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

NOVEMBER 2022

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.

Acknowledgements

There are many people who have helped and supported me along the way. Without them, I would not have the pleasure of writing these acknowledgements.

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.

I am very grateful for the statistical expertise and input from Hilary Cowie across the analyses in this PhD. I'd also like to thank Prof Ben Armstrong for discussions regarding statistical analysis.

I would like to thank Dr Paul Whaley for providing very useful feedback and discussing an initial draft of the systematic review. Ken Dixon and Russell Burke are thanked for their advice on the search terms and methods.

I am grateful for the support and tuition assistance from IOM throughout my PhD studies.

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!

Table of Contents

List of tables

Chapter 6

List of figures

Chapter 6

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 µm ($PM_{2.5}$) is especially harmful for respiratory outcomes, including asthma, chronic obstructive pulmonary disease (COPD), and respiratory infections (Kurt et al., 2016). Both indoor and outdoor $PM_{2.5}$ 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.

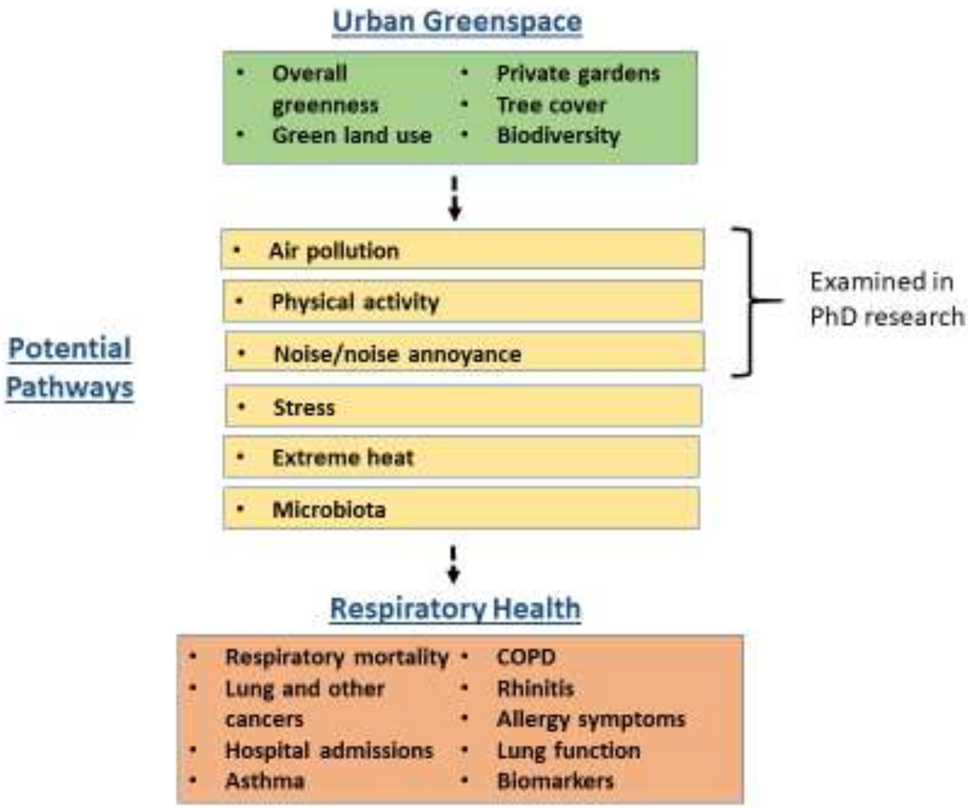


Figure 2. Urban greenspace and potential pathways to respiratory health, indicating those investigated in the PhD research.

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.

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. Does greenspace mitigate air pollution and motivate physical activity?: A case study of four European cities. Presented at: World Conference on Forests for Public Health; 10 May 2019; Athens, Greece.

Mueller W, Steinle S, Loh M, Vardoulakis S, Nopadol P, Kliengchuay W, Sahanavin N, Sillaparassamee R, Nakhapakorn K, Tantrakarnapa K, Cherrie JW. Modelling Health Impacts from Long-term Exposure to Outdoor Air Pollution in Thailand. Presented at: 12th UK & Ireland Occupational & Environmental Epidemiology Meeting; 1 April 2019; Edinburgh, UK.

Mueller W, Steinle S, Loh M, Vardoulakis S, Nopadol P, Kliengchuay W, Sahanavin N, Sillaparassamee R, Nakhapakorn K, Tantrakarnapa K, Cherrie JW. *Health Impact Assessment from Long-term Exposure to Outdoor Air Pollution in Thailand*. Presented at: Joint International Tropical Medicine Meeting (JITMM) 2018; 12-14 December, 2018; Bangkok, 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 trends of air pollution in Thailand and Effects on Health.* Poster presented at: ISES-ISEE 2018 Joint Annual Meeting; 26-30 August, 2018; Ottawa, Canada.

Mueller W, Cowie H, Horwell CJ, Hurley F. *Health impact assessment of ash from volcanic eruptions: A review of evidence*. Poster presented at: 2018 Planetary Health Annual Meeting; 29-31 May, 2018; Edinburgh, UK.

Mueller W, Steinle S, Loh M, Vardoulakis S, Nopadol P, Kliengchuay W, Sahanavin N, Sillaparassamee R, Nakhapakorn K, Tantrakarnapa K, Cherrie JW. *Long-term trends of air pollution in Thailand.* Poster presented at: 6th UK and Ireland Exposure Science Conference; 24 April, 2018; London UK.

Peer-reviewed publications

Mueller, W., Vardoulakis, S., Steinle, S., Loh, M., Johnston, H.J., Precha, N., Kliengchuay, W., Sahanavin, N., Nakhapakorn, K., Sillaparassamee, R. and Tantrakarnapa, K., 2021. A health impact assessment of long-term exposure to particulate air pollution in Thailand. *Environmental Research Letters*, *16*(5), p.055018.

Mueller, W., Tantrakarnapa, K., Johnston, H.J., Loh, M., Steinle, S., Vardoulakis, S. and Cherrie, J.W., 2021. Exposure to ambient particulate matter and biomass burning during pregnancy: associations with birth weight in Thailand. *Journal of Exposure Science & Environmental Epidemiology*, pp.1-11.

Steinle, S., Johnston, H.J., Loh, M., Mueller, W., Vardoulakis, S., Tantrakarnapa, K., Cherrie, J.W. 2020. In utero exposure to particulate air pollution during pregnancy: Impact on birth weight and health through the life course. *Int. J. Environ. Res. Public Health*, 17, 8948.

Mueller, W., Cowie, H., Horwell, C.J., Hurley, F. and Baxter, P.J., 2020. Health Impact Assessment of volcanic ash inhalation: A comparison with outdoor air pollution methods. *GeoHealth*, p.e2020GH000256.

Mueller, W., Loh, M., Vardoulakis, S., Johnston, H.J., Steinle, S., Precha, N., Kliengchuay, W., Tantrakarnapa, K. and Cherrie, J.W., 2020. Ambient particulate matter and biomass burning: an ecological time series study of respiratory and cardiovascular hospital visits in northern Thailand. *Environmental Health*, *19*(1), pp.1-12.

Mueller, W. Cowie, H., Horwell, C.J., Baxter, P.J., McElvenny, D., Booth, M., Cherrie, J.W., Cullinan, P., Jarvis, D., Ugarte, C., Inoue, H. 2020. Standardized epidemiological protocols for populations affected by volcanic eruptions. *Bulletin of the World Health Organization*, 98, pp.362–364.

1.6 References

Abhijith, K.V., Kumar, P., Gallagher, J., McNabola, A., Baldauf, R., Pilla, F., Broderick, B., Di Sabatino, S. and Pulvirenti, B., 2017. Air pollution abatement performances of green infrastructure in open road and built-up street canyon environments–A review. *Atmospheric Environment*, *162*, pp.71-86.

Alvarsson, J.J., Wiens, S. and Nilsson, M.E., 2010. Stress recovery during exposure to nature sound and environmental noise. *International Journal of Environmental Research and Public Health*, *7*(3), pp.1036-1046.

Baldacci, S., Maio, S., Cerrai, S., Sarno, G., Baïz, N., Simoni, M., Annesi-Maesano, I., Viegi, G. and Study, H.E.A.L.S., 2015. Allergy and asthma: Effects of the exposure to particulate matter and biological allergens. *Respiratory Medicine*, *109*(9), pp.1089-1104.

Cameron, R.W., Blanuša, T., Taylor, J.E., Salisbury, A., Halstead, A.J., Henricot, B. and Thompson, K., 2012. The domestic garden–Its contribution to urban green infrastructure. *Urban Forestry & Urban Greening*, *11*(2), pp.129-137.

Cordova-Rivera, L., Gibson, P.G., Gardiner, P.A. and McDonald, V.M., 2018. A systematic review of associations of physical activity and sedentary time with asthma outcomes. *The Journal of Allergy and Clinical Immunology: In Practice*, *6*(6), pp.1968-1981.

da Silveira Fleck, A., Sadoine, M.L., Buteau, S., Suarthana, E., Debia, M. and Smargiassi, A., 2021. Environmental and Occupational Short-Term Exposure to Airborne Particles and FEV1 and FVC in Healthy Adults: A Systematic Review and Meta-Analysis. *International Journal of Environmental Research and Public Health*, *18*(20), p.10571.

Diener, A. and Mudu, P., 2021. How can vegetation protect us from air pollution? A critical review on green spaces' mitigation abilities for air-borne particles from a public health perspective-with implications for urban planning. *Science of The Total Environment*, p.148605.

Eisenman, T.S., Churkina, G., Jariwala, S.P., Kumar, P., Lovasi, G.S., Pataki, D.E., Weinberger, K.R. and Whitlow, T.H., 2019. Urban trees, air quality, and asthma: An interdisciplinary review. *Landscape and Urban Planning*, *187*, pp.47-59.

Erbas, B., Jazayeri, M., Lambert, K.A., Katelaris, C.H., Prendergast, L.A., Tham, R., Parrodi, M.J., Davies, J., Newbigin, E., Abramson, M.J. and Dharmage, S.C., 2018. Outdoor pollen is a trigger of child and adolescent asthma emergency department presentations: A systematic review and meta-analysis. *Allergy*, *73*(8), pp.1632-1641.

Fecht, D., Hansell, A.L., Morley, D., Dajnak, D., Vienneau, D., Beevers, S., Toledano, M.B., Kelly, F.J., Anderson, H.R. and Gulliver, J., 2016. Spatial and temporal associations of road traffic noise and air pollution in London: Implications for epidemiological studies. *Environment International*, *88*, pp.235-242.

Foraster, M., Eze, I.C., Vienneau, D., Brink, M., Cajochen, C., Caviezel, S., Héritier, H., Schaffner, E., Schindler, C., Wanner, M. and Wunderli, J.M., 2016. Long-term transportation noise annoyance is associated with subsequent lower levels of physical activity. *Environment International*, *91*, pp.341-349.

Geidl, W., Schlesinger, S., Mino, E., Miranda, L. and Pfeifer, K., 2020. Dose–response relationship between physical activity and mortality in adults with noncommunicable diseases: a systematic review and meta-analysis of prospective observational studies. *International Journal of Behavioral Nutrition and Physical Activity*, *17*(1), pp.1-18.

Götschi, T., de Nazelle, A., Brand, C., Gerike, R. and PASTA Consortium, 2017. Towards a comprehensive conceptual framework of active travel behavior: A review and synthesis of published frameworks. *Current Environmental Health Reports*, *4*(3), pp.286-295.

Hartley, K., Ryan, P., Brokamp, C. and Gillespie, G.L., 2020. Effect of greenness on asthma in children: A systematic review. *Public Health Nursing*, *37*(3), pp.453-460.

James, P., Hart, J.E., Hipp, J.A., Mitchell, J.A., Kerr, J., Hurvitz, P.M., Glanz, K. and Laden, F., 2017. GPS-Based Exposure to Greenness and Walkability and Accelerometry-Based Physical Activity. *Cancer Epidemiology, Biomarkers & Prevention*, *26*(4), pp.525-532.

Jansen, M., Kamphuis, C., Pierik, F.H., Ettema, D.F. and Dijst, M.J., 2018. Neighborhood-based PA and its environmental correlates: a GIS-and GPS based cross-sectional study in the Netherlands. *BMC Public Health*, *18*(1), pp.1-8.

Keeler, B.L., Hamel, P., McPhearson, T., Hamann, M.H., Donahue, M.L., Meza Prado, K.A., Arkema, K.K., Bratman, G.N., Brauman, K.A., Finlay, J.C. and Guerry, A.D., 2019. Social-ecological and technological factors moderate the value of urban nature. *Nature Sustainability*, *2*(1), pp.29-38.

Kondo, M.C., Fluehr, J.M., McKeon, T. and Branas, C.C., 2018. Urban green space and its impact on human health. *International Journal of Environmental Research and Public Health*, *15*(3), p.445.

Kruize, H., van der Vliet, N., Staatsen, B., Bell, R., Chiabai, A., Muiños, G., Higgins, S., Quiroga, S., Martinez-Juarez, P., Aberg Yngwe, M. and Tsichlas, F., 2019. Urban green space: creating a triple win for environmental sustainability, health, and health equity through behavior change. *International Journal of Environmental Research and Public Health*, *16*(22), p.4403.

Kurt, O.K., Zhang, J. and Pinkerton, K.E., 2016. Pulmonary health effects of air pollution. *Current Opinion in Pulmonary Medicine*, *22*(2), p.138.

Lelieveld, J., Pozzer, A., Pöschl, U., Fnais, M., Haines, A. and Münzel, T., 2020. Loss of life expectancy from air pollution compared to other risk factors: a worldwide perspective. *Cardiovascular Research*, *116*(11), pp.1910-1917.

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A.M., De Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M.J. and Lupp, G., 2017. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research*, *158*, pp.301-317.

Marselle, M.R., Hartig, T., Cox, D.T., de Bell, S., Knapp, S., Lindley, S., Triguero-Mas, M., Böhning-Gaese, K., Braubach, M., Cook, P.A. and de Vries, S., 2021. Pathways linking biodiversity to human health: A conceptual framework. *Environment International*, *150*, p.106420.

McTiernan, A., Friedenreich, C.M., Katzmarzyk, P.T., Powell, K.E., Macko, R., Buchner, D., Pescatello, L.S., Bloodgood, B., Tennant, B., Vaux-Bjerke, A. and George, S.M., 2019. Physical activity in cancer prevention and survival: a systematic review. *Medicine and Science in Sports and Exercise*, *51*(6), p.1252.

Meng, Q.Y., Turpin, B.J., Korn, L., Weisel, C.P., Morandi, M., Colome, S., Zhang, J., Stock, T., Spektor, D., Winer, A. and Zhang, L., 2005. Influence of ambient (outdoor) sources on residential indoor and personal PM2. 5 concentrations: analyses of RIOPA data. *Journal of Exposure Science & Environmental Epidemiology*, *15*(1), pp.17-28.

Nawrath, M., Elsey, H. and Dallimer, M., 2021. Why cultural ecosystem services matter most: Exploring the pathways linking greenspaces and mental health in a low-income country. *Science of The Total Environment*, p.150551.

Nieuwenhuijsen, M.J., 2021. Green infrastructure and health. *Annual Review of Public Health*, *42*, pp.317-328.

Piercy, K.L., Troiano, R.P., Ballard, R.M., Carlson, S.A., Fulton, J.E., Galuska, D.A., George, S.M. and Olson, R.D., 2018. The Physical Activity Guidelines for Americans. *JAMA*, 320(19), pp.2020-2028.

Rook, G.A., Lowry, C.A. and Raison, C.L., 2013. Microbial 'Old Friends', immunoregulation and stress resilience. *Evolution, Medicine, and Public Health*, *2013*(1), pp.46-64.

Ruokolainen, L., Hertzen, L., Fyhrquist, N., Laatikainen, T., Lehtomäki, J., Auvinen, P., Karvonen, A.M., Hyvärinen, A., Tillmann, V., Niemelä, O. and Knip, M., 2015. Green areas around homes reduce atopic sensitization in children. *Allergy*, *70*(2), pp.195-202.

Salmond, J.A., Tadaki, M., Vardoulakis, S., Arbuthnott, K., Coutts, A., Demuzere, M., Dirks, K.N., Heaviside, C., Lim, S., Macintyre, H. and McInnes, R.N., 2016. Health and climate related ecosystem services provided by street trees in the urban environment. *Environmental Health*, *15*(1), p.S36.

Selway, C.A., Mills, J.G., Weinstein, P., Skelly, C., Yadav, S., Lowe, A., Breed, M.F. and Weyrich, L.S., 2020. Transfer of environmental microbes to the skin and respiratory tract of humans after urban green space exposure. *Environment International*, *145*, p.106084.

Shaffer, R.M., Sellers, S.P., Baker, M.G., de Buen Kalman, R., Frostad, J., Suter, M.K., Anenberg, S.C., Balbus, J., Basu, N., Bellinger, D.C. and Birnbaum, L., 2019. Improving and expanding estimates of the global burden of disease due to environmental health risk factors. *Environmental Health Perspectives*, *127*(10), p.105001.

Taylor, L. and Hochuli, D.F., 2017. Defining greenspace: Multiple uses across multiple disciplines. *Landscape and Urban Planning*, *158*, pp.25-38.

Twohig-Bennett, C. and Jones, A., 2018. The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes. *Environmental Research*, *166*, pp.628-637.

van Renterghem, T. and Botteldooren, D., 2016. View on outdoor vegetation reduces noise annoyance for dwellers near busy roads. *Landscape and Urban Planning*, *148*, pp.203-215.

van Renterghem, T., Forssén, J., Attenborough, K., Jean, P., Defrance, J., Hornikx, M. and Kang, J., 2015. Using natural means to reduce surface transport noise during propagation outdoors. *Applied Acoustics*, *92*, pp.86-101.

Wu, K., Guo, B., Guo, Y., Han, M., Xu, H., Luo, R., Hong, Z., Zhang, B., Dong, K., Wu, J. and Zhang, N., 2022. Association between residential greenness and gut microbiota in Chinese adults. *Environment International*, *163*, p.107216.

Yang, H., He, D., Lu, Y., Ren, C. and Huang, X., 2021a. Disentangling residential self-selection from the influence of built environment characteristics on adiposity outcomes among undergraduate students in China. *Cities*, *113*, p.103165.

Yang, B.Y., Zhao, T., Hu, L.X., Browning, M.H., Heinrich, J., Dharmage, S.C., Jalaludin, B., Knibbs, L.D., Liu, X.X., Luo, Y.N. and James, P., 2021b. Greenspace and human health: An umbrella review. *The Innovation*, *2*(4), p.100164.

Zhang, J., Yu, Z., Zhao, B., Sun, R. and Vejre, H., 2020. Links between green space and public health: a bibliometric review of global research trends and future prospects from 1901 to 2019. *Environmental Research Letters*, *15*(6), p.063001.

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
1. 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. ii. Investigate the overall direction and magnitude of reported associations.	Systematic review	Identification of pathways for analysis in objectives 2, 3 and 4.	Chapter 3 Paper: 'Exposure to urban greenspace and pathways to respiratory health: an exploratory systematic review'
2. a) Quantify the association between residential metrics of urban greenspace and indoor levels of $PM_{2.5}$.	Random-effects generalised least squares	Establish greenspace metrics to be adopted in objectives 3 and 4.	Chapter 4 Paper: 'Urban greenspace and the indoor environment: Pathways to health via indoor

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

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

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.

London School of Hygiene & Tropical Medicine
Keppel Street, London WC1E 7HT

T: +44 (0)20 7299 4646
F: +44 (0)20 7299 4656
www.lshtm.ac.uk

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**

*If yes, please attach evidence of retention. If no, or if the work is being included in its published format, please attach evidence of permission from the copyright holder (publisher or other author) to include this work.

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

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)	I performed the literature search, reviewed the papers, wrote the first draft of the manuscript, and responded to the reviewer comments.

SECTION E

Student Signature	William Mueller
Date	18/04/2022

Supervisor Signature	Paul Wilkinson
Date	12/07/2022

Science of the Total Environment 829 (2022) 154447

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

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

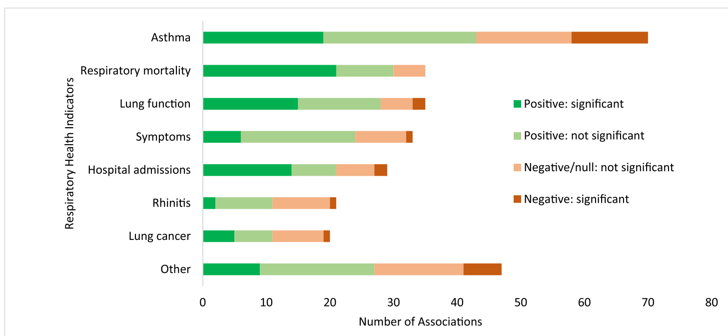
William Mueller [a,b,*], James Milner [b], Miranda Loh [a], Sotiris Vardoulakis [c], Paul Wilkinson [b]

[a] Institute of Occupational Medicine, Edinburgh, UK
[b] London School of Hygiene & Tropical Medicine, UK
[c] National Centre for Epidemiology and Population Health, Australian National University, Australia

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



ARTICLE INFO

Article history:
Received 11 May 2021
Received in revised form 4 March 2022
Accepted 6 March 2022
Available online 11 March 2022

Editor: Wei Huang

Keywords:
Greenness
Built environment
Vegetation
Asthma
Respiratory mortality

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.

* Corresponding author at: Institute of Occupational Medicine, Research Avenue North, Edinburgh, Midlothian EH14 4AP, UK.
E-mail address: will.mueller@iom-world.org (W. Mueller).

http://dx.doi.org/10.1016/j.scitotenv.2022.154447

Contents

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 ($PM_{2.5}$) 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 (Haahtela 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 [FEV_1]), 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 (Klompmaker et al., 2021) where studies used individual-level health data. The number of participants included in experimental studies ranged from 24 (Moshammer 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

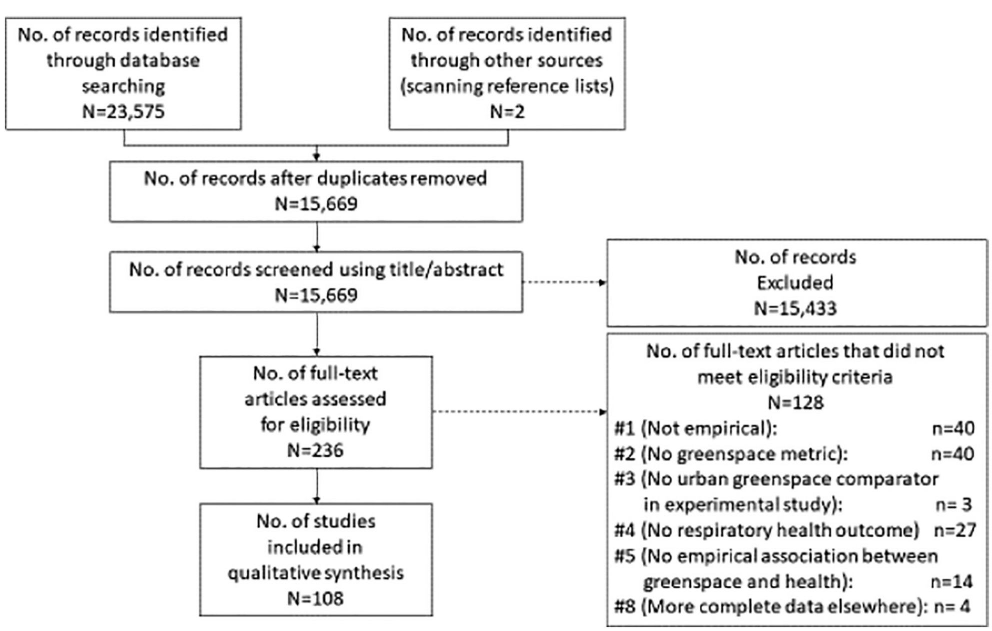


Fig. 1. A flow diagram of the search results, with reasons for excluded studies.

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	Ecolo-gical	$n = 1296$ 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	Ecolo-gical	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	Ecolo-gical	*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 km2 area)	Respiratory mortality	Age-adjusted rates. Models adjusted for air pollutants (CO, NO2, O3, PM10, PM2.5, and SO2)	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 NO2 (p = 0.049) and O3 (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 (PM2.5, PM10, NO2 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
							$PM_{2.5}$.	
Klompmaker, 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	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 km^2 (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 15–64 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
Klompmaker, 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	SO2, surface reflectance (proxy for humidity and O3)	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
			(>65 yrs) in U.S. counties with populations larger than 200,000	for each county (MODIS at 250 m resolution)	admissions	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	increase in NDVI: All respiratory disease: PM10: −1.29 (−3.36, 0.83) PM2.5: −0.01 (−1.03, 1.01)	
Kim, 2021	Ecological	$n = 2301$ census tracts	General population in Los Angeles County, US	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	Asthma emergency department visits	SES, air pollution	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
							OR = 1.08 (0.82 to 1.42)	
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	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

(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
				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
				LUG in each 'circuit' (quintiles)			0.78 (0.50 to 1.23)	
Kurnia Febriawan and da Silva Sodre, 2018	Ecological	Not specified, only reported prevalence of asthma as %	General population in Western Australia	Enhanced Vegetation Index (EVI) from MODIS; Either positive or negative values	Asthma prevalence	Humidity, Rainfall, SES	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
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	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 β = 0.10 to 0.14 Garden β = 0.07 to 0.09 Forest: β = −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 Leipzig, Amt für Geoinformation und Amt für Stadtgrün und Gewasser); 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 (055 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
							0.37 ($p < 0.05$)	
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	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);	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	PM10 adjusting for greenness as a covariate: FVC $\beta = -0.22\%$, $p = 0.09$; FEV1 $\beta = -0.34\%$, $p = 0.15$	Probably Low
Sinharay, 2018	Experi-mental	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	No difference in lung function in COPD patients at the end of the walk between Oxford St and Hyde Park.	Probably Low
Moshammer, 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	Change in lung function in road vs park: FVC (24 h) = −50.03 ($p = 0.005$) FEV1 = −13.12 ($p = 0.49$)	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 ≤ 0.8)	Sex, BMI, parental education, air pollution, road proximity, indoor factors (e.g. smoking, cooking fuel)	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
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 ≥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.	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
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	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, $p = 226$ Resonant frequency: −0.092, $p = 0.091$ Frequency dependence of resistance: 0.025, $p = 0.639$	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.	Effect modification by residential greenness: In areas of high greenness, exposure to low pollen	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 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)	Probably Low
Cilluffo et al., 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	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
Sinharay, 2018	Experi-mental	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, Austra & 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
							−0.13 (−1.08 to 0.83) Persistent rhinitis −0.29 (−1.14 to 0.56)	
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 (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 Wheezing: 0.96 (0.71 to 1.30) Bronchitis: 1.18 (0.86 to 1.62) Greenspace distance Wheezing: 0.92 (0.715to 1.13) Bronchitis: 1.04 (0.84 to 1.26)	Probably High
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	Respiratory symptoms (wheezing, cough)	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) 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)	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)	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
							Urban parks (Q4:Q1) Ever rhinitis OR = 0.97 (0.76 to 1.24)	
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 (m2) 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	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 Gewasser); 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	Experi-mental	*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
Moshammer, 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: β = -0.01 (−0.02 to 0.001) Boys: β = -0.01 (−0.04 to 0.01) Broadleaves Girls: β = -0.04 (−0.20 to 0.12) Boys: β = -0.14 (−0.49 to 0.22) Coniferous Girls: β = -0.51 (−1.33 to 0.32) Boys: β = −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(*oli*) 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(*oli*) 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 (°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)	
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	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
				Residential buffers at 100 m, 300 m, 500 m, 1000 m, 3000 m at birth and 15 years old		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.	
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)	Age, education, % predicted of FEV1, modified Medical Research Council (mMRC) score, anxiety, body mass index (BMI) and mean steps/day, and centres. Smoking and physical activity tested as potential confounders.	Regression coefficients for distance to blue/green space (per 100 m): CAT score: β = 0.03 (0.002 to 0.06) CCQ-score: β = 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.

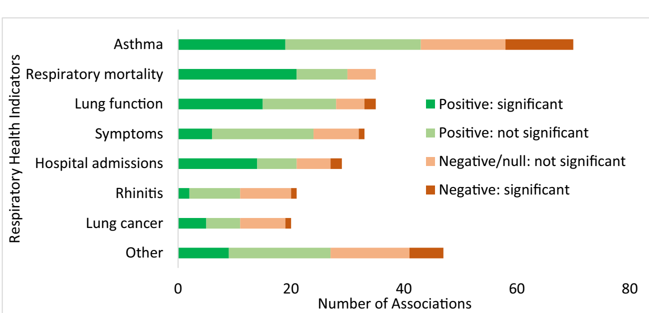


Fig. 3. The number of associations suggesting significant positive (i.e., better health), significant negative (i.e., poorer health), non-significant positive or non-significant negative/null associations for a given health indicator and greenspace exposure ($n = 290$).

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

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.

Funding

None received.

