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Original article

A novel approach using synthetic population models to assess how urban vegetation alters health inequalities in PM2.5 exposure

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ABSTRACT

Poor air quality is a significant environmental risk factor for health. Urban vegetation has the potential to improve air quality through the removal of harmful pollutants. Our analysis combines atmospheric chemistry transport models with novel health impact assessment methods to estimate the health and equity impacts of $PM_{2.5}$ removal by urban vegetation on London's all-cause mortality. An atmospheric chemistry model that represents meteorological and chemical interactions was used to determine the change in annual average $PM_{2.5}$ concentrations attributable to urban vegetation. The impact of $PM_{2.5}$ change on annual mortality and how those impacts varied by inequality were determined using a georeferenced synthetic population representative of the London population, with input data on the change in concentrations, area-level mortality rates, and existing exposure-response coefficients. We found socio-economic and area disparities in both $PM_{2.5}$ exposure and in the reduction in annual concentrations attributable to urban vegetation. Although annual mean $PM_{2.5}$ exposure was highest in the most deprived areas, the most affluent areas had a greater reduction in exposure (1.17 μg/m^3) compared to the most deprived areas (1.05 μg/m^3). Avoided annual deaths were estimated as 408 (95%CI: 309–457), equivalent to a 7% reduction in mortality attributed to $PM_{2.5}$. There was less indication of inequality in the avoided deaths when grouped by deprivation deciles. Urban vegetation can help reduce mortality impacts associated with $PM_{2.5}$ in the Greater London region, with variations by area and by socio-economic status. To address inequities in pollutant removal and maximise health benefits, green interventions should be implemented alongside actions that reduce pollution at source.

1. Introduction

Air pollution presents a significant health challenge. In the UK, between 29,000 and 43,000 deaths per year are attributable to the annual mortality burden associated with ambient air pollution (Mitsakou et al., 2022). Exposure to harmful pollutants leads to avoidable acute and chronic ill health from a range of conditions such as cardiovascular and respiratory illnesses, dementia and cancer (Department of Health and Social Care DHSC, 2022), impacting productivity and generating considerable health and economic costs. Other wider impacts on children's wellbeing include cognitive and developmental impairment (Milojevic et al., 2021) and low birth weight. There are variations in air pollution exposure in the UK population by neighbourhood, socio-economic deprivation and ethnic diversity (Milojevic et al., 2017; Fecht et al., 2015); a study based in England found that the most deprived 20 per cent of neighbourhoods had higher air pollution levels than the least deprived neighbourhoods (Fecht et al., 2015).

The UK government considers poor air quality as "the largest environmental risk to public health" (House of Commons Library, 2024). Mechanisms to minimise or prevent harmful exposures and reduce health risks are governed by domestic and international commitments such as UK Government concentration and exposure targets which, for $PM_{2.5}$, include a 'maximum annual mean concentration of 10 μg/m^3 to be met across England by 2040' and a '35% reduction in population

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exposure by 2040 compared to the base year of 2018' (House of Commons Library, 2024). Meeting these targets in urban areas requires a suite of actions to reduce air pollution concentrations, such as emission reductions and/or capture/removal of pollution. Interventions such as Low Emission Zones discourage the use of motorized vehicles whilst encouraging healthy behaviour such as active travel. There is evidence of their effectiveness in improving air quality and, as a consequence, improving health outcomes, such as a reduction in circulatory and respiratory illnesses and child health outcomes, as well as an increase in productivity (Broster and Terzano, 2025). However, while they have been successful in reducing pollutant concentrations, there is a limit to their application in that easy wins have been achieved by regulating industrial sources and vehicles, but future gains could be more challenging to achieve as other sources are more diffuse (e.g. from cooking, domestic heating and transboundary pollution). Also, while some stricter schemes such as the London Ultra Low Emission Zones have been shown to reduce $PM_{2.5}$ concentrations (27% reduction from 2017 to 2020 (Greater London Authority, 2020)), there has been a backlash associated with the financial penalties for non-compliant drivers, and how charges may disproportionately affect low-income households.

Ecosystem-based actions for air pollutant reduction are relatively low-cost multi-functional solutions to complement transport-based interventions, with the added advantage of providing multiple health co-benefits through providing shade and cooling, noise and flood mitigation, and mental and physical health benefits (Jones et al., 2022; Twohig-Bennett and Jones, 2018; Murage et al., 2021). Well-functioning interventions can utilise vegetation to influence pollutant removal through processes such as 1) deposition, where air pollutants settle on the plants' surface, or are absorbed by leaf stomata, 2) dispersion, where plants change the trajectory and velocity of pollutants, and 3) modification, where plants transform gaseous and particulate pollutants either on their surface or within their structures (Diener and Mudu, 2021a).

