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Analysis of inequalities in personal exposure to $PM_{2.5}$: A modelling study for the Greater London school-aged population

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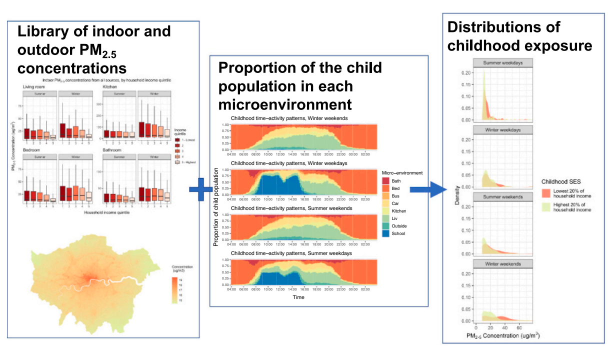
HIGHLIGHTS

- Personal exposure model estimating $PM_{2.5}$ exposure for ~1.3 million children 4–16 years old in the Greater London region
- Children from low-income homes generally have higher personal exposure to $PM_{2.5}$, but the relationship is non-linear.
- 57 % of London's school-aged population have a daily exposure which exceeds guideline 24-h limits set by the WHO.
- The child survey population spent on average 68 % and 80% of their time in the home on weekdays and weekends, respectively.
- Residential indoor sources of $PM_{2.5}$ are a large contributor to personal exposure for school children in London.

GRAPHICAL ABSTRACT



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ABSTRACT

Exposure to air pollution can lead to negative health impacts, with children highly susceptible due to their immature immune and lung systems. Childhood exposure may vary by socio-economic status (SES) due to differences in both outdoor and indoor air pollution levels, the latter of which depends on, for example, building quality, overcrowding and occupant behaviours; however, exposure estimates typically rely on the outdoor component only. Quantifying population exposure across SES requires accounting for variations in time-activity patterns, outdoor air pollution concentrations, and concentrations in indoor microenvironments that account for pollution-generating occupant behaviours and building characteristics. Here, we present a model that estimates personal exposure to $PM_{2.5}$ for ~1.3 million children aged 4–16 years old in the Greater London region from different income groups. The model combines 1) A national time-activity database, which gives the percentage of each group in different residential and non-residential microenvironments throughout a typical day; 2) Distributions of modelled outdoor $PM_{2.5}$ concentrations; 3) Detailed estimates of domestic indoor concentrations for different housing and occupant typologies from the building physics model, *EnergyPlus*, and; 4) Non-domestic

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concentrations derived from a mass-balance approach. The results show differences in personal exposure across socio-economic groups for children, where the median daily exposure across all scenarios (winter/summer and weekends/weekdays) is 17.2 μg/m^3 (95%CIs: 12.1 μg/m^3–41.2 μg/m^3) for children from households in the lowest income quintile versus 14.5 μg/m^3 (95%CIs: 11.5 μg/m^3 – 27.9 μg/m^3) for those in the highest income quintile. Though those from lower-income homes generally fare worse, approximately 57 % of London's school-aged population across *all* income groups, equivalent to 761,976 children, have a median daily exposure which exceeds guideline 24-h limits set by the World Health Organisation. The findings suggest residential indoor sources of $PM_{2.5}$ are a large contributor to personal exposure for school children in London. Interventions to reduce indoor exposure in the home (for example, via the maintenance of kitchen extract ventilation and transition to cleaner cooking fuels) should therefore be prioritised along with the continued mitigation of outdoor sources in Greater London.

1. Introduction

The social determinants of health are wider drivers of population health such as the environmental, cultural, political and economic conditions in which people are born, grow, live and work (Marmot and Weil, 2020). As many of these resources are unfairly distributed across different subgroups of the population, they are often attributed to the growing health inequalities gap that exists in higher-income countries despite overall improvements in health outcomes across the population. The quality of the built environment is a recognised determinant of health likely to have contributed to the growing health inequalities gap seen across England over the last two decades (Bennett et al., 2018; Marmot, 2020), as the places where people live and work can shape population health significantly (PHE, 2017). This occurs through mechanisms such as the quality of housing people live in, their exposure to environmental risks, such as air pollution, access to green spaces and distance to local amenities (PHE, 2017). Air pollution, both indoor and outdoor, is a prominent issue, particularly in urban areas, which is recognised as being unequally distributed across populations of different socio-economic status (SES) (Dimitroulopoulou et al., 2022; Fecht et al., 2015; Ferguson et al., 2020; Hajat et al., 2015; Osborne et al., 2021). Drivers of unequal air pollution exposure have been identified as: ambient levels of air pollution at the home address; housing quality, including the extent of dwelling ventilation; indoor sources of pollution such as smoking and cooking activities; and the amount of time certain population groups spend indoors (Ferguson et al., 2021). These factors combine to reinforce unequal exposures, with limited opportunities for low-income individuals to directly reduce their exposure to air pollution. Vulnerable subgroups, such as children from low-income backgrounds, are especially powerless to change their surrounding environment and improve their exposure to air pollution, relying entirely on the adults and institutions they live amongst (World Health Organization, 2018).

Exposure to air pollution has been associated with various health effects, such as higher incidence of mental health disorders (Bakolis et al., 2021; Yang et al., 2023), adverse birth outcomes (Blanc et al., 2022) and cardiorespiratory diseases (Halios et al., 2022). Children are particularly susceptible to the negative health impacts of air pollution exposure due to their immature immune and lung systems (Cai et al., 2020; Whitehouse and Grigg, 2021). Childhood exposure to *outdoor* air pollution is linked to childhood asthma (Khreis et al., 2018), poor early-life organ development (Exley et al., 2022) and reduced lung function growth (Gauderman et al., 2002, 2015). Across London, outdoor concentrations of air pollution have been positively associated with the number of respiratory-related GP consultations, with a larger effect in children (Ashworth et al., 2021). In the *indoor* environment, high levels of indoor $PM_{2.5}$ in schools have been associated with reduced lung function, particularly in those with existing allergies (Branco et al., 2020), while increased exposures at home were linked to lower cognitive ability in three year olds (Midouhas et al., 2018).

Children between the ages of 7–12 years old spend upwards of 87 % of their time indoors (Coombs et al., 2016) and infants may spend over 90 % of their time indoors (Coombs et al., 2016; Sloan et al., 2017). Using the London Travel Demand Survey (LTDS), Smith et al. (2016) estimated that children living in London between the ages of 5–17 years old spend 97.7 % of their time in an indoor environment. *Indoor* air pollution therefore contributes more strongly to overall childhood exposure than outdoor air pollution (Holgate et al., 2021). However, current exposure models are limited by their lack or oversimplification of the impact buildings characteristics and indoor emissions have on exposure (Sokhi et al., 2022).

Recognition of the variations in exposure and susceptibility that exists between children and adults has led to the development of exposure models which estimate disparities between different age groups (Dimitroulopoulou et al., 2017; Smith et al., 2016). Such studies emphasise that modelling population exposure using a *blanket*-approach may mask disparities between subgroups of the population. However, studies which model indoor and outdoor air pollution exposure have not yet been performed for populations of different SES, nor with detailed housing and occupant behaviour data representative of different population subgroups. Incorporating variations in time-activity patterns, housing quality and individual behaviours between socio-economic groups can allow for the identification of building and/or behavioural interventions which reduce exposure, informing policy and reducing health inequalities.

Here, we present a model which quantifies personal exposure to $PM_{2.5}$ across SES, using household income as a proxy of childhood SES, for school-aged children (4–16 years old) within Greater London. To achieve this aim, the objectives were to:

- Use spatially-mapped outdoor air pollution data to obtain distributions of outdoor concentrations for different levels of neighbourhood deprivation;
- Use building physics models to estimate indoor air pollution concentrations from indoor and outdoor sources for all London households in a representative housing survey. In addition to detailed housing information, the dataset contains information on household income and smoking behaviour used to link to outdoor pollution concentrations and specify indoor emissions, respectively;
- Model non-domestic (school and transport) indoor concentrations as a function of outdoor concentrations using a mass-balance approach;
- Derive time-activity patterns from time-use survey data for children from different household income groups and use these along with the estimated concentrations in the above micro-environments to estimate exposures for a typical winter and summer weekday and weekend.

2. Methods

2.1. Exposure model overview

Development of the model required finding common linkages between unique datasets. The workflow consists of three linked steps; 1) to compile a dataset of $PM_{2.5}$ concentrations in indoor and outdoor microenvironments in ten-minute time-intervals, using a variety of methods, 2) produce probabilistic childhood time-activity patterns from empirical survey data, and 3) overlay the datasets of $PM_{2.5}$ concentrations with the probabilistic time-activity patterns to produce distributions of exposure for different income groups.

A summary of the different models and datasets used for each component is shown in Table 1, outlining the socio-economic metric enabling linkage with other datasets.

At the base of the model is a population of children aged 4–16 years old in the 2010–2011 English Housing Survey (EHS) (DCLG, 2011a), each with a *Personal Identifier* and personal characteristics such as age. This dataset was chosen as following this year, the EHS underwent a cost review where the survey sample size was significantly reduced and data content limited, preventing the specification of indoor emissions across the housing stock for a representative population. Each individual can be linked to EHS household data (collected through interviews) and dwelling data (collected through a physical building survey) using a unique case number. The EHS dwellings data was used to develop building simulation models for the home to estimate the infiltration of outdoor air pollution and indoor concentrations from indoor sources, and define a distribution of outdoor $PM_{2.5}$ concentrations where the home is located.

