Green Health

Examining the role of green space characteristics and their proximity in green space health pathways

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Green Health

Examining the role of green space characteristics and their proximity in green space health pathways

Dissertation

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by

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To Genay and Sophia

for being the wonderful family that they are

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Preface

Since I started my undergraduate studies, I have been fascinated and overwhelmed by the responsibility of urban planners for the daily living environment of so many people. That also led me to question current design practices, continuously asking myself: “How do we know what this particular urban morphology does to people’s lives? Where is the evidence that this is actually better?” My interest grew over time, especially regarding green spaces, health and behaviour and I was lucky enough to have the opportunity to go down the research pathway and continue my exploration.

Unsurprisingly, I came across the works of Jan Gehl, Jane Jacobs and Charles Montgomery early on, which, like so many, have strongly influenced me. While I found myself often agreeing with the critics about modernist architecture and the car-dependant city, it is clear that the functional city emerged as a necessary response to pressing public health concerns of the past, such as unhealthy hygienic conditions and severe air pollution. Nevertheless, the question arose whether we are doomed to correct mistakes in the planning of previous generations or whether it is not possible to proactively design a sustainable human habitat. What do the other disciplines know about the impact of the built environment on humans? What does a sustainable human habitat look like?

This dissertation therefore attempts to break down these disciplinary boundaries, going the first couple of steps towards understanding the human habitat by examining green space health relations. Nevertheless, due to my training, it is written from an urban planning perspective and stepping into interdisciplinary research has sometimes been challenging. But now that I am already out there, I hope this work invites others to join me in navigating these interdisciplinary waters, and together, build bridges between the disciplines. By sharing knowledge, we can collectively contribute to more informed urban planning practices.

Acknowledgements

This dissertation is the product of several opportunities given to me by others. I would like to take this opportunity to express my sincere thanks for this.

First and foremost, I would like to thank my supervisory team. Without the continuous support of Uta Pottgiesser, so much would not have been possible. I owe her the connection to Delft, the opportunity to participate in a European research project and so much more. Arjan van Timmeren has always been an anchor for me through his experience, calmness and continuity and always gave me the feeling of being able to pursue a career in academia. He was also the one who brought me together with Mariëlle Beenackers. I am very grateful that she accepted the invitation to collaborate. Only the continuous exchange, her expertise in public health and the talent to communicate this to an urban planner have brought me this far. Thank you all three from the bottom of my heart!

I would also like to thank my colleagues in the URBiNAT project for the wonderful transdisciplinary collaboration - especially Gonçalo Canto Moniz, who manages the project with remarkable calm and warm-heartedness despite the adverse internal complicated transdisciplinary nature of the project and the external circumstances of a pandemic and war in Europe. Many thanks to Kathrin Volk for her trust in me and the opportunity to work independently on the project. This gave me the opportunity to develop and grow. Similarly, I would like to thank Hans-Peter Rohler, who has helped me start on the journey through lively discussions but has also allowed me to find my own way through this dissertation.

My special thanks also go to Oliver Hall, who gave me my first role in research back in 2016 and has continuously supported me for more than eight years now. Without you, I also would not be here right now. Thank you also to my educators in urban planning at Detmold School for Design, especially Reiner Staubach, Martin Hoelscher, Stefan Hartlock, Axel Häusler, Kathrin Volk and Oliver Hall for their early career support and always stimulating exchange.

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A big thank you also to my former and current colleagues for being the great team that they are, namely Alvaro Balderrama, Anica Dragutinovic, Christine Kousa, Lars Winking, Victoria Davalos, Maximilian Müh, Armanda Barbossa Jardim, Johanna Dorf, Benjamin Dally, Christine Naumann, Julia and Christoph Kirch, Kristina Hermann and Julia Krick. Last but not least, I would like to express my sincere thanks to the board of the Institute for Design Strategies (IDS) for their continuous support, especially for allowing me to focus more on my doctoral research when I needed the time.

A special thanks goes to my family – both the German and the Italian side – who have always supported me on my journey to get here and given me the feeling that they are proud of me, regardless of academic degrees. I would like to thank my parents for letting me have my own experiences when I wanted to, and always being there for me when it mattered.

My deepest gratitude goes to my beloved wife Genay. We walked together through a turbulent time with the birth of our wonderful daughter Sophia, the renovation and move to a new home, the extraordinary circumstances of the COVID pandemic and most recently the slow death of our much-loved dog Lilly. Without your unconditional support and sacrifices, this dissertation would never have been completed. Thank you from the bottom of my heart for always having my back. I know you have suffered with me. Sophia, now Daddy will have more time to play. I promise!

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Glossary

Athens Charter: The Athens Charter, formulated from the 1933 C.I.A.M. (an association of 25 famous architects to promote modern architecture), advocated for a "Functional City," addressing health issues stemming from industrialization, and has significantly influenced post-war urban development. Despite its contested origin and varying interpretations, recognizing the inherent plurality in its formation provides a nuanced perspective on its pivotal role in the evolution of modern urban planning and architectural practices. (Gold, 2019)

Confounder: A confounder is a variable that is not on the causal pathway and can introduce a spurious or confounded association if not controlled for because it affects both the (health) outcome and the (green space) exposure (Szklo & Nieto, 2014).

Effect Modifier: An effect modifier (moderator) is a variable that influences the relationship between green space exposure and the health outcome; a certain effect may be more pronounced in certain contextual situations compared to others (Szklo & Nieto, 2014).

Epidemiology: *"The study of the determinants, occurrence, and distribution of health and disease in a defined population"* (Brachman, 1996)

Epidemiologic Transition: *"The epidemiologic transition describes changing patterns of population distributions in relation to changing patterns of mortality, fertility, life expectancy, and leading causes of death. The perspective has its origins in demography, but finds a compatible conceptual home in public health and epidemiology in particular."* (McKeown, 2009)

Greenness: The degree of greenness describes the coverage of an area with biomass (e.g. grass, shrubs or trees). A usual proxy for greenness is a vegetation index that calculates the degree of greenness based on satellite images. This doctoral research uses the normalized difference vegetation index (NDVI, Tucker, 1979).

Green Spaces: The term green space is used and interpreted in very different ways (Taylor & Hochuli, 2017), but often describes a collective term for areas covered with vegetation. In this dissertation, the term is also used as a collective term that includes concepts such as greenness as a characteristic of green spaces.

Health: "Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity." (WHO - World Health Organization, 1946)

Mediator: *"Mediation occurs when a third variable, referred to as a mediator construct, intervenes between two other directly related constructs."* (Hair et al., 2021)

Mental Illness: *"Mental illness entails the occurrence of disorders of cognition, affect, and behaviour, typically defined through The Diagnostic and Statistical Manual of Mental Disorders"* (American Psychiatric Association, 2013). *"These include highly prevalent conditions such as depression, anxiety, dementia, and substance use disorders, as well as less common but often severe illnesses such as schizophrenia, autism, and bipolar disorder."* (Bratman et al., 2019a)

Mental Health: "*Mental health is defined by the WHO as "a state of well-being in which [an] individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community."* (WHO - World Health Organization, 2023a). Mental health is further defined in the two-continua model, as positive mental health that is constituted by the combination of emotional, social, and psychological well-being, and mental illness. The two-continua model asserts that the absence of mental illness is not solely indicative of positive mental well-being; hence, emotional, social, and psychological well-being are primary considerations for assessing mental health (Yeo & Suárez, 2022). *This doctoral research uses the mental health continuum scale* (Keyes, 2018) *to measure positive mental health.*

Nature: Nature or sometimes natural environment is a concept hard to grasp in this multidisciplinary research field (Hartig et al., 2014), but usually includes flora and fauna, thus blue spaces and green spaces as well as their inhabitants.

Non-communicable Diseases: *"The four Non-communicable diseases (NCDs) initially targeted were cardiovascular diseases, diabetes, cancer, and chronic respiratory disease. Major risk factors selected for quantified reductions in population prevalence were unhealthy diets, physical inactivity, tobacco, and alcohol. Mental health has now been added by WHO to the targeted NCDs and air pollution has joined the list of major risk factors."* (Reddy, 2020)

Physical Health: "*Physical health describes the condition of your body. This includes whether you have an illness, injury or a health condition."* (NHS Foundation Trust, 2023)

Public Health: *"the science and art of preventing disease, prolonging life, and promoting health through the organized efforts and informed choices of society, organizations, public and private communities, and individuals."* (Winslow, 1920)

Satellite District: The term satellite district usually refers to a district on the outskirts of the city or even outside of the city's administrative boundaries that is partly or fully planned according to the principles of the functional city. Most often they contain a significant portion of social housing areas built in the post-World War II period.

Semi-public green spaces: Semi-public green spaces describe a phenomenon of residential green spaces that induce a sense of perceived permission or prohibition to use the space, which normally arises from urban morphology (closed block vs. singular high-rise structures) and social control, i.e. being visible from balconies and windows.

Sensitivity Analysis: "In a broad sense, one can define a sensitivity analysis as one in which several statistical models are considered simultaneously or in which a statistical model is further scrutinized using specialized tools, such as diagnostic measures." (National Research Council (US) Panel on Handling Missing Data in Clinical Trials. The Prevention and Treatment of Missing Data in Clinical Trials, 2010)

Structural Equation Modelling "*Structural equation modelling (SEM) is a very general, very powerful multivariate technique. It uses a conceptual model, path diagram and system of linked regression-style equations to capture complex and dynamic relationships within a web of observed and unobserved variables. Although similar in appearance, SEM is fundamentally different from regression. In a regression model, there exists a clear distinction between dependent and independent variables. In SEM, however, such concepts only apply in relative terms since a dependent variable in one model equation can become an independent variable in other components of the SEM system. It is precisely this type of reciprocal role a variable plays that enables SEM to infer causal relationships."* (Gunzler et al., 2013)

Urbanism: "*We see Urbanism as an interdisciplinary planning and design activity that focuses on the (re)creation of sustainable urban landscapes aimed toward climate adaptability, circularity, social equity, and ecologically inclusive urbanisation at all scales."* (TU Delft, n.d.)

Urban Planning: *"Urban planning encompasses the preparation of plans for and the regulation and management of towns, cities, and metropolitan regions. [...] Urban planning is concerned with the social, economic, and environmental consequences of delineating spatial boundaries and influencing spatial distributions of resources. The purposes and means of achieving such distributions have varied significantly historically and geographically, often in response to challenges to prevailing approaches that reveal the political nature of planning interventions and the limitations of technical knowledge claims."* (Huxley & Inch, 2020)

Well-being: The well-being literature distinguishes between two primary theories: hedonic and eudaimonic well-being. The hedonic theory conceptualizes well-being as happiness, satisfaction, and interest in life, later termed emotional well-being (EWB). In contrast, the eudaimonic theory arose from criticisms of hedonic theory's narrowness, emphasizing individual functioning within social and psychological realms, leading to the development of multidimensional models of social well-being (SWB) and psychological well-being (PWB). (Yeo & Suárez, 2022)

Summary

This doctoral research explores if and how green spaces are able to mitigate the global disease burden of non-communicable diseases (NCDs), by examining the role of green space characteristics and their proximity for three key theorized pathways: **(1)** The inviting character of green spaces to be more physically active and their health benefits; **(2)** the ability of green spaces to promote social cohesion and in turn mental health; **(3)** and the mitigation potential of green spaces to reduce air pollution and their associated health benefits. However, inconsistencies in research methodologies, definitions, and design hamper the synthesis of findings in the green space health research domain. This dissertation aims to bridge these gaps by developing a theoretical and methodological framework examining the proximity to and key characteristics of green spaces, focusing on their role in physical activity, social cohesion, and air pollution health pathways. The main research question is:

How do proximity to and characteristics of green spaces affect pathways to human health?

To answer this main research question, the research ties in with the EU Horizon2020 project URBiNAT, an initiative exploring the benefits of nature-based solutions (NBS) in deprived urban areas across Europe. Self-reported data from this project, derived from surveys conducted in the four European cities Nantes, Porto, Sofia and Høje-Taastrup, serves as the foundational dataset for the thesis' case studies.

In **Chapters 2 and 3** the methodological contribution to the research field is presented. It introduces PRIGSHARE (Preferred Reporting Items in Greenspace Health Research) and its complementary open-source script, AID-PRIGSHARE. PRIGSHARE offers a 21-item checklist that aids in the systematic evaluation and comparison of studies, focusing on aspects like objectives, scope, types of green space assessments and context variables. AID-PRIGSHARE simplifies the resource-intensive process of green space assessment by automating the generation of key indicators such as surrounding greenness, accessible green space, green corridors and green space uses within specified distances from 100 to 1,500 m, every 100 m. Jointly, they aim to synchronize research efforts in this field, allowing for more precise and coherent studies while accommodating diverse research designs.

In **Chapter 4** the empirical findings reveal key relationships between green space characteristics within walkable distances, with physical activity and health. A main outcome is that residing near green spaces, especially green corridors with diverse uses within 800 m, or a 10-minute walk, was associated with higher physical activity and indirect health benefits. However, a higher quantity of green space uses and greater surrounding greenness at larger distances (1,100–1,500 meters) showed a negative correlation with physical activity and health, which could be related to the increased car-dependency of greener or more rural districts. While this research focuses on four European so-called satellite districts, it underscores the importance of proximity and green space characteristics in the green space health research field. It concludes by emphasizing the value of interconnected, multi-use green spaces, given their potential to combat physical inactivity and its associated health risks.

Chapter 5 discusses the empirical findings on the green space mental health associations through increased social cohesion. The study found that certain green space characteristics are linked with elevated levels of social cohesion, which in turn appear to favour mental health outcomes. Specifically, accessible greenness (including vegetation along streets) and green spaces within a surrounding area of up to 1,500 meters, green corridors in an intermediate surrounding of up to 800 meters, and mix of use in green spaces measured in 700 to 1,300 meters, showed significant indirect associations to mental health. However, the study found no direct positive effects of any green space variables on mental health, suggesting that the benefits are fully mediated by social cohesion. These insights into how and where these mechanisms occur provide important evidence for urban planners and public health decision-makers on the importance of how to design neighbourhood green spaces to foster social cohesion and mental health.

Chapter 6 reveals the empirical findings about the green space health associations that are mediated through lower air pollution. In this study, only two green space characteristics were associated with indirect health effects through lower self-rated air pollution. First, the area of green corridors measured in intermediate surroundings of 800-1,000 m was significantly related to experiencing lower air pollution and indirect health effects. Second, accessible green spaces were also associated with lower self-rated air pollution and indirect health effects at network distances of 1,400-1,500 m. These findings support the idea that the connectivity of green spaces is vital for mitigating air pollution. These findings offer important support for urban planners aiming to reduce air pollution and its associated health risks, suggesting to focus on interconnected green networks.

In concluding **Chapter 7**, the results are synthesised to present several key insights that have broad implications for urban planning, public health policies, and future green space research. Despite its limitations of self-reported data, cross-sectional study design and constraints in model complexity, the synthesis of the results of the individual studies in this doctoral research indicates distinct thresholds for distances in which every pathway operates and which green space characteristics are the driving features of those mechanisms. For future research, these new insights offer a foundation to examine causality or more complex pathway chains. For practitioners, it makes a strong case for designing connected, multifunctional green space corridors rather than isolated patches, to optimize positive health outcomes associated with green spaces. These insights not only contribute to WHO's Urban Health Research Agenda but also offer specific, actionable recommendations that could profoundly impact public health promotion strategies aimed at combating non-communicable diseases (NCDs).

Samenvatting

Dit doctoraatsonderzoek onderzoekt of en hoe groene ruimten in staat zijn om de wereldwijde ziektelast van niet-overdraagbare aandoeningen (NCD's) te verlichten. Het richt zich opde rol van verschillende kenmerken van en nabijheid tot groene ruimten voor drie belangrijke theoretische paden: **(1)** het uitnodigende karakter van groene ruimten om meer fysiek actief te zijn en de gezondheidsvoordelen daarvan; **(2)** het vermogen van groene ruimten om sociale cohesie en op hun beurt mentale gezondheid te bevorderen; **(3)** en het mitigatiepotentieel van groene ruimten om luchtvervuiling te verminderen en de bijbehorende gezondheidsvoordelen. Inconsistenties in onderzoeksmethoden, definities en ontwerp vormen echter een uitdaging voor de synthese van bevindingen in het onderzoek naar groene ruimte en gezondheid. Dit proefschrift heeft als doel deze hiaten te overbruggen door een theoretisch en methodologisch kader te ontwikkelen waarin de nabijheid toten de belangrijkste kenmerken van groene ruimten worden onderzocht in relatie tot gezondheid. belangrijkste onderzoeksvraag is:

Hoe beïnvloeden nabijheid tot en kenmerken van groene ruimten de gezondheidspaden van mensen?

Dit onderzoek sluit aan bij het EU Horizon2020 project URBiNAT, dat de voordelen van op de natuur gebaseerde oplossingen (nature based solutions, NBS) in gedepriveerde stedelijke gebieden in heel Europa onderzoekt. Zelfgerapporteerde gegevens uit enquêtes in de vier Europese steden Nantes, Porto, Sofia en Høje-Taastrup dienen als basisgegevens voor de casestudies van dit proefschrift.

In **hoofdstuk 2 en 3** wordt de methodologische bijdrage aan het onderzoeksveld gepresenteerd. Hier wordt PRIGSHARE (Preferred Reporting Items in Greenspace Health Research) geïntroduceerd, samen met het bijbehorende open-source script AID-PRIGSHARE. PRIGSHARE biedt een checklist van 21 items die helpen bij het systematisch evalueren en vergelijken van studies op het gebied van groene ruimten en gezondheid. PRIGSHARE richt zich op aspecten zoals doelstellingen, reikwijdte, manieren van meten van groene ruimten en op contextvariabelen. AID-PRIGSHARE vereenvoudigt het resource-intensieve proces van groenonderzoek door automatisch belangrijke indicatoren te genereren, zoals de hoeveelheid omliggend groen, toegankelijke groene ruimte, groene corridors en groengebruik binnen gespecificeerde afstanden van 100 tot 1.500 m, voor elke 100 m. Samen

streven deze instrumenten ernaar om onderzoeksinspanningen op dit gebied te synchroniseren, waardoor nauwkeuriger en coherente studies mogelijk worden en tegelijkertijd ruimte wordt geboden aan verschillende onderzoeksopzetten.

In **hoofdstuk 4** worden de empirische bevindingen beschreven over de associaties tussen groen, fysieke activiteit en gezondheid. Een belangrijke uitkomst is dat wonen in de buurt van groene ruimten, met name groene corridors met gevarieerd gebruik binnen 800 m, of 10 minuten lopen, geassocieerd was met meer fysieke activiteit en indirecte gezondheidsvoordelen. Op grotere afstanden (1.100-1.500 meter) was een grotere hoeveelheid groengebruik en meer groen in de omgeving echter negatief geassocieerd met fysieke activiteit en gezondheid. Dit zou verband kunnen houden met de grotere auto-afhankelijkheid van groenere of meer landelijke wijken. Hoewel dit onderzoek zich richt op vier Europese “satellietwijken”, onderstreept het onderzoek het belang van nabijheid en kenmerken van de groene ruimte in het onderzoeksveld naar de gezondheid van de groene ruimte. De studie in dit hoofdstuk benadrukt de waarde van onderling verbonden, multifunctionele groene ruimten voor hun potentieel om fysieke inactiviteit en de bijbehorende gezondheidsrisico's te bestrijden.

Hoofdstuk 5 bespreekt de empirische bevindingen over de associaties tussen groen en mentale gezondheid, via sociale cohesie. Uit het onderzoek bleek dat bepaalde kenmerken van groene ruimten verband houden met een hogere mate van sociale cohesie, die op hun beurt gunstig lijken te zijn voor de mentale gezondheid van inwoners. Met name toegankelijk groen (inclusief vegetatie langs straten) en groene ruimten binnen een straal van maximaal 1.500 meter, groene corridors in een omgeving van maximaal 800 meter van de inwoner, en een mix van gebruik in groene ruimten tussen 700 tot 1.300 meter, vertoonden significante indirecte associaties met mentale gezondheid. Het onderzoek vond echter geen directe positieve effecten van groenvariabelen op de mentale gezondheid, wat suggereert dat de voordelen volledig worden gemedieerd door sociale cohesie. Deze inzichten in hoe en waar deze mechanismen optreden, bieden belangrijke aanwijzingen voor stedelijke planners en beleidsmakers op het gebied van volksgezondheid over het belang van het ontwerpen van groene ruimten in buurten om sociale cohesie en mentale gezondheid te bevorderen.

Hoofdstuk 6 beschrijft de empirische bevindingen over de associaties tussen groen en gezondheid, gemedieerd door een lagere luchtvervuiling. In dit onderzoek werden slechts twee kenmerken van groene ruimten in verband gebracht met indirecte gezondheidseffecten via lagere zelfgerapporteerde luchtvervuiling. Ten eerste was de oppervlakte van groene corridors, gemeten in een omgeving van 800-1.000 m, significant gerelateerd aan het ervaren van minder luchtvervuiling en indirecte gezondheidseffecten. Ten tweede werden toegankelijke groene ruimten ook in verband gebracht met lagere zelfgerapporteerde luchtvervuiling en indirecte gezondheidseffecten op afstanden van 1.400-1.500 m. Deze bevindingen ondersteunen het idee dat de verbondenheid van groene ruimten van vitaal belang is voor het verminderen van luchtvervuiling. Deze bevindingen bieden belangrijke ondersteuning voor stedelijke planners die luchtvervuiling en de bijbehorende gezondheidsrisico's willen terugdringen en suggereren om zich te richten op onderling verbonden groene netwerken.

In het afsluitende **hoofdstuk 7** worden de resultaten samengevat tot een aantal belangrijke inzichten die brede implicaties hebben voor stedelijke planning, volksgezondheidsbeleid en toekomstig groenonderzoek. Ondanks de beperkingen van de zelfgerapporteerde gegevens, de cross-sectionele onderzoeksopzet en de beperkingen in de complexiteit van het statistische model, geeft de synthese van de resultaten van de afzonderlijke studies in dit promotieonderzoek duidelijke drempels aan voor de afstanden waarbinnen elk van de theoretische paden kan werken en welke groenkenmerken de drijvende krachten zijn achter die mechanismen. Voor toekomstig onderzoek bieden deze nieuwe inzichten een basis om causaliteit of complexere routes te onderzoeken. Voor mensen uit de praktijk pleiten deze inzichten sterk voor het ontwerpen van aaneengesloten, multifunctionele groencorridors in plaats van geïsoleerde plekken, om de positieve gezondheidsresultaten van groen te optimaliseren. Deze inzichten dragen niet alleen bij aan de onderzoeksagenda voor stedelijke gezondheid van de WHO, maar bieden ook specifieke, uitvoerbare aanbevelingen die van grote invloed kunnen zijn op strategieën ter bevordering van de volksgezondheid die gericht zijn op het bestrijden van niet-overdraagbare ziekten (NCD's).

1 Introduction

1.1 Green Spaces as an important element to combat the global disease burden of non-communicable diseases

Non-communicable diseases (NCDs) are by far the largest cause of natural deaths worldwide (Bai et al., 2023). The latest global disease burden Report 2019 attributes 74% of global deaths to them. This has not always been the case. For a long time, communicable diseases were considered the greatest risk (McKeown, Thomas, 1976). It is only since the Athens Charter, improvements in urban infrastructure and the hygienic improvements of modernist architecture that communicable diseases are no longer the main problem in developed countries (Frumkin et al., 2004). However, this epidemiological transition is far from undisputed and the significant increase in life expectancy is likely much more complex (Mackenbach, 2020; McKeown, 2009). Moreover, the recent global COVID-19 pandemic reminded us to not solely focus on non-communicable diseases. Still, the large share of deaths which are attributable to NCDs highlights the importance of action in the five main categories of cancer, respiratory and cardiovascular diseases, diabetes and mental health (UN General Assembly, 2018).

The biggest risk factors for NCDs are considered to be inactivity, loneliness, eating and drinking habits, smoking and air pollution (UN General Assembly, 2018), which are at least partly due to the built environment and our car-dependant lifestyle (Frumkin et al., 2004; Nieuwenhuijsen, 2021). So while we have successfully reduced communicable diseases through 20th-century improvements in urban design (McKeown, Thomas, 1976), we have created new problems for ourselves through 20th-century urbanism. Urban design in the 21st century is now tasked with reducing these risk factors (Giles-Corti et al., 2016; Nieuwenhuijsen, 2021; WHO Regional Office for Europe, 2012).

Green spaces are considered one of the key elements of the built environment with potential multiple benefits on health according to recent WHO publications (WHO Regional Office for Europe, 2016a, 2021). The focus on green space has led to a sharp increase in the number of studies on green space health effects (R. Zhang et al., 2021), as well as research on green spaces in general since the social and political relevance is also fuelled by the key contribution of a green transformation of our cities to combating climate change and climate adaptation (Nieuwenhuijsen, 2021), and other societal challenges like the loss of biodiversity (European Commission. Directorate-General for Research and Innovation., 2021b).

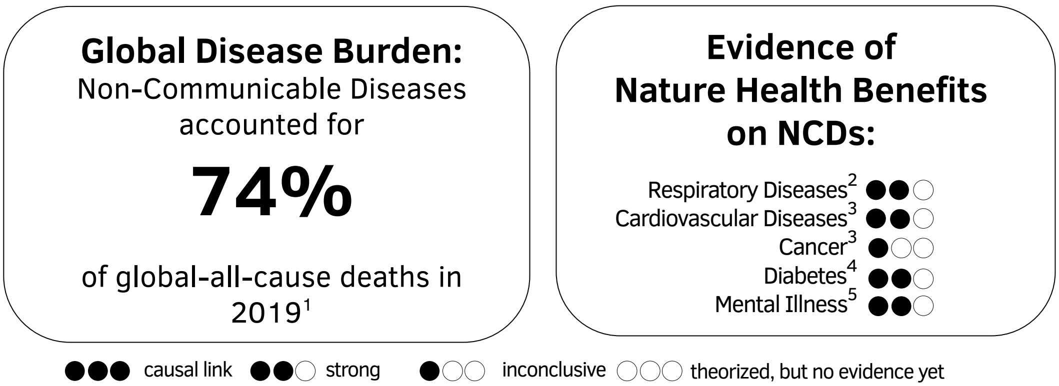

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FIG. 1.1 Evidence of the benefits of nature in reducing main NCD diseases

This steadily increasing number of studies was recently evaluated by a couple of research teams to summarize the available evidence of green spaces in their ability to reduce the risk of the main NCD categories (Figure 1.1). For example, a recent review found strong evidence for the association of green spaces with a reduced risk of respiratory diseases (Mueller et al., 2022). Yang and colleagues found convincing evidence for the potential of green spaces to reduce the prevalence of cardiovascular diseases, and some evidence for an association with reduced risk of cancer (Yang et al., 2021). Another review summarized the evidence on the associations of green spaces with type 2 diabetes and found, that green spaces are associated with a reduced risk of type 2 diabetes, mainly through increased physical activity and reduced obesity (De la Fuente et al., 2021). Regarding mental health, Bratman and colleagues concluded in a recent review that there is strong evidence for the short-term effects of contact with nature on mental health in addition to some longitudinal studies that have shown potential long-term benefits such as improved cognitive function, memory and attention (Bratman et al., 2019a). Although most of the evidence is still cross-sectional and thus unable to establish causality, the mounting body of evidence points towards a positive relationship between green spaces and health.

1.2 Key Concepts in Green Space Health Research

There are many hypotheses and theories that try to explain how green spaces, as an element of the built environment, affect health and well-being. Most of them focus on specific domains that have been summarized in the foundational work of Markevych and colleagues as *Mitigation* (reducing environmental stressors), *Restoration* (being in or surrounded by nature) and *Instoration* (nudging towards healthy activities) as shown in Figure 2 (Markevych et al., 2017).

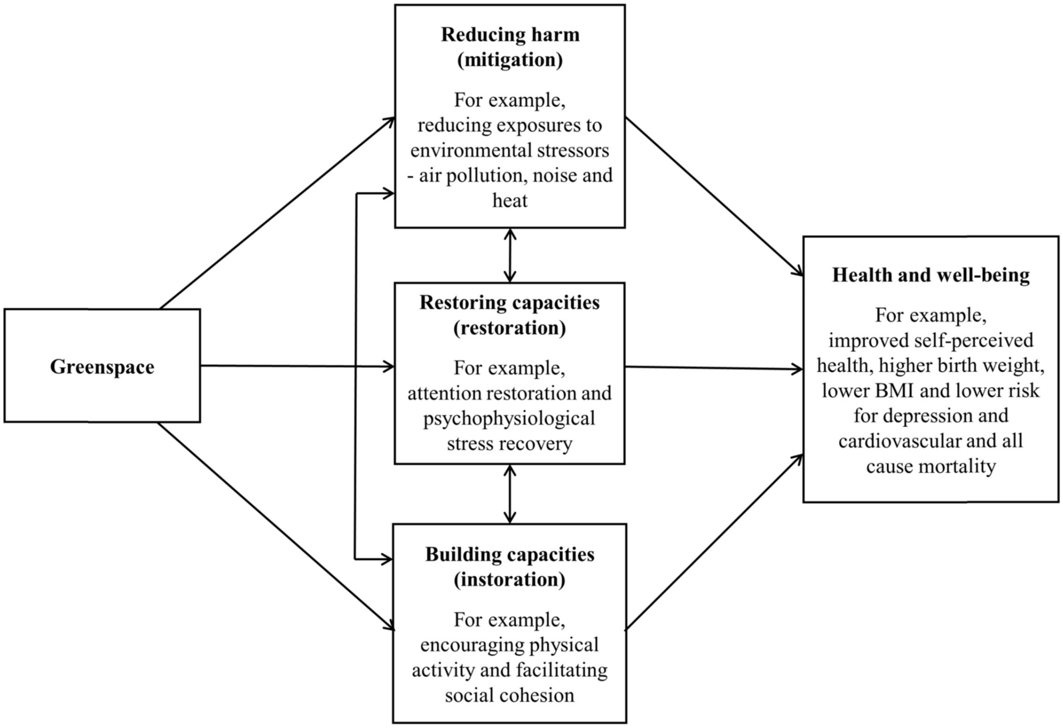


FIG. 1.2 Pathways between green space and health (Markevych et al 2017)

1.2.1 Mitigation – Reduction of environmental stressors

Mitigation as a pathway is based on the mechanism of filtering, masking, and reducing environmental stressors through vegetation. In addition, replacing an emission source with green spaces or creating distance through green space is often also categorized as a mitigation effect (Markevych et al., 2017). They are thought to act as effective barriers that reduce or buffer against air pollution, excessive heat, and noise pollution. For example, the reduction of heat island effects through green spaces has been documented (Iungman et al., 2023). Additionally, green spaces have been associated with noise mitigation (Van Renterghem, 2019), and their ability to mitigate air pollution (Nowak et al., 2014, 2018). The capability to reduce artificial light pollution at night in urban areas is also expected (Browning et al., 2022). The degree of vegetation correlates with reduced sealing in urban environments, which makes the urban environment less vulnerable to extreme weather events, effectively mitigating disaster risks (Tidball & Krasny, 2013).

1.2.2 Instoration - Inviting people to lead healthier lifestyles

The *Instoration* mechanisms summarize the ability of green spaces to invite nearby residents to a healthier lifestyle. It has been shown that accessible green spaces can encourage people to be more physically active (Van Hecke et al., 2018). Physical activity itself is well understood and relates to different health outcomes like CVD, obesity and mental health (Twohig-Bennett & Jones, 2018). In addition, physical activity performed outdoors compared to an indoor environment is considered to have a higher impact on health (Thompson Coon et al., 2011). Green spaces have also been associated with more social interaction and increased social cohesion (Wan et al., 2021a). In addition, it is theorized that some types of urban green spaces, e.g. community gardens or urban fruit trees, can positively influence eating behaviour, but with little evidence so far (Hume et al., 2022). In general, providing those activating settings in a neighbourhood invites their inhabitants not only into more social cohesion and physical activity, but also contributes to more time spent in nature in general. This in turn leads to more sunlight exposure and the formation of vitamin D (Rosenthal et al., 1984), as well as exposure to fresh(er) air in nature, especially in comparison to indoor spaces (Wolkoff, 2018). In addition, direct contact with Nature is associated with *Restoration* mechanisms.

1.2.3 Restoration – Renewal of resources

Effects via the *Restoration* pathway are assumed to develop through direct contact with nature. Foremost, there is a strong body of evidence that various types of nature experiences are positively associated with mental health, and reduce the risk of mental illnesses (Bratman et al., 2019a). Experiencing nature improves cognition, learning capabilities, and creativity (Marselle et al., 2021; WHO Regional Office for Europe, 2016a) and research has developed a convincing body of evidence related to cognitive development in children (Dadvand et al., 2015; Preuß et al., 2019). Contact with nature is additionally associated with short-term effects on mood, vitality, reduction of hyperactivity, and increase of brain activity, as well as long-term effects on mental health, life satisfaction, well-being, sleep qualities, social contacts and a reduced suicide rate (WHO Regional Office for Europe, 2021). The positive effects on general mental health are explained through either *Stress Reduction Theory* (SRT; Ulrich et al., 1991) or *Attention Restoration Theory* (ART; Kaplan, 1995). SRT mainly argues for the absence of stressors in natural environments, while ART focuses on the effortless attention that nature's features trigger in a person, thereby activating the rest of the neurocognitive mechanism. In summary, this pathway describes direct relations between humans and elements of nature. In addition, the so-called old-friend hypothesis speaks of a positive effect on the immune system through contact with a number of microorganisms native to nature (Kuo, 2015; Rook, 2013), but according to others without convincing evidence yet (Yang et al., 2021).

1.2.4 Causing harm

However, green spaces are not only associated with positive effects. Contact with nature has always been associated with an increased risk of communicable diseases, e.g. from ticks or mosquitoes (Lõhmus & Balbus, 2015), an increased exposure to pesticides and herbicides (Marselle et al., 2021; WHO Regional Office for Europe, 2016a) and, depending on the region in the world, an increased risk from contact with wild animals (Marselle et al., 2021). In addition, green spaces are associated with an increased risk of injury (Marselle et al., 2021; WHO Regional Office for Europe, 2016a) and sometimes also with increased crime rates (Kimpton et al., 2017). Moreover, increased sunlight exposure might also increase the risk of skin cancer (Astell-Burt, Feng, et al., 2014). Furthermore, green spaces not only reduce environmental stressors, they can also cause new ones, such as pollen (Marselle et al., 2021) or cause air pollution themselves via volatile organic compounds (VOCs) that can react with other airborne chemicals to form air pollution, especially ozone (Duan et al., 2023; Gu et al., 2021; Sicard et al., 2022).

1.3 Problem statement

Despite the advancements and synthesis in the green space health research field, several challenges remain to advance in the urban green transformation of the 21st century and mitigate the risk factors associated with NCDs. In this rapidly evolving and dynamic research field, viewed from a variety of different science fields, layer after layer of the complex interrelations is uncovered (Barton & Grant, 2006; R. M. Collins et al., 2020; Hartig et al., 2014; Markevych et al., 2017). But by combining and synthesizing these very different mainly monodisciplinary studies, questions about the heterogeneity of results arise frequently (Gascon et al., 2015; Kabisch et al., 2017; Labib et al., 2020; Twohig-Bennett & Jones, 2018).

The first reason identified for the heterogeneity in results is the varying understanding of spatial urban contexts so that green spaces are defined very heterogeneously or not at all (Taylor & Hochuli, 2017). The second reason for the heterogeneous results seems to be that buffer types and buffer distances used vary between and within different research domains in green space health research (Labib et al., 2020). A third challenge is related to the study designs. To advance the field, sensitivity analyses are required to be able to compare different characteristics of green spaces and proximities to green spaces within studies, since the heterogeneity of study designs in the field does not allow for meta-analysis across studies. Consequently, the lack of comparability of the studies means that it is still unclear what proximity is necessary to trigger a particular impact pathway. Similarly, it remains largely unknown which green space characteristics are important for specific green space health pathways. This limits the practical applicability of the evidence in this research field.

In order to overcome these barriers, a common research protocol and definitions (Browning et al., 2022; R. M. Collins et al., 2020; X.-X. Liu et al., 2022; Markevych et al., 2017; Taylor & Hochuli, 2017; R. Zhang et al., 2021), as well as sensitivity analysis for green space characteristics (Davis et al., 2021; Labib et al., 2020) and proximities (R. M. Collins et al., 2020; Labib et al., 2020; Markevych et al., 2017) are frequently requested.

1.4 Research Aim

This dissertation aims to contribute to the interdisciplinary green space health research field by developing a theoretical and methodological framework that can provide evidence for the importance of the proximity to and characteristics of green spaces. The empirical results aim to analyse these factors for exemplary green space health pathways that are considered of major importance to mitigate the risk of NCDs: (1) physical activity to health, (2) social cohesion to mental health and (3) air pollution to health. The main research question of this doctoral research therefore is as follows:**How do proximity to and characteristics of green spaces affect pathways to human health?**

This dissertation is divided into sub-questions to get to the answer to the main research question and consists of consecutive studies on the theoretical and methodological framework (Chapter 2) and the necessary automatization in spatial data assessment (Chapter 3) followed by three individual studies studying the pathways of physical activity to health (Chapter 4), social cohesion to mental health (Chapter 5) and air pollution to health (Chapter 6). The sub-questions answered are as follows:

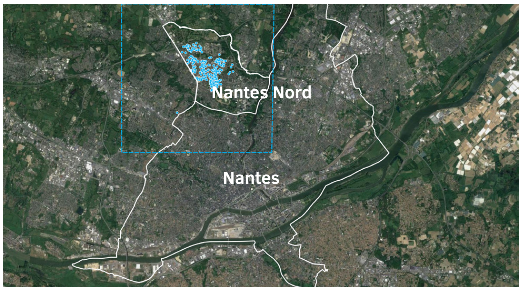
- **Sub RQ1:** What is the current state of knowledge in the related research fields and what are common risks of bias? (Chapter 2)
- **Sub RQ2:** How to reduce the barriers in the field for sensitivity analysis? (Chapter 3)
- **Sub RQ3:** How are proximity and characteristics of green spaces related to physical activity and health? (Chapter 4)
- **Sub RQ4:** How are proximity and characteristics of green spaces related to social cohesion and mental health? (Chapter 5)
- **Sub RQ5:** How are proximity and characteristics of green spaces related to air pollution and health? (Chapter 6)

1.5 Methodological Framework

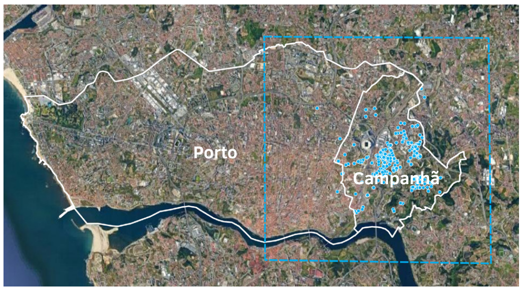
1.5.1 Research Setting – The URBiNAT project

This doctoral research is connected to the European H2020 innovation action project URBiNAT – Urban Innovative & Inclusive Nature, which aims to demonstrate how nature-based solutions can be used to improve the lives of residents in deprived neighbourhoods. Within the project, three European cities act as frontrunners and implement a cluster of nature-based solutions as a “healthy corridor” in their districts in the project lifetime (2018-2024). These districts are Porto Campanhã in Portugal, Nantes Nord in France, and Sofia Nadezhda in Bulgaria. In addition, four follower cities will also go through the same process and will have consolidated urban plans for these districts by the end of the project. The follower cities are Høje-Taastrup in Denmark, Brussels in Belgium, Siena in Italy and Nova Gorica in Slovenia. This doctoral research builds upon data collected from the URBiNAT Neighbourhood Survey (Cardinali, Bodenan, et al., 2023), which was conducted in the four cities of Porto, Nantes, Sofia and Høje-Taastrup between 2019 and 2021. It contains data on 1365 individuals on self-perceived health, mental health, physical activity, socializing activity, environmental quality of life and personal indicators such as age or gender (see Chapter 1.5.3).

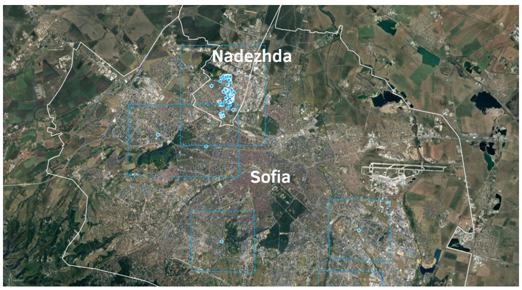
The case studies for the dissertation are composed of the cities where the URBiNAT Neighbourhood Survey was conducted until 2021. These are Porto, Sofia, Nantes and Høje-Taastrup and provide a unique dataset of European satellite city districts (Figure 1.3). The following overview of the case studies synthesizes information from the local diagnostics of the project (Ferilli et al., 2019, 2021). All the neighbourhoods have been classified by their local authorities as deprived neighbourhoods with a significant demand for improvement. More detailed socio-demographic profiles of the studied population can be found in chapters 4, 5 and 6.



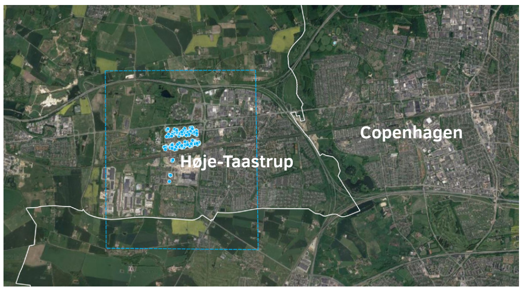
a) Nantes - Nord



b) Porto - Campanhã



c) Sofia - Nadezhda



d) Greater Copenhagen - Høje-Taastrup

FIG. 1.3 A European perspective on satellite districts (adapted, European Space Agency, 2021).
Blue dots indicate residences from survey participants.

1.5.1.1 Nantes - Nord

The Nantes Nord district is located in the northwestern part of the city and borders Orvault and the Erdre River. Its unique valley morphology with 7 rivers significantly constrains mobility, with only two crossing points at the Le Cens River to reach the city centre. Still, Nantes Nord is well-connected through transport infrastructures and features a heterogeneous socio-demographic composition with roughly 25,000 inhabitants. Social housing is one of the major housing typologies in the district with 4,500 units out of 12,760 dwellings in total, followed by one-family homes. Four of these social housing neighbourhoods are labelled as priority neighbourhoods in need of change (Figure 1.4). Nantes Nord is also a green district with over 60% vegetated areas, resulting in 62 m^2 of green space per inhabitant. Special to this district is its gentrification tendency in some areas due to its potential of 30,000 students from Nantes University and high-tech industries, while simultaneously experiencing urban violence, frequent reports of insecurity, high unemployment as well as overweight and obesity, especially in children in comparison to other areas.

FIG. 1.4 Nantes – Nord (Maps Data: Google, © 2023)

1.5.1.2 Porto – Campanhã

The Campanhã district is located at the eastern border of Porto and contains several main highways and slopes acting as barriers in the district between the main neighbourhoods of Cerco do Porto, Lagarteiro and Falcao. Campanhã has about 32,000 inhabitants and is a very green district compared to the central city, occupying 50.01% of the total area, or approximately 82m² per inhabitant, with vacant lots, public parks and gardens, and remnants of Campanhã agricultural landscape as key components. With 3,700 dwellings that provide housing for 8,283 residents, Campanhã is also the district with the highest density in social housing in Porto. Other dominant urban typologies are single-storey one-family homes and multi-story residential housing. Special to this district is that social housing neighbourhoods often provide better living conditions compared to other available housing opportunities for the poorer part of the society, like the common single-story private houses (Figure 5). In addition, the district Campanhã is perceived to not be a part of Porto, as stated by both Campanhã and non-Campanhã residents.

FIG. 1.5 Porto – Campanhã (Maps Data: Google, © 2023)

1.5.1.3 Sofia - Nadezhda

Nadezhda is located in the northwestern part of Sofia. Currently, Nadezhda has 67,905 inhabitants in 29,376 dwellings. The dominant urban typology is collective mid-rise and high-rise apartment buildings built mostly between the '50s and '80s, followed by one-family homes in some areas and a recognizable industrial zone. The presence of Northern Park and three urban gardens contribute to the green environment of the area, with a total land area dedicated to public green spaces being 16.68 ha, or 27.78 m^2 per resident. Although most of the green spaces in Nadezhda are categorized as green in housing estates (61%), followed by community (8%) and private gardens (8%), as well as green areas alongside railways and roads (8%) and in industrial zones (7%). Special to Nadezhda is the absence of social housing due to the wave of privatizations of dwellings after the fall of the Soviet republic in the early 1990s. Ten years later, in 2001, 96.5% of the dwellings were privately owned while the plots were owned by the municipality (Hegedüs et al., 2014), leading to the fact that all of these neighbourhood green spaces count officially as public green spaces.

FIG. 1.6 Sofia – Nadezhda (Maps Data: Google, © 2023)

1.5.1.4 Greater Copenhagen - Høje-Taastrup

Høje-Taastrup Municipality has about 51,000 inhabitants and is located just across the western border of Copenhagen. The development of Høje-Taastrup accelerated as part of the finger plan of greater Copenhagen, a regional development plan across five axes, which set Høje-Taastrup as a regional transportation hub in the 1950s. Until today, public transport connects well to the region and Copenhagen. Today, 26% of the population lives in social housing. The central part of Høje-Taastrup consists of mid-rise apartment or social housing buildings, followed by rowhouses and one-family homes. The municipality is very green and the rural origin is still visible in its surroundings. Special to Høje-Taastrup is that Gregersen, the main study area in URBiNAT, has regularly experienced problems with young delinquents, who caused perceived insecurity by residents, and have been convicted of various offences and have either been in prison or secure institutions. Moreover, under Danish law, this social housing complex Gadehavegård will undergo a radical transformation to mix the neighbourhood, reducing social housing from 100% to 40%. At the time of the project, some residents had already started to move out into new flats.

FIG. 1.7 Greater Copenhagen – Høje-Taastrup (Maps Data: Google, © 2023)

1.5.2 Step 1: Creating a Theoretical Framework

A scoping literature review serves the purpose of creating an overview of the current state of the multidisciplinary research field. It builds the theoretical and methodological framework on how to assess relevant variables and uncovers common risks of bias (Chapter 2). Through the evidence in the current literature, a logical flow of assessment decisions was designed for the theorized mechanistic pathways between green space and health, especially by distinguishing plausible green space assessments by pathway. To limit the scope, we focused on land-use indicators as a proxy for accessible green spaces (*Instoration*) and satellite-based assessments as a proxy for greenness or natural environment (*Mitigation* and *Restoration*). Both assessment strategies can also be used to assess potential negative health impacts that may derive from vegetation, contact with nature, or behaviour (*Causing harm*).

1.5.3 Step 2: Data Collection

This doctoral research uses two complementary sources for data collection (Figure 1.8). The data collection builds on the URBiNAT Neighbourhood Survey, a dataset of individuals across the four cities (dataset 1) and complements it with spatial analyses of their living environment based on publicly accessible data (dataset 2). Both datasets were combined using the addresses of the study participants.

Dataset 1 consists of the 1365 respondents of the URBiNAT Neighbourhood Survey (Cardinali, Bodenan, et al., 2023) which is based on validated short-form questionnaires. It contains data on the dependent variables self-rated health (single item questionnaire, World Health Organization, 1998), mental health (Mental Health Continuum Short-Form, Keyes, 2018), as well as the mediators air pollution and social cohesion (Environmental Quality of Life Scale, Fleury-Bahi et al., 2013) and physical activity (International Physical Activity Questionnaire, IPAQ, 2002). In addition, the dataset provides personal context indicators, such as years lived in the neighbourhood, age, gender, disabilities, education, employment status and income, as well as self-rated indicators for local context variables like satisfaction with shops, leisure facilities and public transport (Environmental Quality of Life Scale, Fleury-Bahi et al., 2013). The complete URBiNAT Neighbourhood Survey can be found in the appendix (A1.1).

Dataset 2 is based on publicly accessible spatial data. Green space, building and street shape files were retrieved from OpenStreetMap (OpenStreetMap contributors, 2017). Satellite Images for the NDVI (Normalized Difference Vegetation Index, Tucker, 1979) calculation were downloaded from the European Environmental Agency. From Eurostat rasterised population data was used to further enhance the dataset with information about population density. The data is collected in a buffer of 1,500 m around survey participants and processed inside QGIS (v3.22) based on the developed guidelines in step 1 (see Chapter 2). After controlling for bias, the green space characteristics were constructed with a developed QGIS script, designed to automatize the QGIS processes and thus reduce the barriers in data collection and increase feasibility for spatial sensitivity analysis (see Chapter 3). For this doctoral research, 11 green space characteristics are calculated (greenness, green spaces, green corridors, total green space, green space uses), each in different buffer types (Euclidean and network) and distances (from 100 – 1,500 m every 100m) adding up to 105 (physical activity and social cohesion) to 135 green space indicators (air pollution) per studied pathway. The cities themselves act as dummy variables to reflect differences in climate, society and culture.

