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Urban greenspace and the indoor environment: Pathways to health via indoor particulate matter, noise, and road noise annoyance

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ABSTRACT

Background/Aim: The exposome includes urban greenspace, which may affect health via a complex set of pathways, including reducing exposure to particulate matter (PM) and noise. We assessed these pathways using indoor exposure monitoring data from the HEALS study in four European urban areas (Edinburgh, UK; Utrecht, Netherlands; Athens and Thessaloniki, Greece).

Methods: We quantified three metrics of residential greenspace at 50 m and 100 m buffers: Normalised Difference Vegetation Index (NDVI), annual tree cover density, and surrounding green land use. NDVI values were generated for both summer and the season during which the monitoring took place. Indoor $PM_{2.5}$ and noise levels were measured by Dylos and Netatmo sensors, respectively, and subjective noise annoyance was collected by questionnaire on an 11-point scale. We used random-effects generalised least squares regression models to assess associations between greenspace and indoor $PM_{2.5}$ and noise, and an ordinal logistic regression to model the relationship between greenspace and road noise annoyance.

Results: We identified a significant inverse relationship between summer NDVI and indoor $PM_{2.5}$ (-1.27 µg/m^3 per 0.1 unit increase [95% CI -2.38 to -0.15]) using a 100 m residential buffer. Reduced (i.e., < 1.0) odds ratios (OR) of road noise annoyance were associated with increasing summer (OR = 0.55 [0.31 to 0.98]) and season-specific (OR = 0.55 [0.32 to 0.94]) NDVI levels, and tree cover density (OR = 0.54 [0.31 to 0.93] per 10 percentage point increase), also at a 100 m buffer. In contrast to these findings, we did not identify any significant associations between greenspace and indoor noise in fully adjusted models.

Conclusions: We identified reduced indoor levels of $PM_{2.5}$ and noise annoyance, but not overall noise, with increasing outdoor levels of certain greenspace indicators. To corroborate our findings, future research should examine the effect of enhanced temporal resolution of greenspace metrics during different seasons, characterise the configuration and composition of green areas, and explore mechanisms through mediation modelling.

1. Introduction

The exposome represents the comprehensive range of exposures that may interact with the genome throughout the life course (Wild, 2012). Such exposures may also interact and modify one another; urban greenspace and greenness have received much focus as environmental features that entail multifaceted pathways to benefit health (World Health Organization (WHO), 2016). As a concept, greenspace represents diverse landscape features in myriad arrangements, both in natural (e.g., parks) and non-natural (e.g., street trees) settings with a variety of functions (Hartig et al., 2014). Key pathways have been put forward outlining how greenspace may affect health, including via the reduction of harm (e.g., mitigating air pollution and noise) (Markevych et al., 2017). Fine airborne particles and noise are top environmental

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risk factors of concern (Mitsakou et al., 2019) and are associated with significant negative health impacts in Europe (Recio et al., 2016; WHO, 2018); therefore, any such exposure reductions from greenspace may provide significant benefits at a population level.

There are several potential mechanisms for vegetation to mitigate air pollution levels. Leaf stomata can absorb gases, including SO_2, NO_2, and O_3, as well as provide an effective surface area on which to accumulate PM through both wet and dry deposition (Bottalico et al., 2016). Surrounding residential greenness has also been linked to lower levels of both outdoor and indoor $PM_{2.5}$ at residences (Dadvand et al., 2012) and schools (Dadvand et al., 2015). Despite these reported associations with improved air quality, vegetation can have its own contribution to ambient pollutant concentrations, including the release of pollen and biogenic volatile organic compounds, which can be precursors to the formation of O_3 and secondary organic aerosols; the latter of these compounds contributes to $PM_{2.5}$ (Salmond et al., 2016).

Greenspace can both reduce noise and introduce positive soundscapes. Greenness or vegetation can provide natural sounds (Alvarsson et al., 2010), as well as block artificial noise through an acoustic mechanism (van Renterghem et al., 2015). The perception of any noise reductions from greenspace, which may be independent from actual reductions in sound levels, may occur through visual blocking of the source, the presence of greenness itself, and/or associated natural sounds, all of which may also depend on personal characteristics (van Renterghem, 2018). Noise annoyance can facilitate poor health beyond increasing overall stress levels, including lowered perceived restorative quality of the home environment (von Lindern et al., 2016) and deterrence of physical activity (Foraster et al., 2016). Therefore, there is the potential for greenspace to affect both direct and indirect pathways of noise impacts on health (Basner et al., 2014).

One challenging issue in understanding the effects of greenness is its temporal instability, which may vary in temperate settings if assessed during different times of the year (Ren et al., 2017). Some methodological approaches employed to date to address this seasonal variability include taking measurements during maximum potential greenness (e.g., during the summer [Andrusaityte et al., 2016; Vienneau et al., 2017] or spring/autumn [Dadvand et al., 2014]) and collating images from each season to calculate annual average values (Hystad et al., 2014), but these methods do not address variation in a given year. As seasonal measurements of greenspace can affect associations with health outcomes (Dzhambov et al., 2018b), the distinction is important. Whilst previous studies have largely quantified spatial variation of greenness, e.g., multiple buffer sizes, the influence of temporal misalignment has yet to be fully explored (Helbich, 2019).

Outdoor sources have been shown to contribute to over half of indoor $PM_{2.5}$ concentrations (Meng et al., 2005) and to over 60% of the total burden of disease attributable to indoor air pollution exposure in Europe (Asikainen et al., 2016). A review suggests few studies have focussed on the impact of greenspace on indoor air quality and noise (Wang et al., 2014). Further, as many people spend as much as 90% of their time indoors (Tong et al., 2016), examining the impact of greenspace on the indoor environment would be valuable to quantify its contribution to potential health pathways. Therefore, the purpose of this study was to characterise the effects of greenspace using three metrics, at different spatial and temporal scales, on indoor $PM_{2.5}$, noise, and reported road noise annoyance. A model of the examined pathways to health is presented in Fig. 1.

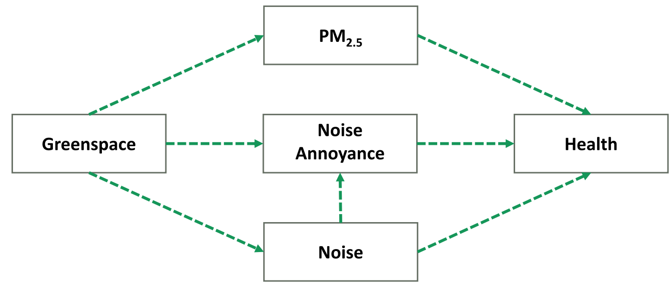

Fig. 1. The three greenspace pathways to health to be investigated.

2. Materials and methods

2.1. Study design and population

This study was part of the larger EU-funded Health and Environment-wide Associations based on Large population Surveys (HEALS; http://www.heals-eu.eu) with the specific objective to use and assess sensors to characterise the environments of families with young children. The study included households situated in four European urban areas and the surrounding environs (approximate population; https://www.citypopulation.de): Edinburgh, UK (500,000); Utrecht, Netherlands (350,000); Thessaloniki, Greece (800,000); and Athens, Greece (3,170,000). There were $n = 21$ (40%) homes located in Utrecht, with the others distributed across the Netherlands. Participants with a child under the age of three years old were eligible and were recruited in each city through advertising via universities, childcare groups, and word of mouth. Household and personal monitoring periods spanned approximately one week, including the installation of a Netatmo Weather Station (Netatmo, France) and Dylos DC1700™ (Dylos Corp., USA) sensors to measure indoor levels of noise and PM, respectively (see Fig. 2). These instruments were placed in the living rooms of homes, with the exception of the Netatmo sensors in the two Greek cities, which were placed in the child's bedroom to better characterise the child's microenvironments (Stamatelopoulou et al., 2019). During the monitoring period, participants were asked to complete questionnaires pertaining to socioeconomic data, household information, and noise annoyance. Ethical approval was sought and received for each study area (UK: Heriot Watt University Ethics Review Board, 2015–07; Netherlands: METC Brabant NW2015-07; Athens: NCSRD Ethics Review Board, 2015–04: 260/2015–1671; Thessaloniki: Aristotle University Ethics Committee 140,540/2018).

