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**Potential pathways of urban greenspace to respiratory health:
Air pollution and physical activity**

William Mueller

**Thesis submitted in accordance with the requirements for the
degree of**

Doctor of Philosophy

**of the
University of London**

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Department of Public Health, Environments & Society

Faculty of Public Health & Policy

LONDON SCHOOL OF HYGIENE & TROPICAL MEDICINE

Funded by the Institute of Occupational Medicine

Declaration

I, William Mueller, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

Background: Urban greenspace has been associated with better health across a range of outcomes, such as mental and cardiovascular health. In contrast, research findings relating to respiratory health are heterogeneous. Several important pathways, such as lower exposure to air pollution, increased opportunity for physical activity, and reduced noise annoyance, may link greenspace with better respiratory health; however, these have not been sufficiently explored.

Methods: In this thesis, I aimed to extend the knowledge base by completing a systematic review to assess the potential pathways underpinning urban greenspace and respiratory health, and also to synthesise the direction and magnitude of effect with different health indicators. Further, I analysed personal and home sensor data of air pollutants, physical activity, and noise with a suite of objective greenspace markers: the normalised difference vegetation index (NDVI), tree cover, and green land use. Study settings included urban centres in Europe and Delhi, India.

Results: Many of the studies identified in the systematic review were positive (i.e., beneficial) with health, with the most consistent positive evidence for respiratory mortality. For the other indicators of health, particularly asthma, there was inconsistency in the direction and imprecision in effect estimates. In the European study, only NDVI was found to be associated with lower indoor concentrations of PM_{2.5}. While there did not appear to be an indication of the relationship between greenspace metrics and indoor noise levels, there were clear reductions in the odds of reported road noise annoyance with NDVI and tree cover. In Delhi, PM_{2.5} reductions were weakly associated with NDVI and tree cover within trips, but only in the spring/summer/monsoon season; there was a suggestion of higher PM_{2.5} concentrations with green land use across trips. For physical activity, there did not seem to be an important relationship with average greenspace surrounding the home. Nevertheless, when quantifying the greenspace specifically in the environments where exercise occurred, there was a strong positive relationship again with NDVI and tree cover, and more so for cycling than walking.

Conclusion: The empirical results of this PhD support several different pathways to health, with the exception of noise levels, with the strongest associations for physical activity. At the same time, findings were not universal: there were important nuances, for example, how and where the greenspace environment was characterised. In summary, my PhD research findings can assist with the interpretation of these specific underlying mechanisms related to epidemiological studies of greenspace and respiratory health.

In memory of Prof Paul Wilkinson.

I am so fortunate to have received your guidance during my PhD studies. Your insight and wisdom will be a continued source of inspiration for me.

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I am most grateful to the members of my supervisory committee: Prof Paul Wilkinson, Dr James Milner (both LSHTM), Dr Miranda Loh (IOM), and Prof Sotiris Vardoulakis (IOM/ANU). I very much appreciate the many hours spent over the years discussing greenspace and what it means for health. Your esteemed guidance has helped me develop this dissertation and its contents, and, more, to hone my thinking about epidemiology and exposure science.

I would like to specifically acknowledge individuals on the HEALS and DAPHNE project teams, who provided valuable background and contextual information on the research studies, as well as helpful feedback on the analysis: Susanne Steinle, Eelco Kuijpers, Juha Pärkkä, Dimitris Chapizanis, Asimina Stamatelopoulou (HEALS) and Zoë Petard, Mark Cherrie, Naveen Puttaswamy, Kalpana Balakrishnan, D.K. Arvind, Paul Cullinan, Mark Miller (DAPHNE). I owe a special thanks to Eija Parmes and Reinier Sterkenburg for imparting their GIS wisdom.

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To my parents, thank you for your unwavering support. Mom: thank you for your devotion to reading my academic papers on your phone. Dad: thank you for sending pieces of note in the *BMJ*.

To Vicky, thank you for all your encouragement, support and help with Rowan so I could finish!

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List of Abbreviations

| | |
|------------------|--|
| BVOC | Biogenic Volatile Organic Compound |
| CI | Confidence Interval |
| COPD | Chronic Obstructive Pulmonary Disease |
| DAPHNE | Delhi Air Pollution and Health Effects |
| FeNO | Fractional Exhaled Nitric Oxide |
| FEV ₁ | Forced Expiratory Volume in 1 s |
| GIS | Geographic Information System |
| GLU | Green Land Use |
| GPS | Global Positioning System |
| GS | Greenspace |
| HEALS | Health and Environment-wide Associations based on Large population Surveys |
| ICD | International Coding of Disease |
| IOM | Institute of Occupational Medicine |
| IQR | Interquartile Range |
| IRR | Incidence Rate Ratio |
| LMIC | Lower and Middle Income Country |
| MET | Metabolic Equivalent Task |
| MVPA | Moderate to Vigorous Physical Activity |
| NDVI | Normalised Difference Vegetation Index |
| NIR | Near Infrared |
| NO | Nitric Oxide |
| NO ₂ | Nitrogen Dioxide |
| O ₃ | Ozone |
| OR | Odds Ratio |
| OSF | Open Science Framework |
| OSM | OpenStreetMap |
| PA | Physical Activity |
| PECO | Population, Exposure, Comparator, Outcome |
| PF | Parks or Forests |
| PM | Particulate Matter |

| | |
|-------------------|--|
| PM _{2.5} | Particulate Matter with an aerodynamic diameter of <2.5 µm |
| PM ₁₀ | Particulate Matter with an aerodynamic diameter of <10 µm |
| RCT | Randomised Controlled Trial |
| rH | Relative humidity |
| RR | Relative Risk |
| SD | Standard Deviation |
| SES | Socioeconomic Status |
| SEP | Socioeconomic Position |
| SHS | Second-Hand Smoke |
| SMR | Standardised Mortality Ratio |
| SO ₂ | Sulphur Dioxide |
| TC | Tree Cover |
| TCD | Tree Cover/Canopy Density |
| WHO | World Health Organization |

PART I: Background to the thesis

1 Introduction

1.1 Context: Urban greenspace and pathways to respiratory health

As cities grow more populated and densely built, urban greenspace allows city dwellers to experience some semblance of the natural environment. The notion of greenspace refers to a multitude of natural features, involving different forms and functions. Although greenspace may be used as an umbrella term to imply any natural area, I employ a definition based on a commonality of urban vegetation or greenery (Taylor & Hochuli, 2017). Greenspace here is distinct from bluespace, which instead encompasses bodies of water.

There are many forms and structures of urban greenspace. For example, green land use can refer to grassy urban parks, forests, or other such areas, also including those used for recreation. Trees are an important component of greenspace that can be integrated into green land use, as well as in built-up areas on streets. Other examples of urban vegetation, which have also been termed 'green infrastructure', include green walls and roofs; these structures can incorporate vegetation in urban environments where space is very limited. Private gardens, with various degrees of flora, also contribute to overall urban greenspace (Cameron et al., 2012). Some examples of different types of urban greenspace are illustrated in Figure 1.

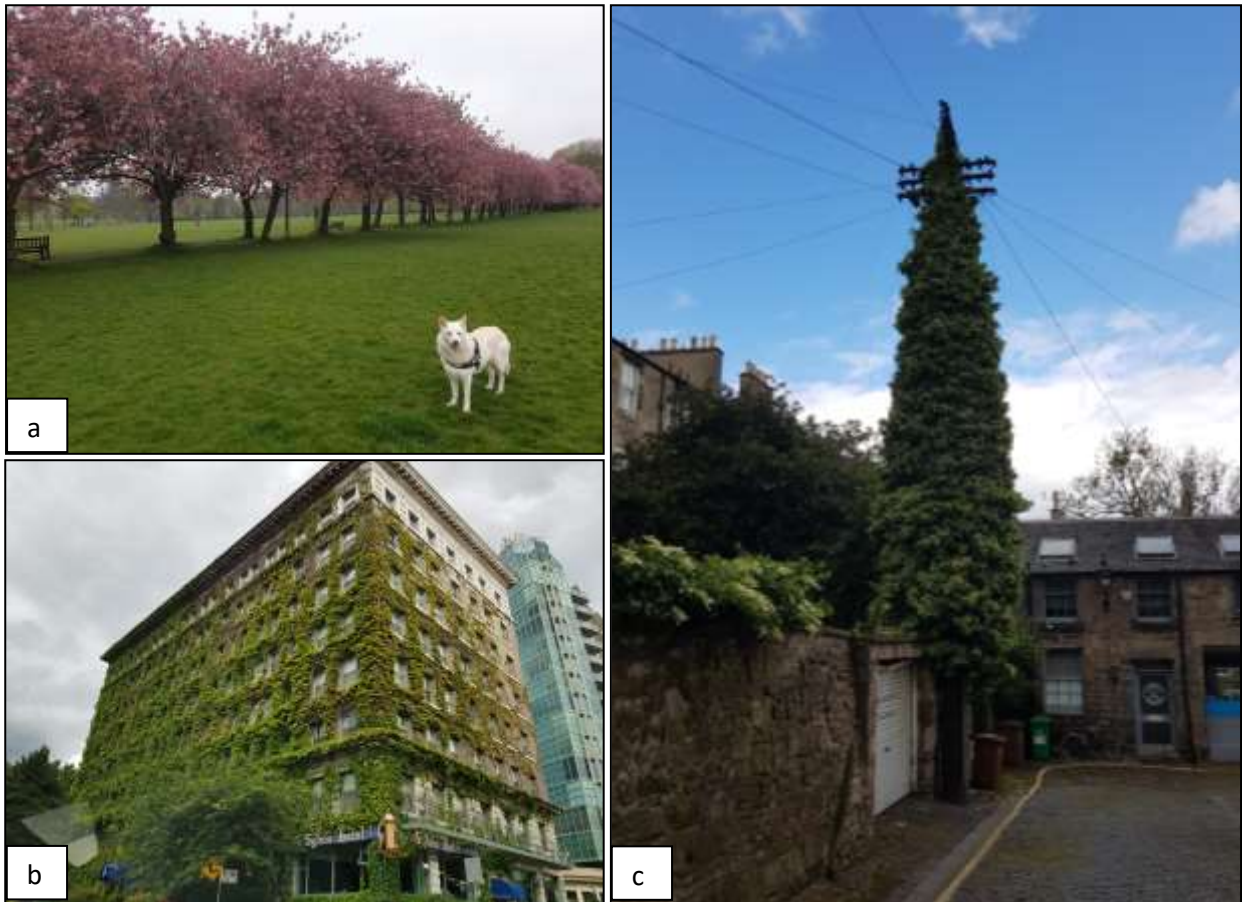


Figure 1. Some examples of urban greenspace, including a) parks (Edinburgh, UK), b) green walls (Vancouver, Canada), and c) other green infrastructure (Edinburgh, UK) (own photos).

The relationship between greenspace and health has become a well-studied research topic, with thousands of relevant papers published annually in recent years (Zhang et al., 2020). Emerging findings from this extensive literature base indicate positive associations between greenspace and numerous health indicators, including better pregnancy outcomes, mental health, and cardiovascular conditions (Nieuwenhuijsen, 2021). Indeed, exposure to urban greenspace involves multiple pathways with the potential to affect health. These pathways have been broadly categorised into four major domains: reducing harm (e.g., lower exposure to air pollution), restoring capacities (e.g., attention restoration), building capacities (e.g., space for physical activity), and, as a negative impact, causing harm (e.g., release of allergens) (Markevych et al., 2017; Marselle et al., 2021). Along with health benefits, urban greenery may have the potential to additionally offer substantial social (e.g., attractive spaces for social interactions) and ecological (e.g., reducing urban heat island effect) benefits, so it may be an

appealing tool to promote public health and other policies (Keeler et al., 2019; Kruize et al., 2019). Nevertheless, despite the wide evidence base and pathways potentially underlying observed associations, further clarity is needed to identify and substantiate specific mechanisms (Zhang et al., 2020).

1.2 Motivation of the PhD research

While a growing body of research has identified associations between exposure to urban greenspace and better health across a wide range of different health outcomes (Yang et al., 2021a), the evidence for respiratory health is more limited and heterogeneous (Twohig-Bennett & Jones, 2018; Kondo et al., 2018). Moreover, published reviews on greenspace and health have either given insufficient attention to respiratory health or have focussed on specific aspects or subgroups, such as childhood asthma (Hartley et al., 2020). An important knowledge gap to address in the thesis work was to complete a systematic review across a broad range of respiratory outcomes, which was used to develop a conceptual framework with greenspace.

Even with the limited evidence of respiratory health impacts, there are several mechanisms by which urban greenspace could offer benefits. A key pathway connecting greenspace and respiratory health might be the reduction of air pollution exposure, which, on average globally, amounts to nearly 9 million deaths each year and almost three years of lost life expectancy per person (Lelieveld et al., 2020). Particulate matter with an aerodynamic diameter of $<2.5 \mu\text{m}$ ($\text{PM}_{2.5}$) is especially harmful for respiratory outcomes, including asthma, chronic obstructive pulmonary disease (COPD), and respiratory infections (Kurt et al., 2016). Both indoor and outdoor $\text{PM}_{2.5}$ levels have been linked to increased symptoms of asthma and rhinitis (Baldacci et al., 2015). A meta-analysis indicated acute, deleterious effects on lung function in adults exposed to particulates (da Silveira Fleck et al., 2021).

Although there is the potential for substantial benefits from improved air quality, the relationship with greenspace is complex, involving the interaction of numerous factors. Greener areas may be associated with lower air pollution levels simply because they entail fewer sources of air pollution.

There are also a number of physical mechanisms by which vegetation may filter the air, especially via trees, though there are also processes where trees could worsen air quality. Leaves provide an effective broad surface area on which to accumulate particulate matter (PM) through deposition (Salmond et al., 2016), and greenspaces can provide open areas to help with the dispersion of airborne particulates (Diener & Modu, 2021). However, vegetation can have its own contribution to ambient pollutants: trees produce biogenic volatile organic compounds (BVOCs) in times of stress, including higher temperatures and pathogen attacks, conditions to which urban trees may be more frequently exposed via climate change (Eisenman et al., 2019). Trees and grasses can release large volumes of pollen and fungal spores, potentially leading to increases in emergency department presentation for children and adolescents (Erbas et al., 2018). Dense tree canopies may prevent the dispersion of air pollutants in street canyon environments, leading to localised accumulations of higher ambient concentrations (Abhijith et al., 2017). Local factors and types of greenspace must be considered to maximise air quality improvements.

As well as improved air quality, another important service provided by greenspace may be more access to areas to engage in exercise and sport. Evidence has amassed on the extensive health benefits from engaging in physical exercise and achieving better cardiorespiratory fitness (Piercy et al., 2018), which may provide benefits for different respiratory health outcomes. Reviews have indicated reduced lung cancer risks and better outcomes for asthma and mortality from COPD related to more physical activity, although further longitudinal and randomised controlled trial (RCT) research is needed to confirm mechanisms and clarify the direction of these relationships (e.g., to address reverse causality) (Cordova-Rivera et al., 2018; McTiernan et al., 2019; Geidl et al., 2020). To date, few studies employ objective measures of physical activity and/or greenspace use, providing some suggestive evidence of a positive association (Jansen et al., 2018). While greenness might encourage some degree of physical activity, other neighbourhood attributes, such as walkability, have demonstrated a stronger influence (James et al., 2017). Other factors related to the built environment may impede physical activity levels, such as residential noise annoyance (Foraster et al., 2013). Ultimately, greenspace is among the

complex web of neighbourhood and individual factors, such as safety/security, convenience, enjoyment, and habit, all of which influence the likelihood of engaging in physical activity and active travel (Gotschi et al., 2017). A key contribution of this PhD work is to examine how greenspace in different environments is related to objective markers of physical activity.

Air pollution and physical activity have the potential to be important pathways linking greenspace and improved respiratory health, yet there are also other routes leading to better respiratory health. One such pathway is noise, which is often closely linked to air pollution (Fecht et al., 2016). Dense foliage can block unpleasant artificial noise, either through an acoustic mechanism (van Renterghem et al., 2015) or visual perception (van Renterghem & Botteldooren, 2016). Natural soundscapes, such as those emanating from greenspaces (Alvarsson et al., 2010), have been associated with stress reduction, all of which, in turn, may promote overall immune function (Rook et al., 2013). Verdant areas in urban environments may also boost immune systems by offering positive contact to microbiota (Ruokolainen et al., 2014; Selway et al., 2020; Wu et al., 2022). Even though these other pathways may not involve a strong direct impact, understanding the totality of pathways could help assess the overall potential to affect respiratory health.

An important limitation of much of the greenspace research is the use of residential exposure, when in reality, individuals are highly mobile and are exposed to much more than immediate home environments. As such, epidemiological studies of air pollution often rely on area-based, rather than personal-level, exposure measurements, such as networks of monitoring stations and land use regression models. Residential exposures can be useful since individuals spend most of their time at home indoors, though indoor levels of air pollution may be more relevant for air pollution experienced in residential environments. At the same time, over half of indoor PM_{2.5} concentrations may originate from outdoor sources (Meng et al., 2005), so reductions in ambient concentrations could also benefit the indoor environment. Time spent in non-residential microenvironments may be substantial, for example, school, work, and in transit, for which residential greenspace levels may not be

representative. There is a need to investigate greenspace microenvironments beyond those at home addresses.

Another challenge to disentangle the observational evidence between greenspace and health is possible unmeasured selection bias: healthier people may be more inclined to choose lush areas to live in and enjoy, compared to less healthy people who may place less importance on being close to greenery (Yang et al., 2021b). Investigating pathways may provide clearer mechanistic evidence that is less clouded by issues of selection bias. Another important limitation of the existing body of work is the focus on high income countries, such as North American and European settings, relative to other parts of the globe (Nawrath et al., 2021). Examining the extent to which physical activity and air pollution are influenced by greenspace in different settings would help provide context-specific information to understand particular mechanisms of action.

1.3 Scope

The PhD research examines the relationship between urban greenspace and respiratory health. The two main components of the research involve (1) undertaking a broad literature review to collate empirical evidence on this topic and (2) assessing via three empirical analyses specific pathways related to urban greenspace, namely air pollution and physical activity, as well as noise. This approach provides an overview of existing epidemiological studies identified through the review, including the characterisation of greenspace exposure and health outcomes under investigation, and more detailed insights into the above pathways. For the air pollution pathway, this research focuses on indoor (i.e., home) and outdoor (i.e., during active travel) exposure to PM_{2.5}, which represents a significant burden on health compared to other air pollutants (Shaffer et al., 2019). Related to physical activity, greenspace is defined as both that around the home and that in which the exercise occurs. Indoor noise levels and road noise annoyance are also addressed in the research to clarify links with greenspace. The potential pathways connecting urban greenspace and respiratory health indicators, with those investigated in the PhD research, are presented in Figure 2.

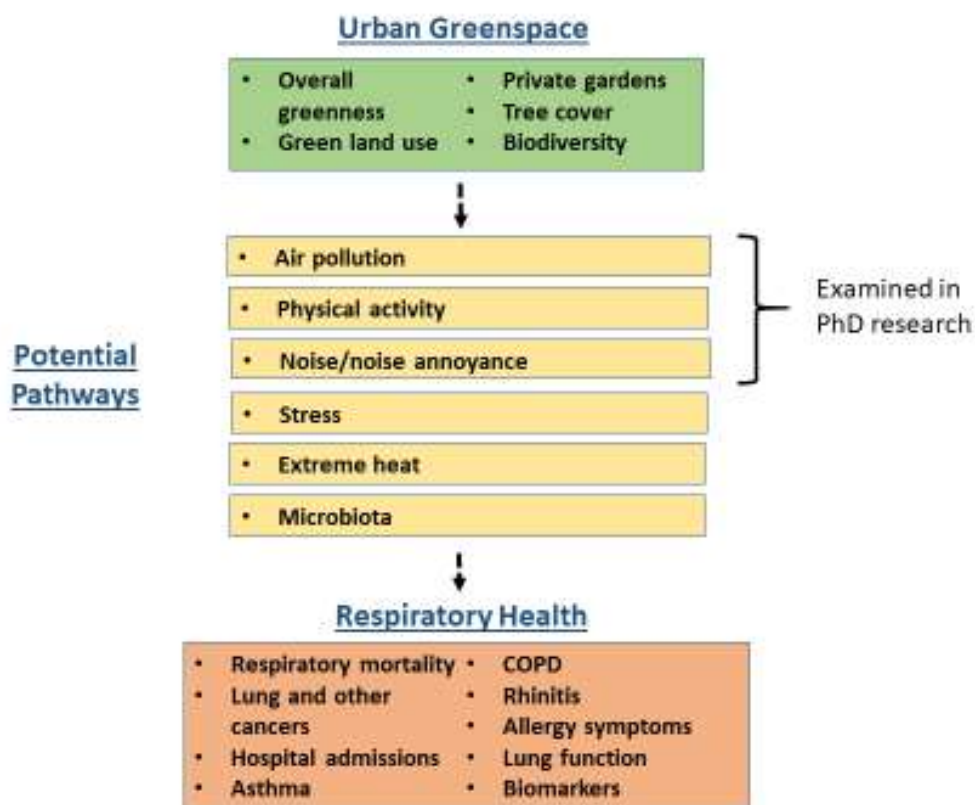


Figure 2. Urban greenspace and potential pathways to respiratory health, indicating those investigated in the PhD research.

The empirical analyses are based on data from two research projects: Health and Environment-wide Associations based on Large population Surveys (HEALS) and the Delhi Air Pollution and Health Effects (DAPHNE) study. These projects used sensors to collect residential and personal-level air pollution measurements and objective physical activity data in European and South Asian settings. These datasets, along with a common suite of greenspace metrics, are used to examine potential pathways to health in these diverse settings.

This work represents a research paper-based thesis. There are four individual papers, all of which have been accepted for publication in peer-reviewed journals. These papers are included as separate chapters in the thesis and constitute stand-alone work. There will be some unavoidable overlap in content. Postscripts to the papers have been added to discuss any impactful research published

subsequent to the paper, as well as any additional analysis that was not included in the final publication.

1.4 Thesis outline

This thesis is structured into three main parts. First, the background provides the context, scope, aims and objectives, and detailed literature review in the format of a published paper examining available evidence on urban greenspace and respiratory health. The second part presents the key empirical results of the thesis work, including three published papers. The final part of the thesis bridges together the main findings, addresses strengths and limitations with recommendations for future research, and concludes with the policy implications of the work.

1.5 Other relevant presentations and publications

I completed the PhD research on a part-time basis while being employed at the Institute of Occupational Medicine (IOM). During this time, I also presented and published other air pollution research that is related to my PhD research topic, which I list below (also including PhD-related presentations).

Conference presentations

Mueller W, Wilkinson P, Milner J, Loh M, Vardoulakis S, Petard Z, Puttaswamy N, Balakrishnan K, Arvind DK. Personal exposure to outdoor particulate matter and greenspace in Delhi, India. Presented at: 33rd Annual Conference of the International Society for Environmental Epidemiology (ISEE 2021); 23-26 August 2021; New York, USA (virtual).

Mueller, W., Steinle, S., Pärkkä, J., Parmes, E., Liedes, H., Kuijpers, E., Pronk, A., Sarigiannis, D., Karakitsios, S., Chapizanis, D., Maggos, T, Stamatelopoulou, A., Wilkinson, P., Milner, J., Vardoulakis, S., Loh, M. Neighbourhood and trip-based greenspace in four European areas: Associations with physical activity. Poster discussion presented at: 32nd Annual Conference of the International Society for Environmental Epidemiology (ISEE 2020); 24-27 August 2020; Washington D.C., USA (virtual).

Mueller W, Loh M, Vardoulakis S, Johnston HJJ, Steinle S, Nopadol P, Kliengchuay W, Tantrakarnapa K, Cherrie JW. Exposure to ambient particulate matter during pregnancy: Associations with birth weight in Thailand. Presented at: 32nd Annual Conference of the International Society for Environmental Epidemiology (ISEE 2020); 24-27 August 2020; Washington D.C., USA (virtual).

Mueller W, Steinle S, Loh M, Vardoulakis S, Nopadol P, Kliengchuay W, Sahanavin N, Sillaparassamee R, Nakhapakorn K, Tantrakarnapa K, Cherrie JW. Ambient particulate matter and biomass burning: An ecological time series study of respiratory and cardiovascular hospital visits in northern Thailand. Presented at: 2019 International Symposium for Environmental Epidemiology, Exposure Science and Environmental Health (ISEE-ESEH 2019); 11-12 December 2019; Chiang Mai, Thailand.

Mueller W, Steinle S, Loh M, Vardoulakis S, Nopadol P, Kliengchuay W, Sahanavin N, Sillaparassamee R, Nakhapakorn K, Tantrakarnapa K, Cherrie JW. Long-term Exposure to Outdoor Air Pollutants in Thailand: A Health Impact Assessment. Poster presented at: ISEE 2019; 25-28 August 2019; Utrecht, Netherlands.

Mueller W, Steinle S., Pärkkä J, Parmes E, Liedes H, Kuijpers E, Sarigiannis D, Chapizanis D, Maggos T, Stamatelopoulou M, Wilkinson P, Milner J, Vardoulakis S, Loh M. Health Effects of Greenspace on Outdoor Physical Activity & Indoor PM 2.5 and Noise : A Case Study of 4 European Cities. Poster discussion presented at: ISEE 2019; 25-28 August 2019; Utrecht, Netherlands.

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2 Aims and objectives of the thesis

The main aim of this PhD thesis is to examine the relationship between urban greenspace and respiratory health by focussing on two key pathways: reduction in air pollution exposure and increased opportunity for physical activity.

2.1 Objective one

Research question:

Does the presence of greenspace contribute to respiratory health via associations with lower air pollution and/or higher physical activity levels, or through another mechanism?

Objective:

1. Perform a systematic review to synthesise the evidence relating urban greenspace and respiratory health.

Specific objectives:

1. i) Identify potential causal pathways linking urban greenspace components to respiratory health outcomes.
1. ii) Investigate the overall direction and magnitude of reported associations.

2.2 Objective two

Research question:

Do individuals who live in areas with more greenspace have lower exposures to environmental hazards, such as air pollution and noise?

Objectives:

2. a) Quantify the association between residential metrics of urban greenspace and indoor levels of PM_{2.5}.

2. b) Quantify the association between residential metrics of urban greenspace and indoor noise levels and road noise annoyance.

2.3 Objective three

Research questions:

Does the amount of greenspace surrounding the home affect active travel levels of individuals?

Are active travel journeys with more greenspace associated with higher physical activity levels?

Objectives:

3. a) Quantify the association between residential metrics of urban greenspace and moderate to vigorous physical activity (MVPA) as an objective PA metric.
3. b) Quantify the association between greenspace during bouts of physical activity and Metabolic Equivalent Tasks (METs).

2.4 Objective four

Research questions:

Are segments with more greenspace along walking journeys associated with lower exposure to air pollution?

Are walking journeys with more greenspace on average associated with lower overall exposure to air pollution?

Objective:

4. a) Quantify the association *within* walking journeys between microenvironment-level greenspace and personal exposures to PM_{2.5}.
4. b) Quantify the association *across* walking journeys between microenvironment-level greenspace and personal exposures to PM_{2.5}.

2.5 Summary

The overall structure and flow of the PhD is presented in Table 1. Objective 1 is addressed in the review paper (chapter 3). Objectives 2 to 4 are included in the empirical analysis papers (chapters 4-6). Table 1 also highlights the methods applied in each of the chapters, as well as any research outputs to be used in subsequent chapters (i.e., the 'Use of results' column).

Table 1. Overall PhD structure and flow.

| Objectives | Methods | Use of results | Chapter/paper |
|--|---|--|--|
| <p>1. Perform a systematic review to synthesise the evidence relating urban greenspace and respiratory health.</p> <p>i. Identify potential causal pathways linking urban greenspace components to respiratory health outcomes.</p> <p>ii. Investigate the overall direction and magnitude of reported associations.</p> | <p>Systematic review</p> | <p>Identification of pathways for analysis in objectives 2, 3 and 4.</p> | <p>Chapter 3</p> <p>Paper: ‘Exposure to urban greenspace and pathways to respiratory health: an exploratory systematic review’</p> |
| <p>2. a) Quantify the association between residential metrics of urban greenspace and indoor levels of PM_{2.5}.</p> | <p>Random-effects generalised least squares</p> | <p>Establish greenspace metrics to be adopted in objectives 3 and 4.</p> | <p>Chapter 4</p> <p>Paper: ‘Urban greenspace and the indoor environment: Pathways to health via indoor</p> |

| | | | |
|--|---|--|--|
| <p>b) Quantify the association between residential metrics of urban greenspace and indoor noise levels and road noise annoyance.</p> | <p>regression analysis Ordinal logistic regression analysis</p> | <p>Comparison of indoor PM_{2.5} levels in objective 4.</p> | <p>particulate matter, noise, and road noise annoyance'</p> |
| <p>3. a) Quantify the association between residential metrics of urban greenspace and moderate to vigorous physical activity (MVPA) as an objective PA metric.</p> <p>b) Quantify the association between greenspace during bouts of physical activity and Metabolic Equivalent of Tasks (METs).</p> | <p>Mixed effects regression analysis</p> | <p>Develop methodology for GIS data processing and analysis for objective 4.</p> | <p>Chapter 5 Paper: 'Neighbourhood and path-based greenspace in three European countries: associations with objective physical activity'</p> |
| <p>4. a) Quantify the association <i>within</i> walking journeys between microenvironment-level greenspace and personal exposures to PM_{2.5}.</p> | <p>Fixed effects regression analysis using 1-</p> | | <p>Chapter 6</p> |

| | | | |
|---|--|--|--|
| <p>b) Quantify the association <i>across</i> walking journeys between microenvironment-level greenspace and personal exposures to PM_{2.5}.</p> | <p>minute averaged data</p> <p>Mixed effects regression analyses with trip-level averaged data</p> | | <p>Paper: 'The relationship between greenspace and personal exposure to PM_{2.5} during walking trips in Delhi, India'</p> |
|---|--|--|--|

3 Background literature review

3.1 Introduction

This chapter provides a literature review of urban greenspace and respiratory health in the form of a systematic review paper. The purpose of the systematic review is two-fold: to identify potential mechanisms whereby greenspace may lead to improved health and to synthesise existing evidence on exposures to urban greenspace and different metrics of respiratory health. This comprehensive survey of the literature helps set the context for the following analytical chapters.

This chapter addresses research objectives 1 a) Perform a systematic review to synthesise the evidence relating urban greenspace and respiratory health; i) Identify potential causal pathways linking urban greenspace components to respiratory health outcomes; and ii) investigate the overall direction and magnitude of reported associations.

This study included as a review paper in chapter 3 was accepted for publication in *Science of the Total Environment* in March 2022. The supplementary material from this paper is included in Appendix 1.

Cover sheet and research paper follow on subsequent pages.

RESEARCH PAPER COVER SHEET

Please note that a cover sheet must be completed for each research paper included within a thesis.

SECTION A – Student Details

| | | | |
|---------------------|--|-------|----|
| Student ID Number | 1800264 | Title | Mr |
| First Name(s) | William | | |
| Surname/Family Name | Mueller | | |
| Thesis Title | Potential pathways of urban greenspace to respiratory health: Air pollution and physical activity | | |
| Primary Supervisor | Prof Paul Wilkinson | | |

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

| | | | |
|--|----------------------------------|---|-----|
| Where was the work published? | Science of the Total Environment | | |
| When was the work published? | 2022 | | |
| If the work was published prior to registration for your research degree, give a brief rationale for its inclusion | N/A | | |
| Have you retained the copyright for the work?* | Yes | Was the work subject to academic peer review? | Yes |

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SECTION C – Prepared for publication, but not yet published

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| Stage of publication | Choose an item. |

SECTION D – Multi-authored work

| | |
|---|---|
| <p>For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)</p> | <p>I performed the literature search, reviewed the papers, wrote the first draft of the manuscript, and responded to the reviewer comments.</p> |
|---|---|

SECTION E

| | |
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Exposure to urban greenspace and pathways to respiratory health: An exploratory systematic review

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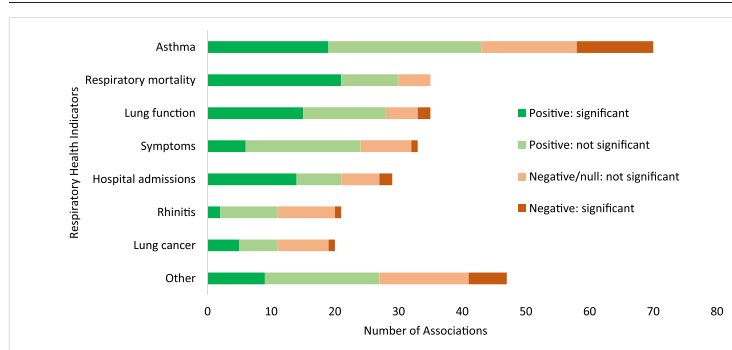
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HIGHLIGHTS

- We identified 108 papers examining greenspace and respiratory health.
- A wide range of health indicators were included, with asthma being the most common.
- Positive associations were most strongly related to reduced respiratory mortality.
- For other health outcomes, effect estimates were often inconsistent or imprecise.

GRAPHICAL ABSTRACT



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ABSTRACT

Background/objective: Urban greenspace may have a beneficial or adverse effect on respiratory health. Our objective was to perform an exploratory systematic review to synthesise the evidence and identify the potential causal pathways relating urban greenspace and respiratory health.

Methods: We followed PRISMA guidelines on systematic reviews and searched five databases for eligible studies during 2000–2021. We incorporated a broad range of urban greenspace and respiratory health search terms, including both observational and experimental studies. Screening, data extraction, and risk of bias, assessed using the Navigation Guide criteria, were performed independently by two authors. We performed a narrative synthesis and discuss suggested pathways to respiratory health.

Results: We identified 108 eligible papers ($n = 104$ observational, $n = 4$ experimental). The most common greenspace indicators were the overall greenery or vegetation (also known as greenness), green land use/land cover of physical area classes (e.g., parks, forests), and tree canopy cover. A wide range of respiratory health indicators were studied, with asthma prevalence being the most common. Two thirds ($n = 195$) of the associations in these studies were positive (i.e., beneficial) with health, with 31% ($n = 91$) statistically significant; only 9% ($n = 25$) of reported associations were negative (i.e., adverse) with health and statistically significant. The most consistent positive evidence was apparent for respiratory mortality. There were $n = 35$ (32%) 'probably low' and $n = 73$ (68%) 'probably high' overall ratings of bias. Hypothesised causal pathways for health benefits included lower air pollution, more physically active populations, and exposure to microbial diversity; suggested mechanisms with poorer health included exposure to pollen and other aeroallergens.

Conclusion: Many studies showed positive association between urban greenspace and respiratory health, especially lower respiratory mortality; this is suggestive, but not conclusive, of causal effects. Results underscore the importance of contextual factors, greenspace metric employed, and the potential bias of subtle selection factors, which should be explored further.

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1. Introduction

As more of the global population moves to inhabit cities, urban greenspace will provide an important and accessible source of nature. Urban greenspace, also referred to as greenness or green infrastructure, can involve parks and forests, as well as street trees, gardens, and numerous other arrangements of vegetation. Systematic reviews have identified beneficial associations between greenspace and specific health outcomes, notably mental health (van den Berg et al., 2015), all-cause and cardiovascular disease mortality (Gascon et al., 2016), physical activity (Kondo et al., 2018), and other indicators of health and wellbeing (Twohig-Bennett and Jones, 2018). While there are likely many mechanisms by which greenspace or biodiversity could affect health, four major domains have been proposed: reducing harm (e.g., mitigating air pollution), restoring capacities (e.g., attention restoration), building capacities (e.g., encouraging physical activity), and causing harm (e.g., allergens) (Markevych et al., 2017; Marselle et al., 2021). All of these pathways may be relevant for respiratory health, particularly reducing harm from air pollution. Although systematic reviews of greenspace have focussed on specific aspects of respiratory health, such as childhood asthma (Hartley et al., 2020) and allergic respiratory diseases in children (Lambert et al., 2017) and youth (Ferrante et al., 2020), a review has not to date been undertaken focussing on the potential relationships and pathways across respiratory health outcomes.

The respiratory system is composed of the upper (e.g., nasal passages) and lower (e.g., trachea, lungs) respiratory tracts and functions to provide

exchange of oxygen and carbon dioxide. Its development and healthy maintenance appear to involve an intricate web of environmental and genetic factors, with specific susceptibility to harm in early life (Stocks et al., 2013). The respiratory system includes a complex suite of microbiota, including bacteria, viruses, and fungi, that are affected by various environmental exposures and are believed to play a key role in fighting off pathogens and promoting overall health (Man et al., 2017). For example, the risk of childhood asthma was found to be lower in those residing on traditional farms, which was linked to enhanced microbial diversity in these settings (Ege et al., 2011). Adverse environmental exposures throughout the life course can cause demonstrable harm: the inhalation of particulate matter of <2.5 μm ($\text{PM}_{2.5}$) resulted in over 2 million respiratory-related deaths globally in 2017 (Bu et al., 2021), and the leading causes of global disability-adjusted life years for chronic respiratory diseases are smoking for men and household/ambient air pollution for women (Soriano et al., 2020). Therefore, it would be useful to gain a better understanding of the role of greenspace to mitigate exposures to air pollution, as well as with other potential pathways to health.

Although greener areas may entail better air quality due to fewer pollution sources, there are also a number of physical mechanisms by which vegetation may filter the air. Leaves contain stomata, which can absorb gases, including SO_2 , NO_2 , and O_3 , and also provide an effective, broad surface area on which to accumulate PM through deposition (Salmond et al., 2016). At the same time, trees can contribute ambient pollutants via the release of biogenic volatile organic compounds (BVOCs), such as terpenes and isoprenes, leading to precursors for O_3 and secondary organic aerosols

(Eisenman et al., 2019). Dense tree canopies may prevent dispersion of traffic-related air pollutants in street canyon environments, causing higher street-level air pollution concentrations (Abhijith et al., 2017). Trees and grasses can release large volumes of pollen and fungal spores, potentially leading to allergic reactions (Dadvand et al., 2014), and in urban settings with high traffic volume, pollen can bind to diesel exhaust particles, which may exacerbate inflammatory responses to allergens (Esposito et al., 2012).

In addition to air quality, there are other possible links between urban greenspace and respiratory health, including more direct pathways. For example, green areas in urban environments may offer positive contact to microbiota (Ruokolainen et al., 2015); insufficient exposure to such biotic factors at a young age may lead to improperly developed immune systems (Rook et al., 2013), with linkage to inflammatory conditions, including asthma, as noted earlier (Haahntela et al., 2013). Although physical activity may induce breathing difficulties in those with compromised respiratory systems, known as exercise-induced bronchoconstriction, reviews suggest an overall positive effect of exercise, including lung function improvements in asthmatic children (Wanrooij et al., 2014). Vegetation and tree canopies could alleviate urban heat island effects (Gunawardena et al., 2017), leading to fewer adverse respiratory health events during periods of extreme heat (Takaro et al., 2013). Nevertheless, green areas are not always synonymous with better health. For example, research identified differential effects of greenspace with adverse associations of eyes and nose symptoms in urban settings, but protective relationships in rural environments, potentially due to more high allergenicity plants in cities (Fuertes et al., 2014b). With this mix of interrelated pathways, it is unsurprising that broad reviews on health have suggested the overall respiratory benefits of trees and other vegetation are not so clear-cut (Fong et al., 2018; Kondo et al., 2018).

Here, we focus on the association of respiratory health with urban greenspace, as opposed to greenspace in rural areas, as the role of greenspace in more built-up urban areas may have an even more important role for population health (Lachowycz and Jones, 2013). Therefore, our objective was to perform an exploratory systematic review to synthesise the evidence relating urban greenspace and respiratory health, and investigate the overall direction and magnitude of reported associations. We then used this evidence to help identify potential causal pathways linking urban greenspace components to respiratory health outcomes.

2. Methods

We followed the PRISMA guidelines on systematic reviews (Moher et al., 2009) and published our review protocol on the OSF registry (<https://osf.io/jvs46>).

2.1. Search strategy

We searched the following five databases for studies in English: Medline, Embase, Global Health, Scopus, and the Cochrane Library. The study period included the following dates: 01 January 2000 to 31 December 2018. A streamlined update of the search was performed using the Scopus database from January 2019 to October 2021, following peer review. References from eligible studies, as well as from any relevant review papers identified in the search, were scanned for additional eligible studies. Any other references known by the research team that met the eligibility criteria, but were not identified from the above search strategy, were also included. We did not search grey literature. Our greenspace search terms and medical subject headings focussed on urban areas and were intentionally broad to capture a wide array of studies.

The main health outcome for the search included disease coding of the respiratory system (i.e., International Coding of Disease-10 [ICD-10] C30-C39 [malignant neoplasms of respiratory and intrathoracic organs], J00-J99 [diseases of the respiratory system]), including mortality, morbidity, and hospital admissions. In addition to the main health outcomes, other indicators of respiratory health were eligible for the review, such as lung function measurements (e.g., Forced Expiratory Volume in 1 s [FEV₁]),

asthma (or other respiratory) medication use, respiratory symptoms, asthma control, and any other related respiratory health outcomes identified during the course of the review. To be as inclusive as possible with this broad range of health indicators, we did not pre-specify summary measures. The full list of search terms for each database and PECO (population, exposure, comparator, outcome) statement are presented in Table S1.

2.2. Selection eligibility

Observational studies were to include one or more objective measurements of, or proximity to, urban greenspace/greenness/greenery, including but not limited to, parks, gardens, street trees, and urban forests. Exposure assessment could have been based on residential/work or other address, and also may have included personal monitoring, including visits to or use of greenspace. For intervention/experimental studies, the setting needed to include an area with urban greenspace (e.g., park, forest), and non-green/urban setting comparator. As an example, study subjects may have spent time or engaged in a specific activity in urban greenspace, which was then compared to doing the same in a non-green/urban environment. Table 1 presents the selection eligibility criteria.

2.3. Data extraction & risk of bias

All search results from each of the databases were pooled in EndNote. After duplicates were removed, two reviewers (WM + PW/JM/ML/SV) first screened each title and abstract for relevant papers. A similar process was then followed whereby two authors reviewed independently the full text of all relevant papers using the above eligibility criteria. Any discrepancies were discussed and decided by a third reviewer, if needed. The following data were extracted independently by two reviewers from the eligible papers using a template data extraction sheet: author, year, study design, sample size, study population, setting, time period, description of greenspace exposure (including distance/area measure), greenspace exposure metric, control exposure (for experimental studies), health outcome, source of health outcome, number of cases, confounders/covariates, effect estimate measure, main results. Where it was possible, we standardised effect estimates per 0.1-unit increase in surrounding NDVI or 10% increase in tree canopy or green land use/land cover. In summary figures, we indicate whether reported exposure-outcome effect estimates and confidence intervals (CI) are positive (i.e., beneficial) or negative (i.e., adverse)/null for a given respiratory health indicator. For studies examining multiple buffer radii, we include either the main reported results or those closest to a radius of 250 m, a commonly used metric. We report results specifically for urban populations, if available, and prioritise results representing the longest period of follow-up in a given study.

The risk of bias in the studies was assessed independently by two authors using the Navigation Guide methodology and criteria for making risk of bias determinations, as set out in Johnson et al. (2016). This rating involved the assignment of 'low', 'probably low', 'probably high', 'high',

Table 1
The eligibility criteria used to identify relevant papers.

| # | Criteria |
|---|---|
| 1 | Empirical peer-reviewed studies. |
| 2 | For observational studies, exposure includes one or more objective measurements of, or proximity to, urban greenspace/greenness/greenery. |
| 3 | For experimental/intervention studies, setting must include a green area, i.e. park, forest, and non-green/urban setting comparator. |
| 4 | Outcome must include respiratory health, i.e., ICD – 10 C00-C14, C30-C39, J00-J99 mortality/morbidity, hospital admissions, lung function measurements, medication use, asthma control. |
| 5 | Assesses empirically the association between greenspace metric and respiratory health outcome. |
| 6 | Studies that use human participants. |
| 7 | Studies in English. |
| 8 | Contains most complete data if also published elsewhere. |

Table 2
The Navigation Guide criteria used to assess the risk of study bias.

| # | Criteria |
|---|--|
| 1 | Are the study groups free from baseline differences? |
| 2 | Was knowledge of the exposure groups adequately prevented during the study? |
| 3 | Were exposure assessment methods robust? |
| 4 | Were outcome assessment methods robust? |
| 5 | Were confounding and effect modification adequately addressed? |
| 6 | Were incomplete outcome data adequately addressed? |
| 7 | Are reports of the study free of suggestion of selective outcome reporting? |
| 8 | Was the study free of support from a company, study author, or other entity having a financial interest in any of the exposures studied? |
| 9 | Was the study apparently free of other problems that could put it at a risk of bias? |

or 'not applicable' to the nine criteria outlined in Table 2. For criterion #5 (confounding), we specified as tier 1 (important) confounders: age, sex, socioeconomic status (SES), and tobacco smoking (including exposure to secondhand smoke [e.g., in studies of children]). Tier 2 (other potentially relevant) confounders included air pollution exposure and physical activity; however, these may be on the causal pathway to respiratory health and therefore should also include a mediation analysis (only relevant for statistically significant results). All tier 1 and 2 covariates needed to be adjusted for in multivariate models for a study to be assigned a 'low' rating (with mediation analysis if associations were statistically significant). Adjustment for all tier 1 and fewer than two tier 2 confounders (with mediation analysis) would be assigned a 'probably low' rating, and adjusting for some tier 1 or performing only crude analyses would be rated as 'probably high' or 'high' risk of bias, respectively (Eick et al., 2020). If multiple health outcomes were included in a single study, we assigned to the study the highest bias rating for any of the individual outcomes (i.e., criterion #4 in Table 2). Each study was then assigned an overall grading based on the highest bias category allotted to the nine criteria. We evaluated the overall quality and strength of evidence for each health outcome, according to the Navigation Guide as detailed in Johnson et al. (2016) and Pega et al. (2020). One author (WM) conducted an initial evaluation of quality and strength; studies were assumed to be of a moderate quality and subsequently downgraded or upgraded according to set criteria, which was then used in part to inform the overall strength of evidence (see Tables S2 & S3 for criteria). These assessments were revised following discussion and agreement with all other authors.

Finally, we completed a narrative synthesis of multiple respiratory health outcomes to examine the overall direction of association and also to comment on the overall quality and potential biases in the eligible studies (Campbell et al., 2020). To support our exploratory review, we illustrate hypothesised pathways for which urban greenspace may affect health. Given the broad inclusion of greenspace exposure indicators, buffer sizes, and respiratory health outcomes included in our review scope, we concluded that it would not be appropriate to undertake meta-analysis of published coefficients of association.

3. Results

The initial database search identified 15,667 unique studies, after the removal of duplicates, to which we added two studies from the manual search of references. From the screening of titles and abstracts of these papers, we identified 236 potentially eligible studies. We inspected the full text of these studies and after applying the exclusion criteria (Table S4), we identified 108 eligible papers to assess the evidence of urban greenspace exposure and respiratory health outcomes (see Fig. 1).

3.1. Study characteristics

Characteristics of the reviewed studies, including greenspace exposures, health outcomes, and main respiratory health results, are presented in Tables 3-10. The years of publication of the studies ranged from 2007 ($n = 1$) to 2022 ($n = 1$), with the highest number published in 2021 ($n = 24$) and none published in 2011. Most ($n = 104$) of the eligible studies were observational, with the remaining four having an experimental design. The observational studies included both ecological (i.e., aggregated health data) ($n = 36$) and individual-level ($n = 68$) health data ($n = 32$ cross-sectional; $n = 19$ cohort/longitudinal; $n = 8$ birth cohort; $n = 7$ case-crossover/case-control; $n = 2$ panel). The statistical sample size of observational studies ranged dramatically, from 8 urban areas (Bernat et al., 2016) to 26,455 urban residential areas (Alcock et al., 2017) in the ecological studies, and from 57 (Cole-Hunter et al., 2018) to 10.5 million (Klompaker et al., 2021) where studies used individual-level health data. The number of participants included in experimental studies ranged from 24 (Moshhammer et al., 2019) to 119 (Sinharay et al., 2018). Study demographics included children, adults, and older adults, as well as the general population. The maximum follow-up time for a longitudinal study

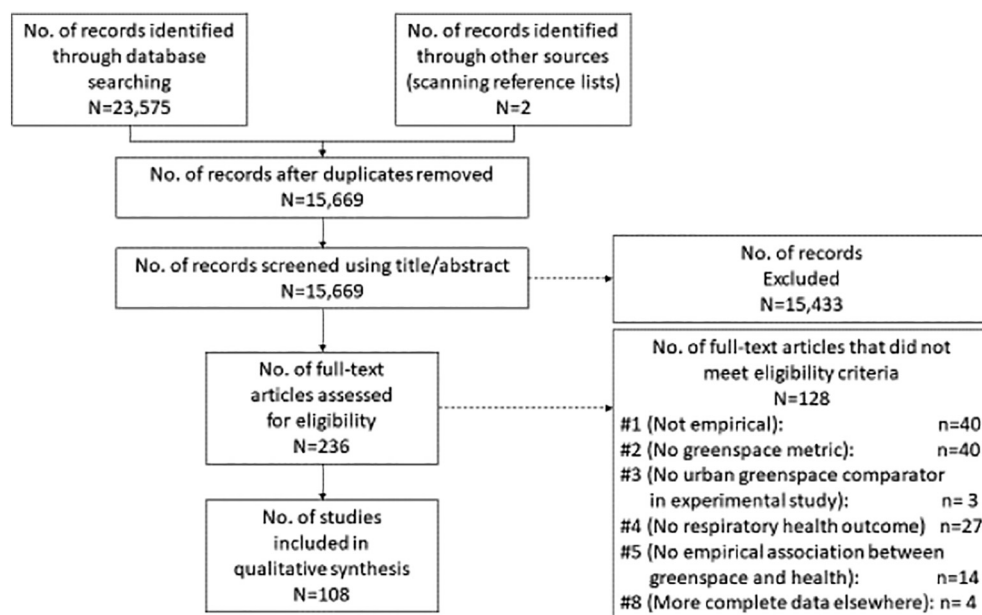


Fig. 1. A flow diagram of the search results, with reasons for excluded studies.

Table 3
Study characteristics of the respiratory mortality studies, ordered by risk of bias and year.

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|------------------------|-----------------|---------------------------------------|---|---|--|--|---|----------------------|
| Richardson, 2010 | Ecological | n = 6432 wards (population of 28.6 M) | Adults in the UK aged 16–64 years | 2 Land use datasets (Generalised Land Use Dataset, CORINE), % of greenspace by area | Respiratory mortality | Age-group, income deprivation, air pollution and country, synthetic estimates of smoking for English wards only | IRR of respiratory mortality for >75% vs <25%: GS 0.89 (0.83 to 0.96) males 0.96 (0.88 to 1.05) females | Probably Low |
| Villeneuve, 2012 | Cohort | n = 574,840 | Adults aged 35+ years in 10 urban areas in Ontario, Canada | NDVI - Landsat (30 m cell); residential levels at cohort inception; 500 m residential buffer | Non-malignant respiratory disease (J00-J99) mortality | Age, sex, income, marital status, ambient air pollution, and contextual neighbourhood characteristics. Also estimated smoking and physical activity. | Rate Ratio per 0.1 NDVI (500 m buffer) increase* = 0.96 (95% CI 0.95 to 0.97) | Probably Low |
| James, 2016 | Cohort | n = 108,630 | US Nurses (women) in 11 US states | NDVI vegetation (MODIS); NDVI with 250/1250 m home buffers; current season NDVI and cumulative average NDVI | Respiratory mortality | Race/ethnicity, smoking status, smoking, fixed individual-level SES, area-level SES, weight status, region, urbanicity, physical activity, air pollution, social engagement, and mental health | Continuous NDVI (250 m) (per 0.1-unit increase): 0.73 (0.59 to 0.90) Mediation analysis with air pollutants and physical activity explained <10% of association. | Probably Low |
| Crouse, 2017 | Cohort | n = 1,265,000 | Non-immigrant adults (aged ≥ 19 years) in 30 Canadian cities | NDVI vegetation (MODIS); Annual residential max NDVI at 250 m & 500 m buffers | Respiratory mortality | Aboriginal and minority status, marital status, education, employment, income, population density, air pollution | Hazard Ratio per 0.1-unit NDVI (250 m)*: 0.93 (0.91 to 0.95) | Probably Low |
| Wang, 2017 | Cohort | n = 3544 | Adults aged ≥ 65 years in Hong Kong | NDVI vegetation (IKONOS) 15 m resolution; % of greenspace within 300 m of home (counting cells >0.1 NDVI) | Respiratory disease mortality | Age, sex, marital status, years lived in Hong Kong), SES, lifestyle factors (smoking, alcohol intake, diet quality), self-rated health and housing type, physical activity, mental health | Hazard Ratio (per 10% increase in 300 m buffer): Respiratory disease mortality: 1.004 (0.928 to 1.087) | Probably Low |
| Kim, 2019 | Ecological | n = 73 districts | General population in 7 cities in Korea | NDVI (MODIS; 250 m); Median value of NDVI for the summer period (May–October) | Age and sex standardised respiratory disease (J00–99) and chronic lower respiratory disease (J40–47) mortality | PM10, neighbourhood SES, smoking rates, and healthcare infrastructure status | % increase with IQR increase: Respiratory disease = 1.85% (– 0.76% to 4.52%); Chronic lower respiratory disease = – 3.75% (– 8.50% to 1.24%) | Probably Low |
| Kasdagli, 2021 | Ecological | n = 1035 municipal units | General population in Greece | NDVI greenness (MODIS; 1 km); Mean NDVI in May per municipal unit | Respiratory mortality | Air pollutants (PM2.5, NO2, BC and O3), % unemployed, % working with education; % born in Greece, lung cancer mortality (proxy for smoking) | Relative risk for IQR increase in NDVI: NDVI: RR = 0.92 (0.89 to 0.95) | Probably Low |
| Hu et al., 2007 | Ecological | 20 zipcodes | General population, Pensacola metropolitan region of Florida. | Greenness (Landsat), 1.5 km buffers around randomly selected points | Asthma mortality | Point source pollution sites and emissions, traffic count | Quantitative results not presented: ‘modeling of mortality rates shows the similar relationship [with hospitalisations]’. See results in Table 5 below. | Probably High |
| Donovan, 2013 | Ecological | n = 1296 counties | General adult population in USA (15 states) | % of county covered by ash tree canopy | Chronic lower respiratory tract (J40–47) mortality | Race/ethnicity, income, education, poverty, years of ash borer infestation | Mortality rate (per 100,000) per 10% increase in ash canopy*: – 52.2 (– 77.9 to – 26.4) | Probably High |
| Gronlund et al., 2015* | Case-cross-over | n = 344 zip codes | Adults aged 65 years and older in Michigan, USA | Green land cover (30 m resolution) classified as green and non-green% greenspace in each zipcode | Respiratory mortality | Sex, age, deprivation, education, ethnicity, age of building, air quality, temperature | OR in areas of high and low greenspace: No quantitative results given for respiratory mortality, but graphs indicate positive association; CIs cross 1.0 during extreme heat days | Probably High |
| Vienneau, 2017 | Cohort | n = 4,284,680 | General population in Switzerland | NDVI summer vegetation values (Landsat, 30 m resolution), Green land use; Residential buffers of | Respiratory mortality (J00-J99) | Civil status, job position, education, neighbourhood socio-economic position | Hazard Ratio per 0.1-unit NDVI: 0.94 (0.93 to 0.96) per 10% Green land use: 0.98 (0.98 to 0.99) | Probably High |

(continued on next page)

Table 3 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|---------------------|-------------------|--|---|--|--|---|--|----------------------|
| | | | | 500 m | | (SEP), geographic region, area type, altitude, air pollution (PM10), and transportation noise | | |
| Shen and Lung, 2017 | Ecological | n = 48 administrative districts | General population in Taipei, Taiwan | Proportion of greenspace patches, mean distance between patches, patch density | Pneumonia mortality, chronic lower respiratory disease mortality | Air pollutants, mean annual temperature | Partial least squares model coefficients: Largest Patch Percentage: - 0.131 Landscape Proportion: - 0.010 Patch Distance: 0.027 Fragmentation: 0.112 | Probably High |
| Xu, 2017 | Ecological | n = 199 (Tertiary Planning Units) | Adults aged 20+ years in Hong Kong | NDVI vegetation (30 m resolution); Mean NDVI of Tertiary Planning Unit (TPU) | Chronic respiratory disease mortality | Age, gender, population density, and area-level socio-economic variables | RR per 0.1-unit NDVI:* Chronic respiratory disease mortality = 0.98 (0.95 to 1.00) | Probably High |
| Orioli, 2019 | Cohort | n = 1,263,721 | Adults aged 30+ years in Rome, Italy | Leaf area index (LAI) NDVI (greenness) (Landsat; 30 m); Residential buffers of 300 m and 1000 m | Respiratory disease mortality (ICD-9:460–519) | Age, sex, education, marital status, occupational status, birthplace, area-level SEP, mediation for air pollution and noise, subset with smoking data | Hazard ratio for IQR increase in NDVI: LAI (300 m) HR = 1.014 (0.988 to 1.041) NDVI (300 m) HR = 1.011 (0.986 to 1.038) | Probably High |
| Wang, 2019 | Ecological | n = 369 census tracts | General population in Philadelphia, US | Percentage of greenspace (PLAND), mean area of greenspace (AREA_MN), fragmentation of greenspace (PD), greenspace connectedness (COHESION), aggregation of the greenspace pattern (AI), and complexity of the shape of the greenspace (SHAPE_AM); Per census tract | Chronic lower respiratory disease mortality | Percentage of people aged 65 years and older, the percentage of females, the percentage of white residents, median household income, the percentage of holders of a bachelor's degree or higher, and population density | Percentage change in expected count of the studied causes of death: PLAND = -0.509 (- 1.410, 0.401) AREA_MN = 0.001 (- 0.004 to 0.005) PD = 0.200 (- 0.060 to 0.461) COHESION = -35.609 (- 46.688 to - 22.221) AI = - 8.552 (- 16.222 to - 0.180) SHAPE_AM = -5.190 (- 9.697 to - 0.459) | Probably High |
| Lee, 2020a | Ecological | n = 1,173,773 deaths (n units of analysis unspecified) | General population in Taiwan | NDVI (greenness) (MODIS; 250 m) Forest and park land cover (Taiwan Land-use Investigation); Mean NDVI in each township across the study period | Respiratory disease mortality | Total population, age, sex ratio, taxable income, precipitation, time trend, and temperature. | Risk ratio: NDVI Respiratory mortality: RR = 0.721 (0.632 to 0.824) Forest/park Respiratory mortality: RR = 0.903 (0.883 to 0.923) | Probably High |
| Jaafari, 2020 | Ecological | n = 87 study units | General population in Tehran, Iran | Greenspace defined by total class area, cohesion index, patch density, shape index, and total edge; Greenspace metrics calculated at study unit (10 km ² area) | Respiratory mortality | Age-adjusted rates. Models adjusted for air pollutants (CO, NO ₂ , O ₃ , PM ₁₀ , PM _{2.5} , and SO ₂) | Path coefficients from structural equation modeling: Greenspace- > Respiratory mortality = - 0.305 (p < 0.001) | Probably High |
| Sun, 2020 | Case-crossover | n = 66,820 in the cohort (3159 deaths) | Adults aged 65+ years in Hong Kong | NDVI (2001, 2006; Landsat; 30 m); Mean NDVI in 250 m and 500 m residential buffers | Respiratory mortality | Ambient temperature, relative humidity, influenza epidemics, public holidays, and air pollution (with interaction term with low/high greenness) | Effect modification by residential greenness: Elders living in the low greenness areas were associated with a higher risk of pneumonia mortality attributed to NO ₂ (p = 0.049) and O ₃ (p = 0.025) - interactions | Probably High |
| Bauwelinck, 2021 | Population cohort | n = 2,185,170 | Adults aged 30+ years in urban areas in Belgium | Surrounding greenness [(NDVI) and modified soil adjusted vegetation index (MSAVI2)]; Surrounding greenspace (Urban Atlas (UA), CORINE (CLC)); NDVI, MSAVI2, UA, and CLC within residential buffers of 300 m, 500 m, 1000 m | Respiratory mortality (ICD-10: J00-J99) | Age, sex, marital status, country of birth, education level, employment status, area mean income, and air pollutants (PM _{2.5} , PM ₁₀ , NO ₂ and black carbon) with mediation analysis. | Hazard ratio (HR): NDVI (300 m): 0.95 (0.93–0.97) Greenspace (Urban Atlas) (300 m): 0.98 (0.96–0.99) Mediation analysis: 18–60% of association between residential green space and respiratory mortality is potentially partially mediated by | Probably High |

Table 3 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|--------------------|-------------------|------------------------|--------------------------------------|--|---|--|---|----------------------|
| Klompaker, 2021 | Population cohort | n = 10,481,566 | Adults aged 30+ years in Netherlands | NDVI (Landsat 30 m resolution) Greenspace (national land-use database of the Netherlands - TOP10NL); Residential buffers of 300 m and 1000 m | Respiratory disease mortality (J00-J99) | Age, sex, marital status, region of origin, standardised household income, PC4 composite SES, mean income neighbourhood, unemployment neighbourhood, percentage of immigrants neighbourhood, mean income region, unemployment region and percentage of immigrants region | PM _{2.5} . Hazard ratio (HR) for IQR increase: Respiratory disease mortality: NDVI (300 m) = 0.954 (0.943 to 0.965) Greenspace (300 m) = 0.962 (0.951 to 0.972) | Probably High |

GS = Greenspace; IRR = Incidence Rate Ratio; IQR = Interquartile Range; NDVI = Normalised Difference Vegetation Index; OR = Odds Ratios; RR = Relative Risk; SES/P = Socioeconomic Status/Position.

* Standardised from reported values.

design was 24 years (Fuertes et al., 2020). The research was undertaken in 26 countries across Europe, the Americas, Asia (including Australasia and South Asia), with one global analysis including data from 94 countries (Fuertes et al., 2014a).

3.2. Greenspace indicators

The three most frequent indicators were (1) the overall greenery or vegetation (also known as greenness), commonly characterised by the Normalised Difference Vegetation Index (NDVI) through satellite remote sensing, but also more recently through eye-level views (e.g., Yu et al., 2021a, 2021b); (2) green land use/land cover, including physical area classes such as parks and forests; and (3) the amount of tree cover or canopy, which also addressed specific types, such as ash tree canopy (Donovan et al., 2013) or allergenic species (Stas et al., 2021) (see Fig. 2). Other, less typical examples of greenspace indicators were biodiversity indices (Liddicoat et al., 2018) and domestic gardens (Alcock et al., 2017). Where data were available at the individual level, greenspace exposure was predominantly defined within circular buffers around the residential address (e.g., mean NDVI value, proportionate area of green land use/land cover), ranging from a radius of 100 m to 5 km, but most routinely from 200 m to 500 m. In some instances, greenspace was characterised also at the work (Hoehner et al., 2013) or school (Dzhambov et al., 2021) address. In studies relying on ecologic-level data, the amount of greenspace covering an administrative area was frequently defined as the exposure, which spanned much larger areas than those of residential buffers, for example, up to 59 km² (Fuertes et al., 2014a). Other greenspace metrics included the presence (Dadvand et al., 2014) or number (Hoehner et al., 2013) of parks within a certain distance to the residential address, and the fragmentation of surrounding vegetation cover (Prist et al., 2016). The time-period of greenspace exposure measurements, if stated, overlapped with the study period (typically a point in time), with NDVI mainly assessed during the summer (e.g., Andrusaityte et al., 2016), but in some cases, as annual (Pun et al., 2018) or lifetime (Fuertes et al., 2020) averages.