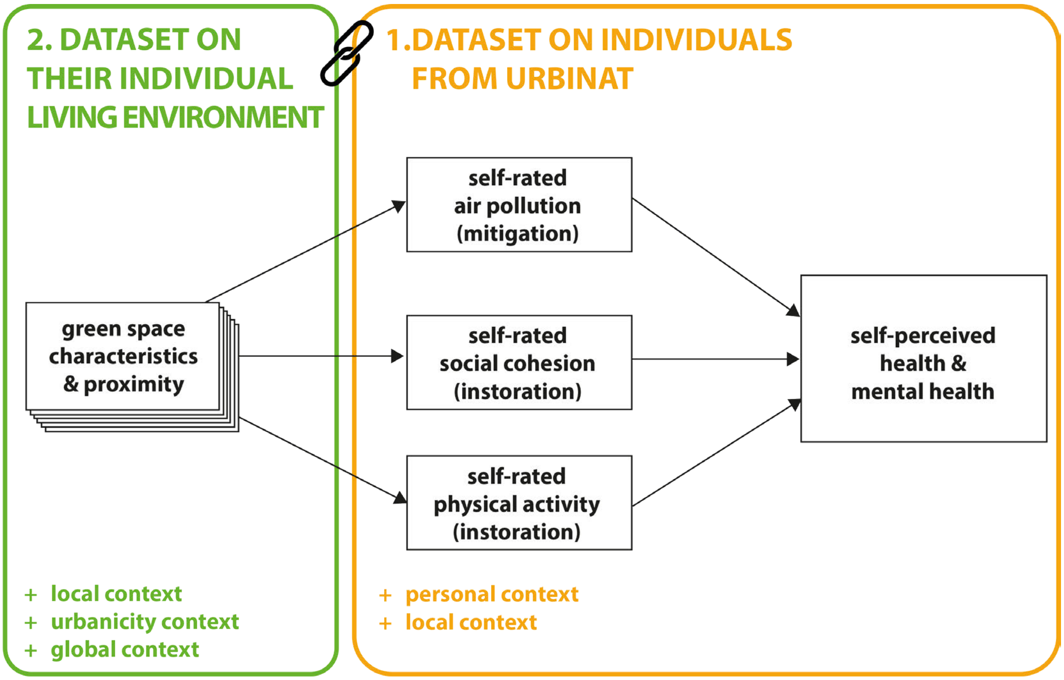


FIG. 1.8 Data Collection divided into individual and spatial data.

1.5.4 Step 3: Statistical Analysis

To examine the role of green space characteristics and their proximity in the chosen pathways, this doctoral research uses structural equation modelling as it is considered the method of choice for pathway analysis compared to other possible techniques (A. M. Dzhambov et al., 2020). The statistical software used is R with the lavaan package (Rosseel, 2023). For the automatization of the structural equation modelling, a function in R was developed that automatically performs structural equation modelling for a list of green space indicators. It stores the results as tables and plots automatically (see Appendix A1.2). This enabled the comparison of 105-135 structural equation models. These results on green space characteristics and proximity have been published and discussed for the physical activity health pathway (Chapter 4), the social cohesion mental health pathway (Chapter 5), and the air pollution health pathway (Chapter 6).

1.6 Relevance and impact

This research effectively contributes to the recent WHO urban health research agenda, which considered it a priority to strengthen links between urban health research findings and actions to promote urban health (WHO - World Health Organization, 2022). It provides detailed evidence on how to design urban green space to maximize health benefits and reduce the global disease burden of our time: NCDs (UN General Assembly, 2018). The selected pathways of activity, social cohesion and air pollution reduction reflect key risk factors in NCDs and will support the WHO Brief for Action published in 2017 (WHO Regional Office for Europe, 2017) and the required actions defined by the NCD Alliance and the Global Climate & Health Alliance (Beagley, Jess et al., 2016) with new insights for the green urban transformation of the 21st century. These expected detailed insights on the distance and green space characteristics that are decisive for each pathway will allow detailed guidance for urban planning practitioners and decision-makers that go beyond the current prevailing view of simple quantities of green space per inhabitant or hectare.

In science, this doctoral research aims to overcome current major barriers in the research field by identifying the reasons for the heterogeneity of past results, developing common research guidelines, and methodological support – especially for non-spatial disciplines – and providing novel insights about the influence of green space characteristics and their proximity to individuals on selected green space health mechanisms. This has the potential to provide a promising pathway to further longitudinal studies that aim to improve causal evidence on how to design urban green spaces for health.

1.6.1 Structure of the dissertation

This dissertation is structured as follows. Chapter 2, published as reporting guidelines, comprehensively explains the theoretical framework of this research and shows important variables and measurement methods that should be applied in this research field. Chapter 3 shows the development and release of the AID-PRIGSHARE tool that can automate the generation of different green space indicators around residential addresses. The following chapters 4, 5 and 6 build on this foundation to analyse and discuss the green space health pathways from different perspectives. Chapter 4 examines the four neighbourhoods of Nantes-Nord, Porto Campanhã, Sofia Nadezhda and Høje-Taastrup for the relationships between green space characteristics, physical activity and health depending on their characteristics and proximity to the place of residence. Chapter 5 analyses the relationship between green space characteristics, social cohesion and mental health for the 1365 participants of the study. Finally, Chapter 6 examines the impact pathway of air pollution mitigation and the relevant green space characteristics, as well as the proximity to the place of residence. Chapter 7 summarizes and synthesizes the main results. It concludes the dissertation with implications for research, urban design and planning practitioners, as well as decision-makers.

FIG. 1.9 Structure of the Dissertation

TOC

2 Theoretical & Methodological Framework

Published as Cardinali, M.; Beenackers, M.; van Timmeren A.; Pottgiesser U. (2023). Preferred Reporting Items in Green Space Health Research - Guiding principles for an interdisciplinary field. Environmental Research 228 (2023) 115893. https://doi.org/10.1016/j.envres.2023.115893

ABSTRACT

The relationship between green spaces and health is attracting more and more societal and research interest. The research field is however still suffering from its differing monodisciplinary origins. Now in a multidisciplinary environment on its way to a truly interdisciplinary field, there is a need for a common understanding, precision in green space indicators, and coherent assessment of the complexity of daily living environments. In several reviews, common protocols and open-source scripts are considered a high priority to advance the field. Realizing these issues, we developed PRIGSHARE (Preferred Reporting Items in Greenspace Health Research). It is accompanied by an open-source script that supports non-spatial disciplines in assessing greenness and green space on different scales and types. The PRIGSHARE checklist contains 22 items that have been identified as a risk of bias and are necessary for understanding and comparison of studies. The checklist is divided into the following topics: objectives (3 items), scope (3 items), spatial assessment (8 items), vegetation assessment (4 items), and context assessment (4 items). For each item, we include a pathway-specific (if relevant) rationale and explanation. The PRIGSHARE guiding principles should be helpful to support a high-quality assessment and synchronize the studies in the field while acknowledging the diversity of study designs.

KEYWORDS greenspace, well-being, public health, pollution, behaviour, stress

2.1 Introduction

Green spaces are attracting increasing societal and research interest, as a primary feature of the built environment capable of reducing the risk potential for non-communicable diseases (NCDs). The development in this area is due to the recognition of the multidimensional framework of health and the epidemiological transition towards NCDs as the leading cause of death (Hartig et al., 2014). Coupled with the focus on greening our cities to combat climate change and promote quality of life in cities in a rapidly urbanizing global population, this field of research has gained even more momentum. This is reflected in the sheer volume of research produced annually (R. Zhang et al., 2021), but more importantly in the shift from a monodisciplinary perspective of mainly epidemiology, psychology, human geography, environmental and health sciences to a multidisciplinary field that is on its way to becoming interdisciplinary (Hartig et al., 2014; R. Zhang et al., 2021). To this date, much of the available evidence on a variety of health outcomes points toward a positive green space-health relationship.

Bringing together the various fields of research in recent years has highlighted the multidimensional effects of green spaces on physical and mental health (WHO Regional Office for Europe, 2016a). For example, a recent review summarized the evidence on nature and mental health and reported a variety of likely positive effects of nature on increased positive affect, happiness, subjective well-being, positive social interactions, and a decrease in mental distress, among others (Bratman et al., 2019a). Furthermore, evidence from longitudinal studies points towards a positive influence of contact with nature on cognitive function, memory, attention, impulse inhibition, school performance, imagination, and creativity (Bratman et al., 2019a). Similarly, another recent review highlighted the evidence of positive effects of green space on physical health through reduced all-cause mortality, stroke-specific mortality, total cardiovascular disease morbidity, cardiometabolic factors, low birth weight, and physical inactivity (Yang et al., 2021). Yang et al, also reported there is limited evidence that green spaces may reduce the risk of cancer, and respiratory-specific mortality, as well as influence hormone levels (Yang et al., 2021). Lastly, also negative health effects can emerge from green spaces through increased risk of allergies, infectious diseases, and harmful microbiota (Marselle et al., 2021).

However, bringing these different fields of research on nature, biodiversity, and green spaces from a variety of disciplines together has raised new questions. While layer after layer of the complex interrelations has been uncovered, questions about the quality and comparability of previous studies arise frequently in reviews (Gascon et al., 2015; Labib et al., 2020; Twohig-Bennett & Jones, 2018). Very high heterogeneity of study designs, exposure assessment, and outcomes are recognized. This heterogeneity of results is likely related to the different disciplinary skills but is partly also founded in the complexity of real-life settings, where the signal-to-noise ratio is very low (Hartig et al., 2014). Thus, to advance in the field, the overall comparability, quality, and rigor of the studies need to level up in precision, transparency, and robustness.

Consequently, one of the priorities is a joint baseline and agreeing on common wording, next to common quality standards, and sharing relevant theories. One important milestone in this regard was the foundational paper of a group of leading experts that identified three main pathways (Markevych et al., 2017). These widely accepted pathways are *Mitigation* (reducing environmental stressors such as air pollution, noise pollution, and heat island effects), *Restoration* (restorative effects of contact with nature through the restoration of attention and stress reduction), and *Instoration* (affordances of green spaces that encourage into more physical or socializing activities). This theoretical concept was later complemented with a fourth pathway *Causing harm* to summarize the negative effects that may arise, especially from the context of biodiversity and health (Marselle et al., 2021).

While the pathways are widely accepted, the methodological quality still needs to be improved through a precise common indicator definition within and across pathways wherever possible (Davis et al., 2021; X.-X. Liu et al., 2022; R. Zhang et al., 2021). This includes especially a common understanding of green space itself, as the type, features, area, and perception of green spaces are diverse (Taylor & Hochuli, 2017). In this respect, a sensitivity analysis of multiple greenspace indicators is requested to better understand the mechanisms and the sensitivity in which they react to health outcomes or pathways (Davis et al., 2021; Labib et al., 2020). Lastly, the transparency of studies needs to be improved by the rigorous and precise definition and reporting of indicators and context variables to facilitate understanding in this interdisciplinary field (Browning et al., 2022; R. M. Collins et al., 2020; Markevych et al., 2017). It is a priority to translate identified risks of bias that are known in certain research fields into common protocols to ensure the quality and comparability of studies in the field, enabling not only meta-analysis but a truly interdisciplinary field.

This chapter, therefore, aims to develop reporting guidelines to assess green spaces and report on green space research to assist the multidisciplinary field. PRIGSHARE (Preferred Reporting Items in Green Space Health Research) is designed as a transparent guide to help frame studies within or across pathways and assess relevant variables accordingly. It focuses on the flow of assessment decisions, starting with the objective of the study, the scope of the study, how to capture green spaces depending on the objective of the study, as well as the relevant contextual variables

PRIGSHARE, therefore, distinguishes green space assessment in surrounding vegetation, contact with nature or accessible green space according to the theorized mechanistic pathways, where the *Mitigation* pathway aligns with the surrounding vegetation assessment, the *Restoration* pathway aligns with the contact with nature assessment, and the *Instoration* pathway with the accessible green space assessment. The *Causing harm* pathway will be included as a potential negative counterpart of the three other pathways since the appropriate assessment depends on the type of harm. This helps to communicate study designs in a common language and works as a guide to assess and report on green space health research. We have outlined this chapter according to other successful guiding principles like PRISMA (Page et al., 2021). The maximum value is gained by using it together with the open-source script (Cardinali, Beenackers, et al., 2023a). This script tackles the effort needed for sensitivity analysis. The QGIS script automatically generates different green space indicators at different distances based on land-use data and vegetation indices provided. While this reporting guideline focuses on assessments via land-use maps or satellite images, we acknowledge different views and possibilities of green space assessments, in the research field. We designed PRIGSHARE in a modular way to be enhanced by other techniques like the 3D street view visual assessments or the LiDAR technology (Light Detection and Ranging) for 3D scanning. Likewise, biodiversity assessments, biomass measurements, self-reported and perceived green space measures, wilderness experiments, and studies that research contact with nature as a treatment are not yet included. We encourage other authors to adapt or enlarge the reporting guideline for their purposes.

2.2 Development of PRIGSHARE

The PRIGHSHARE reporting guidelines are based on a non-systematic literature review of reviews of the field. Other relevant sources were included through snowballing and expert consultation. The first author developed the initial reporting guidelines and proposed the items to the co-authors. The proposal was discussed and refined within the core research team (all authors), which was then presented in a round of expert consultation from geospatial analysis, public health, and behavioral science. Following this consultation round, the core research team refined the guidelines.

Through the evidence in the current literature, we built a logical flow of assessment decisions for the theorized mechanistic pathways between green space and health, especially by distinguishing plausible green space assessments by pathway. We summarized identified risk of bias for each assessment section, and each item listed. To limit the length of the reporting guideline and the associated workload, we focused on land-use indicators as a proxy for accessible green spaces (*Instoration*) and satellite-based assessments as a proxy for greenness or natural environment (*Mitigation* and *Restoration*). Both assessment strategies can also be used to assess potential negative health impacts that may derive from vegetation, contact with nature, or behavior (*Causing harm*). To demonstrate the spatial risk of bias for different assessment decisions and data sources we used test data from the cities in the EU-funded URBiNAT project (Nantes-Nord, Porto-Campanhã, Sofia-Nadezhda, and Høje-Taastrup).

TABLE 2.1 Checklist of items to include when reporting research on green space health effects

#	Section/Topic	Checklist Item
OBJECTIVE		
1	Health Outcome(s)	Specify the health outcome(s) being researched
2	Pathway(s)	Position the research within a theoretical pathway (Mitigation, Restoration, Instoration).
3	Green Space Focus	Provide a clear definition of green space features being researched, distinguishing between surrounding vegetation, contact with nature, and accessible green spaces.
SCOPE		
4	Type of Distance	Specify the type of distance used with rationale (Euclidean Distance (ED), Network Distance (ND), Buffered Service Area (BSA), Administrative Units (AU)).
5	Walkability Network	If accessibility to green spaces is part of the study design, indicate if the walkability network used to generate isochrones or buffered service areas has been checked for bias and how.
6	Distance	Give a rationale for the chosen distance and indicate if different distances were tested (Sensitivity Analysis).
SPATIAL ASSESSMENT		
7	Proxy for Exposure Variable	Define the spatial indicators used in research and indicate if different indicators were tested (Sensitivity Analysis).
8	Data Source	Indicate which database was used, the acquisition time, and if there has been an adjustment for potential bias (expert assessment).
9	Public Ownership Bias	Indicate if the dataset was controlled for the usability of green spaces from public-owned plots and how.
10	Residential Ownership Bias	Indicate how semi-public residential green spaces have been handled.
11	Classification Bias	Indicate how green spaces have been classified.
12	Usability Bias	Indicate if the usability of green spaces was checked and report inclusion/exclusion criteria.
13	Connectivity Bias	(Optional) Indicate if the database has been corrected for green space network connectivity and how.
VEGETATION OR NATURE ASSESSMENT		
14	Proxy for Exposure Variable	Specify the indicator(s) used to assess surrounding vegetation or nature and indicate if the sensitivity was tested.
15	Data Source	Provide the data source of the satellite images and their resolution together with important information such as image acquisition dates and cloud cover percentages.
16	Handling of Blue Spaces	Indicate how blue spaces have been handled.
17	Handling of Seasons	Explain how variance in vegetation indices due to seasonality or changes in the built environment was handled.
CONTEXT ASSESSMENT		
18	Personal Context	Give a rationale for the chosen personal context variables that have been tested or controlled for.
19	Local Context	Give a rationale for the chosen local context variables that have been tested or controlled for.
20	Urbanicity Context	Give a rationale for the chosen urbanicity context variables that have been tested or controlled for.
21	Global Context	Indicate in which climate, societal, and cultural setting the study was conducted. If several settings are part of the research explain how the results were controlled for potential confounding and tested for effect modification.

2.3 How to use this chapter

We present each checklist item (Table 2.1) followed up by an explanation and its rationale for inclusion based on current literature. The items are ordered by their ability to predefine other items and clustered in sub-topics. It is preferred, however not necessary, to report them in this specific order. Also, not all items are relevant for every study design, some will want to report their spatial assessment (items 7-13), and others their assessment of vegetation or natural environment (14-17). To support and keep track of item reporting, we provide a template for researchers in the supplementary material (A2.1). Whether researchers decide to do a vegetation assessment, a spatial assessment, or both, we encourage the use of the supporting open-source script which will produce several green space indicators (spatial assessment) and greenness indicators (vegetation or nature assessment) in distances from 100-1.500m every 100m (Cardinali, Beenackers, et al., 2023a). It is worth noting, however, that the validity of these indicators will depend on the extent to which the data entered have been checked for risk of bias (Table 2.1 categories: scope, spatial, and/or vegetation assessment).

2.4 The PRIGSHARE Items

2.4.1 Objectives

ITEM 1: HEALTH OUTCOME(S)

Specify the health outcome(s) being researched.

Explanation: A clear definition of the health outcomes that are the target of the research will guide the associated impact pathways and the overall study design. This is because most health outcomes are associated with one or more dominant pathways between green space and health. For example, the association between green spaces and cancer is thought to be primarily associated with the mitigation pathway of green spaces and secondarily with restoration effects (Porcherie et al., 2021). Cardiovascular health outcomes, including obesity, are primarily associated with the effect of green spaces to increase physical activity, with a secondary effect on psychological effects from being active in natural environments (Markevych et al., 2017). These psychological effects in turn appear to be primarily related to spending time in nature, mediated by restorative effects (A. M. Dzhambov, Hartig, et al., 2018; R. Zhang et al., 2021). Evidence for respiratory health effects associated with green spaces is still limited (Yang et al., 2021), but is theorized by the air pollution mitigation pathway, which is very well documented (Diener & Mudu, 2021; Ferrini et al., 2020; Xing & Brimblecombe, 2018). A possible combination of all these effects links a reduction in all-cause mortality to green spaces (Yang et al., 2021). Next to these positive effects, also negative health effects might be associated with certain dominant pathways, like allergic responses by surrounding vegetation (Marselle et al., 2021), infectious diseases by contact with nature (Lõhmus & Balbus, 2015), and increased unintentional injuries, especially for children, by accessible green spaces (WHO Regional Office for Europe, 2010). Overall, it appears that certain impact pathways dominate depending on the health outcome being researched and are often associated with other pathways. Researchers are therefore advised to clearly define their outcomes, position their research, and embed it in theory to facilitate understanding regarding the scope of the study.

Furthermore, the health effects occur after different exposure durations and may be interlinked over time. So far, these underlying complex mechanisms are still unclear and require further mechanistic studies to uncover (Yang et al., 2021). They are also thought to reinforce or attenuate each other, particularly through the factor of time (Hartig et al., 2014; Hunter et al., 2019; Markevych et al., 2017; White et al., 2020). One of the best-understood relationships is that between green space and physical activity. While it is unclear what duration of green space exposure is needed to encourage more physical activity, the activity itself has short-term effects on mental health and general well-being (Gascon et al., 2015), medium-term effects on obesity, and ultimately long-term effects on a variety of diseases that can lead to higher morbidity and mortality (Guh et al., 2009; Warburton et al., 2006). Since several of these temporal pathways are likely to exist, future studies should specify which type of impact it focuses on (short-term, medium-term, long-term). In addition, whenever possible, several sequential health effects over time should be included in longitudinal study designs to allow for a better understanding of potential relationships over time. Intervention studies are limited in this respect, as the usual short follow-up time means that medium- to long-term effects are not included (Hunter et al., 2019). However, the increased availability of high-quality longitudinal green exposure data also increases the possibilities for quasi-experimental designs that optimally use the natural variation across time and space in green spaces and greenness. In contrast, cross-sectional studies are not able to detect any causal relationships, which limits their potential in generating new evidence at this state of knowledge in the research field (Markevych et al., 2017). In summary, regardless of the study design, researchers should position their study in terms of the time of the effect, which reflects the health outcome(s) being studied. This will facilitate future meta-analyses and increase the possibility of categorizing the research findings.

ITEM 2: PATHWAY(S)

Position the research within a theoretical pathway (Mitigation, Restoration, Instoration).

Explanation: The choice of the pathway(s) considered pre-determines plausible definitions of green space indicators and the scope of assessment. Although the three pathways are likely to work simultaneously, the individual mechanistic pathways between green space and health are based on different aspects of green space.

Mitigation as a pathway is based on the mechanism of filtering, masking, and reducing environmental stressors through vegetation. In addition, replacing an emission source or creating distance through green space is often also categorized as a mitigation effect (Markevych et al., 2017). Depending on the study design, researchers may want to distinguish between an effect due to competing land uses, where a different type of buffer to the emitting source like a building, could lead to a similar effect, and a mitigation effect, due to the mechanism of vegetation in masking, filtering and reducing environmental stressors. Strong evidence for beneficial mitigation effects exists in the reduction of heat island effects (Iungman et al., 2023), the reduction of noise emissions (Van Renterghem, 2019), and the reduction of air pollution (Nowak et al., 2014, 2018). Additionally, a reduction in light pollution in urban areas is expected (Browning et al., 2022). Furthermore, the degree of vegetation correlates with reduced sealing in urban environments, which in turn mitigates the health risks of extreme weather events (Tidball & Krasny, 2013). Researchers interested in mitigation effects should therefore focus on indicators that can represent the degree of vegetation (4.4 Vegetation assessment, items 14-17).

Effects via the *Restoration* pathway are assumed to develop through the experience of nature. There is a strong body of evidence that various types of nature experiences have positive effects on mental health, and reduce the risk of mental illnesses (Bratman et al., 2019a). The dominant concepts are the *Stress Reduction Theory* (Kaplan, 1995) and the *Attention Restoration Theory* (Ulrich et al., 1991). Recent research confirms that hearing natural sounds improves mental health (Van Renterghem, 2019). Seeing nature, even through a window or virtual through a screen increases recovery from injuries and releases stress (Marselle et al., 2021; Ulrich, 1984). Experiencing nature improves cognition, learning capabilities, and creativity (Marselle et al., 2021; WHO Regional Office for Europe, 2016a). There is also a discussion of positive effects on immune defences through direct contact with nature, but without evidence yet (Yang et al., 2021). Researchers interested in restoration effects should therefore focus on the assessment of nature experience, where vegetation indices might be an appropriate proxy (4.4 vegetation assessment, items 14-17), with special attention on blue spaces, as well as dose and frequency of contact with nature.

In the *Instoration* pathway, green spaces are thought of as a behavioural setting that encourages people to engage in health-promoting behaviours such as physical activity or social interaction (Van Hecke et al., 2018; Wan et al., 2021a). Researchers interested in these behavioural effects of green space should therefore assess those behavioural settings in people’s daily living environment, through spatial indicators (4.3 Spatial assessment, items 7-13).

In contrast, green spaces can also cause harm. Vegetation not only reduces environmental stressors. It can also introduce new ones like airborne allergens, that may cause allergic symptoms (Marselle et al., 2021). In addition, trees emit volatile organic compounds (VOCs). Although VOCs from trees themselves are not particularly harmful to human health, they can react with other airborne chemicals to form air pollution (Duan et al., 2023; Gu et al., 2021). Furthermore, some tree species conversely form more ozone (O_3) than they remove and may negatively impact air quality and thus people's health (Sicard et al., 2022). Also contact with nature can potentially be harmful. Direct contact with nature can have negative impacts, e.g. through an increased risk of vector-borne diseases (Lõhmus & Balbus, 2015) and increased exposure to pesticides and herbicides (Marselle et al., 2021; WHO Regional Office for Europe, 2016a). Lastly, accessible green spaces not only invite social and physical activity. They are also associated with an increase in injuries (Marselle et al., 2021; WHO Regional Office for Europe, 2016a) and a potential increase in crime rates (Kimpton et al., 2017).

To summarize, the chosen pathway will limit plausible definitions of green space exposure (see Figure 2.1). Furthermore, the chosen pathway will narrow down potential mediators to examine, if this is the target of the research. In addition, we suggest including positive and negative aspects into the three pathways linked through their main causing aspect of green spaces: being surrounded by vegetation (*Mitigation*), being in nature (*Restoration*), or having access to green spaces (*Instoration*). This categorization will support meta-analyses of these very different aspects of green spaces and make trade-offs visible. We, therefore, ask researchers to associate their research clearly and precisely with one or more of these impact pathways, as they pre-determine plausible green space indicators.

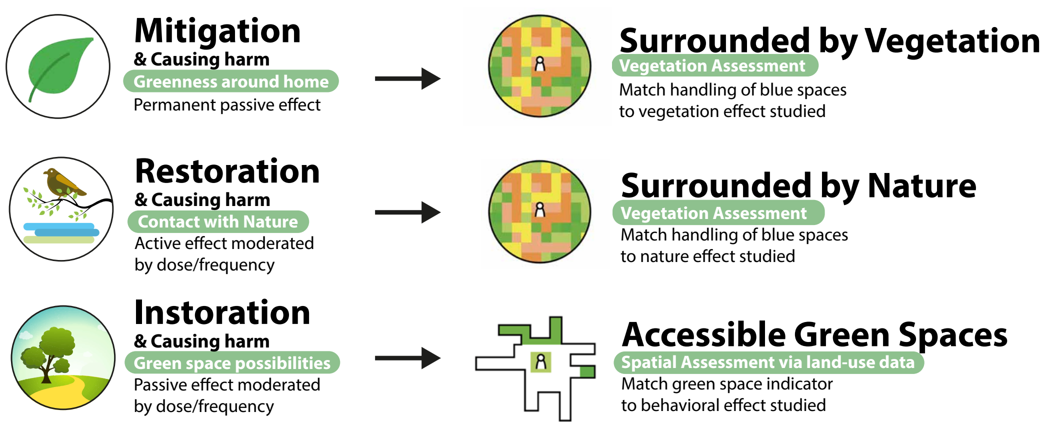


FIG. 2.1 Green space assessment by dominating positive effect pathway and potentially harmful effects

ITEM 3: GREEN SPACE FOCUS

Provide a clear definition of green space features being researched, distinguishing in particular between surrounding vegetation, contact with nature, and accessible green spaces.

Explanation: A clear definition of green space itself forms the basis for the following assessment strategies. In green space health research, the term green space is often used interchangeably when spatially accessible features (green spaces) or the level of vegetation (greenness) is addressed, which is problematic since they associate with different theoretical pathways (Markevych et al., 2017). In addition, most research publications up to 2017 did not define precisely what they mean by green space (Taylor & Hochuli, 2017). When researchers defined green space, it was done very heterogeneously (Labib et al., 2020; Markevych et al., 2017; Taylor & Hochuli, 2017). The frequent use of the umbrella term "greenspace" (note the words being written as one in opposition to green space as two separate words) to simultaneously refer to both green space and greenness (Markevych et al., 2017) might have been a contributing factor in blurring the definition of these very different attributes of vegetation and usable green space. The interchangeable use of the term "greenspace" has the potential to add more noise to a research environment, which is known to have a low signal-to-noise ratio (Hartig et al., 2014). For example, measuring accessible green spaces using NDVI-like indices (Normalized Difference Vegetation Index, Tucker, 1979), can introduce noise into the data because it includes data on green structures that are not accessible, such as private gardens, slopes, or shrubs (Labib et al., 2020). Likewise, the measurement of greenness via land use indices undercuts vegetation in private green spaces and does not capture green elements such as trees in streets, leading to inaccurate results. This is reflected by recent studies that studied both greenness and green space and found significant effects on one indicator, while the other was insignificant (Browning et al., 2022; Davis et al., 2021; Gascon et al., 2018; Luo et al., 2020). Therefore, we recommend that a clear distinction is made between accessible green spaces, which lead to a spatial assessment via land-use indicators (4.3), and vegetation-based or nature-based variables, which can be captured through a vegetative assessment (4.4). This definition should be based on studied health outcomes and associated pathways and will also determine plausible buffer types and distances.

2.4.2 Scope

ITEM 4: TYPE OF DISTANCE

Specify the type of distance used with rationale (Euclidean Distance (ED), Network Distance (ND), Buffered Service Area (BSA), Administrative Units (AU)).

Explanation*:* The type of distance is founded on the theoretical pathways between green space and health. Depending on which pathways are being focused on, the effect is generated either by surrounding vegetation/nature or by accessible green spaces. Surrounding vegetation or nature can be measured using normal Euclidean buffers (ED), although they are limited in handling barriers like buildings (Ferrini et al., 2020). In contrast, accessibility should be measured in walkable distances (Labib et al., 2020; Markevych et al., 2017). To assess walkable distances, Isochrones that form a network distance (ND) is a widely accepted measure. Although it is known that Isochrones tend to be imprecise at smaller distances (Frank et al., 2017). This is because isochrones are constructed through a polygon stretched over the endpoints of the network, which adds inaccessible areas to the isochrone. A more accurate approach for smaller walkable distances may be a buffered service area (BSA), which reduces inaccuracy in the assessment but especially relies on an accurate walkability layer (see item 5). To demonstrate the differences, we constructed a test sample that compares different types of distance measurements for a distance of 500m (Figure 2.2). The total accessible area changes significantly starting from BSA at 100% to ND at 136% and ED at 335%. If surrounding vegetation or nature is the target of research and ED is assumed as 100%, ND represents only 41%, and with BSA only 30% of the surrounding area is covered. A fourth approach, not further discussed here, is the use of administrative units (AU). An area calculation based on administrative units would introduce the modifiable area unit problem (MAUP) and the workaround using centroids of administrative units is known to be an inaccurate proxy of the individual environment (R. M. Collins et al., 2020; Labib et al., 2020). In some cases, however, no other data quality is available. In these cases, the results should be interpreted with appropriate caution. We recommend researchers explicitly select and describe the type of assessment used in relation to the pathways considered.

FIG. 2.2 Types of distance measurement: Types of Distance measurement and accuracy for 500m in Høje-Taastrup. *Red: 25m Buffered Service Area (BSA), Yellow: Network Distance (ND), Green: Euclidean Distance (ED)*

ITEM 5: WALKABILITY NETWORK

If accessibility to green spaces is part of the study design, indicate if the walkability network used to generate isochrones or buffered service areas has been checked for bias and how.

Explanation*:* It is important to note that the accuracy of isochrones and BSA relies on the accuracy of the walkability network. This network is not equivalent to the available street network, with highways and railways being only the most obvious mobility types that act as barriers and need to be excluded. Another potential bias is missing or unconnected sidewalks, especially when primary roads are excluded from the network. Additionally, in some cases, informal paths are a substantial amount of the walkability network in a studied area. An analysis of the URBiNAT case studies showed that 5-13% of the total paths are informal and thus not in any database (Ferilli et al., 2019). All of this has the potential to distort the accuracy of network distances. Thus, we encourage researchers to report the data source and specify if and how they checked the accuracy of the walkability network.

ITEM 6: SCALE

Give a rationale for the chosen distance and indicate if different distances were tested (sensitivity analysis).

Explanation: Depending on the pathways considered, the area of effect might vary greatly. The different effect pathways are associated with different effect ranges in which they operate (Browning et al., 2022; Labib et al., 2020). In addition, detectable health effects react very sensitively to the buffer distance chosen and modify the measured effect (Browning & Lee, 2017; A. M. Dzhambov, Markevych, Hartig, et al., 2018; Hartig et al., 2014; Hu et al., 2021; Labib et al., 2020). While some of these findings can be explained by the low signal-to-noise ratio and heterogeneity in study designs, different ranges in the effect pathways are also hypothesized. It is plausible that the effect decreases at greater distances and varies between pathways. For example, mitigation effects might work in a larger radius than restoration effects. Restoration effects are tied to the range of human senses. They require direct contact with nature, unlike mitigation effects. Mitigation occurs between vegetation and environmental stressors. Human senses are only indirectly involved, which may lead to a larger effect range. That is why study designs with moving smaller buffers via GPS trackers are a promising approach to better capture the dose and frequency of contact with nature. In the case of Instoration, there is limited evidence of the nudging effects of green spaces operating at walkable distances of less than 1000 m (Labib et al., 2020). Although there are certain trends in the effect range of individual pathways visible, further studies are needed to verify these outcomes. Accordingly, if possible, sensitivity analyses of multiple distances should be included in the study design to facilitate meta-analysis, where the AID-PRIGSHARE tool might be helpful (Cardinali, Beenackers, et al., 2023a).

2.4.3 Spatial Assessment

ITEM 7: PROXY FOR EXPOSURE VARIABLE

Define the spatial indicators used in research and indicate if different indicators were tested (Sensitivity Analysis).

Explanation: There is no consensus on how to assess green spaces since it requires interpretation. Depending on the pathways considered, the approaches and results vary widely. There is an agreement, however, that simply surveying the quantity of accessible green spaces is insufficient to measure the *Instoration* and *Restoration* effects (Gascon et al., 2015; Labib et al., 2020; Markevych et al., 2017; Twohig-Bennett & Jones, 2018). Green spaces consist of several features and can vary in type, usability, size, and characteristics which influence the potential for different types of activity (Labib et al., 2020). For more information on the underlying mechanisms, we refer to Gibson's theory of affordances and the theory of behaviour settings by Barker (Barker, 1968; Gibson, 1979). Gibson theorized that objects have perceived values and meanings beyond their visual appearance, which influence our interaction with that object (Gibson, 1979). Barker's Theory of behaviour settings, emphasizes that each spatial object or setting determines a plausible set of behaviours that has to be learned and can differ by culture (Barker, 1968). It is plausible that bigger continuous green space networks nudge people differently than a small pocket park (Markevych et al., 2017). In addition, pocket parks will most likely have a different effect depending on their usability, design quality, and who uses them (Wan et al., 2021a). While for adults, bigger green spaces or chained networks of green spaces might invite physical activity, smaller green spaces tend to invite socializing activities. These relations plausibly differ by age group. Children can be nudged into active physical activity on small playgrounds, while adults will probably be nudged into sedentary activities through benches. Thus, the amount or diversity of uses in green spaces might be suitable to measure effects on socializing activities, while the connectivity of green spaces might be best suited to measure effects on physical activity. Therefore, we encourage researchers to provide a clear definition of the exposure variable in connection to the measured health outcomes and targeted population groups. In addition, we highly recommend a sensitivity analysis to compare different green space indicators, as well as testing of composite green space indicators that incorporate more than one feature of green spaces in future studies (again, the open-source script might be helpful, Cardinali, Beenackers et al., 2023a).

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ITEM 8: DATA SOURCE

Indicate which database was used, the acquisition time, and if there has been an adjustment for potential bias (expert assessment).

Explanation: Common European data sources for green spaces, like Urban Atlas, recommended by the WHO (WHO Regional Office for Europe, 2016a) and OpenStreetMap often provide a low level of accuracy of the information required in this field of research. For the behavioral pathway, it is required to construct a green space indicator that can validly represent the behavioral setting that leads potentially to more physical or socializing activity. Therefore, research cannot rely on greenness but should construct an indicator that uses publicly accessible green spaces and/or their usability. For this, land-use datasets are needed. However, they have a high risk to be biased, as they are not designed for this kind of research and are based on cadaster maps. Figure 3 shows OpenStreetMap and Urban Atlas data on an area in Høje-Taastrup, Denmark, and how this often leads to incomplete and misleading green space data. A comparison between Urban Atlas and OpenStreetMap shows different types of misinterpretation and a general overestimation of available green spaces compared to an expert assessment. Setting the expert map at 100%, OpenStreetMap overestimates green spaces by 23% and Urban Atlas by 59%. From this test sample, OpenStreetMap seems more accurate but should be treated with caution as well. Since it is open source, the added green spaces by the GIS community might vary greatly from city to city. That is why land-use data sets usually require expert knowledge to preprocess before they should be used in spatial and statistical analysis. In addition, OpenStreetMap data is especially likely to change over time. This causes problems in longitudinal study designs when observed changes in the dataset are likely to reflect changes in the reporting/assessment of the environment, rather than changes in the actual environment. Furthermore, it makes it important to report the acquisition time. We, therefore, encourage researchers to report the data source, if and how the data was harmonized in longitudinal studies, as well as how the dataset was pre-processed to avoid bias (see 4.3.3-4.3.8).

ITEM 9: PUBLIC OWNERSHIP BIAS

Indicate if the dataset was controlled for the usability of green spaces from public-owned plots and how.

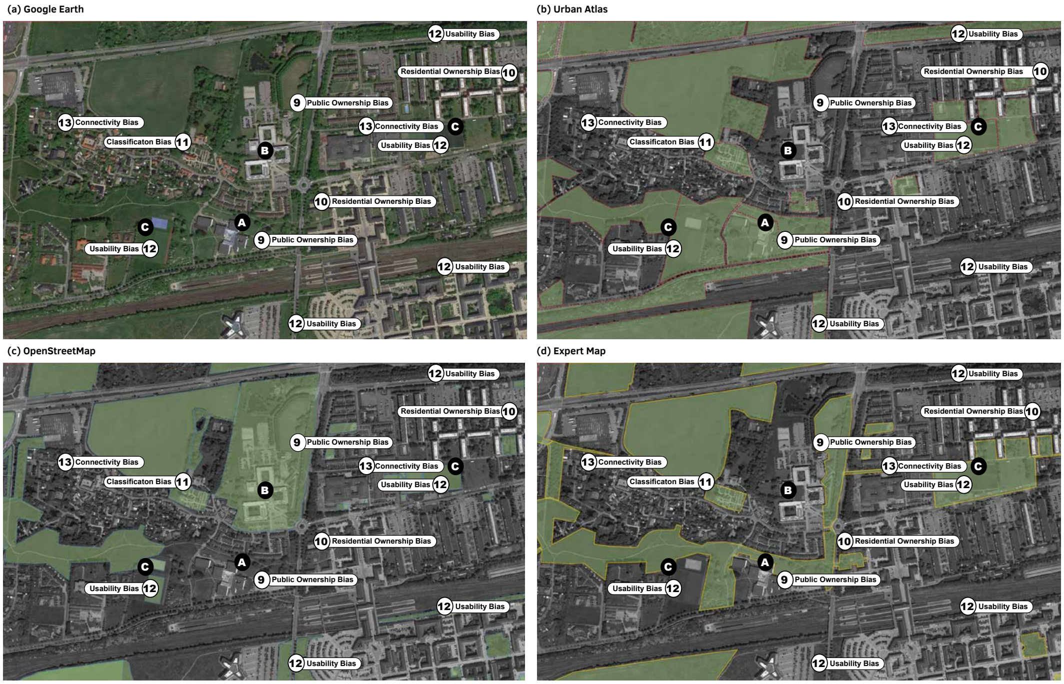

FIG. 2.3 Green space data quality: Differences in green space quantity by data source and associated errors demonstrated with sample data from Høje-Taastrup: (9) Public Ownership Bias (10) Residential Ownership Bias (11) Classification Bias (12) Usability Bias (13) Connectivity Bias; (A) Gymnasium, (B) Town Hall, (C) Sports Field; (4a) Maps Data: Google, © 2022(4b) Urban Atlas -159%, (4c) OpenStreetMap - 123%, (4d) Expert Map – 100%

Explanation: Because land use maps are categorized according to the ownership of a particular plot of land, rather than its usability or green space coverage, misclassification often occurs. We recommend that researchers pay particular attention to modernist public buildings, whose building structures often sit within a substantial green space of local importance (see Figure 2.3). Since the categorization of the plot can refer to the function of the building or the function of the green space on the plot, it is frequently over- or underrepresented. In the test sample of Høje-Taastrup, this effect can be seen twice in a rather small area (in this example a gymnasium and a town hall).

The example in the south shows a gymnasium (A) that is incorrectly categorized by both Urban Atlas (too much space) and OpenStreetMap (none of the space). The example further north shows the town hall (B), where this misclassification also occurs, but this time Urban Atlas does not capture the green space at all, while Open Street Map includes too much of the plot. This leads to an overall bias in the green space indicator, triggering particularly high biases in the smaller buffers. We encourage researchers to check land use maps for these errors and report this clearly.

ITEM 10: RESIDENTIAL OWNERSHIP BIAS

Indicate how semi-public residential green spaces have been handled.

***Explanation*:** Besides publicly accessible green spaces, semi-public green spaces can play an influential role in the everyday activities of people and likely introduce bias if not handled correctly. In some countries, semi-public green spaces are considered private, and in others public, while it can be argued that they are neither. These residential green spaces, especially in highly urbanized areas, are an important extension of the private space of their residents, which was especially visible during the lockdowns during the COVID-19 pandemic (Labib et al., 2022). At the same time, they generally create perceived residential ownership which likely leads to non-use among non-residents, creating this semi-public phenomenon. This effect is plausibly related to the urban morphology (e.g. closed block vs. point high-rise structures) which determines the openness of the residential green space and its connectivity to the overall green space network. For the green space assessment, this leads to a necessary individual expert assessment, of whether these places belong to the public green space network or if they should be considered private for residents. In the Høje-Taastrup test sample (see Figure 2.3) this assessment discovered a very important entry to the local green space network (centre of the map) and divides the social housing residential green spaces (north-east of the map) into publicly used and privately used. We suggest that researchers report how they handled residential bias to reduce noise in the dataset.

ITEM 11: CLASSIFICATION BIAS

Indicate how green spaces have been classified.

Explanation*:* Public green spaces in land-use maps do not equal publicly used green spaces. According to Labib et al. (2020), issues remain regarding which green spaces should be considered in the Instoration pathway. Some studies focus on public parks only (Reyes-Riveros et al., 2021), while others include forests, cemeteries, and agricultural land (Discher et al., 2022). To complicate things further, it must be added that the consideration of green space typologies will depend on the cultural context of the study (see also 4.5.4 Global Context). Contrary to most cemeteries in northern societies, cemeteries are rather grey (not green) in southern societies and should be treated differently depending on the cultural context. In principle, however, we argue that a pure extraction of public green spaces from land use databases would exclude (semi-) natural environments that are being used to walk, cycle, or meet. In Figure 3, a typical cluster of agricultural land, forest, and a cemetery is shown that is used by the residents and would not be captured if only public parks were considered. Thus, if only public parks are the target of research, we still recommend capturing other (semi-) natural environments and testing for effect modification, as these spaces might explain partly the observed effect (see 4.5.2 Local Context). Researchers should clearly define and explain the classification of included and excluded green spaces.

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ITEM 12: USABILITY BIAS

Indicate if the usability of green spaces was checked and report inclusion/exclusion criteria.

FIG. 2.4 Usability bias: Left, unusable greenery slopes in Porto Campanhã, Portugal, right, unusable street greenery between lanes in Porto Campanhã, Portugal (Maps Data: Google, © 2022)

Explanation*:* Green spaces in land-use maps are not all usable for residents, most commonly because of inaccessibility or non-usability. A potential bias concerns fenced green areas, which are often found around sports fields, but also around cemeteries and sometimes around agricultural areas (Figure 2.3). In the example of Høje-Taastrup, the southwestern sports field is fenced and exclusively for students, while the northwestern sports field is open to everyone (C). In addition, it can also be seen that green areas around sports fields are often not properly classified, as they are also subject to ownership bias. More typical issues in land-use maps are the inclusion of green areas on steep slopes, green areas consisting exclusively of dense vegetation such as shrubs, and non-usable greenery between street lanes or along railroad tracks (Figure 2.4). It is worth noting however, that while these types of non-usable green spaces are not able to create an inviting behavioural setting themselves, they might be able to increase the inviting character of existing settings nearby, e.g. by reducing environmental stressors or the addition of natural sounds and scenery. Depending on the presence of these types of green spaces and the research question, this may substantially affect the measured results.

Consequently, it is important to use site visits, local expertise, and/or tools such as Google Street View to specifically check the dataset for this susceptibility to error. Although this might not be feasible in study designs that include larger spatial areas., researchers should be aware that these non-accessible green spaces will introduce noise in the dataset. Researchers should therefore check the land-use dataset for usability and state the rationale for inclusion and exclusion in the dataset.

ITEM 13: CONNECTIVITY BIAS

(Optional) Indicate if the database has been corrected for green space network connectivity and how.

Explanation: If physical activity is a goal of the research, the connectivity of green spaces as a potential network for green mobility is an important factor to consider. It seems plausible that the more destinations can be reached by green mobility, the higher the incentive to use this network (Roscoe et al., 2022). It is recommended to investigate linear green spaces, which are often not part of the databases but are essential for the local green network. In the example from Høje-Taastrup, two of these linear connections are present, turning fragmented green spaces into a green network (Figure 2.3). In addition, to map this indicator correctly, polygonal structures interrupted by roads or railroad tracks must be reconnected manually where pedestrian crossings exist. Other possible indicators might be the total line length of pathways within green spaces. We encourage researchers, therefore, to investigate this and report whether they corrected their dataset for connectivity bias.

2.4.4 Vegetation and Nature Assessment

ITEM 14: PROXY FOR EXPOSURE VARIABLE

Specify the indicator(s) used to assess surrounding vegetation or nature and indicate if the sensitivity was tested.

Explanation*:* Different vegetation assessments can lead to different results and need to be adapted to the pathway researched. Vegetation indices, like NDVI, are the most used proxy for green spaces in general and not only for greenness, thus largely independent of the pathways. However they produce different results depending on the vegetation index used (Markevych et al., 2017). In addition, it remains unknown which of these indices provides the most accurate results (Labib et al., 2020). Other possible assessment strategies are land cover maps, processed street view visuals through computational tools, and 3D assessments with LiDAR technology. Land cover maps like CORINE ignore green areas smaller than 25 ha, including all street trees and private green areas (Labib et al., 2020), making them less suitable as a proxy for vegetation. Indicators based on processed street view images are limited in their applicability in the interdisciplinary field, because of the expert knowledge required in handling and processing (Markevych et al., 2017). LiDAR technology is a promising technique, enabling the measurement of vegetation in 3D using point clouds. However, LiDAR datasets are not yet widely available. Furthermore, the calculation of the indicators is significantly more complex than 2D vegetation indices, so the application is limited here as well. The major advantage of 3D measurement is seen mainly in the better distinguishability of trees and grassed areas since trees are said to have a greater health effect (Schmidt, 2022). In a recent study, Giannico et al. compared traditional 2D NDVI from Rome with a 3D vegetation index, developed with the LiDAR Technology, and highlighted the differences through low Pearson correlations between 0.33 at 50m buffer 0.47 at 300m buffer between the two indices (Giannico et al., 2022). However, a large part of the differences might be explainable through the rather low resolution of the 2D indicator of 30x30m. The recent availability of high-resolution satellite images of e.g. Sentinel2 in 10x10m resolution might lead to a higher similarity between LiDAR and satellite-based spatial indices. Therefore, to justify the higher effort of the 3D measurement, more tests are needed to verify the hypothesized improvement in data quality through LiDAR. Especially since green walls that cannot be captured with 2D indices are still rare in urban settings. Thus, in the following (sections 4.4.2-4.4.4), we will only refer to the robust and dominantly used vegetation indices and how to adapt between measuring natural (green-blue) environments compared to pure greenness (only vegetation). Lastly, we would like to explicitly encourage sensitivity analyses of different indicator types or indices (Cardinali, Beenackers, et al., 2023a).

ITEM 15: DATA SOURCE

Provide the data source of the satellite images and their resolution together with important information such as image acquisition dates and cloud cover percentages.

Explanation*:* It is well documented that low resolutions of satellite images lead to inaccurate vegetation indices. Low resolutions are not capable of capturing smaller green areas (Labib et al., 2020; Markevych et al., 2017) and might not be capable of distinguishing between grass and trees. With the introduction of Sentinel 2 for Europe, 10x10m resolutions are becoming standard, increasing the accuracy and robustness of this greenness assessment. To evaluate the quality of the greenness indicator used, researchers should provide the satellite and its resolution together with contextual information such as image acquisition dates and cloud cover percentages.

ITEM 16: HANDLING OF BLUE SPACES

Indicate how blue spaces have been handled.

Explanation*:* Blue spaces in vegetation indexes can be a source of bias. They should be treated differently in mitigation compared to restoration pathways. In the restorative pathway, blue spaces are also associated with positive effects on health (White et al., 2020). That is why blue spaces are often manually edited in vegetation indexes, trying to represent the natural environment instead of just greenness when restoration effects are studied. If left untouched, blue spaces will receive lower scores in NDVI than buildings or streets. Water has a low reflectance in red and almost none in near-infrared, which leads to low NDVI values (e.g. Nantes Test Sample: -0.2 for a bigger river compared to +0.2 for a building with a grey roof). Thus, blueness can conceal the presence of greenness, while they are working together as a restorative natural experience. Within the mitigation pathway, blue spaces likely have a different impact depending on the environmental stressor of interest. Blue spaces might be less impactful in

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reducing air pollution or in noise mitigation, but they play an important role in temperature reduction. Leading experts usually recommend setting waterbodies to zero or missing when greenness is the target of research to avoid a lower mean vegetation index through the presence of “blueness” (Markevych et al., 2017). Both strategies will increase the mean NDVI value but to a different extent. However, blue spaces should not be ignored completely as they can lead to spurious relations and should instead be included as a stand-alone indicator. For example, present water surfaces may seemingly increase the temperature reduction effect of vegetation. Besides this, blue spaces might be treated differently depending on their size. Small water streams can potentially be ignored since they will not substantially alter the vegetation index and serve as an inherent feature of the natural environment, in which they are located in. For larger water bodies like rivers, lakes, and oceans researchers need to decide if blue spaces are set to missing, to zero, or left untouched. Researchers should base their decision on the research question and the definition of green space used. In any case, we encourage researchers, to report on how they treated blue spaces to increase study transparency and facilitate meta-analyses.

ITEM 17: HANDLING OF TEMPORAL CHANGES IN VEGETATION INDICES

Explain how variance in vegetation indices due to seasonality or changes in the built environment was handled.