2.2. Data collection and processing

2.2.1. Greenspace

Three metrics were used to define surrounding levels of residential greenspace: the Normalised Difference Vegetation Index (NDVI); tree cover density, and green land use (see Fig. 3). Chlorophyll levels in healthy green vegetation, as a measure of greenness, reflect more light in the near infrared (NIR) wavelength, whilst absorbing light in the red spectrum. These wavelengths can be used from satellite images to calculate a NDVI score of -1 to $+1$ ([NIR - Red]/[NIR + Red]; Rhew et al., 2011), with values close to $+1$ indicating dense levels of healthy greenery. To calculate the NDVI for each residence, we used Sentinel-2 satellite images available from the Copernicus Open Access Hub at 10-m spatial and five-day temporal resolutions, which include adjustments for atmospheric aerosol and water vapour. Images were selected based on maximum cloud coverage of 10% and to represent greenness levels during both the summer and the specific season during which the

Fig. 2. The a) Dylos and b) Netatmo sensors used to monitor indoor $PM_{2.5}$ and noise, respectively.

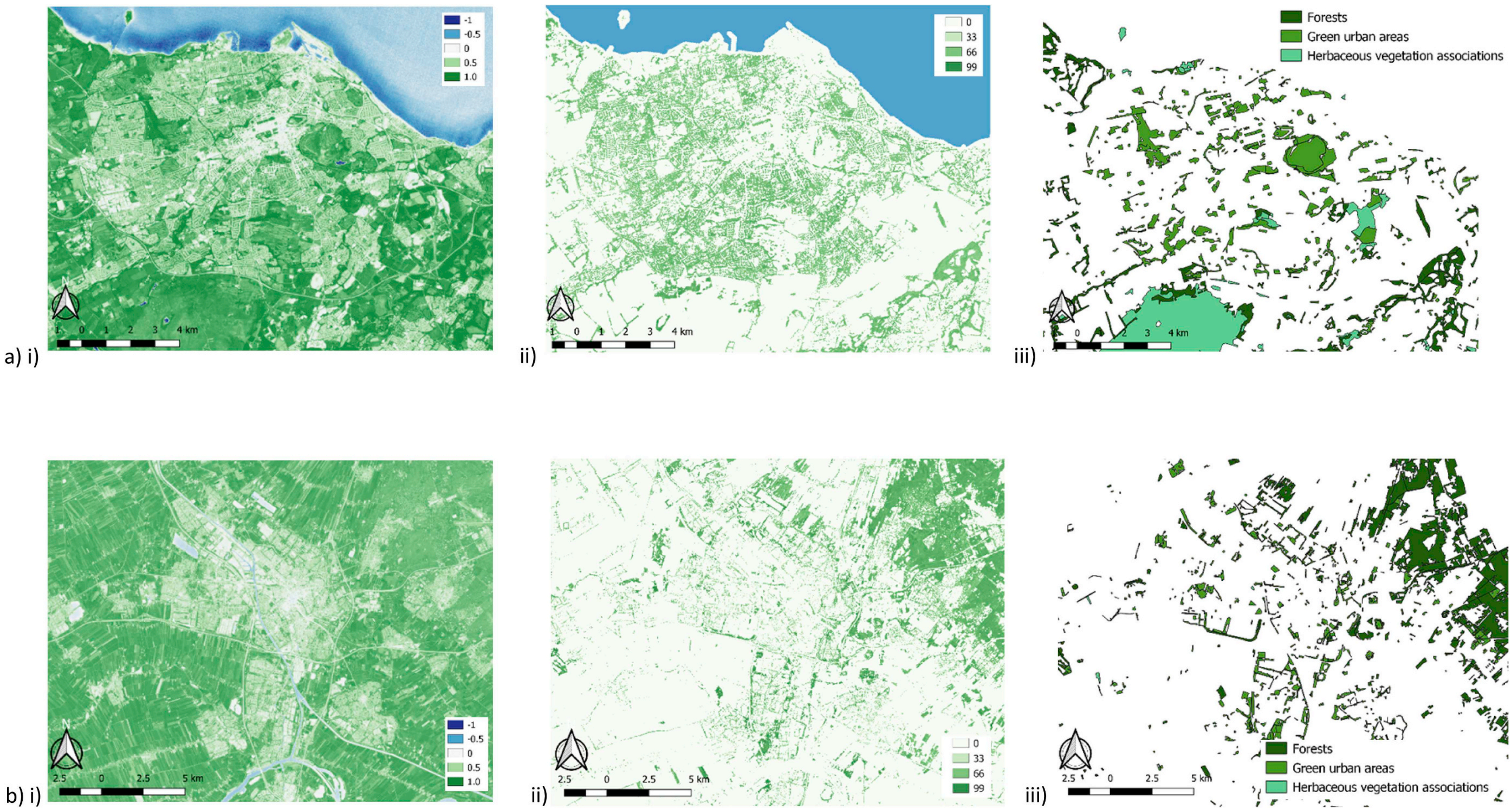

Fig. 3. a-d Maps of a) Edinburgh, UK; b) Utrecht, Netherlands; c) Thessaloniki, Greece; and d) Athens, Greece, presenting i) summer NDVI, ii) tree cover density (%), and iii) green land use. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

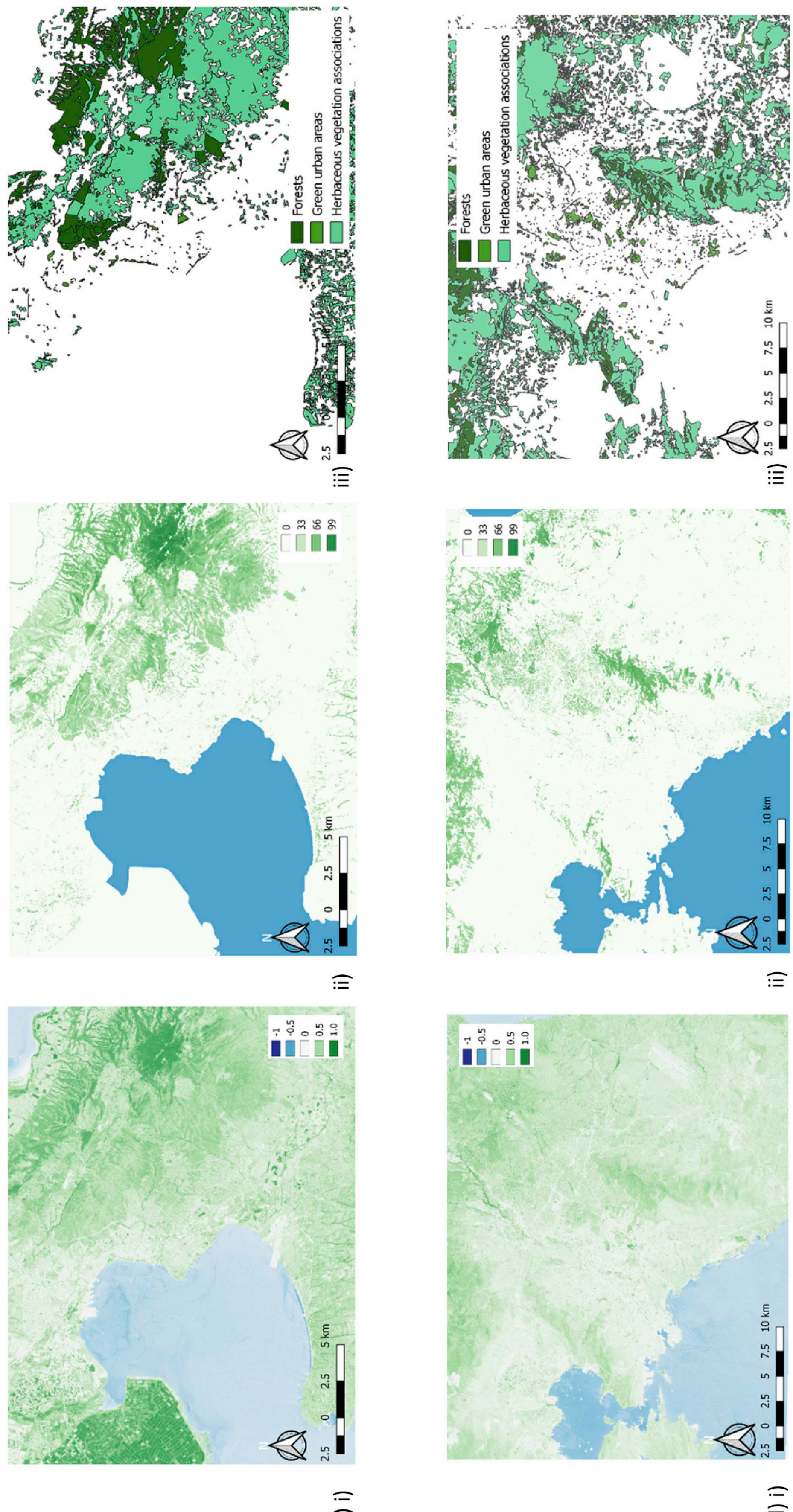

Fig. 3. (*continued*)

Table 1
Descriptive characteristics of indoor and outdoor home environments in the four study sites.

