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Urban green spaces, self-rated air pollution and health: A sensitivity analysis of green space characteristics and proximity in four European cities

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ABSTRACT

Exploring the influence of green space characteristics and proximity on health via air pollution mitigation, our study analysed data from 1,365 participants across Porto, Nantes, Sofia, and Høje-Taastrup. Utilizing OpenStreetMap and the AID-PRIGSHARE tool, we generated nine green space indicators around residential addresses at 15 distances, ranging from 100m to 1500m. We performed a mediation analysis for these 135 green space variables and revealed significant associations between self-rated air pollution and self-rated health for specific green space characteristics. In our study, indirect positive effects on health via air pollution were mainly associated with green corridors in intermediate Euclidean distances (800-1,000m) and the amount of accessible green spaces in larger network distances (1,400–1,500m). Our results suggest that the amount of connected green spaces measured in intermediate surroundings seems to be a prime green space characteristic that could drive the air pollution mitigation pathway to health.

1. Introduction

Air pollution is considered one of the major risk factors for non-communicable diseases (NCDs) (WHO - World Health Organization, 2013). Next to respiratory illnesses, air pollution is also associated with cardiovascular diseases, impaired neural development, depression, suicide, cognitive capacities, happiness and life satisfaction (Cohen et al., 2017; Liu et al., 2021; Lu, 2020; Pope et al., 2017; Vos et al., 2015; WHO Regional Office for Europe, 2016). Since the rise of the Industrial Revolution, urban planners and health professionals alike are aware of the air pollution problems in cities and the associated health risks. Air pollution alongside other environmental stressors was one of the main driving factors for the rise of the functional city in the early 20th century, where industrial and residential uses were separated. However, with the dependence on cars, the problems with air pollution never disappeared for these high-industrialized, often high-income countries. They are even stronger for low-to-middle-income countries currently undergoing rapid urbanisation. According to the WHO ambient air pollution in 2019 was still associated with 4.2 million premature deaths, and 99% of the world population lived in neighbourhoods where the WHO air quality guidelines were not met (WHO - World Health Organization, 2023).

Current evidence suggests that green spaces can help to reduce air pollution and thus promote human health by two main mechanisms (Diener and Mudu, 2021; Markevych et al., 2017; Mueller et al., 2022). The primary cause seems to be related to the fact that primary pollutants are not present in green spaces (Markevych et al., 2017), which may explain the association with positive health effects (Mueller et al., 2022). The second mechanism is related to direct deposition, dispersion and absorption of air pollutants through green spaces. But for this mechanism, the evidence in urban settings is still inconsistent, potentially because its effects are highly dependent on how green spaces are integrated into the urban fabric (Diener and Mudu, 2021; Markevych et al., 2017). On the one hand, it has been shown that vegetation can mitigate both gaseous pollutants by absorbing through leaf stomata and particulate matter by deposition on plant surfaces (Diener and Mudu, 2021). On the other hand, vegetation may also increase air pollution by emitting volatile organic compounds that can react with other airborne chemicals to form air pollution (Duan et al., 2023; Gu et al., 2021), or by capturing air pollution in street canyons (Janhäll, 2015; WHO Regional Office for Europe, 2016), and cause harm by introducing airborne allergens (Marselle et al., 2021). Despite these potential trade-offs, most of the evidence points towards a positive relationship between green space, air quality and both mental and physical health.

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However, especially due to the variety in study designs and heterogeneity in results, the pathway remains under investigation. It remains unknown what kind of proximity to what kind of green spaces is needed to be able to effectively reduce air pollution (Kumar et al., 2019; Qiu et al., 2021). Surrounding Vegetation (or greenness) seems to be the prime feature that is associated with air pollution mitigation (Diener and Mudu, 2021; Xing and Brimblecombe, 2019), but also airflow and air exchange through the connectivity of green spaces may play an important role that needs to be investigated (Qiu et al., 2021; Shen and Lung, 2017). Up to 2020, only 60% of studies found a mediating effect of air pollution on mental health and physical health markers (Dzhambov et al., 2020), but the frequent use of Land-use regression (LUR) models may lead to biased results since green space is already included in these LUR models to estimate local air pollution (Beelen et al., 2013; Eeftens et al., 2012, 2016; Rao et al., 2014). However, objectively measured air pollution data is rarely available at scale and self-rated air pollution is subject to bias due to its subjectivity (Brody et al., 2004; Piro et al., 2008), limiting advancement in the field. In addition, previous research was often based on different definitions of green space in terms of type and distance (Taylor and Hochuli, 2017), which makes it hard to identify where and how this pathway operates. There is a need for a systematic investigation that incorporates various indicators of green spaces and greenness, accounting for different buffer types and distances to enable direct comparisons between green space characteristics (Cardinali et al., 2023b; Markevych et al., 2017). Furthermore, the general quality and rigour of studies still need to improve, including more contextual factors of the complex living environment (Cardinali et al., 2023b; Mueller et al., 2022; Qiu et al., 2021), e.g. the spatial distribution and morphology of examined green spaces, differences in urbanicity or baseline air pollution levels. This will enable a comprehensive analysis of the necessary conditions of green spaces to be able to reduce air pollution and provide insights into the potential health benefits.

The aim of this study is therefore to help close this research gap by conducting a sensitivity analysis of different green space and vegetation-based indicators at varying distances to identify patterns of associations between green spaces, self-rated air pollution, and self-rated health. We hypothesize that immediate surrounding greenness will show a reduction in self-rated air pollution due to the filtering capacity of vegetation (Diener and Mudu, 2021; Xing and Brimblecombe, 2019). In addition, we expect green corridors to reduce self-rated air pollution due to the effects of airflow and deposition (Qiu et al., 2021; Shen and Lung, 2017). Furthermore, we test different indicator configurations e.g. by adding private and semi-public green spaces and testing a range of both Euclidean and network distances to deepen our understanding of how and in what distance this pathway operates. By examining these associations, this research seeks to contribute to the existing knowledge base and provide valuable insights for public health interventions through urban planning aimed at tackling the global disease burden associated with air pollution by optimizing the design of green spaces to enhance air quality.

2. Methods

2.1. Study design and sampling

We followed the STROBE Reporting Guidelines for cross-sectional studies (Table A1, Elm et al., 2007). We collected data for this study following the same protocol as outlined in a previous study from the URBiNAT project (Cardinali et al., 2024a, b). To qualify for participation, individuals needed to be at least 14 years old. Participants were selected at random, and the surveys were carried out by local survey companies hired by the cities and instructed by the research team. In Porto and Sofia, surveys were conducted in person, while in Nantes and Høje-Taastrup, potential participants were approached by phone. Upon contact, individuals were briefed about the project's objective, the survey's role, and asked for informed consent. Before, the survey had been approved by the URBiNAT project's ethics committee. No rewards were offered for participation. Data were collected from a total of 1650 participants of which 1365 participants reported their address and were eligible for this study. The study participants are distributed across the four cities as follows: 439 from Porto (August 2019), 293 from Nantes and 432 from Sofia (both December 2019), as well as 201 from Høje-Taastrup (August 2021).

All study areas are designed as satellite districts (urban districts purposely built on the outskirts of a city and according to functional city principles, for their location within cities see Fig. A1) but show distinct urban characteristics, as illustrated in Fig. 1. Nantes featured two radial green infrastructures leading from and to the city centre, with one of them running alongside a river. Its main roads and motorways are mostly bypasses which usually do not get very close to the residential areas. In contrast, Porto's riverside was less accessible due to its car-centric infrastructure and elevation level. In addition, the amount and proximity of its main roads suggest a high exposure to traffic air pollution. Sofia's public green spaces were relatively less connected and consisted of three primary green areas. Its main roads mainly consist of a radial infrastructure that is not getting too close to residential areas. Høje-Taastrup showcased smaller but interconnected green spaces within its urban landscape and showed the most agricultural surroundings. The narrow spatial distribution of study participants in Høje-Taastrup is near three main roads.