The four experimental studies involved visits to parks or forests to represent greenspace areas, all of which relied on urban streetscapes for the control environment. The duration of greenspace exposure ranged from 45 min (Cavalcante de Sá et al., 2016) to 2 h (Sinharay et al., 2018).

3.3. Health outcomes: overview

Of the 290 associations included in the studies, 195 (67%) included point estimates or coefficients of a positive association between greenspace and respiratory health; the CIs or reported *p*-values of 91 (31% overall) associations did not cross 1 or were below 0.05, respectively. The other one

third (*n* = 95; 33%) suggested negative or null associations between greenspace and respiratory health, of which 25 (9% overall) included CIs or *p*-values that did not cross 1 or were below 0.05, respectively (Fig. 3).

The extent of analysis ranged from univariate methods indicating ecologic correlates between greenspace and health (e.g., Khan et al., 2010; Bernat et al., 2016) to more sophisticated multivariate models examining potential pathways to health through mediation analyses (e.g., James et al., 2016). Although most observational studies included a metric of greenspace as the exposure and a respiratory health indicator as the outcome, some incorporated the latter only as a mediator between greenspace and poor general health (Ulmer et al., 2016) or greenspace and stress (Pun et al., 2018); other analyses included greenspace as a covariate, rather than the primary exposure (Cole-Hunter et al., 2018). In the experimental research on greenspace, all 4 studies showed at least some positive association with exposure to greenspace compared to a trafficked road, though one found post-intervention lung function improvements only in healthy participants (i.e., not COPD patients) (Sinharay et al., 2018).

3.4. Risk of bias

In each of the risk of bias categories, the majority of the ratings were 'Not Applicable', 'Low', or 'Probably Low' (see Fig. S1). Disagreements on ratings were resolved by discussion and agreement with a third reviewer in 80 instances (8% of all ratings). At least one study was assigned a 'probably high' bias rating for criteria #1 (study groups free from baseline differences), #3 (robust exposure assessment), #4 (robust outcome assessment), #5 (confounding and effect modification), #6 (incomplete outcome data), and #9 (other sources of bias). There was the most potential for bias regarding #5 (confounding) ('Probably High'/'High' ratings: *n* = 57) and outcome assessment (#4) ('Probably High' ratings: *n* = 18). Thirteen studies included a 'probably high' rating in more than one criterion. Based on the highest bias grading in each study, there were 35 (32%) 'Probably Low' and 73 (68%) 'Probably High'/'High' overall ratings. The individual bias assessment categories and rationale for each study are included in Tables S5-S12.

3.5. Health outcomes: individual

3.5.1. Respiratory mortality

Respiratory mortality was an outcome in 20 studies (10 ecological studies, 8 cohort studies, and 2 case-crossover; see Table 3). Risk of bias was rated as "probably low" for 7 of these (4 cohort studies, 3 ecological studies) and "probably high" for the remaining 13. Confounder control included adjustment for all tier 1 confounders in the "probably low" studies, but only 2 fully adjusted for smoking at the individual level. One study included a

Table 4

Study characteristics of the lung cancer (incidence & mortality) studies, ordered by risk of bias and year.

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|---------------------------|-------------------|--|--|---|--|---|--|----------------------|
| Li, 2008 | Ecological | n = 47 prefectures | General population, Japan | % of forest coverage in each prefecture | Standardised Mortality Ratio of lung cancer | Smoking prevalence, Human Development Index (for SES) | Partial correlation coefficients between % forest cover and lung cancer SMR: -0.325 ($p < 0.05$) in females; -0.251 ($p > 0.05$) in males | Probably Low |
| Richardson, 2010 | Ecological | n = 6432 wards (population of 28.6 M) | Adults in the UK aged 16–64 years | 2 Land use datasets (Generalised Land Use Dataset, CORINE), % of greenspace by area | Lung cancer mortality | Age-group, income deprivation, air pollution and country, synthetic estimates of smoking for English wards only | IRR of respiratory mortality for Lung cancer of 75% + GS vs <25%: 0.96 (0.90 to 1.02) males 1.02 (0.94 to 1.11) females | Probably Low |
| Richardson, 2010 | Ecological | n = 1009 census area units (population of 1,546,405) | Adults aged 15–50 years in small urban areas, New Zealand | [1] Usable greenspace; [2] Non-usable greenspace; Quartiles of green land cover in census units (%) | Lung cancer mortality | Age, sex, socio-economic deprivation, smoking, air pollution and population density | IRR for Q4:Q1 greenspace (model 4): [1] total greenspace 1.12 (0.94 to 1.32); [2] usable greenspace 1.02 (0.90 to 1.15) | Probably Low |
| Kim, 2019 | Ecological | n = 73 districts | General population in 7 cities in Korea | NDVI (MODIS; 250 m); Median value of NDVI for the summer period (May–October) | Age and sex standardised lung cancer (C33–34) mortality. | PM10, neighbourhood SES, smoking rates, and healthcare infrastructure status | % increase with IQR increase: Lung cancer = 1.10% (-1.22% to 3.47%) | Probably Low |
| Sakhvidi et al., 2021 | Cohort | n = 19,408 | Workers (age 35–50 years at baseline) at the French national electricity and gas company in France | NDVI (greenness) (Landsat; 30 m) (1989 Urban greenspace (artificial, non-agricultural vegetated areas) (European CORINE land use dataset); Mean NDVI during May–July at 100 m, 300 m, 500 m, 1000 m residential buffers (1989–2016) Residential distance to urban greenspace (1990, 2000, 2006, and 2012) | Lung cancer incidence | Smoking, passive smoking, alcohol drinking, socio-occupational status, marital status, body mass index, vegetable consumption, education, occupational exposure to carcinogens, age at enrolment, 10 years cumulative exposure to air pollution (PM2.5), distance to major roads, population density, and deprivation | Hazard ratio per IQR increase in NDVI or proximity to greenspace: NDVI (300 m) OR = 0.846 (0.653 to 1.095) Proximity to urban greenspace OR = 1.015 (0.882 to 1.169) | Probably Low |
| Mitchell and Popham, 2008 | Ecological | n = 40,813,236 | Adults <60 years (female) & 65 years (male), England | Proportion of Lower Super Output Area (LSOA) covered in greenspace | Lung cancer mortality | Age, sex, deprivation, population density, urban or rural classification. | Incidence Rate Ratio (IRR) Q5:Q1 Greenspace 0.96 (0.91 to 1.02) | Probably High |
| Richardson et al., 2012 | Ecological | n = 49 cities in the US (43 M population) | General population | Green land cover (30 m resolution from the National Land Cover Database); % by area | Lung cancer mortality | Household income, race, air pollution, % car ownership, sprawl index | Change in mortality rate per 10 percentage point increase in city GS coverage*: Male: 2.2 (-4.4 to 8.7) Female: 0.6 (-3.9 to 5.0) | Probably High |
| Bixby et al., 2015 | Ecological | n = 50 cities (~11 M population) | Adults aged 15–64 years in English cities with population > 100,000 | Green land cover (20–30 m resolution); Proportion of city covered by green land (quintiles) | Lung cancer mortality (ICD – 10 C33–34) | Income, air pollution, age and sex distribution | RR: Q5 to Q1 greenness: Men: 0.97 (95% CI: 0.84 to 1.12) Women: 1.01 (95% CI: 0.84 to 1.22) | Probably High |
| Xu, 2017 | Ecological | n = 199 (Tertiary Planning Units) | Adults aged 20+ years in Hong Kong | NDVI vegetation (30 m resolution); Mean NDVI of Tertiary Planning Unit (TPU) | Lung cancer mortality | Age, gender, population density, and area-level socio-economic variables | RR per 0.1-unit NDVI: Lung cancer = 1.02 (0.99 to 1.04) | Probably High |
| Klompaker, 2021 | Population cohort | n = 10,481,566 | Adults aged 30+ years in Netherlands | NDVI (Landsat 30 m resolution) Greenspace (national land-use database of the Netherlands - TOP10NL); Residential buffers of 300 m and 1000 m | Lung cancer mortality (C34) | Age, sex, marital status, region of origin, standardised household income, PC4 composite SES, mean income neighbourhood, unemployment neighbourhood, percentage of immigrants neighbourhood, mean income region, unemployment region and percentage of immigrants region | Hazard ratio (HR) for IQR increase: NDVI (300 m) = 0.926 (0.915 to 0.937) Greenspace (300 m) = 0.952 (0.942 to 0.963) | Probably High |
| Lee, 2020a | Ecological | n = 1,173,773 deaths (n units of analysis) | General population in Taiwan | NDVI (greenness) (MODIS; 250 m) Forest and park land cover | Lung cancer mortality | Total population, age, sex ratio, taxable income, precipitation, time trend, and | Risk ratio: NDVI RR = 0.871 (0.735 to 1.032) | Probably High |

Table 4 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|--------------------|------------|-----------------------------|---------------------------------------|---|----------------------------|--|--|----------------------|
| | | unspecified) | | (Taiwan Land-use Investigation); Mean NDVI in each township across the study period | | temperature. | Forest/park RR = 0.885 (0.865 to 0.905) | |
| Sun et al., 2021 | Ecological | n = 841 neighbourhood units | General population in Shanghai, China | NDVI (greenness) (1 km res); Mean NDVI in each neighbourhood | Lung cancer incidence | Urban form, road traffic, demographic factors, SES factors | Incidence Rate Ratio: NDVI IRR = 0.137 (0.057 to 0.329) | Probably High |

GS = Greenspace; IQR = Interquartile Range; IRR = Incidence Rate Ratio; NDVI = Normalised Difference Vegetation Index; OR = Odds Ratios; RR = Relative Risk; SES = Socioeconomic Status; SMR = Standardised Mortality Ratio.

* Standardised from reported values.

mediation analysis with PM_{2.5} and physical activity. Six of the 7 studies with a risk of bias rated as “probably low” include positive associations, of which 5 have CIs excluding 1, suggesting that living in a greener area was associated with lower respiratory mortality. The other study has a point estimate with a negative association, but the CI includes 1. Several longitudinal studies identified stronger associations of greenspace with lower respiratory mortality in younger ages (Villeneuve et al., 2012; Crouse et al., 2017; Vienneau et al., 2017).

3.5.2. Lung cancer

Lung cancer was the outcome for 12 studies (10 ecological, 2 cohort; see Table 4). Risk of bias was rated as “probably low” for 5 of these, with only 1 study (cohort) adjusting for individual-level smoking habits. Among the 5 studies with risk of bias rated as “probably low”, point estimates are positive and negative; however all but one of the CIs include 1.

3.5.3. Respiratory hospital visits

Hospital visits were examined in 13 studies (10 ecological, 2 cohort, and 1 time series study; see Table 5). Risk of bias was rated as “probably low” for 3 of these and “probably high” for the remaining 10 (9 ecological, 1 time series). Adjustment for individual-level risk factors was possible only in the cohort studies. Among the 3 studies with risk of bias rated as “probably low”, 1 includes point estimates of negative associations with CIs that exclude 1, suggesting areas with more greenspace have higher rates of hospital admission. The other 2 studies include negative and positive point estimates, with CIs for two positive estimates including 1.

3.5.4. Asthma (excluding mortality and hospital visits)

Asthma prevalence (also incidence, inhaler use, control) was the outcome for 38 studies (20 cross-sectional, 6 ecological, 8 cohort, 3 case-control, and 1 panel study; see Table 6). Risk of bias was rated as “probably low” for 8 of these (3 cross-sectional, 3 cohort, 1 case-control, and the panel study). Confounder control included adjustment for all tier 1 confounders in these 8 studies and smoking at an individual-level. Among those studies with risk of bias rated as “probably low”, 6 include point estimates with a positive association, of which 5 have CIs that exclude 1, suggesting that living in an area with more greenspace is protective against asthma. However, 3 studies, including 2 of the above, present point estimates with negative associations and CIs that exclude 1, indicating higher asthma in areas with more greenspace.

3.5.5. Lung function

Lung function was the outcome for 14 studies (4 cross-sectional, 4 cohort, 3 experimental, 2 case-control, and 1 panel study; see Table 7). Risk of bias was rated as “probably low” for 6 of these (3 experimental, 1 case-control, 1 cross-sectional, and the panel study). Confounder control included adjustment for tier 1 confounders, with all studies either excluding smokers or controlling for smoking at an individual-level; 2 studies included mediation analysis with air pollution or physical activity. Among those studies with risk of bias rated as “probably low”, 4 have point

estimates of positive associations that exclude 1, suggesting better lung function in greener areas. The remaining 2 studies have point estimates with non-significant CIs.

3.5.6. Respiratory symptoms

Respiratory symptoms were the outcome for 12 studies (5 cross-sectional, 4 cohort, 3 experimental, 1 ecological, and 1 case-crossover study; see Table 8). Risk of bias was rated as “probably low” for 6 of these (4 cross-sectional, 1 cohort, and 1 experimental study). Adjustment included all tier 1 confounders in these 6 studies, which included control for parental smoking. Among those studies with risk of bias rated as “probably low”, 2 studies have point estimates with CIs that exclude 1, suggesting positive associations with greenspace; however another study contains a negative point estimate with CIs that exclude 1. The remaining 3 studies have point estimates that are positive (2), or negative and positive (1), all with non-significant CIs.

3.5.7. Rhinitis

Rhinitis was the outcome for 12 studies (7 cohort, 3 cross-sectional, 1 ecological, and 1 case-control study; see Table 9). Risk of bias was rated as “probably low” for only 2 of the cohort studies, which adjusted for all tier 1 confounders, including parental smoking. These studies have point estimates indicating negative and positive associations, though the CIs include 1.

3.5.8. Other health indicators

There were 20 studies that examined indicators of health not previously mentioned, including cardiorespiratory fitness, respiratory infections, various biomarkers (e.g., exhaled NO), and Covid-19 mortality. Risk of bias was rated as “probably low” for 7 of these (5 cross-sectional and 2 experimental studies; see Table 10). Confounder control included adjustment for individual-level tier 1 confounders in these studies. Among those studies with risk of bias rated as “probably low”, the results for 6 studies include point estimates, or other quantitative results, that suggest a positive association, of which 2 have a CI that excludes 1. Two studies, including 1 of the above, incorporate results indicating a negative association, of which 1 is statistically significant.

3.5.9. Overall quality & strength of evidence

We evaluated the overall quality of evidence separately for each health outcome using the eight criteria in the Navigation Guide. We assessed the evidence related to respiratory mortality to be of ‘moderate’ quality; we rated the quality of evidence for all other examined health outcomes to be ‘low’. The most common reasons for downgrading the quality of evidence was due to the ‘inconsistency’ and ‘imprecision’ criteria for differing risk estimates and wide confidence intervals (see Tables 11, S13 & S14 for details). Similarly, we rated the overall strength of evidence of better health to be ‘limited’ for respiratory mortality, and ‘inadequate’ for the remaining respiratory health outcomes.

Table 5
Study characteristics of the hospital visits studies, ordered by risk of bias and year.

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|-----------------------|-------------|--|---|--|---|--|--|----------------------|
| Sbihi et al., 2017 | Cohort | n = 68,195 | Children aged ≤10 years (born 1999–2002) in Vancouver, Canada | NDVI vegetation (Landsat); Residential postal code NDVI during pregnancy using 100 m | Asthma trajectories | Sex, parity, First Nations status, birth weight, gestational duration, breastfeeding, mode of delivery, household income, maternal education, smoking, air pollutants. | Relative Risk Ratio NDVI - Q3 vs Q0: Transient: 0.91 (0.80 to 1.05) Late onset: 1.05 (0.90 to 1.23) Early onset: 1.01 (0.81 to 1.25) | Probably Low |
| Liddicoat, 2018 | Ecological | n = 364 Local Government Areas (LGAs) | General population in Australia | Vegetation diversity, Proportion of Eucalyptus forest, Proportion of open trees; Average value within LGA (250 m grid metric data aggregated to 3 km radius) | Respiratory hospital admissions | SES, temperature, species richness, % overweight, % smoking, distance to coast, precipitation, land use mix, other biodiversity indicators | Standardised regression coefficients: Proportion of eucalyptus forests: -0.0270 p = 0.0055 Diversity of vegetation: -0.0324 p = 0.0033 Proportion of open trees: -0.0121 p = 0.3738 | Probably Low |
| Lee, 2020b | Cohort | n = 11,281 | Children at age 4 with allergic rhinitis recruited in Taiwan | NDVI (greenness) (MODIS; 250 m) Urban parks; Mean NDVI in each township across the study period during January, April, July, and October. Mean urban park % in each township | Allergic rhinitis outpatient visits | Air temperature, relative humidity, PM2.5 concentrations, socioeconomic status (income tax level as a proxy), road network, industrial area, population size, sex ratio, year, season, township urbanization level | Relative risk (1 unit increase in NDVI; 1% increase in urban parks): NDVI: RR = 1.084 (1.059, 1.111) Urban parks: RR = 1.057 (1.056–1.058) | Probably Low |
| Hu, 2007 | Ecological | 20 zipcodes | General population, Pensacola metropolitan region of Florida. | Greenness (Landsat), 1.5 km buffers around randomly selected points | Asthma hospitalisations | Point source pollution sites and emissions, traffic count | Association between greenness and Standardised Morbidity Ratio: Greenness effect -0.221 (p = 0.230) for spatial lag model; -0.2590 (p = 0.077) for spatial error model | Probably High |
| Lovasi, 2008 | Ecological | n = 42 health service catchment areas | Children <15 years, New York City, USA | Street tree density in United Hospital Fund (UHF) area | Asthma hospitalisations | SES, race, population density, distance to pollution sources | Relative risk (RR) per SD of tree density: Hospitalisations RR = 0.89 (0.75 to 1.06) | Probably High |
| Ayres-Sampaio, 2014 | Ecological | n = 278 | General population in Portugal | NDVI Vegetation (MODIS); Seasonal average NDVI of each municipality | Asthma hospital admissions | Temperature, humidity, air pollution | Pearson correlation coefficients: r = -0.498, -0.407, -0.376, -0.439 for NDVI and winter, spring, summer, autumn admissions | Probably High |
| Lee, 2014 | Ecological | n = 143 | General population in Korea | Forest cover; Proportion of forest cover within a city | Number of outpatients, number of visits | Age distribution, air pollution, medical providers | Parameter estimate from structural equation model: Estimate = -0.05, p < 0.00 | Probably High |
| Alcock, 2017 | Ecological | n = 26,455 urban residential areas | General population, England | Green land use, % of greenspace and gardens in lower super output areas, density of mature trees | Emergency hospitalisations for asthma | Air pollution, deprivation, age structure | Mean change to asthma rate per % greenspace: Greenspace (+1%) -3.89 (-4.65 to -3.14) Gardens (+1%) -4.35 (-5.5 to -3.19) Trees (+50/km ²) -9.14 (-11.19 to -7.09) | Probably High |
| Alvarez-Mendoza, 2019 | Ecological | 892 hospital admissions | General population in Quito, Ecuador | NDVI; Monthly median NDVI in each parish | Chronic respiratory disease hospital admissions | SO ₂ , surface reflectance (proxy for humidity and O ₃) | Odds ratio: 0.2395 (p = 0.219) | Probably High |
| Douglas, 2019 | Ecological | n = 2347 census tracts | General population in Los Angeles County, US | Public parks and open space (Los Angeles County Department of Parks and Recreation); Acres of public parks and open space per census tract | Asthma emergency department visits | Diesel particulate matter, % poverty, % <10 years old, race/ethnicity | Regression coefficient: Public park and open space = -8.05 (p < 0.001) | Probably High |
| Lai, 2019 | Ecological | n = 174 zip codes | General population in New York City, US | Street trees; Number of street trees per 1000 ft. street length | Asthma emergency department visits | Indoor/outdoor air pollution, tree allergenicity, age (<17 or >65 years), % public housing | Geographically weighted regression coefficient: Street trees = -0.01 (p > 0.05) | Probably High |
| Heo, 2019 | Time series | n = 364 | Medicare enrollees | NDVI greenness; Population-average NDVI | Respiratory hospital | Median household income, percent of the population ≥ | % change in hospitalization risk associated with a 1 IQR | Probably High |

Table 5 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|--------------------|------------|------------------------|---|---|--|--|--|----------------------|
| Kim, 2021 | Ecological | n = 2301 census tracts | (>65 yrs) in U.S. counties with populations larger than 200,000 General population in Los Angeles County, US | for each county (MODIS at 250 m resolution) Trees (Los Angeles Regional Imagery Acquisition Consortium) Greenspace (Los Angeles Regional Imagery Acquisition Consortium); Areas covered by trees; Median size of tree patch; Cluster of patches; % private greenspace; % recreational greenspace; % semi-public greenspace | admissions Asthma emergency department visits | 65 years, percent of persons >65 years in poverty, population density, mean of annual level of PM10 (or PM2.5), and latitude of the county SES, air pollution | increase in NDVI: All respiratory disease: PM10: -1.29 (-3.36, 0.83) PM2.5: -0.01 (-1.03, 1.01) Regression coefficients: Spatial error model: Areas covered by trees = -52.911 (p < 0.05); Size of tree patch = -0.033 (p < 0.05); Cluster of patches = 15.232 (p < 0.05); % private greenspace = 13.428 (p > 0.05); % recreational greenspace = 9.543 (p > 0.05); % semi-public greenspace = 1.014 (p > 0.05) | Probably High |

NDVI = Normalised Difference Vegetation Index; OR = Odds Ratios; RR = Relative Risk; SES = Socioeconomic Status; SD = Standard Deviation; SMR = Standardised Mortality Ratio.

4. Discussion

Our evidence review was aimed at summarising published evidence on the associations of urban greenspace with respiratory health and the hypothesised causal pathways that these associations may reflect. We searched five databases of peer-reviewed studies and identified 108 eligible papers, including 104 observational and four experimental studies. Two thirds of the associations in these studies were positive with health, with 31% positive and statistically significant; only 9% reported associations with health that were negative and statistically significant. The most consistent positive evidence was apparent for respiratory mortality. In the following discussion, we first highlight relevant pathways to health, as suggested in the reviewed studies; we then discuss the findings for each health outcome and assess the overall evidence.

4.1. Hypothesised causal pathways

A range of mechanisms with respiratory health were offered in the reviewed papers, though few studies actually tested these hypotheses. Positive pathways for health included the abatement of the urban heat island effect and outdoor air pollution; reduced exposure to indoor allergens (e.g., by encouraging more time outside and/or introducing more diverse microbiota); reduced stress (e.g., via reduced noise exposure/annoyance); and opportunities for physical activity. Suggested negative pathways for health were exposure to pollen and other aeroallergens, and monocultures, which may entail pesticide use and reduced biodiversity. In addition to suggesting these pathways, the studies underscored the importance of contextual factors when interpreting results, which may affect the exposure, health outcome, or their interrelationship. We illustrate some of the potential pathways and contextual factors for consideration in Fig. 4.

4.2. Respiratory mortality

The analyses of respiratory mortality (excluding that from lung cancer) showed the most consistent positive findings (i.e., a lowered risk) with greenspace, with some studies including a narrow list of causes of death (e.g., chronic lower respiratory disease [J40-J47] [Xu et al., 2017]) and others examining all respiratory diseases (i.e., J00-J99 [Vienneau et al., 2017]). This general trend agrees with a meta-analysis of greenspace and all-cause mortality in cohort studies, which estimated a 3%–6% lower risk of mortality per 0.1-unit increase in residential NDVI levels (Rojas-Rueda et al., 2019). A causal association with greenspace may reflect a

combination of the pathways in Fig. 4 (e.g., less exposure to air pollution, greater opportunity for physical activity). Studies with mediation analysis found the individual contribution of some of these pathways explained from less than 10% (James et al., 2016; Vienneau et al., 2017) up to 60% (PM_{2.5}) (Bauwelinck et al., 2021) of observed associations. Potential benefits may not be universal, as one study suggested positive associations in men only (Richardson and Mitchell, 2010); concerns of perceived neighbourhood safety or greenspace quality may discourage greenspace utilisation, especially for women.

4.3. Lung cancer

The lung cancer studies showed a lower proportion of positive results than those for respiratory mortality. The most important risk factor for lung cancer is tobacco smoking (Alberg et al., 2013), but only one of the studies examining lung cancer could control for individual-level smoking habits. The latency period for lung cancer can span multiple decades (Shibuya et al., 2005), which would require the assessment of exposures over an extended period of time in epidemiological studies (Hystad et al., 2013). There is emerging evidence that the amount of surrounding residential greenspace may be associated with lower current smoking and higher smoking cessation, which would provide an effective pathway for reduced lung cancer (Martin et al., 2020). The lack of robust adjustment for smoking and application of ecological study design, where populations are likely to be dynamic over time, hinders the interpretation of the lung cancer evidence related to greenspace exposure.

4.4. Asthma & hospital visits

Context may play a key role in interpreting the mixed evidence presented in the studies on asthma. For example, in one study, asthma prevalence in areas of higher greenspace was found to be lower only in the presence of heavy traffic (Feng and Astell-Burt, 2017). While Andrusaityte et al. (2016) found higher childhood asthma prevalence in areas with higher NDVI and no such links with residential proximity to a park, Dadvand et al. (2014) found the opposite (i.e., higher asthma closer to parks [not forests], but no relationship to NDVI). Urban parks may be more likely to incorporate exotic flora, potentially contributing to higher allergenicity, than perhaps more native plants in forests. NDVI reflects all vegetation, much of which may not produce pollen; pollen can travel over long distances, though proximate taxa have shown to be influential for pollen concentration levels (Charalampopoulos et al., 2018). In addition, a number of

Table 6
Study characteristics of the asthma studies, ordered by risk of bias and year.

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|------------------------|-----------------|--|---|---|--|--|---|----------------------|
| Lovasi et al., 2013 | Cohort | n = 492 (5 years) n = 427 (7 years) | African American and Dominican children aged <7 years in New York City, USA | Tree canopy from 2001 (LiDAR plus aerial imagery and vector data); % of area within 250 m of address | Asthma prevalence | Sex, age, ethnicity, maternal asthma, previous birth, other previous pregnancy, Medicaid enrolment, smoking, population density, percent poverty, percent park land, and estimated traffic volume. | Prevalence ratios (or RRs) per 10% increase in neighbourhood tree canopy*: Asthma at age 7: 1.22 (1.03 to 1.43) | Probably Low |
| Sbihi et al., 2015 | Cohort | 65,000 children (8214 cases) | Children aged 0–10 years old in Vancouver, Canada | NDVI vegetation during pregnancy were calculated for 100-m areas around residential postal codes | Asthma diagnosis | Individual covariates include the month/year of birth, sex, First Nations status, and maternal parity, age, smoking during pregnancy, and initiation of breastfeeding. Participants were assigned neighbourhood-level socioeconomic indicators (household income and maternal education), air pollutants | ORs per 0.1-unit increase in NDVI during pre-school years*: aOR = 0.96 (95% CI: 0.94 to 0.99) Distance to nearest park: aOR = 0.98 (0.95 to 1.00) No associations during school years. | Probably Low |
| Andrusaityte, 2016 | Case-control | n = 1489 (n = 112 asthma cases, n = 1377 controls) | Children aged 4–6 years in Kaunas, Lithuania | [1] NDVI (Landsat), [2] land use (Urban Atlas); Average residential NDVI using 100 m, 300 m, 500 m buffers; Residential distance to park <1000 m (binary) | Parent report of clinically diagnosed asthma | Mother's age at childbirth, maternal education, parental asthma, maternal smoking during pregnancy, breastfeeding, antibiotic use, keeping a cat, living in a flat and ambient PM2.5 and NO2 | Odds Ratio: Per 0.1-unit increase in NDVI – 100*: OR = 1.38 (1.09 to 1.75); Results non-significant when including park distance. Distance to a city park <1000 m: OR = 0.96 (0.55 to 1.68) | Probably Low |
| Su et al., 2017 | Panel | n = 140 (5660 rescue inhaler use events) | Convenience sampled participants (<18 years) in Louisville, Kentucky, USA | Land cover: forest, shrub land, and grassland/herbaceous cover; Land cover proportion when rescue inhaler used - 250 m buffer | Asthma rescue inhaler use | Air pollution, pollen, and mold spore counts, and meteorological information, land use. Smoking in sensitivity analysis. | Rate ratio per IQR of %: Vegetation cover: 0.829 (95% CI: 0.800 to 0.857) Tree cover: 0.825 (95% CI: 0.796 to 0.854) | Probably Low |
| Donovan, 2018 | Cohort | n = 49,956 | Children born in 1998 followed up from 0 to 18 years of age in New Zealand | NDVI vegetation (Landsat, max annual value) and Land cover (2012); Average lifetime NDVI in residential meshblocks (mean buffer ~255 m), Proportion of natural land cover in meshblocks | Asthma based on pharmacy (7 + prescriptions) and hospital discharge records (J45–46) | Air pollution (major road length, mean annual NO2), premature birth, low birth weight, antibiotic use, parental smoking, ethnicity, birth order, number of siblings, parental occupation, NZDep social deprivation index | OR per 0.1-unit increase in NDVI*: 0.93 (0.89 to 0.98) Per SD increase in land cover: Number of natural land cover types: 0.933 (0.885 to 0.985) Exotic conifer land cover: 1.042 (1.009 to 1.075) Gorse land cover: 1.032 (1.004 to 1.060) | Probably Low |
| Eldeirawi et al., 2019 | Cross-sectional | n = 1915 | Mexican American children in Chicago, US | NDVI (Landsat 30 m resolution); Residential buffers of 100 m, 250 m, 500 m | Parent-reported asthma | Age, sex, country, urban/rural, family history of asthma, smoking in the home, proximity to traffic arterials, population density, SES + others | Odds ratio for IQR increase in NDVI: NDVI (250 m): Lifetime asthma: | Probably Low |

Table 6 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|--------------------|-----------------|--|--|---|---|---|--|----------------------|
| Zeng, 2020 | Cross-sectional | n = 59,754 | Children aged 2–17 years in 7 cities in Northeast China | NDVI, Soil adjusted vegetation index (SAVI) (Both use Landsat; 30 m); Summer NDVI around each school at 100 m, 300 m, 500 m, and 1000 m buffers. | Current asthma | Age, gender, parental education, family income, breastfeeding, low birthweight, preterm, residential area, SHS, mold in home, home coal usage, and family history of asthma, PM10, NO2 | OR = 1.08 (0.82 to 1.42) Odds ratio (OR) per 0.1 unit increase in NDVI or SAVI: NDVI (300 m) Current asthma OR = 0.87 (0.82 to 0.92) Air pollution was found to be a strong mediator for asthma | Probably Low |
| Dzhambov, 2021 | Cross-sectional | n = 1251 | School children, aged 8–12 years. in Alpine towns, Austria & Italy | NDVI (July–August 2003; Landsat, 30 m) Tree canopy cover (2000; Landsat; 30 m) Domestic garden (study questionnaire); Residential buffers of 100 m, 300 m, 500 m, school buffer of 100 m | Parent-reported current asthma symptoms, ever asthma symptoms | Age, gender, maternal education, low birth weight, maternal smoking during pregnancy, duration of breastfeeding, cumulative risk of secondhand smoking/pneumonia/bronchitis in the 1st year of life, number of green months during pregnancy, geographic region | Odds ratio for IQR increase: NDVI (500 m): Ever asthma: OR = 0.81 (0.64 to 1.03) Tree cover (500 m): Ever asthma: OR = 0.94 (0.73 to 1.22) Gardens (Presence): Ever asthma: OR = 0.71 (0.51 to 1.00) | Probably Low |
| Lovasi, 2008 | Ecological | n = 42 health service catchment areas | Children <15 years, New York City, USA | Street tree density in United Hospital Fund (UHF) area | Asthma prevalence | SES, race, population density, distance to pollution sources | Relative risk (RR) per SD of tree density: Prevalence RR = 0.71 (0.64 to 0.79) | Probably High |
| Maas, 2009 | Cross-sectional | n = 345,143 individuals | General population, Netherlands | Green land cover), % of greenspace within 1 km and 3 km around home postcode | Prevalence rate of Asthma, COPD | Age, sex, SES, urbanicity | Odds Ratio (OR) for 10% increase in greenspace within 1 km: Asthma, COPD: 0.97 (0.96 to 0.98) | Probably High |
| Khan, 2010 | Cross-sectional | n = 987 | General population in Karachi, Pakistan | Vegetative area (Landsat land cover; Area of vegetative land in each union council | Asthma prevalence | None. | Correlation between asthma prevalence and vegetative land cover: r = 0.43 | Probably High |
| Pilat, 2012 | Ecological | n = 14 Metropolitan Statistical Areas (MSAs) | Children aged <17 years in Texas, USA | Mean NDVI vegetation & % tree canopy in MSAs | Asthma prevalence | Relative humidity, temperature, ozone, particulate matter, and ethnicity | Semipartial correlation between asthma residual and NDVI/tree canopy: NDVI: r = 0.052 (p = 0.880) Tree canopy: r = -0.328 (p = 0.325) | Probably High |
| Dadvand 2014 | Cross-sectional | n = 3178 | School children aged 9–12 years; Sabadell, Spain | NDVI Vegetation (Landsat), Land use (parks, forests); Mean NDVI 100 m, 250 m, 500 m, 1000 m residential buffers and Living within 300 m of a | Current asthma | SES, type of school, urban vulnerability, age, sex, exposure to environmental tobacco smoke, having older siblings, parental history of asthma | Adjusted ORs for 0.1-unit increase in NDVI (250 m): 1.02 (0.82 to 1.28)* Adjusted ORs for living within 300 m of: parks 1.60 | Probably High |

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Table 6 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|----------------------|-----------------|--|---|--|---|--|--|----------------------|
| | | | | park or forest | | | (1.09 to 2.36); forests 1.02 (0.56 to 1.87) | |
| Brokamp et al., 2016 | Cohort | n = 762 | Atopic children aged ≤7 years old in USA | NDVI vegetation; Mean of 400 m residential buffer | Asthma diagnosis at age 7 | Air pollution, neighbourhood deprivation, race | Unadjusted OR (unit not given) = 0.15 (0.01 to 2.04) | Probably High |
| Bernat, 2016 | Ecological | n = 8 urban areas | General population in 8 urban areas in Lithuania | Forest coverage, recreational forests, forest remoteness; % (coverage/remoteness) or ha/1000 inhabitants in urban areas | Asthma cases per 1000 | Other exposures included, e.g. air pollutants, but independent correlation analysis only | Correlations: Asthma Coverage: r = -0.29 Remoteness: r = 0.17 Recreational: r = -0.63 | Probably High |
| Ulmer, 2016 | Cross-sectional | n = 7910 in cohort n = 4820 in analysis | General population (adults <65 years of age) in California, USA | Tree cover (LIDAR data); 250 m residential buffer | Asthma included as a mediator | Sex, age, race, education, income, smoking status, park percentage near home, walkability | Mediation analysis, also assess association between asthma and tree canopy: Odds of asthma for 10% increase in tree canopy: OR = 0.90 (0.79 to 1.02) | Probably High |
| Chen et al., 2017 | Cross-sectional | n = 150 | Children aged 9–17 years with physician-diagnosed asthma in Chicago, USA | NDVI vegetation (Landsat) - averaged across year; 250 m residential buffer | Asthma control and functional limitations | SES, season, age, sex, ethnicity, asthma severity, medication use | Regression coefficients predicting asthma outcomes: Asthma control: 0.05 (-9.05 to 17.46); Asthma functional limitations: 0.02 (-4.27 to 5.27) | Probably High |
| Feng, 2017 | Cross-sectional | n = 4447 | Children aged 6–7 years old, Australia | Green land use (parkland); % of parkland in Statistical Areas stratified into 0–20%, 20–40%, >40% | Asthma prevalence | Age, gender, maternal education, area SES, geographic remoteness, traffic volume, perceived safety | OR of asthma with GS: >40% GS: 1.15 (0.73 to 1.82) OR of asthma with heavy traffic and GS: >40% GS: 0.32 (0.12 to 0.84) | Probably High |
| Tischer et al., 2017 | Cohort | n = 2472 | Children aged 4 years in Asturias, Gipuzkoa, Sabadell and Valencia, Spain | NDVI vegetation (Landsat), Green land use (Urban Atlas); Mean NDVI within 300 m home buffer (average between birth and age 4), Greenspace within 300 m of home | Asthma prevalence | Sex, maternal education, maternal allergy, breast feeding, pets at home, maternal smoking during pregnancy, second hand smoke, area deprivation, air pollution (NO2), sensitivity analysis with physical activity | ORs (3rd vs 1st tertile) of NDVI and distance (<300 m) to greenspace for all 4 regions combined: NDVI Asthma: 1.82 (0.71 to 4.67) Greenspace distance Asthma: 0.60 (0.31 to 1.18) | Probably High |
| Ihlebaek, 2018 | Cross-sectional | n = 8638 | Adults aged 30–76 years Oslo, Norway | [1] Vegetation cover greenness (VCG) from satellite data (10 m resolution), [2] land use greenness (LUG) from municipal plans; % of VCG and proportion of | Self-reported asthma | Circuit (area) level covariates: mean income, % living in an owned house and mean education. Individual: civil status, use of alcohol, smoking status, physical activity, type of work, number of negative life events, number of good friends and degree of interest from other people. | Men Q5:Q1 OR = [1] 0.94 (0.51 to 1.74) and [2] 0.73 (0.40 to 1.35) Women Q5:Q1 OR = [1] 0.81 (0.51 to 1.30) and [2] | Probably High |

Table 6 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|---|-----------------|--|---|--|--|---|--|----------------------|
| Kurnia Febriawan and da Silva Sodre, 2018 | Ecological | Not specified, only reported prevalence of asthma as % | General population in Western Australia | LUG in each 'circuit' (quintiles) Enhanced Vegetation Index (EVI) from MODIS; Either positive or negative values | Asthma prevalence | Humidity, Rainfall, SES | 0.78 (0.50 to 1.23) Proportion high asthma in area of low EVI = 79.97%; high EVI = 20.03% | Probably High |
| Zock, 2018 | Cross-sectional | n = 4450 | General population in the Netherlands | Natural and agricultural green land use (from LGN-72012); Proportion of green land use within a neighbourhood | Asthma & COPD (combined) prevalence | Sex, age (continuous), household income and SES (individual level) and municipality and neighbourhood (group level), air pollution, noise, blue space | OR per 10% increase in green land use: Natural green = 0.92 (0.81 to 1.04) Total green = 0.97 (0.94 to 1.02) | Probably High |
| DePriest, 2019 | Cross-sectional | n = 196 | Children aged 3–12 years with persistent asthma in US | NDVI; Neighbourhood level | Asthma control | Age, sex, social risk index, season, medication, allergen sensitisation, secondhand smoke | Odds ratio (unit not given): 1.01 (0.93, 1.10) | Probably High |
| Li, 2019 | Cross-sectional | n = 5643 | Middle school students in Suzhou, China | NDVI (Greenness) (Landsat; 30 m), Parks; Mean NDVI from images in March, June, October, December 2014 at 100 m, 200 m, 500 m, 1000 m residential buffers; Distance from home to nearest park | Doctor-diagnosis of asthma | Age, sex, environmental tobacco smoke (ETS) at home, parental education, parental history of asthma, air pollution, pets in the home, and dampness and mold | Odds ratio for IQR increase in NDVI or Q4:Q1 distance to a park: NDVI (200 m) Ever asthma OR = 1.01 (0.88 to 1.16) Urban parks (Q4:Q1) Ever asthma OR = 0.70 (0.50 to 0.96) | Probably High |
| Hsieh, 2019 | Case-control | n = 3520 cases n = 3520 controls | Children <18 years of age in Taiwan | Green cover (NDVI value ≥ 0.4) (Landsat and Thermal Infrared Sensor satellites); Quintile of green cover for township of residence | Asthma incidence | Matched on sex, age, first diagnosis year. Adjusted for air pollutants, urbanization degree, frequency of healthcare provider visits, and mean township family income | Odds ratio (reference: Q1 green cover): Q5:Q1 green cover: OR = 1.10 (0.92 to 1.32); p for trend = 0.0289 | Probably High |
| Alasauskas, 2020 | Cross-sectional | 51,235 school children, including 3065 with asthma. | School children, aged 7–17 years. in Vilnius, Lithuania | Green spaces defined as areas with trees and bushes.; Distance to green space | Asthma prevalence | Adjusted for air pollutants, age, sex, proximity to roads, green spaces, | Odds ratio for distance to greenspace: 1.336 (1.060 to 1.653) | Probably High |
| Squillaciotti, 2020 | Cross-sectional | n = 187 | Children (10–13 years old) in Turin, Italy | NDVI (greenness) (Landsat; 30 m); Mean NDVI in a 300 m residential buffer | Asthma prevalence | Air pollutants, namely PM10, NO2 and NO, age, sex, BMI and urinary cotinine levels | Odds ratio of tertile 3 (highest) to tertile 1 (lowest) NDVI (300 m) Asthma OR = 0.13 (0.02 to 0.70) | Probably High |
| Aerts, 2020 | Ecological | n = 1872 census tracts | 6–18 year old children in Belgium | Relative covers of forest, grassland and garden from the Belgian National Geographic Institute (NGI-IGN); % cover in census tracts | Asthma prevalence (using sales data of reimbursed medication for obstructive airway disease) | Models were adjusted for air pollution (PM10), housing quality and administrative region | Parameter estimates per IQR increase of relative cover: Grassland $\beta = 0.10$ to 0.14 Garden $\beta = 0.07$ to 0.09 Forest: $\beta = -0.013$ to 0.010 | Probably High |

(continued on next page)

Table 6 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|-----------------------------|-------------------|---------------------------------------|--|---|--|---|--|----------------------|
| Kuiper, 2020 | Cohort | n = 1106 parents n = 1949 children | Parents (exposure) Children (outcome) in Bergen (Norway) and Umea, Uppsala, and Gothenburg (Sweden) | NDVI (Greenness; Landsat); Mean NDVI in summer in 100 m, 300 m, 500 m and 1000 m during 0–18 years of age for parents and 0–10 years of age for offspring. | Early onset asthma (parent reported) | Grandparental education, grandparental asthma; parental asthma, offspring's own air pollution/greenness exposures and air pollution/greenness exposures during pregnancy were included as potential mediators | Odds ratio for tertile 3 to tertile 1 of parent's exposure: Early onset asthma: Mother: OR = 1.00 (0.59 to 1.72) Father: OR = 0.67 (0.31 to 1.42) | Probably High |
| Markevych et al., 2020 | Cohort | n = 631 | Children up to 15 years old in Leipzig, Germany | NDVI (greenness) (Landsat; 30 m), Trees (Stadt Geoinformation und Amt für Stadtgrün und Gewässer); Mean NDVI; Total number of trees, Number of allergenic trees in 100 m, 300 m, 500 m, and 1000 m around home birth address. | Asthma (parent reported of doctor diagnosis) | Age, sex, season of birth, parental atopy and parental education. | Odds ratio for tertile 3 to tertile 1 of birth exposure: NDVI (300 m) Asthma: OR = 0.61 (0.39 to 0.95) Trees (300 m) Asthma: OR = 0.80 (0.55 to 1.18) Allergenic trees (300 m) Asthma: OR = 1.49 (0.98 to 2.27) | Probably High |
| Commodore, 2021 | Cross-sectional | n = 855 | Multi-racial children aged 4–8 years old in Various US states: DE, NY, CA, NY, IL, NJ, AL | Public parks ascertained in the Preschool-aged Children's Physical Activity Questionnaire (Pre-PAQ); Presence of park | Parent-reported asthma/asthma-like symptoms | Sex, race-ethnic group, family history of asthma, Maternal education level, Obese status of child, pets, exposure to environmental tobacco smoke, traffic, urban-rural status | Odds ratio: Presence of parks: 2.65 (1.14, 6.15) | Probably High |
| Razavi-Termeh, 2021b | Cross-sectional | n = 872 cases | General population in Tehran, Iran | NDVI (2009–2019; Landsat; 30 m); Annual average | Asthma prevalence | Air pollution parameters (O3, CO, NO2, SO2, PM 10, and PM 2.5), meteorological parameters (rainfall, temperature, humidity, pressure, and wind speed), distance to streets | Gini index: Higher asthma prevalence in areas with lower NDVI | Probably High |
| Yu, 2021b | Cross-sectional | n = 59,754 | Children aged 2–17 years in 7 cities in Northeast China | Eye-level greenness (Tencent map); Green view index (GVI) for grass, trees, overall around schools at 800 m and 1000 m buffers | Asthma prevalence | age, sex, parental education, family income, obesity, pet kept in home, and exercise time. Effect modification by PM2.5 | Odds ratio per IQR increase in GVI (800 m): GVI (800 m) Doctor diagnosed asthma: Trees: OR = 0.76 (0.72 to 0.80) Grass: OR = 1.04 (1.00 to 1.08) (Overall: OR = 0.77 (0.73 to 0.81)) | Probably High |
| Cavaleiro Rufo et al., 2021 | Population cohort | n = 1050 | Children at ages 4 and 7 years. in Porto, Portugal | NDVI; Residential buffers of 100 m, 200 m, 300 m during 2005–2006 | Parent-reported asthma/asthma-like symptoms | Sex, maternal history of asthma, household crowding, maternal education, distance to nearest major road and neighbourhood SES. | Odds ratio: NDVI (100 m) (T3:T1): Asthma - age 4: 0.28 (p > 0.05) Asthma - age 7: 0.37 (p > 0.05) Wheezing - age 7: 0.49 (p > 0.05) Dry cough - age 7: 0.91 (p > 0.05) Rhinitis - age 7: | Probably High |

Table 6 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|----------------------|------------------------------|--------------------------------------|--|--|--|--|--|----------------------|
| Dong, 2021 | Ecological | n = 140 neighbourhood units | General population in Toronto, Canada | 1) Ratio of tree areas to shrub and grass areas (Toronto Parks, Forestry and Recreation), 2) Tree diversity, 3) Percentage of greenspace; Neighbourhood level | Asthma prevalence | Age, sex, air pollution (mediator), income, household size, % of visible minorities | 0.37 (p < 0.05) Regression coefficients: Ratio of tree area to shrub/grasses: -0.19 (p > 0.05) Tree diversity: 0.07 (p > 0.05) % of greenspace: 0.12 (p > 0.05) | Probably High |
| Donovan, 2021 | Ecological | n = 498 cities, 26,367 census tracts | Adults in US cities | Plant diversity from Global Biodiversity Information Facility Overall greenness (NDVI) from USGS EROS Archive; Taxonomic diversity at census level. Maximum NDVI at census level. | Asthma prevalence | SES, race, ethnicity, air quality, climate zone, obesity %, PM2.5 (examined effect modification) | Standardised regression coefficients (per 1 SD): Taxonomic diversity = -0.0528 (-0.0638 to -0.0418) NDVI = 0.0383 (0.0290 to 0.0475) | Probably High |
| Kuiper et al., 2021 | Matched case-control, cohort | n = 3428 | Adults (age 18–40 years) in Norway, Sweden | NDVI (greenness) (Landsat; 30 m); Residential buffer of 300 m (mean value in May, June, July every 5 years from 1984 to 2014) | Asthma (self-reported of doctor diagnosis), asthma attack in the last 12 months | O3, NO2, parental education and parental asthma | Odds ratio for 0.1-unit increase in NDVI (asthma): NDVI (300 m) Physician diagnosed asthma OR = 1.00 (0.98 to 1.01) Asthma attack (lifetime) OR = 0.95 (0.77 to 1.17) | Probably High |
| Razavi-Termeh, 2021a | Cross-sectional | n = 872 cases | Children in Tehran, Iran | Parks; Distance to parks | Asthma prevalence | Air pollution parameters (O3, CO, NO2, SO2, PM 10, and PM 2.5), meteorological parameters (rainfall, temperature, humidity, pressure, and wind speed), distance to streets | Random forest model: Positive association between distance to park and asthma prevalence | High |

GS = Greenspace; IQR = Interquartile Range; NDVI = Normalised Difference Vegetation Index; OR = Odds Ratios; RR = Relative Risk; SHS: Secondhand smoke; SES = Socioeconomic Status; SD = Standard Deviation; SMR = Standardised Mortality Ratio.

* Standardised from reported values.

studies included self-or parent-reported health information, which, unless a robust and validated questionnaire was used to ascertain health status (e.g., ISAAC), were assigned a ‘probably high’ bias rating. Self-reported health can vary by country (Jürges, 2007), and reports of child health have been shown to vary by parental gender (Waters et al., 2000). Therefore, this differential assessment of health may have hampered the interpretation of evidence on a multi-country scale via different study designs. Overall, the available evidence of greenspace exposure and asthma was too heterogeneous and inconsistent to make inferences on the direction or causality of associations; such contradictory findings could be attributed to different greenspace metrics or uncontrolled confounding, such as body mass index (Beasley et al., 2015).

4.5. Respiratory symptoms & rhinitis

Studies have examined respiratory symptoms related to asthma and rhinitis, with most unable to identify a clear association. There are different

putative factors associated with the development of rhinitis, depending on the sub-type (i.e., allergic, infectious, chronic), including pollen, viruses, environmental tobacco smoke (Roberts et al., 2013), and other air pollutants (Lu et al., 2020). The lack of robust associations, and even inconsistent results in the same study, suggests the presence of more important underlying mechanisms, though a potential role for greenspace in causal pathways cannot be ruled out. Greenspace indicators may have been too crude to disentangle net effects to exposures that, for example, involve allergenic features linked to certain species, (e.g., birch tree pollen [Biedermann et al., 2019]).

4.6. Lung function & other health outcomes

While still somewhat inconsistent overall, some of the more recent studies indicated better lung function in school children with higher surrounding levels of greenspace (e.g., Yu et al., 2021a; Zhang et al., 2021; Zhou et al., 2021). The experimental studies examining lung function or mucociliary clearance also found better function in green areas compared

Table 7
Study characteristics of the lung function studies, ordered by risk of bias and year.

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|---------------------|-----------------|--|--|---|--|--|---|----------------------|
| Huang et al., 2016 | Experimental | n = 40 | Young, healthy college students in Beijing, China | 2 h exposure in an urban park Control: Transport hub (high air pollution) | Pulmonary function: (FEV1) and peak expiratory flow (PEF)) | Age, sex, BMI, day of week, time of measurement, site, temperature and relative humidity and air pollutants: PM2.5, BC, and CO. | Transport hub vs. park % change: FEV1 1 h - 3.48 (- 4.43 to - 2.53) vs. -0.32 (- 1.28 to 0.64); PEF 1 h - 4.51 (- 5.66 to - 3.36) vs. -1.91 (- 3.01 to - 0.81); PM10 adjusting for greenness as a covariate: FVC β = - 0.22%, p = 0.09; FEV1 β = - 0.34%, p = 0.15 | Probably Low |
| Cole-Hunter, 2018 | Panel | n = 57 | Healthy adults aged 18–60 years in Barcelona, Spain | NDVI vegetation - spring (Landsat); NDVI using 100 m, 300 m, 500 m buffers around residential and occupational addresses | Lung function - spirometry {FEV1, FVC, SUM} | age, height, weight, BMI, sex, air pollution (NO2, NOx, O3, PM10, PMCoarse, PM2.5), noise, fungal and pollen spores, weather, total-PA, neighbourhood-greenness and noise | No difference in lung function in COPD patients at the end of the walk between Oxford St and Hyde Park. | Probably Low |
| Sinharay, 2018 | Experimental | n = 40 COPD; n = 39 IHD; n = 40 healthy controls | Men and women aged 60 years + with (GOLD) COPD, and healthy volunteers in London, UK | 2 h walk in an urban park (Hyde Park) Control: 2 h walk on a busy street (Oxford St) | Lung function up to 26 h after walking | Air pollution (main exposure), group, location, time of measurement, temperature, relative humidity, smoking history | Change in lung function in road vs park: FVC (24 h) = - 50.03 (p = 0.005) FEV1 = - 13.12 (p = 0.49) | Probably Low |
| Moshhammer, 2019 | Experimental | n = 24 | Students (age range 21–33) in Vienna | Park ("Augarten", a large park in the centre of Vienna); 1 h walk | Lung function | Single exposure models | Odds ratio: NDVI (300 m): lag1: OR = 0.044 (0.022 to 0.065) lag2: OR = 0.036 (0.014 to 0.057) lag3: OR = 0.049 (0.027 to 0.070) | Probably Low |
| Zhang, 2021 | Case-control | n = 1900 cases n = 87 controls | Schoolchildren age 9–11 years in Tianjin, China | NDVI (2015–2017; Landsat; 30 m); Mean NDVI at 100 m, 300 m, 500 m residential buffer for three periods: lag1 (Jul-Sep), lag2 (Apr-Jun) and lag3 (Jan-Mar) | Impaired lung function (FEV1/FVC \leq 0.8) | Sex, BMI, parental education, air pollution, road proximity, indoor factors (e.g. smoking, cooking fuel) | Odds ratio (OR) for airflow obstruction/spirometric restrictions or change in FEV/FVC per IQR increase in NDVI: NDVI (300 m) Airflow obstruction OR = 0.99 (0.85 to 1.17) Spirometric restrictions: OR = 0.55 (0.45 to 0.68) FEV1: B = 61 (47 to 76) FVC B = 63 (41 to 71) | Probably Low |
| Zhou, 2021 | Cross-sectional | n = 6740 | School children aged 6–15 years in 7 cities in Northeast China | NDVI, Soil adjusted vegetation index (SAVI) (Both use Landsat; 30 m); Mean NDVI around schools using 300 m, 500 m, 1000 m buffers. | Lung function: obstructive (FEV1/FVC < 0.8), restrictive (FEV1/FVC \geq 0.8 but FVC < 80% of predicted) | Age, sex, height, weight, parent education level, family income, environment tobacco exposure, home coal use, pet keeping, home renovation, family history of atopy, prematurity and season. | Spearman Correlation Coefficient: NDVI within 500 m: Respiratory system resistance: - 0.078, p = 0.149 Respiratory system reactance: 0.032, p = 0.559 Area under reactance curve - 0.065, p = 0.226 Resonant frequency: - 0.092, p = 0.091 Frequency dependence of resistance: 0.025, p = 0.639 | Probably Low |
| Boeyen et al., 2017 | Cross-sectional | n = 360 | Children aged 5–12 years in heavy industrial area in Western Australia | NDVI vegetation (Landsat at 30 m resolution); Residential means using buffers 100, 200, 300, 500 m | Lung function using Forced Oscillation Technique - respiratory system resistance and reactance, Area under reactance curve, resonant frequency, Frequency dependence of resistance | Personal (Age, height, weight, asthma, smoking history, pets, parent education) Housing (age, heating type, wood burning, distance to major road | Effect modification by residential greenness: In areas of high greenness, exposure to low pollen | Probably High |
| Lambert, 2019 | Cohort | n = 486 | Adolescents age 12 and 18 years in Melbourne, Australia | NDVI (greenness) (Landsat; 30 m); Residential buffers at 100 m, 500 m, 1000 m at | Lung function: pre (12,18 years)and post (18 years) bronchodilator spirometry (FEV1, FVC, | Age, height, sex, URTI before 5 weeks, mother's education. | | Probably High |

Table 7 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|----------------------|------------------------------|------------------------|--|--|---------------------------------------|---|--|----------------------|
| | | | | birth | FEV1/FVC) | | grains in first 3 months associated with higher FEV1 and FVC. | |
| Squillacioti, 2020 | Cross-sectional | n = 187 | Children (10–13 years old) in Turin, Italy | NDVI (greenness) (Landsat; 30 m); Mean NDVI in a 300 m residential buffer | Lung function | Air pollutants, namely PM10, NO2 and NO, age, sex, BMI and urinary cotinine levels | Regression coefficient for lung function: NDVI (300 m) Lung function (FVC) B = -0.07 (-0.22 to 0.90) | Probably High |
| Fuertes, 2020 | Birth cohort | n = 7094 | 15 and 24 year olds in Bristol, Bath & North Somerset, East Somerset, North Somerset and South Gloucestershire, UK | NDVI greenness Proportion of green spaces (urban green spaces, forests and agricultural land); NDVI: buffers (100 – 1000 m) and proportion of green spaces within 300 m around birth, eight-, 15- and 24-year home addresses | Lung function | Sex, age, height, weight, older siblings, breast feeding daycare attendance, parental education, maternal smoking and reported smoking by the participants | Regression coefficients for IQR increase (NDVI) or presence (green space): Lifetime average NDVI (300 m): FEV1 = 21.5 (-14.3 to 57.4) FVC = 3.5 (-38.7 to 45.8) Green space (urban): FEV = 14.4 (-16.6 to 45.4) FVC = -1.8 (-38.6 to 34.9) | Probably High |
| Lambert, 2020 | Cohort | n = 160 | Children with a family history of asthma or allergic disease, aged 8 and 14 years in Sydney, Australia | NDVI (greenness) (Landsat; 30 m); Residential buffers at 100 m and 500 m at same seasons of lung function measurement | Lung function | Atopy status, current asthma, daily PM2.5, daily NO2, smoking during pregnancy, maternal asthma and seasonality. | Effect modification by residential greenness: No clinically meaningful effect modification. | Probably High |
| Yu, 2021a | Cross-sectional | n = 6740 | School children aged 6–15 years in 7 cities in Northeast China | Eye-level greenness (Tencent map); Green view index around schools at 800 m, 1000 m, 1500 m buffers | Lung impairment | Age, sex, BMI, parental education, family income, low birthweight, preterm birth, exercise per week and keeping pets in the home. Mediation with (PM1, PM2.5, PM10, and NO2.) | OR of lung impairment per IQR increase in Green view index (GVI): GVI (800 m) FEV1 < 85% predicted: OR = 0.73 (0.63 to 0.84) FVC < 85% predicted: OR = 0.83 (0.74 to 0.93) Results were attenuated and mediated with addition of air pollutants. | Probably High |
| Lambert et al., 2021 | Cohort | n = 2334 | Adolescents age 15 years in Germany | NDVI (greenness) (Landsat; 30 m); Residential buffers at 100 m, 300 m, 500 m, 1000 m, 3000 m at birth and 15 years old | Lung function | Area, age, sex, height, weight, asthma sensitisation, birth factors, early lung infections and indoor second-hand smoke exposure; parental education; parental atopy; seasonally adjusted vitamin D | Effect modification by residential greenness: No effect modification on lung function (FEV1, FVC). | Probably High |
| Kuiper, 2021 | Matched case-control, cohort | n = 3428 | Adults (age 18–40 years) in Norway, Sweden | NDVI (greenness) (Landsat; 30 m); Residential buffer of 300 m (mean value in May, June, July every 5 years from 1984 to 2014) | Lung function (lower limit of normal) | O3, NO2, parental education and parental asthma | Odds ratio for 0.1-unit increase in NDVI NDVI (300 m) Low lung function FEV1: OR = 1.74 (1.15 to 2.63) FVC: OR = 1.57 (1.00 to 2.45) | Probably High |

GS = Greenspace; IQR = Interquartile Range; NDVI = Normalised Difference Vegetation Index; OR = Odds Ratios; RR = Relative Risk; SES = Socioeconomic Status; SD = Standard Deviation; SMR = Standardised Mortality Ratio.

with urban/built environments; however, these differences could relate to lower exposure to air pollutants, or some intrinsic property, while in the green environment, or both.

4.7. Overall synthesis of evidence

From the synthesis of studies performed in our narrative review, the strongest evidence of a positive association between greenspace and health

related to respiratory mortality. Although a minority of those studies (7/20) were assigned a 'probably low' rating of bias, five found indicative dose response relationships of decreased mortality with higher greenspace levels; the two showing increases were not statistically significant. Respiratory mortality as a health indicator represents a broad range of disease, for which nearly every pathway in Fig. 4 may apply, but so too can common biases, such as residential self-selection. While it appears that a beneficial association exists with mortality, and potentially respiratory hospital

Table 8
Study characteristics of the respiratory symptoms studies, ordered by risk of bias and year.