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:**

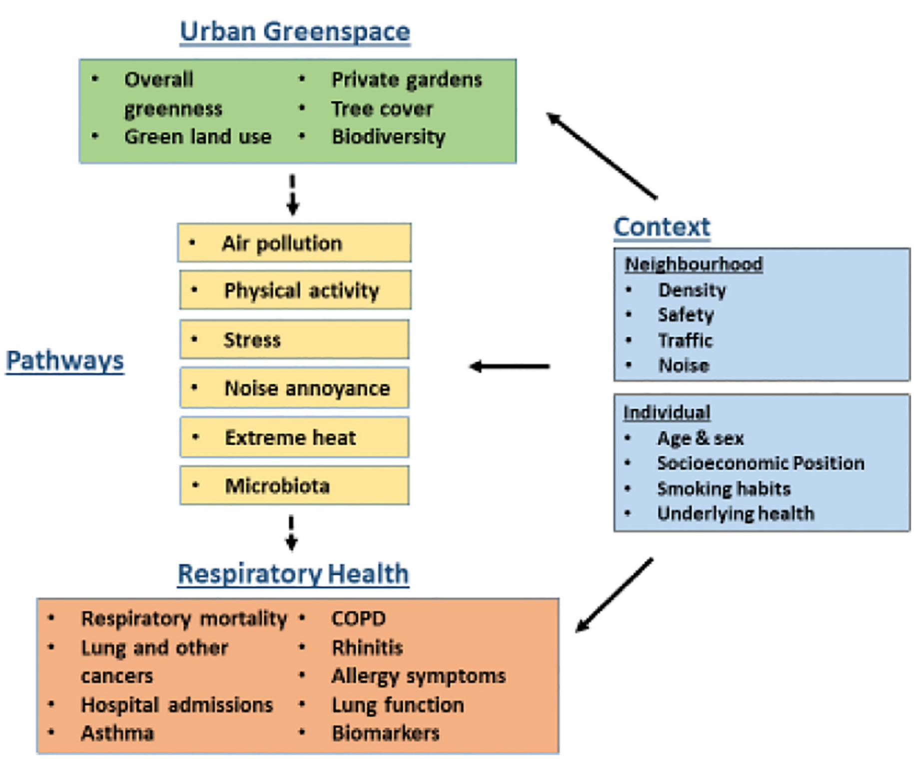


Fig. 4. A diagram of the possible pathways linking urban greenspace and respiratory health with potential neighbourhood and individual modifiers.

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.

Acknowledgements

Russell Burke and Ken Dixon are thanked for their helpful input into the systematic search strategy. We are grateful for Dr. Paul Whaley's input on the systematic review methods.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.154447.

References

Abhijith, K.V., Kumar, P., Gallagher, J., McNabola, A., Baldauf, R., Pilla, F., Broderick, B., Di Sabatino, S., Pulvirenti, B., 2017. Air pollution abatement performances of green infrastructure in open road and built-up street canyon environments–a review. Atmos. Environ. 162, 71–86.

Aerts, R., Dujardin, S., Nemery, B., Van Nieuwenhuyse, A., Van Orshoven, J., Aerts, J.M., Somers, B., Hendrickx, M., Bruffaerts, N., Bauwelinck, M., Casas, L., 2020. Residential green space and medication sales for childhood asthma: a longitudinal ecological study in Belgium. Environ. Res. 189, 109914.

Alasauskas, S., Ustinaviciene, R., Kavaliauskas, M., 2020. Residential links to air pollution and school children with asthma in Vilnius (population study). Medicina 56 (7), 346.

Alberg, A.J., Brock, M.V., Ford, J.G., Samet, J.M., Spivack, S.D., 2013. Epidemiology of lung cancer: diagnosis and management of lung cancer: american College of Chest Physicians evidence-based clinical practice guidelines. Chest 143 (5), e1S–e29S.

Alcock, I., White, M., Cherrie, M., Wheeler, B., Taylor, J., McInnes, R., Im Kampe, E.O., Vardoulakis, S., Sarran, C., Soyiri, I., Fleming, L., 2017. aA cross-sectional study. Environment international 109, 29–41.

Alvarez-Mendoza, C.I., Teodoro, A., Ordonez, J., Benitez, A., Freitas, A., Fonseca, J., 2019. Modeling the prevalence of respiratory chronic diseases risk using satellite images and environmental data. OctoberRemote Sensing Technologies and Applications in Urban Environments IV. 11157. International Society for Optics and Photonics, p. 1115705.

Andrusaityte, S., Grazuleviciene, R., Kudzyte, J., Bernotiene, A., Dedele, A., Nieuwenhuijsen, M.J., 2016. Associations between neighbourhood greenness and asthma in preschool children in Kaunas, Lithuania: a case–control study. BMJ Open 6 (4).

Arbillaga-Etxarri, A., Gimeno-Santos, E., Barberan-Garcia, A., Benet, M., Borrell, E., Dadvand, P., Foraster, M., Marín, A., Monteagudo, M., Rodriguez-Roisin, R., Vall-Casas, P., 2017. Socio-environmental correlates of physical activity in patients with chronic obstructive pulmonary disease (COPD). Thorax 72 (9), 796–802.

Ayres-Sampaio, D., Teodoro, A.C., Sillero, N., Santos, C., Fonseca, J., Freitas, A., 2014. An investigation of the environmental determinants of asthma hospitalizations: an applied spatial approach. Appl. Geogr. 47, 10–19.

Bauwelinck, M., Casas, L., Nawrot, T.S., Nemery, B., Trabelsi, S., Thomas, I., Aerts, R., Lefebvre, W., Vanpoucke, C., Van Nieuwenhuyse, A., Deboosere, P., 2021. Residing in urban areas with higher green space is associated with lower mortality risk: a census-based cohort study with ten years of follow-up. Environ. Int. 148, 106365.

Beasley, R., Semprini, A., Mitchell, E.A., 2015. Risk factors for asthma: is prevention possible? Lancet 386 (9998), 1075–1085.

van den Berg, M., Wendel-Vos, W., van Poppel, M., Kemper, H., van Mechelen, W., Maas, J., 2015. Health benefits of green spaces in the living environment: a systematic review of epidemiological studies. Urban For. Urban Green. 14 (4), 806–816.

Bernat, A., Marozas, V., Žalkauskas, R., 2016. The relation of forest and air pollution with human health in urban territories of Lithuania. Acta Biol. Univ. Daugavpiliensis. 16 (2), 2016.

Biedermann, T., Winther, L., Till, S.J., Panzner, P., Knulst, A., Valovirta, E., 2019. Birch pollen allergy in Europe. Allergy 74 (7), 1237–1248.

Bixby, H., Hodgson, S., Fortunato, L., Hansell, A., Fecht, D., 2015. Associations between green space and health in English cities: an ecological, cross-sectional study. PLoS One 10 (3), e0119495.

Boeyen, J., Callan, A.C., Blake, D., Wheeler, A.J., Franklin, P., Hall, G.L., Shackleton, C., Sly, P.D., Hinwood, A., 2017. Investigating the relationship between environmental factors and respiratory health outcomes in school children using the forced oscillation technique. Int. J. Hyg. Environ. Health 220 (2), 494–502.

Brokamp, C., LeMasters, G.K., Ryan, P.H., 2016. Residential mobility impacts exposure assessment and community socioeconomic characteristics in longitudinal epidemiology studies. J. Expo. Sci. Environ. Epidemiol. 26 (4), 428–434.

Bu, X., Xie, Z., Liu, J., Wei, L., Wang, X., Chen, M., Ren, H., 2021. Global PM2. 5-attributable health burden from 1990 to 2017: estimates from the global burden of disease study 2017. Environmental Research 197, 111123.

Campbell, M., McKenzie, J.E., Sowden, A., Katikireddi, S.V., Brennan, S.E., Ellis, S., Hartmann-Boyce, J., Ryan, R., Shepperd, S., Thomas, J., Welch, V., 2020. Synthesis without meta-analysis (SWiM) in systematic reviews: a reporting guideline. BMJ 368.

Cavalcante de Sá, M., Nakagawa, N.K., de André, C.D.S., Carvalho-Oliveira, R., de Santana Carvalho, T., Nicola, M.L., de André, P.A., Saldiva, P.H.N., Vaisberg, M., 2016. Aerobic exercise in polluted urban environments: effects on airway defense mechanisms in young healthy amateur runners. J. Breath Res. 10 (4), 046018.

Cavaleiro Rufo, J., Paciência, I., Hoffimann, E., Moreira, A., Barros, H., Ribeiro, A.I., 2021. The neighbourhood natural environment is associated with asthma in children: a birth cohort study. Allergy 76 (1), 348–358.

Charalampopoulos, A., Lazarina, M., Tsiripidis, I., Vokou, D., 2018. Quantifying the relationship between airborne pollen and vegetation in the urban environment. Aerobiologia 34 (3), 285–300.

Chen, E., Miller, G.E., Shalowitz, M.U., Story, R.E., Levine, C.S., Hayen, R., Sbihi, H., Brauer, M., 2017. Difficult family relationships, residential greenspace, and childhood asthma. Pediatrics 139 (4).

Cherrie, M.P., Shortt, N.K., Mitchell, R.J., Taylor, A.M., Redmond, P., Thompson, C.W., Starr, J.M., Deary, I.J., Pearce, J.R., 2018. Green space and cognitive ageing: a retrospective life course analysis in the Lothian birth cohort 1936. Soc. Sci. Med. 196, 56–65.

Cilluffo, G., Ferrante, G., Fasola, S., Montalbano, L., Malizia, V., Piscini, A., Romaniello, V., Silvestri, M., Stramondo, S., Stafoggia, M., Ranzi, A., 2018. Associations of greenness, greyness and air pollution exposure with children's health: a cross-sectional study in southern Italy. Environ. Health 17 (1), 1–12.

Cohen-Cline, H., Turkheimer, E., Duncan, G.E., 2015. Access to green space, physical activity and mental health: a twin study. J. Epidemiol. Community Health 69 (6), 523–529.

Cole-Hunter, T., de Nazelle, A., Donaire-Gonzalez, D., Kubesch, N., Carrasco-Turigas, G., Matt, F., Foraster, M., Martinez, T., Ambros, A., Cirach, M., Martinez, D., 2018. Estimated effects of air pollution and space-time-activity on cardiopulmonary outcomes in healthy adults: a repeated measures study. Environ. Int. 111, 247–259.

Commodore, S., Ferguson, P.L., Neelon, B., Newman, R., Grobman, W., Tita, A., Pearce, J., Bloom, M.S., Svendsen, E., Roberts, J., Skupski, D., 2021. Reported neighborhood traffic and the odds of asthma/asthma-like symptoms: a cross-sectional analysis of a multi-racial cohort of children. Int. J. Environ. Res. Public Health 18 (1), 243.

Crouse, D.L., Pinault, L., Balram, A., Hystad, P., Peters, P.A., Chen, H., van Donkelaar, A., Martin, R.V., Ménard, R., Robichaud, A., Villeneuve, P.J., 2017. Urban greenness and mortality in Canada's largest cities: a national cohort study. Lancet Planet. Health 1 (7), e289–e297.

Dadvand, P., Villanueva, C.M., Font-Ribera, L., Martinez, D., Basagaña, X., Belmonte, J., Vrijheid, M., Gražulevičienė, R., Kogevinas, M., Nieuwenhuijsen, M.J., 2014. Risks and benefits of green spaces for children: a cross-sectional study of associations with sedentary behavior, obesity, asthma, and allergy. Environ. Health Perspect. 122 (12), 1329.

Dadvand, P., Rivas, I., Basagaña, X., Alvarez-Pedrerol, M., Su, J., Pascual, M.D.C., Amato, F., Jerret, M., Querol, X., Sunyer, J., Nieuwenhuijsen, M.J., 2015. The association between greenness and traffic-related air pollution at schools. Sci. Total Environ. 523, 59–63.

DePriest, K., Butz, A., Curriero, F.C., Perrin, N., Gross, D., 2019. Associations among neighborhood greenspace, neighborhood violence, and children's asthma control in an urban city. Ann. Allergy Asthma Immunol. 123 (6), 608–610.

Dong, Y., Liu, H., Zheng, T., 2021. Association between green space structure and the prevalence of asthma: a case study of Toronto. Int. J. Environ. Res. Public Health 18 (11), 5852.

Donovan, G.H., Butry, D.T., Michael, Y.L., Prestemon, J.P., Liebhold, A.M., Gatziolis, D., Mao, M.Y., 2013. The relationship between trees and human health: evidence from the spread of the emerald ash borer. Am. J. Prev. Med. 44 (2), 139–145.

Donovan, G.H., Gatziolis, D., Longley, I., Douwes, J., 2018. Vegetation diversity protects against childhood asthma: results from a large New Zealand birth cohort. Nat. Plants 4 (6), 358–364.

Donovan, G.H., Landry, S.M., Gatziolis, D., 2021. The natural environment, plant diversity, and adult asthma: a retrospective observational study using the CDC's 500 cities project data. Health Place 67, 102494.

Douglas, J.A., Archer, R.S., Alexander, S.E., 2019. Ecological determinants of respiratory health: examining associations between asthma emergency department visits, diesel particulate matter, and public parks and open space in Los AngelesCalifornia. Preventive Medicine Reports 14, 100855.

Dzhambov, A.M., Lercher, P., Rüdisser, J., Browning, M.H., Markevych, I., 2021. Allergic symptoms in association with naturalness, greenness, and greyness: a cross-sectional study in schoolchildren in the Alps. Environ. Res. 198, 110456.

Ege, M.J., Mayer, M., Normand, A.C., Genuneit, J., Cookson, W.O., Braun-Fahrländer, C., Heederik, D., Piarroux, R., von Mutius, E., 2011. Exposure to environmental microorganisms and childhood asthma. N. Engl. J. Med. 364 (8), 701–709.

Eick, S.M., Goin, D.E., Chartres, N., Lam, J., Woodruff, T.J., 2020. Assessing risk of bias in human environmental epidemiology studies using three tools: different conclusions from different tools. Syst. Rev. 9 (1), 1–13.

Eisenman, T.S., Churkina, G., Jariwala, S.P., Kumar, P., Lovasi, G.S., Pataki, D.E., Weinberger, K.R., Whitlow, T.H., 2019. Urban trees, air quality, and asthma: an interdisciplinary review. Landsc. Urban Plan. 187, 47–59.

Eldeirawi, K., Kunzweiler, C., Zenk, S., Finn, P., Nyenhuis, S., Rosenberg, N., Persky, V., 2019. Associations of urban greenness with asthma and respiratory symptoms in mexican american children. Ann. Allergy Asthma Immunol. 122 (3), 289–295.

Esposito, V., Lucariello, A., Savarese, L., Cinelli, M.P., Ferraraccio, F., Bianco, A., De Luca, A., Mazzarella, G., 2012. Morphology changes in human lung epithelial cells after exposure to diesel exhaust micron sub particles (PM1. 0) and pollen allergens. Environ. Pollut. 171, 162–167.

Fan, J., Guo, Y., Cao, Z., Cong, S., Wang, N., Lin, H., Wang, C., Bao, H., Lv, X., Wang, B., Gao, Y., 2020. Neighborhood greenness associated with chronic obstructive pulmonary disease: a nationwide cross-sectional study in China. Environ. Int. 144, 106042.

Feng, X., Astell-Burt, T., 2017. Is neighborhood green space protective against associations between child asthma, neighborhood traffic volume and perceived lack of area safety? Multilevel analysis of 4447 australian children. Int. J. Environ. Res. Public Health 14 (5), 543.

Ferrante, G., Asta, F., Cilluffo, G., De Sario, M., Michelozzi, P., La Grutta, S., 2020. The effect of residential urban greenness on allergic respiratory diseases in youth: a narrative review. World Allergy Organ. J. 13 (1), 100096.

Fong, K.C., Hart, J.E., James, P., 2018. A review of epidemiologic studies on greenness and health: updated literature through 2017. Curr. Environ. Health Reports 5 (1), 77–87.

Fuertes, E., Butland, B.K., Anderson, H.R., Carlsten, C., Strachan, D.P., Brauer, M., ISAAC Phase Three Study Group, 2014. Childhood intermittent and persistent rhinitis prevalence and climate and vegetation: a global ecologic analysis. Annals of Allergy, Asthma & Immunology 113 (4), 386–392.

Fuertes, E., Markevych, I., von Berg, A., Bauer, C.P., Berdel, D., Koletzko, S., Sugiri, D., Heinrich, J., 2014b. Greenness and allergies: evidence of differential associations in two areas in Germany. J. Epidemiol. Community Health 68 (8), 787–790.

Fuertes, E., Markevych, I., Bowatte, G., Gruzieva, O., Gehring, U., Becker, A., Berdel, D., Von Berg, A., Bergström, A., Brauer, M., Brunekreef, B., 2016. Residential greenness is differentially associated with childhood allergic rhinitis and aeroallergen sensitization in seven birth cohorts. Allergy 71 (10), 1461–1471.

Fuertes, E., Markevych, I., Thomas, R., Boyd, A., Granell, R., Mahmoud, O., Heinrich, J., Garcia-Aymerich, J., Roda, C., Henderson, J., Jarvis, D., 2020. Residential greenspace and lung function up to 24 years of age: the ALSPAC birth cohort. Environ. Int. 140, 105749.

Gascon, M., Triguero-Mas, M., Martínez, D., Dadvand, P., Rojas-Rueda, D., Plasència, A., Nieuwenhuijsen, M.J., 2016. Residential green spaces and mortality: a systematic review. Environ. Int. 86, 60–67.

Gernes, R., Brokamp, C., Rice, G.E., Wright, J.M., Kondo, M.C., Michael, Y.L., Donovan, G.H., Gatziolis, D., Bernstein, D., LeMasters, G.K., Lockey, J.E., 2019. Using high-resolution residential greenspace measures in an urban environment to assess risks of allergy outcomes in children. Sci. Total Environ. 668, 760–767.

Gronlund, C.J., Berrocal, V.J., White-Newsome, J.L., Conlon, K.C., O'Neill, M.S., 2015. Vulnerability to extreme heat by socio-demographic characteristics and area green space among the elderly in Michigan, 1990–2007. Environ. Res. 136, 449–461.

Gunawardena, K.R., Wells, M.J., Kershaw, T., 2017. Utilising green and bluespace to mitigate urban heat island intensity. Sci. Total Environ. 584, 1040–1055.

Haahtela, T., Holgate, S., Pawankar, R., Akdis, C.A., Benjaponpitak, S., Caraballo, L., Demain, J., Portnoy, J., von Hertzen, L., 2013. The biodiversity hypothesis and allergic disease: world allergy organization position statement. World Allergy Organ. J. 6 (1), 1.

Hartley, K., Ryan, P., Brokamp, C., Gillespie, G.L., 2020. Effect of greenness on asthma in children: a systematic review. Public Health Nurs. 37 (3), 453–460.

Heo, S., Bell, M.L., 2019. The influence of green space on the short-term effects of particulate matter on hospitalization in the US for 2000–2013. Environ. Res. 174, 61–68.

Hoehner, C.M., Allen, P., Barlow, C.E., Marx, C.M., Brownson, R.C., Schootman, M., 2013. Understanding the independent and joint associations of the home and workplace built environments on cardiorespiratory fitness and body mass index. Am. J. Epidemiol. 178 (7), 1094–1105.

Holt, E.W., Lombard, Q.K., Best, N., Smiley-Smith, S., Quinn, J.E., 2019. Active and passive use of green space, health, and well-being amongst university students. Int. J. Environ. Res. Public Health 16 (3), 424.

Houlden, V., Weich, S., Porto de Albuquerque, J., Jarvis, S., Rees, K., 2018. The relationship between greenspace and the mental wellbeing of adults: a systematic review. PloS one 13 (9), e0203000.

Hsieh, C.J., Yu, P.Y., Tai, C.J., Jan, R.H., Wen, T.H., Lin, S.W., Tseng, C.C., 2019. Association between the first occurrence of asthma and residential greenness in children and teenagers in Taiwan. Int. J. Environ. Res. Public Health 16 (12), 2076.

Hu, Z., Liebens, J., Rao, R., 2007. Exploring relationship between asthma and air pollution: a geospatial methodology using dasymetric mapping, GIS analysis, and spatial statistics. JulyGeoinformatics 2007: Geospatial Information Science. 6753. International Society for Optics and Photonics.

Huang, J., Deng, F., Wu, S., Zhao, Y., Shima, M., Guo, B., Liu, Q., Guo, X., 2016. Acute effects on pulmonary function in young healthy adults exposed to traffic-related air pollution in semi-closed transport hub in Beijing. Environ. Health Prev. Med. 21 (5), 312–320.

Hystad, P., Carpiano, R.M., Demers, P.A., Johnson, K.C., Brauer, M., 2013. Neighbourhood socioeconomic status and individual lung cancer risk: evaluating long-term exposure measures and mediating mechanisms. Soc. Sci. Med. 97, 95–103.

Ihlebæk, C., Aamodt, G., Aradi, R., Claussen, B., Thorén, K.H., 2018. Association between urban green space and self-reported lifestyle-related disorders in OsloNorway. Scandinavian journal of public health 46 (6), 589–596.

Jaafari, S., Shabani, A.A., Moeinaddini, M., Danehkar, A., Sakieh, Y., 2020. Applying landscape metrics and structural equation modeling to predict the effect of urban green space on air pollution and respiratory mortality in Tehran. Environ. Monit. Assess. 192 (7), 1–15.

James, P., Hart, J.E., Banay, R.F., Laden, F., 2016. Exposure to greenness and mortality in a nationwide prospective cohort study of women. Environ. Health Perspect. 124 (9), 1344–1352.

Johnson, P.I., Koustas, E., Vesterinen, H.M., Sutton, P., Atchley, D.S., Kim, A.N., Campbell, M., Donald, J.M., Sen, S., Bero, L., Zeise, L., 2016. Application of the navigation guide systematic review methodology to the evidence for developmental and reproductive toxicity of triclosan. Environ. Int. 92, 716–728.

Jürges, H., 2007. True health vs response styles: exploring cross-country differences in self-reported health. Health Econ. 16 (2), 163–178.

Kaczynski, A.T., Mowen, A.J., 2011. Does self-selection influence the relationship between park availability and physical activity? Prev. Med. 52 (1), 23–25.

Kasdagli, M.I., Katsouyanni, K., de Hoogh, K., Lagiou, P., Samoli, E., 2021. Associations of air pollution and greenness with mortality in Greece: an ecological study. Environ. Res. 196, 110348.

Khan, I.A., Arsalan, M.H., Siddiqui, M.F., Zeeshan, S., Shaukat, S.S., 2010. Spatial association of asthma and vegetation in Karachi: a gis perspective. Pak. J. Bot. 42 (5), 3547–3554.

Kim, D., Ahn, Y., 2021. The contribution of neighborhood tree and greenspace to asthma emergency room visits: an application of advanced spatial data in Los Angeles County. Int. J. Environ. Res. Public Health 18 (7), 3487.

Kim, H.J., Min, J.Y., Kim, H.J., Min, K.B., 2020. Association between green areas and allergic disease in korean adults: a cross-sectional study. Ann. Occup. Environ. Med. 32 (1).

Kim, S., Kim, H., Lee, J.T., 2019. Interactions between ambient air particles and greenness on cause-specific mortality in seven korean metropolitan cities, 2008–2016. Int. J. Environ. Res. Public Health 16 (10), 1866.

Klompmaker, J.O., Janssen, N.A., Bloemsma, L.D., Marra, M., Lebret, E., Gehring, U., Hoek, G., 2021. Effects of exposure to surrounding green, air pollution and traffic noise with non-accidental and cause-specific mortality in the dutch national cohort. Environ. Health 20 (1), 1–16.

Kondo, M.C., Fluehr, J.M., McKeon, T., Branas, C.C., 2018. Urban green space and its impact on human health. Int. J. Environ. Res. Public Health 15 (3), 445.

Kuiper, I.N., Markevych, I., Accordini, S., Bertelsen, R.J., Bråbäck, L., Christensen, J.H., Forsberg, B., Halvorsen, T., Heinrich, J., Hertel, O., Hoek, G., 2020. Associations of preconception exposure to air pollution and greenness with offspring asthma and hay fever. Int. J. Environ. Res. Public Health 17 (16), 5828.

Kuiper, I.N., Svanes, C., Markevych, I., Accordini, S., Bertelsen, R.J., Bråbäck, L., Christensen, J.H., Forsberg, B., Halvorsen, T., Heinrich, J., Hertel, O., 2021. Lifelong exposure to air pollution and greenness in relation to asthma, rhinitis and lung function in adulthood. Environ. Int. 146, 106219.

Kurnia Febriawan, H., da Silva Sodre, C.M., 2018. An exploratory analysis in mapping of asthma risk in Western Australia. Indones. J. Geogr. 50 (1), 97–108.

Kwon, M.Y., Lee, J.S., Park, S., 2019. The effect of outdoor air pollutants and greenness on allergic rhinitis incidence rates: a cross-sectional study in Seoul, Korea. Int. J. Sustain. Dev. World 26 (3), 258–267.

Lachowycz, K., Jones, A.P., 2013. Towards a better understanding of the relationship between greenspace and health: development of a theoretical framework. Landsc. Urban Plan. 118, 62–69.

Lambert, K.A., Bowatte, G., Tham, R., Lodge, C., Prendergast, L., Heinrich, J., Abramson, M.J., Dharmage, S.C., Erbas, B., 2017. Residential greenness and allergic respiratory diseases in children and adolescents–a systematic review and meta-analysis. Environ. Res. 159, 212–221.

Lambert, K.A., Lodge, C., Lowe, A.J., Prendergast, L.A., Thomas, P.S., Bennett, C.M., Abramson, M.J., Dharmage, S.C., Erbas, B., 2019. Pollen exposure at birth and adolescent lung function, and modification by residential greenness. Allergy 74 (10), 1977–1984.

Lambert, K.A., Katelaris, C., Burton, P., Cowie, C., Lodge, C., Garden, F.L., Prendergast, L.A., Toelle, B.G., Erbas, B., 2020. Tree pollen exposure is associated with reduced lung function in children. Clin. Exp. Allergy 50 (10), 1176–1183.

Lambert, K.A., Markevych, I., Yang, B.Y., Bauer, C.P., Berdel, D., von Berg, A., Bergmann, K.C., Lodge, C., Koletzko, S., Prendergast, L.A., Schikowski, T., 2021. Association of early life and acute pollen exposure with lung function and exhaled nitric oxide (FeNO). A prospective study up to adolescence in the GINIplus and LISA cohort. Sci. Total Environ. 763, 143006.

Larkin, A., Hystad, P., 2019. Evaluating street view exposure measures of visible green space for health research. J. Expo. Sci. Environ. Epidemiol. 29 (4), 447–456.

Lee, H.Y., Wu, C.D., Chang, Y.T., Chern, Y.R., Lung, S.C.C., Su, H.J., Pan, W.C., 2020. Association between surrounding greenness and mortality: an ecological study in Taiwan. Int. J. Environ. Res. Public Health 17 (12), 4525.

Lee, H.Y., Wu, Y.H., Asri, A.K., Chen, T.H., Pan, W.C., Yu, C.P., Su, H.J., Wu, C.D., 2020. Linkage between residential green spaces and allergic rhinitis among asian children (case study: Taiwan). Landsc. Urban Plan. 202, 103868.

Lee, K.S., Lee, J.S., Kwon, J.H., 2014. The effects of urban forests on the medical care use for respiratory disease in Korea: a structural equation model approach. Int. J. Public Policy 10 (4–5), 195–208.

Li, L., Hart, J.E., Coull, B.A., Cao, S.J., Spengler, J.D., Adamkiewicz, G., 2019. Effect of residential greenness and nearby parks on respiratory and allergic diseases among middle school adolescents in a chinese city. Int. J. Environ. Res. Public Health 16 (6), 991.

Li, Q., Kobayashi, M., Kawada, T., 2008. Relationships between percentage of forest coverage and standardized mortality ratios (SMR) of cancers in all prefectures in Japan. Open Public Health J. 1 (1).

Liddicoat, C., Bi, P., Waycott, M., Glover, J., Lowe, A.J., Weinstein, P., 2018. Landscape biodiversity correlates with respiratory health in Australia. J. Environ. Manag. 206, 113–122.

Lovasi, G.S., Quinn, J.W., Neckerman, K.M., Perzanowski, M.S., Rundle, A., 2008. Children living in areas with more street trees have lower prevalence of asthma. J. Epidemiol. Community Health 62 (7), 647–649.

Lovasi, G.S., O'Neil-Dunne, J.P., Lu, J.W., Sheehan, D., Perzanowski, M.S., MacFaden, S.W., King, K.L., Matte, T., Miller, R.L., Hoepner, L.A., Perera, F.P., 2013. Urban tree canopy and asthma, wheeze, rhinitis, and allergic sensitization to tree pollen in a New York City birth cohort. Environ. Health Perspect. 121 (4), 494–500.

Lu, C., Norbäck, D., Li, Y., Deng, Q., 2020. Early-life exposure to air pollution and childhood allergic diseases: an update on the link and its implications. Expert. Rev. Clin. Immunol. https://doi.org/10.1080/1744666X.2020.1804868.