Indoor concentrations in non-domestic micro-environments were estimated by applying a mass-balance equation to the outdoor concentration level assigned to each child, adapted from the INDAIR model (Dimitroulopoulou et al., 2001, 2006), defined in Table 1. Finally, time-activity information was developed for children from the NatCen Time-Use survey (Gershuny and Sullivan, 2017) and linked to each individual based on the household income quintile reported in the EHS to produce distributions of exposure for childhood income groups, adapted from the

Table 1
A summary of the different models and dataset used for each model component, shown with their source and the socio-economic metric used to link each component.

Component	Model	Datasets			
		Name	Description and use	Socio-economic metric used to link to other model components	Source(s)
Domestic	EnergyPlus: Whole building energy simulation software which dynamically models building performance using building characteristics such as geometry, building materials, floor space, airtightness, and occupant behaviour (e.g. window opening frequencies) as inputs (US DOE, 2020)	2011 English Housing Survey	Nationally representative housing survey which includes information for a representative population and the type and features of the dwellings they live in. A parameterised version of this dataset was used as inputs in to EnergyPlus. Results were weighted to represent 1,336,803 children aged between 4 and 16 years old in London across 824,215 different households.	• Household income quintile • 2010 IMD[a]	(DCLG, 2011a)
Non-domestic	INDAIR probabilistic framework: An indoor air pollution model which takes key model inputs in the form of probability density functions, making it suited to estimating indoor concentrations in the absence of detailed building input data, as is generally the case for the non-domestic building stock. (Dimitroulopoulou et al., 2001, 2006)	Distribution of classroom/vehicle air change rates (ACH)	Distributions of ACH were constructed from the literature and randomly sampled from, before applying a mass-balance equation to estimate indoor concentrations of $PM_{2.5}$ form outdoor sources in non-domestic microenvironments.	There were no socio-economic effects in the non-domestic component, other than the outdoor concentration.	(Chaudhry and Elumalai, 2020; Knibbs et al., 2009; Korsavi et al., 2020; Ott et al., 2008; Zhang et al., 2013)
Outdoors	–	Spatially-mapped outdoor concentrations of $PM_{2.5}$ for London LSOAs in 2013	Annual average outdoor $PM_{2.5}$ concentrations for London LSOAs. Each concentration was joined to a 2010 IMD decile ranking, linking by LSOA, to create a distribution of outdoor concentrations for each IMD decile. One of ten distributions was then sampled from to assign each child an outdoor concentration, depending on the area IMD decile the child's household was classified under in the 2011 EHS.	2010 IMD	(GLA, 2017)
		2010 Indices of Multiple Deprivation	Small-area statistic ranking English LSOA's in terms of their relative levels of deprivation, aggregating by decile. As above, this ranking was spatially linked with outdoor $PM_{2.5}$ concentrations and a distribution of outdoor $PM_{2.5}$ constructed for each decile to assign an outdoor concentration for each child.		(DCLG, 2011b)
Time-activity profiles	EXPAIR: A personal exposure model which combines a dataset of indoor and outdoor air pollution concentrations with probabilistic time-activity information in the equivalent microenvironment to produce distributions of exposure for different population groups (Dimitroulopoulou et al., 2017)	2015 NatCen Time-Use Survey	Nationally representative time-use survey recording participants activities for a representative weekday and weekend. The dataset was used to determine probabilistic childhood time-activity patterns, where the proportion of the child population (0.0–1.0) was used to weight the $PM_{2.5}$ concentration in each microenvironment at the equivalent timestamp.	Household income quintile	(Gershuny and Sullivan, 2017)

[a] Indices of Multiple Deprivation (IMD) decile ranking.

EXPAIR model (Dimitroulopoulou et al., 2017). Results are aggregated by household income groups to assess socio-economic inequalities in childhood exposure to $PM_{2.5}$. Household income quintile is a relative measure included in the EHS where all surveyed households are divided into five equal groups based on their net income (i.e. those in the bottom 20 %, followed by the next 20 %, and so on). These can be used to compare income levels of particular groups to the overall survey population. The subsequent sections provide more details on the parameterisation of each component.

2.2. Dataset of indoor and outdoor $PM_{2.5}$ concentrations

2.2.1. Outdoor concentrations

An outdoor air pollution level was assigned to each child surveyed in the EHS using modelled outdoor concentrations, obtained from gridded (1 km × 1 km) annual mean $PM_{2.5}$ concentrations in 2013 for Greater London (GLA, 2017), a year concurrent to the EHS data. As the EHS is not a geolocated database, the outdoor concentration was assigned according to the 2010 *Indices of Multiple Deprivation* (IMD) ranking the child's home was classified under, as this information is available in the EHS. The IMD ranks English Lower-layer super output areas (LSOAs) on a number of domains characterising the local environment to give a ranking of relative deprivation. LSOAs are geographic areas with approximately 1500 residents or 650 households, designed to improve comparability when reporting small area statistics in England. Each ranking is aggregated into deciles, where 1 indicates an LSOA is amongst the top 10 % most-deprived LSOAs in England, and 10 indicates the LSOA is amongst the top 10 % *least*-deprived LSOAs in England.

Annual average $PM_{2.5}$ concentrations were spatially joined to LSOA boundaries and linked to 2010 IMD deciles (DCLG, 2011b) (shown in S1 of the Appendix) to create a distribution of outdoor $PM_{2.5}$ concentrations for LSOAs in each IMD decile (Fig. 1). As information on the LSOA each surveyed household is located in is not available in the EHS, an outdoor $PM_{2.5}$ level was sampled from one of the ten distributions shown in Fig. 1, depending on the IMD decile ranking of each child's household recorded in the EHS. Mean outdoor $PM_{2.5}$ concentrations were 16.3 μg/m^3 and 15.4 μg/m^3 in the most and least deprived 10 % of LSOAs, respectively, but differences were marginal due to the limited spatial variation of $PM_{2.5}$ across London.

To account for temporal variations in outdoor $PM_{2.5}$, sampled annual averages were scaled according to the hour of day, accounting for daily and seasonal variations. The proportion by which to scale values was calculated from hourly measured data for 2013 (GLA, 2019) for a typical winter and summer day. S1 of the Appendix shows the diurnal variation of the outdoor concentrations across the London area for a representative summer and winter day, when the annual mean concentration is 16 μg/m^3.

2.2.2. Domestic indoor concentrations

The building physics tool EnergyPlus (US DOE, 2020) was used to model domestic indoor $PM_{2.5}$ concentrations for the 1996 London buildings surveyed in the 2010–11 English Housing Survey (EHS) (DCLG, 2011a) for a representative summer and winter week. The representative summer week was defined as 01/07–07/07 and 01/01–07/01 was selected as a typical winter week.

Inputs were taken directly from the EHS for dwelling type, building fabric types, ceiling height, floor area, the presence of a working extractor fan, while estimating roof, window, wall and floor U-value and overall building permeability using the Reduced data Standard Assessment Procedure (Rd SAP) (BRE, 2009). Eight dwelling archetypes broadly representative of the London housing stock were used. Window opening was modelled as a function of indoor and outdoor temperature, where windows were opened when the indoor temperature exceeded 23 °C and if the zonal temperature exceeded the outdoor temperature (as per Taylor et al. (2016)) as indoor temperature is consistently found to be one of the primary drivers of window-opening (Fabi et al., 2012; Yao and Zhao, 2017). A Test Reference Year (TRY) weather file for Islington, London, was used (Eames et al., 2011), assumed to be

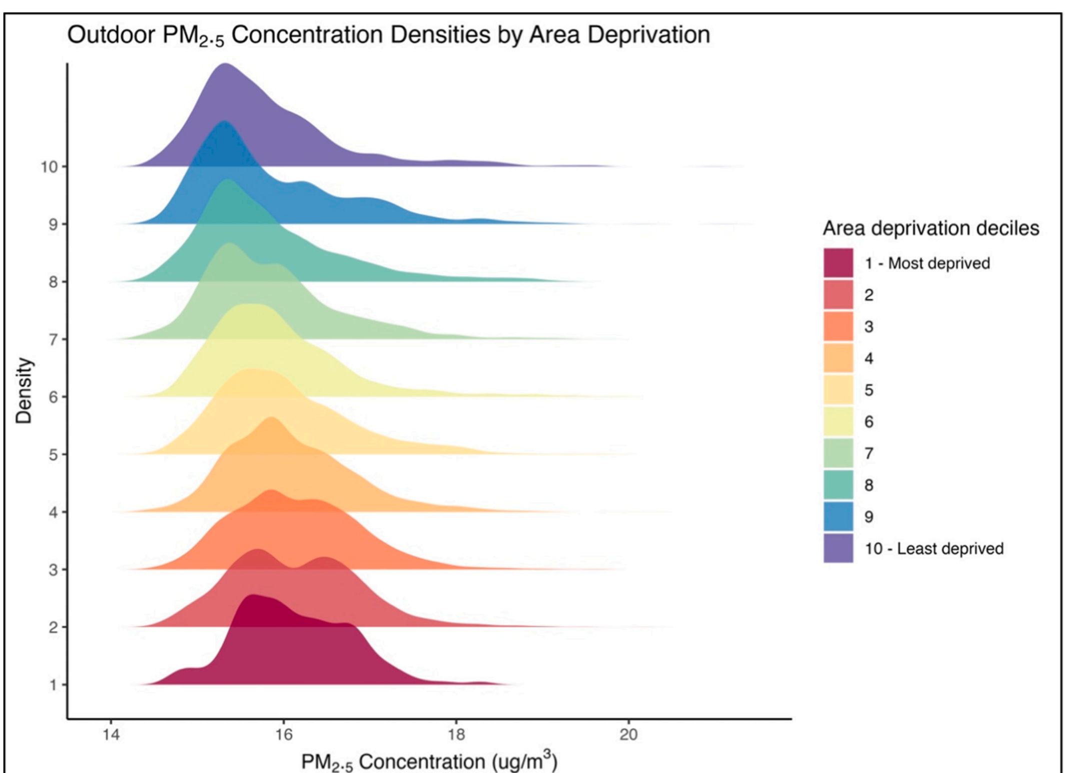

Fig. 1. Distributions of outdoor concentrations of $PM_{2.5}$, aggregated by area deprivation decile (DCLG, 2011b; GLA, 2017).