The aggregate health benefits of using urban vegetation to provide air pollutant mitigation can be substantial. For example, estimates using the Environmental Benefits Mapping and Analysis Program (BenMAP) model suggest trees and forests in the conterminous United States can remove up to 17 million tonnes of air pollution annually, leading to the avoidance of 850 deaths and 670,000 incidences of acute respiratory symptoms (Nowak et al., 2014). A study using the atmospheric chemistry transport model EMEP4UK to calculate pollutant removal by urban vegetation across England and Wales estimated an annual removal of 28, 700 tonnes of $PM_{2.5}$, NO_2, SO_2, and O_3, resulting in 1120 fewer respiratory and cardiovascular hospital admissions and 240 fewer deaths (Jones et al., 2019).

The mechanisms by which urban vegetation reduces air pollution concentrations are complex, as described earlier, and the pollution removal efficiency varies by context since it is determined by pollutant concentrations, interactions between pollutant chemistry and meteorology (Nemitz et al., 2020)' as well as by plant species characteristics (Diener and Mudu, 2021a). While the range of methodologies and approaches to modelling these effects can result in variation in estimates (Khalili et al., 2024; Kumar et al., 2024), atmospheric chemistry transport models are particularly powerful in estimating aggregate health impacts since they accurately represent the meteorological and chemical interactions and processes in the atmosphere that determine pollutant concentrations. However, a key limitation in previous studies that use such modelling approaches is the granularity of translating those changes in exposure into health impacts. One previous study estimated hospital admissions and Life Years Lost using aggregate mortality data at the Local Authority level (Jones et al., 2019). This approach can hide important spatial and demographic variation in vulnerability due to socio-economic and environmental exposure factors, which can vary considerably between local areas, and which limits understanding of the equity issues around both pollutant exposure and measures to address them. The extent to which neighbourhood variations in air pollution result in disparities in health outcomes has also been previously studied, with one study suggesting the drivers of observed socioeconomic gradients in $PM_{2.5}$-attributable Life Years Lost are a combined effect of the gradient in underlying mortality rates across deprivation groups, as well as variations in air pollutant concentrations (Milojevic et al., 2017). One method to address these limitations is through constructing synthetic populations to undertake health impact assessments by assigning demographic, health risks and environmental exposures to individuals in the population, which can, to some extent, help address the ecological fallacy associated with the use of area-level measures. Synthetic populations offer several benefits over area-level administrative data; by reconstructing individual-level characteristics such as age, sex, occupation, health status and so on, they use individual-level data that enables simulation of how synthetic "agents" interact. This allows testing of complex 'what-if' scenarios, providing researchers and policymakers with a powerful tool to explore and test policy options.

This study seeks to better understand the health benefits provided by urban vegetation linked to lower air pollutant concentrations among populations with different deprivation levels. We used data on changes in $PM_{2.5}$ concentration due to urban vegetation cover in London, estimated using the EMEP4UK atmospheric chemistry transport model, which incorporates chemical interactions and atmospheric transport of pollutants across space and time. The impact of the $PM_{2.5}$ change on health and the variability of effects by equity groups was estimated using a novel georeferenced 'synthetic population' of individuals with characteristics (age, gender, socioeconomic status) and mortality rates, which as a whole are representative of the population of the Greater London area. There is some evidence suggesting $PM_{2.5}$ accounts for up to 70% of the health and economic burden of all major air pollutants. Although considering $PM_{2.5}$ might seem conservative, it is likely to capture most of the air pollution-related health impact. In addition, there currently isn't a unanimous approach for multi-pollutant assessment, as such methods are still in development.

2. Methods

Air pollutant concentrations in London, representing the year 2019, were calculated using the atmospheric chemistry transport model EMEP4UK v4.36 (Vieno et al., 2016). The model was run using hourly meteorology calculated using the Weather Research and Forecast model (WRF v4.2.2) (National Centre for Atmospheric Research NCAR, 2019) for 2019. This version of EMEP4UK was run at 0.055° x 0.055° grid resolution, approximately 5×6 km^2 over this area. The EMEP4UK model includes several chemical species, but only results for $PM_{2.5}$ are reported here because it constitutes the majority of air quality-related health impacts in the UK (Jones et al., 2019). The vertical column is divided into 21 vertical layers with the lowest model layer (near the ground surface) having a height of 45 m and up to 2 km at the vertical boundary (~16 km) as described in Simpson et al. (2012) (Simpson et al., 2012).

The 2019 input emissions were derived from the UK National Atmospheric Emissions Inventory (NAEI) published in 2021, and the EMEP Centre on Emission Inventories and Projections (CEIP) (CEIP,). Input on Land cover data was taken from the CEH Land Cover Map LCM2019 at 25 m resolution. The 21 land cover classes were supplemented by three additional classes for urban woodland, urban grassland and urban freshwater, created from more detailed mapping, applicable to capture these elements within city areas (Jones et al., 2019). These used the natural vegetation layer from Ordnance Survey Master Map, differentiating woodland from grassland by reference to surveyor mapping notes describing areas with trees. The urban extent was defined using a morphological definition of settlements based on Ordnance Survey mapping data, modified to incorporate areas of woodland, grassland and water within the urban boundary (Jones et al., 2019). The resulting 24 land cover classes were aggregated to eight classes that are included in EMEP4UK: deciduous woodland, coniferous woodland, cropland, grassland, other vegetation, water, bare soil, urban (built fabric). The definition of urban includes only green and blue space within the urban footprint (Jones et al., 2019, i.e. excludes non-urban woodland that falls within the administrative boundary.