Lu, Y., 2018. The association of urban greenness and walking behavior: using google street view and deep learning techniques to estimate residents' exposure to urban greenness. Int. J. Environ. Res. Public Health 15 (8), 1576.

Maas, J., Verheij, R.A., de Vries, S., Spreeuwenberg, P., Schellevis, F.G., Groenewegen, P.P., 2009. Morbidity is related to a green living environment. J. Epidemiol. Community Health 63 (12), 967–973.

Man, W.H., de Steenhuijsen Piters, W.A., Bogaert, D., 2017. The microbiota of the respiratory tract: gatekeeper to respiratory health. Nat. Rev. Microbiol. 15 (5), 259–270.
Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A.M., De Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M.J., Lupp, G., 2017. Exploring pathways linking greenspace to health: theoretical and methodological guidance. Environ. Res. 158, 301–317.
Markevych, I., Ludwig, R., Baumbach, C., Standl, M., Heinrich, J., Herberth, G., de Hoogh, K., Pritsch, K., Weikl, F., 2020. Residing near allergenic trees can increase risk of allergies later in life: LISA Leipzig study. Environ. Res. 191, 110132.
Marselle, M.R., Triguero Mas, M., Nieuwenhuijsen, M.J., Bonn, A., 2021. Pathways linking biodiversity to human health: A conceptual framework. Environ Int. 2021 May (150), 106420.
Martin, L., White, M.P., Pahl, S., May, J., Wheeler, B.W., 2020. Neighbourhood greenspace and smoking prevalence: results from a nationally representative survey in England. Soc. Sci. Med. 265, 113448.
McCormack, G.R., 2017. Neighbourhood built environment characteristics associated with different types of physical activity in Canadian adults. Chronic Dis. Injuries Can. 37 (6).
Mitchell, R., Popham, F., 2008. Effect of exposure to natural environment on health inequalities: an observational population study. Lancet 372 (9650), 1655–1660.
Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G., Prisma Group, 2009. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med 6 (7), e1000097.
Moitra, S., Foraster, M., Arbillaga-Etxarri, A., Marín, A., Barberan-Garcia, A., Rodríguez-Chiaradia, D.A., Balcells, E., Koreny, M., Torán-Monserrat, P., Vall-Casas, P., Rodríguez-Roisin, R., 2022. Roles of the physical environment in health-related quality of life in patients with chronic obstructive pulmonary disease. Environ. Res. 203, 111828.
Mokhtarian, P.L., Cao, X., 2008. Examining the impacts of residential self-selection on travel behavior: a focus on methodologies. Transp. Res. B Methodol. 42 (3), 204–228.
Moshammer, H., Panholzer, J., Ulbing, L., Udvarhelyi, E., Ebenbauer, B., Peter, S., 2019. Acute effects of air pollution and noise from road traffic in a panel of young healthy adults. Int. J. Environ. Res. Public Health 16 (5), 788.
Orioli, R., Antonucci, C., Scortichini, M., Cerza, F., Marando, F., Ancona, C., Manes, F., Davoli, M., Michelozzi, P., Forastiere, F., Cesaroni, G., 2019. Exposure to residential greenness as a predictor of cause-specific mortality and stroke incidence in the Rome longitudinal study. Environ. Health Perspect. 127 (2), 027002.
Paciência, I., Rufo, J.C., Ribeiro, A.I., Mendes, F.C., Farraia, M., Silva, D., Delgado, L., Moreira, A., 2020. Association between the density and type of trees around urban schools and exhaled nitric oxide levels in schoolchildren. Eur. Ann. Allergy Clin. Immunol. 53 (1), 29–36.
Pega, F., Chartres, N., Guha, N., Modenese, A., Morgan, R.L., Martínez-Silveira, M.S., Loomis, D., 2020. The effect of occupational exposure to welding fumes on trachea, bronchus and lung cancer: A protocol for a systematic review and meta-analysis from the WHO/ILO Joint Estimates of the Work-related Burden of Disease and Injury. 145. Environment international, p. 106089.
Pilat, M.A., McFarland, A., Snelgrove, A., Collins, K., Waliczek, T.M., Zajicek, J., 2012. The effect of tree cover and vegetation on incidence of childhood asthma in metropolitan statistical areas of Texas. HortTechnology 22 (5), 631–637.
Prist, P.R., Uriarte, M., Tambosi, L.R., Prado, A., Pardini, R., Metzger, J.P., D'Andrea, P.S., 2016. Landscape, environmental and social predictors of Hantavirus risk in São Paulo, Brazil. PloS One 11 (10), e0163459.
Pun, V.C., Manjourides, J., Suh, H.H., 2018. Association of neighborhood greenness with self-perceived stress, depression and anxiety symptoms in older US adults. Environ. Health 17 (1), 1–11.
Razavi-Termeh, S.V., Sadeghi-Niaraki, A., Choi, S.M., 2021. Asthma-prone areas modeling using a machine learning model. Sci. Rep. 11 (1), 1–16.
Razavi-Termeh, S.V., Sadeghi-Niaraki, A., Choi, S.M., 2021. Spatial modeling of asthma-prone areas using remote sensing and ensemble machine learning algorithms. Remote Sens. 13 (16), 3222.
Richardson, E., Pearce, J., Mitchell, R., Day, P., Kingham, S., 2010b. The association between green space and cause-specific mortality in urban New Zealand: an ecological analysis of green space utility. BMC Public Health 10 (1), 240.
Richardson, E.A., Mitchell, R., 2010a. Gender differences in relationships between urban green space and health in the United Kingdom. Soc. Sci. Med. 71 (3), 568–575.
Richardson, E.A., Mitchell, R., Hartig, T., De Vries, S., Astell-Burt, T., Frumkin, H., 2012. Green cities and health: a question of scale? J. Epidemiol. Community Health 66 (2), 160–165.
Roberts, G., Xatzipsalti, M., Borrego, L.M., Custovic, A., Halken, S., Hellings, P.W., Papadopoulos, N.G., Rotiroti, G., Scadding, G., Timmermans, F., Valovirta, E., 2013. Paediatric rhinitis: position paper of the european academy of allergy and clinical immunology. Allergy 68 (9), 1102–1116.
Rojas-Rueda, D., Nieuwenhuijsen, M.J., Gascon, M., Perez-Leon, D., Mudu, P., 2019. Green spaces and mortality: a systematic review and meta-analysis of cohort studies. Lancet Planet. Health 3 (11), e469–e477.
Rook, G.A., Lowry, C.A., Raison, C.L., 2013. Microbial 'old friends', immunoregulation and stress resilience. Evolution, Medicine, and Public Health 2013 (1), 46–64.
Ruokolainen, L., Hertzen, L., Fyhrquist, N., Laatikainen, T., Lehtomäki, J., Auvinen, P., Karvonen, A.M., Hyvärinen, A., Tillmann, V., Niemelä, O., Knip, M., 2015. Green areas around homes reduce atopic sensitization in children. Allergy 70 (2), 195–202.
Russette, H., Graham, J., Holden, Z., Semmens, E.O., Williams, E., Landguth, E.L., 2021. Greenspace exposure and COVID-19 mortality in the United States: January–July 2020. Environ. Res. 198, 111195.
Sakhvidi, M.J.Z., Yang, J., Siemiatycki, J., Dadvand, P., de Hoogh, K., Vienneau, D., Goldberg, M., Zins, M., Lequy, E., Jacquemin, B., 2021. Greenspace exposure and cancer incidence: a 27-year follow-up of the french GAZEL cohort. Sci. Total Environ. 787, 147553.
Salmond, J.A., Tadaki, M., Vardoulakis, S., Arbuthnott, K., Coutts, A., Demuzere, M., Dirks, K.N., Heaviside, C., Lim, S., Macintyre, H., McInnes, R.N., 2016. Health and climate related ecosystem services provided by street trees in the urban environment. Environ. Health 15 (1), S36.
Sarkar, C., Zhang, B., Ni, M., Kumari, S., Bauermeister, S., Gallacher, J., Webster, C., 2019. Environmental correlates of chronic obstructive pulmonary disease in 96 779 participants from the UK biobank: a cross-sectional, observational study. Lancet Planet. Health 3 (11), e478–e490.
Sbihi, H., Tamburic, L., Koehoorn, M., Brauer, M., 2015. Greenness and incident childhood asthma: a 10-year follow-up in a population-based birth cohort. Am. J. Respir. Crit. Care Med. 192 (9), 1131–1133.
Sbihi, H., Koehoorn, M., Tamburic, L., Brauer, M., 2017. Asthma trajectories in a population-based birth cohort. Impacts of air pollution and greenness. American journal of respiratory and critical care medicine 195 (5), 607–613.
Shen, Y.S., Lung, S.C.C., 2017. Mediation pathways and effects of green structures on respiratory mortality via reducing air pollution. Sci. Rep. 7 (1), 1–9.
Shibuya, K., Inoue, M., Lopez, A.D., 2005. Statistical modeling and projections of lung cancer mortality in 4 industrialized countries. Int. J. Cancer 117 (3), 476–485.
Sinharay, R., Gong, J., Barratt, B., Ohman-Strickland, P., Ernst, S., Kelly, F.J., Zhang, J.J., Collins, P., Cullinan, P., Chung, K.F., 2018. Respiratory and cardiovascular responses to walking down a traffic-polluted road compared with walking in a traffic-free area in participants aged 60 years and older with chronic lung or heart disease and age-matched healthy controls: a randomised, crossover study. Lancet 391 (10118), 339–349.
Soriano, J.B., Kendrick, P.J., Paulson, K.R., Gupta, V., Abrams, E.M., Adedoyin, R.A., Adhikari, T.B., Advani, S.M., Agrawal, A., Ahmadian, E., Alahdab, F., 2020. Prevalence and attributable health burden of chronic respiratory diseases, 1990–2017: a systematic analysis for the global burden of disease study 2017. Lancet Respir. Med. 8 (6), 585–596.
Squillacioti, G., Bellisario, V., Levra, S., Piccioni, P., Bono, R., 2020. Greenness availability and respiratory health in a population of urbanised children in North-Western Italy. Int. J. Environ. Res. Public Health 17 (1), 108.
Stas, M., Aerts, R., Hendrickx, M., Delcloo, A., Dendoncker, N., Dujardin, S., Linard, C., Nawrot, T., Van Nieuwenhuyse, A., Aerts, J.M., Van Orshoven, J., 2021. Exposure to green space and pollen allergy symptom severity: a case-crossover study in Belgium. Sci. Total Environ. 781, 146682.
Stocks, J., Hislop, A., Sonnappa, S., 2013. Early lung development: lifelong effect on respiratory health and disease. Lancet Respir. Med. 1 (9), 728–742.
Su, J.G., Barrett, M.A., Henderson, K., Humblet, O., Smith, T., Sublett, J.W., Nesbitt, L., Hogg, C., Van Sickle, D., Sublett, J.L., 2017. Feasibility of deploying inhaler sensors to identify the impacts of environmental triggers and built environment factors on asthma short-acting bronchodilator use. Environ. Health Perspect. 125 (2), 254–261.
Sun, S., Sarkar, C., Kumari, S., James, P., Cao, W., Lee, R.S.Y., Tian, L., Webster, C., 2020. Air pollution associated respiratory mortality risk alleviated by residential greenness in the chinese elderly health service cohort. Environ. Res. 183, 109139.
Sun, W., Bao, P., Zhao, X., Tang, J., Wang, L., 2021. Road traffic and urban form factors correlated with the incidence of lung cancer in high-density areas: an ecological study in downtown ShanghaiChina. Journal of Urban Health 98 (3), 328–343.
Takaro, T.K., Knowlton, K., Balmes, J.R., 2013. Climate change and respiratory health: current evidence and knowledge gaps. Expert Rev. Respir. Med. 7 (4), 349–361.
Taylor, L., Hochuli, D.F., 2017. Defining greenspace: multiple uses across multiple disciplines. Landsc. Urban Plan. 158, 25–38.
Tischer, C., Gascon, M., Fernández-Somoano, A., Tardón, A., Materola, A.L., Ibarluzea, J., Ferrero, A., Estarlich, M., Cirach, M., Vrijheid, M., Fuertes, E., 2017. Urban green and grey space in relation to respiratory health in children. Eur. Respir. J. 49 (6).
Twohig-Bennett, C., Jones, A., 2018. The health benefits of the great outdoors: a systematic review and meta-analysis of greenspace exposure and health outcomes. Environ. Res. 166, 628–637.
Ulmer, J.M., Wolf, K.L., Backman, D.R., Tretheway, R.L., Blain, C.J., O'Neil-Dunne, J.P., Frank, L.D., 2016. Multiple health benefits of urban tree canopy: the mounting evidence for a green prescription. Health Place 42, 54–62.
Vienneau, D., de Hoogh, K., Faeh, D., Kaufmann, M., Wunderli, J.M., Röösli, M., SNC Study Group, 2017. More than clean air and tranquillity: residential green is independently associated with decreasing mortality. Environ. International 108, 176–184.
Villeneuve, P.J., Jerrett, M., Su, J.G., Burnett, R.T., Chen, H., Wheeler, A.J., Goldberg, M.S., 2012. A cohort study relating urban green space with mortality in Ontario, Canada. Environ. Res. 115, 51–58.
Wang, D., Lau, K.K.L., Yu, R., Wong, S.Y., Kwok, T.T., Woo, J., 2017. Neighbouring green space and mortality in community-dwelling elderly Hong Kong Chinese: a cohort study. BMJ Open 7 (7).
Wang, H., Tassinary, L.G., 2019. Effects of greenspace morphology on mortality at the neighbourhood level: a cross-sectional ecological study. Lancet Planet. Health 3 (11), e460–e468.
Wanrooij, V.H., Willeboordse, M., Dompeling, E., van de Kant, K.D., 2014. Exercise training in children with asthma: a systematic review. Br. J. Sports Med. 48 (13), 1024–1031.
Waters, E., Doyle, J., Wolfe, R., Wright, M., Wake, M., Salmon, L., 2000. Influence of parental gender and self-reported health and illness on parent-reported child health. Pediatrics 106 (6), 1422–1428.
Whaley, P., Edwards, S.W., Kraft, A., Nyhan, K., Shapiro, A., Watford, S., Wattam, S., Wolffe, T., Angrish, M., 2020. Knowledge organization systems for systematic chemical assessments. Environ. Health Perspect. 128 (12), 125001.
Wu, J., Yang, M., Xiong, L., Wang, C., Ta, N., 2021. Health-oriented vegetation community design: innovation in urban green space to support respiratory health. Landsc. Urban Plan. 205, 103973.
Xu, L., Ren, C., Yuan, C., Nichol, J.E., Goggins, W.B., 2017. An ecological study of the association between area-level green space and adult mortality in Hong Kong. Climate 5 (3), 55.
Yu, H., Hu, L.W., Zhou, Y., Qian, Z., Schootman, M., LeBaige, M.H., Zhou, Y., Xiong, S., Shen, X., Lin, L.Z., Zhou, P., 2021. Association between eye-level greenness and lung function in urban Chinese children. Environ. Res. 202, 111641.

Yu, H., Zhou, Y., Wang, R., Qian, Z., Knibbs, L.D., Jalaludin, B., Schootman, M., McMillin, S.E., Howard, S.W., Lin, L.Z., Zhou, P., 2021. Associations between trees and grass presence with childhood asthma prevalence using deep learning image segmentation and a novel green view index. Environ. Pollut. 286, 117582.

Zeng, X.W., Lowe, A.J., Lodge, C.J., Heinrich, J., Roponen, M., Jalava, P., Guo, Y., Hu, L.W., Yang, B.Y., Dharmage, S.C., Dong, G.H., 2020. Greenness surrounding schools is associated with lower risk of asthma in schoolchildren. Environ. Int. 143, 105967.

Zhang, J., Wang, Y., Feng, L., Hou, C., Gu, Q., 2022. Effects of air pollution and green spaces on impaired lung function in children: a case-control study. Environ. Sci. Pollut. Res. 29 (8), 11907–11919.

Zhang, M.J., Dong, R., Wang, X.X., 2021. Plants with health risks undermine residents' perceived health status, evaluations and expectations of residential greenery. Landsc. Urban Plan. 216, 104236.

Zhou, Y., Bui, D.S., Perret, J.L., Lowe, A.J., Lodge, C.J., Markevych, I., Heinrich, J., Bloom, M.S., Knibbs, L.D., Jalaludin, B., Yang, B.Y., 2021. Greenness may improve lung health in low–moderate but not high air pollution areas: seven northeastern cities' study. Thorax 76 (9), 880–886.

Zock, J.P., Verheij, R., Helbich, M., Volker, B., Spreeuwenberg, P., Strak, M., Janssen, N.A., Dijst, M., Groenewegen, P., 2018. The impact of social capital, land use, air pollution and noise on individual morbidity in dutch neighbourhoods. Environ. Int. 121, 453–460.

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.

London School of Hygiene & Tropical Medicine
Keppel Street, London WC1E 7HT

T: +44 (0)20 7299 4646
F: +44 (0)20 7299 4656
www.lshtm.ac.uk

RESEARCH PAPER COVER SHEET

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

<u>SECTION A – Student Details</u>

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.

<u>SECTION B – Paper already published</u>

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**

*If yes, please attach evidence of retention. If no, or if the work is being included in its published format, please attach evidence of permission from the copyright holder (publisher or other author) to include this work.

<u>SECTION C – Prepared for publication, but not yet published</u>

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

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)	I conceived the study design, performed the analysis, wrote the first draft of the paper, and responded to reviewer comments.

SECTION E

Student Signature	William Mueller
Date	18/04/2022

Supervisor Signature	Paul Wilkinson
Date	12/07/2022

Environmental Research 180 (2020) 108850

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

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

William Mueller[a,b,*], Susanne Steinle[a], Juha Pärkkä[c], Eija Parmes[c], Hilkka Liedes[c], Eelco Kuijpers[d], Anjoeka Pronk[d], Denis Sarigiannis[e], Spyros Karakitsios[e], Dimitris Chapizanis[e], Thomas Maggos[f], Asimina Stamatelopoulou[f], Paul Wilkinson[b], James Milner[b], Sotiris Vardoulakis[a], Miranda Loh[a]

[a] Institute of Occupational Medicine, Edinburgh, UK
[b] London School of Hygiene & Tropical Medicine, UK
[c] VTT Technical Research Centre of Finland, Finland
[d] TNO, Netherlands
[e] Aristotle University of Thessaloniki, Greece
[f] National Centre for Scientific Research 'Demokritos', Athens, Greece

ARTICLE INFO

Keywords:
Greenspace
Particulate matter
Noise annoyance
Air pollution
Exposome

ABSTRACT

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

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

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

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

1. Introduction

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

* Corresponding author. Institute of Occupational Medicine, Edinburgh, UK.
E-mail address: will.mueller@iom-world.org (W. Mueller).

https://doi.org/10.1016/j.envres.2019.108850
Received 28 May 2019; Received in revised form 18 October 2019; Accepted 20 October 2019
Available online 22 October 2019
0013-9351/

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

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

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

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

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

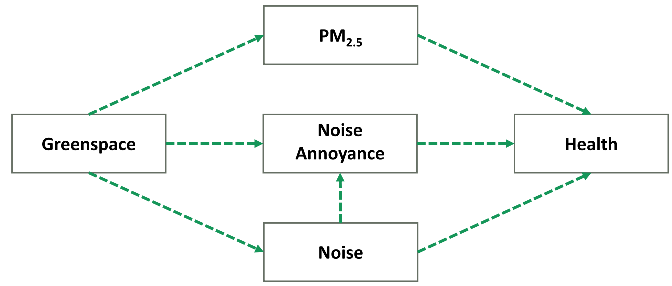


Fig. 1. The three greenspace pathways to health to be investigated.

2. Materials and methods

2.1. Study design and population

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

2.2. Data collection and processing

2.2.1. Greenspace

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

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

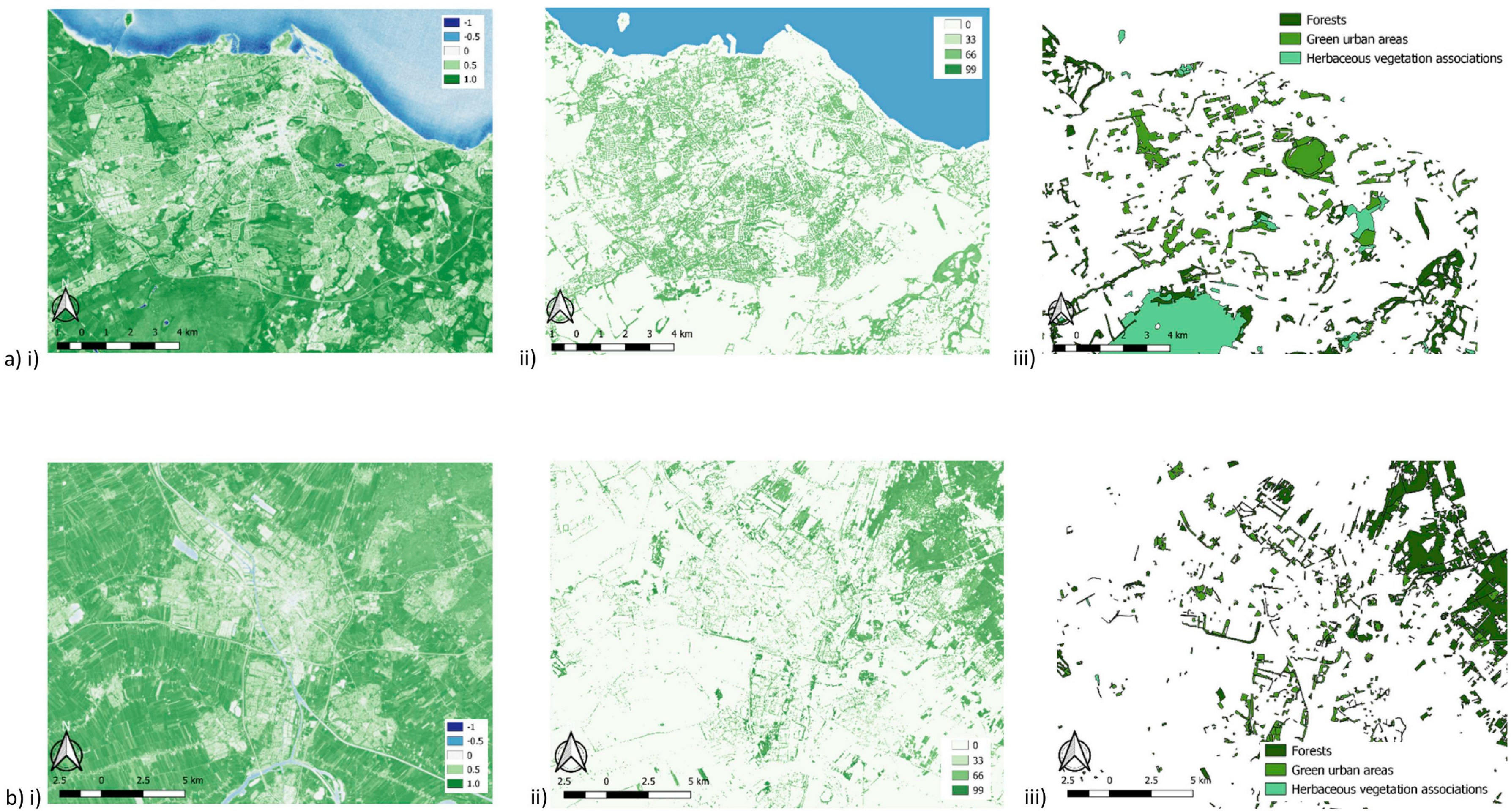


Fig. 3. a-d Maps of a) Edinburgh, UK; b) Utrecht, Netherlands; c) Thessaloniki, Greece; and d) Athens, Greece, presenting i) summer NDVI, ii) tree cover density (%), and iii) green land use. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version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

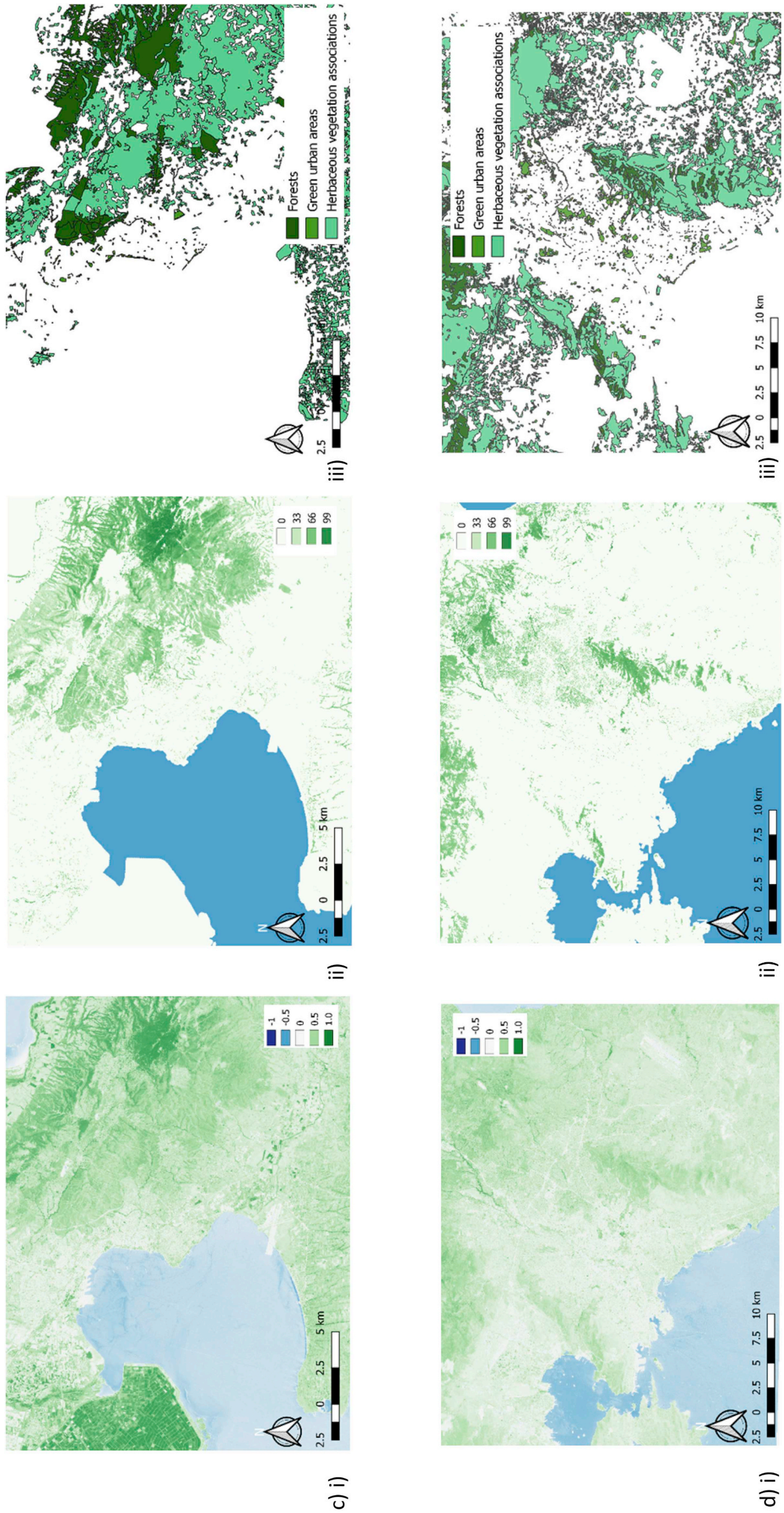


Fig. 3. (*continued*)

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

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

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

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

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

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

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

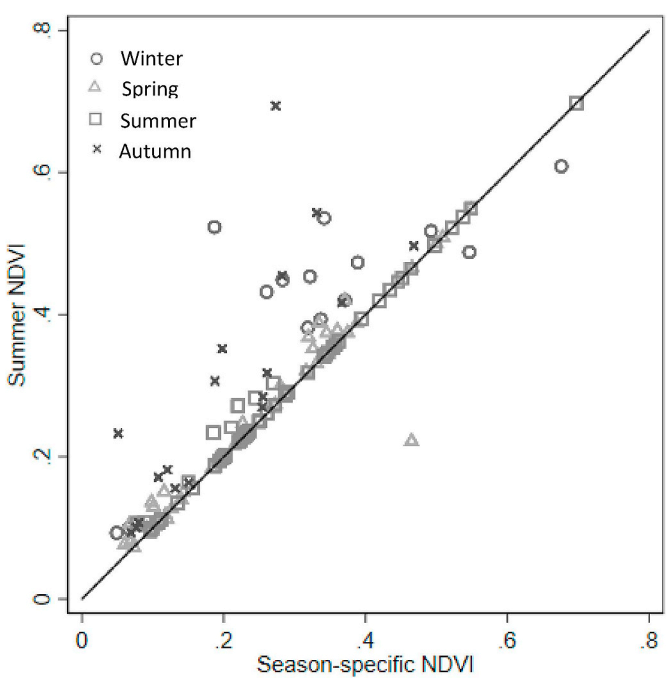


Fig. 4. A scatterplot of summer and season-specific NDVI values assigned to each residential address (100 m buffer).