sufficiently representative of outdoor conditions.

Concentrations of $PM_{2.5}$ from cooking, smoking and outdoor sources were included in the housing model. Dwellings in the EHS sample with at least one occupant who identified as a smoker were assumed to allow smoking to occur indoors, in the living room. This was carried out at a frequency of eleven cigarettes per day, which is in line with empirical data for smoking habits in the UK (Office for National Statistics, 2017). Within the EHS sample, the proportion of households with at least one smoker was 23.1 % for homes in the lowest income quintile, versus 9.6 % for those in the highest income quintile. Kitchen extract fans were modelled to work as per building regulations, except in homes where the EHS had indicated they were absent or broken (57 % of homes in the lowest income quintile, versus 40 % of homes in the highest income quintile). The emission rate for cooking and smoking was assumed to be 1.6 mg/min and 0.9 mg/min, respectively (Dimitroulopoulou et al., 2006). The indoor $PM_{2.5}$ deposition rate was kept constant at 0.19 h^{-1} (Long et al., 2001). The particle penetration factor was assumed to be 0.8 when windows were open and 1.0 when windows were closed (Chen and Zhao, 2011).

2.2.3. Non-domestic indoor concentrations

Detailed information relating to non-domestic environments is seldom available and archetypes rarely follow a prescribed form (Schwartz et al., 2021), meaning a different approach was taken for modelling indoor $PM_{2.5}$ concentrations in schools and vehicles. The INDAIR probabilistic modelling approach was applied (Dimitroulopoulou et al., 2001, 2006), which estimates indoor concentrations using a mass-balance equation with building inputs taken via probability density functions to account for the underlying uncertainty in these parameters.

A distribution of building air change rates (ACH) was constructed for schools based on measurements carried out in eight naturally-ventilated primary schools in Coventry, a city 160 km north of London (Korsavi et al., 2020), shown in Table 2. There were no studies examining ACH in travel microenvironments in the UK. Therefore, a distribution of ACH for cars and buses was generated using reported ACH values in published international studies (Chaudhry and Elumalai, 2020; Knibbs et al., 2009; Ott et al., 2008; Zhang et al., 2013), outlined in S2 of the Appendix and summarised in Table 2. Car and bus windows were assumed to be open in summer and closed in winter. Distributions for all scenarios were assumed to follow a lognormal distribution, as is the case for studies measuring ACH in a range of environments (Persily, 1989; Shi et al., 2015).

The ACH of each child's school and transport microenvironment was assigned by randomly sampling from the distributions for the corresponding season, and the following mass-balance equation applied (Diapouli et al., 2013):

$$\frac{dC_{in}(t_i)}{dt_i} = a \bullet P \bullet C_{out}(t_i) - (a+k) \bullet C_{in}(t_i) + \frac{Q}{V} \quad (1)$$

Where C_{in} is the indoor concentrations (μg/m^3) for each ten-minute interval (t_i); C_{out} is the outdoor concentration sampled for individual's home, also in ten-minute intervals; P is the penetration factor (dimensionless); a is the air change rate (h^{-1}); k is the deposition rate (h^{-1}); V is the volume of the indoor space (m^3) and Q is the indoor emission rate (μg/h).

Table 2
The distribution of classroom and vehicle air change rates used to parametrise the mass-balance equation in the non-domestic component of the exposure model. All scenarios were assumed to follow a lognormal distribution, shown in S2 of the Appendix.

Microenvironment	Measured air change rates (h^{-1})		Source(s)
	Summer	*Winter*	
School	3.84 ± 2.65	3.02 ± 1.92	(Korsavi et al., 2020)
Car	39.0 ± 22.0	12.6 ± 8.0	(Knibbs et al., 2009; Ott et al., 2008)
Bus	18.3 ± 10.5	2.9 ± 1.7	(Chaudhry and Elumalai, 2020; Zhang et al., 2013)

The volume for school classrooms was assumed to be 167.4 m^3, in line with space requirements for UK classrooms (National Education Union, 2019) and 2.5 m^3 and 66 m^3 for cars and buses, respectively (Smith et al., 2016). The indoor emission rate due to resuspension from occupant movement was assumed to be 120 μg/h per person, taken from an empirical study which determined $PM_{2.5}$ emission rates for various activities (Nasir and Colbeck, 2013). The number of students was assumed to be 28, the London average for Key Stage 1 (Mayor of London, 2017). Indoor emissions from resuspension were also considered in the transport microenvironments, as student activity within the limited cabin space of buses has been found to increase indoor particle concentrations significantly (Gulliver and Briggs, 2004; Zhang et al., 2013; Zuurbier et al., 2010). Buses were assumed to have 21 passengers (the average occupancy level for London buses between 2007 and 2019 (Department for Transport, 2023)), whilst cars were assumed to have two. Values for deposition rate and penetration factor were assumed to be the same as the housing model. Tabulated values for all input parameters are included in S2 of the Appendix.

2.3. Time-activity patterns

The NatCen Time-use survey (Gershuny and Sullivan, 2017) was used to develop time-activity patterns for outdoor, domestic and non-domestic (travel and school) microenvironments. The survey sampled 4741 households across the UK between 2014 and 2015, collecting data on individual daily activities and household circumstances. Participants were required to keep a time-activity diary where they recorded their location and activity for a representative weekday and weekend in ten-minute intervals (Gershuny and Sullivan, 2017). Included in the survey is information on individual's household income quintile, which was linked to that of individuals in the EHS. Childhood responses from across the UK were included, as when the NatCen data was subset to only those surveyed in London and disaggregated by season (summer/winter), type of day (weekend/weekday) and household income quintile (1–5) to link with the dataset of $PM_{2.5}$ concentrations, sample sizes were as little as two participants. Such small sample sizes may bias the exposure results, for example if one of the children had stayed home from school on a weekday.

Micro-environments where ≥10 % of the child survey population were for any given 10-min interval were included in our analysis. These included domestic microenvironments (bathroom, bedroom, kitchen, living room), outdoors, school, cars and buses. The child survey population did not spend a significant amount of time on the London underground. Survey responses where the child had indicated they were not in any of the eight main micro-environments, for example if the survey participant reported being in a commercial building such as a shop or restaurant, were removed from the analyses as <3 % of the child survey population reported being in other micro-environments for any of the given 144 ten-minute time intervals. The resulting dataset showed the proportion (0.0–1.0) of the total child survey population in each of the eight micro-environments in ten-minute intervals for a representative weekday and weekend (S3 of the Appendix). The time-activity data was analysed for both summer (June, July and August) and winter (January, February and December).

2.4. Individual exposures estimates

The dataset of indoor and outdoor $PM_{2.5}$ concentrations was linked with the childhood time-activity patterns for the corresponding season/type of day using household income quintile. The model simulates personal exposure by linking micro-environment $PM_{2.5}$ concentrations with probabilistic population time-activity data, first applied to a child population by the EXPAIR exposure model (Dimitroulopoulou et al., 2006, 2017). To assess inequalities in childhood $PM_{2.5}$ exposure, daily exposure at ten-minute time intervals was calculated for the EHS sample of children within each income group using the following equation:

$$E_k(t_i) = \sum_{j=1}^{8} C_{jk} P_j(t_i) \tag{2}$$

Where $E_k(t_i)$, the microenvironment weighted average exposure for child, k, at each 10-min time-step (t_i); C_{jk} is the indoor concentration in microenvironment j ($n = 8$) for child k at time-stamp (t_i); and $P_j(t_i)$ is the proportion of the child population in micro-environment j at time-stamp (t_i).

Each child's, k, daily median exposure ($\widetilde{E}_k$) for each type of day and season combination (weekday/weekend, winter/summer) was then calculated using the following eq. (3):

$$\widetilde{E}_k = med\{E_k(t_i)\} \tag{3}$$

Finally, for each day type (weekday/weekend, winter/summer) we report the population weighted median (and 95 % CIs) daily child exposure for children within each income quintile:

$$\widetilde{E}_l = med\{w_k \widetilde{E}_k\} \tag{4}$$

Where w_k is the EHS population weight used to scale up from the EHS sample to the London school-aged population (those aged 4–16 years old).

