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The relationship between greenspace and personal exposure to $PM_{2.5}$ during walking trips in Delhi, India☆

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ABSTRACT

The presence of urban greenspace may lead to reduced personal exposure to air pollution via several mechanisms, for example, increased dispersion of airborne particulates; however, there is a lack of real-time evidence across different urban contexts. Study participants were 79 adolescents with asthma who lived in Delhi, India and were recruited to the Delhi Air Pollution and Health Effects (DAPHNE) study. Participants were monitored continuously for exposure to $PM_{2.5}$ (particulate matter with an aerodynamic diameter of less than 2.5 μm) for 48 h. We isolated normal day-to-day walking journeys (n = 199) from the personal monitoring dataset and assessed the relationship between greenspace and personal $PM_{2.5}$ using different spatial scales of the mean Normalised Difference Vegetation Index (NDVI), mean tree cover (TC), and proportion of surrounding green land use (GLU) and parks or forests (PF). The journeys had a mean duration of 12.7 (range 5, 53) min and mean $PM_{2.5}$ personal exposure of 133.9 (standard deviation = 114.8) μg/m^3. The within-trip analysis showed weak inverse associations between greenspace markers and $PM_{2.5}$ concentrations only in the spring/summer/monsoon season, with statistically significant associations for TC at the 25 and 50 m buffers in adjusted models. Between-trip analysis also indicated inverse associations for NDVI and TC, but suggested positive associations for GLU and PF in the spring/summer/monsoon season; no overall patterns of association were evident in the autumn/winter season. Associations between greenspace and personal $PM_{2.5}$ during walking trips in Delhi varied across metrics, spatial scales, and season, but were most consistent for TC. These mixed findings may partly relate to journeys being dominated by walking along roads and small effects on $PM_{2.5}$ of small pockets of greenspace. Larger areas of greenspace may, however, give rise to observable spatial effects on $PM_{2.5}$, which vary by season.

1. Introduction

Long-term exposure to ambient $PM_{2.5}$ (particulate matter with an aerodynamic diameter of less than 2.5 μm) was responsible for 8.8 million deaths and nearly three years of lost life expectancy per person globally in 2015 (Lelieveld et al., 2020). Inhaled $PM_{2.5}$ can penetrate deeply into the lungs and may enter the bloodstream, leading to impairment of the respiratory, cardiovascular, metabolic, and neurological systems via mechanisms of oxidative stress, mutagenicity, and inflammation (Feng et al., 2016; Fu et al., 2019). Short-term (daily) $PM_{2.5}$ exposures have been associated with higher mortality (Liu et al., 2019), increased asthma hospital visits and admissions (Zheng et al., 2015; Fan et al., 2016), and asthma exacerbations (Orellano et al., 2017) in children and adults. Nine of the ten cities with the highest annual $PM_{2.5}$ concentrations in the world are located in India (IQAir, 2021), where over 1 million attributable deaths from $PM_{2.5}$ occur annually (Balakrishnan et al., 2019).

There is increasing evidence that greenspace may be beneficial for health, including cardiovascular, respiratory, wellbeing, and other health indicators (Kondo et al., 2018; Twohig-Bennett & Jones, 2018;

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Wendelboe-Nelson et al., 2019; Mueller et al., 2022). Several broad themes have been suggested to explain how greenspace may affect human health: reducing harm (e.g., mitigating air pollution), restoring capacities (e.g., attention restoration), and building capacities (e.g., encouraging physical activity), but also potentially causing harm (e.g., allergens) (Markevych et al., 2017; Marselle et al., 2021). Thus, an important mechanism for greenspace to reduce harm may be lower exposure to ambient air pollution – either because green areas have a lower density of pollution sources or because of the effect of various forms of vegetation in helping to remove some pollutants from the air (Salmond et al., 2016). As increasingly more of the world's population inhabits cities, natural areas will become an integral, though constrained, component of dense built environments (Haaland & van Den Bosch, 2015). Therefore, it is important to promote health benefits of urban greenspace and minimise any negative impacts, yet most of the existing greenspace research has been undertaken in high income settings, thus representing only a minority of the global population (Nawrath et al., 2021).

Vegetation, predominantly leafy surfaces, can accumulate ambient particles through dry deposition (Han et al., 2020), and expanses of green open area can aid in dispersing airborne pollutants (Xing & Brimblecombe, 2020a), thus reducing ambient concentrations. In a review by Diener and Mudu (2021), greater reductions have been observed via dispersion (up to 50% of $PM_{2.5}$ [Xing & Brimblecombe, 2020b]) compared to deposition (up to 15% of PM_1 [Viippola et al., 2020]). Coniferous needles, small rough broadleaves, lanceolate or ovate shape, and waxy coatings appear to be most effective for PM removal via deposition (Corada et al., 2020); however, deposited PM may be resuspended into the air without wash-off during periods with little precipitation (Pace & Grote, 2020). At the same time, dense tree canopies may impede dispersion of dust and traffic emissions on busy roads and street canyons (Abhijith et al., 2017), and trees may release biogenic volatile organic compounds (BVOCs), leading to the formation of $PM_{2.5}$ as secondary organic aerosols (Lun et al., 2020; Salmond et al., 2016); these mechanisms could contribute to higher local PM concentrations. Many studies have demonstrated the potential for particle deposition on different plant species (Cai et al., 2017), including several in Indian settings. Road segments with trees in Bangalore were found to have significantly lower concentrations of suspended PM than adjacent segments without trees (Vailshery et al., 2013). Other environmental monitoring studies suggest that leaves have varied capacities to capture dust, with higher quantities found on leaves during winter, when higher ambient concentrations occur (Das & Prasad, 2012; Chaudhary & Rathore, 2018).

In high ambient air pollution settings, walking has been associated with some of the highest personal exposure to $PM_{2.5}$ (Lin et al., 2020; Peng et al., 2021). In Delhi, India, walking has been related to the greatest $PM_{2.5}$ exposures compared to most other travel modes, except rickshaws (Maji et al., 2021), as well as the highest inhaled dose per km travelled (Goel et al., 2015). Neither of these studies incorporated greenspace, and in fact few studies have examined personal $PM_{2.5}$ exposures and greenspace across different microenvironments. Research in Wuhan, China found a weak negative correlation between both forest and green land coverage in commuting paths with $PM_{2.5}$ concentrations using satellite and ground monitoring data (Guo et al., 2019), and von Schneidemesser et al. (2019) found lower exposure to particles (size range of 10–300 nm) when cyclists travelled through greenspaces or parks in Berlin, Germany. In settings such as Delhi, where PM concentrations vary greatly within each year, the effect of greenspace on personal exposure may vary with season (Lei et al., 2021).