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|--------------------|-----------------|--|--|--|---|---|---|----------------------|
| Lovasi, 2013 | Cohort | n = 492 (5 years) n = 427 (7 years) | African American and Dominican children aged <7 years in New York City, USA | Tree canopy from 2001 (LiDAR plus aerial imagery and vector data); % of area within 250 m of address | Asthma, wheeze, rhinitis, allergies (including grass and tree pollen) | Sex, age, ethnicity, maternal asthma, previous birth, other previous pregnancy, Medicaid enrolment, smoking, population density, percent poverty, percent park land, and estimated traffic volume. | Prevalence ratios (or RRs) per 10% increase in neighbourhood tree canopy*: Wheeze at age 7: 1.17 (0.96 to 1.41) Nasal symptoms OR Q4:Q1 0.99 (0.84 to 1.17) Pulmonary symptoms OR Q4:Q1 0.97 (0.78 to 1.20) | Probably Low |
| Cilluffo, 2018 | Cross-sectional | n = 219 | Children aged 8–10 years in Palermo, Italy | NDVI vegetation (ASTER); NDVI raster cell of residential address (200m ²) | Self-reported nasal, pulmonary symptoms | Gender, age (years), maternal and paternal education, parental history of allergy, breastfeeding, preterm birth, smoking, atopy, doctor diagnosed asthma and parental history of allergy, greyness, air pollution | COPD patients more likely to experience symptoms after Oxford St compared to Hyde Park. ORs: cough: 1.95 (0.96 to 3.95) sputum 3.15 (1.39 to 7.13) shortness of breath 1.86 (0.97 to 3.57) wheeze 4.00 (1.52 to 10.50) | Probably Low |
| Sinharay, 2018 | Experimental | n = 40 COPD; n = 39 IHD; n = 40 healthy controls | Men and women aged 60 years + with (GOLD) COPD, and healthy volunteers in London, UK | 2 h walk in an urban park (Hyde Park) Control: 2 h walk on a busy street (Oxford St) | Symptoms | Air pollution (main exposure), group, location, time of measurement, temperature, relative humidity, smoking history | COPD patients more likely to experience symptoms after Oxford St compared to Hyde Park. ORs: cough: 1.95 (0.96 to 3.95) sputum 3.15 (1.39 to 7.13) shortness of breath 1.86 (0.97 to 3.57) wheeze 4.00 (1.52 to 10.50) | Probably Low |
| Eldeirawi, 2019 | Cross-sectional | n = 1915 | Mexican American children in Chicago, US | NDVI (Landsat 30 m resolution); Residential buffers of 100 m, 250 m, 500 m | Parent-reported asthma-like symptoms | Age, sex, country, urban/rural, family history of asthma, smoking in the home, proximity to traffic arterials, population density, SES + others | Odds ratio for IQR increase in NDVI (250 m): Lifetime wheezing: OR = 0.93 (0.78 to 1.12) Current dry cough at night: OR = 1.12 (0.85 to 1.47) | Probably Low |
| Zeng, 2020 | Cross-sectional | n = 59,754 | Children aged 2–17 years in 7 cities in Northeast China | NDVI, Soil adjusted vegetation index (SAVI) (Both use Landsat; 30 m); Summer NDVI around each school at 100 m, 300 m, 500 m, and 1000 m buffers. | Current wheeze | Age, gender, parental education, family income, breastfeeding, low birthweight, preterm, residential area, SHS, mold in home, home coal usage, and family history of asthma, PM10, NO2 | Odds ratio (OR) per 0.1 unit increase in NDVI (300 m) Current wheeze OR = 0.93 (0.89 to 0.98) Air pollution was found not to be a mediator for wheeze. | Probably Low |
| Dzhambov, 2021 | Cross-sectional | n = 1251 | School children, aged 8–12 years. in Alpine towns, Austria & Italy | NDVI (July–August 2003; Landsat, 30 m) Tree canopy cover (2000; Landsat; 30 m) Domestic garden (study questionnaire); Residential buffers of 100 m, 300 m, 500 m, school buffer of 100 m | Parent-reported ever allergic rhinitis symptoms | Age, gender, maternal education, low birth weight, maternal smoking during pregnancy, duration of breastfeeding, cumulative risk of secondhand smoking/pneumonia/bronchitis in the 1st year of life, number of green months during pregnancy, geographic region | Odds ratio for IQR increase: NDVI (500 m): OR = 0.83 (0.67 to 1.03) Tree cover (500 m): OR = 0.86 (0.68 to 1.09) Gardens (Presence): OR = 0.85 (0.62 to 1.17) | Probably Low |
| Fuertes, 2014b | Cohort | n = 5803 | Children <10 years old; Germany | NDVI (summer values); Residential NDVI at 500 m, 800 m, 1000 m, 3000 m at birth, 6 and 10 years old. | Eyes and nose symptoms | Age, sex, parental history of atopy, older siblings, maternal smoking, parental education, air pollution, population density | Odds ratios (ORs) per IQR increase in greenness exposure. NDVI w/ 500 m buffer: Eyes/nose symptoms OR = 1.00 (0.88 to 1.14) | Probably High |
| Fuertes, 2014a | Ecological | n = 222 (population centres) | Children aged 6–7 and 13–14 years; Global (94 countries) | NDVI Vegetation (MODIS); Mean NDVI of ~59 km ² area | Self/parent-reported intermittent and persistent rhinitis symptoms | Temperature, precipitation, vapour pressure, GNI per capita, population density, and climate type, air pollutants in sensitivity analysis | Mean difference in country/centre-level prevalence per 100 children per 0.1-unit NDVI* In country: Intermittent rhinitis 0.80 (–0.88 to 2.48) Persistent rhinitis 0.95 (–0.38 to 2.28) In centre: Intermittent rhinitis | Probably High |

Table 8 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|----------------------|-------------------|------------------------|---|--|---|--|--|----------------------|
| Tischer, 2017 | Cohort | n = 2472 | Children aged 4 years in Asturias, Gipuzkoa, Sabadell and Valencia, Spain | NDVI vegetation (Landsat), Green land use (Urban Atlas); Mean NDVI within 300 m home buffer (average between birth and age 4), Greenspace within 300 m of home | Wheezing, bronchitis | Sex, maternal education, maternal allergy, breast feeding, pets at home, maternal smoking during pregnancy, second hand smoke, area deprivation, air pollution (NO ₂), sensitivity analysis with physical activity | -0.13 (-1.08 to 0.83) Persistent rhinitis -0.29 (-1.14 to 0.56) ORs (3rd vs 1st tertile) of NDVI and distance (<300 m) to greenspace for all 4 regions combined: NDVI Wheezing: 0.96 (0.71 to 1.30) Bronchitis: 1.18 (0.86 to 1.62) <u>Greenspace distance</u> Wheezing: 0.92 (0.715 to 1.13) Bronchitis: 1.04 (0.84 to 1.26) Odds ratio of tertile 3 (highest) to tertile 1 (lowest) NDVI (300 m) Bronchitis OR = 0.14 (0.05 to 0.45) | Probably High |
| Squillaciotti, 2020 | Cross-sectional | n = 187 | Children (10–13 years old) in Turin, Italy | NDVI (greenness) (Landsat; 30 m); Mean NDVI in a 300 m residential buffer | Respiratory symptoms (wheezing, cough) | Air pollutants, namely PM10, NO ₂ and NO, age, sex, BMI and urinary cotinine levels | Odds ratio of tertile 3 (highest) to tertile 1 (lowest) NDVI (300 m) Bronchitis OR = 0.14 (0.05 to 0.45) | Probably High |
| Stas, 2021 | Case-crossover | n = 144 | Adults sensitized to Betulaceae pollen in Belgium | Grassland, Garden, Forest cover, Density of allergenic trees (Alnus, Betula and Corylus); Dynamic exposure every 5 s (1 km buffer) | Daily allergy symptom severity score | Birch pollen, air pollutants; subgroup analysis on age, sex, region | Odds ratio for 10% increase in land cover: Garden OR = 0.987 (0.706 to 1.380) Grass OR = 0.655 (0.446 to 0.960) Forest OR = 0.748 (0.521 to 1.074) Alnus OR = 0.625 (0.427 to 0.917) Betula OR = 2.014 (1.162 to 3.490) Corylus OR = 0.707 (0.413 to 1.209) Odds ratio: NDVI (100 m) (T3: T1): Wheezing - age 7: 0.49 (p > 0.05) Dry cough - age 7: 0.91 (p > 0.05) | Probably High |
| Cavaleiro Rufo, 2021 | Population cohort | n = 1050 | Children at ages 4 and 7 years in Porto, Portugal | NDVI; Residential buffers of 100 m, 200 m, 300 m during 2005–2006 | Parent-reported asthma/asthma-like symptoms | Sex, maternal history of asthma, household crowding, maternal education, distance to nearest major road and neighbourhood SES. | Odds ratio: NDVI (100 m) (T3: T1): Wheezing - age 7: 0.49 (p > 0.05) Dry cough - age 7: 0.91 (p > 0.05) | Probably High |

GS = Greenspace; IQR = Interquartile Range; NDVI = Normalised Difference Vegetation Index; OR = Odds Ratios; RR = Relative Risk; SES = Socioeconomic Status; SD = Standard Deviation; SMR = Standardised Mortality Ratio.

* Standardised from reported values.

admissions (21/28 associations were positive), the contribution and importance of different mechanisms is not yet clear. This trend is consistent with research on greenspace and other broad indicators of wellbeing, such as mental health, where multiple potential pathways have been identified, but mechanism-specific evidence is not yet sufficient (Houlden et al., 2018). Although indicators of asthma were the most studied outcome (38 studies), findings were too inconsistent to reach definitive conclusions. Studies of rhinitis and respiratory symptoms did not provide compelling evidence of improved health. The experimental studies demonstrated some improved lung function, but entailed poor characterisation of the greenspace environment; such associations may very likely have been

prompted by lower concentrations of ambient air pollutants in lower traffic settings, rather than specifically in urban greenspace.

While we deemed the possibility of residential self-selection not to be necessarily a high source of bias, as indicated in previous studies (Kaczynski and Mowen, 2011; McCormack, 2017; Lu, 2018), it is a pervasive issue in the greenspace literature. Healthier people or those who are more health-conscious, may choose to live in greener areas where there may be, as an example, more opportunities for exercise or lower exposure to air pollution (Cohen-Cline et al., 2015). It is also possible that those with some forms of respiratory condition exacerbated by aeroallergens, for example, might move away from green areas where

Table 9
Study characteristics of the rhinitis studies, ordered by risk of bias and year.

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|---------------------|-----------------|--|--|---|--|---|---|----------------------|
| Lovasi, 2013 | Cohort | n = 492 (5 years) n = 427 (7 years) | African American and Dominican children aged <7 years in New York City, USA | Tree canopy from 2001 (LiDAR plus aerial imagery and vector data); % of area within 250 m of address | Rhinitis | Sex, age, ethnicity, maternal asthma, previous birth, other previous pregnancy, Medicaid enrolment, smoking, population density, percent poverty, percent park land, and estimated traffic volume. | Prevalence ratios (or RRs) per 10% increase in neighbourhood tree canopy*: Rhinitis at age 7: 1.52 (0.56 to 4.08) | Probably Low |
| Gernes et al., 2019 | Birth cohort | n = 478 | Children aged 7 years in Ohio and Kentucky, USA | NDVI greenness Land cover-derived urban greenspace (Tree canopy, grass/shrub coverage); NDVI - Landsat Scene Path at 30 m resolution. Image from June 2010. Urban greenspace: 2.5 m resolution. All metrics use 400 m residential buffers, plus 100 m and 80 m | Allergic rhinitis at age 7 (parent-reported) | Race, sex, environmental tobacco smoke exposure, exposure to traffic-related air pollution, mother's education (7 years), and neighbourhood SES (7 years). | Odds ratio per IQR increase in NDVI or 10% increase in urban greenspace: NDVI (400 m): OR = 0.95 (0.76, 1.20) Urban greenspace: OR = 0.90 (0.69, 1.19) | Probably Low |
| Dadvand 2014 | Cross-sectional | n = 3178 | School children aged 9–12 years; Sabadell, Spain | NDVI Vegetation (Landsat), Land use (parks, forests); Mean NDVI 100 m, 250 m, 500 m, 1000 m residential buffers and Living within 300 m of a park or forest | Current allergic rhinoconjunctivitis | SES, type of school, urban vulnerability, age, sex, exposure to environmental tobacco smoke, having older siblings, parental history of asthma | Adjusted ORs for 0.1-unit increase in NDVI (250 m): 0.98 (0.88 to 1.11)* Adjusted ORs for living within 300 m of parks 1.10 (0.90 to 1.35); forests 1.27 (0.94 to 1.70) OR per 0.1-unit NDVI*: 6–8 years = 1.00 (0.83 to 1.20); 10–12 years = 0.98 (0.84 to 1.14) | Probably High |
| Fuertes, 2016 | Cohort | n = 13,016 | Children aged 6–8 and 10–12 years in Australia, Canada, Germany, Netherlands, Sweden | NDVI vegetation at 500 m, 100 m residential buffers | Allergic rhinitis | Parental atopy, older siblings, maternal smoking, SES, group, region, and cohort. | OR per 0.1-unit NDVI*: 6–8 years = 1.00 (0.83 to 1.20); 10–12 years = 0.98 (0.84 to 1.14) | Probably High |
| Tischer, 2017 | Cohort | n = 2472 | Children aged 4 years in Asturias, Gipuzkoa, Sabadell and Valencia, Spain | NDVI vegetation (Landsat), Green land use (Urban Atlas); Mean NDVI within 300 m home buffer (average between birth and age 4), Greenspace within 300 m of home | Allergic rhinitis | Sex, maternal education, maternal allergy, breast feeding, pets at home, maternal smoking during pregnancy, second hand smoke, area deprivation, air pollution (NO2), sensitivity analysis with physical activity | ORs (3rd vs 1st tertile) of NDVI and distance (<300 m) to greenspace for all 4 regions combined: NDVI Allergic rhinitis: 0.57 (0.22 to 1.50) Greenspace distance Allergic rhinitis: 0.67 (0.34 to 1.30) | Probably High |
| Kwon et al., 2019 | Ecological | n = 423 administrative units | Adults age 20+ years in Seoul, South Korea | NDVI (greenness) (Landsat; 30 m); Mean NDVI level for each district | Allergic rhinitis | Air pollutants (SO2, PM10, O3, NO2, CO), power plants, traffic, age, income, manufacturing employee ratio | Spatial lag model coefficient: NDVI = 0.386 (p = 0.056) | Probably High |
| Li, 2019 | Cross-sectional | n = 5643 | Middle school students in Suzhou, China | NDVI (Greenness) (Landsat; 30 m) Parks; Mean NDVI from images in March, June, October, December 2014 at 100 m, 200 m, 500 m, 1000 m residential buffers Distance from home to nearest park | Doctor-diagnosis of rhinitis | Age, sex, environmental tobacco smoke (ETS) at home, parental education, parental history of asthma, air pollution, pets in the home, and dampness and mold | Odds ratio for IQR increase in NDVI or Q4:Q1 distance to a park: NDVI (200 m) Ever rhinitis OR = 0.95 (0.86 to 1.06) | Probably High |

Table 9 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|----------------------|------------------------------|---------------------------------------|--|--|---|---|--|----------------------|
| Kim, 2020 | Cross-sectional | n = 219,298 | Adults in Korea | Forests, parks and reserves, greenness, greenways, and riparian areas. (Korean Statistical Information Service); Green areas (m ²) per capita | Allergic rhinitis | Age, sex, marriage, education, monthly income, and job categories + smoking and alcohol + physical activity and self-reported stress + urbanity and body mass index | Urban parks (Q4:Q1) Ever rhinitis OR = 0.97 (0.76 to 1.24) Odds ratio of Q4:Q1 green area: Physician's diagnosis: OR = 0.94 (0.89 to 0.99) | Probably High |
| Kuiper, 2020 | Cohort | n = 1106 parents n = 1949 children | Parents (exposure) Children (outcome) in Bergen (Norway) and Umea, Uppsala, and Gothenburg (Sweden) | NDVI (Greenness; Landsat); Mean NDVI in summer in 100 m, 300 m, 500 m and 1000 m during 0–18 years of age for parents and 0–10 years of age for offspring. | Hay fever/Allergic rhinitis | Grandparental education, grandparental asthma; parental asthma, offspring's own air pollution/greenness exposures and air pollution/greenness exposures during pregnancy were included as potential mediators | Odds ratio for tertile 3 to tertile 1 of parent's exposure: Hay fever: Mother: OR = 1.57 (0.72 to 3.43) Father: OR = 1.35 (0.44 to 4.19) | Probably High |
| Markevych, 2020 | Cohort | n = 631 | Children up to 15 years old in Leipzig, Germany | NDVI (greenness) (Landsat; 30 m), Trees (Stadt Leipzig, Amt für Geoinformation und Amt für Stadtgrün und Gewässer); Mean NDVI, Total number of trees, Number of allergenic trees in 100 m, 300 m, 500 m, and 1000 m around home birth address. | Allergic rhinitis (parent reported of doctor diagnosis) | Age, sex, season of birth, parental atopy and parental education. | Odds ratio for tertile 3 to tertile 1 of birth exposure: NDVI (300 m) OR = 0.77 (0.59 to 1.01) Trees (300 m) OR = 1.53 (1.16 to 2.02) Allergenic trees (300 m) OR = 1.28 (0.97 to 1.87) | Probably High |
| Cavaleiro Rufo, 2021 | Population cohort | n = 1050 | Children at ages 4 and 7 years. in Porto, Portugal | NDVI; Residential buffers of 100 m, 200 m, 300 m during 2005–2006 | Parent-reported asthma/asthma-like symptoms | Sex, maternal history of asthma, household crowding, maternal education, distance to nearest major road and neighbourhood SES. | Odds ratio: NDVI (100 m) (T3:T1): Rhinitis - age 7: 0.37 (p < 0.05) | Probably High |
| Kuiper, 2021 | Matched case-control, cohort | n = 3428 | Adults (age 18–40 years) in Norway, Sweden | NDVI (greenness) (Landsat; 30 m); Residential buffer of 300 m (mean value in May, June, July every 5 years from 1984 to 2014) | Rhinitis | O3, NO2, parental education and parental asthma | Odds ratio for 0.1-unit increase in NDVI (300 m) OR = 1.01 (0.92 to 1.11) | Probably High |

GS = Greenspace; IQR = Interquartile Range; NDVI = Normalised Difference Vegetation Index; OR = Odds Ratios; RR = Relative Risk; SES = Socioeconomic Status; SD = Standard Deviation; SMR = Standardised Mortality Ratio.

exposures to pollens are higher (Dadvand et al., 2014). On the other hand, reverse-causation might, in some cases, result in the selective migration to green areas of people with established respiratory conditions to avoid more polluted environments (e.g., Pun et al., 2018). Selection bias of this kind may not be diminished by a longitudinal study design (where individuals would continue to select their residential locations over time) and may be relevant for a variety of health outcomes. Moreover, income effects may remain as a potential source of bias even in studies which have ostensibly controlled for SES effects, as dwellings facing green areas are generally more desirable, and hence more expensive, than ones facing busy roads. The direction of bias for this wealth/income effect is likely to favour the selection of healthier populations in greener areas, but the direction and magnitude of bias for the other selection effects largely remain unquantified and may depend on the exposure, population, and health metric under investigation. In addition to the methodological challenges of residential self-selection, exposure levels may also depend on the subject, with the perceived importance

of different greenspace characteristics varying across individuals; this phenomenon could cause misclassification of 'dose' and lead to challenges of interpretation across studies.

4.8. Strengths and limitations

Our study represents the first systematic review to identify and examine greenspace pathways of effect across broad indicators of respiratory health. Our methods benefitted from the use of an extensive search strategy, which was not likely to have missed relevant and impactful papers; still, there was the potential of the streetlight effect, whereby our search terms and understanding of greenspace may have been constrained by previously established concepts (Whaley et al., 2020). Two papers were not captured initially from the database search strategy, due to addressing biodiversity (i.e., not explicitly including 'green' environments) (Liddicoat et al., 2018) and excluding mention of respiratory health in the title or abstract (Maas et al., 2009). Although

Table 10
Study characteristics of the other respiratory health studies, ordered by risk of bias and year.

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|-------------------------|-----------------|-------------------------------------|---|---|--|---|--|----------------------|
| Hoehner, 2013 | Cross-sectional | n = 8857 (home) n = 4734 (work) | Adults aged 18–90 years in Dallas, USA | Parks, vegetation (1 m res NDVI from the National Agriculture Imagery Program 2004); Number of parks within 1600 m buffer; Distance to park with a trail; Average number of park features within 1600 m; Proportion of vegetation (800 m) | Cardiorespiratory fitness (via an exercise test) | Sex, age, marital status, children in home, educational status, smoking status, body mass index, census block group-level percent below 200% poverty, race, and built environment variables. | Regression coefficients (standard error) predicting cardiorespiratory fitness (home greenspace): Proportion of vegetation: 0.423 (0.187) p-value = 0.02 Number of parks: -0.003 (0.008) p-value = 0.71 Average number of park features: -0.028 (0.023) p-value = 0.22 Distance to closest park: -0.012 (0.016) p-value = 0.44 | Probably Low |
| Cavalcan-te de Sa, 2016 | Experimental | n = 38 | Young, healthy amateur runners in Sao Paolo, Brazil | Running in an urban forest Control: Running on a street | Airway defense markers: nasal mucociliary clearance, pH of exhaled breath condensate (EBC) and number of epithelial and inflammatory cells in nasal lavage fluid (NLF) | Air pollutants, relative humidity, day of the week | Number of subjects with impaired Mucociliary Clearance doubled in the Street group and decreased in the Forest group. | Probably Low |
| Arbillaga-Etxarri, 2017 | Cross-sectional | n = 410 | COPD patients in Catalonia, Spain | NDVI - Landsat (30 m cell), Proximity to greenspace <300 m; Residential NDVI at 100, 300, 500, 1000 m | Minutes/day of moderate-vigorous physical activity | Age, sex, socio-economic status, smoking, dyspnoea, 6-min walking test and HAD-anxiety. | No quantitative results for GS indicators, but minutes/day MVPA slightly greater in <median greenness and > median proximity to green/blue space (not statistically significant) | Probably Low |
| Sarkar et al., 2019 | Cross-sectional | n = 96,779 (n = 77,679 in analysis) | Adults aged 39+ years in UK (22 cities of England, Wales, and Scotland) | NDVI (greenness); Mean NDVI in a 500 m residential buffer | COPD prevalence | PM2.5, urbanicity, sociodemographics, lifestyle variables, neighbourhood socioeconomic status, anthropometrics, comorbidities, and haematological biomarkers | OR per IQR increase in NDVI: NDVI (500 m) OR = 0.89 (0.84 to 0.93) | Probably Low |
| Moshhammer, 2019 | Experimental | n = 24 | Students (age range 21–33) in Vienna | Park (“Augarten”, a large park in the centre of Vienna); 1 h walk | Exhaled Nitric Oxide (eNO) | Single exposure models | Increase in eNO after exercise near road compared to park. | Probably Low |
| Fan, 2020 | Cross-sectional | n = 66,752 | Adults aged 40+ years in China | NDVI (2010–2014 Jan/Apr/Jun/Oct; Landsat 30 m resolution); Residential buffers of 100, 300, 500, 1000, 2000, 3000 and 5000 m | COPD prevalence | Place of residence, smoke, height, history of tuberculosis, severe pulmonary disease in childhood, biomass or coal in home environment, dust/hazardous chemical gases in workplace, relative humidity and temperature, and PM2.5 concentrations | Odds ratio for IQR increase in NDVI: NDVI (300 m) for urban populations: OR = 1.14 (1.01 to 1.27) | Probably Low |
| Paciência, 2020 | Cross-sectional | n = 845 | Primary school children in Porto, Portugal | Tree density and dominant tree type (coniferous/ | Spirometry - Exhaled Nitric Oxide (NO) | Age, sex, asthma, atopy, parental education level and exposure to tobacco | Standardised regression coefficient for | Probably Low |

Table 10 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|--------------------|-----------------|--|--|---|--|--|---|----------------------|
| | | | | deciduous) (2015; Copernicus Land Monitoring Service); 500 m buffer around school | | smoke at home. | change in NO: Tree cover density Girls: $\beta = -0.01$ (-0.02 to 0.001) Boys: $\beta = -0.01$ (-0.04 to 0.01) Broadleaves Girls: $\beta = -0.04$ (-0.20 to 0.12) Boys: $\beta = -0.14$ (-0.49 to 0.22) Coniferous Girls: $\beta = -0.51$ (-1.33 to 0.32) Boys: $\beta = -1.16$ (-3.09 to 0.76) | |
| Maas, 2009 | Cross-sectional | n = 345,143 individuals | General population, Netherlands | Green land cover), % of greenspace within 1 km and 3 km around home postcode | Prevalence rate of (1) Upper respiratory tract infection, (2) Bronchi(<i>oli</i>) tis/pneumonia | Age, sex, SES, urbanicity | Odds Ratio (OR) for 10% increase in greenspace within 1 km: Upper respiratory tract infection: 0.97 (0.96 to 0.98) Bronchi(<i>oli</i>) tis/pneumonia: 0.99 (0.97 to 1.00) | Probably High |
| Bernat, 2016 | Ecological | n = 8 urban areas | General population in 8 urban areas in Lithuania | Forest coverage, recreational forests, forest remoteness; % (coverage/remoteness) or ha/1000 inhabitants in urban areas | Acute upper respiratory infections per 1000 | Other exposures included, e.g. air pollutants, but independent correlation analysis only | Correlations: Upper respiratory infections: Coverage: $r = 0.39$ Remoteness: $r = -0.26$ Recreational: $r = -0.24$ | Probably High |
| Prist, 2016 | Ecological | n = 645 municipalities (population ~ 42 million) | General population in Sao Paulo, Brazil | Native vegetation cover; % of vegetation cover and fragmentation (# of patches) | Hantavirus Pulmonary Syndrome (HPS) | HDI, mean annual temperature ($^{\circ}$ C), total annual precipitation (mm), and rural male population > 14 years old | Graphical results of standardised coefficients from Fig. 3: In Cerrado, slight negative effect of habitat cover and patches on HPS risk, marginal negative effect in Atlantic Forest; all non-significant. | Probably High |
| Chen, 2017 | Cross-sectional | n = 150 | Children aged 9–17 years with physician-diagnosed asthma in Chicago, USA | NDVI vegetation (Landsat) - averaged across year; 250 m residential buffer | Airway inflammation, glucocorticoid expression in T-helper cells (relevant to airway inflammation) | SES, season, age, sex, ethnicity, asthma severity, medication use | Regression coefficients predicting asthma outcomes: T-helper cell GR expression: 0.06 (-52.56 to 108.84); FeNO: -0.01 (-168.89 to 145.76) | Probably High |
| Pun, 2018 | Cohort | n = 4118 | Older adults aged 57–85 years in the US | NDVI vegetation (MODIS - 250 m resolution) (summer); 250 m & 1000 m residential buffers | History of respiratory illness (emphysema, chronic obstructive pulmonary disorder, and asthma) | Age, gender, race/ethnicity, season, region, education attainment, family income, median household income level, current smoking, physical activity, social support, history of illnesses, BMI and physical function, loneliness, roadway distance, urbanicity | History of respiratory disease mediated greenness and stress by -3.80% | Probably High |
| Li, 2019 | Cross-sectional | n = 5643 | Middle school students in Suzhou, China | NDVI (Greenness) (Landsat; 30 m), Parks; Mean NDVI from images in March, June, | Doctor-diagnosis of pneumonia | Age, sex, environmental tobacco smoke (ETS) at home, parental education, parental history of asthma, air | Odds ratio for IQR increase in NDVI or Q4:Q1 distance to a park: NDVI (200 m) | Probably High |

(continued on next page)

Table 10 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|-----------------------|-----------------|------------------------|--|---|--|--|---|----------------------|
| | | | | October, December 2014 at 100 m, 200 m, 500 m, 1000 m residential buffers; Distance from home to nearest park | | pollution, pets in the home, and dampness and mold | Ever pneumonia OR = 0.95 (0.87 to 1.05) Urban parks (Q4:Q1) Ever pneumonia OR = 0.92 (0.74 to 1.15) | |
| Squillaciotti, 2020 | Cross-sectional | n = 187 | Children (10–13 years old) in Turin, Italy | NDVI (greenness) (Landsat; 30 m); Mean NDVI in a 300 m residential buffer | Bronchitis | Air pollutants, namely PM10, NO2 and NO, age, sex, BMI and urinary cotinine levels | Odds ratio of tertile 3 (highest) to tertile 1 (lowest) Bronchitis OR = 0.14 (0.05 to 0.45) | Probably High |
| Lambert, 2020 | Cohort | n = 160 | Children with a family history of asthma or allergic disease, aged 8 and 14 years in Sydney, Australia | NDVI (greenness) (Landsat; 30 m); Residential buffers at 100 m and 500 m at same seasons of lung function measurement | Exhaled NO | Atopy status, current asthma, daily PM2.5, daily NO2, smoking during pregnancy, maternal asthma and seasonality. | Effect modification by residential greenness: No clinically meaningful effect modification. | Probably High |
| Russette et al., 2021 | Ecological | n = 3049 counties | General population in USA | Leaf area index (LAI) (2011–2015; MODIS; 250 m); Mean LAI in county | COVID – 19 mortality | Education, overcrowding, Medicaid (ages 18–64), age 65 and over, race (Black and Native American), physical inactivity, and neighbour COVID – 19 mortality average | Mortality Rate Ratio (MRR) compared to decile 1 of LAI: MRR of decile 10 (highest LAI) = 0.59 (0.50 to 0.69) | Probably High |
| Wu, 2021 | Cross-sectional | n = 993 | Adults with respiratory disease (asthma, bronchitis and cough in the past five years) in Shanghai, China | Greenness (NDVI, SAVI, RVI, EVI) (30 m) Tree type; 500 m buffer around community Ratio of evergreen and deciduous to overall green area | Respiratory disease prevalence | individual socio-economic characteristics (age, gender, and BMI) and air pollution around communities (PM2.5, automobile exhaust, building dust, industry exhaust, and garbage smell) as control variables | Logit regression model: NDVI B = -0.789 (p < 0.05) Ratio of evergreen B = 0.011 (p > 0.05) Ratio of deciduous B = 0.025 (p > 0.05) | Probably High |
| Zhang, 2021 | Cross-sectional | n = 2023 | General population in Nanjing, China | Vegetation cover (Google Earth), plant diversity (Flora of China); Vegetation coverage and species richness in residential compounds | Self-reported allergic diseases and respiratory diseases | Gender, age, plant factors, building age | Regression coefficients related to health impairment: “Allergic diseases: Diversity of plants with airborne fibers = -0.065 (p-value = 0.683) Diversity of plants with pollen = 0.107 (p-value = 0.002) Diversity of overall plants = -0.026 (p-value = 0.029) Veg cover = -0.011 (p-value = 0.032) Respiratory diseases: Diversity of plants with airborne fibers = 0.412 (p-value = 0.015) Diversity of plants with pollen = 0.037 (p-value = 0.303) Diversity of overall plants = -0.007 (p-value = 0.576) Veg cover = -0.011 (p-value = 0.061)” | Probably High |
| Lambert, 2021 | Cohort | n = 2334 | Adolescents age 15 years in Germany | NDVI (greenness) (Landsat; 30 m); | Exhaled NO | Area, age, sex, height, weight, asthma | Effect modification by residential | Probably High |

Table 10 (continued)

| First author, year | Study type | Sample size/# of cases | Study population and setting | Greenspace data/exposure metric | Respiratory health outcome | Confounders/covariates | Main results (95% CI) | Overall risk of bias |
|---------------------|-----------------|------------------------|---|--|---------------------------------------|--|---|----------------------|
| Moitra et al., 2022 | Cross-sectional | n = 407 | Mild-to-very severe COPD patients in Barcelona, Spain | Green land use (Urban Atlas 2007); Residential distance to blue/green space within 500 m | Health related quality of life (COPD) | sensitisation, birth factors, early lung infections and indoor second-hand smoke exposure; parental education; parental atopy; seasonally adjusted vitamin D | greenness: Higher exhaled NO in greener areas. Regression coefficients for distance to blue/green space (per 100 m): CAT score: $\beta = 0.03$ (0.002 to 0.06) CCQ-score: $\beta = 0.02$ (-0.02 to 0.06) | Probably High |

FeNO = Fractional Exhaled Nitric Oxide; GS = Greenspace; NDVI = Normalised Difference Vegetation Index; OR = Odds Ratios; RR = Relative Risk; SES = Socioeconomic Status; SD = Standard Deviation; SMR = Standardised Mortality Ratio.

| | Asthma | Respiratory mortality | Lung Function | Symptoms | Hospital Admissions | Rhinitis | Lung Cancer | Other |
|----------------|--------|-----------------------|---------------|----------|---------------------|----------|-------------|-------|
| NDVI/Greenness | 26 | 16 | 30 | 18 | 12 | 12 | 6 | 14 |
| Green LULC | 33 | 18 | 5 | 9 | 6 | 8 | 12 | 19 |
| Tree cover | 8 | 1 | 0 | 5 | 7 | 1 | 2 | 8 |
| Biodiversity | 2 | 0 | 0 | 0 | 3 | 0 | 0 | 6 |
| Gardens | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |

Fig. 2. A heat map of the frequencies of different exposure-health associations investigated in the identified studies (n = 290).

we implemented a publication year cut-off of 2000, it was not likely that this resulted in the exclusion of any eligible papers, as the earliest identified study in our review was published in 2007. The broad focus of the review constrained the detail into which we could address and explore a given mechanism of specific exposure-health associations. The application and comparability of the risk of bias assessment was hindered by the varied range of methods, exposures, and health outcomes; some study biases may have been more problematic for certain study designs, but were not assigned as such as meaningful contextual information was

often omitted (e.g., completion of routine health data, blinding of study personnel) and not easily comparable. Although the main focus of our review was exposure to urban greenspace, several of the studies examined and combined risk estimates representing both urban and rural areas; to be inclusive, we incorporated these studies, though it was not possible to parse out the results pertaining specifically to the urban populations.

4.9. Recommendations for future research

To provide the most value, future observational studies examining health should attempt to isolate specific mechanisms of action through, for example, mediation analyses (James et al., 2016; Vienneau et al., 2017), and focus on exposure-health pathways with inconsistent evidence (e.g., childhood asthma and surrounding land use). The measurement of species presence, and adoption of other more specific metrics of vegetation/green infrastructure, might help explain contrasting findings. Such research can help answer the questions: What are the beneficial/harmful components of different types of greenspace and how can they be magnified/mitigated? Studies of diverse individuals in less studied regions (e.g., low and middle income countries [LMICs]) should be prioritised, complete with subgroup analyses. Longitudinal studies with dynamic greenspace exposure metrics would be useful to explore critical windows (e.g., Cherrie et al., 2018), as well as the use of other methods to address self-selection biases (Mokhtarian and Cao, 2008). Interpretation of experimental studies would be improved with better characterisation of

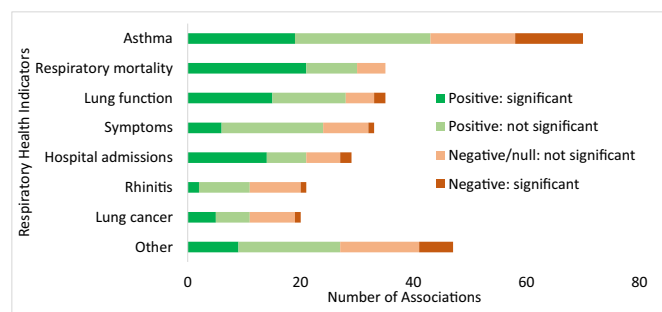


Fig. 3. The number of associations suggesting significant positive (i.e., better health), significant negative (i.e., poorer health), non-significant positive or non-significant negative/null associations for a given health indicator and greenspace exposure (n = 290).

Table 11
A summary of the quality and strength assessments.

| Health outcome | Quality criteria | | | | | | | | Overall quality | Strength |
|-----------------------|------------------|--------------|---------------|-------------|------------------|--------------|---------------|-------------|-----------------|------------|
| | Risk of bias | Indirectness | Inconsistency | Imprecision | Publication bias | Large effect | Dose-response | Confounding | | |
| Respiratory mortality | 0 | 0 | 0 | 0 | 0 | 0 | +1 | 0 | Moderate | Limited |
| Hospital admissions | -1 | 0 | -1 | 0 | 0 | 0 | 0 | 0 | Low | Inadequate |
| Lung cancer | 0 | 0 | -1 | 0 | 0 | 0 | 0 | 0 | Low | Inadequate |
| Asthma | -1 | 0 | -1 | -1 | 0 | 0 | 0 | 0 | Low | Inadequate |
| Lung function | 0 | 0 | -1 | -1 | 0 | 0 | 0 | 0 | Low | Inadequate |
| Respiratory symptoms | 0 | -1 | -1 | -1 | 0 | 0 | 0 | 0 | Low | Inadequate |
| Rhinitis | -1 | 0 | 0 | -1 | 0 | 0 | 0 | 0 | Low | Inadequate |

greenspaces, including natural features, subjective factors of importance (Taylor and Hochuli, 2017), and doses of exposure (e.g., Holt et al., 2019), as well as justification and characterisation of control settings. In addition, further investigation of specific pathways with greenspace (even in the absence of a health outcome) would help crystallise the most efficacious mechanisms and identify other potentially important contextual moderating factors.

4.10. Conformity with published protocol

We adhered to the methods described in the published review protocol though with minor revisions following the peer review process. We expanded the search date end from 31 December 2018 to 3 October 2021 and added an assessment of the strength and quality of studies within each major health outcome. We narrowed the scope of respiratory health outcomes by omitting ICD-10 codes C00-C14: malignant neoplasms of lip, oral cavity.

5. Conclusion

We summarised studies of urban greenspace and respiratory health and the hypothesised pathways of effect. The 108 identified studies included different greenspace exposure metrics, respiratory health outcomes, and

research methods. The most compelling evidence for a positive association related to reduced risks of respiratory mortality. The evidence is consistent with, but not conclusive of a causal association, the possible pathways of which may relate to reduced exposures to air pollution, noise and heat, more physically active local populations, reduced stress and improved immune function. The findings for other outcomes were less consistent and included studies reporting negative as well as positive associations between green space and respiratory health (e.g. higher prevalence of asthma in greener areas). The inconsistent and heterogeneous results underscore the potential importance of contextual factors, variations in greenspace metric employed, and the possible bias of subtle selection factors, all of which should be explored further in future research.

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CRediT authorship contribution statement

William Mueller: Conceptualization, Methodology, Writing – original draft. **James Milner:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Miranda Loh:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Sotiris Vardoulakis:**

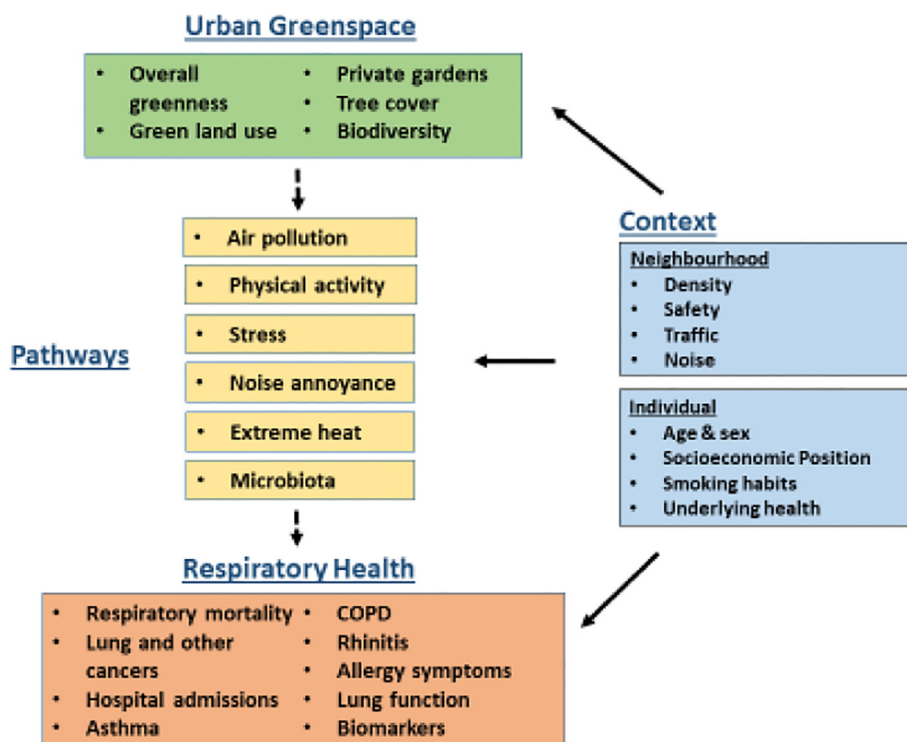


Fig. 4. A diagram of the possible pathways linking urban greenspace and respiratory health with potential neighbourhood and individual modifiers.

Conceptualization, Methodology, Supervision, Writing – review & editing.
Paul Wilkinson: Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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PART II: Results

4 Urban greenspace and indoor health

4.1 Introduction

This chapter represents the first research paper of the results section. The purpose of this paper is to explore different possible pathways to health involving the indoor home environment, namely reductions of exposures to PM_{2.5} and noise, and road noise annoyance. The analysis is based on sensor data and surveys from participants in the HEALS study. This study addresses evidence gaps by quantifying links between metrics of greenspace and specifically the indoor environment, where most people spend the majority of their time.

This chapter addresses research objectives 2 a) Quantify the association between residential metrics of urban greenspace and indoor levels of PM_{2.5} and 2 b) Quantify the association between residential metrics of urban greenspace and indoor noise levels and road noise annoyance.

This study included as a results paper in chapter 4 was accepted for publication in *Environmental Research* in October 2019. The supplementary material from this paper is included in Appendix 2.

A postscript follows the research paper, which summarises recent relevant papers relating to these particular pathways to health.

Cover sheet and research paper follow on subsequent pages.

RESEARCH PAPER COVER SHEET

Please note that a cover sheet must be completed for each research paper included within a thesis.

SECTION A – Student Details

| | | | |
|---------------------|--|-------|----|
| Student ID Number | 1800264 | Title | Mr |
| First Name(s) | William | | |
| Surname/Family Name | Mueller | | |
| Thesis Title | Potential pathways of urban greenspace to respiratory health: Air pollution and physical activity | | |
| Primary Supervisor | Prof Paul Wilkinson | | |

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

| | | | |
|--|------------------------|---|-----|
| Where was the work published? | Environmental Research | | |
| When was the work published? | 2020 | | |
| If the work was published prior to registration for your research degree, give a brief rationale for its inclusion | N/A | | |
| Have you retained the copyright for the work?* | Yes | Was the work subject to academic peer review? | Yes |

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SECTION C – Prepared for publication, but not yet published

| | |
|---|-----------------|
| Where is the work intended to be published? | |
| Please list the paper's authors in the intended authorship order: | |
| Stage of publication | Choose an item. |

SECTION D – Multi-authored work

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| <p>For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)</p> | <p>I conceived the study design, performed the analysis, wrote the first draft of the paper, and responded to reviewer comments.</p> |
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SECTION E

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| Date | 18/04/2022 |

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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 Dyllos 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} ($-1.27 \mu\text{g}/\text{m}^3$ 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 $\text{PM}_{2.5}$ 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 $\text{PM}_{2.5}$ (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 $\text{PM}_{2.5}$ 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 $\text{PM}_{2.5}$, noise, and reported road noise annoyance. A model of the examined pathways to health is presented in Fig. 1.

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

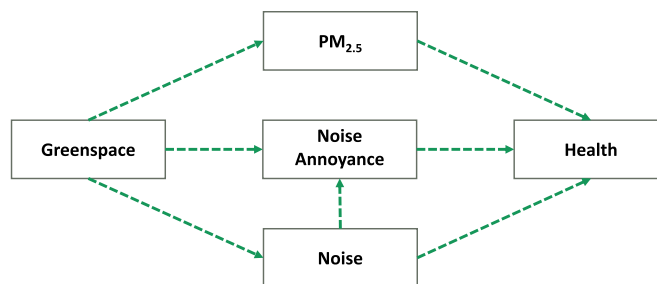


Fig. 1. The three greenspace pathways to health to be investigated.

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 Dyllos 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: NCSR 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 $+1$ $([\text{NIR} - \text{Red}]/[\text{NIR} + \text{Red}])$; (Rhow 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) Dyllos and b) Netatmo sensors used to monitor indoor $\text{PM}_{2.5}$ and noise, respectively.

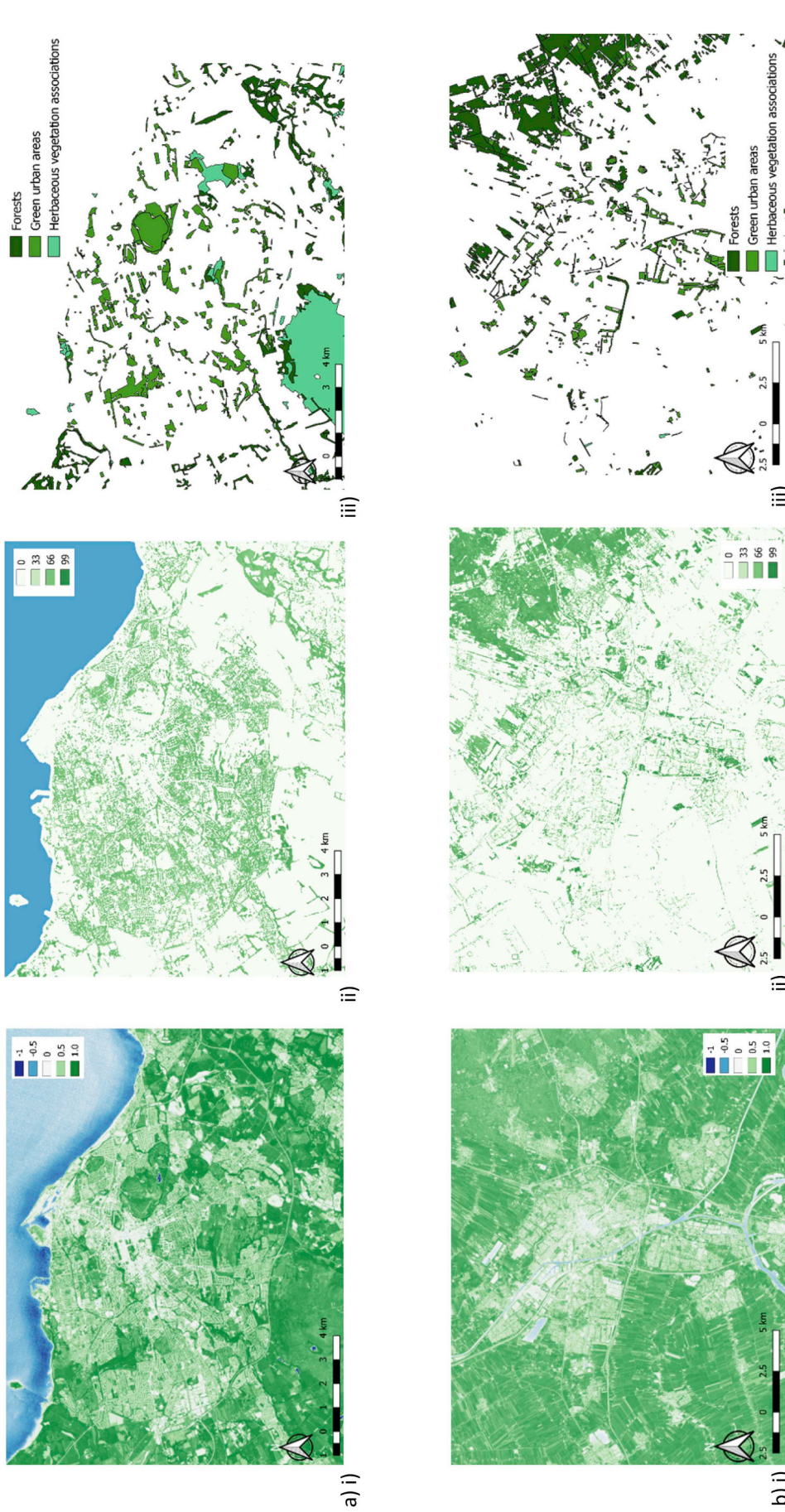


Fig. 3. a-d Maps of a) Edinburgh, UK; b) Utrecht, Netherlands; c) Thessaloniki, Greece; and d) Athens, Greece, presenting i) summer NDVI, ii) tree cover density (%), and iii) green land use. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version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

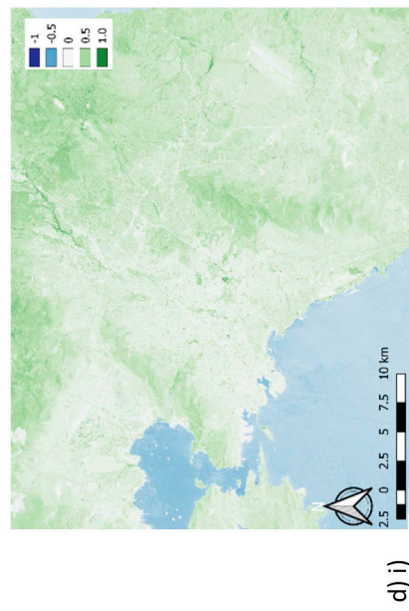
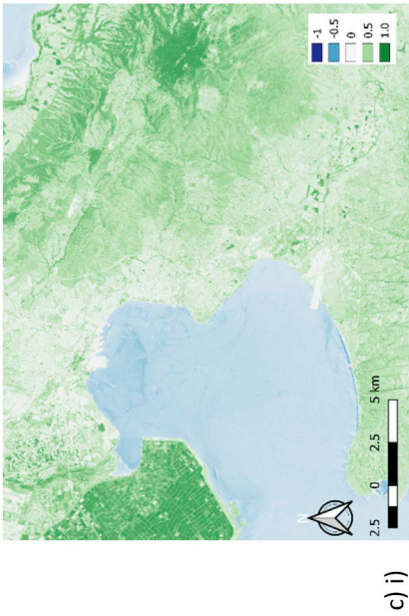
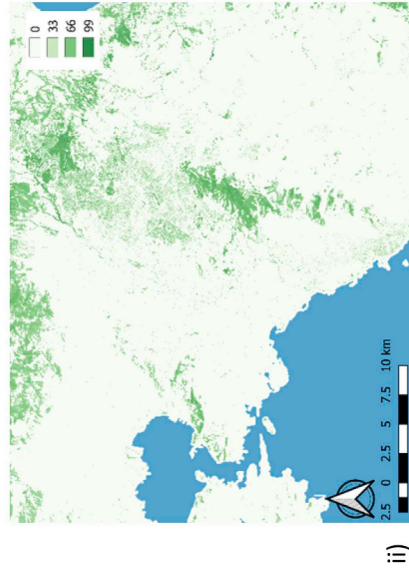
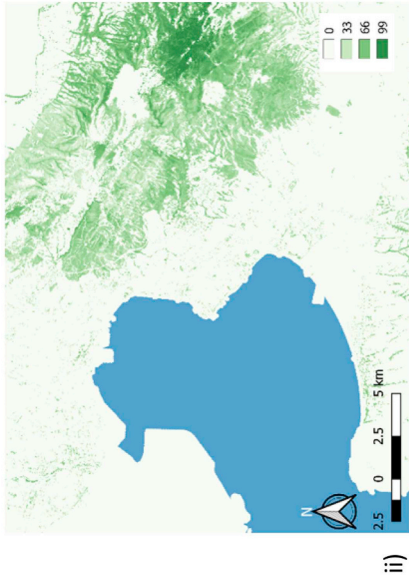
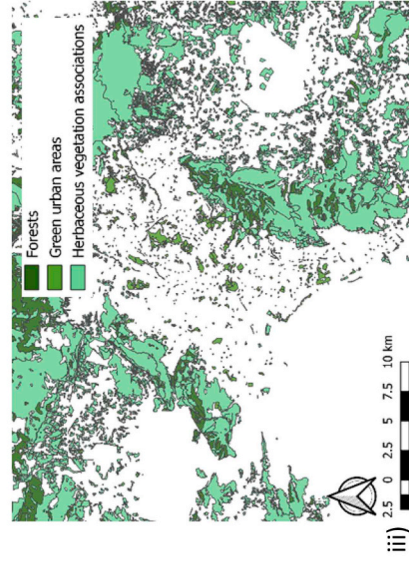
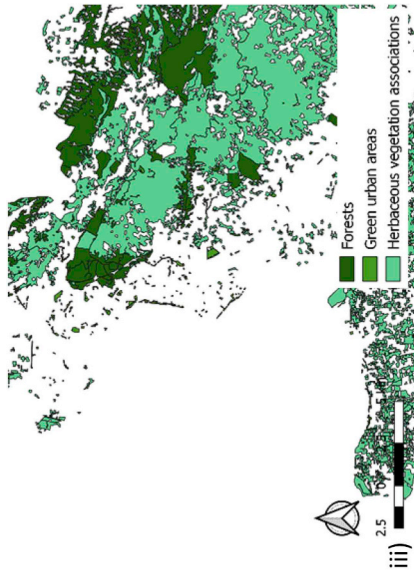


Fig. 3. (continued)

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 ($\geq 0.5 \mu\text{m}$ and $\geq 2.5 \mu\text{m}$) 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

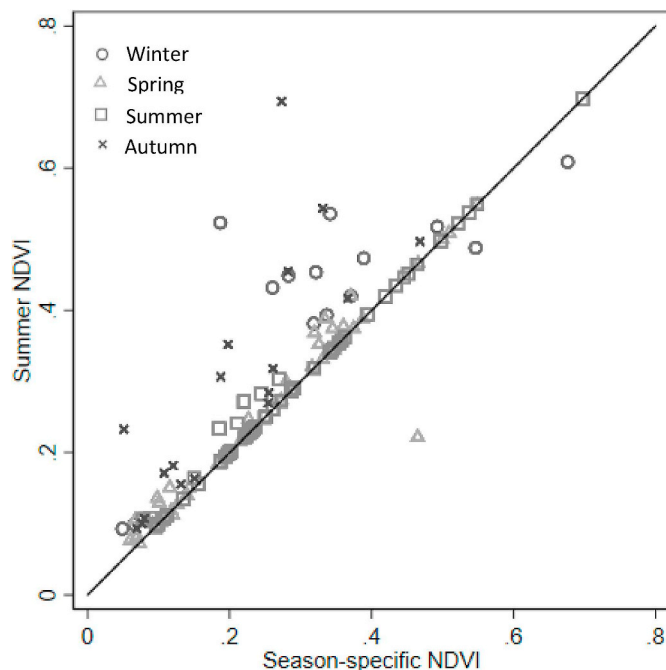


Fig. 4. A scatterplot of summer and season-specific NDVI values assigned to each residential address (100 m buffer).

completion of the HEALS fieldwork; therefore, we excluded Thessaloniki from the indoor $PM_{2.5}$ analysis.

2.2.3. Noise

The Netatmo sensors logged mean indoor decibel levels every 5 min. In addition to noise levels, the Netatmo 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 Moshhammer 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; Moshhammer 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 | 0.02 | -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 |

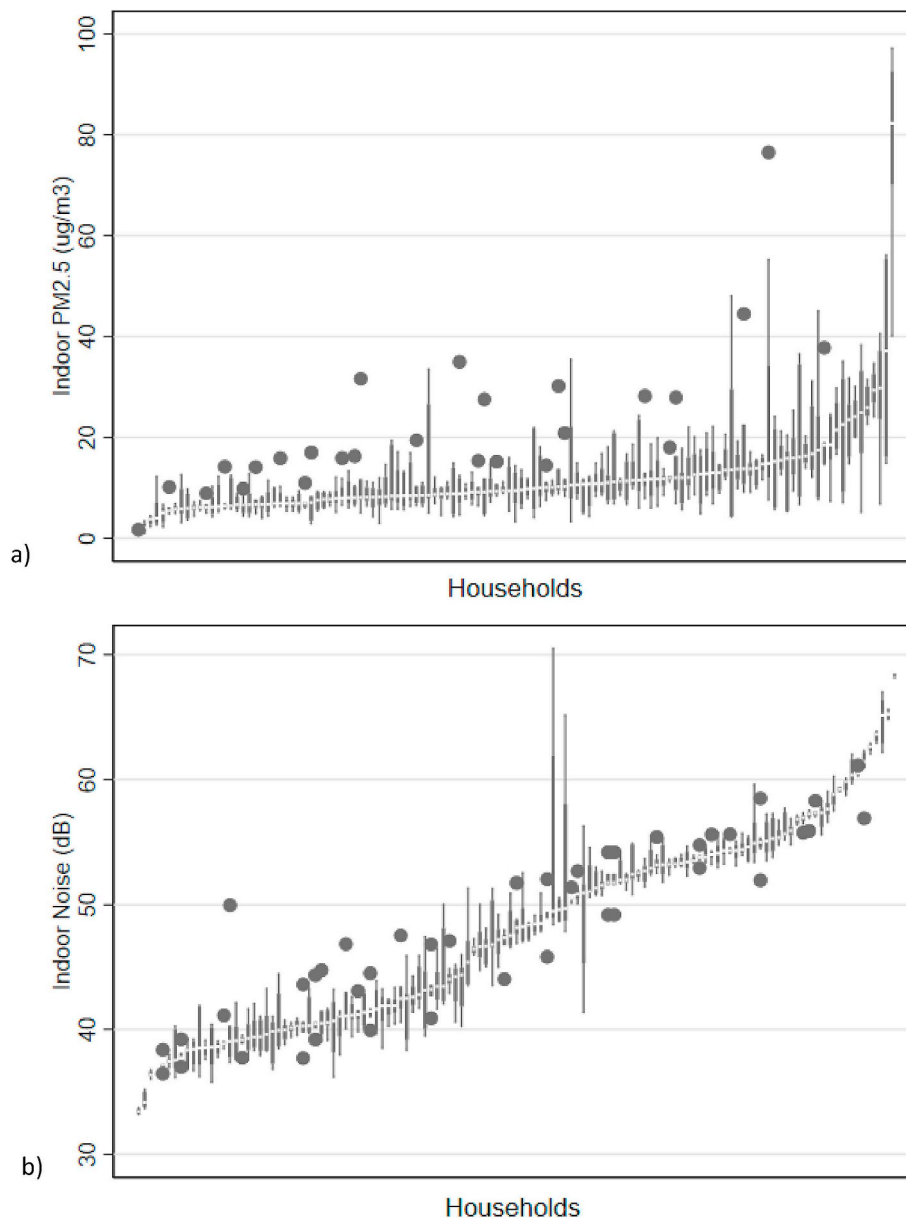


Fig. 5. Boxplots of daily means for each home address representing indoor a) $PM_{2.5}$ and b) indoor noise, presented from low to high values.

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).

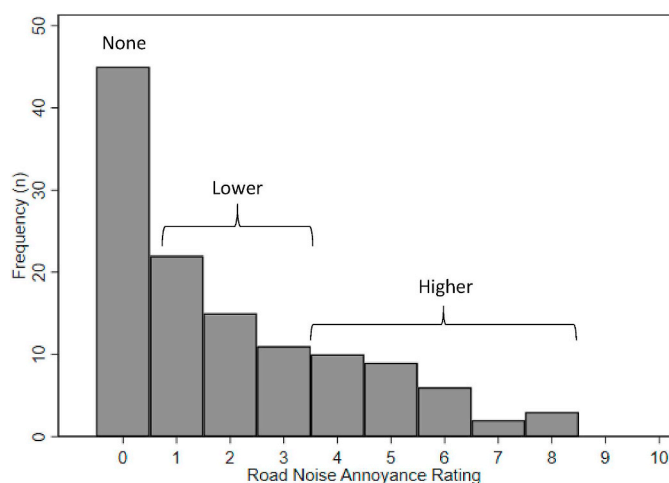


Fig. 6. A histogram of reported road noise annoyance, using an 11-point scale of 0 ('not at all annoying') to 10 ('extremely annoying') (n = 123). Categories used for analysis ('none', 'lower', 'higher') are indicated.

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).

Table 3
Random-effects generalised least squares regression output for indoor PM_{2.5} levels (µg/m³).

| 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.

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/m³ (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/m³ [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/m³), 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 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 µm 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 (Bloemsa 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.

Funding

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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: NCSR 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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4.4 Postscript to research paper

Several relevant studies have been published since acceptance of this research paper in October 2019. While no papers were identified that examined relationships between outdoor greenspace and indoor levels of PM_{2.5}, several studies investigated the perceived levels of anthropogenic noise associated with visual greenspace, including a systematic review, and another studied the physical buffering of noise sources by vegetation.

Schäffer et al. (2020) analysed noise annoyance data from a stratified random sample of the Swiss population with different noise sources (i.e., road, railway, aircraft) and also metrics of greenspace (i.e., vegetation, green land use, visible vegetation, and recreation areas). Similar to my results, these authors found that residential green were associated with reduced annoyance to road traffic, with the strongest associations linked to NDVI. Interestingly, these authors found visible vegetation was associated with reduced road noise annoyance in cities, where most of my study participants lived, but not in rural areas. In contrast, two laboratory-based studies did not identify consistent effects of noise annoyance reduction with greenspace. Chung et al. (2020) found images of mountain greenery had the potential to aggravate noise annoyance of a trafficked road, whereas those of 'tree-clumps' had an attenuating effect. Haapakangas et al. (2020) studied the masking effect of vegetation (broadleaf trees and shrubs) on images and soundscapes of an industrial site and did not observe any pattern of attenuating noise perceptions. These differences in results from observational and experimental study designs were also noted in a systematic review examining greenery and noise annoyance, which authors hypothesised may be due to short-term vs long-term exposures (Hasegawa & Lau, 2021). A study examining greenspace and traffic noise levels in Sydney, Australia calculated a weak negative correlation between a green view index of trees generated from Google Street view images and traffic noise data from crowd-sourced mobile phone data (calibrated with traffic data), suggesting lower noise levels with higher values of the green view index (Nourmohammadi et al., 2021). Although these findings are heterogeneous, they do suggest that, in line with my results, greenspace metrics may be associated with reduced road noise annoyance, but the greenspace

exposure, context, and type of noise all may influence the strength and even direction (as indicated in one of the laboratory studies) of association. None of these studies sufficiently distinguishes between the role of greenspace to attenuate noise annoyance by visual distraction and/or physical dampening of the noise source.

4.5 References

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Haapakangas, A., Hongisto, V. and Oliva, D., 2020. Audio-visual interaction in perception of industrial plants—Effects of sound level and the degree of visual masking by vegetation. *Applied Acoustics*, 160, p.107121.

Hasegawa, Y. and Lau, S.K., 2021. Audiovisual Bimodal and Interactive Effects for Soundscape Design of the Indoor Environments: A Systematic Review. *Sustainability*, 13(1), p.339.

Nourmohammadi, Z., Lilasathapornkit, T., Ashfaq, M., Gu, Z. and Saberi, M., 2021. Mapping urban environmental performance with emerging data sources: a case of urban greenery and traffic noise in Sydney, Australia. *Sustainability*, 13(2), p.605.

Schäffer, B., Brink, M., Schlatter, F., Vienneau, D. and Wunderli, J.M., 2020. Residential green is associated with reduced annoyance to road traffic and railway noise but increased annoyance to aircraft noise exposure. *Environment International*, 143, p.105885.

5 Urban greenspace and physical activity levels

5.1 Introduction

This next chapter of the results section includes a research paper investigating greenspace exposure and physical activity levels, also using data from the HEALS study. The paper includes two different analyses to provide complementary perspectives, namely greenspace levels in the residential environment and greenspace levels in those environments where participants engage in exercise (in this case, specifically walking and cycling). The main objective of this study was to use objective markers of both greenspace and physical activity to compare the importance of association between different environments (i.e., residential address and physical activity spaces).

This chapter addresses research objectives 3 a) Quantify the association between residential metrics of urban greenspace and moderate to vigorous physical activity (MVPA) as an objective PA metric, and b) Quantify the association between greenspace during bouts of physical activity and Metabolic Equivalent Tasks (METs).

This study included as the second results paper in chapter 4 was accepted for publication in *BMC Public Health* in January 2021. The supplementary material from this paper is included in Appendix 3.

A postscript follows the research paper, which summarises recent relevant papers relating to greenspace and objective physical activity.

Cover sheet and research paper follow on subsequent pages.

RESEARCH PAPER COVER SHEET

Please note that a cover sheet must be completed for each research paper included within a thesis.

SECTION A – Student Details

| | | | |
|---------------------|--|-------|----|
| Student ID Number | 1800264 | Title | Mr |
| First Name(s) | William | | |
| Surname/Family Name | Mueller | | |
| Thesis Title | Potential pathways of urban greenspace to respiratory health: Air pollution and physical activity | | |
| Primary Supervisor | Prof Paul Wilkinson | | |

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

| | | | |
|--|-------------------|---|-----|
| Where was the work published? | BMC Public Health | | |
| When was the work published? | 2021 | | |
| If the work was published prior to registration for your research degree, give a brief rationale for its inclusion | N/A | | |
| Have you retained the copyright for the work?* | Yes | Was the work subject to academic peer review? | Yes |

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SECTION C – Prepared for publication, but not yet published

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| Stage of publication | Choose an item. |

SECTION D – Multi-authored work

| | |
|---|--|
| <p>For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)</p> | <p>I conceived the study design, performed the analysis, wrote the first draft of the paper, and responded to reviewer comments.</p> |
|---|--|

SECTION E

| | |
|--------------------------|-----------------|
| Student Signature | William Mueller |
| Date | 18/04/2022 |


| | |
|-----------------------------|----------------|
| Supervisor Signature | Paul Wilkinson |
| Date | 12/07/2022 |

RESEARCH ARTICLE

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Neighbourhood and path-based greenspace in three European countries: associations with objective physical activity

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Abstract

Background: Greenspace has been associated with health benefits in many contexts. An important pathway may be through outdoor physical activity. We use a novel approach to examine the link between greenspace microenvironments and outdoor physical activity levels in the HEALS study conducted in Edinburgh (UK), the Netherlands, and Athens and Thessaloniki (Greece).

Methods: Using physical activity tracker recordings, 118 HEALS participants with young children were classified with regard to daily minutes of moderate to vigorous physical activity (MVPA); 60 were classified with regard to the metabolic equivalent task (MET)-minutes for each of the 1014 active trips they made. Greenspace indicators were generated for Normalised Difference Vegetation Index (NDVI), tree cover density (TCD), and green land use (GLU). We employed linear mixed-effects models to analyse (1) daily MVPA in relation to greenspace within 300 m and 1000 m of residential addresses and (2) trip MET-minutes in relation to average greenspace within a 50 m buffer of walking/cycling routes. Models were adjusted for activity, walkability, bluespace, age, sex, car ownership, dog ownership, season, weekday/weekend day, and local meteorology.

Results: There was no clear association between MVPA-minutes and any residential greenspace measure. For example, in fully adjusted models, a 10 percentage point increase in NDVI within 300 m of home was associated with a daily increase of 1.14 (95% CI – 0.41 to 2.70) minutes of MVPA. However, we did find evidence to indicate greenspace markers were positively linked to intensity and duration of activity: in fully adjusted models, 10 percentage point increases in trip NDVI, TCD, and GLU were associated with increases of 10.4 (95% CI: 4.43 to 16.4), 10.6 (95% CI: 4.96 to 16.3), and 3.36 (95% CI: 0.00 to 6.72) MET-minutes, respectively. The magnitude of associations with greenspace tended to be greater for cycling.