To assess temporal variations in exposure by income group, Eq. 3 was applied:

$$E_l(t_i) = \frac{1}{N_l} \sum_{k=1}^{N_{l,EHS}} w_k \sum_{j=1}^{8} C_{jk} P_j(t_i) \tag{5}$$

Where $E_l(t_i)$ is the population weighted average exposure for children within income quintile, l, at each ten-minute time interval (t_i); N_l ($= \sum_{k=1}^{N_{l,EHS}} w_k$) is the total number of children within income quintile, l; $E_k(t_i)$, is the microenvironment weighted average exposure for child, k, at each 10-min time-step (t_i) as defined in Eq. 2.

2.5. Statistical analysis

To assess if differences in average daily exposures between income groups were statistically significant, a Kruskal-Wallis rank sum test was carried out. The Kruskal-Wallis test is a non-parametric approach to a one-way ANOVA (Kruskal, 1952), used to determine how one factor affects a response variable. This test is appropriate, as the data for average daily exposure was not normally distributed. The assumption of normality was checked using a Shapiro-Wilk's test, (Kassambara, 2019), confirming that average exposure to $PM_{2.5}$ was not normally distributed ($p = 1.33e\text{-}56$). All data preparation, integration and analysis was performed using R statistical software version 4.2.0. (R Core Team, 2022).

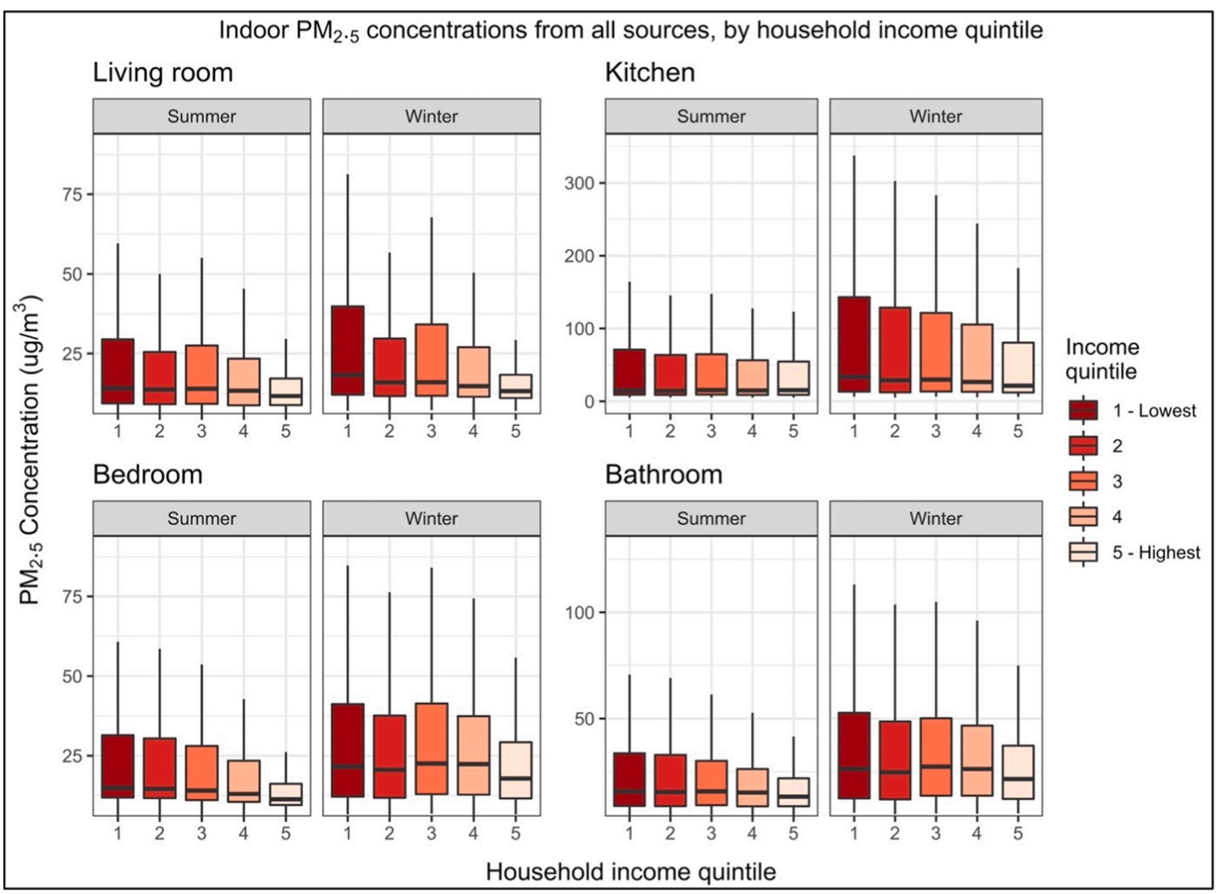

Fig. 2. The distribution of indoor $PM_{2.5}$ concentrations for each of the four micro-environments, in summer and winter, across household income quintile. Boxplots are comprised of data points for $PM_{2.5}$ concentration levels in all 824,215 households at each ten-minute interval, aggregated by season with concentrations on weekday and weekends pooled together. The central line in each boxplot represents the median, whilst the box shows the inter-quartile range (IQR) and the lower and upper whiskers show the minimum and maximum for each group, respectively.

3. Results

3.1. Microenvironment $PM_{2.5}$ concentrations

3.1.1. Home environment

Fig. 2 displays the distribution of indoor concentrations of $PM_{2.5}$ from both indoor and outdoor sources modelled for the home environment for each season. Distributions are constructed for ten-minute intervals ($n = 144$) for each 24-h period (one representative weekend and weekday per season). Children living in homes in the lowest income quintile had the highest indoor concentration of $PM_{2.5}$ in each of the four micro-environments in both seasons. The relationship between household income status and indoor concentrations of $PM_{2.5}$ generally followed a linear pattern, as shown in Fig. 2, with homes in the highest income quintile subject to the lowest indoor $PM_{2.5}$. However, the relationship varied for different home micro-environments/season combinations, as the temperature-dependent window-opening threshold will play a role in reducing indoor concentrations in the summer in homes with higher internal temperatures.

3.1.2. School

The distribution of indoor concentrations of $PM_{2.5}$ in the school environment on weekdays, aggregated by season, is shown in Fig. 3. Results are aggregated by IMD decile rather than household income quintile, as outdoor concentrations were assigned to each child using the area-IMD ranking their household came under, and the infiltration of outdoor $PM_{2.5}$ is the primary source of air pollution in the school and transport microenvironments. Median indoor concentrations of $PM_{2.5}$ were 13.0 μg/m^3 (IQR: 12.2–13.7 0 μg/m^3) in the summer and 16.7 μg/m^3 (IQR: 15.7–17.7 0 μg/m^3) in the winter. Concentrations were higher in winter due to the higher levels of outdoor $PM_{2.5}$ and lower classroom ACH limiting the removal of resuspended $PM_{2.5}$ from occupant movement within the classroom. Classroom concentrations were higher in schools in more deprived areas (median indoor PM was 16.9 μg/m^3 vs. 16.5 μg/m^3 for schools in the most and least deprived areas in winter, respectively. Equivalent values for summer were 13.0 μg/m^3 vs 12.8 μg/m^3, respectively), though differences were marginal due to the limited spatial variation of $PM_{2.5}$ across London.

3.1.3. Travel

The distribution of indoor $PM_{2.5}$ concentrations in bus and car micro-environments is shown below in Fig. 4. Alike with the school microenvironment, concentrations were higher in winter than in summer for both transport environments due to the higher ambient outdoor levels in winter and lower vehicle ACH limiting the removal of resuspended $PM_{2.5}$ from occupant movement. Levels of indoor $PM_{2.5}$ were higher in the bus microenvironment than the car (median indoor $PM_{2.5}$ in winter was 16.6 μg/m^3 and 20.5 μg/m^3 in the car and bus, respectively, and 11.9 μg/m^3 and 12.6 μg/m^3 for summer, respectively) due to the greater occupant density of the bus leading to higher $PM_{2.5}$ generated from resuspension. This is in agreement with other studies (Adams et al., 2001; Rivas et al., 2017a; Vouitsis et al., 2014).

3.2. Population exposure

Population weighted average exposures to $PM_{2.5}$ in ten-minute intervals ($E_I(t_i)$ - see Eq. 5) for the five income quintiles are shown in Fig. 5. Daily peaks were largely driven by residential indoor sources, such as cooking and smoking events. On weekdays, the peak before 8 am was driven by cooking events, which then drops to background school concentrations (~14 μg/m^3) where there are no indoor sources other than resuspension. Likewise on weekends, peak exposure is driven by indoor sources in the home micro-environment. Personal exposure is highest in winter as lower window-opening frequencies limits the role of ventilation to reduce indoor concentrations. Night-time exposure is the lowest, as though the model accounts for zonal interchange between the kitchen and bedroom, bedroom concentrations are largely driven by outdoor background levels.

