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Towards cleaner air: $PM_{2.5}$ exposure and disparities around childcare providers in England

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ABSTRACT

Air pollution poses a significant health risk for young children, particularly in urban and deprived areas. Exposure to fine particulate matter ($PM_{2.5}$) during early life may contribute to long-term adverse health outcomes. This study examined changes in $PM_{2.5}$ concentrations around Early Years Providers (EYPs; childcare providers) in England from 2018 to 2022. We assessed associations between small-area socio-demographic characteristics and exposure levels exceeding the World Health Organisation (WHO) 2021 annual air quality guideline (>5 μg/m^3). We integrated data on EYPs locations from Ordnance Survey with annual $PM_{2.5}$ estimates from DEFRA using Geographic Information Systems and socio-demographic indicators — deprivation, urbanicity, and ethnic composition. A Bayesian spatial regression model with random effects was used to estimate adjusted associations between $PM_{2.5}$ levels and local population characteristics. The number of EYPs ranged from 15,780 in 2018 to 18,427 in 2019. Mean $PM_{2.5}$ levels around EYPs changed by 17.8 % over the study period (from 9.4 μg/m^3 [SD = 1.8] in 2018 to 7.8 μg/m^3 [SD = 1.5] in 2022). However, $PM_{2.5}$ levels at over 96 % of EYPs remained above the WHO, 2021 annual guideline throughout. Higher $PM_{2.5}$ concentrations were observed in EYPs located in more deprived, urban, and predominantly non-white communities. Despite recent improvements, $PM_{2.5}$ levels around most EYPs in England remain above recommended thresholds. Targeted interventions in deprived urban areas are needed to reduce young children's exposure and address environmental health inequalities.

1. Introduction

Poor ambient air quality is associated with increased mortality and morbidity (Tong, 2019) and the reduction of these effects is designated as one of the United Nations Sustainable Development Goals (SDG target 3.9.1) (UNGA, 2015). Poor air quality contributes to an estimated 29, 000 to 43,000 premature deaths annually in the UK (Mitsakou et al., 2022). Children, particularly preschool-aged children, are especially vulnerable to the adverse effects of air pollution due to their smaller and developing airways, higher breathing rates, and greater time spent outdoors including at nurseries and schools, compared to adults (Goldizen et al., 2016; Schraufnagel et al., 2019). Understanding the impact of air pollution exposure on this vulnerable population is therefore crucial.

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There is no established safe level of ambient air pollution exposure (Marks, 2022). The 2021 World Health Organization Air Quality Guidelines (WHO AQG) for fine particulate matter that are 2.5 μm or less in diameter ($PM_{2.5}$) recommends an annual mean concentration target of 5 μg/m^3 (WHO, 2021). However, recognising that not all regions can achieve this target immediately, the WHO also introduced interim targets as milestones on the path toward 5 μg/m^3. These interim targets are set at 35, 25, 15, and 10 μg/m^3 (WHO, 2021). The WHO does not mandate a specific global deadline for achieving these interim targets, as the pace of implementation varies by country and region, depending on local air quality challenges, policies, and capacities. These interim targets serve as benchmarks for governments and policymakers to aim for in reducing air pollution over time. In the UK, the government has set an annual mean concentration target of 10 μg/m^3 of $PM_{2.5}$ to be achieved by 2040 under the Environment Act (DEFRA, 2023b).

Exposure to fine particulate matter in childhood is linked to a range of health problems. Short-term exposure exacerbates asthma and other respiratory conditions (Liu et al., 2018; Wang et al., 2021), while chronic exposure may lead to lifelong reductions in lung function (Zhang et al., 2022), and increase the risk of asthma development (Whitty and Jenkins, 2022). There is increasing evidence of links between air pollution exposure and reduced cognitive function (Chandra et al., 2022; COMEAP, 2023).

Given these concerns, there has been large media and research interest in air quality around schools, including a literature review that included 14 studies in the UK alone (Osborne et al., 2021a). In 2021, a study concluded that approximately one third of state-funded schools providing education up to the age of 18 years with over 3.3 million students were located in areas where the WHO guideline for $PM_{2.5}$ (then 10 μg/m^3) was exceeded in 2017 (Osborne et al., 2021b). The study also highlighted that these high-pollution areas disproportionately affected socio-economically disadvantaged and ethnically diverse pupils, with such schools often situated near major roads and lacking greenspace (Osborne et al., 2021b). Mahfouz et al. (2024) reported that 100 % of new schools' sites in England breached the WHO AQG for $PM_{2.5}$.

However, these studies have focused mostly on schools and commuting routes in London, and none have examined the air quality around Early Years Providers (EYPs), which include nurseries, kindergartens and preschools that offer childcare services for children under 5 years old. Only one study, not peer reviewed, has specifically examined $PM_{2.5}$ exposure around EYPs; and this focused solely on $PM_{2.5}$ concentrations around EYPs in London (Greater London Authority, 2024). This study recommended measures to reduce emissions and exposure, including "no engine idling" schemes, reducing emissions from boilers and kitchens, creating school streets, adding green barriers, promoting active travel, and trialling indoor air filtration systems (Greater London Authority, 2024).

Our aim was to examine changes in $PM_{2.5}$ around EYPs in England from 2018 to 2022 and to identify neighbourhood characteristics associated with EYPs located in areas where $PM_{2.5}$ levels exceed international guidelines. Our objectives were to (i) evaluate temporal changes in $PM_{2.5}$ concentrations at EYPs focusing on variations in exposure by socio-demographic factors; (ii) identify any clustering of EYPs in areas where $PM_{2.5}$ exceeds the UK target to be reached by 2040 (WHO interim target level of 10 μg/m^3); and (iii) evaluate the association between small-area level socio-demographic (deprivation, ethnicity, and rural-urban classification) and $PM_{2.5}$ concentrations around EYPs.

2. Material and methods

2.1. Data sources

2.1.1. Early Years Providers

EYPs locations in England were sourced from the Ordnance Survey (OS) "Points of Interest™" data (Ordnance Survey (GB), 2018, 2019, 2020, 2021, 2022), which are updated quarterly. For this study, we used OS Points of Interest data published in March of each year for the period 2018 to 2022. We selected "Nursery Schools and Pre and After School Care" from that dataset with the PointX class code of "05320397". This category covered: After School Care, Child Care, Childcare Services, Creche, Day Nursery, Independent Nursery School, Independent Pre-Preparatory School, Nurseries and Creches, Nursery School, Organised Children's Play Schemes, Playgroups, Pre School-Education, and Pre School. This list of EYPs was then de-duplicated to provide one EYPs per location as EYPs were sometimes categorised under more than one service type (e.g. nurseries that also provided after-school care).

2.1.2. $PM_{2.5}$

We focused on $PM_{2.5}$ concentrations for our main analyses as the regulated ambient air pollutant with the greatest evidenced impact on health in the UK (COMEAP, 2023; Garcia et al., 2023). Data on $PM_{2.5}$ concentrations was sourced from the UK Air Information Resource (AIR) (DEFRA, 2023c), which provides annual mean concentrations of $PM_{2.5}$ across 1 km * 1 km grids in England. We attributed grid-based $PM_{2.5}$ concentration values to point locations representing EYPs using a spatial join for each year from 2018 to 2022. These point locations correspond to the x, y coordinates of the EYPs, enabling the assignment of air pollution data to their exact geographic positions.