Conclusions: More strenuous or longer walking and cycling trips occurred in environments with more greenspace, but levels of residential greenspace did not have a clear link with outdoor MVPA. To build on our research, we suggest future work examine larger, more diverse populations and investigate the influence of greenspace for trip purpose and route preference.

Keywords: Greenspace, Physical activity, Exposure, Walking, Cycling

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Background

Increased residential greenspace (e.g., parks) or greenness (e.g., street trees) has shown to be associated with beneficial health, such as better self-reported health and reduced all-cause and cardiovascular mortality [55]. Research has now progressed to explore potential causal mechanisms. As strong links have been made between physical activity (PA) and numerous health outcomes, particularly for cardiovascular outcomes [59], an important pathway to health may be access to areas in which to engage in PA. Moreover, though still an active research area, exercise specifically undertaken in green areas may enhance the proven benefits of PA [46].

Nevertheless, research on the importance of greenspace for exercise has produced mixed results. Cross-sectional studies relying on self-reported data to assess the relationship between residential greenspace and PA identified positive associations in populations in Australia [2], Canada [35], and the US [52], while other work in Denmark [44], Netherlands [33], and Scotland [37] found no such links. With the emergence of low-cost GPS-equipped sensors and devices [32], researchers can now better track objective measures of PA and actual greenspace use, though these studies too have found equivocal results: the amount of residential greenspace was related to higher levels of overall moderate to vigorous PA (MVPA) [23], but in another study, associations were found only with PA when undertaken within green areas (i.e., not overall PA) [53].

Recommendations from agencies, including the World Health Organization (WHO), prescribe a minimum weekly dose of 150 min of moderate intensity or 75 min of vigorous PA, yet a recent global survey found over a quarter of individuals were not achieving these salubrious levels [18]. Though greenspace may help promote active travel and facilitate outdoor PA, for example, through appealing tree-lined streets or accessible parks, other neighbourhood attributes, such as overall walkability (e.g., street connectivity, population density, mixed use development) and access to services, have been found to be more important [14, 22]. Even if a positive link with greenspace is established, a further complicating factor is that self-selection may bias findings if healthier individuals choose to live in greener areas with more options for outdoor exercise [10]; if present, this bias would result in exaggerated health benefits of greenspace.

Our study explored two distinct research questions to advance our understanding of the association of greenspace and PA within the built environment: 1) whether the availability of residential greenspace is associated with increased MVPA and 2) whether individuals choose routes with on average higher greenspace levels for longer/more active journeys. In addition, for the second question, we also assessed the greenspace associations separately for walking and cycling trips.

Methods

Study design and population

Data were obtained from the EU-funded study, Health and Environment-wide Associations based on Large population Surveys (HEALS; <http://www.heals-eu.eu>), which employed indoor and personal sensors to characterise the environments of families with young children. The study included a sample of households concentrated in Edinburgh, UK; Utrecht and elsewhere in the Netherlands; and Thessaloniki and Athens, Greece. Individuals aged 18 years or older with a young child (< 3 years of age) were eligible to participate in the HEALS study ($n = 131$) and were recruited through advertising via universities, childcare groups, and word of mouth. Informed written consent was provided by all participants. Personal monitoring periods lasted approximately 1 week during 2015 and 2016 and entailed indoor monitoring of air pollutants and noise and the participant wearing a physical activity tracker device. Questionnaires were developed in the HEALS study to gather household data, including socioeconomic position (SEP) (see [supplementary material](#)).

Greenspace

We assigned three indicators of urban greenspace: the Normalised Difference Vegetation Index (NDVI), tree cover density (TCD), and green land use (GLU), similar to a previous analysis using the HEALS dataset published by the authors [36]. Each indicator provides potentially overlapping, but distinct, perspectives of greenspace: NDVI (− 1 to + 1) represents the overall greenness of a given area, TCD provides the percentage (0–100%) of an area covered by the canopy of trees as visible from satellites, and GLU indicates areas used for specific types of green land (parks, forests, sports pitches, etc.) (see Fig. 1).

For each study area, NDVI values were calculated using Sentinel-2 satellite images available from the Copernicus Open Access Hub at 10-m spatial and five-day temporal resolutions. NDVI raster data with values of < − 0.1 represent water or ice and were excluded from greenness calculations [15]. Images from summer with cloud coverage of < 10% were selected to maximise spatial contrasts of greenness. Images produced within 1 year of the personal monitoring periods were retrieved, except for those in and around Edinburgh, due to cloud coverage (See Table S1 for exact image dates). Average annual TCD based on Sentinel-2 and Landsat 8 satellite images (20 m spatial resolution) for Europe in 2015 was also obtained from the Copernicus Hub. Coastal waters were excluded in the calculation of TCD values. GLU was based on CORINE land use data (2012), which has been refined subsequently through data fusion with other spatial datasets (e.g., Urban Atlas, OpenStreet Map) and is publicly available as a 100 m raster dataset

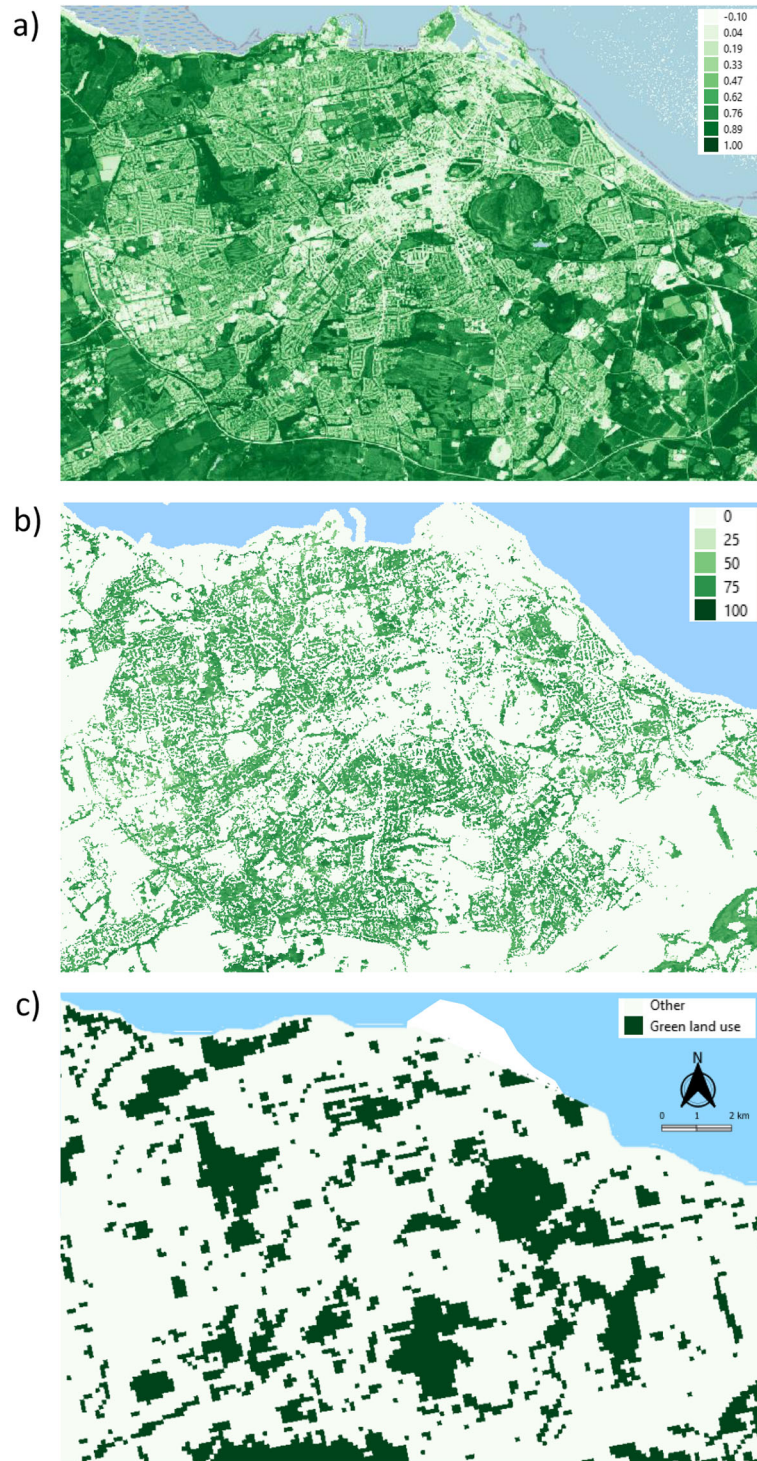


Fig. 1 Maps of Edinburgh, UK to illustrate **a** Normalised Difference Vegetation Index (−0.1 to 1.0), **b** tree cover density (0–100%), and **c** green land use. Basemap from©OpenStreetMap contributors (www.openstreetmap.org), available under the Open Database License

[40]. Unlike the original CORINE dataset, this enhanced version distinguishes between green and non-green sport and leisure facilities. The following categories were combined to create a GLU map: green urban areas, green

sport and leisure facilities, broad-leaved forest, coniferous forest, mixed forest, natural grasslands, moors and heathland, sclerophyllous vegetation, and transitional woodland-shrub. Mean values of NDVI and TCD, and

the proportion of GLU, were calculated in 300 m and 1000 m radial buffers around home addresses. These sizes were selected to represent a reasonable walking distance to greenspace (300 m; [56]) and to reflect a larger, neighbourhood scale (1000 m; [3]). Additional details of the methods for each indicator can be found in Mueller et al. [36].

Physical activity

During the personal monitoring periods, study participants wore a Fitbit flex device (original version) on their wrist (Fitbit Inc., San Francisco, CA, USA) [12] and installed the 'Moves' app (moves-app.com) [13] on their mobile phones; participants were asked to keep their Fitbit and phone with them whenever possible. Fitbits recorded the total number of steps completed each minute and the Moves app recorded GPS locations and the duration, distance, and activity (i.e., walking, running, cycling, vehicle transport) based on its algorithm to identify discrete trips. The Fitbit flex has been found to reliably record steps compared to gold standards (Optogait system and ActivePAL device) [28], and the Moves app can correctly record the location and type of separate trips [4, 47].

To take advantage of both the physical activity sensor and mobile phone app deployed in the HEALS study, we derived two PA metrics that made use of the particular data provided by each sensor: daily minutes of MVPA steps (Fitbit) and Metabolic Equivalent Task minutes (MET-minutes) (Moves app); METs represent the energy cost of an activity relative to a resting state [1]. Daily steps were calculated by summing minutes with ≥ 100 steps as recorded by the Fitbit flex (equivalent to ≥ 3 METs) [41] across the monitoring period. These daily values were then divided by the number of days with at least 12 h of data (i.e., 75% complete data, assuming 8 h of sleep), where at least four such days had been recorded during the monitoring period. Out of 133 individuals who were provided Fitbits (some households had multiple participants), 124 (93%) provided sufficient data for analysis.

MET-minutes were calculated by assigning a specific MET to those trips identified by the Moves app to be 'walking', 'running', or 'cycling', depending on the activity; average speed (based on distance and duration, as recorded by Moves); and overall grade change (steepness) during each trip using values set out in Ainsworth et al. [1]. To account for steepness in the calculation of METs, topographical GIS maps (30 m resolution) were acquired from the Japan Aerospace Exploration Agency, based on the Advanced Land Observing Satellite (ALOS-2; [50]). Where no METs were specified by Ainsworth et al. [1] for a given combination of activity/speed/grade, values were interpolated or extrapolated ($n = 3$) (see Table S2 for a complete list of METs used in analysis). METs

were multiplied by the duration of each trip to calculate MET-minutes. GPS points were converted to lines in QGIS v.3.10.1 [39] and visual inspection was used to remove trips either with straight lines that did not appear to follow road networks or that traversed bodies of water ($n = 16$). Only six trips were assigned as 'running,' which were subsequently excluded from analysis. Values above five standard deviations (SD) in excess of the mean were excluded for MET-minutes ($n = 7$) and duration ($n = 2$). To select trips that occurred outdoors, those of < 3 min in duration or < 100 m in distance were excluded from analysis. As with the daily steps calculation, Moves data were used only from individuals with at least 18 h (i.e., 75%) of complete data on four or more days during the monitoring period. Out of 123 individuals who downloaded Moves onto their phones, 69 (56%) provided sufficient data for analysis. Since few ($n = 4$) participants in Thessaloniki generated sufficient Moves data, this study centre was excluded from the trip-based analysis.

Walkability

As certain features of the built environment may be more likely to encourage physical activity [14], we calculated walk scores to capture the degree of walkability of residential and travel environments. Similar to previous studies (e.g., [19, 22, 57]), walk scores were calculated based on GIS data using three factors: population density, intersection counts, and land use mix. As well as walking, these same built environment factors may also encourage cycling [26]. Population density was based on global 1×1 km gridded estimates for 2015 [7]. Intersection counts were calculated using QGIS via road networks from OpenStreetMap shapefiles downloaded during March–April 2019 from Geofabrik (<https://download.geofabrik.de/>). Auto-oriented (i.e., non-pedestrian accessible) roads were removed by deleting feature classes for 'motorway', 'service', or 'trunk', and the processing tool in QGIS, 'v.clean', was employed to identify intersections of two or more distinct roads. Land use mix was based on the refined CORINE dataset, including 'commercial/service facilities', 'public facilities', and 'sport and leisure green/built-up'. Z-scores of each walk score (i.e., mean population density, total intersection counts, and presence of specific land uses) were calculated across all home addresses for the 300 m and 1000 m buffers and were summed to create a walk score. Walk scores calculated separately within and across study areas were highly correlated for both 300 m ($r = 0.88$) and 1000 m ($r = 0.91$) buffers; the latter metric was used for analysis.

To examine the association of greenspace and MET-minutes between different trips taken by the same individual, linear buffers of 50 m were generated for each trip for which mean values of NDVI and TCD, as well as

the proportion of GLU, were calculated; a smaller buffer size has been shown to be most strongly associated with MVPA [21]. To account for different trip distances, the number of intersections within each trip buffer was divided by the total distance, which was then used to calculate walk scores in a similar fashion as described above.

Other covariates

As well as walkability, we adjusted for bluespace, daily meteorology, and season as other environmental factors. We accounted for bluespace by identifying any bodies of water in residential and trip buffers, as bluespace has been shown to be positively correlated with physical activity, especially walking [16, 38]. We included in our definition of bluespace the following CORINE land cover types: ‘water courses’, ‘water bodies’, ‘coastal lagoons’, ‘estuaries’, and ‘sea and ocean’. We obtained for the dates of the personal monitoring periods weather data, including daily maximum temperature and wind speed, and total precipitation from the US National Centers for Environmental Information [27] from the following stations (latitude, longitude): Edinburgh Royal Botanic Garden (55.967, -3.210); Schiphol, Netherlands (52.316, 4.790); and Hellinikon, Greece (37.900, 23.750). Season was assigned to each monitoring period based on the majority of dates that occurred in a given season. As noted above, during the monitoring periods, participants also completed questionnaires on SEP and other information, including employment status (e.g., working, in school, caring for family), highest education completed, car ownership, and household pets.

Statistical analysis

We used mixed regression methods to examine associations between greenspace and physical activity metrics. Each greenspace metric (mean NDVI score, mean TCD, and proportion of GLU,) was rescaled such that regression coefficients represented the change in outcome for a 10 percentage point increase in the relevant parameter, an approach adopted by Mueller et al. [36].

Models were developed to assess:

- (i) the *between-individuals* association of MVPA with residential greenspace (seeking to answer the question of whether people living in greener areas have higher levels of MVPA),

and

- (ii) the association, *within individuals*, of MET-minutes with trip-based greenspace (seeking to answer the question of whether longer/more active journeys

are undertaken in areas with more greenspace compared with shorter/less active journeys).

For (i), with daily MVPA-minutes as the outcome, regression models with a random intercept for study centre were separately developed for residential greenspace metric at 300 m and 1000 m buffers around the home. Model results are presented with various levels of pre-specified confounder adjustment: (1) an unadjusted model, (2) a model adjusted for age using cubic splines with three knots, sex, season, and bluespace (any), and (3) a model with additional adjustment for car ownership, dog ownership, walk score, education, and employment.

For (ii), regression models with random intercepts for both study centre and individual and robust standard errors were separately developed for each of the three greenspace metrics: NDVI, TCD, and GLU. Results are again presented with adjustment for different sets of pre-specified confounders: (1) an unadjusted model, (2) a model with adjustment for age, sex, season, and bluespace (any), and (3) a model with additional adjustments for education, employment status, walk score, day of week, weather conditions on the day of activity, mean residential greenspace (1000 m buffer), car ownership, and dog ownership. Effect modification by activity (i.e., walking and cycling) was examined by including in the models an interaction term between greenspace metric and activity. Cubic splines were included into the model for age and temperature. Geospatial analysis was performed using QGIS and statistical analysis was undertaken using Stata v15 [48].

Results

A total of 131 households enrolled in the HEALS study across the four study centres, with personal monitoring periods spanning from March 2015 to June 2016. There were 118 and 60 individuals who provided sufficient data and for whom covariate data were available in the neighbourhood and trip-based greenspace analyses, respectively. Descriptive characteristics pertaining to those individuals are presented in Table 1. The mean duration of MVPA-minutes was just under 12 min per day, with a maximum of nearly 40 min. The number of trips recorded for each participant ranged from one to 96, with a mean of 30.3 (SD = 23.8); the mean trip duration was just over 9 min. There was a total of 1014 trips, of which 676 (66.7%) were walking and 338 (33.3%) cycling; 89.9% ($n = 304$) of the cycling trips were in the Netherlands. The mean METs for each trip was 3.8; when accounting for duration, mean MET-minutes equated to 37.0.

Mean residential greenspace values were slightly higher for the 1000 m compared to the 300 m buffer (Table 1). The average trip-based NDVI was 0.27, with minimum and maximum values of -0.04 and 0.83,

Table 1 Descriptive characteristics of the study participants

| Characteristics | Mean (SD) or N (%) | |
|---------------------------|------------------------------------|--------------------------------|
| | Neighbourhood Greenspace (n = 118) | Trip-based Greenspace (n = 60) |
| Age (years) | 35.0 (5.1) | 34.8 (4.0) |
| Sex | | |
| Male | 43 (36.4%) | 20 (33.3%) |
| Female | 75 (63.6%) | 40 (66.7%) |
| Daily MVPA-minutes | 11.9 (9.8) | – |
| METs | – | 3.8 (1.3) |
| MET-minutes | – | 37.0 (39.0) |
| Duration (minutes) | – | 9.3 (7.7) |
| Valid data days | – | 6.5 (2.9) |
| Walk score | | |
| 300 m residential | –0.02 (2.31) | |
| 1000 m residential | –0.04 (2.34) | |
| 50 m trip-based | | 0.02 (1.86) |
| Study Centre Participants | | |
| Athens | 25 (21.2%) | 20 (33.3%) |
| Edinburgh | 26 (22.0%) | 11 (18.3%) |
| Thessaloniki | 23 (19.5%) | 0 (0.0%) |
| Utrecht | 44 (37.3%) | 29 (48.3%) |
| Car owner | 104 (88.1%) | 58 (96.7%) |
| Dog owner | 5 (4.2%) | 4 (6.7%) |
| Season monitored | | |
| Winter | 13 (11.0%) | 4 (6.4%) |
| Spring | 39 (33.1%) | 15 (23.8%) |
| Summer | 49 (41.5%) | 35 (55.6%) |
| Autumn | 17 (14.4%) | 9 (14.3%) |
| University educated | 88 (74.6%) | 54 (90.0%) |
| Employed | 93 (78.8%) | 52 (86.7%) |
| Any bluespace | 13 (11.0%) | 19 (31.7%) |
| NDVI (–0.1 to 1.0) | | |
| 300 m residential | 0.31 (0.16) | |
| 1000 m residential | 0.35 (0.18) | |
| 50 m trip-based | – | 0.27 (0.15) |
| TCD (Percentage) | | |
| 300 m residential | 10.5 (10.4) | |
| 1000 m residential | 11.7 (11.2) | |
| 50 m trip-based | – | 9.2 (10.6) |
| GLU (Proportion) | | |
| 300 m residential | 0.07 (0.11) | |
| 1000 m residential | 0.13 (0.13) | |
| 50 m trip-based | – | 0.08 (0.16) |
| Meteorological factors | | |
| Temperature (°C) | – | 22.1 (6.6) |
| Days with rain | – | 2.0 (4.5) |
| Wind speed (knots) | – | 13.5 (5.7) |

respectively. Trip-based TCD levels ranged from 0 to 73.5%, with 85.5% ($n = 864$) of trips containing tree cover. The percentage of trips with any GLU was 31.2% ($n = 316$), with three (0.3%) trips occurring entirely in places of GLU. The greenspace metrics were weakly to moderately correlated, with NDVI and TCD consistently having the strongest associations. Greenspace metrics were mostly negatively correlated with walk score. There was little apparent correlation between residential greenspace metrics and daily MVPA-minutes. By contrast, trip-based greenspace was moderately correlated with MET-minutes, with coefficient values ranging from 0.44 (GLU) to 0.59 (TCD) (Table 2).

The analysis of residential greenspace and MVPA-minutes did not provide clear evidence of associations with greenspace at either the 300 m or 1000 m buffers (Table 3). Coefficients of the increase in MVPA were generally small, and confidence intervals included 0 in fully adjusted models for all greenspace metrics (Table 3). Of the covariates, only walk score in the NDVI model (300 m buffer) showed a clear positive trend (1.13 MVPA-minutes [95% CI: 0.03 to 2.23]) per 1-unit increase in walk scores in fully adjusted models (data not shown).

All average trip-based greenspace coefficients were positively associated with MET-minutes in the unadjusted and adjusted models. NDVI and TCD were most strongly related to MET-minutes, compared to GLU, with very similar coefficient values (10.41 [95% CI: 4.43 to 16.39] and 10.63 [95% CI: 4.96 to 16.30] additional MET-minutes per 10 percentage point increase, respectively). Although less precise, estimates of the absolute increase in MET-minutes for cycling trips were consistently higher than those for walking (Table 4). Select environmental covariates also were positively linked with MET-minutes across the greenspace models, particularly walk score and the presence of bluespace (data not shown).

Discussion

Proximity to greenspace, typically in a residential setting, has been associated with a host of positive health outcomes. In this study, we used objective indicators to explore greenspace and outdoor PA as a potential underlying mechanism for health. We found no evidence to suggest individuals who lived in greener neighbourhoods engaged in greater levels of MVPA than those residing in less green areas. On the other hand, we found strong support that individuals choose greener settings for physically active travel of higher intensity and/or longer duration.

Residential greenspace

We found no clear evidence that the amount of greenspace around the home was associated with overall

MVPA. A similar finding has been reported in some studies [53, 54] but not in others [23, 43], with some of the earlier work examining comparable residential greenspace metrics and objective PA, the majority of which examined GLU as the exposure of interest. The number of parks within a 1 km residential buffer, but not the residential distance to the nearest park, was associated with objective MVPA in a group of US adults [42]. Likewise, the number of parks within 500 m and 1 km buffers was also found to be the strongest indicator for MVPA minutes in an eight-country study; park area within those same buffer sizes (a metric similar to the GLU metric in the current study) did not indicate a correlation with PA [45]. Sallis et al. [43] also found parks within 500 m of residential addresses to be positively associated with objective MVPA, after adjusting for walkability features (also significant), in a large sample of individuals from 10 countries. A study examining GLU (i.e., parks and other green land uses) and objective MVPA in Dutch adults aged 45–65 years found positive results, but only with smaller buffers (25–400 m) [23]. Triguero-Mas et al. [53] found overall MVPA activity was not associated with GLU situated within 300 m of home addresses in European adults, but was associated with contact and exercise specifically in natural outdoor environments; researchers did not account for walkability. We identified only one previous study that examined residential NDVI, which found no statistical links with overall objectively measured MVPA, and an inverse relationship with MVPA within a 1 km home buffer, in a sample of adult trail users in the US, [54]. We are unaware of any previous studies that compare the amount of residential tree canopy to objective measures of PA.

While some studies have found positive correlations between residential greenspace and objective MVPA, albeit mainly with the number of nearby parks, the existing evidence is neither consistent nor comprehensive. Our study found a mix of positive and negative greenspace effects, which may have achieved statistical significance (in either direction) with a larger sample size. Sample size notwithstanding, there are several reasons that may explain the lack of stronger findings: walkability indicators have typically been shown to be as or more important than nearby greenspace [54] (identified in the current study), the physical environment may be less important to influence exercise in parents of young children [6], PA in nearby parks has been found to constitute a small proportion of overall PA [49], and perhaps most pertinent is that MVPA may have occurred outside the 300 m and 1000 m buffers employed in the present study. Most participants in our study owned a car; Hillsdon et al. [20] found that car owners engaged in more than 60% of outdoor PA outside of the neighbourhood, as defined by an 800 m residential

Table 2 Correlation matrix for the a) 300 m and b) 1000 m residential address buffers, and c) 50 m trip-based buffer (values from -1 to +1 are presented from dark red to dark green, respectively)

| | NDVI | TCD | GLU | Any bluespace | Walk score | MVPA-minutes |
|---------------|-------|-------|-------|---------------|------------|--------------|
| NDVI | 1 | | | | | |
| TCD | 0.69 | 1 | | | | |
| GLU | 0.35 | 0.32 | 1 | | | |
| Any bluespace | -0.04 | -0.13 | -0.04 | 1 | | |
| Walk score | -0.43 | -0.14 | -0.20 | 0.25 | 1 | |
| MVPA-minutes | 0.02 | 0.01 | -0.11 | 0.01 | 0.19 | 1 |

a) 300 m

| | NDVI | TCD | GLU | Any bluespace | Walk score | MVPA-minutes |
|---------------|-------|-------|-------|---------------|------------|--------------|
| NDVI | 1 | | | | | |
| TCD | 0.42 | 1 | | | | |
| GLU | 0.17 | 0.30 | 1 | | | |
| Any bluespace | -0.01 | 0.07 | -0.23 | 1 | | |
| Walk score | -0.67 | -0.07 | -0.25 | 0.21 | 1 | |
| MVPA-minutes | -0.05 | -0.02 | -0.17 | 0.11 | 0.15 | 1 |

b) 1,000 m

| | NDVI | TCD | GLU | Any bluespace | Walk score | METs | Duration | MET-minutes |
|---------------|-------|-------|-------|---------------|------------|------|----------|-------------|
| NDVI | 1 | | | | | | | |
| TCD | 0.71 | 1 | | | | | | |
| GLU | 0.45 | 0.68 | 1 | | | | | |
| Any bluespace | 0.09 | -0.02 | -0.02 | 1 | | | | |
| Walk score | -0.44 | -0.19 | 0.14 | 0.13 | 1 | | | |
| METs | 0.43 | 0.19 | 0.02 | 0.47 | 0 | 1 | | |
| Duration | 0.55 | 0.63 | 0.47 | 0.21 | -0.07 | 0.33 | 1 | |
| MET-minutes | 0.57 | 0.59 | 0.44 | 0.33 | -0.08 | 0.53 | 0.95 | 1 |

c) 50 m

buffer. Thus, the amount of greenspace within a residential area may not be as important for people with access to a vehicle.

Path-based greenspace

In our analysis of trip-specific data, we found positive links between the amount of vegetation (NDVI) and tree coverage, and to a lesser degree GLU, with longer and more active journeys. Few studies have used a GPS approach to combine greenspace exposure with objective PA in adults, but all have found some indication of a

positive trend with PA. James et al. [22] assessed momentary exposure to NDVI, as opposed to trip-level averages as analysed in the current study, in female nurses in the US and found a positive relationship with accelerometer counts per minute, particularly when walkability was low. A study of a similar design to that of James et al. recruited trail users in the US and found NDVI to be positively associated with a higher likelihood of MVPA [51]. Houston [21] used a land cover map (including greenspace as tree canopy, irrigated grass cover, or non-irrigated grass cover/bare soil) and identified

Table 3 Regression analysis results of residential greenspace and daily minutes of moderate to vigorous intensity steps (MVPA-minutes)

| Model | Greenspace metric | Change in daily MVPA-minutes (95% CI) for a 10 percentage point increase in greenspace marker based on buffer around place of residence | |
|--|-------------------|---|------------------------|
| | | 300 m | 1000 m |
| Model 1: unadjusted | NDVI | -0.71 (-2.21 to 0.78) | -1.10 (-2.53 to 0.33) |
| | TCD | -0.42 (-2.44 to 1.61) | -0.63 (-2.44 to 1.17) |
| | GLU | -0.89 (-2.45 to 0.68) | -1.43 (-2.81 to -0.04) |
| Model 2: model 1 + adjustment for age + sex + season + bluespace | NDVI | -0.45 (-1.84 to 0.94) | -0.60 (-1.88 to 0.69) |
| | TCD | -0.13 (-2.03 to 1.77) | -0.42 (-2.09 to 1.25) |
| | GLU | -0.91 (-2.47 to 0.64) | -1.13 (-2.52 to 0.25) |
| Model 3: model 2 + adjustment for walk score + car + dog + education + employment | NDVI | 1.14 (-0.41 to 2.70) | 0.39 (-1.09 to 1.86) |
| | TCD | 0.27 (-1.73 to 2.28) | -0.59 (-2.30 to 1.12) |
| | GLU | -0.49 (-2.16 to 1.17) | -0.97 (-2.40 to 0.47) |

n = 4 study centres; *n* = 118 individuals

significant positive associations with the likelihood of adults engaging in MVPA. The amount of GLU at trip origin and end was associated with a higher probability of walking in a study in France, which found that trip-level characteristics outweighed those of the residential environment [8]. A study of adults in Barcelona that also used the Moves app found both the proportion of large parks and tree density along routes to be positively associated with walking minutes [58].

We found higher effects of greenspace on cycling compared to walking, though the former had a wider range of possible effects. Few previous studies have examined greenspace with objective adult physical activity measures of both walking and cycling. Le et al. [31] quantified the built environment surrounding bicycle and pedestrian counters in 20 US cities and found a greater positive effect on cycling than walking (though greenspace and bluespace were combined in their analysis).

Our results with objective measures support studies of self-reported cycling. Commuters in Barcelona were more likely to be cyclists with higher greenness in the study/work environment; interestingly, the greenness of the route was not significant, though commuting journeys were estimated by shortest distance rather than those actually travelled [11]. Questionnaire respondents in Stockholm reported greenery to be one of the most important factors to stimulate cycle commuting [60]. Although we looked at all active trips (i.e., not just those for commuting), our results build on this earlier research to suggest that greenness, through both overall vegetation and trees, might enhance and encourage all active transport by providing a more pleasant route.

Overall findings

We examined both residential and active transport environments, which provided an opportunity to compare

Table 4 Regression analysis results of MET-minutes with trip-based greenspace for overall and activity-specific findings

| Model | Greenspace metric | Change in MET-minutes (95% CI) per 10 percentage point increase in mean trip-greenspace (50 m buffer) | | |
|---|-------------------|---|----------------------|-----------------------|
| | | MET-minutes | | |
| | | Overall | Walking ^a | Cycling ^a |
| Model 1: unadjusted | NDVI | 7.34 (2.25 to 12.44) | 4.24 (2.57 to 5.91) | 13.65 (6.23 to 21.07) |
| | TCD | 9.16 (2.63 to 15.69) | 6.34 (3.78 to 8.91) | 23.91 (2.85 to 44.97) |
| | GLU | 3.15 (0.12 to 6.17) | 2.96 (0.60 to 5.32) | 7.29 (-2.94 to 17.53) |
| Model 2: model 1 + adjustment for age + sex + season + bluespace | NDVI | 7.20 (2.39 to 12.01) | 4.30 (2.83 to 5.77) | 13.73 (5.83 to 21.67) |
| | TCD | 8.56 (3.04 to 14.09) | 5.89 (3.91 to 7.87) | 23.32 (2.54 to 44.09) |
| | GLU | 3.18 (-0.01 to 6.37) | 2.90 (0.40 to 5.39) | 7.89 (-2.70 to 18.48) |
| Model 3: model 2 + adjustment for walk score + residential greenspace + car + dog + education + employment + weekday + weather | NDVI | 10.41 (4.43 to 16.39) | 7.81 (4.12 to 11.50) | 15.53 (8.60 to 22.45) |
| | TCD | 10.63 (4.96 to 16.30) | 8.10 (4.93 to 11.28) | 22.79 (5.24 to 40.34) |
| | GLU | 3.36 (0.00 to 6.72) | 3.29 (0.27 to 6.30) | 6.00 (-3.34 to 15.34) |

n = 3 study centres; *n* = 60 individuals; *n* = 1014 trips

^aAdjusted for interaction between greenspace and activity

and contrast these exposures using the same dataset. We found no evidence to support the residential environment being associated with objective MVPA, though our analysis was based on steps and therefore would have only pertained to walking or running. This analysis also only related to the availability of greenspace, not necessarily its use. We also examined greenspace levels of the entire route for those trips involving walking or cycling. Whereas contemporaneous momentary designs (i.e., matching exposure and PA at points in time) are more likely to reveal typical behaviours in certain settings (e.g., less PA in commercial areas and more PA in natural areas, such as greenspaces) [9], our analysis took into account average characteristics of the entire route. Therefore, our approach was more equipped to answer the question: given an individual has decided to undertake PA, how is greenspace associated with the intensity and duration of activity? In other words, how does the presence of greenspace factor in the selection of environments through which individuals choose to travel or exercise? We found clear evidence indicating both NDVI and TCD as greenspace markers were positively linked to intensity and duration of activity, while adjusting for other characteristics of the built environment. Certain such characteristics, namely walk score, were consistently related to higher levels of PA; nevertheless, the different scales of greenspace markers and walk score render it difficult to identify which is the more influential factor for PA. We also found positive links to MVPA with the proportion of GLU along a route, but not specifically for cycling trips. The use of a particular greenspace for a specific activity, namely cycling in this case, may be more dependent on certain features, including size, cycling routes, and wooded areas, which were not quantified explicitly in the overall area-based GLU metric employed in our study [44]. In addition, the GLU map we used was based on a lower spatial resolution (100 m) than the NDVI (10 m) or TCD (20 m) metrics. Therefore, the use of this coarser resolution, with greater aggregation of features and potential exclusion of smaller parks, might help explain the weaker associations we observed between GLU and PA indicators [30].

Strengths and limitations

Our study had several key strengths. We assessed the importance of both the residential and active route settings, thus developing dynamic and multi-contextual environmental exposures [29], with two objective MVPA indicators. We also used three different objective indicators to help characterise greenspace features of the built environment, with two different residential buffer sizes to help address the modifiable areal unit problem [21]. These advantages

notwithstanding, there were some limitations to our research. Although we did not explicitly address reasons for choosing residential locations, we attempted to control for self-selection in the trip-based analysis by including residential greenspace levels and found our results to be unchanged. Several greenspace and PA studies have attempted to account for self-selection by including reasons for choosing to live in their neighbourhood (e.g., access to places that support PA, access to local services). Associations with PA have persisted after adjustment for such factors [24, 34]. Therefore, it is not likely that residential self-selection would have strongly biased our results. However, it would have been beneficial for our analysis, and understanding of the importance and role of greenspace, to know the purpose(s) of each trip.

While the Moves app has been shown to accurately provide location, speed, and duration, the software has had challenges identifying multi-modal trips, which may have been included as discrete events in our analysis [4]. In addition, there was a lower proportion of participants with complete Moves data than that provided by the Fitbit; this might be due to phones running out of batteries or being switched off. Our sample size was quite modest, and our study demographic was limited to parents of young children, which could restrict the generalisability of key findings. Although Candelaria et al. [5] found little difference in the amount of objective MVPA recorded between parents of young and older children and non-parents, the mean MVPA-minutes in our sample was much lower than Candelaria et al. and in studies with other demographics [25] (~ 12 vs > 30 mins/day). If MVPA steps were underestimated in our study, any association with residential greenspace levels might have been hindered. The majority of our study sample was university educated and owned a car, indicative of a higher SEP; lower SEP individuals might experience different relationships between greenspace and MVPA [17]. As noted above, the environments of study/work may be important, but we did not have this information for all study participants. We also were not able to distinguish whether study subjects were currently working or on maternity/paternity leave. We characterised surrounding streets and intersections using maps from 2019, though personal monitoring took place over 2015–2016; therefore, some misclassification of walkability may have been introduced by any road network changes occurring in the intervening years, but it is expected that any impact on our results would have been minimal. Each subject participated in only one personal monitoring period in the HEALS study; repeating data collection with participants during different times of the year may provide insights into the role of temporal/seasonal factors of greenspace and PA.

Conclusion

We examined PA as a potential explanatory pathway for observed associations between health and greenspace, assessing both residential and trip-specific environments. We found little evidence to suggest residential greenspace was associated with higher levels of MVPA, regardless of where that may take place. On the other hand, we found clear, positive associations between intensity and duration of activities with the average amount of greenness and tree coverage along a route, which was true for both walking and even more so for cycling. We suggest future research to build on this proposed model of specific pathways by examining larger, more diverse populations, while also investigating the influence of greenspace for trip purpose and route preference.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s12889-021-10259-0>.

Additional file 1.

Abbreviations

GLU: Green land use; HEALS: Health and Environment-wide Associations based on Large population Surveys; MET: Metabolic task equivalent; MVPA: Moderate to vigorous physical activity; NDVI: Normalised Difference Vegetation Index; PA: Physical activity; SEP: Socioeconomic position; SD: Standard deviation; TCD: Tree cover density; WHO: World Health Organization

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Authors' contributions

DS and ML conceived the research; SS, EK, AP, SK, DC, TM, AS and ML collected the data; WM, PW, JM, SV, ML designed the study; LC and EP assisted with data processing; WM analysed the data; WM, PW, JM, SV, JP, EK and ML contributed to interpretation of the data; WM wrote the first draft of the manuscript; all authors edited and approved the final manuscript.

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Availability of data and materials

Access to the personal data used in this study is governed by the HEALS Data Management Plan. The environmental datasets obtained in this study are publicly available from the specific references herein. The datasets generated and/or analysed during the current study are not publicly available due to reasons of ensuring anonymity for study subjects. Specific data may be made available from the corresponding author on reasonable request.

Ethics approval and consent to participate

Ethical approval was received for each study centre (UK: Heriot Watt University Ethics Review Board 2015–07, London School of Hygiene and Tropical Medicine Observational / Interventions Research Ethics Committee 17028; Netherlands: Medisch Ethische Toetsingscommissie Brabant NW2015–07; Athens: National Centre for Scientific Research 'Demokritos' Ethics Review

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Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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5.4 Postscript to research paper

Several relevant studies have been published subsequent to my paper examining greenspace exposures and aspects of physical activity using objective markers. However, the study populations are slightly different than that of my research (i.e., parents of young children), which include young (<30 years old), middle-age (40-69 years old), and older (≥ 65 years old) adults.

Franěk & Režný (2021) conducted an experimental study where undergraduate students walked on a set route in Hradec Králové, Czech Republic. The route was selected to contain varied levels of greenery, and they measured how walking speed correlated to these route characteristics. They found individuals walked at slower speeds on segments where there were more natural features (e.g., mature oak trees and a meadow). Study authors interpreted these results to imply that study participants were more engaged in their surroundings when greenery was higher. These findings differ from my study, which demonstrated that physical activity, as measured through METs, was greater with higher greenspace levels. However, the walking speed differences in the Franěk & Režný study were quite modest (3.5 to 3.7 miles per hour), so the implications for physical exertion were likely not substantial. The pre-determined route in their study also may have affected behaviours, whereas in my study, participants selected their own routes, likely differing by purpose of each trip.

An analysis of 12,986 middle-age participants in the UK Biobank cohort (Greater London area only) examined MVPA minutes based on 7 day accelerometer data (Roscoe et al., 2022). Study authors used a similar metric of walkability (i.e., z-scores based on population density, street connectivity, and destination density) and residential buffer size (1,000 m) as my study. However, they also integrated two measures of greenspace (tree cover and ground cover) into the walkability metric, thus developing a 'green walkability' indicator. Their results suggested stronger associations for green walkability compared to walkability (i.e., without greenspace), with strongest findings for tree cover walkability: the highest quintile of tree cover walkability was associated with an additional 3.64 (95% CI: 1.54-5.84) MVPA minutes compared to the lowest quintile. While my study did not identify

statistically significant positive associations with residential greenspace, there was an association with walkability, which Roscoe et al. also identified (though a borderline association). My study also found the largest increase in MVPA minutes to be associated with tree cover in the physical activity environment. Roscoe et al. identified the strongest positive associations with tree cover. Although there are some discrepancies in my results, mainly with respect to residential associations, Roscoe et al. combined greenspace with walkability, so direct comparisons are not possible. There was overlap in the results, which both indicate a positive relationship between greenspace and MVPA, and most notably with tree cover.

A study of older adults in Barcelona, Spain compared neighbourhood features (500 m around home address) to physical activity minutes based on accelerometer data (Akinci et al., 2021). Authors found a positive association between the percentage of greenspace, but not street tree density, and physical activity minutes. Walkability was calculated using a similar method as that of my study. These results conflict with my findings related to available greenspace within the residential environment, for which I did not identify any statistical associations. Differences in results may be related to the use of different outcomes: I defined physical activity minutes as those with ≥ 100 steps, whereas it is not clear in the methods how Akinci et al. classified physical activity time.

Another study using data from older adults in Barcelona, from the same research project as Akinci et al., investigated physical activity time in relation to greenspace visits (Vich et al., 2021). Results indicated a strong positive association between visits to greenspace and physical activity minutes, but not with the duration of time spent in such spaces. Authors surmised much of the additional activity time was attributed to travel to/from the greenspace. These findings do overlap with my results, showing that greenspace visits are related to more physical activity. In my analysis, I characterised greenspace levels using trip averages, which would also incorporate travel to greenspaces, not just activity in the greenspace itself.

In addition for this analysis, I explored the feasibility of using the likelihood of engaging in active travel for short trips (e.g., those where the destination is ≤ 1 km of home) based on residential greenspace levels. In other words, I wanted to investigate whether individuals who lived in greener areas would be more likely to use active travel for shorter trips compared to those residing in neighbourhoods with less greenspace. For example, such an analysis could use a logistic regression method to compare the odds of using active travel for a short trip based on increases in residential greenspace. Unfortunately, there were only 39 participants with a total of 287 trips (207 active, 80 non-active) within 1 km of home, so there were insufficient data to perform this analysis.

5.5 References

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6 Urban greenspace and outdoor air pollution

6.1 Introduction

This chapter focuses on greenspace and personal exposure to air pollution. Much of the current greenspace and health literature stems from Europe and North America, often occurring in locations with relatively low ambient air pollution concentrations. This analysis widens the evidence base by taking place in one of the most polluted cities in the world: Delhi, India. The study includes multiple greenspace metrics at different scales, and it benefits from personal PM_{2.5} exposure measurements from the DAPHNE research study. Two analyses involving exposures during outdoor walking trips are undertaken to assess air pollution exposures in both greener segments of a trip and in greener trips.

This paper addresses research objective 4 a) Quantify the association *within* walking journeys between microenvironment-level greenspace and personal exposures to PM_{2.5} and 4 b) Quantify the association *across* walking journeys between microenvironment-level greenspace and personal exposures to PM_{2.5}.

This chapter of the results section was accepted for publication in the journal, *Environmental Pollution*, in April 2022. The supplementary material from this paper is included in Appendix 4.

Cover sheet and research paper follow on subsequent pages.

RESEARCH PAPER COVER SHEET

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SECTION A – Student Details

| | | | |
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| Student ID Number | 1800264 | Title | Mr |
| First Name(s) | William | | |
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| Thesis Title | Potential pathways of urban greenspace to respiratory health: Air pollution and physical activity | | |
| Primary Supervisor | Prof Paul Wilkinson | | |

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

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| Where was the work published? | Environmental Pollution | | |
| When was the work published? | 2022 | | |
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|---|--|

SECTION E

| | |
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| Date | 18/04/2022 |

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| Supervisor Signature | Paul Wilkinson |
| Date | 12/07/2022 |



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

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ABSTRACT

The presence of urban greenspace may lead to reduced personal exposure to air pollution via several mechanisms, for example, increased dispersion of airborne particulates; however, there is a lack of real-time evidence across different urban contexts. Study participants were 79 adolescents with asthma who lived in Delhi, India and were recruited to the Delhi Air Pollution and Health Effects (DAPHNE) study. Participants were monitored continuously for exposure to PM_{2.5} (particulate matter with an aerodynamic diameter of less than 2.5 μm) for 48 h. We isolated normal day-to-day walking journeys (n = 199) from the personal monitoring dataset and assessed the relationship between greenspace and personal PM_{2.5} using different spatial scales of the mean Normalised Difference Vegetation Index (NDVI), mean tree cover (TC), and proportion of surrounding green land use (GLU) and parks or forests (PF). The journeys had a mean duration of 12.7 (range 5, 53) min and mean PM_{2.5} personal exposure of 133.9 (standard deviation = 114.8) μg/m³. The within-trip analysis showed weak inverse associations between greenspace markers and PM_{2.5} concentrations only in the spring/summer/monsoon season, with statistically significant associations for TC at the 25 and 50 m buffers in adjusted models. Between-trip analysis also indicated inverse associations for NDVI and TC, but suggested positive associations for GLU and PF in the spring/summer/monsoon season; no overall patterns of association were evident in the autumn/winter season. Associations between greenspace and personal PM_{2.5} during walking trips in Delhi varied across metrics, spatial scales, and season, but were most consistent for TC. These mixed findings may partly relate to journeys being dominated by walking along roads and small effects on PM_{2.5} of small pockets of greenspace. Larger areas of greenspace may, however, give rise to observable spatial effects on PM_{2.5}, which vary by season.

1. Introduction

Long-term exposure to ambient PM_{2.5} (particulate matter with an aerodynamic diameter of less than 2.5 μm) was responsible for 8.8 million deaths and nearly three years of lost life expectancy per person globally in 2015 (Lelieveld et al., 2020). Inhaled PM_{2.5} can penetrate deeply into the lungs and may enter the bloodstream, leading to impairment of the respiratory, cardiovascular, metabolic, and neurological systems via mechanisms of oxidative stress, mutagenicity, and inflammation (Feng et al., 2016; Fu et al., 2019). Short-term (daily)

PM_{2.5} exposures have been associated with higher mortality (Liu et al., 2019), increased asthma hospital visits and admissions (Zheng et al., 2015; Fan et al., 2016), and asthma exacerbations (Orellano et al., 2017) in children and adults. Nine of the ten cities with the highest annual PM_{2.5} concentrations in the world are located in India (IQAir, 2021), where over 1 million attributable deaths from PM_{2.5} occur annually (Balakrishnan et al., 2019).

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

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

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

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

In this study, we quantify the minute-by-minute relationship between greenspace indicators and personal $PM_{2.5}$ exposure during normal day-to-day walking trips in Delhi, India (i.e., within trips). We also investigate this relationship at the trip-level (i.e., between trips) to assess overall associations, which allows us to compare and contrast results both related to those of greener segments and greener trips. Thus,

these insights contribute valuable, initial evidence on the role of greenspace with personal $PM_{2.5}$ exposure in a high ambient air pollution setting. We hypothesised that personal exposures to $PM_{2.5}$ would be lower along segments in walking journeys (i.e., within trips) with more greenspace and for overall walking journeys (i.e., between trips) with more greenspace.

2. Methods

2.1. Study location

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

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

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

2.2. Study participants

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

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

2.3. Air pollution measurements

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

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

2.4. Greenspace indicators

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

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

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

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

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

(continued on next page)

Table 1 (continued)

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

^a n = 79 participants; n = 199 trips.

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

2.5. Identification of walking journeys

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

2.6. Other covariates

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

2.7. Data analysis

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

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

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

2.8. Sensitivity analysis

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

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

3. Results

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

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

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



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

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

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

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

The patterns of inverse association observed in the unadjusted *between-trip* analyses were broadly similar to those of the *within-trip* analyses for NDVI and TC (Fig. 5). Point estimates became progressively

more negative at larger radii of averaging in the spring/summer/monsoon season. By contrast, the results for GLU and PF in the spring/summer/monsoon season suggested positive associations with personal $PM_{2.5}$ exposure at all radii of averaging (with confidence intervals excluding 0, except at the 250 m radius). The results for the autumn/winter season were all fairly flat (i.e., no association for any marker) and showed no clear pattern of change in point estimates across the radii of averaging. NDVI and TC coefficients in spring/summer/monsoon season were attenuated in adjusted models; GLU and PF coefficients were less affected (Table S4).

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

4. Discussion

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

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

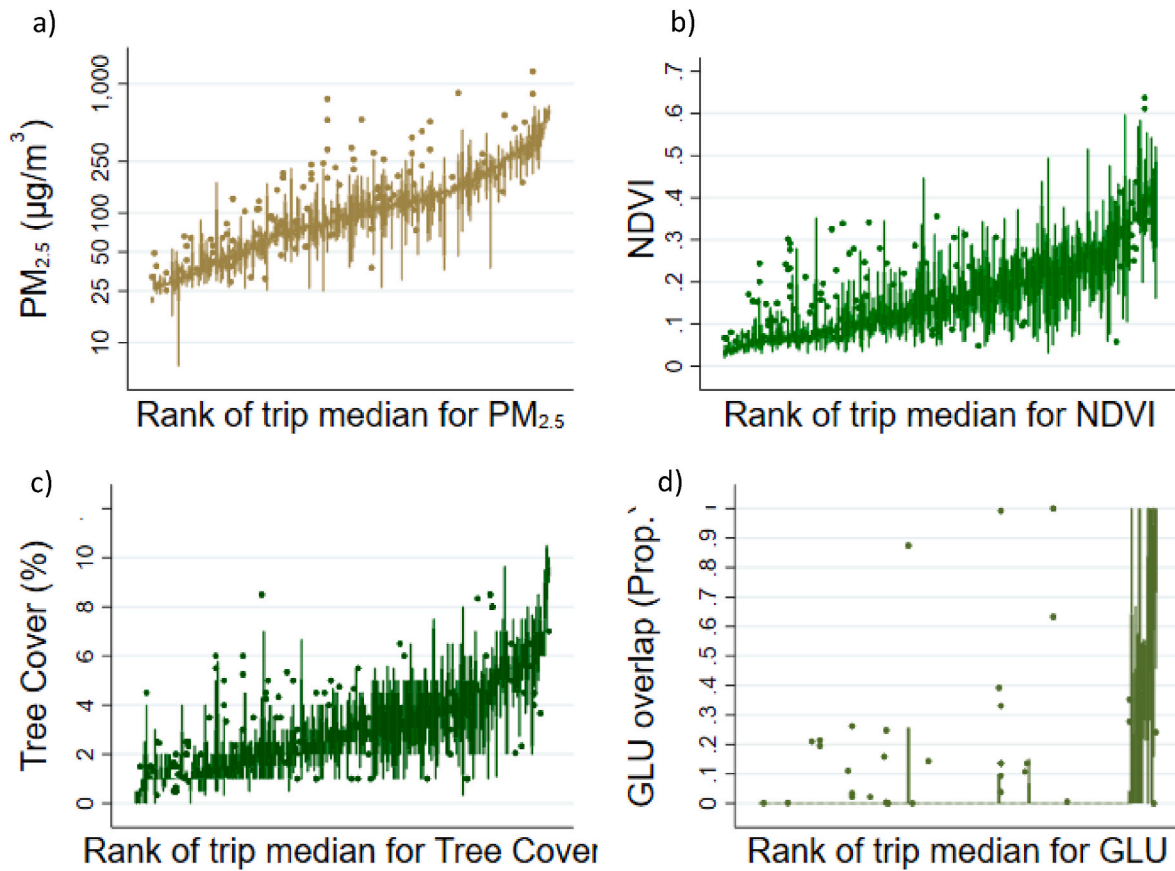


Fig. 2. Within- and between-trip variation in a) $PM_{2.5}$ concentrations ($\mu g/m^3$, log-scale), b) NDVI, c) tree cover (%), and d) proportion overlap of green land use (GLU) based on data for the 25 m radius of averaging around 1-min trip locations. Vertical bars indicate the interquartile range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

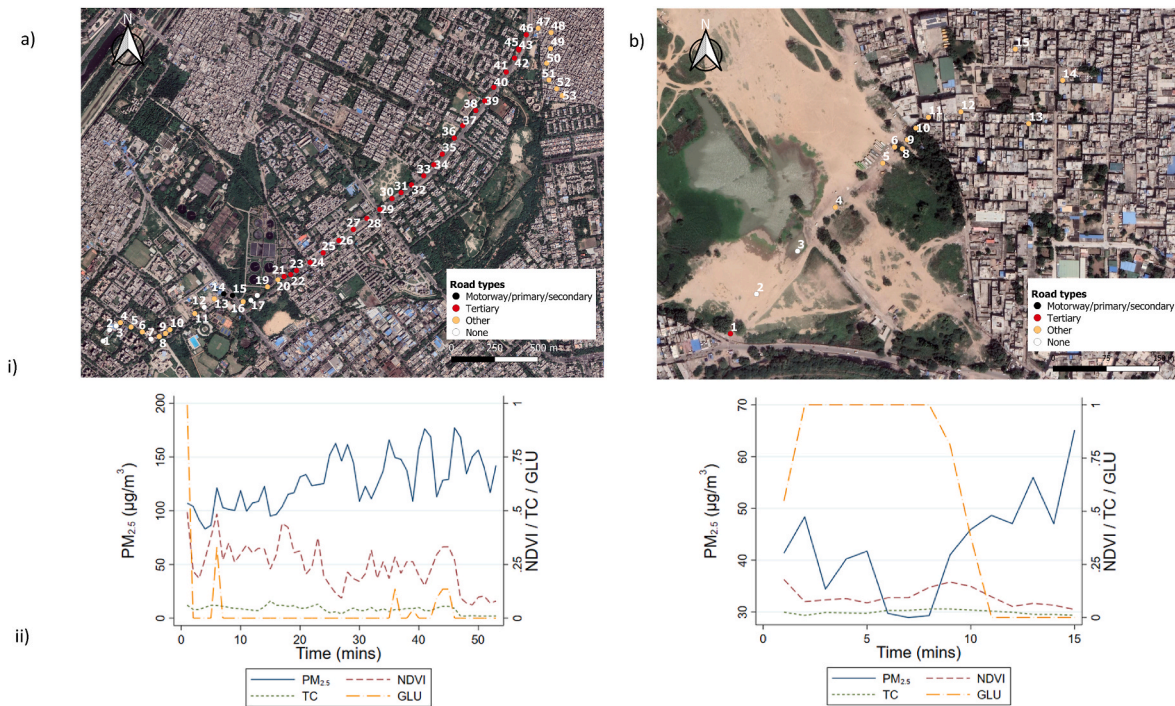


Fig. 3. Two example walking trips: a) Trip 1, in winter and b) Trip 2, in the monsoon season indicating different road type categories. For each trip we show: (i) map data ©Google Maps, (30th December 2016) with a trace of the walk route and (ii) line graphs of the minute changes in $PM_{2.5}$ concentrations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

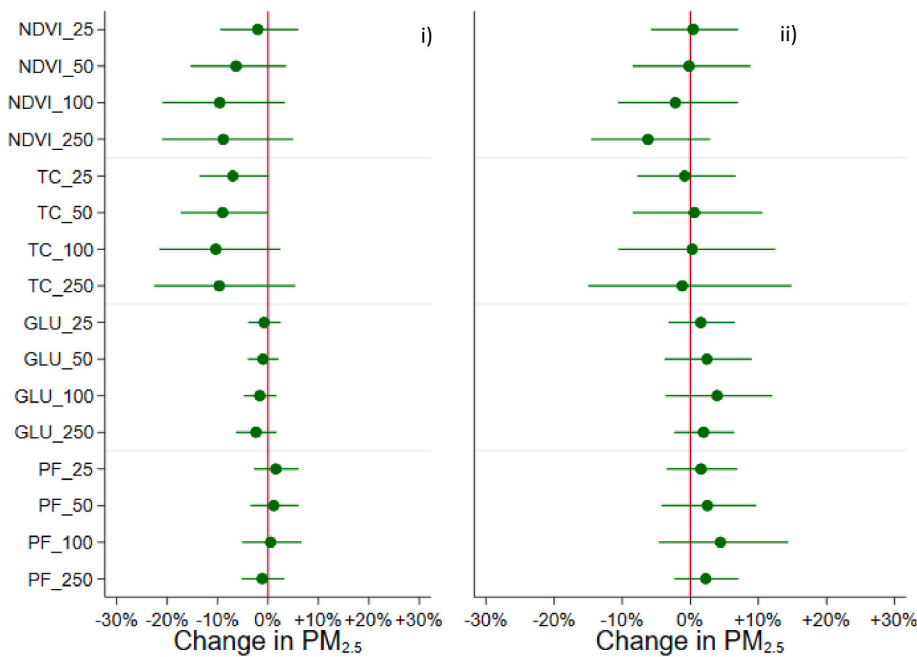


Fig. 4. Plots of regression coefficients for (i) the spring/summer/monsoon season and (ii) the autumn/winter season of within-journey changes in 1 min averaged $PM_{2.5}$ in relation to markers of greenspace. Coefficients represent an interquartile range (IQR) increase in Normalised Difference Vegetation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

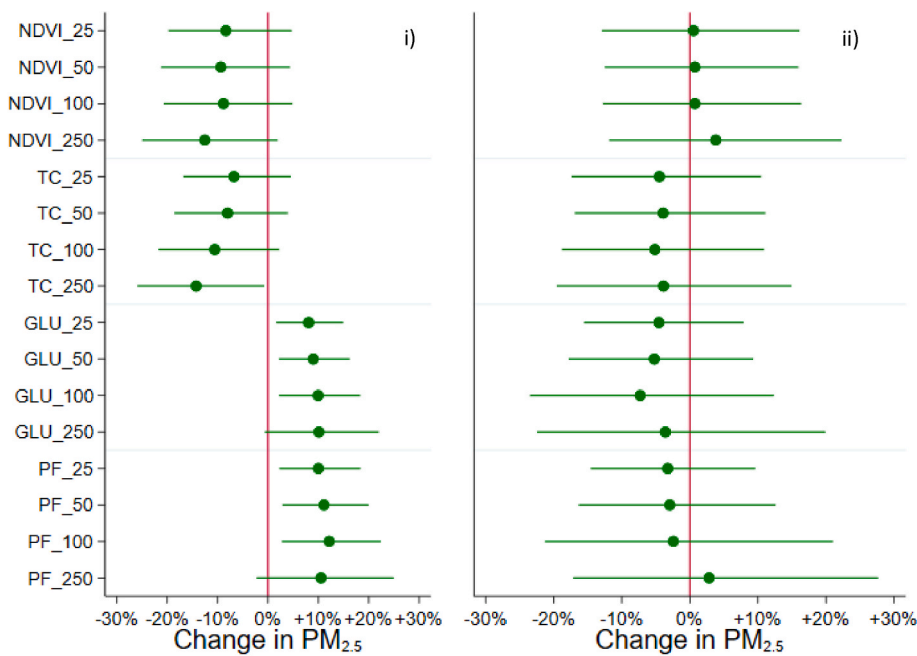


Fig. 5. Plots of regression coefficients for (i) the spring/summer/monsoon season and (ii) the autumn/winter season of between-location (between-trip) analysis of trip mean $PM_{2.5}$ concentrations in relation to markers of greenspace. Coefficients represent an interquartile range (IQR) increase in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

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

There are limited other studies that have examined the relationship between personal $PM_{2.5}$ exposures and greenspace, some of which identify inverse associations. Hart et al. (2020) used a bicycle-based sampling method in Dallas, USA to measure $PM_{2.5}$ and derived an NDVI-based vegetation footprint and height using Light Detection and Ranging (LiDAR) data. These authors found a negative relationship

between $PM_{2.5}$ and the amount of vegetation, but a positive link with vegetation height, suggesting taller trees may have hindered air pollution dispersion. von Schneidmesser et al. (2019) used cycling monitoring data from routes around Berlin, Germany to sample particle number concentrations in the $<PM_{10}$ range and found reductions of 22% compared to the ambient average when cycling in parks or large greenspaces not directly next to a road. $PM_{2.5}$ reductions of up to 50% were identified while walking inside a park in Madrid, Spain, when 200 m from a major road (Gómez-Moreno et al., 2019). Roberts & Helbich (2021) assessed exposures in the Netherlands for both residential and mobile environments and found a negative correlation between NDVI and land use regression-based $PM_{2.5}$; however, they did not differentiate between travel mode, nor indoor or outdoor settings. Guo et al. (2019) found weak negative correlations ($r < -0.2$) between green land use and

modelled PM_{2.5} concentrations using data based on commuters' exposure in Wuhan, China; similarly, this study also did not distinguish exposure between travel modes.

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

Ambient PM_{2.5} concentrations in Delhi demonstrate strong seasonal trends, with much higher concentrations in October–January, when biomass burning is an important contributor, than during July–September, when rains scavenge ambient particles (Jain et al., 2020). While only borderline statistically significant, we did find more negative coefficients in spring/summer/monsoon seasons across radius sizes for all greenspace indicators within trips. Although particle deposition tends to increase with higher ambient concentrations (Cai et al., 2017), the observed associations could indicate the potential of particle deposition during periods when vegetation is closer to important sources (e.g., traffic) (Janhäll, 2015), compared to a higher contribution from more distal sources in winter, such as crop residue burning from surrounding agricultural areas (Jain et al., 2020). More generally, it has been estimated that up to 60% of ambient PM_{2.5} in Delhi originates from outside the city (Amann et al., 2017); in this case, urban greenspaces, as microenvironments with relatively fewer PM_{2.5} sources and the capacity to capture nearby particle emissions, may be less effective to reduce personal exposures. The autumn/winter months also coincide with the period when deciduous trees start to shed leaves, and thus would be less effective for particle deposition (Xu et al., 2020); nevertheless, tree bark and branches can also accumulate particulates (Xu et al., 2019). Alternatively, these seasonal trends may indicate that mitigation mechanisms related to greenspace may be more effective, or detectable, during periods of lower ambient concentrations. A study of monitoring stations in Nanjing, China found correlations between green cover and lower PM_{2.5} concentrations; however, this relationship was not apparent when ambient concentrations were in excess of 75 µg/m³, which also typically occurred in the winter (Chen et al., 2016).

4.1. Overall interpretation

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

4.2. Strengths and limitations

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

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

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

5. Conclusion

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

Author statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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

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PART III: Discussion

7 Discussion

7.1 Context of the thesis

The research undertaken in this thesis aimed to expand the evidence base to lead to improved understanding of the associations between urban greenspace and respiratory health outcomes. While many studies have confirmed positive associations for mental health (Bratman et al., 2019), potential benefits for respiratory health appear to be less consistent, with several studies indicating poorer health with higher levels of greenspace markers (e.g., Lovasi et al., 2013; Andrusaityte et al., 2016; Alasauskas et al., 2020). It is necessary to provide firmer evidence on the associations between greenspace and outcomes such as respiratory health, for which research findings are more heterogeneous. A more nuanced understanding of the specific pathways for which greenspace may lead to better (or worse) health would be advantageous to encourage positive services and minimise any disservices of greenspace management and development in urban settings.