Table 3 shows median daily exposure ($\widetilde{E}_I$ - see Eq. 4) with 95 % confidence intervals for each income quintile across both winter and summer and the type-of-day. Children in the lowest income quintile generally had higher median daily exposure, whilst those in the highest income quintile consistently had the lowest exposure across all scenarios, but the relationship between income group and exposure is non-linear. Median daily exposure across all four scenarios (winter/summer, weekends/weekdays) was 17.1 μg/m^3 (95%CIs: 12.1 μg/m^3–41.2 μg/m^3) for children from homes in the lowest income quintile and 14.4 μg/m^3 (95%CIs: 11.5 μg/m^3 – 27.9 μg/m^3) for those from the highest income homes.

The Kruskal-Wallis test confirmed that there were significant differences in median daily exposures between income quintiles across the four scenarios. Pairwise comparisons were then computed using Wilcoxon rank sum test to analyse inter-group variance, shown in S4 of the Appendix. Only children in the highest income group had significantly *lower* exposure than all other income groups across all season and type-of-day scenarios. The statistical significance of other pairwise

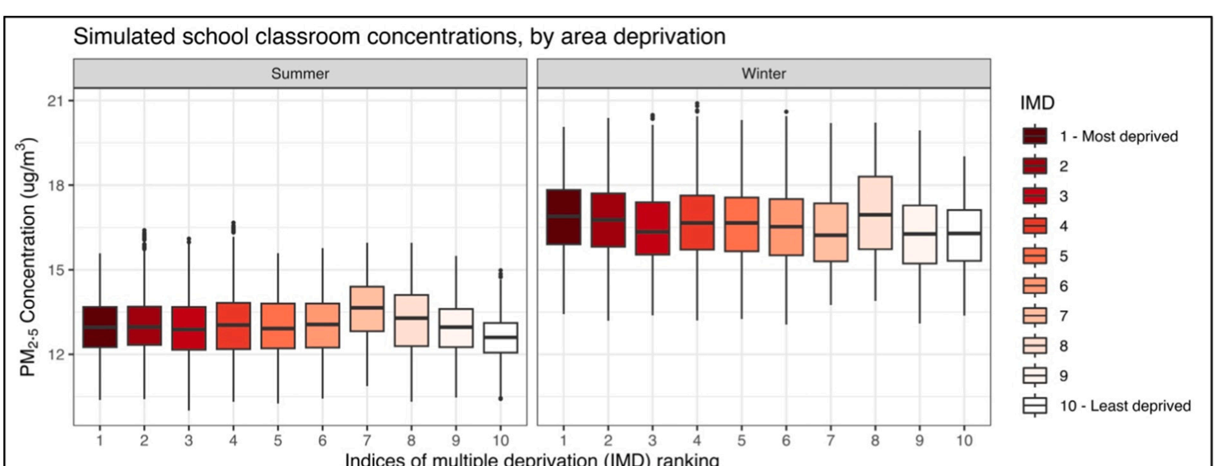

Fig. 3. Distribution of school classroom concentrations for summer and winter, aggregated by Indices of Multiple Deprivation (IMD) ranking. Boxplots are comprised of data points for $PM_{2.5}$ concentration levels in ten-minute intervals throughout a typical weekday for summer and winter. The central line in each boxplot represents the median, whilst the box shows the inter-quartile range (IQR) and the lower and upper whiskers show the minimum and maximum for each group, respectively. Black data points show outliers.

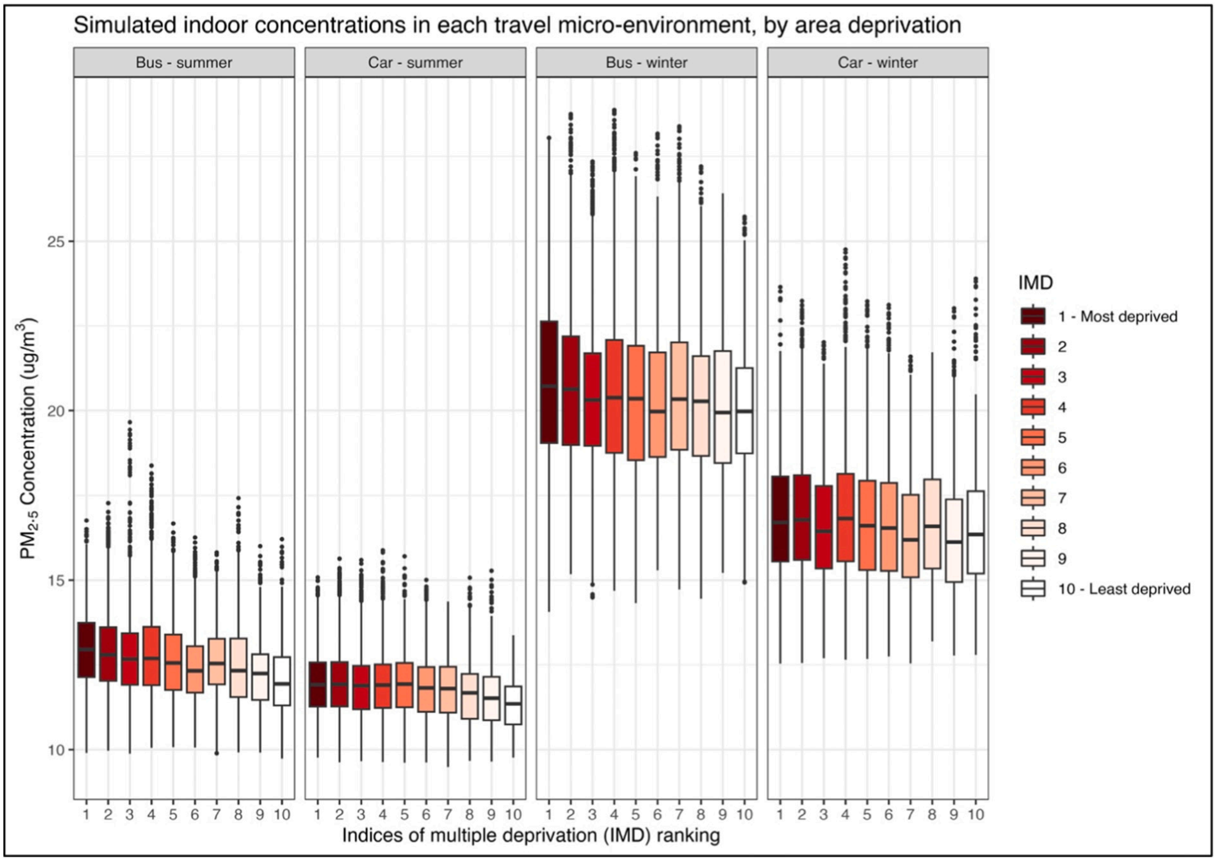

Fig. 4. Distribution of school classroom concentrations for summer and winter, aggregated by area deprivation. Boxplots are comprised of data points for $PM_{2.5}$ concentration levels in ten-minute intervals in each micro-environment aggregated by season, with weekdays and weekends pooled together. The central line in each boxplot represents the median, whilst the box shows the inter-quartile range (IQR) and the lower and upper whiskers show the minimum and maximum for each group, respectively. Black data points show outliers.

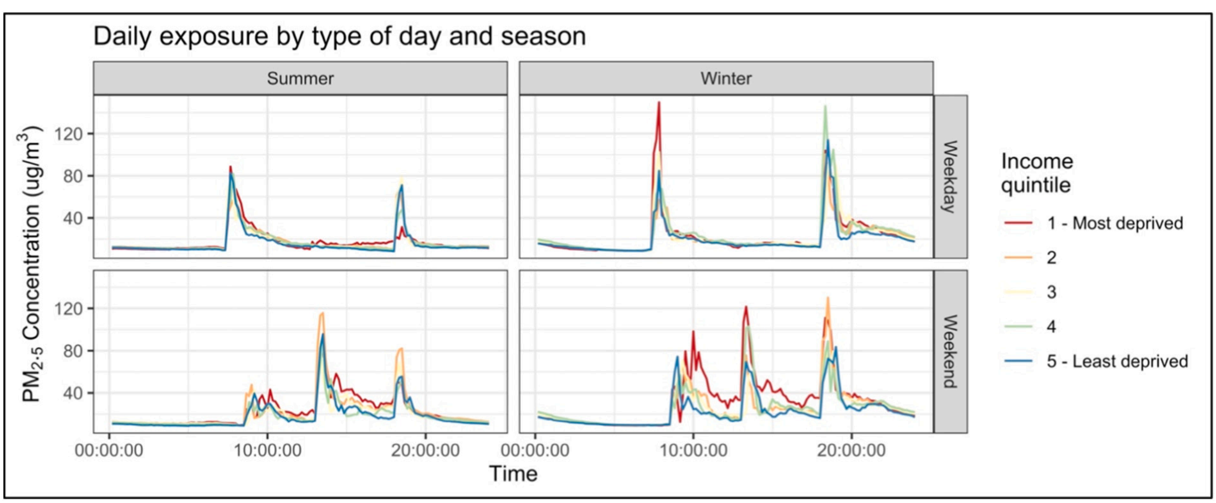

Fig. 5. *Estimated exposure in ten-minute intervals, by type of day and season, aggregated by childhood household income quintile for all 1,336,803 school-aged children in the Greater London population. Note that concentrations represent a ten-minute median, resulting in higher peak concentrations than if levels were averaged over a 1-h time interval. Daily activities were inferred from the NatCen Time-Use survey* (Gershuny and Sullivan, 2017) *but it is acknowledged that the profiles shown here represent an overall 'average' and individual time-activity patterns are highly variable and will differ from one day to the other.*

comparisons varied across the different scenarios.