2.2. Green space

We obtained spatial data from OpenStreetMap in January 2023 and manually corrected it to the timestamp of the survey conduction and controlled for bias (see Fig. 1). With the help of the PRIGSHARE Reporting Guidelines (Table A2), the green space data was adjusted manually for public ownership bias, residential ownership bias, classification bias, usability bias and connectivity bias (Cardinali et al., 2023b). Especially, the manual connection of green spaces enabled the investigation of green space corridors. We manually (1) connected green space polygons that were interrupted by a road but had a crossing, (2) merged green spaces directly next to each other, and (3) added linear green spaces that consisted of walkable pathways with greenery. A detailed table with the inclusion/exclusion criteria can be viewed in the appendix (Table A3). To assess greenness around study participants we used the frequently used Normalized Difference Vegetation Index (NDVI, Tucker, 1979). For the calculation of the NDVI, we gathered sentinel 2 (L2A) data in 10×10m resolution from the European Space Agency ESA from the specific cloud-free time points of the survey conducted in the city (2021). Since water bodies show negative NDVI values, we set larger water bodies like the rivers in Porto and Nantes manually to missing, as recommended by Markevych et al. (2017).

Based on this data we constructed nine indicators (Fig. 2) in QGIS (v 3.22) for our sensitivity analysis in distances from 100m (immediate surrounding) to 1500m (neighbourhood perspective), every 100m, with the help of the AID-PRIGSHARE tool (Cardinali et al., 2023a), summing up to a total of 135 green space indicators to identify distance patterns as well as potential differences between green space characteristics. Firstly, we assessed greenness with three indicators based on NDVI. One represents mean surrounding greenness (2A) measured by mean NDVI within Euclidean buffers. Another represents cumulative surrounding greenness (2B) measured by the sum of NVDI values within Euclidean buffers which might better reflect the quantity of vegetation in an area. The third one measures mean accessible greenness (2C) with mean NDVI in network distance. Secondly, we assessed surrounding green space with three public green space indicators: surrounding green spaces within Euclidean distance (2D), surrounding green corridors (2E) where the whole green space network that intersects the buffer is counted, and surrounding total green space (2F) where in addition also the individual private or semi-public green space for the surveyed individual is added. Thirdly, we assessed the same indicators with network distances (2G-2I)

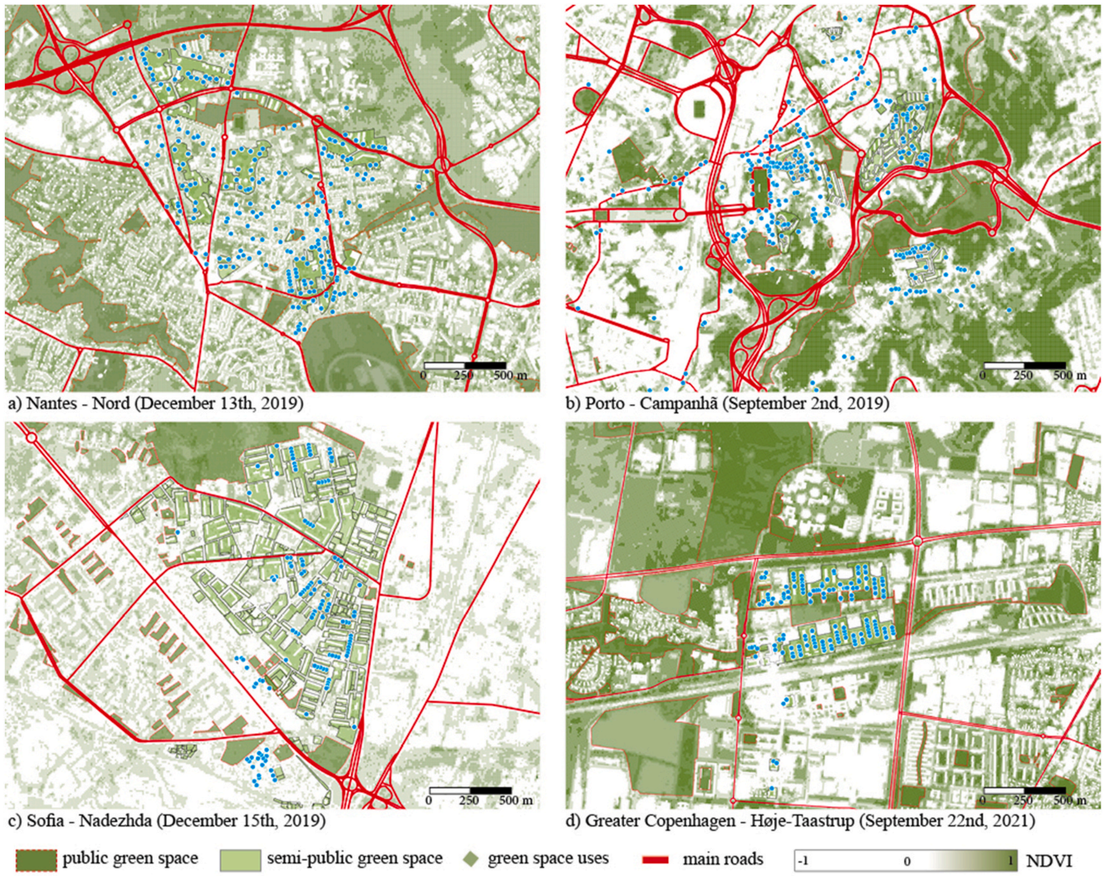

Fig. 1. Study areas green space: a) Nantes – Nord (France); b) Porto – Campanhã (Portugal), c) Sofia – Nadezhda (Bulgaria), d) Greater Copenhagen – Høje-Taastrup (Denmark); blue points indicate the residential address of the study participants. For better readability only the study areas are covered – e.g. some respondents do not live in the main study area.

to measure accessible green spaces and to examine differences between accessible and surrounding green spaces.

2.3. Self-rated air pollution

Self-rated air pollution was measured by a 5-point Likert scale asking for the level of inconvenience caused by air pollution in the neighbourhood (smoke, dust, exhaust fumes) from 1 (no inconvenience) to 5 (very high inconvenience). This item was part of the Environmental Quality of Life Scale (Fleury-Bahi et al., 2013) and the exact wording can be found in the appendix (A4). Self-rated air pollution variables are frequently used in similar studies (Chang et al., 2020; Dzhambov et al., 2018; Liu et al., 2019; Wang et al., 2019, 2020). They can show a strong relation to modelled air pollution if adjusted for contextual factors (Piro et al., 2008) and provide the advantage of fine-grained spatial data points, through the geolocated address of individuals. This is especially an advantage when immediate surroundings around individuals' homes are of interest and objectively measured air pollution or fine-grained land-use regression models are not available. It has been shown that low-resolution LUR models may overlook some of the associations due to the substantial variability (Forastiere, 2005). But even if fine-grained LUR models for $PM_{2.5}$ or NO_2 are available, we strongly suggest checking beforehand if green space indicators are already included as a predictor variable in these models (Examples include ESCAPE from Beelen et al., 2013; Eeftens et al., 2012; and the Global NO_2 Model from Larkin et al., 2017). If so, we suggest not using them to measure the influence of green space as this would lead to an overestimation of the impact of green spaces. In these cases, a self-rated air pollution variable is useful if no objectively measured air pollution data is available. However, self-rated air pollution is also associated with several limitations due to its subjectivity (Brody et al., 2004; Piro et al., 2008). These will be elaborated on in the discussion. The item was reverse coded to ease interpretation of the results, meaning a higher score implies lower inconvenience due to air pollution.

2.4. Self-rated health

Perceived general health was assessed by the 1-item questionnaire (World Health Organization, 1998), known to be a valuable indicator of human health status (Jylhä, 2009). Self-rated health is a well-established indicator linked to both physical and mental health (Baćak and Ólafsdóttir, 2017; Hamplová et al., 2022; Jylhä, 2009; Lundberg and Manderbacka, 1996). The question asked, "How is your health in general?". Answers were given on a 5-point Likert scale from (1) very bad to (5) very good and were included as an ordinal variable in the model.