I performed a systematic review to detail and quantify the relationships identified in research to date between distinct greenspace markers and specific indicators relevant for respiratory health. I carried out analyses of empirical data to help address research gaps of specific pathways, including those operating through exposure to air pollution, physical activity, and exposure to/perception of noise. These analyses examined multiple greenspace markers, and how relationships differed across temporal (intra-annual) and spatial variations in Europe and South Asia settings. The synthesis of the systematic review of existing evidence and the findings from empirical analyses add to current knowledge and provide insights about the potential positive and negative impacts of greenspace related to pathways of air pollution, physical activity, and noise.

The chapters in this thesis had the following objectives:

1. To perform a systematic review to synthesise the evidence relating urban greenspace and respiratory health (Chapter 3).
2. a) To quantify the association between residential metrics of urban greenspace and indoor levels of PM_{2.5}. and b) Quantify the association between residential metrics of urban greenspace and indoor noise levels and road noise annoyance.(Chapter 4).
3. a) To quantify the association between residential metrics of urban greenspace and moderate to vigorous physical activity (MVPA) as an objective PA metric and b) the association between greenspace during bouts of physical activity and Metabolic Equivalent of Tasks (METs) (Chapter 5).
4. a) To quantify the association within walking journeys between microenvironment-level greenspace and personal exposures to PM_{2.5} and b) Quantify the association across walking journeys between microenvironment-level greenspace and personal exposures to PM_{2.5} (Chapter 6).

Thesis chapters 4 to 6 include the published research papers with discussions of individual findings and strengths/limitations. This discussion chapter attempts to summarize lessons learned from across the research as a whole, noting overall strengths and weaknesses, as well as highlighting opportunities for future research and inputs to policy.

7.2 Summary of PhD main findings

The main findings from the review chapter of the background and those of the results sections are summarised here.

7.2.1 Chapter 3: Exposure to urban greenspace and pathways to respiratory health: an exploratory systematic review

Many studies of urban greenspace and respiratory health have been conducted. Although much of the evidence was mixed, findings were strongest for respiratory mortality. Of the 290 associations identified in the systematic review of studies examining urban greenspace and respiratory health

outcomes, two thirds (n=195) were positive (i.e. beneficial) with health, with the remaining third either negative (i.e. adverse) (n=90; 31%) or null (n=5; 2%) with health. The highest proportion (60%) of statistically significant positive evidence for a given health outcome was for respiratory mortality. For the other indicators of health, particularly asthma, there was inconsistency in the direction and/or imprecision of effect estimates. Study authors suggested possible causal pathways for health benefits, including lower air pollution, more physically active populations, and exposure to microbial diversity, with suggested mechanisms with poorer health as exposure to pollen and other aeroallergens; however, these pathways were rarely quantitatively assessed in the studies.

7.2.2 Chapter 4: Urban greenspace and the indoor environment: Pathways to health via indoor particulate matter, noise, and road noise annoyance

Certain urban greenspace markers, such as overall greenness (NDVI) and tree cover, were associated with lower indoor PM_{2.5} concentrations and road noise annoyance, but not indoor noise levels. This chapter addressed the 2nd overall objective of the thesis: to quantify associations between residential greenspace markers on the one hand and *indoor* PM_{2.5} concentrations and *indoor* noise and road noise annoyance on the other. Analyses were based on approximately 1-week home monitoring periods using data from the HEALS project, which occurred in and around four European settings (Edinburgh, UK; Utrecht, Netherlands; Athens and Thessaloniki, Greece).

Out of the four residential greenspace markers that I examined (i.e., NDVI in summer, NDVI for the same season as when pollution and noise monitoring was undertaken, tree cover, and green land use), only NDVI in summer was found to be associated with lower indoor concentrations of PM_{2.5} (-1.3 [95% CI: -2.4 to -0.2] µg/m³) in fully adjusted models at the 100 m buffer. There did not appear to be a clear indication of the relationship between any of the greenspace metrics and indoor noise levels. Nevertheless, there were clear reductions in the odds of reported road noise annoyance associated with NDVI (both summer NDVI and season-specific images) and tree cover (ORs ranging from 0.54 [95% CI: 0.31-0.93] to 0.55 [95% CI: 0.31-0.98]).

7.2.3 Chapter 5: Neighbourhood and path-based greenspace in three European countries: associations with objective physical activity

While residential greenspace was not linked to overall objective physical activity, activity intensity and duration were higher in locations with more overall greenness and tree cover. This chapter aimed to complete the 3rd objective of assessing how greenspace is related to specific markers of physical activity. Greenspace was characterised at both the residential environment and the physical activity space. Physical activity was defined as daily minutes of moderate to vigorous intensity steps (MVPA-minutes) and Metabolic Equivalent Task (MET-minutes). This study also used data from the HEALS study, including personal monitoring of individuals living in the same four European locales (Edinburgh, UK; Utrecht, Netherlands; Athens and Thessaloniki, Greece).

There did not seem to be an important relationship between average greenspace surrounding the home and higher physical activity. However, when quantifying the greenspace specifically in the environments where exercise occurred, there was a strong relationship again with NDVI and tree cover, and more so for cycling than walking. For example, a 0.1 increase in mean NDVI of a physical activity path was associated with 7.81 (4.12 to 11.50) and 15.53 (8.60 to 22.45) MET-minutes for walking and cycling, respectively.

7.2.4 Chapter 6: The relationship between greenspace and personal exposure to PM_{2.5} during walking trips in Delhi, India

Modest reductions of personal PM_{2.5} exposure were found while walking in areas of Delhi with higher overall greenness and tree cover, but not during the autumn/winter season. The final results chapter addressed the fourth objective to examine greenspace in microenvironments and personal exposure to PM_{2.5}. This study included a panel of adolescents with asthma living in Delhi, India, using data from the DAPHNE study. A similar suite of greenspace markers were used (i.e., NDVI, tree cover, green land use) to examine associations with personal PM_{2.5} concentrations while walking through the built environment.

The analysis used two sets of methods to help quantify associations with exposure and greenspace during a walking trip (i.e. within-trip analysis) and also average greenspace across trips (i.e. between-trip analysis). In addition, because Delhi experiences large fluctuations in PM_{2.5} concentrations and sources during different times of the year, I examined this relationship separately by broad seasons (i.e., spring/summer/monsoon and autumn/winter). In the within-trip analysis, I found mostly non-statistically significant PM_{2.5} reductions associated with greenspace markers, but only in the spring/summer/monsoon season. As a contrast, the between-trip analysis indicated broadly similar patterns for NDVI and tree cover, but suggested positive associations for green land use in the spring/summer/monsoon season. No statistically significant associations for either analysis were found in the autumn/winter season. These results demonstrate the important spatial and temporal contexts that are needed to interpret the role of greenspace with exposure to particulate air pollutants in a setting such as Delhi, India.

7.2.5 Synthesis of results across review and empirical chapters

Many epidemiological studies have been undertaken to investigate the association between markers of urban greenspace and indicators of respiratory health. While the preponderance of published studies report positive associations with health, the estimates of most individual studies for most outcomes were imprecise and together did not provide conclusive evidence for any specific association. Of all outcomes examined, the evidence was perhaps strongest for greenspace and lower respiratory mortality based on the proportion of studies reporting such an association.

The evidence of my PhD analyses supports pathways to respiratory health operating through lower indoor and personal particulate air pollution exposure, enhanced opportunity for physical activity, and decreased perceived noise levels (though not actual noise levels). Findings were not entirely consistent: there were important nuances, for example, in how, where, and when the greenspace environment was characterised. Across the analyses, statistical associations were identified only with NDVI and tree cover, and not green land cover (with the exception of higher PM_{2.5} concentrations

across trips in Delhi). There were important spatial and temporal influences on the characterisation of greenspace. Larger areas of averaging greenspace markers tended to result in stronger statistical associations. Both the time of year for which monitoring was performed and greenspace was defined affected results, with larger effects estimates related to the summer period.

While the specific pathways that I examined in my PhD research may not be exhaustive of those potentially interacting with respiratory health, the inconsistencies in study results identified in the review may be partly explained by differences in the specific definition of greenspace used, in addition to the relative importance of these pathways for a given respiratory health outcome. In summary, my PhD research findings can assist with the interpretation of these specific underlying mechanisms related to epidemiological studies of greenspace and respiratory health.

7.3 Strengths of the research and contributions of the PhD to the field

Several key strengths of the research will be highlighted and discussed in more detail. First, a systematic review was performed to assess the current state of the science regarding greenspace and multiple markers of respiratory health.

For the analytical papers, it was a strength that I was able to use, and compare findings for, a set of distinct indicators of greenspace and at multiple scales of averaging, reflecting different aspects of the green environment. Similar results were often found between overall greenness and tree cover, but contrasts were observed with green land cover. This discrepancy could point to the implications of different types of land use/land cover to represent greenspace, as well as using different data sources (e.g., satellite imagery vs open source) and levels of resolution.

Third, research findings based on personal monitoring provide deeper insight and direct quantitative evidence of greenspace and exposure pathways that are known to be harmful (i.e., air pollution exposure) or beneficial (i.e., engaging in physical activity) to respiratory health.

Fourth, the research setting provided a contrast of lower (Europe) and higher (South Asia) air pollution environments, which also entailed greenspace in temperate and tropical contexts, respectively.

7.3.1 Exploratory systematic review

The systematic review was a new synthesis of evidence focused specifically on greenspace and a wide range of respiratory outcomes. Previous systematic reviews had focussed on specific health endpoints, for example childhood asthma (Hartley et al., 2020) and allergic respiratory diseases in children (Lambert et al., 2017) and youths (Ferrante et al., 2020). My review extended the evidence from these earlier publications by bridging research findings across the full life course, from exposure at birth to older ages (i.e., not just children), and from incidence to mortality. This synthesis informs research on greenspace exposure across different populations and settings within a wide range of respiratory health indicators. My review also suggests potential pathways by which greenspace may be relevant for respiratory health outcomes, such as air pollution, physical activity, stress, noise annoyance, extreme heat, and microbiota. At the same time, these pathways were infrequently examined quantitatively, which suggests future opportunities for empirical research involving mediation analysis and meta-analyses of specific greenspace-respiratory health associations.

7.3.2 Suite of greenspace metrics

I characterised greenspace consistently by using three different metrics: the normalised difference vegetation index (NDVI – a measure of the overall greenness), tree cover (the percentage of an area covered by tree canopy), and green land use (assigned to land with predominantly natural features, such as forests, or recreational areas, such as parks). In the analyses of the HEALS data in Europe (chapters 4 and 5), these three metrics were derived from remotely sensed satellite images available from the Copernicus programme. I used these same three metrics for the analysis of the DAPHNE data, albeit some of the sources were necessarily different to accommodate tree cover and land use data for India. Using multiple indicators that can capture different forms or features of urban greenspace is useful for assessing individual pathways to health and to provide practical, context-specific findings.

For example, areas of recreational greenspace may provide open spaces to engage in physical activity and to socialise, but may not provide as good of a barrier as trees to block visual perception of noise sources. Indeed, I found that relationships did vary depending on the indicator: across the three studies, NDVI and tree cover had much clearer associations with PM_{2.5}, road noise annoyance, and physical activity than did green land use. These results suggest the potential value of integrating greenery or tree cover across urban areas for these particular pathways, such as appropriately selected and positioned street trees, instead of developing new green land use, which would also tend to be much more costly. A possible reason for the discrepancy in associations is that NDVI and tree cover are continuous measures, whereas green land use classifications, especially 'parks' could in fact be quite variable in terms of natural features, ranging anywhere from dusty, unkempt areas to well-managed public gardens. Using consistent metrics across studies, and, further, identifying some agreement in the relative strength of associations, provided more confidence in my findings.

I assessed spatial variability by comparing numerous areas of greenspace averaging in each of the analyses. The specific sizes (e.g., 300, 1000 m) were selected to represent local and neighbourhood scales and were commonly used in other studies of urban greenspace. An advantage with the inclusion of different metrics and pathways is the ability to assess the importance of the scale of greenspace in different scenarios. There was some evidence of greater effect estimates with the use of larger areas of averaging, as documented in the HEALS study (chapter 4) and the DAPHNE study (chapter 6). Larger areas, which also have shown to be more consistent with health elsewhere (Su et al., 2019), may demonstrate better associations due to reduced error/misclassification with greater averaging (particularly for lower resolution data) and the potential importance of neighbourhood-level greenspace (rather than very local microenvironments) to reduce air pollution. There was no difference in scale for the analysis of residential greenspace and physical activity; here, the activity space proved to be the salient feature rather than the scale of averaging.

Finally, I explored effects of temporal variation, where possible, using NDVI images from different periods of the year. For analyses where it is important to examine a distinct period and pathway, for example walking trips and air pollution exposure on certain dates (chapter 6), it may be better to capture season-specific vegetation. On the other hand, when examining more long-term effects (e.g., residential greenspace and overall health), it might be more useful to average temporal differences and/or use a metric that maximises variation in exposures between individuals.

7.3.3 Pathways of effect

My research findings provide evidence relevant to the pathways by which greenspace may have beneficial (or adverse) effects on respiratory health, specifically by characterizing the associations between greenspace and both air pollution and physical activity. However, as my analyses did not include data on respiratory outcomes, I was not able to examine the degree to which greenspace-respiratory outcome associations were affected by adjustment for these 'exposures', nor were mediation analyses possible (further discussion provided below in section 7.4.1).

The studies made use of home and personal monitoring of exposure and activity instead of reliance on proxy or self-reported data. A large body of epidemiological work has investigated the relationship between indicators of urban greenspace and health, as evidenced by the 100+ studies identified in my review. Some of the higher quality and more recent studies performed mediation analysis to assign health benefits to specific pathways, but such methods were the minority. In the case of air pollution, another active area of research involves environmental monitoring in urban contexts to study the effects of green infrastructure (e.g., Cai et al., 2017; Han et al., 2020; Diener & Mudu, 2021). The research in this PhD has connected these fields by studying real-time exposures at the individual-level, which were based on objective greenspace markers and metrics of physical activity and air pollution. I was able to identify and characterise the greenspace and air pollution/physical activity levels that were spatially linked to the microenvironments in which study participants spent time and actually used. My findings indicate modest PM_{2.5} reductions related to NDVI at the home environment in

European and tree cover in the Delhi context. These findings are aligned with those mediation results showing smaller contributions (<10%) from lower PM_{2.5} concentrations (James et al., 2016), but not those indicating stronger reductions (Bauwelinck et al., 2021). The findings of the physical activity analysis (chapter 5) demonstrate the importance of separating greenspace at the home and place where physical activity occurs, as I found no associations with the former, but clear findings with the latter. My findings regarding the home environment are consistent with a review of objectively measured physical activity and proximity/density of parks in the USA, which found only a quarter of eligible studies (n=5/20) identified a positive association (Bancroft et al., 2015). Another review found that time spent in urban greenspace was commonly associated with moderate to vigorous physical activity (MVPA) in 5/6 studies, which also coincides with my findings of greater effort or duration of walking or cycling in greener areas (Kondo et al., 2018). Additional research could be undertaken to better understand the importance of greenspace with different types of activities in different subgroups.

7.3.4 Comparison of study settings

Another important strength of the thesis research was examining greenspace across environments with a range of ambient air pollution concentrations. The mean PM_{2.5} concentrations recorded from ground monitoring networks during the study periods in the European settings ranged from 6.2 µg/m³ (Edinburgh, UK) to 12.4 µg/m³ (Athens, UK), whereas the mean concentration during walking journeys in Delhi, India was more than 10 times higher (134 µg/m³). Ambient concentrations in Delhi vary considerably within a year, with much greater concentrations occurring during October-February (autumn/winter), owing to changing contributions of pollutant sources and meteorological conditions. Due to these important differences, I analysed relationships with greenspace separately and found evidence of lower PM_{2.5} concentrations only outside of the autumn/winter period, when concentrations are lowest. Since I also found statistical associations between residential greenspace and indoor PM_{2.5} concentrations in the European setting (a relatively low PM_{2.5} environment), it may be easier to detect such relationships when particulate concentrations are lower or when there is less

variation. Emissions from crop residue burning from outside of Delhi become more important during autumn/winter, a distal source with which greenspace may have little association. It is valuable to study the effects of urban greenspace in low to middle income countries and the global south, for which greenspace may provide benefits for health, but which is at present understudied compared to higher income settings (Rigolon et al., 2018; Nawrath et al., 2021). Further, when investigating greenspace, particularly when studying certain types, for example trees, it is useful to contrast temperate and tropical settings, which may entail distinct species that have different capacities relating to deposition and dispersion of airborne particulate matter.

7.4 Limitations of the thesis

In this section, I will discuss overall limitations of the PhD research. Potential limitations of the individual research components of this thesis are discussed within the results chapters (i.e., 4-6) and so will not be repeated here. Although there are most certainly more limitations to this work, I will discuss the three in this section that in my view are the most important points to consider when interpreting the overall results. First, none of my empirical analyses contained data on respiratory health status/outcome, but rather were confined to analyses of determinants of exposure. Second, the sample sizes of the studies were relatively modest. Third, the studies for which data were analysed were not designed with the explicit intention of examining associations with urban greenspace, and may not have maximised opportunities to capture sufficient greenspace variation.

7.4.1 *Absence of respiratory health metric in analysis*

The overall goal of the PhD research was to examine specific pathways by which urban greenspace may affect respiratory health, namely reduction of air pollution and noise exposure and enhanced opportunities for physical activity. However, these analyses did not explicitly examine greenspace and health, and instead relied on characterising patterns of exposure in relation to greenspace for two sets of established risks factors for health, specifically air pollution/noise and physical activity. Under a number of assumptions, the observed patterns of exposure to these risk factors can be translated to

estimates of health effect by applying published exposure-response relationships, though the results would contain multiple uncertainties and could be viewed as no more than indicative. Despite the many assumptions, this estimation would be instructive, given the overall research goal of examining associations between urban greenspace and respiratory health.

The results of chapter 4 indicate lower indoor $PM_{2.5}$ exposures with higher levels of overall greenness at the residential level ($-1.3 \mu\text{g}/\text{m}^3$ [equivalent to a $\sim 10\%$ reduction of the overall mean of $12.4 \mu\text{g}/\text{m}^3$] per 0.1 increase in 100 m average NDVI surrounding the residential address). This mean is very close to the UK mean of outdoor $PM_{2.5}$ ($12 \mu\text{g}/\text{m}^3$) used in the 2015 Global Burden of Disease study. As an illustrative example, using the Global Exposure Mortality Model (GEMM), a reduction of $1.3 \mu\text{g}/\text{m}^3$ would lead to 493 (10%), 521 (11%), and 1,167 (13%) fewer COPD, lung cancer, and lower respiratory infection deaths attributed to $PM_{2.5}$ exposure in the UK, respectively, for the population of age 25+ years (Burnett et al., 2018). There are many assumptions inherent in these estimations, including equivalent exposure to and health impacts from ambient and indoor concentrations. This example shows the non-trivial change in deaths associated with the calculated reduction in $PM_{2.5}$.

Quantifying health benefits from reduced exposure to indoor $PM_{2.5}$ assumes lower concentrations over a long-term period, given people spend most of their time inside ($>90\%$ [Tong et al., 2016]). Extending benefits of reduced acute exposure to $PM_{2.5}$, such as during walking trips as analysed in chapter 6, is more challenging. Adolescent populations tend to spend much of their time inside, with $<10\%$ allocated to outdoor time (Matz et al., 2015), so reductions during this period can only have fairly modest impacts on overall exposure levels. Still, time spent commuting, and especially walking during periods of rush hour traffic, can potentially lead to an individual's highest exposure to $PM_{2.5}$ concentrations (Lin et al., 2020; Peng et al., 2021). As an illustrative example, suppose an asthmatic adolescent in Delhi is exposed to indoor $PM_{2.5}$ concentrations of $58 \mu\text{g}/\text{m}^3$ (Pant et al., 2017) for the majority of the day, then spends 1 hour walking outside and is exposed to concentrations of $102 \mu\text{g}/\text{m}^3$ (mean concentration in spring/summer/monsoon in chapter 6). Walking in an area with a 1 IQR higher

tree cover would on average be associated with a 10% reduction in PM_{2.5} concentrations (102 to 92 µg/m³), according to my results (50 m buffer). This reduction would entail a -0.4 µg/m³ change in the daily mean concentration (i.e., 59.8 to 59.4 µg/m³). The relative risk for asthma emergency department visits from a meta-analysis (Fan et al., 2016) was 3.6% per 10 µg/m³, which, at these daily mean concentrations, would be marginally reduced from 23.6% to 23.4%. This is a small reduction in emergency department visits, however, there would likely also be fewer exacerbations not leading to a hospital visit, though this is not possible to quantify here. The confidence intervals for my calculated risk estimates in chapter 6 were close to 0, which is consistent with no change in concentration, and thus no corresponding impact on respiratory health. It is also worth mentioning here that the 'between' trip analysis identified increases in personal exposure related to trips with more green land use. As noted in chapter 6, these findings might be caused from higher concentrations in roads circumventing parks or activities generating particles in or around parks, such as cooking stalls. Such increases in exposure would also need to be accounted for to determine the net benefits related to greenspace.

The published paper in chapter 4 also found reduced odds of road noise annoyance with higher levels of both residential NDVI and tree cover. Road noise annoyance is a source of psychological distress, which may adversely affect the respiratory system through impacting the immune system, causing sleep disturbances, and producing oxidative stress (Recio et al., 2016). One study demonstrated that road noise annoyance, and not actual noise levels, was independently associated with respiratory symptoms and current asthma (Eze et al., 2018). While there are several plausible biological mechanisms and empirical data linking road noise annoyance and poorer respiratory health, more evidence is needed before being able to quantify the related benefits of lower annoyance.

The published paper presented in chapter 5 included clear increases in physical activity levels, in terms of effort and/or duration, in areas of higher greenness as measured by NDVI and tree cover. For example, walking and cycling in areas with 10 percentage-point more tree cover were associated with

an additional 8.1 and 22.8 MET-minutes, respectively. The World Health Organization (WHO) recommends at least 150 minutes/week of moderate-intensity aerobic physical activity or 75 minutes/week of vigorous intensity aerobic physical activity, or equivalent combination (WHO, 2020); these recommendations are equivalent to 7.5 MET-hours/week (Arem et al., 2015). Using the above results from chapter 5, and assuming these activities were done on a daily basis, the additional METs associated with tree cover for walking and cycling would represent 13% and 35%, respectively, of the recommended 7.5 MET-hours/week. Achieving the WHO weekly guidelines of physical activity has been shown to lead to clear reductions (31%) in all-cause mortality (Arem et al., 2015). Research involving individuals with COPD also suggests beneficial reductions in respiratory mortality (55% [95% CI: 0.19% to 75%]) for those meeting these guidelines (Cheng et al., 2018). However, one potential bias that may attenuate some of these associations with physical activity is residential self-selection, which involves healthier individuals choosing to live in greener areas. At the same time, in my analysis there was no indication that residential greenspace levels were associated with an objective metric of overall moderate to vigorous physical activity. I also adjusted for residential greenspace levels in the analysis of activity locations, which would have helped correct for this self-selection issue. In summary, although these calculations involve uncertainty, the observed associations in the results chapters can be quantified to estimate the potential magnitude of impacts to respiratory health.

7.4.2 Modest sample sizes and representativeness

While the studies entailed modest numbers of participants (n=131 household in HEALS; n=181 participants in DAPHNE), with fewer included in analysis due to missing covariates or incomplete/unreliable sensor data, repeated measures from each individual were analysed to bolster statistical power. Despite the restricted amount of data available, the sample sizes were sufficient to identify statistically significant findings in each of the three analytical papers. However, more data, particularly in the DAPHNE study analysis, may have helped distinguish findings between the two seasons. This is especially true for autumn/winter, which included greater variation in personal exposure concentrations and thus would require a larger sample to detect an effect with the

greenspace indicators. Unfortunately, the COVID-19 pandemic cut short the participation in the DAPHNE study.

The two study populations were quite specific (families with young children of generally high socioeconomic status in HEALS; adolescents with asthma in DAPHNE), which on the one hand is beneficial for analysis when there are smaller sample sizes (i.e., participants are more similar and there are less factors to control for), but on the other hand, it is not possible to observe effects in different subpopulations or subgroups. This issue relates to the external validity of the study. There are no major constraints as to why findings would not be generalisable to the broader population, but it would have been interesting to examine any nuances in effects according to different demographic characteristics or other subgroups. Another related issue is the representativeness of the personal monitoring periods and whether participants would have been more likely to engage in healthier behaviour due to being observed, the so-called 'Hawthorne effect' (McCambridge et al., 2014). Since greenspace was not included in the study design, participants would have no notions about the greenspace focus and thus would not have been likely to adjust their behaviour with respect to green areas. It is also not likely that individuals living in greener areas would have adjusted their behaviours in any way, compared to those residing in less green neighbourhoods.

7.4.3 Studies not designed explicitly for greenspace

Following on from the last point in the previous subsection, a limitation of the PhD research was using data from studies where greenspace was not integrated or conceptualised at the design stage. An important implication of this exclusion would have been not maximising or exploiting variation in greenspace for participant recruitment. For example, with the exception of the Edinburgh participants in the HEALS study, the mean tree cover for residential and personal study areas in the HEALS and DAPHNE studies was <10%. Prioritising or expanding study participant locations to maximise greenspace variation may have resulted in more definitive statistical associations. Selecting

participants nearer to green land use or who walked to school in the DAPHNE study would have allowed for more refined estimates examining personal exposure to PM_{2.5}.

7.5 Reflections on the approach

During the course of the PhD research, which I began in January 2018, I developed many skills while undertaking the review and analytical components. In the following section, I will reflect on each of these chapters, focussing on both what I learned and what challenges I faced.

In the development of the review protocol, I acquired knowledge on the inputs and methods needed to perform a comprehensive and robust systematic review. The first-hand experience selecting search terms and medical subject headings gave me an appreciation of how important the inputs are to framing the review content. Performing the search gave me a working understanding of the different scientific databases, including the strengths and limitations of each. The experience using the Navigation Guide for the risk of bias, quality, and strength assessments helped reinforce my understanding of the best methods to undertake epidemiological studies. Finally, distilling and summarising the key learnings and outputs from the 108 papers was quite difficult, but was very rewarding when finally establishing and presenting conclusions in a manuscript. However, in future reviews, I will be more inclined to either scale down the potential number of papers (for instance, by including a narrower review question), or if a large number of studies is unavoidable, select a higher level review type that is more descriptive and summarises the types of studies (e.g., scoping, mapping), rather than scrutinises results and potential biases. I would try to use automated processes or machine learning to screen papers and potentially extract data to be more efficient. I feel much more equipped now in approaching and deciding on the most appropriate type of review and also framing a valid research question.

Through the use of the HEALS study datasets to examine greenspace and the indoor environment and physical activity, I gained a valuable and widely applicable skillset to perform geospatial analysis and process sensor data. As this was the first analytical paper, I spent considerable time interpreting the

results and discussing with my supervisory committee the potential role of greenspace with indoor PM_{2.5} and noise. The other collaborators (and eventual co-authors) on the HEALS study were very helpful to me for navigating the collection and processing of remotely sensed data. I think it would have been helpful for my analysis if there were more uptake of time-activity diaries by the participants, which may have led to more refined analysis of indoor PM_{2.5} and noise. It would have been valuable to understand the nature of outdoor trips, to better categorise bouts of physical activity for leisure, exercise, commute, or other. One other point that may have been valuable to include and could be addressed in future research is that I had work addresses only for a limited number of study participants. It would have been interesting to examine greenspace and the role of workplace environments and commuting behaviours.

As with the HEALS study analyses, I also gained valuable experience analysing and processing geospatial data from the DAPHNE study, as well as developing an algorithm to identify physical activity (such identification had relied on a mobile phone application, 'Moves', in the HEALS study). However, a lot of time was spent performing quality checks and removing unreliable GPS data, as there were many instances of poor GPS signal, either by the participant being indoors or outside in densely built areas. It would have been more efficient to automate and reliably omit data with poor GPS signal. As the pollution concentrations and sources in Delhi change over the course of a year, it would have been interesting to somehow capture the emission sources. This may have allowed more insight into the observed differences in the relationship between greenspace and personal PM_{2.5} exposure across the seasons. One other limitation of the DAPHNE data was that there were few examples of outdoor journeys through green land use, for example, parks. Participants could have been encouraged to visit parks and greenspaces, which would have provided more data for analysis, but then this may not have necessarily reflected their usual exposure levels.

7.6 Areas for future research

Many further questions for research have arisen during the course of my work. The vast majority of studies identified by the systematic review were observational, and potentially open to bias of self-selection. Evidence from (natural) experimental studies could add valuable complementary evidence, *if* the interventions are at sufficient scale and the methods of implementation conducted in ways that minimise risk of bias. Also identified in the review was a need for more in-depth analyses to understand the heterogeneity in the studies of asthma. While the chapter 5 results found positive associations with physical activity and greenness/tree cover, it would be useful to include quality/characteristics of greenspaces; this research might help explain why there was little association with green land use. There is a need to conduct more in depth studies of greenspace and outdoor air pollution in LMIC environments where there is substantial variation in concentration levels and sources across the year; also studying residential greenspace and the indoor environment would help understand any effects on overall exposure levels. Finally, the PhD results should be considered in light of the COVID-19 pandemic and related behaviour changes, including working habits. The following section describes these possible future areas of research in more detail.

7.6.1 *More Intervention and experimental study designs*

Out of 108 studies included in the systematic review on urban greenspace and respiratory health, only four were of an experimental design. These studies unanimously found benefits of various degrees in lung function, symptoms, or other health indicators related to spending time in a park or forest environment compared to a busy road setting (Cavalcante de Sá et al., 2016; Huang et al., 2016; Sinharay et al., 2018; Moshammer et al., 2019). However, it was not possible to distinguish benefits from the greenspace environment itself other than reduced exposure to air pollutants, as measured by the studies. Expanding the settings to multiple greenspace environments with different landscapes and vegetation compositions in these types of experimental designs could elucidate whether better health is attributed solely to lower air pollution, or mediated by other pathways, for instance, reduced stress (Franklin et al., 2020). Research outputs could then provide useful information on how to

maximise respiratory health benefits from greenspace (e.g., informing decisions to minimise air pollution exposure and other related pathways, such as enhance psychosocial benefits).

It would be useful to examine greenspace and respiratory health outcomes via natural experiments. These types of experiments can help circumvent the issue of self-selection bias that was discussed in the systematic review chapter. So far, there appears to be only one example of these studies to date, which found greater lower respiratory mortality where there was a loss of trees in the USA due to infestations of the emerald ash borer (Donovan et al., 2013). However, there are other natural and quasi-experimental studies that have examined physical activity, rather than a respiratory health outcome. Some of this research has found increased physical activity with an urban renewal project in Denmark (Andersen et al., 2017) and more walking time in individuals living nearby a greenway development in China (He et al., 2021), whereas other studies have not detected differences in physical activity levels with implementation of greenways (Auchincloss et al., 2019; Hunter et al., 2021). It would be useful to gain a better understanding of the reasons and contexts that may explain these disparate results. Another related research opportunity is to assess respiratory health benefits associated with green prescriptions, a nature-based intervention involving patients spending time in a natural environment to promote physical and mental health (Robinson & Breed, 2019). Green prescriptions also pertain to maximising the benefits of physical activity, which is discussed in the following section.

7.6.2 Greenspace features to maximise physical activity

The results in chapter 5 demonstrated that greater greenspace, in terms of NDVI and tree cover, was strongly linked to more intense and/or longer sessions of physical activity. This contrasted with no such association between residential greenspace and overall physical activity during the week-long monitoring periods. However, a limitation in this research was that only the amount of greenspace was measured, and not any indication of type or quality. Cycle paths or walkways connecting

residential areas to local amenities and places of work may be very different from open fields, even though the area-based measure of greenspace might be far lower.

In my research, it was interesting that the amount of green land use had the weakest association with MET-minutes for walking and was not statistically associated with cycling. A reason could be that only green land use with certain features may be conducive to physical activity. Research shows that quality and features of greenspace matter for physical activity, especially those that are large, clean, maintained, and situated close to home (Akpinar, 2016), and those that include desirable surroundings, facilities, amenities, absence of incivilities, and bird biodiversity (Knobel et al., 2021). These studies were conducted using self-reported physical activity behaviour; it would be useful to compare features based on objective metrics of physical activity to corroborate and possibly expand on these prior findings.

As discussed in the post-script to the research paper in chapter 5, it would be useful to perform an analysis comparing the likelihood of using active travel for short trips given neighbourhood quantities of greenspace. I attempted to conduct this work using the HEALS dataset, but there were insufficient data to do so. As far as I am aware, no other study has examined this specific research question, though others have investigated similar questions. For example, a study of primary schoolchildren in Beijing, China found streetscape greenery had little association with whether children walked to school (Wang et al., 2022). In another case, a study using survey data in the US found greater neighbourhood walking was associated with the percentage of forest, but not open space (Besser & Mitsova, 2021). Generating more insights into the role of greenspace on active travel in short trips could provide valuable information on how to encourage physical activity on a population level.

In addition to encouraging greater intensity or time spent engaging in cardiorespiratory exercise, physical activity undertaken in green areas, known as “green exercise”, may provide more benefits than that performed in non-green environments (e.g., indoors). However, a review concluded there were few substantiated advantages from engaging in green exercise, other than enjoyment of the

activity. The authors concluded that many of the studies were of smaller sample size and inadequate quality to properly establish benefits (Lahart et al., 2019). Exercise in greenspace may be superior for health if air pollution exposure in such locations is meaningfully lower, particularly since breathing rates are increased during periods of exertion. Evidence is particularly lacking for higher air pollution environments in LMIC settings, so much more research is required to understand the complex interplay between greenspace, exercise, and air pollution in these contexts (Tainio et al., 2021), including what short- and long-term implications there may be with respiratory health outcomes.

7.6.3 Better characterisation of greenspace and personal PM_{2.5} exposure in LMICs

The findings in chapter 6 suggest differing associations with personal PM_{2.5} exposure depending on the greenspace metric and season examined. It would be valuable to build on these results by performing an experimental study similar to that of Sinharay et al. (2018) where participants walk in both a greenspace and urban environment in Delhi, or other high air pollution urban environment in a LMIC context. To directly measure respiratory health, lung function measurements and recording of any symptoms would be taken before and at several intervals after the walk. Sinharay et al. (2018) found improvements in lung function after walking in a park in both healthy and COPD patients, but, in COPD patients, there were no differences in the benefits observed after walking in the park or road route. It would be important to include groups of participants with different health statuses.

To better characterise greenspace, this experiment could be performed in several different greenspace locations with differing designs and vegetation compositions, which would be measured and quantified in the study. Including multiple greenspace environments with personal exposure to air pollutants would help disentangle associations with features of the greenspace and those from air pollutants. It would also be beneficial to capture exposure to other air pollutants, such as O₃ and NO₂, in addition to PM. As the ambient concentrations fluctuate significantly across the year, it would also be very useful to perform the experiment at least during two points of the year with differing ambient pollutant levels, such as winter and summer.

It would be valuable to compare the results of chapter 4 (residential greenspace and indoor PM_{2.5} concentrations) with studies in LMIC settings. The surrounding greenspace, housing structures, and indoor pollutant sources all may differ in non-European geographies. Comparing and verifying these research findings would assist with understanding the association with greenspace and overall PM_{2.5} exposure, given the significant time spent indoors.

7.6.4 Further studies of greenspace and asthma

The studies identified in the systematic review with asthma as an outcome were heterogeneous in quality and findings. Even though this was the most studied outcome, additional research involving large-scale longitudinal studies of asthma incidence would improve the understanding of asthma development and greenspace exposure. One option for a study to address this issue is to establish a multi-city birth cohort and to follow-up participants over time. Including multiple cities, potentially in different countries, even continents, would provide variation in the types of greenspace, potential susceptibilities to asthma, air pollution levels, and likely other asthma risk factors. While ambitious, this study would advance the evidence much more than additional piecemeal studies of low quality and could address directly the potential biases of reverse causality and self-selection bias. For instance, surveys could include asking participants for any motivations for changing residential addresses. Exposure to specific allergenic species of trees and grasses, as well as pollen concentrations from these species (Neumann et al., 2019), would help the interpretation of associations with greenspace. Undertaking this research in multiple geographies would allow investigation into risks according to differing vulnerabilities to climate change (D'Amato et al., 2020). Finally, to assess how greenspace is related to the development of asthma if any associations are detected, mediation analysis could help disentangle and quantify the importance of mechanisms underpinning the relationship between greenspace exposure and asthma development.

7.6.5 Greenspace research addressing COVID-19

During the COVID-19 pandemic, greenspace was one area of refuge where people could socialise, exercise, and spend time outdoors with a relatively low risk of virus transmission (Lu et al., 2021). Increased use of greenspace may continue after the lifting of pandemic restrictions (Venter et al., 2021). As some proportion of remote working will likely also persist in the years to follow, there is an opportunity to investigate the importance of greenspace for engaging in healthy behaviours, such as physical activity (Soga et al., 2021). It would be interesting to compare the use of residential greenspace for physical activity in remote workers compared to those who have returned to the office. Greenspace in the workplace environment could also be characterised to assess if this has any influence on physical activity levels, in combination with modes of commuting. Such a study design could investigate physical activity levels in remote vs non-remote workers and explore how greenspace may factor in any observed associations. These results would build on the findings in chapter 5 regarding the positive effects of greenspace and environments used for physical activity.

7.7 Policy implications of the thesis

The results of my PhD research indicate positive pathways to health, including lower exposure to air pollutants and road noise annoyance, and increased physical activity, which contribute to the growing evidence base supporting urban greenspace and better health. Since the findings from the systematic review and empirical analyses were predominantly positive, as is suggestive of much of the research in this area (Yang et al., 2021), outputs can be used to further promote the conservation, maintenance, and expansion of urban greenspace. However, while the overall results appear to be in the direction of a beneficial health effect, translating these research findings into policy-oriented guidance is challenging, especially as the various analyses undertaken in the thesis work did not unanimously indicate opportunities for better health with higher greenspace levels. There is additional uncertainty given that the focus of my research was on pathways to health and not directly on respiratory health outcomes, though the magnitude and direction of effect can provide relevant evidence for possible health impacts. Although there is still uncertainty surrounding the specific pathways, health indicators,

and contexts under which exposure to greenspace could maximise health, urban greening policies would likely provide a net benefit. There is a need to ensure any environmental or health disbenefits are minimised.

One urban initiative that this research supports is the allocation of space to promote public and pedestrian-friendly transport, such as cycling and walking (Nieuwenhuijsen et al., 2019). These policies have numerous motivations, not least reducing CO₂ emissions, improving air quality, and encouraging more active transport modes. The interest and implementation of these areas will likely have been accelerated because of COVID-19 related measures, during which streets in many cities were closed to facilitate easier physical distancing (Barbarossa, 2020). Adding trees and green infrastructure may enhance the appeal of active travel in pedestrian-priority streets and neighbourhoods. According to the results in chapter 5, tree cover was linked both to increased METs for walking and cycling trips, so treed routes may further entice active travel. Of the three indicators examined (i.e., NDVI [overall greenness], tree cover, and green land use), the weakest findings with walking and cycling pertained to green land use. From a policy perspective, expanding green infrastructure, such as trees, on existing paths or streets may be both more feasible and better to facilitate walking and cycling, rather than expending limited resources developing new green land use in already built-up urban environments. As chapter 4 suggested lower indoor PM_{2.5} concentrations and road noise annoyance with more outdoor residential greenspace, greening these paths may also further promote better indoor air quality and reduced perception of road noise. Planting trees along these paths would also provide shade and cooler temperatures, thus lessening heat from climate change and facilitating more active travel modes (Rahman et al., 2020).

The WHO recommends urban residents to have access to public greenspace of at least 0.5 hectares within 300 m of home (WHO, 2017). However, research in the UK shows that more deprived areas have lower proportions of greenspace (Pearce et al., 2010). Inequities in availability were exacerbated during COVID-19 lockdowns, as Black, Asian and Minority Ethnic communities spent less time outside

and in greenspace (Mell & Whitten, 2021). A priority for policy should be to ensure all communities have sufficient access to public greenspaces, and that there are adequate funds to maintain this infrastructure. Despite the lower availability, some studies indicate that residents in lower SES areas could enjoy even more health benefits from nearby greenspace (Twohig-Bennett & Jones, 2018); at the same time, these areas need to be perceived as safe and context-appropriate in order to be properly used and enjoyed by residents (Roe et al., 2016). The systematic review in chapter 3 identified two thirds of associations between greenspace and respiratory health were positive (31% overall were positive and statistically significant), with the strongest positive associations with lower respiratory mortality. Lung disease is more prevalent in communities of higher deprivation, thus increasing the proportion of greenspace in these areas may maximise the potential benefits (BLF, 2016). A goal of achieving universal access to greenspace would preclude problems of green gentrification, whereby the introduction of greenspace can increase the value of a neighbourhood and displace lower income earners (Sharifi et al., 2021); more research is needed on how to best prevent the occurrence of this phenomenon. However, in the meantime, context-appropriate greenspace development involving as much as possible the participation of residents should progress in deprived areas to achieve higher equality and promote better respiratory and overall health.

7.8 Concluding statements

There is an extensive and growing evidence base between urban greenspace and respiratory health, which, when taken together, suggest mainly beneficial associations. This PhD examined potential pathways that may support a causal association with health, specifically the association of greenspace with lower air pollution exposure, greater levels of physical activity, and reductions in absolute or perceived noise levels. Although I identified positive associations within each of these pathways, my findings varied depending on how and where greenspace was defined; but were most consistent with tree cover. These pathways are not unique to respiratory health and could likely promote other mostly positive impacts in urban areas, such as better mental health, as well as environment and climate benefits. Research in this area would benefit from a broader demographic of research participants,

and though still inconclusive, the evidence on greenspace and respiratory health should be a consideration in urban greening initiatives.

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Appendix 1. Supplementary material: Exposure to urban greenspace and pathways to respiratory health: An exploratory systematic review

Supplementary Material

Exposure to urban greenspace and pathways to respiratory health: an exploratory systematic review

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Search terms

Search terms for Medline (title + abstract):

Search concept 1 (Greenspace):

1. (greenspace? or green-space? or greening or greenery or greenness or green land use? or green land cover? or urban green* or green infrastructure? or green roo* or green wall*).ti,ab.
2. exp Environment Design/
3. exp Forests/
4. ((woodland? or woods) and urban*).ti,ab.
5. ((forest? and urban*) not (random forest? or forest fire?)).ti,ab.
6. street tree?.ti,ab.
7. exp Trees/
8. (tree? not decision tree?).ti,ab
9. (park or parks or parkland?).ti,ab.
10. (NDVI and green*).ti,ab.
11. exp Parks, Recreational/
12. garden?.ti,ab.
13. exp Gardens/
14. (vegetati* not (vegetative state*)).ti,ab.
15. lawn?.ti,ab.
16. or/1-15

Search concept 2 (Respiratory Health):

17. respiratory.ti,ab.
18. exp Respiratory System/
19. (lung or lungs).ti,ab.
20. pulmonary.ti,ab.
21. asthma*.ti,ab.
22. exp asthma/
23. copd or chronic obstructive pulmonary disease?.ti,ab.
24. exp Lung Diseases/
25. bronchitis.ti,ab.
26. emphysema.ti,ab.
27. breath*.ti,ab.
28. (allerg* and (respiratory or breath* or asthma* or rhinitis or sinusitis or hay-fever)).ti,ab.
29. cough*.ti,ab.
30. exp Respiration Disorders/
31. wheez*.ti,ab.
32. or/17-31

Search strategy (title, abstract):

33. 16 and 32
34. (33) not (Animals/ not (Animals/ and Humans/))
35. limit 34 to (english language and yr="2000 -2018")
36. (35) not (comment or english abstract or editorial or letter or case reports).pt.

Language: English

Dates: Review everything published from 01 January 2000 - 31 December 2018

Filter for human studies only: NOT (Animals/ NOT (Animals/ AND Humans/))

Filter for publication type: not (comment or english abstract or editorial or letter or case reports)

Search terms for Global Health (title + abstract):

Search concept 1 (Greenspace):

1. (greenspace? or green-space? or greening or greenery or greenness or green land use? or green land cover? or urban green* or green infrastructure? or green roo* or green wall*).ti,ab.
2. exp forests/
3. ((woodland? or woods) and urban*).ti,ab.
4. ((forest? and urban*) not (random forest? or forest fire?)).ti,ab.
5. street tree?.ti,ab.
6. exp street trees/
7. exp trees/
8. (tree? not decision tree?).ti,ab
9. (park or parks or parkland?).ti,ab.
10. (NDVI and green*).ti,ab.
11. exp parks/
12. exp urban parks/
13. exp greenspace/
14. garden?.ti,ab.
15. exp gardens/
16. exp public parks/
17. exp public gardens/
18. (vegetati* not (vegetative state*)).ti,ab.
19. lawn?.ti,ab.
20. or/1-19

Search concept 2 (Respiratory Health):

21. respiratory.ti,ab.
22. exp respiratory system/
23. (lung or lungs).ti,ab.
24. pulmonary.ti,ab.
25. asthma*.ti,ab.
26. exp asthma/
27. copd or chronic obstructive pulmonary disease?.ti,ab.
28. bronchitis.ti,ab.
29. emphysema.ti,ab.
30. breath*.ti,ab.
31. (allerg* and (respiratory or breath* or asthma* or rhinitis or sinusitis or hay-fever)).ti,ab.
32. cough*.ti,ab.
33. exp respiratory diseases/
34. wheez*.ti,ab.
35. or/21-34

Search strategy (title, abstract):

36. 20 and 35
37. (36) not (Animals/ not (Animals/ and Humans/))
38. limit 37 to (english language and yr="2000 -2018")
39. 38 not (abstract only or book chapter or editorial).pt.

Language: English

Dates: Review everything published from 01 January 2000 - 31 December 2018

Filter for human studies only: NOT (Animals/ NOT (Animals/ AND Humans/))

Filter for publication type: not (abstract only or book chapter or editorial)

Search terms for Embase (title + abstract):

Search concept 1 (Greenspace):

1. (greenspace? or green-space? or greening or greenery or greenness or green land use? or green land cover? or urban green* or green infrastructure? or green roo* or green wall*).ti,ab.
2. exp forest/
3. ((woodland? or woods) and urban*).ti,ab.
4. ((forest? and urban*) not (random forest? or forest fire?)).ti,ab.
5. street tree?.ti,ab.
6. exp tree/
7. (tree? not decision tree?).ti,ab
8. (park or parks or parkland?).ti,ab.
9. (NDVI and green*).ti,ab.
10. exp recreational park/
11. garden?.ti,ab.
12. (vegetati* not (vegetative state*)).ti,ab.
13. lawn?.ti,ab.
14. or/1-13

Search concept 2 (Respiratory Health):

15. respiratory.ti,ab.
16. exp respiratory system/
17. (lung or lungs).ti,ab.
18. pulmonary.ti,ab.
19. asthma*.ti,ab.
20. exp asthma/
21. copd or chronic obstructive pulmonary disease?.ti,ab.
22. bronchitis.ti,ab.
23. emphysema.ti,ab.
24. breath*.ti,ab.
25. (allerg* and (respiratory or breath* or asthma* or rhinitis or sinusitis or hay-fever)).ti,ab.
26. cough*.ti,ab.
27. exp respiratory tract disease/
28. wheez*.ti,ab.
29. or/15-28

Search strategy (title, abstract):

30. 14 and 29
31. (30) not (Animals/ not (Animals/ and Humans/))
32. limit 31 to (english language and yr="2000 -2018")
33. 32 not (abstract or conference abstract or editorial or letter or note).pt.

Language: English

Dates: Review everything published from 01 January 2000 - 31 December 2018

Filter for human studies only: NOT (Animals/ NOT (Animals/ AND Humans/))

Filter for publication type: NOT (abstract or conference abstract or editorial or letter or note).pt.

Search terms for Scopus (title + abstract + keyword):

Search concept 1 (Greenspace):

1. (greenspace? or green-space? or greening or greenery or greenness or green land use? or green land cover? or urban green* or green infrastructure? or green roo* or green wall*).ti,ab.
2. ((woodland? or woods) and urban*).ti,ab.
3. ((forest? and urban*) not (random forest? or forest fire?)).ti,ab.
4. street tree?.ti,ab.
5. (tree? not decision tree?).ti,ab
6. (park or parks or parkland?).ti,ab.
7. (NDVI and green*).ti,ab.
8. garden?.ti,ab.
9. (vegetati* not (vegetative state*)).ti,ab.
10. lawn?.ti,ab.
11. or/1-10

Search concept 2 (Respiratory Health):

12. respiratory.ti,ab.
13. (lung or lungs).ti,ab.
14. pulmonary.ti,ab.
15. asthma*.ti,ab.
16. copd or chronic obstructive pulmonary disease?.ti,ab.
17. bronchitis.ti,ab.
18. emphysema.ti,ab.
19. breath*.ti,ab.
20. (allerg* and (respiratory or breath* or asthma* or rhinitis or sinusitis or hay-fever)).ti,ab.
21. cough*.ti,ab.
22. wheez*.ti,ab.
23. or/12-22

PUBYEAR aft 1999 and pubyear bef 2019 AND LANGUAGE (english)

Search terms for Cochrane Library (title + abstract + keyword):

Search concept 1 (Greenspace):

1. (greenspace? or green-space? or greening or greenery or greenness or green land use? or green land cover? or urban green* or green infrastructure? or green roo* or green wall*).ti,ab.
2. ((woodland? or woods) and urban*).ti,ab.
3. ((forest? and urban*) not (random forest? or forest fire?)).ti,ab.
4. street tree?.ti,ab.
5. (tree? not decision tree?).ti,ab
6. (park or parks or parkland?).ti,ab.
7. (NDVI and green*).ti,ab.
8. garden?.ti,ab.
9. (vegetati* not (vegetative state*)).ti,ab.

10. lawn?.ti,ab.
11. exp environment design/
12. exp forests/
13. exp trees/
14. exp parks, recreational/
15. or/1-14

Search concept 2 (Respiratory Health):

12. respiratory.ti,ab.
13. (lung or lungs).ti,ab.
14. pulmonary.ti,ab.
15. asthma*.ti,ab.
16. copd or chronic obstructive pulmonary disease?.ti,ab.
17. bronchitis.ti,ab.
18. emphysema.ti,ab.
19. breath*.ti,ab.
20. (allerg* and (respiratory or breath* or asthma* or rhinitis or sinusitis or hay-fever)).ti,ab.
21. cough*.ti,ab.
22. wheez*.ti,ab.
23. exp respiratory system/
24. exp asthma/
25. exp lung diseases/
26. exp respiration disorders/
27. or/15-26

in Title Abstract Keyword - with Cochrane Library publication date Between Jan 2000 and Dec 2018

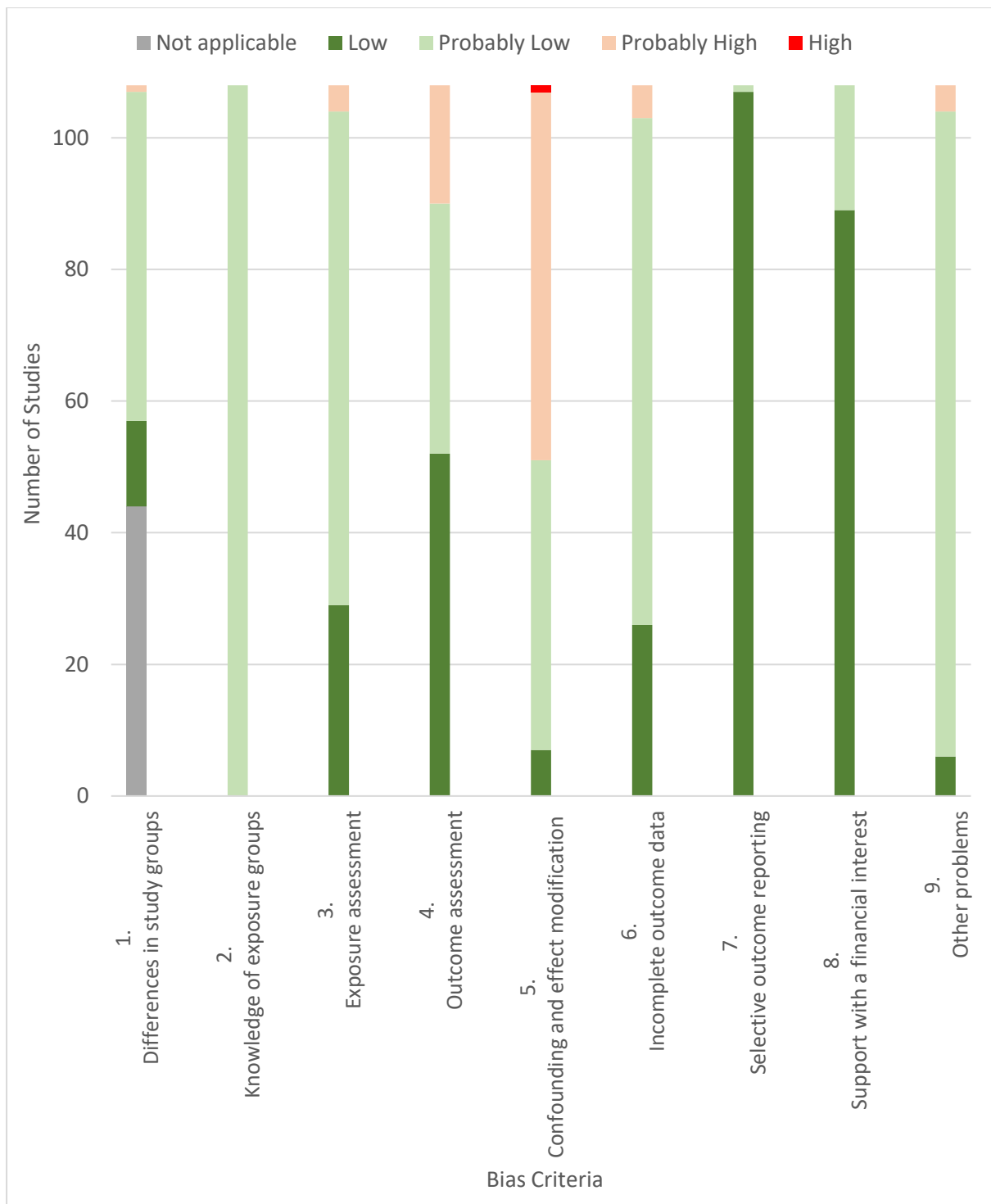


Figure S1. The distribution of the risk of bias ratings for each criterion.

Table S1. PECO (population, exposure, comparator, outcome) statement.

| PECO | Criteria |
|-------------|--|
| Population | Adults and children living in urban areas. |
| Exposure | Observational: Urban greenspace/greenness/greenery. Exposures may be based on residential or work address, or personal monitoring, for example. Experimental: The setting must include an area with urban greenspace (e.g., park, forest) and the experiment may include, for example, spending time or engaging in a specific activity in an urban greenspace. |
| Comparator | Observational: Individuals or group exposed to lower levels of urban greenspace. Experimental: Same activity, but in a less green or more urban setting. |
| Outcome | Any empirically collected respiratory health indicator. |

Table S2. The criteria used to assess the overall quality of evidence, following Johnson et al. (2016).

| Downgrading Factors | Summary of criteria for downgrading |
|-------------------------------------|---|
| Risk of bias | Study limitations – a substantial risk of bias across body of evidence |
| Indirectness | Evidence was not directly comparable to the question of interest (i.e., population, exposure, comparator, outcome) |
| Inconsistency | Widely different estimates of effect in similar populations (heterogeneity or variability in results) |
| Imprecision | Studies had few participants and few events (wide confidence intervals as judged by reviewers) |
| Publication Bias | Studies missing from body of evidence, resulting in an over or underestimate of true effects from exposure |
| Upgrading Factors | Summary of criteria for upgrading |
| Large magnitude of effect | Upgraded if modeling suggested confounding alone unlikely to explain associations with large effect estimate as judged by reviewers |
| Dose response | Upgraded if consistent relationship between dose and response in one or multiple studies, and/or dose response across studies |
| Confounding minimizes effect | Upgraded if consideration of all plausible residual confounders or biases would underestimate the effect or suggest a spurious effect when results show no effect |

Table S3. The definitions used for the strength of evidence, following Johnson et al. (2016).

| Strength Rating* | Definition |
|--------------------------------------|--|
| Sufficient evidence of better health | A positive relationship is observed between exposure and outcome where chance, bias, and confounding can be ruled out with reasonable confidence. The available evidence includes results from one or more well-designed, well-conducted studies, and the conclusion is unlikely to be strongly affected by the results of future studies. |
| Limited evidence of better health | A positive relationship is observed between exposure and outcome where chance, bias, and confounding cannot be ruled out with reasonable confidence. Confidence in the relationship is constrained by such factors as: the number, size, or quality of individual studies, or inconsistency of findings across individual studies. As more information becomes available, the observed effect could change, and this change may be large enough to alter the conclusion. |
| Inadequate evidence of better health | The available evidence is insufficient to assess effects of the exposure. Evidence is insufficient because of: the limited number or size of studies, low quality of individual studies, or inconsistency of findings across individual studies. More information may allow an assessment of effects. |
| Evidence of lack of better health | No relationship is observed between exposure and outcome, and chance, bias and confounding can be ruled out with reasonable confidence. The available evidence includes consistent results from more than one well-designed, well-conducted study at the full range of exposure levels that humans are known to encounter, and the conclusion is unlikely to be strongly affected by the results of future studies. The conclusion is limited to the age at exposure and/or other conditions and levels of exposure studied. |

*To be more applicable to potential benefits of urban greenspace, we have substituted “better health” for “toxicity”.