Fig. 6 shows distribution of median daily exposure for children by household income quintile, across each type-of-day and season scenarios. Daily personal exposure was higher on weekends than weekdays, due to the child spending more time at home where there are indoor emissions from cooking and smoking. Exposure was highest in winter versus summer, due to lower window-opening frequencies in the home and the higher ambient concentrations. The figure shows that median daily exposure is generally higher for children from lower income homes, but that children from *all* income groups face $PM_{2.5}$ exposure

Table 3
Distribution of median (95%CIs) daily exposure to $PM_{2.5}$, by childhood household income quintile.

Income quintile	Population (*n*)	Median (95%CI) $PM_{2.5}$ exposure ($\mu g/m^3$)			
		Winter weekdays	Winter weekends	Summer weekdays	Summer weekends
1 - Lowest	129,132	16.5 (13.1–27.8)	24.4 (16.0–44.0)	13.5 (11.9–23.7)	15.8 (11.0–20.1)
2	288,496	16.9 (13.8–29.0)	22.8 (14.5–42.3)	13.3 (12.0–23.5)	16.3 (11.5–20.5)
3	225,424	16.6 (13.9–28.0)	22.3 (15.3–46.2)	12.7 (11.9–26.6)	13.8 (10.9–21.8)
4	324,783	16.5 (13.8–31.6)	22.2 (15.7–42.2.)	12.9 (12.0–25.1)	13.9 (11.6–20.8)
5 - Highest	368,968	15.1 (13.7–25.2)	18.7 (14.7–39.4)	11.8 (11.5–23.8)	13.0 (10.9–17.9)

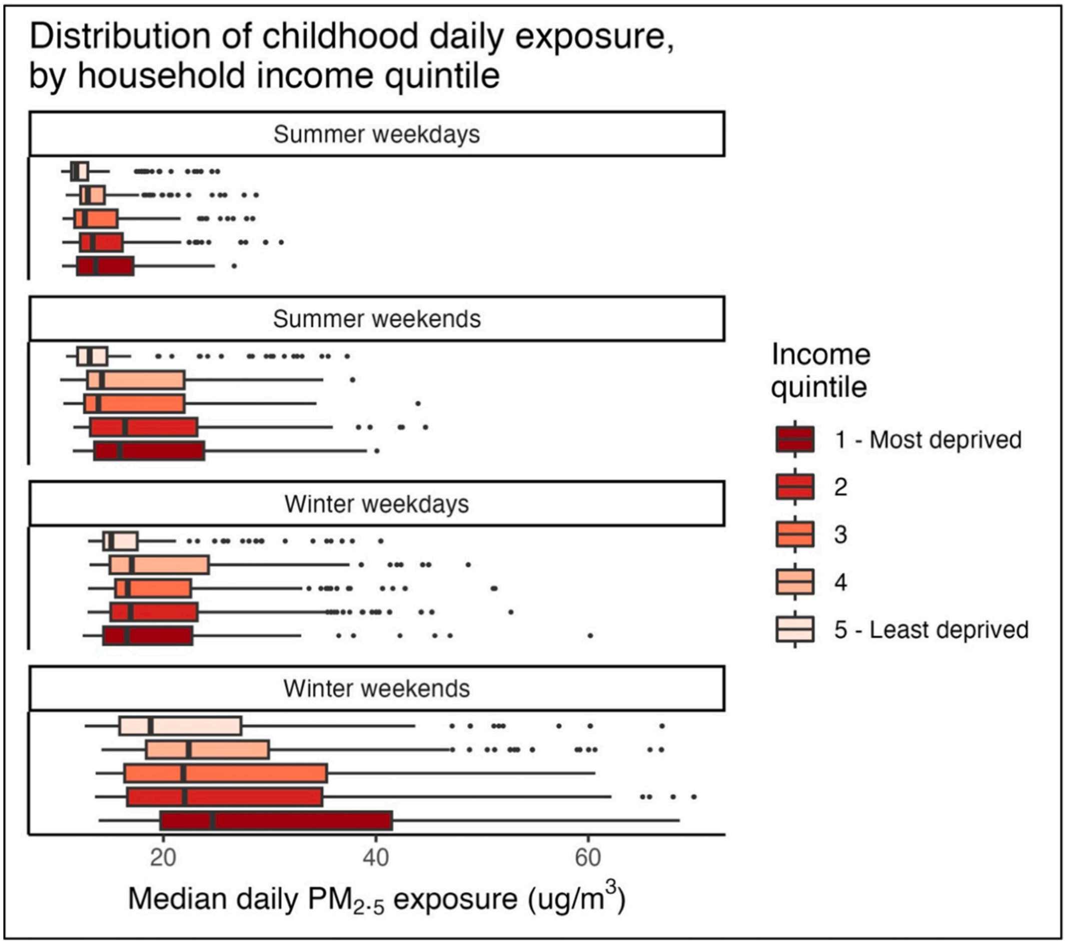

Fig. 6. Distribution of childhood personal exposure by childhood socio-economic status (SES) for different types of days and season, for school-aged children in the Greater London population.

above the recommended 24-h guideline limit of 15 $\mu g/m^3$ (World Health Organization, 2021).

To assess the proportion of school-aged children subject to $PM_{2.5}$ concentrations above the recommended 24-h WHO guideline limit, we calculate the percent in each income group with a median daily exposure higher than 15 $\mu g/m^3$, for each season and type-of-day. Results are shown in Fig. 7. Whilst lower-income groups generally fare worse, all groups experience high exposure to $PM_{2.5}$. Across the four scenarios, an average of 57 % of children, equivalent to 761,976 individuals aged between 4 and 16 years old, had a median daily exposure which exceeded 15 $\mu g/m^3$.

4. Discussion

This paper describes a model that estimates exposure disparities between children of different income groups for the Greater London population, accounting for differences in ambient air pollution levels, detailed housing characteristics, school and transport exposures, and behaviour. Median daily exposure was 17.2 $\mu g/m^3$ for children in the lowest income quintile versus 14.5 $\mu g/m^3$ for those in the highest income quintile across all season/type-of-day scenarios, but a considerable number ($n = 761{,}976$) of children across *all* income groups experienced exposure above the recommended 24-h guideline limit (15 $\mu g/m^3$, (World Health Organization, 2021)). The home was the most important micro-environment for exposure, as the child population spent on average 80.9 % (95%CIs; 60.0 %–100.0 %) of their time there on weekends and 67.8 % (95%CIs; 52.1 %–93.5 %) on weekdays (S3 of the Appendix). Lower-income homes experienced the highest indoor concentrations, driven by higher smoking rates, higher outdoor concentrations and dwellings with smaller internal volumes and lower levels of background ventilation. The results shown here support wider findings from empirical studies in high-income countries, where lower-SES homes experienced higher concentrations of indoor air pollution (Ferguson et al., 2020).

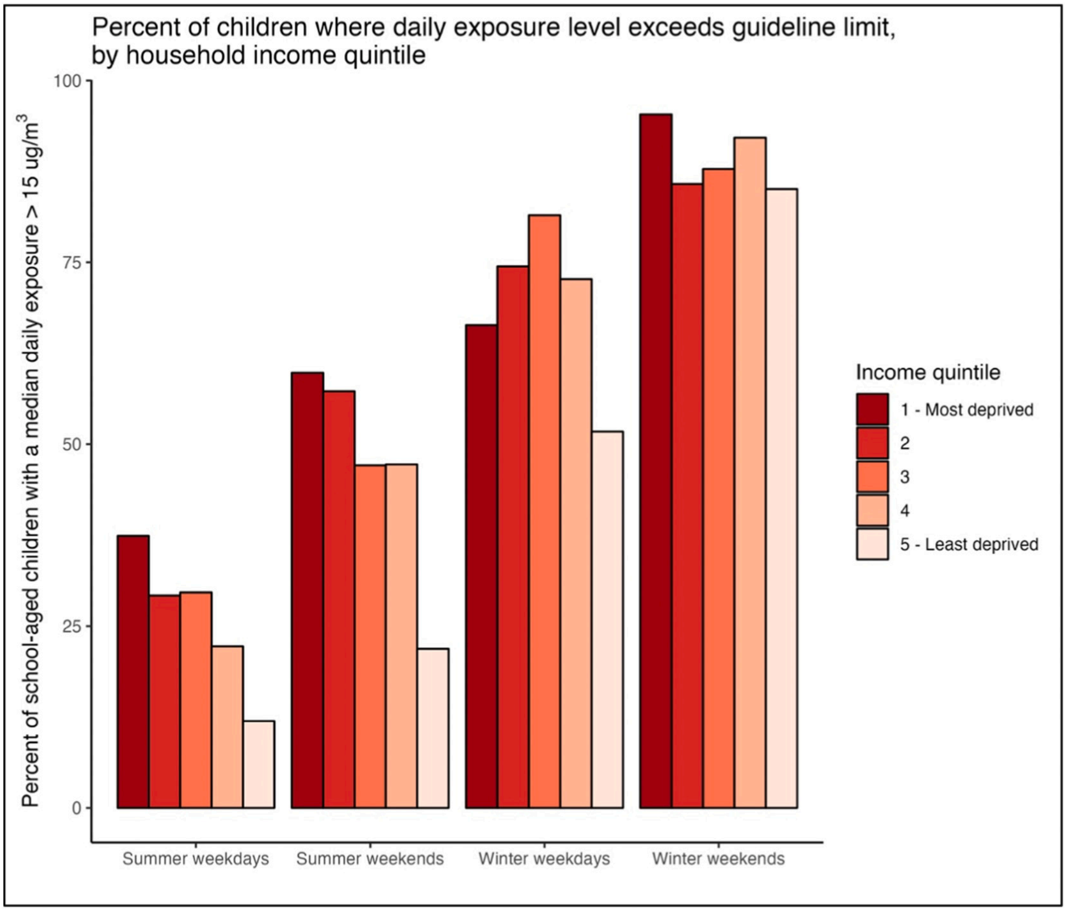

Fig. 7. The percent of children with a daily exposure which exceeds the World Health Organisations 24-h guideline limit of 15 μg/m^3 (World Health Organization, 2021), by household income quintile.