In this study, we quantify the minute-by-minute relationship between greenspace indicators and personal $PM_{2.5}$ exposure during normal day-to-day walking trips in Delhi, India (i.e., within trips). We also investigate this relationship at the trip-level (i.e., between trips) to assess overall associations, which allows us to compare and contrast results both related to those of greener segments and greener trips. Thus, these insights contribute valuable, initial evidence on the role of greenspace with personal $PM_{2.5}$ exposure in a high ambient air pollution setting. We hypothesised that personal exposures to $PM_{2.5}$ would be lower along segments in walking journeys (i.e., within trips) with more greenspace and for overall walking journeys (i.e., between trips) with more greenspace.

2. Methods

2.1. Study location

The study took place in the Delhi-National Capital Region (NCR), India. The city of Delhi (28° 37′N, 77°12′E, population 25.8 million in 2018) is the world's second most populous city (United Nations, 2018). It has a subtropical climate with five distinct seasons: winter (December–January), spring (February–March), summer (April–June), monsoon (July–September), and autumn (October–November). Average daily temperatures can range from 5 °C in winter to 45 °C in summer (Delhi Tourism and Transportation Development Corporation, 2021).

Air quality varies substantially across seasons, and often exceeds the National Ambient Air Quality Standard of 60 μg/m^3 24 h mean for $PM_{2.5}$. Ambient $PM_{2.5}$ concentrations are typically highest during autumn/early winter, in part due to biomass and agricultural crop residue burning: 20% of $PM_{2.5}$ concentrations is attributable to non-local fires during this period, a figure that can reach as high as 75% during air pollution episodes (Kulkarni et al., 2020). Fireworks of annual Diwali celebrations in October/November can also result in very high spikes in $PM_{2.5}$ (Chen et al., 2020). By contrast, lower concentrations occur during the monsoon season assisted by wet deposition. Seasonal mean concentrations of $PM_{2.5}$ range from 76 μg/m^3 in the monsoon period to around 288 μg/m^3 in winter (Tiwari et al., 2014). The top three sources of $PM_{2.5}$ in Delhi during the years 2013–2016 were biomass burning (23%), vehicle emissions (16%), and soil dust (13%) (Jain et al., 2020), though the contribution from transport has been estimated elsewhere to be as high as 45%, excluding resuspended road dust (Sahu et al., 2011). $PM_{2.5}$ in Delhi exhibits diurnal variation, with concentrations at a minimum during mid-afternoon (influenced by increased mixing from solar radiation) and rising during evening rush hour and remaining elevated at night when trucks are permitted to enter the city after 23:00 (Murthy et al., 2020).

Delhi has approximately 20% green cover (Ramaiah & Avtar, 2019). The centre contains the highest proportion of stable vegetation with large, attractive parks and gardens (Paul & Nagendra, 2017) and also has a greater range of species and more mature street trees (Bhalla & Bhattacharya, 2015). Leaf-fall in Delhi mostly occurs by mid-January to March before the hot, dry season; leaves typically reappear by May or June, prior to monsoon rains (Krishen, 2006; Paul & Nagendra, 2015).

2.2. Study participants

Study participants were recruited as part of the Delhi Air Pollution and Health Effects (DAPHNE) study, which aimed to establish quantitative exposure-response relationships with air pollution and maternal and respiratory health (https://www.urbanair-india.org/daphne). Participants were adolescents who were receiving outpatient care for asthma at, and who lived within a 40 km radius of, the paediatric pulmonology outpatient clinic at the All India Institute of Medical Sciences (AIIMS). Asthmatic adolescents were selected for the DAPHNE study population, since the prevalence of asthma symptoms in children and adolescents is increasing, particularly in low and middle income countries (LMICs) (Ferrante & La Grutta, 2018); this panel can facilitate future examination of air pollution and lung growth, a research gap especially relevant for individuals with asthma (Schultz et al., 2017). Personal monitoring, involving the completion of exposure and health questionnaires and collection of personal exposure data to $PM_{2.5}$ using novel high resolution sensors over 48 h periods, commenced in August

2018 and was ongoing until disrupted by the Covid-19 pandemic in March 2020. As of that time, 690 asthmatic subjects had been screened, with 254 being found eligible (i.e., not excluded by age, distance to clinic, individual/school unwilling to participate, or health condition); 181/254 (71%) provided informed consent for follow-up health and exposure measurements. The current analysis is based on a panel of 79 asthmatic adolescents who provided data on walking journeys (details in section 2.5). Participants ranged from ages 10 to 18 (mean = 13) years and were mostly (71%) male; a quarter (25%) of households had completed studies beyond secondary school (e.g., professional or post-graduate degree) (Table 1). Ethics approval for the DAPHNE study was granted by the Institute Ethics Committee of AIIMS (Reference numbers: IEC-256/May 05, 2017, RP-26/2017, OP-13/August 03, 2018).

2.3. Air pollution measurements

Each participant was given a personal AirSpeck particle sensor (Figure S1) and an Android phone with the AirRespeck app (Arvind et al., 2016, 2018a, b). The phone and sensor were provided in a satchel, which was to be worn by participants whenever possible during each 48 h monitoring period (up to three monitoring sessions). The sensor's inlet fan was positioned within a gap in the satchel such that air samples were pulled directly from the outside air. The AirSpeck device measures particle counts using an optical counter in 16 bins of sizes between 0.38 and 17 μm, as well as temperature and relative humidity (rH), with a sampling rate of 30 s. All data are transmitted wirelessly to the App and stored as time- and GPS-stamped data. To calibrate each AirSpeck device for the aerosol composition of Delhi, the sensors were co-located with a continuous particulate reference monitor (FH 62 C14 series, Thermo Fisher Scientific Inc., USA) situated at the Indian Institute Of Technology–Delhi campus. The AirSpeck $PM_{2.5}$ data were averaged to match the sampling interval of the reference monitor $PM_{2.5}$ data. As high rH values can affect the reliability of sensor measurements (Jayaratne et al., 2018), a piecewise least-squares linear regression model was used to calculate two slopes (m_{low}, m_{high}) and intercepts (c_{low}, c_{high}) (see Equation (1)) for periods of high and low rH. The regression model was repeatedly run to test a range of rH thresholds (65–95%) until one was identified that minimised the squared error between the calibrated and reference $PM_{2.5}$. This tuning process was repeated for each sensor individually (see example plots in Figures S2, S3). Calibrated data from personal monitoring were converted to 1 min mean concentrations and linked to GPS location data.