Model validation of the reference run for EMEP4UK output was conducted by comparing model outputs of the pollutant against measured concentrations from 180 monitoring stations within the UK Automatic Urban and Rural Network (AURN) (Defra,)' which provides high-quality monitoring data. AURN monitoring stations typically have sample probes and inlets positioned between 1.5 and 4 m, and theEMEP4UK model projects the modelled concentration at 3 m above ground. Model evaluation statistics were applied to hourly $PM_{2.5}$ concentrations at each individual site and to the annual mean PM2.5 concentration of all sites where the data capture was > = 75%. The following were assessed: fraction of prediction within a factor of two (FAC2), mean bias (MB), normalised mean bias (NMB), root mean squared error (RMSE) and Pearson correlation coefficient (r).

Two separate land cover scenarios were set up to quantify pollution removed by urban vegetation. Calculating the effects of vegetation in a dynamic model requires a counterfactual without vegetation. The counterfactual land cover used was 'bare soil' since that allows a separate calculation of the effect of all other vegetation types, and is a recommended approach for natural capital accounting (United Nations, 2021). This represents an inert counterfactual to assess the benefit of current urban vegetation, i.e. it holds the structural complexity of the surrounding built environment constant, and only changes the vegetation which is the focus of this analysis. The two scenarios run in a UK domain were:

1. **Urban vegetation** – current land cover in urban areas (woodland and grassland) within the urban extent retained, all vegetation outside of the urban extent set to bare soil, including all areas that lie outside of the urban extent, but within the local authority administrative boundary
2. **Counterfactual** – all vegetation classes set to bare soil.

The change in quantity of pollutant removed and change in pollutant concentrations was calculated by comparing the Urban vegetation run with the Counterfactual.

3. Quantification of population health impact

We quantified long-term (annual) $PM_{2.5}$-attributable all-cause mortality under the two scenarios at the individual level by generating a synthetic population of geo-referenced individuals with combinations of socio-demographic characteristics reflecting those in London. This approach enables an assessment of the effects of interventions and the distribution of these effects across population groups. The number of modelled individuals (n = 8,673,713) by gender and age for each London borough (n = 32, excluding the City of London due to insufficient data) was based on age- and gender-specific population data from the Office for National Statistics' (ONS) Nomis data service. As a marker of socio-economic status, each individual was assigned to one of 10 deciles (1 = highest deprivation, 10 = lowest deprivation) of English Indices of Multiple Deprivation (IMD, 2019), an area-based marker of deprivation generated at Lower Super Output Area (LSOA) level, which are small geographies with an average population of 2000. Individuals were also assigned an all-cause annual mortality rate appropriate for their borough, gender and age using borough-specific Nomis mortality data for 2023. The 5-year age-grouped data were converted to single-year-of-age by fitting exponential models and smoothing using a Lowess (Locally Weighted Scatterplot Smoothing) method, a non-parametric regression method that fits multiple regressions in local neighbourhoods of the data.

The $PM_{2.5}$ concentrations in $\mu g/m^3$ under each scenario were extracted at the LSOA level. For each borough, we fitted lognormal distributions to the LSOA $PM_{2.5}$ concentrations under the Urban vegetation scenario and the changes in concentrations between the two scenarios. We then assigned exposures under each scenario to individuals in the synthetic population by sampling from the relevant distributions for their borough. We further applied an adjustment for IMD to each individual's sampled exposure. This adjustment (multiplier) was derived by performing linear regression of $PM_{2.5}$ on IMD decile.

The impact of the $PM_{2.5}$ removal on mortality was modelled at the individual level by applying the change in $PM_{2.5}$ concentration, and a published epidemiological relationship (exposure-response function) to the baseline all-cause mortality rates (adjusted for deprivation decile). We used the standard comparative risk assessment (CRA) approach in which the relative risk (RR) of mortality was calculated for each individual's change in $PM_{2.5}$ exposure. To calculate the RRs, we applied the log-linear exposure-response function recommended for use in the UK by the Committee on the Medical Effects of Air Pollutants (COMEAP) (Committee on the Medical Effects of Air Pollutants COMEAP, 2022) of 1.08 (95% CI: 1.06, 1.09) per 10 $\mu g/m^3$ annual average $PM_{2.5}$ based on a systematic review and meta-analysis of global cohort studies (Chen and Hoek, 2020). The RRs were then used to calculate each individual's attributable fraction using the standard epidemiological formula [(RR - 1) / RR], and this was multiplied by each individual's baseline mortality to calculate the attributable risk of mortality. Finally, we summed the attributable risks over the population to calculate the total $PM_{2.5}$-attributable deaths under each scenario for each borough and for the whole of London. The level of uncertainty in the health impacts (lower and upper limits) was determined using the 95% CI on the exposure-response function.