2.5. Context variables

We gathered data on potential confounders at personal, local, urbanicity, and global levels. The personal context was assessed with data on age, sex, disabilities (y/n), years lived in the neighbourhood, years of education, and monthly net income, as well as employment status (y/n). Most of these are social determinants of health that could confound the relationship (Cardinali et al., 2023b). Moreover, it has been shown, that especially in the context of self-rated air pollution inaccuracies can occur, if not controlled for demographics, socioeconomic status as well as existing illnesses, even if not respiratory

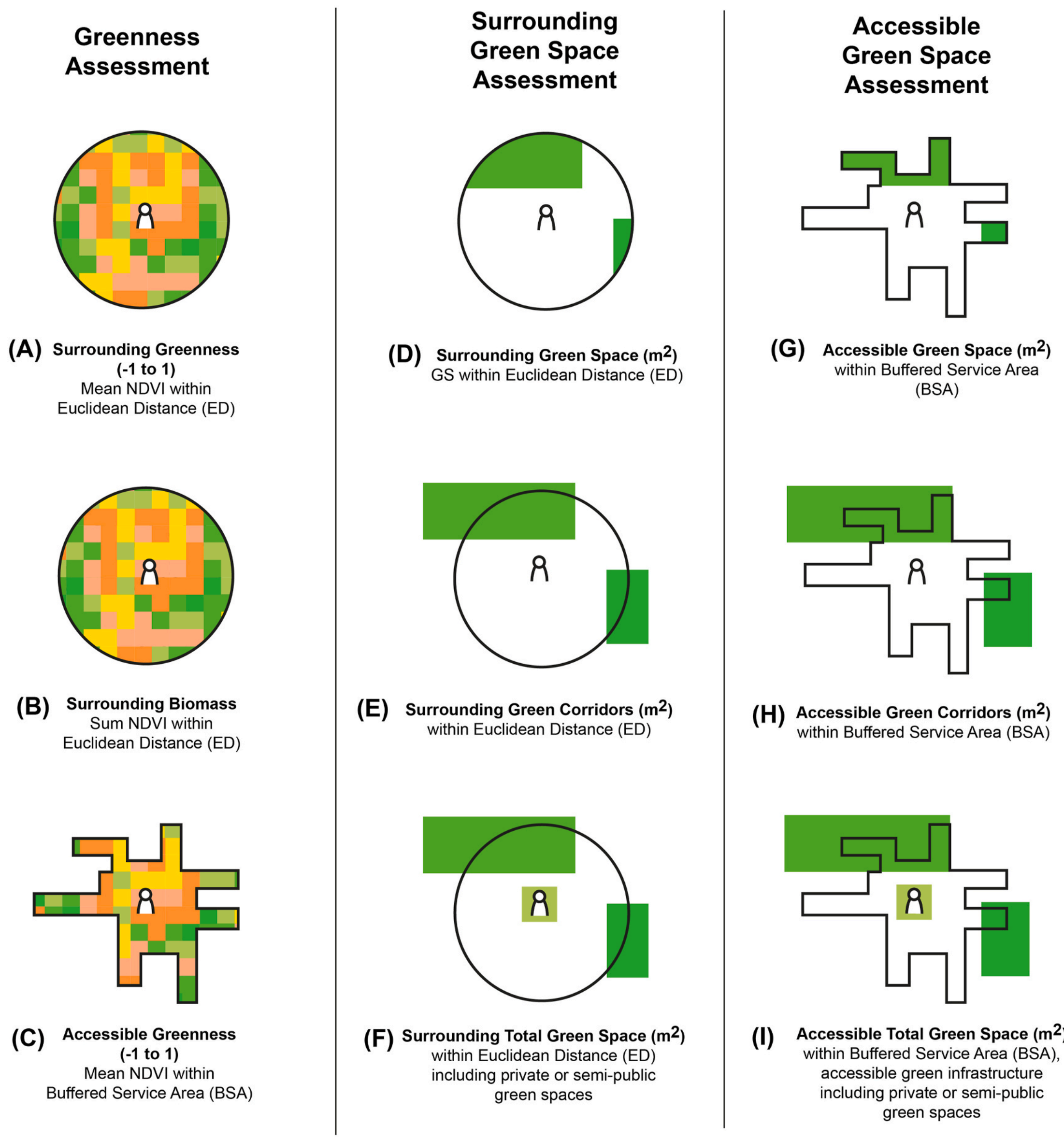

Fig. 2. Green space indicators: Indicators used in the sensitivity analysis. **Notes:** Network distances are measured as 25m buffered service areas (walkable distance in m in every direction). Green Corridor and Total green space indicators (E, F, H, I) count every green space that intersects with the Euclidean buffer or network distances, while green space indicators (D, G) count only those green spaces that are within the buffer type.

(Pantavou et al., 2018; Pelgrims et al., 2022; Piro et al., 2008). To adjust for these influences on self-rated air pollution we used the available binary variable on disabilities as a proxy, which asked for any sensorial, motor, cognitive or organic disability that requires personal assistance or particular equipment or care. To harmonise between cases across countries, monthly net income was centred around the mean minimum wage of the country. Furthermore, we adjusted for years lived in the neighbourhood to add a measure that represents time to the surrounding green space characteristics. This is especially important in pathway analysis with cross-sectional data (Markevych et al., 2017) as in this case from green space exposure to self-rated air pollution to self-rated health. Since the time spent in the neighbourhood is different for employed and unemployed, and employment status also impacts health (Friedland and Price, 2003; Ross and Mirowsky, 1995), we also adjusted for employment status as a proxy for the actual time spent in the neighbourhood and thus the potential exposure to neighbourhood air pollution.

We accounted for the local difference in traffic pollution by quantifying the surface area of main roads within a 500m radius of the residential address. For this, we used OpenStreetMap data and filtered for motorways, primary, secondary and tertiary roads, thus including all roads that connect neighbourhoods, districts or cities. We buffered those street lines by 6 m to reflect differences in street width and associated traffic (see also Fig. 1). In addition, we used 5-point Likert scale items to measure local satisfaction with shops, leisure facilities, and public transport as part of the environmental quality of life questionnaire (Fleury-Bahi et al., 2013). These variables serve as covariates in this study, to adjust for differences in the local context which might influence behaviour-related associations between green space and health (Cardinali et al., 2023b). In this study on self-rated air pollution, we expect this to affect mainly the direct association between green space and health in the structural equation model (Fig. 3, path c).

For the urbanicity context, we used rasterized 2018 population density data from Eurostat, with a resolution of 1 km × 1 km (Eurostat, 2023). Moreover, to account for different cultural and climate contexts we included the city samples as a dummy variable in our model. This approach also allowed us to control for temporal differences (pre- or post-pandemic), potential differences in baseline city-wide air pollution caused by for example local industry, and seasonal variations during the

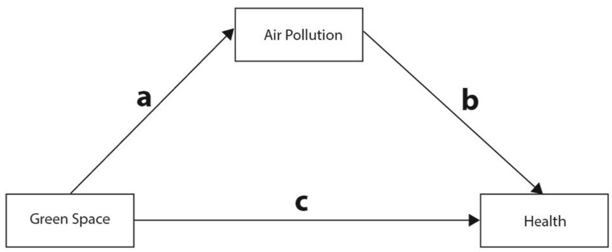

Fig. 3. Conceptual diagram showing theoretically indicated pathways linking green space to air pollution and health. The green space indicator was exchanged 135 times for each structural equation model.

time of survey conduction which is known to influence air pollution levels (Diener and Mudu, 2021; Shi et al., 2017), all while preserving the statistical power.