2.2.3. Noise

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

2.2.4. Outdoor and indoor home characteristics

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

2.3. Statistical analysis

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

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

Table 2
Pearson correlation coefficients of greenspace and urban characteristics.

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

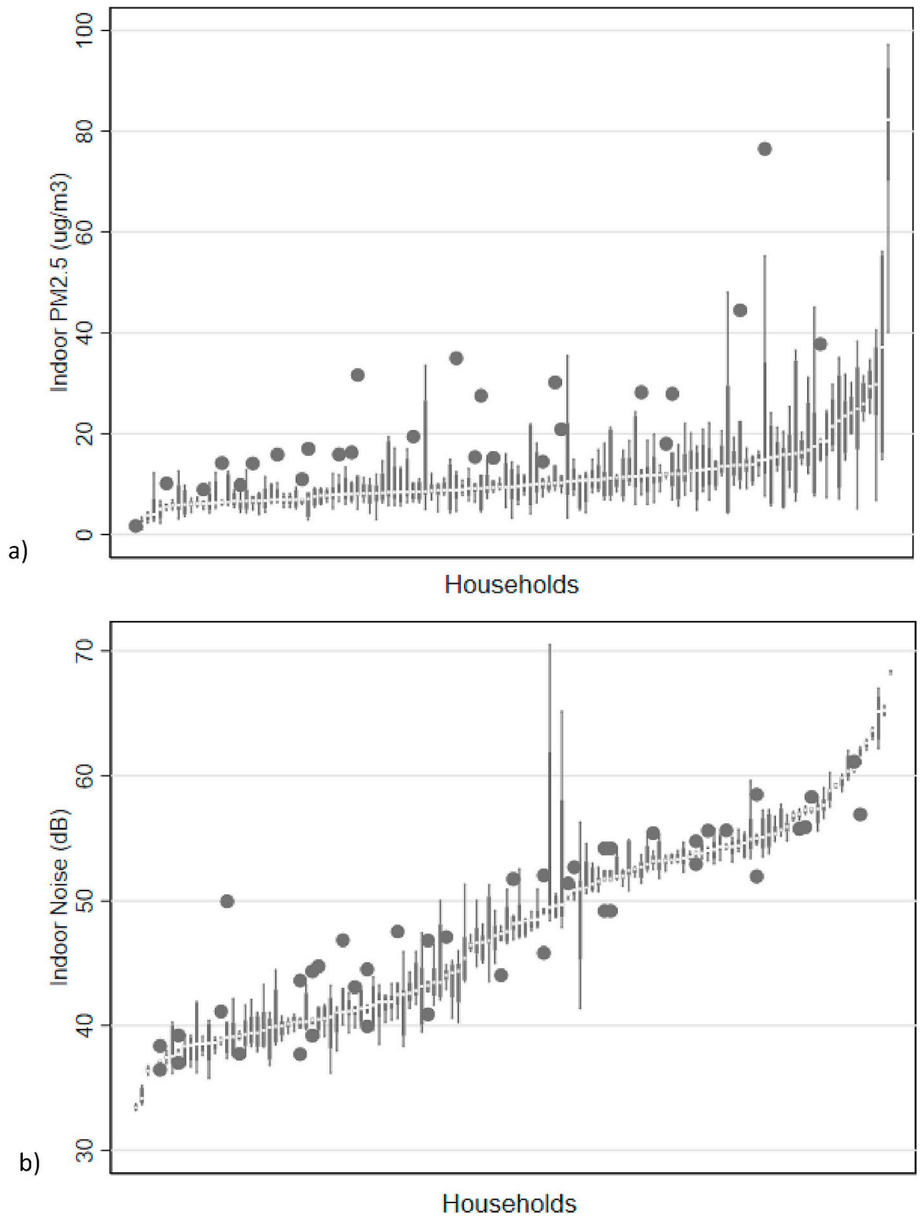


Fig. 5. Boxplots of daily means for each home address representing indoor a) $PM_{2.5}$ and b) indoor noise, presented from low to high values.

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

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

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

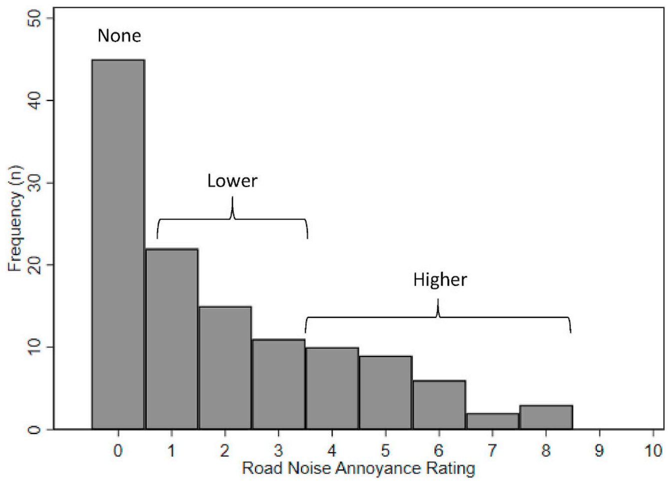


Fig. 6. A histogram of reported road noise annoyance, using an 11-point scale of 0 ('not at all annoying') to 10 ('extremely annoying') (n = 123). Categories used for analysis ('none', 'lower', 'higher') are indicated.

3. Results

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

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

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

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

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

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

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

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

[a] Excludes Thessaloniki.

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

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

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

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

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

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

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

4. Discussion

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

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

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

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

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

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

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

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

4.1. Strengths and limitations

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

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

5. Conclusions

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

Funding

This study was part of the HEALS project, which was funded from the European Union's Seventh Programme for research, technological development and demonstration under grant agreement No 603,946.

Ethical review

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

Acknowledgements

We thank Hilary Cowie for her input to statistical methods and manuscript review. We are grateful to Reinier Sterkenburg and Meredith Franklin for providing expertise on GIS and spatial analysis. Remy Franken and John Cherrie are acknowledged for their work on the HEALS project. Luc Cluitmans is thanked for providing data management assistance. This study was part of the HEALS project, which was funded from the European Union's Seventh Programme for research, technological development and demonstration under grant agreement No 603946.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2019.108850.

References

Abhijith, K.V., Kumar, P., Gallagher, J., McNabola, A., Baldauf, R., Pilla, F., Broderick, B., Di Sabatino, S., Pulvirenti, B., 2017. Air pollution abatement performances of green infrastructure in open road and built-up street canyon environments–A review. Atmos. Environ. 162, 71–86.
Alvarsson, J.J., Wiens, S., Nilsson, M.E., 2010. Stress recovery during exposure to nature sound and environmental noise. Int. J. Environ. Res. Public Health 7 (3), 1036–1046.
Andrusaityte, S., Grazuleviciene, R., Kudzyte, J., Bernotiene, A., Dedele, A., Nieuwenhuijsen, M.J., 2016. Associations between neighbourhood greenness and asthma in preschool children in Kaunas, Lithuania: a case–control study. BMJ Open 6 (4), e010341.
Asikainen, A., Carrer, P., Kephalopoulos, S., de Oliveira Fernandes, E., Wargocki, P., Hänninen, O., 2016. Reducing burden of disease from residential indoor air exposures in Europe (HEALTHVENT project). Environ. Health 15 (1), S35.
Basner, M., Babisch, W., Davis, A., Brink, M., Clark, C., Janssen, S., Stansfeld, S., 2014. Auditory and non-auditory effects of noise on health. The Lancet 383 (9925), 1325–1332.
Bloemsma, L.D., Gehring, U., Klompmaker, J.O., Hoek, G., Janssen, N.A., Smit, H.A., Vonk, J.M., Brunekreef, B., Lebret, E., Wijga, A.H., 2018. Green space visits among adolescents: frequency and predictors in the PIAMA birth cohort study. Environ. Health Perspect. 126 (4), 047016.
Bottalico, F., Chirici, G., Giannetti, F., De Marco, A., Nocentini, S., Paoletti, E., Salbitano, F., Sanesi, G., Serenelli, C., Travaglini, D., 2016. Air pollution removal by green infrastructures and urban forests in the city of Florence. Agriculture and Agricultural Science Procedia 8, 243–251.
Brant, R., 1990. Assessing Proportionality in the Proportional Odds Model for Ordinal Logistic Regression. Biometrics, pp. 1171–1178.
Bratman, G.N., Anderson, C.B., Berman, M.G., Cochran, B., De Vries, S., Flanders, J., Folke, C., Frumkin, H., Gross, J.J., Hartig, T., Kahn, P.H., 2019. Nature and mental health: an ecosystem service perspective. Sci. Adv. 5 (7), eaax0903.
Center for International Earth Science Information Network - CIESIN - Columbia University, 2018. Gridded Population of the World, Version 4 (GPWv4): Population Density, Revision 11. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC).
Dadvand, P., de Nazelle, A., Triguero-Mas, M., Schembari, A., Cirach, M., Amoly, E., Figueras, F., Basagaña, X., Ostro, B., Nieuwenhuijsen, M., 2012. Surrounding greenness and exposure to air pollution during pregnancy: an analysis of personal monitoring data. Environ. Health Perspect. 120 (9), 1286.
Dadvand, P., Villanueva, C.M., Font-Ribera, L., Martinez, D., Basagaña, X., Belmonte, J., Vrijheid, M., Gražulevičienė, R., Kogevinas, M., Nieuwenhuijsen, M.J., 2014. Risks and benefits of green spaces for children: a cross-sectional study of associations with sedentary behavior, obesity, asthma, and allergy. Environ. Health Perspect. 122 (12), 1329.

Dadvand, P., Rivas, I., Basagaña, X., Alvarez-Pedrerol, M., Su, J., Pascual, M.D.C., Amato, F., Jerret, M., Querol, X., Sunyer, J., Nieuwenhuijsen, M.J., 2015. The association between greenness and traffic-related air pollution at schools. Sci. Total Environ. 523, 59–63.
Dzhambov, A., Markevych, I., Tilov, B., Arabadzhiev, Z., Stoyanov, D., Gatseva, P., Dimitrova, D., 2018a. Lower noise annoyance associated with GIS-derived greenspace: pathways through perceived greenspace and residential noise. Int. J. Environ. Res. Public Health 15 (7), 1533.
Dzhambov, A.M., Markevych, I., Tilov, B.G., Dimitrova, D.D., 2018b. Residential greenspace might modify the effect of road traffic noise exposure on general mental health in students. Urban For. Urban Green. 34, 233–239.
Fecht, D., Hansell, A.L., Morley, D., Dajnak, D., Vienneau, D., Beevers, S., Toledano, M.B., Kelly, F.J., Anderson, H.R., Gulliver, J., 2016. Spatial and temporal associations of road traffic noise and air pollution in London: implications for epidemiological studies. Environ. Int. 88, 235–242.
Foraster, M., Eze, I.C., Vienneau, D., Brink, M., Cajochen, C., Caviezel, S., Héritier, H., Schaffner, E., Schindler, C., Wanner, M., Wunderli, J.M., 2016. Long-term transportation noise annoyance is associated with subsequent lower levels of physical activity. Environ. Int. 91, 341–349.
Franchini, M., Mannucci, P.M., 2018. Mitigation of air pollution by greenness: a narrative review. Eur. J. Intern. Med. 55, 1–5.
Franken, R., Maggos, T., Stamatelopoulou, A., Loh, M., Kuijpers, E., Bartzis, J., Steinle, S., Cherrie, J.W., Pronk, A., 2019. Comparison of methods for converting Dylos particle number concentrations to PM 2.5 mass concentrations. Indoor Air. https://doi.org/10.1111/ina.12546.
Gascon, M., Triguero-Mas, M., Martínez, D., Dadvand, P., Rojas-Rueda, D., Plasència, A., Nieuwenhuijsen, M.J., 2016. Residential green spaces and mortality: a systematic review. Environ. Int. 86, 60–67.
Geraghty, D., O'Mahony, M., 2016. Investigating the temporal variability of noise in an urban environment. Int. J. Sustain. Built Environ 5 (1), 34–45.
Grinde, B., Patil, G., 2009. Biophilia: does visual contact with nature impact on health and well-being? Int. J. Environ. Res. Public Health 6 (9), 2332–2343.
Grote, R., Samson, R., Alonso, R., Amorim, J.H., Cariñanos, P., Churkina, G., Fares, S., Thiec, D.L., Niinemets, Ü., Mikkelsen, T.N., Paoletti, E., 2016. Functional traits of urban trees: air pollution mitigation potential. Front. Ecol. Environ. 14 (10), 543–550.
Guo, Y., Zeng, H., Zheng, R., Li, S., Barnett, A.G., Zhang, S., Zou, X., Huxley, R., Chen, W., Williams, G., 2016. The association between lung cancer incidence and ambient air pollution in China: a spatiotemporal analysis. Environ. Res. 144, 60–65.
Harrison, R.M., Laxen, D., Moorcroft, S., Laxen, K., 2012. Processes affecting concentrations of fine particulate matter (PM2. 5) in the UK atmosphere. Atmos. Environ. 46, 115–124.
Hartig, T., Mitchell, R., De Vries, S., Frumkin, H., 2014. Nature and health. Annu. Rev. Public Health 35, 207–228.
Helbich, M., 2019. Spatiotemporal contextual uncertainties in green space exposure measures: exploring a time series of the normalized difference vegetation indices. Int. J. Environ. Res. Public Health 16 (5), 852.
Helbich, M., Yao, Y., Liu, Y., Zhang, J., Liu, P., Wang, R., 2019. Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing, China. Environ. Int. 126, 107–117.
Hystad, P., Davies, H.W., Frank, L., Van Loon, J., Gehring, U., Tamburic, L., Brauer, M., 2014. Residential greenness and birth outcomes: evaluating the influence of spatially correlated built-environment factors. Environ. Health Perspect. 122 (10), 1095.
Irga, P.J., Burchett, M.D., Torpy, F.R., 2015. Does urban forestry have a quantitative effect on ambient air quality in an urban environment? Atmos. Environ. 120, 173–181.
Jang, H.S., Lee, S.C., Jeon, J.Y., Kang, J., 2015. Evaluation of road traffic noise abatement by vegetation treatment in a 1: 10 urban scale model. J. Acoust. Soc. Am. 138 (6), 3884–3895.
Jarosińska, D., Héroux, M.È., Wilkhu, P., Creswick, J., Verbeek, J., Wothge, J., Paunović, E., 2018. Development of the WHO environmental noise guidelines for the European region: an introduction. Int. J. Environ. Res. Public Health 15 (4), 813.
Klingberg, J., Broberg, M., Strandberg, B., Thorsson, P., Pleijel, H., 2017. Influence of urban vegetation on air pollution and noise exposure–a case study in Gothenburg, Sweden. Sci. Total Environ. 599, 1728–1739.
Lohr, V.I., Pearson-Mims, C.H., 1996. Particulate matter accumulation on horizontal surfaces in interiors: influence of foliage plants. Atmos. Environ. 30 (14), 2565–2568.
Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A.M., De Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M.J., Lupp, G., 2017. Exploring pathways linking greenspace to health: theoretical and methodological guidance. Environ. Res. 158, 301–317.
Meng, Q.Y., Turpin, B.J., Korn, L., Weisel, C.P., Morandi, M., Colome, S., Zhang, J., Stock, T., Spektor, D., Winer, A., Zhang, L., 2005. Influence of ambient (outdoor) sources on residential indoor and personal PM 2.5 concentrations: analyses of RIOPA data. J. Expo. Sci. Environ. Epidemiol. 15 (1), 17.
Mitsakou, C., Dimitroulopoulou, S., Heaviside, C., Katsouyanni, K., Samoli, E., Rodopoulou, S., Costa, C., Almendra, R., Santana, P., Dell'Olmo, M.M., Borrell, C., 2019. Environmental public health risks in European metropolitan areas within the EURO-HEALTHY project. Sci. Total Environ. 658, 1630–1639.
Morakinyo, O., Mokgobu, M., Mukhola, M., Hunter, R., 2016. Health outcomes of exposure to biological and chemical components of inhalable and respirable particulate matter. Int. J. Environ. Res. Public Health 13 (6), 592.
Moshammer, H., Panholzer, J., Ulbing, L., Udvarhelyi, E., Ebenbauer, B., Peter, S., 2019. Acute effects of air pollution and noise from road traffic in a panel of young healthy adults. Int. J. Environ. Res. Public Health 16 (5), 788.
Okokon, E., Turunen, A., Ung-Lanki, S., Vartiainen, A.K., Tiittanen, P., Lanki, T., 2015. Road-traffic noise: annoyance, risk perception, and noise sensitivity in the Finnish adult population. Int. J. Environ. Res. Public Health 12 (6), 5712–5734.
Recio, A., Linares, C., Banegas, J.R., Díaz, J., 2016. Road traffic noise effects on cardiovascular, respiratory, and metabolic health: an integrative model of biological mechanisms. Environ. Res. 146, 359–370.
Ren, Z., Pu, R., Zheng, H., Zhang, D., He, X., 2017. Spatiotemporal analyses of urban vegetation structural attributes using multitemporal Landsat TM data and field measurements. Ann. For. Sci. 74 (3), 54.
Requia, W.J., Roig, H.L., Adams, M.D., Zanobetti, A., Koutrakis, P., 2016. Mapping distance-decay of cardiorespiratory disease risk related to neighborhood environments. Environ. Res. 151, 203–215.
Rhew, I.C., Vander Stoep, A., Kearney, A., Smith, N.L., Dunbar, M.D., 2011. Validation of the normalized difference vegetation index as a measure of neighborhood greenness. Ann. Epidemiol. 21 (12), 946–952.
Roy, S., Byrne, J., Pickering, C., 2012. A systematic quantitative review of urban tree benefits, costs, and assessment methods across cities in different climatic zones. Urban For. Urban Green. 11 (4), 351–363.
Rugel, E.J., Henderson, S.B., Carpiano, R.M., Brauer, M., 2017. Beyond the Normalized Difference Vegetation Index (NDVI): developing a natural space index for population-level health research. Environ. Res. 159, 474–483.
Salmond, J.A., Tadaki, M., Vardoulakis, S., Arbuthnott, K., Coutts, A., Demuzere, M., Dirks, K.N., Heaviside, C., Lim, S., Macintyre, H., McInnes, R.N., 2016. Health and climate related ecosystem services provided by street trees in the urban environment. Environ. Health 15 (1), S36.
Salomons, E.M., Pont, M.B., 2012. Urban traffic noise and the relation to urban density, form, and traffic elasticity. Landsc. Urban Plan. 108 (1), 2–16.
Schüle, S., Nanninga, S., Dreger, S., Bolte, G., 2018. Relations between objective and perceived built environments and the modifying role of individual socioeconomic position. A cross-sectional study on traffic noise and urban green space in a large German city. Int. J. Environ. Res. Public Health 15 (8), 1562.
Scott, S.C., Goldberg, M.S., Mayo, N.E., 1997. Statistical assessment of ordinal outcomes in comparative studies. J. Clin. Epidemiol. 50 (1), 45–55.
Shepherd, D., Welch, D., Dirks, K., McBride, D., 2013. Do quiet areas afford greater health-related quality of life than noisy areas? Int. J. Environ. Res. Public Health 10 (4), 1284–1303.
Stamatelopoulou, A., Asimakopoulos, D.N., Maggos, T., 2019. Effects of PM, TVOCs and comfort parameters on indoor air quality of residences with young children. Build. Environ. 150, 233–244.
Su, J.G., Dadvand, P., Nieuwenhuijsen, M.J., Bartoll, X., Jerrett, M., 2019. Associations of green space metrics with health and behavior outcomes at different buffer sizes and remote sensing sensor resolutions. Environ. Int. 126, 162–170.
Sæbø, A., Popek, R., Nawrot, B., Hanslin, H.M., Gawronska, H., Gawronski, S.W., 2012. Plant species differences in particulate matter accumulation on leaf surfaces. Sci. Total Environ. 427, 347–354.
Tong, Z., Chen, Y., Malkawi, A., Adamkiewicz, G., Spengler, J.D., 2016. Quantifying the impact of traffic-related air pollution on the indoor air quality of a naturally ventilated building. Environ. Int. 89, 138–146.
van den Bosch, M., Nieuwenhuijsen, M., 2017. No time to lose-Green the cities now. Environ. Int. 99, 343.
van den Bosch, M.A., Mudu, P., Uscila, V., Barrdahl, M., Kulinkina, A., Staatsen, B., Swart, W., Kruize, H., Zurlyte, I., Egorov, A.I., 2016. Development of an urban green space indicator and the public health rationale. Scand. J. Public Health 44 (2), 159–167.
van Renterghem, T., 2018. Towards explaining the positive effect of vegetation on the perception of environmental noise. Urban For. Urban Green. https://doi.org/10.1016/j.ufug.2018.03.007.
van Renterghem, T., Botteldooren, D., 2016. View on outdoor vegetation reduces noise annoyance for dwellers near busy roads. Landsc. Urban Plan. 148, 203–215.
van Renterghem, T., Attenborough, K., Maennel, M., Defrance, J., Horoshenkov, K., Kang, J., Bashir, I., Taherzadeh, S., Altreuther, B., Khan, A., Smyrnova, Y., 2014. Measured light vehicle noise reduction by hedges. Appl. Acoust. 78, 19–27.
van Renterghem, T., Forssén, J., Attenborough, K., Jean, P., Defrance, J., Hornikx, M., Kang, J., 2015. Using natural means to reduce surface transport noise during propagation outdoors. Appl. Acoust. 92, 86–101.
Vienneau, D., de Hoogh, K., Faeh, D., Kaufmann, M., Wunderli, J.M., Röösli, M., SNC Study Group, 2017. More than clean air and tranquillity: residential green is independently associated with decreasing mortality. Environ. Int. 108, 176–184.
von Lindern, E., Hartig, T., Lercher, P., 2016. Traffic-related exposures, constrained restoration, and health in the residential context. Health & Place 39, 92–100.
Wang, Y., Bakker, F., De Groot, R., Wörtche, H., 2014. Effect of ecosystem services provided by urban green infrastructure on indoor environment: a literature review. Build. Environ. 77, 88–100.
WHO, 2018. Environmental Noise Guidelines for the European Region. World Health Organization Regional Office for Europe, Copenhagen, Denmark.
Wild, C.P., 2012. The exposome: from concept to utility. Int. J. Epidemiol. 41 (1), 24–32.
Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT press.
World Health Organization (WHO), 2016. Urban Green Spaces and Health–A Review of Evidence. World Health Organization, Geneva, Switzerland.
Yli-Pelkonen, V., Setälä, H., Viippola, V., 2017. Urban forests near roads do not reduce gaseous air pollutant concentrations but have an impact on particles levels. Landsc. Urban Plan. 158, 39–47.
Zhou, W., Qian, Y., Li, X., Li, W., Han, L., 2014. Relationships between land cover and the surface urban heat island: seasonal variability and effects of spatial and thematic resolution of land cover data on predicting land surface temperatures. Landsc. Ecol. 29 (1), 153–167.

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

Chung, W.K., Leung, T.M., Chau, C.K. and Tang, S.K., 2020. Comparing the effects of visibility of different neighborhood greenery settings on the preference ratings and noise annoyance responses to road traffic noises. *Applied Acoustics*, *169*, p.107474.

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.

London School of Hygiene & Tropical Medicine
Keppel Street, London WC1E 7HT

T: +44 (0)20 7299 4646
F: +44 (0)20 7299 4656
www.lshtm.ac.uk

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**

*If yes, please attach evidence of retention. If no, or if the work is being included in its published format, please attach evidence of permission from the copyright holder (publisher or other author) to include this work.

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

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)	I conceived the study design, performed the analysis, wrote the first draft of the paper, and responded to reviewer comments.

SECTION E

Student Signature	William Mueller
Date	18/04/2022

Supervisor Signature	Paul Wilkinson
Date	12/07/2022

Mueller et al. BMC Public Health (2021) 21:282
https://doi.org/10.1186/s12889-021-10259-0

BMC Public Health

RESEARCH ARTICLE Open Access

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

William Mueller[1,2*], Paul Wilkinson[2], James Milner[2], Sotiris Vardoulakis[1,3], Susanne Steinle[1], Juha Pärkkä[4], Eija Parmes[4], Luc Cluitmans[4], Eelco Kuijpers[5], Anjoeka Pronk[5], Denis Sarigiannis[6], Spyros Karakitsios[6], Dimitris Chapizanis[6], Thomas Maggos[7], Asimina Stamatelopoulou[7] and Miranda Loh[1]

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

* Correspondence: will.mueller@iom-world.org
[1]Institute of Occupational Medicine, Edinburgh, UK
[2]London School of Hygiene & Tropical Medicine, London, UK
Full list of author information is available at the end of the article

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

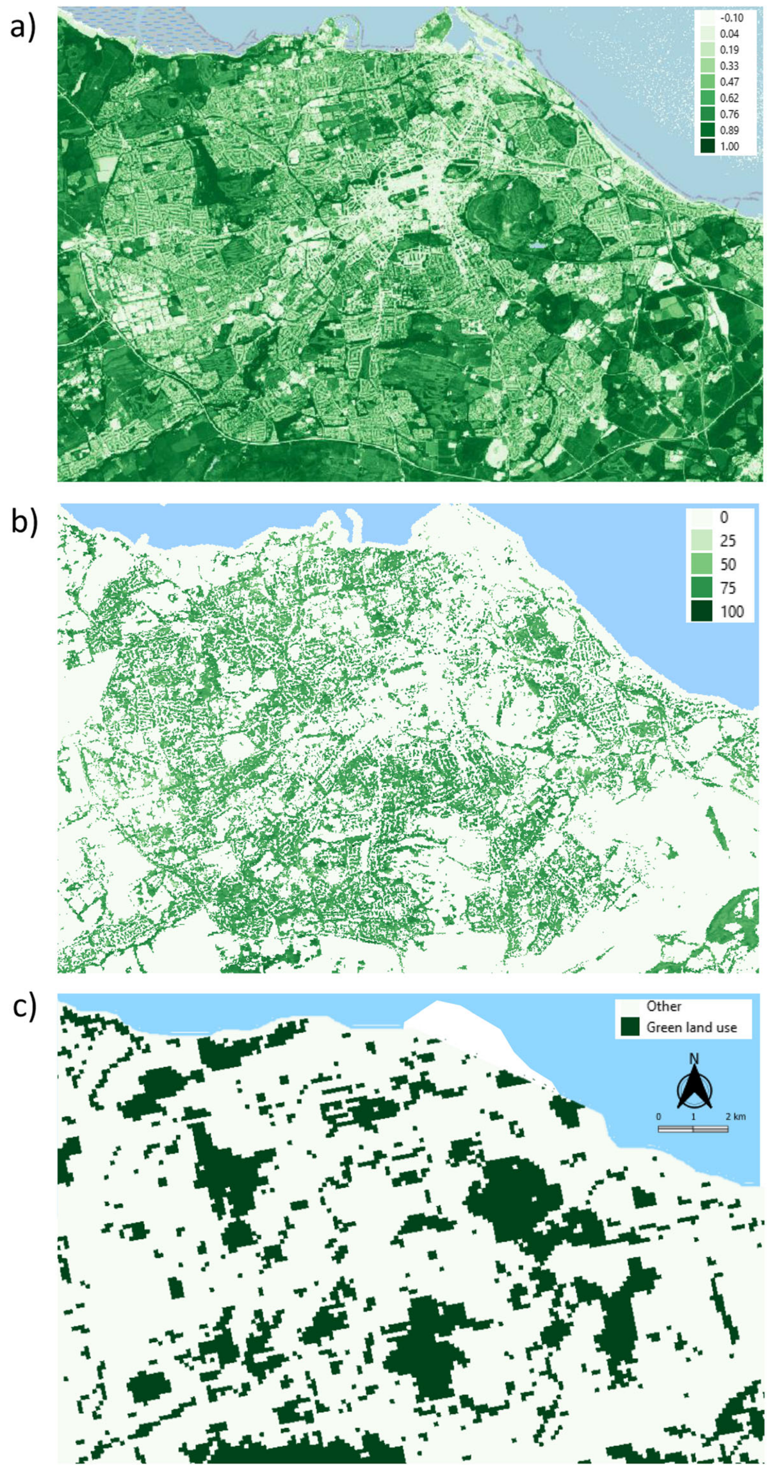


Fig. 1 Maps of Edinburgh, UK to illustrate **a** Normalised Difference Vegetation Index (– 0.1 to 1.0), **b** tree cover density (0–100%), and **c** green land use. Basemap from©OpenStreetMap contributors (www.openstreetmap.org), available under the Open Database License

[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

[a]Adjusted 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

Acknowledgements

We thank all of the participants in the HEALS study. Dr. Paul Kelly is thanked for his valuable input in the analysis.

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.

Funding

The HEALS project was funded from the European Union's Seventh Programme for research, technological development and demonstration under grant agreement No 603946. The funder had no role in the design of the study; collection, analysis, and interpretation of data; or in writing the manuscript.