$$PM_{2.5,calibrated} = \begin{cases} m_{low} \times PM_{2.5,measured} + c_{low}, & if\ rH_{measured} < rH_{threshold} \\ m_{high} \times PM_{2.5,measured} + c_{high}, & if\ rH_{measured} \geq rH_{threshold} \end{cases} \quad (1)$$

2.4. Greenspace indicators

We classified each minute of each person's journey using four indicators of greenspace within commonly used radii of 25, 50, 100, and 250 m to capture the immediate and neighbourhood microenvironments around the participant's 1 min mean GPS location: the Normalised Difference Vegetation Index (NDVI), tree cover (TC), green land use (GLU), and parks or forests (PF) (Mueller et al., 2020, 2021).

NDVI represents the greenness of a given area based on remotely sensed spectral reflectance measurements in the red (visible) and near-infrared regions of the electromagnetic spectrum (Rhew et al., 2011). It has continuous values ranging from −1 (ice) to 0 (rock, built-up surfaces) to +1 (dense vegetation). TC indicates the percentage (0–100%) covered by the canopy of trees as visible from satellites. GLU includes parks, forests, sports pitches, and other such natural or green types of land use.

NDVI values were calculated using Sentinel-2 satellite images available from the Copernicus Open Access Hub at 10 m spatial and five-day temporal resolutions (European Space Agency, 2015). To remove the influence of bluespaces (e.g., rivers, lakes), NDVI raster data with

Table 1
Descriptive characteristics of the trip data (n = 1,817 observations) and study participants[a].

Characteristic	n (%) or mean (SD)
$PM_{2.5}$ (μg/m^3)	133.9 (114.8)
NDVI (-0.1 to 1.0)	0.17 (0.12)
25 m	0.16 (0.10)
50 m	0.17 (0.09)
100 m	0.18 (0.08)
250 m	
Tree cover (%)	3.0 (2.0)
25 m	2.9 (1.8)
50 m	3.0 (1.6)
100 m	3.3 (1.5)
250 m	
Green land use overlap (proportion)	
25 m	0.04 (0.17)
50 m	0.04 (0.15)
100 m	0.04 (0.12)
250 m	0.05 (0.09)
Parks or forest overlap (proportion)	
25 m	0.03 (0.15)
50 m	0.03 (0.13)
100 m	0.03 (0.10)
250 m	0.04 (0.08)
Presence of motorway/primary/secondary roads within 25m (y/n)	
25 m	80 (4.4%)
50 m	279 (15.4%)
100 m	457 (25.2%)
250 m	806 (44.4%)
Presence of tertiary roads within 25m (y/n)	
25 m	171 (9.4%)
50 m	220 (12.1%)
100 m	338 (18.6%)
250 m	707 (38.9%)
Presence of other roads within 25m (y/n)	
25 m	1,429 (78.7%)
50 m	1,635 (90.0%)
100 m	1,750 (96.3%)
250 m	1,814 (99.8%)
Population density (persons/km^2)	13,301 (8,539)
Season	
Winter	649 (35.7%)
Spring	125 (6.9%)
Summer	241 (13.3%)
Monsoon	628 (34.6%)
Autumn	174 (9.6%)
Time of day	
06:00–11:59	574 (31.6%)
12:00–17:59	728 (40.1%)
18:00–22:59	515 (28.3%)
Day of the week	
Weekday	1,615 (88.9%)
Weekend	202 (11.1%)
Year	
2018	200 (11.0%)
2019	1,328 (73.1%)
2020	289 (15.9%)
Temperature (°C)	25.8 (8.9)
Relative humidity (%)	67.9 (16.0)
Precipitation (any)	44 (2.4%)
Wind speed (m/s)	2.2 (1.4)
Wind direction	
None	123 (6.8%)
North	411 (22.6%)
East	428 (23.6%)
West	588 (32.4%)
South	267 (14.7%)
Gender	
Male	56 (70.9%)
Female	23 (29.1%)
Age (years)	13.1 (1.9)
Highest household education	
Professional/Honours	5 (6.3%)
Graduate/Postgraduate/Diploma	15 (19.0%)

(continued on next page)

Table 1 (*continued*)

Characteristic	n (%) or mean (SD)
Intermediate/Secondary school	20 (25.3%)
High School Certificate	17 (21.5%)
Middle School Certificate	7 (8.9%)
Primary School/Literate	6 (7.6%)
Illiterate	9 (11.4%)

[a] n = 79 participants; n = 199 trips.

values of < -0.1 were excluded from greenness calculations. Images with cloud coverage of <10% were identified on February 9, April 10, June 29, and October 17, 2019 to reflect specific vegetation levels during different seasons. Mean NDVI values were calculated from the image closest to when the journey occurred. Average annual tree cover of woody vegetation of height in excess of 5 m in 2015 was extracted from the Landsat Vegetation Continuous Fields tree cover layer (30 m spatial resolution) (Sexton et al., 2013). GLU was based on open-sourced vector data (OpenStreetMap (OSM) data downloaded from www.geofabrik.de on February 25, 2020), and a shapefile was created to include all polygons categorised as allotments, cemetery, forest, grass, heath, meadow, nature reserve, orchard, park, recreation ground, or scrub; farms were excluded from the GLU layer (See Figure S4 for greenspace maps). A separate PF shapefile was generated based on a subset of the GLU layer, which included only park and forest polygons. Mean values of NDVI, TC, and the proportion of GLU, and separately PF, were calculated for 25, 50, 100, and 250 m radii around personal GPS coordinates.