2.6. Statistical analysis

Data handling and processing follow the same protocol as outlined in a previous study (Cardinali et al., 2024a, b). 2.97% of the relevant data for this study were missing. Missing data could be classified as missing at random (MAR). Thus, a multiple imputation technique is considered the most appropriate to handle the missing data (Mirzaei et al., 2022). We used the multiple imputation software package miceforest 5.6.4 in Python (Wilson, 2022), with 10 iterations on all available data to estimate the missing variables. The last step of data handling was to standardize the dataset by min-max scaling (0–1) as all our variables, except NDVI-related indicators, can only be positive. Standardization ensured that all indicators were on the same scale, allowing for valid comparisons and precise model computation (Kline, 2015).

We applied structural equation modelling (SEM) using the lavaan package (Rosseel, 2023) in R (v 4.2.3) and the diagonal weighted least squares estimator on a basic single-mediator model (Fig. 3) to perform a sensitivity analysis on the nine green space indicators, each at 15 distances, adding up to a total of 135 SEMs. The full model including all control variables can be found in the supplementary material (Fig. A2) as well as an example of the summary statistics for one green space indicator (Table A5). These just-identified (saturated) mediation models were chosen to bypass the potential complexity that would be introduced with over-identified models through variations in model fit across the 135 models, which would make this large-scale sensitivity analysis unmanageable and negatively affect the main aim of this research to compare the proximity and green space characteristics in their ability to influence the air pollution health pathway.

In the subsequent results and discussion, we use the standard terms of partial effects (a or b), indirect effects (a*b), direct effects (c) and total effects (a*b + c) in SEM. However, it is important to emphasize these are, in fact, associations due to the cross-sectional study design. Given that indirect effects and total effects are products and not linear, we report bootstrap-generated standard errors and confidence intervals for all regression paths (5000 samples for every structural equation model). The relationship was considered significant when the bootstrapped 95% confidence intervals did not include zero.

We then analysed the correlation matrix for all green space characteristics aiming to determine if the significant findings stemmed from unique features of green spaces or represented alternative measures for a common mechanism. Using the cut-off points of Dancey and Reidy (2007) we interpret a weak to moderate correlation (<0.6) between green space characteristics as indicating at least partly distinct influences on the observed outcomes. Conversely, strong correlations (>0.6) imply a shared underlying mechanism. This analysis was conducted using Pearson's r for each green space characteristic that showed significant results either to self-rated air pollution (path a) or directly to health (path c). A detailed breakdown of these correlations can be found in Table A6 in the supplementary material.

3. Results

3.1. Characteristics of the sample

This study used the same sample as a previous study from the URBiNAT project (Cardinali et al., 2024a,b). The total sample comprised 201 inhabitants from Høje-Taastrup (Denmark), 293 from Nantes (France), 439 from Porto (Portugal), and 432 from Sofia (Bulgaria). The city samples are composed of roughly 50% of men and women in Høje-Taastrup, Nantes, and Sofia. In Porto, the sample was composed of nearly 64% men and 36% women. Porto also had the most people over 65 years with 41.0% compared to Nantes with only 17.1% of survey respondents and the highest proportion of people with disabilities (39.6%). The mean (SD) years of education were 12.49 (2.55) in Høje-Taastrup, 12.57 (3.37) in Nantes, 7.02 (3.70) in Porto, and 13.11 (2.68) in Sofia. The majority of the participants were employed, with significant differences between cities. The mean income harmonized as a percentage of minimum wage of the country was roughly between 140% and 150% in Høje-Taastrup, Nantes, and Sofia, but only 40% in Porto. Self-perceived health as the main outcome indicator was the highest in Nantes with 76.5% reporting good or very good health, and lowest in Porto with 46.9%. For more details on the samples, we refer to Table 1.

There were noteworthy variations in urbanicity context amongst the cities, with Sofia demonstrating the highest mean population density and Høje-Taastrup displaying the lowest. The local context also showed significant differences in all included variables. Self-rated air pollution ranges from 80.1% reporting weak or no inconvenience in Høje-Taastrup to 33.8% in Sofia. Surrounding main roads (SD) was the highest in Porto with a mean area of 70,872 m^2 (20,180 m^2) within a 500 m buffer. The lowest covered area with main roads near residents was found in Sofia with a mean of 24,430 m^2 (14,499 m^2).

3.2. Indirect effects – how green space indicators relate to health via self-rated air pollution

We found associations between surrounding and accessible green corridors as well as total green space indicators to self-rated air pollution and indirectly on health, but not for indicators representing greenness (Fig. 4, Table A8). The indirect effects (a*b) showed similar patterns compared to the partial effects (a) (see Supplementary Table A7 and Fig. A3) due to the stable significant association (b) between air pollution and health (ß: 0.08; CI: 0.02, 0.15). Greenness (Fig. 4A-C) showed no significant indirect relation to health for any distance, but a clearly visible low point for accessible greenness (which includes street green) measured in 500m network buffer (ß: −0.046; CI: −0.154, 0.007). Surrounding green spaces (Fig. 4D) presented a plateau at 1100–1300m, although not significant. The indirect effects of surrounding green corridors (Fig. 4E) on health via self-rated air pollution started negatively, with a non-significant low at 200m (ß: −0.021; CI: −0.062, 0.001). They then turned positive and showed a clear plateau of significant positive associations for distances from 800 to 1000m, with a peak at 900m (ß: 0.053; CI: 0.013, 0.121). Surrounding total green space (Fig. 4F) displayed the same patterns, peaking at the same point at 900m (ß: 0.053; CI: 0.013, 0.127). Accessible green space (Fig. 4G) showed no indirect health effects for distances up to 1100m and then started climbing to a significant association at 1400–1500m (ß: 0.035; CI: 0.002, 0.105). Green corridors in network distances (Fig. 4H) presented a longer and shifted significant plateau of positive associations (900m–1300m) compared to surrounding green corridors, with a peak at 1000m (ß: 0.044; CI: 0.009, 0.108). Accessible total green space (Fig. 4I) reacted almost identically. The highest estimate was found for surrounding green corridors and total green spaces at 900m (ß: 0.053; CI: 0.013, 0.127). The investigation of the correlation matrix indicated the expected strong collinearity between the nested green space

Table 1
– Characteristics of the sample (unstandardized).