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 Board 2015–04: 260/2015–1671; Thessaloniki: Aristotle University Ethics Committee 140540/2018). Informed written consent was provided by all participants.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Author details

[1]Institute of Occupational Medicine, Edinburgh, UK. [2]London School of Hygiene & Tropical Medicine, London, UK. [3]National Centre for Epidemiology and Population Health, Australian National University, Canberra, Australia. [4]VTT Technical Research Centre of Finland, Finland. [5]TNO, Netherlands. [6]Aristotle University of Thessaloniki, Thessaloniki, Greece. [7]National Centre for Scientific Research 'Demokritos', Athens, Greece.

Received: 22 July 2020 Accepted: 17 January 2021
Published online: 04 February 2021

References

1. Ainsworth BE, Haskell WL, Herrmann SD, Meckes N, Bassett DR Jr, Tudor-Locke C, Greer JL, Vezina J, Whitt-Glover MC, Leon AS. 2011 compendium of physical activities: a second update of codes and MET values. Med Sci Sports Exerc. 2011;43(8):1575–81.
2. Astell-Burt T, Feng X, Kolt GS. Green space is associated with walking and moderate-to-vigorous physical activity (MVPA) in middle-to-older-aged adults: findings from 203 883 Australians in the 45 and up study. Br J Sports Med. 2014;48(5):404–6.
3. Browning M, Lee K. Within what distance does "greenness" best predict physical health? A systematic review of articles with GIS buffer analyses across the lifespan. Int J Environ Res Public Health. 2017;14(7):675.
4. Bucher D, Cellina F, Mangili F, Raubal M, Rudel R, Rizzoli AE, Elabed O. Exploiting fitness apps for sustainable mobility-challenges deploying the GoEco! App. In: ICT for sustainability 2016. Amsterdam: Atlantis Press; 2016.
5. Candelaria JI, Sallis JF, Conway TL, Saelens BE, Frank LD, Slymen DJ. Differences in physical activity among adults in households with and without children. J Phys Act Health. 2012;9(7):985–95.
6. Carson V, Rosu A, Janssen I. A cross-sectional study of the environment, physical activity, and screen time among young children and their parents. BMC Public Health. 2014;14(1):61.
7. Center for International Earth Science Information Network - CIESIN - Columbia University. Gridded Population of the World, version 4 (GPWv4): population density, revision 11. Palisades: NASA Socioeconomic Data and Applications Center (SEDAC); 2018. https://doi.org/10.7927/H49C6VHW.
8. Chaix B, Kestens Y, Duncan DT, Brondeel R, Méline J, El Aarbaoui T, Pannier B, Merlo J. A GPS-based methodology to analyze environment-health associations at the trip level: case-crossover analyses of built environments and walking. Am J Epidemiol. 2016;184(8):579–89.
9. Chaix B, Meline J, Duncan S, Merrien C, Karusisi N, Perchoux C, Lewin A, Labadi K, Kestens Y. GPS tracking in neighborhood and health studies: a step forward for environmental exposure assessment, a step backward for causal inference? Health Place. 2013;21:46–51.
10. Cohen-Cline H, Turkheimer E, Duncan GE. Access to green space, physical activity and mental health: a twin study. J Epidemiol Community Health. 2015;69(6):523–9.
11. Cole-Hunter T, Donaire-Gonzalez D, Curto A, Ambros A, Valentin A, Garcia-Aymerich J, Martínez D, Braun LM, Mendez M, Jerrett M, Rodriguez D. Objective correlates and determinants of bicycle commuting propensity in an urban environment. Transp Res Part D Transp Environ. 2015;40:132–43.
12. Diaz KM, Krupka DJ, Chang MJ, Peacock J, Ma Y, Goldsmith J, Schwartz JE, Davidson KW. Fitbit®: an accurate and reliable device for wireless physical activity tracking. Int J Cardiol. 2015;185:138–40.
13. Evenson KR, Furberg RD. Moves app: a digital diary to track physical activity and location. Br J Sports Med. 2017;51(15):1169–70.
14. Gascon M, Götschi T, de Nazelle A, Gracia E, Ambròs A, Márquez S, Marquet O, Avila-Palencia I, Brand C, Iacorossi F, Raser E. Correlates of walking for travel in seven European cities: the PASTA project. Environ Health Perspect. 2019;127(9):097003.

15. Gascon M, Sánchez-Benavides G, Dadvand P, Martínez D, Gramunt N, Gotsens X, Cirach M, Vert C, Molinuevo JL, Crous-Bou M, Nieuwenhuijsen M. Long-term exposure to residential green and blue spaces and anxiety and depression in adults: a cross-sectional study. Environ Res. 2018;162:231–9.
16. Gascon M, Zijlema W, Vert C, White MP, Nieuwenhuijsen MJ. Outdoor blue spaces, human health and well-being: a systematic review of quantitative studies. Int J Hyg Environ Health. 2017;220(8):1207–21.
17. Giles-Corti B, Donovan RJ. Socioeconomic status differences in recreational physical activity levels and real and perceived access to a supportive physical environment. Prev Med. 2002;35(6):601–11.
18. Guthold R, Stevens GA, Riley LM, Bull FC. Worldwide trends in insufficient physical activity from 2001 to 2016: a pooled analysis of 358 population-based surveys with 1· 9 million participants. Lancet Glob Health. 2018;6(10): e1077–86.
19. Hajna S, Ross NA, Joseph L, Harper S, Dasgupta K. Neighbourhood walkability and daily steps in adults with type 2 diabetes. PLoS One. 2016; 11(3):e0151544.
20. Hillsdon M, Coombes E, Griew P, Jones A. An assessment of the relevance of the home neighbourhood for understanding environmental influences on physical activity: how far from home do people roam? Int J Behav Nutr Phys Act. 2015;12(1):100.
21. Houston D. Implications of the modifiable areal unit problem for assessing built environment correlates of moderate and vigorous physical activity. Appl Geogr. 2014;50:40–7.
22. James P, Hart JE, Hipp JA, Mitchell JA, Kerr J, Hurvitz PM, Glanz K, Laden F. GPS-based exposure to greenness and walkability and accelerometry-based physical activity. Cancer Epidemiol Biomark Prev. 2017;26(4):525–32.
23. Jansen M, Kamphuis CB, Pierik FH, Ettema DF, Dijst MJ. Neighborhood-based PA and its environmental correlates: a GIS-and GPS based cross-sectional study in the Netherlands. BMC Public Health. 2018;18(1):233.
24. Kaczynski AT, Mowen AJ. Does self-selection influence the relationship between park availability and physical activity? Prev Med. 2011;52(1):23–5.
25. Kantomaa MT, Tikanmäki M, Kankaanpää A, Vääräsmäki M, Sipola-Leppänen M, Ekelund U, Hakonen H, Järvelin MR, Kajantie E, Tammelin TH. Accelerometer-measured physical activity and sedentary time differ according to education level in young adults. PLoS One. 2016;11(7): e0158902.
26. Kärmeniemi M, Lankila T, Ikäheimo T, Puhakka S, Niemelä M, Jämsä T, Koivumaa-Honkanen H, Korpelainen R. Residential relocation trajectories and neighborhood density, mixed land use and access networks as predictors of walking and bicycling in the northern Finland birth cohort 1966. Int J Behav Nutr Phys Act. 2019;16(1):88.
27. Klein Tank AMG, Wijngaard JB, Können GP, Böhm R, Demarée G, Gocheva A, Mileta M, et al. Daily dataset of 20th-century surface air temperature and precipitation series for the European Climate Assessment. Int J Climatol. 2002;22(12):1441–53.
28. Kooiman TJ, Dontje ML, Sprenger SR, Krijnen WP, van der Schans CP, de Groot M. Reliability and validity of ten consumer activity trackers. BMC Sports Sci Med Rehabil. 2015;7(1):24.
29. Kwan MP. The limits of the neighborhood effect: contextual uncertainties in geographic, environmental health, and social science research. Ann Am Assoc Geogr. 2018;108(6):1482–90.
30. Labib SM, Lindley S, Huck JJ. Spatial dimensions of the influence of urban green-blue spaces on human health: a systematic review. Environ Res. 2019; 180:108869.
31. Le HT, Buehler R, Hankey S. Correlates of the built environment and active travel: evidence from 20 US metropolitan areas. Environ Health Perspect. 2018;126(07):077011.
32. Loh M, Sarigiannis D, Gotti A, Karakitsios S, Pronk A, Kuijpers E, Annesi-Maesano I, Baiz N, Madureira J, Oliveira Fernandes E, Jerrett M. How sensors might help define the external exposome. Int J Environ Res Public Health. 2017;14(4):434.
33. Maas J, Verheij RA, Spreeuwenberg P, Groenewegen PP. Physical activity as a possible mechanism behind the relationship between green space and health: a multilevel analysis. BMC Public Health. 2008;8(1):206.
34. McCormack GR. Neighbourhood built environment characteristics associated with different types of physical activity in Canadian adults. Health Promot Chronic Dis Prev Can. 2017;37(6):175–85.
35. McMorris O, Villeneuve PJ, Su J, Jerrett M. Urban greenness and physical activity in a national survey of Canadians. Environ Res. 2015;137:94–100.
36. Mueller W, Steinle S, Pärkkä J, Parmes E, Liedes H, Kuijpers E, Pronk A, Sarigiannis D, Karakitsios S, Chapizanis D, Maggos T. Urban greenspace and the indoor environment: pathways to health via indoor particulate matter, noise, and road noise annoyance. Environ Res. 2020;180:108850.
37. Ord K, Mitchell R, Pearce J. Is level of neighbourhood green space associated with physical activity in green space? Int J Behav Nutr Phys Act. 2013;10:127.
38. Pasanen TP, White MP, Wheeler BW, Garrett JK, Elliott LR. Neighbourhood blue space, health and wellbeing: the mediating role of different types of physical activity. Environ Int. 2019;131:105016.
39. QGIS Development Team. QGIS geographic information system: Open Source Geospatial Foundation Project; 2014. https://qgis.org
40. Rosina K, Batista e Silva F, Vizcaino P, Herrera MM, Freire S, Schiavina M. Increasing the detail of European land use/cover data by combining heterogeneous data sets. Int J Digit Earth. 2020;13(5):602–26. https://doi.org/10.1080/17538947.2018.1550119.
41. Rowe DA, Welk GJ, Heil DP, Mahar MT, Kemble CD, Calabró MA, Camenisch K. Stride rate recommendations for moderate-intensity walking. Med Sci Sports Exerc. 2011;43(2):312–8.
42. Saelens BE, Sallis JF, Frank LD, Cain KL, Conway TL, Chapman JE, Slymen DJ, Kerr J. Neighborhood environment and psychosocial correlates of adults' physical activity. Med Sci Sports Exerc. 2012;44(4):637–46.
43. Sallis JF, Cerin E, Conway TL, Adams MA, Frank LD, Pratt M, Salvo D, Schipperijn J, Smith G, Cain KL, Davey R. Physical activity in relation to urban environments in 14 cities worldwide: a cross-sectional study. Lancet. 2016;387(10034):2207–17.
44. Schipperijn J, Bentsen P, Troelsen J, Toftager M, Stigsdotter UK. Associations between physical activity and characteristics of urban green space. Urban For Urban Green. 2013;12(1):109–16.
45. Schipperijn J, Cerin E, Adams MA, Reis R, Smith G, Cain K, Christiansen LB, Van Dyck D, Gidlow C, Frank LD, Mitáš J. Access to parks and physical activity: an eight country comparison. Urban For Urban Green. 2017;27:253–63.
46. Shanahan DF, Franco L, Lin BB, Gaston KJ, Fuller RA. The benefits of natural environments for physical activity. Sports Med. 2016;46(7):989–95.
47. Stamatelopoulou A, Chapizanis D, Karakitsios S, Kontoroupis P, Asimakopoulos DN, Maggos T, Sarigiannis D. Assessing and enhancing the utility of low-cost activity and location sensors for exposure studies. Environ Monit Assess. 2018;190(3):155.
48. StataCorp. Stata statistical software: release 15. College Station: StataCorp LLC; 2017.
49. Stewart OT, Moudon AV, Littman AJ, Seto E, Saelens BE. Why neighborhood park proximity is not associated with total physical activity. Health Place. 2018;52:163–9.
50. Tadono T, Nagai H, Ishida H, Oda F, Naito S, Minakawa K, Iwamoto H. Generation of the 30 M-mesh global digital surface model by Alos prism: ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences; 2016. p. 157–62.
51. Tamura K, Wilson JS, Goldfeld K, Puett RC, Klenosky DB, Harper WA, Troped PJ. Accelerometer and GPS data to analyze built environments and physical activity. Res Q Exerc Sport. 2019;90(3):395–402.
52. Thornton CM, Kerr J, Conway TL, Saelens BE, Sallis JF, Ahn DK, Frank LD, Cain KL, King AC. Physical activity in older adults: an ecological approach. Ann Behav Med. 2017;51(2):159–69.
53. Triguero-Mas M, Donaire-Gonzalez D, Seto E, Valentín A, Smith G, Martínez D, Carrasco-Turigas G, Masterson D, Van den Berg M, Ambròs A, Martínez-Íñiguez T. Living close to natural outdoor environments in four European cities: adults' contact with the environments and physical activity. Int J Environ Res Public Health. 2017;14(10):1162.
54. Troped PJ, Wilson JS, Matthews CE, Cromley EK, Melly SJ. The built environment and location-based physical activity. Am J Prev Med. 2010; 38(4):429–38.
55. Twohig-Bennett C, Jones A. The health benefits of the great outdoors: a systematic review and meta-analysis of greenspace exposure and health outcomes. Environ Res. 2018;166:628–37.
56. van den Bosch MA, Mudu P, Uscila V, Barrdahl M, Kulinkina A, Staatsen B, Swart W, Kruize H, Zurlyte I, Egorov AI. Development of an urban green space indicator and the public health rationale. Scand J Public Health. 2016; 44(2):159–67.
57. van Dyck D, Cardon G, Deforche B, Sallis JF, Owen N, De Bourdeaudhuij I. Neighborhood SES and walkability are related to physical activity behavior in Belgian adults. Prev Med. 2010;50:S74–9.

58. Vich G, Marquet O, Miralles-Guasch C. Green streetscape and walking: exploring active mobility patterns in dense and compact cities. J Transp Health. 2019;12:50–9.
59. Wahid A, Manek N, Nichols M, Kelly P, Foster C, Webster P, Kaur A, Friedemann Smith C, Wilkins E, Rayner M, Roberts N. Quantifying the association between physical activity and cardiovascular disease and diabetes: a systematic review and meta-analysis. J Am Heart Assoc. 2016; 5(9):e002495.
60. Wahlgren L, Schantz P. Exploring bikeability in a metropolitan setting: stimulating and hindering factors in commuting route environments. BMC Public Health. 2012;12(1):168.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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

Akinci, Z.S., Delclòs-Alió, X., Vich, G. and Miralles-Guasch, C., 2021. Neighborhood Urban Design and Outdoor Later Life: An Objective Assessment of Out-of-Home Time and Physical Activity Among Older Adults in Barcelona. *Journal of Aging and Physical Activity*, *1*(aop), pp.1-12.

Franěk, M. and Režný, L., 2021. Environmental Features Influence Walking Speed: The Effect of Urban Greenery. *Land*, *10*(5), p.459.

Roscoe, C., Sheridan, C., Geneshka, M., Hodgson, S., Vineis, P., Gulliver, J. and Fecht, D., 2022. Green Walkability and Physical Activity in UK Biobank: A Cross-Sectional Analysis of Adults in Greater London. *International Journal of Environmental Research and Public Health*, *19*(7), p.4247.

Vich, G., Delclòs-Alió, X., Maciejewska, M., Marquet, O., Schipperijn, J. and Miralles-Guasch, C., 2021. Contribution of park visits to daily physical activity levels among older adults: Evidence using GPS and accelerometery data. *Urban Forestry & Urban Greening*, p.127225.

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.

LONDON SCHOOL of HYGIENE &TROPICAL MEDICINE

London School of Hygiene & Tropical Medicine
Keppel Street, London WC1E 7HT

T: +44 (0)20 7299 4646
F: +44 (0)20 7299 4656
www.lshtm.ac.uk

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 Pollution		
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**

*If yes, please attach evidence of retention. If no, or if the work is being included in its published format, please attach evidence of permission from the copyright holder (publisher or other author) to include this work.

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

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)	I conceived the study design, performed the analysis, wrote the first draft of the paper, and responded to reviewer comments.

SECTION E

Student Signature	William Mueller
Date	18/04/2022

Supervisor Signature	Paul Wilkinson
Date	12/07/2022

Environmental Pollution 305 (2022) 119294

Contents lists available at ScienceDirect

Environmental Pollution

journal homepage: www.elsevier.com/locate/envpol

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

William Mueller[a,b,*], Paul Wilkinson[b,c], James Milner[b,c], Miranda Loh[a], Sotiris Vardoulakis[d], Zoë Petard[e], Mark Cherrie[a], Naveen Puttaswamy[f], Kalpana Balakrishnan[f], D.K. Arvind[e]

[a] *Research, Institute of Occupational Medicine, Edinburgh, UK*
[b] *Department of Public Health, Environments and Society, London School of Hygiene & Tropical Medicine, London, UK*
[c] *Centre on Climate Change and Planetary Health, London School of Hygiene & Tropical Medicine, London, UK*
[d] *National Centre for Epidemiology and Population Health, Research School of Population Health, Australian National University, Canberra, Australia*
[e] *Centre for Speckled Computing, School of Informatics, University of Edinburgh, Scotland, UK*
[f] *Department of Environmental Health Engineering, Sri Ramachandra Institute of Higher Education and Research, Chennai, India*

ARTICLE INFO

Keywords:
Air pollution
Greenness
NDVI
Tree cover
Built environment

ABSTRACT

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

1. Introduction

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

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

☆ This paper has been recommended for acceptance by Admir Créso Targino.

* Corresponding author. Research, Institute of Occupational Medicine, Edinburgh, UK.
E-mail address: will.mueller@iom-world.org (W. Mueller).

https://doi.org/10.1016/j.envpol.2022.119294
Received 27 December 2021; Received in revised form 8 April 2022; Accepted 9 April 2022
Available online 15 April 2022
0269-7491/© 2022 Published by Elsevier Ltd.

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

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

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

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

2. Methods

2.1. Study location

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

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

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

2.2. Study participants

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

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

2.3. Air pollution measurements

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

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

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 (Rhew et al., 2011). It has continuous values ranging from −1 (ice) to 0 (rock, built-up surfaces) to +1 (dense vegetation). TC indicates the percentage (0–100%) covered by the canopy of trees as visible from satellites. GLU includes parks, forests, sports pitches, and other such natural or green types of land use.

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

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

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

(continued on next page)

Table 1 (*continued*)

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

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

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

2.5. Identification of walking journeys

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

2.6. Other covariates

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

2.7. Data analysis

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

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

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

2.8. Sensitivity analysis

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

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

3. Results

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

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

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

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

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

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

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

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

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

4. Discussion

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

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

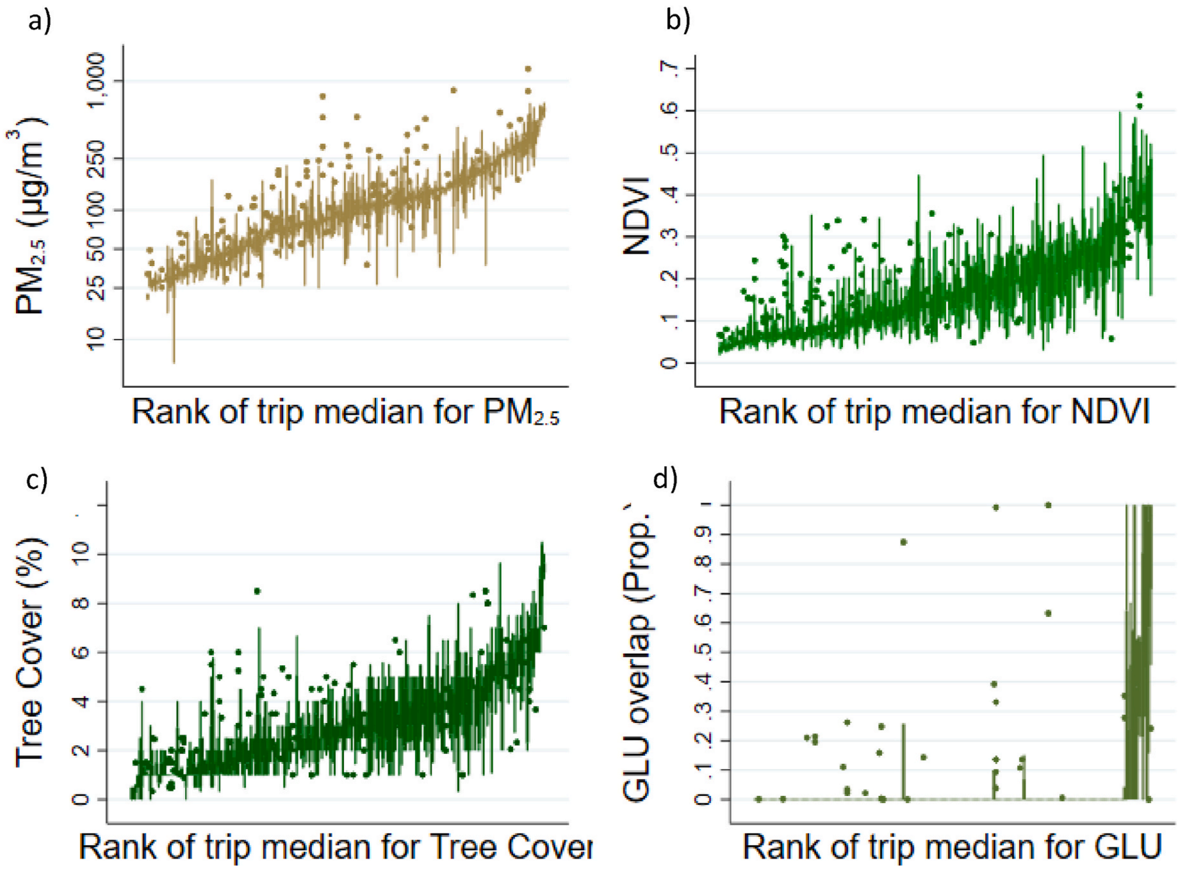


Fig. 2. Within- and between-trip variation in a) $PM_{2.5}$ concentrations (μg/m^3, log-scale), b) NDVI, c) tree cover (%), and d) proportion overlap of green land use (GLU) based on data for the 25 m radius of averaging around 1-min trip locations. Vertical bars indicate the interquartile range for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

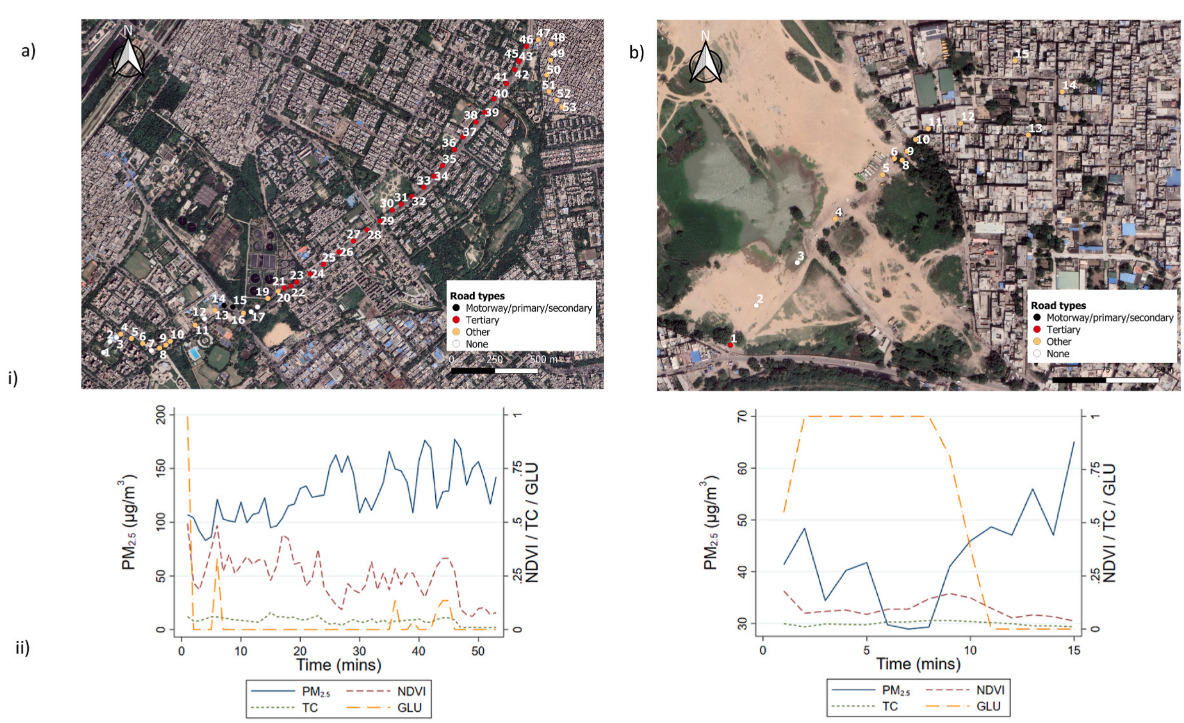


Fig. 3. Two example walking trips: a) Trip 1, in winter and b) Trip 2, in the monsoon season indicating different road type categories. For each trip we show: (i) map data ©Google Maps, (30th December 2016) with a trace of the walk route and (ii) line graphs of the minute changes in $PM_{2.5}$ concentrations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

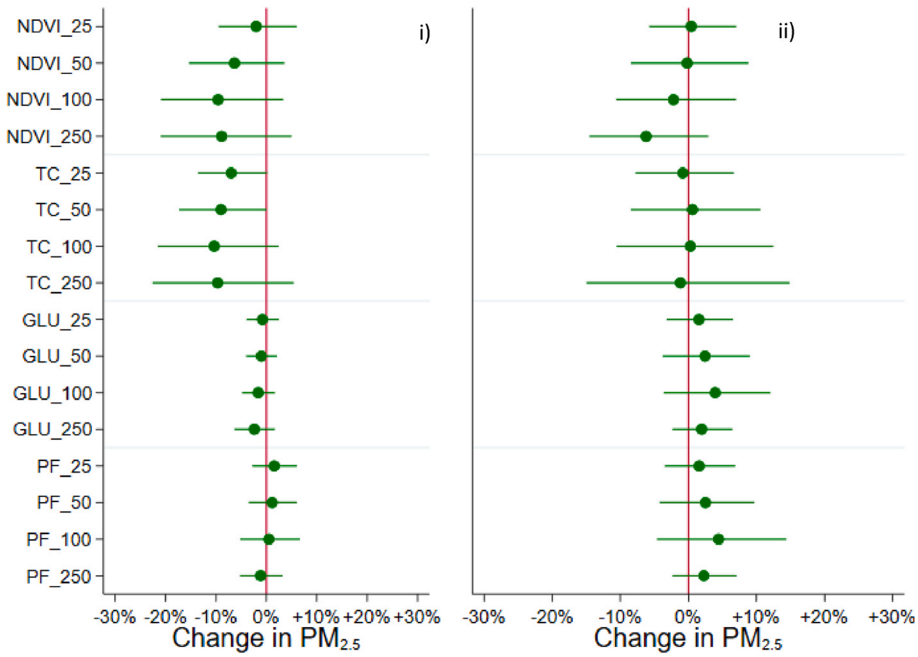


Fig. 4. Plots of regression coefficients for (i) the spring/summer/monsoon season and (ii) the autumn/winter season of within-journey changes in 1 min averaged $PM_{2.5}$ in relation to markers of greenspace. Coefficients represent an interquartile range (IQR) increase in Normalised Difference Vegetation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

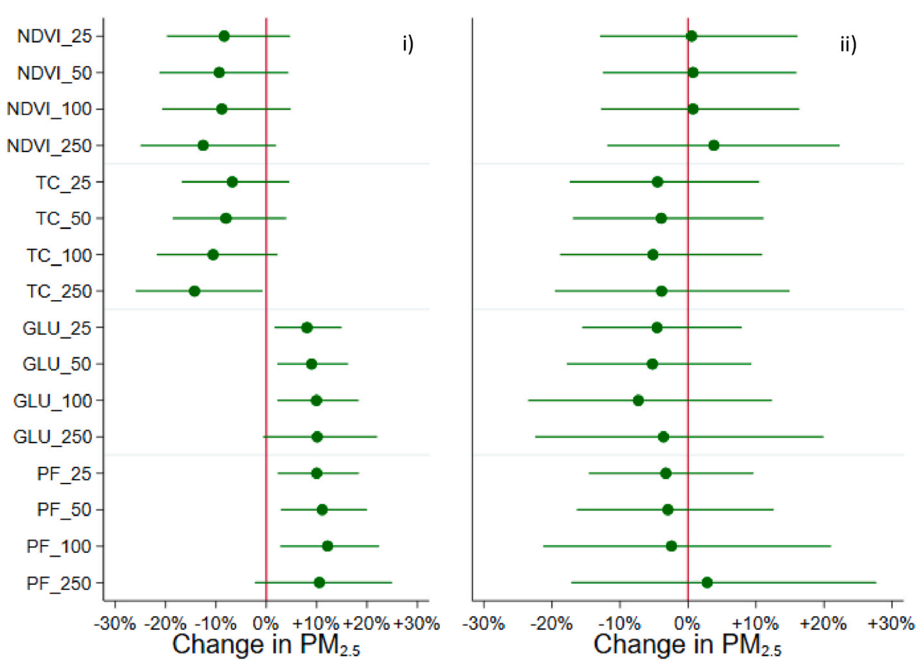


Fig. 5. Plots of regression coefficients for (i) the spring/summer/monsoon season and (ii) the autumn/winter season of between-location (between-trip) analysis of trip mean $PM_{2.5}$ concentrations in relation to markers of greenspace. Coefficients represent an interquartile range (IQR) increase in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

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

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

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

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

4.1. Overall interpretation

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

4.2. Strengths and limitations

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

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

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

5. Conclusion

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

Author statement

William Mueller: Conceptualisation, Methodology, Formal analysis, Writing – original draft, Visualisation. Paul Wilkinson: Conceptualisation, Methodology, Writing – review & editing, Supervision. James Milner: Conceptualisation, Methodology, Writing – review & editing, Supervision. Miranda Loh: Conceptualisation, Methodology, Writing – review & editing, Supervision, Funding acquisition. Sotiris Vardoulakis: Conceptualisation, Methodology, Writing – review & editing, Supervision. Zoë Petard: Software, Validation, Data curation. Mark Cherrie: Data curation, Writing – review & editing. Naveen Puttaswamy: Investigation. Kalpana Balakrishnan: Project administration, Funding acquisition, Investigation. DK Arvind: Project administration, Funding acquisition, Resources, Writing – review & editing.