4. Results

Deprivation levels vary across London, with a greater concentration of deprived neighbourhoods in the inner city boroughs of North East and South Central London (Fig. 1A). Fig. 1B suggests outer London boroughs and those in the periphery have a greater amount of urban vegetation, with Richmond upon Thames having a substantially higher proportion of urban vegetation than any other borough (Supplementary Table 2). The model evaluations show good agreement between modelled estimates and the observed $PM_{2.5}$ concentration from 76 UK sites (Supplementary Table 1 and Supplementary Figure 1)

There were significant and positive correlations between borough-level deprivation and 'mean $PM_{2.5}$ exposure' (0.787, <0.01) and 'reduction in exposure concentrations' (0.710, <0.01) (Table 1and Fig. 2). Borough-level deprivation had a significant and negative correlation with urban vegetation (-0.501, <0.01), and a weak and negative correlation with avoided deaths (-0.341, 0.06) although this relationship did not reach statistical significance (Table 1 and Fig. 2).

Our modelling suggests that the presence of urban vegetation in London reduces annual mean $PM_{2.5}$ concentrations in London by absolute values of 1.0–1.25 $\mu g/m^3$, with the greatest reductions seen in boroughs located in West London (Hillingdon, Richmond upon Thames and Kingston upon Thames) and North West London (Hillingdon, Enfield, Barnet, Harrow, Hounslow) (Fig. 3 and Supplementary Table 2). The larger reductions in concentration seen in these boroughs could be related to several things; firstly, with some exceptions, these neighbourhoods have a slightly higher fraction of urban trees (Fig. 1B and Supplementary Table 2), and secondly, these boroughs (with some exceptions) have proportionally fewer deprived neighbourhoods compared to other London boroughs (Fig. 1A and Supplementary Table 2).

The number of avoided deaths annually is estimated as 408 (95% CI: 309–457) in total across London (Fig. 3, Supplementary Table 2). Outer London boroughs have the greatest avoided deaths, which are highest in Bromley (22), Croydon (21), Barnet (21), and Havering (19) (Fig. 3, Supplementary Table 3). The total avoided deaths across London is

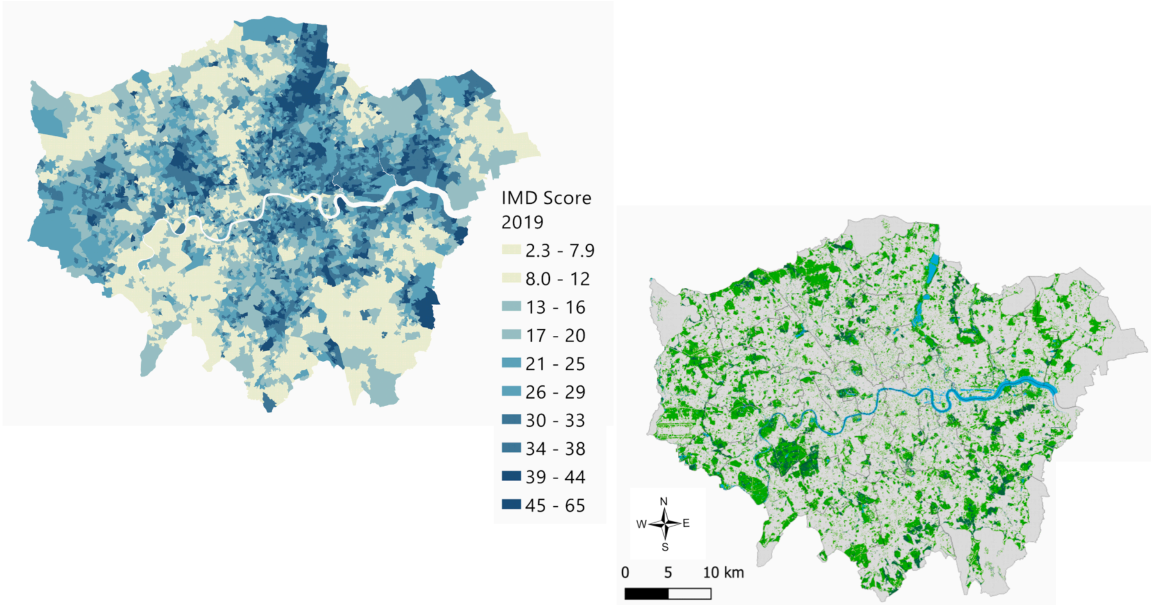

Fig. 1. A&B – A) London Index of Multiple Deprivation (IMD) Score in 2019 by Lower Super Output Areas (LSOA) – a higher IMD indicates greater level of deprivation, B) Coverage of urban green space (trees – dark green, grass – light green) and urban blue space (freshwater) in the London boroughs, used as input to the EMEP model.