Context	Indicator	Høje-Taastrup	Nantes	Porto	Sofia	p
Global	city sample (n)	201	293	439	432	
Urbanicity	*population density (mean (SD))*	4028.65 (1336.94)	5616.27 (2353.62)	4829.28 (1632.50)	9021.14 (3689.54)	<0.001
Local	***self-rated Air Pollution (%)***					<0.001
	no inconvenience	109 (54.2)	157 (53.6)	142 (32.3)	25 (5.8)	
	weak inconvenience	52 (25.9)	52 (17.7)	62 (14.1)	121 (28.0)	
	moderate inconvenience	32 (15.9)	53 (18.1)	67 (15.3)	188 (43.5)	
	high inconvenience	7 (3.5)	12 (4.1)	85 (19.4)	81 (18.8)	
	very high inconvenience	1 (0.5)	19 (6.5)	83 (18.9)	17 (3.9)	
	main roads within 500m surroundings (0 – 11.02 ha, mean (SD))	2.49 (0.98)	4.40 (1.81)	7.09 (2.02)	2.44 (1.45)	<0.001
	satisfaction with shops (Likert 1–5, mean(SD))	3.98 (1.08)	3.48 (1.07)	3.41 (1.39)	3.82 (0.86)	<0.001
	satisfaction with leisure facilities (Likert 1–5, mean(SD))	3.78 (1.11)	2.85 (1.16)	3.34 (1.36)	3.28 (0.88)	<0.001
	satisfaction with public transport (Likert 1–5, mean(SD))	4.45 (0.90)	4.43 (0.66)	3.59 (1.44)	3.85 (0.63)	<0.001
Personal	***gender (%)***					<0.001
	Male	105 (52.2)	129 (44.0)	159 (36.2)	204 (47.2)	
	Female	96 (47.8)	162 (55.3)	280 (63.8)	228 (52.8)	
	Diverse	0 (0.0)	2 (0.7)	0 (0.0)	0 (0.0)	
	age group (%)[a]					<0.001
	15–24	13 (6.5)	32 (10.9)	18 (4.1)	46 (10.6)	
	25–44	57 (28.4)	125 (42.7)	94 (21.4)	171 (39.6)	
	45–64	66 (32.8)	86 (29.4)	147 (33.5)	128 (29.6)	
	over 65	65 (32.3)	50 (17.1)	180 (41.0)	87 (20.1)	
	mean years lived in Neighbourhood (SD)	16.60 (13.76)	14.53 (15.03)	28.90 (20.08)	22.41 (12.34)	<0.001
	mean net income as % of minimum wage (SD)	141% (93%)	149% (63%)	40% (66%)	143% (73%)	<0.001
	mean years of education (SD)	12.40 (2.51)	12.46 (3.38)	7.03 (3.72)	13.16 (2.67)	<0.001
	has disabilities (%)	20 (10.0)	46 (15.7)	174 (39.6)	67 (15.5)	<0.001
	employed (%)	115 (57.2)	166 (56.7)	126 (28.7)	318 (73.6)	<0.001
	self-perceived Health (%)					<0.001
	very good	50 (24.9)	87 (29.7)	39 (8.9)	149 (34.5)	
	Good	74 (36.8)	137 (46.8)	167 (38.0)	170 (39.4)	
	Fair	48 (23.9)	51 (17.4)	142 (32.3)	86 (19.9)	
	Bad	23 (11.4)	17 (5.8)	60 (13.7)	27 (6.2)	
	very bad	6 (3.0)	1 (0.3)	31 (7.1)	0 (0.0)	
green space characteristics	*surrounding Greenness in 500m Euclidean distance (-1 to 1, mean (SD))*	0.46 (0.05)	0.42 (0.03)	0.37 (0.08)	0.23 (0.04)	<0.001
	Cumulative surrounding greenness in 500m Euclidean distance (1384.33 – 4775.13, mean (SD))	3630.87 (374.23)	3327.87 (251.12)	2963.04 (666.85)	1847.63 (288.29)	<0.001
	accessible greenness in 500m network distance (-1 to 1, mean (SD))	0.44 (0.04)	0.39 (0.04)	0.34 (0.06)	0.24 (0.04)	<0.001
	surrounding green space in 500m Euclidean distance (0 - 30.02 ha, mean (SD))	9.89 (3.73)	6.12 (4.80)	6.24 (3.89)	6.90 (7.77)	<0.001
	surrounding green corridors in 500m Euclidean distance (0 - 537.79 ha, mean (SD))	59.75 (21.63)	70.91 (67.41)	19.15 (11.89)	44.35 (85.01)	<0.001
	surrounding total green space in 500m Euclidean distance (0 - 539.15 ha, mean (SD))	64.77 (19.93)	74.17 (67.03)	21.57 (13.59)	48.41 (86.41)	<0.001
	accessible green space in 500m network distance (0 – 16.32 ha, mean (SD))	3.70 (1.45)	1.64 (1.56)	2.35 (2.11)	3.12 (3.68)	<0.001
	accessible green corridors in 500m Network distance (0 - 154.30 ha, mean (SD))	51.76 (17.59)	56.92 (66.64)	9.74 (9.81)	28.93 (37.99)	<0.001
	accessible total green space in 500m network distance (0 - 158.66 ha, mean (SD))	56.77 (16.33)	60.18 (66.51)	12.16 (10.37)	32.99 (41.47)	<0.001

[a] age was used as a continuous variable in the analysis and is only shown here in groups to highlight the differences across samples.

characteristics (D, E, H, I), indicating the same underlying mechanism (0.87–0.99) (Table A6). However, the correlation of accessible green space to other indicators was moderate (0.37–0.46). This indicates partially unique mechanisms for self-rated air pollution from green corridors and accessible green spaces.

3.3. Direct effects – how green space indicators relate to health

The direct effects, factually adjusted for air pollution, showed clear patterns of proximity and differed by the assessed green space characteristic (Table A9). Surrounding greenness (Fig. 5A) showed a positive association in immediate distances, although not significant and a significant plateau for distances for intermediate distances of 600–900m, reaching its maximum at 700m (ß: 0.566; CI: 0.064, 1.051). Cumulative surrounding greenness (Fig. 5B) behaved almost identically with somewhat higher estimates. On the contrary, accessible greenness (Fig. 5C) was not associated with direct health effects at any distance but showed an increasing pattern from 500 to 1400m distance. Surrounding green spaces (Fig. 5D) showed two significant positive peaks. The first is in the immediate surroundings at 200m (ß: 0.427; CI: 0.064, 0.813). The second is at intermediate distances of 700–900m, with a peak at 800m (ß: 0.340; CI: 0.020, 0.662). Surrounding green corridors (Fig. 5E) and total green space (Fig. 5F) showed an identical pattern with significant positive associations at 400–600m, very similar estimates and a

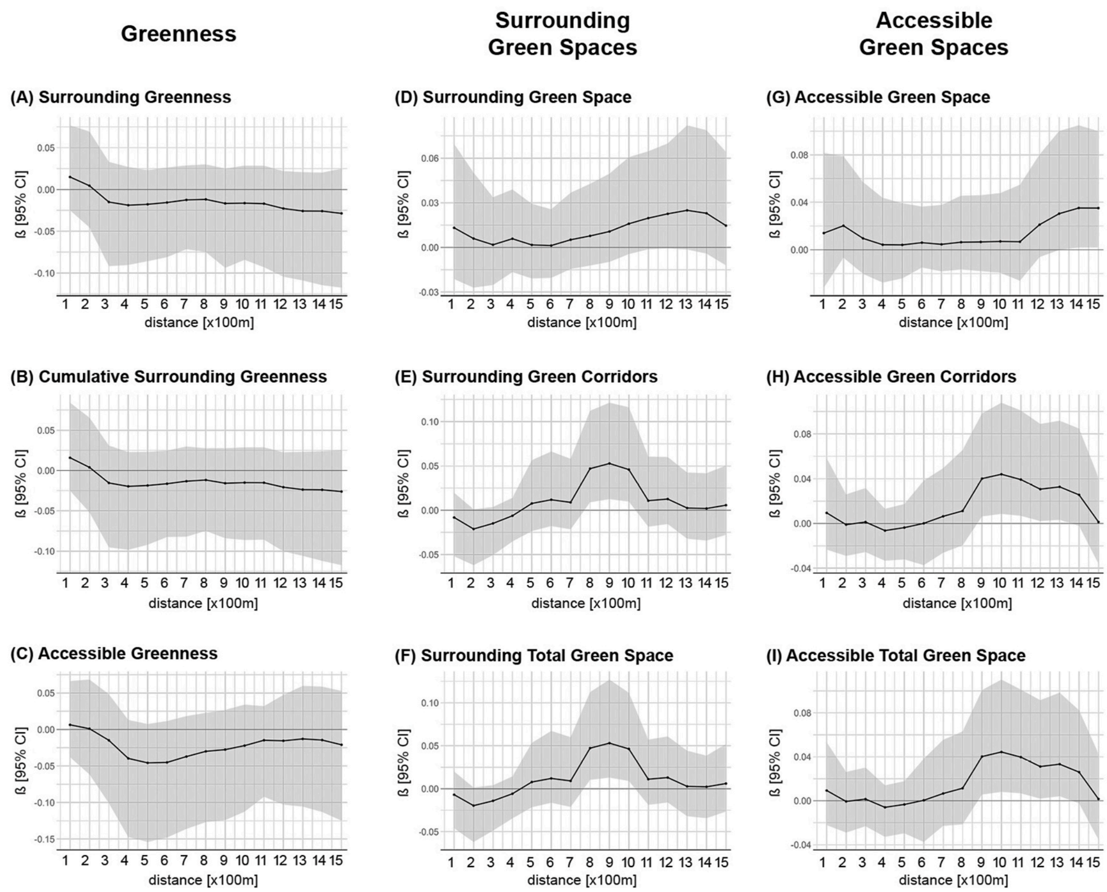

Fig. 4. Indirect Effects (a*b) Green Space – Self-rated Air Pollution – Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 135 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