Variable	Edinburgh				Utrecht				Thessaloniki				Athens			
	n	%	Mean	SD	n	%	Mean	SD	n	%	Mean	SD	n	%	Mean	SD
Greenspace																
NDVI - summer (50 m) (−1 to +1)	29	100	0.43	0.12	52	100	0.29	0.11	25	100	0.13	0.07	25	100	0.18	0.07
NDVI - summer (100 m) (−1 to +1)	29	100	0.45	0.11	52	100	0.31	0.11	25	100	0.15	0.08	25	100	0.19	0.07
NDVI - seasonal (50 m) (−1 to +1)	29	100	0.35	0.15	52	100	0.28	0.10	25	100	0.13	0.10	25	100	0.16	0.07
NDVI - seasonal (100 m) (−1 to +1)	29	100	0.37	0.14	52	100	0.31	0.10	25	100	0.14	0.10	25	100	0.17	0.07
Tree cover density (50 m) (%)	29	100	22.9	17.7	52	100	3.7	7.2	25	100	0.6	1.4	25	100	5.7	8.3
Tree cover density (100 m) (%)	29	100	23.0	13.6	52	100	6.5	7.6	25	100	1.5	3.2	25	100	6.6	8.3
Proportion of green land use (50 m) (%)	28	97	2.1	7.4	37	71	0.08	0.5	25	100	1.4	6.9	25	100	3.7	9.3
Missing	1	3	–	–	15	29	–	–	0	0	–	–	0	0	–	–
Proportion of green land use (100 m) (%)	28	97	4.1	9.5	37	71	0.8	2.3	25	100	1.4	6.4	25	100	4.4	9.2
Missing	1	3	–	–	15	29	–	–	0	0	–	–	0	0	–	–
Outcomes																
Indoor $PM_{2.5}$ (μg/m^3)	29	100	11.8	4.9	44	85	12.0	11.8	25	100	16.1	8.1	25	100	10.2	3.0
# of days per dwelling	–	–	6.5	0.7	–	–	5.9	2.7	–	–	6.6	1.1	–	–	6.1	1.1
Missing	0	0	–	–	8	15	–	–	0	0	–	–	0	0	–	–
Indoor noise (dB)	28	97	52.4	5.6	49	94	50.9	8.2	23	92	42.0	4.6	25	100	43.1	4.5
# of days per dwelling	–	–	6.5	0.8	–	–	6.7	1.2	–	–	6.4	1.2	–	–	6.0	1.0
Missing	1	3	–	–	3	6	–	–	2	8	–	–	0	0	–	–
Road noise annoyance (0–10)	29	100	1.3	2.2	48	92	1.6	2.0	21	84	2.9	2.2	25	100	2.8	2.2
Missing	0	0	–	–	4	8	–	–	4	16	–	–	0	0	–	–
Covariates																
Distance to major road (m)	29	100	336	320	52	100	1048	815	25	100	788	853	25	100	883	924
Proportion of surrounding roads (50 m) (%)	28	97	10.4	5.3	37	71	16.5	9.6	25	100	17.6	6.7	25	100	15.4	5.5
Missing	1	3	–	–	15	29	–	–	0	0	–	–	0	0	–	–
Proportion of surrounding roads (100 m) (%)	28	97	10.7	4.3	37	71	16.8	7.2	25	100	17.9	5.4	25	100	16.1	6.5
Missing	1	3	–	–	15	29	–	–	0	0	–	–	0	0	–	–
Distance to rail/tram (m)	29	100	1365	1973	52	100	1772	2766	25	100	4766	3971	25	100	2115	1343
Distance to nearest ground monitor (m)	29	100	7931	8496	52	100	6421	5510	–	–	–	–	25	100	3696	2109
Population density (1000s)	29	100	4.5	3.7	52	100	2.7	1.6	25	100	11.5	6.0	25	100	7.4	4.9
Outdoor $PM_{2.5}$ (μg/m^3)	26	90	6.2	3.0	47	90	7.6	6.0	–	–	–	–	19	76	12.4	4.8
Missing	3	10	–	–	5	10	–	–	–	–	–	–	6	24	–	–
Monitoring season																
Winter	11	38	–	–	2	4	–	–	2	8	–	–	0	0	–	–
Spring	0	0	–	–	23	44	–	–	19	76	–	–	0	0	–	–
Summer	10	34	–	–	27	52	–	–	0	0	–	–	19	76	–	–
Autumn	8	28	–	–	0	0	–	–	4	16	–	–	6	24	–	–
Smoker																
Yes	0	0	–	–	0	0	–	–	5	20	–	–	12	48	–	–
No	29	100	–	–	48	92	–	–	17	68	–	–	13	52	–	–
Missing	0	0	–	–	4	8	–	–	3	12			0	0		
Number of Occupants	29	100	3.6	0.6	50	96	3.8	0.7	25	100	2.6	0.8	25	100	3.6	0.7
Missing	0	0	–	–	2	4	–	–	0	0	–	–	0	0	–	–
Use of fireplace																
Yes	2	7	–	–	5	10	–	–	0	0	–	–	0	0	–	–
No	27	93	–	–	41	79	–	–	22	88	–	–	22	88	–	–
Missing	0	0	–	–	6	12	–	–	3	12	–	–	3	12	–	–
Cooking with gas																
Yes	19	66	–	–	35	67	–	–	0	0	–	–	2	8	–	–
No	10	34	–	–	13	25	–	–	22	88	–	–	23	92	–	–
Missing	0	0	–	–	4	8	–	–	3	12	–	–	0	0	–	–
Age (years)	28	97	35.1	3.2	50	96	35.1	4.6	25	100	33.6	9.1	25	100	36.3	2.3
Missing	1	3	–	–	2	4	–	–	0	0	–	–	0	0	–	–
Gender																
Male	3	10	–	–	35	67	–	–	11	44	–	–	0	0	–	–
Female	26	90	–	–	15	29	–	–	14	56	–	–	25	100	–	–
Missing	0	0	–	–	2	4	–	–	0	0	–	–	0	0	–	–
Pets (cat or dog)																
Yes	9	31	–	–	10	19	–	–	1	4	–	–	3	12	–	–
No	20	69	–	–	38	73	–	–	21	84	–	–	22	88	–	–
Missing	0	0	–	–	4	8	–	–	3	12	–	–	0	0	–	–
Open windows (≥1/week)																
Yes	24	83	–	–	45	87	–	–	22	88	–	–	25	100	–	–
No	5	17	–	–	3	6	–	–	0	0	–	–	0	0	–	–
Missing	0	0	–	–	4	8	–	–	3	12	–	–	0	0	–	–
Noise sensitivity (1–5)	28	97	2.6	0.8	48	92	2.6	1.1	20	80	3.0	1.0	25	100	2.9	1.1
Missing	1	3	–	–	4	8	–	–	5	20	–	–	0	0	–	–
Temperature - Indoor (°C)	28	97	18.6	1.9	49	94	21.8	1.9	23	92	22.8	2.9	25	100	26.6	2.1
Missing	1	3	–	–	3	6	–	–	2	8	–	–	0	0	–	–
Relative Humidity - Indoor (%)	28	97	62.9	7.8	49	94	60.1	7.3	23	92	60.6	6.4	25	100	55.1	8.4
Missing	1	3	–	–	3	6	–	–	2	8	–	–	0	0	–	–
Total participants	29	–	–	–	52	–	–	–	25	–	–	–	25	–	–	–

indoor monitoring took place (as close to the actual dates of monitoring as possible). Images were retrieved within one year of the monitoring periods (i.e., 2015/2016) except for the Edinburgh locations, where acceptable cloud coverage occurred across the study area only during 2017–2018 (See Table S1).