Modelled median 24-h concentrations of indoor $PM_{2.5}$ across all four micro-environments in homes were 27.3 μg/m^{-3} and 14.9 μg/m^{-3} in winter and summer (Fig. 3), respectively, exceeding the 24-h guideline limit of 15 μg/m^{-3} set by the World Health Organisation (WHO) (World Health Organization, 2021). Modelled results for homes align well with empirical data, though the precise time-resolution varies between measurements conducted in different studies. Wheeler et al. (2000) monitored indoor $PM_{2.5,}$ observing 5-day mean concentrations in London homes in Winter, Spring and Summer of 29 μg/m^{-3}, 24 μg/m^{-3} and 19 μg/m^{-3}, respectively. Indoor concentrations of $PM_{2.5}$ in other English homes have been recorded as 13 μg/m^3 and 12 μg/m^3 (48-h mean) in kitchens and living rooms, respectively, in Oxford (Wigzell et al., 2000),19 μg/m^3 (48-h mean) in Yorkshire (Mohammadyan and Ashmore, 2005) and 22.6 μg/m^{-3} (5-day median) in Manchester (Gee et al., 2002).

A number of empirical studies support our findings that cooking emissions strongly influence exposure (Nasir and Colbeck, 2013; Vardoulakis et al., 2020), especially for children (Buonanno et al., 2013; Holgate et al., 2021). Measurements conducted in the South-East of England found that cooking resulted in peak concentrations of $PM_{2.5}$ in the kitchen of 130 μg/m^3 for electric cooking (Nasir and Colbeck, 2013), which reflects our finding that concentrations are highest in the kitchen and is similar to our estimated concentrations (Fig. 5). A more recent study monitoring $PM_{2.5}$ in children's bedrooms found median concentrations of 14 μg/m^{-3} across 18 flats in East London (Cooper et al., 2021). This figure is within the range of median exposures given in Table 3 for different seasons and type-of-days (11.8 μg/m^3–24.4 μg/m^3), which will be strongly influenced by the bedroom given the amount of time children spend there. A study in Spain found that exposure in children's bedrooms were responsible for 60 % of the daily inhaled dose of air pollutants (Lizana et al., 2020). A recent study found that 12.7 % of childhood asthma can be attributed to domestic gas stove use in the US (Gruenwald et al., 2022), demonstrating indoor exposures may have serious health impacts.

Modelled 24-h median concentrations of indoor $PM_{2.5}$ in school classrooms were 13.0 μg/m^3 and 16.7 μg/m^3 in summer and winter, respectively. The results are at the lower end of $PM_{2.5}$ concentration estimates recorded in London classrooms, which ranged from 21 μg/m^3–54 μg/m^3 and 17 μg/m^3–28 μg/m^3 in the heating and non-heating season, respectively (Mumovic et al., 2018). More recent monitoring data from three South London primary schools recorded indoor $PM_{2.5}$ concentrations of 2.64 μg/m^3–11.51 μg/m^3 before and after a number of interventions were introduced (Abhijith et al., 2022). Ambient concentrations were the main driver of indoor levels in the modelled results presented here and elevated outdoor concentrations in deprived areas led to unequal exposure in the classroom. Outdoor concentrations of $PM_{2.5}$ are highly correlated with indoor classroom concentrations in London (Chatzidiakou et al., 2012) and deprived schools generally experience the highest levels of outdoor air pollution in London (Brook and King, 2017) and England (Osborne et al., 2021), but concentrations may also be influenced by classroom ventilation, occupation and room volume (Chatzidiakou et al., 2012).

Modelled median $PM_{2.5}$ levels in the transport micro-environments were 16.6 μg/m^3 and 20.5 μg/m^3 in the car and bus during winter, respectively, and 11.9 μg/m^3 and 12.6 μg/m^3 in summer, respectively. Concentrations in the travel micro-environment were higher in the bus micro-environment and during winter, which agrees with much of the existing literature (Mitsakou et al., 2021; Rivas et al., 2017a,Rivas et al., 2017b; Vouitsis et al., 2014; Zuurbier et al., 2010). Within London, empirical concentrations of $PM_{2.5}$ during car and bus commuting have been reported as 7.3 $\mu g/m^{-3}$ and 13.9 $\mu g/m^{-3}$ (Rivas et al., 2017a) and 7.4 $\mu g/m^{-3}$ and 13.2 $\mu g/m^{-3}$, respectively (Rivas et al., 2017b), which are comparable with the values presented here. The higher within-transport PM concentrations estimated in the results here relative to 2017 levels may reflect that the ambient data for London is from 2013, and outdoor concentrations in London have gradually declined throughout the last decade (GLA, 2020).

No association between commuting-based exposure and deprivation has been found in London (Rivas et al., 2017a). However, this was estimated by comparing typical commuting modes along four different routes where the origin location had varying levels of deprivation (Rivas et al., 2017a). To accurately gauge the potential scope of inequalities in commuting-based exposure, models must account for variations in micro-environment concentrations, route selection and different modal-use between income groups. Additionally, the London underground is consistently found to be the *most* polluted way to travel in London by a significant margin (Rivas et al., 2017a; Rivas et al., 2017b). Concentrations of $PM_{2.5}$ at various intervals on the underground network have been recorded as high as 885 $\mu g/m^{-3}$ (Smith et al., 2020). Though the childhood survey population did not spend a significant amount of time on the underground, the tube has approximately 2.8 million daily users (Smith et al., 2020). Therefore, excluding this environment is likely to lead to exposure misclassification for a sizeable portion of those living in London.

4.1. Strengths and limitations

We use detailed building and occupant information to model $PM_{2.5}$ exposures at a high temporal resolution between income groups. The findings demonstrate the importance of indoor sources, especially in the home, in contributing to overall childhood exposure. The model can assess how personal exposure varies for school children in ten-minute intervals, revealing high peaks in exposure generated from indoor activities. These peaks may be masked when hourly or daily median or mean values are reported alone. A number of empirical studies have highlighted the contribution of cooking emissions on childhood exposure (Gruenwald et al., 2022; Holm et al., 2018), but this finding is rarely reflected in existing personal exposure models.

The work described here has several limitations. The model employs a probabilistic approach via the time-activity patterns, outdoor concentrations and building/vehicle air change rates for non-domestic microenvironments, but a number of key inputs were deterministic. A single deposition rate was used, inferred from empirical data (Long et al., 2001). Particle deposition has been found to vary with ventilation rate (Liu et al., 2018), surface texture (Abadie et al., 2001) and room temperature (Zhou et al., 2017), thus the single deposition rate used here may not capture the breadth of particle deposition in reality. Smoking was assumed to occur indoors in households which had at least one resident smoker, at a frequency of 11 cigarettes per day. In reality, smoking preferences will vary from one individual to another and smoking indoors in the presence of children has become a social taboo following the introduction of public smoking bans. Whilst we accept that the model could be improved by the incorporation of stochastic data in place of the deterministic inputs, we assume that the proportion of model error due to each deterministic input would be evenly distributed across the London population, thus the relative differences in exposure between income groups would remain the same.

The housing dataset used to parameterise the home environment was taken from 2011. Despite the low turnover of the domestic building stock in England, the London housing market has high rates of residential mobility (Champion and Gordon, 2021). The demographic and socio-economic circumstances of the London population will have changed over the last decade, which will have implications for the way the results are aggregated. Likewise, the outdoor air pollution data was from 2013, and outdoor concentrations in London have steadily decreased over the last decade due to the Mayor's Environment Strategy (GLA, 2020). However, a more recent analysis of outdoor air pollution inequalities from 2019 found a difference of 0.7 $\mu g/m^3$ in $PM_{2.5}$ between the most and least deprived areas of London, suggesting that whilst absolute levels of air pollution may have decreased, relative inequalities remained the same (GLA, 2021). Though we acknowledge that a number of model inputs are dated, the 2011 EHS was the only housing dataset for which information pertaining to building features and occupant behaviours was available, allowing for the modelling of indoor concentrations inside the homes of a representative population. As the main aim of this work was to present a tool able to quantify exposure disparities between different population groups, inputs may be updated as newer data becomes available. One of the main strengths of using the 2011 EHS is it enables the specification of indoor emissions from indoor sources in smoking households, which has previously been overlooked in personal exposure models (Smith et al., 2016). Up to 19 % of the adult population are smokers in some London boroughs (Office for Health Improvement and Disparities, 2022), and smoking can lead to significant variations in indoor $PM_{2.5}$ (Wallace et al., 2006). It is therefore important to consider how smoking may indirectly affect the health of those other than the smoker, as the work here has done, especially given the vulnerability of childhood health to second-hand smoke (Turner et al., 2020).