maximum at 600m (ß: 0.560; CI: 0.096, 1.156). Both indicators then turned negative with a non-significant low at 1300m distance (ß: −0.428; CI: −0.876, 0.013). Accessible green spaces (Fig. 5G) showed a similar pattern to surrounding green spaces but with no significant associations and less strong estimates. Accessible green corridors (Fig. 5H) showed a sharp one-peak pattern at 900m (ß: 0.664; CI: 0.186, 1.257). Accessible total green spaces (Fig. 5I) behaved very similarly, with somewhat lower estimates. The overall strongest association was found for accessible green corridors at 900m (ß: 0.664; CI: 0.186, 1.257) (Fig. 5H). Similar to the peak of the partial effects, the investigation of the correlation matrix showed the expected strong collinearity between nested green space characteristics (A & B; D, E, H & I) (Table A6). However, we found a weak to moderate correlation to other green space characteristics for surrounding greenness (0.17–0.28), surrounding green space at 200m (0.09–0.49) and 800m (0.28–0.49), and surrounding green corridors (0.11–0.42). This suggests partially independent mechanisms to health for greenness, green space and green corridors at intermediate distances, as well as green spaces in immediate distances to health.

3.4. *Total effects – how green space indicators, directly and indirectly, related to health*

The total effects (direct + indirect effects) in the structural equation, acted similarly to the direct effects (Fig. 6, Table A10), due to the larger effect size in the direct associations (maximum ß 0.664) and the indirect associations (maximum ß 0.053). The overall strongest association was found for accessible green corridors at 800m (ß: 0.675; CI: 0.191, 1.269).

4. Discussion

4.1. *Main findings*

Our comprehensive and rigorous sensitivity analysis examined 135 structural equation models to unveil differences in the associations between green space air pollution nuisance and health, depending on green space characteristics and their proximity to a person's home. In our study, only two green space characteristics were associated with indirect health effects through lower experienced air pollution. First, the area of green corridors measured in intermediate surroundings of 800 m–1000 m was significantly related to lower experienced air pollution and indirect health effects. Second, accessible green spaces were also associated with lower self-rated air pollution and indirect health effects at network distances of 1400–1500m. Interestingly, we did not find a significant association between any tested greenness variable and air pollution. Our results support the theory that to mitigate air pollution through deposition, dispersion and absorption of air pollutants, green space connectivity seems to be an important characteristic.

Furthermore, we found direct effects on health deriving from partially unique green space characteristics. Surrounding greenness in intermediate distances (600–800 m), immediate (200 m) and intermediate (700–900 m) surrounding green spaces and green corridors in 400–600 m or 500–800 m when measured in network distance, were all associated with health. In our results, these mechanisms also dominated the total effects between green space characteristics and health essentially masking the indirect pathway through air pollution. This suggests that mechanisms can easily remain undiscovered in study designs that do not analyse specific pathways, which might partly explain the

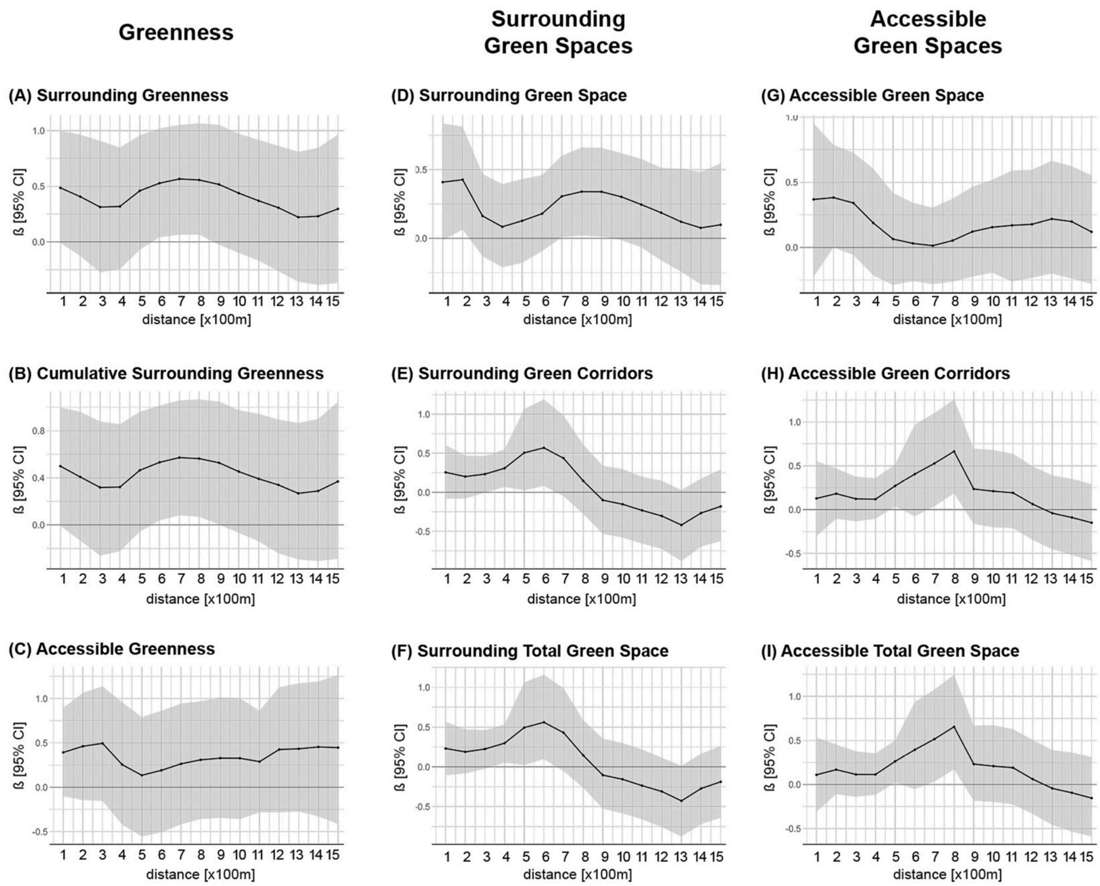

Fig. 5. Direct Effects (c) Green Space – Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 135 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

heterogeneity in the results of previous studies.

4.2. Connectivity of green spaces and self-rated air pollution

Our results confirm our hypothesis that the connectivity of green spaces is an important characteristic of this pathway and is best detectable in Euclidean distances. Furthermore, mainly green space corridors at medium distances (800-1,300m depending on the indicator) were associated with self-rated air pollution and indirect health effects, which is in line with a recent study based on monitoring stations (Venter et al., 2024). A possible explanation for the role of connected green space might be the barrier effect of these types of green spaces which combines the three aspects of deposition, dispersion and absorption (Diener and Mudu, 2021). Moreover, green corridors increase ventilation in urban environments, which is arguably much stronger than the removal capacity of green spaces (Vos et al., 2013). In addition, the results might be partly explained by conflicting land use, meaning that bigger green spaces usually do not contain pollution sources (Mueller et al., 2022). Notably, our results corroborate the research of Shen and Lung (Shen and Lung, 2017), who concluded that the connectivity of green spaces can be an important factor in reducing air pollution and subsequently reducing lung diseases. Consistent with recent literature our findings on the pathway from green space to air pollution annoyance to self-rated health suggest that instead of a high average level of greenness in an area, the area covered with green space corridors, likely due to increased ventilation, may be a better predictor for the pathway of green space health effects through air pollution mitigation. Lastly, our results suggest that this mechanism potentially operates in intermediate surroundings of not more than 800-1,000m Euclidean distance or 900-1300 m network distance.