Tree cover density (0–100%) reflects the tree canopy at 20 m resolution during 2015, and the Urban Atlas dataset distinguishes different types of land use in urban areas at 10 m resolution, most recently available for 2012; both variables were extracted from the Copernicus hub. We included the following green land use classes from Urban Atlas: 'green urban areas,' 'forests,' and 'herbaceous vegetation associations.' Green urban areas contain at least 0.25 ha and represent green recreational areas, excluding private gardens. 'Sports and leisure facilities' contain a mix of amenities (e.g., golf courses, amusement parks) and were excluded due to the inclusion of non-green areas (van den Bosch et al., 2016).

All residential greenspace levels were assessed using buffer sizes of 50 m and 100 m, based on geocoded addresses, and calculated using the specific coordinate reference system for each country. These areas were selected based on the smallest buffers employed in previous research (Su et al., 2019) and to maximise relevance for potential impacts of greenspace on the indoor environment. Mean NDVI and tree cover density values were calculated at each residential buffer size, and the proportion of surrounding green land use was calculated by summing the total land area of the above mentioned green land use classes within each residential buffer size. A small number of home addresses (n = 16; 12%) were located outside of the Urban Atlas coverage (n = 15 in Utrecht and n = 1 in Edinburgh); therefore, land use was not calculated for these addresses, which ultimately were excluded from analysis.

2.2.2. Particulate matter ($PM_{2.5}$)

The Dylos sensors logged indoor particle counts continually at 1-min intervals using two bin sizes (≥0.5 µm and ≥2.5 µm) and converted them into $PM_{2.5}$ concentrations (Franken et al., 2019). Sensors were set up only inside homes. Day- and dwelling-specific outdoor air quality was estimated using $PM_{2.5}$ concentrations using data from the nearest ambient monitoring station with available data. Airborne $PM_{2.5}$ monitoring in Thessaloniki commenced in September 2016, after the completion of the HEALS fieldwork; therefore, we excluded Thessaloniki from the indoor $PM_{2.5}$ analysis.

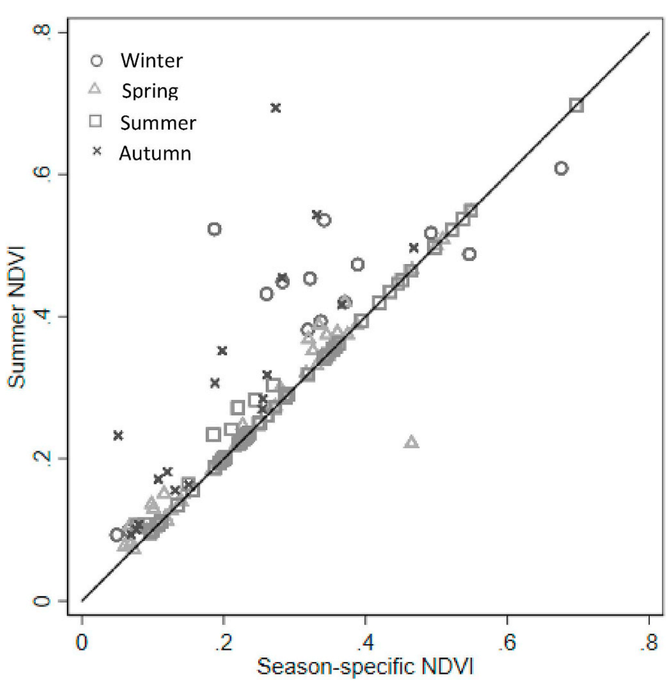

Fig. 4. A scatterplot of summer and season-specific NDVI values assigned to each residential address (100 m buffer).

2.2.3. Noise

The Netatmo sensors logged mean indoor decibel levels every 5 min. In addition to noise levels, the Netamo sensors also logged indoor temperature, relative humidity, and carbon dioxide. As with PM concentrations, only indoor noise was measured, so we employed the distance to the nearest major road as an indicator for traffic noise sources, as described in the following section. Questionnaires were administered to participants to gauge road, railway, and other noise annoyance, including the question (asked during the initial home visit): 'Thinking about the last 12 months, when at home, what number from 0 (not at all annoying) to 10 (extremely annoying) best shows how bothered, annoyed or disturbed you were by noise from the sources mentioned [above]?' These terms have been used in previous noise annoyance studies (e.g., Dzhambov et al., 2018a). Respondents could also indicate if they did not notice road traffic noise. To account for noise sensitivity, we asked participants how sensitive they were to noise in general based on a five-point scale (1 = 'not at all', 2 = 'slightly', 3 = 'moderately', 4 = 'very', 5 = 'extremely').

2.2.4. Outdoor and indoor home characteristics

We were unable to obtain outdoor noise maps as GIS files for all cities; therefore, to adopt a consistent approach to account for traffic sources, we used the distance to the nearest major road, which has been shown to be associated with higher noise and $PM_{2.5}$ levels (Fecht et al., 2016). Population density was assigned to each residential address using global 1 × 1 km gridded estimates for the year 2015 (Center for International Earth Science Information Network - CIESIN - Columbia University, 2018). The population density value was assigned from the specific grid cell in which the home address was located. Distances from residential addresses to the nearest major roads (i.e., primary roads and motorways) and railways (i.e., rail and tram) were calculated using OpenStreetMap shapefiles downloaded during Moshammer et al., 2019 from Geofabrik (https://download.geofabrik.de/). The proportionate surrounding road land use (i.e., 'Fast transit roads and associated land' and 'Other roads and associated land') was calculated using the Urban Atlas dataset. Household questionnaires provided details on other potentially important indoor sources of PM and noise, including smoking habits of occupants, use of fireplaces for heating, use of gas for cooking, the presence of pets, and how often windows are opened when weather permits.

2.3. Statistical analysis

We examined associations between greenspace markers and $PM_{2.5}$ and noise parameters by repeated measures regression models reflecting the panel nature of the data (repeated days of measurements within households in each of four cities; Moshammer et al., 2019). Separate models were developed for (i) indoor $PM_{2.5}$, (ii) noise, and (iii) road noise annoyance as the outcome. We included dwelling-days where measurements were complete for ≥12 h. For $PM_{2.5}$, the outcome was the mean concentration for day of measurement in each dwelling. For indoor noise, we analysed daily mean noise levels in dB. For subjective ratings of road noise annoyance, we used an ordinal logistic regression model with the original 11-point ratings classified into three relative groups of similar size: 'no annoyance' (including 'not at all annoying' [original 11-point rating scores of '0'] and the response 'don't notice'; n = 46), 'lower' (scores of 1–3; n = 47), and 'higher' (scores ≥ 4; n = 30). These models satisfied the proportional odds assumption (Brant, 1990). The resulting odds ratios (ORs) represent the likelihood of road noise annoyance above a given cut-point (none/lower/higher) per increment in greenspace marker (Scott et al., 1997).

All three outcomes were assessed in relation to four markers of greenspace calculated using buffers of 50 m and, separately, 100 m

Table 2
Pearson correlation coefficients of greenspace and urban characteristics.