Table 1 –
correlation between exposure (mean $PM_{2.5}$), change in exposure (mean reduction in $PM_{2.5}$ concentration), outcome (avoided deaths) and (IMD and greenspace) variables.

	Avoided deaths	Mean $PM_{2.5}$	Reduction in mean $PM_{2.5}$	IMD 2019	% of urban vegetation
Avoided deaths	1.000				
Mean $PM_{2.5}$	-0.678 (<0.01)	1.000			
Reduction in mean $PM_{2.5}$	-0.473 (0.01)	0.661 (<0.01)	1.000		
IMD 2019	-0.341 (0.06)	0.787 (<0.01)	0.710 (<0.01)	1.000	
% of urban greenspace	0.276 (0.126)	-0.512 (0.03)	-0.631 (<0.01)	-0.501 (<0.01)	1.000

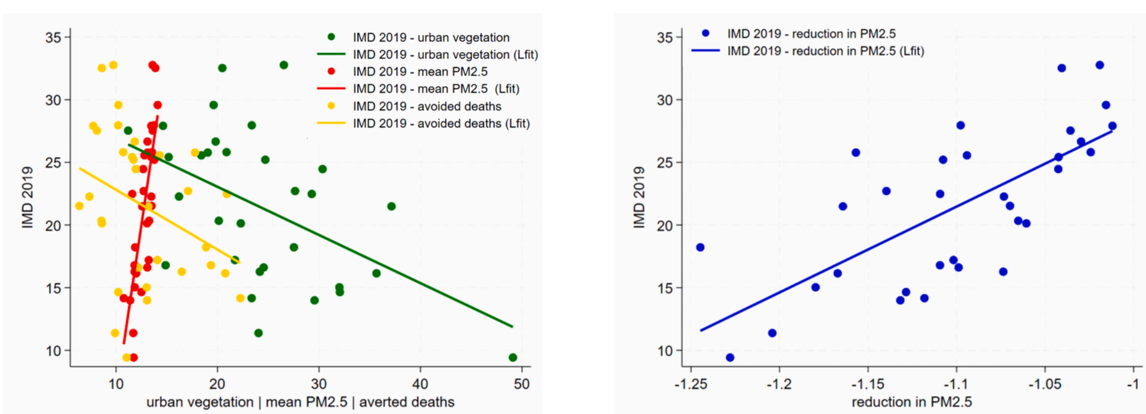

Fig. 2. – Scatterplots and fitted lines showing the correlation between borough-level deprivation (IMD, 2019) the percentage of urban greenspace, $PM_{2.5}$ concentration, change (reduction) in $PM_{2.5}$ concentration, and avoided deaths. A higher IMD score indicates a greater level of deprivation. Reduction in $PM_{2.5}$ concentrations is plotted separately due to differences in scale.

equivalent to 7% (95% CI: 5.3% – 7.8%) of mortality attributable to air pollution across London annually, calculated from a baseline of 5856 deaths attributable to $PM_{2.5}$ annually.

When the reduction in $PM_{2.5}$ is grouped into deprivation deciles (Fig. 4A, Supplementary Table 3), the mean exposure (blue bars) is highest in the most deprived neighbourhoods and ranges from 13.7 μg/m^3 in the most deprived boroughs, compared to 11.5 μg/m^3 in the least deprived boroughs. The most deprived neighbourhoods also see the least change in pollutant concentration due to tree cover (orange line), ranging from a 1.05 μg/m^3 reduction in $PM_{2.5}$ in the most deprived boroughs to a 1.17 μg/m^3 reduction in $PM_{2.5}$ in the least deprived boroughs (Fig. 4A and Supplementary Table 3).

The annual estimated deaths avoided do not indicate a similar pattern and are fairly equally distributed across the inequality deciles (Fig. 4B). There is a gradual increase in avoided deaths from the most deprived decile 1 to decile 5, which drops after the 6th decile and