4.3. Greenness and self-rated air pollution

Contrary to our initial expectations, no indicator that tried to capture greenness (A-C) was associated with the self-rated air pollution at any buffer distance in our study. This is in line with part of the previous studies gathered by Dzhambov and colleagues on the mediating role of air pollution using NDVI as their green space measure (Dzhambov et al., 2020). These studies did not find a mediation effect for air pollution but did find a significant total effect on a variety of health and mental health outcomes using NDVI as their green space measure (Agay-Shay et al., 2014; Crouse et al., 2019; Cusack et al., 2018; Dzhambov, 2018; Dzhambov et al., 2018b; Fong et al., 2018; Hystad et al., 2014; Markevych et al., 2014a, b; Sbihi et al., 2015). Notably, all of the above studies were conducted in North America, Europe or Israel and not in countries with severe air pollution which suggests that the severity of air pollution might be an influential factor in detecting a mitigation effect of greenness.

Another influential factor for the contradicting results might be related to the fragmentation of green spaces. Although the following studies gathered by Dzhambov et al. (2020) that were able to detect a mediation effect looked at a variety of different health outcomes, they share the similarity of a 30 × 30m resolution or lower to calculate the NDVI values (Chang et al., 2020; Crous-Bou et al., 2020; Dadvand et al., 2012; Dzhambov et al., 2018a; Gascon et al., 2018; James et al., 2016; Klompmaker et al., 2019a, b; Laurent et al., 2013, 2019; Liao et al., 2019; Liu et al., 2019; Orioli et al., 2019; Thiering et al., 2016; Wang et al., 2019; Xiao et al., 2020; Yang et al., 2019, 2020). It has been shown

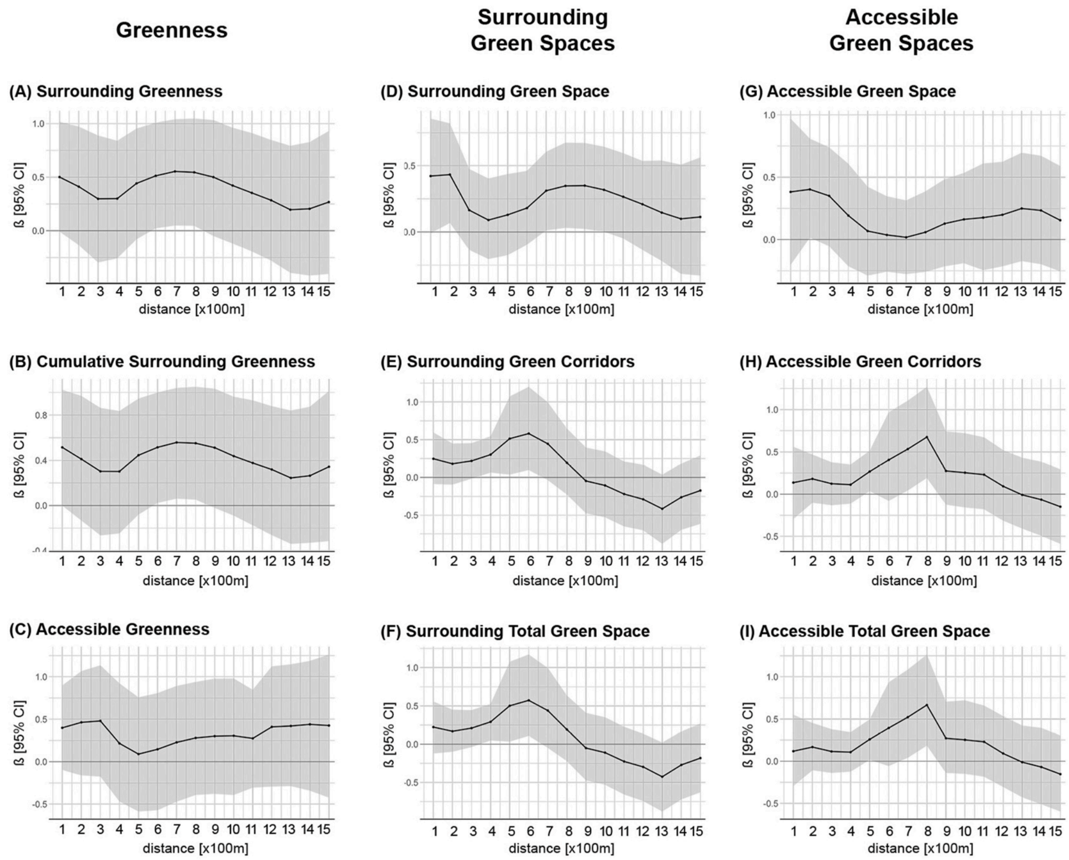

Fig. 6. Total Effects (a*b + c) Green Space – Self-rated Air pollution - Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 135 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

that these resolutions are unable to detect smaller green spaces (Markevych et al., 2017). Since small fragmented green spaces might even increase secondary air pollutants ($PM_{2.5}$ and O_3) and create negative links to health (Shen and Lung, 2017) not including those might explain these differences. This is also in line with similar results in a recent study which used 10 × 10 m resolution and was not able to detect a significant mediation between greenness, air pollution and self-rated health (Dzhambov et al., 2023). Similarly, including those smaller green spaces with an NDVI based on a 10 × 10 m resolution in our study might have led to health trade-offs and resulted in insignificant findings. This further suggests that the connectivity of green spaces seems to be an important characteristic that enables green spaces to reduce air pollution inconvenience.

Moreover, compared to green corridor indicators, which describe a relatively clear urban morphology, the mean vegetation index can be similar in very different urban contexts, potentially masking some of the effects. This might also partly explain our null findings since highly context-dependent mechanisms, such as the street canyon effect, may lead to green spaces being positive in one situation and ineffective in mitigating air pollution or even negative in another (Hewitt et al., 2020; Janhäll, 2015; Shen and Lung, 2017; Venter et al., 2024). More research is needed to understand the mechanisms more precisely, especially since negative mechanisms are theorised, which need to be avoided by evidence-based urban design guidelines.

Another reason for our non-significant findings might be the validity of our air pollution variable, which might not be precise enough to detect associations with greenness (see 4.6 Strength and limitations). Especially, since a recent study based on 2615 monitoring stations from Venter and colleagues suggests that the air pollution mitigation effect of trees is only moderate at best and highly variable (Venter et al., 2024). In addition, there could be trade-offs with negative greenness effects like pollen, entrapment of pollution in green canyons, or unmeasured confounders like atopy, essentially masking the beneficial effect of greenness on air pollution.

4.4. *Green space characteristics and higher perceived air pollution*

Surrounding green corridors and to some extent, greenness indicators showed a pattern of negative associations with self-rated air pollution in immediate distances, although non-significant. This could be related to fragmented green spaces and urban morphology leading to settings where ventilation is reduced, potentially trapping pollutants (Abhijith et al., 2017; Janhäll, 2015). In close buffer distances, the covered area is small and the chances are high that green spaces might be more often fragmented, which is associated with an increase in air pollution and negative health effects in some studies (Diener and Mudu, 2021; Shen and Lung, 2017). Furthermore, trees emit volatile organic compounds (VOCs) that can react with other airborne chemicals to form secondary air pollutants (Duan et al., 2023; Gu et al., 2021), which might be especially noticeable in fragmented green spaces between buildings that can block air exchange, similar to the street canyon effect where tree canopies can hinder air-exchange and increase air pollution (Abhijith et al., 2017; Janhäll, 2015). The street canyon effect might also partially explain why we found the strongest negative estimate for accessible greenness which largely overlaps with the road network. See the work of Abhijith et al. (2017); Baldauf (2017); Diener and Mudu (2021); Janhäll (2015) for a deeper understanding of how roadside vegetation can either lead to an increase or decrease in nearby air quality.

Higher perceived air pollution near green spaces may also be related to pollen dispersion, a concept with theoretical support but limited empirical evidence (Anenberg et al., 2020; Lam et al., 2021). Pollen's limited travel distance might reduce its perceived impact beyond immediate vicinities, potentially able to explain the observed indirect negative association to self-rated air pollution near green corridors and a positive one further away. Lastly, the self-rated air pollution indicator might also be susceptible to confounding effects of persons with asthma in our sample (Piro et al., 2008).