Explanation*:* Vegetation indexes vary by season and by year. Depending on the study design and timestamp of health outcome variables, a pure snapshot of greenness might not be sufficient. With the instalment of Sentinel-2, the availability of cloud-free satellite images at any time point in the year has become a lot easier. Before the Sentinel-2 database with daily images was available, most of the research only used a single summer day image to produce the vegetation index (Markevych et al., 2017). However, calculating the vegetation index from one satellite image potentially introduces bias, in particular during harvest times (Barbati et al., 2013). In addition, seasonality in general can affect the calculated values. Depending on the study design satellite images should be assessed at several time points and merged into one image before calculating a vegetation index. The vegetation index may also differ in different time stamps because of the transformation of the built environment. Green spaces might be demolished for a new residential area, or an old industrial site might be transformed into a park during a longitudinal assessment, which should be seen as a potential to study causal relations with quasi-experimental methods or fixed effects analysis. In any case, we encourage researchers to specify how a potential variation in vegetation indices between different time stamps has been handled or exploited.

2.4.5 Context Assessment

The context of the study is important, and each study should carefully consider which confounders should be controlled for and which effect modifiers should be tested. A confounder is a variable that is not on the causal pathway and can introduce a spurious or confounded association if not controlled for because it affects both the health outcome and the green exposure (Szklo & Nieto, 2014). An effect modifier (moderator) is a variable that influences the relationship between green space exposure and the health outcome; a certain effect may be more pronounced in certain contextual situations compared to others (Szklo & Nieto, 2014).

ITEM 18: PERSONAL CONTEXT

Give a rationale for the chosen personal context variables that have been tested or controlled for.

Explanation*:* At the personal level, many confounding factors and effect modifiers are considered in environmental studies. Generally, socioeconomic status (SES), age, gender, employment, and disability are considered. For example, neighbourhood SES is not only thought to have a dominant influence on people's health but is also associated with the level and quality of green spaces in the residential environment, making it a confounder in most of the research designs in the field (Browning & Lee, 2017; Markevych et al., 2017; van den Bosch & Ode Sang, 2017a). Furthermore, since study designs are predominantly about the surrounding green space around an individual's home, a broad consensus has emerged that an important moderating effect is the actual frequency and duration of exposure (Gascon et al., 2015; Hartig et al., 2014; Markevych et al., 2017). Here, occupation and age groups can serve as proxy variables. These variables can measure potential differences in the duration and frequency of exposure in the neighbourhood. For example, this may explain, in part, why neighbourhoods with a high proportion of unemployed people have been shown to benefit more from green spaces (Dadvand, de Nazelle, et al., 2012).

In addition, pathway-specific context variables should be considered. On the Instoration (behavioural) pathway, it is particularly important to locate indicators that can affect the relationships between the stimulus character of green spaces and behaviour. For example, owning a dog potentially changes the measured stimulating effect of green spaces, from a stimulated to a required activity. In addition, owning a private green space likely modifies the measured relationship between green spaces and health (Labib et al., 2022; X. Zhang et al., 2021). Private gardens enable an effortless transition between inside and outside, which potentially leads to more but shorter doses of nature and may affect the ability of public green spaces to invite owners to physical or socializing activities. In the same way, different cultural habits in everyday behaviour may also change the exposure to green spaces or the relationship between green spaces and behaviour. It is also discussed that subjective evaluation of green spaces, such as perceived safety or perceived quality, modifies the effect, which might result in differences between men and women (Gascon et al., 2015; Markevych et al., 2017). The restoration pathway relies on stress levels or attentional fatigue to measure the restorative effects of greenness, which may differ by age group, occupation, and SES, as well as personal living conditions and stress levels at home (Amerio et al., 2020). The mitigation pathway passively reduces environmental stressors around the residential environment. These environmental stressors tend to be more frequent where rents are low, as they reflect the low quality of the living environment (V. O. Li et al., 2018). In addition, the quality of buildings, whose purpose is to protect against environmental stressors, is often lower where rents are low, reflecting the lower quality of housing. Surprisingly little is known about the modifying effect of the quality of the building envelope in the green space mitigation pathway, even though the very function of buildings is to protect against external environmental impacts. It is therefore plausible that the measured mitigation effects differ significantly between buildings of different epochs, construction types, and degrees of renovation. This could explain part of the effect in socially disadvantaged areas, where a stronger correlation between green spaces and health is often found (Dadvand, de Nazelle, et al., 2012). Thus, we encourage authors to carefully reflect on the personal context domain that may lead to a necessary adjustment for confounders and testing for (pathway-specific) effect modifiers.

ITEM 19: LOCAL CONTEXT

Give a rationale for the chosen local context variables that have been tested or controlled for.

Explanation*:* Green space itself is embedded in an anthropogenic local context that influences other metrics. First, green space assessment can hardly be isolated from the living environment in which it is located. Especially in the behavioural domain, other influences likely affect the measured relationship. The most commonly considered factors are neighbourhood walkability, the mix of uses, and access to public transportation (Labib et al., 2020). It is also plausible that perceived neighbourhood safety has a strong influence on general open space use (van den Bosch & Ode Sang, 2017a). Second, the spatial distribution of emitting sources in relation to green spaces and the individuals of the study may cause spurious relations or conclusions. Depending on the studied area, it is possible to measure the influence of a third variable, e.g. the absence of artificial light, rather than the effect of green spaces due to competing land uses (Stanhope et al., 2021). But since confounders and mediators are statistically identical and can only be distinguished based on the underlying theory (MacKinnon et al., 2000), it may vary how those competing land uses are included in the study design (see also item 2: Pathway(s)). Third, the choice of place of residence is a highly segregating process, leading to more or less segregated environments with distinct tendencies in key personal health determinants. In fact, a local environment can often be assigned to one or more milieu-specific settings. This carries a high risk that omitted variables such as socioeconomic status will bias research findings (Browning & Rigolon, 2018; Gascon et al., 2015). Fourth, spatial artifacts can occur and bias the measured association between green space and health outcomes. The closer individuals in the study live together, the more their daily living environments overlap. This results in very similar green space measurements, especially at larger buffer distances. These forms of spatial autocorrelation or geographical bias can be tested with Moran's I in GIS, a form of geographically weighted regression (Labib et al., 2020). Researchers are therefore encouraged to control for local confounding variables, test for potential (pathway-specific) effect modifiers, and discuss possible limitations. This should be dependent on their study design, while particular care should be taken in the Instoration pathway.

ITEM 20: URBANICITY CONTEXT

Give a rationale for the chosen urbanicity context variables that have been tested or controlled for.

Explanation*:* The degree of urbanization may moderate the measured impacts. First, the environmental stressors that occur are significantly more prevalent in more urban environments, which influences the need for, and likely the measured strength of, mitigating and restorative effects (Browning et al., 2022). It is also likely that the relationship between the amount of available green space and specific health benefits is not linear and approaches a certain threshold asymptomatically. This would mean that more green space no longer has the same effect on human health beyond a certain amount of green space. This might explain partly the measured differences between rural, suburban, and urban areas. Second, daily routines, particularly for working age groups, are different in rural and suburban areas compared to urban structures. Daily habits are highly dependent on the urban context in which daily life takes place. Density and mix of uses determine to a large extent the number of jobs, infrastructure facilities, leisure, and mobility opportunities and can thus be understood as incentives for pedestrian mobility instead of car-dependent mobility, which will lead to more time spent outdoors (Gehl, 2013). In addition, the degree of urbanicity acts as a proxy for the time needed to reach the destinations of daily life (Montgomery, 2013) and thus of the remaining leisure time after work that can potentially be spent in green spaces. Therefore, it seems only plausible that green spaces develop different affordances in each case. To summarize, the urban context should always be reported and included as a moderating variable when different settings occur in the study design. For example, population density seems to be a suitable measure for this purpose.

ITEM 21: GLOBAL CONTEXT

Indicate in which climate, societal, and cultural setting the study was conducted. If several settings are part of the research explain how the results were controlled for potential confounding and tested for effect modification.

Explanation*:* Cultural settings, societal conditions, and climate vary widely around the world and thus influence the comparability of individual local study results.

Firstly, climate zones arguably determine the necessity for intensive or less intensive mitigation of environmental stressors, especially heat. In addition, the potential negative impacts of green spaces through disease vectors vary for different climate zones (Rossati, 2017). It is important to note that those climate classifications can vary significantly even within larger countries like the United States (Kottek et al., 2006). Secondly, because of different climate zones, different urban morphologies, architectural designs, and cultural habits have evolved. These behavioural settings also likely influence daily habits, like the amount and intensity of physical activity (Merrill et al., 2005) and social interaction outdoors. Thirdly, the diversity of individual societies also leads to different starting points concerning other health determinants (Dahlgren & Whitehead, 1991, 2021). These include the health care system as well as other social, economic, and environmental conditions. In addition, there is also evidence that the stress levels of societies might be different (Gallup, 2019). To summarize, different global contexts have different conditions in environmental stressors (*Mitigation*), seem to have different starting conditions in stress levels and well-being (*Restoration*), as well as different behavioural settings and habits (*Instoration*). Global contexts also differ in potential negative health impacts of green spaces and in different societal conditions that influence a variety of health outcomes. Thus, different global contexts will likely add another layer of noise and complexity to the data, whether in a direct comparison within a study or a later evaluation by a review. Therefore, we invite researchers to indicate how they address these contextual factors, for example, by stratifying the data set by city samples or by adding the city as a confounding variable into the model. However, even if only one case study is part of the study design, researchers are asked to report the global context in terms of climatic and cultural conditions to aid the interpretation of the results and facilitate comparisons and future meta-analyses.

2.5 Discussion

PRIGSHARE (Preferred Reporting Items in Green Space Health Research) was developed to structure important items to consider and report in the green space health research field into an ordered reporting guideline. This was a returning demand from the field to upscale the quality and robustness of studies (Browning et al., 2022; Davis et al., 2021; R. Zhang et al., 2021). The developed checklist guides researchers from the research question to a precise definition of green space, depending on the dominant mechanistic pathway, to an appropriate approach to scope, green space indicators, and inclusion of important contextual variables (Table 2.1). At each step, examples of misconceptions and inaccuracies in data collection, as well as confounding variables and possible effect modifications, are discussed (see also Figures 2.1-2.4). This should help researchers achieve a high-quality, transparent, and understandable study design and thus consequently robust study outcomes.

The flow of Assessment Decisions

An important achievement is the transparent and guided flow of assessment decisions from the health variable to the theoretical impact pathways and the definition of green space indicators. Until now, this decision tree has often been applied implicitly and subsequently could not be correctly repeated by others, leading to a variety of incomparable approaches. The PRIGSHARE reporting guideline is an attempt to make these dependencies visible (Figure 2.5). Rather than justifying the chosen distance in a study design with policy recommendations, as a recurring previous practice pointed out by Labib et al (Labib et al., 2020), PRIGSHARE guides by the theorized underlying mechanisms of the pathways in choosing buffer types and distances. At the same time, it also makes clear that one green space indicator is not enough to investigate all impact pathways and supports researchers with a tool for sensitivity analysis, to further advance the understanding of the area of effect of specific green space health mechanisms (Cardinali, Beenackers, et al., 2023a).
In summary, PRIGSHARE's flow of assessment illustrates how different mechanistic pathways translate into different decisions regarding assessment methods and chosen variables. PRIGSHARE will make it easier to categorize and compare studies, and potentially streamline the assessment by pathway thus fostering review quality through comparability and available meta-information.

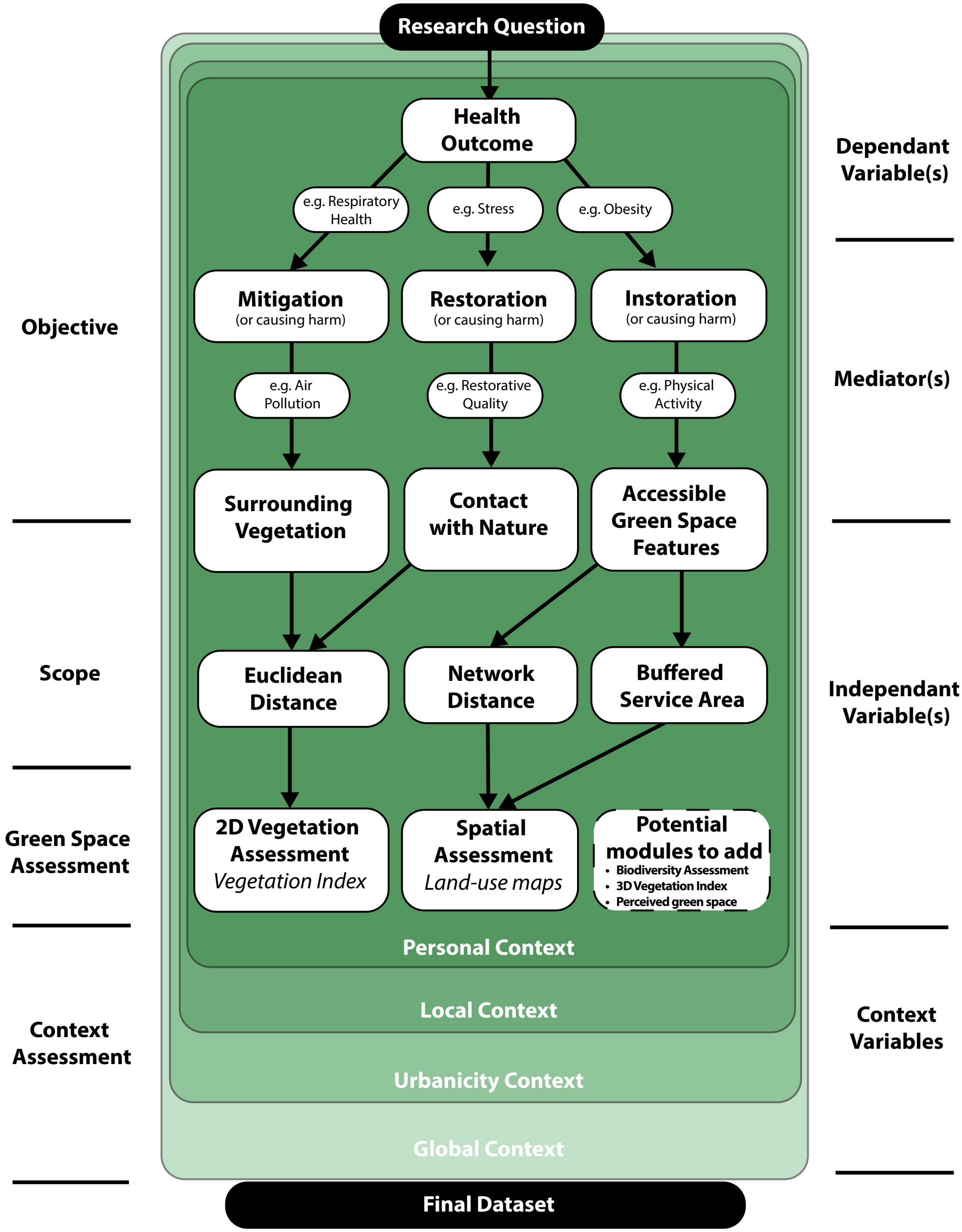

FIG. 2.5 Flow of assessment: The suggested flow of assessment decisions depending on health outcome(s) and associated pathway(s)

The modularity of the green space assessment strategy

Another strength of the PRIGSHARE reporting guideline is the modular use of green space assessment strategies, allowing other researchers to add new modules, e.g. for 3D visual assessments via street view applications, perception of green space, 3D vegetation indexes based on LiDAR Technology, or a module for active tracking of green spaces dose and frequency via GPS. Because of the discussed weaknesses of established assessment strategies and the simultaneous impact of green space components, new assessment strategies are likely to be adopted. Therefore, PRIGSHARE establishes a robust framework where these assessment strategies can be added or exchanged without affecting other modules of the reporting guideline. For this reason, we encourage other researchers to enhance and adapt PRIGSHARE further to their needs by adding green space assessment modules, preferably published in open access and scripts in open source.

The robust framework and its potential to include new research areas

PRIGSHARE is also able to include new sub-fields in greenspace-health research that are emerging. These new areas derive in parts from the nature-based solutions movement (European Commission. Directorate-General for Research and Innovation., 2021a, 2021b). Firstly, there is increasing recognition in this research field of the already known disaster risk reduction potential of green spaces (Hartig et al., 2014), able to mitigate the risk of injuries and lives lost due to extreme weather events. Secondly, there is a potential that green spaces and trees in particular are able to reduce exposure to artificial light pollution at night. Both can be categorized as mitigation effects where greenness is an appropriate proxy. Thirdly, contact with the microbial biodiversity of nature is considered to strengthen the immune system (Markevych et al., 2017; Sandifer et al., 2015). It can be argued that this fits into the restoration pathway since it requires actual contact with nature. In summary, the robustness of the reporting guidelines allows for the expansion and refinement of existing impact pathways without substantially affecting the guideline structure. Theoretically, even additional pathways could be included.

Risk of bias assessment

While PRIGSHARE is not a quality assessment tool, it helps assess the constructed dataset's appropriateness, accuracy, and completeness to answer the research question. The reporting guideline provides an overview of a set of potential noise in the data set that arises from inaccuracies or missing effect modifiers and confounding variables in the research field. This overview will support the existing risk of bias assessment tools like OHAT (Office of Health Assessment and Translation, National Institute of Environmental Health Sciences, OHAT, 2015) that are used in systematic reviews to assess the study quality. Thus, PRIGSHARE will help make future reviews in the research field more robust overall.

Feasibility for different study types

The feasibility of PRIGSHARE for larger cohort or registry-based studies on the Instoration pathway might be limited. Instoration pathway studies require a spatial assessment via land-use data which is associated with a substantial correction effort compared to vegetative assessments. Due to the wide spatial spread of participants in cohort or registry-based studies, the spatial correction effort becomes unfeasible. This limits the applicability of parts of PRIGSHARE in larger cohort studies if available green space data is not greatly improved. Currently, researchers usually have to decide between a high level of precision in spatial data to increase the validity of the results on the one hand and feasibility on the other hand. In addition, manually editing spatial data will negatively affect the reproducibility of the study. To tackle both problems, we suggest an open-source green space layer, where these corrected expert maps can be stored and shared. In general, the low data quality of existing databases should be taken as an opportunity to look for new standards to increase the precision and usability of green space data.

Analytical Processing

The PRIGSHARE reporting guidelines are limited in their guidance about conducting and reporting the analytical process that is to follow the data assessment. In section 4.5, we encourage researchers to carefully consider potential confounders and effect modifiers but there are of course also other aspects of the data analysis that are important. Although we acknowledge that data analysis is an inherent part of the publishing process, we consider extensive guidance on this topic as out of the scope of this chapter. For guidance on mediation analysis, which seeks to better understand the pathway mechanisms, we refer to the review on analytical approaches in green space health research of Dzhambov and colleagues (A. M. Dzhambov et al., 2020). Furthermore, general reporting guidelines in public health can support more universal reporting needs, including analytical processes, specific to the used study type such as the STROBE statement for observational research (Elm et al., 2007) the CONSORT statement (Schulz et al., 2010) for trials or the TRIPOD statement (G. S. Collins et al., 2015) for prediction studies.

Limitations

The PRIGSHARE reporting guideline was tested with data from four European cities. We acknowledge that there will probably be differences in terms of general data quality, data accessibility, and types of errors for non-European cities. In addition, the green space data quality of Urban Atlas and OpenStreetMap was only demonstrated for one city to show the general principle. While we are confident that these data quality issues are measurable everywhere in Europe, the error tolerance accordingly represents only a general direction. In addition, due to the wide science area, the discussed confounders and effect modifiers should only be seen as frequent examples rather than a comprehensive list.

2.6 Conclusion

The PRIGSHARE reporting guideline brings together knowledge from different disciplines to support a high-quality assessment of green spaces and to synchronize the studies in this interdisciplinary field while acknowledging the diversity of study designs. PRIGSHARE has the potential to support reducing the heterogeneity in assessment and outcomes which will advance the overall understanding of green space health pathways. Although PRIGSHARE stemmed from identified problems from existing reviews in the field, it is not yet possible to prove that this reporting guideline can achieve its ambitious goal of synchronizing the field and uplifting the quality of studies. It will largely depend on the uptake and use of PRIGSHARE and its frequent update in a rapidly growing field of research.

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3 Measuring green space with computational tools

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ABSTRACT

In the interdisciplinary field of green space health research, there is a demand to reduce the effort to assess green space, especially for non-spatial disciplines. To address this issue, we developed AID-PRIGSHARE, an open-source script that automates over 400 QGIS processes to substantially reduce the time-intensive task of generating green space indicators. AID-PRIGSHARE calculates greenness, green space amount, access to green infrastructure, and green space uses within distances of 100-1500m around geolocations. This substantially reduces the effort for sensitivity analysis and may provide support for research that aims to understand the impact of green space indicators on health outcomes.

KEYWORDS green space; sensitivity analysis; indicator; GIS; script; automatization

3.1 Introduction

In quantitative research on the effects of green spaces on behaviour, physical health, and mental health, researchers rely heavily on spatial indicators. Especially for the non-spatial disciplines, processing these spatial data is a significant hurdle for their research (Markevych et al., 2017). Furthermore, it is still largely unclear which distances and aspects of green spaces are relevant for the different impact pathways (Markevych et al., 2017). To this date, researchers often rely on artificial distances (often 300m or 500m) justified by policy documents, mostly independent of the pathway studied (Labib et al., 2020). It is however likely that both the distance and aspect of green space that drives the assumed impact, differ significantly between pathways (Cardinali, Beenackers, et al., 2023b). In the *Mitigation* pathway, the main aspect seems to be the potential of vegetation to reduce environmental stressors (Browning et al., 2022; Iungman et al., 2023; Nowak et al., 2014; Van Renterghem, 2019). In the *Restoration* pathway, it is assumed that contact with nature triggers recreational function and stress reduction (Bratman et al., 2019a). In the *Instoration* pathway, the inviting character of publicly accessible green spaces is theorized to increase physical activity and social exchange (Van Hecke et al., 2018; Wan et al., 2021a). Sensitivity analyses that test different distances and green space indicators are therefore an important element for the research field (Davis et al., 2021; Labib et al., 2020). To significantly reduce the effort required for this and to make it easier for non-spatial disciplines in particular, we have developed AID-PRIGSHARE (Cardinali, Beenackers, et al., 2023c). AID-PRISGHARE is an open-source script that allows researchers to automatically generate a variety of green space indicators at several distances with minimal effort.

3.2 Software features & architecture

AID-PRIGSHARE was developed within QGIS v3.22 (QGIS Development Team, 2023) with the graphical modeler feature to automate specific repetitive processes that are necessary to compare different indicators and/or different buffers. Next to Euclidean buffers, 25m buffered service areas (BSA) to calculate network distances are available. BSA are a more precise version of network distances, especially for smaller distances (Frank et al., 2017). The algorithm will calculate the chosen indicators for distances between 100m and 1500m with 100m increments. AID-PRIGSHARE allows the user to choose which of the following green space indicators should be generated by the algorithm:

A Mean vegetation index (e.g. NDVI) in Euclidean distance (-1 to 1)
B Mean vegetation index (e.g. NDVI) in BSA (-1 to 1)
C The total amount of public green space within BSA (m^2)
D Public green space ratio (public green space/total buffer area) within BSA (0-1)
E Access to green infrastructure within BSA (m^2)
F Distance to the nearest public green space (rounded in steps of 100m)
G The total amount of green space uses (playgrounds, sports fields, gardening,..) within BSA (number)
H Diversity of green space uses within network distance (number)
I The total amount of private green space of an individual (m^2))
J The total amount of semi-public green space of an individual (m^2)

The architecture of the script combines the necessary steps to generate a specific indicator in a task chain that is repeated for every distance. See Figure 3.1 for a graphical overview of the algorithm and Figure 3.2 for the specific tasks chained together to generate the individual green space indicators. Next to the mandatory input of the geolocation of points (e.g. the home address of an individual surveyed) and corresponding ID field, the input is optional and depends on the requested tasks. The script uses Boolean operators to indicate which tasks should be performed. To reduce computation time, the script makes use of intermediate results and reuses them to create additional indicators.

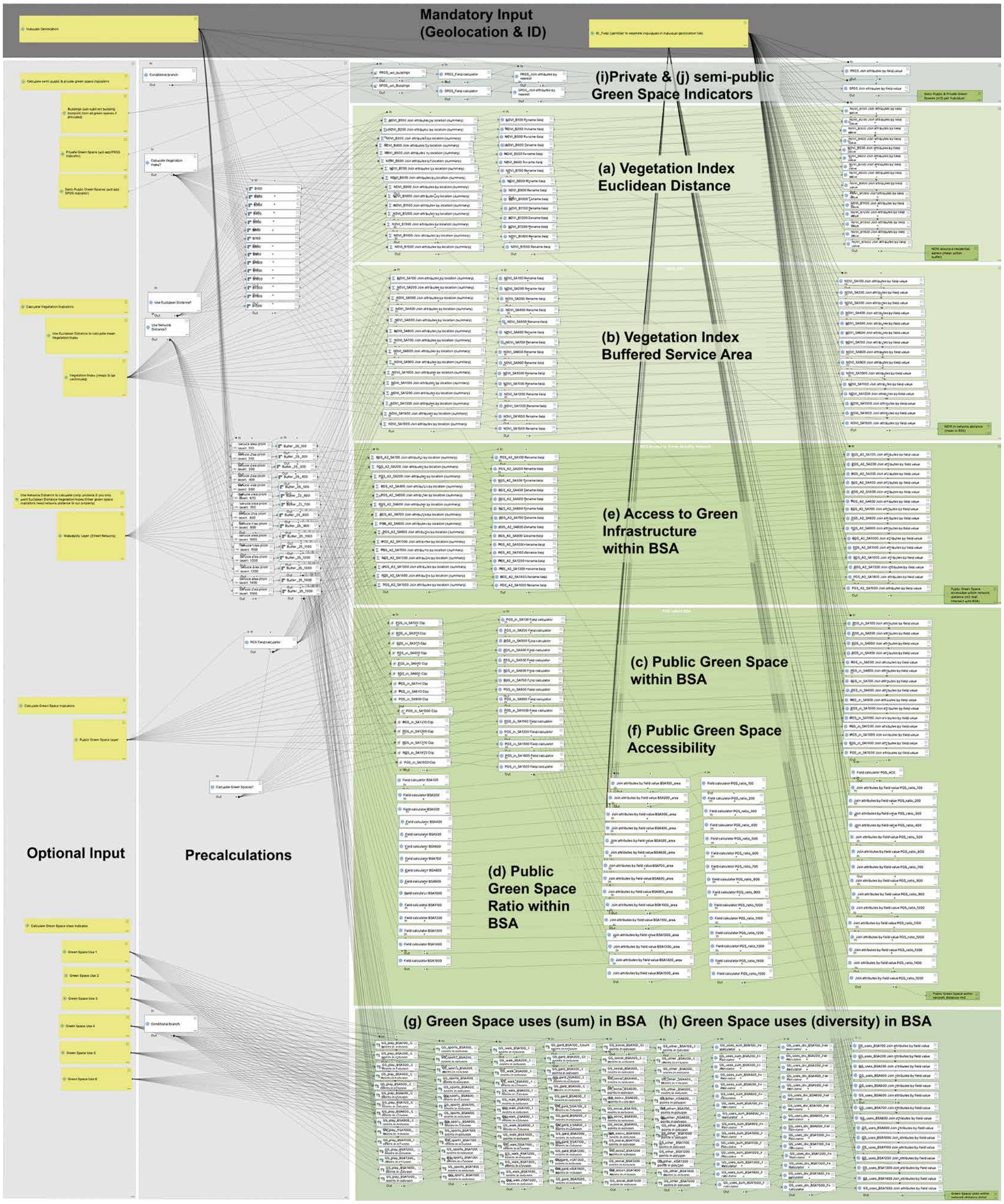

FIG. 3.1 Graphical overview of the model. A high-resolution image can be viewed at the GitHub repository (Cardinali, Beenackers, et al., 2023c)

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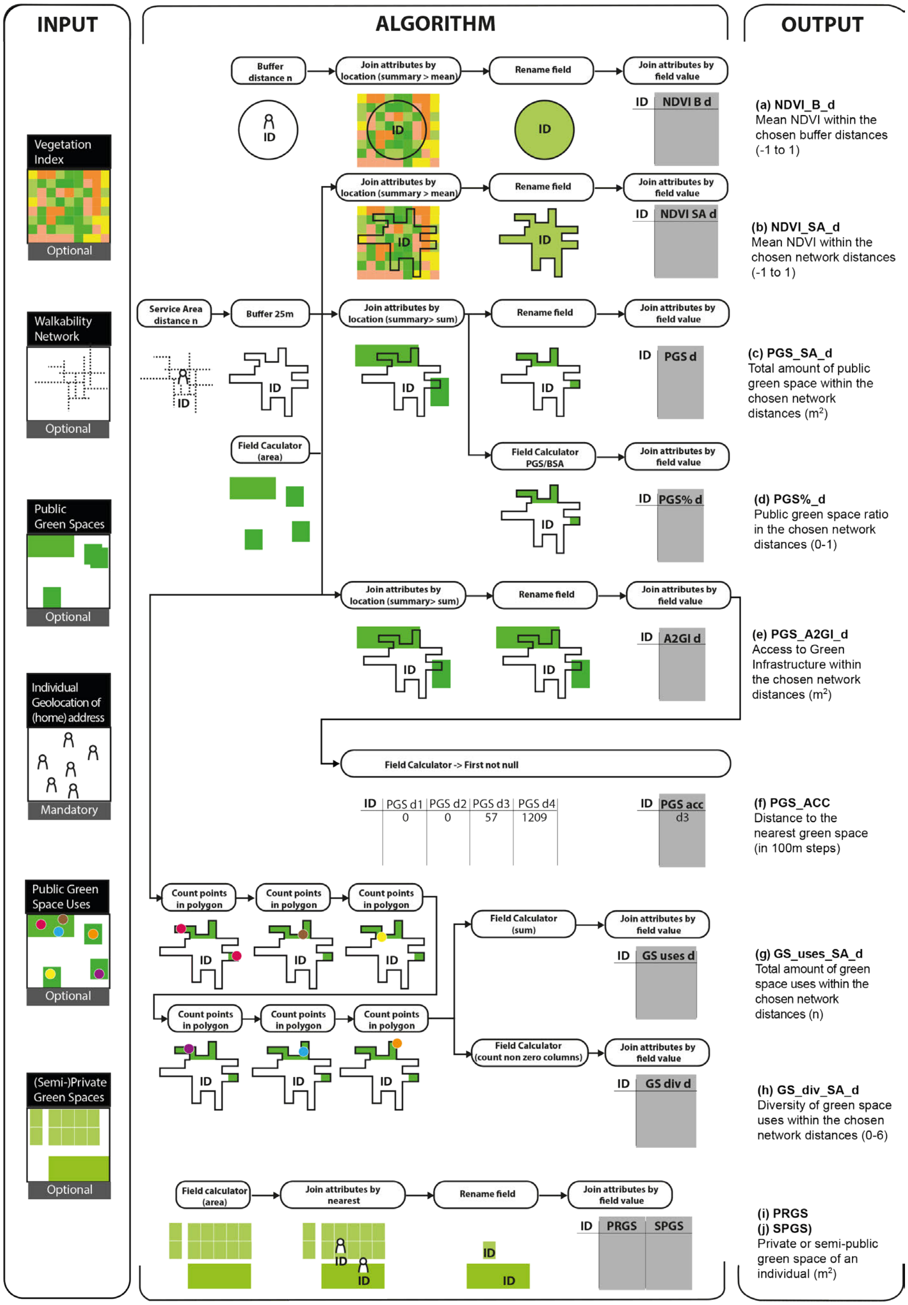

FIG. 3.2 a-j: Left to right flow diagram with specific tasks performed by the algorithm, depending on the user input.

3.3 Software Demonstration with Case Study

Figures 3.3, 3.4, and 3.5 demonstrate the application of the tool in a case study in Nantes Nord, France. In the first step, the necessary input layers were generated. The vegetation index is based on modified Copernicus Sentinel data [2019] processed by Sentinel Hub (European Space Agency, 2021). The spatial layers were downloaded from OpenStreetMap (OpenStreetMap contributors, 2017). All layers have been checked individually for bias with the PRIGSHARE Reporting Guidelines (Cardinali, Beenackers, et al., 2023c). The spatial data should cover an area at least 1500m larger than the outermost points of the address layer as seen in Figure 3 to cover accessibility within 1500m. Then the AID-PRIGSHARE.model3 file can be executed from the browser panel within QGIS which will open the input mask (Figure 4). After deciding on the indicators to be generated via the checkboxes and providing all necessary layers for those tasks below the accompanying checkbox, the script can be executed. For the approximately 400 addresses of this case study, the script will take about 8 hours to run. The computation time varies by the number of observations, spatial spread, and available computational power. The script expands the attribute table of the geolocation layer with the indicators requested. It will generate a new layer for every indicator, but not for every distance. See Figure 5 for an example output of mean NDVI within Euclidean Distance.

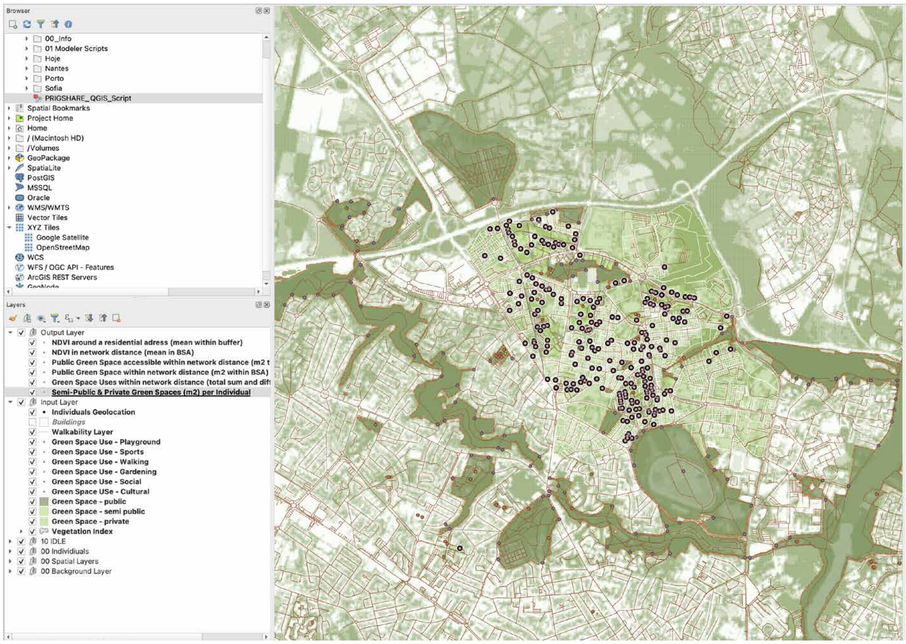

FIG. 3.3 Input layers of case study in Nantes Nord (France), after the risk of bias assessment with PRIGSHARE Reporting Guidelines (Cardinali, Beenackers, et al., 2023c).

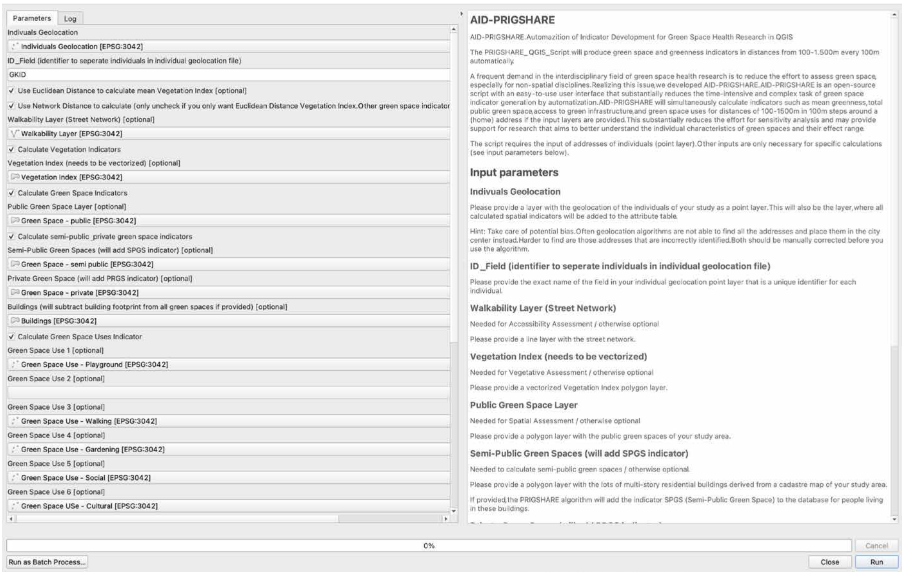

FIG. 3.4 User Interface with input mask on the left side and additional information on the right side.

	NDVI_B100	NDVI_B200	NDVI_B300	NDVI_B400	NDVI_B500	NDVI_B600	NDVI_B700	NDVI_B800	NDVI_B900	NDVI_B1000	NDVI_B1100	NDVI_B1200	NDVI_B1300	NDVI_B1400	NDVI_B1500
1	0,492463	0,468375	0,442931	0,447288	0,436569	0,430593	0,42714	0,42044	0,427555	0,440249	0,459879	0,476341	0,485412	0,498735	0,513067
2	0,438977	0,40252	0,42101	0,453189	0,45289	0,426027	0,412984	0,408015	0,415936	0,429087	0,443028	0,465248	0,484622	0,505043	0,516083
3	0,485601	0,48124	0,486096	0,480122	0,483087	0,487096	0,494744	0,491576	0,499902	0,505365	0,509256	0,514975	0,518513	0,520318	0,522964
4	0,432794	0,392449	0,404973	0,431058	0,433706	0,430832	0,423256	0,414912	0,417736	0,431101	0,452119	0,471206	0,485605	0,491317	0,495025
5	0,443667	0,416935	0,41648	0,439237	0,447368	0,42063	0,413073	0,413965	0,420268	0,434489	0,44748	0,465008	0,485399	0,504513	0,512025
6	0,310038	0,349382	0,366512	0,353851	0,357086	0,383131	0,403329	0,41776	0,433213	0,450741	0,466501	0,475012	0,481171	0,490018	0,497893
7	0,401946	0,422735	0,407544	0,424974	0,438331	0,420339	0,413399	0,409444	0,41391	0,423013	0,44375	0,465626	0,482525	0,500034	0,513336
8	0,39036	0,39566	0,416393	0,424684	0,418702	0,425033	0,433502	0,436218	0,443353	0,455093	0,466202	0,478073	0,482432	0,488602	0,498126
9	0,428362	0,419548	0,451478	0,480274	0,484922	0,485493	0,48473	0,489685	0,48946	0,491159	0,498833	0,505942	0,514529	0,522752	0,529647
10	0,393031	0,437821	0,474968	0,465815	0,43922	0,42288	0,417442	0,412487	0,419968	0,437839	0,457618	0,477343	0,486871	0,49021	0,491062
11	0,442096	0,453203	0,439218	0,427341	0,419369	0,416371	0,42343	0,440111	0,454376	0,462546	0,464987	0,471414	0,481145	0,489606	0,49945
12	0,442096	0,453203	0,439218	0,427341	0,419369	0,416371	0,42343	0,440111	0,454376	0,462546	0,464987	0,471414	0,481145	0,489606	0,49945
13	0,586902	0,48245	0,477863	0,470323	0,47441	0,483796	0,496173	0,507818	0,512137	0,50572	0,501596	0,500109	0,500976	0,500483	0,500753
14	0,378746	0,402897	0,428827	0,441332	0,450149	0,444894	0,435867	0,427007	0,42706	0,438637	0,454453	0,46782	0,483507	0,487591	0,487789
15	0,452667	0,412946	0,401189	0,396603	0,412824	0,418146	0,412086	0,416379	0,417281	0,425926	0,446445	0,465472	0,479786	0,495757	0,508361
16	0,356176	0,404328	0,3926	0,403978	0,424964	0,431515	0,432459	0,429138	0,431537	0,437263	0,451099	0,464541	0,475883	0,489132	0,494254
17	0,455978	0,473154	0,443342	0,430347	0,431489	0,437504	0,441467	0,447785	0,450396	0,459366	0,466374	0,48088	0,498808	0,515104	0,522671
18	0,404417	0,43149	0,463156	0,46626	0,444848	0,43077	0,420447	0,416718	0,419157	0,433878	0,457298	0,477687	0,485249	0,488246	0,489979
19	0,4392	0,437366	0,471177	0,471074	0,442566	0,432621	0,418458	0,416017	0,429872	0,445112	0,457169	0,469781	0,492683	0,508537	0,517208
20	0,413591	0,487187	0,494847	0,469246	0,433049	0,417642	0,416141	0,434344	0,453404	0,468581	0,475422	0,480129	0,482211	0,484058	0,485812
21	0,479968	0,41531	0,442748	0,460711	0,442494	0,427594	0,415896	0,414252	0,427492	0,443169	0,452492	0,467064	0,490053	0,506489	0,513138
22	0,473615	0,44039	0,466139	0,460933	0,4693	0,479441	0,486367	0,485618	0,494812	0,500319	0,503658	0,512291	0,516899	0,518807	0,524419
23	0,433911	0,449431	0,429088	0,420344	0,415849	0,414992	0,42333	0,444021	0,457664	0,463089	0,464382	0,472404	0,480789	0,488707	0,497245
24	0,347505	0,367222	0,396847	0,402165	0,415212	0,428563	0,444587	0,450036	0,450991	0,45642	0,459238	0,4616	0,469917	0,477815	0,487255
25	0,341239	0,404076	0,46863	0,481384	0,454683	0,430973	0,417864	0,411173	0,420867	0,433778	0,44924	0,466311	0,490622	0,508408	0,52051
26	0,32031	0,388193	0,391268	0,371072	0,37346	0,388331	0,408141	0,419721	0,427393	0,441292	0,459319	0,468274	0,480331	0,488402	0,496436
27	0,379779	0,364919	0,377927	0,40313	0,43753	0,447734	0,450516	0,45439	0,463056	0,473437	0,475716	0,472653	0,469745	0,477115	0,484094
28	0,348191	0,375821	0,372009	0,390841	0,412485	0,420565	0,426413	0,428101	0,433442	0,436467	0,45041	0,462319	0,474732	0,487931	0,496565
29	0,547202	0,536587	0,503288	0,473831	0,438702	0,424273	0,417809	0,422303	0,432614	0,44931	0,464061	0,474156	0,481471	0,48532	0,488366
30	0,457732	0,522694	0,535649	0,549064	0,567146	0,572164	0,552226	0,527331	0,511749	0,505581	0,500895	0,499745	0,502244	0,502968	0,504088
31	0,429034	0,422137	0,387853	0,39664	0,4055	0,407486	0,406254	0,411028	0,42523	0,439501	0,456372	0,472935	0,485454	0,495522	0,49697
32	0,414745	0,409233	0,448984	0,475994	0,465154	0,463311	0,472579	0,483605	0,500117	0,505257	0,51061	0,515076	0,52275	0,533254	0,540768
33	0,476939	0,438123	0,461647	0,459485	0,439093	0,429485	0,418585	0,418983	0,436236	0,449242	0,458507	0,472804	0,492588	0,506453	0,512432
34	0,402538	0,407139	0,380428	0,387279	0,400711	0,404625	0,406055	0,413797	0,423565	0,438461	0,456055	0,469486	0,48375	0,493264	0,498715
35	0,341239	0,404033	0,468617	0,481269	0,454654	0,431015	0,417834	0,411115	0,420843	0,433818	0,449241	0,466364	0,490627	0,508349	0,520506
36	0,385614	0,394414	0,452115	0,497396	0,503367	0,495001	0,506489	0,505734	0,496154	0,490216	0,487881	0,485942	0,481276	0,480644	0,484023
37	0,332916	0,36293	0,375977	0,391823	0,406518	0,42481	0,428693	0,43491	0,437969	0,440062	0,451466	0,460825	0,4739	0,485394	0,495157
38	0,429715	0,52394	0,538602	0,558085	0,575017	0,574926	0,552071	0,527616	0,512015	0,506347	0,500736	0,498926	0,50221	0,503346	0,504265
39	0,47788	0,520079	0,54027	0,530517	0,544814	0,558611	0,551028	0,527338	0,511146	0,503936	0,501452	0,500976	0,501036	0,501728	0,501761
40	0,208521	0,273257	0,325839	0,35383	0,383841	0,410107	0,425518	0,44646	0,468435	0,483496	0,490446	0,48858	0,483531	0,48293	0,484125

FIG. 3.5 Automated Indicator Generation of the AID-PRIGSHARE Open-Source Script with the input data from Nantes Nord (France).

3.4 Software Impacts

The software chapter presents “AID-PRIGSHARE”, a free and open-source script for QGIS. Our tool automates and combines over 400 steps to generate a variety of green space indicators, for multiple types of indicators and distances ranging from 100m to 1500m, every 100m in one algorithm (see Figure 3.1). Currently, the required expert knowledge, the sheer amount of tasks, and the computation time that needs to be performed to be able to do a sensitivity analysis is a barrier

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in the field, especially for non-spatial disciplines (Markevych et al., 2017). In light of these challenges, AID-PRIGSHARE offers a promising solution. AID-PRIGSHARE has the potential to significantly impact the research field of green space and health by enabling a feasible spatial sensitivity analysis. This drastically reduces the effort needed to calculate these indicators and makes it feasible for researchers:

- to compare different types of green space indicators
- to analyse the area of effect of green space indicators on health outcomes by comparing different buffer sizes
- to make the variance visible that derives from chosen buffer types and distances

AID-PRIGSHARE is designed to be user-friendly and accessible. Especially for non-spatial disciplines and improve access to spatial indicators for research. It is designed in a way so that it can be executed by users with little prior knowledge. Although the validity of the output will depend on the validity of the input (Cardinali, Beenackers, et al., 2023c). It has the potential to lead to a more interdisciplinary approach to research in this field, which can result in more comprehensive and nuanced findings. In addition, it might also enable post-hoc sensitivity analysis of already published studies to further explore the robustness of those findings and contribute to reducing and explaining the current heterogeneity in findings in green space health research. Overall, AID-PRIGSHARE has the potential to greatly benefit the research field of green space and health by streamlining research processes and facilitating interdisciplinary collaboration.

While AID-PRIGSHARE offers many benefits, it is important to also consider its current limitations. Currently, it is not possible to ask the algorithm to calculate only specific distances. Due to the approach using the graphical modeler, the software cannot make use of functions and loops which limits its capabilities and efficiency. In addition, there might be several other indicators worth exploring, that are not yet part of the algorithm. It is planned to add these features in future updates. Additionally, the software is on purpose not able to automatically download and pre-process the necessary input data, which might still be a hurdle for non-spatial experts. We decided to not integrate this feature, because this would lead to a risk that the necessary step of data verification of the green space data and its necessary adaptation to the research question could be skipped. The research field of green space health is known for a low signal-to-noise ratio (Hartig et al., 2014). Thus reducing the risk of bias and noise in the data set is a very important step in this field of research. For guidance in this process, we refer to the PRIGSHARE reporting guidelines (Cardinali, Beenackers, et al., 2023b).

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4 The green space – physical activity – health pathway

Published as Cardinali, M.; Beenackers, M.; van Timmeren A.; Pottgiesser U. (2024). The relation between proximity to and characteristics of green spaces to physical activity and health: A multi-dimensional sensitivity analysis in four European cities. Environmental Research (2024) 117605.https://doi.org/10.1016/j.envres.2023.117605

ABSTRACT

Non-communicable diseases are the global disease burden of our time, with physical inactivity identified as one major risk factor. Green spaces are associated with increased physical activity of nearby residents. But there are still gaps in understanding which proximity and what characteristics of green spaces can trigger physical activity. This study aims to unveil these differences with a rigorous sensitivity analysis. We gathered data on self-reported health and physical activity from 1365 participants in selected neighbourhoods in Porto, Nantes, Sofia, and Høje-Taastrup. Spatial data were retrieved from OpenStreetMap. We followed the PRIGSHARE guidelines to control for bias. Around the residential addresses, we generated seven different green space indicators for 15 distances (100-1,500 m) using the AID-PRIGSHARE tool. We then analysed each of these 105 green space indicators together with physical activity and health in 105 adjusted structural equation models. Green space accessibility and green space uses indicators showed a pattern of significant positive associations to physical activity and indirect to health at distances of 1,100 m or less, with a peak at 600 m for most indicators. Greenness in close proximity (100 m) had significant positive effects on physical activity and indirect effects on health. Surrounding greenness showed positive direct effects on health at 500–1,100 m and so do green corridors in 800 m network distance. In contrast, a high quantity of green space uses, and surrounding greenness measured in a larger radius (1,100–1,500 m) showed a negative relationship with physical activity and indirect health effects. Our results provide insight into how green space characteristics can influence health at different scales, with important implications for urban planners on how to integrate accessible green spaces into urban structures and public health decision-makers on the ability of green spaces to combat physical inactivity.

KEYWORDS greenspace, mediator, behaviour, sedentary lifestyle, public health

4.1 Introduction

Non-communicable diseases (NCDs) are the global disease burden of our time and were associated with 74% of global all-cause deaths in 2019 (Bai et al., 2023). The main NCD clusters are cardiovascular diseases, diabetes, cancer, chronic respiratory diseases and mental health with physical inactivity as one of the main risk factors (UN General Assembly, 2018). It has been shown that inactivity is closely related to our daily living environment in general and to the modern and car-dependent lifestyle in particular (Carlin et al., 2017; Cerin et al., 2014; Sallis et al., 2016). Previous research has demonstrated that interventions in urban design and transport have the potential to provide large, long-lasting, and immediate benefits for health (de Sa et al., 2022) and that approximately 70% of studies found evidence that changes in the built environment can lead to changes in physical activity (McCormack et al., 2022). Especially green spaces are associated with an increase in physical activity levels, among a variety of other direct and indirect health benefits (WHO Regional Office for Europe, 2016a). Because of this multitude of benefits, green spaces are given a major role in the necessary upcoming urban transformation of the 21st century (Giles-Corti et al., 2016).