Table S4. Reasons for exclusion for studies involving a full text screen.

| Author | Year | Title | Eligibility Criteria # (1-8) |
|-------------------|------|---|------------------------------|
| Abizadeh | 2013 | Analyzing urban green space function emphasizing green space features in District 2 of Tabriz metropolis in Iran | 4 |
| Achilleos | 2017 | Acute effects of fine particulate matter constituents on mortality: A systematic review and meta-regression analysis | 1 |
| Aerts | 2018 | Biodiversity and human health: Mechanisms and evidence of the positive health effects of diversity in nature and green spaces | 1 |
| Al Saeed | 2007 | Sensitization to allergens among patients with allergic rhinitis in warm dry climates | 2 |
| Almeida | 2017 | Forecasting asthma hospital admissions from remotely sensed environmental data | 5 |
| Altintas | 2004 | Relationship between pollen counts and weather variables in east-Mediterranean coast of Turkey. Does it affect allergic symptoms in pollen allergic children? | 2 |
| Amorim | 2013 | Pedestrian exposure to air pollution in cities: Modeling the effect of roadside trees | 4 |
| Arbillaga-Etxarri | 2016 | Validation of walking trails for the Urban Training™ of chronic obstructive pulmonary disease patients | 4 |
| Arnold | 2016 | Vegetation delight?: Greenness and reduced risk of nonaccidental death | 1 |
| Bauch | 2015 | Public health impacts of ecosystem change in the Brazilian Amazon | 2 |
| Beck | 2013 | High environmental ozone levels lead to enhanced allergenicity of birch pollen | 2 |
| Beridze | 2018 | Childhood asthma in Batumi, Georgia: Prevalence and environmental correlates | 2 |
| Bibi | 2002 | Comparison of positive allergy skin tests among asthmatic children from rural and urban areas living within small geographic area | 2 |
| Bird | 2007 | Natural greenspace | 1 |
| Burton | 2012 | Streets ahead? The role of the built environment in healthy ageing | 1 |
| Calderon-Ezquerro | 2018 | Pollen in the atmosphere of Mexico City and its impact on the health of the pediatric population | 2 |

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| Cardoso | 2014 | Outdoor exercise under different concentrations of PM _{2,5} and effects on CC16 protein in healthy individuals, Sao Paulo/ Brazil | 1 |
| Carinanos | 2002 | Privet pollen (<i>Ligustrum</i> sp.) as potential cause of pollinosis in the city of Cordoba, south-west Spain | 4 |
| Castell | 2018 | Localized real-time information on outdoor air quality at kindergartens in Oslo, Norway using low-cost sensor nodes | 4 |
| Cetta | 2009 | Prospective study in schoolchildren of Milan of health effects (respiratory damage and airway inflammation) from traffic related air pollution | 2 |
| Chang | 2018 | Residential ambient traffic in relation to childhood pneumonia among urban children in Shandong, China: A cross-sectional study | 2 |
| Cohen | 2008 | The built environment and collective efficacy | 4 |
| Crepat | 2000 | Pollens, particles, pollution: The 7th National Congress of the Societe Francaise d'Aerobiologie (SOFRAB), Strasbourg, April 12, 2000 | 1 |
| Crouse | 2018 | Associations between Living Near Water and Risk of Mortality among Urban Canadians | 8 |
| Datzmann | 2018 | Outdoor air pollution, green space, and cancer incidence in Saxony: a semi-individual cohort study | 4 |
| Day | 2007 | Place and the experience of air quality | 4 |
| de Keijzer | 2017 | The association of air pollution and greenness with mortality and life expectancy in Spain: A small-area study | 4 |
| DePriest | 2018 | Investigating the relationships among neighborhood factors and asthma control in African American children: A study protocol | 1 |
| Egorov | 2017 | Vegetated land cover near residence is associated with reduced allostatic load and improved biomarkers of neuroendocrine, metabolic and immune functions | 4 |
| Einecke | 2017 | The nearer the park, the fewer respiratory symptoms | 1 |
| Fons | 2018 | Preliminary PCR-TTGE analyses of bacterial communities associated with pollen from anemophilous trees: potential impacts on plants and human health | 4 |
| Fu | 2018 | Long-term atmospheric visibility trends and characteristics of 31 provincial capital cities in China during 1957-2016 | 4 |
| Garib | 2017 | Possible effect of landscape design on IgE recognition profiles of two generations revealed with micro-arrayed allergens | 2 |

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| Gascon | 2016 | Residential green spaces and mortality: A systematic review | 1 |
| Gibbs | 2015 | Eucalyptus pollen allergy and asthma in children: a cross-sectional study in South-East Queensland, Australia | 2 |
| Gill | 2016 | Aerial pollen diversity in Punjab and their clinical significance in allergic diseases | 2 |
| Giroux | 2002 | Exhaled NH ₃ and excreted NH ₄ ⁺ in children in unpolluted or urban environments | 2 |
| Giroux | 2001 | Exhaled NO in asthmatic children in unpolluted and urban environments | 2 |
| Glew | 2004 | Comparison of pulmonary function between children living in rural and urban areas in northern Nigeria | 2 |
| Gonianakis | 2006 | A 10-year aerobiological study (1994-2003) in the Mediterranean island of Crete, Greece: grasses and other weeds, aerobiological data, and botanical and clinical correlations | 2 |
| Green | 2018 | Landscape Plant Selection Criteria for the Allergic Patient | 1 |
| Im | 2016 | Comparison of Effect of Two-Hour Exposure to Forest and Urban Environments on Cytokine, Anti-Oxidant, and Stress Levels in Young Adults | 4 |
| Jackson | 2003 | The relationship of urban design to human health and condition | 1 |
| Jacobs | 2015 | Moving into green healthy housing | 2 |
| Jenkins | 2011 | Respiratory quotients and Q10 of soil respiration in sub-alpine Australia reflect influences of vegetation types | 4 |
| Jia | 2016 | Health Effect of Forest Bathing Trip on Elderly Patients with Chronic Obstructive Pulmonary Disease | 3 |
| Kanani Sadat | 2015 | Fuzzy spatial association rule mining to analyze the effect of environmental variables on the risk of allergic asthma prevalence | 5 |
| Kanani-Sadat | 2014 | Investigating the relation between prevalence of asthmatic allergy with the characteristics of the environment using association rule mining | 8 |
| Karatzas | 2018 | New European Academy of Allergy and Clinical Immunology definition on pollen season mirrors symptom load for grass and birch pollen-induced allergic rhinitis | 2 |
| Karimipour | 2016 | Mapping the vulnerability of asthmatic allergy prevalence based on environmental characteristics through fuzzy spatial association rule mining | 5 |

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| Keddem | 2015 | Mapping the urban asthma experience: Using qualitative GIS to understand contextual factors affecting asthma control | 2 |
| Kmenta | 2016 | Pollen information consumption as an indicator of pollen allergy burden | 2 |
| Kondo | 2018 | Urban Green Space and Its Impact on Human Health | 1 |
| Konishi | 2014 | Particulate matter modifies the association between airborne pollen and daily medical consultations for pollinosis in Tokyo | 2 |
| Krajewska-Wojtys | 2016 | Local allergic rhinitis to pollens is underdiagnosed in young patients | 2 |
| Kuehn | 2018 | Pollution exposure counteracts exercise benefits: Exercise in green spaces, pollution reductions recommended | 1 |
| Lambert | 2017 | Residential greenness and allergic respiratory diseases in children and adolescents - A systematic review and meta-analysis | 1 |
| Lanki | 2017 | Acute effects of visits to urban green environments on cardiovascular physiology in women: A field experiment | 4 |
| Lee | 2014 | Cardiac and pulmonary benefits of forest walking versus city walking in elderly women: A randomised, controlled, open-label trial | 3 |
| Leh | 2011 | Urban environmental health: respiratory illness and urban factors in Kuala Lumpur City, Malaysia | 5 |
| Lombardi | 2011 | The possible influence of the environment on respiratory allergy: A survey on immigrants to Italy | 2 |
| Loureiro | 2005 | Urban versus rural environment - Any differences in aeroallergens sensitization in an allergic population of Cova da Beira, Portugal? | 2 |
| Mao | 2017 | Prevalence trends in the characteristics of patients with allergic asthma in Beijing, 1994 to 2014 | 2 |
| May | 2011 | Adult asthma exacerbations and environmental triggers: a retrospective review of ED visits using an electronic medical record | 2 |
| McCurdy | 2010 | Using nature and outdoor activity to improve children's health | 1 |
| McFarlane | 2013 | Land-use change and emerging infectious disease on an island continent | 1 |
| Moore | 2006 | Population health effects of air quality changes due to forest fires in British Columbia in 2003: estimates from physician-visit billing data | 2 |

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| Mwendwa | 2012 | Benefits and challenges of Urban green spaces | 1 |
| N/A | 2006 | Forests and human health | 1 |
| Nct | 2016 | Effect of Vegetation in Kindergartens on the Immune Response of Children | 1 |
| Notas | 2015 | Accurate prediction of severe allergic reactions by a small set of environmental parameters (NDVI, temperature) | 4 |
| Nowak | 2014 | Tree and forest effects on air quality and human health in the United States | 5 |
| Nowak | 2018 | Air pollution removal by urban forests in Canada and its effect on air quality and human health | 1 |
| Olaniyan | 2017 | A prospective cohort study on ambient air pollution and respiratory morbidities including childhood asthma in adolescents from the western Cape Province: study protocol | 1 |
| Piotrowska-Weryszko | 2014 | Plant pollen content in the air of Lublin (central-eastern Poland) and risk of pollen allergy | 2 |
| Radauer-Preiml | 2016 | Nanoparticle-allergen interactions mediate human allergic responses: Protein corona characterization and cellular responses | 2 |
| Ranjan | 2016 | Assessment of air quality impacts on human health and vegetation at an industrial area | 5 |
| Rao | 2017 | Assessing the Potential of Land Use Modification to Mitigate Ambient NO ₂ and Its Consequences for Respiratory Health | 1 |
| Rao | 2014 | Assessing the relationship among urban trees, nitrogen dioxide, and respiratory health | 1 |
| Rashid | 2015 | Breathing spaces in inner urban neighbourhoods in Sydney: The impact of sustainable open spaces | 4 |
| Ratola | 2017 | Modelling benzo[a]pyrene in air and vegetation for different land uses and assessment of increased health risk in the Iberian Peninsula | 5 |
| Rengganis | 2017 | Pollen Serum Specific IgE Sensitization in Respiratory Allergic Patients in Jakarta, Indonesia | 2 |
| Romanillos | 2018 | Protected natural areas: In sickness and in health | 4 |
| Roy | 2012 | A systematic quantitative review of urban tree benefits, costs, and assessment methods across cities in different climatic zones | 1 |

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| Ruffoni | 2013 | A 10-year survey on asthma exacerbations: Relationships among emergency medicine calls, pollens, weather, and air pollution | 2 |
| Ruokolainen | 2015 | Green areas around homes reduce atopic sensitization in children | 4 |
| Sbihi | 2016 | Perinatal air pollution exposure and development of asthma from birth to age 10 years | 8 |
| Schmidt | 2016 | Pollen overload: Seasonal allergies in a changing climate | 1 |
| Schulz | 2018 | Is the built environment associated with morbidity and mortality? A systematic review of evidence from Germany | 1 |
| Seo | 2015 | Clinical and immunological effects of a forest trip in children with asthma and atopic dermatitis | 3 |
| Shafaghat | 2016 | Environmental-conscious factors affecting street microclimate and individuals' respiratory health in tropical coastal cities | 1 |
| Shah | 2014 | Natural products; pharmacological importance of family cucurbitaceae: A brief review | 4 |
| Sinharay | 2014 | Cardio-respiratory outcomes in COPD following ambient exposures to diesel traffic emissions: "Oxford Street 2" | 1 |
| Sinharay | 2014 | Ambient exposure to diesel traffic particles and cardio-respiratory outcomes in healthy and in COPD subjects: 'Oxford street 2' | 1 |
| Soyiri | 2018 | Green spaces could reduce asthma admissions | 1 |
| Spellerberg | 2006 | Silver birch (<i>Betula pendula</i>) pollen and human health: problems for an exotic tree in New Zealand | 1 |
| Spira-Cohen | 2010 | Personal exposures to traffic-related particle pollution among children with asthma in the South Bronx, NY | 4 |
| Steinman | 2003 | Bronchial hyper-responsiveness and atopy in urban, peri-urban and rural South African children | 2 |
| Suro-Maldonado | 2006 | Air quality, particulate matter, and geographic characterization in a potential asthma prone region of eastern central Puerto Rico | 2 |
| Tan | 2017 | Particle exposure and inhaled dose during commuting in Singapore | 5 |
| Taramarcaz | 2015 | Prevalence of ragweed allergy in rural Geneva - a pilot study | 2 |
| Toth | 2011 | Micro-regional hypersensitivity variations to inhalant allergens in the city of Zagreb and Zagreb county | 4 |

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| Twohig-Bennett | 2018 | The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes | 1 |
| van den Bosch | 2017 | Urban natural environments as nature-based solutions for improved public health – A systematic review of reviews | 1 |
| van Dorn | 2017 | Urban planning and respiratory health | 1 |
| Vujcic | 2016 | The socioeconomic and health effects of green infrastructure on the Vracar municipality, city of Belgrade | 2 |
| Wang | 2016 | Prevalence and trends of sensitisation to aeroallergens in patients with allergic rhinitis in Guangzhou, China: a 10-year retrospective study | 2 |
| Waqar | 2010 | Possible effects of cultivated plants in the development of allergy in population of Sindh, Pakistan | 1 |
| Willis | 2011 | Measuring health benefits of green space in economic terms | 1 |
| Xu | 2018 | Impact of Built Environment on Respiratory Health: An Empirical Study | 5 |
| Zandbergen | 2009 | Methodological issues in determining the relationship between street trees and asthma prevalence | 1 |
| Zhao | 2014 | Morning exercise and PM2.5/PM10 | 4 |
| Fuertes | 2021 | Complex interplay between greenness and air pollution in respiratory health | 1 |
| Wang | 2021 | Review of associations between built environment characteristics and severe acute respiratory syndrome coronavirus 2 infection risk | 1 |
| Denpetkul | 2021 | Daily ambient temperature and mortality in Thailand: Estimated effects, attributable risks, and effect modifications by greenness | 2 |
| Guilbert | 2019 | Personal exposure to traffic-related air pollutants and relationships with respiratory symptoms and oxidative stress: A pilot cross-sectional study among urban green space workers | 2 |
| Liu | 2020 | Residence proximity to traffic-related facilities is associated with childhood asthma and rhinitis in Shandong, China | 2 |
| Ramirez-Leyva | 2021 | Patterns of allergen sensitization in patients with asthma in Yaqui Valley, Mexico | 2 |
| Abhijith | 2021 | Evaluation of respiratory deposition doses in the presence of green infrastructure | 4 |

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| Gisler | 2021 | Associations of air pollution and greenness with the nasal microbiota of healthy infants: A longitudinal study | 4 |
| Jia | 2021 | Road traffic and air pollution: Evidence from a nationwide traffic control during coronavirus disease 2019 outbreak | 4 |
| Lu | 2021 | Green spaces mitigate racial disparity of health: A higher ratio of green spaces indicates a lower racial disparity in SARS-CoV-2 infection rates in the USA | 4 |
| Amoatey | 2020 | Long-term exposure to ambient PM2.5 and impacts on health in Rome, Italy | 5 |
| Almeida | 2020 | Influence of urban forest on traffic air pollution and children respiratory health | 5 |
| Jangid | 2021 | Investigating the Effect of Lockdown During COVID-19 on Land Surface Temperature Using Machine Learning Technique by Google Earth Engine: Analysis of Rajasthan, India | 5 |
| Lovinsky-Desir | 2021 | Locations of Adolescent Physical Activity in an Urban Environment and Their Associations with Air Pollution and Lung Function | 5 |
| Wang | 2020 | Spatiotemporal variability in long-term population exposure to PM2.5 and lung cancer mortality attributable to PM2.5 across the Yangtze River Delta (YRD) region over 2010–2016: A multistage approach | 5 |
| Klomp maker | 2020 | Surrounding green, air pollution, traffic noise exposure and non-accidental and cause-specific mortality | 8 |

Table S5. Individual risk of bias assessments for the mortality studies.

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|------------|------|--------------------------------|----------------------------------|----------------------------------|--|--|--|---------------------------------------|----------------------------------|--|---|---------------------------------------|--|---------------------------------|---|--|---|------------------------------------|--|---------------|
| Bauwelinck | 2021 | Not applicable | Population level study | Probably low | Population study with objective exposure, lack of blinding not likely to affect results. | Low | Objective metrics (NDVI, land use) with good description of methods | Low | Routine statistics | Probably high | No smoking exposure data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Government research grants | Probably low | Potential for self-selection bias | Probably High |
| Crouse | 2017 | Low | Nationally representative cohort | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure - NDVI | Low | Mortality from Statistics Canada | Probably low | Included Tier 1 confounding variables in analysis, no physical activity | Probably Low | Mortality database assumed to be complete. | Low | Outcomes are reported | Low | No funding received. | Probably Low | No data on use of greenspace. Self-selection issue | Probably Low |
| Donovan | 2013 | Not Applicable | Population study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metric, but only at area level | Low | Routine statistics | Probably High | No smoking, air pollution or physical activity data | Low | No indication of incomplete data | Low | All outcome data presented | Probably Low | No financial disclosures reported by authors. | Probably Low | Selection bias issue | Probably High |
| Gronlund | 2015 | Not Applicable | Population study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Only examined non-green space areas. Not clear which land covers were included in this definition. | Low | State death records | Probably high | No smoking data | Probably Low | Mortality data assumed to be mostly complete | Probably Low | Quantitative results not provided for respiratory mortality | Low | Various government and academic research grants | Probably Low | No other areas of bias present. | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------|------|--------------------------------|------------------|----------------------------------|--|--|--|---------------------------------------|--|--|---|---------------------------------------|---|---------------------------------|-----------------------------|--|---|------------------------------------|-----------------------------------|---------------|
| Hu | 2007 | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably high | Not clear exactly how vegetation was being assigned from Landsat imagery | Low | Routine statistics assumed to be accurate | Probably high | Not clear how SMRs were generated and limited variables | Probably Low | Does not appear to be missing outcome data | Low | All outcome data presented. | Low | Funded by USEPA | Probably Low | No other areas of bias present. | Probably High |
| Jaafari | 2020 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (greenspace composition and configuration), but no QA/QC | Low | Routine statistics | Probably high | No SES, smoking, or physical activity data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Probably low | Does not mention, but not likely to be a source of bias | Probably low | Potential for self-selection bias | Probably High |
| James | 2016 | Probably Low | Large cohort | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | For environmental variables methods robust, physical activity, mental health and social engagement based on questionnaire possibly biased. | Low | Previously validated methods; physician coded deaths | Low | Tier 1 confounders included, with mediation analyses | Low | Response rate >90% | Low | All outcome data presented. | Low | Funded by research grants, no conflicts of interest. | Low | No other areas of bias present. | Probably Low |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-------------|------|--------------------------------|------------------|----------------------------------|--|--|---|---------------------------------------|--------------------|--|--|---------------------------------------|---|---------------------------------|-----------------------|--|--|------------------------------------|-----------------------------------|---------------|
| Kasdagli | 2021 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Low | Routine statistics | Probably low | All tier 1 confounders adjusted for (lung mortality as a proxy for smoking), air pollution examined separately, but no mediation analysis or physical activity | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Probably low | No funding source listed, but declare no competing financial interests | Probably low | Potential for self-selection bias | Probably Low |
| Kim | 2019 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Low | Routine statistics | Probably low | All tier 1 confounders and air pollution, no physical activity | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by government grants | Probably low | Potential for self-selection bias | Probably Low |
| Klompmaaker | 2021 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI, land cover), clear description and use of multiple buffers | Low | Routine statistics | Probably high | All tier 1 confounders (indirect adjustment for smoking but not for respiratory mortality) and air pollution, no physical activity | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by research grants | Probably low | Potential for self-selection bias | Probably High |
| Lee | 2020 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (NDVI, land cover), but no QA/QC | Low | Routine statistics | Probably high | No smoking or physical activity data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by government grants | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|------------|------|--------------------------------|---|----------------------------------|--|--|--|---------------------------------------|--------------------------------|--|---|---------------------------------------|--|---------------------------------|-----------------------------|--|--|------------------------------------|-----------------------------------|---------------|
| Orioli | 2019 | Low | Population cohort based on census data | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI, leaf area index), with clear description and multiple buffers | Low | Routine statistics | Probably high | Smoking analysis excludes respiratory mortality, mediation with air pollution, no physical activity data | Low | Mortality assumed to be complete | Low | Outcomes are reported | Probably low | No funding source listed, but declare no competing financial interests | Probably low | Potential for self-selection bias | Probably High |
| Richardson | 2010 | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective measure - Land use and ran QA/QC | Low | Routine statistics | Probably Low | Included Tier 1 confounders (area-level smoking) and examined effects separately by sex. No physical activity | Probably Low | Mortality statistics are mostly complete | Low | All outcome data presented. | Low | Funded by the Forestry Commission. | Low | No other areas of bias present. | Probably Low |
| Shen | 2017 | Not Applicable | Population study | Probably Low | Population study with objective exposure, lack of blinding not likely to affect results. | Probably Low | Used objective measures, QA/QC not clear | Low | Routine statistics | Probably high | Only examined mediators: AP & temp | Probably Low | Assumed routine stats mostly complete | Low | Outcomes are reported | Low | Research grants. | Probably Low | Self-selection bias | Probably High |
| Sun | 2020 | Probably low | Population level study (9% of Hong Kong older adults) | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (NDVI), with clear description and multiple buffers | Low | Routine statistics (mortality) | Probably high | No adjustment for SES, smoking, NDVI included as an effect modifier | Low | Mortality assumed to be complete | Low | Outcomes are reported | Low | Funded by government research grant | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|------------|------|--------------------------------|-----------------------------------|----------------------------------|--|--|--|---------------------------------------|-----------------------------|--|---|---------------------------------------|---|---------------------------------|---------------------------|--|--|------------------------------------|--|---------------|
| Vienneau | 2017 | Low | Population cohort | Probably Low | Cohort study with objective exposure, lack of blinding not likely to affect results. | Probably Low | Used objective measures, QA/QC not clear | Low | Death certificates | Probably high | No smoking data, mediation with air pollution, no physical activity | Probably Low | Does not address missing outcome data, but likely complete if using mortality | Low | Outcomes are reported. | Low | Research grants. | Probably Low | Did not account for selection bias, i.e., whether healthier people chose to live in greener areas, and no data on use of greenspace. | Probably High |
| Villeneuve | 2012 | Low | Random sample at population level | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Potential for some exposure misclassification, did not outline QAQC. | Low | Canadian Mortality database | Probably Low | Tier 1 confounders included, but some adjustment based on indirect methods. Authors note potential for residual confounding by sociodemographics. No mediation analysis | Probably Low | Uses Canadian Mortality Database, states <5% missing. | Low | Mortality is reported on. | Low | Funding provided by the Canadian Institutes for Health Research and Health Canada. | Probably Low | Did not account for selection bias, i.e., whether healthier people chose to live in greener areas, and no data on use of greenspace. | Probably Low |
| Wang | 2019 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (landscape metrics), but no QA/QC | Low | Routine statistics | Probably high | No smoking data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | No funding | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|--------|------|--------------------------------|---------------------------------|----------------------------------|--|--|--|---------------------------------------|-----------------------------------|--|---|---------------------------------------|--|---------------------------------|------------------------|--|-----------------------------------|------------------------------------|-----------------------------------|---------------|
| Wang | 2017 | Probably Low | Recruitment from same community | Probably Low | Objective exposure, lack of blinding not likely to affect results. | Probably Low | Used objective measure (NDVI), but an unorthodox method (i.e., >0.1 cells) | Low | Death certificates | Low | Tier 1 and 2 confounders accounted for, no mediation, but no significant results | Probably Low | Unclear how much missing outcome data there is | Low | Outcomes are reported. | Low | No funding received. | Probably Low | Selection bias issue | Probably Low |
| Xu | 2017 | Not Applicable | Study uses routine statistics | Probably Low | Not clear, but probably did not affect outcome. | Probably Low | Used objective measure (NDVI) | Low | Used routine mortality statistics | Probably high | Included some confounding variables in analysis, but exclude air pollution and smoking. | Low | Mostly complete outcome data. | Low | Outcomes are reported. | Low | No conflict of interest declared. | Probably Low | Potential for self-selection bias | Probably High |

Table S6. Individual risk of bias assessments for the hospital admissions studies.

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|--------|------|--------------------------------|------------------|----------------------------------|--|--|---|---------------------------------------|--------------------|--|---|---------------------------------------|--|---------------------------------|------------------------|--|------------------|------------------------------------|-----------------------------------|---------------|
| Alcock | 2017 | Not Applicable | Population study | Probably Low | Population study with objective exposure, lack of blinding not likely to affect results. | Low | Included 3 different greenspace indicators. | Low | Routine statistics | Probably high | Did not adjust for smoking, but noted that deprivation is correlated to smoking rates | Probably Low | Routine stats would be mostly complete | Low | Outcomes are reported. | Low | Research grants. | Probably Low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-----------------|------|--------------------------------|-------------------------------|----------------------------------|--|--|---|---------------------------------------|----------------------------------|--|--|---------------------------------------|---|---------------------------------|------------------------|--|--|------------------------------------|--|---------------|
| Alvarez-Mendoza | 2019 | Not applicable | Population study | Probably low | Population study with objective exposure, lack of blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Low | Routine statistics | Probably high | No smoking exposure data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Probably low | No mention of funding, but not likely to have biased findings. | Probably low | Potential for self-selection bias | Probably High |
| Ayres-Sampaio | 2014 | Not Applicable | Study uses routine statistics | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Used objective measure (NDVI) - but not clear at what spatial scale | Low | Used routine hospital admissions | Probably high | Included temperature, air pollutants using LUR, humidity, but only present univariate analyses | Low | Outcome data appear to be complete | Low | Outcomes are reported. | Probably Low | Does not state where funding came from | Probably Low | No adjustment for SES, but perhaps too large of a scale (i.e. municipality level). Potential for selection bias. | Probably High |
| Douglas | 2019 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (land cover), but no QA/QC | Low | Routine statistics | Probably high | No smoking exposure data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Supported by government funding | Probably low | Potential for self-selection bias | Probably High |
| Heo | 2019 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (NDVI) with clear description of methods | Low | Routine statistics | Probably high | No smoking exposure data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Supported by government funding | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|--------|------|--------------------------------|--|----------------------------------|--|--|--|---------------------------------------|--|--|--|---------------------------------------|---|---------------------------------|--|--|---|------------------------------------|-----------------------------------|---------------|
| Hu | 2007 | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably high | Not clear exactly how vegetation was being assigned from Landsat imagery | Low | Routine statistics assumed to be accurate | Probably high | Not clear how SMRs were generated and limited variables | Probably Low | Does not appear to be missing outcome data | Low | All outcome data presented. | Low | Funded by USEPA | Probably Low | No other areas of bias present. | Probably High |
| Kim | 2021 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (Tree and greenspace area), with clear description of methods | Low | Routine statistics | Probably high | No smoking or physical activity data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by university grants | Probably low | Potential for self-selection bias | Probably High |
| Lai | 2019 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (Street trees), but no QA/QC | Low | Routine statistics | Probably high | No smoking or physical activity data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Probably low | Does not mention, but not likely to be a source of bias | Probably low | Potential for self-selection bias | Probably High |
| Lee | 2020 | Probably low | Used Longitudinal Health Insurance Database to identify subjects | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Low | Routine statistics | Probably high | No smoking data | Probably low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by university grants | Probably low | Potential for self-selection bias | Probably High |
| Lee | 2014 | Not Applicable | Population study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metric, but quality of data not clear | Probably Low | Objective exposure metric, but quality of data not clear | Probably high | Examine structural equation modelling, but do not take into account SES, smoking etc | Probably Low | No indication of incomplete data | Low | All outcome data are presented, though no protocol provided. | Probably Low | Not clear, but likely not a source of bias. | Low | No other areas of bias present. | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-----------|------|--------------------------------|------------------|----------------------------------|--|--|---|---------------------------------------|--|--|--|---------------------------------------|--|---------------------------------|----------------------------|--|--|------------------------------------|-----------------------------------|---------------|
| Liddicoat | 2018 | Not Applicable | Population study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Many different biodiversity indicators, but none representing overall greenspace exposure | Low | Routine statistics | Probably Low | Included Tier 1 and 2 confounding variables, no mediation | Probably Low | Omitted areas with missing data | Low | All outcome data presented | Probably Low | Does not state where funding was from, but likely not a source of bias | Probably Low | Potential for self-selection bias | Probably Low |
| Lovasi | 2008 | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure - street trees, but limited information on methods | Low | Routine statistics | Probably high | Did not include any information on smoking. | Low | No incomplete data | Low | Report on outcome of model | Low | Funded by research grant | Probably Low | Self-selection bias | Probably High |
| Sbihi | 2017 | Not Applicable | Population study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure - NDVI, but limited information on methods and QA/QC | Low | Physician billing and hospital discharge records | Probably low | Included Tier 1 confounding variables in analysis. No physical activity. | Probably Low | Ministry of Health data assumed to be complete | Low | Report on outcome of model | Low | Research grants from Health Canada | Probably Low | Self-selection bias | Probably Low |

Table S7. Individual risk of bias assessments for the lung cancer studies.

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-------------|------|--------------------------------|------------------|----------------------------------|--|--|---|---------------------------------------|--|--|--|---------------------------------------|---|---------------------------------|-------------------------------------|--|-----------------------------|------------------------------------|--|---------------|
| Bixby | 2015 | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Robust methods, but no discussion of QA/QC | Low | Deaths from Office for National Statistics | Probably high | Did not account for smoking (but did use income - not sufficient for lung cancer), nor physical activity | Probably Low | Used mortality data from ONS, so would likely be mostly complete. | Low | Present results from main outcomes. | Low | No funding received. | Probably Low | Did not account for selection bias, i.e., whether healthier people chose to live in greener areas, and no data on use of greenspace. | Probably High |
| Kim | 2019 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Low | Routine statistics | Probably low | All tier 1 confounders and air pollution, no physical activity | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by government grants | Probably low | Potential for self-selection bias | Probably Low |
| Klomp maker | 2021 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI, land cover), clear description and use of multiple buffers | Low | Routine statistics | Probably high | All tier 1 confounders (indirect adjustment for smoking but not for respiratory mortality) and air pollution, no physical activity | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by research grants | Probably low | Potential for self-selection bias | Probably High |
| Lee | 2020 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (NDVI, land cover), but no QA/QC | Low | Routine statistics | Probably high | No smoking or physical activity data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by government grants | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|------------|------|--------------------------------|------------------|----------------------------------|--|--|---|---------------------------------------|---|--|---|---------------------------------------|--|---------------------------------|-----------------------------|--|---|------------------------------------|--|---------------|
| Li | 2008 | Not Applicable | Population study | Probably Low | Objective exposure (% of forest cover), lack of blinding not likely to affect results. | Probably Low | Used objective measure (% forest cover), but no QA/QC noted | Low | Routine statistics | Probably low | Tier 1 confounders accounted for, did not account for air pollution or physical activity | Probably Low | Population data used, so assumed to be mainly complete | Low | Outcomes are reported. | Probably Low | Does not indicate where funding was received from | Probably Low | Selection bias issue Mismatch of exposure and health data, but likely not high source of bias | Probably Low |
| Mitchell | 2008 | Not Applicable | Population study | Probably Low | Population study | Probably Low | Uses land use database | Low | Mortality from Office for National Statistics | Probably high | Only group-level confounders, no smoking rates, though is related to SES | Probably Low | ONS mortality data is mostly complete | Low | All outcome data presented. | Low | No funding received. | Probably Low | Did not account for selection bias, i.e., whether healthier people chose to live in greener areas, and no data on use of greenspace. | Probably High |
| Richardson | 2010 | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective measure - Land use and ran QA/QC | Low | Routine statistics | Probably Low | Included Tier 1 confounders (area-level smoking) and examined effects separately by sex. No physical activity | Probably Low | Mortality statistics are mostly complete | Low | All outcome data presented. | Low | Funded by the Forestry Commission. | Low | No other areas of bias present. | Probably Low |
| Richardson | 2012 | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure - Land use | Low | Routine statistics | Probably high | Included important confounders, e.g. SES, air pollution, and examined effects separately | Probably Low | Mortality statistics are mostly complete | Low | All outcome data presented. | Low | Funded by the UK Forestry Commission. | Probably Low | Fairly small sample size. | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------------|------|--------------------------------|-------------------------------|----------------------------------|---|--|--|---------------------------------------|-----------------------------------|--|--|---------------------------------------|--|---------------------------------|----------------------------|--|--------------------------------------|------------------------------------|--|---------------|
| Richardson | 2010 | Not Applicable | Ecological study | Probably Low | No blinding, but the outcome and the outcome measurement are not likely to be influenced by lack of blinding. | Probably Low | Detailed, high resolution classification method (though not much QA information). | Low | Routine statistics | Probably Low | Included all Tier 1 confounders and reported ORs separately by potential modifiers (area-level smoking). No physical activity. | Probably Low | Mortality data, so mostly complete | Low | All outcome data presented | Low | Research grants. | Probably Low | Potential for exposure misclassification (automated process at national scale), no account of wider exposure (e.g. buffers around areas) | Probably Low |
| Sun | 2021 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Low | Routine statistics | Probably high | No smoking data (though adjusted for factors related to smoking, e.g. education) | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by government research grants | Probably low | Potential for self-selection bias | Probably High |
| Xu | 2017 | Not Applicable | Study uses routine statistics | Probably Low | Not clear, but probably did not affect outcome. | Probably Low | Used objective measure (NDVI) | Low | Used routine mortality statistics | Probably high | Included some confounding variables in analysis, but exclude air pollution and smoking. | Low | Mostly complete outcome data. | Low | Outcomes are reported. | Low | No conflict of interest declared. | Probably Low | Potential for self-selection bias | Probably High |
| Zare Sakhvidi | 2021 | Probably low | Prospective study of workers | Probably low | Exposure assigned using objective measurement - blinding not | Low | Objective metrics (NDVI, distance to greenspace), with clear description, multiple | Low | Routine statistics | Probably low | All tier 1 and 2 confounders, no physical activity (but BMI included) | Low | Cancer incidence records assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|--------|------|--------------------------------|-------|----------------------------------|-------|--|-------|---------------------------------------|-------|--|-------|---------------------------------------|-------|---------------------------------|-------|--|-------|------------------------------------|-------|---------|
|--------|------|--------------------------------|-------|----------------------------------|-------|--|-------|---------------------------------------|-------|--|-------|---------------------------------------|-------|---------------------------------|-------|--|-------|------------------------------------|-------|---------|

likely to affect results. images and buffer sizes

Table S8. Individual risk of bias assessments for the asthma studies.

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-----------|------|--------------------------------|------------------|----------------------------------|--|--|---|---------------------------------------|--------------------|--|--------------------------|---------------------------------------|---|---------------------------------|-----------------------|--|----------------------------|------------------------------------|-----------------------------------|---------------|
| Aerts | 2020 | Not applicable | Population study | Probably low | Population study with objective exposure, lack of blinding not likely to affect results. | Probably low | Objective metric (land cover), but no QA/QC | Low | Routine statistics | Probably high | No smoking exposure data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Government research grants | Probably low | No other biases identified | Probably High |
| Alasuskas | 2020 | Not applicable | Population study | Probably low | Population study with objective exposure, lack of blinding not likely to affect results. | Probably low | Objective metric (distance to greenspace), but no QA/QC | Low | Routine statistics | Probably high | No smoking exposure data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | No external funding | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|----------------|------|--------------------------------|---|----------------------------------|--|--|---|---------------------------------------|---|--|--|---------------------------------------|---|---------------------------------|----------------------------|--|-------------------------------|------------------------------------|---|---------------|
| Andrusaityte | 2016 | Probably Low | Asthma more prevalent where mothers less educated, suffered from asthma, smoked during pregnancy, where children living in a flat and used antibiotics during first year of life. | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Indirect evidence that suggests that methods were robust but lack of QA/QC information. | Probably Low | Parent-reported questionnaire - ISAAC methods used | Probably Low | Included Tier 1 confounding variables in analysis, no mediation with air pollution | Low | Does not appear to be missing outcome data | Low | Outcomes are reported. | Low | EC grant | Probably Low | Some potential for measurement error and fairly small sample size, lack of self-selection bias. | Probably Low |
| Bernat | 2016 | Not Applicable | Population study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metric, but quality of data not clear | Probably Low | Health records from national statistics, but not clear how these data are collected, e.g. GP visits | Probably High | Only examined one variable at a time | Probably Low | No indication of incomplete data | Low | All outcome data presented | Probably Low | Does not say, but likely not. | Probably high | Selection bias issue | Probably High |
| Brokamp | 2016 | Probably Low | Participants either live <400 m or >1,500 m from the nearest major road, used for air pollution estimates. | Probably Low | Objective exposure (NDVI), lack of blinding not likely to affect results. | Low | Used objective measure (NDVI) and included residential history | Probably Low | Doctor-diagnosis/battery of tests, e.g. lung function | Probably High | No smoking data. Tested interaction between exposure variables. | Probably Low | Right censored children with missing residential data | Low | Outcomes are reported. | Low | Funded by grants from NIEHS | Probably Low | Potential for self-selection bias | Probably High |
| Cavaleiro Rufo | 2021 | Probably low | Participants recruited at birth | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Probably low | Parent-reported based on validated questionnaire (ISAAC) | Probably high | No smoking exposure data | Low | Does not appear to be missing data | Low | Outcomes are reported | Low | Government research grants | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-----------|------|--------------------------------|--|----------------------------------|--|--|--|---------------------------------------|---|--|--|---------------------------------------|-------------------------------------|---------------------------------|----------------------------|--|-----------------------------------|------------------------------------|--|---------------|
| Chen | 2017 | Probably Low | Recruited through same health system | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure - NDVI, but no QA/QC | Probably high | Both objective and more subjective (e.g., parent reported) outcomes recorded in study | Probably high | Recorded some Tier 1 confounders and examined effect modification, but no smoking or air pollution | Low | No incomplete data | Low | Report on outcome of model | Low | Funded by research grant | Probably Low | Issues have already been mentioned, lack of self-selection | Probably High |
| Commodore | 2021 | Probably low | Participants recruited at birth | Probably low | Exposure based on study questionnaire, lack of blinding not likely to affect results | Probably high | Self-reported: presence of park | Probably low | Parent-reported based on validated questionnaire (ISAAC) | Probably low | Included all tier 1 variables, but did not examine separate effects of air pollution | Low | Outcome data appears to be complete | Low | Outcomes are reported | Low | Government research grants | Probably low | Potential for self-selection bias | Probably High |
| Dadvand | 2014 | Probably Low | All children from included primary schools invited to participate. Response rate = 58% | Probably Low | Objective exposure (NDVI, parks/forests), lack of blinding not likely to affect results. | Probably Low | Included 2 types of greenspace indicators, but not much QAQC | Probably High | Questionnaire based (parent reported) | Probably Low | Included Tier 1 confounders, separate assessment of air pollutants, effect modification by SES | Low | No apparent missing outcome data | Low | Outcomes are reported. | Low | Funded by the European Commission | Probably Low | Risk of self-selection bias | Probably High |
| DePriest | 2019 | Probably low | Not clear how recruitment was undertaken, but adjust for characteristics in regression models. | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Probably high | Parent reported symptoms and inhaler use | Probably low | Included all tier 1 variables, but did not examine separate effects of air pollution | Probably low | Used imputation methods | Low | Outcomes are reported | Low | Government research grants | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|----------|------|--------------------------------|----------------------------|----------------------------------|--|--|---|---------------------------------------|--|--|---|---------------------------------------|---|---------------------------------|----------------------------|--|-----------------------------------|------------------------------------|-----------------------------------|---------------|
| Dong | 2021 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (land cover), but no QA/QC | Low | Routine statistics | Probably high | No smoking exposure data, but included mediation with air pollution | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Government research grants | Probably low | Potential for self-selection bias | Probably High |
| Donovan | 2021 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (plant diversity, greenness), with clear descriptions | Low | Routine statistics | Probably high | Excludes age | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | No external funding | Probably low | Potential for self-selection bias | Probably High |
| Donovan | 2018 | Not Applicable | Population study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Multiple greenspace indicators and for NDVI, included lifetime residential exposure | Low | Used 2 types of routine statistics | Probably Low | Included Tier 1 confounders, though no physical activity | Probably Low | Removed individuals with missing data: sample decreased from 57.4k to 50.0k | Low | All outcome data presented | Probably Low | Not clear where funding was from. | Probably Low | No other areas of bias present. | Probably Low |
| Dzhambov | 2021 | Probably low | Recruited from 49 schools. | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Multiple greenspace metrics at different buffers using both home and school locations | Probably low | Parent reported symptoms using a validated questionnaire | Probably low | Included all tier 1 variables and mediation with air pollution | Probably Low | Very little missing data: performed complete case analysis | Low | Outcomes are reported | Low | Supported by government funding | Probably low | Potential for self-selection bias | Probably Low |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-----------|------|--------------------------------|---|----------------------------------|--|--|--|---------------------------------------|--|--|--|---------------------------------------|---|---------------------------------|-----------------------------|--|---|------------------------------------|--|---------------|
| Eldeirawi | 2019 | Probably low | Recruitment included all students from 15 schools | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Probably low | Parent reported symptoms using a validated questionnaire | Low | Included all tier 1 variables, no mediation with air pollution or physical activity, but no significant findings | Probably low | Does not appear to be missing data | Low | Outcomes are reported | Low | Supported by university and government grants | Probably low | Potential for self-selection bias | Probably Low |
| Feng | 2017 | Low | Nationally representative cohort | Probably Low | Objective exposure, lack of blinding not likely to affect results. | Probably Low | Green land use, but no QA/QC | Probably Low | Parent-reported questionnaire - ISAAC methods used | Probably high | Controlled for a number of factors, also examined effects of safety and traffic, but no smoking | Low | Only n = 10 were omitted from survey due to lack of outcome data. | Low | Outcomes are reported. | Low | Funded by numerous research grants. | Probably Low | Self-selection, but recruited at birth Perceptions of traffic and safety could be biased in reporting but likely non-differential | Probably High |
| Hsieh | 2019 | Probably low | Sampled from national database | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably high | No rationale provided for definition of NDVI>0.4 for greenspace | Low | Doctor diagnosis | Probably high | No smoking exposure or physical activity data | Probably Low | Insurance database assumed to be mostly complete | Low | Outcomes are reported | Low | Supported by government funding | Probably low | Potential for self-selection bias | Probably High |
| Ihlebaek | 2018 | Low | Recruited from large cohort study. | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Indirect evidence that suggests that methods were robust but lack of | Probably high | Self-reported outcome | Probably low | Included Tier 1 confounders, but no air pollution | Probably Low | High proportion (50%) of missing data | Low | All outcome data presented. | Low | No funding received. | Probably Low | Did not account for selection bias, i.e., whether healthier people chose to live in greener areas, and no | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|--------|------|--------------------------------|--|----------------------------------|--|--|--|---------------------------------------|---|--|--|---------------------------------------|---|---------------------------------|------------------------|--|-----------------------------------|------------------------------------|--|---------------|
| Khan | 2010 | Probably Low | Not clear how participants were enrolled or if there were any differences between groups | Probably Low | Objective exposure (land cover), lack of blinding not likely to affect results. | Probably low | Objective measure, but no evidence of QA/QC | Probably High | Questionnaire based | Probably High | Did not include any information on confounding | Low | No apparent missing outcome data | Low | Outcomes are reported. | Probably Low | Not clear where funding was from. | Probably High | Very little information on methods, confounding variables. | Probably High |
| Kuiper | 2020 | Probably low | Parent and child recruited in birth cohort | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI), multiple images taken during the year and every 5 years, multiple residential buffers used | Probably high | Parent-reported (does not indicate validated questionnaire) | Probably high | No smoking or physical activity data | Probably low | Does not appear to be missing data | Low | Outcomes are reported | Low | Funded by research grants | Probably low | Potential for self-selection bias | Probably High |
| Kuiper | 2021 | Probably low | Recruited in cohort study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (NDVI), with images every 5 years and multiple buffers | Probably low | Spirometry collected in study with trained technicians | Probably low | Considered all relevant confounders in a DAG | Probably low | Imputed missing data with clear methodology | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|------------------|------|--------------------------------|--|----------------------------------|--|--|---|---------------------------------------|--|--|---|---------------------------------------|---|---------------------------------|-----------------------------|--|--|------------------------------------|---|---------------|
| Kurnia Febriawan | 2018 | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure, but crude indicator (e.g., positive or negative values) | Probably Low | Not clear how asthma proportion was calculated | Probably High | Few confounders included, excluded air pollution, smoking | Probably Low | Not clear what proportion were missing. | Low | All outcome data presented. | Probably Low | Not sufficient info, but probably free of company support. | Probably High | Lots of issues, e.g. how EVI was calculated, errors throughout. | Probably High |
| Li | 2019 | Probably low | Schools were randomly selected for participation | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI, distance to parks), clear description, multiple residential buffers used | Probably low | Parent reported symptoms using a validated questionnaire | Probably low | Adjusted for all tier 1 confounders, but does not include air pollution or physical activity | Probably low | Low proportion of missing data. | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |
| Lovasi | 2008 | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure - street trees, but limited information on methods | Low | Routine statistics | Probably high | Did not include any information on smoking. | Low | No incomplete data | Low | Report on outcome of model | Low | Funded by research grant | Probably Low | Self-selection bias | Probably High |
| Lovasi | 2013 | Probably Low | Convenience sample through prenatal clinics | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metric of tree canopy at birth and 7 years of age | Probably Low | Parent-reported questionnaire, validated Brief Respiratory Questionnaire (BRQ) and International Study of Asthma and Allergies in Childhood (ISAAC) questionnaire, objective allergen test | Probably Low | Included Tier 1 confounders. Air pollution not explicitly included, but traffic volume would be an indicator. No physical activity. | Probably Low | Used multiple imputation for missing covariate data | Low | All outcome data presented | Low | Various government and academic research grants | Probably Low | Potential for self-selection bias | Probably Low |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------------|------|--------------------------------|----------------------------------|----------------------------------|--|--|---|---------------------------------------|--|--|---|---------------------------------------|--|---------------------------------|----------------------------|--|--|------------------------------------|-----------------------------------|---------------|
| Maas | 2009 | Low | Nationally representative sample | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Used green land cover surrounding home postcodes, with two buffer sizes | Probably Low | GP visits, which should be reliable | Probably High | Included some confounders, but excluded smoking and air pollution | Probably Low | Included an 'unknown' category for missing variables | Low | All outcome data presented | Low | Scientific grant | Probably Low | Potential for self-selection bias | Probably High |
| Markevych | 2020 | Probably low | Population-based birth cohort | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (NDVI, Trees), with clear description and multiple buffers | Probably low | Parent-reported doctor diagnosis at numerous time points | Probably low | All tier 1 confounders, separate analysis for air pollution, no physical activity | Probably high | Not clear how much data is missing, but additional analysis for subjects with partial missing outcome data | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably High |
| Pilat | 2012 | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective exposure metric (NDVI, tree canopy), but MSA might be too large of a potential exposure area. | Probably high | Questionnaire | Probably high | No smoking data | Low | No missing data | Low | All outcome data presented | Probably Low | Not clear where funding was from. | Probably high | Very small sample size | Probably High |
| Razavi-Termeh | 2021 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (parks), but no QA/QC | Low | Routine statistics | High | Tier 1 confounders missing (e.g. age, sex) | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | No funding source listed, but declare no competing interests | Probably low | Potential for self-selection bias | High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------------|------|--------------------------------|--|----------------------------------|--|--|---|---------------------------------------|--|--|--|---------------------------------------|---|---------------------------------|--|--|--------------------------------------|------------------------------------|-----------------------------------|---------------|
| Razavi-Termeh | 2021 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (NDVI), multiple years used | Low | Routine statistics | Probably high | Tier 1 confounders missing (e.g. age, sex) | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by government research grants | Probably low | Potential for self-selection bias | Probably High |
| Sbihi | 2015 | Not Applicable | Population study | Probably Low | Population study with objective exposure, lack of blinding not likely to affect results. | Low | Objective measure - NDVI and calculated seasonal values | Low | Used physician billing and hospital records | Probably low | Included Tier 1 confounders, and examined effects by including air pollutants. No physical activity. | Probably Low | Routine stats would be mostly complete | Low | All outcome data are presented, though no protocol provided. | Low | Government, research grants | Probably Low | Self-selection issue | Probably Low |
| Squillacioti | 2020 | Probably low | Recruitment from schools, methodology not clear, but likely not a source of bias | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Probably low | Spirometry with clear protocol Self-report based on ISAAC questionnaire | Probably high | No adjustment for SES | Probably low | Small proportion excluded who did not have outcome (or complete covariate) data (36/223) without outcome data | Low | Outcomes are reported | Low | No external funding | Probably low | Potential for self-selection bias | Probably High |
| Su | 2017 | Low | No separate study groups | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure - land use | Low | Objective - inhaler use | Probably low | Tier 1 confounders included, no physical activity | Probably Low | Not clear if inhaler usage was complete | Low | All outcome data presented. | Low | Research grants. | Probably Low | No other areas of bias present. | Probably Low |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------|------|--------------------------------|--|----------------------------------|--|--|--|---------------------------------------|---|--|--|---------------------------------------|--|---------------------------------|----------------------------|--|-----------------------------------|------------------------------------|-----------------------------------|---------------|
| Tischer | 2017 | Probably Low | Population-based birth cohort. Differences in groups, but accounted for in analysis | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metrics of multiple greenspace indicators at birth and 4 years of age | Probably High | Parent-reported questionnaire | Low | Included all Tier 1 and 2 confounders, no associations so no mediation | Low | Does not appear to be missing outcome data | Low | All outcome data presented | Low | Various research grants | Probably Low | No other areas of bias present. | Probably High |
| Ulmer | 2016 | Probably Low | Random recruitment from population | Probably Low | Objective exposure, lack of blinding not likely to affect results. | Probably Low | Used objective measures, QA/QC not clear | Probably high | Questionnaire - asked about doctor-diagnosed asthma | Probably low | Tier 1 confounders accounted for, no air pollution or physical activity | Probably Low | Unclear how much missing outcome data there is | Low | Outcomes are reported. | Low | Funded by the Forest Service. | Probably low | Self-selection bias | Probably High |
| Yu | 2021 | Probably low | Participants recruited from schools in randomly selected urban districts in Chinese cities | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (eye-level greenness), with clear description | Probably low | Parent-reported based on validated questionnaire | Probably high | No smoking, mediation analysis with air pollution | Probably low | High response rate with complete data | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably High |
| Zeng | 2020 | Probably low | Participants recruited from schools in randomly selected urban districts in Chinese cities | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI, SAVI) with clear description and multiple buffers | Probably low | Parent-reported based on validated questionnaire | Low | All tier 1 and 2 confounders, with mediation analysis for tier 2 confounders | Probably low | High response rate with complete data | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |
| Zock | 2018 | Low | a stratified random sample was drawn from 40 Dutch municipalities | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metric, but quality of data not clear | Low | Health records from a GP database | Probably high | No smoking data | Probably Low | No indication of incomplete data | Low | All outcome data presented | Low | Academic research grants | Probably low | Selection bias issue | Probably High |

Table S9. Individual risk of bias assessments for the lung function studies.

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-------------|------|--------------------------------|--|----------------------------------|--|--|--|---------------------------------------|---|--|--|---------------------------------------|---|---------------------------------|-----------------------------|--|---|------------------------------------|---|---------------|
| Boeyen | 2017 | Probably Low | Recruited from 10 schools, not clear if other characteristics differ | Probably Low | Population study with objective exposure, lack of blinding not likely to affect results. | Probably low | Used NDVI, but no QA/QC | Probably Low | Objective outcome measured in study | Probably High | Examine numerous personal and indoor characteristics, but only through univariate analysis | Low | No incomplete data | Low | Outcomes are reported. | Low | Funded by the Centre for Ecosystem Management and Department of Health | Probably Low | Potential for self-selection bias | Probably High |
| Cole-Hunter | 2018 | Probably Low | Recruitment from two methodologically comparable studies | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Uses objective exposure measures and describe in detail analysis and QAQC methods. Includes time at occupational address, but not occupational exposure. | Probably Low | Used validated protocol for lung function | Low | Included Tier 1 confounding variables in analysis (excluded smokers). Included mediation analysis. | Low | Does not appear to be missing outcome data | Low | All outcome data presented. | Probably Low | Grants, also used data from studies funded by Coca-Cola, but statement of no influence on publication | Probably Low | Small sample size, uncertainty in exposure measurements | Probably Low |
| Fuertes | 2020 | Probably low | Large birth cohort | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (NDVI), with images at different ages | Probably low | Lung function ascertained in study using defined criteria | Probably low | All tier 1 confounders, but no physical activity | Probably high | Data available for only 1,763 of 14,471 participants alive at one year of age | Low | Outcomes are reported | Low | Supported by government funding | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------|------|--------------------------------|---|----------------------------------|---|--|---|---------------------------------------|---|--|--|---------------------------------------|--|---------------------------------|------------------------|--|---|------------------------------------|-----------------------------------|---------------|
| Huang | 2016 | Probably Low | Same population for both parts of the study | Probably Low | Exposure assigned using objective measurement - not possible to blind participants. Likely would not affect health outcome. | Probably Low | No information on greenspace, but controlled time spent there | Probably Low | Measured lung function using validated methods | Probably Low | Accounted for Tier 1 confounders, subjects served as their own controls. Smokers excluded. No physical activity. | Low | Mostly complete outcome data. | Low | Outcomes are reported. | Low | Funded through various research grants. | Probably Low | Small sample size (n = 40). | Probably Low |
| Kuiper | 2021 | Probably low | Recruited in cohort study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (NDVI), with images every 5 years and multiple buffers | Probably low | Spirometry collected in study with trained technicians | Probably low | Considered all relevant confounders in a DAG | Probably low | Imputed missing data with clear methodology | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |
| Lambert | 2020 | Probably low | Recruitment pre-birth | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (NDVI), no QA/QC, multiple residential buffers used | Probably low | Lung function ascertained in study using defined criteria | Probably high | Did not adjust for SES, greenness was included only as an effect modifier | Probably high | High proportion lost to follow up (only include 160/616) | Low | Outcomes are reported | Probably low | Does not mention, but not likely to be a source of bias | Probably low | Potential for self-selection bias | Probably High |
| Lambert | 2019 | Probably low | Selected from randomised control trial of infants | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (NDVI), multiple residential buffers used, birth address only | Probably low | Lung function ascertained in study using defined criteria | Probably high | No smoking or physical activity data | Probably low | 78% had lung function measurements | Low | Outcomes are reported | Low | University and academic grant funding | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------------|------|--------------------------------|---|----------------------------------|--|--|--|---------------------------------------|--|--|--|---------------------------------------|--|---------------------------------|------------------------|--|---|------------------------------------|-----------------------------------|---------------|
| Lambert | 2021 | Probably low | Two birth cohorts with similar recruitment methods | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (NDVI), no QA/QC, multiple residential buffers used | Probably low | Lung function ascertained in study using defined criteria | Probably low | Adjusted for all tier 1 confounders, but greenness was included only as an effect modifier | Probably high | High proportion lost to follow up (only include 2334/9085) | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably High |
| Moshammer | 2019 | Low | Each participant walked in each setting | Probably low | Participants would know the difference between the two settings, but not likely to affect objective health outcomes. | Probably low | Controlled activity and time in the greenspace, but did not characterise | Probably high | Spirometry collected in study, but does not indicate protocol | Probably low | Participants served as their own controls | Low | Does not appear to be missing data | Low | Outcomes are reported | Low | No funding received | Low | No other biases identified | Probably High |
| Sinharay | 2018 | Probably Low | Differences between groups, but purpose was to assess differential effects. Participants were to do both experimental and control walk. | Probably Low | Participants would know the difference between the two settings, but not likely to affect objective health outcomes. | Probably Low | Controlled activity and time in the greenspace, but did not characterise | Probably Low | Objective outcomes recorded in study | Probably Low | SES not included, but not likely to bias experimental study. Examined interaction of time, group and location. | Low | No apparent missing outcome data | Low | Outcomes are reported. | Low | British Heart Foundation - no influence on study. | Low | No other areas of bias present. | Probably Low |
| Squillaciotti | 2020 | Probably low | Recruitment from schools, methodology not clear, but likely not a source of bias | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Probably low | Spirometry with clear protocol Self-report based on ISAAC questionnaire | Probably high | No adjustment for SES | Probably low | Small proportion excluded who did not have outcome (or complete covariate) data (36/223) | Low | Outcomes are reported | Low | No external funding | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|--------|------|--------------------------------|--|----------------------------------|--|--|---|---------------------------------------|---|--|---|---------------------------------------|--|---------------------------------|-----------------------|--|--|------------------------------------|-----------------------------------|---------------|
| Yu | 2021 | Probably low | Participants recruited from schools in randomly selected urban districts in Chinese cities | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (eye-level greenness), with clear description | Probably low | Lung function ascertained in study using defined criteria | Probably high | No smoking, mediation analysis with air pollution | Probably low | without outcome data Does not appear to be missing data | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably High |
| Zhang | 2021 | Probably low | Participants recruited from schools and selected randomly | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (NDVI) with clear description and multiple buffers | Probably low | Lung function ascertained in study using defined criteria | Probably low | All tier 1 confounders, no physical activity | Probably low | Recruited cases until sufficient numbers were achieved | Low | Outcomes are reported | Probably low | No funding source listed, but declare no competing interests | Probably low | Potential for self-selection bias | Probably Low |
| Zhou | 2021 | Probably low | Participants recruited from schools in randomly selected urban districts in Chinese cities | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI, SAVI), with clear description | Probably low | Lung function ascertained in study using defined criteria | Probably low | All tier 1 confounders, interaction with air pollution and mediation with physical activity | Probably low | Does not appear to be missing data | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |

Table S10. Individual risk of bias assessments for the respiratory symptoms studies.

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|----------------|------|--------------------------------|---|----------------------------------|--|--|---|---------------------------------------|--|--|--|---------------------------------------|--|---------------------------------|------------------------|--|---|------------------------------------|--|---------------|
| Cavaleiro Rufo | 2021 | Probably low | Participants recruited at birth | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Probably low | Parent-reported based on validated questionnaire (ISAAC) | Probably high | No smoking exposure data | Low | Does not appear to be missing data | Low | Outcomes are reported | Low | Government research grants | Probably low | Potential for self-selection bias | Probably High |
| Cilluffo | 2018 | Probably Low | Recruited from two schools | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure - NDVI, but limited information on methods and QA/QC | Probably Low | Parent-reported questionnaire - ISAAC methods used | Probably Low | Included Tier 1 confounding variables in analysis, no mediation with air pollution | Low | Does not appear to be missing outcome data | Low | Outcomes are reported. | Low | No funding received. | Probably Low | No other areas of bias present. Self-selection mitigated partially through studying children | Probably Low |
| Dzhambov | 2021 | Probably low | Recruited from 49 schools. | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Multiple greenspace metrics at different buffers using both home and school locations | Probably low | Parent reported symptoms using a validated questionnaire | Probably low | Included all tier 1 variables and mediation with air pollution | Probably Low | Very little missing data: performed complete case analysis | Low | Outcomes are reported | Low | Supported by government funding | Probably low | Potential for self-selection bias | Probably Low |
| Eldeirawi | 2019 | Probably low | Recruitment included all students from 15 schools | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Probably low | Parent reported symptoms using a validated questionnaire | Low | Included all tier 1 variables, no mediation with air pollution or physical activity, but no significant findings | Probably low | Does not appear to be missing data | Low | Outcomes are reported | Low | Supported by university and government grants | Probably low | Potential for self-selection bias | Probably Low |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------|-------|--------------------------------|--|----------------------------------|--|--|--|---------------------------------------|--|--|---|---------------------------------------|---|---------------------------------|--|--|---|------------------------------------|-----------------------------------|---------------|
| Fuertes | 2014a | Not Applicable | Ecological study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure - NDVI, but lack of QA/QC details | Probably Low | Parent or child-reported questionnaire - ISAAC methods used | Probably high | Did not include any information on smoking. | Probably Low | Imputed missing data | Low | Report on outcome of model | Low | Funding from sources including Canadian Institutes of Health Research, DoH and NERC | Probably Low | Self-selection bias | Probably High |
| Fuertes | 2014b | Probably low | Two birth cohorts with objective exposure metric | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective measure - NDVI | Probably high | Self-reported outcome (but based on doctor diagnosis) | Probably low | Included Tier 1 confounders, and examined effects separately by PM, NO2, Population density. No physical activity. | Probably Low | Does not address missing outcome data | Low | All outcome data presented, at least with the 500 m NDVI buffers | Low | Numerous research grants | Low | No other areas of bias present. | Probably High |
| Lovasi | 2013 | Probably Low | Convenience sample through prenatal clinics | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metric of tree canopy at birth and 7 years of age | Probably Low | Parent-reported questionnaire, validated Brief Respiratory Questionnaire (BRQ) and International Study of Asthma and Allergies in Childhood (ISAAC) questionnaire, objective allergen test | Probably Low | Included Tier 1 confounders. Air pollution not explicitly included, but traffic volume would be an indicator. No physical activity. | Probably Low | Used multiple imputation for missing covariate data | Low | All outcome data presented | Low | Various government and academic research grants | Probably Low | Potential for self-selection bias | Probably Low |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------------|------|--------------------------------|---|----------------------------------|--|--|---|---------------------------------------|--|--|--|---------------------------------------|---|---------------------------------|----------------------------|--|--|------------------------------------|-----------------------------------|---------------|
| Sinharay | 2018 | Probably Low | Differences between groups, but purpose was to assess differential effects. Participants were to do both experimental and control walk. | Probably Low | Participants would know the difference between the two settings, but not likely to affect objective health outcomes. | Probably Low | Controlled activity and time in the greenspace, but did not characterise | Probably Low | Objective outcomes recorded in study | Probably Low | SES not included, but not likely to bias experimental study. Examined interaction of time, group and location. | Low | No apparent missing outcome data | Low | Outcomes are reported. | Low | British Heart Foundation - no influence on study. | Low | No other areas of bias present. | Probably Low |
| Squillaciotti | 2020 | Probably low | Recruitment from schools, methodology not clear, but likely not a source of bias | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Probably low | Spirometry with clear protocol Self-report based on ISAAC questionnaire | Probably high | No adjustment for SES | Probably low | Small proportion excluded who did not have outcome (or complete covariate) data (36/223) without outcome data | Low | Outcomes are reported | Low | No external funding | Probably low | Potential for self-selection bias | Probably High |
| Stas | 2021 | Probably low | Recruitment not clear, but likely not a source of bias | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (greens space, allergenic tree density), with clear description | Probably high | Self-reported in mobile phone app | Probably low | No adjustment for SES, smoking, but case-crossover design so subjects act as own controls | Probably low | Complete cases analysis on 144/189 subjects. | Low | Outcomes are reported | Low | No funding source listed, but declare no competing interests | Probably low | Potential for self-selection bias | Probably High |
| Tischer | 2017 | Probably Low | Population-based birth cohort. Differences in groups, but accounted | Probably Low | Exposure assigned using objective measurement - blinding not | Probably Low | Objective exposure metrics of multiple greenspace indicators at birth and | Probably High | Parent-reported questionnaire | Low | Included all Tier 1 and 2 confounders, no associations so no mediation | Low | Does not appear to be missing outcome data | Low | All outcome data presented | Low | Various research grants | Probably Low | No other areas of bias present. | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|--------|------|--------------------------------|---|----------------------------------|---|--|--|---------------------------------------|--|--|--|---------------------------------------|---------------------------------------|---------------------------------|-----------------------|--|-----------------------------------|------------------------------------|-----------------------------------|--------------|
| Zeng | 2020 | Probably low | Participants recruited from schools in randomly selected urban districts in Chinese cities for in analysis | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. likely to affect results. | Low | Objective metrics (NDVI, SAVI) with clear description and multiple buffers 4 years of age | Probably low | Parent-reported based on validated questionnaire | Low | All tier 1 and 2 confounders, with mediation analysis for tier 2 confounders | Probably low | High response rate with complete data | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |

Table S11. Individual risk of bias assessments for the rhinitis studies.

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|----------------|------|--------------------------------|--|----------------------------------|--|--|--|---------------------------------------|--|--|--|---------------------------------------|------------------------------------|---------------------------------|------------------------|--|-----------------------------------|------------------------------------|-----------------------------------|---------------|
| Cavaleiro Rufo | 2021 | Probably low | Participants recruited at birth | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Probably low | Parent-reported based on validated questionnaire (ISAAC) | Probably high | No smoking exposure data | Low | Does not appear to be missing data | Low | Outcomes are reported | Low | Government research grants | Probably low | Potential for self-selection bias | Probably High |
| Dadvand | 2014 | Probably Low | All children from included primary schools invited to participate. Response rate = 58% | Probably Low | Objective exposure (NDVI, parks/forests), lack of blinding not likely to affect results. | Probably Low | Included 2 types of greenspace indicators, but not much QAQC | Probably High | Questionnaire based (parent reported) | Probably Low | Included Tier 1 confounders, separate assessment of air pollutants, effect modification by SES | Low | No apparent missing outcome data | Low | Outcomes are reported. | Low | Funded by the European Commission | Probably Low | Risk of self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------|------|--------------------------------|--|----------------------------------|--|--|--|---------------------------------------|---|--|---|---------------------------------------|--|---------------------------------|------------------------|--|--|------------------------------------|---|---------------|
| Fuertes | 2016 | Probably High | Similar NDVI ranges across cohorts, though differences in prevalence. Does not indicate how recruitment was done. Based on two studies of differing designs. | Probably Low | Objective exposure (NDVI), lack of blinding not likely to affect results. | Low | Used objective measure (NDVI) and note QA/QC, include month/year of NDVI image | Probably High | Mix of doctor-diagnosed and parent-report of symptoms | Probably low | Tier 1 confounders included and examination of effect modification between NDVI and sex, population density and NO2. No physical activity | Probably Low | Does not indicate missing data | Low | Outcomes are reported. | Probably Low | Combination of many different grants, including private companies, though funders had no involvement in the study. | Probably Low | Selection bias issue Exposure and health variables harmonised, despite being differently collected in various cohorts, also confounders, e.g. NO2 not necessarily measured same way; however authors have acknowledged potential sources of bias | Probably High |
| Gernes | 2019 | Probably low | Recruitment from birth records | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI, land cover), multiple buffers used | Probably low | Parent reported symptoms using a validated questionnaire | Probably low | All tier 1 confounders, air pollution not examined separately, no physical activity | Probably low | Does not appear to be missing data | Low | Outcomes are reported | Low | Supported by government funding | Probably low | Potential for self-selection bias | Probably Low |
| Kim | 2020 | Probably low | Nationwide community-based survey | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (Green areas), but no QA/QC | Probably high | Self-reported (does not indicate validated questionnaire) | Probably low | All tier 1 confounders, includes physical activity, but no air pollution | Probably low | Low proportion of missing data. Analysis on complete data. | Low | Outcomes are reported | Low | Funded by university grants | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|--------|------|--------------------------------|--|----------------------------------|--|--|--|---------------------------------------|---|--|--|---------------------------------------|---|---------------------------------|-----------------------|--|-----------------------------------|------------------------------------|-----------------------------------|---------------|
| Kuiper | 2021 | Probably low | Recruited in cohort study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (NDVI), with images every 5 years and multiple buffers | Probably low | Spirometry collected in study with trained technicians | Probably low | Considered all relevant confounders in a DAG | Probably low | Imputed missing data with clear methodology | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |
| Kuiper | 2020 | Probably low | Parent and child recruited in birth cohort | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI), multiple images taken during the year and every 5 years, multiple residential buffers used | Probably high | Parent-reported (does not indicate validated questionnaire) | Probably high | No smoking or physical activity data | Probably low | Does not appear to be missing data | Low | Outcomes are reported | Low | Funded by research grants | Probably low | Potential for self-selection bias | Probably High |
| Kwon | 2019 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (NDVI), but no QA/QC | Low | Routine statistics | Probably high | No smoking or physical activity data | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by government grants | Probably low | Potential for self-selection bias | Probably High |
| Li | 2019 | Probably low | Schools were randomly selected for participation | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI, distance to parks), clear description, multiple residential buffers used | Probably low | Parent reported symptoms using a validated questionnaire | Probably low | Adjusted for all tier 1 confounders, but does not include air pollution or physical activity | Probably low | Low proportion of missing data. | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-----------|------|--------------------------------|---|----------------------------------|--|--|--|---------------------------------------|--|--|---|---------------------------------------|--|---------------------------------|----------------------------|--|---|------------------------------------|-----------------------------------|---------------|
| Lovasi | 2013 | Probably Low | Convenience sample through prenatal clinics | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metric of tree canopy at birth and 7 years of age | Probably Low | Parent-reported questionnaire, validated Brief Respiratory Questionnaire (BRQ) and International Study of Asthma and Allergies in Childhood (ISAAC) questionnaire, objective allergen test | Probably Low | Included Tier 1 confounders. Air pollution not explicitly included, but traffic volume would be an indicator. No physical activity. | Probably Low | Used multiple imputation for missing covariate data | Low | All outcome data presented | Low | Various government and academic research grants | Probably Low | Potential for self-selection bias | Probably Low |
| Markevych | 2020 | Probably low | Population-based birth cohort | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (NDVI, Trees), with clear description and multiple buffers | Probably low | Parent-reported doctor diagnosis at numerous time points | Probably low | All tier 1 confounders, separate analysis for air pollution, no physical activity | Probably high | Not clear how much data is missing, but additional analysis for subjects with partial missing outcome data | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably High |
| Tischer | 2017 | Probably Low | Population-based birth cohort. Differences in groups, but accounted for in analysis | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metrics of multiple greenspace indicators at birth and 4 years of age | Probably High | Parent-reported questionnaire | Low | Included all Tier 1 and 2 confounders, no associations so no mediation | Low | Does not appear to be missing outcome data | Low | All outcome data presented | Low | Various research grants | Probably Low | No other areas of bias present. | Probably High |

Table S12. Individual risk of bias assessments for the other outcomes studies.