2.5. Identification of walking journeys

We identified walking journeys by minute-by-minute analysis of personal mobile phone GPS data. Walking trips were defined as sequences of at least 5 min' duration where individuals travelled >100 m in 2 min at a speed of <10 km/h (Stewart et al., 2017; Van Hecke et al., 2018). We allowed interruptions of up to 5 min in the travel record to account for brief breaks en route (e.g., to wait for traffic lights) (Carlson et al., 2015). We excluded data where the GPS accuracy was recorded as being poorer than 200 m, journeys made between 22:59 and 6.00, and where recorded $PM_{2.5}$ concentrations were <1 or ≥2,000 μg/m^3. Home and school addresses were geocoded by the study team during personal monitoring periods; all trips were included regardless of origin/destination. We then visually inspected each selected journey to confirm that it appeared to be a real journey with a linear sequence of locations along roads and paths using OSM (www.openstreetmap.org).

2.6. Other covariates

For each journey location, we also assembled data on the presence and total length of motorways, primary, secondary, tertiary roads, and railways calculated using the OSM data, and the mean population density calculated using 1 × 1 km estimates for 2020 (CIESIN, 2018). Three-hourly temperature, relative humidity, precipitation, and wind speed and direction (over the previous 10 min) data (Yadav et al., 2019) were obtained from a single meteorological monitoring station at Safdarjung airport in Delhi (28°35′04″N, 077°12′21″E) (www.rp5.ru).

2.7. Data analysis

We analysed the association of the natural logarithm of the 1 min mean concentration of $PM_{2.5}$ with each of the four indices of greenspace and four radii of averaging using various levels of covariate control. The logarithm of exposure was selected to account for the skewed distribution of $PM_{2.5}$ concentrations, as evidenced previously in an Indian setting (Milà et al., 2018).

Within-trip analysis of changes in $PM_{2.5}$ in relation to greenspace markers at 1 min resolution was based on a fixed effects regression model of time-varying panel data within individual trips (Gunasekara et al., 2014). Results by season (autumn/winter or spring/summer/monsoon) were determined by fitting an interaction term. Models were fitted without adjustment for other covariates (model 1) and adjusting for time-varying location-specific markers of the type of road within the 25 m radius (see 'traffic analysis' in supplementary material), presence of railways, and population density (model 2). All models included robust standard errors. Greenspace coefficients are reported as the average percentage change in $PM_{2.5}$ concentration for an interquartile range (IQR) increase of NDVI and TC, or a 0.1 increase in the proportion of overlapping GLU and PF determined for each 1 min time segment of the walking trip.

Between-location (between-trip) analysis of trip-mean $PM_{2.5}$ in relation to greenspace markers was based on a mixed effects regression model of trip-level averaged data with a random intercept for participant and personal monitoring period (i.e., removing any 'within-trip' effects [Bell et al., 2019]). Results by season (autumn/winter or spring/summer/monsoon) were again determined by fitting a season interaction term. Models were fitted without adjustment for covariates (model 1); with adjustment for the busiest type of road within a 25 m buffer anywhere on the journey, presence of railways, and population density (model 2); adjustment for time of day (morning [6:00–10:59], afternoon [11:00–17:59], evening [18:00–22:59]), weekday/weekend day, year, temperature, precipitation, rH, wind speed, and wind direction as a categorical variable (model 3); and adjustment for the covariates of both models 2 & 3 (model 4). The coefficients represent the percentage increase in $PM_{2.5}$ for the trip-mean level of greenspace marker as defined above under the within-trip analyses.

2.8. Sensitivity analysis

We also report separate analyses for the within-trip analyses using 2 min averaging of personal $PM_{2.5}$ concentrations (to smooth the variability of the minute-by-minute data), and adjusting for a marker of average visibility at each trip location in the between trip analysis (as an indicator of obstruction from physical structures in the built environment - see 'visibility analysis' in supplementary material).

Statistical analysis included only trips with complete data for all covariates. Geospatial analysis was undertaken in QGIS v.3.10.1 (QGIS, 2014) and statistical analysis in Stata v16 (StataCorp, 2019).

3. Results

There were 79 participants who provided data on a total of 199 walking trips, with between 1 and 10 trips per person (approximate locations shown in Fig. 1). The mean trip duration was 12.7 (standard deviation [SD] = 9.2; maximum = 53) min and the mean distance was 733 (SD = 580; maximum = 3361) m. Slightly more than half of the walking journeys started/ended within 100 m of home (105/199, 53%), school (48/199, 24%), or the AIIMS clinic (43/199, 22%); the large majority (164/199, 82%) of trips involved at least one of these locations.

Mean NDVI values were <0.20 at all radii of averaging (highest in February [mean = 0.19] and lowest in June [0.14] [25 m radius]), but showed appreciable variation within and between trips, as did the percent of TC, which had an overall mean of 3% (Table 1, Fig. 2). NDVI and TC IQRs ranged from 0.11 to 0.17 and 2.4%–3.0%, respectively (Table S1). The percent of GLU was very low for the large majority of trips but reached 100% for some locations of a proportion of trips (at radii up to 100 m, or radii up to 50 m for park or forest land) – Fig. 2.

There was a strong correlation ($r \geq 0.85$) between NDVI and TC, but only weak correlations between both NDVI and TC and GLU ($r < 0.30$) (Table S2, Figure S5). Correlations among other covariates were mainly weak with the exception of a moderate negative relationship between rH and temperature ($r = -0.59$) (Table S2).

Fig. 1. Heatmap showing the density (darker red) of trip locations around Delhi, India, with locations of trip examples in Fig. 3a & b indicated as such. Basemap from © Stamen Design, under a Creative Commons Attribution (CC BY 3.0) license. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

The overall mean concentration of $PM_{2.5}$ was 133.9 μg/m^3, with variation both between (SD = 104.9 μg/m^3) and within (SD = 53.5 μg/m^3) trips (Fig. 2). Concentrations were higher in autumn/winter (mean = 172, SD = 126 μg/m^3) and lower in the spring/summer/monsoon season (mean = 102, SD = 93 μg/m^3) (Figure S6).

In Fig. 3, we map as illustrative examples two individual walking trips and the co-variation in their minute-by-minute $PM_{2.5}$ and greenspace indicators. Trip 1 shows a gradual rise in $PM_{2.5}$ concentration and fall in NDVI over the journey, with appreciable minute-to-minute variations. Some local increases in NDVI appear to be associated with modest reductions in $PM_{2.5}$, and there is a moderate negative correlation ($r = -0.50$) between NDVI and $PM_{2.5}$. Trip 2 is a shorter trip (in the monsoon season), much of which occurs in areas classified as GLU. Again, there appears to be an increase in $PM_{2.5}$ as the walker leaves the area of very high GLU and a moderate negative correlation ($r = -0.44$) between $PM_{2.5}$ and NDVI.