If and how green space relates to health has been extensively studied in relation to public health in the past decades (R. Zhang et al., 2021). A growing body of evidence suggests three main pathways between green space and health by (1) surrounding vegetation that can reduce environmental pollution (Mitigation pathway) or induce environmental stressors like pollen (causing harm), (2) through direct contact with nature by reducing stress and increasing cognitive capacities (Restoration pathway) or contact with wildlife (causing harm), and (3) encouraging healthy behaviour (Instoration pathway), which could potentially also lead to more injuries (causing harm) (Cardinali, Beenackers, et al., 2023c; Markevych et al., 2017; Marselle et al., 2021). Within the Instoration pathway, one of these health behaviours relates mainly to residents near green spaces being more physically active which then potentially cascades into a positive influence on a variety of mental and physical health outcomes, like reduced risk of cardiovascular diseases, diabetes, and obesity, as well as improved mental health and well-being (Yang et al., 2021).

Nevertheless, despite the growing evidence and policy attention, there is still a significant research gap in understanding how green spaces influence physical activity and health outcomes, particularly the proximity and characteristics of green spaces required to increase physical activity. In addition, the influence of specific features of green spaces like their connectivity and usability remain of research interest. For example, studies investigating the relationship between greenness and physical health have yielded mixed results, with only a third of the studies showing a significant positive relationship (Browning & Lee, 2017). Furthermore, only 50% of the studies that analysed an indirect effect via physical activity showed a significant indirect effect (A. M. Dzhambov et al., 2020) or they demonstrated significant relationships for one green space indicator, while another was insignificant (Browning et al., 2022; Luo et al., 2020). Additionally, depending on the study focus, different buffer sizes and types have been selected and rarely for a sequence of distances (Labib et al., 2020). Thus, it remains unclear which proximity to and what characteristics of green spaces are related to positive health outcomes. In particular for physical activity, it is unknown what kind of proximity is needed to encourage physical activity and in turn, if this link is strong enough to result in significant indirect health effects. More research and rigorous sensitivity analysis are warranted on the pathway between green space and health to understand the heterogeneity of existing literature (Cardinali, Beenackers, et al., 2023c; Markevych et al., 2017). Up to now, this uncertainty limits our ability to optimally design effective interventions and policies that can promote healthy and sustainable urban environments.

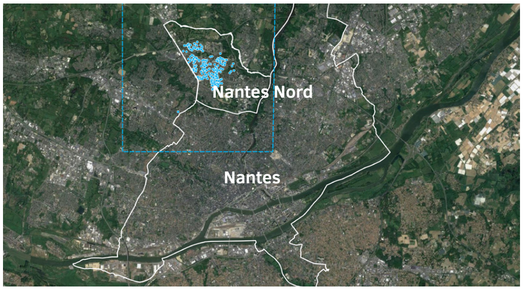
This chapter aims to address this gap by exploring and comparing the relation of different green space characteristics and their proximity to physical activity and health in a rigorous sensitivity analysis. We hypothesize differences in green space characteristics, e.g. a stronger relationship of physical activity to the green space characteristics of accessibility, connectivity and green space uses than to greenness (Cardinali, Beenackers, et al., 2023c), and expect a significant indirect effect, especially in walkable distances based on previous research (Akpinar, 2016; McCormack et al., 2010; Sugiyama et al., 2010). Understanding the influence of specific green space characteristics and their relative proximity to residents should enable a better understanding of the heterogeneity of past results in the field and contribute important insights for urban planners and decision-makers on how to integrate green spaces in our cities for maximum effect on health in general and physical activity in particular.

4.2 Methods

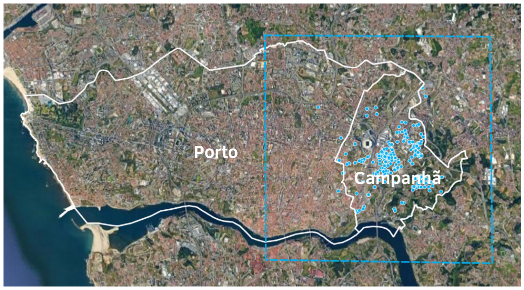
4.2.1 Study design and sampling

We gathered data from 1365 participants in selected neighbourhoods in Porto (Portugal), Nantes (France), Sofia (Bulgaria) and Høje-Taastrup (Denmark) as part of the URBiNAT project. We collected data in Porto around September 2019, conducted the survey in Nantes and Sofia around December 2019, and obtained the sample from Høje-Taastrup in September 2021. Participants had to be 14 years or older to be included in the study and were selected at random. Local polling companies contracted by the municipality administered the questionnaires with guidance and protocols provided by the authors. The administration in Porto was done face-to-face. The administration in Nantes, Sofia and Høje-Taastrup was done via phone. When contacted, people were informed about the purpose of the project, the role of this questionnaire, and asked for informed consent. The questionnaire took about 20–25 minutes to complete and was approved by the ethics committee of the URBiNAT project. No incentives were offered.

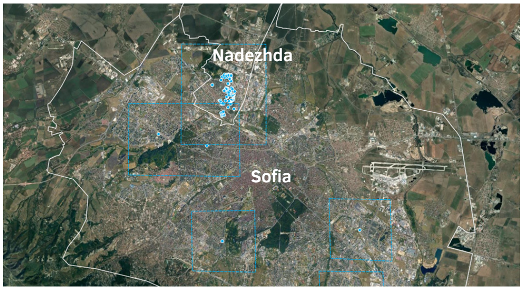
The study areas have different urban characteristics of importance (see Figure 4.1). Nantes Nord, a district with around 20,000 inhabitants, is located on the northern outskirts of the Nantes Metropole, but with a well-connected public transport. Porto Campanhã is a district of similar size but is located on hilly terrain and divided by car-centric infrastructure. Sofia Nadezhda, again a district of similar size, is well connected with public transport. In contrast to the other cities, flats in Sofia Nadezhda are mostly individual property instead of rented and plots are state-owned instead of owned by a residential company. Høje-Taastrup, is a satellite city of greater Copenhagen, which is more rural but well-connected via public transport. In addition, respondents from Høje-Taastrup were clustered in a much smaller geographical area.



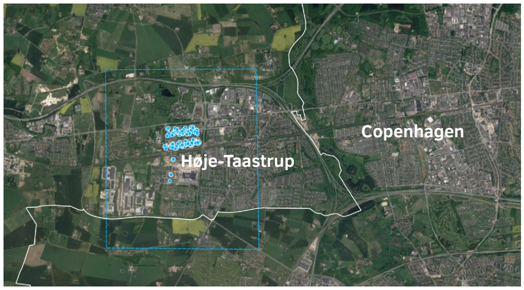
a) Nantes - Nord



b) Porto - Campanhã



c) Sofia - Nadezhda



d) Greater Copenhagen - Høje-Taastrup

FIG. 4.1 Study areas overview: a) Nantes - Nord (France); b) Porto - Campanhã (Portugal), c) Sofia - Nadezhda (Bulgaria), d) Greater Copenhagen - Høje-Taastrup (Denmark).
White line indicates administrative borders; blue dotted line indicates the study area(s); blue points indicate the residential address of the study participants.

4.2.2 Green Space Characteristics

We obtained the necessary spatial data for the four study areas from OpenStreetMap in January 2023 and manually corrected it to the timestamp of the survey conduction. To control for bias, we followed the PRIGSHARE Reporting Guidelines (Cardinali, Beenackers, et al., 2023c, Table A4.1). A table with the inclusion/exclusion criteria can be viewed in the appendix (Table A4.2). As a basis for greenness indicators, we calculated the Natural Difference Vegetation Index (NDVI) with sentinel 2 data in 10x10 m resolution from the EEA (European Space Agency, 2021) from cloud-free time points in the month of the survey conduction in the city (see Figure 4.2 for exact dates). The NDVI is calculated through rasterised satellite images in near-infrared and red light (NDVI=(NIR-Red)/(NIR+Red)) (Tucker, 1979). Its values range from -1.0 to 1.0, where 0.2-0.5 usually indicate sparse vegetation like shrubs or grassland and values of 0.6 and higher indicate dense vegetation like trees. Sealed surfaces like streets or buildings usually range around 0.0-0.1 and negative values arise from water bodies and clouds. That is why we manually set larger water bodies like the rivers in Porto and Nantes to missing.

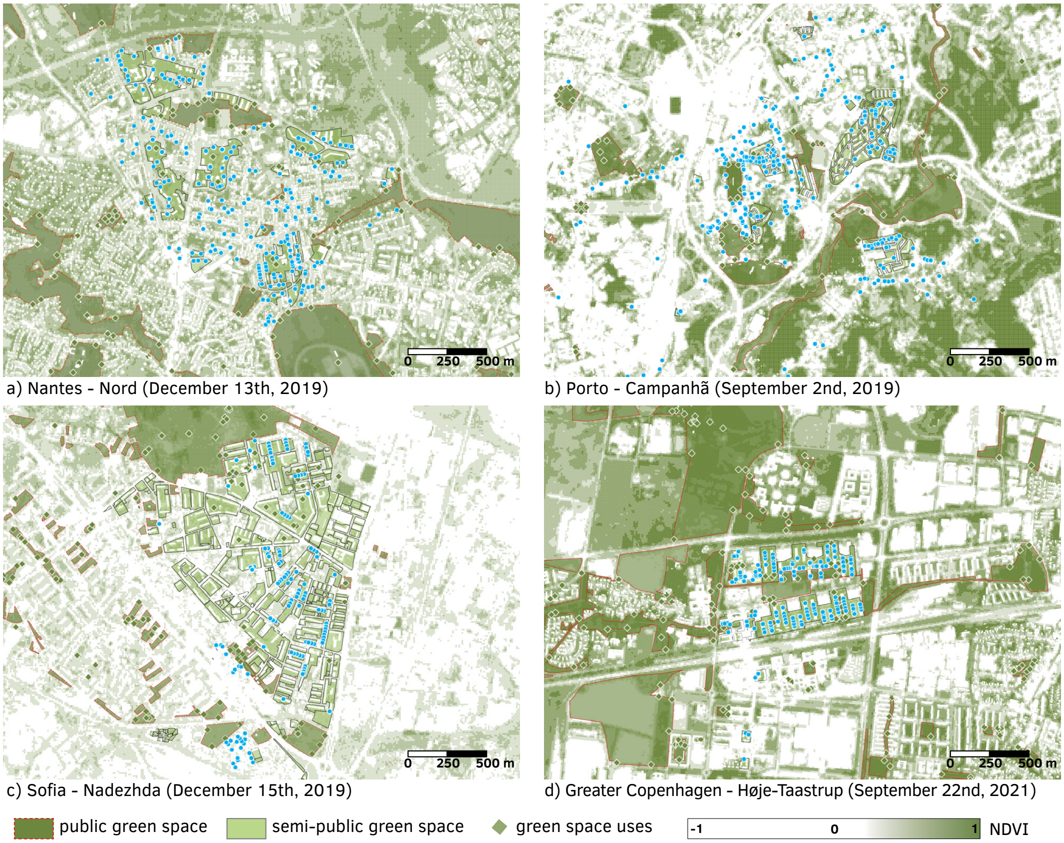


FIG. 4.2 Study areas green space: a) Nantes Nord (France); b) Porto Campanhã (Portugal), c) Sofia Nadezhda (Bulgaria), d) Greater Copenhagen Høje-Taastrup (Denmark). *Blue points indicate the residential addresses of the study participants. For better readability only the study areas are covered (e.g. some respondents do not live in the main study area) and private green space is not shown.*

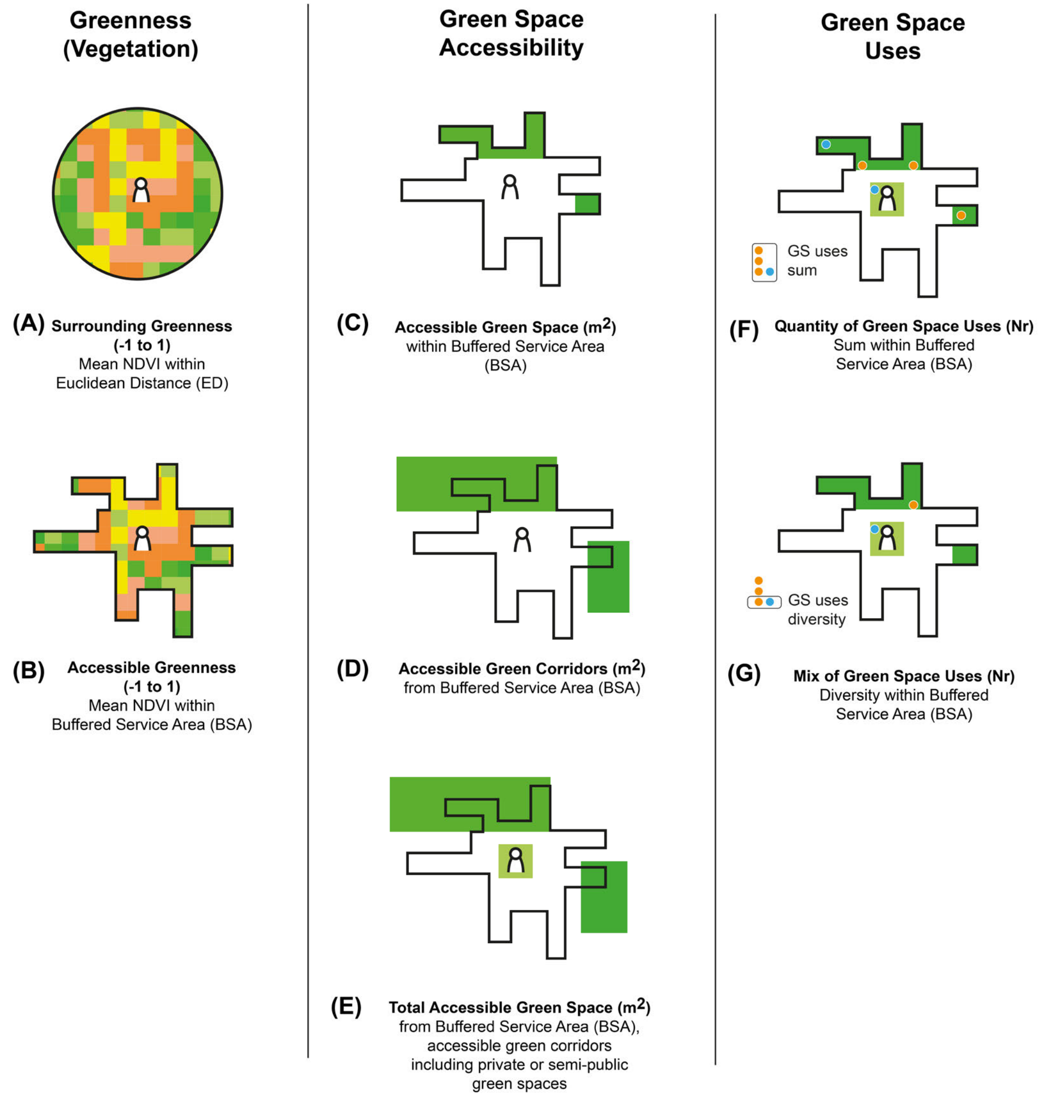


FIG. 4.3 Green space characteristics: Indicators used in the sensitivity analysis.

Based on this curated data, we constructed seven indicators on specific green space characteristics (see Figure 4.3) in buffer distances from 100-1,500 m, every 100 m, using the AID-PRIGSHARE tool (Cardinali, Beenackers, et al., 2023b). Firstly, we assessed greenness with two indicators based on NDVI – one with Euclidean buffers (A), and one with a buffered service area (BSA) as a proxy for the network distance (B), representing surrounding vegetation and accessible vegetation.

Secondly, we assessed green space accessibility with three indicators: accessible green spaces in network distance (C), accessible green corridors (D), and total accessible green space, including individual private or semi-public green space of the individual plot (E). Thirdly, we assessed green space uses by counting points of green space uses (playgrounds, gardens, sports fields, social facilities, cultural facilities and walking entries to bigger green spaces) present in the accessible green spaces. To represent the quantity of green space uses, we counted the total number of uses in green spaces within network distance (F). We counted the number of different uses (G) to capture the mix of uses.

4.2.3 Physical Activity

We assessed participants' physical activity with the help of the International Physical Activity Questionnaire short form (IPAQ, 2002). The items asked about the vigorous, moderate, and walking activity during the last 7 days. The raw input was then truncated to a minimum of 1 and a maximum of 7 days of activity, and to a minimum of 0.2 hours to 8 hours maximum to account for outliers in the raw data. We followed the guidance of IPAQ to convert the obtained results in minutes/week into metabolic time equivalent of task (MET) values according to their category. Total time spent per week on vigorous physical activity was multiplied by 8.0, moderate physical activity by 4.0, and walking by 3.3 to represent the MET equivalent (IPAQ, 2002). The disadvantage of the original IPAQ categorization of low, moderate and high categories is the significant loss in dimensionality of the data. In contrast, numerical variables of physical activity are heavily right skewed and can be categorised as a zero-inflated count variable, which can cause problems in structural equation modelling (Rosseel, 2023). We tested a cube-root transformation of the data to receive closer-to-normal distribution like other researchers (A. M. Dzhambov, Markevych, Tilov, et al., 2018), but this didn't improve the model convergence and bootstrapping behaviour. For this reason, we decided to transform the numerical indicator of MET-Minutes/Week to an ordinal variable but still tried to maintain as much of the data dimensionality as possible by using 8 categories to reflect physical activity levels (very high: > 12,000, high: 7,500-12,000, high-moderate 5,000-7,500, moderate: 3,600-5,000, low moderate: 2,400-3,600, low: 1,600-2,400, very low: 400-1,600, no: 0-400). A sensitivity analysis for both categorial indicators confirmed the superior behaviour of the 8-category version of the physical activity variable (see Figure A4.1 for a histogram).

4.2.4 Health

We assessed perceived general health by the 1-item questionnaire (World Health Organization, 1998). The question asked, “How is your health in general?”. Answers were given on a 5-point Likert scale item from (5) very good to (1) very bad. The variable was included as an ordinal variable in the analysis.

4.2.5 Context Variables

In line with the PRIGSHARE Reporting Guidelines (Cardinali, Beenackers, et al., 2023c), we obtained data on potential confounders in personal, local, urbanicity, and global context. To assess the personal context, we gathered data on age, sex, disabilities (sensorial, motor, cognitive or organic), years lived in the neighbourhood, occupation, years of education, and monthly net income. To harmonize between cases across countries, monthly net income was centred around the mean minimum wage of the country and is shown in percentages of minimum wage. Local context was accounted for by using 5-point Likert scale items to measure perceived safety, satisfaction with shops, services, leisure facilities, and public transport as part of the environmental quality of life questionnaire (Fleury-Bahi et al., 2013). To account for the urbanicity context, we obtained 2018 population density data from Eurostat (Eurostat, 2023). Furthermore, we controlled for the global and climate context by including the city samples as a dummy variable in the model. By doing this, we also controlled for differences in timing (pre- or post-pandemic) and differences in the season when the survey was conducted while maintaining the statistical power. The PRIGSHARE reporting guidelines also prescribe to assess modifying variables (Cardinali, Beenackers, et al., 2023c). This assessment was out of scope for this study because of the number of structural equation models to perform and compare (see 2.6). This limitation will be debated in the discussion.

4.2.6 Statistical Analysis

Data handling and processing were done in Python. Missing data could be classified as missing at random (MAR) since missingness was associated with other observed variables. Thus, a multiple imputation technique is considered the most appropriate to handle the missing data (Mirzaei et al., 2022). We used multiple imputation software package of miceforest 5.6.3 in Python (Wilson, Samuel, 2022), with 10 iterations to estimate the missing variables. The final step of data processing was to standardize the dataset by min-max scaling (0-1) since all our variables, except NDVI, can only be positive. This ensured that all variables were on the same scale, thus allowing for meaningful comparisons and accurate model estimation (Kline, 2015).

Structural equation modelling (SEM) was performed in R with the lavaan package (Rosseel, 2023) on a one-mediator model (see Figure 4.4) using the diagonal weighted least squares estimator. The full model including all control variables can be found in the supplementary material (Figure A4.2). Sensitivity analysis was done by exchanging the green space indicator 105 times (7 indicators, each for 15 distances). The rest of the model remained unchanged. An example of the summary statistics for one green space indicator can be found in the supplementary material (Table A4.3). By using a single mediator model, we avoid adding another level of complexity to the research framework through potential differences in the model fit of the 105 models, which would make this large-scale sensitivity analysis unfeasible and work against the main goal of this research to compare green space indicators and relative proximity of green spaces.

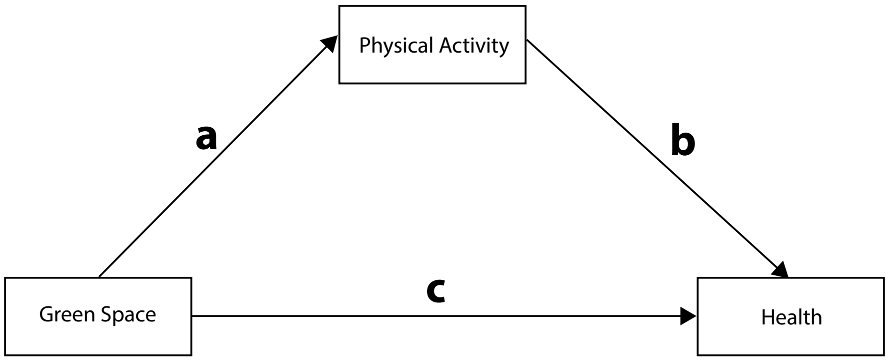


FIG. 4.4 Conceptual Model: Conceptual diagram showing theoretically indicated pathways linking green space to physical activity and health. The green space indicator was exchanged 105 times for each structural equation model.

In the following results and discussion, we use the common phrases of partial effects (a or b), indirect effects (a*b), direct effects (c) and total effects (a*b +c) in SEM, but want to highlight that these are in fact associations, due to the cross-sectional study design. Since indirect effects and total effects are products and not linear, we used bootstrap-generated standard errors and confidence intervals for all regression paths (5,000 samples for every structural equation model). The relationship was considered significant when the bootstrapped 95% confidence intervals did not include zero. To further examine the unique contribution of a green space characteristic, we compared the significant green space characteristics in a correlation matrix (see supplementary material Table A4.4). We used the cut-off points of Dancey and Reidy, with zero (0), weak (0.1-0.3), moderate (0.4-0.6), strong (0.7-0.9), and perfect correlation (1.0) (Dancey & Reidy, 2007).

4.3 Results

4.3.1 Characteristics of the sample

The participants lived on average between 14-29 years in their current neighbourhood (see Table 4.1). The global city sample includes 201 residents from Høje-Taastrup (Denmark), 293 residents from Nantes (France), 439 residents from Porto (Portugal), and 432 residents from Sofia (Bulgaria). The sample was composed of roughly 50% of men and women in Høje-Taastrup, Nantes, and Sofia. In Porto, the sample was composed of nearly 64% men and 36% women. The mean (SD) age of the participants was 53.66 (SD: 18.43) in Høje-Taastrup and 58.12 (18.20) years in Porto, and a considerably younger sample in Nantes 45.66 (17.59) and Sofia 45.47(16.52). In total, the age ranged from 15 to 99 years. The samples also differed significantly in the number of people with disabilities, ranging from 10.0% in Høje-Taastrup to 39.6% in Porto. The mean years of education were around 12 years in Høje-Taastrup, Nantes and Sofia, but only seven in Porto. In terms of occupation, the majority of the participants were employed, with significant differences between cities. The mean (SD) income was 141 % of the minimum wage: (93%) in Høje-Taastrup, 149 % (63%) in Nantes, 40% (66%) in Porto, and 143% (73%) in Sofia. The overall perceived safety, as well as the neighbourhood characteristics of shops, leisure facilities, and public transport, were also significantly different among the cities. In addition, the sample differed significantly in terms of population density, with Sofia having the highest mean population density and Høje-Taastrup having the lowest. Self-rated physical activity was the highest in Høje-Taastrup with 37.8% reporting very low or no activity, followed by Sofia (50.1%), Nantes (54.0%), and Porto (73.2%). Very good or good self-perceived health was the highest in Nantes (76.5%), followed by Sofia (73.9%), Høje-Taastrup (61.7%) and Porto (46.9%).

TABLE 4.1 Characteristics of the sample (unstandardized)

Context	Indicator	Høje-Taastrup	Nantes	Porto	Sofia	p
global	*city sample (n)*	201	293	439	432	
urbanicity	*population density (mean (SD))*	4028.65 (1336.94)	5616.27 (2353.62)	4829.28 (1632.50)	9021.14 (3689.54)	<0.001
local	*perceived safety, Likert 1-5 (mean (SD))*	3.59 (1.14)	2.75 (1.27)	3.65 (1.39)	2.80 (0.63)	<0.001
	satisfaction with shops, Likert 1-5 (mean (SD))	3.98 (1.08)	3.48 (1.07)	3.41 (1.39)	3.82 (0.86)	<0.001
	satisfaction with leisure facilities, Likert 1-5 (mean (SD))	3.78 (1.11)	2.85 (1.16)	3.34 (1.36)	3.28 (0.88)	<0.001
	satisfaction with public transport, Likert 1-5 (mean (SD))	4.45 (0.90)	4.43 (0.66)	3.59 (1.44)	3.85 (0.63)	<0.001
personal	**gender (%)**					<0.001
	male	52.2%	44.0%	36.2%	47.2%	
	female	47.8%	55.3%	63.8%	52.8%	
	diverse	0.0%	0.7%	0.0%	0.0%	
	age group (%)					<0.001
	15-24	6.5%	10.9%	4.1%	10.6%	
	25-44	28.4%	42.7%	21.4%	39.6%	
	45-64	32.8%	29.4%	33.5%	29.6%	
	over 65	32.3%	17.1%	41.0%	20.1%	
	mean years lived in neighbourhood (SD)	16.60 (13.76)	14.53 (15.03)	28.90 (20.08)	22.41 (12.34)	<0.001
	mean net income as % of minimum wage (SD)	141% (93%)	149% (63%)	40% (66%)	143% (73%)	<0.001
	mean years of education (SD)	12.40 (2.51)	12.46 (3.38)	7.03 (3.72)	13.16 (2.67)	<0.001
	Has disabilities (%)	10.0%	15.7%	39.6%	15.5%	<0.001
	employed (%)	57.2%	56.7%	28.7%	73.6%	<0.001
	physical activity (%)					<0.001
	very high activity	9.5%	5.5%	0.2%	0.7%	
	high activity	7.0%	2.4%	3.2%	2.5%	
	high-medium activity	12.4%	5.8%	2.7%	4.2%	
	medium activity	10.0%	8.2%	6.2%	6.9%	
	low -medium activity	10.4%	9.2%	9.8%	17.1%	
	low activity	12.9%	15.0%	4.8%	19.0%	
	very low activity	25.4%	40.3%	34.9%	30.3%	
	no activity	12.4%	13.7%	38.3%	19.2%	

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TABLE 4.1 Characteristics of the sample (unstandardized)

Context	Indicator	Høje-Taastrup	Nantes	Porto	Sofia	p
personal	**self-perceived health (%)**					<0.001
	very good	24.9%	29.7%	8.9%	34.5%	
	good	36.8%	46.8%	38.0%	39.4%	
	fair	23.9%	17.4%	32.3%	19.9%	
	bad	11.4%	5.8%	13.7%	6.2%	
	very bad	3.0%	0.3%	7.1%	0.0%	
green space characteristics	*surrounding greenness in 500 m Euclidean distance (-1 to 1, mean (SD))*	0.46 (0.05)	0.42 (0.03)	0.37 (0.08)	0.23 (0.04)	<0.001
	accessible greenness in 500 m network distance (-1 to 1, mean (SD))	0.44 (0.04)	0.39 (0.03)	0.34 (0.06)	0.24 (0.04)	<0.001
	accessible green space in 500 m network distance (0 - 16.32 hectare, mean (SD))	3.70 (1.45)	1.64 (1.56)	2.35 (2.11)	3.12 (3.68)	<0.001
	accessible green corridors in 500 m network distance (0 – 154.30 hectare, mean (SD))	51.76 (17.59)	56.92 (66.64)	9.74 (9.81)	28.93 (37.99)	<0.001
	accessible total green space in 500 m network distance (0 – 158.66 hectare, mean (SD))	56.77 (16.33)	60.18 (66.51)	12.16 (10.37)	32.99 (41.47)	<0.001
	quantity of green space uses in 500 m network distance (0 - 34, mean (SD))	21.17 (7.49)	6.13 (4.04)	5.15 (4.39)	10.17 (6.70)	<0.001
	mix of green space uses in 500 m network distance (0 - 5, mean (SD))	3.75 (0.65)	2.10 (0.82)	1.83 (1.01)	2.36 (1.13)	<0.001

4.3.2 Partial effects – How green space indicators are associated with physical activity

We observed clear and distinct patterns in the associations between green space and physical activity (path a) in terms of proximity to green spaces and green space characteristics (Table 4.2). Surrounding greenness (Fig 4.5A) showed a two-sided pattern starting with positive significance in the immediate surrounding of 100 m (ß: 0.542; CI: 0.048, 1.023) and turning negative in larger Euclidean distances of 900-1,500 m with a peak at 1,300 m, although not significant. Accessible greenness (Fig 4.5B) showed a similar pattern and stronger relation to physical activity levels in the immediate surrounding of 100 m (ß: 0.753; CI: 0.221, 1.283) and no negative significant association in the higher buffers. Accessible green space (Fig 4.5C) presented a significant positive association with physical activity at 500-600 m, with a peak at 500 m (ß: 0.401; CI: 0.087, 0.679). Access to green corrid4.ors (Fig 4.5D) showed a clear pattern of significant positive associations with physical activity in distances of 200-800 m, with a peak at 600 m (ß: 0.657; CI: 0.150, 1.227). Accessible total green space (Fig 4.5E) reacted similarly but more consistently and showed significant associations with physical activity up to 800 m, with a peak at 600 m (ß: 0.765; CI: 0.260, 1.355). The quantity of green space uses (Fig 4.5F) showed positive significant associations with physical activity at 600-700 m, with a peak at 600 m (ß: 0.516; CI: 0.196, 0.840). In addition, the indicator turned to significant negative associations with physical activity at distances of 1,100-1,500 m, with a peak at 1,100 m (ß: -1.068; CI: -1.667, -0.504). On the contrary, the mix of green space uses in network distance (Fig 4.5G) again showed a clear positive plateau (200-1,000 m) of significant associations with physical activity and again a peak at 600 m (ß: 0.554; CI: 0.298, 0.814). The overall strongest positive association to physical activity was related to accessible total green space in 600 m network distance.

4.3.3 Indirect effects – How green space indicators are indirectly associated with health via physical activity

We observed clear patterns in the indirect effects (path a*b) in terms of proximity to green spaces and different green space characteristics (Table 4.3), which were very similar to the partial effects (a) due to the stable significant association (b) between physical activity and health (ß: 0.16; CI: 0.10, 0.21). Surrounding greenness (Fig 4.6A) showed the same two-sided pattern starting with positive significance in the immediate surrounding of 100 m (ß: 0.085; CI: 0.013, 0.188) and turning negative in larger Euclidean distances of 800-1,500 m with a peak at 1,300 m, although not significant. Accessible greenness (Fig 4.6B) reacted similarly but created stronger associations to indirect health effects in the immediate surrounding of 100 m (ß: 0.118; CI: 0.038, 0.243). Accessible green space within network distance (Fig 4.6C) showed a significant positive indirect health relation at 400-700 m, with a peak at 500 m (ß: 0.064; CI: 0.015, 0.126). Access to green corridors (Fig 4.6D) showed a clear plateau of positive indirect health associations in distances from 200-800 m, with a peak at 600 m (ß: 0.104; CI: 0.030, 0.224). Accessible total green space (Fig 4.6E) reacted similarly from 100-800 m, with a peak at 600 m but with a higher estimate (ß: 0.120; CI: 0.042, 0.243). The quantity of green space uses (Fig 4.6F) showed positive significant associations with physical activity at 500-700 m, with a peak at 600 m (ß: 0.082; CI: 0.031, 0.154). Similar to the partial effect, the indicator turned to significant negative associations with indirect health effects at distances of 1,100-1,500 m, with a peak at 1,100 m (ß: -0.171; CI: -0.317, -0.078). On the contrary, the mix of green space uses in network distance (Fig 4.6G) again showed a clear positive plateau (200-1,000 m) of significant associations with indirect health effects and a peak at 600 m (ß: 0.090; CI: 0.045, 0.155). The overall strongest positive association of indirect health effects via physical activity was related to accessible total green space in 600 m network distance.

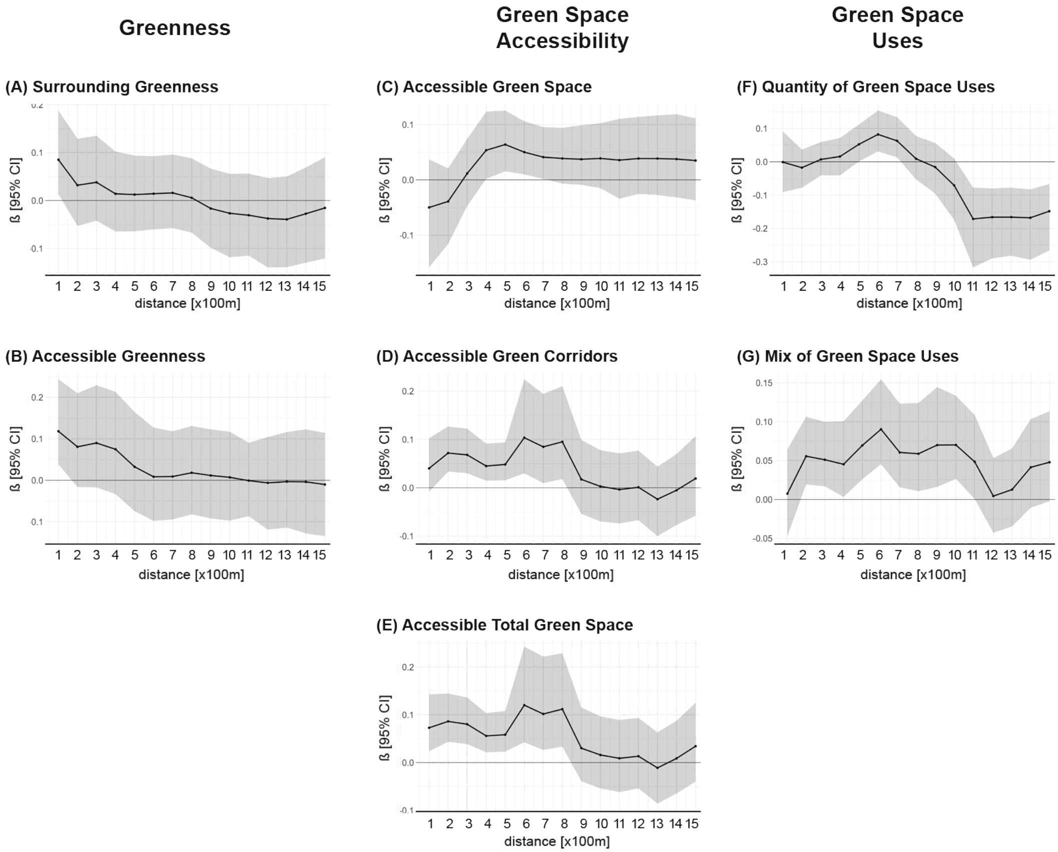

FIG. 4.5 Indirect Effects (a*b). Green Space – Physical Activity – Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 105 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, perceived neighbourhood safety, satisfaction with shops, leisure facilities, public transport, population density and city; 5,000 Bootstrap Samples; shaded grey area show 95% confidence interval.

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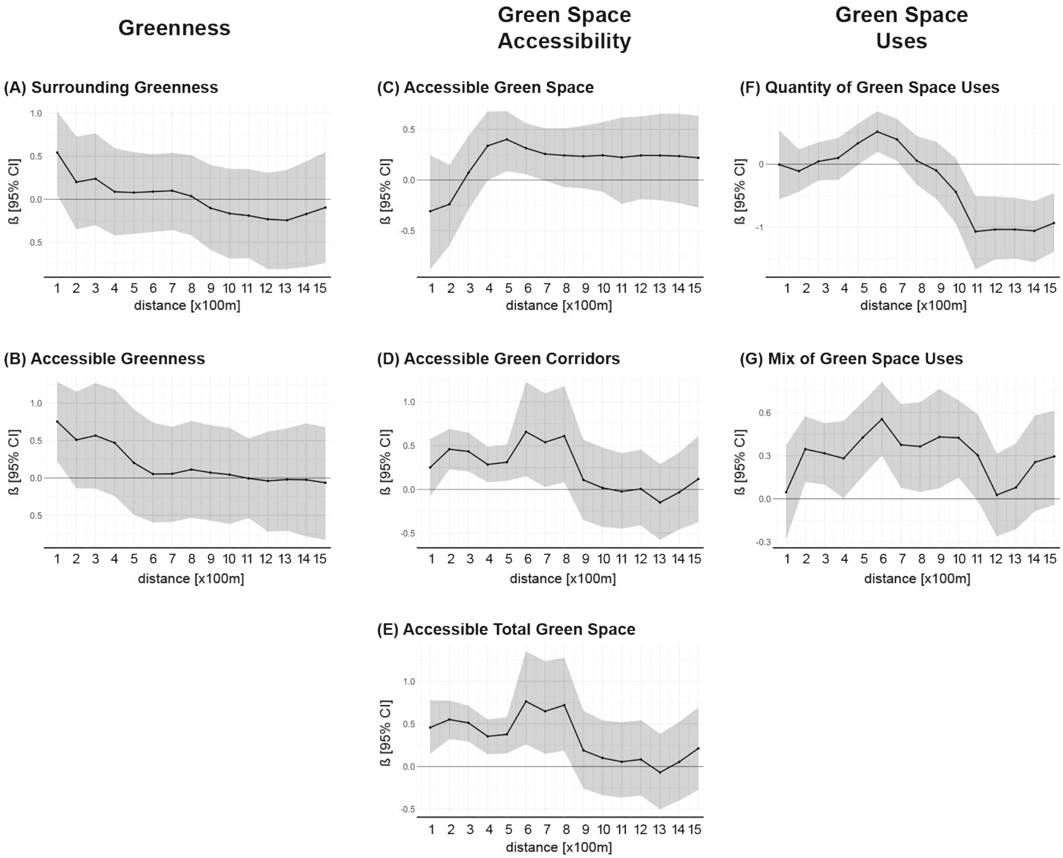

FIG. 4.6 Partial Effects (a). Green Space – Physical Activity Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 105 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, perceived neighbourhood safety, satisfaction with shops, leisure facilities, public transport, population density and city; 5,000 Bootstrap Samples; shaded grey area show 95% confidence interval.

TABLE 4.2 Partial Effects (a). Green Space – Physical Activity Sensitivity Analysis.

Standardized Estimated ß (95% CI) for partial effects (a) of green space indicators on physical activity in the 105 structural equation models each with 5,000 bootstrap samples.

Greenness				
Distance	(A) Surrounding GN		(B) Accessible GN	
100	**0.542 (0.048, 1.023)**	*	**0.753 (0.221, 1.283)**	*
200	0.200 (-0.350, 0.728)		0.509 (-0.138, 1.154)	
300	0.239 (-0.302, 0.764)		0.567 (-0.143, 1.266)	
400	0.087 (-0.420, 0.593)		0.469 (-0.243, 1.183)	
500	0.078 (-0.402, 0.547)		0.203 (-0.491, 0.917)	
600	0.089 (-0.379, 0.523)		0.052 (-0.595, 0.740)	
700	0.100 (-0.358, 0.541)		0.056 (-0.588, 0.683)	
800	0.036 (-0.419, 0.513)		0.113 (-0.533, 0.761)	
900	-0.102 (-0.588, 0.400)		0.072 (-0.569, 0.705)	
1000	-0.165 (-0.688, 0.354)		0.044 (-0.616, 0.671)	
1100	-0.190 (-0.684, 0.351)		-0.006 (-0.537, 0.528)	
1200	-0.232 (-0.813, 0.306)		-0.039 (-0.718, 0.620)	
1300	-0.244 (-0.811, 0.343)		-0.020 (-0.705, 0.662)	
1400	-0.171 (-0.785, 0.440)		-0.024 (-0.781, 0.730)	
1500	-0.096 (-0.739, 0.548)		-0.064 (-0.827, 0.679)	

Green Space Accessibility						
Distance	(C) Accessible GS		(D) Accessible GC		(E) Accessible TGS	
100	-0.309 (-0.881, 0.247)		0.251 (-0.076, 0.576)		0.458 (0.150, 0.777)	*
200	-0.240 (-0.648, 0.150)		0.458 (0.229, 0.691)	*	0.552 (0.323, 0.774)	*
300	0.072 (-0.294, 0.437)		0.433 (0.204, 0.648)	*	0.513 (0.293, 0.715)	*
400	0.337 (-0.005, 0.676)		0.284 (0.082, 0.488)	*	0.355 (0.144, 0.553)	*
500	**0.401 (0.087, 0.679)**	*	0.310 (0.097, 0.512)	*	0.378 (0.153, 0.580)	*
600	0.314 (0.057, 0.560)	*	**0.657 (0.150, 1.227)**	*	**0.765 (0.260, 1.355)**	*
700	0.257 (-0.007, 0.511)		0.538 (0.028, 1.097)	*	0.649 (0.148, 1.235)	*
800	0.243 (-0.071, 0.511)		0.609 (0.081, 1.177)	*	0.721 (0.185, 1.279)	*
900	0.234 (-0.082, 0.534)		0.108 (-0.351, 0.567)		0.189 (-0.259, 0.657)	
1000	0.244 (-0.116, 0.571)		0.017 (-0.429, 0.478)		0.100 (-0.338, 0.542)	
1100	0.223 (-0.237, 0.618)		-0.023 (-0.447, 0.415)		0.056 (-0.365, 0.520)	
1200	0.242 (-0.190, 0.628)		0.006 (-0.411, 0.453)		0.083 (-0.341, 0.546)	
1300	0.242 (-0.200, 0.655)		-0.148 (-0.576, 0.289)		-0.069 (-0.502, 0.385)	
1400	0.236 (-0.229, 0.655)		-0.033 (-0.456, 0.421)		0.054 (-0.401, 0.524)	
1500	0.219 (-0.272, 0.633)		0.118 (-0.376, 0.610)		0.213 (-0.277, 0.695)	

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TABLE 4.2 Partial Effects (a). Green Space – Physical Activity Sensitivity Analysis.

Standardized Estimated ß (95% CI) for partial effects (a) of green space indicators on physical activity in the 105 structural equation models each with 5,000 bootstrap samples.

Green Space Usability				
Distance	(F) Quantity of GSU		(G) Mix Of GSU	
100	-0.006 (-0.556, 0.538)		0.047 (-0.286, 0.374)	
200	-0.110 (-0.439, 0.237)		0.346 (0.116, 0.575)	*
300	0.044 (-0.257, 0.349)		0.317 (0.099, 0.528)	*
400	0.099 (-0.251, 0.416)		0.281 (0.003, 0.543)	*
500	0.329 (-0.015, 0.642)		0.426 (0.159, 0.674)	*
600	**0.516 (0.196, 0.840)**	*****	**0.554 (0.298, 0.814)**	*****
700	0.393 (0.052, 0.719)	*	0.375 (0.076, 0.660)	*
800	0.057 (-0.323, 0.450)		0.364 (0.048, 0.673)	*
900	-0.098 (-0.549, 0.354)		0.430 (0.073, 0.765)	*
1000	-0.440 (-0.944, 0.096)		0.424 (0.147, 0.686)	*
1100	**-1.068 (-1.667, -0.504)**	*****	0.303 (-0.014, 0.589)	
1200	-1.036 (-1.513, -0.511)	*	0.027 (-0.262, 0.314)	
1300	-1.036 (-1.496, -0.534)	*	0.079 (-0.211, 0.387)	
1400	-1.057 (-1.553, -0.582)	*	0.255 (-0.086, 0.582)	
1500	-0.934 (-1.387, -0.459)	*	0.295 (-0.043, 0.611)	

Notes: *Adjusted for sex, age, disabilities, education, income, occupation, years lived in the neighbourhood, perceived neighbourhood safety, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);*
***** *Coefficient is statistically significant; bold estimates indicate highest significant positive and negative estimate within specific indicator.*

TABLE 4.3 Indirect Effects (a*b). Green Space – Physical Activity – Health Sensitivity Analysis.

Standardized estimated ß (95% CI) for the indirect effect (a*b) of green space indicators, mediated by physical activity on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Greenness				
Distance	(A) Surrounding GN		(B) Accessible GN	
100	**0.085 (0.013, 0.188)**	*	**0.118 (0.038, 0.243)**	*
200	0.032 (-0.053, 0.129)		0.081 (-0.017, 0.210)	
300	0.038 (-0.042, 0.135)		0.090 (-0.017, 0.229)	
400	0.014 (-0.065, 0.102)		0.075 (-0.033, 0.213)	
500	0.012 (-0.064, 0.094)		0.032 (-0.075, 0.165)	
600	0.014 (-0.060, 0.093)		0.008 (-0.098, 0.127)	
700	0.016 (-0.058, 0.096)		0.009 (-0.094, 0.118)	
800	0.006 (-0.067, 0.088)		0.018 (-0.082, 0.131)	
900	-0.017 (-0.099, 0.067)		0.012 (-0.092, 0.123)	
1000	-0.027 (-0.118, 0.056)		0.007 (-0.098, 0.117)	
1100	-0.031 (-0.115, 0.056)		-0.001 (-0.087, 0.090)	
1200	-0.037 (-0.140, 0.047)		-0.006 (-0.119, 0.104)	
1300	-0.039 (-0.139, 0.050)		-0.003 (-0.114, 0.116)	
1400	-0.028 (-0.130, 0.069)		-0.004 (-0.128, 0.123)	
1500	-0.015 (-0.121, 0.090)		-0.010 (-0.135, 0.114)	

Green Space Accessibility						
Distance	(C) Accessible GS		(D) Accessible GC		(E) Accessible TGS	
100	-0.050 (-0.158, 0.037)		0.040 (-0.008, 0.103)		0.073 (0.024, 0.143)	*
200	-0.039 (-0.116, 0.021)		0.072 (0.033, 0.127)	*	0.086 (0.043, 0.145)	*
300	0.012 (-0.047, 0.074)		0.068 (0.030, 0.122)	*	0.080 (0.039, 0.136)	*
400	0.054 (0.002, 0.124)	*	0.045 (0.014, 0.091)	*	0.056 (0.021, 0.104)	*
500	**0.064 (0.015, 0.126)**	*	0.048 (0.015, 0.094)	*	0.058 (0.023, 0.108)	*
600	0.050 (0.010, 0.106)	*	**0.104 (0.030, 0.224)**	*	**0.120 (0.042, 0.243)**	*
700	0.041 (0.002, 0.096)	*	0.085 (0.010, 0.194)	*	0.102 (0.027, 0.222)	*
800	0.039 (-0.007, 0.094)		0.095 (0.018, 0.210)	*	0.112 (0.033, 0.229)	*
900	0.037 (-0.009, 0.099)		0.017 (-0.054, 0.099)		0.030 (-0.039, 0.115)	
1000	0.039 (-0.015, 0.103)		0.003 (-0.070, 0.078)		0.016 (-0.054, 0.097)	
1100	0.036 (-0.034, 0.111)		-0.004 (-0.074, 0.071)		0.009 (-0.062, 0.089)	
1200	0.039 (-0.025, 0.114)		0.001 (-0.067, 0.077)		0.013 (-0.054, 0.094)	
1300	0.039 (-0.028, 0.117)		-0.024 (-0.100, 0.044)		-0.011 (-0.086, 0.063)	
1400	0.038 (-0.032, 0.119)		-0.005 (-0.077, 0.070)		0.009 (-0.065, 0.088)	
1500	0.035 (-0.037, 0.111)		0.019 (-0.058, 0.107)		0.034 (-0.040, 0.125)	

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TABLE 4.3 Indirect Effects (a*b). Green Space – Physical Activity – Health Sensitivity Analysis.