4.5. Green space health effects associated with other mechanisms

In this study, we have focused on the theorised mediating role of air pollution between green space and health, but there are also potential associations captured in the direct effects of our models. Surrounding greenness showed a clear association with health in intermediate distances, peaking at 700m surroundings. This is in line with the review and meta-analysis of Browning and Lee, who concluded that surrounding greenness was best in predicting physical health in buffer distances of 500–999 m around homes (Browning and Lee, 2017). Our results also imply a positive relationship between green corridors and health beyond reduced air pollution annoyance, which might partly be explained by the importance of air-exchange corridors which have been studied in their ability to reduce urban heat island effects (Gunawardena et al., 2017; Kuang et al., 2015; Ren et al., 2016; Wong et al., 2010). In addition, the positive association between green spaces and green space corridors with health are consistent with the findings on green space physical activity pathways where significant associations were found for similar distances (Akpinar, 2016; Cardinali et al., 2024b; McCormack et al., 2010; Sugiyama et al., 2010). While our findings do not allow for disentangling all pathways individually, they do imply that several mechanisms act simultaneously, work at different distances, and rely on different green space characteristics (Cardinali et al., 2023b; Markevych et al., 2017). This has the potential to mask individual mechanisms depending on the study design.

4.6. Strengths and limitations

Our study is characterised by the systematic analysis of green space characteristics and their proximity to individual homes. To our knowledge, such a comprehensive sensitivity analysis has not been done on the pathway from green space via self-rated air pollution to self-rated health and provides new insights into how and where this pathway operates. Our study allows the comparison of different green space characteristics and highlights the potential importance of the connectivity of green spaces to effectively reduce air pollution annoyance.

However, the scale and complexity of this study design also come with limitations. As we used just-identified models with 0 degrees of freedom, we can only judge the quality of the models based on theory, but not with model fit indices, as for this an over-identified model would be needed. In addition, our study design limited the ability to examine the results in more detail for possible effect modification, although different vulnerabilities to air pollution in age groups are to be expected. Another potential limitation arises from not explicitly addressing non-linear relationships between green space characteristics, self-rated air pollution, and self-rated health, which may have led to an over-simplification of the complex relationships. On a related note, the sensitivity analysis approach with 135 structural equation models may have led to vulnerability to noise in the dataset, especially in cases where the true relationship between a green space characteristic and self-rated air pollution approaches zero. In general, the sensitivity analysis approach and reduced model complexity lead to limited precision in the examined mechanisms and should be treated accordingly.

Although we performed a detailed analysis of green space indicators, there may be limitations regarding generalizability. While we adjusted for temperature and seasonality through our city dummy variables, we could not account for differences in weather conditions between the approximate two months of survey conduction in the cities. This might have affected our results since meteorological conditions such as temperature, humidity and ventilation can easily mask the green space air pollution relationship (Diener and Mudu, 2021; Shi et al., 2017). In addition, it needs to be acknowledged that while NDVI is the most common method to measure greenness, the less known Soil Adjusted Vegetation Index (SAVI, Huete, 1988) might deliver more precise results due to its adjustment for soil reflection (Silleos et al., 2006). However, a recent study in Europe found no better performance of SAVI compared to NDVI (Sadeh et al., 2021). Furthermore, our case studies have been carried out in European climate zones and predominantly only in a certain category of urban satellite districts with specific socio-economic characteristics. This might have also reduced the variability in larger buffers. All this limits the generalisation of our results.

In addition, our study relies heavily on survey data, which is associated with the uncertainties of self-reported data such as social desirability, recall or reporting bias. In particular, self-reported air pollution variables have been associated with inaccuracies through the influence of visual perception and socio-demographic variables (Brody et al., 2004; Cobbold et al., 2022; Guo et al., 2016). Similarly, Pelgrims and colleagues found inaccuracies in self-rated air pollution alone, but a reasonable classification of relative exposure levels in their models, once they included socioeconomic status and other contextual factors (Pelgrims et al., 2022). Although we are confident that our self-rated air pollution variable is equally robust, since we followed a similar approach, it is important to acknowledge this potential limitation. Furthermore, we cannot rule out reverse causation where people with lower self-rated health report higher perceived air pollution. Although we did adjust for disabilities and addressed this issue partially, not all health issues were captured in this proxy which means we cannot rule out that people with chronic illnesses reported higher air pollution than those without (Pantavou et al., 2018; Piro et al., 2008).

Moreover, our one-item question on health only allows for an interpretation towards general health overall, and not specific health concerns like respiratory illnesses, cardiovascular diseases, impaired neural development, depression, suicide, cognitive capacities, happiness and life satisfaction (Cohen et al., 2017; Liu et al., 2021; Lu, 2020; Pope et al., 2017; Vos et al., 2015; WHO Regional Office for Europe, 2016). The relation to respiratory-specific health outcomes may be stronger (Mueller et al., 2022). Self-rated health is an indicator that encompasses both mental and physical health and could include both the physiological pathways and the psychological pathways from air pollution to health (Lu, 2020). However, since our exposure is perceived rather than measured air pollution, the psychological pathways may be over-represented, especially the ones related to perceived health risks (Orru et al., 2018). Furthermore, although we adjusted our model for indicators of neighbourhood satisfaction that could confound this association, we cannot exclude the possibility of some residual confounding by unmeasured psychological factors (Hajian Tilaki, 2012). Lastly, the study employed a cross-sectional design, which precludes establishing causal relationships between green space, self-rated air pollution and health outcomes.

4.7. Further research avenues and implications

Our results support the theory that green space corridors may contribute effectively to reducing air pollution annoyance and do not contradict the hypothesized negative associations with fragmented green spaces (Shen and Lung, 2017). They are also in line with recent findings of Venter and colleagues suggesting that the role of urban vegetation in air pollution reduction is more complex than greening cities (Venter et al., 2024). Currently, urban green space strategies often work with the percentage of green space per hectare or with green space per citizen. Both concepts fail to take the positive health aspect of connectivity into account and might easily result in fragmented green spaces, potentially even harmful by increasing local air pollution.

More research is needed to confirm the importance of green space connectivity, preferably with local air quality monitoring stations as they allow for a fine-grained objective assessment, which might lead to a change in urban green space strategies. Building on our research, we recommend using Euclidean distance when trying to capture the air pollution pathway and integrate the ratio of fragmentation and connectivity of green spaces in future studies. Another research avenue is to test more complex structural equation models (effect modification, serial and parallel mediation), to better understand the chain of effects between green space characteristics, air pollution and health. Most importantly, more longitudinal studies are needed to establish the theorized causal relationship. This study may support in setting up these more complex research frameworks.

4.8. Conclusion

We investigated nine green space indicators in 15 distances to get insights into how the proximity to and the characteristics of green spaces influence air pollution annoyance and in turn self-rated health. Our results indicate that it is mainly the connectivity of green spaces, measured in intermediate Euclidean distances (800–1000 m), that may lead to lower air pollution annoyance. Interestingly, we did not find any greenness indicators that were able to influence self-rated air pollution, in line with recent studies that suggest a complex and minimal role of air pollution mitigation of greenness. Although our study is limited to European satellite districts and relies on self-reported air pollution, it supports the available evidence that the connectivity of green spaces may be an important green space characteristic when it comes to reducing air pollution in cities. With this, our study adds important insights into how green spaces should be planned and implemented in cities, essentially calling for a connected system of green spaces instead of fragmented smaller parks, to reduce air pollution annoyance and in turn improve the overall health of their residents.

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Conflicts of interest

The authors declare they have no conflicts of interest related to this work to disclose.

CRediT authorship contribution statement

Marcel Cardinali: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mariëlle A. Beenackers:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Investigation, Formal analysis. **Arjan van Timmeren:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Conceptualization. **Uta Pottgiesser:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT 4.0 in order to proofread the text. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2024.103300.

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