	Indoor $PM_{2.5}$ (μm3)	Indoor noise (dB)	Road noise annoyance (0–10)	Distance to major road (m)	% of nearby road (50 m)	% of nearby road (100 m)	Distance to nearest rail (m)	Pop'n density (per km^2)	NDVI - summer (50 m)	NDVI - summer (100 m)	NDVI - seasonal (50 m)	NDVI - seasonal (100 m)	Tree cover density (50 m)	Tree cover density (100 m)	Green land use (50 m)	Green land use (100 m)
Indoor $PM_{2.5}$ (μm3)	1															
Indoor noise (dB)	0.03	1														
Road noise annoyance (0–10)	0.02	−0.13	1													
Distance to major road (m)	0.14	−0.07	−0.21	1												
% of nearby road (50 m)	0.04	−0.11	0.29	−0.11	1											
% of nearby road (100 m)	−0.02	−0.14	0.31	−0.21	0.77	1										
Distance to nearest rail (m)	0.20	−0.33	−0.16	0.28	−0.04	−0.09	1									
Population density (per km^2)	0.05	−0.39	0.40	−0.33	0.23	0.37	−0.01	1								
NDVI - summer (50 m)	0.04	0.38	−0.32	0.00	−0.37	−0.51	−0.09	−0.55	1							
NDVI - summer (100 m)	0.05	0.43	−0.38	0.05	−0.33	−0.51	−0.12	−0.60	0.95	1						
NDVI - seasonal (50 m)	0.03	0.36	−0.32	0.09	−0.30	−0.45	−0.04	−0.55	0.86	0.84	1					
NDVI - seasonal (100 m)	0.03	0.41	−0.38	0.15	−0.26	−0.44	−0.07	−0.61	0.81	0.88	0.96	1				
Tree cover density (50 m)	−0.05	0.21	−0.18	−0.19	−0.26	−0.32	−0.25	−0.18	0.68	0.61	0.53	0.47	1			
Tree cover density (100 m)	−0.07	0.23	−0.27	−0.16	−0.20	−0.34	−0.25	−0.24	0.67	0.69	0.58	0.61	0.88	1		
Green land use (50 m)	−0.06	−0.18	−0.10	0.11	−0.07	−0.07	0.17	−0.13	0.07	0.04	0.03	0.04	0.06	0.03	1	
Green land use (100 m)	−0.05	−0.12	−0.14	0.14	−0.08	−0.12	0.10	−0.18	0.15	0.18	0.13	0.16	0.14	0.15	0.87	1

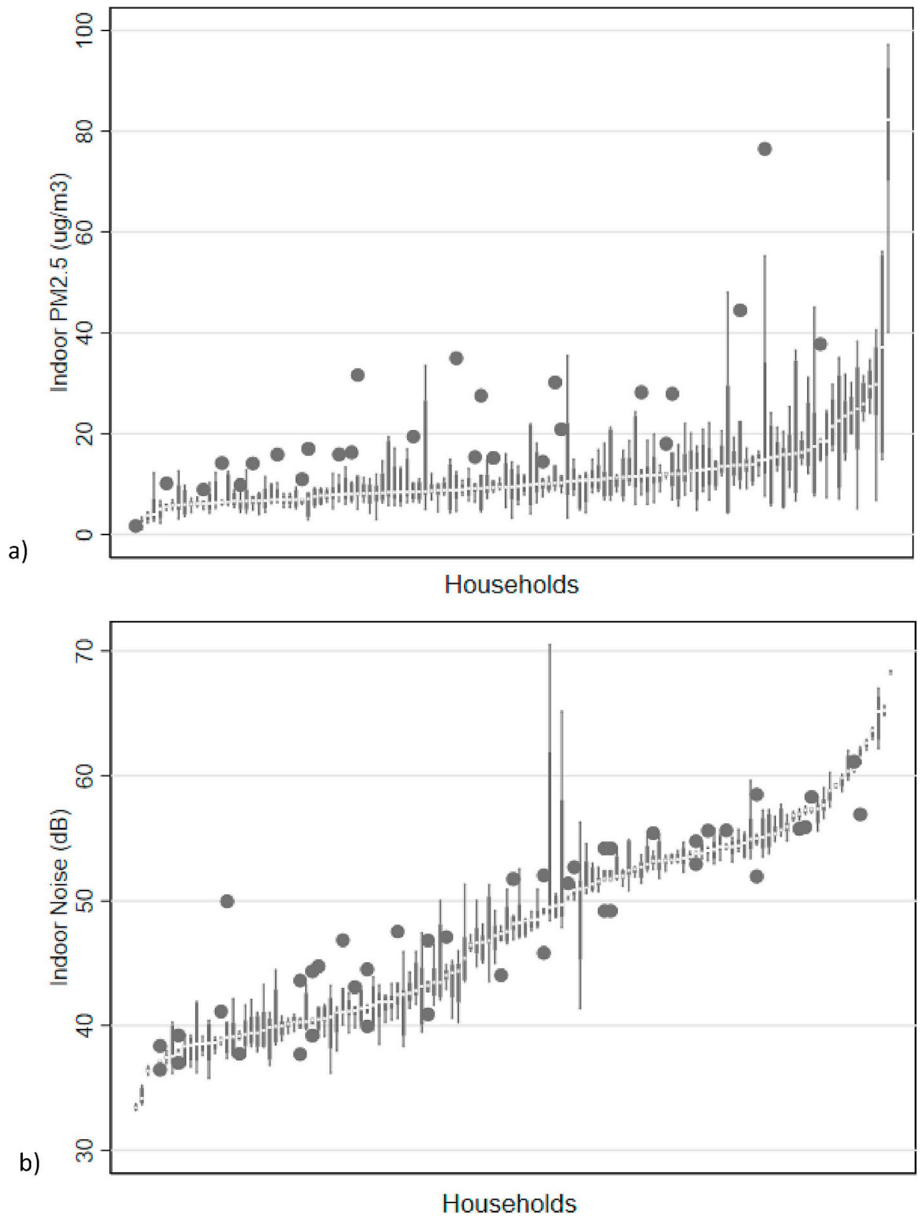

Fig. 5. Boxplots of daily means for each home address representing indoor a) $PM_{2.5}$ and b) indoor noise, presented from low to high values.

around the place of residence: (i) mean NDVI in the summer months, (ii) mean NDVI in the season of dwelling measurement, (iii) mean tree cover density, and (iv) proportion of the land classified as green land use. Regression coefficients represent the change in outcome for a 0.1 increase in the mean NDVI score, or 10 percentage point increase in tree cover density or proportion of green land use, a standardised approach adopted in previous work (e.g., Gascon et al., 2016). Autocorrelation in the repeated measurements for each home was found to be present for both $PM_{2.5}$ and noise data using the Wooldridge test ($p < 0.001$); therefore, robust standard errors were used (Wooldridge, 2010).

For each outcome, we present three sets of models for confounder adjustment: model 1 – the unadjusted results; model 2 – the effect of greenspace markers adjusted for outdoor $PM_{2.5}$, season, city, population density, distances to road and rail, and the proportion of surrounding road land use; and model 3 – the effect of greenspace with further adjustment for smoking, use of a fireplace for heating, gas for cooking, the number of occupants, presence of pets (cats/dogs), opening windows ≥1/week, and mean temperature and relative humidity. These fixed covariate selections were made *a priori.* 'Season' was the predominant season during the monitoring period for each home. Variables with skewed distributions (population density and distances to the nearest major road and railway) were log-transformed. Road noise annoyance models were also adjusted for the age and sex of the respondent. Noise sensitivity was included in the road noise annoyance models as a continuous variable (Okokon et al., 2015).

To assess the potential presence of instrument measurement bias, median $PM_{2.5}$ and noise values were compared across the specific Dylos and Netatmo units using Kruskal-Wallis tests ($p > 0.05$ in all instances). A secondary analysis was carried out using binary indicators for the presence of any surrounding green land use and tree cover. For the $PM_{2.5}$ and noise models, a spatial term was added to assess the latitude and longitude coordinates of residential addresses (Guo et al., 2016). Geospatial analysis was conducted using QGIS (Bonn v3.2.1) and statistical analysis was undertaken using Stata (v15).

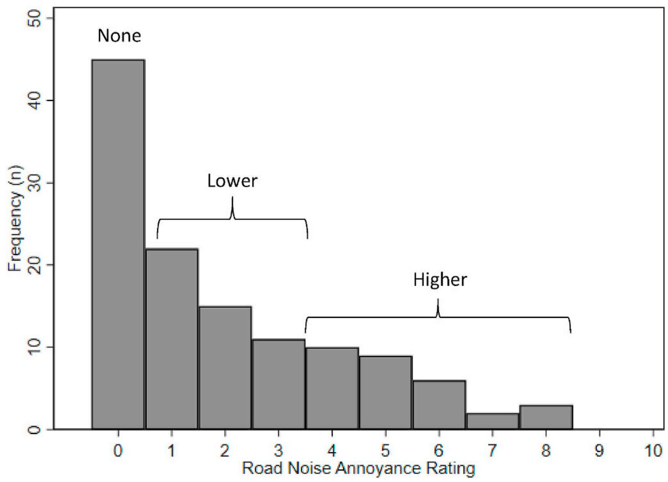

Fig. 6. A histogram of reported road noise annoyance, using an 11-point scale of 0 ('not at all annoying') to 10 ('extremely annoying') (n = 123). Categories used for analysis ('none', 'lower', 'higher') are indicated.