2.1.3. Data sources for small-area level characteristics

To examine area-level socio-demographic characteristics, we used the Lower Super-Output Area (LSOA) corresponding to each EYP's geographic location. LSOAs consist of 400 to 1200 households and typically have a resident population ranging from 1000 to 3000 people (ONS, n.d.).

We used the Ministry of Housing, Communities and Local Government's (Noble et al., 2019) Income Deprivation Affecting Children Index (IDACI) to assess deprivation of the LSOAs in which the EYPs were located. IDACI is a LSOA-level measure of child poverty based on the proportion of children aged 0–15 years living in income-deprived households. Income-deprived households are defined as those where occupants are receiving income-related benefits (e.g. income support, jobseeker's allowance, working families tax credit, and/or disabled persons tax credit) (Noble et al., 2019). Data on the ethnic group distribution by LSOA was obtained from the 2021 England and Wales Census data (ONS, 2023). The Rural-Urban classification for LSOA in England for 2011 was obtained from the Department for Environment, Food and Rural Affairs (DEFRA, 2013). We assigned these LSOA-level data on small-area characteristics from polygon-based spatial datasets to point locations representing EYPs through a spatial join for each year from 2018 to 2022.

2.1.4. Variable definitions

Our primary outcomes were: a) the $PM_{2.5}$ concentration levels at the locations of EYPs in England and b) the proportion of EYPs situated at locations where $PM_{2.5}$ concentrations exceeded the WHO AQGs (WHO, 2021). We examined the latter using two thresholds: in comparison with the WHO guidelines level (5 μg/m^3), and the UK target to reach by 2040/WHO interim target of 10 μg/m^3 (WHO, 2021). These thresholds allowed us to assess the distribution of exposure relative to both guidelines for the protection of health, and legal limits.

The IDACI deprivation measure ranks areas in England based on deprivation, with values ranging from 1 (most deprived) to 32,844 (least deprived), representing the total number of LSOAs. For our analysis, we categorised this variable into quintiles: Quintile 1 (most deprived) to Quintile 5 (least deprived).

We categorised LSOAs as 'white' where >50 % of the population identified as white and as 'other than white' where >50 % of the population identified as Asian, black, mixed, or other racial/ethnic groups. This classification was chosen because, during preliminary analysis, the number of EYPs in LSOAs where ethnic minority groups comprised >50

% of the population was very small (fewer than 8 % of providers). Further dividing these areas into more specific ethnic group categories according to most frequently recorded group would have reduced the statistical power of the analysis.

We used the 2011 Rural-Urban Classification for LSOAs in England (DEFRA, 2013) to create a binary variable, 'Rural' and 'Urban'. The rural category encompasses towns and fringe areas, villages, hamlets, and isolated dwellings, while the urban category includes major and minor conurbations, as well as cities and towns (DEFRA, 2013). This binary classification was chosen to increase the statistical power of the analysis.

We used calendar year of the study period to explore trends in $PM_{2.5}$ around EYPs. The study period (2018–2022) included the national lockdown periods implemented in response to the COVID-19 pandemic in England (Brown and Kirk-Wade, 2021). The first lockdown in England began on March 23, 2020, with partial easing of restrictions starting on 10 May and more substantial lifting on July 4, 2020. A second, shorter lockdown took place from 5 November to December 2, 2020, after which a regional tier system was introduced. A third national lockdown commenced on January 6, 2021, followed by a phased easing of restrictions: schools reopened on 8 March, non-essential businesses on 12 April, and indoor hospitality on 17 May. Most remaining legal restrictions were lifted on July 19, 2021, marking the end of the lockdown periods.

2.2. Statistical methods

We evaluated the number and proportion of EYPs between 2018 and 2022 that were situated in areas where $PM_{2.5}$ levels exceeded the WHO AQG ($\leq$5 μg/m^3) and the lowest interim target ($\leq$10 μg/m^3). For categorical variables (IDACI, ethnic composition, and urbanicity), we calculated the annual total and respective percentage of EYPs, while for continuous variables ($PM_{2.5}$ annual mean concentration), we reported the mean, standard deviation (SD), median, minimum, maximum values, and interquartile range for each year. To explore variations in $PM_{2.5}$ concentrations across different socio-demographic factors, we created boxplots stratified by year. We assessed within-year comparisons of $PM_{2.5}$ concentrations using non-parametric tests. For multiple categories (e.g. IDACI quintiles), we used the Kruskal-Wallis test to evaluate differences in $PM_{2.5}$ concentrations for each study year. When significant differences were detected, we conducted Dunn's post-hoc test with Bonferroni adjustment for pairwise comparisons. For binary categorical variables (e.g. rural-urban classification), we applied the Wilcoxon rank-sum test to assess differences in $PM_{2.5}$ concentrations within each year, with p-values adjusted for multiple comparisons.

To identify spatial clustering of EYPs exceeding the $PM_{2.5}$ WHO lowest interim target, we analysed the spatial pattern of air pollution exposure using Global Moran's I and Local Moran's I. We first used Global Moran's I (Moran, 1948) to measure the overall degree of spatial autocorrelation between annual concentrations of $PM_{2.5}$ at each EYP. A Global Moran's I near 1 (or −1) indicates values of locations that are close in space tend to be similar (or dissimilar) to each other, and a Moran's I close to 0 implies a scatter of random values across space. A statistically significant Moran's I ($p < 0.05$) is indicative of the existence of a significant spatial autocorrelation in the data values. For each year, we calculated the Global Moran's I statistic to assess the spatial autocorrelation of $PM_{2.5}$ concentrations at the EYP level. The neighbours of each EYP are defined as those within a circle of a 2 km radius centred at that EYP. The resulting spatial weights matrix is row standardised so that all weights lie between 0 and 1 (Esri, 2024). This method is commonly used when the distribution of features might be biased by sampling design or aggregation, and it helps to mitigate bias due to varying numbers of neighbours (Esri, 2024). Row-standardised weighting is particularly suitable for fixed distance neighbourhoods (Esri, 2024).

To identify priority intervention zones and track progress towards air quality targets, we then used Local Moran's I (Anselin, 1995) to analyse spatial patterns (clusters and outliers) of EYPs exposure to $PM_{2.5}$. Local Moran's I value indicates positive spatial autocorrelation whereby, in the context of our study, EYP locations that are close in space tend to have similar $PM_{2.5}$ values. It was calculated according to the following criteria, using the nearest neighbour algorithm: Euclidean distance as the measurement method, a threshold distance of 2 km to establish spatial relationships. The row-standardised spatial weights matrix is the same as that used for calculating the Global Moran's I. This technique classifies EYPs into four categories based on their spatial association with annual $PM_{2.5}$ concentrations: High-High (significant clusters of high $PM_{2.5}$ values), Low-Low (significant clusters of low $PM_{2.5}$ values), High-Low (high $PM_{2.5}$ values near low values), and Low-High (low $PM_{2.5}$ values near high values). The cut-off value for classifying high or low $PM_{2.5}$ concentrations varied across the study period, with values ranging from 7.5 μg/m^3 in 2021 to 9.6 μg/m^3 in 2019, reflecting year-to-year variation in $PM_{2.5}$ levels. To ensure comparability across years, we assess High-High clusters by counting the number of clusters where $PM_{2.5}$ concentrations exceed 10 μg/m^3 each year, and we assess Low-Low clusters by counting those where $PM_{2.5}$ concentrations are $\leq$10 μg/m^3. This approach allows us to consistently compare the presence and distribution of high and low concentration clusters in relation to the WHO guidelines over time. To assess the likelihood of cluster or outlier status, we employed 9999 permutations, determining significance with a p-value threshold of $\leq$0.05, adjusted for multiple testing using the False Discovery Rate (FDR) correction (Benjamini and Hochberg, 1995). Permutation testing is a robust, non-parametric method commonly used in spatial analysis to generate empirical distributions under the null hypothesis (Anselin, 1995). In this context, permutations involved randomly reassigning data values to different locations 9999 times, creating a distribution of spatial patterns that could occur purely by chance. By comparing our observed spatial pattern to this random distribution, we determined if the observed clusters and outliers were statistically significant or if they could likely have arisen randomly. Given that we performed multiple tests across many locations, each with its own potential p-value, the likelihood of false positives increased - meaning we might have identified random clusters as significant. The FDR correction addressed this by adjusting the p-value threshold downward from 0.05 to a more stringent level, effectively controlling for the increased risk of false positives across multiple tests (Benjamini and Hochberg, 1995). This adjusted threshold better reflects a true 95 percent confidence level across the dataset, ensuring that clusters identified as significant were unlikely to be due to random chance. Both spatial autocorrelation, cluster and outlier analysis and mapping were conducted in ArcMap 10.3.1 for Desktop (Esri, 2015) and ArcGIS Pro 3.2.0 (Esri, 2023).

