G., de Hoogh, K., Marra, M., et al., 2015. Associations between air pollution and socioeconomic characteristics, ethnicity and age profile of neighbourhoods in England and the Netherlands. *Environ Pollut* 198, 201–210. <https://doi.org/10.1016/j.envpol.2014.12.014>.
- [96] Wheeler, B.W., Ben-Shlomo, Y., 2005. Environmental equity, air quality, socioeconomic status, and respiratory health: a linkage analysis of routine data from the Health Survey for England. *J Epidemiol Commu Health* 59 (11), 948–954. <https://doi.org/10.1136/jech.2005.036418>.