Standardized estimated ß (95% CI) for the indirect effect (a*b) of green space indicators, mediated by physical activity on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Green Space Uses				
Distance	(F) Quantity of GSU		(G) Mix Of GSU	
100	-0.001 (-0.091, 0.092)		0.007 (-0.047, 0.064)	
200	-0.018 (-0.078, 0.037)		0.056 (0.019, 0.106)	*
300	0.007 (-0.041, 0.059)		0.051 (0.017, 0.100)	*
400	0.016 (-0.041, 0.071)		0.045 (0.003, 0.101)	*
500	0.053 (0.001, 0.112)	*	0.069 (0.026, 0.127)	*
600	**0.082 (0.031, 0.154)**	*****	**0.090 (0.045, 0.155)**	*****
700	0.063 (0.013, 0.134)	*	0.060 (0.016, 0.123)	*
800	0.009 (-0.053, 0.077)		0.059 (0.011, 0.124)	*
900	-0.016 (-0.095, 0.057)		0.070 (0.016, 0.145)	*
1000	-0.071 (-0.175, 0.010)		0.070 (0.027, 0.133)	*
1100	**-0.171 (-0.317, -0.078)**	*****	0.048 (0.001, 0.109)	*
1200	-0.166 (-0.290, -0.080)	*	0.004 (-0.043, 0.053)	
1300	-0.166 (-0.282, -0.078)	*	0.013 (-0.035, 0.066)	
1400	-0.168 (-0.294, -0.083)	*	0.041 (-0.011, 0.103)	
1500	-0.148 (-0.266, -0.066)	*	0.048 (-0.002, 0.113)	

Notes: *Adjusted for sex, age, disabilities, education, income, occupation, years lived in the neighbourhood, perceived neighbourhood safety, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);*
****:*** *Coefficient is statistically significant; bold estimates indicate highest significant positive and negative estimate within specific indicator.*

4.3.4 Direct effects – How green space indicators are associated with health

The direct effects, adjusted for physical activity (path c), showed clear patterns in terms of proximity to green spaces and differed by green space characteristics (Table 4.4). Surrounding greenness (Fig 4.7A) showed a clear positive plateau for intermediate distances of 500-1,100 m with a peak at 800 m (ß: 0.643; CI: 0.201, 1.106). Accessible greenness (Fig 4.7B) showed an almost linear pattern, with a significant association at 1,200 m and 1,400 m (ß: 0.693; CI: 0.031, 1.271). Accessible green space (Fig 4.7C) showed a peak in immediate proximity but was not significant. Access to green corridors (Fig 4.7D) showed a one-clear peak at 800 m (ß: 0.606; CI: 0.093, 1.272), and was also significant at 500 m network distance. Accessible total green space (Fig 4.7E) reacted similarly with a peak at 800 m, but this time with a slightly lower estimate and consistency in the pattern (ß: 0.584; CI: 0.065, 1.212). The quantity of green space uses in network distance (Fig 4.7F) showed a significant negative direct association with health in the immediate surrounding of 100 m (ß: -0.543; CI: -1.003, -0.054). The diversity of green space uses in network distance (Fig 4.7G) showed a stable negative pattern through all distances, but was only significant at 1,000 m and 1,300 m distance with a peak at 1000 m (ß: -0.369; CI: -0.656, -0.077). The overall strongest positive direct association with health was related to green corridors measured in 600 m network distance.

4.3.5 Total effects – How green space indicators, directly and indirectly, relate to health

The total effects (path a*b + c) in the structural equation model behaved similarly to the direct effects (Table 4.5), due to the differences in effect size between direct (path c, maximum ß 0.693) and indirect effects (path a*b, maximum ß 0.120), with the exception of surrounding greenness. Surrounding greenness (Fig 4.8A) showed a double peak in the total effects, with a significant effect at 100 m and a significant pattern for intermediate distances of 600-1,100 m with a peak at 800 m (ß: 0.649; CI: 0.201, 1.122). Accessible greenness showed an almost linear pattern, with significant associations at 1,200 m and 1,400 m (ß: 0.689; CI: 0.019, 1.383). Accessible green space (Fig 4.8C) showed a peak in immediate proximity but was not significant. Access to green corridors (Fig 4.8D) and accessible total green space (Fig 4.8E) showed significant associations in network distances of 500 m, 700 m, and 800 m, both with a peak at 800 m. The quantity of green space uses (Fig 4.8F) showed a significant negative relation to health in the immediate proximity of 100 m (ß: -0.544; CI: -1.009; -0.054). The total effect of the mix of green space uses on

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health (Fig 4.8G) reacted similarly to the direct effects, but only showed a significant negative association at 1,000 m (ß: -0.299; CI: -0.580, -0.003). The overall strongest positive total association with health was related to accessible green corridors in 800 m network distance.

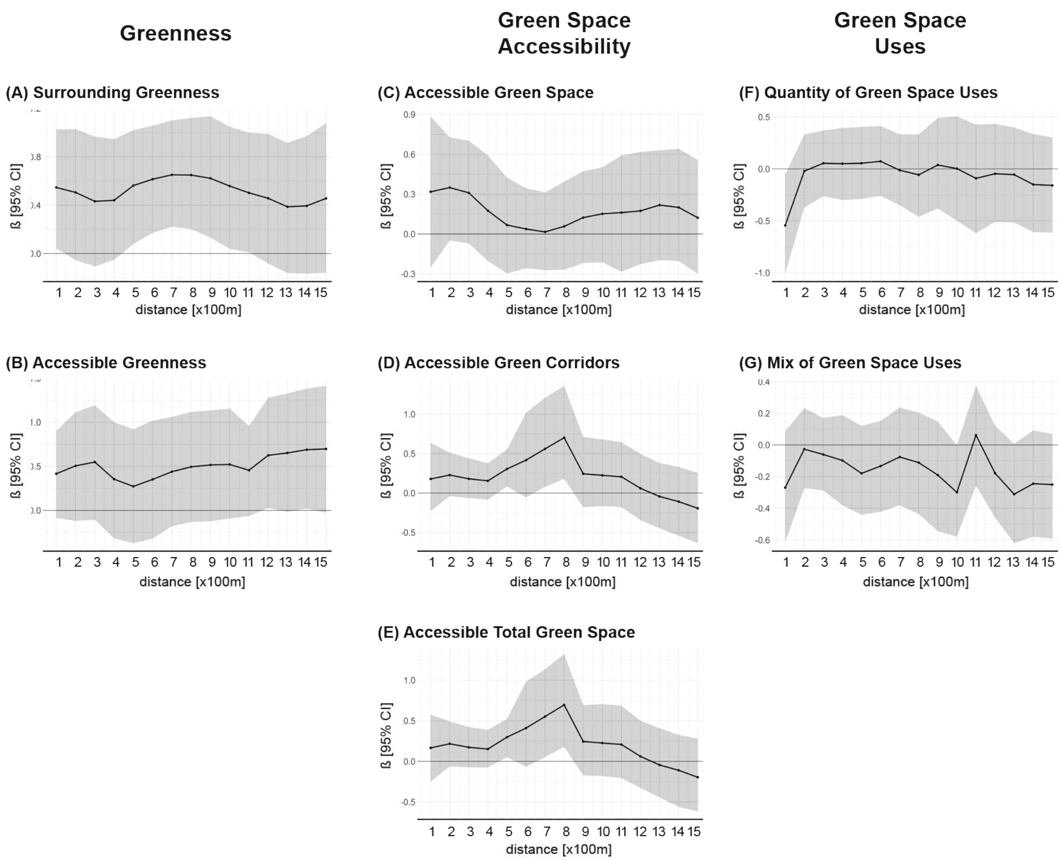

FIG. 4.7 Total Effects (a*b +c). Green Space – Physical Activity – Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 105 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, perceived neighbourhood safety, satisfaction with shops, leisure facilities, public transport, population density and city; 5,000 Bootstrap Samples; shaded grey area show 95% confidence interval.

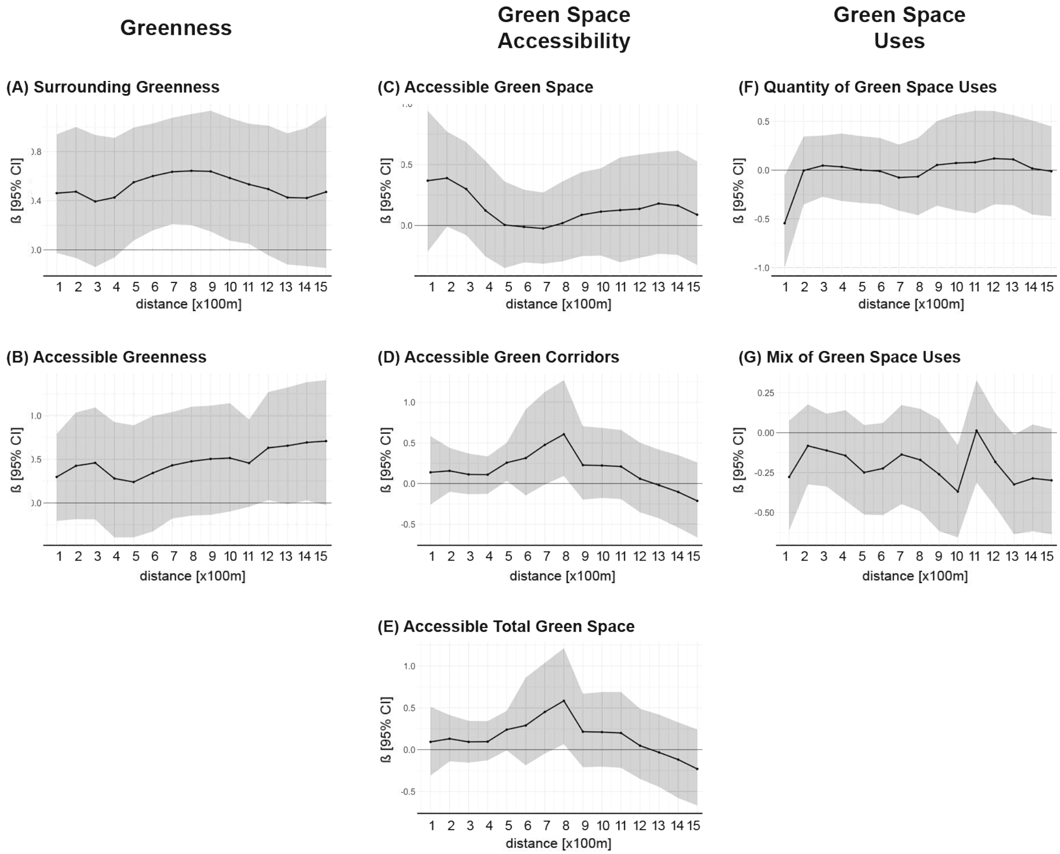

FIG. 4.8 Direct Effects (c). Green Space – Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 105 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, perceived neighbourhood safety, satisfaction with shops, leisure facilities, public transport, population density and city; 5,000 Bootstrap Samples; shaded grey area show 95% confidence interval.

TABLE 4.4 Direct Effects (c). Green Space – Health Sensitivity Analysis.

Standardized estimated ß (95% CI) for the direct effect (c) of green space indicators on self-perceived general health in the 105 structural equation models each with 5,000 bootstrap samples.

Greenness				
Distance	**(A) Surrounding GN**		**(B) Accessible GN**	
100	0.461 (-0.026, 0.941)		0.298 (-0.206, 0.793)	
200	0.474 (-0.067, 1.001)		0.425 (-0.186, 1.035)	
300	0.394 (-0.140, 0.935)		0.459 (-0.189, 1.094)	
400	0.426 (-0.061, 0.912)		0.280 (-0.395, 0.927)	
500	0.550 (0.075, 0.996)	*	0.240 (-0.395, 0.889)	
600	0.601 (0.159, 1.029)	*	0.343 (-0.326, 0.997)	
700	0.635 (0.209, 1.075)	*	0.430 (-0.179, 1.040)	
800	**0.643 (0.201, 1.106)**	*	0.476 (-0.145, 1.102)	
900	0.639 (0.149, 1.133)	*	0.504 (-0.136, 1.115)	
1000	0.585 (0.075, 1.074)	*	0.514 (-0.099, 1.143)	
1100	0.533 (0.048, 1.027)	*	0.456 (-0.044, 0.955)	
1200	0.494 (-0.045, 1.011)		0.631 (0.031, 1.271)	*
1300	0.426 (-0.120, 0.948)		0.655 (-0.014, 1.322)	
1400	0.422 (-0.133, 0.994)		**0.693 (0.028, 1.384)**	*
1500	0.471 (-0.148, 1.091)		0.708 (-0.024, 1.407)	

Green Space Accessibility						
Distance	**(C) Accessible GS**		**(D) Accessible GC**		**(E) Accessible TGS**	
100	0.367 (-0.215, 0.942)		0.138 (-0.258, 0.584)		0.093 (-0.311, 0.512)	
200	0.388 (-0.011, 0.770)		0.156 (-0.102, 0.440)		0.131 (-0.140, 0.414)	
300	0.298 (-0.080, 0.684)		0.112 (-0.132, 0.369)		0.093 (-0.155, 0.345)	
400	0.122 (-0.255, 0.530)		0.110 (-0.126, 0.334)		0.096 (-0.128, 0.342)	
500	0.004 (-0.350, 0.360)		0.256 (0.033, 0.501)	*	0.239 (-0.009, 0.464)	
600	-0.012 (-0.304, 0.294)		0.313 (-0.146, 0.913)		0.290 (-0.187, 0.862)	
700	-0.026 (-0.315, 0.270)		0.476 (-0.012, 1.127)		0.451 (-0.047, 1.038)	
800	0.018 (-0.295, 0.361)		**0.606 (0.093, 1.272)**	*	**0.584 (0.065, 1.212)**	*
900	0.086 (-0.252, 0.438)		0.227 (-0.198, 0.705)		0.214 (-0.209, 0.669)	
1000	0.113 (-0.247, 0.469)		0.222 (-0.177, 0.685)		0.210 (-0.204, 0.689)	
1100	0.125 (-0.303, 0.559)		0.210 (-0.192, 0.660)		0.199 (-0.217, 0.689)	
1200	0.135 (-0.267, 0.582)		0.059 (-0.355, 0.503)		0.048 (-0.351, 0.490)	
1300	0.179 (-0.234, 0.601)		-0.020 (-0.428, 0.416)		-0.033 (-0.446, 0.419)	
1400	0.163 (-0.243, 0.614)		-0.103 (-0.541, 0.350)		-0.118 (-0.578, 0.327)	
1500	0.088 (-0.326, 0.526)		-0.213 (-0.662, 0.260)		-0.230 (-0.667, 0.243)	

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TABLE 4.4 Direct Effects (c). Green Space – Health Sensitivity Analysis.

Standardized estimated ß (95% CI) for the direct effect (c) of green space indicators on self-perceived general health in the 105 structural equation models each with 5,000 bootstrap samples.

Green Space Usability					
Distance				(G) Mix Of GSU	
100		**-0.543 (-1.003, -0.054)**	*	-0.277 (-0.612, 0.076)	
200		-0.004 (-0.353, 0.346)		-0.082 (-0.324, 0.178)	
300		0.047 (-0.273, 0.355)		-0.111 (-0.337, 0.119)	
400		0.034 (-0.316, 0.376)		-0.143 (-0.425, 0.141)	
500		0.002 (-0.336, 0.349)		-0.249 (-0.513, 0.049)	
600		-0.009 (-0.348, 0.331)		-0.224 (-0.516, 0.062)	
700		-0.076 (-0.415, 0.263)		-0.136 (-0.447, 0.174)	
800	*	-0.066 (-0.461, 0.329)		-0.170 (-0.493, 0.150)	
900		0.054 (-0.364, 0.504)		-0.260 (-0.616, 0.085)	
1000		0.073 (-0.412, 0.572)		**-0.369 (-0.656, -0.077)**	*
1100		0.080 (-0.441, 0.609)		0.014 (-0.312, 0.330)	
1200		0.120 (-0.350, 0.607)		-0.183 (-0.464, 0.123)	
1300		0.111 (-0.359, 0.564)		-0.324 (-0.636, -0.012)	*
1400		0.018 (-0.455, 0.510)		-0.286 (-0.617, 0.052)	
1500		-0.011 (-0.473, 0.449)		-0.298 (-0.637, 0.024)	

Notes: *Adjusted for sex, age, disabilities, education, income, occupation, years lived in the neighbourhood, perceived neighbourhood safety, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);*
***** *Coefficient is statistically significant; bold estimates indicate highest significant positive and negative estimate within specific indicator.*

4.3.6 Collinearity between significant green space characteristics

To further examine if the measured associations stem from unique mechanisms or just act as an alternative measure of the same underlying construct, we examined the correlation matrix of the significant green space characteristics at their peak values for the partial (path a) and direct effects (path c) (Table A4.4).

As described in section 4.3.2, the peak associations for the partial effect (path a) were between physical activity and surrounding greenness in 100 m (A), accessible greenness in 100 m (B), accessible green space 500 m (C), accessible green corridors in 600 m (D), accessible total green spaces in 600 m (E), quantity of green space uses in 600 m was positive and 1,100 m negative (F), an mix of green space uses in 600 m (G). The investigation of the correlation matrix indicated the expected strong collinearity between the nested green space characteristics when measured in similar distances (A & B; D & E; F & G). However, the correlation across the different sets of indicators (e.g. between A and D or between E and G), was weak for accessible greenness (-0.03-0.18), green space (0.03-0.25), green corridors (0.06-0.23), green space uses at 600m (0.18-0.26), except for a strong correlation between accessible green spaces and green space uses (0.55-0.61). We found a weak to moderate correlation for the negative association of the quantity of green space uses at 1,100 m to other green space characteristics (-0.03-0.25). This indicates partially unique mechanisms to physical activity from greenness, green space accessibility, green corridors and green space uses.

As described in section 4.3.4, the peak associations for the direct effect (path c) were between self-assessed health and surrounding greenness in 800 m (A), accessible greenness in 1,400 m (B), accessible green corridors in 800 m (D), accessible total green space in 800m (E), as well as negative associations for quantity of green space uses in 100m (F), and mix of green space uses in 1,000 m (G). Similar to the peak of the partial effects, the investigation of the correlation matrix showed the expected strong collinearity between nested green space characteristics (A & B, D & E), although surrounding and accessible greenness peaked at different distances. However, we found a weak correlation to other green space characteristics for surrounding greenness (-0.32-0.17), green corridors (0.00-0.21), as well as the negative association with the quantity of green space uses (0.00-0.24), and mix of green space uses (-0.32-0.24), indicating partially unique mechanisms to health.

4.4 Discussion

4.4.1 Main findings

In our study, we examined associations between 105 different green space indicators, physical activity and health in a sample across four European cities. We found that greenness was associated with physical activity and indirect health benefits in the immediate surroundings (100 m). Accessible green corridors, preferably with a mix of use, were associated with higher levels of physical activity and possible indirect health benefits when they can be reached within 800 m, or a 10 min walk. On the contrary, direct health effects were only associated with green space at intermediate or larger buffers depending on the green space indicator. Surrounding greenness (500 m-1,100 m) and accessible green corridors (500 m, 800 m) were significantly associated with direct health effects and identified as unique green space characteristics. We also found significant negative patterns. A high quantity of green space uses in larger network distances (1,100-1,500 m) showed negative associations with physical activity and negative indirect health effects. A high number of green spaces uses in immediate distance (100 m) and a high mix of uses in 1,000 m and 1,300 m network distance was associated with negative health outcomes. To our knowledge, we are the first to test such a rigorous sensitivity analysis for the green space physical activity health pathway, expanding our understanding of how and where these mechanisms occur.

Our results support the theory that different mechanistic pathways between green space and health rely on different green space characteristics, work at different distances and may even change direction depending on the analysed green space characteristics and proximity. Furthermore, our total effects suggest that different mechanistic pathways may mask each other. This should be considered when further disentangling the specific pathways to improve our understanding of the effects of green spaces on health. Lastly, the comparison between green space indicators showed that the inclusion of connectivity of green spaces as well as semi-public and private green spaces led both to stronger and more robust patterns of significant associations with physical activity and with health, highlighting the risk of bias on the one side and the importance of these aspects on the other side.

4.4.2 Green space health effects via physical activity

Our study indicates that greenness in immediate proximity (100 m), as well as green space, green corridors reachable within a 10-minute walk (up to 800 m distance) and green space uses up to 1,000 m are significantly associated with higher physical activity and indirect health effects. This is consistent with previous research that found a positive association between public open spaces and leisure-time physical activity, as well as maintaining or initiating recreational walking (Motomura et al., 2022; Sugiyama et al., 2013). Specifically, our results support the theory that the immediate surroundings, connectivity and usability of green spaces seem to matter the most, which is in line with previous studies (Akpinar, 2016; McCormack et al., 2010; Sugiyama et al., 2010). Together, our findings add to the body of evidence that suggests a positive relationship between nearby green space, physical activity, and general health (Luo et al., 2020; Markevych et al., 2017; Yang et al., 2021) and they show in more detail how and where these relationships might occur.

Our findings also suggest that more greenness might not always be beneficial for physical activity and health if it is not accessible. We observed a pattern of (non-significant) negative indirect health effects for surrounding greenness, but not for accessible greenness in buffer distances of 1,100-1,500 m. In addition, we found a very similar significant plateau of negative indirect effects on health for the quantity of green space uses at the same distances of 1,100-1,500 m. This might be related to physical inactivity and the car-dependent lifestyle (Chandrabose et al., 2022; Kleinert & Horton, 2016; Sallis et al., 2016) prevalent in satellite districts that are usually much greener than their central urban counterparts and thus often may also have a higher quantity of green space uses. In addition, peer behaviour in these districts may also play a role, as evidence suggests that individuals' physical activity levels are influenced by the behaviour of their peers (Finnerty et al., 2010), although not consistent (Tucunduva Philippi et al., 2016).

However, it is also plausible that larger distance associations stem from changes in the signal-to-noise ratio. Arguably, the inviting character of green space uses or pure greenery might disappear at larger distances, gradually reducing the association to physical activity and therefore allowing the noise in the dataset to dominate the results. There seem to be certain thresholds, or necessary perspectives, that form boundaries in which the hypothesized positive relationship is detectable. For example, accessible green spaces (Fig 4.6C) showed a non-significant negative association in immediate distances, before turning positive and significant when measured in intermediate surroundings of 400-700 m. This might be related to the necessary quantity of green spaces needed to trigger physical activity and is also in line with the results on green space corridors and total accessible green spaces where this widened perspective is built into the indicator (e.g. it is measuring the green space area beyond the buffer boundaries and semi-public green spaces), leading to detectable positive significant effects at immediate distances.

Furthermore, our study results might help to explain why half of the previous mediation analyses on physical activity did not find a significant relationship (A. M. Dzhambov et al., 2020). Firstly, we could demonstrate that the results react very sensitively to the buffer distance used in the analysis and might even turn a positive association into a negative association in some cases. Secondly, our results highlight the differences in greenness and green space indicators for studies exploring physical activity. These differences corroborate the theory that physical activity is more related to the green space characteristics of accessibility, connectivity and green space uses than to greenness, especially at the common distances researched of 300-500 m (Cardinali, Beenackers, et al., 2023c; Labib et al., 2020). In our study, physical activity was stronger and more consistently related to spatial green space indicators than to indicators based on vegetation indices. Thirdly, our findings suggest that the way in which the green space indicators are set up plays an important role in increasing the consistency and magnitude of the findings, which is important due to the very low signal-to-noise ratio in green space health research (Hartig et al., 2014). In our study the connectivity of green spaces and how private and semi-public green spaces were included made a significant difference in the estimates, which - to our knowledge – were both mostly not included in previous research.

4.4.3 Green space health effects via other pathways

All measured positive direct patterns (factually adjusted for physical activity) are associated with intermediate distances. We hypothesize that this might be mainly related to mitigation effects, as restoration effects are more likely to be associated with immediate contact with nature (Cardinali, Beenackers, et al., 2023c), which might be able to explain our almost significant association for greenness and health at immediate distances of 100 m. The clear pattern of positive direct relations with health for surrounding greenness within 500-1,100 m is in line with previous research on mitigation which might be related to better air quality due to fewer pollution sources and the associated mechanisms of vegetation of deposition and dispersion (Mueller et al., 2022). Furthermore, our results are in line with the review of Browning & Lee (Browning & Lee, 2017), who found a trend that plateaued between 500-1,000 m distance in studies where individual addresses were used, a trend that is quite consistent with our results. Additionally, our results suggest that the connectivity of green spaces could play a role since only access to green

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corridors (D) and total access to green space (E) showed a significant pattern while green space in network distance (C) did not (Figure 4.3). This might especially be related to the importance of air-exchange corridors which have been studied in their ability to reduce urban heat island effects (Gunawardena et al., 2017; Kuang et al., 2015; Ren et al., 2016; Wong et al., 2010), to reduce air pollution through their cooling (Aram et al., 2019) and cleaning effect, through deposition and dispersion (Hewitt et al., 2020). However, the pattern is not as consistent as the surrounding greenness pattern, which might be explained by the general problems with the quality of available green space data (Cardinali, Beenackers, et al., 2023c).

The negative associations between health and quantity and mix of green space uses might be a spurious relation reflecting the typically high amount of green space uses in satellite districts instead of a real direct association between green space uses and health. It is important to consider that these direct associations are factually adjusted for physical activity, which is likely the main link to green space uses. This may lead to a true null or very small relationship, which allows for spurious relations to be observed, reflecting the high signal-to-noise ratio (Hartig et al., 2014). Thus, these negative health outcomes are likely caused by other factors associated with these neighbourhoods. Although we controlled for socio-demographic indicators, we did not specifically control for peer behaviour like smoking, drinking or an unhealthy diet (Lazzeri et al., 2014; Morton et al., 2020), which could be more prevalent in these districts (Sorensen et al., 2013; Warren Andersen et al., 2016) and partially explain these negative associations between green space uses and health.

4.4.4 Trade-offs and masking between pathways

Our findings indicate that information on specific pathways may remain concealed if they are not disentangled. This aligns with recent theories that the *Instoration* pathway via physical activity operates differently than mitigation or restoration pathways (Cardinali, Beenackers, et al., 2023c; Labib et al., 2020; Markevych et al., 2017). In our results, the degree of surrounding vegetation (A) in buffer distances of around 500-1,100 m shows a clear positive direct relation to health while we observed a negative trend for the indirect effects via physical activity. Similarly, accessible green corridors (D) and accessible total green space (E) from 500-1,000 m, show differing patterns of significance when comparing direct and indirect effects. Moreover, while the mix of green space uses (G) shows positive relations to physical activity and thus indirectly to health, they showed consistent negative direct associations to health. This mechanism might be able to partly explain the heterogeneity of past results, frequently recognized as a barrier in the field (Cardinali, Beenackers, et al., 2023c; Markevych et al., 2017). Lack of information on specific pathways may hinder making well-informed policy and urban design decisions regarding green spaces as these choices may depend on the specific health problems in an area and therefore the specific green space characteristics or distances.

4.4.5 Strengths and limitations

To the best of our knowledge, our study is the first to conduct rigorous analyses of the area of effect of the green space - physical activity - health pathway, while also testing different green space characteristics considered crucial for this relationship. Due to our study design, we could reveal patterns of significance, as well as peaks in significant estimates, and changes in the direction of the relationship due to proximity. Similarly, it allowed for the comparison of green space characteristics, revealing potential important nudging effects of connectivity and usability of green spaces.

However, several limitations of the study need to be considered when interpreting the findings. Our study primarily relied on self-reported data for most of its indicators, making it vulnerable to biases such as social desirability, recall or reporting bias. Particularly, the use of the International Physical Activity Questionnaire Short Form (IPAQ-SF) as a measure of physical activity may have limited the accuracy of the data collected. Previous research has shown that the IPAQ-SF tends to overestimate physical activity levels, with a weak correlation to objective measures of activity or fitness (Lee et al., 2011). We also had to transform the variable into an ordinal indicator to resolve the zero-inflated count variable issue. While this may mitigate some of the aforementioned overestimation, it essentially led to a loss in data granularity. Similarly, using Likert items for the control indicators may not have provided a fully accurate measure of these variables. Furthermore, the use of an ordinal item to measure health as one of the main variables of interest allows only for a general picture of the analysed pathways. Moreover, while we adjusted for seasonal differences (through the data acquisition of the satellite image which formed the basis of the greenness indicators and the dummy city variable) there may still be considerable variation in weather conditions within the weeks of the data collection, which might affect the studied associations.

More limiting factors emerge from the study design. The methodological approach that compared 105 structural equation models made it unfeasible to further stratify by gender or age, potentially overlooking differences in associations between green space, physical activity and health for these groups. This also limits the ability to include variables that act as confounders on physical activity and health but which are also mediators on the pathway from green space to physical activity, like environmental pollution indicators. In addition, we cannot rule out residual confounding, despite controlling for the main confounders like socio-economic status. For example, unmeasured variables like smoking, alcohol and dietary habits might affect our results, although the expected bias is low since these variables are also associated with socio-economic status (Fewell et al., 2007). Furthermore, the study employed a cross-sectional design, which precludes establishing causal relationships between green space and health outcomes. Finally, there is a potential selection bias, as the study recruited participants from a specific geographic area, and participants who agreed to participate may differ from those who did not. All the above-mentioned factors limit the generalisability of our findings.

4.4.6 Future Research and Implications

Further research is needed to confirm these results and expand on them, preferably with more objective measures of physical activity and more detailed health outcomes. In addition, our findings may serve as an important point of departure for designing more complex and resource-intensive longitudinal studies to establish causality. They might also serve as a starting point for more detailed analysis with effect modification, e.g., to analyse the differences for different age groups. Moreover, the negative indirect and direct relationship between the quantity of green space uses with physical activity and health should be further explored, e.g., by including peer behaviour in future studies. In addition, while we hypothesize that our measured direct health effects are mainly mitigation effects, more research is needed to confirm this. Given that we conducted our study on European satellite districts, exploring other regions in the world and even more central parts of cities is needed to confirm our findings in other areas. These avenues of research could contribute to a more comprehensive understanding of the relationship between different green space characteristics, physical activity and health outcomes. Despite the need for further research, our results show potentially important implications for future studies in this research area.

Our findings suggest that studies should carefully consider which green space characteristic they want to examine since this will likely determine the calibration of buffer types and distances to capture the desired effects on physical activity and health. Where greenness seems to function only in immediate surroundings, accessible green spaces and green space uses are associated with physical activity and health in walkable distances of up to 800 m. According to our results, most of these indicators show the clearest associations, e.g. the highest estimate, at 600 m network distance. Going beyond these walkable catchment areas may allow for spurious relations to show and lead to insignificant or even negative findings.

These results further indicate that more attention should be paid to counteracting effects between pathways and noise in the dataset that might cover the relationship of interest. In our study, many of the green space characteristics showed significant indirect effects, but most of them summed up to non-significant total effects. This indicates the necessity of isolating the specific pathway of interest in study designs, for instance through pathway analysis. Specifically, when there's a high signal-to-noise ratio in one pathway and a low one in another, it may result in inconclusive outcomes. Furthermore, if one pathway reveals a distinct relationship at a certain distance while the other shows no relationship, the aggregated results might be rendered insignificant. It seems that without calibrating green space characteristics and buffer distance for one specific pathway, potential trade-offs or obscured effects can arise. We anticipate that more of these offsetting effects exist between green space health pathways and sub-pathways at specific distances. Further research is needed to better understand these trade-offs.

For practitioners and decision-makers, our results also suggest that current urban greening strategies may not be sufficient to exploit the full range of positive effects of green spaces on health. Currently, many green space strategies are based on simple green space/resident or green space/hectare ratios that are not able to take into account the connectivity and mix of use of those spaces. Instead, green space strategies should rather strive to further extend and interconnect existing green spaces if the target is to encourage physical activity. This applies in particular to the linkage of semi-public green spaces with the urban green network. Furthermore, our results suggest that it can make sense to check existing green spaces for their usability and accessibility and thus use the hidden potentials of green spaces in the city, with less effort.

Although there is a mounting body of evidence about the beneficial effects of green spaces, most of it is based on cross-sectional studies. To better inform policy analysis, planning, and design processes with robust implications, it is essential to advance the field with more longitudinal and quasi-experimental studies reflecting on the impact of urban green regeneration. These studies are vital for developing a comprehensive understanding of the implications of green spaces in urban settings.

4.5 Conclusion

We implemented a unique study design that compared 105 structural equation models, to explore the roles of green space characteristics and proximity in the green space-physical activity-health pathway. Our results indicate that residents are more likely to increase their physical activity, and experience indirect health effects when living in immediate proximity to greenness, as well as to green corridors, preferably with multiple potential uses and within a distance up to 800 m. Additionally, we discovered that intermediate distances of 500-1,100 m are associated with direct health effects, which we hypothesise to be mainly mitigation effects. Although our study is limited to four European satellite districts, it provides important implications for green space health research by unveiling the influence of proximity to green spaces and their characteristics. Moreover, our results suggest that it is important for urban planning strategies to consider not only the ratio of green spaces per hectare or person but also the potential of well-connected green spaces and their mix of uses to reduce physical inactivity, a major risk factor for non-communicable diseases.

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5 The green space – social cohesion – mental health pathway

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ABSTRACT

In recent decades, there has been a rise in mental illnesses. Community infrastructures are increasingly acknowledged as important for sustaining good mental health. Moreover, green spaces are anticipated to offer advantages for both mental health and social cohesion. However, the mediating pathway between green space, social cohesion and mental health and especially the proximity and characteristics of green spaces that trigger these potential effects remain of interest. We gathered data from 1365 individuals on self-reported social cohesion and mental health across four satellite districts in European cities: Nantes (France), Porto (Portugal), Sofia (Bulgaria), and Høje-Taastrup (Denmark). Green space data from OpenStreetMap was manually adjusted using the PRIGSHARE guidelines. We used the AID-PRIGSHARE tool to generate 7 indicators about green space characteristics measured in distances from 100-1,500 m, every 100 m. This resulted in 105 different green space variables that we tested in a single mediation model with structural equation modelling. Accessible greenness (900-1,400 m), accessible green spaces (900-1,500 m), accessible green space corridors (300-800 m), accessible total green space (300-800), and mix of green space uses (700-1,100 m) were significantly associated with social cohesion and indirectly with mental health. Green corridors also showed negative indirect and direct associations with mental health in larger distances. Surrounding greenness and the quantity of green space uses were not associated with social cohesion nor indirectly with mental health. We also observed no positive direct associations between any green space variable in any distance to mental health. Our results suggest that

accessibility, connectivity, mix of use and proximity are key characteristics that drive the relationship between green spaces, social cohesion and mental health. This gives further guidance to urban planners and decision-makers on how to design urban green spaces to foster social cohesion and improve mental health.

KEYWORDS green space, mediation, social cohesion, well-being, structural equation modelling

5.1 Introduction

The prevalence of mental illness has constantly increased in recent decades (Ferrari et al., 2022). Depending on the analysis technique, mental illnesses could be attributed to between 4.9% (Ferrari et al., 2022) - 16% (Arias et al., 2022) of global disability-adjusted life years (DALYs) in 2019. Mental health encompasses the absence of mental illness and the presence of psychological well-being (Bratman et al., 2019b) and is defined by the WHO as "a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well, and contribute to their community" (WHO - World Health Organization, 2023a). Community structures are considered an important factor in maintaining good mental health (Santini et al., 2020) and are related to the built environment (Giles-Corti et al., 2016). Especially, urban green spaces are increasingly recognized for their positive impacts on both mental health and social cohesion (WHO Regional Office for Europe, 2016b, 2021).

The current body of evidence suggests a number of positive effects of direct contact with green spaces on mental health (Bratman et al., 2019b; WHO Regional Office for Europe, 2016b, 2021). These effects are divided into short-term and long-term effects (Bratman et al., 2019b; WHO Regional Office for Europe, 2021). According to a recent review, green space exposure is associated with positive *short-term* effects on affect, vitality, restorative outcomes, stress, hyperactivity, and brain activity, as well as *long-term* effects on overall mental health, mental illness, satisfaction with life, quality of life, wellbeing, sleep quality, social contacts and suicide rate (WHO Regional Office for Europe, 2021). Still today, the two main theories on how direct contact with nature improves mental health are the Attention Restoration Theory (ART) and the Stress Reduction Theory (SRT). ART assumes that interaction with nature triggers restorative mechanisms, with positive changes in psychological states, cognitive functioning and performance (Ulrich, 1984). The SRT assumes a stress-reducing effect of green spaces, on the one hand through the absence of environmental stressors, on the other hand through the presence of calming sounds of nature (Kaplan, 1995). Beyond these individual-based restoration theories, two more theories have emerged to provide a framework for how environments such as green spaces can contribute to social and communal well-being (Hartig, 2021). The Relational Restoration Theory (RRT) emphasizes the social and relational aspects of restoration. The Collective Restoration Theory (CRT) suggests that groups or communities can experience a sense of restoration together, not just as isolated individuals.

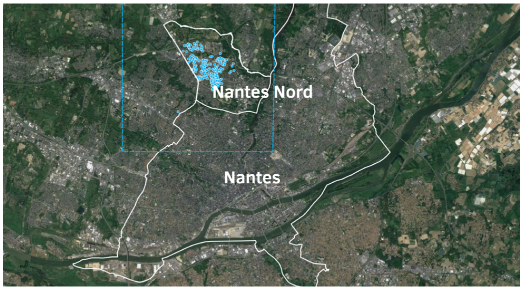
However, the exact mechanisms remain under investigation. For example. it is not yet clear whether passive effects of surrounding neighbourhood green spaces (in contrast to actual direct contact with nature) on mental health can also be expected, especially through increased social cohesion. There is evidence for both partial effects, from green space to social cohesion (Giles-Corti et al., 2016; Wan et al., 2021b) and from social cohesion to mental health (Santini et al., 2020). So far, however, the research results of the entire impact pathway are inconclusive according to recent reviews (A. Dzhambov et al., 2020; R. Zhang et al., 2021). Moreover, a recent review by Astell-Burt and colleagues on green space and reduced loneliness acknowledged the intuitive link through social connections but also acknowledged the general scarcity of literature (Astell-Burt et al., 2022). In addition, a variety of definitions and study designs exist (Taylor & Hochuli, 2017). Thus, it remains unclear which type and characteristics of green spaces are related to social cohesion and mental health (Clarke et al., 2023; WHO Regional Office for Europe, 2021) and what proximity to the residence is required for an association (Clarke et al., 2023; Wan et al., 2021b).

This study, therefore, investigates the link between green spaces, social cohesion and mental health in a comprehensive sensitivity analysis for 7 different green space indicators and 15 relative proximity measures from 100m-1500m. The aim is to identify the differences between green space types, characteristics and their relative proximity to the place of residence in their direct and indirect impact on mental health. We hypothesize a stronger link between social cohesion and green space than to greenness (Cardinali, Beenackers, et al., 2023c), and an indirect effect on mental health (Rugel et al., 2019; van den Berg et al., 2019). Greenness refers to the degree of vegetation of an area often without taking accessibility into account, whereas green spaces are usually defined as publicly accessible areas covered with vegetation. With our results, we aim to help disentangle the influence of specific green space characteristics and provide important insights for urban planners and public health decision-makers on how to design public green spaces to help promote local social cohesion and mental health.

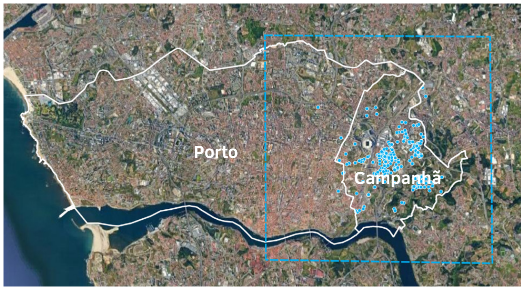
5.2 Methods

5.2.1 Study design and sampling

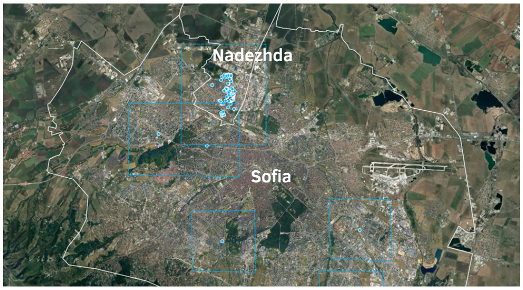
The Urban Inclusive Innovative Nature (URBiNAT) project aims to contribute to an understanding of the effects of nature-based solutions on residents in low to middle-income satellite neighbourhoods. URBiNAT collected data from 1365 participants in Europe: 439 in Porto Campanhã (Portugal), 293 in Nantes Nord (France), 432 in Sofia Nadezhda (Bulgaria) and 201 in Høje-Taastrup as part of Greater Copenhagen (Denmark). These neighbourhoods, developed for the more disadvantaged social classes, share several common characteristics. Built predominantly in the second half of the 20th century, they are satellite neighbourhoods, e.g. districts built purposely on the outskirts of the city and partly or fully planned according to the principles of the functional (car-dependant, mono-functional) city. However, they differ in geographical and cultural context, distance to the city centre, public transport, dominance of car-centric infrastructure, and especially green spaces (see Figure 5.1).



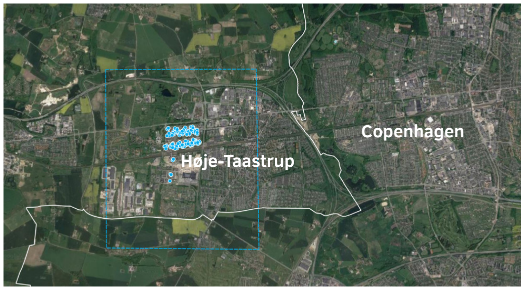
a) Nantes - Nord



b) Porto - Campanhã



c) Sofia - Nadezhda



d) Greater Copenhagen - Høje-Taastrup

FIG. 5.1 Study areas overview: a) Nantes - Nord (France); b) Porto - Campanhã (Portugal), c) Sofia - Nadezhda (Bulgaria), d) Greater Copenhagen - Høje-Taastrup (Denmark); white line indicates administrative borders; blue dotted line indicates the study area(s); blue points indicate the residential address of the study participants.

To be eligible for participation, individuals had to be at least 14 years old. Participants were chosen randomly, and the surveys were conducted by local survey companies hired by the cities and instructed by the research team. In Porto and Sofia, surveys were administered in person, while in Nantes and Høje-Taastrup, they were conducted over the phone. Upon contact, individuals were briefed about the project's objective, the survey's role, and asked for informed consent. Before, the survey had been approved by the URBiNAT project's ethics committee. No incentives were provided for participation. The survey in Porto was conducted around August 2019. In Nantes and Sofia, surveys were carried out around December 2019, while data from Høje-Taastrup was collected in August 2021.

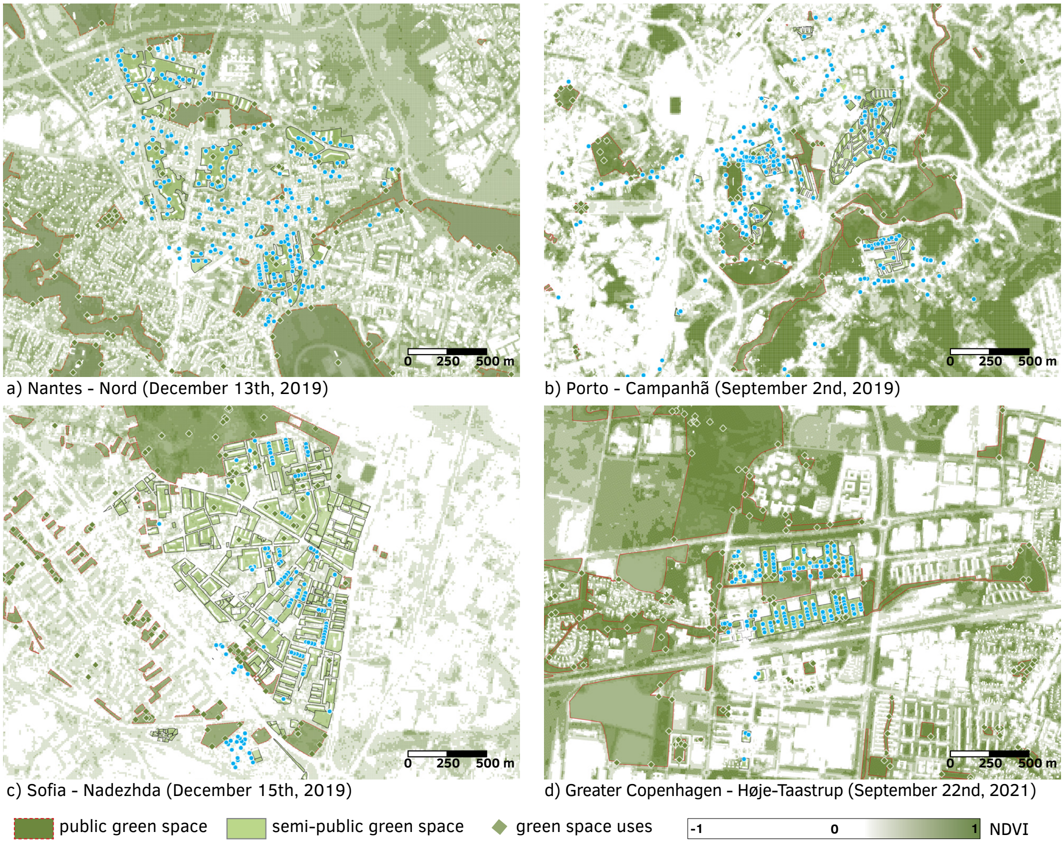


FIG. 5.2 Study areas green space: a) Nantes - Nord (France); b) Porto - Campanhã (Portugal), c) Sofia - Nadezhda (Bulgaria), d) Greater Copenhagen - Høje-Taastrup (Denmark); blue points indicate the residential address of the study participants. For better readability only the study areas are covered (e.g. some respondents do not live in the main study area) and private green space is not shown.

5.2.2 Green Space

We obtained the necessary spatial data for the four study areas from OpenStreetMap in January 2023 and manually corrected it to the timestamp of the survey conduction and controlled for bias with the help of the PRIGSHARE Reporting Guidelines (Cardinali et al., 2023, Table A5.1). We adjusted the retrieved spatial data manually based on site visits, aerial pictures and GoogleStreetview. Furthermore, in order to be able to analyse the green corridors around survey participants we manually (1) connected green infrastructure that was interrupted by a road but has a crossing, (2)

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merged green spaces directly next to each other, and (3) added linear green spaces that consist of walkable pathways with greenery. A table with the inclusion/exclusion criteria for the spatial data can be viewed in the appendix (Table A5.2).

As a basis for greenness indicators, we calculated the Natural Difference Vegetation Index (NDVI) with sentinel 2 data in 10x10 m resolution from the EEA (European Space Agency, 2021) from cloud-free time points in the month of the survey conduction in the city (see Figure 5.2 for exact dates). The NDVI is calculated with rasterised satellite images in near-infrared and red light (NDVI=(NIR-Red)/(NIR+Red)) (Tucker, 1979). Its values range from -1.0 to 1.0, where 0.2-0.5 usually is associated with sparse vegetation like shrubs or grassland and values of 0.6 and higher show dense vegetation like trees. Sealed surfaces range around 0.0-0.1 and negative values originate from water bodies and clouds. For this study, we manually set larger water bodies like the rivers in Porto and Nantes to missing, as recommended by Markevych et al. (2017).

Based on this curated data and the geocoded addresses of individuals, we constructed seven indicators (see Figure 5.3) in distances from 100 m to 1,500 m, every 100 m, with the help of the AID-PRIGSHARE tool (Cardinali, Beenackers, et al., 2023a). Firstly, we assessed greenness with two indicators based on NDVI, surrounding greenness with Euclidean buffers (A), and accessible greenness with network distance (B). Secondly, we assessed green space with three public green space indicators: accessible green spaces in network distance (C), green corridors accessible from network distance, basically a measure for a green mobility network accessible from specific distances (D), and total accessible green space, where individual private or semi-public green spaces from the individual plot are added to the green corridor indicator for each individual (E). Thirdly, we manually assessed green space usability by counting points of green space uses (playgrounds, public gardens, sports fields, social facilities, cultural facilities and walking entries to bigger green spaces) present in the accessible green spaces through open street map data, Google Street View and expert knowledge from local site visits. To represent the quantity of green space uses we counted the total number of uses in green spaces within network distance (F). To measure the mix of uses we counted the number of different uses (G). All network distances were measured through 25m buffered service areas, recognized to be more precise, especially in the smaller buffers compared to isochrones (Frank et al., 2017).

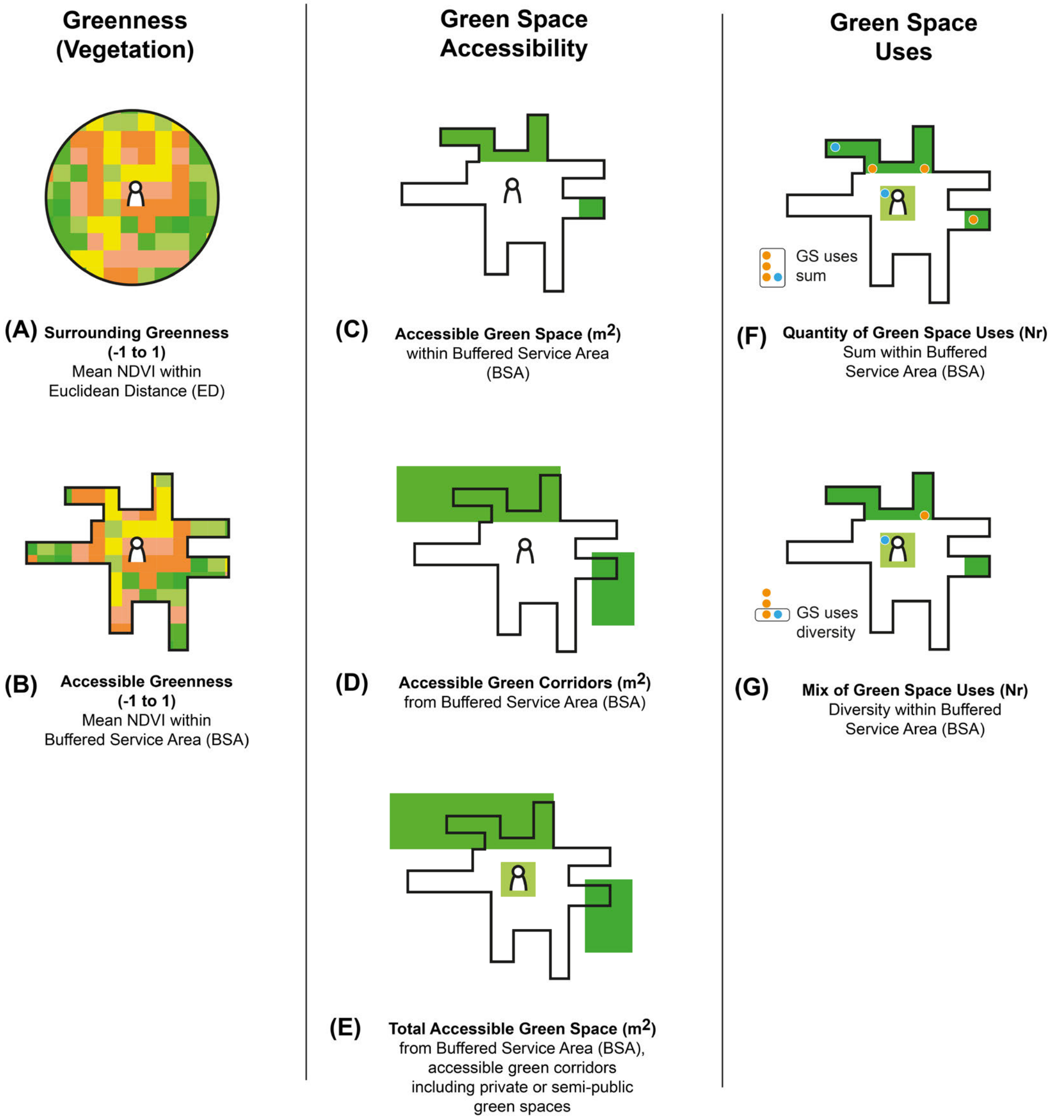

FIG. 5.3 Green space indicators: Indicators used in the sensitivity analysis. Notes: Network distances are measured as 25m buffered service areas (walkable distance in m in every direction). Green Corridor and Total green space indicators (E, F, H, I) count every green space that intersects with the Euclidean buffer or network distances, while green space indicators (D, G) count only those green spaces that are within the buffer type.