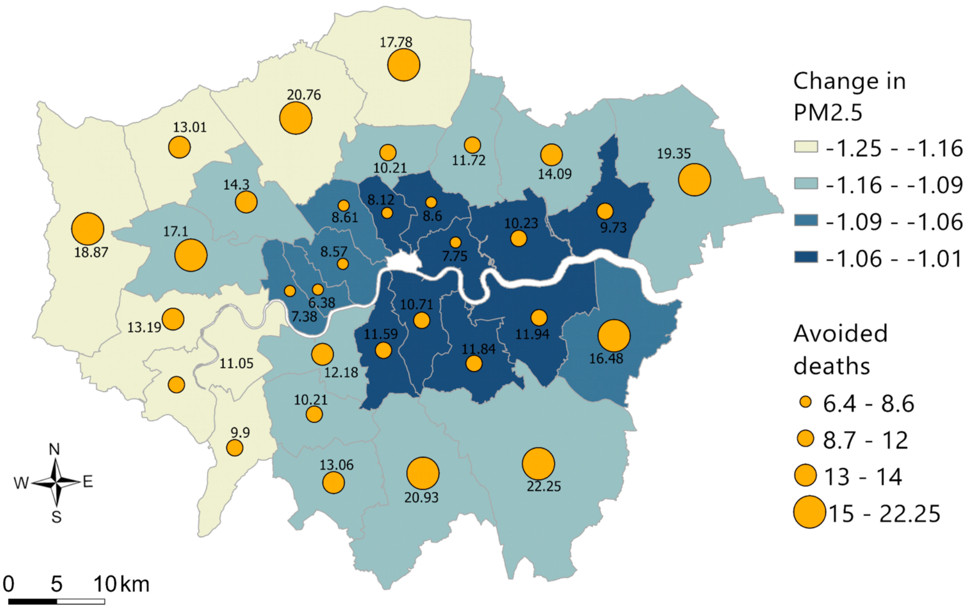

Fig. 3. – Borough-level reduction in the mean $PM_{2.5}$ concentration and number of avoided deaths. The lighter shade shows areas with the greatest reduction in $PM_{2.5}$ concentration, and the graduated symbols show the average deaths avoided by size.

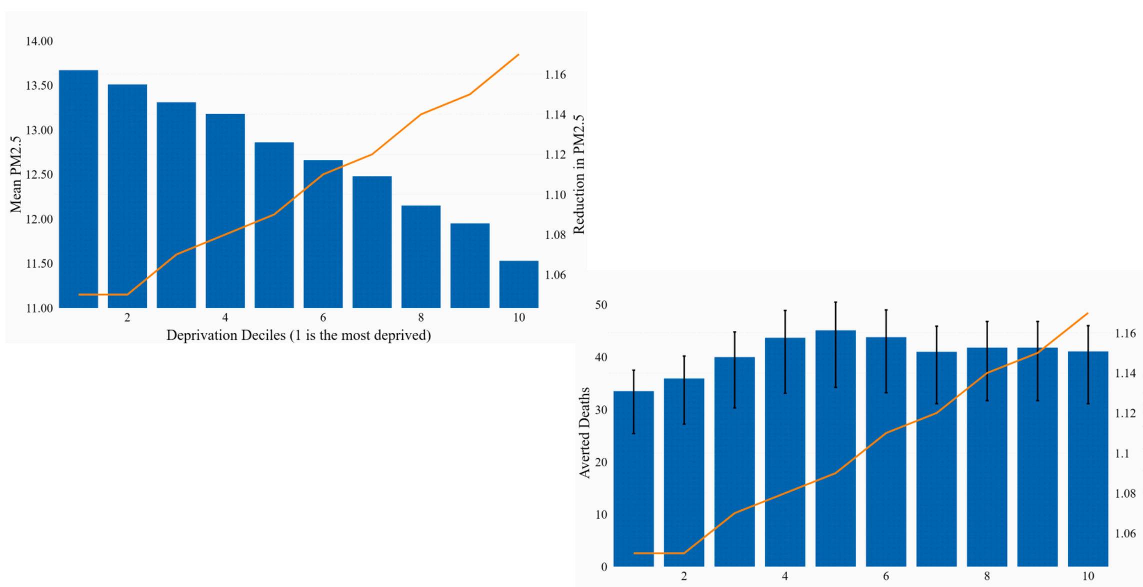

Fig. 4. (A&B) - A) shows the mean ambient $PM_{2.5}$ concentration (blue bars) by deprivation deciles. B) shows the estimated deaths avoided also by deprivation deciles, the error bars are the lower and upper limits determined using the 95% CIs for the exposure-response function. The orange line in both figures is the mean reduction (absolute values) in $PM_{2.5}$ concentration attributed to vegetation cover; a larger number represents a greater reduction in $PM_{2.5}$, i.e. reduced exposure.

plateaus up until the 10th decile.

5. Discussion

Our analysis reveals urban vegetation in the London region can reduce annual mean $PM_{2.5}$ concentrations by up to 1.25 μg/m^3 (10.5% from a baseline of 11.88 μg/m^3 in Hillingdon borough), with variations by local area. The reduction in pollutant exposure across London contributes to avoided mortality, estimated as 408 avoided deaths annually, or 7% of all deaths attributable to long-term effects of $PM_{2.5}$. The impacts of urban vegetation on pollutant removal and mortality are not evenly spread across the region; more deprived local areas show the least change in pollutant reduction, despite these areas having a higher mean baseline $PM_{2.5}$ concentration. The variation in avoided deaths by inequality deciles is less striking, with a noticeable trend whereby avoided deaths increase with increasing deprivation, but only for the most deprived 50% of the population. The relationship between IMD and avoided mortality becomes essentially flat for the least deprived 50%.