To evaluate the association between small-area level sociodemographic (deprivation, ethnicity, and rural-urban classification) and $PM_{2.5}$ concentrations near EYPs, we developed a Bayesian spatial regression model with random effects. The response variable was the mean annual concentration of $PM_{2.5}$ at each EYP. Although we tested this variable for normality using the Kolmogorov-Smirnov test and visualised it through plots (Fig. S 2), $PM_{2.5}$ concentrations did not strictly follow a normal distribution. Nonetheless, we assumed a normal distribution, as this assumption pertains to the residuals rather than the data itself, and Bayesian hierarchical models are robust, especially when handling aggregated or slightly non-normally distributed data (Gelman et al., 2013). The Bayesian framework enabled us to construct realistic models that incorporated spatial dependencies and accounted for variability in $PM_{2.5}$ exposure (Cheng et al., 2021). This approach also allowed us to assess the robustness of our conclusions under different model assumptions and incorporate uncertainty from both data and model parameters.

Let y_{it} represent the $PM_{2.5}$ concentration at each EYP $i = 1, \ldots, N$ in year t (with $t = 1, \ldots, 5$, with 1 representing 2018). The model is specified as:

$$y_{it} \sim Normal(\mu_{it}, \sigma^2)$$

Where:

$$y_{it} = \beta_0 + \beta_1 {}^*IDACI_{it} + \beta_2 {}^*Ethnicity_{it} + \beta_3 {}^*Urbanicity_{it} + \gamma_t + u_{LSOA[i]} + v_{LSOA[i]} \quad \text{(Equation 1)}$$

In this equation, β_0 is the intercept, while $\beta_1, \ldots, \beta_4$ are the regression coefficients for the covariates: IDACI (Income Deprivation Affecting Children Index, 2019 Quintiles at LSOA population level), Ethnicity (Ethnic Composition at LSOA population level), Urbanicity (at LSOA population level), and $\gamma_1, \ldots, \gamma_5$ are the year effects with $\gamma_1 = 0$ (i.e. setting 2018 as the reference). The term $u_{LSOA[i]}$ denotes the spatially structured random effect modelled via the Besag intrinsic conditional autoregressive structure to account for spatial dependence between neighbouring LSOAs; $v_{LSOA[i]}$ represents the spatially unstructured random effect at the LSOA level, capturing random noise or additional residual variability not explained by the covariates.

Spatial random effects were specified using the Besag–York–Mollié (BYM) model (Besag et al., 1991), combining spatially structured random effects, modelled via an intrinsic conditional autoregressive (ICAR) model and spatially unstructured random effects (modelled via an exchangeable normal distribution) (IID) (Besag, 1974). To account for spatial dependency, we defined neighbourhood structures among LSOAs using Rook's case contiguity, where two LSOAs are considered neighbours if they share a common boundary (Besag, 1974; Besag et al., 1991). This adjacency information was incorporated into the model via an adjacency matrix, enabling to capture spatially structured random effects based on the assumption that geographically close areas exhibit similar $PM_{2.5}$ levels (Cressie, 2015), a feature of our data that we will show in Fig. 1 and in Table S2.

Prior distributions were assigned to the model parameters, including the regression coefficients and the random effects. Vague normal priors N (0, 1000) were used for the regression coefficients, reflecting minimal prior knowledge about their values. The precision parameters for the random effects were assigned a Gamma (1, 0.00005), providing a non-informative prior that allows the data to drive the estimation. Precision parameters are the inverse of variance, controlling the spread or variability of random effects in the model. High precision indicates low variance, leading to more tightly clustered values around the mean, whereas low precision suggests higher variability (Gelman et al., 2013).

The analysis was conducted using the Integrated Nested Laplace Approximation (INLA) method via the R-INLA package (Rue et al., 2009). INLA is particularly suited for fitting complex spatial models efficiently, even with large datasets like the one used in this study because it significantly reduces computational burdens compared to traditional Markov Chain Monte Carlo (MCMC) methods (Rue et al., 2009). We also considered different versions of the model: one with covariates only; one with random effects only, and the intercept-only model. Model comparison was performed using the Deviance Information Criterion (DIC) and the Watanabe-Akaike Information Criterion (WAIC), both of which evaluate model fit and complexity. The model with the lowest DIC and WAIC values was selected as the most parsimonious, final model. To assess model fit, we compared fitted versus observed $PM_{2.5}$ values using a scatter plot, examining the alignment of data points along a 45-degree reference line (y = x). This visual check allowed us to evaluate the model's predictive accuracy across the range of $PM_{2.5}$ concentrations and detect any systematic deviations.

2.3. Sensitivity analysis

One limitation of the UK-Air modelled concentration maps is their coarse spatial resolution (1 km × 1 km), which may obscure finer-scale variability in pollutant levels and lead to inaccuracies when estimating exposure at specific school locations (Osborne et al., 2021b). To assess the potential impact of this limitation and to demonstrate the convergent validity of our main exposure, we conducted a sensitivity analysis using higher-resolution data (10 m × 10 m) for $PM_{2.5}$ concentration data for Birmingham and its surrounding areas (referred to here as