3. Results

A total of 131 households were enrolled in the indoor monitoring study across the four study centres, with the highest representation from the Netherlands (n = 52; 39.7%). The monitoring period commenced in March 2015 and finished in June 2016. About three quarters of the households (n = 98; 74.8%) had measurements taken during spring or summer. The number of occupants within each household varied from two to six (mean = 3.5; SD = 0.8), and 17 (13.0%) homes included a smoker, all of which were situated in Greece. Overall, the proximity to a major road was closer (mean = 809 m; SD = 805) than to the nearest railway (2319 m; SD = 2927). The mean distance to the nearest ground air pollution monitor across all addresses was approximately 6200 m (SD = 6100). Table 1 presents the full descriptive characteristics separately for each study site.

Since most of the households were monitored during the spring and summer, mean summer and season-specific NDVI levels were similar (or the same) for many homes, with slightly higher values using the 100 m buffer (see Fig. 4). The mean residential tree cover densities and green land use proportions were higher using the 100 m buffer, though n = 23 (18%) and n = 91 (69%) home addresses had no surrounding trees or green land use, respectively. Mean tree cover density at residences was higher in Edinburgh (> 20%), compared to those of the other locations (< 10%) (see Table 1).

Pearson correlation coefficients of the associations among the greenspace and urban indicators, namely roads/rail, and population density, as well as between noise and road noise annoyance are shown in Table 2. NDVI values and tree cover density were moderately positively correlated (r = 0.47 to 0.69), and both metrics were weakly correlated with the proportion of green land use (r < 0.20). Weak correlations (r < ± 0.26) were present between the distances to major roads and rails and any of the greenspace metrics. NDVI was the greenspace indicator most strongly negatively correlated with the proportion of surrounding roads and population density (r = −0.26 to −0.61).

The mean number of days at each residence with ≥12 h of data for indoor $PM_{2.5}$ and noise were 6.5 (SD = 1.1) and 6.4 (SD = 1.2), respectively. Mean indoor $PM_{2.5}$ concentrations were 12.4 μg/m^3 (SD = 8.6); n = 12 households were not assigned any outdoor $PM_{2.5}$ values due to missing data. Mean noise levels were 48.1 dB (SD = 7.7), and n = 37 (28.2%) households had at least one day with mean noise levels ≥ 55 dB (see Fig. 5). Mean road noise annoyance out of a scale of 10 was 2.0 (SD = 2.2), with no significant correlation with indoor noise levels (r = −0.11; p = 0.216). Seventy-eight (59.5%) participants reported some road noise annoyance (i.e., a rating of > 0) (see Fig. 6).

Results of the regression models are shown in Tables 3–5. In general, for a given greenspace metric, coefficients and ORs were similar for the 50 m and 100 m buffers, with some associations achieving statistical significance with the latter size. By contrast, between greenspace metrics, effect sizes of coefficients and ORs varied more substantially. In the unadjusted models, none of the greenspace metrics were significantly associated with indoor $PM_{2.5}$ levels. In the fully adjusted model at the 100 m buffer, a statistically significant inverse association was observed for indoor $PM_{2.5}$ and summer NDVI (−1.27 μg/m^3 [95% CI -2.38 to −0.15] per 0.1-unit increase). Therefore, based on the mean measured indoor $PM_{2.5}$ levels (12.4 μg/m^3), an increase of 0.1 in summer NDVI was associated with a 10.2% (95% CI 1.2%–19.2%) decrease in indoor $PM_{2.5}$ concentrations. As an internal validation to the models, other covariates also were significant ($p < 0.05$) predictors of indoor $PM_{2.5}$ concentrations. Outdoor $PM_{2.5}$ concentrations were significantly positively associated with indoor levels in each of the models ($p < 0.001$); additionally, in select models, city, season (coefficients for spring were lower than that of winter; $p < 0.05$), and smoking (borderline significance; $p < 0.10$) were associated with increased indoor $PM_{2.5}$ levels (data not shown).

In the indoor noise model, the unadjusted coefficients for NDVI and tree cover were positive and significant, with green land use negative and significant. This trend, however, was reversed in the adjusted models, though none attained statistical significance ($p > 0.05$). Homes in both the Greek cities had significantly lower noise levels than the Edinburgh and Utrecht households ($p < 0.001$). The number of occupants

Table 3
Random-effects generalised least squares regression output for indoor $PM_{2.5}$ levels (μg/m^3).

Model	Greenspace metric	Cities[a]	House-holds (groups)	Days (obs.)	Change in $PM_{2.5}$ (95% CI) for a 0.1 (NDVI) or 10 percentage point (tree cover/green land use) increase in greenspace marker based on buffer around place of residence	
					50 m	100 m
Model 1: unadjusted	NDVI-summer	3	86	514	0.08 (−0.65 to 0.81)	0.12 (−0.56 to 0.80)
	NDVI-season	3	86	514	−0.10 (−0.80 to 0.60)	−0.11 (−0.80 to 0.58)
	Tree cover	3	86	514	0.35 (−0.40 to 1.09)	0.24 (−0.63 to 1.12)
	Green land use	3	77	453	0.00 (−0.94 to 0.95)	0.04 (−0.91 to 0.99)
Model 2: adjusted for outdoor $PM_{2.5}$, season, city, log population density, log distance to road/rail, proportion of surrounding road land use	NDVI-summer	3	77	453	−0.77 (−1.83 to 0.30)	−0.86 (−1.88 to 0.16)
	NDVI-season	3	77	453	−0.08 (−0.82 to 0.66)	−0.12 (−0.87 to 0.63)
	Tree cover	3	77	453	−0.16 (−0.88 to 0.56)	−0.23 (−1.08 to 0.61)
	Green land use	3	77	453	−0.08 (−0.72 to 0.56)	−0.22 (−0.80 to 0.35)
Model 3: model 2 + smoking, use of fireplace for heat, gas for cooking, number of occupants, presence of cats/dogs, windows opened ≥1/week, mean temperature and relative humidity	NDVI-summer	3	72	421	−0.94 (−2.03 to 0.15)	**−1.27 (-2.38 to -0.15)**
	NDVI-season	3	72	421	−0.48 (−1.29 to 0.34)	−0.62 (−1.42 to 0.17)
	Tree cover	3	72	421	−0.27 (−0.98 to 0.45)	−0.40 (−1.29 to 0.49)
	Green land use	3	72	421	−0.09 (−0.91 to 0.72)	−0.15 (−0.94 to 0.63)

[a] Excludes Thessaloniki.

Table 4
Random-effects generalised least squares regression output for indoor noise levels (dB).

Model	Greenspace metric	Cities	House-holds (groups)	Days (obs.)	Change in dB (95% CI) for a 0.1 (NDVI) or 10 percentage point (tree cover/green land use) increase in greenspace marker based on buffer around place of residence	
					50 m	100 m
Model 1: unadjusted	NDVI-summer	4	125	794	**1.81 (1.14 to 2.49)**	**1.96 (1.28 to 2.65)**
	NDVI-season	4	125	794	**1.59 (0.80 to 2.38)**	**1.77 (0.97 to 2.57)**
	Tree cover	4	125	794	**1.24 (0.37 to 2.11)**	**1.33 (0.35 to 2.31)**
	Green land use	4	111	698	**−2.09 (-3.60 to -0.59)**	−1.23 (−3.17 to 0.72)
Model 2: adjusted for season, city, log population density, log distance to road/rail, proportion of surrounding road land use	NDVI-summer	4	111	698	−0.11 (−1.33 to 1.11)	0.17 (−1.37 to 1.71)
	NDVI-season	4	111	698	−0.25 (−1.30 to 0.81)	−0.26 (−1.41 to 0.88)
	Tree cover	4	111	698	−0.02 (−0.98 to 0.93)	−0.23 (−1.45 to 0.98)
	Green land use	4	111	698	−0.47 (−1.41 to 0.47)	−0.39 (−1.48 to 0.70)
Model 3: model 2 + smoking, use of fireplace for heat, gas for cooking, number of occupants, presence of cats/dogs, windows opened ≥1/week, mean temperature and relative humidity	NDVI-summer	4	107	673	−0.54 (−1.82 to 0.74)	−0.53 (−2.10 to 1.04)
	NDVI-season	4	107	673	−0.52 (−1.62 to 0.59)	−0.60 (−1.83 to 0.62)
	Tree cover	4	107	673	−0.19 (−1.13 to 0.75)	−0.44 (−1.60 to 0.73)
	Green land use	4	107	673	0.18 (−0.83 to 1.19)	0.54 (−0.55 to 1.63)

Table 5
Ordinal logistic regression output for road noise annoyance using categories for none/lower/higher.