The results of regression analyses for all greenspace markers are shown in Figs. 4 and 5 and Supplementary Tables S3 & S4. In unadjusted models of the *within-trip* analysis, confidence intervals all included 0. In the spring/summer/monsoon season, point estimates were below 0 for NDVI, TC, and GLU; despite these relationships being non-significant, there was a tendency of stronger (negative) associations at larger radii of averaging. In the autumn/winter season, there was no clear general pattern of association, although there were only positive associations with GLU and PF. Coefficients were similar in adjusted models, with TC (25, 50 m) including confidence intervals below 0. Additional coefficients were nominally statistically significant using 2 min averaged $PM_{2.5}$ data (Figure S7).

The patterns of inverse association observed in the unadjusted *between-trip* analyses were broadly similar to those of the *within-trip* analyses for NDVI and TC (Fig. 5). Point estimates became progressively more negative at larger radii of averaging in the spring/summer/monsoon season. By contrast, the results for GLU and PF in the spring/summer/monsoon season suggested positive associations with personal $PM_{2.5}$ exposure at all radii of averaging (with confidence intervals excluding 0, except at the 250 m radius). The results for the autumn/winter season were all fairly flat (i.e., no association for any marker) and showed no clear pattern of change in point estimates across the radii of averaging. NDVI and TC coefficients in spring/summer/monsoon season were attenuated in adjusted models; GLU and PF coefficients were less affected (Table S4).

An analysis of average visibility across each trip found TC was associated with reduced $PM_{2.5}$ concentrations only where there was high visibility, with no statistically significant findings with the other greenspace markers (Table S5).

4. Discussion

Reduction of exposure to air pollution is one of the possible pathways by which greenspace may have beneficial effects on health. Our study provides insight into this relationship in the high-pollution setting of Delhi, India. This contrasts with the majority of research in this field, which has focused on lower pollution environments in mainly high-income settings.

Overall, our findings suggest generally weak patterns of association, which are season-specific. The results of the within-trip analysis were suggestive of lower concentrations of personal $PM_{2.5}$ exposure with higher levels of greenspace, notably NDVI and TC (although most confidence intervals overlapped 0), but only during the spring/summer/monsoon season. Point estimates of the size of the effect increased with the radius of averaging, possibly suggesting the importance of larger scale greenness, rather than small pockets. The results of the trip-level

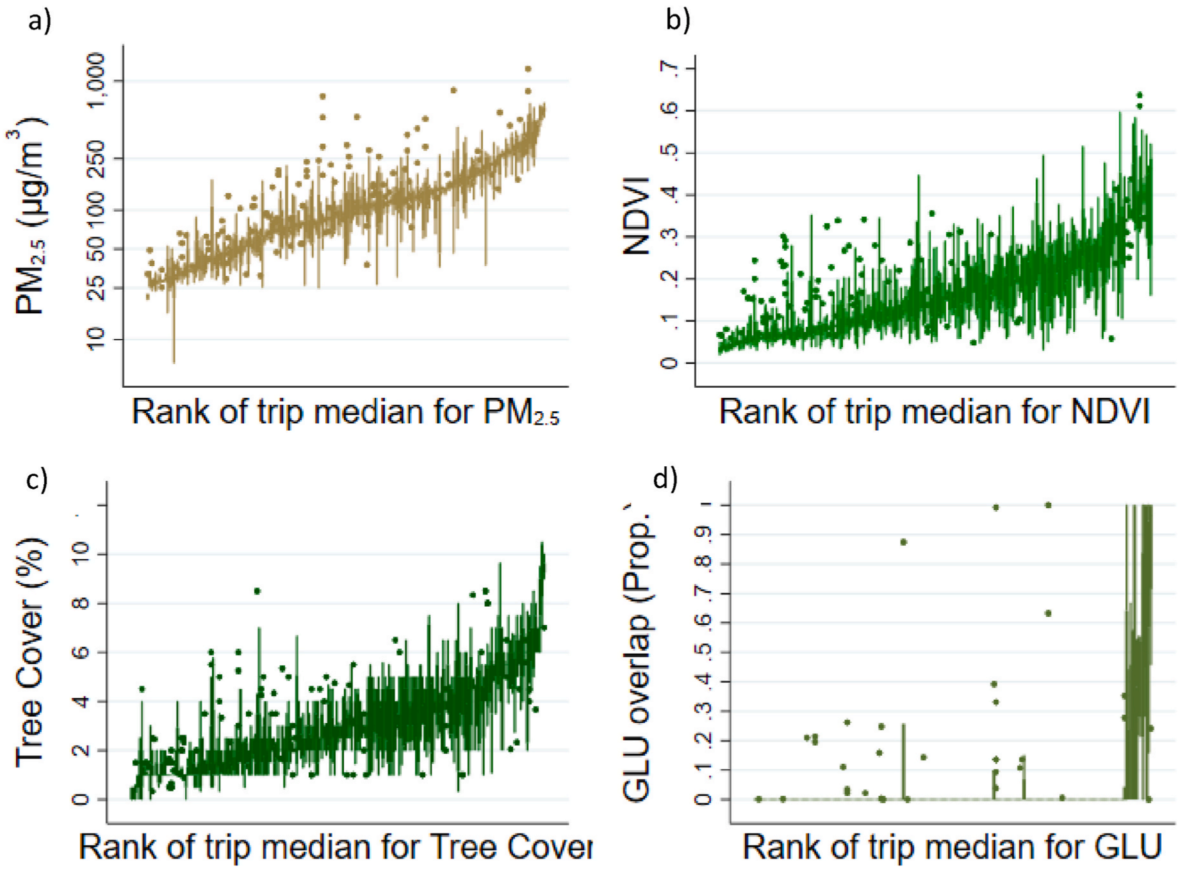

Fig. 2. Within- and between-trip variation in a) $PM_{2.5}$ concentrations (μg/m^3, log-scale), b) NDVI, c) tree cover (%), and d) proportion overlap of green land use (GLU) based on data for the 25 m radius of averaging around 1-min trip locations. Vertical bars indicate the interquartile range for individual trips and the dots indicate outliers. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