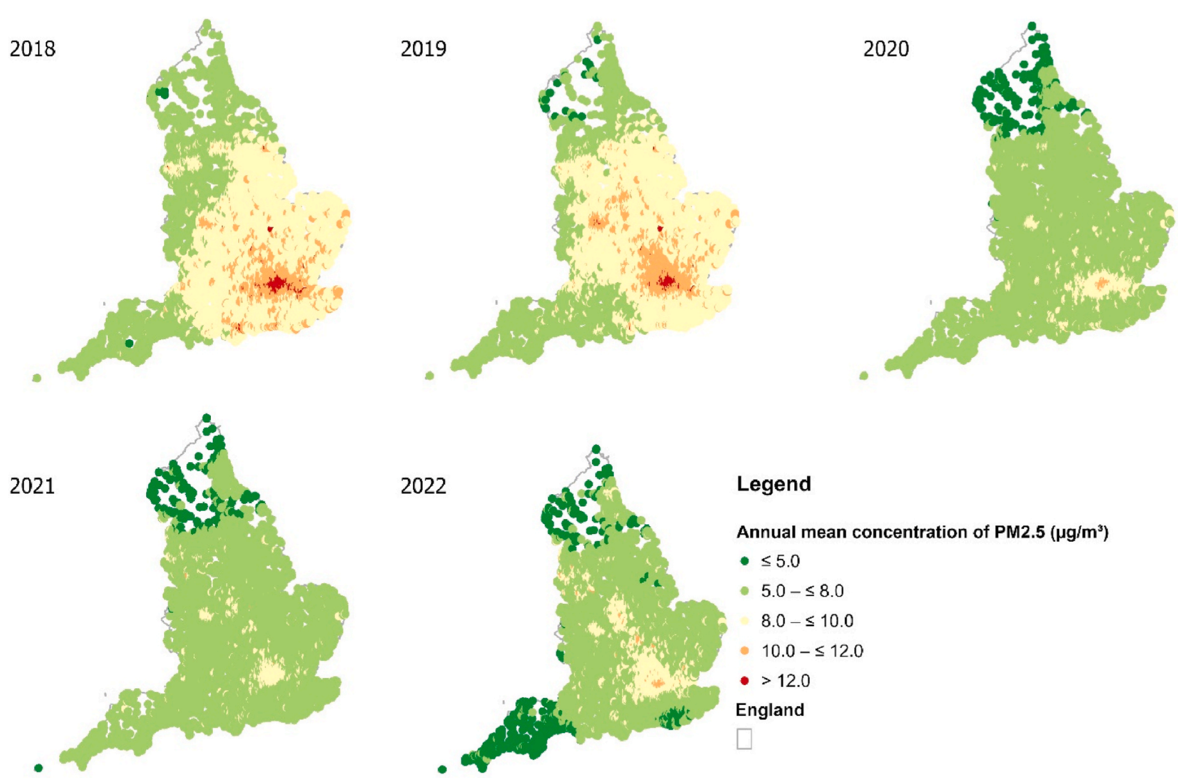

Fig. 1. Annual mean concentrations of $PM_{2.5}$ (µg/m^3) estimated at each Early Year Provider's (EYPs) location across England during the period of 2018–2022.

Birmingham). Birmingham was selected as it is one of the largest urban conurbations in England, with diverse socio-demographic characteristics and significant air pollution challenges, making it a representative area for validation. Furthermore, the additional data used have been peer-reviewed and are derived from high-resolution modelling techniques, validated against local observations, providing a robust benchmark for comparison (Zhong et al., 2021, 2024). For this analysis, we compared exposure results obtained from two datasets for the year 2019: the UK Air Information Resource (UK-AIR) (DEFRA, 2023c), which provides $PM_{2.5}$ data at a 1 km × 1 km resolution and that we used for our main analysis, and the WM-Air ADMS-Urban model (Zhong et al., 2021; Zhong et al., 2024) which offers a finer street-scale resolution of 10 m × 10 m. By focusing on Birmingham, where high-resolution data were available, we assessed whether the coarser UK-AIR dataset yielded similar results to the more detailed WM-Air model for 2019. We used the Wilcoxon signed-rank test with continuity correction to evaluate differences between the two datasets, thereby assessing the consistency of $PM_{2.5}$ estimates across resolutions and validating our exposure measurements for EYPs.

3. Results

A total of 21,893 unique EYPs were identified in England between 2018 and 2022. The number of EYPs registered in each year ranged from 15,780 in 2018 to 18,427 in 2019 (See Supplementary material: Table S 1)

From 2018 to 2022, the annual mean $PM_{2.5}$ concentration near EYPs in England decreased by 17.8 % (from 9.4 μg/m^3, SD = 1.8–7.8 μg/m^3, SD = 1.5, Table S 1). Despite this downward trend, the annual mean concentration of $PM_{2.5}$ near EYPs remained above the WHO AQG of 5 μg/m^3 throughout (Table S 1; Fig. 1). However, during this period, we observed a substantial increase in the proportion of EYPs locations that

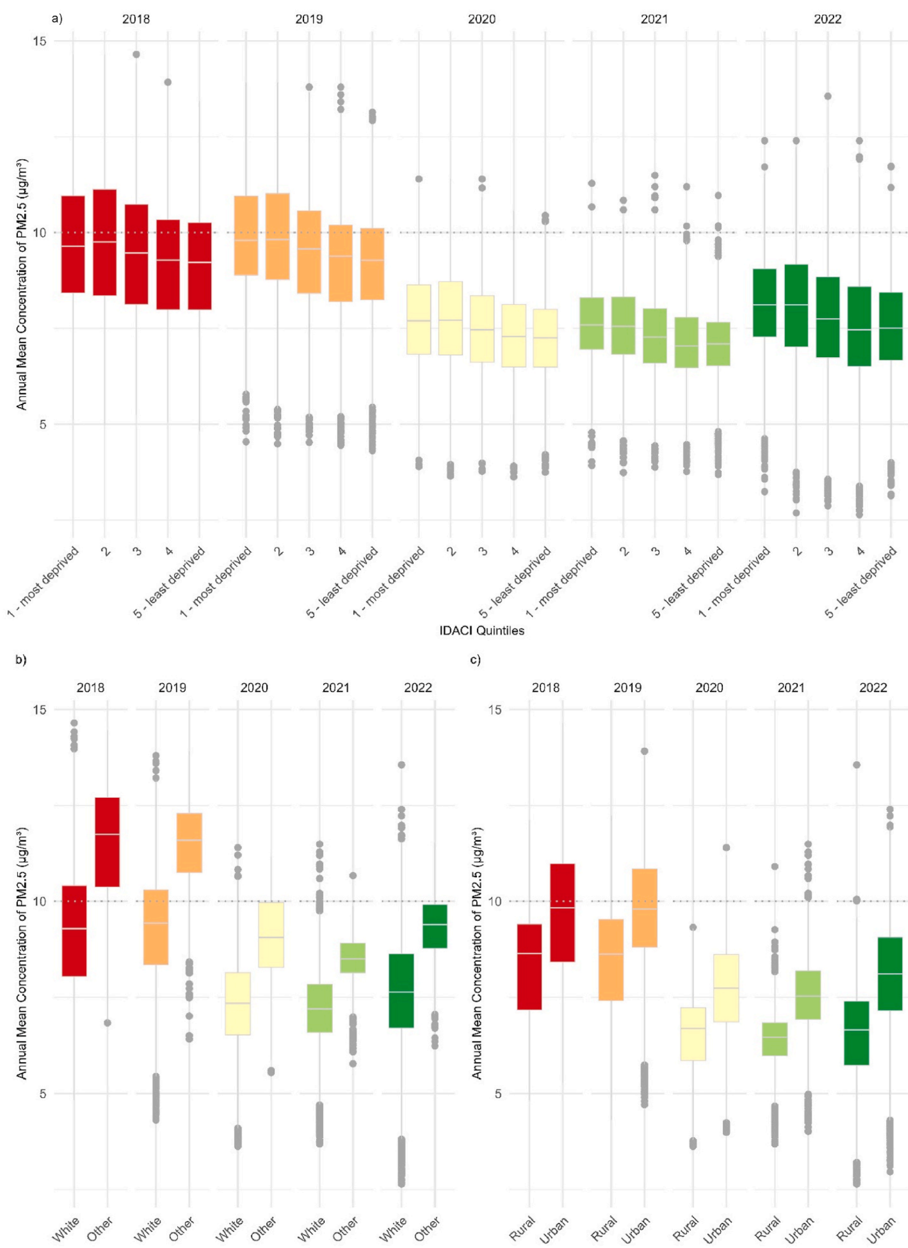

Fig. 2. Annual Mean $PM_{2.5}$ Concentration (μg/m^3) around Early Years Providers (EYPs) in England by Socio-Demographic Factors, 2018–2022: (a) IDACI Quintiles (Income Deprivation Affecting Children Index), (b) Ethnicity, and (c) Rural-Urban Classification. Each boxplot illustrates the distribution of $PM_{2.5}$ levels for each category per year, with a horizontal dotted line at the 10 μg/m^3 WHO AQG lowest interim target.