Model	Greenspace metric	Cities	n	Odds ratio (95% CI) of road noise annoyance for a 0.1 (NDVI) or 10 percentage point (tree cover/green land use) increase in greenspace marker based on buffer around place of residence	
				50 m	100 m
Model 1: unadjusted	NDVI-summer	4	123	**0.54 (0.41 to 0.71)**	**0.52 (0.39 to 0.68)**
	NDVI-season	4	123	**0.52 (0.39 to 0.70)**	**0.50 (0.38 to 0.67)**
	Tree cover	4	123	**0.74 (0.57 to 0.98)**	**0.65 (0.48 to 0.88)**
	Green land use	4	109	0.72 (0.42–1.24)	0.67 (0.40–1.12)
Model 2: adjusted for season, city, log population density, log distance to road, proportion of surrounding road land use	NDVI-summer	4	109	0.71 (0.44–1.15)	**0.56 (0.32 to 0.98)**
	NDVI-season	4	109	0.66 (0.42–1.02)	**0.55 (0.33 to 0.92)**
	Tree cover	4	109	0.86 (0.59–1.25)	0.69 (0.43–1.10)
	Green land use	4	109	0.79 (0.43–1.44)	0.78 (0.44–1.39)
Model 3: model 2 + noise sensitivity, age, sex, windows opened ≥1/week	NDVI-summer	4	104	0.71 (0.44–1.15)	**0.55 (0.31 to 0.98)**
	NDVI-season	4	104	0.67 (0.43–1.04)	**0.55 (0.32 to 0.94)**
	Tree cover	4	104	0.78 (0.52–1.16)	**0.54 (0.31 to 0.93)**
	Green land use	4	104	0.55 (0.23–1.31)	0.63 (0.30–1.34)

($p \leq 0.014$) and having windows open ($p \leq 0.008$) were associated with higher indoor noise, whilst the presence of pets (cat or dog) ($p \leq 0.004$) was associated with decreased indoor noise (data not shown).

NDVI and tree cover density at both buffer sizes were associated with lower road noise annoyance in the unadjusted models. In the fully adjusted models, there was reduced odds of road noise annoyance associated with a 10 percentage point increase in tree cover (OR = 0.54 [0.31 to 0.93]) and per 0.1 increase in summer (OR = 0.55 [0.31 to 0.98]) and seasonal (OR = 0.55 [0.32 to 0.94]) NDVI each at the 100 m buffer, with no observed significance at the 50 m buffer size. Population density was associated with increased road noise annoyance in several of the adjusted models ($p < 0.05$) (data not shown).

In the additional analysis using the fully adjusted models, binary indicators included negative coefficients or ORs < 1.0 (consistently only for the 50 m buffer) for the presence of trees or green land use, but none that was statistically significant with indoor $PM_{2.5}$ ($p \geq 0.218$), noise ($p \geq 0.079$), or road noise annoyance ($p \geq 0.158$). Coefficients for latitude and longitude were not significant in the noise models ($p \geq 0.632$) and mostly not significant in the $PM_{2.5}$ models, except for longitude in the NDVI (seasonal) 50 m buffer model ($p = 0.043$); the NDVI coefficient remained not significant (data not shown).

4. Discussion

Urban greenspace may promote positive pathways to health, including the reduction of harmful exposures, though a better understanding is needed on the robustness of associations across temporal and spatial scales. In the present study, we identified significant associations of reduced indoor levels of $PM_{2.5}$ and attenuated road noise annoyance, with NDVI and tree cover density (noise annoyance only) as metrics of nearby residential greenspace, after adjustment for urban landscape and indoor characteristics. By contrast, we did not find strong evidence of an association with indoor noise at the local scales of greenspace employed in this study.

Our study results indicate stronger inverse associations with indoor $PM_{2.5}$ and noise annoyance using larger greenspace buffer sizes (i.e., 100 m compared to 50 m). Studies examining health outcomes also indicate trends of stronger associations with greenspace buffer sizes up to 500 m (Su et al., 2019), though other research suggests the importance of capturing larger areas (i.e., > 500 m) to better reflect neighbourhood features (Requia et al., 2016). Ideally, buffer sizes should be consistent with the precision of the exposure metric, as well as the spatial and temporal resolution of the outcome data (Rugel et al., 2017). In the case of the present study, a 100 m buffer may have better characterised surrounding greenspace at the local level compared to that based on 50 m, a non-trivial portion of which would have been consumed by the home address; in addition, raster pixel size would have less influence at the larger buffer size.

Though NDVI levels and tree cover densities were moderately positively correlated, an association with indoor $PM_{2.5}$ was only identified with the former, and, interestingly, only for summer levels. Other studies that identified reductions in indoor PM levels with NDVI have assigned summer levels only, despite monitoring also occurring in other seasons (Dadvand et al., 2012, 2015). If vegetation contributes to reduced PM levels, then it would be expected that the season-specific NDVI coefficients would better reflect the intra-annual vegetation differences and be most strongly associated with lower $PM_{2.5}$ levels, yet this was not observed in the present study.

Although season-specific NDVI values may provide a more representative indication of greenness, there are several issues to consider when interpreting results from different periods of the year. The entire tree structure (e.g., trunk, branches), and not only leaves, may reduce $PM_{2.5}$ via deposition (Klingberg et al., 2017; Grote et al., 2016), which would be unaffected by changing vegetation during the year and therefore would not be captured in the season-specific NDVI values that better reflect fluctuating leaf canopies. Standardisation of exposure using summer NDVI levels might entail less measurement error of images compared with those from various periods during the year due to, for example, the angle of the sun. With the timing of maximum NDVI levels during summer, when ambient $PM_{2.5}$ levels appear to be lowest (e.g., in the UK) (Harrison et al., 2012), examining associations only during the summer period may overestimate effect sizes, thus justifying the need to monitor also in other seasons. In addition, indoor compared to outdoor air quality may differ more during colder months (e.g., from opening windows less), potentially reducing the influence of the outdoor environment. Winter NDVI images with snow may underestimate greenness, as values would be shifted toward zero (Zhou et al., 2014). Therefore, seasonal values, while providing additional information, also should be compared to those from summer. Alternatively, the inverse association between NDVI and $PM_{2.5}$ may have been linked to another spatial feature for which greenspace was an indicator, though we endeavoured to account for other potential $PM_{2.5}$ sources.

A review examining the costs and benefits associated with urban trees identified 20 of 22 studies that demonstrated evidence of trees and decreased PM levels (Roy et al., 2012), yet we did not identify any such association in the current study. More specifically, Irga et al. (2015) found tree canopy coverage within 100 m to be the best predictor of reduced PM concentrations after adjusting for traffic, and Yli-Pelkonen et al. (2017) corroborated these findings by presenting decreased PM concentrations (on average 23% lower) in treed vs open areas. There are several reasons why indoor $PM_{2.5}$ levels may not have been associated with the amount of tree cover in the present study. Dense tree canopies may prevent dispersion of air pollutants in street canyon environments, leading to higher ambient concentrations (Abhijith et al., 2017). Tree height, as well as other characteristics, including leaf properties, which we did not take into account, are believed to be responsible for the observed manifold differences to capture PM among different tree and shrub species (Sæbø et al., 2012). It is possible that tree pollen may have reached inside the homes, though pollen would not have contributed to indoor $PM_{2.5}$ levels, since plant pollen tends to be $> 10\,\mu m$ in size (Morakinyo et al., 2016). Ultimately, there were few cases of high tree cover density in the residential buffers, thus mitigating the potential for any reduced PM dispersion caused by street trees. Therefore, it is most likely that there were too few cases of tree cover in this study to identify any significant associations with indoor environments.