Funding

This study was funded jointly by the UK Natural Environment Research Council and Medical Research Council (NE/P016340/, project DAPHNE - Delhi Air Pollution: Health and Effects).

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.

Acknowledgements

Andrew Bates and Darius Fischer are acknowledged for their work with the air pollution sensors. We thank Prof Paul Cullinan and Dr Mark Miller for their input on air pollution exposure. We are grateful for discussions with Hilary Cowie and Prof Ben Armstrong on the analysis. We thank all those on the DAPHNE research team and are very grateful to all of the participants in the DAPHNE study.

Appendix A. Supplementary data

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

References

Abhijith, K.V., Kumar, P., Gallagher, J., McNabola, A., Baldauf, R., Pilla, F., Broderick, B., Di Sabatino, S., Pulvirenti, B., 2017. Air pollution abatement performances of green infrastructure in open road and built-up street canyon environments–A review. Atmos. Environ. 162, 71–86.

Aerts, R., Dujardin, S., Nemery, B., Van Nieuwenhuyse, A., Van Orshoven, J., Aerts, J.M., Somers, B., Hendrickx, M., Bruffaerts, N., Bauwelinck, M., Casas, L., 2020. Residential green space and medication sales for childhood asthma: a longitudinal ecological study in Belgium. Environ. Res. 189, 109914.

Amann, M., Purohit, P., Bhanarkar, A.D., Bertok, I., Borken-Kleefeld, J., Cofala, J., Heyes, C., Kiesewetter, G., Klimont, Z., Liu, J., Majumdar, D., 2017. Managing future air quality in megacities: a case study for Delhi. Atmos. Environ. 161, 99–111.

Arvind, D.K., Mann, J., Bates, A., Kotsev, K., 2016. August. The AirSpeck family of static and mobile wireless air quality monitors. In: 2016 Euromicro Conference on Digital System Design (DSD). IEEE, pp. 207–214.

Arvind, D.K., Bates, C.A., Fischer, D.J., Mann, J., 2018a. March. Spatially-resolved estimation of personal dosage of airborne particulates for ambulatory subjects using wearable sensors. In: 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI). IEEE, pp. 29–32.

Arvind, D.K., Bates, C.A., Fischer, D.J., Mann, J., 2018b. March. A sensor data collection environment for clinical trials investigating health effects of airborne pollution. In: 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI). IEEE, pp. 88–91.

Balakrishnan, K., Dey, S., Gupta, T., Dhaliwal, R.S., Brauer, M., Cohen, A.J., Stanaway, J. D., Beig, G., Joshi, T.K., Aggarwal, A.N., Sabde, Y., 2019. The impact of air pollution on deaths, disease burden, and life expectancy across the states of India: the Global Burden of Disease Study 2017. Lancet Planet. Health 3 (1), e26–e39.

Basu, S., Nagendra, H., 2020. The street as workspace: assessing street vendors' rights to trees in Hyderabad, India. Landsc. Urban Plann. 199, 103818.

Bell, A., Fairbrother, M., Jones, K., 2019. Fixed and random effects models: making an informed choice. Qual. Quantity 53 (2), 1051–1074.

Bhalla, P., Bhattacharya, P., 2015. Urban biodiversity and green spaces in Delhi: a case study of new settlement and Lutyens' Delhi. J. Hum. Ecol. 52 (1–2), 83–96.

Cai, M., Xin, Z., Yu, X., 2017. Spatio-temporal variations in PM leaf deposition: a meta-analysis. Environ. Pollut. 231, 207–218.

Cai, L., Zhuang, M., Ren, Y., 2020. Spatiotemporal characteristics of NO2, PM2. 5 and O3 in a coastal region of southeastern China and their removal by green spaces. Int. J. Environ. Health Res. 1–17.

Carlson, J.A., Saelens, B.E., Kerr, J., Schipperijn, J., Conway, T.L., Frank, L.D., Chapman, J.E., Glanz, K., Cain, K.L., Sallis, J.F., 2015. Association between Neighborhood Walkability and GPS-Measured Walking, Bicycling and Vehicle Time in Adolescents, 32. Health & Place, pp. 1–7.

Center for International Earth Science Information Network (CIESIN), Columbia University, 2018. Documentation for the Gridded Population of the World, Version 4 (GPWv4), Revision 11 Data Sets. Palisades NY: NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/H45Q4T5F.

Chatzidiakou, L., Krause, A., Popoola, O.A., Di Antonio, A., Kellaway, M., Han, Y., Squires, F.A., Wang, T., Zhang, H., Wang, Q., Fan, Y., 2019. Characterising low-cost sensors in highly portable platforms to quantify personal exposure in diverse environments. Atmos. Meas. Tech. 12 (8), 4643–4657.

Chaudhary, I.J., Rathore, D., 2018. Suspended particulate matter deposition and its impact on urban trees. Atmos. Pollut. Res. 9 (6), 1072–1082.

Chen, J., Zhu, L., Fan, P., Tian, L., Lafortezza, R., 2016. Do green spaces affect the spatiotemporal changes of PM 2.5 in Nanjing? Ecological Processes 5 (1), 1–13.

Chen, M., Dai, F., Yang, B., Zhu, S., 2019. Effects of neighborhood green space on PM2. 5 mitigation: evidence from five megacities in China. Build. Environ. 156, 33–45.

Chen, Y., Wild, O., Conibear, L., Ran, L., He, J., Wang, L., Wang, Y., 2020. Local characteristics of and exposure to fine particulate matter (PM2. 5) in four indian megacities. Atmos. Environ. X (5), 100052.

Churkina, G., Kuik, F., Bonn, B., Lauer, A., Grote, R., Tomiak, K., Butler, T.M., 2017. Effect of VOC emissions from vegetation on air quality in Berlin during a heatwave. Environ. Sci. Technol. 51 (11), 6120–6130.

Corada, K., Woodward, H., Alaraj, H., Collins, C.M., de Nazelle, A., 2020. A systematic review of the leaf traits considered to contribute to removal of airborne particulate matter pollution in urban areas. Environ. Pollut. 116104.

Dadvand, P., de Nazelle, A., Triguero-Mas, M., Schembari, A., Cirach, M., Amoly, E., Figueras, F., Basagaña, X., Ostro, B., Nieuwenhuijsen, M., 2012. Surrounding greenness and exposure to air pollution during pregnancy: an analysis of personal monitoring data. Environ. Health Perspect. 120 (9), 1286–1290.

Dadvand, P., Rivas, I., Basagaña, X., Alvarez-Pedrerol, M., Su, J., Pascual, M.D.C., Amato, F., Jerret, M., Querol, X., Sunyer, J., Nieuwenhuijsen, M.J., 2015. The

association between greenness and traffic-related air pollution at schools. Sci. Total Environ. 523, 59–63.
Das, S., Prasad, P., 2012. Particulate matter capturing ability of some plant species: implication for phytoremediation of particulate pollution around Rourkela Steel Plant, Rourkela, India. Nat. Environ. Pollut. Technol. 11 (4), 657–665.
Delhi Tourism and Transportation Development Corporation, 2021. Seasons of Delhi. Last Accessed on 6 April 2021. https://delhitourism.gov.in//delhitourism/aboutus/seasons_of_delhi.jsp.
Diener, A., Mudu, P., 2021. How can vegetation protect us from air pollution? A critical review on green spaces' mitigation abilities for air-borne particles from a public health perspective-with implications for urban planning. Sci. Total Environ. 796, 148605.
European Space Agency (ESA), 2015. Sentinel-2 User Handbook. Available at: https://sentinel.esa.int/documents/247904/685211/Sentinel-2_User_Handbook.
Fan, J., Li, S., Fan, C., Bai, Z., Yang, K., 2016. The impact of PM2. 5 on asthma emergency department visits: a systematic review and meta-analysis. Environ. Sci. Pollut. Control Ser. 23 (1), 843–850.
Farrell, W.J., Cavellin, L.D., Weichenthal, S., Goldberg, M., Hatzopoulou, M., 2015. Capturing the urban canyon effect on particle number concentrations across a large road network using spatial analysis tools. Build. Environ. 92, 328–334.
Feng, S., Gao, D., Liao, F., Zhou, F., Wang, X., 2016. The health effects of ambient PM2. 5 and potential mechanisms. Ecotoxicol. Environ. Saf. 128, 67–74.
Ferrante, G., La Grutta, S., 2018. The burden of pediatric asthma. Frontiers Pediatrics 6, 186.
Fu, P., Guo, X., Cheung, F.M.H., Yung, K.K.L., 2019. The association between PM2. 5 exposure and neurological disorders: a systematic review and meta-analysis. Sci. Total Environ. 655, 1240–1248.
Goel, R., Gani, S., Guttikunda, S.K., Wilson, D., Tiwari, G., 2015. On-road PM2. 5 pollution exposure in multiple transport microenvironments in Delhi. Atmos. Environ. 123, 129–138.
Gómez-Moreno, F.J., Artíñano, B., Ramiro, E.D., Barreiro, M., Núñez, L., Coz, E., Dimitroulopoulou, C., Vardoulakis, S., Yagüe, C., Maqueda, G., Sastre, M., 2019. Urban vegetation and particle air pollution: experimental campaigns in a traffic hotspot. Environ. Pollut. 247, 195–205.
Gunasekara, F.I., Richardson, K., Carter, K., Blakely, T., 2014. Fixed effects analysis of repeated measures data. Int. J. Epidemiol. 43 (1), 264–269.
Guo, L., Luo, J., Yuan, M., Huang, Y., Shen, H., Li, T., 2019. The influence of urban planning factors on PM2. 5 pollution exposure and implications: a case study in China based on remote sensing, LBS, and GIS data. Sci. Total Environ. 659, 1585–1596.
Haaland, C., van Den Bosch, C.K., 2015. Challenges and strategies for urban green-space planning in cities undergoing densification: a review. Urban For. Urban Green. 14 (4), 760–771.
Han, D., Shen, H., Duan, W., Chen, L., 2020. A review on particulate matter removal capacity by urban forests at different scales. Urban For. Urban Green. 48, 126565.
Hart, R., Liang, L., Dong, P., 2020. Monitoring, mapping, and modeling spatial–temporal patterns of PM2. 5 for improved understanding of air pollution dynamics using portable sensing technologies. Int. J. Environ. Res. Publ. Health 17 (14), 4914.
IQAir, 2021. World's Most Polluted Cities 2020 (PM2.5. Last accessed 26 April 2021 from: https://www.iqair.com/world-most-polluted-cities.
Jain, S., Sharma, S.K., Vijayan, N., Mandal, T.K., 2020. Seasonal characteristics of aerosols (PM2. 5 and PM10) and their source apportionment using PMF: a four year study over Delhi, India. Environ. Pollut. 262, 114337.
Janhäll, S., 2015. Review on urban vegetation and particle air pollution–Deposition and dispersion. Atmos. Environ. 105, 130–137.
Jayaratne, R., Liu, X., Thai, P., Dunbabin, M., Morawska, L., 2018. The influence of humidity on the performance of a low-cost air particle mass sensor and the effect of atmospheric fog. Atmos. Meas. Tech. 11 (8), 4883–4890.
Kondo, M.C., Fluehr, J.M., McKeon, T., Branas, C.C., 2018. Urban green space and its impact on human health. Int. J. Environ. Res. Publ. Health 15 (3), 445.
Krishen, P., 2006. Trees of Delhi: A Field Guide. Penguin Books India.
Kulkarni, S.H., Ghude, S.D., Jena, C., Karumuri, R.K., Sinha, B., Sinha, V., Kumar, R., Soni, V.K., Khare, M., 2020. How much does large-scale crop residue burning affect the air quality in Delhi? Environ. Sci. Technol. 54 (8), 4790–4799.
Labib, S.M., Lindley, S., Huck, J.J., 2020. Scale effects in remotely sensed greenspace metrics and how to mitigate them for environmental health exposure assessment. Comput. Environ. Urban Syst. 82, 101501.
Lei, Y., Davies, G.M., Jin, H., Tian, G., Kim, G., 2021. Scale-dependent effects of urban greenspace on particulate matter air pollution. Urban For. Urban Green. 61, 127089.
Lelieveld, J., Pozzer, A., Pöschl, U., Fnais, M., Haines, A., Münzel, T., 2020. Loss of life expectancy from air pollution compared to other risk factors: a worldwide perspective. Cardiovasc. Res. 116 (11), 1910–1917.
Lin, C., Hu, D., Jia, X., Chen, J., Deng, F., Guo, X., Heal, M.R., Cowie, H., Wilkinson, P., Miller, M.R., Loh, M., 2020. The relationship between personal exposure and ambient PM2. 5 and black carbon in Beijing. Sci. Total Environ. 737, 139801.
Liu, C., Chen, R., Sera, F., Vicedo-Cabrera, A.M., Guo, Y., Tong, S., Coelho, M.S., Saldiva, P.H., Lavigne, E., Matus, P., Valdes Ortega, N., 2019. Ambient particulate air pollution and daily mortality in 652 cities. N. Engl. J. Med. 381 (8), 705–715.
Lun, X., Lin, Y., Chai, F., Fan, C., Li, H., Liu, J., 2020. Reviews of emission of biogenic volatile organic compounds (BVOCs) in Asia. J. Environ. Sci. 95, 266–277.
Maji, K.J., Namdeo, A., Hoban, D., Bell, M., Goodman, P., Nagendra, S.S., Barnes, J., De Vito, L., Hayes, E., Longhurst, J., Kumar, R., 2021. Analysis of various transport modes to evaluate personal exposure to PM2. 5 pollution in Delhi. Atmos. Pollut. Res. 12 (2), 417–431.
Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A.M., De Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M.J., Lupp, G., 2017. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. Environ. Res. 158, 301–317.
Marselle, M.R., Hartig, T., Cox, D.T., De Bell, S., Knapp, S., Lindley, S., Triguero-Mas, M., Böhning-Gaese, K., Braubach, M., Cook, P.A., De Vries, S., 2021. Pathways linking biodiversity to human health: A conceptual framework. Environ. Int. 150, 106420.
Milà, C., Salmon, M., Sanchez, M., Ambros, A., Bhogadi, S., Sreekanth, V., Nieuwenhuijsen, M., Kinra, S., Marshall, J.D., Tonne, C., 2018. When, where, and what? Characterizing personal PM2. 5 exposure in periurban India by integrating GPS, wearable camera, and ambient and personal monitoring data. Environ. Sci. Technol. 52 (22), 13481–13490.
Morakinyo, O.M., Mokgobu, M.I., Mukhola, M.S., Hunter, R.P., 2016. Health outcomes of exposure to biological and chemical components of inhalable and respirable particulate matter. Int. J. Environ. Res. Publ. Health 13 (6), 592.
Mueller, W., Steinle, S., Pärkkä, J., Parmes, E., Liedes, H., Kuijpers, E., Pronk, A., Sarigiannis, D., Karakitsios, S., Chapizanis, D., Maggos, T., et al., 2020. Urban greenspace and the indoor environment: pathways to health via indoor particulate matter, noise, and road noise annoyance. Environ. Res. 180, 108850.
Mueller, W., Wilkinson, P., Milner, J., Vardoulakis, S., Steinle, S., Pärkkä, J., Parmes, E., Cluitmans, L., Kuijpers, E., Pronk, A., Sarigiannis, D., et al., 2021. Neighbourhood and path-based greenspace in three European countries: associations with objective physical activity. BMC Publ. Health 21 (1), 1–13.
Mueller, W., Milner, J., Loh, M., Vardoulakis, S., Wilkinson, P., 2022. Exposure to urban greenspace and pathways to respiratory health: an exploratory systematic review. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2022.154447 (in press).
Murthy, B.S., Latha, R., Tiwari, A., Rathod, A., Singh, S., Beig, G., 2020. Impact of mixing layer height on air quality in winter. J. Atmos. Sol. Terr. Phys. 197, 105157.
Nawrath, M., Guenat, S., Elsey, H., Dallimer, M., 2021. Exploring uncharted territory: do urban greenspaces support mental health in low-and middle-income countries? Environ. Res. 110625.
Nemitz, E., Vieno, M., Carnell, E., Fitch, A., Steadman, C., Cryle, P., Holland, M., Morton, R.D., Hall, J., Mills, G., Hayes, F., 2020. Potential and limitation of air pollution mitigation by vegetation and uncertainties of deposition-based evaluations. Philos.Trans. Royal Soc. A 378 (2183), 20190320.
Orellano, P., Quaranta, N., Reynoso, J., Balbi, B., Vasquez, J., 2017. Effect of outdoor air pollution on asthma exacerbations in children and adults: systematic review and multilevel meta-analysis. PLoS One 12 (3), e0174050.
Pace, R., Grote, R., 2020. Deposition and resuspension mechanisms into and from tree canopies: a study modeling particle removal of conifers and broadleaves in different cities. Front. Forests Global Change 3, 26.
Paul, S., Nagendra, H., 2015. Vegetation change and fragmentation in the mega city of Delhi: mapping 25 years of change. Appl. Geogr. 58, 153–166.
Paul, S., Nagendra, H., 2017. Factors influencing perceptions and use of urban nature: surveys of park visitors in Delhi. Land 6 (2), 27.
Peng, L., Shen, Y., Gao, W., Zhou, J., Pan, L., Kan, H., Cai, J., 2021. Personal exposure to PM2. 5 in five commuting modes under hazy and non-hazy conditions. Environ. Pollut. 289, 117823.
QGIS Development Team, 2014. QGIS Geographic Information System: Open Source Geospatial Foundation Project. https://qgis.org.
Ramaiah, M., Avtar, R., 2019. Urban green spaces and their need in cities of rapidly urbanizing India: a review. Urban Science 3 (3), 94.
Rhew, I.C., Vander Stoep, A., Kearney, A., Smith, N.L., Dunbar, M.D., 2011. Validation of the normalized difference vegetation index as a measure of neighborhood greenness. Ann. Epidemiol. 21 (12), 946–952.
Roberts, H., Helbich, M., 2021. Multiple environmental exposures along daily mobility paths and depressive symptoms: a smartphone-based tracking study. Environ. Int. 156, 106635.
Sahu, S.K., Beig, G., Parkhi, N.S., 2011. Emissions inventory of anthropogenic PM2. 5 and PM10 in Delhi during commonwealth games 2010. Atmos. Environ. 45 (34), 6180–6190.
Salmond, J.A., Tadaki, M., Vardoulakis, S., Arbuthnott, K., Coutts, A., Demuzere, M., Dirks, K.N., Heaviside, C., Lim, S., Macintyre, H., McInnes, R.N., 2016. Health and climate related ecosystem services provided by street trees in the urban environment. Environ. Health 15 (1), 95–111.
Schultz, E.S., Litonjua, A.A., Melén, E., 2017. Effects of long-term exposure to traffic-related air pollution on lung function in children. Curr. Allergy Asthma Rep. 17 (6), 1–13.
Sexton, J.O., Song, X.P., Feng, M., Noojipady, P., Anand, A., Huang, C., Kim, D.H., Collins, K.M., Channan, S., DiMiceli, C., Townshend, J.R., 2013. Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS vegetation continuous fields with lidar-based estimates of error. Int. J. Digital Earth 6 (5), 427–448.
StataCorp, 2019. Stata Statistical Software: Release 16. College Station. StataCorp LLC.
Stewart, T., Schipperijn, J., Snizek, B., Duncan, S., 2017. Adolescent school travel: is online mapping a practical alternative to GPS-assessed travel routes? J. Transport Health 5, 113–122.
Su, J.G., Jerrett, M., de Nazelle, A., Wolch, J., 2011. Does exposure to air pollution in urban parks have socioeconomic, racial or ethnic gradients? Environ. Res. 111 (3), 319–328.
Tainio, M., Andersen, Z.J., Nieuwenhuijsen, M.J., Hu, L., de Nazelle, A., An, R., Garcia, L. M., Goenka, S., Zapata-Diomedi, B., Bull, F., de Sá, T.H., 2021. Air pollution, physical activity and health: a mapping review of the evidence. Environ. Int. 147, 105954.
Tiwari, S., Bisht, D.S., Srivastava, A.K., Pipal, A.S., Taneja, A., Srivastava, M.K., Attri, S. D., 2014. Variability in atmospheric particulates and meteorological effects on their mass concentrations over Delhi, India. Atmos. Res. 145, 45–56.

Twohig-Bennett, C., Jones, A., 2018. The health benefits of the great outdoors: a systematic review and meta-analysis of greenspace exposure and health outcomes. Environ. Res. 166, 628–637.

United Nations (UN), 2018. The World's Cities in 2018. Department of Economic and Social Affairs. Population Division, World Urbanization Prospects, pp. 1–34.

Vailshery, L.S., Jaganmohan, M., Nagendra, H., 2013. Effect of street trees on microclimate and air pollution in a tropical city. Urban For. Urban Green. 12 (3), 408–415.

Van Hecke, L., Verhoeven, H., Clarys, P., Van Dyck, D., Van de Weghe, N., Baert, T., Deforche, B., Van Cauwenberg, J., 2018. Factors related with public open space use among adolescents: a study using GPS and accelerometers. Int. J. Health Geogr. 17 (1), 1–16.

Viippola, V., Yli-Pelkonen, V., Järvi, L., Kulmala, M., Setälä, H., 2020. Effects of forests on particle number concentrations in near-road environments across three geographic regions. Environ. Pollut. 266, 115294.

von Schneidemesser, E., Steinmar, K., Weatherhead, E.C., Bonn, B., Gerwig, H., Quedenau, J., 2019. Air pollution at human scales in an urban environment: impact of local environment and vehicles on particle number concentrations. Sci. Total Environ. 688, 691–700.

Wendelboe-Nelson, C., Kelly, S., Kennedy, M., Cherrie, J.W., 2019. A scoping review mapping research on green space and associated mental health benefits. Int. J. Environ. Res. Publ. Health 16 (12), 2081.

Xing, Y., Brimblecombe, P., 2019. Role of vegetation in deposition and dispersion of air pollution in urban parks. Atmos. Environ. 201, 73–83.

Xing, Y., Brimblecombe, P., 2020a. Trees and parks as "the lungs of cities". Urban For. Urban Green. 48, 126552.

Xing, Y., Brimblecombe, P., 2020b. Urban park layout and exposure to traffic-derived air pollutants. Landsc. Urban Plann. 194, 103682.

Xu, X., Yu, X., Mo, L., Xu, Y., Bao, L., Lun, X., 2019. Atmospheric particulate matter accumulation on trees: a comparison of boles, branches and leaves. J. Clean. Prod. 226, 349–356.

Xu, X., Xia, J., Gao, Y., Zheng, W., 2020. Additional focus on particulate matter wash-off events from leaves is required: a review of studies of urban plants used to reduce airborne particulate matter pollution. Urban For. Urban Green. 48, 126559.

Yadav, R., Sahu, L.K., Beig, G., Tripathi, N., Maji, S., Jaaffrey, S.N.A., 2019. The role of local meteorology on ambient particulate and gaseous species at an urban site of western India. Urban Clim. 28, 100449.

Zheng, X.Y., Ding, H., Jiang, L.N., Chen, S.W., Zheng, J.P., Qiu, M., Zhou, Y.X., Chen, Q., Guan, W.J., 2015. Association between air pollutants and asthma emergency room visits and hospital admissions in time series studies: a systematic review and meta-analysis. PLoS One 10 (9), e0138146.

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] $\mu g/m^3$) 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 pubic 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 $\mu g/m^3$ (Edinburgh, UK) to 12.4 $\mu g/m^3$ (Athens, UK), whereas the mean concentration during walking journeys in Delhi, India was more than 10 times higher (134 $\mu g/m^3$). 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 μg/m^3 [equivalent to a ~10% reduction of the overall mean of 12.4 μg/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 μg/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 μg/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 μg/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 μg/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/m^3), according to my results (50 m buffer). This reduction would entail a -0.4 μg/m^3 change in the daily mean concentration (i.e., 59.8 to 59.4 μg/m^3). The relative risk for asthma emergency department visits from a meta-analysis (Fan et al., 2016) was 3.6% per 10 μg/m^3, 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 O_3 and NO_2, 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 CO_2 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.

7.9 References

Akpinar, A., 2016. How is quality of urban green spaces associated with physical activity and health?. *Urban Forestry & Urban Greening*, *16*, pp.76-83.

Alasauskas, S., Ustinaviciene, R. and Kavaliauskas, M., 2020. Residential links to air pollution and school children with asthma in Vilnius (population study). *Medicina*, *56*(7), p.346.

Andersen, H.B., Christiansen, L.B., Klinker, C.D., Ersbøll, A.K., Troelsen, J., Kerr, J. and Schipperijn, J., 2017. Increases in use and activity due to urban renewal: Effect of a natural experiment. *American Journal of Preventive Medicine*, *53*(3), pp.e81-e87.

Andrusaityte, S., Grazuleviciene, R., Kudzyte, J., Bernotiene, A., Dedele, A. and Nieuwenhuijsen, M.J., 2016. Associations between neighbourhood greenness and asthma in preschool children in Kaunas, Lithuania: a case–control study. *BMJ Open*, 6(4).

Arem, H., Moore, S.C., Patel, A., Hartge, P., De Gonzalez, A.B., Visvanathan, K., Campbell, P.T., Freedman, M., Weiderpass, E., Adami, H.O. and Linet, M.S., 2015. Leisure time physical activity and mortality: a detailed pooled analysis of the dose-response relationship. *JAMA Internal Medicine*, *175*(6), pp.959-967.

Auchincloss, A.H., Michael, Y.L., Kuder, J.F., Shi, J., Khan, S. and Ballester, L.S., 2019. Changes in physical activity after building a greenway in a disadvantaged urban community: A natural experiment. *Preventive Medicine Reports*, *15*, p.100941.

Bancroft, C., Joshi, S., Rundle, A., Hutson, M., Chong, C., Weiss, C.C., Genkinger, J., Neckerman, K. and Lovasi, G., 2015. Association of proximity and density of parks and objectively measured physical activity in the United States: A systematic review. *Social Science & Medicine*, *138*, pp.22-30.

Barbarossa, L., 2020. The post pandemic city: Challenges and opportunities for a non-motorized urban environment. An overview of Italian cases. *Sustainability*, *12*(17), p.7172.

Bauwelinck, M., Casas, L., Nawrot, T.S., Nemery, B., Trabelsi, S., Thomas, I., Aerts, R., Lefebvre, W., Vanpoucke, C., Van Nieuwenhuyse, A. and Deboosere, P., 2021. Residing in urban areas with higher green space is associated with lower mortality risk: a census-based cohort study with ten years of follow-up. *Environment International*, *148*, p.106365.

Besser, L.M. and Mitsova, D.P., 2021. Neighborhood Green Land Cover and Neighborhood-Based Walking in US Older Adults. *American Journal of Preventive Medicine*, *61*(1), pp.e13-e20.

Bratman, G.N., Anderson, C.B., Berman, M.G., Cochran, B., De Vries, S., Flanders, J., Folke, C., Frumkin, H., Gross, J.J., Hartig, T. and Kahn Jr, P.H., 2019. Nature and mental health: An ecosystem service perspective. *Science Advances*, *5*(7), p.eaax0903.

British Lung Foundation (BLF), 2016. *The battle for breath: the impact of lung disease in the UK*.

Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C.A., Apte, J.S., Brauer, M., Cohen, A., Weichenthal, S. and Coggins, J., 2018. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proceedings of the National Academy of Sciences*, *115*(38), pp.9592-9597.