met the $\leq$10 μg/m^3 guideline of annual mean concentration of $PM_{2.5}$, rising from 62 % ($n = 9862$) in 2018 to 94 % ($n = 15,702$) in 2022. Nevertheless, by 2022, 90 % ($n = 14,958$) of the EYPs were located in areas with mean annual concentration of $PM_{2.5}$ between 5 and 10 μg/m^3. EYPs were located in LSOAs with a predominantly white population and this was consistent across study years (Table S 1). Urban areas housed between 78 % (2018: $n = 12,264$) and 80 % (2020: $n = 14,031$) of EYPs, emphasising a significant urban concentration. The distribution of EYPs across IDACI quintiles were also consistent across the study period and evenly distributed across quintiles (16–23 % in each) suggesting an even spread across deprivation quintiles (Table S 1).

Fig. 2 illustrates the annual mean $PM_{2.5}$ concentration from 2018 to 2022, highlighting variation across factors such as deprivation (IDACI quintiles), ethnicity, and rural-urban classification. In 2018 and 2019, the concentration of EYPs in areas where $PM_{2.5}$ levels exceeded the WHO interim target (>10 μg/m^3) was higher in the most deprived areas (IDACI Quintiles 1 and 2) compared to the least deprived areas (Quintile 5). Specifically, in 2018, 43.6 % of EYPs in Quintile 1 (1111 out of 2550) were above the target, compared to 30.5 % in Quintile 5 (1098 out of 3605). A Kruskal-Wallis test indicated significant differences in $PM_{2.5}$ levels across IDACI quintiles ($H(4) = 288.1$, $p < 0.001$). Following this, Dunn's post-hoc test revealed significant pairwise differences, including between Quintile 1 and Quintile 5 ($z = -11.9$, $p < 0.001$, Bonferroni-adjusted), indicating that Quintile 1 had a significantly higher proportion of EYPs exposed to $PM_{2.5}$ above 10 μg/m^3 compared to Quintile 5. In 2019, this trend persisted, with 44.7 % of EYPs in Quintile 1 (1558 out of 3484) exceeding the target versus 27.8 % in Quintile 5 (1068 out of 3843) ($H(4) = 539.0$, $p < 0.001$, $z = -17.7$, $p < 0.001$, Bonferroni-adjusted) (Fig. 2a). Although there was a decrease in the proportion of EYPs with high exposure (>10 μg/m^3) across all IDACI quintiles in 2020 (mean = 7.5 μg/m^3, SD = 1.3) and 2021 (mean = 7.3 μg/m^3, SD = 1.0), $PM_{2.5}$ levels began to rise again in 2022 (mean = 7.8 μg/m^3, SD = 1.5), particularly impacting EYPs in the most deprived quintiles (Fig. 2a).

While only a small proportion of EYPs were located in LSOAs predominantly composed of 'other than white' ethnic groups (8.3 % in 2018, $n = 1313$; 8.8 % in 2019, $n = 1618$) (Table S 1), the majority of these providers were exposed to $PM_{2.5}$ levels above the WHO AQG lowest interim target of 10 μg/m^3 (Fig. 2b). Specifically, in 2018, 78.8 % of EYPs in 'other than white' LSOAs (1035 out of 1313) exceeded the target, increasing to 83.6 % (1353 out of 1618) in 2019, compared to those in predominantly 'white' LSOAs (33.8 %, $n = 4883$ out of 14,467 in 2018; 32.1 %, 5401 out of 16,809 in 2019) (Fig. 2b). In 2020, similar disparities in $PM_{2.5}$ levels according to ethnic composition of the LSOA population were observed throughout the study period, although $PM_{2.5}$ concentrations decreased during 2020 and 2021 (Fig. 2b). The Wilcoxon rank-sum test indicated significant differences in annual $PM_{2.5}$ exposure for EYPs located in 'white' versus 'other than white' LSOAs across all years from 2018 to 2022 ($p < 0.001$, Bonferroni-adjusted).

We found substantial rural-urban differences in $PM_{2.5}$ exposure levels. The Wilcoxon rank-sum test consistently demonstrated significantly higher annual $PM_{2.5}$ concentrations in urban compared to rural areas for each year in the 2018–2022 period ($p < 0.001$, Bonferroni-adjusted). In 2018 and 2019, a higher proportion of urban EYPs (2018: 46.3 %, 5679 out of 12,264; 2019: 44.2 %, 6419 out of 14,531) were located in areas that exceeded the interim $PM_{2.5}$ guidelines compared to rural EYPs (2018: 6.8 %, 239 out of 3516; 2019: 8.6 %, 335 out of 3896) (Fig. 2c). This disparity sharply declined during of 2020 and 2021, with the proportion of EYPs in areas exceeding $PM_{2.5}$ levels of 10 μg/m^3 in 2020 falling to 6.4 % for urban EYPs (894 out of 14,031) and 0 % for rural EYPs, and in 2021 to 0.2 % (22 out of 13,503) in urban areas and 0.1 % (2 out of 3308) in rural areas (Fig. 2c).

The full model to estimate the EYPs exposure to $PM_{2.5}$, incorporating both covariates and LSOAs' random effects, yielded the lowest DIC and WAIC values compared to the models with only random effects or only covariates (Table S 3). The scatter plot comparing fitted versus observed $PM_{2.5}$ values demonstrates a good model fit, as shown by the close alignment of data points along the 45° reference line (Fig. S 2). This alignment indicates the observed $PM_{2.5}$ values were modelled reliably, providing the support for using this model to assess the covariate effects. Table 1 presents the posterior mean and 95 % credible interval for each regression coefficient (β) from Equation (1).

Each estimate represents the expected change in $PM_{2.5}$ concentration (μg/m^3) associated with a change to a socio-demographic category while holding all other covariates fixed and having adjusted for LSOA-level variation through the random effects. The variance for the independent (IID) random effects was 0.00003 (95 % credible interval (CI): 0.00001, 0.00018), reflecting minimal variability among these unstructured effects (Table 1). In contrast, the ICAR model's variance was 0.27 (95 % CI: 0.26, 0.28), indicating a much higher variation in the spatially structured random effects, thus highlighting their importance for accounting for the spatial structure in the exposure data (Table 1).

Across the study period from 2018 to 2022, EYPs in less deprived IDACI quintiles were consistently located in areas with lower $PM_{2.5}$ levels compared to those in the most deprived quintile (reference group). The largest difference in $PM_{2.5}$ concentrations was observed between the most and the least deprived quintile, with a reduction of -0.2 μg/m^3 (95 % CI: 0.2 to -0.2; Table 1) in the least, compared to the most deprived areas. EYPs located in 'Other than white' LSOAs also had higher $PM_{2.5}$ concentrations, with an average difference of 0.1 μg/m^3 (95 % CI: 0.1 to 0.1) compared to EYPs in predominantly white LSOAs (Table 1). In rural areas, $PM_{2.5}$ concentrations for EYPs were substantially lower than in urban areas, with an average difference of -0.5 μg/m^3 (95 % CI: 0.5 to -0.5; Table 1).