Deprivation is a key determinant of the extent by which green spaces potentially alter air pollution concentrations. In addition to having higher air pollution levels, deprived neighbourhoods have higher levels of baseline mortality rates and lower proportions of urban vegetation. The difference in proportion of vegetation is striking when we compare inner London vs outer London boroughs; For example, Richmond Upon Thames has over four times more urban vegetation than Islington, which is a substantial difference, particularly given that the proportion of vegetation cover incorporated in this study was limited to the urban extent and excluded any non-urban woodland that falls within the administrative boundary. The equity implications of the reduction in pollutant exposure due to removal by vegetation are complex. A key underlying factor is the spatial distribution of different socio-economic groups. For example, Aarhus in Denmark showed the greatest exposure to $PM_{2.5}$ in the highest income areas of the city, with a contrasting and non-linear relationship with deprivation in Paris, where exposure was greatest for the most deprived segment of the population, followed by the least deprived segment of the population.

A previous study (Jones et al., 2019) for Great Britain found that there were 240 fewer deaths, 900 fewer respiratory and 220 fewer cardiovascular hospital admissions as a result of air pollution removal (across multiple pollutants) by urban green and blue spaces. The economic value of the health gains was estimated to be £ 136 million annually. Our estimated impact on mortality (avoided deaths) is substantially greater than these previous estimates. The differences can largely be attributed to the application of the novel geo-referenced population model that characterises the health impact of the pollutant at an individual level, thereby taking into consideration spatial and demographic variation in vulnerability due to socio-economic and environmental exposure factors, which can vary considerably between groups and localities.

Notwithstanding, there are some limitations of our study. The analysis is based on a single year (2019), although this can be justified; a previous study on pollutant changes due to vegetation found that change in PM2.5 concentration was strongly dependent on the background concentrations. However, the background concentrations in London are unlikely to change drastically year on year. Also, as this is a modelling study, two additional years might not make a huge difference, as we would be applying the same Committee on the Medical Effects of Air Pollutants (COMEAP) recommended epidemiological function each year.

We focused our analysis on quantifying the impact of $PM_{2.5}$ reduction and therefore did not capture the full potential of the pollution abatement of urban vegetation; however, previous health impact assessments suggest up to three-quarters of this reduction is attributed to reductions in $PM_{2.5}$ concentrations (Jones et al., 2019). Furthermore, our analysis did not account for vegetation's potential to increase harmful allergens, which can worsen conditions such as asthma (Eisenman et al., 2019), or in some circumstances, worsen air quality by reducing local ventilation and increasing pollutant concentrations (Kumar et al., 2024). Our study focuses on changes in $PM_{2.5}$ concentration due to dry deposition processes. This might underestimate the overall influence of vegetation, since it doesn't include the barrier or dispersion effects, which are widely reported in the literature and which can lead to much greater reductions in pollutant concentration at individual locations (Khalili et al., 2024). Although the geo-referenced population is an important contribution in modelling individual-level health impacts, the model relies on predetermined epidemiological functions of the association between long-term $PM_{2.5}$ exposure and all-cause mortality that may not precisely reflect the London population. Further model refinements are necessary, including adjusting the mortality rates to reflect differences in deprivation. Our analysis focuses on long-term health impacts, which constitute the majority of the overall health burden. However, it does not account for short-term effects, which contribute additional health impacts not captured in the current estimates. Lastly, the level of uncertainty determined using the 95% CIs for the exposure-response function only accounts for the uncertainty in the exposure-response coefficients and does not represent the full model uncertainty. Other sources of uncertainty, such as potential model error in EMEP4UK, land-use classification error, exposure allocation from LSOAs to boroughs, synthetic population sampling, and differences in the years of mortality data, have not been incorporated into the confidence interval.

Urban vegetation and particularly trees can create multifunctional ecosystems that are increasingly recognised for their potential to address societal challenges linked across the environment, socio-economic issues, and health and wellbeing (Jones et al., 2022). The health benefits are linked to the generation of ecosystem services, or the provision of goods and services that can provide recreational spaces to support mental and physical health, regulate ecosystem processes (for example by improving air and water quality), and provide a buffer against extreme events such as floods, although they may also affect the abundance of disease vectors (Murage et al., 2025). Furthermore, compared to engineered solutions, urban vegetation delivers these services at relatively lower economic costs (Seddon et al., 2020) and with great potential for carbon sequestration and storage; an estimated 17.6% of all city areas worldwide are suitable for reforestation, which would offset 82.4 ± 25.7 $MtCO_2e\ yr^{-1}$ of carbon emissions, which forms a considerable level of city-wide carbon emissions in most regions (Teo et al., 2021). This capacity of urban vegetation to support mitigation and resilience has accelerated the implementation of nature-based solutions across cities as policymakers seek cost-effective means of adapting to the impacts of climate change (UNEP, 2021) whilst limiting further warming.