5.2.3 Social Cohesion

According to recent reviews, social cohesion is still defined very heterogeneously (Clarke et al., 2023; Fonseca et al., 2019), but usually refers to the ability of a community to ensure the well-being of all its members (Council of Europe, 2008). Social cohesion also refers to the level of engagement and social trust among community members (Speer et al., 2001). We captured this construct with the 5-point Likert scale item of self-rated satisfaction with participants' neighbourhood relations (conviviality, mutual aid, solidarity) from 1 (not at all satisfied) to 5 (very satisfied) of the environmental quality of life scale (Fleury-Bahi et al., 2013). The item was used as an ordinal variable in the analysis.

5.2.4 Mental Health

Mental health was assessed through the Mental Health Continuum Short Form (MHC-SF) (Keyes, 2018). The 14-item MHC-SF is a known reliable and robust scale to obtain differentiated results on emotional, social, and psychological well-being in line with the definition of the World Health Organization as "a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well, and contribute to their community" (WHO - World Health Organization, 2023a). Each item is scored from 1-5 with a higher summary score indicating better mental health (see supplementary material A5.3 for a table with the items). The total sum of the scale ranged from 14-70 and was used as a numerical variable in the model.

5.2.5 Context Variables

In line with the PRIGSHARE Reporting Guidelines (Cardinali, Beenackers, et al., 2023c), we obtained data on potential confounders in personal, local, urbanicity, and global context.

To assess the *personal context*, we gathered data on age (in years), sex (male, female, diverse), employment status, years of education, and monthly net income, as all of them may change the measured relationship (Browning & Lee, 2017; Markevych et al., 2017; van den Bosch & Ode Sang, 2017b). To harmonize between cases across countries, monthly net income was centred around the mean minimum wage of the country and is shown in percentages of minimum wage. In addition, we collected data on whether the respondents had a disability since this might limit their engagement with green spaces and could have an influence on their well-being. We also collected data on the number of years a respondent lived in the neighbourhood since this may influence their place attachment, ability to rate social cohesion, their momentary well-being and their long-term exposure to green space characteristics in the neighbourhood.

We controlled for *local context* variables that might affect social cohesion and mental health (Cardinali, Beenackers, et al., 2023c). We used the satisfaction with shops, leisure facilities, and public transport measured with 5-point Likert scale items, measured from 1 (not at all satisfied) to 5 (very satisfied) as part of the environmental quality of life questionnaire (Fleury-Bahi et al., 2013) as a proxy to account for those local context variables. We did not include data on neighbourhood safety, although it might influence open space use (van den Bosch & Ode Sang, 2017b) since it is potentially on the pathway between social cohesion and mental health.

To control for the *urbanicity context*, we obtained rasterized 2018 population density data (*residents/km*^{2}) from Eurostat (Eurostat, 2023) since population density is associated with social cohesion and mental health (Hong et al., 2014).

The *global and climate context* was addressed by including the city samples as a dummy variable in the model as the cultural, societal, as well as climate conditions likely vary widely between the study areas and otherwise bias the results (Cardinali, Beenackers, et al., 2023c). In addition, this allowed us to adjust for the differences in timing (pre- or post-pandemic) and the season when the survey was conducted. In contrast to a stratified analysis, the dummy variable approach allowed us to maintain the necessary statistical power. The PRIGSHARE reporting guidelines also prescribe to assess modifying variables, like differences in age groups (Cardinali, Beenackers, et al., 2023c). This investigation was out of scope for this study because of the number of structural equation models to perform and compare (see 2.6). This limitation will be debated in the discussion.

5.2.6 Statistical Analysis

Data handling and processing were done in Python. Missing data could be characterized as missing at random (MAR) since missingness was associated with other observed variables. Thus, a multiple imputation technique is considered the most appropriate to handle the missing data (Mirzaei et al., 2022). We used multiple imputation software package of miceforest 5.6.3 in Python (Wilson, Samuel, 2022), with 10 iterations to estimate the missing variables. The final step of data processing was to standardize the dataset by min-max scaling (0-1) since all our variables, but NDVI, can only be positive. The standardization ensured that all variables were on the same scale, thus allowing for meaningful comparisons and accurate model estimation (Kline, 2015).

Structural equation modelling (SEM) was performed in R with the lavaan package (Rosseel, 2023) on a single mediator model (Figure 5.4) using the diagonal weighted least squares estimator. The full model including all control variables can be found in the supplementary material (Figure A5.1). Sensitivity analysis was done by exchanging the green space indicator 105 times (7 indicators, each for 15 distances). The rest of the model remained unchanged. As the Porto sample showed very distinct characteristics an additional sensitivity analysis was done to test if the results remained robust to the exclusion of this subgroup.

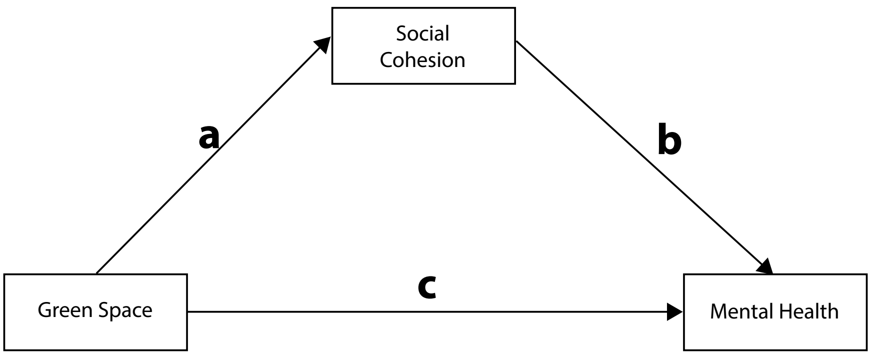

FIG. 5.4 Conceptual Model: Conceptual diagram showing theoretically indicated pathways linking green space to social cohesion and mental health. The green space indicator was exchanged 105 times for each structural equation model.

An example of the summary statistics for one green space indicator can be found in the supplementary material (Table A5.4). These single mediator models are just-identified (0 degrees of freedom) and serve the main goal of this research to compare green space indicators and the relative proximity of green spaces. However, this leads to the fact that the quality of the model can only be judged on theoretical grounds and not with model fit indices, which might be expected from SEM Models.

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

5.3 Results

5.3.1 Characteristics of the sample

The total sample contained 201 individuals from Høje-Taastrup (Denmark), 293 from Nantes (France), 439 from Porto (Portugal), and 432 from Sofia (Bulgaria). The population density varied among the cities, with Sofia demonstrating the highest with 9021.14 (3689.54) residents/km^2 and Høje-Taastrup displaying the lowest at 4028.65 (1336.94) residents/km^2. The local context also showed significant differences in all included variables (Table 5.1). Self-rated social cohesion was rated best in Porto with 81.1% of respondents satisfied or very satisfied with the social cohesion, followed by Nantes (62.8%), Høje-Taastrup (60.7%), and Sofia (53.4%).

Personal indicators also differed between the study areas. The city samples are composed of roughly 50% of men and women in Høje-Taastrup, Nantes, and Sofia. In Porto, the sample was composed of nearly 64% men and 36% women. Porto also had the most people over 65 years with 41.0% compared to Nantes with only 17.1% and the highest proportion of people with disabilities (39.6%). The mean (SD) years of education were 12.49 (2.55) in Høje-Taastrup, 12.57 (3.37) in Nantes, 7.02 (3.70) in Porto, and 13.11 (2.68) in Sofia. Most of the participants were employed, with significant differences between cities. The mean income, harmonized as a percentage of minimum wage of the country, was roughly between 140-150% in Høje-Taastrup, Nantes, and Sofia, but only 40% in Porto. The mean reported mental health (SD) was similar across the city samples and rated at 55.23 (9.31) in Porto, 54.93 (10.82) in Høje-Taastrup, 52.75 (6.45) in Sofia and 50.13 (12.45) in Nantes.

TABLE 5.1 Characteristics of the sample (unstandardized)

Context	*Indicator*	Høje-Taastrup	Nantes	Porto	Sofia	p
global	*city sample (n)*	201	293	439	432	
urbanicity	*Population density (residents/ km^2, mean (SD))*	4028.65 (1336.94)	5616.27 (2353.62)	4829.28 (1632.50)	9021.14 (3689.54)	<0.001
local	**self-rated social cohesion (%)**					<0.001
	very satisfied	28.4%	15.7%	49.4%	8.3%	
	satisfied	32.3%	47.1%	31.7%	45.1%	
	moderately satisfied	21.4%	22.2%	13.0%	39.4%	
	not satisfied	12.4%	6.5%	2.7%	7.2%	
	not at all satisfied	5.5%	8.5%	3.2%	0.0%	
	self-rated satisfaction with shops (%)					<0.001
	very satisfied	39.3%	11.3%	28.0%	23.6%	
	satisfied	33.8%	51.5%	28.5%	40.5%	
	moderately satisfied	14.4%	19.1%	13.2%	30.1%	
	not satisfied	10.0%	10.6%	17.1%	5.8%	
	not at all satisfied	2.5%	7.5%	13.2%	0.0%	
	self-rated satisfaction with leisure facilities (%)					<0.001
	very satisfied	31.3%	4.8%	22.6%	6.9%	
	satisfied	32.3%	29.7%	33.0%	35.2%	
	moderately satisfied	23.4%	27.3%	15.3%	37.3%	
	not satisfied	9.0%	21.8%	14.4%	20.1%	
	not at all satisfied	4.0%	16.4%	14.8%	0.5%	
	self-rated satisfaction with public transport (%)					<0.001
	very satisfied	62.7%	50.2%	35.3%	12.3%	
	satisfied	26.9%	44.4%	29.6%	61.3%	
	moderately satisfied	6.0%	4.1%	9.6%	25.2%	
	not satisfied	1.5%	1.0%	10.3%	1.2%	
	not at all satisfied	3.0%	0.3%	15.3%	0.0%	

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TABLE 5.1 Characteristics of the sample (unstandardized)

Context	*Indicator*	Høje-Taastrup	Nantes	Porto	Sofia	p
personal	**gender (%)**					<0.001
	male	52.2%	44.0%	36.2%	47.2%	
	female	47.8%	55.3%	63.8%	52.8%	
	diverse	0.0%	0.7%	0.0%	0.0%	
	age group (%)*					<0.001
	15-24	6.5%	10.9%	4.1%	10.6%	
	25-44	28.4%	42.7%	21.4%	39.6%	
	45-64	32.8%	29.4%	33.5%	29.6%	
	over 65	32.3%	17.1%	41.0%	20.1%	
	mean years lived in neighbourhood (SD)	16.60 (13.76)	14.53 (15.03)	28.90 (20.08)	22.41 (12.34)	<0.001
	mean net income as % of minimum wage (SD)	141% (93%)	149% (63%)	40% (66%)	143% (73%)	<0.001
	mean years of education (SD)	12.40 (2.51)	12.46 (3.38)	7.03 (3.72)	13.16 (2.67)	<0.001
	has disabilities (%)	10.00%	15.70%	39.60%	15.50%	<0.001
	employed (%)	57.20%	56.70%	28.70%	73.60%	<0.001
	Mental Health, 14-70 (mean (SD))	54.93 (10.82)	50.13 (12.45)	55.23 (9.31)	52.75 (6.45)	<0.001
green space characteristics	*surrounding greenness in 500 m Euclidean distance (-1 to 1, mean (SD))*	0.46 (0.05)	0.42 (0.03)	0.37 (0.08)	0.23 (0.04)	<0.001
	accessible greenness in 500 m network distance (-1 to 1, mean (SD))	0.44 (0.04)	0.39 (0.03)	0.34 (0.06)	0.24 (0.04)	<0.001
	accessible green space in 500 m network distance (0 - 16.32 hectare, mean (SD))	3.70 (1.45)	1.64 (1.56)	2.35 (2.11)	3.12 (3.68)	<0.001
	accessible green corridors in 500 m network distance (0 – 154.30 hectare, mean (SD))	51.76 (17.59)	56.92 (66.64)	9.74 (9.81)	28.93 (37.99)	<0.001
	accessible total green space in 500 m network distance (0 – 158.66 hectare, mean (SD))	56.77 (16.33)	60.18 (66.51)	12.16 (10.37)	32.99 (41.47)	<0.001
	quantity of green space uses in 500 m network distance (0 - 34, mean (SD))	21.17 (7.49)	6.13 (4.04)	5.15 (4.39)	10.17 (6.70)	<0.001
	mix of green space uses in 500 m network distance (0 - 5, mean (SD))	3.75 (0.65)	2.10 (0.82)	1.83 (1.01)	2.36 (1.13)	<0.001

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

5.3.2 Partial effects – How green space indicators are associated with social cohesion

Greenness, green space and green space uses indicators were correlated differently to social cohesion. Surrounding greenness (Fig 5.5A) showed an almost constant pattern of association to social cohesion regardless of the tested proximity, although none were significant. Accessible greenness (Fig 5.5B) showed a more sensitive behaviour to the measured distance with a plateau of positive significant associations with social cohesion for a proximity between 700-900 m, with a peak at 700 m (ß: 0.745; CI: 0.031, 1.462). This pattern was even clearer for accessible green spaces (Fig 5.5C), where the association increased continuously the larger the catchment area of the measurement and showed significant associations to social cohesion from 900-1500m. The plots of accessible green corridors (Fig 5.5D) and total green spaces (Fig 5.5E) showed divergent patterns, peaking at the 800m catchment area. After this, the coefficient declined continuously until a negative significant association with social cohesion when measured in a 1,500 m catchment area. The quantity of green space uses (Fig 5.5F) was not associated with social cohesion in our study. On the other hand, the mix of green space uses (Fig 5.5G) showed a plateau of positive associations for uses measured at 700m and above, not all of which were significant. For detailed results we refer to Table 5.2. The sensitivity analysis without the Porto sample showed similar results in green space accessibility and green space uses indicator, but differences in greenness indicators (Table A5.5). Both surrounding greenness and accessible greenness showed overall higher estimates and patterns of significant associations.

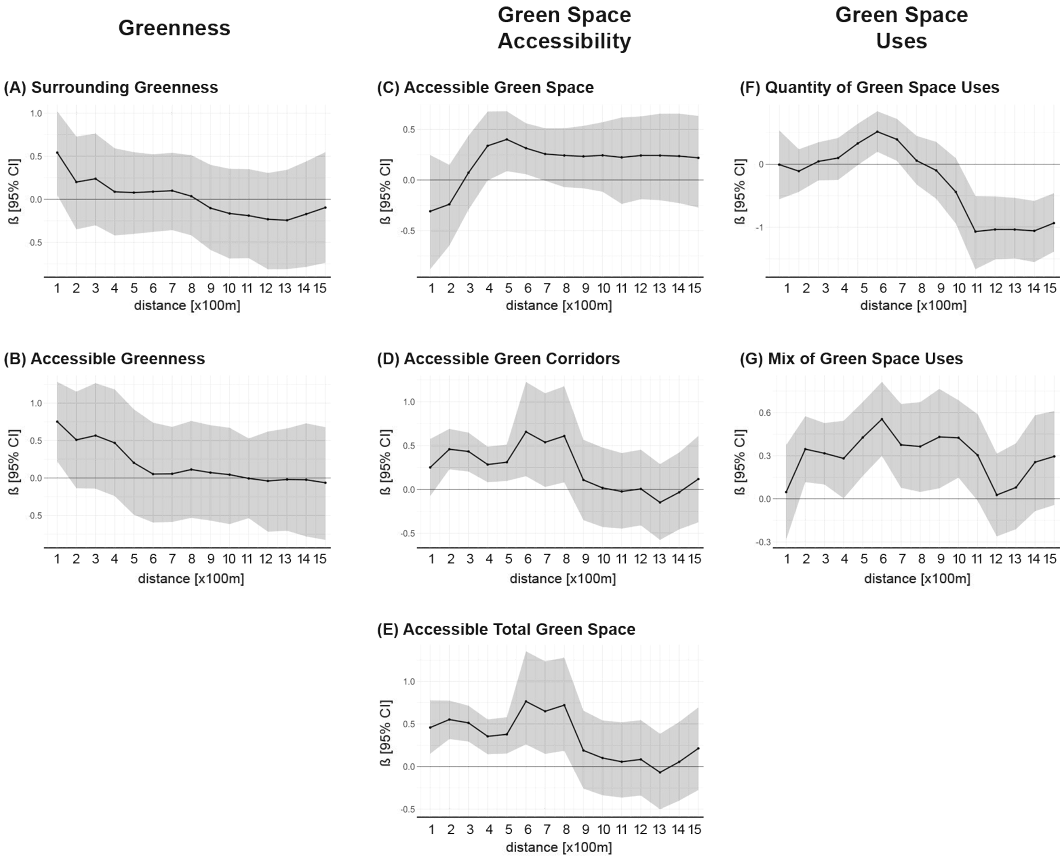

FIG. 5.5 Partial Effects (a). Green Space – Social cohesion Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 105 structural equation models; adjusted for sex, age, disabilities, years of education, income, employment status, years lived in the neighbourhood, well-being, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

5.3.3 Indirect effects – How green space indicators are indirectly associated with health via social cohesion

Social cohesion mediated the effect from green space to mental health but with clear differences between the type of green space indicator and catchment area. Basically, the slopes were very similar to the partial effects, including the behaviour of the subsample without Porto (Table A5.6), as the relation between social cohesion and mental health (b) was constant (ß: 0.03; CI: 0.02, 0.03). We found a statistically significant positive mediating effect of social cohesion for accessible greenness measured in 700-900 m (Fig 5.6B), accessible green space measured in 900-1,500 m (Fig 5.6C), accessible green corridors and total green spaces measured in 300-800 m (Fig 5.6D-E), and mix of green space uses measured in 700-900 m and 1,100-1,300 m (Fig 5.6G). In addition, accessible green corridors and total green space also showed a significant negative indirect relationship at a 1,500 m network distance. For detailed results we refer to Table 5.3.

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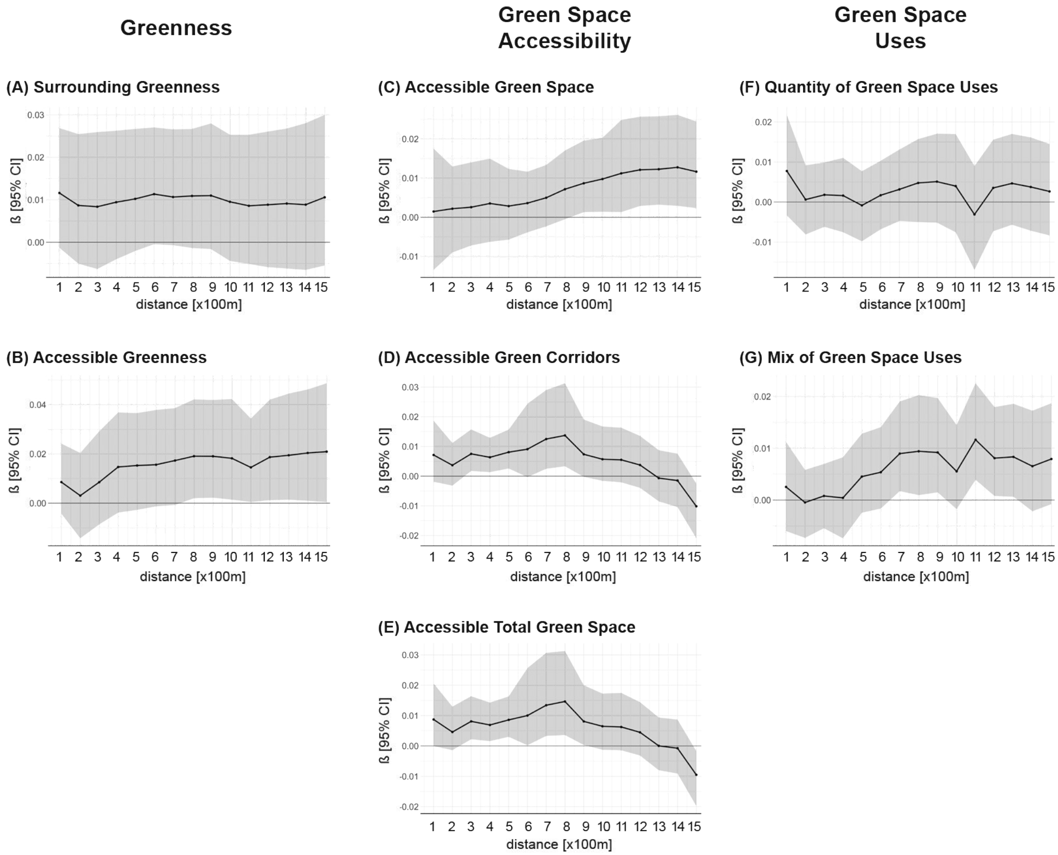

FIG. 5.6 Indirect Effects (a*b). Green Space – Social cohesion – Mental Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 105 structural equation models; adjusted for sex, age, disabilities, years of education, income, employment status, years lived in the neighbourhood, well-being, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

TABLE 5.2 Partial Effects (a). Green Space – Social cohesion Sensitivity Analysis.

Standardized Estimated ß (95% CI) for partial effects (a) of green space indicators on social cohesion in the 105 structural equation models each with 5000 bootstrap samples.

Greenness				
Distance	(A) Surrounding GN		(B) Accessible GN	
100	0.453 (-0.088, 0.963)		0.336 (-0.199, 0.874)	
200	0.338 (-0.231, 0.929)		0.119 (-0.563, 0.781)	
300	0.326 (-0.260, 0.940)		0.333 (-0.361, 1.035)	
400	0.368 (-0.188, 0.938)		0.572 (-0.188, 1.321)	
500	0.401 (-0.107, 0.952)		0.594 (-0.164, 1.296)	
600	0.447 (-0.068, 0.955)		0.609 (-0.106, 1.352)	
700	0.420 (-0.066, 0.919)		0.675 (-0.064, 1.386)	
800	0.430 (-0.081, 0.945)		0.745 (0.031, 1.462)	*
900	0.433 (-0.114, 0.979)		0.743 (0.039, 1.479)	*
1000	0.374 (-0.205, 0.919)		0.709 (0.005, 1.435)	*
1100	0.336 (-0.231, 0.905)		0.565 (-0.023, 1.183)	
1200	0.346 (-0.268, 0.947)		0.728 (-0.017, 1.482)	
1300	0.357 (-0.286, 0.976)		0.759 (-0.018, 1.543)	
1400	0.347 (-0.287, 0.996)		0.797 (-0.020, 1.619)	
1500	0.416 (-0.246, 1.091)		0.818 (-0.057, 1.684)	

Green Space Accessibility						
Distance	(C) Accessible GS		(D) Accessible GC		(E) Accessible TGS	
100	0.058 (-0.536, 0.657)		0.278 (-0.097, 0.679)		0.339 (-0.037, 0.722)	
200	0.086 (-0.347, 0.490)		0.143 (-0.126, 0.417)		0.179 (-0.071, 0.459)	
300	0.101 (-0.273, 0.507)		0.292 (0.050, 0.547)	*	0.315 (0.068, 0.567)	*
400	0.138 (-0.250, 0.531)		0.250 (0.041, 0.463)	*	0.272 (0.048, 0.496)	*
500	0.112 (-0.227, 0.456)		0.314 (0.075, 0.536)	*	0.334 (0.106, 0.563)	*
600	0.141 (-0.158, 0.422)		0.352 (-0.039, 0.861)		0.387 (-0.011, 0.878)	
700	0.194 (-0.111, 0.483)		0.483 (0.071, 0.993)	*	0.518 (0.115, 1.059)	*
800	0.280 (-0.044, 0.602)		**0.532 (0.120, 1.092)**	*****	**0.568 (0.119, 1.075)**	*****
900	0.340 (0.025, 0.677)	*	0.285 (-0.037, 0.655)		0.313 (0.000, 0.702)	
1000	0.383 (0.040, 0.719)	*	0.220 (-0.079, 0.572)		0.249 (-0.062, 0.607)	
1100	0.438 (0.030, 0.860)	*	0.214 (-0.097, 0.571)		0.243 (-0.074, 0.603)	
1200	0.473 (0.093, 0.866)	*	0.146 (-0.160, 0.482)		0.174 (-0.130, 0.519)	
1300	0.479 (0.100, 0.870)	*	-0.026 (-0.334, 0.331)		0.002 (-0.307, 0.352)	
1400	**0.496 (0.094, 0.903)**	*****	-0.058 (-0.388, 0.305)		-0.029 (-0.352, 0.324)	
1500	0.452 (0.068, 0.829)	*	-0.408 (-0.732, -0.083)	*	-0.381 (-0.697, -0.047)	*

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TABLE 5.2 Partial Effects (a). Green Space – Social cohesion Sensitivity Analysis.

Standardized Estimated ß (95% CI) for partial effects (a) of green space indicators on social cohesion in the 105 structural equation models each with 5000 bootstrap samples.

Green Space Usability				
Distance	(F) Quantity of GSU		(G) Mix Of GSU	
100	0.302 (-0.173, 0.773)		0.099 (-0.238, 0.417)	
200	0.024 (-0.299, 0.355)		-0.018 (-0.270, 0.227)	
300	0.071 (-0.242, 0.373)		0.031 (-0.205, 0.265)	
400	0.063 (-0.289, 0.423)		0.017 (-0.285, 0.317)	
500	-0.033 (-0.367, 0.306)		0.177 (-0.109, 0.470)	
600	0.066 (-0.258, 0.391)		0.210 (-0.081, 0.497)	
700	0.124 (-0.194, 0.468)		0.349 (0.037, 0.651)	*
800	0.187 (-0.211, 0.579)		0.364 (0.007, 0.703)	*
900	0.199 (-0.218, 0.621)		0.357 (0.036, 0.684)	*
1000	0.156 (-0.312, 0.623)		0.216 (-0.077, 0.518)	
1100	-0.121 (-0.640, 0.360)		**0.455 (0.139, 0.786)**	*****
1200	0.138 (-0.304, 0.568)		0.315 (-0.001, 0.642)	
1300	0.182 (-0.246, 0.609)		0.321 (0.004, 0.644)	*
1400	0.147 (-0.286, 0.605)		0.253 (-0.116, 0.606)	
1500	0.104 (-0.338, 0.534)		0.310 (-0.062, 0.650)	

Notes: *Adjusted for sex, age, disabilities, years of education, income, employment status, years lived in the neighbourhood, well-being, satisfaction with shops, leisure facilities, public transport, population density and city.*

Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with individual accessible private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);*

***** *Coefficient is statistically significant; bold estimates indicate the distance with the highest significant estimate.*

TABLE 5.3 Indirect Effects (a*b). Green Space – Social cohesion – Health Sensitivity Analysis.

Standardized estimated ß (95% CI) for the indirect effect (a*b) of green space indicators, mediated by social cohesion on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Greenness				
Distance	(A) Surrounding GN		(B) Accessible GN	
100	0.012 (-0.001, 0.027)		0.009 (-0.004, 0.024)	
200	0.009 (-0.005, 0.025)		0.003 (-0.014, 0.020)	
300	0.008 (-0.006, 0.026)		0.009 (-0.009, 0.029)	
400	0.009 (-0.004, 0.026)		0.015 (-0.004, 0.037)	
500	0.010 (-0.002, 0.027)		0.015 (-0.003, 0.037)	
600	0.011 (0.000, 0.027)		0.016 (-0.001, 0.038)	
700	0.011 (-0.001, 0.027)		0.017 (-0.001, 0.039)	
800	0.011 (-0.001, 0.027)		0.019 (0.002, 0.042)	*
900	0.011 (-0.002, 0.028)		0.019 (0.002, 0.042)	*
1000	0.010 (-0.004, 0.025)		0.018 (0.001, 0.042)	*
1100	0.009 (-0.005, 0.025)		0.015 (0.000, 0.034)	*
1200	0.009 (-0.006, 0.026)		0.019 (0.001, 0.042)	*
1300	0.009 (-0.006, 0.027)		0.019 (0.001, 0.044)	*
1400	0.009 (-0.007, 0.028)		0.020 (0.001, 0.046)	*
1500	0.011 (-0.005, 0.030)		0.021 (0.000, 0.049)	*

Green Space Accessibility						
Distance	(C) Accessible GS		(D) Accessible GC		(E) Accessible TGS	
100	0.001 (-0.013, 0.018)		0.007 (-0.002, 0.019)		0.009 (0.000, 0.021)	
200	0.002 (-0.009, 0.013)		0.004 (-0.003, 0.011)		0.005 (-0.001, 0.013)	
300	0.003 (-0.007, 0.014)		0.008 (0.002, 0.016)	*	0.008 (0.002, 0.016)	*
400	0.004 (-0.006, 0.015)		0.006 (0.001, 0.013)	*	0.007 (0.002, 0.014)	*
500	0.003 (-0.006, 0.012)		0.008 (0.003, 0.016)	*	0.009 (0.003, 0.016)	*
600	0.004 (-0.004, 0.012)		0.009 (0.000, 0.024)		0.010 (0.000, 0.026)	
700	0.005 (-0.002, 0.013)		0.013 (0.002, 0.029)	*	0.013 (0.003, 0.031)	*
800	0.007 (0.000, 0.017)		**0.014 (0.003, 0.031)**	*	**0.015 (0.004, 0.031)**	*
900	0.009 (0.001, 0.020)	*	0.007 (0.000, 0.019)		0.008 (0.000, 0.020)	
1000	0.010 (0.001, 0.020)	*	0.006 (-0.002, 0.017)		0.006 (-0.001, 0.017)	
1100	0.011 (0.001, 0.025)	*	0.006 (-0.002, 0.016)		0.006 (-0.001, 0.017)	
1200	0.012 (0.003, 0.026)	*	0.004 (-0.004, 0.014)		0.004 (-0.003, 0.014)	
1300	0.012 (0.003, 0.026)	*	-0.001 (-0.008, 0.009)		0.000 (-0.008, 0.009)	
1400	**0.013 (0.003, 0.026)**	*	-0.001 (-0.010, 0.008)		-0.001 (-0.009, 0.009)	
1500	0.012 (0.002, 0.024)	*	-0.010 (-0.021, -0.003)	*	-0.009 (-0.020, -0.002)	*

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TABLE 5.3 Indirect Effects (a*b). Green Space – Social cohesion – Health Sensitivity Analysis.

Standardized estimated ß (95% CI) for the indirect effect (a*b) of green space indicators, mediated by social cohesion on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Green Space Usability				
Distance	(F) Quantity of GSU		(G) Mix Of GSU	
100	0.008 (-0.003, 0.022)		0.003 (-0.006, 0.011)	
200	0.001 (-0.008, 0.009)		0.000 (-0.007, 0.006)	
300	0.002 (-0.006, 0.010)		0.001 (-0.005, 0.007)	
400	0.002 (-0.008, 0.011)		0.000 (-0.007, 0.008)	
500	-0.001 (-0.010, 0.008)		0.005 (-0.002, 0.013)	
600	0.002 (-0.007, 0.010)		0.005 (-0.002, 0.014)	
700	0.003 (-0.005, 0.013)		0.009 (0.002, 0.019)	*
800	0.005 (-0.005, 0.016)		0.009 (0.001, 0.020)	
900	0.005 (-0.005, 0.017)		0.009 (0.001, 0.020)	*
1000	0.004 (-0.008, 0.017)		0.006 (-0.002, 0.014)	
1100	-0.003 (-0.017, 0.009)		**0.012 (0.004, 0.023)**	*****
1200	0.004 (-0.007, 0.016)		0.008 (0.001, 0.018)	*
1300	0.005 (-0.006, 0.017)		0.008 (0.001, 0.019)	*
1400	0.004 (-0.007, 0.016)		0.007 (-0.002, 0.017)	
1500	0.003 (-0.008, 0.015)		0.008 (-0.001, 0.019)	

Notes: *Adjusted for sex, age, disabilities, years of education, income, employment status, years lived in the neighbourhood, well-being, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with individual accessible private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);*
******* *Coefficient is statistically significant; bold estimates indicate the distance with the highest significant estimate.*

5.3.4 Direct effects – How green space indicators are associated with health

Green space indicators, factually adjusted for social cohesion, were not directly positively associated with mental health and even showed negative associations for accessible green corridors and accessible total green space in larger catchment areas. We observed no direct association between greenness indicators and mental health (Fig 5.7A, Fig 5.7B). The accessible green spaces also showed no significant direct relationship (Fig 5.7C). However, accessible green corridors (Fig 5.7D) and accessible total green space (Fig 5.7E), showed a significant negative direct association with health, for distances of 1,000 m and 1,200–1,500 m. We did not observe a direct association between the indicators on green space use (Fig 5.7F, Fig 5.7G) and mental health. For detailed results, we refer to Table 5.4. The sensitivity analysis without the Porto sample showed similar results for all indicators (Table A5.7).

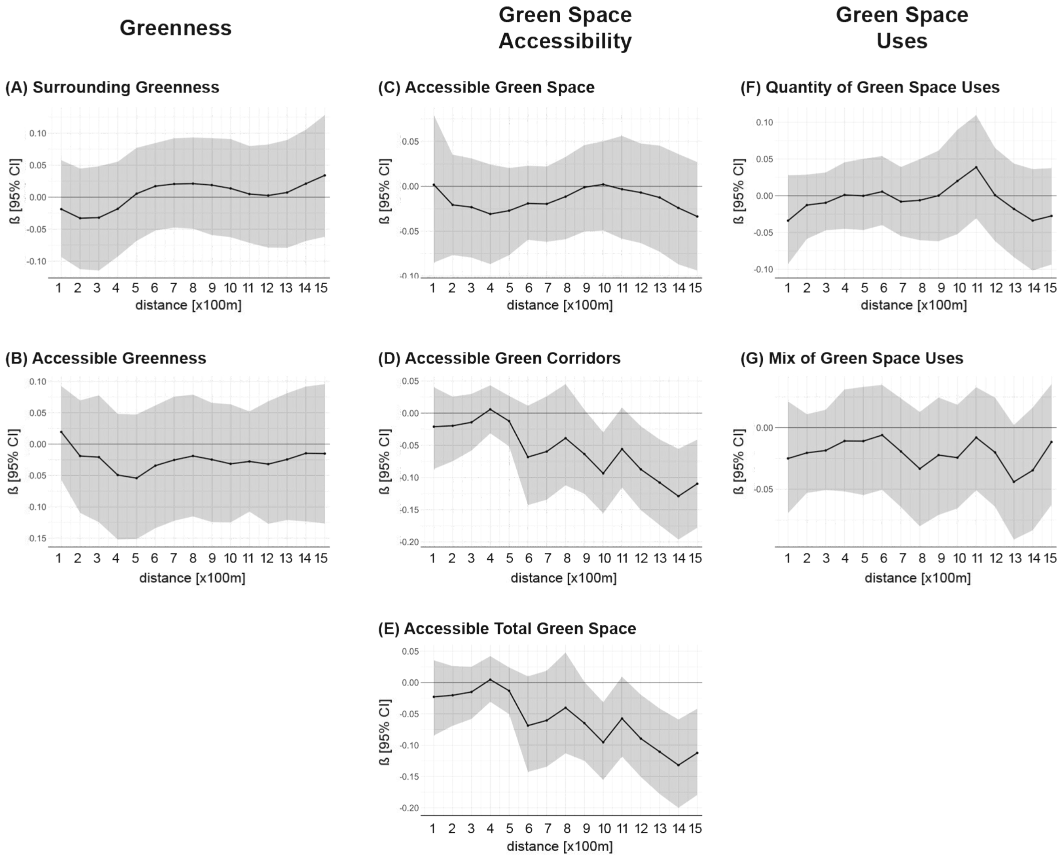

FIG. 5.7 Direct Effects (c). Green Space – Mental Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 105 structural equation models; adjusted for sex, age, disabilities, years of education, income, employment status, years lived in the neighbourhood, well-being, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

5.3.5 Total effects – How green space indicators, directly and indirectly, relate to health

For the total effects, we found no significant positive, but some negative, associations between green space and mental health. The direct effects appeared to dominate the relationship, as the demonstrated patterns were very similar to those of the direct effects (Fig 5.8). None of the indirect effects carried over to a significant total effect. The only remaining significant effects were the negative associations between accessible green corridors (Fig 5.8D) and total green areas (Fig 5.8E) measured with network distances of 1,000 m and 1,200-1,500 m. For detailed results, we refer to Table 5.5. The sensitivity analysis without the Porto sample showed similar results for all indicators, but greenness variables (Table A5.8). Those showed higher estimates due to the strengthened relationship to partial and indirect effects in this subsample.

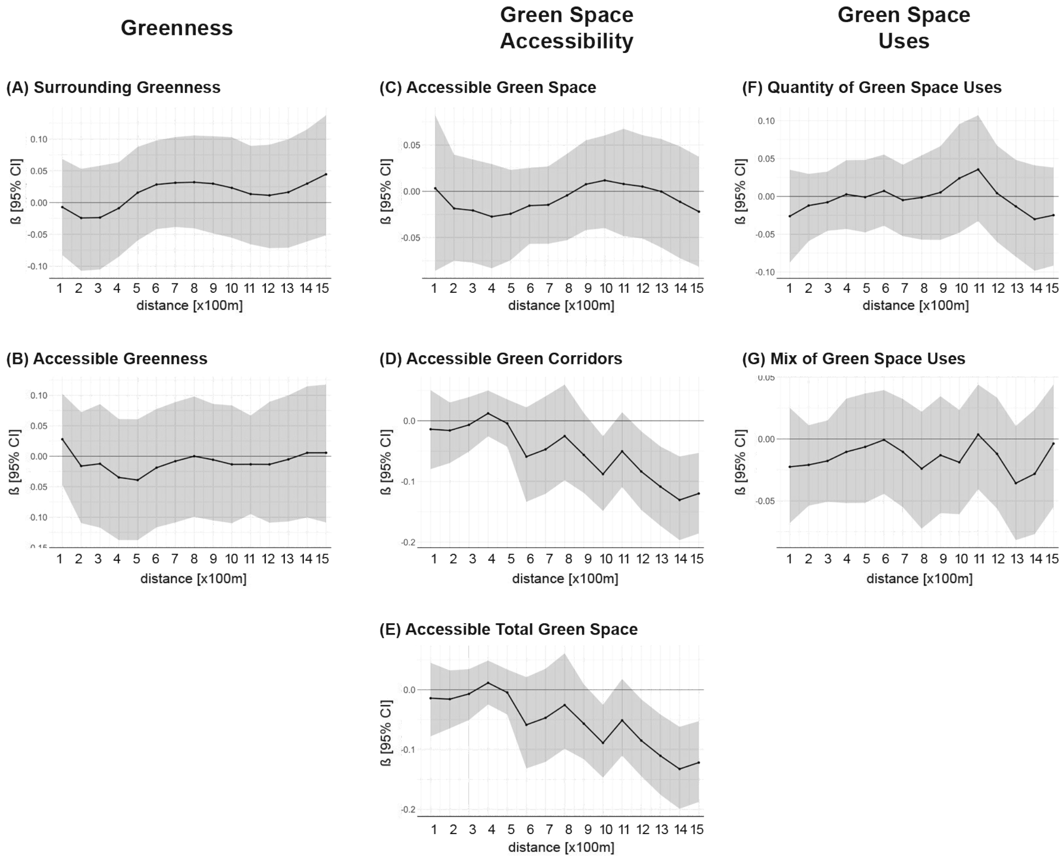

FIG. 5.8 Total Effects (a*b+c). Green Space – Social Cohesion – Mental Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 105 structural equation models; adjusted for sex, age, disabilities, years of education, income, employment status, years lived in the neighbourhood, well-being, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

TABLE 5.4 Direct Effects (c). Green Space – Mental Health Sensitivity Analysis.

Standardized Estimated ß (95% CI) for the direct effect (c) of green space indicators on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Greenness				
Distance	(A) Surrounding GN		(B) Accessible GN	
100	-0.019 (-0.094, 0.058)		0.019 (-0.057, 0.093)	
200	-0.033 (-0.112, 0.045)		-0.019 (-0.110, 0.070)	
300	-0.032 (-0.115, 0.048)		-0.021 (-0.125, 0.078)	
400	-0.018 (-0.093, 0.055)		-0.049 (-0.152, 0.048)	
500	0.005 (-0.068, 0.077)		-0.054 (-0.152, 0.047)	
600	0.017 (-0.052, 0.085)		-0.034 (-0.134, 0.062)	
700	0.021 (-0.048, 0.092)		-0.025 (-0.122, 0.076)	
800	0.021 (-0.049, 0.093)		-0.019 (-0.115, 0.079)	
900	0.019 (-0.059, 0.092)		-0.025 (-0.124, 0.066)	
1000	0.014 (-0.063, 0.091)		-0.032 (-0.125, 0.064)	
1100	0.005 (-0.071, 0.080)		-0.028 (-0.108, 0.052)	
1200	0.003 (-0.079, 0.082)		-0.032 (-0.127, 0.068)	
1300	0.007 (-0.079, 0.089)		-0.025 (-0.121, 0.081)	
1400	0.021 (-0.068, 0.105)		-0.015 (-0.123, 0.092)	
1500	0.034 (-0.062, 0.128)		-0.015 (-0.127, 0.096)	

Green Space Accessibility						
Distance	(C) Accessible GS		(D) Accessible GC		(E) Accessible TGS	
100	0.002 (-0.085, 0.079)		-0.021 (-0.087, 0.040)		-0.023 (-0.085, 0.036)	
200	-0.021 (-0.077, 0.035)		-0.020 (-0.075, 0.026)		-0.020 (-0.069, 0.026)	
300	-0.023 (-0.079, 0.031)		-0.014 (-0.058, 0.030)		-0.015 (-0.058, 0.025)	
400	-0.031 (-0.087, 0.024)		0.006 (-0.031, 0.043)		0.005 (-0.031, 0.042)	
500	-0.027 (-0.077, 0.020)		-0.012 (-0.052, 0.027)		-0.013 (-0.051, 0.024)	
600	-0.019 (-0.060, 0.023)		-0.068 (-0.143, 0.012)		-0.069 (-0.143, 0.010)	
700	-0.020 (-0.062, 0.022)		-0.060 (-0.135, 0.026)		-0.060 (-0.134, 0.019)	
800	-0.012 (-0.059, 0.033)		-0.039 (-0.112, 0.045)		-0.040 (-0.113, 0.048)	
900	-0.001 (-0.050, 0.046)		-0.064 (-0.125, 0.005)		-0.065 (-0.125, 0.001)	
1000	0.002 (-0.049, 0.050)		-0.094 (-0.156, -0.030)	*	-0.095 (-0.155, -0.031)	*
1100	-0.003 (-0.058, 0.056)		-0.056 (-0.116, 0.009)		-0.058 (-0.118, 0.009)	
1200	-0.007 (-0.063, 0.048)		-0.087 (-0.151, -0.020)	*	-0.089 (-0.151, -0.019)	*
1300	-0.013 (-0.073, 0.045)		-0.108 (-0.174, -0.041)	*	-0.111 (-0.178, -0.041)	*
1400	-0.024 (-0.087, 0.036)		**-0.129 (-0.196, -0.056)**	*****	**-0.132 (-0.200, -0.059)**	*****
1500	-0.034 (-0.094, 0.027)		-0.110 (-0.178, -0.041)	*	-0.112 (-0.179, -0.042)	*

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TABLE 5.4 Direct Effects (c). Green Space – Mental Health Sensitivity Analysis.

Standardized Estimated ß (95% CI) for the direct effect (c) of green space indicators on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Green Space Usability				
Distance	(F) Quantity of GSU		(G) Mix Of GSU	
100	-0.034 (-0.093, 0.028)		-0.025 (-0.070, 0.021)	
200	-0.013 (-0.059, 0.029)		-0.020 (-0.053, 0.011)	
300	-0.010 (-0.047, 0.032)		-0.019 (-0.051, 0.015)	
400	0.001 (-0.045, 0.045)		-0.011 (-0.052, 0.031)	
500	0.000 (-0.047, 0.050)		-0.011 (-0.055, 0.033)	
600	0.006 (-0.040, 0.054)		-0.006 (-0.051, 0.035)	
700	-0.008 (-0.055, 0.039)		-0.019 (-0.065, 0.024)	
800	-0.006 (-0.061, 0.050)		-0.033 (-0.080, 0.013)	
900	0.000 (-0.062, 0.061)		-0.022 (-0.071, 0.025)	
1000	0.020 (-0.052, 0.090)		-0.024 (-0.066, 0.019)	
1100	0.039 (-0.031, 0.110)		-0.008 (-0.051, 0.033)	
1200	0.001 (-0.062, 0.065)		-0.020 (-0.064, 0.024)	
1300	-0.018 (-0.084, 0.044)		-0.044 (-0.091, 0.002)	
1400	-0.034 (-0.102, 0.036)		-0.035 (-0.083, 0.016)	
1500	-0.028 (-0.094, 0.038)		-0.012 (-0.063, 0.035)	

Notes: *Adjusted for sex, age, disabilities, education, income, occupation, years lived in the neighbourhood, perceived neighbourhood safety, satisfaction with shops, leisure facilities, public transport, change in elevation within 500m buffer, and population density.*
Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with individual accessible private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);*
***** *Coefficient is statistically significant; bold estimates indicate the distance with the highest significant estimate.*

TABLE 5.5 Total Effects (a*b+c). Green Space – Social cohesion – Mental Health Sensitivity Analysis.

Estimated ß (95% CI) for the total effect (a*b + c) of green space indicators, both indirectly via social cohesion, and directly on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Greenness				
Distance	(A) Surrounding GN		(B) Accessible GN	
100	-0.007 (-0.083, 0.069)		0.028 (-0.047, 0.103)	
200	-0.024 (-0.107, 0.053)		-0.016 (-0.110, 0.072)	
300	-0.024 (-0.105, 0.058)		-0.012 (-0.117, 0.086)	
400	-0.009 (-0.085, 0.064)		-0.035 (-0.137, 0.061)	
500	0.016 (-0.060, 0.088)		-0.039 (-0.138, 0.061)	
600	0.028 (-0.042, 0.098)		-0.019 (-0.117, 0.078)	
700	0.031 (-0.038, 0.103)		-0.008 (-0.109, 0.089)	
800	0.032 (-0.040, 0.106)		0.000 (-0.099, 0.098)	
900	0.030 (-0.048, 0.105)		-0.006 (-0.105, 0.086)	
1000	0.023 (-0.055, 0.103)		-0.013 (-0.110, 0.083)	
1100	0.013 (-0.066, 0.089)		-0.013 (-0.095, 0.067)	
1200	0.011 (-0.072, 0.091)		-0.013 (-0.109, 0.089)	
1300	0.016 (-0.071, 0.100)		-0.005 (-0.107, 0.100)	
1400	0.030 (-0.061, 0.115)		0.006 (-0.100, 0.115)	
1500	0.045 (-0.051, 0.138)		0.006 (-0.109, 0.118)	

Green Space Accessibility						
Distance	(C) Accessible GS		(D) Accessible GC		(E) Accessible TGS	
100	0.003 (-0.086, 0.082)		-0.014 (-0.080, 0.051)		-0.014 (-0.078, 0.045)	
200	-0.019 (-0.075, 0.040)		-0.016 (-0.070, 0.030)		-0.016 (-0.065, 0.032)	
300	-0.021 (-0.077, 0.034)		-0.007 (-0.051, 0.039)		-0.007 (-0.051, 0.034)	
400	-0.027 (-0.083, 0.029)		0.012 (-0.026, 0.050)		0.011 (-0.025, 0.049)	
500	-0.024 (-0.075, 0.023)		-0.004 (-0.043, 0.035)		-0.005 (-0.042, 0.034)	
600	-0.016 (-0.057, 0.025)		-0.059 (-0.134, 0.022)		-0.059 (-0.132, 0.021)	
700	-0.015 (-0.057, 0.027)		-0.047 (-0.120, 0.040)		-0.047 (-0.121, 0.035)	
800	-0.004 (-0.053, 0.041)		-0.025 (-0.098, 0.060)		-0.026 (-0.099, 0.061)	
900	0.008 (-0.042, 0.055)		-0.056 (-0.119, 0.013)		-0.057 (-0.116, 0.009)	
1000	0.012 (-0.040, 0.060)		-0.088 (-0.149, -0.025)	*	-0.089 (-0.147, -0.025)	*
1100	0.008 (-0.048, 0.067)		-0.050 (-0.109, 0.014)		-0.051 (-0.110, 0.018)	
1200	0.005 (-0.051, 0.061)		-0.084 (-0.147, -0.017)	*	-0.085 (-0.145, -0.016)	*
1300	0.000 (-0.061, 0.056)		-0.109 (-0.173, -0.042)	*	-0.110 (-0.176, -0.041)	*
1400	-0.011 (-0.072, 0.048)		**-0.131 (-0.197, -0.059)**	*****	**-0.133 (-0.199, -0.062)**	*****
1500	-0.022 (-0.081, 0.037)		-0.120 (-0.186, -0.053)	*	-0.122 (-0.188, -0.053)	*

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TABLE 5.5 Total Effects (a*b+c). Green Space – Social cohesion – Mental Health Sensitivity Analysis.