Global Moran's I analysis consistently showed significant positive spatial autocorrelation over the five-year study period ($p < 0.005$), indicating a non-random spatial distribution of $PM_{2.5}$ exposure (Table S 2).

Table 1
Posterior mean estimates and 95 % credible intervals from the spatial Bayesian hierarchical model (Equation (1)), examining associations between small-area socio-demographic factors (IDACI quintiles, ethnic composition, and urbanicity) and $PM_{2.5}$ exposure levels around Early Years Providers (EYPs) in England, 2018–2022.

Variables	Posterior Mean	95 % Credible Interval
Intercept (β_0)	9.19	9.12, 9.26
Income Deprivation Affecting Children Index (IDACI) 2019 Quintiles (β_1)		
1 - most deprived (reference)		
2	**−0.03**	**−0.05, -0.01**
3	**−0.07**	**−0.09, -0.05**
4	**−0.15**	**−0.17, -0.12**
5 - least deprived	**−0.19**	**−0.21, -0.17**
Ethnic Composition at LSOA Population Level (β_2)		
White (reference)		
Other than white	**0.12**	**0.08, 0.15**
Urbanicity (β_3)		
Urban (reference)		
Rural	**−0.46**	**−0.48, -0.44**
Year (γ_t)		
2018 (reference)		
2019	**0.03**	**0.02, 0.05**
2020	**−1.98**	**−2, -1.97**
2021	**−2.17**	**−2.19, -2.16**
2022	**−1.75**	**−1.77, -1.74**
Model Hyperparameters		
Variance for the Gaussian observations	0.39	0.38–0.39
Variance for IID ($v_{LSOA[i]}$)	0.00003	0.00001, 0.00018
Variance for ICAR ($u_{LSOA[i]}$)	0.27	0.26, 0.28

* The model includes spatial random effects specified through the BYM model to account for spatial correlation (see the main text for detail). The posterior distribution of each parameter estimate is summarised via the posterior mean and the 95 % Credible Interval. Associations are highlighted in bold where the 95 % Credible Interval does not include zero, indicating higher confidence in the direction of the effect.

The Local Moran's I cluster and outlier analysis in Fig. 3 reveals distinct spatial clustering patterns of $PM_{2.5}$ exposure around EYPs across England over a five-year period (2018–2022). Throughout this period, High-High clusters—areas where EYPs with high $PM_{2.5}$ levels (>10 μg/m^3) are surrounded by other high-exposure EYPs - are consistently located in urbanised and industrial regions, particularly in southern and eastern England. Notable concentrations of High-High clusters were observed around major urban centres, including Greater London, Birmingham, and other parts of the Midlands and Southeast England. Conversely, Low-Low clusters - regions where EYPs with low $PM_{2.5}$ exposure are near other low-exposure EYPs - were primarily situated in northern and rural regions such as Devon, Cornwall, and the northern parts of England. A clear temporal pattern emerged, with a substantial decrease in High-High clusters where the annual mean $PM_{2.5}$ concentration exceeded 10 μg/m^3, dropping from 22.6 % (3565 out of 15,780 EYPs) in 2018 to 5.5 % (916 out of 16,634 EYPs) in 2022. The Low-Low clusters, with annual mean $PM_{2.5}$ concentration below or equal to 10 μg/m^3, ranged between 18.1 % in 2018 (2851 out of 15,780 EYPs) and 12.7 % in 2021 (2141 out of 16,811 EYPs).

3.1. Sensitivity analysis

In the 2019 sensitivity analysis including 850 EYPs in Birmingham, the UK-Air model estimated a higher proportion of EYPs exposed to elevated $PM_{2.5}$ levels (>10 μg/m^3) (83 %, $n = 624$) compared to the WM-Air ADMS-Urban model (70 %, $n = 526$) (Table S 4, Fig. 4). The Wilcoxon signed-rank test demonstrated a statistically significant difference ($V = 17{,}164$, $p < 2.2e\text{-}16$). This indicates that $PM_{2.5}$ modelled concentrations vary significantly depending on the model used, with the observed differences unlikely attributable to random variation alone.

4. Discussion

We observed an 18 % reduction in the annual mean $PM_{2.5}$ concentration around EYPs from 2018 to 2022. Disparities in $PM_{2.5}$ concentrations remained consistent throughout this period however: a greater proportion of EYPs in more deprived, urban, and 'other than white' areas were exposed to $PM_{2.5}$ levels exceeding the WHO AQG lowest interim target of 10 μg/m^3. D During 2020–2021, annual mean $PM_{2.5}$ around EYPs decreased relative to adjacent years; however, disparities in exposure across categories persisted.

$PM_{2.5}$ levels around EYPs consistently exceeded the WHO AQG of 5 μg/m^3, with 4 % (744) meeting this limit by 2022. This aligns with previous research highlighting persistent air quality concerns around educational settings in England. For instance, while Osborne et al. (2021b) demonstrated that nearly a third of state-funded schools exceeded the previous WHO $PM_{2.5}$ guideline of 10 μg/m^3 in 2017, our findings extend this analysis to EYPs, a critical but under-researched group. Similarly, Mahfouz et al. (2024) reported that all new school sites in England failed to meet the updated WHO AQG for $PM_{2.5}$ (5 μg/m^3), underscoring the ongoing challenge of achieving safer air quality in educational environments.

This persistent exceedance underscores ongoing air quality challenges in England, particularly in urban areas with dense traffic and industrial emissions (DEFRA, 2023a). While outdoor air pollution is a significant concern, most research on EYP air quality has traditionally