Cai, M., Xin, Z. and Yu, X., 2017. Spatio-temporal variations in PM leaf deposition: A meta-analysis. *Environmental Pollution*, *231*, pp.207-218.

Cavalcante de Sá, M., Nakagawa, N.K., de André, C.D.S., Carvalho-Oliveira, R., de Santana Carvalho, T., Nicola, M.L., de André, P.A., Saldiva, P.H.N. and Vaisberg, M., 2016. Aerobic exercise in polluted urban environments: effects on airway defense mechanisms in young healthy amateur runners. *Journal of Breath Research*, *10*(4), p.046018.

Cheng, S.W.M., McKeough, Z., Alison, J., Dennis, S., Hamer, M. and Stamatakis, E., 2018. Associations of total and type-specific physical activity with mortality in chronic obstructive pulmonary disease: a population-based cohort study. *BMC Public Health*, *18*(1), pp.1-11.

D'Amato, G., Chong-Neto, H.J., Monge Ortega, O.P., Vitale, C., Ansotegui, I., Rosario, N., Haahtela, T., Galan, C., Pawankar, R., Murrieta-Aguttes, M. and Cecchi, L., 2020. The effects of climate change on respiratory allergy and asthma induced by pollen and mold allergens. *Allergy*, *75*(9), pp.2219-2228.

Diener, A. and Mudu, P., 2021. How can vegetation protect us from air pollution? A critical review on green spaces' mitigation abilities for air-borne particles from a public health perspective-with implications for urban planning. *Science of the Total Environment*, *796*, p.148605.

Donovan, G.H., Butry, D.T., Michael, Y.L., Prestemon, J.P., Liebhold, A.M., Gatziolis, D. and Mao, M.Y., 2013. The relationship between trees and human health: evidence from the spread of the emerald ash borer. *American journal of Preventive Medicine*, *44*(2), pp.139-145.

Eze, I.C., Foraster, M., Schaffner, E., Vienneau, D., Héritier, H., Pieren, R., Thiesse, L., Rudzik, F., Rothe, T., Pons, M. and Bettschart, R., 2018. Transportation noise exposure, noise annoyance and respiratory health in adults: A repeated-measures study. *Environment International*, *121*, pp.741-750.

Fan, J., Li, S., Fan, C., Bai, Z. and Yang, K., 2016. The impact of PM2. 5 on asthma emergency department visits: a systematic review and meta-analysis. *Environmental Science and Pollution Research*, *23*(1), pp.843-850.

Ferrante, G., Asta, F., Cilluffo, G., De Sario, M., Michelozzi, P. and La Grutta, S., 2020. The effect of residential urban greenness on allergic respiratory diseases in youth: A narrative review. *World Allergy Organization Journal*, *13*(1), p.100096.

Franklin, M., Yin, X., McConnell, R. and Fruin, S., 2020. Association of the built environment with childhood psychosocial stress. *JAMA Network Open*, *3*(10), pp.e2017634-e2017634.

Han, D., Shen, H., Duan, W. and Chen, L., 2020. A review on particulate matter removal capacity by urban forests at different scales. *Urban Forestry & Urban Greening*, *48*, p.126565.

Hartley, K., Ryan, P., Brokamp, C. and Gillespie, G.L., 2020. Effect of greenness on asthma in children: A systematic review. *Public Health Nursing*, *37*(3), pp.453-460.

He, D., Lu, Y., Xie, B. and Helbich, M., 2021. Large-scale greenway intervention promotes walking behaviors: A natural experiment in China. *Transportation Research Part D: Transport and Environment*, *101*, p.103095.

Huang, J., Deng, F., Wu, S., Zhao, Y., Shima, M., Guo, B., Liu, Q. and Guo, X., 2016. Acute effects on pulmonary function in young healthy adults exposed to traffic-related air pollution in semi-closed transport hub in Beijing. *Environmental Health and Preventive Medicine*, *21*(5), pp.312-320.

Hunter, R.F., Adlakha, D., Cardwell, C., Cupples, M.E., Donnelly, M., Ellis, G., Gough, A., Hutchinson, G., Kearney, T., Longo, A. and Prior, L., 2021. Investigating the physical activity, health, wellbeing, social and environmental effects of a new urban greenway: a natural experiment (the PARC study). *International Journal of Behavioral Nutrition and Physical Activity*, *18*(1), pp.1-19.

James, P., Hart, J.E., Banay, R.F. and Laden, F., 2016. Exposure to greenness and mortality in a nationwide prospective cohort study of women. *Environmental Health Perspectives*, *124*(9), pp.1344-1352.

Knobel, P., Maneja, R., Bartoll, X., Alonso, L., Bauwelinck, M., Valentin, A., Zijlema, W., Borrell, C., Nieuwenhuijsen, M. and Dadvand, P., 2021. Quality of urban green spaces influences residents' use of these spaces, physical activity, and overweight/obesity. *Environmental Pollution*, *271*, p.116393.

Kondo, M.C., Fluehr, J.M., McKeon, T. and Branas, C.C., 2018. Urban green space and its impact on human health. *International Journal of Environmental Research and Public Health*, *15*(3), p.445.

Lahart, I., Darcy, P., Gidlow, C. and Calogiuri, G., 2019. The effects of green exercise on physical and mental wellbeing: A systematic review. *International Journal of Environmental Research and Public Health*, *16*(8), p.1352.

Lambert, K.A., Bowatte, G., Tham, R., Lodge, C., Prendergast, L., Heinrich, J., Abramson, M.J., Dharmage, S.C. and Erbas, B., 2017. Residential greenness and allergic respiratory diseases in children and adolescents–a systematic review and meta-analysis. *Environmental Research*, *159*, pp.212-221.

Lin, C., Hu, D., Jia, X., Chen, J., Deng, F., Guo, X., Heal, M.R., Cowie, H., Wilkinson, P., Miller, M.R. and Loh, M., 2020. The relationship between personal exposure and ambient PM2. 5 and black carbon in Beijing. *Science of The Total Environment*, *737*, p.139801.

Lovasi, G.S., O'Neil-Dunne, J.P., Lu, J.W., Sheehan, D., Perzanowski, M.S., MacFaden, S.W., King, K.L., Matte, T., Miller, R.L., Hoepner, L.A. and Perera, F.P., 2013. Urban tree canopy and asthma, wheeze, rhinitis, and allergic sensitization to tree pollen in a New York City birth cohort. *Environmental Health Perspectives*, *121*(4), pp.494-500.

Lu, Y., Zhao, J., Wu, X. and Lo, S.M., 2021. Escaping to nature during a pandemic: A natural experiment in Asian cities during the COVID-19 pandemic with big social media data. *Science of the Total Environment*, *777*, p.146092.

Matz, C.J., Stieb, D.M. and Brion, O., 2015. Urban-rural differences in daily time-activity patterns, occupational activity and housing characteristics. *Environmental Health*, *14*(1), pp.1-11.

McCambridge, J., Witton, J. and Elbourne, D.R., 2014. Systematic review of the Hawthorne effect: new concepts are needed to study research participation effects. *Journal of Clinical Epidemiology*, *67*(3), pp.267-277.

Mell, I. and Whitten, M., 2021. Access to nature in a post COVID-19 world: Opportunities for green infrastructure financing, distribution and equitability in urban planning. *International Journal of Environmental Research and Public Health*, *18*(4), p.1527.

Moshammer, H., Panholzer, J., Ulbing, L., Udvarhelyi, E., Ebenbauer, B. and Peter, S., 2019. Acute effects of air pollution and noise from road traffic in a panel of young healthy adults. *International Journal of Environmental Research and Public Health*, *16*(5), p.788.

Nawrath, M., Guenat, S., Elsey, H. and Dallimer, M., 2020. Exploring uncharted territory: Do urban greenspaces support mental health in low-and middle-income countries?. *Environmental Research*, p.110625.

Neumann, J.E., Anenberg, S.C., Weinberger, K.R., Amend, M., Gulati, S., Crimmins, A., Roman, H., Fann, N. and Kinney, P.L., 2019. Estimates of present and future asthma emergency department visits associated with exposure to oak, birch, and grass pollen in the United States. *GeoHealth*, *3*(1), pp.11-27.

Nieuwenhuijsen, M.J., 2021. New urban models for more sustainable, liveable and healthier cities post covid19; reducing air pollution, noise and heat island effects and increasing green space and physical activity. *Environment International*, 157, p.106850.

Nieuwenhuijsen, M., Bastiaanssen, J., Sersli, S., Waygood, E.O.D. and Khreis, H., 2019. Implementing car-free cities: rationale, requirements, barriers and facilitators. In *Integrating Human Health into Urban and Transport Planning* (pp. 199-219). Springer, Cham.

Pant, P., Habib, G., Marshall, J.D. and Peltier, R.E., 2017. PM2. 5 exposure in highly polluted cities: A case study from New Delhi, India. *Environmental Research*, *156*, pp.167-174.

Pearce, J.R., Richardson, E.A., Mitchell, R.J. and Shortt, N.K., 2010. Environmental justice and health: the implications of the socio-spatial distribution of multiple environmental deprivation for health inequalities in the United Kingdom. *Transactions of the Institute of British Geographers*, *35*(4), pp.522-539.

Peng, L., Shen, Y., Gao, W., Zhou, J., Pan, L., Kan, H. and Cai, J., 2021. Personal exposure to PM2. 5 in five commuting modes under hazy and non-hazy conditions. *Environmental Pollution*, *289*, p.117823.

Rahman, M.A., Stratopoulos, L.M., Moser-Reischl, A., Zölch, T., Häberle, K.H., Rötzer, T., Pretzsch, H. and Pauleit, S., 2020. Traits of trees for cooling urban heat islands: A meta-analysis. *Building and Environment*, *170*, p.106606.

Recio, A., Linares, C., Banegas, J.R. and Díaz, J., 2016. Road traffic noise effects on cardiovascular, respiratory, and metabolic health: An integrative model of biological mechanisms. *Environmental Research*, *146*, pp.359-370.

Rigolon, A., Browning, M.H., Lee, K. and Shin, S., 2018. Access to urban green space in cities of the Global South: A systematic literature review. *Urban Science*, *2*(3), p.67.

Robinson, J.M. and Breed, M.F., 2019. Green prescriptions and their co-benefits: Integrative strategies for public and environmental health. *Challenges*, *10*(1), p.9.

Roe, J., Aspinall, P.A. and Ward Thompson, C., 2016. Understanding relationships between health, ethnicity, place and the role of urban green space in deprived urban communities. *International Journal of Environmental Research and Public Health*, *13*(7), p.681.

Sharifi, F., Levin, I., Stone, W.M. and Nygaard, A., 2021. Green space and subjective well-being in the Just City: A scoping review. *Environmental Science & Policy*, *120*, pp.118-126.

Sinharay, R., Gong, J., Barratt, B., Ohman-Strickland, P., Ernst, S., Kelly, F.J., Zhang, J.J., Collins, P., Cullinan, P. and Chung, K.F., 2018. Respiratory and cardiovascular responses to walking down a traffic-polluted road compared with walking in a traffic-free area in participants aged 60 years and older with chronic lung or heart disease and age-matched healthy controls: a randomised, crossover study. *The Lancet*, *391*(10118), pp.339-349.

Soga, M., Evans, M.J., Cox, D.T. and Gaston, K.J., 2021. Impacts of the COVID-19 pandemic on human–nature interactions: Pathways, evidence and implications. *People and Nature*, *3*(3), pp.518-527.

Su, J.G., Dadvand, P., Nieuwenhuijsen, M.J., Bartoll, X. and Jerrett, M., 2019. Associations of green space metrics with health and behavior outcomes at different buffer sizes and remote sensing sensor resolutions. *Environment International*, *126*, pp.162-170.

Tainio, M., Andersen, Z.J., Nieuwenhuijsen, M.J., Hu, L., de Nazelle, A., An, R., Garcia, L.M., Goenka, S., Zapata-Diomedi, B., Bull, F. and de Sá, T.H., 2021. Air pollution, physical activity and health: A mapping review of the evidence. *Environment International*, *147*, p.105954.

Tong, Z., Chen, Y., Malkawi, A., Adamkiewicz, G. and Spengler, J.D., 2016. Quantifying the impact of traffic-related air pollution on the indoor air quality of a naturally ventilated building. *Environment International*, *89*, pp.138-146.

Twohig-Bennett, C. and Jones, A., 2018. The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes. *Environmental Research*, *166*, pp.628-637.

Venter, Z.S., Barton, D.N., Gundersen, V., Figari, H. and Nowell, M.S., 2021. Back to nature: Norwegians sustain increased recreational use of urban green space months after the COVID-19 outbreak. *Landscape and Urban Planning*, *214*, p.104175.

Wang, X., Liu, Y., Zhu, C., Yao, Y. and Helbich, M., 2022. Associations between the streetscape built environment and walking to school among primary schoolchildren in Beijing, China. *Journal of Transport Geography*, *99*, p.103303.

World Health Organization (WHO), 2017. A Brief for Action. *Copenhagen: WHO Regional Office for Europe*.

WHO, 2020. WHO guidelines on physical activity and sedentary behaviour: web annex: evidence profiles.

Yang, B.Y., Zhao, T., Hu, L.X., Browning, M.H., Heinrich, J., Dharmage, S.C., Jalaludin, B., Knibbs, L.D., Liu, X.X., Luo, Y.N. and James, P., 2021. Greenspace and human health: An umbrella review. *The Innovation*, *2*(4), p.100164.

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

William Mueller[1,2], James Milner[2], Miranda Loh[1], Sotiris Vardoulakis[3], Paul Wilkinson[2]

[1] Institute of Occupational Medicine, Edinburgh, UK
[2] London School of Hygiene & Tropical Medicine, UK
[3] National Centre for Epidemiology and Population Health, Australian National University, Australia

Corresponding author:

Mr William Mueller
email: will.mueller@iom-world.org
Address: Institute of Occupational Medicine, Research Avenue North, Edinburgh, Midlothian EH14 4AP

Contents

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

<u>Search strategy (title, abstract)</u>:
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.

<u>Language</u>: English

<u>Dates</u>: Review everything published from 01 January 2000 - 31 December 2018

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

<u>Filter for publication type</u>: 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

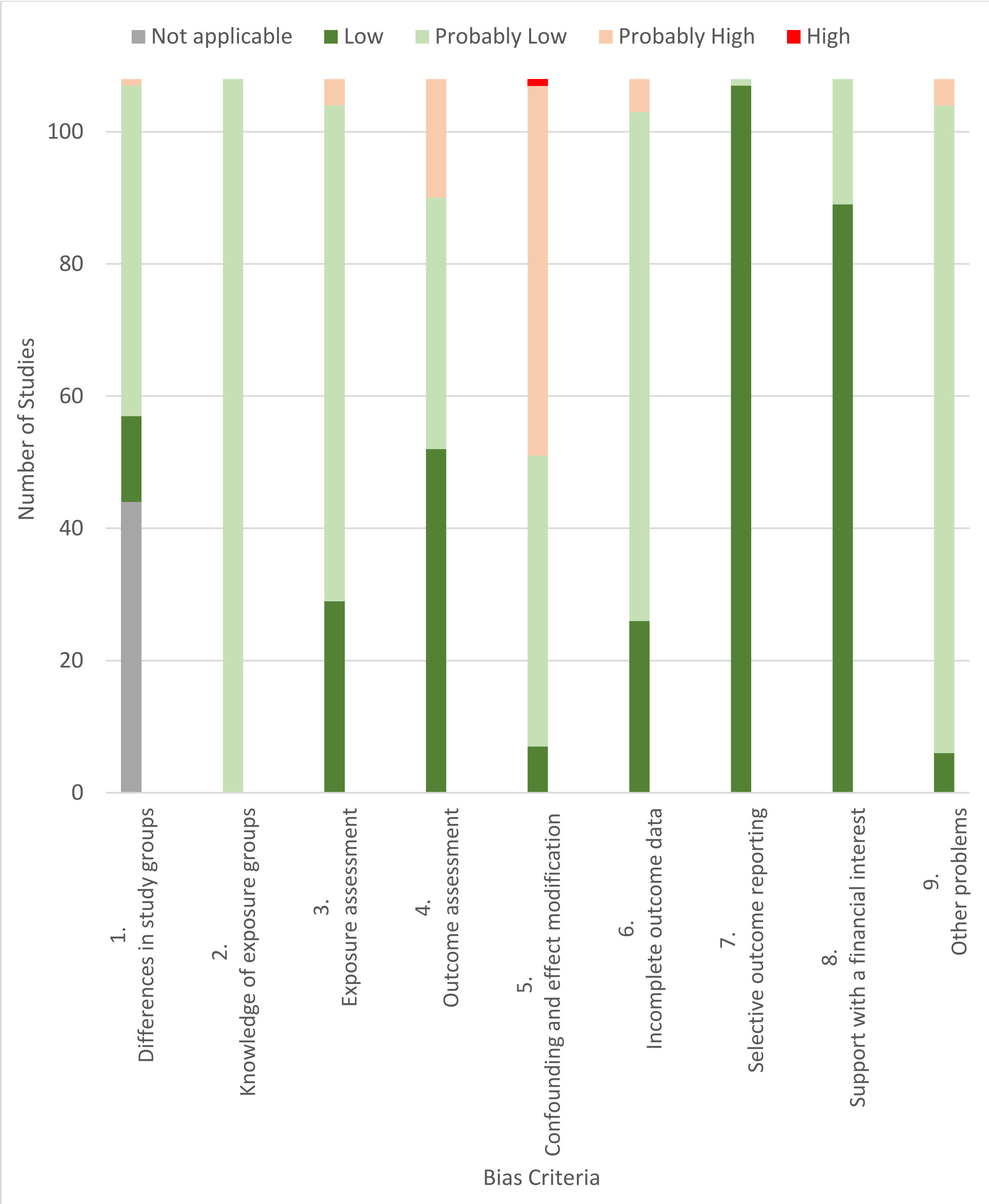


Figure S1. The distribution of the risk of bias ratings for each criterion.

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

Cardoso	2014	Outdoor exercise under different concentrations of PM2,5 and effects on CC16 protein in healthy individuals, Sao Paulo/ Brazil	1
Carinanos	2002	Privet pollen (Ligustrum 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

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 NH3 and excreted Nh4+ 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 va riables 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

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

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 NO2 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

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 (Betula pendula) 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

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

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
Klompmaker	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
Klompmaker	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
Klompmaker	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
											by sex, no adjustment for smoking									
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 outcom e data present ed	Low	Research grants.	Probably Low	Potential for exposure misclassificati on (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	Outco mes are reporte d	Low	Funded by governme nt 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	Outco mes are reporte d.	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	Outco mes are reporte d	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
Alasauskas	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
							QA/QC information.												data on use of greenspace.	
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
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)	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
													without outcome data							
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	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
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
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
			for in analysis		likely to affect results.		4 years of age													
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

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

	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
	Rating=0	Rating=-1	Rating=-1	Rating=-1	Rating=0
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
	Rating=-1	Rating=0	Rating=0	Rating=-1	Rating=0
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	Rating=0 Relatively modest magnitudes of effect	Rating=+1 Studies tend to provide effect estimate per unit (e.g., IQR) increase in greenspace	Rating=0 Not likely that residual confounding would underestimate results
Hospital admissions	Rating=0 Relatively modest magnitudes of effect	Rating=0 Little evidence of a dose-response effect	Rating=0 Not likely that residual confounding would underestimate results
Lung cancer	Rating=0 Relatively modest magnitudes of effect	Rating=0 Little evidence of a dose-response effect	Rating=0 Not likely that residual confounding would underestimate results
Asthma	Rating=0 Some larger magnitudes of effect, but in both directions	Rating=0 Inconsistent	Rating=0 Not likely that residual confounding would underestimate results
Lung function	Rating=0 Some larger magnitudes of effect, but inconsistent	Rating=0 Inconsistent	Rating=0 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**.**

	Monitoring period			
City	**Start**	**End**	**NDVI - summer**	**NDVI - seasonal**
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

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	☐2	☐1		☐	☐
	☐2	☐1		☐	☐
	☐2	☐1		☐	☐
	☐2	☐1		☐	☐
	☐2	☐1		☐	☐
	☐2	☐1		☐	☐
	☐2	☐1		☐	☐
	☐2	☐1		☐	☐

	☐2	☐1		☐	☐
	☐2	☐1		☐	☐

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

No ☐2 Yes ☐1 Please give ages :

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

Married ☐1 Civil partnership ☐2 Single ☐3 Separated ☐4 Divorced ☐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 ☐1 one 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 ☐1 Sometimes ☐2 Never ☐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			b) Religion			c) Place of birth		
	You (a_i)	**Other parent (a_ii)**		**You (b_i)**	**Other parent (b_ii)**		**You (c_i)**	**Other parent (c_ii)**

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

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)		
Study child (b_i = weekday, b_ii = weekend)		
Your partner (if applicable) (c_i = weekday, c_ii = weekend)		
Main earner (if different) (d_i = weekday, d_ii = weekend)		

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

	You (a)	Other parent (b)	Main earner (if different) (c)
None	☐1a	☐1b	☐1c
School	☐2a	☐2b	☐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)	☐1a	☐1b	☐1c
Pupil, student, further training, unpaid work experience	☐2a	☐2b	☐2c
In retirement (including early retirement)	☐3a	☐3b	☐3c
Permanently sick or disabled	☐4a	☐4b	☐4c
Caring for home and/or family (unpaid)	☐5a	☐5b	☐5c
Unemployed	☐6a	☐6b	☐6c
Other (write in)	☐7a	☐7b	☐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)	☐1a	☐1b	☐1c
Job title(Oc1job_b)			
Full time$_1$ or part time$_2$?(Oc1job_c)			
Main job tasks(Oc1job_d)			
Main activity of the employer/business(Oc1job_e)			

Tick box if self employed(Oc1job_f)	☐2a	☐2b	☐2c		
Number of supervisees/ employeesOc1job_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)					
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? (Dc1othr)

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 crèchepID_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

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

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_from)	To (month and year)(Hi2emp_to)	Occupation(Hi2emp_occupation)	Address (if known)(Hi2emp_add)	Indoor or Outdoor Job?(Hi2emp_ind_out	
				Largely Indoor (1)	Largely Outdoor (2)

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

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 Outdoo r

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

<u>IN-HOME ROUTINES</u>
*[**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 <u>whole</u> family away from home on a typical <u>weekday</u>?
☐ 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 <u>whole</u> family away from home on a typical <u>weekend day</u>?
☐ 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

William Mueller[1,2*], Paul Wilkinson[2,3], James Milner[2,3], Miranda Loh[1], Sotiris Vardoulakis[4], Zoë Petard[5], Mark Cherrie[1], Naveen Puttaswamy[6], Kalpana Balakrishnan[6], DK Arvind[5]

[1] Research, Institute of Occupational Medicine, Edinburgh, UK

[2] Department of Public Health, Environments and Society, London School of Hygiene & Tropical Medicine, London, UK

[3] Centre on Climate Change and Planetary Health, London School of Hygiene & Tropical Medicine, London, UK

[4] National Centre for Epidemiology and Population Health, Research School of Population Health, Australian National University, Canberra, Australia

[5] Centre for Speckled Computing, School of Informatics, University of Edinburgh, Scotland, UK

[6] Department of Environmental Health Engineering, Sri Ramachandra Institute of Higher Education and Research, Chennai, India

*Corresponding author

Email: will.mueller@iom-world.org

Telephone: +44 (0) 131 449 8013

Table of Contents

Traffic analysis

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

To assess the link between traffic volume and emissions, we compared from the AirSpeck sensor particle number counts of PM_1, an indicator of traffic emissions (Mishra et al., 2019), to the presence of the highest road type category (i.e., motorway/primary/secondary > tertiary > other) within the four different radius sizes. We found the strongest downward trend from 'motorway/primary/secondary' to 'other' roads at the 25 m radius (non-parametric test for trend p-value<.001; Figure S9). Therefore, for each GPS point, we assigned the road type category according to that within the 25 m radius.

Visibility Analysis

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

To examine any effect modification with visibility, we adapted the between trip analysis using Model 4 with an adjustment (but not an interaction term) for season (i.e., spring/summer/monsoon or autumn/winter). The average overlap of GLU across each trip was used, and the busiest road category present within any individual radius along the trip was included. We performed this analysis based on the 250 m radius, which had the most variation in mean visibility levels, ranging in individual trips from 49-100% (mean=89%, SD=10%). We calculated the coefficients for each greenspace metric based on the minimum and maximum of this range of average visibility (i.e., 49-100%). From this analysis, only the TC coefficient for 100% visibility was associated with a statistically significant reduction in $PM_{2.5}$ concentrations (see Table S5). Although visibility as employed here is a relatively crude indicator for the built environment, the results could imply that the association of lower $PM_{2.5}$ concentrations with trees may only be present in more open, rather than densely built-up areas, as documented elsewhere (Abhijith et al., 2017).

References

Abhijith, K.V., Kumar, P., Gallagher, J., McNabola, A., Baldauf, R., Pilla, F., Broderick, B., Di Sabatino, S. and Pulvirenti, B., 2017. Air pollution abatement performances of green infrastructure in open road and built-up street canyon environments–A review. *Atmospheric Environment*, *162*, pp.71-86.

Farr, T.G., Rosen, P.A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L. and Seal, D., 2007. The shuttle radar topography mission. *Reviews of geophysics*, *45*(2).

Mishra, R.K., Pandey, A., Pandey, G. and Kumar, A., 2019. The effect of odd-even driving scheme on PM2. 5 and PM1. 0 emission. *Transportation Research Part D: Transport and Environment*, *67*, pp.541-552.

Tadono, T., Nagai, H., Ishida, H., Oda, F., Naito, S., Minakawa, K. and Iwamoto, H., 2016. Generation of the 30 M-Mesh Global Digital Surface Model by Alos Prism. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*, *41*.

TomTom. 2020. TomTom Traffic. Available at: https://www.tomtom.com/

Tables and figures

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

Characteristic	Mean (SD)	P5	P25	P50	P75	P95
$PM_{2.5}$ ($\mu g/m^3$)	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

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

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

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

	25 m	**50 m**	**100 m**	**250 m**
Unadjusted analysis (model 1)				
Spring/summer/ monsoon				
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%)
Autumn/winter				
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%)
Adjusted for type of road within the 25 m radius, presence of railways, and population density (model 2)				
Spring/summer/monsoon				
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%)
Autumn/winter				
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%)

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

Table S4. Regression coefficients (95% confidence intervals) of the increase in trip-average $PM_{2.5}$ concentration in relation to greenspace markers* averaged 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>				
Spring/summer/ monsoon				
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%)
Autumn/winter				
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>				
Spring/summer/monsoon				
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%)
Autumn/winter				
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%)

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

	25 m	50 m	100 m	250 m
Adjusted for time of day, weekday/weekend day, year, temperature, precipitation, relative humidity, wind speed, wind direction (model 3)				
Spring/summer/monsoon				
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%)
Autumn/winter				
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%)
Adjusted for the covariates of models 2 & 3 (model 4)				
Spring/summer/monsoon				
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%)
Autumn/winter				
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.

Table S5. Greenspace* coefficients (95% confidence intervals) with effect modification from average 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%)

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

Figure S1. The personal AirSpeck particle sensor.