Estimated ß (95% CI) for the total effect (a*b + c) of green space indicators, both indirectly via social cohesion, and directly on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

	Green Space Usability			
Distance	(F) Quantity of GSU		(G) Mix Of GSU	
100	-0.026 (-0.087, 0.035)		-0.023 (-0.068, 0.025)	
200	-0.012 (-0.059, 0.030)		-0.021 (-0.054, 0.011)	
300	-0.008 (-0.046, 0.033)		-0.018 (-0.051, 0.015)	
400	0.003 (-0.043, 0.048)		-0.010 (-0.052, 0.033)	
500	-0.001 (-0.048, 0.048)		-0.006 (-0.052, 0.037)	
600	0.007 (-0.039, 0.055)		-0.001 (-0.044, 0.040)	
700	-0.005 (-0.052, 0.042)		-0.010 (-0.055, 0.032)	
800	-0.001 (-0.057, 0.054)		-0.024 (-0.073, 0.022)	
900	0.005 (-0.057, 0.066)		-0.013 (-0.060, 0.035)	
1000	0.024 (-0.048, 0.096)		-0.019 (-0.061, 0.023)	
1100	0.036 (-0.033, 0.107)		0.004 (-0.041, 0.044)	
1200	0.004 (-0.060, 0.067)		-0.012 (-0.056, 0.033)	
1300	-0.013 (-0.080, 0.048)		-0.036 (-0.082, 0.011)	
1400	-0.030 (-0.098, 0.041)		-0.028 (-0.077, 0.024)	
1500	-0.025 (-0.092, 0.038)		-0.004 (-0.055, 0.044)	

Notes: *Adjusted for sex, age, disabilities, years of education, income, employment status, years lived in the neighbourhood, well-being, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with individual accessible private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);*
***** *Coefficient is statistically significant; bold estimates indicate the distance with the highest significant estimate.*

5.3.6 Collinearity between significant green space characteristics

To clarify whether the documented associations arise from separate mechanistic processes or merely function as alternative markers of the same underlying variable, we assessed the correlation matrix of all green space characteristics (Table A5.9). We evaluated the peak associations from the partial effects (path a).

As detailed in section 3.2, the peak relations for the partial effect (path a) were between social cohesion and accessible greenness at 800 m (B), accessible green space at 1400 m (C), accessible green corridors at 800 m (D), accessible total green spaces at 800 m (E), mix of green space uses in 1100 m (G), as well as two negative associations for accessible green corridors (D) and accessible total green spaces (E) at 1,500 m. The investigation of the correlation matrix indicated the expected strong collinearity between the nested green space characteristics when measured at similar distances (D & E). However, the correlation across the different sets of indicators (e.g. between A and D or between E and G), was weak to moderate for accessible greenness (-0.18-0.16), accessible green space (-0.06-0.51), green corridors (0.17-0.56), and green space uses (-0.16-0.59). We found a weak to moderate correlation for the negative association of accessible green corridors at 1,500 m to other green space characteristics (0.14-0.56). This indicates partially unique mechanisms to social cohesion from accessible greenness, accessible green spaces, green corridors and green space uses.

5.4 Discussion

5.4.1 Main findings

We found that certain green space characteristics are linked with elevated levels of social cohesion, which in turn appear to favour mental health outcomes. Specifically, accessible greenness (including vegetation along streets) and accessible green spaces in a surrounding area of up to 1,500 meters, as well as green corridors in an intermediate surrounding of up to 800 meters, and mix of use in green spaces measured in 700 to 1,300 meters, showed significant indirect associations to mental health. Moreover, a sensitivity analysis without the Porto sample indicates cross-cultural differences in the relationship between greenness, social cohesion and indirect associations on mental health, but not for green space accessibility or green space uses. On the contrary, we did not find a direct positive effect between any neighbourhood green space characteristics in any of the 105 structural equation models to mental health, including the sensitivity analysis without the Porto sample. Our results shed light on the complex relationship between neighbourhood green spaces, social cohesion and mental health. They suggest a strong relationship between neighbourhood green space characteristics and social cohesion, as well as modest indirect but no direct effects on mental health.

5.4.2 Social cohesion as a mediator in the green space mental health pathway

We identified consistent patterns of indirect associations between accessible greenness, green space corridors and mix of use with mental health through the mediating role of social cohesion. This echoes the findings of several studies on the association between green space and social cohesion or related concepts. For instance, Rugel et al. (2019) discovered that accessible neighbourhood nature was positively associated with mental health through increased social cohesion in a large study of over 1,9 million individuals in Canada. Another study found that the use of green spaces influenced mental health indirectly through social support and collective restoration (Pasanen et al., 2023). Ricciardi and colleagues (2023) reported a mediating effect of social support on geriatric depression symptoms. Similarly, Li et al. (2022) found that green spaces indirectly contributed to reduced anxiety through social cohesion and van den Berg et al. (2019) reported small mental health benefits when visiting green spaces mediated by social cohesion, among other mediators like physical activity and loneliness. In line with our findings on accessible greenness, Liu and colleagues (2020) found an indirect effect of street greenness on mental health through community participation. Our results on green space uses corroborate recent reviews that conclude that green space amenities and utilities are able to foster social cohesion (Clarke et al., 2023) and that bigger green space areas might be better able to support social cohesion through more visitors and different activities (Wan et al., 2021), which might reflect the strong associations with green space corridors and their theorized relation to physical activity (Cardinali et al., 2024).

On the contrary, some studies were not able to find evidence for a mediating effect and reported inconclusive evidence for social cohesion in the green space mental health pathway (A. M. Dzhambov, Markevych, Hartig, et al., 2018). Our sensitivity analysis without the Porto subsample indicates differences in the relationship between greenness and social cohesion between population groups, which might be able to explain part of the remaining inconsistency across studies. Possible explanations include differences in social behavioural patterns across cultures or age groups that change the influence of greenness on social cohesion.

Despite these inconclusive findings and a general heterogeneity in green space, social cohesion and mental health indicators used, our findings are consistent with the majority of studies that suggest a small but consistent mediating role of social cohesion on the green space mental health pathway. Our results add to the body of knowledge, where these relationships might occur and which green space characteristics might be responsible for this relationship.

5.4.3 Direct effects of neighbourhood green space on mental health

We did not find any positive significant relationship between green space characteristics and mental health in any of our structural equation models. Moreover, all coefficients, except green space corridors measured at large distances, were not only not significant but also ranged around zero, indicating the absence of a direct relationship between the tested green space characteristics and mental health. This is in line with the study of Rugel and colleagues in Canada that also found no direct effect between any measure of the natural environment and mental health (Rugel et al., 2019). Similarly, Ricciardi et al. found no direct effect on geriatric depression (Ricciardi et al., 2023), while Zhang and colleagues concluded that green space is

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not a dominant factor contributing to adolescent well-being (Y. Zhang et al., 2022). However, this is in contrast to earlier studies that were able to find a direct association between green space or greenness and mental health in direct proximity (A. M. Dzhambov, Markevych, Hartig, et al., 2018; Y. Liu et al., 2020; van Herzele & de Vries, 2012; Zijlema et al., 2017).

Several factors could explain this inconsistency. Firstly, differences in how green space exposure is measured might contribute to different findings, especially since direct contact with nature is considered to be one of the main drivers for the green space mental health relationship (Bratman et al., 2019b; Cardinali, Beenackers, et al., 2023c; Hartig et al., 2014; Markevych et al., 2017) which might not be captured by green space characteristics around a residential address since it does not measure if there is an actual engagement with these green spaces. Secondly, the variation of the mental health indicator across studies might partly explain the differences since they capture different aspects or even subdomains of psychological well-being or mental illness (Bratman et al., 2019b), which might be influenced differently by green spaces. Thirdly, differences in contextual variables included in the models may be partly responsible for some of the inconsistency in results.

Our results suggest negative associations between accessible green corridors or accessible total green space and mental health at distances of 1000-1500m. This rather counterintuitive finding might be attributed to the null findings explained above since they additionally create a vulnerability to noise in the dataset, allowing spurious relations to dominate the measured relationship. Other research suggests that the composite socio-economic status (SES) of the neighbourhood might be negatively associated with mental health (Segrin & Amanda Cooper, 2023; Sui et al., 2022) in addition to the influence of individual SES. Our results might represent this effect since the studied satellite districts not only have a low composite socio-economic status but were also built according to the urban design principles of modernism with much more green space between the buildings compared to other parts of the city. This might explain our negative findings in larger distances, e.g. in the neighbourhood perspective. Therefore, we do not assume that there is an actual negative effect of the measured green space characteristics on mental health.

5.4.4 Strengths and limitations

The strengths of our study are based on the systematic investigation of green space characteristics and relative proximity to the residence in an elaborate investigation of 105 structural equation models. This allowed us to contribute new insights into how and where neighbourhood green spaces are related to social cohesion and mental health. Due to our mental health indicator, measured in terms of emotional, social, and psychological well-being, instead of the absence of a disease, our results also add a valuable different perspective in this research field compared to the frequent measures of mental illness scales like GHQ-12 or single illnesses like depression.

However, this study design is also associated with certain limitations. For instance, the complexity of the structural equation model was limited, as we chose to work with simple models for reasons of comparability and feasibility. Theoretically indicated dependencies and serial mediation have not been modelled (A. M. Dzhambov, Markevych, Hartig, et al., 2018), as this would have caused variations in model fit across the structural equation models and work against the main aim of the study to compare green space characteristics. For the same reason, we only adjusted for confounders but not model theorized effect modifications due to differences in the life course and gender (Astell-Burt, Mitchell, et al., 2014). Not accounting for these differences may have partly led to masked effects. Furthermore, as we used simple (just-identified) mediation models we can only assume that these models are correct, but not prove it through model fit indices. In addition, the clustering of survey participants in rather small geographical areas might have led to reduced variability in larger buffers. However, due to the four case studies included, we assume that the overall sample has enough variability to justify the inclusion and discussion of larger buffers. Lastly, while we adjusted for seasonal differences in the greenness indicator and the dummy city variable, there still might have been a variation in weather conditions within the weeks of the data collection, which might limit the precision of our results.

Furthermore, our data set is largely based on subjective self-assessments, which are associated with several biases like social desirability, recall or reporting bias. In addition, the ordinal variables in the model, limit the depth of information and make it more difficult to detect subtle correlations. Furthermore, our study design is cross-sectional, which does not allow any conclusions about causal relationships. We could not rule out reverse causation where respondents with lower mental health perceive social cohesion to be lower. Another limitation comes from the characterisation of green spaces. The study does not consider their quality (maintenance, quality of design, amenities, etc.). This quality criteria, which was identified during site visits, has a potential impact on the way green spaces are used, and therefore on their impact on social cohesion and health. Lastly, the recruitment of study participants in specific urban contexts, as well as the missing information on response rates in each city, also constrains the generalisability of our results.

5.4.5 Further research avenues and implications

Further research is needed to confirm and extend our findings. Firstly, further research is needed to better understand the inconsistency in neighbourhood green space associations to mental health, by exploring the differences between actual contact with nature and living near neighbourhood green, as the research results are still inconclusive. Secondly, while our results indicate which green space characteristics can foster social cohesion, the mediators on the pathway between green space characteristics and social cohesion remain of interest. These could potentially be physical activity and social interaction, which should be investigated in more complex serial mediation models, including moderation effects, building on our results about green space characteristics and relative proximity. Thirdly, our results showed a negative relationship between accessible green corridors and mental health, when measured with 1,000-1,500m Euclidean buffers. The theorized reverse causation should be further investigated by trying to reproduce our results in longitudinal studies to analyse the causal pathway, preferably with more diverse urban characteristics, to rule out residual confounding. The sensitivity analysis indicated that cultural differences may be important to consider in future research when analysing the mediating role of social cohesion. Fourthly, by comparing our results to other studies, a potentially important difference is highlighted between the concepts of mental health, mental illness and well-being, which should be further explored in their relationship to green spaces and more precisely distinguished from one another in green space mental health studies. Lastly, more longitudinal study designs are warranted to better understand the causal relationships, and green space thresholds in these pathways (e.g. would adding more green actually lead to more social cohesion?) and also to feed policy analysis, planning and design processes.

5.5 Conclusion

Our study aimed to examine the role of green space characteristics and proximity to residents' homes for social cohesion and mental health. Our results suggest that specific green space characteristics are associated with higher social cohesion and in turn better mental health, namely green space corridors in intermediate surroundings up to 800 m, and mix of use in green spaces approximately in 700-1,300 m surroundings. The association of surrounding greenness with social cohesion and indirectly with mental health was sensitive to the inclusion of the Porto subsample, indicating cross-cultural differences in this relationship, worth to be further investigated. Interestingly, we detected no direct positive association between any neighbourhood green space characteristics in any buffer distance to mental health. Although our study is limited due to its cross-sectional design, our findings provide valuable insights into the potential of green spaces to help promote local social cohesion and indirectly improve mental health. These insights into how and where these mechanisms may occur, provide important evidence for policymakers, urban and landscape planners, and public health decision-makers on how to design and regenerate neighbourhood green spaces to foster social cohesion and mental health.

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6 The green space – air pollution – health pathway

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ABSTRACT

While it is assumed that green space can reduce air pollution and in turn improve health, it remains unknown what kind of proximity to what kind of green spaces drives this mechanism. We explore the influence of green space characteristics and proximity on health through the mediating role of air pollution annoyance with data from 1,365 participants across Porto, Nantes, Sofia, and Høje-Taastrup. Utilizing OpenStreetMap and the AID-PRIGSHARE tool, we generated nine green space indicators around residential addresses at 15 distances, ranging from 100m to 1500m for a sensitivity analysis. We performed a mediation analysis for these 135 green space variables and revealed significant associations between self-rated air pollution and self-rated health only for specific green space characteristics. In our study, indirect positive effects on health via self-rated air pollution were mainly associated with green corridors in intermediate Euclidean distances (800-1,000m) and the amount of accessible green spaces in larger network distances (1,400–1,500m), not with greenness. Our results suggest that instead of pure greenness, the area of green spaces corridors in intermediate surroundings may be the main driver in this pathway of reducing air pollution annoyance and improving health.

KEYWORDS

greenspace, mitigation, air quality, public health, structural equation modelling

6.1 Introduction

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

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

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

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

6.2 Methods

6.2.1 Study design and sampling

We followed the STROBE Reporting Guidelines for cross-sectional studies (Table A6.1, Elm et al., 2007). We collected data for this study following the same protocol as outlined in a previous study from the URBiNAT project (Cardinali et al., 2024). To qualify for participation, individuals needed to be at least 14 years old. Participants were selected at random, and the surveys were carried out by local survey companies hired by the cities and instructed by the research team. In Porto and Sofia, surveys were conducted in person, while in Nantes and Høje-Taastrup, potential participants were approached by phone. Upon contact, individuals were briefed about the project's objective, the survey's role, and asked for informed consent. Before, the survey had been approved by the URBiNAT project's ethics committee. No rewards were offered for participation. Data were collected from a total of 1650 participants of which 1365 participants reported their address and were eligible for this study. The study participants are distributed across the four cities as follows: 439 from Porto (August 2019), 293 from Nantes and 432 from Sofia (both December 2019), as well as 201 from Høje-Taastrup (August 2021).

All study areas are designed as satellite districts (urban districts purposely built on the outskirts of a city and according to functional city principles, for their location within cities see Chapter 1) but show distinct urban characteristics, as illustrated in Figure 6.1. Nantes featured two radial green infrastructures leading from and to the city centre, with one of them running alongside a river. Its main roads and motorways are mostly bypasses which usually do not get very close to the residential areas. In contrast, Porto’s riverside was less accessible due to its car-centric infrastructure and elevation level. In addition, the amount and proximity of its main roads suggest a high exposure to traffic air pollution. Sofia’s public green spaces were relatively less connected and consisted of three primary green areas. Its main roads mainly consist of a radial infrastructure that is not getting too close to residential areas. Høje-Taastrup showcased smaller but interconnected green spaces within its urban landscape and showed the most agricultural surroundings. The narrow spatial distribution of study participants in Høje-Taastrup is near three main roads.

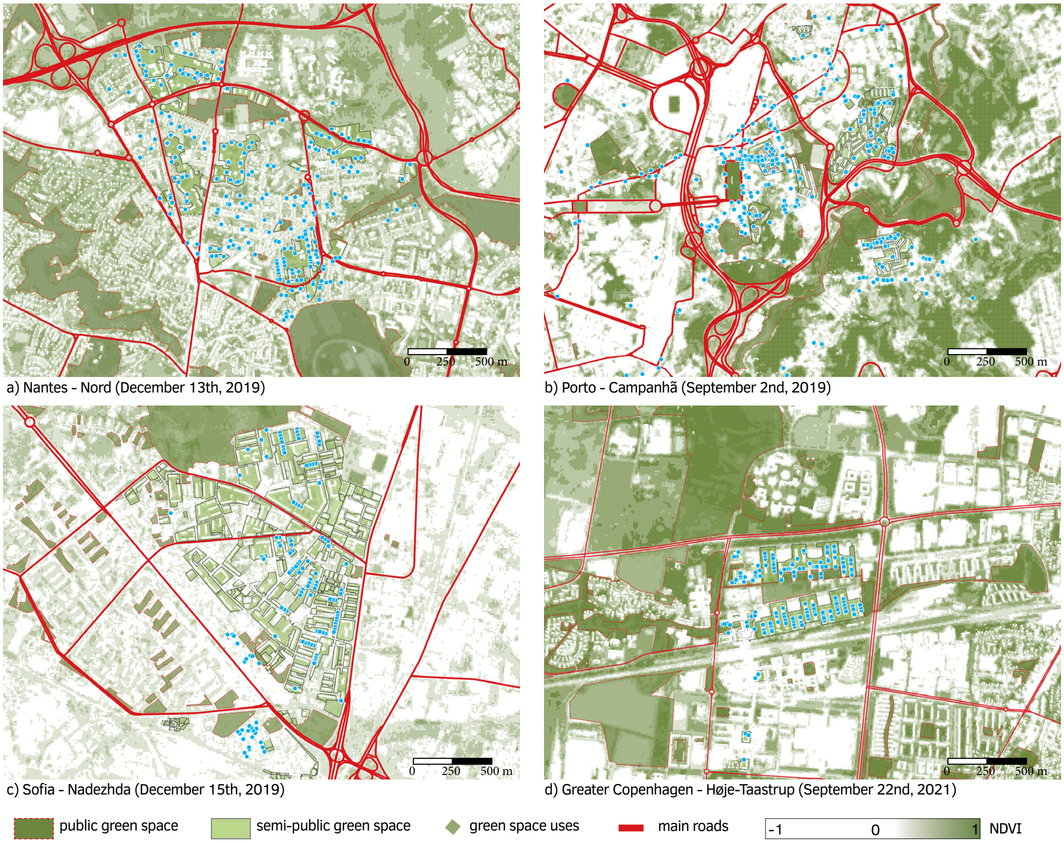

FIG. 6.1 Study areas green space and main roads: a) Nantes – Nord (France); b) Porto – Campanhã (Portugal), c) Sofia – Nadezhda (Bulgaria), d) Greater Copenhagen – Høje-Taastrup (Denmark); blue points indicate the residential address of the study participants. For better readability only the study areas are covered – e.g. some respondents do not live in the main study area.

6.2.2 Green Space

We obtained spatial data from OpenStreetMap in January 2023 and manually corrected it to the timestamp of the survey conduction and controlled for bias (see Figure 6.1). With the help of the PRIGSHARE Reporting Guidelines (Table A6.2), the green space data was adjusted manually for public ownership bias, residential ownership bias, classification bias, usability bias and connectivity bias (Cardinali, Beenackers, et al., 2023b). Especially, the manual connection of green spaces enabled the investigation of green space corridors. We manually (1) connected green space polygons that were interrupted by a road but had a crossing, (2) merged green spaces directly next to each other, and (3) added linear green spaces that consisted of walkable pathways with greenery. A detailed table with the inclusion/exclusion criteria can be viewed in the. appendix (Table A6.3). To assess greenness around study participants we used the frequently used Normalized Difference Vegetation Index (NDVI, Tucker, 1979). For the calculation of the NDVI, we gathered sentinel 2 (L2A) data in 10x10m resolution from the European Space Agency ESA from the specific cloud-free time points of the survey conducted in the city (2021). Since water bodies show negative NDVI values, we set larger water bodies like the rivers in Porto and Nantes manually to missing, as recommended by Markevych et al. (2017).

Based on this data we constructed nine indicators (Fig 6.2) in QGIS (v 3.22) for our sensitivity analysis in distances from 100m (immediate surrounding) to 1500m (neighbourhood perspective), every 100m, with the help of the AID-PRIGSHARE tool (Cardinali, Beenackers, et al., 2023a), summing up to a total of 135 green space indicators to identify distance patterns as well as potential differences between green space characteristics. Firstly, we assessed greenness with three indicators based on NDVI. One represents mean surrounding greenness (6.2A) measured by mean NDVI within Euclidean buffers. Another represents cumulative surrounding greenness (6.2B) measured by the sum of NVDI values within Euclidean buffers which might better reflect the quantity of vegetation in an area. The third one measures mean accessible greenness (6.2C) with mean NDVI in network distance. Secondly, we assessed surrounding green space with three public green space indicators: surrounding green spaces within Euclidean distance (6.2D), surrounding green corridors (6.2E) where the whole green space network that intersects the buffer is counted, and surrounding total green space (6.2F) where in addition also the individual private or semi-public green space for the surveyed individual is added. Thirdly, we assessed the same indicators with network distances (6.2G-6.2I) to measure accessible green spaces and to examine differences between accessible and surrounding green spaces.

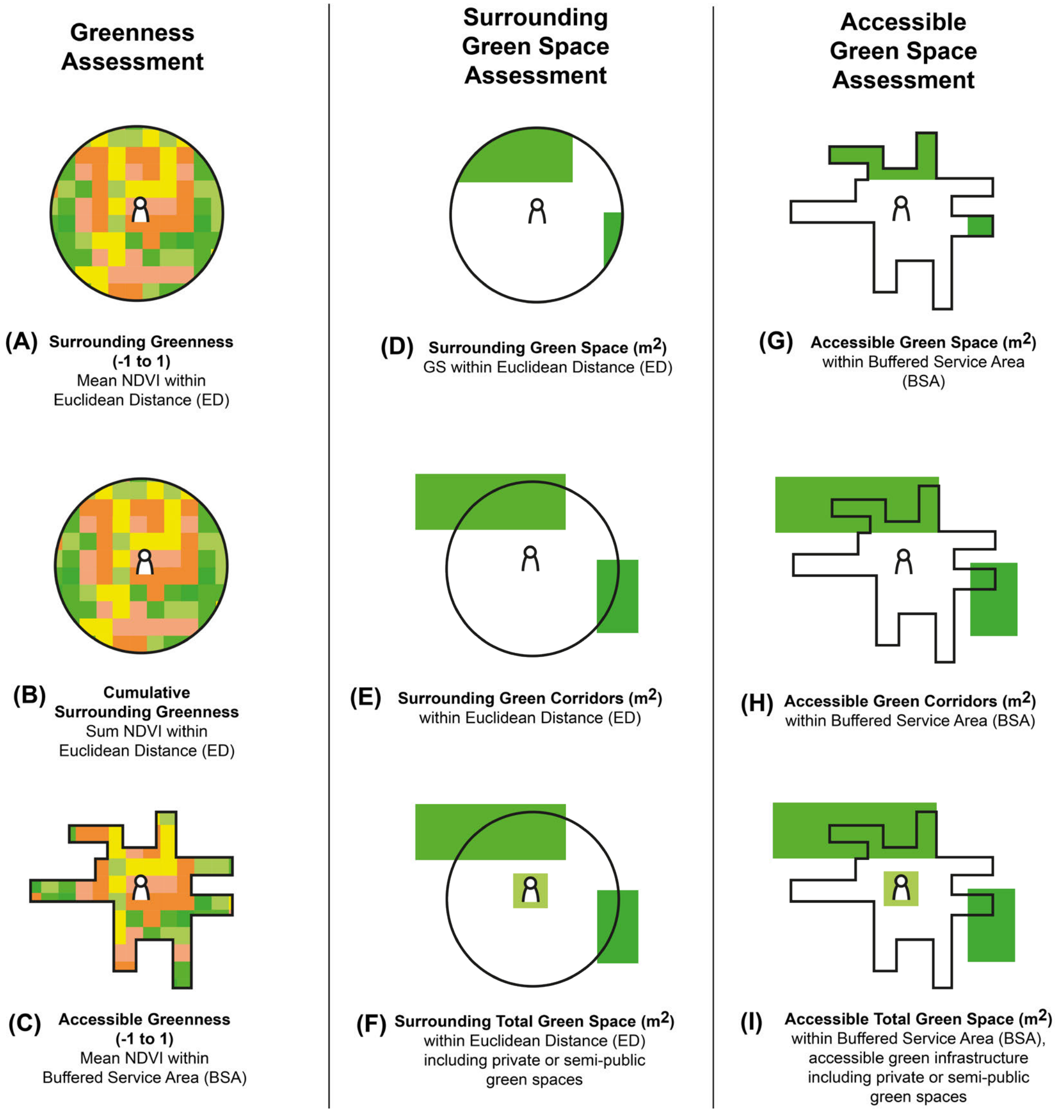

FIG. 6.2 Green space indicators: Indicators used in the Sensitivity Analysis

6.2.3 Self-rated Air Pollution

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

6.2.4 Self-rated Health

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

6.2.5 Context Variables

We gathered data on potential confounders at personal, local, urbanicity, and global levels. The personal context was assessed with data on age, sex, disabilities (y/n), years lived in the neighbourhood, years of education, and monthly net income, as well as employment status (y/n). Most of these are social determinants of health that could confound the relationship (Cardinali, Beenackers, et al., 2023b). Moreover, it has been shown, that especially in the context of self-rated air pollution inaccuracies can occur, if not controlled for demographics, socioeconomic status as well as existing illnesses, even if not respiratory (Pantavou et al., 2018; Pelgrims et al., 2022; Piro et al., 2008). To adjust for these influences on self-rated air pollution we used the available binary variable on disabilities as a proxy, which asked for any sensorial, motor, cognitive or organic disability that requires personal assistance or particular equipment or care. To harmonize between cases across countries, monthly net income was centred around the mean minimum wage of the country. Furthermore, as we ask about neighbourhood characteristics it is important to adjust for years lived in the neighbourhood as well as employment status as a proxy for the actual time spent in the neighbourhood and thus the potential exposure to neighbourhood air pollution.

We accounted for the local difference in traffic pollution by quantifying the surface area of main roads within a 500m radius of the residential address. For this, we used OpenStreetMap data and filtered for motorways, primary, secondary and tertiary roads, thus including all roads that connect neighbourhoods, districts or cities. We buffered those street lines by 6 meters to reflect differences in street width and associated traffic (see also Figure 6.1). In addition, we used 5-point Likert scale items to measure local satisfaction with shops, leisure facilities, and public transport as part of the environmental quality of life questionnaire (Fleury-Bahi et al., 2013). These variables serve as covariates in this study, to adjust for differences in the local context which might influence behaviour-related associations between green space and health (Cardinali, Beenackers, et al., 2023b). In this study on self-rated air pollution, we expect this to affect mainly the direct association between green space and health in the structural equation model (Figure 6.3, path c).

For the urbanicity context, we used rasterized 2018 population density data from Eurostat, with a resolution of 1km x 1km (Eurostat, 2023). Moreover, to account for different cultural and climate contexts we included the city samples as a dummy variable in our model. This approach also allowed us to control for temporal differences (pre- or post-pandemic), potential differences in baseline city-wide air pollution caused by for example local industry, and seasonal variations during the time of survey conduction which is known to influence air pollution levels (Diener & Mudu, 2021; Shi et al., 2017), all while preserving the statistical power.

6.2.6 Statistical Analysis

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

We applied structural equation modelling (SEM) using the lavaan package (Rosseel, 2023) in R (v 4.2.3) and the diagonal weighted least squares estimator on a basic single-mediator model (Fig 6.3) to perform a sensitivity analysis on the nine green space indicators, each at 15 distances, adding up to a total of 135 SEMs. The full model including all control variables can be found in the supplementary material (Fig A6.1) as well as an example for the summary statistics for one green space indicator (Table A6.4). These just-identified (saturated) mediation models were chosen to bypass the potential complexity that would be introduced with overidentified models through variations in model fit across the 135 models, which would make this large-scale sensitivity analysis unmanageable and negatively affect the main aim of this research to compare the proximity and green space characteristics in their ability to influence the air pollution health pathway.

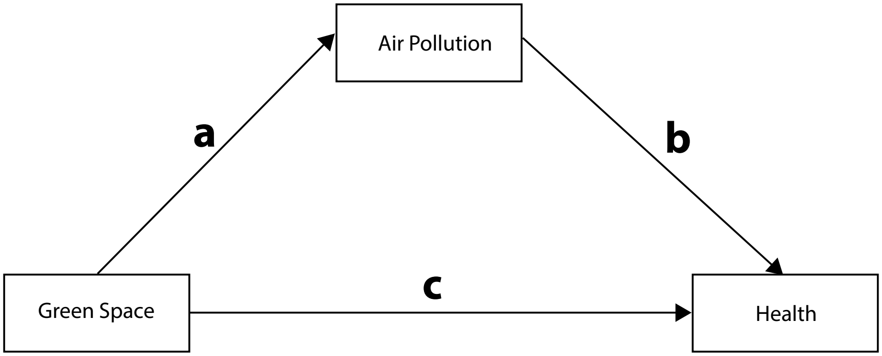

FIG. 6.3 Conceptual diagram: Conceptual diagram showing theoretically indicated pathways linking green space to air pollution and health. The green space indicator was exchanged 135 times for each structural equation model.

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

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

6.3 Results

6.3.1 Characteristics of the sample

This study used the same sample as a previous studies from the URBiNAT project (Cardinali, Beenackers, Fleury-Bahi, et al., 2024; Cardinali, Beenackers, Van Timmeren, et al., 2024). The total sample comprised 201 inhabitants from Høje-Taastrup (Denmark), 293 from Nantes (France), 439 from Porto (Portugal), and 432 from Sofia (Bulgaria). The city samples are composed of roughly 50% of men and women in Høje-Taastrup, Nantes, and Sofia. In Porto, the sample was composed of nearly 64% men and 36% women. Porto also had the most people over 65 years with 41.0% compared to Nantes with only 17.1% of survey respondents and the highest proportion of people with disabilities (39.6%). The mean (SD) years of education were 12.49 (2.55) in Høje-Taastrup, 12.57 (3.37) in Nantes, 7.02 (3.70) in Porto, and 13.11 (2.68) in Sofia. The majority of the participants were employed, with significant differences between cities. The mean income harmonized as a percentage of minimum wage of the country was roughly between 140-150% in Høje-Taastrup, Nantes, and Sofia, but only 40% in Porto. Self-perceived health as the main outcome indicator was the highest in Nantes with 76.5% reporting good or very good health, and lowest in Porto with 46.9%. For more details on the samples, we refer to Table 6.1.

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

TABLE 6.1 Characteristics of the sample (unstandardized)

Context	Indicator	Høje-Taastrup	Nantes	Porto	Sofia	p
global	city sample (n)	201	293	439	432	
urbanicity	population dens104 ity (mean (SD))	4028.65 (1336.94)	5616.27 (2353.62)	4829.28 (1632.50)	9021.14 (3689.54)	<0.001
local	**self-rated Air Pollution (%)**					<0.001
	no inconvenience	54.2%	53.6%	32.3%	5.8%	
	weak inconvenience	25.9%	17.7%	14.1%	28.0%	
	moderate inconvenience	15.9%	18.1%	15.3%	43.5%	
	high inconvenience	3.5%	4.1%	19.4%	18.8%	
	very high inconvenience	0.5%	6.5%	18.9%	3.9%	
	main roads within 500m surroundings (0 – 11.02 hectare, mean(SD))	2.49 (0.98)	4.40 (1.81)	7.09 (2.02)	2.44 (1.45)	<0.001
	satisfaction with shops (Likert 1-5, mean(SD))	3.98 (1.08)	3.48 (1.07)	3.41 (1.39)	3.82 (0.86)	<0.001
	satisfaction with leisure facilities (Likert 1-5, mean(SD))	3.78 (1.11)	2.85 (1.16)	3.34 (1.36)	3.28 (0.88)	<0.001
	satisfaction with public transport (Likert 1-5, mean(SD))	4.45 (0.90)	4.43 (0.66)	3.59 (1.44)	3.85 (0.63)	<0.001
personal	**gender (%)**					<0.001
	male	52.2%	44.0%	36.2%	47.2%	
	female	47.8%	55.3%	63.8%	52.8%	
	diverse	0.0%	0.7%	0.0%	0.0%	
	age group (%)*					<0.001
	15-24	6.5%	10.9%	4.1%	10.6%	
	25-44	28.4%	42.7%	21.4%	39.6%	
	45-64	32.8%	29.4%	33.5%	29.6%	
	over 65	32.3%	17.1%	41.0%	20.1%	
	mean years lived in Neighbourhood (SD)	16.60 (13.76)	14.53 (15.03)	28.90 (20.08)	22.41 (12.34)	<0.001
	mean net income as % of minimum wage (SD)	141% (93%)	149% (63%)	40% (66%)	143% (73%)	<0.001
	mean years of education (SD)	12.40 (2.51)	12.46 (3.38)	7.03 (3.72)	13.16 (2.67)	<0.001
	has disabilities (%)	10.0%	15.7%	39.6%	15.5%	<0.001
	employed (%)	57.2%	56.7%	28.7%	73.6%	<0.001
	self-perceived Health (%)					<0.001
	very good	24.9%	29.7%	8.9%	34.5%	
	good	36.8%	46.8%	38.0%	39.4%	
	fair	23.9%	17.4%	32.3%	19.9%	
	bad	11.4%	5.8%	13.7%	6.2%	
	very bad	3.0%	0.3%	7.1%	0.0%	

>>>

TABLE 6.1 Characteristics of the sample (unstandardized)

Context	Indicator	Høje-Taastrup	Nantes	Porto	Sofia	p
green space characteristics	surrounding Greenness in 500m Euclidean distance (-1 to 1, mean (SD))	0.46 (0.05)	0.42 (0.03)	0.37 (0.08)	0.23 (0.04)	<0.001
	Surrounding biomass in 500m Euclidean distance (1,384.33 – 4,775.13, mean (SD))	3630.87 (374.23)	3327.87 (251.12)	2963.04 (666.85)	1847.63 (288.29)	<0.001
	accessible greenness in 500m network distance (-1 to 1, mean (SD))	0.44 (0.04)	0.39 (0.04)	0.34 (0.06)	0.24 (0.04)	<0.001
	surrounding green space in 500m Euclidean distance (0 - 30.02 hectare, mean (SD))	9.89 (3.73)	6.12 (4.80)	6.24 (3.89)	6.90 (7.77)	<0.001
	surrounding green corridors in 500m Euclidean distance (0 - 537.79 hectare, mean (SD))	59.75 (21.63)	70.91 (67.41)	19.15 (11.89)	44.35 (85.01)	<0.001
	surrounding total green space in 500m Euclidean distance (0 - 539.15 hectare, mean (SD))	64.77 (19.93)	74.17 (67.03)	21.57 (13.59)	48.41 (86.41)	<0.001
	accessible green space in 500m network distance (0 – 16.32 hectare, mean (SD))	3.70 (1.45)	1.64 (1.56)	2.35 (2.11)	3.12 (3.68)	<0.001
	accessible green corridors in 500m Network distance (0 - 154.30 hectare, mean (SD))	51.76 (17.59)	56.92 (66.64)	9.74 (9.81)	28.93 (37.99)	<0.001
	accessible total green space in 500m network distance (0 - 158.66 hectare, mean (SD))	56.77 (16.33)	60.18 (66.51)	12.16 (10.37)	32.99 (41.47)	<0.001

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

6.3.2 Indirect effects – How green space indicators relate to health via self-rated air pollution

We found associations between surrounding and accessible green corridors as well as total green space indicators to self-rated air pollution and indirectly on health, but not for indicators representing greenness (Figure 6.5, Table 6.3). The indirect effects (a*b) showed similar patterns compared to the partial effects (a) (see Figure 6.4, Table A6.2) due to the stable significant association (b) between air pollution and health (ß: 0.08; CI: 0.02, 0.15). Greenness (Fig 6.5A-6.5C) showed no significant indirect relation to health for any distance, but a clearly visible low point for accessible greenness (which includes street green) measured in 500m network buffer (ß: -0.046; CI: -0.154, 0.007). Surrounding green spaces (Fig 6.5D) presented a plateau at 1100-1300m, although not significant. The indirect effects of surrounding green corridors (Fig 6.5E) on health via self-rated air pollution started negatively, with a non-significant low at 200m (ß: -0.021; CI: -0.062, 0.001). They then turned positive and showed a clear plateau of significant positive associations for distances from 800-1000m, with a peak at 900m (ß: 0.053; CI: 0.013, 0.121). Surrounding total green space (Fig 6.45F) displayed the same patterns, peaking at the same point at 900m (ß: 0.053; CI: 0.013, 0.127). Accessible green space (Fig 6.5G) showed no indirect health effects for distances up to 1100m and then started climbing to a significant association at 1400-1500m (ß: 0.035; CI: 0.002, 0.105). Green corridors in network distances (Fig 6.5H) presented a longer and shifted significant plateau of positive associations (900m-1300m) compared to surrounding green corridors, with a peak at 1000m (ß: 0.044; CI: 0.009, 0.108). Accessible total green space (Fig 6.5I) reacted almost identically. The highest estimate was found for surrounding green corridors and total green spaces at 900m (ß: 0.053; CI: 0.013, 0.127). The investigation of the correlation matrix indicated the expected strong collinearity between the nested green space characteristics (D, E, H, I), indicating the same underlying mechanism (0.87-0.99) (Table A6.5). However, the correlation of accessible green space to other indicators was moderate (0.37-0.46). This indicates partially unique mechanisms for self-rated air pollution from green corridors and accessible green spaces.

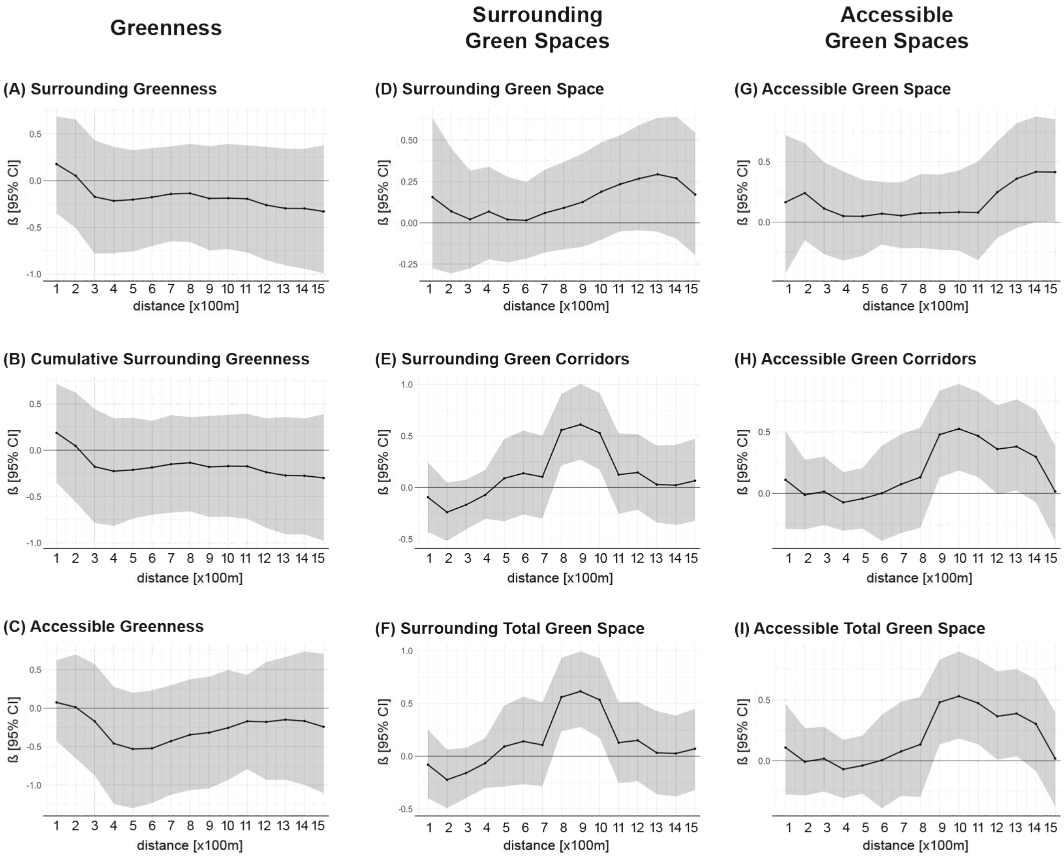

FIG. 6.4 Partial Effects (a) Green Space – Self-rated Air Pollution Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 135 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

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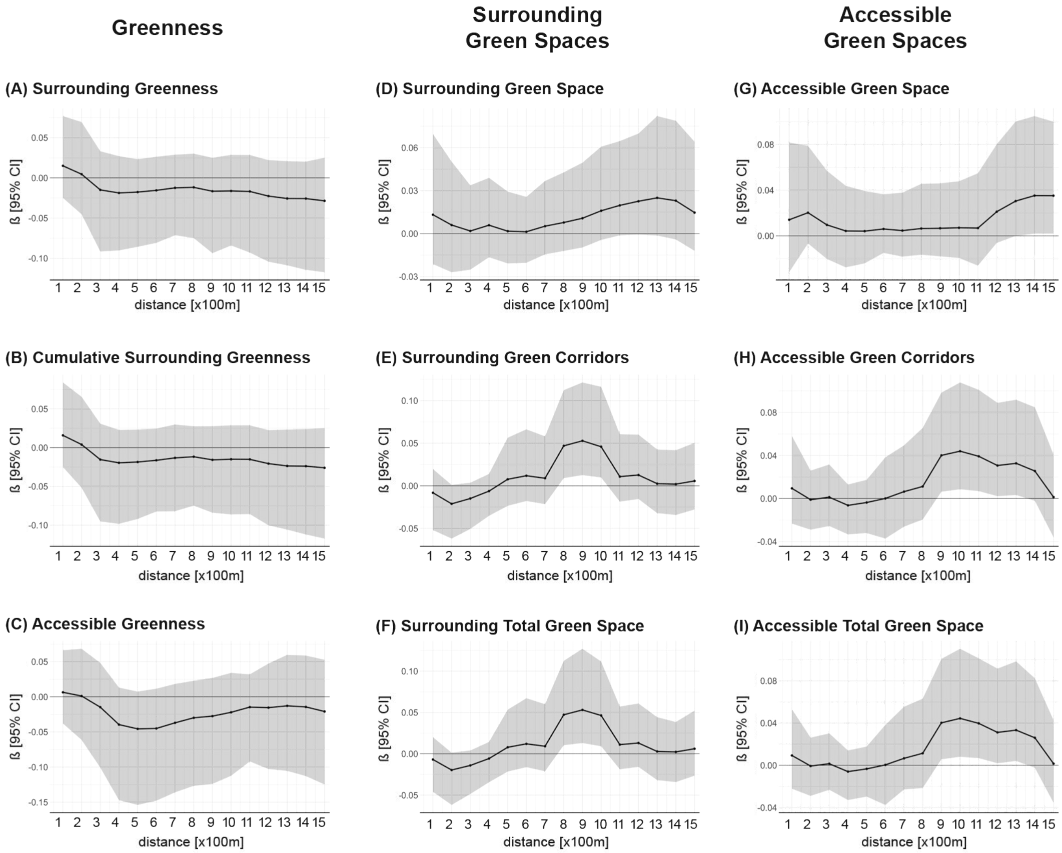

FIG. 6.5 Indirect Effects (a*b) Green Space – Self-rated Air Pollution – Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 135 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

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TABLE 6.2 Partial Effects (a) Green Space – Self-rated Air Pollution Sensitivity Analysis.

Estimated ß (95% CI) for partial effects (a) of green space indicators on physical activity in the 105 structural equation models each with 5000 bootstrap samples.

Greenness						
Distance	**(A) Surrounding Greenness**		**(B) Surrounding Biomass**		**(C) Accessible Greenness**	
100	0.177 (-0.349, 0.687)		0.187 (-0.350, 0.715)		0.075 (-0.427, 0.625)	
200	0.053 (-0.507, 0.654)		0.046 (-0.559, 0.624)		0.013 (-0.649, 0.697)	
300	-0.173 (-0.782, 0.432)		-0.179 (-0.786, 0.444)		-0.171 (-0.874, 0.575)	
400	-0.216 (-0.776, 0.362)		-0.227 (-0.818, 0.345)		-0.458 (-1.243, 0.277)	
500	-0.203 (-0.757, 0.327)		-0.213 (-0.738, 0.350)		-0.530 (-1.299, 0.200)	
600	-0.178 (-0.701, 0.348)		-0.187 (-0.698, 0.317)		-0.522 (-1.232, 0.230)	
700	-0.143 (-0.649, 0.367)		-0.152 (-0.675, 0.378)		-0.428 (-1.124, 0.299)	
800	-0.136 (-0.657, 0.395)		-0.135 (-0.661, 0.358)		-0.345 (-1.065, 0.374)	
900	-0.190 (-0.744, 0.369)		-0.181 (-0.722, 0.369)		-0.317 (-1.041, 0.411)	
1000	-0.187 (-0.733, 0.393)		-0.173 (-0.719, 0.382)		-0.255 (-0.932, 0.496)	
1100	-0.195 (-0.768, 0.377)		-0.174 (-0.741, 0.393)		-0.170 (-0.791, 0.432)	
1200	-0.262 (-0.852, 0.362)		-0.238 (-0.839, 0.344)		-0.178 (-0.930, 0.600)	
1300	-0.297 (-0.907, 0.343)		-0.273 (-0.906, 0.360)		-0.149 (-0.930, 0.663)	
1400	-0.298 (-0.944, 0.341)		-0.276 (-0.911, 0.343)		-0.167 (-0.996, 0.737)	
1500	-0.330 (-0.992, 0.380)		-0.300 (-0.979, 0.389)		-0.242 (-1.103, 0.706)	
Surrounding Green Spaces						
Distance	**(D) Surrounding GS**		**(E) Surrounding GC**		**(F) Surrounding TGS**	
100	0.155 (-0.276, 0.634)		-0.094 (-0.432, 0.245)		-0.080 (-0.399, 0.253)	
200	0.070 (-0.306, 0.451)		-0.240 (-0.517, 0.049)		-0.223 (-0.493, 0.064)	
300	0.021 (-0.276, 0.316)		-0.168 (-0.406, 0.076)		-0.159 (-0.396, 0.080)	
400	0.068 (-0.220, 0.339)		-0.071 (-0.304, 0.171)		-0.066 (-0.302, 0.173)	
500	0.020 (-0.240, 0.278)		0.089 (-0.328, 0.470)		0.092 (-0.289, 0.480)	
600	0.015 (-0.217, 0.247)		0.138 (-0.262, 0.553)		0.141 (-0.266, 0.566)	
700	0.060 (-0.179, 0.322)		0.104 (-0.301, 0.502)		0.107 (-0.286, 0.511)	
800	0.091 (-0.160, 0.368)		0.557 (0.215, 0.910)	*	0.560 (0.236, 0.932)	
900	0.126 (-0.146, 0.419)		**0.611 (0.270, 1.005)**	*	**0.615 (0.277, 0.994)**	*
1000	0.188 (-0.102, 0.487)		0.529 (0.173, 0.918)	*	0.535 (0.173, 0.930)	
1100	0.234 (-0.051, 0.529)		0.125 (-0.255, 0.526)		0.129 (-0.255, 0.512)	
1200	0.267 (-0.046, 0.591)		0.146 (-0.215, 0.516)		0.150 (-0.238, 0.516)	
1300	0.293 (-0.053, 0.635)		0.029 (-0.340, 0.408)		0.032 (-0.361, 0.428)	
1400	0.269 (-0.096, 0.643)		0.023 (-0.364, 0.414)		0.026 (-0.382, 0.386)	
1500	0.171 (-0.194, 0.546)		0.066 (-0.324, 0.475)		0.071 (-0.323, 0.451)	

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TABLE 6.2 Partial Effects (a) Green Space – Self-rated Air Pollution Sensitivity Analysis.

Estimated ß (95% CI) for partial effects (a) of green space indicators on physical activity in the 105 structural equation models each with 5000 bootstrap samples.