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-------------------|------|--------------------------------|---|----------------------------------|--|--|--|---------------------------------------|---|--|---|---------------------------------------|---|---------------------------------|----------------------------|--|--------------------------------|------------------------------------|--|---------------|
| Arbillaga-Etxarri | 2017 | Probably Low | Any variables with potential differences accounted for in regression models | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | No QA/QC, but used objective metrics with different buffer sizes | Probably Low | Patients with COPD diagnosis, objectively measured PA | Probably Low | Included Tier 1 confounders and examined potential effect modification by COPD severity, sex, etc | Low | All patients fulfilled minimum wearing time | Low | All outcome data presented | Low | Government, research grants | Probably Low | No other areas of bias present. | Probably Low |
| Bernat | 2016 | Not Applicable | Population study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metric, but quality of data not clear | Probably Low | Health records from national statistics, but not clear how these data are collected, e.g. GP visits | Probably High | Only examined one variable at a time | Probably Low | No indication of incomplete data | Low | All outcome data presented | Probably Low | Does not say, but likely not. | Probably high | Selection bias issue | Probably High |
| Cavalcante de Sa | 2016 | Low | Recruited from same population | Probably Low | Not clear, but probably did not affect outcome. | Probably Low | Controlled time and activity in forest, but did not characterise the forested area in any way. | Probably Low | Measured biomarkers following protocols. | Probably Low | Controlled for a number of factors, e.g. activity, speed, distance, diet. Excluded smokers. | Low | Outcome data appear to be complete | Low | Outcomes are reported. | Low | Funded through various grants. | Probably Low | Not overly informative in terms of greenspace, but low risk of bias. | Probably Low |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------|------|--------------------------------|---|----------------------------------|--|--|--|---------------------------------------|---|--|--|---------------------------------------|---|---------------------------------|----------------------------|--|--|------------------------------------|-----------------------------------|---------------|
| Chen | 2017 | Probably Low | Recruited through same health system | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective measure - NDVI, but no QA/QC | Probably high | Both objective and more subjective (e.g., parent reported) outcomes recorded in study | Probably high | Recorded some Tier 1 confounders and examined effect modification, but no smoking or air pollution | Low | No incomplete data | Low | Report on outcome of model | Low | Funded by research grant | Probably Low | Potential for self-selection bias | Probably High |
| Fan | 2020 | Low | Nationwide study with probability sampling | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metric (NDVI), with images to represent different seasons and multiple buffers | Probably low | Lung function ascertained in study using defined criteria | Probably low | Included all tier 1 variables, but no mediation with air pollution or physical activity | Probably low | Excluded those without spirometry measurements, study has large sample size | Low | Outcomes are reported | Low | Supported by government funding | Probably low | Potential for self-selection bias | Probably Low |
| Hoehner | 2013 | Probably Low | All participants recruited from the same clinic | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Objective exposure metrics of multiple greenspace indicators at both home and work | Probably Low | Ascertained during study | Probably Low | Tier 1 confounders included, no air pollution | Probably Low | About 25% of participants missing data, so excluded | Low | All outcome data presented | Low | Various research grants, no conflicts of interest declared | Probably low | Potential for self-selection bias | Probably Low |
| Lambert | 2020 | Probably low | Recruitment pre-birth | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (NDVI),no QA/QC, multiple residential buffers used | Probably low | Lung function ascertained in study using defined criteria | Probably high | Did not adjust for SES, greenness was included only as an effect modifier | Probably high | High proportion lost to follow up (only include 160/616) | Low | Outcomes are reported | Probably low | Does not mention, but not likely to be a source of bias | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-----------|------|--------------------------------|--|----------------------------------|--|--|---|---------------------------------------|---|--|--|---------------------------------------|--|---------------------------------|----------------------------|--|-----------------------------------|------------------------------------|-----------------------------------|---------------|
| Lambert | 2021 | Probably low | Two birth cohorts with similar recruitment methods | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (NDVI),no QA/QC, multiple residential buffers used | Probably low | Lung function ascertained in study using defined criteria | Probably low | Adjusted for all tier 1 confounders, but greenness was included only as an effect modifier | Probably high | High proportion lost to follow up (only include 2334/9085) | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably High |
| Li | 2019 | Probably low | Schools were randomly selected for participation | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (NDVI, distance to parks), clear description, multiple residential buffers used | Probably low | Parent reported symptoms using a validated questionnaire | Probably low | Adjusted for all tier 1 confounders, but does not include air pollution or physical activity | Probably low | Low proportion of missing data. | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |
| Maas | 2009 | Low | Nationally representative sample | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably Low | Used green land cover surrounding home postcodes, with two buffer sizes | Probably Low | GP visits, which should be reliable | Probably High | Included some confounders, but excluded smoking and air pollution | Probably Low | Included an 'unknown' category for missing variables | Low | All outcome data presented | Low | Scientific grant | Probably Low | Potential for self-selection bias | Probably High |
| Moitra | 2022 | Probably low | Recruitment from a randomised trial | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably high | Blue and green space combined in 1 single exposure | Probably high | Self-reported (does not indicate validated questionnaire) | Low | All tier 1 confounders, tested air pollution and physical activity as confounders | Probably high | Not clear how much data is missing, analysis done on complete cases. | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably High |
| Moshammer | 2019 | Low | Each participant walked in each setting | Probably low | Participants would know the difference between the two settings, but not likely | Probably low | Controlled activity and time in the greenspace, but did not characterise | Probably high | Spirometry collected in study, but does not indicate protocol | Probably low | Participants served as their own controls | Low | Does not appear to be missing data | Low | Outcomes are reported | Low | No funding received | Low | No other biases identified | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|-----------|------|--------------------------------|---|----------------------------------|--|--|--|---------------------------------------|--|--|--|---------------------------------------|---|---------------------------------|-----------------------------|--|-----------------------------------|------------------------------------|-----------------------------------|---------------|
| | | | | | to affect objective health outcomes. | | | | | | | | | | | | | | | |
| Paciência | 2021 | Probably low | Recruitment included students from 71 classes at 20 schools | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (Tree cover), with clear description | Probably low | Airway inflammation measurements with protocol | Probably low | All tier 1 confounders, no air pollution or physical activity | Low | Small proportion excluded due to poor outcome data (13/858) | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |
| Prist | 2016 | Probably Low | Population study | Probably Low | Population study with objective exposure, lack of blinding not likely to affect results. | Probably Low | Used objective measures, QA/QC not clear | Low | Routine statistics | Probably high | Examined climatic variables, size of population at risk, Human Development Index, no adjustment for smoking. | Probably Low | Routine stats would be mostly complete | Low | Outcomes are reported. | Low | Research grants. | Probably Low | No further issues. | Probably High |
| Pun | 2018 | Low | Data are from a nationally representative study | Probably Low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective outcome (NDVI), of which 3 different temporal and 2 spatial metrics used | Probably high | Self-reported outcome | Probably Low | Included all Tier 1 confounding variables in analysis. No mediation with air pollution | Probably Low | Applied multiple imputation | Low | All outcome data presented. | Low | Funded through research grants | Probably Low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|---------------|------|--------------------------------|--|----------------------------------|--|--|--|---------------------------------------|---|--|---|---------------------------------------|---|---------------------------------|-----------------------|--|--------------------------------------|------------------------------------|-----------------------------------|---------------|
| Russette | 2021 | Not applicable | Population study | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (Leaf area index), clear description, based on multiple years | Low | Routine statistics | Probably high | Missing smoking, no air pollution | Probably Low | Routine stats assumed to be mostly complete | Low | Outcomes are reported | Low | Funded by government research grants | Probably low | Potential for self-selection bias | Probably High |
| Sarkar | 2019 | Probably low | Recruited from large cohort study (UK Biobank) | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (NDVI), with clear description | Probably low | Spirometry with clear protocol | Probably low | All tier 1 and 2 confounders, no mediation analyses | Probably low | Complete cases analysis, large sample-missing data not likely to bias results. | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably Low |
| Squillaciotti | 2020 | Probably low | Recruitment from schools, methodology not clear, but likely not a source of bias | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metric (NDVI), but no QA/QC | Probably low | Spirometry with clear protocol Self-report based on ISAAC questionnaire | Probably high | No adjustment for SES | Probably low | Small proportion excluded who did not have outcome (or complete covariate) data (36/223) without outcome data | Low | Outcomes are reported | Low | No external funding | Probably low | Potential for self-selection bias | Probably High |
| Wu | 2021 | Probably low | Recruitment from Shanghai suburbs with set criteria | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Low | Objective metrics (vegetation coverage, plant community, dominant species), with clear description | Probably high | Self-reported, does not include questions or whether validated questionnaire was used | Probably high | No adjustment for smoking | Probably low | Complete cases analysis with 72% response rate | Low | Outcomes are reported | Low | Funded by various research grants | Probably low | Potential for self-selection bias | Probably High |

| Author | Year | 1. Are study groups different? | Notes | 2. Knowledge of exposure groups? | Notes | 3. Robust exposure assessment methods? | Notes | 4. Robust outcome assessment methods? | Notes | 5. Adequate confounding and effect modification? | Notes | 6. Incomplete outcome data addressed? | Notes | 7. Selective outcome reporting? | Notes | 8. Free of support from interest in exposures? | Notes | 9. Other problems of risk of bias? | Notes | Overall |
|--------|------|--------------------------------|--------------------|----------------------------------|--|--|--|---------------------------------------|---|--|---|---------------------------------------|---------------------------------------|---------------------------------|-----------------------|--|--------------------------------------|------------------------------------|-----------------------------------|---------------|
| Zhang | 2021 | Probably low | Residential survey | Probably low | Exposure assigned using objective measurement - blinding not likely to affect results. | Probably low | Objective metrics (Vegetation and plant diversity), but no QA/QC | Probably high | Self-reported, does not include questions or whether validated questionnaire was used | Probably high | No smoking, air pollution or physical activity data | Probably low | High response rate with complete data | Low | Outcomes are reported | Low | Funded by government academic grants | Probably low | Potential for self-selection bias | Probably High |

Table S13. Assessment of downgrading factors for quality of evidence.

| Health outcome | Risk of bias | Indirectness | Inconsistency | Imprecision | Publication bias |
|------------------------------|--|--|---|--|---|
| | <u>Rating=0</u> | <u>Rating=0</u> | <u>Rating=0</u> | <u>Rating=0</u> | <u>Rating=0</u> |
| Respiratory mortality | 13/20 studies were rated 'probably high', but several of the larger studies were 'probably low'. | Most studies examine adults or older adults. Outcomes were all mortality (rather than a proxy for the outcome). | Most studies show reduced risk or null effect with greenspace exposure | Many of the studies have reasonably narrow CIs | No direct evidence of publication bias, other than those typically of influence |
| | <u>Rating=-1</u> | <u>Rating=0</u> | <u>Rating=-1</u> | <u>Rating=0</u> | <u>Rating=0</u> |
| Hospital admissions | 10/13 studies were rated 'probably high' mainly due to lack of confounding control. | Most of these studies include the general population, though some focussed on children or older adults (65+ years) | Studies show variation in reduced risk/null effect with greenspace (one indicates significantly increased risk) | CIs, when provided, are sufficiently narrow | No direct evidence of publication bias, other than those typically of influence |
| | <u>Rating=0</u> | <u>Rating=0</u> | <u>Rating=-1</u> | <u>Rating=0</u> | <u>Rating=0</u> |
| Lung cancer | 7/12 were rated 'probably high' mainly due to lack of confounding | Most of these studies include adults in the general population | Most studies show null effect with greenspace, but some large ones show a beneficial effect | CIs, when provided, are sufficiently narrow | No direct evidence of publication bias, other than those typically of influence |
| | <u>Rating=-1</u> | <u>Rating=0</u> | <u>Rating=-1</u> | <u>Rating=-1</u> | <u>Rating=0</u> |
| Asthma | 30/38 were rated 'probably high' or 'high' mainly due to outcome measurement and lack of confounding | Most of these studies focussed on children; Few studies included older adults (65+ years). | Studies show reduced, no, or increased risk | Some CIs are very wide | No direct evidence of publication bias, other than those typically of influence |
| | <u>Rating=0</u> | <u>Rating=0</u> | <u>Rating=-1</u> | <u>Rating=-1</u> | <u>Rating=0</u> |
| Lung function | | | | | |

| | | | | | |
|-----------------------------|---|---|---|------------------------|---|
| | 8/14 were rated 'probably high' mainly due to lack of confounding, larger studies tend to be probably low | most of these studies focussed on children; Few studies included older adults (65+ years) | Studies show reduced, no, or increased risk | Some CIs are very wide | No direct evidence of publication bias, other than those typically of influence |
| | <u>Rating=0</u> | <u>Rating=-1</u> | <u>Rating=-1</u> | <u>Rating=-1</u> | <u>Rating=0</u> |
| Respiratory symptoms | 6/12 were rated 'probably high' mainly due to lack of confounding | Most of these studies focussed on children | Studies show reduced, no, or increased risk | Some CIs are very wide | No direct evidence of publication bias, other than those typically of influence |
| | <u>Rating=-1</u> | <u>Rating=0</u> | <u>Rating=0</u> | <u>Rating=-1</u> | <u>Rating=0</u> |
| Rhinitis | 10/12 were rated as 'probably high' mainly due to lack of confounding and outcome | studies include children and adults | Most studies show no effect | Some CIs are very wide | No direct evidence of publication bias, other than those typically of influence |

Table S14. Assessment of upgrading factors for quality of evidence.

| Health outcome | Large magnitude of effect | Dose-response | Residual Confounding Increases Confidence |
|------------------------------|---|---|---|
| Respiratory mortality | <u>Rating=0</u> Relatively modest magnitudes of effect | <u>Rating=+1</u> Studies tend to provide effect estimate per unit (e.g., IQR) increase in greenspace | <u>Rating=0</u> Not likely that residual confounding would underestimate results |
| Hospital admissions | <u>Rating=0</u> Relatively modest magnitudes of effect | <u>Rating=0</u> Little evidence of a dose-response effect | <u>Rating=0</u> Not likely that residual confounding would underestimate results |
| Lung cancer | <u>Rating=0</u> Relatively modest magnitudes of effect | <u>Rating=0</u> Little evidence of a dose-response effect | <u>Rating=0</u> Not likely that residual confounding would underestimate results |
| Asthma | <u>Rating=0</u> Some larger magnitudes of effect, but in both directions | <u>Rating=0</u> Inconsistent | <u>Rating=0</u> Not likely that residual confounding would underestimate results |
| Lung function | <u>Rating=0</u> Some larger magnitudes of effect, but inconsistent | <u>Rating=0</u> Inconsistent | <u>Rating=0</u> Not likely that residual confounding would underestimate results |

Respiratory symptoms

Rating=0

Some larger magnitudes of effect, but inconsistent

Rating=0

Inconsistent

Rating=0

Not likely that residual confounding would underestimate results

Rhinitis

Rating=0

Mostly modest effect sizes, when identified

Rating=0

Inconsistent

Rating=0

Not likely that residual confounding would underestimate results

Appendix 2. Supplementary material: Urban greenspace and the indoor environment: Pathways to health via indoor particulate matter, noise, and road noise annoyance

Supplementary Material

Table S1. Dates of NDVI Images.

| City | Monitoring period | | NDVI - summer | NDVI - seasonal |
|-----------|-------------------|------------|---------------|-----------------|
| | Start | End | | |
| Edinburgh | 23/07/2015 | 28/07/2015 | 27/06/2018 | 27/06/2018 |
| Edinburgh | 01/09/2015 | 08/09/2015 | 27/06/2018 | 27/06/2018 |
| Edinburgh | 19/08/2015 | 25/08/2015 | 27/06/2018 | 27/06/2018 |
| Edinburgh | 05/08/2015 | 11/08/2015 | 27/06/2018 | 27/06/2018 |
| Edinburgh | 04/08/2015 | 11/08/2015 | 27/06/2018 | 27/06/2018 |
| Edinburgh | 17/08/2015 | 24/08/2015 | 27/06/2018 | 27/06/2018 |
| Edinburgh | 11/08/2015 | 17/08/2015 | 27/06/2018 | 27/06/2018 |
| Edinburgh | 21/09/2015 | 28/09/2015 | 27/06/2018 | 27/06/2018 |
| Edinburgh | 13/08/2015 | 20/08/2015 | 27/06/2018 | 27/06/2018 |
| Edinburgh | 17/09/2015 | 23/09/2015 | 27/06/2018 | 27/06/2018 |
| Edinburgh | 02/10/2015 | 08/10/2015 | 27/06/2018 | 11/11/2017 |
| Edinburgh | 07/10/2015 | 13/10/2015 | 27/06/2018 | 11/11/2017 |
| Edinburgh | 29/10/2015 | 04/11/2015 | 27/06/2018 | 11/11/2017 |
| Edinburgh | 16/10/2015 | 21/10/2015 | 27/06/2018 | 11/11/2017 |
| Edinburgh | 04/11/2015 | 10/11/2015 | 27/06/2018 | 11/11/2017 |
| Edinburgh | 17/11/2015 | 24/11/2015 | 27/06/2018 | 16/11/2017 |
| Edinburgh | 26/11/2015 | 03/12/2015 | 27/06/2018 | 11/11/2017 |
| Edinburgh | 13/11/2015 | 19/11/2015 | 27/06/2018 | 11/11/2017 |
| Edinburgh | 07/01/2016 | 14/01/2016 | 27/06/2018 | 08/01/2018 |
| Edinburgh | 11/01/2016 | 18/01/2016 | 27/06/2018 | 08/01/2018 |
| Edinburgh | 25/01/2016 | 01/02/2016 | 27/06/2018 | 09/02/2018 |
| Edinburgh | 15/01/2016 | 21/01/2016 | 27/06/2018 | 08/01/2018 |
| Edinburgh | 22/01/2016 | 29/01/2016 | 27/06/2018 | 09/02/2018 |
| Edinburgh | 08/02/2016 | 15/02/2016 | 27/06/2018 | 08/01/2018 |
| Edinburgh | 29/01/2016 | 05/02/2016 | 27/06/2018 | 08/01/2018 |
| Edinburgh | 27/01/2016 | 03/02/2016 | 27/06/2018 | 09/02/2018 |
| Edinburgh | 17/02/2016 | 23/02/2016 | 27/06/2018 | 26/01/2018 |
| Edinburgh | 05/02/2016 | 12/02/2016 | 27/06/2018 | 08/01/2018 |
| Edinburgh | 12/02/2016 | 19/02/2016 | 27/06/2018 | 08/01/2018 |
| Athens | 29/06/2015 | 06/07/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 30/06/2015 | 05/07/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 06/07/2015 | 13/07/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 07/07/2015 | 13/07/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 13/07/2015 | 20/07/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 14/07/2015 | 20/07/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 20/07/2015 | 26/07/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 22/07/2015 | 28/07/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 27/07/2015 | 03/08/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 28/07/2015 | 03/08/2015 | 10/07/2016 | 10/07/2016 |

| | | | | |
|--------------|------------|------------|------------|------------|
| Athens | 17/08/2015 | 26/08/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 28/08/2015 | 03/09/2015 | 10/07/2016 | 10/07/2016 |
| Athens | 03/09/2015 | 10/09/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 04/09/2015 | 09/09/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 09/09/2015 | 15/09/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 11/09/2015 | 16/09/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 15/09/2015 | 20/09/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 16/09/2015 | 21/09/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 21/09/2015 | 29/09/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 29/09/2015 | 04/10/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 30/09/2015 | 06/10/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 06/10/2015 | 12/10/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 07/10/2015 | 13/10/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 13/10/2015 | 18/10/2015 | 10/07/2016 | 18/09/2016 |
| Athens | 14/10/2015 | 21/10/2015 | 10/07/2016 | 18/09/2016 |
| Thessaloniki | 05/12/2015 | 11/12/2015 | 13/07/2016 | 25/01/2016 |
| Thessaloniki | 09/12/2015 | 16/12/2015 | 13/07/2016 | 25/01/2016 |
| Thessaloniki | 15/12/2015 | 22/12/2015 | 13/07/2016 | 25/01/2016 |
| Thessaloniki | 16/12/2015 | 24/12/2015 | 13/07/2016 | 25/01/2016 |
| Thessaloniki | 14/01/2016 | 20/01/2016 | 13/07/2016 | 25/01/2016 |
| Thessaloniki | 14/01/2016 | 20/01/2016 | 13/07/2016 | 25/01/2016 |
| Thessaloniki | 11/04/2016 | 18/04/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 18/04/2016 | 25/04/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 18/04/2016 | 25/04/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 25/04/2016 | 04/05/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 25/04/2016 | 04/05/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 04/05/2016 | 10/05/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 04/05/2016 | 09/05/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 10/05/2016 | 16/05/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 10/05/2016 | 16/05/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 16/05/2016 | 23/05/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 16/05/2016 | 23/05/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 24/05/2016 | 30/05/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 23/05/2016 | 30/05/2016 | 13/07/2016 | 04/04/2016 |
| Thessaloniki | 30/05/2016 | 06/06/2016 | 13/07/2016 | 13/07/2016 |
| Thessaloniki | 30/05/2016 | 06/06/2016 | 13/07/2016 | 13/07/2016 |
| Thessaloniki | 06/06/2016 | 13/06/2016 | 13/07/2016 | 13/07/2016 |
| Thessaloniki | 07/06/2016 | 14/06/2016 | 13/07/2016 | 13/07/2016 |
| Thessaloniki | 14/06/2016 | 23/06/2016 | 13/07/2016 | 13/07/2016 |
| Thessaloniki | 15/06/2016 | 22/06/2016 | 13/07/2016 | 13/07/2016 |
| Utrecht | 12/03/2015 | 17/03/2015 | 08/09/2016 | 01/05/2016 |
| Utrecht | 17/03/2015 | 24/03/2015 | 08/09/2016 | 21/04/2016 |
| Utrecht | 13/04/2015 | 21/04/2015 | 08/09/2016 | 21/04/2016 |
| Utrecht | 17/04/2015 | 23/04/2015 | 08/09/2016 | 21/04/2016 |

| | | | | |
|---------|------------|------------|------------|------------|
| Utrecht | 22/04/2015 | 29/04/2015 | 08/09/2016 | 21/04/2016 |
| Utrecht | 01/05/2015 | 08/05/2015 | 08/09/2016 | 01/05/2016 |
| Utrecht | 13/05/2015 | 20/05/2015 | 08/09/2016 | 21/04/2016 |
| Utrecht | 15/05/2015 | 22/05/2015 | 08/09/2016 | 21/04/2016 |
| Utrecht | 18/05/2015 | 25/05/2015 | 08/09/2016 | 21/04/2016 |
| Utrecht | 19/05/2015 | 26/05/2015 | 08/09/2016 | 01/05/2016 |
| Utrecht | 19/05/2015 | 26/05/2015 | 08/09/2016 | 01/05/2016 |
| Utrecht | 27/05/2015 | 03/06/2015 | 08/09/2016 | 21/04/2016 |
| Utrecht | 29/05/2015 | 05/06/2015 | 08/09/2016 | 21/04/2016 |
| Utrecht | 02/06/2015 | 08/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 02/06/2015 | 09/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 03/06/2015 | 10/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 04/06/2015 | 11/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 10/06/2015 | 17/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 11/06/2015 | 18/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 15/06/2015 | 22/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 15/06/2015 | 23/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 19/06/2015 | 26/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 22/06/2015 | 29/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 23/06/2015 | 30/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 24/06/2015 | 30/06/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 30/06/2015 | 07/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 01/07/2015 | 07/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 03/07/2015 | 10/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 07/07/2015 | 14/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 10/07/2015 | 16/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 13/07/2015 | 20/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 14/07/2015 | 20/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 17/07/2015 | 23/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 17/07/2015 | 23/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 20/07/2015 | 29/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 21/07/2015 | 29/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 22/07/2015 | 29/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 24/07/2015 | 31/07/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 29/07/2015 | 04/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 29/07/2015 | 06/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 29/07/2015 | 05/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 31/07/2015 | 05/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 03/08/2015 | 11/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 13/08/2015 | 19/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 04/08/2015 | 11/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 05/08/2015 | 12/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 17/08/2015 | 24/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 12/08/2015 | 18/08/2015 | 08/09/2016 | 08/09/2016 |

| | | | | |
|---------|------------|------------|------------|------------|
| Utrecht | 12/08/2015 | 19/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 19/08/2015 | 26/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 24/08/2015 | 31/08/2015 | 08/09/2016 | 08/09/2016 |
| Utrecht | 26/08/2015 | 31/08/2015 | 08/09/2016 | 08/09/2016 |

Table S2. Distance from residential address to nearest ambient air pollution station.

| City | Station | Distance (m) |
|-------------|-------------------------------|---------------------|
| Utrecht | Hague-Rebecquestraat | 6,300 |
| Utrecht | Griftpark | 9,900 |
| Utrecht | Cabauw-Wielsekade | 5,000 |
| Utrecht | Cabauw-Wielsekade | 4,900 |
| Utrecht | Griftpark | 1,000 |
| Utrecht | Hague-Rebecquestraat | 6,300 |
| Utrecht | Griftpark | 6,000 |
| Utrecht | Cabauw-Wielsekade | 5,400 |
| Utrecht | Griftpark | 6,100 |
| Utrecht | Hague-Rebecquestraat | 8,500 |
| Utrecht | Hague-Rebecquestraat | 11,100 |
| Utrecht | Griftpark | 1,100 |
| Utrecht | Griftpark | 8,400 |
| Utrecht | Cabauw-Wielsekade | 3,400 |
| Utrecht | Griftpark | 600 |
| Utrecht | Hague-Rebecquestraat | 12,400 |
| Utrecht | Griftpark | 19,800 |
| Utrecht | Amsterdam Vondelpark | 2,500 |
| Utrecht | Wekerom-Riemterdijk | 21,900 |
| Utrecht | Biest Houtakker-Biestsestraat | 16,500 |
| Utrecht | Wekerom-Riemterdijk | 18,700 |
| Utrecht | Cabauw-Wielsekade | 2,900 |
| Utrecht | Hague-Rebecquestraat | 8,400 |
| Utrecht | Wekerom-Riemterdijk | 21,300 |
| Utrecht | Nijmegen-Ruyterstraat | 17,900 |
| Utrecht | Cabauw-Wielsekade | 4,500 |
| Utrecht | Cabauw-Wielsekade | 4,400 |
| Utrecht | Griftpark | 3,500 |
| Utrecht | Griftpark | 500 |
| Utrecht | Cabauw-Wielsekade | 4,900 |
| Utrecht | Griftpark | 1,300 |
| Utrecht | Griftpark | 8,700 |
| Utrecht | Griftpark | 7,600 |
| Utrecht | Griftpark | 8,800 |
| Utrecht | Griftpark | 6,600 |
| Utrecht | Griftpark | 3,300 |
| Utrecht | Griftpark | 2,800 |

| | | |
|-----------|-----------------|--------|
| Utrecht | Griftpark | 2,400 |
| Utrecht | Griftpark | 3,300 |
| Utrecht | Griftpark | 1,800 |
| Utrecht | Griftpark | 800 |
| Utrecht | Griftpark | 2,400 |
| Utrecht | Griftpark | 8,400 |
| Utrecht | Griftpark | 3,200 |
| Utrecht | Griftpark | 3,000 |
| Utrecht | Griftpark | 3,300 |
| Utrecht | Griftpark | 5,400 |
| Utrecht | Griftpark | 5,700 |
| Utrecht | Griftpark | 500 |
| Utrecht | Griftpark | 3,300 |
| Utrecht | Griftpark | 3,700 |
| Utrecht | Griftpark | 3,500 |
| Athens | Agia Paraskevi | 3,600 |
| Athens | Agia Paraskevi | 4,500 |
| Athens | Marousi | 4,100 |
| Athens | Marousi | 3,500 |
| Athens | Geoponiko | 2,200 |
| Athens | Agia Paraskevi | 3,400 |
| Athens | Peristeri | 3,700 |
| Athens | Agia Paraskevi | 2,400 |
| Athens | Nea Smyrni | 3,000 |
| Athens | Marousi | 4,300 |
| Athens | Peristeri | 1,800 |
| Athens | Agia Paraskevi | 9,500 |
| Athens | Agia Paraskevi | 6,100 |
| Athens | Agia Paraskevi | 7,500 |
| Athens | Agia Paraskevi | 900 |
| Athens | Aristotelous | 1,300 |
| Athens | Aristotelous | 3,700 |
| Athens | Thrakomakedones | 1,800 |
| Athens | Marousi | 3,400 |
| Athens | Agia Paraskevi | 3,700 |
| Athens | Aristotelous | 4,300 |
| Athens | Agia Paraskevi | 7,800 |
| Athens | Nea Smyrni | 2,000 |
| Athens | Nea Smyrni | 1,700 |
| Athens | Peristeri | 2,200 |
| Edinburgh | St Leonards | 10,000 |
| Edinburgh | St Leonards | 6,400 |
| Edinburgh | St Leonards | 1,300 |
| Edinburgh | St Leonards | 4,600 |

| | | |
|-----------|-------------|--------|
| Edinburgh | St Leonards | 2,700 |
| Edinburgh | St Leonards | 9,000 |
| Edinburgh | St Leonards | 12,400 |
| Edinburgh | St Leonards | 27,600 |
| Edinburgh | St Leonards | 41,300 |
| Edinburgh | St Leonards | 8,500 |
| Edinburgh | St Leonards | 1,900 |
| Edinburgh | St Leonards | 4,500 |
| Edinburgh | St Leonards | 3,600 |
| Edinburgh | St Leonards | 9,800 |
| Edinburgh | St Leonards | 800 |
| Edinburgh | St Leonards | 7,400 |
| Edinburgh | St Leonards | 13,700 |
| Edinburgh | St Leonards | 12,800 |
| Edinburgh | St Leonards | 2,400 |
| Edinburgh | St Leonards | 3,200 |
| Edinburgh | St Leonards | 3,300 |
| Edinburgh | St Leonards | 3,900 |
| Edinburgh | St Leonards | 5,900 |
| Edinburgh | St Leonards | 3,400 |
| Edinburgh | St Leonards | 4,300 |
| Edinburgh | St Leonards | 13,600 |
| Edinburgh | St Leonards | 7,600 |
| Edinburgh | St Leonards | 3,000 |
| Edinburgh | St Leonards | 1,100 |

Appendix 3. Supplementary material: Neighbourhood and path-based greenspace in three European countries: associations with objective physical activity

Supplementary Material

Contents

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HEALS socioeconomic questionnaire

HEALS Pilot Study

Socioeconomic Status Questionnaire (To be administered by field staff to adult participant)

HOUSEHOLD ID:

FIELD STAFF NAME:

QUESTIONNAIRE DATE:

QUESTIONNAIRE START TIME:

QUESTIONNAIRE END TIME:

INTERVIEW WITH: CHILD'S MOTHER ₂ CHILD'S FATHER ₁

.....



In this study we are looking at the environment that children live in and how this may affect their health and wellbeing now and in the future. Thank you for taking part.

In this survey we are asking some questions about the people that you and your child live with. We have a particular focus on transport and type of work because this will lead to exposure to different chemicals.

A. HOUSEHOLD QUESTIONS

A1. Please tell us about everybody in your household? [If age not known, please give best estimate]

The main earner is the household member who usually earns the most money (Hh1ppl) (_MEMID)

| Relationship to you e.g. daughter/husband/partner/lodger/parent(p_rel) | Female | Male(gender) | Age(age) | Main earner(main earner) | Study child (study child) |
|--|--------------------------|--------------------------|---|--------------------------|---------------------------|
|  Myself | <input type="checkbox"/> | <input type="checkbox"/> |  | <input type="checkbox"/> | <input type="checkbox"/> |
| | <input type="checkbox"/> | <input type="checkbox"/> | | <input type="checkbox"/> | <input type="checkbox"/> |
| | <input type="checkbox"/> | <input type="checkbox"/> | | <input type="checkbox"/> | <input type="checkbox"/> |
| | <input type="checkbox"/> | <input type="checkbox"/> | | <input type="checkbox"/> | <input type="checkbox"/> |
| | <input type="checkbox"/> | <input type="checkbox"/> | | <input type="checkbox"/> | <input type="checkbox"/> |
| | <input type="checkbox"/> | <input type="checkbox"/> | | <input type="checkbox"/> | <input type="checkbox"/> |
| | <input type="checkbox"/> | <input type="checkbox"/> | | <input type="checkbox"/> | <input type="checkbox"/> |
| | <input type="checkbox"/> | <input type="checkbox"/> | | <input type="checkbox"/> | <input type="checkbox"/> |

| |
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| |

_2_1

| |
|--|
| |
| |

_2_1

A2. Do you have any children who do not currently live in your household? (Hh2nliv_i and Hh2nliv_ii)

No _2Yes _1

Please give



ages :

| |
|--|
| |
|--|

A3a. Please indicate your legal marital status: (Hh3stas)

Married _1Civil partnership _2Single _3Separated _4Divorced _5

Widowed

_6

A3b. If you ARE living with a spouse or partner in what year did you start living together? (Hh4livt)

| |
|--|
| |
|--|

A4a. Does your household include: (Hh5inc)

both your child's parents _1one of your child's parents (yourself) _2

A4b. IF you are NOT living with the child's other parent on average how often does your child usually spend time with him/her? (Hh6time)

5 to 7 nights a week

_5

less than once a fortnight

_2

3 to 4 nights a week

_4

does not see other parent

_1

1 to 2 nights a week or 1 night per fortnight

_3

A5. Does your child's other parent support your child financially nowadays? (Hh7fin)

Regularly _1Sometimes _2Never _3

B. FAMILY BACKGROUND

B1. Please tell us about the ethnicity of yourself and your child's other parent (even if not living with you) (Fb1eth)

a) Ethnic group

You
(a_i)Other
parent
(a_ii)

b) Religion

You
(b_i)Other
parent
(b_ii)

c) Place of birth

You
(c_i)Other
parent
(c_ii)

| | | | | | | | | |
|--|-----------------------------|-----------------------------|-------------|-----------------------------|-----------------------------|------------------------|-----------------------------|-----------------------------|
| White (Scottish/British) | <input type="checkbox"/> 1a | <input type="checkbox"/> 1b | No religion | <input type="checkbox"/> 1a | <input type="checkbox"/> 1b | Scotland | <input type="checkbox"/> 1a | <input type="checkbox"/> 1b |
| White (other) (write in below) | <input type="checkbox"/> 2a | <input type="checkbox"/> 2b | Buddhism | <input type="checkbox"/> 2a | <input type="checkbox"/> 2b | Rest of UK | <input type="checkbox"/> 2a | <input type="checkbox"/> 2b |
| Mixed (write in below) | <input type="checkbox"/> 3a | <input type="checkbox"/> 3b | Christian | <input type="checkbox"/> 3a | <input type="checkbox"/> 3b | Republic of Ireland | <input type="checkbox"/> 3a | <input type="checkbox"/> 3b |
| Arab | <input type="checkbox"/> 4a | <input type="checkbox"/> 4b | Hinduism | <input type="checkbox"/> 4a | <input type="checkbox"/> 4b | Poland | <input type="checkbox"/> 4a | <input type="checkbox"/> 4b |
| Asian (Pakistani, Indian, Bangladeshi) | <input type="checkbox"/> 5a | <input type="checkbox"/> 5b | Jewish | <input type="checkbox"/> 5a | <input type="checkbox"/> 5b | India | <input type="checkbox"/> 5a | <input type="checkbox"/> 5b |
| Asian (Chinese, Japanese, Korean) | <input type="checkbox"/> 6a | <input type="checkbox"/> 6b | Muslim | <input type="checkbox"/> 6a | <input type="checkbox"/> 6b | Pakistan | <input type="checkbox"/> 6a | <input type="checkbox"/> 6b |
| Asian (other) (write in below) | <input type="checkbox"/> 7a | <input type="checkbox"/> 7b | Sikh | <input type="checkbox"/> 7a | <input type="checkbox"/> 7b | Germany | <input type="checkbox"/> 7a | <input type="checkbox"/> 7b |
| Black (African, Caribbean etc) | <input type="checkbox"/> 8a | <input type="checkbox"/> 8b | Other | <input type="checkbox"/> 8a | <input type="checkbox"/> 8a | Other (write in below) | <input type="checkbox"/> 8b | <input type="checkbox"/> 8b |
| Other (write in below) | <input type="checkbox"/> 9a | <input type="checkbox"/> 9b | | | | | | |

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B2. Does your household have a car/van for private use? (Fb2car)

Yes (bought new within the last 6 months) 1 Yes (but not bought new within the last 6 months) 2

No - cannot afford a car 3 No - other reason 4

B2a. If your household has one or more cars how often do the following people travel in it/them, in hours per day: (Fb3crhr)

| | Weekday | Weekend day |
|--|--------------------------|--------------------------|
| Yourself (a _i = weekday, a _{ii} = weekend) | <input type="checkbox"/> | <input type="checkbox"/> |
| Study child (b _i = weekday, b _{ii} = weekend) | <input type="checkbox"/> | <input type="checkbox"/> |
| Your partner (if applicable) (c _i = weekday, c _{ii} = weekend) | <input type="checkbox"/> | <input type="checkbox"/> |
| Main earner (if different) (d _i = weekday, d _{ii} = weekend) | <input type="checkbox"/> | <input type="checkbox"/> |

B3. What is the highest level of successfully completed education for: (Fb4ed)

| | You (a) | Other parent (b) | Main earner (if different) (c) |
|--------|-----------------------------|-----------------------------|--------------------------------|
| None | <input type="checkbox"/> 1a | <input type="checkbox"/> 1b | <input type="checkbox"/> 1c |
| School | <input type="checkbox"/> 2a | <input type="checkbox"/> 2b | <input type="checkbox"/> 2c |

- Vocational/apprenticeship 3a 3b 3c
- University/degree -level 4a 4b 4c
- Other (write in) 5a 5b 5c



B4. What is the current economic activity of: (Fb5ecac)

- | | You
(a) | Other
parent
(b) | Main earner (if
different) (c) |
|---|-----------------------------|---------------------------------|---|
| Working for pay or profit (including unpaid work for a family business or holding; an apprenticeship or paid traineeship; currently on maternity, parental, sick leave or holidays) | <input type="checkbox"/> 1a | <input type="checkbox"/> 1b | <input type="checkbox"/> 1c |
| Pupil, student, further training, unpaid work experience | <input type="checkbox"/> 2a | <input type="checkbox"/> 2b | <input type="checkbox"/> 2c |
| In retirement (including early retirement) | <input type="checkbox"/> 3a | <input type="checkbox"/> 3b | <input type="checkbox"/> 3c |
| Permanently sick or disabled | <input type="checkbox"/> 4a | <input type="checkbox"/> 4b | <input type="checkbox"/> 4c |
| Caring for home and/or family (unpaid) | <input type="checkbox"/> 5a | <input type="checkbox"/> 5b | <input type="checkbox"/> 5c |
| Unemployed | <input type="checkbox"/> 6a | <input type="checkbox"/> 6b | <input type="checkbox"/> 6c |
| Other (write in) | <input type="checkbox"/> 7a | <input type="checkbox"/> 7b | <input type="checkbox"/> 7c |



C. OCCUPATION QUESTIONS

C1. Please tell us about the current (or most recent) job of yourself, your child's other parent and main earner (if different) (Oc1job) (MEMID)

- | | Yourself (MEMID =
1) | Child's other
parent (MEMID
= 2) | Main earner
(if different)
(MEMID = 3) |
|---|---------------------------------|---|---|
| Does not work(Oc1job_a) (if no one applicable works go to section D) | <input type="checkbox"/> 1a | <input type="checkbox"/> 1b | <input type="checkbox"/> 1c |

Job title(Oc1job_b)

| | | |
|--|--|--|
| | | |
| | | |
| | | |
| | | |

Full time₁ or part time₂?(Oc1job_c)

Main job tasks(Oc1job_d)

Main activity of the employer/business(Oc1job_e)

Tick box if self employed(Oc1job_f)

Number of supervisees/
employees(Oc1job_g)

Number of people in
company(Oc1job_h)

Number of hours usually worked per
week?(Oc1job_i)

Usual transport to work (please tick the
one for each person)(Oc1job_j)

| | <input type="checkbox"/> 2a | <input type="checkbox"/> 2b | <input type="checkbox"/> 2c |
|--|-----------------------------|-----------------------------|-----------------------------|
| | | | |
| | | | |
| | | | |

Work mainly at or from
home(1)

3a 3b 3c

A car or van(2)

4a 4b 4c

Bus(3)

5a 5b 5c

Train(4)

6a 6b 6c

Motorcycle, scooter or
moped(5)

7a 7b 7c

Bicycle(6)

8a 8b 8c

On foot(7)

9a 9b 9c

Other means of transport(8)

10a 10b 10c

Don't know(9)

11a 11b 11c


D. DAYCARE QUESTION

D1. Has your child/children EVER being looked after by other people than yourself? (Dc10thr)

Yes ₁ No ₂

D1a. If yes, can you tell us when they started and stopped (if applicable) and how many hours per week they usually spend with each? (Dc2dchr)

| (pID) | Date started (month/year) (a) | Date Stopped (month/year) (if applicable) (b) | Days of the week (c) | Average number of hours per week (include any changes in hours) (d) | If takes place outside your home then please give address (e) |
|-------|-------------------------------------|--|-------------------------------|--|---|
|-------|-------------------------------------|--|-------------------------------|--|---|

| | | | | | |
|---|---|--|--|--|--|
| Child's other parent(pID_1) |  | | | | |
| Partner (if different from father)(pID_2) | | | | | |
| Child's grandparent(s)(pID_3) | | | | | |
| Child's older brother/sister(pID_4) | | | | | |
| Another relative(pID_5) | | | | | |
| A friend or neighbour(pID_6) | | | | | |
| Nanny/carer in home(pID_7) | | | | | |
| Childminder(pID_8) | | | | | |
| Day nursery or crèche(pID_9) | | | | | |
| Special needs nursery(pID_10) | | | | | |
| Playgroup, nursery school or pre-school(pID_11) | | | | | |

E. HISTORIC DATA

We would like to know about the environment that important people in your child’s life have lived and worked in so we would like you to tell us about where you and your child’s other parent and grandparents have lived and worked throughout your lives. Don’t worry if you don’t know all the details – please just tell us the information that you do know.

E1. Please list previous addresses – please be as precise as you can recall but if you do not know the address please give the name of the village/town and country (Hi1add)

E1a. Yourself (Hi1add_pID=1) [for this entry, each address line should be added as an additional number under Hi1add_num, for example, if there are 3 entries in the table, then there should be 3 rows for Hi1add_pID=1, corresponding to Hi1add_num=1, 2, 3]

| From (month and year) Hi1add_from | To (month and year) Hi1add_to | Address (as much information as known) Hi1add_add |
|--|--------------------------------------|--|
| | | |
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| | | |

E1b. Child’s other parent (b) (Hi1add_pID=2)

| From (month and year) Hi1add_from | To (month and year) Hi1add_to | Address (as much information as known) Hi1add_add |
|--|--------------------------------------|--|
| | | |
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|--|--|--|

E2. Please list the employment history of important people in your child’s life (Hi2emp)

E2a. Yourself (Hi2emp_pID = 1) [for this entry, each address line should be added as an additional number under Hi2emp_num, for example, if there are 3 entries in the table, then there should be 3 rows for Hi2_emp_pID=1, corresponding to Hi2emp_num=1, 2, 3]

| From (month and year)(Hi2emp_p_from) | To (month and year)(Hi2emp_p_to) | Occupation(Hi2emp_occupation) | Address (if known)(Hi2emp_add) | Indoor or Outdoor Job?(Hi2emp_ind_out) | |
|---|----------------------------------|-------------------------------|--------------------------------|--|---------------------|
| | | | | Largely Indoor (1) | Largely Outdoor (2) |
| | | | | | |
| | | | | | |
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| | | | | | |
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| | | | | | |
| | | | | | |

E2b. Child’s other parent (Hi2emp_pID = 2)

| From (month and year) | To (month and year) | Occupation | Address (if known) | Indoor or Outdoor Job? | |
|--------------------------|---------------------|------------|--------------------|------------------------|-----------------|
| | | | | Largely Indoor | Largely Outdoor |
| | | | | | |
| | | | | | |

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|--|--|--|--|--|--|
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E2c. Main earner (if different) (Hi2emp_pID = 3)

| From (month and year) | To (month and year) | Occupation | Address (if known) | Indoor or Outdoor Job? | |
|-----------------------|---------------------|------------|--------------------|------------------------|-----------------|
| | | | | Largely Indoor | Largely Outdoor |
| | | | | | |
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HEALS Pilot Study

HOUSEHOLD QUESTIONNAIRE

HOUSEHOLD ID:

QUESTIONNAIRE DATE:

.....

HOUSING CHARACTERISTICS

[Interviewer say: First I will ask you a few general questions about your home].

H1. How many years have you lived in your current home? (Answer in number of years)

_____ -888 = Don't know -999 = Refused

H2. How old is your current home? (Answer in number of years) _____

-888 = Don't know -999 = Refused

H3. Have there been any renovations made to this home since you have been living here?

0 = No 1 = Yes -888 = Don't know -999 = Refused

[Interviewer: Ask #4-5 if response to #3 was "Yes". Otherwise mark "Not applicable"]

H4. In what year(s) was/were renovations made to the home? _____

-777 = Not applicable -888 = Don't know -999 = Refused

H5. What kinds of renovations have been made to the home? (Tick all that apply)

- a) 1 = Wall painting/new wallpaper
- b) 1 = Ceiling
- c) 1 = Floor repair/polishing/varnishing
- d) 1 = Water/sewage system repair
- e) 1 = Window or door repair/replacement
- f) 1 = Insulation repair/replacement
- g) 1 = Wall construction/removing
- h) 1 = Heating/cooling system
- i) 1 = Building an extension to home
- j) 1 = Other (please specify: _____)
- k) 1 = None
- l) -777 = Not applicable
- m) -888 = Don't know
- n) -999 = Refused

H6. Has there ever been any water damage in your home?

0 = No 1 = Yes -888 = Don't know -999 = Refused

[Interviewer: if answer to 6 is "yes", ask 7 and 8. Otherwise mark "Not applicable"]

H7. If yes, where? (Tick all that apply)

- a) 1 = bathroom
- b) 1 = child's bedroom
- c) 1 = living room
- d) 1 = kitchen
- e) 1 = in other rooms
- f) -777 = Not applicable
- g) -888 = Don't know
- h) -999 = Refused

H8. When? _____ month _____ year

- 777 = Not applicable -888 = Don't know -999 = Refused

H9. Do you use the same source of water for drinking and cooking?

- 0 = No 1 = Yes -888 = Don't know -999 = Refused

[Interviewer: if answer to 9 is "no", ask 10 and 11. Otherwise mark "Not applicable"]

H10. What source do you use for drinking?

- 1 = Tap, no home treatment
- 2 = Tap, with home treatment (Specify: _____)
- 3 = Bottled
- 4 = Other (Specify: _____)
- 777 = Not applicable
- 888 = Don't know
- 999 = Refused

H11. What source do you use for cooking?

- 1 = Tap
- 2 = Tap, with home treatment (Specify: _____)
- 3 = Bottled
- 4 = Other (Specify: _____)
- 777 = Not applicable
- 888 = Don't know
- 999 = Refused

H12. Are there any smokers in the household? Please tick any which apply.

- a) 1 = Father
- b) 1 = Mother
- c) 1 = Siblings
- d) 1 = somebody else, Who? _____
- e) -777 = Not applicable
- f) -888 = Don't know
- g) -999 = Refused

[Interviewer: if answer to 12 is 2-5, ask 13 and 14. Otherwise mark "Not applicable"]

H13. If there are smokers in the family, do they smoke

- 1 = usually, indoors
- 2 = usually outdoors (e.g. on the balcony)
- 3 = always outdoors, including visitors
- 777 = Not applicable
- 888 = Don't know
- 999 = Refused

H14. How many cigarettes per day are smoked indoors in your home? (Eg. Father 3, mother 2, sister 5 = 10 cigarettes in all)

- 1 = none
- 2 = 1-5 cigarettes
- 3 = 6-10 cigarettes
- 4 = 11-15 cigarettes
- 5 = 16-20 cigarettes
- 6 = 21-30 cigarettes
- 7 = more than 30 cigarettes
- 777 = Not applicable
- 888 = Don't know
- 999 = Refused

H15. Do you currently have pets? Please tick any which apply.

- a) 1 = no
- b) 1 = dog
- c) 1 = cat
- d) 1 = birds
- e) 1 = other animals, which? _____
- f) -777 = Not applicable
- g) -888 = Don't know
- h) -999 = Refused

IN-HOME ROUTINES

[Interviewer say: Next, I will ask you about some of your household routines]

H16. During what months do you generally cool your home using air conditioning equipment? (Tick all that apply)

- a) 1 = January-March
- b) 1 = April-June
- c) 1 = July-September
- d) 1 = October-December
- e) 1 = none

H17. During what months do you generally heat your home? (Tick all that apply)

- a) 1 =January-March
- b) 1 =April-June
- c) 1 =July-September
- d) 1 =October-December
- e) 1 = none

H18. What is the main heating system in your residence?

- 1 = none
- 2 = Central heating with radiators
- 3 = Electrical heating
- 4 = Under floor heating
- 5 = Heating in the ceiling
- 6 = Air circulating heating system
- 7 = Fireplaces or ovens
- 8 = Other (*Specify:* _____)
- 888 = Don't know
- 999 = Refused

H19. What fuel do you use to heat your home? (Tick all that apply)

- a) 1 = Electricity
- b) 1 = Gas
- c) 1 = Liquid fuel
- d) 1 = Wood burning stove/ fireplace
- e) 1 = Other (*Specify:* _____)
- f) 1 = none
- g) -888 = Don't know
- h) -999 = Refused

H20. When the weather permits, how often do you open windows or doors for several hours a day?

- 1 = Never
- 2 = Less than once a month
- 3 = About one to three times a month
- 4 = About once a week
- 5 = Several times a week
- 6 = Every day
- 888 = Don't know
- 999 = Refused

H21. What type of material are your sofas and armchairs? (Check all that apply)

- a) 1 =Leather
- b) 1 =Upholstered with fabric cloth
- c) 1 =Upholstered with vinyl material
- d) 1 =Other (Specify: _____)
- e) -777 = Not applicable
- f) -888 = Don't know
- g) -999 = Refused

H22. Which best describes your family's habit regarding wearing shoes in the home?

- 1 = Shoes are taken off prior to entering the home
- 2 = Shoes are taken off right away after entering the home
- 3 = Shoes are taken off prior to entering certain rooms
- 4 = Shoes are not routinely taken off while in the home
- 777 = Not applicable
- 888 = Don't know
- 999 = Refused

H23. What kind of stove do you use in cooking? Please tick any which apply.

- 1 = electrical stove
- 2 = gas cooking
- 3 = something else, _____
- 777 = Not applicable
- 888 = Don't know
- 999 = Refused

H24. Do you have a ventilation hood above the stove?

- 0 = No
- 1 = Yes
- 777 = Not applicable
- 888 = Don't know
- 999 = Refused

[Interviewer: if answer to 24 is "yes", ask 25]

H25. If you answered YES, do you use the hood when cooking?

- 1 = regularly
- 2 = every now and then
- 3 = seldom or never

H26. How many hours per day is the whole family away from home on a typical weekday?

- 1 = 0-4 hours per day
- 2 = 5-10 hours per day
- 3 = 11-16 hours per day
- 4 = Greater than 16 hours
- 888 = Don't know 999 = Refused

H27. How many hours per day is the whole family away from home on a typical weekend day?

- 1 = 0-4 hours per day
- 2 = 5-10 hours per day
- 3 = 11-16 hours per day
- 4 = Greater than 16 hours
- 888 = Don't know 999 = Refused

Supplementary Tables

Table S1. Dates (dd/mm/yyyy) of monitoring periods and NDVI images for all HEALS households (n=131).

| City | Monitoring period | | NDVI |
|-----------|-------------------|------------|------------|
| | Start | End | |
| Edinburgh | 23/07/2015 | 28/07/2015 | 27/06/2018 |
| Edinburgh | 01/09/2015 | 08/09/2015 | 27/06/2018 |
| Edinburgh | 19/08/2015 | 25/08/2015 | 27/06/2018 |
| Edinburgh | 05/08/2015 | 11/08/2015 | 27/06/2018 |
| Edinburgh | 04/08/2015 | 11/08/2015 | 27/06/2018 |
| Edinburgh | 17/08/2015 | 24/08/2015 | 27/06/2018 |
| Edinburgh | 11/08/2015 | 17/08/2015 | 27/06/2018 |
| Edinburgh | 21/09/2015 | 28/09/2015 | 27/06/2018 |
| Edinburgh | 13/08/2015 | 20/08/2015 | 27/06/2018 |
| Edinburgh | 17/09/2015 | 23/09/2015 | 27/06/2018 |
| Edinburgh | 02/10/2015 | 08/10/2015 | 27/06/2018 |
| Edinburgh | 07/10/2015 | 13/10/2015 | 27/06/2018 |
| Edinburgh | 29/10/2015 | 04/11/2015 | 27/06/2018 |
| Edinburgh | 16/10/2015 | 21/10/2015 | 27/06/2018 |
| Edinburgh | 04/11/2015 | 10/11/2015 | 27/06/2018 |
| Edinburgh | 17/11/2015 | 24/11/2015 | 27/06/2018 |
| Edinburgh | 26/11/2015 | 03/12/2015 | 27/06/2018 |
| Edinburgh | 13/11/2015 | 19/11/2015 | 27/06/2018 |
| Edinburgh | 07/01/2016 | 14/01/2016 | 27/06/2018 |
| Edinburgh | 11/01/2016 | 18/01/2016 | 27/06/2018 |
| Edinburgh | 25/01/2016 | 01/02/2016 | 27/06/2018 |
| Edinburgh | 15/01/2016 | 21/01/2016 | 27/06/2018 |
| Edinburgh | 22/01/2016 | 29/01/2016 | 27/06/2018 |
| Edinburgh | 08/02/2016 | 15/02/2016 | 27/06/2018 |
| Edinburgh | 29/01/2016 | 05/02/2016 | 27/06/2018 |
| Edinburgh | 27/01/2016 | 03/02/2016 | 27/06/2018 |
| Edinburgh | 17/02/2016 | 23/02/2016 | 27/06/2018 |
| Edinburgh | 05/02/2016 | 12/02/2016 | 27/06/2018 |
| Edinburgh | 12/02/2016 | 19/02/2016 | 27/06/2018 |
| Athens | 29/06/2015 | 06/07/2015 | 10/07/2016 |
| Athens | 30/06/2015 | 05/07/2015 | 10/07/2016 |
| Athens | 06/07/2015 | 13/07/2015 | 10/07/2016 |
| Athens | 07/07/2015 | 13/07/2015 | 10/07/2016 |
| Athens | 13/07/2015 | 20/07/2015 | 10/07/2016 |
| Athens | 14/07/2015 | 20/07/2015 | 10/07/2016 |
| Athens | 20/07/2015 | 26/07/2015 | 10/07/2016 |
| Athens | 22/07/2015 | 28/07/2015 | 10/07/2016 |
| Athens | 27/07/2015 | 03/08/2015 | 10/07/2016 |
| Athens | 28/07/2015 | 03/08/2015 | 10/07/2016 |
| Athens | 17/08/2015 | 26/08/2015 | 10/07/2016 |

| | | | |
|--------------|------------|------------|------------|
| Athens | 28/08/2015 | 03/09/2015 | 10/07/2016 |
| Athens | 03/09/2015 | 10/09/2015 | 10/07/2016 |
| Athens | 04/09/2015 | 09/09/2015 | 10/07/2016 |
| Athens | 09/09/2015 | 15/09/2015 | 10/07/2016 |
| Athens | 11/09/2015 | 16/09/2015 | 10/07/2016 |
| Athens | 15/09/2015 | 20/09/2015 | 10/07/2016 |
| Athens | 16/09/2015 | 21/09/2015 | 10/07/2016 |
| Athens | 21/09/2015 | 29/09/2015 | 10/07/2016 |
| Athens | 29/09/2015 | 04/10/2015 | 10/07/2016 |
| Athens | 30/09/2015 | 06/10/2015 | 10/07/2016 |
| Athens | 06/10/2015 | 12/10/2015 | 10/07/2016 |
| Athens | 07/10/2015 | 13/10/2015 | 10/07/2016 |
| Athens | 13/10/2015 | 18/10/2015 | 10/07/2016 |
| Athens | 14/10/2015 | 21/10/2015 | 10/07/2016 |
| Thessaloniki | 05/12/2015 | 11/12/2015 | 13/07/2016 |
| Thessaloniki | 09/12/2015 | 16/12/2015 | 13/07/2016 |
| Thessaloniki | 15/12/2015 | 22/12/2015 | 13/07/2016 |
| Thessaloniki | 16/12/2015 | 24/12/2015 | 13/07/2016 |
| Thessaloniki | 14/01/2016 | 20/01/2016 | 13/07/2016 |
| Thessaloniki | 14/01/2016 | 20/01/2016 | 13/07/2016 |
| Thessaloniki | 11/04/2016 | 18/04/2016 | 13/07/2016 |
| Thessaloniki | 18/04/2016 | 25/04/2016 | 13/07/2016 |
| Thessaloniki | 18/04/2016 | 25/04/2016 | 13/07/2016 |
| Thessaloniki | 25/04/2016 | 04/05/2016 | 13/07/2016 |
| Thessaloniki | 25/04/2016 | 04/05/2016 | 13/07/2016 |
| Thessaloniki | 04/05/2016 | 10/05/2016 | 13/07/2016 |
| Thessaloniki | 04/05/2016 | 09/05/2016 | 13/07/2016 |
| Thessaloniki | 10/05/2016 | 16/05/2016 | 13/07/2016 |
| Thessaloniki | 10/05/2016 | 16/05/2016 | 13/07/2016 |
| Thessaloniki | 16/05/2016 | 23/05/2016 | 13/07/2016 |
| Thessaloniki | 16/05/2016 | 23/05/2016 | 13/07/2016 |
| Thessaloniki | 24/05/2016 | 30/05/2016 | 13/07/2016 |
| Thessaloniki | 23/05/2016 | 30/05/2016 | 13/07/2016 |
| Thessaloniki | 30/05/2016 | 06/06/2016 | 13/07/2016 |
| Thessaloniki | 30/05/2016 | 06/06/2016 | 13/07/2016 |
| Thessaloniki | 06/06/2016 | 13/06/2016 | 13/07/2016 |
| Thessaloniki | 07/06/2016 | 14/06/2016 | 13/07/2016 |
| Thessaloniki | 14/06/2016 | 23/06/2016 | 13/07/2016 |
| Thessaloniki | 15/06/2016 | 22/06/2016 | 13/07/2016 |
| Utrecht | 12/03/2015 | 17/03/2015 | 08/09/2016 |
| Utrecht | 17/03/2015 | 24/03/2015 | 08/09/2016 |
| Utrecht | 13/04/2015 | 21/04/2015 | 08/09/2016 |
| Utrecht | 17/04/2015 | 23/04/2015 | 08/09/2016 |
| Utrecht | 22/04/2015 | 29/04/2015 | 08/09/2016 |
| Utrecht | 01/05/2015 | 08/05/2015 | 08/09/2016 |
| Utrecht | 13/05/2015 | 20/05/2015 | 08/09/2016 |

| | | | |
|---------|------------|------------|------------|
| Utrecht | 15/05/2015 | 22/05/2015 | 08/09/2016 |
| Utrecht | 18/05/2015 | 25/05/2015 | 08/09/2016 |
| Utrecht | 19/05/2015 | 26/05/2015 | 08/09/2016 |
| Utrecht | 19/05/2015 | 26/05/2015 | 08/09/2016 |
| Utrecht | 27/05/2015 | 03/06/2015 | 08/09/2016 |
| Utrecht | 29/05/2015 | 05/06/2015 | 08/09/2016 |
| Utrecht | 02/06/2015 | 08/06/2015 | 08/09/2016 |
| Utrecht | 02/06/2015 | 09/06/2015 | 08/09/2016 |
| Utrecht | 03/06/2015 | 10/06/2015 | 08/09/2016 |
| Utrecht | 04/06/2015 | 11/06/2015 | 08/09/2016 |
| Utrecht | 10/06/2015 | 17/06/2015 | 08/09/2016 |
| Utrecht | 11/06/2015 | 18/06/2015 | 08/09/2016 |
| Utrecht | 15/06/2015 | 22/06/2015 | 08/09/2016 |
| Utrecht | 15/06/2015 | 23/06/2015 | 08/09/2016 |
| Utrecht | 19/06/2015 | 26/06/2015 | 08/09/2016 |
| Utrecht | 22/06/2015 | 29/06/2015 | 08/09/2016 |
| Utrecht | 23/06/2015 | 30/06/2015 | 08/09/2016 |
| Utrecht | 24/06/2015 | 30/06/2015 | 08/09/2016 |
| Utrecht | 30/06/2015 | 07/07/2015 | 08/09/2016 |
| Utrecht | 01/07/2015 | 07/07/2015 | 08/09/2016 |
| Utrecht | 03/07/2015 | 10/07/2015 | 08/09/2016 |
| Utrecht | 07/07/2015 | 14/07/2015 | 08/09/2016 |
| Utrecht | 10/07/2015 | 16/07/2015 | 08/09/2016 |
| Utrecht | 13/07/2015 | 20/07/2015 | 08/09/2016 |
| Utrecht | 14/07/2015 | 20/07/2015 | 08/09/2016 |
| Utrecht | 17/07/2015 | 23/07/2015 | 08/09/2016 |
| Utrecht | 17/07/2015 | 23/07/2015 | 08/09/2016 |
| Utrecht | 20/07/2015 | 29/07/2015 | 08/09/2016 |
| Utrecht | 21/07/2015 | 29/07/2015 | 08/09/2016 |
| Utrecht | 22/07/2015 | 29/07/2015 | 08/09/2016 |
| Utrecht | 24/07/2015 | 31/07/2015 | 08/09/2016 |
| Utrecht | 29/07/2015 | 04/08/2015 | 08/09/2016 |
| Utrecht | 29/07/2015 | 06/08/2015 | 08/09/2016 |
| Utrecht | 29/07/2015 | 05/08/2015 | 08/09/2016 |
| Utrecht | 31/07/2015 | 05/08/2015 | 08/09/2016 |
| Utrecht | 03/08/2015 | 11/08/2015 | 08/09/2016 |
| Utrecht | 13/08/2015 | 19/08/2015 | 08/09/2016 |
| Utrecht | 04/08/2015 | 11/08/2015 | 08/09/2016 |
| Utrecht | 05/08/2015 | 12/08/2015 | 08/09/2016 |
| Utrecht | 17/08/2015 | 24/08/2015 | 08/09/2016 |
| Utrecht | 12/08/2015 | 18/08/2015 | 08/09/2016 |
| Utrecht | 12/08/2015 | 19/08/2015 | 08/09/2016 |
| Utrecht | 19/08/2015 | 26/08/2015 | 08/09/2016 |
| Utrecht | 24/08/2015 | 31/08/2015 | 08/09/2016 |
| Utrecht | 26/08/2015 | 31/08/2015 | 08/09/2016 |

Table S2. The specific Metabolic Equivalent Task (MET) values assigned for individual trips, as presented by Ainsworth et al. (2011).

| Code | METs | Category | Specific Activities |
|-------------|-------------|-----------------|--|
| 01010 | 4.0 | Bicycling | Bicycling, <10 mph, leisure, to work or for pleasure |
| 01018 | 3.5 | Bicycling | Bicycling, leisure, 5.5 mph |
| 01020 | 6.8 | Bicycling | Bicycling, 10-11.9 mph, leisure, slow, light effort |
| 01030 | 8.0 | Bicycling | Bicycling, 12-13.9 mph, leisure, moderate effort |
| 01040 | 10.0 | Bicycling | Bicycling, 14-15.9 mph, racing or leisure, fast, vigorous effort |
| 01050 | 12.0 | Bicycling | Bicycling, 16-19 mph, racing/not drafting |
| 01060 | 15.8 | Bicycling | Bicycling, > 20 mph, racing, not drafting |
| 17151 | 2.0 | Walking | Walking, less than 2.0 mph, level, strolling, very slow |
| 17170 | 3.0 | Walking | Walking, 2.5 mph, level, firm surface |
| 17180 | 3.3 | Walking | Walking, 2.5 mph, downhill |
| 17190 | 3.5 | Walking | Walking, 2.8 to 3.2 mph, level, moderate pace, firm surface |
| 17200 | 4.3 | Walking | Walking, 3.5 mph, level, brisk, firm surface, walking for exercise |
| 17200+ | 6.0 | Walking | Walking, 3.6 to 4.0 mph, uphill, 1 to 5% grade |
| 17210 | 5.3 | Walking | Walking, 2.9 to 3.5 mph, uphill, 1 to 5% grade |
| 17211 | 8.0 | Walking | Walking, 2.9 to 3.5 mph, uphill, 6% to 15% grade |
| 17220 | 5.0 | Walking | Walking, 4.0 mph, level, firm surface, very brisk pace |
| 17220+ | 7.0 | Walking | Walking, 4.1 to 4.4 mph, uphill, 1 to 5% grade |
| 17230+ | 8.0 | Walking | walking, 4.5 mph, uphill, 1% grade |

'+' indicates the MET code was modified in the present study.