We did not find any significant associations between greenspace and indoor noise, despite many of the homes experiencing indoor noise at levels considered to be harmful to health (i.e., ≥ 55 dB [Jarosińska et al., 2018]). This lack of association resonates with previous studies that found only modest noise reductions, depending on the vegetation type (e.g., hedges; van Renterghem et al., 2014) and design (e.g., green facades; Jang et al., 2015). Studies have found leaves to reduce noise levels (Klingberg et al., 2017), though not as effectively at the specific frequency range of road traffic noise (van Renterghem et al., 2015). As we did not have information about the specific configuration and composition of vegetation surrounding residences (Bratman et al., 2019), other than annual tree cover density, it is possible that the greenness surrounding the study homes were not effective (i.e., on the path of sound wave propagation) for reducing outdoor noise. Unadjusted associations with greenspace were significant and positive, but this was likely driven by the lower NDVI levels in the two Greek cities and strongly influenced from the Netatmo sensor recording noise in the child's bedroom (compared to the living room in the other cities). Once 'city' was adjusted for, associations indicated an inverse relationship, but not significantly so. Greenspace may introduce natural sounds, such as birdsong, which, objectively, would increase overall measured decibel levels (van Renterghem, 2018).

Another possible explanation for the lack of an association with greenspace is that indoor noise sources were more important than those from outside the home, the former of which would likely not be affected by greenspace. As an example, in the noise questionnaire responses, numerous participants noted neighbours as a source of other noise. Pets were associated with lower indoor noise measurements, which was unexpected, since pets essentially constitute another household occupant, representing another potential indoor noise source. Instead, the presence of pets, though more relevant for dog ownership, could be linked to more time spent outdoors, possibly in green spaces (Bloemsma et al., 2018), thus contributing to lower indoor noise due to less time spent at home.

Road noise annoyance was the only outcome in this study that was inversely associated with both season-specific and summer NDVI, as well as tree cover density. Schüle et al. (2018) identified ORs of lowered noise annoyance by NDVI of a similar magnitude to those in the current study, in addition to differences by socioeconomic status (SES), which we did not have sufficient variation to examine. Other studies have identified the complete lack of a view with vegetation being associated with an increased risk of road noise annoyance, with living in a green neighbourhood insufficient to induce such reductions (van Renterghem and Botteldooren, 2016). In the current study, greenspace buffers were relatively small and thus more representative of views (i.e., rather than neighbourhood levels); therefore, those results are not necessarily in contrast with ours. As greenspace was not associated with indoor noise levels, it is more likely that lower road noise annoyance with higher NDVI and tree cover levels were due to a non-acoustic effect. Mechanisms for greenspace to reduce road noise annoyance may include visual blocking of the street and stress reduction (Dzhambov et al., 2018a). Visual and nearby access to greenspace may provide stress restoration through the promotion of tranquillity and opportunity for walking and experiencing nature (van Renterghem, 2018). Regardless of the pathway involved, noise annoyance has been shown to be negatively related to health-related quality of life (Shepherd et al., 2013). Road noise annoyance and noise were not strongly correlated, but this would not necessarily be expected. Indoor noise will reflect outdoor and indoor sources, not just road noise; further, it is estimated that only 30% of noise annoyance is due to sound levels, with high quality greenspace estimated to reduce equivalent noise levels by 10 dB A (van Renterghem, 2018). Positive associations with population density might stem from the perception of congestion, as population density has been shown to have a decreasing relationship with measured traffic noise (Salomons and Pont, 2012).

4.1. Strengths and limitations

We assessed three different greenspace metrics, one of which (NDVI) was calibrated to the same season during which the indoor measurements were collected, and did so across four cities using two spatial areas (i.e., 50 m and 100 m). These relatively small buffer sizes were made possible due to the high spatial resolution of the greenspace metrics (i.e., ≤ 20 m) and objective indoor measurements. These inputs permitted a robust assessment of potential effects on three different outcomes within the same households across space and time. We also adjusted for numerous factors to help disentangle associations between greenspace and pollution sources, for example, the proportion of surrounding roads. The quality of indoor $PM_{2.5}$ measurements was strengthened through the use of a calibration curve for the particle specific sensors, which was developed via another component of the HEALS study (Franken et al., 2019). More broadly, our results contribute to the blossoming literature on greenspace and health, and further endorse the notion to green the cities to reduce sources of harmful PM and noise exposures (van den Bosch and Nieuwenhuijsen, 2017).

These strengths notwithstanding, there were several limitations of our study, which we attempted to mitigate. As the targeted demographic of the study was families with young children, our results may be less generalisable to the broader population. There were relatively high proportions of residential buffer areas that had no tree cover or green land use, thus hampering statistical power to detect an effect. As a secondary analysis, we converted these continuous variables to binary indicators for any tree cover or green land use, though still did not identify any statistical relationships. We did not account for any greenness in the indoor environment, which may have improved air quality (Lohr and Pearson-Mims, 1996; Franchini and Mannucci, 2018); associations with PM levels could have been attenuated if, for example, individuals compensated for a lack of outdoor nature by introducing indoor plants (Grinde and Patil, 2009). Likewise, our greenspace metrics did not capture visual (e.g., window/street views) or vertical greenness (e.g., green walls), which may have the capacity to affect PM levels or portray more precisely residential views of greenspace (Helbich et al., 2019). Nevertheless, the buffer areas we used in this study were quite small (i.e., 50 m & 100 m), and although NDVI represents a bird's eye view of greenness, these localised areas would be more representative of green 'viewsheds' (Markevych et al., 2017). Due to high cloud coverage, we were not able to use the monitoring year to characterise NDVI in Edinburgh, which might have led to exposure misclassification (Helbich, 2019), though this was improved by using images from within the same year period. As a strength of the study, we were able to assess seasonal differences in greenspace, though households were sampled in different seasons. The specific time of the year might have affected our results by different amounts of time spent indoors and potential variation across seasons of $PM_{2.5}$ (Harrison et al., 2012) and noise (Geraghty and O'Mahony, 2016). Nevertheless, we did adjust for season in our models. We did not account for ventilation rates inside the home, which could have affected indoor $PM_{2.5}$ concentrations. A hindrance to the noise analysis was the lack of outdoor noise measurements and the unavailability of outdoor noise models across all study centres, necessitating the use of urban characteristics (e.g., distance to major roads) as a crude indicator for outdoor sources. The availability of such outdoor noise data would have helped facilitate mediation modelling to better understand mechanistic pathways. Another limitation to the interpretation of the noise results was that the sensors were placed in different rooms in the Greek homes compared to that in the other study locations, though part of this effect would have been captured in the 'city' coefficient. As well, we were not able to calibrate the noise sensors.

5. Conclusions

Based on measurements in the indoor environment from homes across four European urban areas, we identified reduced indoor $PM_{2.5}$ concentrations with surrounding greenness, but did not find evidence of such a relationship with noise. Lower reported levels of road noise annoyance were detected with higher residential greenness and tree cover. These positive findings provide evidence of specific pathways of greenspace to health (e.g., lower exposure to $PM_{2.5}$ and road noise annoyance). To corroborate our findings and further refine exposure estimates to greenspace, future research should examine the effect of enhanced temporal resolution of metrics during different seasons, characterise the spatial configuration and composition of green areas, and explore mechanisms through mediation modelling. The completion of time-activity diaries would help parametrise indoor sources of pollution. Finally, completing studies with a larger population, including variability across a range of SES groups, would provide additional insights regarding the pathways to health investigated in this study.

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Ethical review

Ethical approval for research involving human subjects was sought and received for each study area (UK: Heriot Watt University Ethics Review Board, 2015–07; Netherlands: METC Brabant NW2015-07; Athens: NCSRD Ethics Review Board, 2015–04: 260/2015–1671; Thessaloniki: Aristotle University Ethics Committee 140,540/2018).

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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.2019.108850.

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