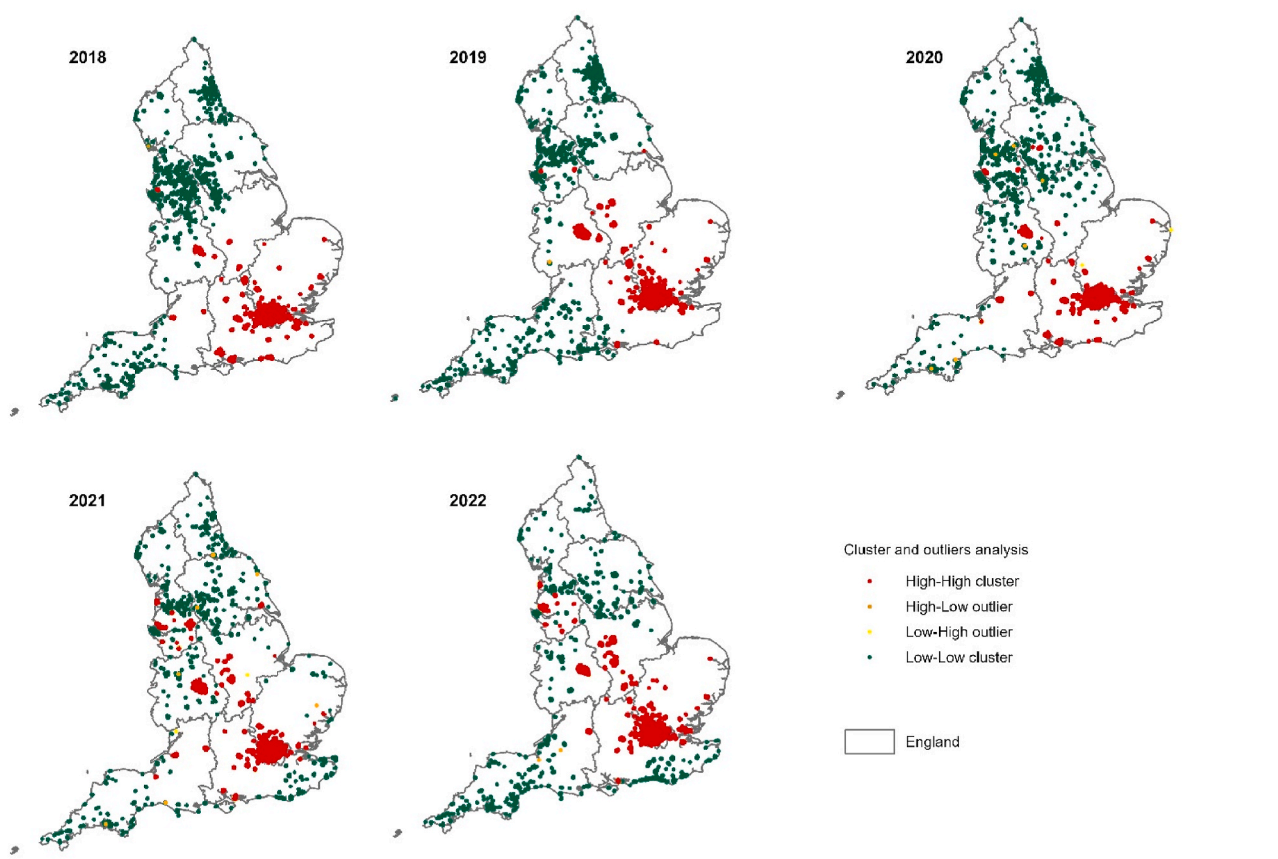

Fig. 3. Local Moran's I cluster and outlier analysis of $PM_{2.5}$ concentration levels at Early Years Providers (EYPs) in England from 2018 to 2022. High-High clusters represent areas where EYPs with high $PM_{2.5}$ concentrations are near others with similarly high levels, while Low-Low clusters indicate areas of low $PM_{2.5}$ concentrations surrounded by similarly low values. High-Low clusters show areas where EYPs with high $PM_{2.5}$ concentrations are near others with lower $PM_{2.5}$ concentrations, and Low-High clusters show the reverse. To enhance visibility, EYPs that were not statistically significant or had no neighbours are excluded from this figure.

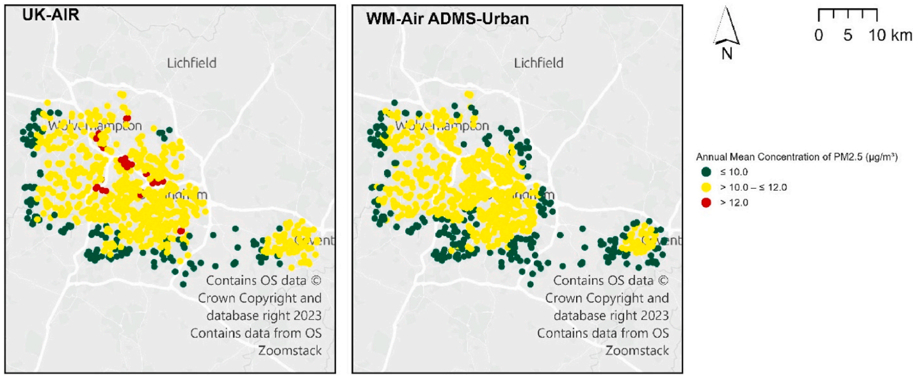

Fig. 4. Spatial visualisation of the mean concentration of $PM_{2.5}$ at each Early Year Provider's location in Birmingham (England, UK) in year 2019, using the UK-Air and WM-Air ADMS-Urban models.

focused on indoor pollutants, often finding that indoor particles matter concentrations are more strongly influenced by indoor sources than by outdoor pollution (Branco et al., 2014; Cano et al., 2012; Nunes et al., 2015). However, indoor and outdoor pollutant levels are interconnected, with indoor/outdoor particle matter ratios varying across cities and pollutant types (Ashmore and Dimitroulopoulou, 2009; Kumar et al., 2024). Exposure to $PM_{2.5}$ in educational settings contributes substantially to children's overall daily $PM_{2.5}$ exposure, even when indoor $PM_{2.5}$ sources are primary contributors. For example, Rose et al. (2024) observed that classrooms in Cardiff (England, UK) had $PM_{2.5}$ and PM_{10} levels above WHO AQG (≤ 5 µg/m^3) during school hours, with 74 %–89 % of $PM_{2.5}$ attributed to outdoor sources. This interaction between outdoor and indoor $PM_{2.5}$ sources highlights the compounded exposure children face, not only within EYPs but also during activities such as school pick-up/drop-off. Edwards and Whitehouse (2018) found elevated black carbon exposure during school hours and commuting times, while Sharma and Kumar (2018) reported that infants in prams can experience up to 60 % higher pollutant concentrations than adults due to their proximity to some emission sources.

The pandemic-associated dip in $PM_{2.5}$ observed during 2020–2021 aligns with global reports of improved air quality linked to reductions in vehicular and industrial activity (Jephcote et al., 2021; Liou et al., 2023). While $PM_{2.5}$ annual concentrations in England saw a slight increase in 2022, compared to 2020 and 2021, urban background $PM_{2.5}$ mean concentrations in 2023 showed a 12 % decrease from 2022 levels, continuing the downward trend observed since 2019 (DEFRA, 2024a).

The spatial clusters of $PM_{2.5}$ concentrations at EYPs closely mirrored the overall $PM_{2.5}$ distribution across England, as reported by DEFRA (2024a). The High-High clusters of EYPs (>10 µg/m^3 of $PM_{2.5}$ concentrations) were highest in urban areas of southern and eastern England may be due to factors such as higher population density, prevailing weather conditions, increased pollution from both domestic sources, and cross-border emissions from mainland Europe (DEFRA, 2024a). In 2023, four of the five air quality monitoring sites recording the highest annual mean $PM_{2.5}$ concentrations in urban areas were situated in the South or East of England, including London, with the fifth located in the Midlands (DEFRA, 2024a) mirroring our results.

We showed consistent disparities in $PM_{2.5}$ exposure, with EYPs located in more deprived, urban areas, and 'other than white' LSOAs experiencing higher levels. Our findings align with broader trends showing that areas with higher levels of socio-economic deprivation often overlap with regions of increased traffic or industrial activity, resulting in elevated air pollution levels (Gadenne et al., 2024; Kaÿmierczak, 2018; Whitty and Jenkins, 2022). Socio-economic inequalities further influence children's exposure to air pollution, affecting the environments where they live, play, and attend school (Mathiarasan and Hüls, 2021). Concerning urbanicity, except for ozone, air pollutant concentrations are typically higher in urban areas compared to rural regions (DEFRA, 2024b). Overall, these findings align with global studies indicating that ethnically diverse neighbourhoods often face the poorest air quality (e.g. Fairburn et al., 2019; Fecht et al., 2015; Gadenne et al., 2024; Jbaily et al., 2022). Osborne et al. (2021b) found that English schools in areas with higher $PM_{2.5}$ concentrations were more likely to have a diverse pupil demographic than schools with lower $PM_{2.5}$ levels. The "disadvantage gap" in educational attainment in the early years foundation stage, ranging from birth to five years old, highlights further disparities, with only four ethnic groups outperforming white British pupils at age 5 in 2023: Chinese, white and Asian, white Irish, and Indian (EPI, 2024).