A simple mass-balance approach was used to estimate indoor concentrations in the school and travel microenvironments, where the only socio-economic effect introduced was the outdoor air pollution concentrations. Pupil intake has steadily increased in state-funded primary and secondary schools in England (Department for Education, 2019), leading to a higher number of pupils per class, which may result in greater particle concentrations due to resuspension from occupant movement (Amato et al., 2014; Morawska et al., 2017). As the mass-balance approach introduced in the non-domestic model component considers the impact of resuspension for a given number of occupants, there is scope to introduce variable classroom occupant densities within the work presented here, but sufficient data to parameterise the equation for classroom occupancy across various levels of school deprivation was not available at the time this model was developed. Furthermore, this approach assumes that, for each child in the sample, their school and travel environments are subject to the same outdoor concentrations as the home. Though many children attend school in the local area, the mean distance travelled to school has gradually increased in England over the last three decades, driven by the increasing size of secondary schools encouraging pupil intake from a wider catchment area and growing levels of household car-ownership (Easton and Ferrari, 2015). However, London pupils have, on average, the shortest commute relative to other areas of the country (Department for Transport, 2020). Thus, this approach may be valid for the Greater London area but would need to be adapted for other areas of England due to differences between the urban form and transport infrastructure.

Though the mass-balance approach employed for the school and transport micro-environments is simplified compared to the housing component, including these environments allows for a better understanding of the factors shaping personal exposure for school children in London. This can lead to better-targeted interventions: Much of the air quality interventions in London have focussed on improving ambient concentrations. Whilst ensuring clean outdoor air is essential for improving population exposure, the work here indicates that ensuring proper kitchen ventilation and accelerating the provision of clean households fuels in UK homes may lead to greater reductions in childhood exposure to $PM_{2.5}$, which is supported by wider research (Gruenwald et al., 2022; Knibbs et al., 2018a,Knibbs et al., 2018b; Lin et al., 2013).

4.2. Implications

The results presented here suggest a statistically significant difference of up to ~5 $\mu g/m^3$ in median $PM_{2.5}$ exposure between children from the most and least income-deprived households in London (winter weekends). A 1 $\mu g/m^3$ increase in $PM_{2.5}$ exposure has been associated with reduced cognitive skills (Hurtado-Díaz et al., 2021) and lower expiratory rates in children (Kim et al., 2020), a 1.29 % increase in all-cause mortality in adults (Vodonos et al., 2018) and lower term birth-weight in pregnant women (Yitshak-Sade et al., 2021). Our findings suggest that those from lower-income households will be more likely to experience these health impacts due to their higher exposure. The health inequalities gap in England has grown over the last decade (Bennett et al., 2018; Marmot, 2020). Rates of childhood poverty have increased since pre-2010, with over four million children affected (Marmot, 2020). London experiences some of the highest rates of childhood poverty across the country, affecting over 800,000 children living in the capital (Leeser, 2021). Unequal health outcomes between populations of different SES begin early on in the life course: Children in deprived areas have higher rates of premature death, poor mental health, increased likelihood of experiencing long-term illness, asthma, unintentional injuries and obesity (Pearce et al., 2019; Wolfe et al., 2014).

Though children from lower-income homes fared worse than those from higher income homes, 57 % of school-aged children in London had a median daily exposure above the WHO 24-h guideline limit. This may lead to significant health implications across the child population. The link between air pollution exposure and childhood asthma is widely studied across the literature (Branco et al., 2020; Knibbs et al., 2018a; Noutsios and Floros, 2014), but more recently an association between air pollution and mental health conditions has begun to emerge (Braithwaite et al., 2019; Horsdal et al., 2019). Outdoor air pollution exposure at the residential address was positively associated with use of mental health services in a South London study (Newbury et al., 2021) and air pollution exposure at age 12 was significantly associated with the onset of depression at age 18 in a study of 284 London-based children (Roberts et al., 2019). Such research demonstrates that the harms of air pollution are not confined to cardio-respiratory effects. As mental health disorders overwhelmingly burden people of lower-SES (Shields-Zeeman and Smit, 2022), reducing population exposure to air pollution, particularly for vulnerable subgroups, may target health inequalities via a number of inroads. The work here argues that a crucial way to achieve this is by mitigating air pollution exposure experienced in indoor environments, particularly the home.

The UK Governments Heat and Buildings Strategy identifies home heating decarbonisation as one means of achieving Net Zero by 2050 (HM Government, 2021). Gas boilers will be phased out in new homes from 2035, but a transition away from gas cooking may also follow as homes begin to use alternate energy vectors such as electricity and hydrogen (Khalid and Foulds, 2020). Electric stoves are generally found to produce lower indoor concentrations of $PM_{2.5}$ compared to gas (Gould et al., 2023). Introducing cleaner cooking fuels across the London housing stock may therefore reduce childhood exposure to $PM_{2.5}$ for children from all income groups, as residential sources are identified as a key driver in the modelled results produced here. Additionally, smoke-free policies have resulted in drastic reductions in childhood second-hand smoke (SHS) exposure across England, where nearly all children with non-smoking parents and three out of four children with at least one smoking parent now live in a smoke-free home (Tattan-Birch and Jarvis, 2022). Further policies to phase out nicotine smoking across the population, such as the generational anti-smoking laws introduced in Malaysia and New Zealand (Dyer, 2022), may reduce childhood exposure inequalities, especially given those from lower-income households are more likely to smoke.

4.3. Future work

The exposure estimates produced here can be used to inform future studies by providing a more complete understanding of the personal exposure school children face, which considers indoor sources, building characteristics and time-activity patterns. The framework can be used to assess a number of *hard* and *soft* policy instruments on exposure in London due to the large number of model inputs. For example, policies focussing on reducing outdoor air pollution concentrations in London may be examined by varying the outdoor input data; the effect of future, low-carbon building policies quantified by modifying building fabric and ventilation properties; and the role of behavioural polices, such as encouraging occupant window opening, ensuring sufficient extract ventilation in rental properties, and indoor smoking bans in multi-dwelling housing assessed.

The tool can be adapted to model additional environmental parameters, such as other air pollutants or environmental heat, across vulnerable subgroups of the population. Additionally, environmental racism is a widely explored topic in the US literature, where Black, Asian, Hispanic or other non-white subgroups of the population are consistently found to be exposed to elevated levels of outdoor air pollution (Gray et al., 2013; Jones et al., 2014). Whilst there is a limited amount of evidence indicating similar disparities are present in the UK (Fecht et al., 2015; Tonne et al., 2018), indoor environments should be considered to assess total exposure as housing conditions play an important role in generating health inequalities from social disadvantage. Variations in travel patterns may drive racial inequalities in exposure to air pollution, as Black children in England are more likely to travel by bus than other ethnic groups (Department for Transport, 2020b), and buses are generally found to be a more polluted way to travel, both in the results presented here and wider research (Adams et al., 2001; Rivas et al., 2017a; Vouitsis et al., 2014). Such information could be incorporated into the tool proposed here by varying the time-activity patterns for other population groups to assess their effect on overall exposure.

5. Conclusion

The work here provides an estimate of personal exposure to $PM_{2.5}$ across multiple microenvironments for the London school-aged population. The results indicate that the population spent 80.9 % and 67.8 % of their time at home on weekends and weekdays, respectively, making the home an important site of exposure for children in London. Median daily exposure was generally higher for children from lower income groups. However, 57 % of Greater London's school-aged children across *all* income groups, equivalent to 761,976 children, had a daily $PM_{2.5}$ exposure which exceeded 24-h guideline limits set by the World Health Organisation (15 $\mu g/m^3$). Exposure was largely driven by the presence of indoor sources in the home, suggesting that efforts to mitigate residential sources of $PM_{2.5}$ should be prioritised in order to protect the health of those most vulnerable. The model can account for variations in outdoor concentrations, housing conditions and population time-activity patterns. Updated housing stock and outdoor concentration data can be incorporated into future iterations of the model to assess the role of changing environmental conditions on population exposure. With rising inequality in London, housing and environmental conditions play an important role in generating health inequalities from social disadvantage. Modelling techniques provide an effective tool to support policy aiming to improve environmental conditions and reduce health inequalities.

Author contributions statement

Conceptualisation, L.F. and J.T.; methodology, L.F., J.T. and P.S.; formal analysis, L.F.; data curation, L.F.; writing: original draft preparation, L.F.; writing: review and editing, L.F., J.T., P.S., M.D. and S.D.;

visualisation, L.F.; and funding acquisition, S.D. and M.D. All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.167056.

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