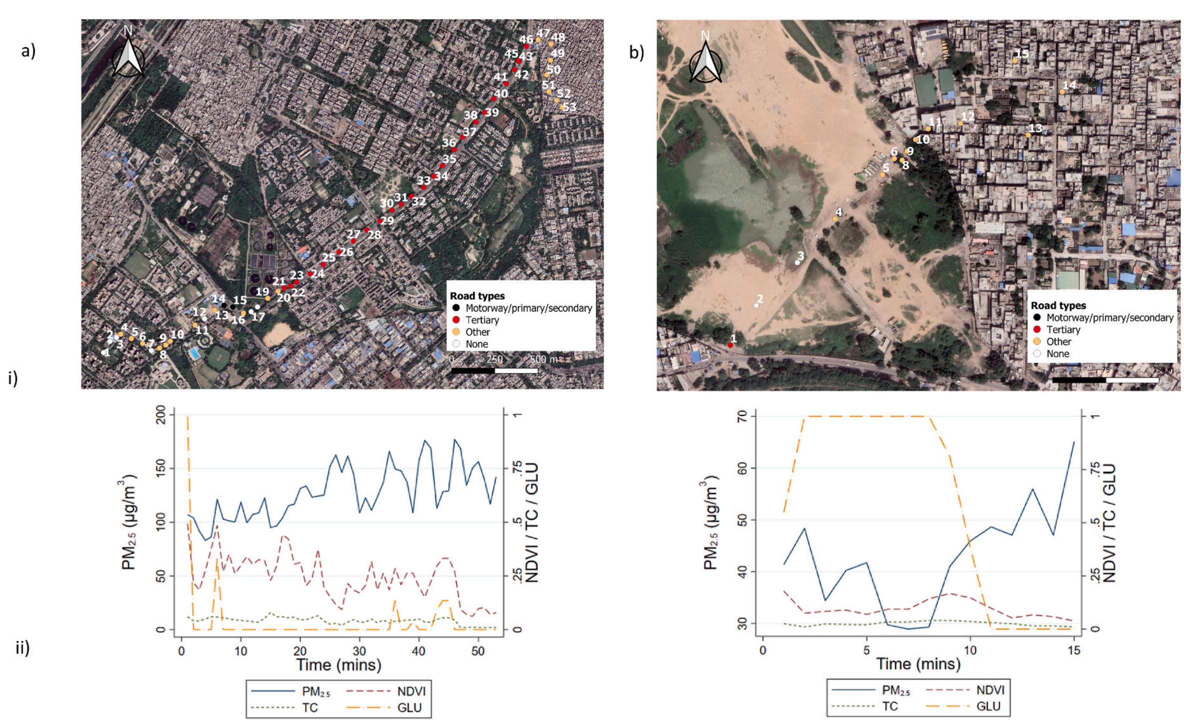

Fig. 3. Two example walking trips: a) Trip 1, in winter and b) Trip 2, in the monsoon season indicating different road type categories. For each trip we show: (i) map data ©Google Maps, (30th December 2016) with a trace of the walk route and (ii) line graphs of the minute changes in $PM_{2.5}$ concentrations and greenspace indicators at the 25 m radius. Numbers on the maps indicate minutes from the start of the journey (same as the x-axis of the $PM_{2.5}$ *vs* time plots).

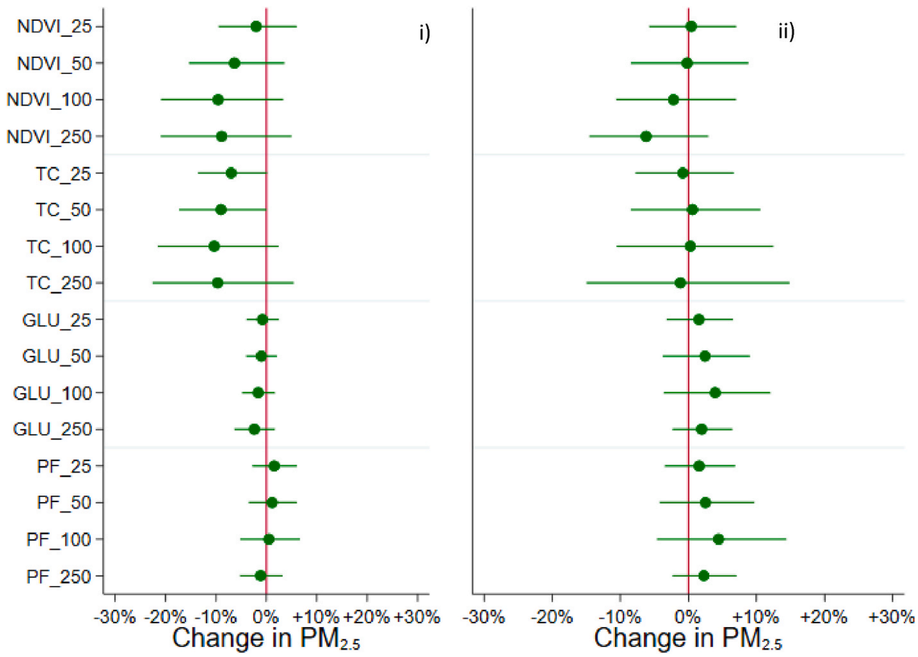

Fig. 4. Plots of regression coefficients for (i) the spring/summer/monsoon season and (ii) the autumn/winter season of within-journey changes in 1 min averaged $PM_{2.5}$ in relation to markers of greenspace. Coefficients represent an interquartile range (IQR) increase in Normalised Difference Vegetation Index (NDVI) and tree cover (TC), and a 0.1 increase in the proportion of green land use (GLU) or parks or forests (PF). All are presented at averaging radii of 25, 50, 100, and 250 m around the point location of the individual. Models include an interaction term for season. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