4.1. Strengths and limitations

This study has several key strengths. It is the first large-scale analysis of $PM_{2.5}$ exposure around EYPs across England, focusing on the vulnerable population of young children within diverse socio-economic settings. By addressing this critical gap in the literature, our study offers insights that could guide future air quality policy and research. The study spans a period of 5 years (2018–2022), enabling us to capture changes in air quality, including the years that COVID-19 lockdowns occurred. Additionally, we validated openly available data (UK-AIR, with a 1×1 km resolution) against the finer WM-Air ADMS-Urban modelled concentrations, revealing variability in $PM_{2.5}$ estimates across models. Notably, UK-AIR predicted relatively higher $PM_{2.5}$ exposures in Birmingham compared to the WM-Air model. These findings align with Osborne et al. (2021b), who similarly highlighted variability in $PM_{2.5}$ estimates depending on the data source, reinforcing the importance of robust model validation.

Nevertheless, some limitations should be noted. The reliance on the UK-AIR model for $PM_{2.5}$ analysis, while comprehensive, is affected by year-to-year changes in modelling approaches, such as updates to emission inventories that are not retroactively applied, complicating longitudinal trend interpretation (DEFRA, 2023c). Modelled data introduces additional uncertainties (Osborne et al., 2021b), and our use of area-level metrics (e.g. predominant ethnicity) oversimplifies area-level ethnic diversity. Our analysis is based on annual $PM_{2.5}$ averages, which smooth out seasonal variations in exposure and do not capture short-term fluctuations (DEFRA, 2022). Additionally, we did not assess other pollutants, such as NO_2 or speciated $PM_{2.5}$ components, which may have varying toxicity depending on their source. Future analyses should consider these factors to provide a more comprehensive understanding of air pollution and its health impacts. We recognise that urbanicity, deprivation, and ethnic composition are not independent phenomena. In England, socio-economically deprived and ethnically diverse populations are disproportionately concentrated in urban areas (Fairburn et al., 2019; Fecht et al., 2015; Gadenne et al., 2024; Kaÿmierczak, 2018). These structural patterns reflect longstanding inequalities shaped by urban planning, transport policy, and housing access. While our Bayesian spatial model accounts for these variables simultaneously and incorporates spatial random effects to reduce bias from spatial confounding, some degree of conceptual and geographic overlap is expected. As such, the individual effect estimates should be interpreted with caution, as they may reflect interconnected structural determinants of air pollution exposure. Furthermore, a national database containing individual-level data on all children attending EYPs in the UK (e.g. children's age, ethnicity, health, or time spent at EYPs) does not exist and as such these individual-level variables could not be assessed in this study. The Office for Standards in Education, Children's Services and Skills (OFSTED) register of childcare providers contains information on the number of childcare places (Ofsted, 2024), but these EYPs are not geolinked by x, y coordinates or Unique Property Reference Number (UPRN), which prevented us from linking these data to our current dataset. We are currently exploring this linkage in a separate study to address this issue. Additionally, this study did not include childminders, who play a significant role in early childcare in England. Childminders are self-employed professionals who provide childcare in their own homes for children ranging from birth to age 8, and sometimes older. As of June 30, 2024, there were over 26,300 registered childminders among England's 61,800 childcare providers, collectively caring for approximately 160,000 children (Ofsted, 2024). Since childminders care for children in their own homes, data on their locations are not openly available. Moreover, the Department for Education's Early Years Census only covers children receiving free hours of care (DfE, 2024a). This gap in data coverage may be reduced in the future, as all children in England aged 9 months and older whose parents are in employment are now eligible for 30 h of free childcare per week, starting from September 2024, offered through EYPs, including nurseries and registered childminders (DfE, 2024b). Addressing these limitations in future research could provide a more comprehensive understanding of air pollution concentrations around EYPs in England.

4.2. Policy implications and future research

Our findings highlight the importance of targeted air quality interventions in urban areas, where young children are most exposed to $PM_{2.5}$. In particular, the resurgence of $PM_{2.5}$ levels in 2022, especially in highly deprived areas, highlights the need for sustained, long-term interventions to address persistent environmental inequalities (Nieuwenhuijsen, 2021). Policy efforts to reduce $PM_{2.5}$ exposure around EYPs may benefit from a focus on traffic emissions (including non-exhaust emissions), domestic combustion (including wood burning), and industrial sources. Prior studies and policy initiatives have proposed a range of strategies to mitigate exposure near educational settings, such as discouraging vehicle idling near childcare facilities, enhancing green infrastructure to improve local air quality, and carefully considering the siting of new EYPs in relation to major roads (Greater London Authority, 2024; UKHSA, 2025; UNICEF UK, 2018). Expanding air quality monitoring in and around childcare environments would also support more targeted interventions. Although we did not evaluate interventions directly, peer-reviewed evaluations show that local, area-level actions (e.g. neighbourhood-to-city scale) can reduce exposure (and in some cases improve child health)—for example, London's LEZ/ULEZ programmes demonstrate roadside NO_2 reductions (Mudway et al., 2019) and are being evaluated for child-health impacts (Tsocheva et al., 2023), Stockholm's congestion tax reduced ambient pollution by ~5–15 % and lowered acute asthma attacks in young children (Simeonova et al., 2021), and Dublin's smoky-coal ban produced substantial mortality benefits (Clancy et al., 2002); together these findings support prioritising high-exposure, deprived urban catchments for action. In addition, near-road mitigation and carefully designed vegetation/physical barriers around schools can lower downwind concentrations, complementing network-level emission reductions (Abhijith et al., 2017). Future research should prioritise finer-scale pollution data and rigorous impact evaluations—particularly in EYP-centred and high-deprivation settings—to assess the effectiveness and equity impacts of such area-based interventions.

5. Conclusion

Although $PM_{2.5}$ levels have decreased around EYPs in England, our findings highlight the need for continued efforts to meet clean air objectives. Persistent inequalities in $PM_{2.5}$ exposure remain, particularly for EYPs located in areas of higher deprivation, with more non-white residents, and in areas that were urban. These inequalities highlight the urgent need for targeted action by local authorities and policymakers to protect vulnerable populations, especially young children.

CRediT authorship contribution statement

Joana Cruz: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Guangquan Li:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis. **Amal Rammah:** Writing – review & editing, Methodology. **Jian Zhong:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Niloofar Shoari:** Writing – review & editing, Methodology. **Selin Akaraci:** Writing – review & editing, Methodology. **Samantha Hajna:** Writing – review & editing, Visualization, Methodology. **Caroline Hart:** Writing – review & editing. **Rosemary C. Chamberlain:** Writing – review & editing, Conceptualization. **Christina Mitsakou:** Writing – review & editing, Conceptualization. **Karen Exley:** Writing – review & editing, Conceptualization. **William Bloss:** Writing – review & editing, Methodology, Conceptualization. **Richard Fry:** Writing – review & editing, Conceptualization. **Steven Cummins:** Writing – review & editing, Methodology, Conceptualization. **Pia Hardelid:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Disclaimer

The views expressed in this article are those of the author(s) and are not necessarily those of UK Health Security Agency or the Department of Health and Social Care.

Ethical considerations: This paper does not relate to a study involving research on or data from human subjects or experimental animals.

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Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2025.123172.

Data availability

I have shared the link to my data and code at the attach step.

Towards Cleaner Air: PM2.5 Exposure and Disparities Around Childcare Providers in England (Original data) (OSF)

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