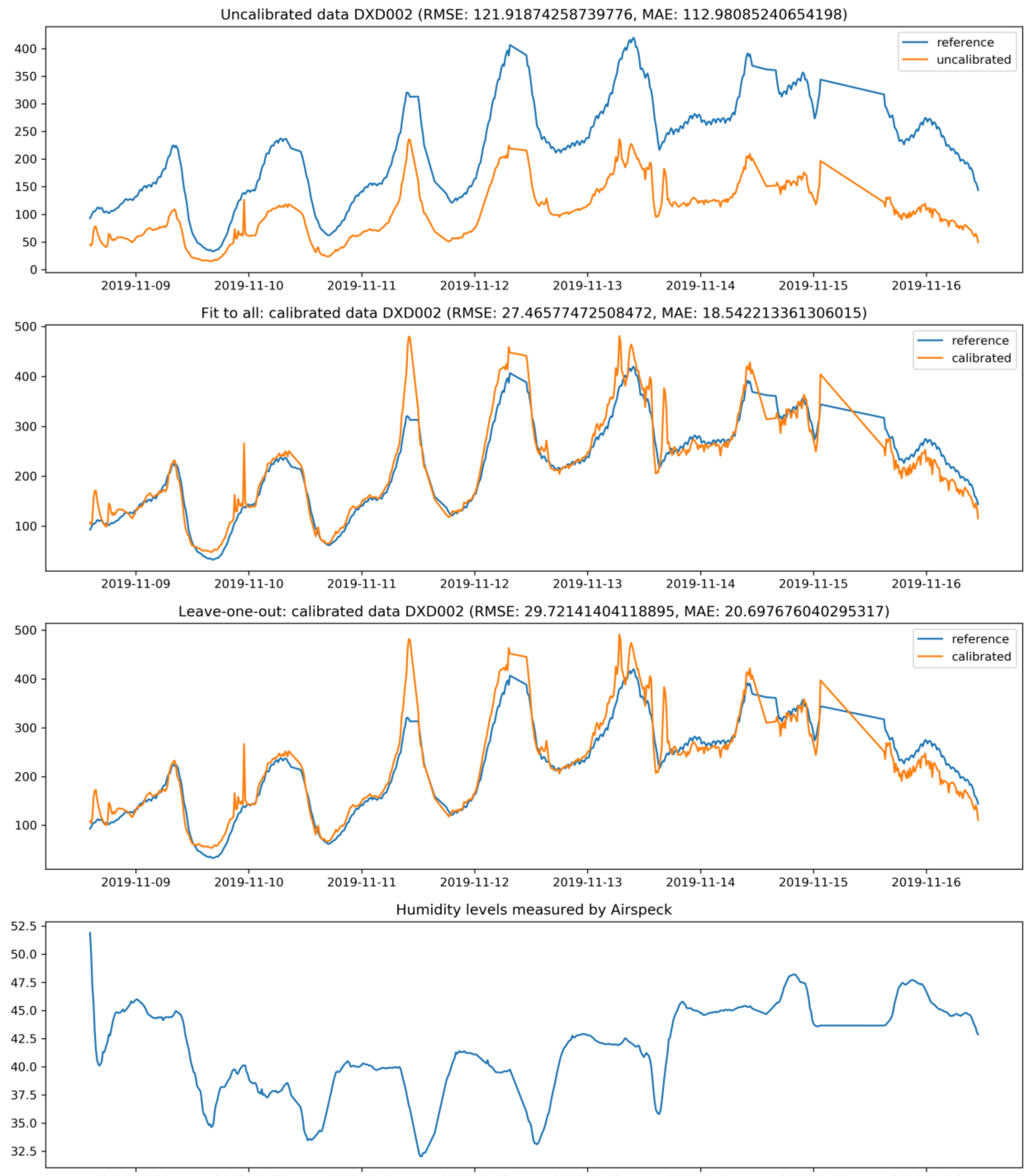
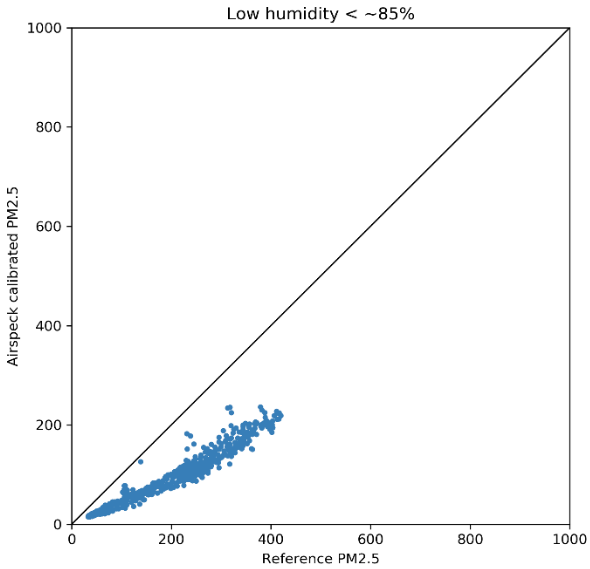
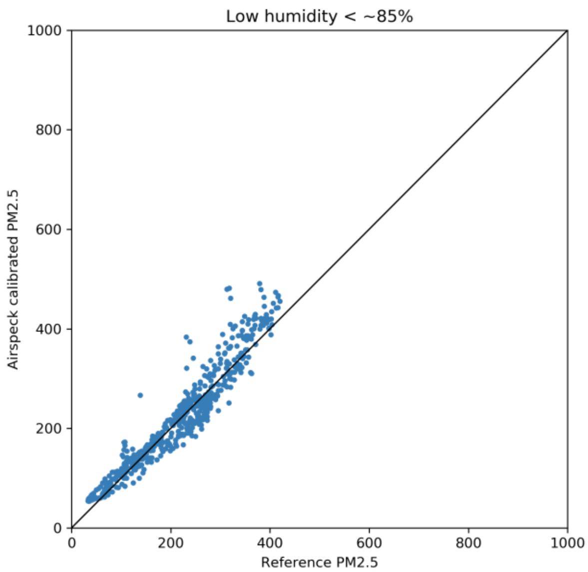


Figure S2. An example line graph of $PM_{2.5}$ data calibration of the AirSpeck with reference monitors in Delhi, India.



a)



b)

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

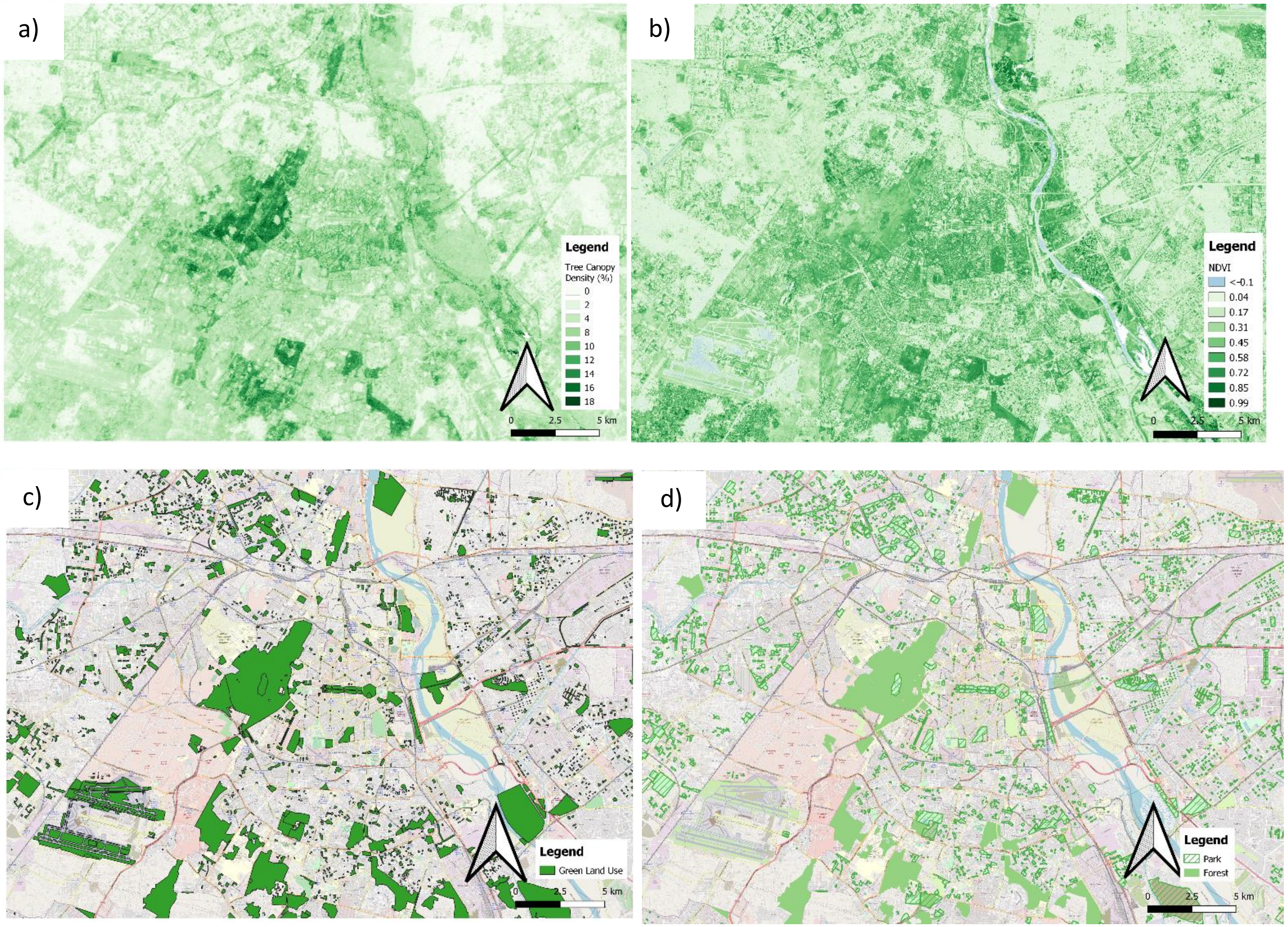
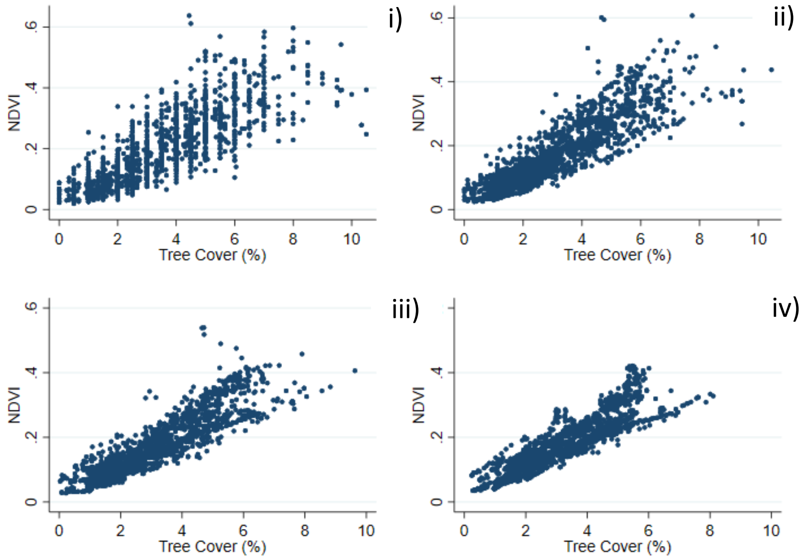
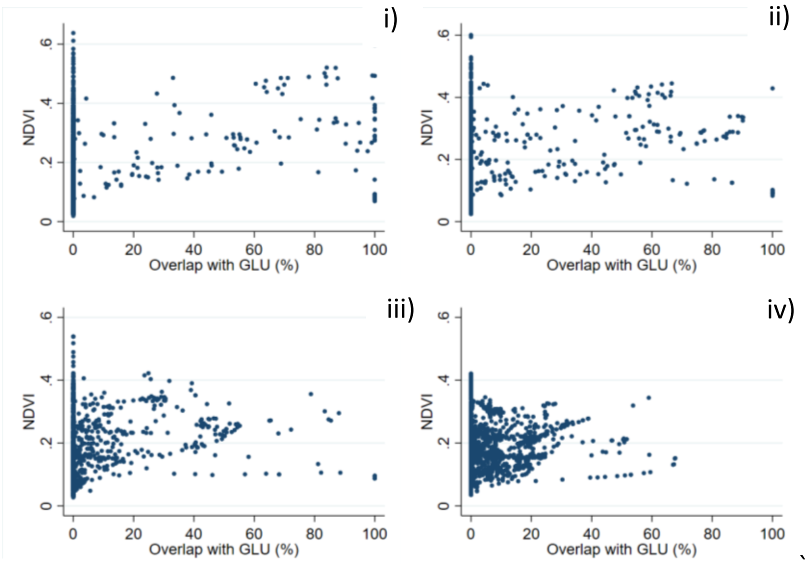
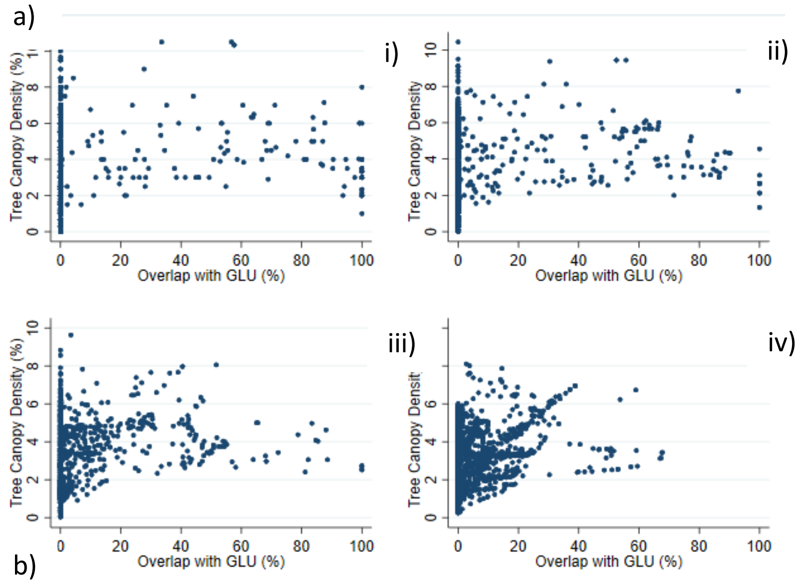


Figure S4. Maps of Delhi greenspace indicators: a) NDVI (image date: 9 February 2019), b) Tree Canopy Density (%), c) green land use, and d) parks or forests. Basemap from ©OpenStreetMap contributors (www.openstreetmap.org), available under the Open Database License.





a)



b)

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

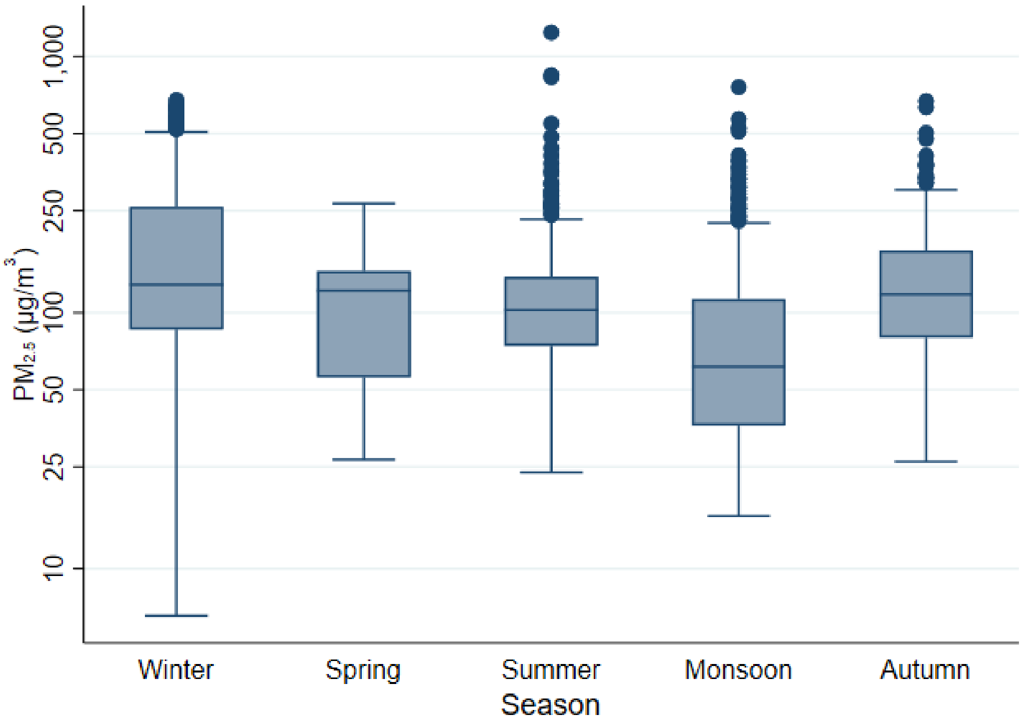


Figure S6. A boxplot of personal $PM_{2.5}$ values (log-scale) recorded during each season in Delhi.

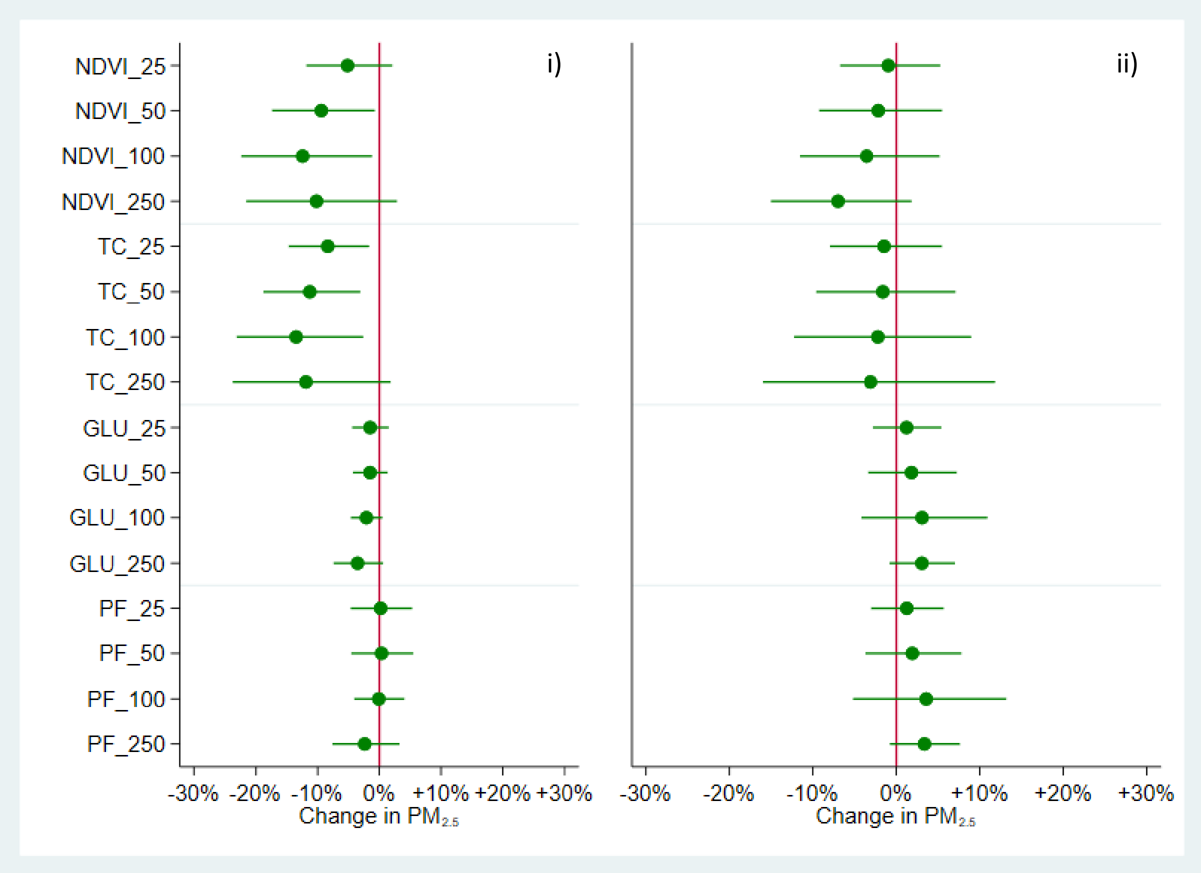


Figure S7. Plots of regression coefficients for (i) the spring/summer/monsoon season and (ii) the autumn/winter season of within-journey changes in 2-minute averaged $PM_{2.5}$ in relation to markers of greenspace. Coefficients represent an interquartile range (IQR) increase in Normalised Difference 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.

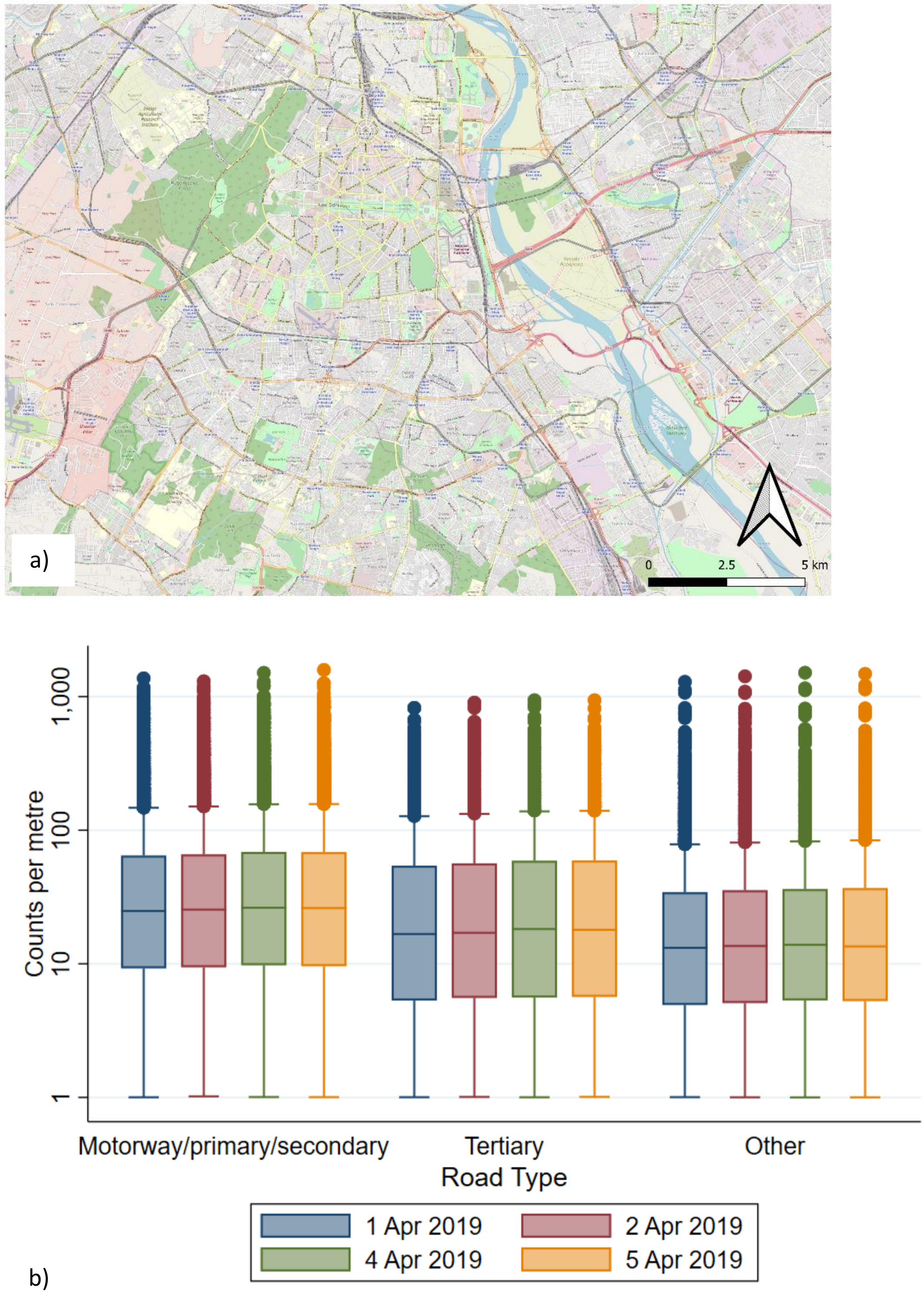


Figure S8. a) A map of the area in Delhi from which traffic count data were analysed and b) a boxplot (log-scale) of traffic counts per metre across the three traffic categories. Basemap from ©OpenStreetMap contributors (www.openstreetmap.org), available under the Open Database License.

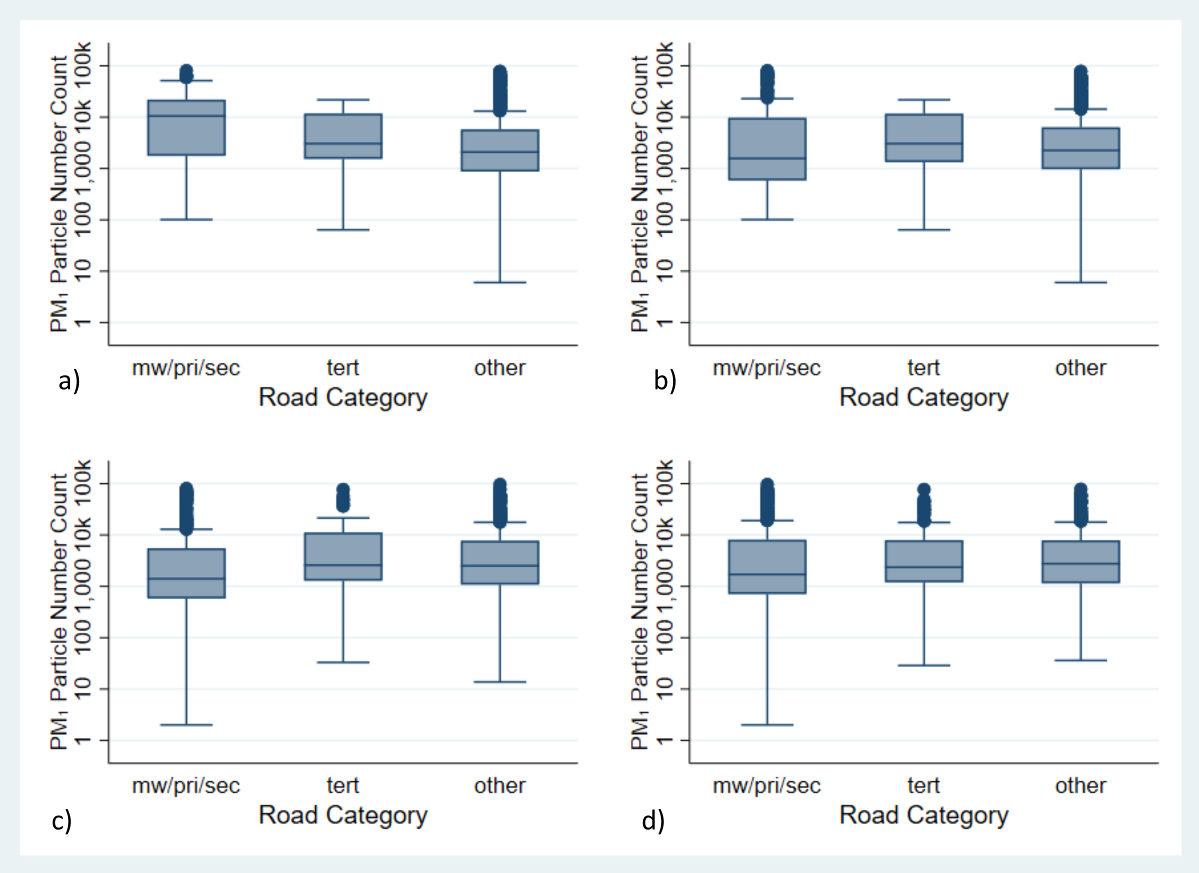


Figure S9. Comparison of PM_1 particle number counts as an indicator of traffic emissions based on the highest road type (mw=motorway; pri=primary; sec=secondary; tert=tertiary) in a) 25m, b) 50m, c) 100m, and d) 250 radii.

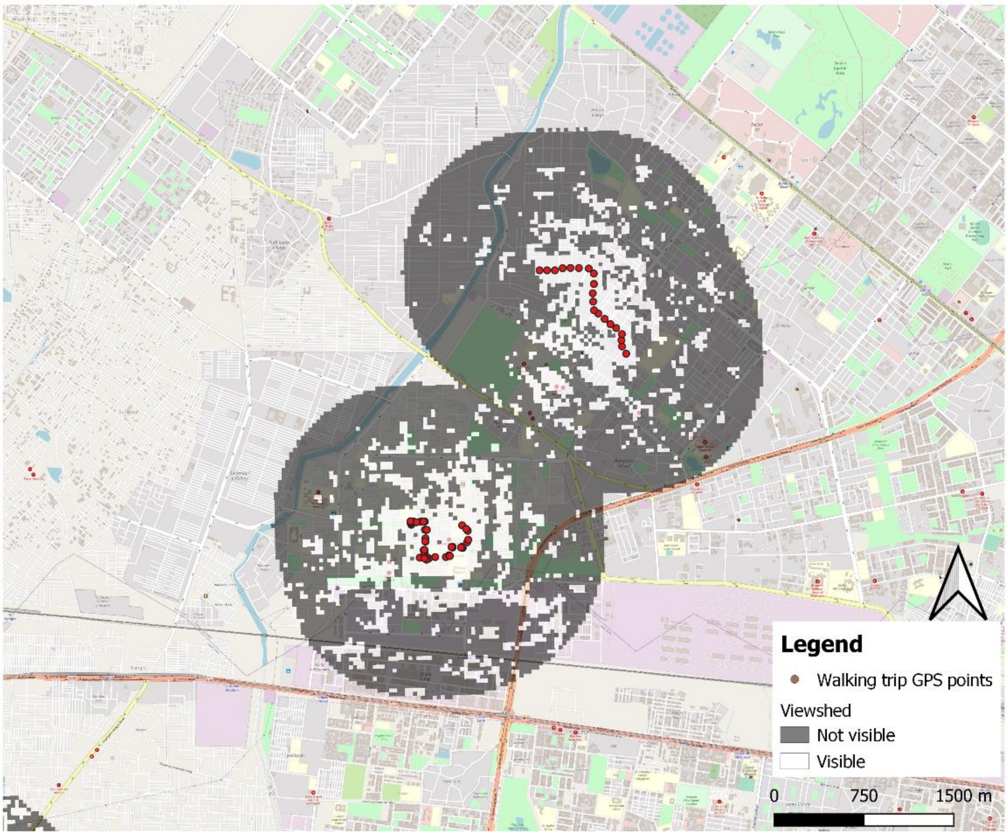


Figure S10. An example of walking trips with 1,000 m viewsheds, illustrating areas that were visible at any point during the route. Basemap from ©OpenStreetMap contributors (www.openstreetmap.org), available under the Open Database License.