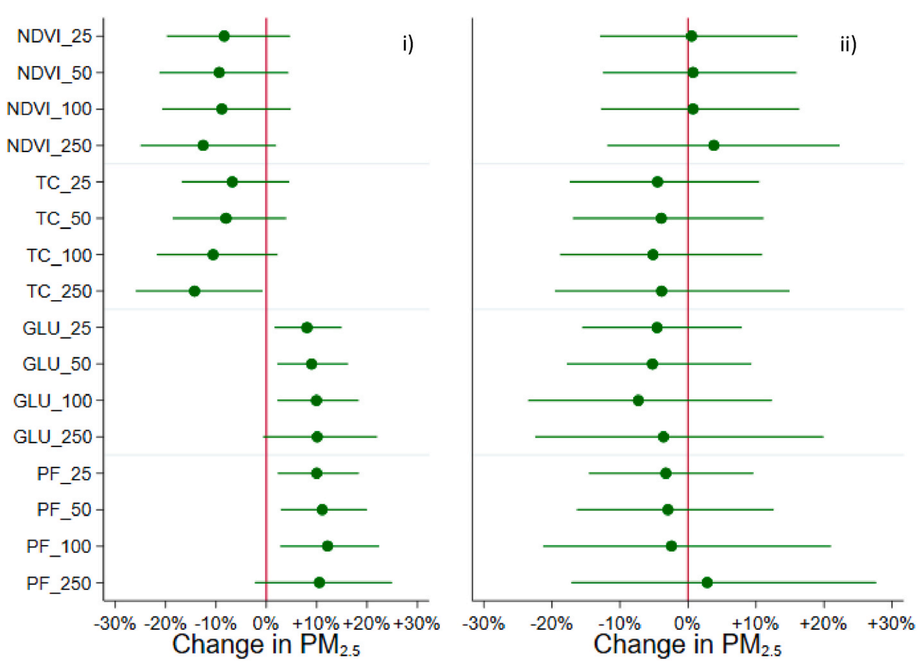

Fig. 5. Plots of regression coefficients for (i) the spring/summer/monsoon season and (ii) the autumn/winter season of between-location (between-trip) analysis of trip mean $PM_{2.5}$ concentrations in relation to markers of greenspace. Coefficients represent an interquartile range (IQR) increase in Normalised Difference Vegetation Index (NDVI) and tree cover (TC), and a 0.1 increase in the proportion of green land use (GLU) or parks or forests (PF). All are presented at averaging radii of 25, 50, 100, and 250 m around the point location of the individual. Models include an interaction term for season. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

averages (i.e., between journeys) with NDVI and TC produced similar findings of reduced exposure to that of the within journey analysis; however, coefficients related to GLU and PF showed positive associations with personal $PM_{2.5}$ exposure. These results may suggest higher overall exposure on walking trips that include GLU or PF. A possible explanation for this finding is that the built environment around parks may have elevated $PM_{2.5}$ concentrations attributed to busy roads either circumventing or leading to the park (Su et al., 2011).

There are limited other studies that have examined the relationship between personal $PM_{2.5}$ exposures and greenspace, some of which identify inverse associations. Hart et al. (2020) used a bicycle-based sampling method in Dallas, USA to measure $PM_{2.5}$ and derived an NDVI-based vegetation footprint and height using Light Detection and Ranging (LiDAR) data. These authors found a negative relationship between $PM_{2.5}$ and the amount of vegetation, but a positive link with vegetation height, suggesting taller trees may have hindered air pollution dispersion. von Schneidemesser et al. (2019) used cycling monitoring data from routes around Berlin, Germany to sample particle number concentrations in the $<PM_1$ range and found reductions of 22% compared to the ambient average when cycling in parks or large greenspaces not directly next to a road. $PM_{2.5}$ reductions of up to 50% were identified while walking inside a park in Madrid, Spain, when 200 m from a major road (Gómez-Moreno et al., 2019). Roberts & Helbich (2021) assessed exposures in the Netherlands for both residential and mobile environments and found a negative correlation between NDVI and land use regression-based $PM_{2.5}$; however, they did not differentiate between travel mode, nor indoor or outdoor settings. Guo et al. (2019) found weak negative correlations ($r < -0.2$) between green land use and modelled $PM_{2.5}$ concentrations using data based on commuters' exposure in Wuhan, China; similarly, this study also did not distinguish exposure between travel modes.

Along with these personal exposure studies, research has also identified lower $PM_{2.5}$ concentrations with higher greenspace exposure in fixed locations (Dadvand et al., 2012; Dadvand et al., 2015; Cai et al., 2020; Mueller et al., 2020). Nevertheless, there are several reasons that may have contributed to the lack of consistent or larger reductions in $PM_{2.5}$ in the present study. As observed in other research with personal sensors (Chatzidiakou et al., 2019), walking in high traffic outdoor settings entailed high variation in minute-to-minute $PM_{2.5}$ exposure within trips, thus presenting a challenge to disentangle potentially subtle effects of particulate removal in urban areas (Nemitz et al., 2020). In addition to the high variation within trips, there were relatively low levels of all four greenspace indicators in the trip microenvironments. Research suggesting $PM_{2.5}$ reductions associated with similar indicators in residential locations has been conducted in the presence of greater vegetation (Mueller et al., 2020); such levels in the present study may have been too low to detect a strong effect. Our greenspace exposure metrics were based on satellite images for overall greenness and tree cover. These data would better capture wider canopies (e.g., broadleaf trees), which are more pertinent for particulate removal by deposition, but would poorly represent denser trees with smaller canopies (e.g., evergreen trees); the latter structure may be more relevant for concentration reductions by dispersion (Han et al., 2020). There were few walking trips that occurred in the interior of GLU. Research suggests detectable $PM_{2.5}$ reductions in parks do not occur for at least 100 m (Xing & Brimblecombe, 2019), and ideally 400 m, in such areas (Chen et al., 2019). Further, there was poor correlation between greenness (and tree canopy) and GLU, implying such areas did not always incorporate vegetation; thus, its presence did not always represent higher greenspace exposure. In hot climates, like Delhi, high temperatures can increase the release of BVOCs in trees, thereby creating higher concentrations of secondary aerosols (Churkina et al., 2017). Trees can also provide valuable shade and more comfortable temperatures, providing a preferable location for street vendors (Basu & Nagendra, 2020); spikes in $PM_{2.5}$ concentrations related to, for example, cooking activities, may be more likely to coincide with tree-lined locales in such instances.