Appendix 4. Supplementary material: The relationship between greenspace and personal exposure to PM_{2.5} during walking trips in Delhi, India

Supplementary material

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

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| 35 | 50m, c) 100m, and d) 250 radii. | 19 |
| 36 | Figure S10. An example of walking trips with 1,000 m viewsheds, illustrating areas that were | |
| 37 | visible at any point during the route. | 20 |
| 38 | | |

39 Traffic analysis

40 We compared OSM road categories to a subset of traffic count data in Delhi during April 2019, which
41 we obtained from TomTom (2020). Nearly 90% of the walking trips occurred on weekdays and since
42 we were limited in the amount of data we could download, we examined total traffic counts on road
43 segments (n=12,406) across Delhi coinciding with the times that trips occurred (i.e., 06:00 to 23:00)
44 (see Figure S8). To standardise road segments, we divided the vehicle counts by the segment length
45 to calculate vehicles/metre. There were similar traffic counts on motorways, primary, and secondary
46 roads; thus, we collapsed these road types into a single category and created separate categories for
47 tertiary and all other roads combined to represent indicators of descending traffic volume (Figure S8).

48 To assess the link between traffic volume and emissions, we compared from the AirSpeck sensor
49 particle number counts of PM₁, an indicator of traffic emissions (Mishra et al., 2019), to the presence
50 of the highest road type category (i.e., motorway/primary/secondary > tertiary > other) within the
51 four different radius sizes. We found the strongest downward trend from
52 'motorway/primary/secondary' to 'other' roads at the 25 m radius (non-parametric test for trend p-
53 value<.001; Figure S9). Therefore, for each GPS point, we assigned the road type category according
54 to that within the 25 m radius.

55 Visibility Analysis

56 As an additional analysis to investigate the potential effect modification of greenspace with more
57 built-up environments, we processed 'viewsheds' for each of the GPS points used in the main analysis
58 (n=1,817). We developed a surface height model by calculating the residual distance between a digital
59 surface model (Tadono et al., 2016) and digital terrain model (Farr et al., 2007) (both at 30 m
60 resolution) for Delhi, India. We then used the GPS points from the walking trips to calculate viewsheds
61 (i.e., visible areas), assuming an observer height of 1.60 m. Viewsheds of 1,000 m were based on full
62 trips; resulting raster data indicated whether the cell was visible at any point during the trip (Figure
63 S10).

64 To examine any effect modification with visibility, we adapted the between trip analysis using Model
65 4 with an adjustment (but not an interaction term) for season (i.e., spring/summer/monsoon or
66 autumn/winter). The average overlap of GLU across each trip was used, and the busiest road category
67 present within any individual radius along the trip was included. We performed this analysis based on
68 the 250 m radius, which had the most variation in mean visibility levels, ranging in individual trips from
69 49-100% (mean=89%, SD=10%). We calculated the coefficients for each greenspace metric based on
70 the minimum and maximum of this range of average visibility (i.e., 49-100%). From this analysis, only
71 the TC coefficient for 100% visibility was associated with a statistically significant reduction in PM_{2.5}
72 concentrations (see Table S5). Although visibility as employed here is a relatively crude indicator for
73 the built environment, the results could imply that the association of lower PM_{2.5} concentrations with
74 trees may only be present in more open, rather than densely built-up areas, as documented elsewhere
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76

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90 **Tables and figures**

91 **Table S1.** Detailed descriptive characteristics of PM_{2.5} and greenspace markers.

| Characteristic | Mean (SD) | P5 | P25 | P50 | P75 | P95 |
|--|------------------|-----------|------------|------------|------------|------------|
| PM _{2.5} (µg/m ³) | 133.9 (114.8) | 29.9 | 59.1 | 101.4 | 158.4 | 367.9 |
| NDVI (-0.1 to 1.0) | | | | | | |
| 25 m | 0.17 (0.12) | 0.04 | 0.07 | 0.13 | 0.24 | 0.39 |
| 50 m | 0.16 (0.10) | 0.05 | 0.08 | 0.13 | 0.23 | 0.37 |
| 100 m | 0.17 (0.09) | 0.05 | 0.09 | 0.14 | 0.22 | 0.35 |
| 250 m | 0.18 (0.08) | 0.06 | 0.12 | 0.17 | 0.23 | 0.33 |
| Tree cover (%) | | | | | | |
| 25 m | 3.0 (2.0) | 1.0 | 1.4 | 2.5 | 4.4 | 6.5 |
| 50 m | 2.9 (1.8) | 0.9 | 1.4 | 2.5 | 4.2 | 6.3 |
| 100 m | 3.0 (1.6) | 1.0 | 1.5 | 2.8 | 4.2 | 5.9 |
| 250 m | 3.3 (1.5) | 1.1 | 2.1 | 3.3 | 4.5 | 5.5 |
| Green land use overlap (proportion) | | | | | | |
| 25 m | 0.04 (0.17) | 0 | 0 | 0 | 0 | 0.33 |
| 50 m | 0.04 (0.15) | 0 | 0 | 0 | 0 | 0.36 |
| 100 m | 0.04 (0.12) | 0 | 0 | 0 | <0.00 | 0.30 |
| 250 m | 0.05 (0.09) | 0 | 0 | 0 | 0.07 | 0.24 |
| Parks or forest overlap (proportion) | | | | | | |
| 25 m | 0.03 (0.15) | 0 | 0 | 0 | 0 | 0.15 |
| 50 m | 0.03 (0.13) | 0 | 0 | 0 | 0 | 0.21 |
| 100 m | 0.03 (0.10) | 0 | 0 | 0 | 0 | 0.24 |
| 250 m | 0.04 (0.08) | 0 | 0 | 0 | 0.06 | 0.22 |

92 P5=5th percentile; P25=25th percentile; P50=50th percentile; P75=75th percentile; P95=95th percentile.

93

94 **Table S2.** Correlation matrix of exposures at a) 25 m, b) 50 m, c) 100 m, d) 250 m radii (n=1,817).

| | PM2.5 | NDVI | TC | GLU (y/n) | Motorway/ primary/ secondary road (y/n) | Tertiary road (y/n) | Other road (y/n) | Rail (y/n) | Population density | Temperature | Relative humidity | Precipitation (y/n) | Wind speed |
|---|--------|--------------|--------|-----------|--|---------------------------|------------------------|---------------|-----------------------|-------------|----------------------|------------------------|---------------|
| PM2.5 | 1.000 | | | | | | | | | | | | |
| NDVI | 0.044 | 1.000 | | | | | | | | | | | |
| TC | -0.027 | 0.850 | 1.000 | | | | | | | | | | |
| GLU (y/n) | -0.011 | 0.254 | 0.219 | 1.000 | | | | | | | | | |
| Motorway/primary/ secondary road (y/n) | 0.043 | 0.070 | 0.120 | -0.052 | 1.000 | | | | | | | | |
| Tertiary road (y/n) | 0.006 | 0.025 | 0.032 | 0.056 | -0.023 | 1.000 | | | | | | | |
| Other road (y/n) | -0.018 | -0.144 | -0.150 | -0.173 | -0.091 | -0.214 | 1.000 | | | | | | |
| Rail (y/n) | -0.043 | 0.016 | 0.005 | -0.017 | -0.012 | -0.019 | -0.040 | 1.000 | | | | | |
| Population density | -0.063 | 0.017 | -0.054 | 0.084 | -0.055 | 0.080 | -0.153 | -0.027 | 1.000 | | | | |
| Temperature | -0.287 | -0.218 | -0.079 | 0.061 | -0.029 | -0.040 | 0.018 | -0.038 | -0.209 | 1.000 | | | |
| Relative humidity | 0.118 | 0.019 | -0.045 | 0.014 | -0.081 | -0.021 | 0.072 | -0.044 | 0.250 | -0.593 | 1.000 | | |
| Precipitation (y/n) | -0.061 | 0.022 | 0.017 | 0.053 | -0.008 | 0.006 | 0.002 | -0.006 | -0.065 | -0.062 | 0.181 | 1.000 | |
| Wind speed | -0.197 | 0.037 | 0.056 | -0.018 | -0.025 | -0.078 | 0.046 | -0.035 | -0.021 | 0.160 | -0.169 | -0.053 | 1.000 |
| | PM2.5 | NDVI | TC | GLU (y/n) | Motorway/ primary/ secondary road (y/n) | Tertiary road (y/n) | Other road (y/n) | Rail (y/n) | Population density | Temperature | Relative humidity | Precipitation (y/n) | Wind speed |
| PM2.5 | 1.000 | | | | | | | | | | | | |
| NDVI | 0.050 | 1.000 | | | | | | | | | | | |
| TC | -0.019 | 0.888 | 1.000 | | | | | | | | | | |
| GLU (y/n) | -0.004 | 0.279 | 0.268 | 1.000 | | | | | | | | | |
| Motorway/primary/ secondary road (y/n) | -0.034 | 0.108 | 0.147 | -0.126 | 1.000 | | | | | | | | |
| Tertiary road (y/n) | -0.019 | 0.038 | 0.044 | 0.065 | -0.093 | 1.000 | | | | | | | |
| Other road (y/n) | 0.014 | -0.162 | -0.159 | -0.179 | 0.061 | -0.180 | 1.000 | | | | | | |
| Rail (y/n) | -0.040 | 0.093 | 0.064 | -0.026 | -0.032 | -0.028 | -0.099 | 1.000 | | | | | |
| Population density | -0.064 | 0.030 | -0.049 | 0.150 | -0.230 | 0.121 | -0.166 | -0.013 | 1.000 | | | | |
| Temperature | -0.287 | -0.232 | -0.072 | 0.048 | -0.003 | -0.057 | 0.056 | -0.049 | -0.207 | 1.000 | | | |
| Relative humidity | 0.118 | 0.022 | -0.052 | 0.024 | 0.001 | 0.006 | 0.053 | -0.051 | 0.248 | -0.593 | 1.000 | | |
| Precipitation (y/n) | -0.061 | 0.015 | 0.023 | 0.048 | 0.111 | 0.006 | 0.013 | -0.007 | -0.065 | -0.062 | 0.181 | 1.000 | |
| Wind speed | -0.197 | 0.025 | 0.053 | 0.010 | 0.119 | -0.100 | -0.024 | -0.015 | -0.019 | 0.160 | -0.169 | -0.053 | 1.000 |

| | PM2.5 | NDVI | TC | GLU (y/n) | Motorway/ primary/ secondary road (y/n) | Tertiary road (y/n) | Other road (y/n) | Rail (y/n) | Population density | Temperature | Relative humidity | Precipitation (y/n) | Wind speed |
|---|--------|--------------|--------|-----------|--|---------------------------|------------------------|---------------|-----------------------|-------------|----------------------|------------------------|---------------|
| PM2.5 | 1.000 | | | | | | | | | | | | |
| NDVI | 0.083 | 1.000 | | | | | | | | | | | |
| TC | -0.011 | 0.904 | 1.000 | | | | | | | | | | |
| GLU (y/n) | -0.085 | 0.225 | 0.266 | 1.000 | | | | | | | | | |
| Motorway/primary/ secondary road (y/n) | -0.083 | 0.107 | 0.198 | -0.087 | 1.000 | | | | | | | | |
| Tertiary road (y/n) | -0.003 | 0.007 | 0.001 | 0.056 | -0.160 | 1.000 | | | | | | | |
| Other road (y/n) | 0.043 | -0.148 | -0.159 | -0.100 | 0.046 | -0.154 | 1.000 | | | | | | |
| Rail (y/n) | -0.010 | 0.156 | 0.119 | -0.049 | -0.054 | -0.026 | -0.036 | 1.000 | | | | | |
| Population density | -0.066 | 0.049 | -0.043 | 0.147 | -0.270 | 0.099 | -0.157 | -0.003 | 1.000 | | | | |
| Temperature | -0.287 | -0.254 | -0.060 | 0.064 | 0.056 | -0.067 | 0.030 | -0.027 | -0.205 | 1.000 | | | |
| Relative humidity | 0.118 | 0.026 | -0.072 | -0.001 | -0.052 | 0.003 | 0.072 | -0.079 | 0.245 | -0.593 | 1.000 | | |
| Precipitation (y/n) | -0.061 | 0.016 | 0.022 | 0.055 | 0.093 | -0.004 | 0.019 | -0.014 | -0.065 | -0.062 | 0.181 | 1.000 | |
| Wind speed | -0.197 | -0.010 | 0.044 | 0.011 | 0.177 | -0.088 | -0.045 | 0.056 | -0.016 | 0.160 | -0.169 | -0.053 | 1.000 |
| | PM2.5 | NDVI | TC | GLU (y/n) | Motorway/ primary/ secondary road (y/n) | Tertiary road (y/n) | Other road (y/n) | Rail (y/n) | Population density | Temperature | Relative humidity | Precipitation (y/n) | Wind speed |
| PM2.5 | 1.000 | | | | | | | | | | | | |
| NDVI | 0.128 | 1.000 | | | | | | | | | | | |
| TC | -0.007 | 0.885 | 1.000 | | | | | | | | | | |
| GLU (y/n) | -0.176 | 0.078 | 0.190 | 1.000 | | | | | | | | | |
| Motorway/primary/ secondary road (y/n) | -0.071 | 0.293 | 0.338 | 0.040 | 1.000 | | | | | | | | |
| Tertiary road (y/n) | -0.057 | -0.039 | -0.002 | 0.113 | -0.172 | 1.000 | | | | | | | |
| Other road (y/n) | 0.009 | 0.029 | 0.026 | 0.042 | 0.036 | -0.051 | 1.000 | | | | | | |
| Rail (y/n) | -0.024 | 0.139 | 0.161 | -0.128 | 0.032 | 0.112 | -0.156 | 1.000 | | | | | |
| Population density | -0.075 | 0.005 | -0.089 | 0.168 | -0.112 | 0.168 | -0.037 | 0.007 | 1.000 | | | | |
| Temperature | -0.287 | -0.290 | 0.002 | 0.159 | -0.021 | -0.012 | 0.032 | -0.039 | -0.203 | 1.000 | | | |
| Relative humidity | 0.118 | 0.028 | -0.111 | -0.069 | -0.039 | -0.028 | -0.010 | -0.028 | 0.240 | -0.593 | 1.000 | | |
| Precipitation (y/n) | -0.061 | 0.022 | 0.038 | 0.047 | 0.061 | -0.043 | 0.004 | -0.003 | -0.067 | -0.062 | 0.181 | 1.000 | |
| Wind speed | -0.197 | -0.025 | 0.047 | 0.030 | 0.147 | -0.087 | -0.024 | 0.042 | -0.008 | 0.160 | -0.169 | -0.053 | 1.000 |

96 **Table S3.** Regression coefficients (95% confidence intervals) of the increase in 1-minute average concentrations of PM_{2.5} in relation to greenspace markers*
 97 averaged at 25, 50, 100 and 250 m radii around the point location: within-journey analysis.

| | 25 m | 50 m | 100 m | 250 m |
|---|-------------------------|-------------------------|-------------------------|-------------------------|
| <u>Unadjusted analysis (model 1)</u> | | | | |
| <i>Spring/summer/ monsoon</i> | | | | |
| NDVI (+1 IQR) | -2.0% (-9.5% to 6.1%) | -6.3% (-15.3% to 3.6%) | -9.6% (-20.9% to 3.3%) | -8.9% (-20.9% to 5.0%) |
| TC (+1 IQR) | -7.0% (-13.6% to 0.2%) | -9.0% (-17.3% to 0.1%) | -10.4% (-21.5% to 2.4%) | -9.7% (-22.6% to 5.4%) |
| GLU (+0.1 overlap) | -0.8% (-3.9% to 2.5%) | -1.0% (-4.0% to 2.1%) | -1.6% (-4.8% to 1.7%) | -2.4% (-6.3% to 1.7%) |
| PF (+0.1 overlap) | 1.6% (-2.8% to 6.1%) | 1.2% (-3.5% to 6.1%) | 0.5% (-5.2% to 6.6%) | -1.1% (-5.3% to 3.2%) |
| <i>Autumn/winter</i> | | | | |
| NDVI (+1 IQR) | 0.4% (-5.8% to 7.0%) | -0.2% (-8.5% to 8.8%) | -2.2% (-10.6% to 7.0%) | -6.2% (-14.5% to 2.9%) |
| TC (+1 IQR) | -0.8% (-7.8% to 6.7%) | 0.6% (-8.5% to 10.6%) | 0.3% (-10.6% to 12.5%) | -1.2% (-15.0% to 14.9%) |
| GLU (+0.1 overlap) | 1.5% (-3.2% to 6.5%) | 2.4% (-3.8% to 9.0%) | 3.9% (-3.6% to 12.1%) | 2.0% (-2.4% to 6.5%) |
| PF (+0.1 overlap) | 1.6% (-3.5% to 6.9%) | 2.5% (-4.2% to 9.7%) | 4.4% (-4.6% to 14.4%) | 2.3% (-2.3% to 7.1%) |
| <u>Adjusted for type of road within the 25 m radius, presence of railways, and population density (model 2)</u> | | | | |
| <i>Spring/summer/monsoon</i> | | | | |
| NDVI (+1 IQR) | -2.4% (-9.6% to 5.4%) | -6.6% (-15.2% to 2.8%) | -10.4% (-21.0% to 1.6%) | -8.6% (-20.4% to 5.0%) |
| TC (+1 IQR) | -7.6% (-13.9% to -0.8%) | -9.8% (-17.6% to -1.3%) | -11.2% (-21.7% to 0.6%) | -9.2% (-21.8% to 5.4%) |
| GLU (+0.1 overlap) | -0.6% (-3.8% to 2.8%) | -0.8% (-3.8% to 2.3%) | -1.8% (-4.8% to 1.4%) | -2.3% (-6.2% to 1.6%) |
| PF (+0.1 overlap) | 2.0% (-2.5% to 6.6%) | 1.6% (-3.3% to 6.6%) | 0.4% (-5.5% to 6.6%) | -1.3% (-5.4% to 3.0%) |
| <i>Autumn/winter</i> | | | | |
| NDVI (+1 IQR) | 0.5% (-5.5% to 6.9%) | -0.1% (-7.9% to 8.4%) | -2.2% (-9.7% to 5.9%) | -5.4% (-13.3% to 3.1%) |
| TC (+1 IQR) | -1.2% (-8.3% to 6.4%) | 0.0% (-8.9% to 9.8%) | 0.0% (-10.0% to 11.1%) | -0.6% (-14.2% to 15.0%) |
| GLU (+0.1 overlap) | 1.9% (-2.9% to 7.0%) | 2.9% (-3.4% to 9.6%) | 5.5% (-2.5% to 14.2%) | 2.7% (-1.3% to 6.7%) |
| PF (+0.1 overlap) | 2.0% (-3.2% to 7.4%) | 3.1% (-3.8% to 10.4%) | 6.5% (-3.2% to 17.1%) | 2.9% (-1.3% to 7.3%) |

98 *NDVI=Normalised Difference Vegetation Index; TC=Tree cover; GLU=Green land use; PF=Parks or forests.

99 **Table S4.** Regression coefficients (95% confidence intervals) of the increase in trip-average PM_{2.5} concentration in relation to greenspace markers* averaged
 100 at 25, 50, 100, and 250 m radii around the point location: between-journey analysis.

| | 25 m | 50 m | 100 m | 250 m |
|--|-------------------------|-------------------------|-------------------------|--------------------------|
| <u>Unadjusted analysis (model 1)</u> | | | | |
| <i>Spring/summer/ monsoon</i> | | | | |
| NDVI (+1 IQR) | -8.3% (-19.8% to 4.7%) | -9.4% (-21.3% to 4.4%) | -8.8% (-20.7% to 4.8%) | -12.6% (-25.0% to 1.9%) |
| TC (+1 IQR) | -6.7% (-16.8% to 5.7%) | -8.0% (-18.6% to 3.9%) | -10.6% (-21.7% to 2.2%) | -14.3% (-25.9% to -0.8%) |
| GLU (+0.1 overlap) | 8.1% (1.7% to 14.9%) | 9.0% (2.2% to 16.3%) | 10.0% (2.2% to 18.3%) | 10.1% (-0.6% to 22.0%) |
| PF (+0.1 overlap) | 10.0% (2.2% to 18.4%) | 11.1% (2.9% to 20.0%) | 12.1% (2.8% to 22.4%) | 10.5% (-2.3% to 25.0%) |
| <i>Autumn/winter</i> | | | | |
| NDVI (+1 IQR) | 0.5% (-12.9% to 16.1%) | 0.7% (-12.5% to 16.0%) | 0.7% (-12.8% to 16.3%) | 3.8% (-11.9% to 22.3%) |
| TC (+1 IQR) | -4.5% (-17.4% to 10.5%) | -3.9% (-16.9% to 11.2%) | -5.1% (-18.8% to 10.9%) | -3.9% (-19.6% to 14.9%) |
| GLU (+0.1 overlap) | -4.5% (-15.5% to 7.9%) | -5.2% (-17.8% to 9.3%) | -7.3% (-23.5% to 12.3%) | -3.6% (-22.5% to 19.9%) |
| PF (+0.1 overlap) | -3.2% (-14.6% to 9.6%) | -2.9% (-16.3% to 12.6%) | -2.4% (-21.3% to 21.0%) | 2.8% (-17.2% to 27.7%) |
| <u>Adjusted for road within a 25 m radius, presence of railways and population density (model 2)</u> | | | | |
| <i>Spring/summer/monsoon</i> | | | | |
| NDVI (+1 IQR) | -6.4% (-18.5% to 7.4%) | -7.4% (-20.0% to 7.2%) | -7.5% (-20.2% to 7.1%) | -11.4% (-24.5% to 3.9%) |
| TC (+1 IQR) | -5.1% (-15.8% to 6.9%) | -6.5% (-17.7% to 6.2%) | -9.5% (-21.4% to 4.2%) | -14.0% (-26.2% to 0.3%) |
| GLU (+0.1 overlap) | 10.3% (3.5% to 17.5%) | 11.2% (3.9% to 18.9%) | 13.4% (4.8% to 22.8%) | 11.0% (-0.7% to 24.0%) |
| PF (+0.1 overlap) | 12.8% (4.7% to 21.4%) | 13.8% (5.3% to 22.9%) | 14.2% (4.6% to 24.6%) | 11.6% (-1.4% to 26.2%) |
| <i>Autumn/winter</i> | | | | |
| NDVI (+1 IQR) | -1.3% (-14.8% to 14.5%) | -1.0% (-14.6% to 14.7%) | -0.9% (-14.7% to 15.1%) | 1.1% (-14.7% to 19.9%) |
| TC (+1 IQR) | -6.0% (-19.1% to 9.1%) | -5.4% (-18.6% to 9.9%) | -7.1% (-21.0% to 9.2%) | -7.1% (-22.8% to 11.8%) |
| GLU (+0.1 overlap) | -5.2% (-16.2% to 7.1%) | -4.3% (-16.8% to 10.1%) | -6.5% (-22.8% to 13.3%) | -2.3% (-21.4% to 21.4%) |
| PF (+0.1 overlap) | -4.7% (-15.8% to 7.9%) | -3.2% (-16.4% to 11.9%) | -1.7% (-20.8% to 22.0%) | 3.1% (-16.9% to 27.9%) |

101 *NDVI=Normalised Difference Vegetation Index; TC=Tree cover; GLU=Green land use; PF=Parks or forests.

102

| | 25 m | 50 m | 100 m | 250 m |
|---|-------------------------|-------------------------|-------------------------|-------------------------|
| <u>Adjusted for time of day, weekday/weekend day, year, temperature, precipitation, relative humidity, wind speed, wind direction (model 3)</u> | | | | |
| <i>Spring/summer/monsoon</i> | | | | |
| NDVI (+1 IQR) | -6.2% (-17.8% to 7.0%) | -7.3% (-19.4% to 6.6%) | -7.2% (-19.2% to 6.6%) | -9.6% (-22.4% to 5.4%) |
| TC (+1 IQR) | -4.7% (-15.0% to 6.7%) | -5.7% (-16.5% to 6.4%) | -7.7% (-19.1% to 5.3%) | -10.5% (-22.6% to 3.5%) |
| GLU (+0.1 overlap) | 6.8% (0.3% to 13.6%) | 7.6% (0.7% to 15.0%) | 8.3% (0.4% to 16.9%) | 8.1% (-2.4% to 19.8%) |
| PF (+0.1 overlap) | 9.1% (1.4% to 17.3%) | 10.0% (1.8% to 18.7%) | 10.9% (1.6% to 21.0%) | 10.1% (-2.2% to 24.0%) |
| <i>Autumn/winter</i> | | | | |
| NDVI (+1 IQR) | 2.7% (-10.7% to 18.2%) | 1.7% (-11.4% to 16.7%) | 0.7% (-12.5% to 15.8%) | 4.2% (-11.1% to 22.1%) |
| TC (+1 IQR) | -5.3% (-18.0% to 9.3%) | -5.2% (-18.0% to 9.5%) | -6.7% (-20.1% to 9.0%) | -4.1% (-19.6% to 14.4%) |
| GLU (+0.1 overlap) | -0.5% (-12.1% to 12.6%) | -0.9% (-14.2% to 14.4%) | -2.9% (-20.0% to 18.0%) | -1.5% (-20.6% to 22.3%) |
| PF (+0.1 overlap) | 1.6% (-10.4% to 15.3%) | 3.0% (-11.4% to 19.8%) | 7.2% (-14.1% to 33.9%) | 9.2% (-12.1% to 35.6%) |
| <u>Adjusted for the covariates of models 2 & 3 (model 4)</u> | | | | |
| <i>Spring/summer/monsoon</i> | | | | |
| NDVI (+1 IQR) | -4.7% (-16.9% to 9.2%) | -5.6% (-18.4% to 9.2%) | -5.9% (-18.8% to 9.0%) | -8.9% (-22.4% to 6.9%) |
| TC (+1 IQR) | -3.6% (-14.5% to 8.7%) | -4.6% (-16.1% to 8.4%) | -6.9% (-19.1% to 7.3%) | -10.9% (-23.6% to 4.0%) |
| GLU (+0.1 overlap) | 8.7% (2.0% to 15.9%) | 9.4% (2.2% to 17.1%) | 10.7% (2.2% to 19.9%) | 8.8% (-2.3% to 21.3%) |
| PF (+0.1 overlap) | 11.3% (3.4% to 19.8%) | 11.9% (3.6% to 20.9%) | 12.3% (2.9% to 22.6%) | 10.4% (-2.1% to 24.5%) |
| <i>Autumn/winter</i> | | | | |
| NDVI (+1 IQR) | 1.8% (-11.9% to 17.6%) | 1.3% (-12.3% to 16.9%) | 0.3% (-13.3% to 16.0%) | 3.0% (-12.8% to 21.7%) |
| TC (+1 IQR) | -6.3% (-19.2% to 8.5%) | -5.8% (-18.8% to 9.2%) | -7.6% (-21.3% to 8.5%) | -6.2% (-21.9% to 12.8%) |
| GLU (+0.1 overlap) | -1.5% (-13.1% to 11.5%) | -1.1% (-6.8% to 4.9%) | -1.6% (-19.1% to 19.6%) | 0.2% (-19.3% to 24.4%) |
| PF (+0.1 overlap) | 0.0% (-12.0% to 13.5%) | 2.5% (-11.8% to 19.0%) | 8.9% (-13.0% to 36.2%) | 10.1% (-11.5% to 36.9%) |

*NDVI=Normalised Difference Vegetation Index; TC=Tree cover; GLU=Green land use; PF=Parks or forests.

103 **Table S5.** Greenspace* coefficients (95% confidence intervals) with effect modification from average
 104 visibility at minimum (49%) and maximum (100%) levels.

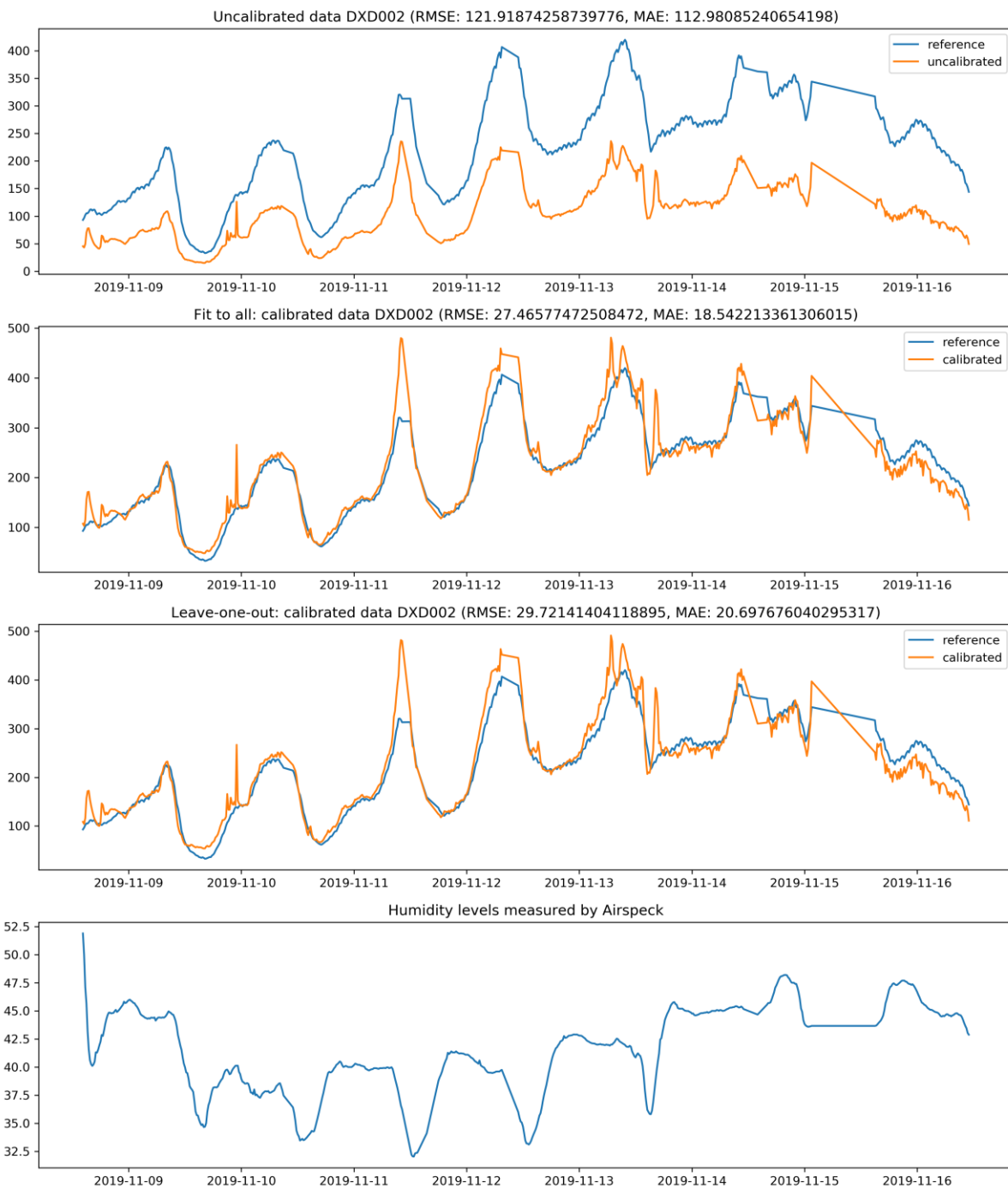
| Greenspace metric | 49% visibility | 100% visibility |
|--------------------|--------------------------|--------------------------|
| NDVI (+1 IQR) | 19.6% (-26.7% to 95.1%) | -15.6% (-31.2% to 3.6%) |
| TC (+1 IQR) | 27.2% (-20.0% to 102.3%) | -24.6% (-38.6% to -7.3%) |
| GLU (+0.1 overlap) | 12.2% (-28.7% to 76.5%) | 2.7% (-13.5% to 22.1%) |
| PF (+0.1 overlap) | 17.4% (-23.6% to 80.5%) | 6.2% (-10.5% to 26.0%) |

105 *NDVI=Normalised Difference Vegetation Index; TC=Tree cover; GLU=Green land use; PF=Parks or
 106 forests.



107

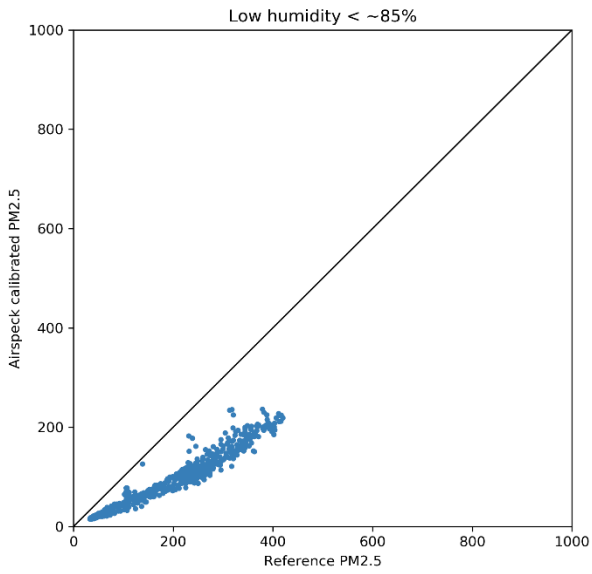
108 **Figure S1.** The personal AirSpeck particle sensor.



110

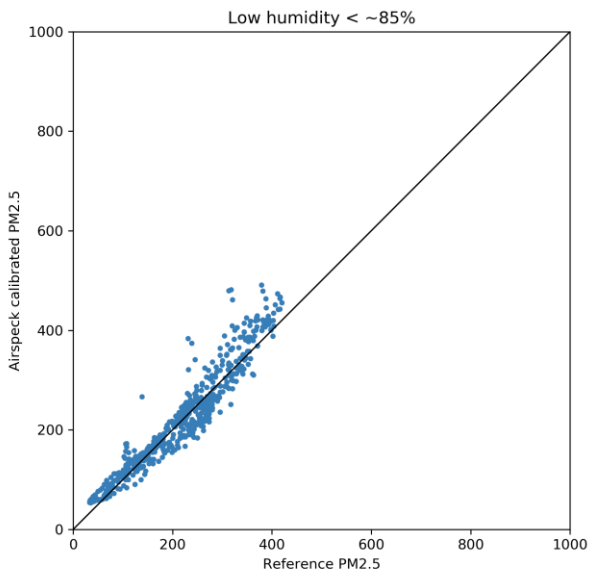
111

112 **Figure S2.** An example line graph of PM_{2.5} data calibration of the AirSpeck with reference monitors in
113 Delhi, India.



114

115 a)



116

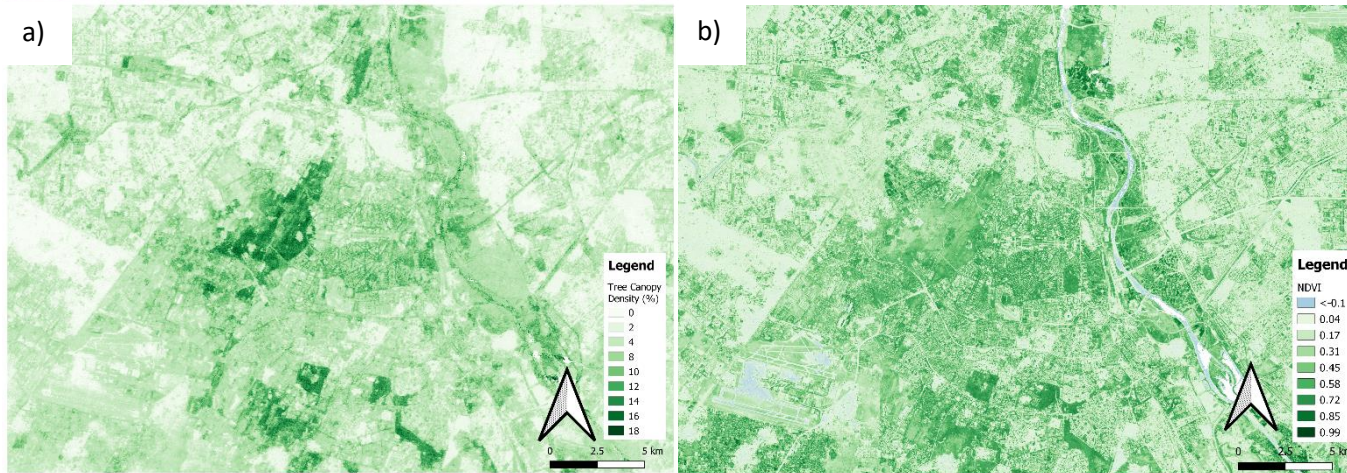
117 b)

118 **Figure S3.** Example scatterplots of a) uncalibrated and b) calibrated AirSpeck $PM_{2.5}$ data at low
 119 humidity.

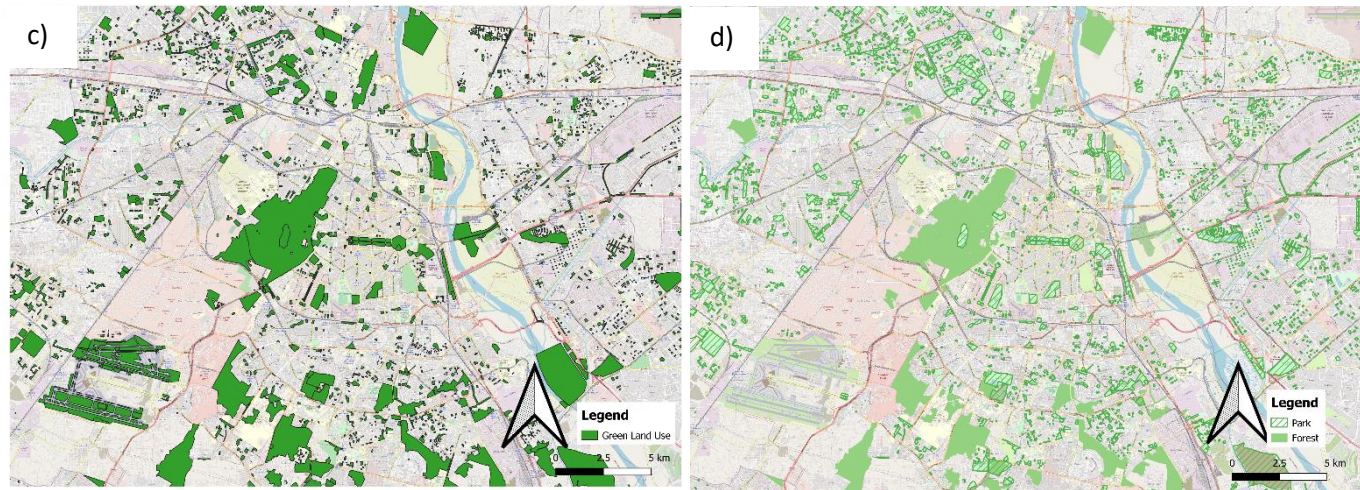
120

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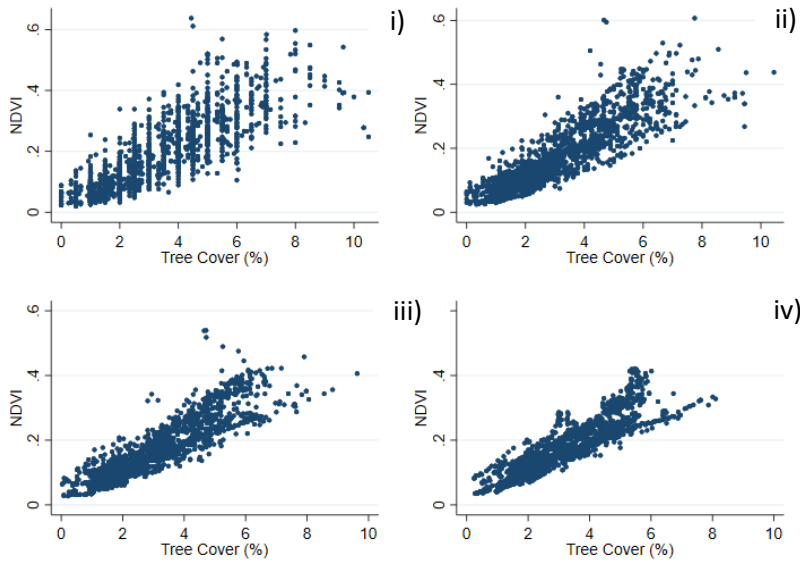
122



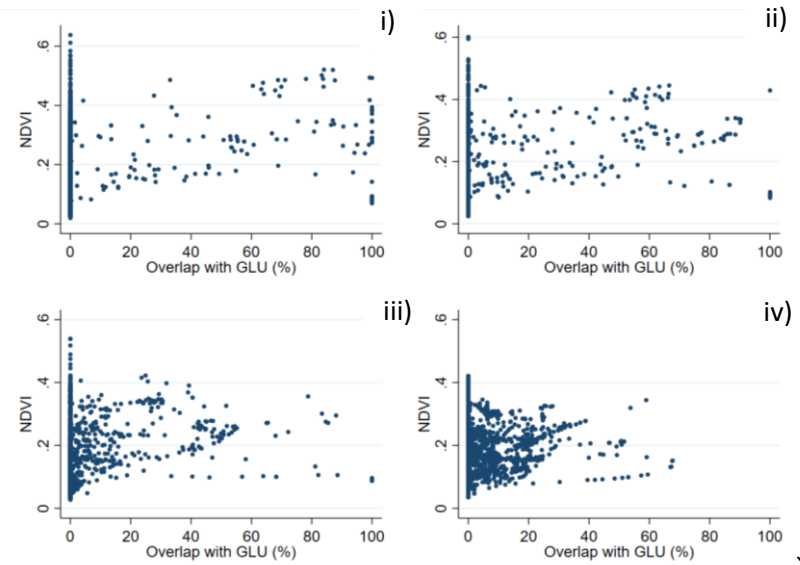
123



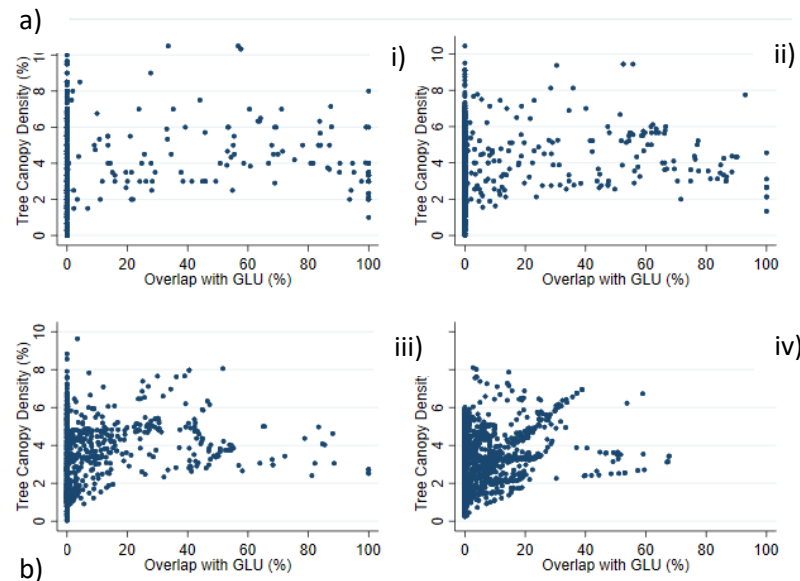
124 **Figure S4.** Maps of Delhi greenspace indicators: a) NDVI (image date: 9 February 2019), b) Tree Canopy Density (%), c) green land use, and d) parks or
125 forests. Basemap from ©OpenStreetMap contributors (www.openstreetmap.org), available under the Open Database License.



126

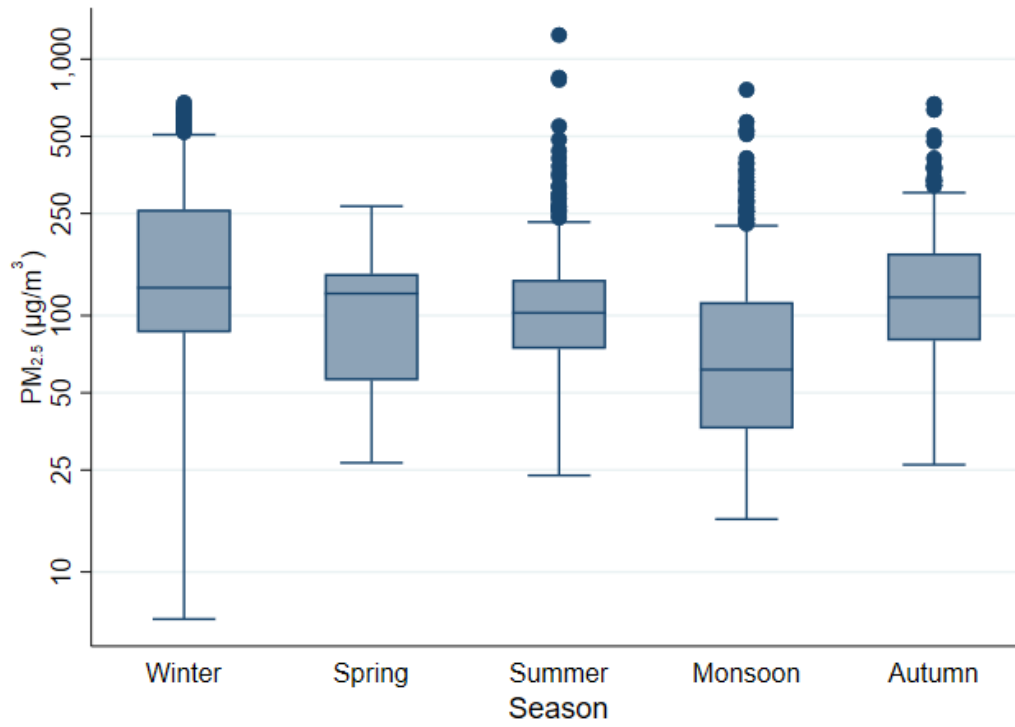


127



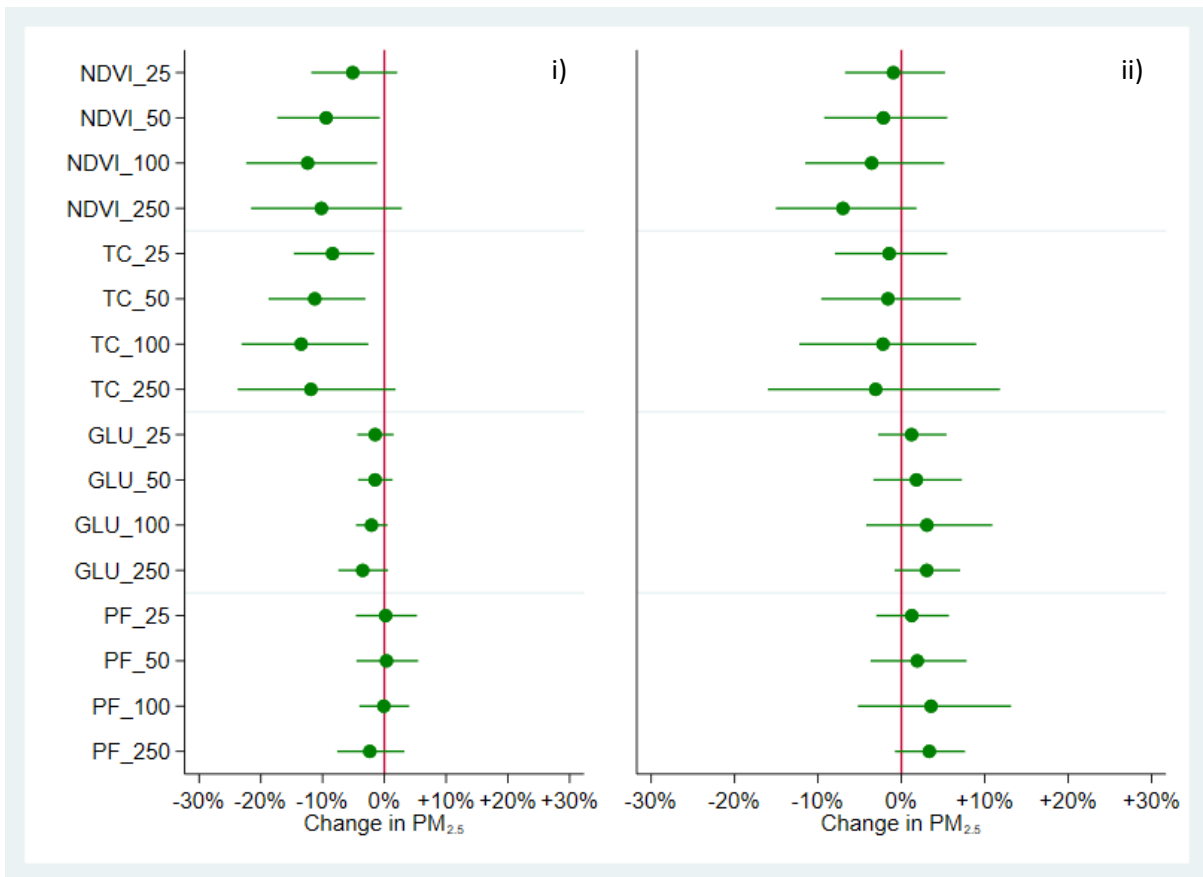
128

129 **Figure S5.** Scatterplots of a) mean NDVI and Tree Cover (%), b) mean NDVI and GLU (% overlap), and
 130 c) Tree Cover (%) and GLU (% overlap) at the i) 25 m, ii) 50 m, iii), 100 m, and iv) 250 m radii.



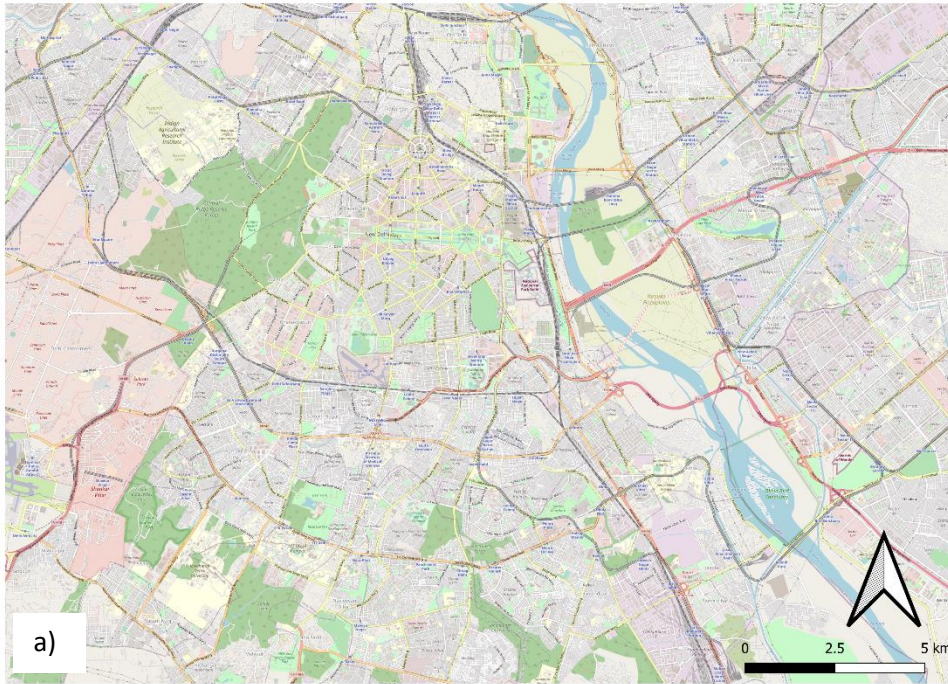
131

132 **Figure S6.** A boxplot of personal PM_{2.5} values (log-scale) recorded during each season in Delhi.

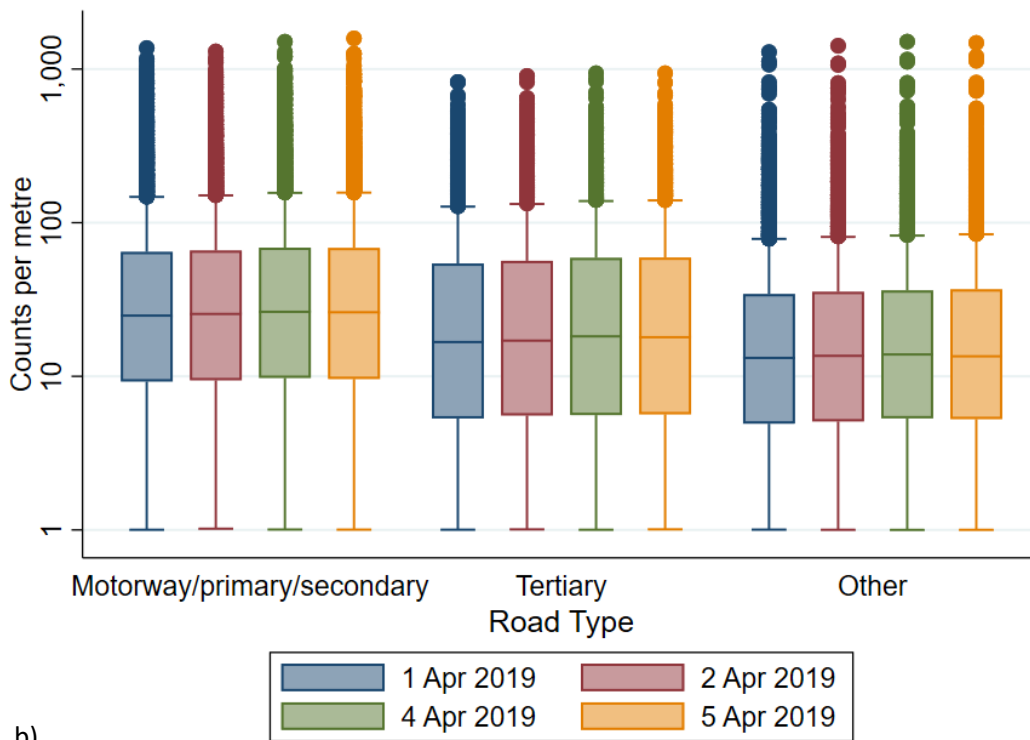


133

134 **Figure S7.** Plots of regression coefficients for (i) the spring/summer/monsoon season and (ii) the
 135 autumn/winter season of within-journey changes in 2-minute averaged $PM_{2.5}$ in relation to markers
 136 of greenspace. Coefficients represent an interquartile range (IQR) increase in Normalised Difference
 137 Vegetation Index (NDVI) and tree cover (TC), and a 0.1 increase in the proportion of green land use
 138 (GLU) or parks or forests (PF). All are presented at averaging radii of 25, 50, 100, and 250 m around
 139 the point location of the individual. Models include an interaction term for season.



140



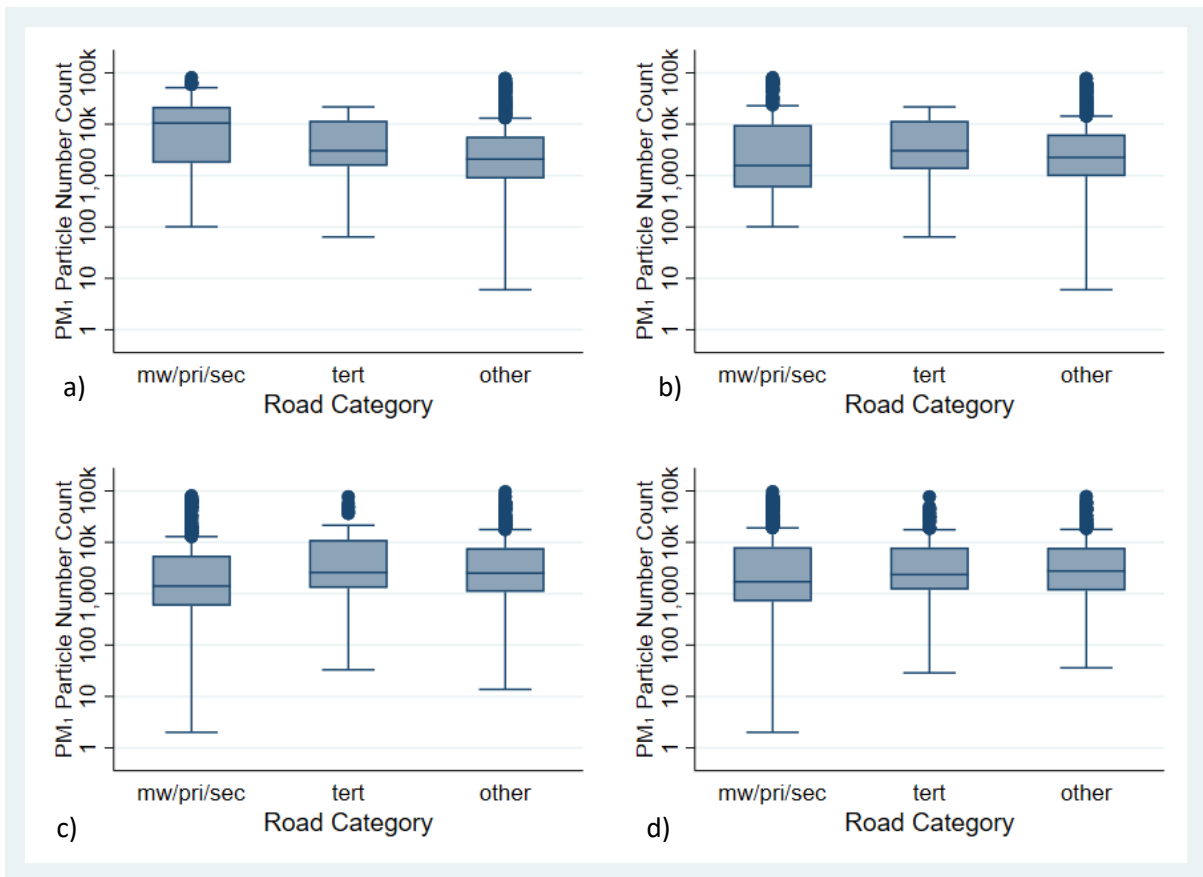
b)

141

142 **Figure S8.** a) A map of the area in Delhi from which traffic count data were analysed and b) a boxplot
 143 (log-scale) of traffic counts per metre across the three traffic categories. Basemap from
 144 ©OpenStreetMap contributors (www.openstreetmap.org), available under the Open Database
 145 License.

146

147



148

149 **Figure S9.** Comparison of PM₁ particle number counts as an indicator of traffic emissions based on
 150 the highest road type (mw=motorway; pri=primary; sec=secondary; tert=tertiary) in a) 25m, b) 50m,
 151 c) 100m, and d) 250 radii.

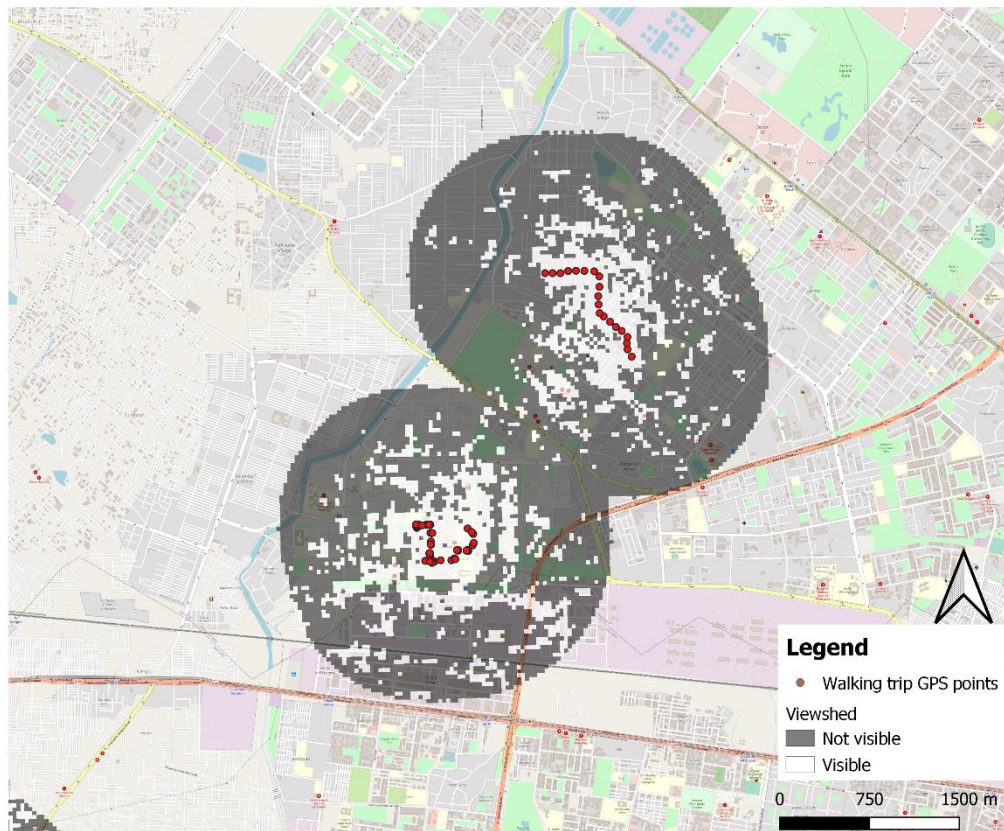


Figure S10. An example of walking trips with 1,000 m viewsheds, illustrating areas that were visible at any point during the route. Basemap from ©OpenStreetMap contributors (www.openstreetmap.org), available under the Open Database License.