The implementation of new urban green interventions should be mindful of unintended consequences, including the potential increase in inequities. Although our analysis showed all areas benefited from air pollution removal, the less deprived areas were larger beneficiaries owing to their higher existing vegetation cover. There is a strong case to support increasing the proportion of urban vegetation in the most deprived settings to help achieve a distributional effect of the positive impacts. Unfortunately, areas that experience greater levels of air pollution are also more likely to be more deprived, and with limited space for increasing vegetation cover, which greatly reduces the potential for mitigation using these methods (Defra, 2018).

Overall, the potential for improving air quality using vegetation is modest compared with interventions that reduce emissions at source (Nemitz et al., 2020; Defra, 2018). Traffic interventions such as Low Emissions Zones, which reduce the number of journeys made by highly polluting vehicles, have been shown to potentially reduce the inequalities associated with air pollution exposure by delivering greater air quality improvements in the most deprived settings (Williamson et al., 2019). Therefore, urban vegetation interventions should complement rather than replace these traffic solutions and be co-designed in a more integrated manner to maximise the additional co-benefits they provide to city residents.

The health impact assessment estimates that urban vegetation can help avoid up to 7% of all deaths attributable to $PM_{2.5}$ in London. The benefits of urban vegetation on air quality should be considered in the context of any trade-offs, including potential to worsen existing inequalities. More affluent areas saw the greatest reduction in air pollutants, although the reduction in mortality was relatively evenly spread across deprivation deciles. Other disbenefits may include asthma exacerbation from plant pollen and other aeroallergens (Eisenman et al., 2019) or the potential to create habitats for vectors that may transmit disease. Urban trees are the primary driver of tree-pollen allergies, a major health issue affecting up to 50% of some urban populations (Salmond et al., 2016), which is linked to increases in local allergen exposure from regreening efforts (Xing et al., 2023) and changes in plant phenology due to warmer weather, which affects the timing of the onset of pollen release, the total volume of pollen produced, and the length of the flowering season (Salmond et al., 2016). Some plant species also emit biogenic volatile organic compounds (BVOCs) as a reaction to stress in their environment, such as high light intensities, temperatures or low water availability (Salmond et al., 2016; Diener and Mudu, 2021b). In the presence of sunlight, BVOCs react with vehicular and industrial nitrogen oxides (NOx) to drive up ground-level ozone concentrations (Salmond et al., 2016; Diener and Mudu, 2021b; Zhao et al., 2025), which may accumulate locally when ventilation is limited. Other studies, however, report that BVOC can also directly absorb ozone formation, thereby lowering ambient ozone levels (Zhao et al., 2025). This dual role of urban trees as an ozone sink and source makes disentangling the impact on health difficult to quantify.

Structuring urban vegetation to maximise the rate at which air flows through and exits city spaces is a key mechanism for diluting trapped emissions and mitigating the localised buildup of harmful pollutants (Pugh et al., 2012; Peng et al., 2020), but this was beyond the scope of this study. Future research should also consider the substantial wider benefits associated with other ecosystem services, such as generating a cooling effect, flood mitigation, and their impacts on physical health, mental wellbeing, and biodiversity.

Decision makers are increasingly seeking nature-based solutions as low-cost climate actions; these solutions also have strong public endorsement due to their climate adaptation and mitigation potential. Any work on understanding the impacts of land use conversion to expand the current levels of urban vegetation will have relevance for public health and urban planning policies. Air quality mitigation benefits are largely linked to $PM_{2.5}$ reduction, but previous studies suggest that even large-scale conversion of existing open urban greenspace to forest would only minimally lower PM2.5 levels, partly due to larger sources of $PM_{2.5}$ outside the urban extent. As such, the air quality impacts of urban vegetation need to be considered in the context of the wider benefits, such as on physical and mental health, flood mitigation and cooling effect, which are appreciably higher and evidenced to address deprivation.

There is limited evidence on the combined effects of increasing urban vegetation across multiple outcomes; focusing only on the air pollution reduction potential of greenspaces may underestimate its overall impact on human health. Addressing these evidence gaps will require methodological integration to leverage the combined knowledge base across disciplines such as natural, health and social sciences.

Ethics statement

No ethical approval was required for this study as it did not involve human or animal subjects

Data Access statement

The authors do not have permission to share data

CRediT authorship contribution statement

Peninah Murage: Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Conceptualization. **James Milner:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Alice Fitch:** Writing – review & editing, Methodology, Formal analysis. **Helen L. Macintyre:** Writing – review & editing, Writing – original draft, Resources, Methodology, Conceptualization. **Massimo Vieno:** Writing – review & editing, Validation, Investigation, Funding acquisition, Formal analysis. **Kamal Maji:** Writing – review & editing, Validation, Methodology, Formal analysis. **Laurence Jones:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Shakoor Hajat:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

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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.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2026.129665.

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