Ambient $PM_{2.5}$ concentrations in Delhi demonstrate strong seasonal trends, with much higher concentrations in October–January, when biomass burning is an important contributor, than during July–September, when rains scavenge ambient particles (Jain et al., 2020). While only borderline statistically significant, we did find more negative coefficients in spring/summer/monsoon seasons across radius sizes for all greenspace indicators within trips. Although particle deposition tends to increase with higher ambient concentrations (Cai et al., 2017), the observed associations could indicate the potential of particle deposition during periods when vegetation is closer to important sources (e.g., traffic) (Janhäll, 2015), compared to a higher contribution from more distal sources in winter, such as crop residue burning from surrounding agricultural areas (Jain et al., 2020). More generally, it has been estimated that up to 60% of ambient $PM_{2.5}$ in Delhi originates from outside the city (Amann et al., 2017); in this case, urban greenspaces, as microenvironments with relatively fewer $PM_{2.5}$ sources and the capacity to capture nearby particle emissions, may be less effective to reduce personal exposures. The autumn/winter months also coincide with the period when deciduous trees start to shed leaves, and thus would be less effective for particle deposition (Xu et al., 2020); nevertheless, tree bark and branches can also accumulate particulates (Xu et al., 2019). Alternatively, these seasonal trends may indicate that mitigation mechanisms related to greenspace may be more effective, or detectable, during periods of lower ambient concentrations. A study of monitoring stations in Nanjing, China found correlations between green cover and lower $PM_{2.5}$ concentrations; however, this relationship was not apparent when ambient concentrations were in excess of 75 $\mu g/m^3$, which also typically occurred in the winter (Chen et al., 2016).

4.1. Overall interpretation

Overall, our results do not indicate a strong relationship between exposure to different types of urban greenspace and personal exposure to $PM_{2.5}$ in walking journeys in Delhi, a high air pollution setting in a LMIC context. Nevertheless, our findings provide some suggestive evidence for modest reductions in personal $PM_{2.5}$ exposure during segments of walking trips with more overall greenness and TC in spring, summer, and monsoon seasons. Greenness and TC on a neighbourhood scale may be more relevant, as larger radius sizes were linked to stronger $PM_{2.5}$ reductions, albeit these estimates entailed greater uncertainty than those based on smaller areas. At the same time, smaller radius sizes would have entailed less spatial overlap and thus may have reflected more greenspace variation at each location along the walking path (Labib et al., 2020). Walking trips with greater average NDVI and TC measures were suggestive of lower personal $PM_{2.5}$ exposures; by contrast, GLU and PF were associated with higher concentrations. Nevertheless, further support for the potential role of trees in modifying personal $PM_{2.5}$ exposure was provided by results of the trip-level visibility analysis, for which statistically significant $PM_{2.5}$ reductions were identified only for TC exposure and only in areas with high visibility (i.e., where pollution dispersion was less likely to be obstructed by the built environment).

4.2. Strengths and limitations

Our study benefitted from the use of high spatial and temporal resolution personal monitoring of real-time $PM_{2.5}$ data across different seasons in Delhi, India, a high ambient air pollution environment. Routes were determined by participants and therefore represented realistic exposure scenarios. We used four indicators of greenspace at four spatial radius sizes to examine associations with particulates at local and neighbourhood scales, and we analysed separately the associations with greenspace within and between trips. The results of our study represent initial quantification of the air quality associations with greenspace in Delhi: a setting where the concentrations, sources, and contributions of $PM_{2.5}$ vary widely across the year. Nevertheless, there were several limitations. We were not able to obtain a reliable dataset of urban morphology, specifically buildings, for which increased height on narrow streets may have adversely affected ambient particulate concentrations (Farrell et al., 2015). However, our additional analysis of visibility at the trip level suggested that associations with reduced $PM_{2.5}$ may be stronger in more open areas, as suggested elsewhere (Abhijith et al., 2017). Although we did not quantify characteristics of greenspaces, such as shape or density, research that did (in Zhengzhou, China) found no such associations with $PM_{2.5}$ concentrations (Lei et al., 2021). We did not capture trees at the species level, for which particle deposition and dispersion may have varied; adding this information may have refined our estimates. We were also not able to distinguish pollen from anthropogenic PM sources, which may have under estimated particulate reductions associated with tree cover. Nevertheless, pollen grains are typically larger (17–58 μm), although some pollen fragments may have been included in the measured $PM_{2.5}$ concentrations (Morakinyo et al., 2016). It was apparent in the dataset that many of the walking trips did not traverse GLU; it is possible that asthmatic participants may have avoided certain areas if exposure to certain species (e.g., grasses) triggered asthma symptoms (Aerts et al., 2020). More broadly, asthmatic participants in a high air pollution setting may have avoided walking trips when possible (Tainio et al., 2021). The GPS signal in Delhi was often weak and thus unreliable to link to high resolution spatial data, which reduced the potential sample size of the study. Further, the suspension of personal monitoring in the wake of Covid-19 also served to restrict the study sample size. The NDVI and TC data were obtained from satellite images and were complete, unlike the user-generated data of OSM that we used for GLU. To assess completeness, we calculated the overlap of each radius size with any land use (i.

e., not just GLU and excluding the well-defined road network) and points of interest and found 9% (250 m) to 29% (25 m) of personal GPS points did not intersect with any such identified areas (data not shown); therefore, some GLU areas may have been omitted. Ultimately, due to the completeness of satellite imagery compared to user-generated datasets, we have a higher degree of confidence in the results for the NDVI and TC markers than those for GLU and PF.

To extend the findings in the current study, future research should focus on additional air quality monitoring of personal exposures particularly inside, but also outside of, greenspaces in Delhi, and other high ambient air pollution contexts, across seasons, ideally with enhanced detail on plant species and greenspace morphology. At the same time, ambitious, multi-pronged emission reduction policies and interventions are urgently required to address the multiple sources of $PM_{2.5}$ in Delhi (Amann et al., 2017).

5. Conclusion

Our study found weak evidence of reductions in personal exposure to $PM_{2.5}$ in areas of higher greenspace, notably tree cover, within walking trips only in the spring, summer, and monsoon season. By contrast, higher $PM_{2.5}$ exposure was associated with those trips having more overall green land use (e.g., parks, forests, recreation grounds) during this same time of year. This period excludes autumn and winter, when Delhi experiences the poorest air quality, suggesting little association with greenspace when PM concentrations are high and there are larger contributions from distant sources. Our results warrant further investigations with larger sample sizes into the role of greenspace in high ambient air pollution environments, particularly in relation to different vegetation types and greenspace morphology. Nevertheless, the relatively small effect of urban vegetation on personal $PM_{2.5}$ exposure concentrations suggests measures beyond exposure avoidance are necessary, such as significant emissions control, to minimise the harmful impacts on health of ambient $PM_{2.5}$.

Author statement

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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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2022.119294.

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