Accessible Green Spaces						
Distance	(G) Accessible GS		(H) Accessible GC		(I) Accessible TGS	
100	0.165 (-0.424, 0.719)		0.110 (-0.289, 0.507)		0.109 (-0.276, 0.468)	
200	0.240 (-0.149, 0.653)		-0.013 (-0.293, 0.274)		-0.007 (-0.285, 0.268)	
300	0.112 (-0.265, 0.495)		0.014 (-0.257, 0.300)		0.018 (-0.252, 0.279)	
400	0.049 (-0.319, 0.420)		-0.074 (-0.304, 0.174)		-0.069 (-0.307, 0.172)	
500	0.048 (-0.279, 0.350)		-0.043 (-0.286, 0.206)		-0.039 (-0.269, 0.208)	
600	0.070 (-0.185, 0.333)		0.001 (-0.386, 0.388)		0.005 (-0.389, 0.378)	
700	0.053 (-0.216, 0.328)		0.074 (-0.323, 0.480)		0.077 (-0.289, 0.484)	
800	0.074 (-0.213, 0.397)		0.131 (-0.281, 0.534)		0.134 (-0.297, 0.526)	
900	0.077 (-0.228, 0.394)		0.478 (0.130, 0.836)	*	0.479 (0.134, 0.830)	*
1000	0.082 (-0.236, 0.427)		**0.525 (0.186, 0.890)**	*****	**0.530 (0.182, 0.897)**	*****
1100	0.079 (-0.315, 0.501)		0.467 (0.132, 0.826)	*	0.473 (0.136, 0.830)	*
1200	0.248 (-0.130, 0.668)		0.359 (-0.009, 0.717)		0.365 (0.009, 0.734)	*
1300	0.359 (-0.048, 0.818)		0.380 (0.024, 0.765)	*	0.387 (0.036, 0.752)	*
1400	**0.415 (0.001, 0.873)**	*****	0.297 (-0.074, 0.680)		0.302 (-0.084, 0.671)	
1500	0.413 (0.008, 0.850)	*****	0.015 (-0.386, 0.389)		0.019 (-0.373, 0.401)	

Notes: *Adjusted for sex, age, disabilities, education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *GS: Green Space; GC: Green Corridors; TGS: Total Green Space;* ******* *Coefficient is statistically significant; bold indicates significant highs or lows.*

TABLE 6.3 Indirect Effects (a*b) Green Space – Self-rated Air Pollution – Health Sensitivity Analysis.

Estimated ß (95% CI) for partial effects (a) of green space indicators on physical activity in the 105 structural equation models each with 5000 bootstrap samples.

Greenness						
Distance	(A) Surrounding Greenness		(B) Surrounding Biomass		(C) Accessible Greenness	
100	0.015 (-0.025, 0.077)		0.016 (-0.025, 0.084)		0.006 (-0.038, 0.066)	
200	0.005 (-0.045, 0.069)		0.004 (-0.052, 0.066)		0.001 (-0.061, 0.068)	
300	-0.015 (-0.092, 0.033)		-0.015 (-0.095, 0.031)		-0.015 (-0.101, 0.048)	
400	-0.019 (-0.090, 0.027)		-0.020 (-0.098, 0.023)		-0.040 (-0.147, 0.013)	
500	-0.018 (-0.086, 0.023)		-0.019 (-0.092, 0.023)		-0.046 (-0.154, 0.007)	
600	-0.016 (-0.081, 0.026)		-0.016 (-0.082, 0.025)		-0.045 (-0.148, 0.012)	
700	-0.012 (-0.071, 0.029)		-0.013 (-0.082, 0.030)		-0.037 (-0.136, 0.018)	
800	-0.012 (-0.075, 0.030)		-0.012 (-0.075, 0.028)		-0.030 (-0.127, 0.023)	
900	-0.017 (-0.094, 0.025)		-0.016 (-0.084, 0.028)		-0.028 (-0.124, 0.027)	
1000	-0.016 (-0.084, 0.029)		-0.015 (-0.086, 0.029)		-0.022 (-0.112, 0.034)	
1100	-0.017 (-0.093, 0.028)		-0.015 (-0.086, 0.029)		-0.015 (-0.092, 0.032)	
1200	-0.023 (-0.104, 0.022)		-0.021 (-0.100, 0.023)		-0.015 (-0.103, 0.047)	
1300	-0.026 (-0.109, 0.021)		-0.024 (-0.106, 0.023)		-0.013 (-0.106, 0.060)	
1400	-0.026 (-0.114, 0.020)		-0.024 (-0.112, 0.024)		-0.014 (-0.113, 0.059)	
1500	-0.029 (-0.117, 0.025)		-0.026 (-0.117, 0.025)		-0.021 (-0.125, 0.053)	
Surrounding Green Spaces						
Distance	(D) Surrounding GS		(E) Surrounding GC		(F) Surrounding TGS	
100	0.013 (-0.021, 0.070)		-0.008 (-0.052, 0.020)		-0.007 (-0.046, 0.020)	
200	0.006 (-0.027, 0.050)		-0.021 (-0.062, 0.001)		-0.020 (-0.062, 0.001)	
300	0.002 (-0.025, 0.034)		-0.015 (-0.051, 0.004)		-0.014 (-0.049, 0.004)	
400	0.006 (-0.017, 0.039)		-0.006 (-0.035, 0.014)		-0.006 (-0.035, 0.014)	
500	0.002 (-0.021, 0.029)		0.008 (-0.024, 0.056)		0.008 (-0.022, 0.053)	
600	0.001 (-0.020, 0.026)		0.012 (-0.018, 0.066)		0.012 (-0.016, 0.067)	
700	0.005 (-0.015, 0.037)		0.009 (-0.022, 0.058)		0.009 (-0.021, 0.060)	
800	0.008 (-0.012, 0.043)		0.047 (0.009, 0.112)	*	0.047 (0.010, 0.112)	
900	0.011 (-0.010, 0.050)		**0.053 (0.013, 0.121)**	*****	**0.053 (0.013, 0.127)**	*****
1000	0.016 (-0.004, 0.061)		0.046 (0.010, 0.116)	*	0.046 (0.009, 0.112)	
1100	0.020 (-0.001, 0.065)		0.011 (-0.019, 0.061)		0.011 (-0.019, 0.057)	
1200	0.023 (-0.001, 0.070)		0.013 (-0.016, 0.060)		0.013 (-0.016, 0.061)	
1300	0.025 (-0.001, 0.082)		0.002 (-0.032, 0.043)		0.003 (-0.032, 0.044)	
1400	0.023 (-0.004, 0.079)		0.002 (-0.034, 0.042)		0.002 (-0.034, 0.038)	
1500	0.015 (-0.012, 0.064)		0.006 (-0.028, 0.050)		0.006 (-0.027, 0.052)	

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TABLE 6.3 Indirect Effects (a*b) Green Space – Self-rated Air Pollution – Health Sensitivity Analysis.

Estimated ß (95% CI) for partial effects (a) of green space indicators on physical activity in the 105 structural equation models each with 5000 bootstrap samples.

Accessible Green Spaces						
Distance	(G) Accessible GS		(H) Accessible GC		(I) Accessible TGS	
100	0.014 (-0.032, 0.082)		0.009 (-0.023, 0.058)		0.009 (-0.022, 0.053)	
200	0.020 (-0.007, 0.079)		-0.001 (-0.029, 0.026)		-0.001 (-0.029, 0.026)	
300	0.010 (-0.020, 0.057)		0.001 (-0.026, 0.032)		0.002 (-0.023, 0.030)	
400	0.004 (-0.028, 0.044)		-0.006 (-0.033, 0.013)		-0.006 (-0.033, 0.014)	
500	0.004 (-0.024, 0.039)		-0.004 (-0.032, 0.017)		-0.003 (-0.030, 0.018)	
600	0.006 (-0.015, 0.036)		0.000 (-0.037, 0.038)		0.000 (-0.038, 0.038)	
700	0.005 (-0.018, 0.038)		0.006 (-0.026, 0.049)		0.007 (-0.023, 0.055)	
800	0.006 (-0.017, 0.046)		0.011 (-0.020, 0.066)		0.011 (-0.021, 0.063)	
900	0.007 (-0.018, 0.046)		0.040 (0.006, 0.098)	*	0.040 (0.006, 0.101)	*
1000	0.007 (-0.019, 0.048)		**0.044 (0.009, 0.108)**	*****	**0.044 (0.008, 0.110)**	*****
1100	0.007 (-0.026, 0.055)		0.039 (0.007, 0.101)	*	0.040 (0.007, 0.101)	*
1200	0.021 (-0.006, 0.080)		0.031 (0.002, 0.089)	*	0.031 (0.002, 0.092)	*
1300	0.030 (0.000, 0.100)		0.033 (0.003, 0.092)	*	0.033 (0.004, 0.098)	*
1400	**0.035 (0.002, 0.105)**	*****	0.026 (-0.002, 0.085)		0.026 (-0.002, 0.082)	
1500	0.035 (0.002, 0.100)	*	0.001 (-0.036, 0.041)		0.002 (-0.035, 0.043)	

Notes: *Adjusted for sex, age, disabilities, education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *GS: Green Space; GC: Green Corridors; TGS: Total Green Space;*
******* *Coefficient is statistically significant; bold indicates significant highs or lows.*

6.3.3 Direct effects – How green space indicators relate to health

The direct effects, factually adjusted for air pollution, showed clear patterns of proximity and differed by the assessed green space characteristic (Table 6.4). Surrounding greenness (Fig 6.6A) showed a positive association in immediate distances, although not significant and a significant plateau for distances for intermediate distances of 600-900m, reaching its maximum at 700m (ß: 0.566; CI: 0.064, 1.051). Cumulative surrounding greenness (Fig 6.6B) behaved almost identically with somewhat higher estimates. On the contrary, accessible greenness (Fig 6.6C) was not associated with direct health effects at any distance but showed an increasing pattern from 500-1400m distance. Surrounding green spaces (Fig 6.6D) showed two significant positive peaks. The first is in the immediate surroundings at 200m (ß: 0.427; CI: 0.064, 0.813). The second is at intermediate distances of 700-900m, with a peak at 800m (ß: 0.340; CI: 0.020, 0.662). Surrounding green corridors (Fig 6.6E) and total green space (Fig 6.56F) showed an identical pattern with significant positive associations at 400-600m, very similar estimates and a maximum at 600m (ß: 0.560; CI: 0.096, 1.156). Both indicators then turned negative with a non-significant low at 1300m distance (ß: -0.428; CI: -0.876, 0.013). Accessible green spaces (Fig 6.6G) showed a similar pattern to surrounding green spaces but with no significant associations and less strong estimates. Accessible green corridors (Fig 6.6H) showed a sharp one-peak pattern at 900m (ß: 0.664; CI: 0.186, 1.257). Accessible total green spaces (Fig 6.6I) behaved very similarly, with somewhat lower estimates. The overall strongest association was found for accessible green corridors at 900m (ß: 0.664; CI: 0.186, 1.257) (Fig 6.6H). Similar to the peak of the partial effects, the investigation of the correlation matrix showed the expected strong collinearity between nested green space characteristics (A & B; D, E, H & I) (Table A6.5). However, we found a weak to moderate correlation to other green space characteristics for surrounding greenness (0.17-0.28), surrounding green space at 200m (0.09-0.49) and 800m (0.28-0.49), and surrounding green corridors (0.11-0.42). This suggests partially independent mechanisms to health for greenness, green space and green corridors at intermediate distances, as well as green spaces in immediate distances to health.

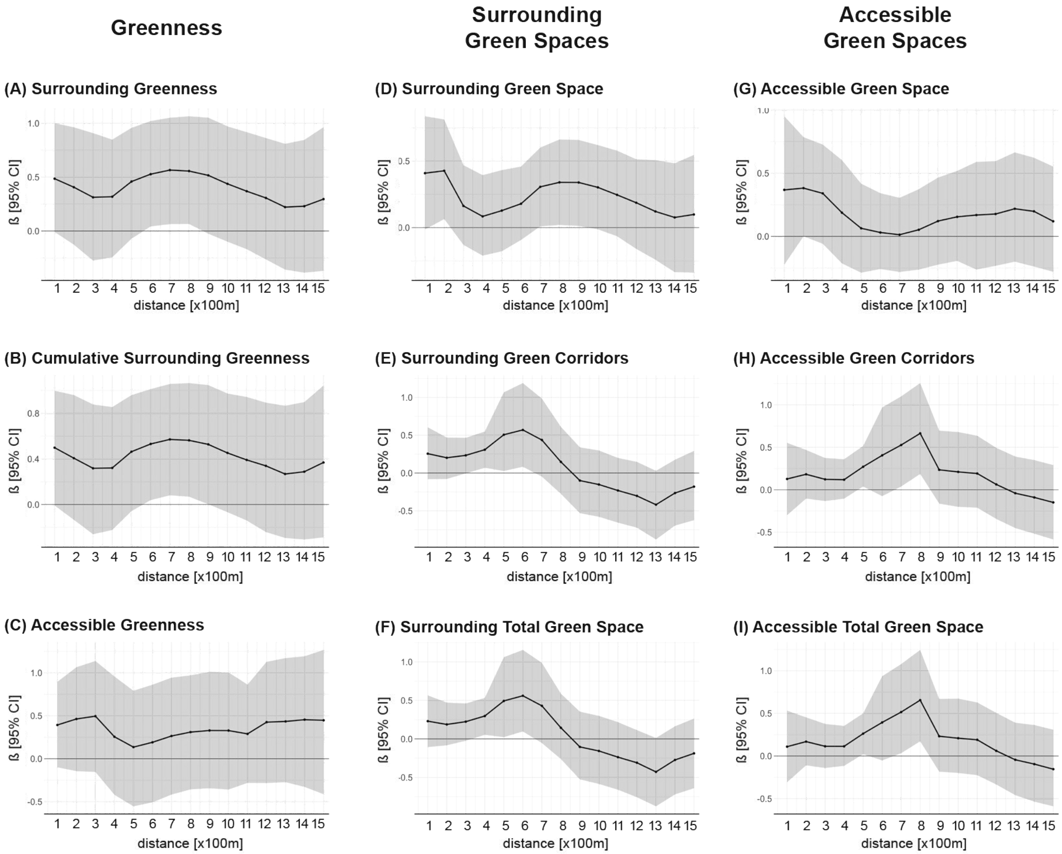

FIG. 6.6 Direct Effects (c) Green Space – Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 135 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

6.3.4 Total effects – How green space indicators, directly and indirectly, related to health

The total effects (direct + indirect effects) in the structural equation, acted similarly to the direct effects (Fig 6.7, Table 6.5), due to the larger effect size in the direct associations (maximum ß 0.664) and the indirect associations (maximum ß 0.053). The overall strongest association was found for accessible green corridors at 800m (ß: 0.675; CI: 0.191, 1.269).

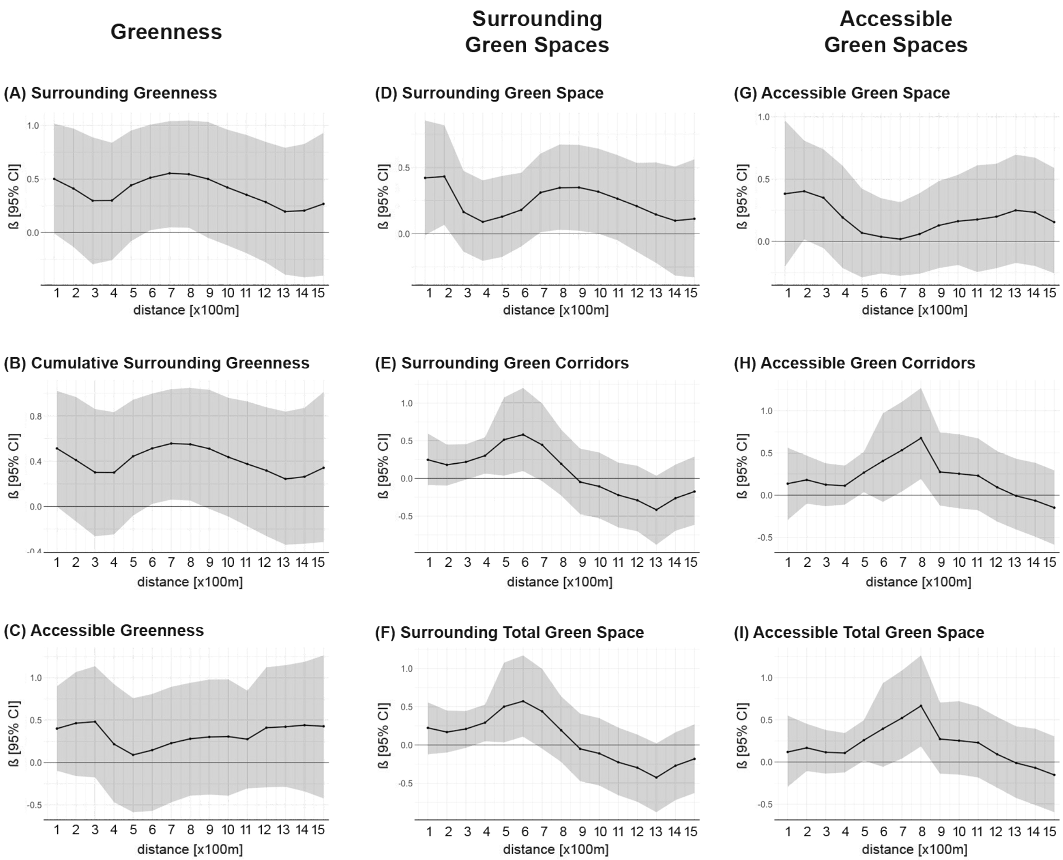

FIG. 6.7 Total Effects (a*b+c) Green Space – Self-rated Air Pollution - Health Sensitivity Analysis. Standardized Estimated ß (95% CI) of the 135 structural equation models; adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city. 5000 Bootstrap Samples, shaded grey area show 95% confidence interval.

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TABLE 6.4 Direct Effects (c) Green Space – Health Sensitivity Analysis.

Estimated ß (95% CI) for partial effects (a) of green space indicators on physical activity in the 105 structural equation models each with 5000 bootstrap samples.

Greenness						
Distance	(A) Surrounding Greenness		(B) Surrounding Biomass		(C) Accessible Greenness	
100	0.486 (-0.009, 1.001)		0.499 (-0.009, 0.999)		0.393 (-0.100, 0.895)	
200	0.407 (-0.127, 0.963)		0.407 (-0.134, 0.961)		0.462 (-0.145, 1.065)	
300	0.313 (-0.274, 0.909)		0.318 (-0.261, 0.878)		0.495 (-0.154, 1.138)	
400	0.318 (-0.244, 0.848)		0.321 (-0.224, 0.855)		0.256 (-0.420, 0.957)	
500	0.459 (-0.072, 0.957)		0.463 (-0.059, 0.960)		0.135 (-0.555, 0.791)	
600	0.528 (0.042, 1.020)	*	0.531 (0.039, 1.013)		0.191 (-0.508, 0.862)	
700	**0.566 (0.064, 1.051)**	*	**0.571 (0.081, 1.058)**	*	0.265 (-0.418, 0.944)	
800	0.556 (0.065, 1.065)	*	0.563 (0.069, 1.066)	*	0.310 (-0.357, 0.970)	
900	0.517 (-0.025, 1.052)		0.528 (0.003, 1.048)	*	0.328 (-0.344, 1.013)	
1000	0.438 (-0.099, 0.971)		0.453 (-0.067, 0.974)		0.328 (-0.359, 1.005)	
1100	0.370 (-0.169, 0.917)		0.391 (-0.140, 0.944)		0.289 (-0.282, 0.863)	
1200	0.307 (-0.263, 0.863)		0.339 (-0.242, 0.894)		0.426 (-0.283, 1.128)	
1300	0.222 (-0.358, 0.809)		0.268 (-0.293, 0.867)		0.434 (-0.274, 1.171)	
1400	0.230 (-0.387, 0.846)		0.288 (-0.307, 0.899)		0.454 (-0.329, 1.193)	
1500	0.296 (-0.370, 0.963)		0.369 (-0.288, 1.044)		0.447 (-0.413, 1.267)	
Surrounding Green Spaces						
Distance	(D) Surrounding GS		(E) Surrounding GC		(F) Surrounding TGS	
100	0.409 (-0.014, 0.836)		0.256 (-0.082, 0.605)		0.231 (-0.107, 0.566)	
200	**0.427 (0.064, 0.813)**	*	0.201 (-0.079, 0.469)		0.188 (-0.083, 0.472)	
300	0.163 (-0.130, 0.469)		0.233 (-0.005, 0.465)		0.224 (-0.024, 0.460)	
400	0.084 (-0.211, 0.394)		0.308 (0.069, 0.548)	*	0.297 (0.053, 0.532)	*
500	0.128 (-0.178, 0.432)		0.506 (0.026, 1.067)	*	0.493 (0.023, 1.062)	*
600	0.179 (-0.093, 0.459)		**0.569 (0.082, 1.189)**	*	**0.560 (0.096, 1.156)**	*
700	0.306 (0.009, 0.601)		0.436 (-0.048, 0.985)		0.430 (-0.053, 0.989)	
800	**0.340 (0.020, 0.662)**	*	0.147 (-0.276, 0.611)		0.145 (-0.262, 0.588)	
900	0.339 (0.012, 0.658)	*	-0.100 (-0.531, 0.340)		-0.104 (-0.526, 0.354)	
1000	0.302 (-0.013, 0.620)		-0.152 (-0.579, 0.298)		-0.157 (-0.585, 0.300)	
1100	0.246 (-0.065, 0.578)		-0.231 (-0.657, 0.200)		-0.237 (-0.660, 0.218)	
1200	0.187 (-0.160, 0.513)		-0.303 (-0.724, 0.147)		-0.310 (-0.758, 0.114)	
1300	0.121 (-0.242, 0.507)		-0.419 (-0.880, 0.029)		-0.428 (-0.876, 0.013)	
1400	0.076 (-0.335, 0.483)		-0.265 (-0.696, 0.176)		-0.273 (-0.721, 0.164)	
1500	0.099 (-0.339, 0.546)		-0.180 (-0.624, 0.292)		-0.188 (-0.640, 0.264)	

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TABLE 6.4 Direct Effects (c) Green Space – Health Sensitivity Analysis.

Estimated ß (95% CI) for partial effects (a) of green space indicators on physical activity in the 105 structural equation models each with 5000 bootstrap samples.

Accessible Green Spaces						
Distance	(G) Accessible GS		(H) Accessible GC		(I) Accessible TGS	
100	0.368 (-0.224, 0.951)		0.127 (-0.300, 0.552)		0.109 (-0.308, 0.532)	
200	0.382 (0.000, 0.786)		0.182 (-0.105, 0.469)		0.168 (-0.110, 0.453)	
300	0.341 (-0.058, 0.727)		0.123 (-0.134, 0.374)		0.114 (-0.141, 0.376)	
400	0.188 (-0.214, 0.604)		0.118 (-0.105, 0.360)		0.113 (-0.116, 0.353)	
500	0.064 (-0.288, 0.418)		0.271 (0.038, 0.516)	*	0.262 (0.021, 0.500)	*
600	0.031 (-0.258, 0.342)		0.405 (-0.076, 0.969)		0.394 (-0.052, 0.935)	
700	0.013 (-0.282, 0.305)		0.527 (0.038, 1.100)	*	0.515 (0.032, 1.078)	*
800	0.052 (-0.263, 0.374)		**0.664 (0.186, 1.257)**	*	**0.655 (0.172, 1.244)**	*
900	0.121 (-0.224, 0.465)		0.235 (-0.164, 0.696)		0.232 (-0.185, 0.669)	
1000	0.155 (-0.194, 0.519)		0.210 (-0.202, 0.680)		0.209 (-0.199, 0.673)	
1100	0.169 (-0.263, 0.590)		0.191 (-0.212, 0.636)		0.190 (-0.225, 0.628)	
1200	0.177 (-0.233, 0.596)		0.063 (-0.345, 0.494)		0.061 (-0.334, 0.506)	
1300	0.219 (-0.200, 0.665)		-0.041 (-0.452, 0.391)		-0.045 (-0.460, 0.390)	
1400	0.198 (-0.239, 0.623)		-0.091 (-0.518, 0.350)		-0.095 (-0.536, 0.364)	
1500	0.119 (-0.280, 0.553)		-0.150 (-0.587, 0.291)		-0.155 (-0.591, 0.308)	

Notes: *Adjusted for sex, age, disabilities, education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *GS: Green Space; GC: Green Corridors; TGS: Total Green Space;* ***** *Coefficient is statistically significant; bold indicates significant highs or lows.*

TABLE 6.5 Total Effects (a*b+c) Green Space – Self-rated Air Pollution – Health Sensitivity Analysis.

Estimated ß (95% CI) for partial effects (a) of green space indicators on physical activity in the 105 structural equation models each with 5000 bootstrap samples.

Greenness						
Distance	(A) Surrounding Greenness		(B) Surrounding Biomass		(C) Accessible Greenness	
100	0.501 (-0.009, 1.017)		0.514 (-0.001, 1.024)		0.399 (-0.098, 0.899)	
200	0.411 (-0.134, 0.971)		0.411 (-0.133, 0.970)		0.464 (-0.160, 1.067)	
300	0.298 (-0.296, 0.888)		0.302 (-0.264, 0.863)		0.481 (-0.176, 1.136)	
400	0.300 (-0.258, 0.839)		0.301 (-0.247, 0.836)		0.216 (-0.469, 0.923)	
500	0.441 (-0.080, 0.953)		0.445 (-0.080, 0.946)		0.089 (-0.587, 0.758)	
600	0.512 (0.022, 1.008)	*	0.515 (0.023, 1.000)	*	0.146 (-0.572, 0.808)	
700	**0.553 (0.048, 1.040)**	*	**0.558 (0.061, 1.040)**	*	0.228 (-0.471, 0.893)	
800	0.545 (0.046, 1.046)	*	0.551 (0.052, 1.050)	*	0.280 (-0.392, 0.939)	
900	0.500 (-0.049, 1.033)		0.512 (-0.021, 1.034)		0.301 (-0.379, 0.979)	
1000	0.421 (-0.119, 0.961)		0.438 (-0.089, 0.963)		0.305 (-0.392, 0.981)	
1100	0.353 (-0.193, 0.911)		0.376 (-0.175, 0.930)		0.274 (-0.306, 0.847)	
1200	0.284 (-0.279, 0.847)		0.318 (-0.262, 0.879)		0.410 (-0.293, 1.123)	
1300	0.196 (-0.393, 0.792)		0.244 (-0.339, 0.841)		0.421 (-0.287, 1.147)	
1400	0.204 (-0.418, 0.827)		0.264 (-0.330, 0.874)		0.440 (-0.341, 1.187)	
1500	0.267 (-0.403, 0.930)		0.343 (-0.314, 1.013)		0.426 (-0.424, 1.263)	
Surrounding Green Spaces						
Distance	(D) Surrounding GS		(E) Surrounding GC		(F) Surrounding TGS	
100	0.422 (-0.009, 0.855)		0.247 (-0.088, 0.596)		0.224 (-0.121, 0.557)	
200	**0.433 (0.068, 0.820)**	*	0.180 (-0.096, 0.450)		0.168 (-0.099, 0.451)	
300	0.165 (-0.135, 0.475)		0.218 (-0.016, 0.454)		0.210 (-0.038, 0.444)	
400	0.090 (-0.204, 0.404)		0.302 (0.064, 0.546)	*	0.292 (0.048, 0.528)	*
500	0.129 (-0.175, 0.437)		0.514 (0.037, 1.073)	*	0.501 (0.033, 1.076)	*
600	0.180 (-0.096, 0.461)		**0.581 (0.098, 1.201)**	*	**0.572 (0.109, 1.171)**	*
700	0.311 (0.012, 0.606)	*	0.445 (-0.036, 0.996)		0.439 (-0.048, 0.995)	
800	0.348 (0.031, 0.674)	*	0.194 (-0.228, 0.649)		0.192 (-0.222, 0.636)	
900	**0.350 (0.023, 0.671)**	*	-0.048 (-0.475, 0.395)		-0.051 (-0.472, 0.409)	
1000	0.318 (0.002, 0.644)	*	-0.107 (-0.529, 0.345)		-0.110 (-0.530, 0.352)	
1100	0.266 (-0.049, 0.594)		-0.221 (-0.650, 0.211)		-0.225 (-0.657, 0.228)	
1200	0.209 (-0.135, 0.536)		-0.290 (-0.702, 0.167)		-0.297 (-0.742, 0.136)	
1300	0.146 (-0.219, 0.539)		-0.416 (-0.881, 0.036)		-0.425 (-0.879, 0.021)	
1400	0.099 (-0.316, 0.508)		-0.263 (-0.695, 0.183)		-0.271 (-0.721, 0.166)	
1500	0.113 (-0.329, 0.562)		-0.174 (-0.616, 0.290)		-0.182 (-0.628, 0.270)	

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TABLE 6.5 Total Effects (a*b+c) Green Space – Self-rated Air Pollution – Health Sensitivity Analysis.

Estimated ß (95% CI) for partial effects (a) of green space indicators on physical activity in the 105 structural equation models each with 5000 bootstrap samples.

Accessible Green Spaces						
Distance	(G) Accessible GS		(H) Accessible GC		(I) Accessible TGS	
100	0.382 (-0.203, 0.970)		0.136 (-0.294, 0.561)		0.119 (-0.294, 0.551)	
200	**0.402 (0.016, 0.809)**	*	0.181 (-0.101, 0.469)		0.168 (-0.108, 0.454)	
300	0.350 (-0.054, 0.740)		0.124 (-0.131, 0.377)		0.115 (-0.138, 0.380)	
400	0.192 (-0.214, 0.607)		0.112 (-0.112, 0.350)		0.107 (-0.124, 0.344)	
500	0.068 (-0.289, 0.424)		0.267 (0.035, 0.513)	*	0.259 (0.016, 0.497)	
600	0.037 (-0.258, 0.347)		0.405 (-0.080, 0.969)		0.394 (-0.057, 0.935)	
700	0.018 (-0.277, 0.314)		0.533 (0.043, 1.106)	*	0.522 (0.040, 1.086)	
800	0.059 (-0.260, 0.387)		**0.675 (0.191, 1.269)**	*	**0.666 (0.185, 1.265)**	
900	0.128 (-0.215, 0.484)		0.275 (-0.124, 0.743)		0.272 (-0.139, 0.706)	
1000	0.162 (-0.190, 0.534)		0.254 (-0.157, 0.721)		0.253 (-0.149, 0.721)	
1100	0.176 (-0.246, 0.610)		0.230 (-0.179, 0.672)		0.230 (-0.183, 0.659)	
1200	0.198 (-0.215, 0.623)		0.093 (-0.313, 0.521)		0.092 (-0.305, 0.535)	
1300	0.249 (-0.173, 0.696)		-0.008 (-0.407, 0.431)		-0.011 (-0.427, 0.423)	
1400	0.234 (-0.198, 0.672)		-0.065 (-0.493, 0.384)		-0.069 (-0.510, 0.396)	
1500	0.155 (-0.255, 0.590)		-0.148 (-0.588, 0.294)		-0.153 (-0.596, 0.305)	

Notes: *Adjusted for sex, age, disabilities, education, income, occupation, years lived in the neighbourhood, main roads area within 500m buffer, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *GS: Green Space; GC: Green Corridors; TGS: Total Green Space;* ***** *Coefficient is statistically significant; bold indicates significant highs or low.*

6.4 Discussion

6.4.1 Main findings

Our comprehensive and rigorous sensitivity analysis examined 135 structural equation models to unveil differences in the associations between green space air pollution nuisance and health, depending on green space characteristics and their proximity to a person's home. In our study, only two green space characteristics were associated with indirect health effects through lower experienced air pollution. First, the area of green corridors measured in intermediate surroundings of 800 m – 1,000 m was significantly related to lower experienced air pollution and indirect health effects. Second, accessible green spaces were also associated with lower self-rated air pollution and indirect health effects at network distances of 1400-1500m. Interestingly, we did not find a significant association between any tested greenness variable and air pollution. Our results support the theory that to mitigate air pollution through deposition, dispersion and absorption of air pollutants, green space connectivity seems to be an important characteristic.

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

6.4.2 Connectivity of green spaces and self-rated air pollution

Our results confirm our hypothesis that the connectivity of green spaces is an important characteristic of this pathway and is best detectable in Euclidean distances. Furthermore, mainly green space corridors at medium distances (800-1,300m depending on the indicator) were associated with self-rated air pollution and indirect health effects, which is in line with a recent study based

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

6.4.3 Greenness and self-rated air pollution

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

Another influential factor for the contradicting results might be related to the fragmentation of green spaces. Although the following studies gathered by Dzhambov et al (2020) that were able to detect a mediation effect looked at a variety of different health outcomes, they share the similarity of a 30x30m resolution or

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lower to calculate the NDVI values (Chang et al., 2020; Crous-Bou et al., 2020; Dadvand, Sunyer, et al., 2012; A. M. Dzhambov, Hartig, et al., 2018; Gascon et al., 2018; James et al., 2016; Klompmaker, Hoek, et al., 2019; Klompmaker, Janssen, et al., 2019; Laurent et al., 2013, 2019; Liao et al., 2019; Y. Liu et al., 2019; Orioli et al., 2019; Thiering et al., 2016; Wang et al., 2019; Xiao et al., 2020; Yang et al., 2019, 2020). It has been shown that these resolutions are unable to detect smaller green spaces (Markevych et al., 2017). Since small fragmented green spaces might even increase secondary air pollutants (PM2.5 and O3) and create negative links to health (Shen & Lung, 2017) not including those might explain these differences, This is also in line with similar results in a recent study which used 10x10 m resolution and was not able to detect a significant mediation between greenness, air pollution and self-rated health (A. M. Dzhambov et al., 2023). Similarly, including those smaller green spaces with an NDVI based on a 10x10 m resolution in our study might have led to health trade-offs and resulted in insignificant findings. This further suggests that the connectivity of green spaces seems to be an important characteristic that enables green spaces to reduce air pollution inconvenience.

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

Another reason for our non-significant findings might be the validity of our air pollution variable, which might be not precise enough to detect associations with greenness (see 4.6 Strength and limitations). Especially since a recent study based on 2,615 monitoring stations from Venter and colleagues suggests that the air pollution mitigation effect of trees is only moderate at best and highly variable (Venter et al., 2024). In addition, there could be trade-offs with negative greenness effects like pollen, entrapment of pollution in green canyons, or unmeasured confounders like atopy, essentially masking the beneficial effect of greenness on air pollution.

6.4.4 Green space characteristics and higher perceived air pollution

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

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

6.4.5 Green space health effects associated with other mechanisms

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

6.4.6 Strengths and limitations

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

However, the scale and complexity of this study design also come with limitations. As we used just-identified models with 0 degrees of freedom, we can only judge the quality of the models based on theory, but not with model fit indices, as for this an over-identified model would be needed. In addition, our study design limited the ability to examine the results in more detail for possible effect modification, although different vulnerabilities to air pollution in age groups are to be expected. Another potential limitation arises from not explicitly addressing non-linear relationships between green space characteristics, self-rated air pollution, and self-rated health, which may have led to an oversimplification of the complex relationships. In general, the reduced model complexity leads to limited precision in the examined mechanisms and should be treated accordingly.

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

In addition, our study relies heavily on survey data, which is associated with the uncertainties of self-reported data such as social desirability, recall or reporting bias. In particular, self-reported air pollution variables have been associated with inaccuracies through the influence of visual perception and socio-demographic variables (Brody et al., 2004; Cobbold et al., 2022; Guo et al., 2016). Similarly, Pelgrims and colleagues found inaccuracies in self-rated air pollution alone, but a reasonable classification of relative exposure levels in their models, once they included socioeconomic status and other contextual factors (2022). Although we are confident that our self-rated air pollution variable is equally robust, since we followed a similar approach, it is important to acknowledge this potential limitation. Furthermore, in our analysis of the indirect pathway to health, the self-rated air pollution variable might lead to reverse causation. Although we did adjust for disabilities and addressed this issue partially, not all health issues were captured in this proxy which means we cannot rule out that people with chronic illnesses reported higher air pollution than those without (Pantavou et al., 2018; Piro et al., 2008). Moreover, our one-item question on health only allows for an interpretation towards general health overall, and not to specific health concerns like respiratory diseases. The relation to respiratory-specific health outcomes may be stronger (Mueller et al., 2022). Lastly, the study employed a cross-sectional design, which precludes establishing causal relationships between green space, self-rated air pollution and health outcomes.

6.4.7 Further research avenues and implications

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

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

6.5 Conclusion

We investigated nine green space indicators in 15 distances to get insights into how the proximity to and the characteristics of green spaces influence air pollution annoyance and in turn self-rated health. Our results indicate that it is mainly the connectivity of green spaces, measured in intermediate Euclidean distances (800 – 1,000 m), that may lead to lower air pollution annoyance. Interestingly, we did not find any greenness indicators that were able to influence self-rated air pollution, in line with recent studies that suggest a complex and minimal role of air pollution mitigation of greenness. Although our study is limited to European satellite districts and relies on self-reported air pollution, it supports the available evidence that the connectivity of green spaces may be an important green space characteristic when it comes to reducing air pollution in cities. With this, our study adds important insights into how green spaces should be planned and implemented in cities, essentially calling for a connected system of green spaces instead of fragmented smaller parks, to reduce air pollution annoyance and in turn improve the overall health of their residents.

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7 Conclusion & Recommendations

7.1 Introduction

This doctoral research explored and evaluated the role of green space characteristics and their proximity to residents in mitigating the global disease burden of non-communicable diseases (NCDs). The focus was on the impact of green spaces on physical activity, air pollution and social cohesion which in turn are hypothesized to contribute to NCDs.

Current research in this field lacks consistency in evaluating the role of green space characteristics and their proximity to residents in influencing NCD risk factors. This limits the ability to transfer green space health evidence into informed urban design. The existing literature shows variability in the definition of green space – if defined at all - and chosen buffer distances and types, leading to inconsistent and incomparable findings. This complexity is further exacerbated by differing impact pathways grounded in various monodisciplinary theories that still need to be synthesized into a cohesive interdisciplinary research framework for meta-analyses and further advancements. To address these challenges, this doctoral research has pursued the following objectives:

1. Consolidating monodisciplinary knowledge into a common theoretical framework to address existing fragmentation in the research field.
2. Conceptualizing a research design capable of capturing multidimensional and multiscale variables for extensive sensitivity analyses.
3. Studying the proximity and characteristics of green spaces in the following impact pathways:
   a. Green space - physical activity - health
   b. Green space - social cohesion - mental health
   c. Green space - air pollution – health

This concluding chapter provides a comprehensive synthesis of the findings of the individual chapters to answer the main research question of **"How do the proximity to and characteristics of green spaces affect pathways to human health?"**. It concludes by offering recommendations for future research, urban planning practitioners, and decision-makers.

7.2 Summary of the Main Results

SUB-RQ1:

What is the current state of knowledge in the related research fields and what are common risks of bias?

Chapter 2, presented an overview of the current state of knowledge in the research field and synthesised available knowledge into a structured reporting guideline. It specifically built on recent reviews and the foundational paper of Markevych et al (2017), which itself had a predecessor with Hartig & Frumkin (2014). While the role of the chapter in the dissertation was to set up a foundational theoretical framework and methodological assistance, the publication also addressed a frequent demand from the field to upscale the quality and robustness of studies (Browning et al., 2022; Davis et al., 2021; R. Zhang et al., 2021).

The developed checklist guides researchers from the research question to a precise definition of green space, depending on the dominant mechanistic pathway, to an appropriate approach to scope, green space indicators, and inclusion of important contextual variables. PRIGSHARE has the potential to support reducing the heterogeneity in assessment and outcomes which will advance the overall understanding of green space health pathways. In summary, PRIGSHARE's flow of assessment illustrates how different mechanistic pathways translate into different decisions regarding assessment methods and chosen variables. This synthesized guideline will make it easier to categorize and compare studies if adopted by other researchers, and potentially streamline the assessment by pathway thus fostering review quality through comparability and available meta-information. Lastly, it indicates that one green space indicator is not enough to investigate all impact pathways and confirms the necessity of sensitivity analysis in tested distances (item 6 of the guideline) and green space characteristics (items 7 and 14) to advance the research field.

SUB- RQ2:

How to reduce the barriers in the field for sensitivity analysis?

In **Chapter 3** the free and open-source script for QGIS is described. This tool was developed to guide non-spatial disciplines to automatically assess a variety of green space characteristics. Currently, the required expert knowledge, the sheer amount of tasks, and the computation time needed to be able to do a sensitivity analysis is a barrier in the field, especially for non-spatial disciplines (Markevych et al., 2017).

AID-PRIGSHARE has the potential to significantly impact the research field of green space and health by enabling a feasible spatial sensitivity analysis. This drastically reduces the effort needed to calculate these indicators and makes it feasible to compare different types of green space indicators and to analyse the area of effect of green space indicators on health outcomes by comparing different buffer sizes. The tool automates and combines over 400 GIS processes to generate a variety of green space indicators, for multiple types of indicators and distances ranging from 100m to 1500m, every 100m, in one algorithm. It has the potential to lead to a more interdisciplinary approach to research in this field, which can result in more comprehensive and nuanced findings. In addition, it might also enable post-hoc sensitivity analysis of already published studies to further explore the robustness of those findings and contribute to reducing and explaining the current heterogeneity in findings in green space health research. Overall, AID-PRIGSHARE has the potential to greatly benefit the research field of green space and health by streamlining research processes and facilitating interdisciplinary collaboration.

SUB-RQ3:

How are proximity and characteristics of green spaces related to physical activity and health?

Chapter 4, analysed and compared 105 structural equation models to answer how proximity and green space characteristics influence the mechanistic pathway from green space to health through physical activity. The study indicates that greenness in immediate proximity (100 m), as well as green space, green corridors reachable within a 10-minute walk (up to 800 m distance), and green space uses up to 1000 m are significantly associated with higher physical activity and indirect health effects.

Together, the findings add to the body of evidence that suggests a positive relationship between nearby green space, physical activity, and general health (Luo et al., 2020; Markevych et al., 2017; Yang et al., 2021), and they show in more detail how and where these relationships might occur. The findings also suggest that more greenness might not always be beneficial for physical activity and health if it is not accessible. Two of the green space characteristics, surrounding greenness and quantity of green spaces uses measured in a larger environment, were negatively associated with physical activity. This is hypothesized to be either through the car-dependant lifestyle prevalent in these satellite districts (Chandrabose et al., 2022; Kleinert & Horton, 2016; Sallis et al., 2016) or through peer-behaviour influence on physical activity levels (Finnerty et al., 2010; Tucunduva Philippi et al., 2016). More research is needed to examine this negative relationship.

SUB- RQ4:

How are proximity and characteristics of green spaces related to social cohesion and mental health?

Chapter 5 again analysed the aforementioned dataset – this time under the perspective of the mechanistic pathway through social cohesion and indirectly on mental health. The study found evidence for small indirect associations of neighbourhood green spaces on mental health via social cohesion, but not for positive direct effects. Significant associations were detected for accessible greenness (which includes street vegetation, but not private gardens) measured in larger catchment areas between 900-1,400 m, green corridors in intermediate distances (300-800 m) and mix of green space uses in 700-1,300 m catchment. Fourth, while the indirect effects were rather small, the same green space characteristics showed strong associations with social cohesion.

The results shed light on the complex relationship between neighbourhood green spaces, social cohesion and mental health. They suggest a strong relationship between neighbourhood green spaces and social cohesion, but only small indirect effects on mental health, which highlight two specific aspects of green space mental health research. First, it is expected that the differences from other studies in the field are due to the unmeasured active direct contact with nature, which supposedly drives most of the green space mental health pathways. Furthermore, the study used a positive mental health scale, which is different from other studies that used mental illness or specific mental health characteristics as their mental health outcome variable. This suggests that passive contact with nature, by pure surroundings, is not enough to trigger positive mental health benefits directly, but indirectly through social cohesion. Furthermore, a negative direct association between green corridors or total green space and mental health at distances of 1000-1500m was found, which we hypothesize to be reverse causation, meaning that people with on average poorer mental health live in neighbourhoods that are greener, which could potentially be the case in our satellite neighbourhoods with lots of green space and multi-story housing.

SUB- RQ5:

How are proximity and characteristics of green spaces related to air pollution and health?

Chapter 6 seeks to answer how green space characteristics and their proximity to individual homes influence the perceived air pollution mitigation pathway. For this study, the AID-PRIGSHARE algorithm was adapted to capture more greenness and green space indicators instead of green uses. The results suggest that air pollution mitigation mainly happens through green corridors in 800-1,000 m surrounding.

The results offer a nuanced perspective on previous findings in the field, suggesting that a widely connected green space area helps with dispersion and acts as a barrier to the deposition of air pollutants. In contrast, smaller fragmented green spaces showed no association in the study, which supports the findings of Shen and Lung (Shen & Lung, 2017), who even found harmful effects of fragmented green spaces through increased secondary pollutants. Furthermore, the study showed comparable negative associations for immediate greenness and green corridors, which could be related to the same effects of volatile organic compounds that can form air pollution (Duan et al., 2023; Gu et al., 2021), but also be related to the dispersion of pollen (Marselle et al., 2021). Both effects might be especially noticeable at close distances. In general, this study supports the theory that mainly green space corridors contribute effectively to air pollution mitigation.

7.3 Answering the main research question

7.3.1 Green Space Characteristics

The results show that **greenness** reacts differently to the impact pathways and is very sensitive to proximity (Figure 7.1). In particular, only greenness in immediate proximity (100 m) seems to invite physical activity and only greenness measured in neighbourhood distances (800 – 1,400 m) was associated with increased social cohesion. Similarly, other health effects (path c in studies) were only detectable in walkable to neighbourhood proximity (600-1,400 m), which we hypothesize to be mainly mitigation effects such as heat or noise mitigation due to the intermediate distance in which they occur. Self-assessed air pollution was not associated with the degree of vegetation. Negative effects might occur, especially at the neighbourhood level (900-1,400 m), where a high level of greenness was associated with physical inactivity, although not significant. In summary, neighbourhood greenness seems to be an important green space characteristic to consider to mitigate the risk of NCDs, although many of the potential positive mechanisms were not specifically studied in this doctoral research (path c in studies).

In the Instoration pathway, **accessibility of greenness and green space** seems to be an important characteristic according to the results (Figure 7.2-7.3). For the degree of vegetation, the accessibility of greenness amplifies the association with physical activity and thus indirectly on health by about 40% in the immediate vicinity and shows an overall significantly more positive pattern over all distances. The associations with social cohesion are also significantly stronger and more pronounced. Conformingly, accessible green spaces also show a positive association at walkable distances on physical activity and on social cohesion at neighbourhood distances. The results thus support the theory that the accessibility of vegetation and green spaces strongly influences the impact pathways based on physical activity or social interaction. In contrast, the mitigation of air pollution seems to be negatively associated with accessible vegetation at shorter distances, although not significant. These findings might be explainable through the street canyon phenomenon, where air pollution can be trapped under tree canopies. Furthermore, the results in the direct effects (path c) suggest that accessible green space in the immediate surroundings (200 m) may also be associated with other mechanistic pathways (Figure 7.3). In summary, the results indicate that accessibility to greenness and green spaces is an important factor to consider to reduce physical inactivity and foster social cohesion, but also shows that street green might cause negative effects through the air pollution pathway.

Besides accessibility, **connectivity of green spaces** seems to be an important green space characteristic for all tested green space health pathways. All tested mediators react particularly sensitively when the connectivity of green spaces is included, e.g. when not only green space patches within the buffer are captured, but the total green corridor that is accessible within a certain distance. The mediators of physical activity and social cohesion showed a clear pattern of significant associations to green corridors in walkable distances up to 800 m. The association with self-rated air pollution was even stronger dependent on the inclusion of connectivity of green spaces to detect any association and was only measurable in a surrounding area of about 800-1,000 m. The results for path (c) also show that there may be other mechanisms that respond positively to green corridors at walkable distances. These results indicate that green space corridors might be one of the most important green space characteristics in combating the global disease burden of NCDs since it was consistently positively associated with all measured pathways.

The results indicate that **semi-public and private green spaces** are an important factor in the Instoration pathway. Considering semi-public and private green spaces accessible to the individual study respondents in the green space corridor indicator made the results in the physical activity and social cohesion pathway more robust, especially in immediate surroundings. It also led to around 15% higher effect sizes for physical activity and 5% higher effect sizes for social cohesion. The association with air pollution mitigation was also consistently slightly higher and more robust, but the difference in effect size was rather small at under 1%. Overall, this provides evidence, that including semi-public and private green spaces can reduce bias in the data if adequately treated, especially in studies on the Instoration pathway (see also Chapter 2, item 10).

The results suggest that the sheer number of **green space uses** is unlikely to lead to positive effects via physical activity or social cohesion, but the mix of uses very much might (Figure 7.6-7.7). The *Instoration* mediators showed a positive relationship to physical activity up to a distance of 1,100 m and to social cohesion for about 700-1,300 m. On the contrary, for the amount of green space use, it seems that the indicator is prone to generate spurious correlations when measured in larger distances, likely because the true association approaches zero beyond walkable distances, allowing unmeasured variables like other health behaviour of residents of socially disadvantaged neighbourhoods to take over the relationship. Likely due to a similar mechanism, green space uses showed a constant negative direct association (path c) with health and with the quantity of green space uses at immediate distances (see Chapter 5). Since these direct associations are factually adjusted for physical activity or social cohesion this may lead to a true null or very small relationship, which allows for spurious relations to be observed. In summary, while the results of this doctoral research indicate that the multifunctionality of green spaces is an important characteristic to consider in practice, leading to more active lifestyles of nearby residents and increased social cohesion, indirect effects at neighbourhood distances (path a*b) and direct effects in general (path c) should be interpreted with caution in those study designs.

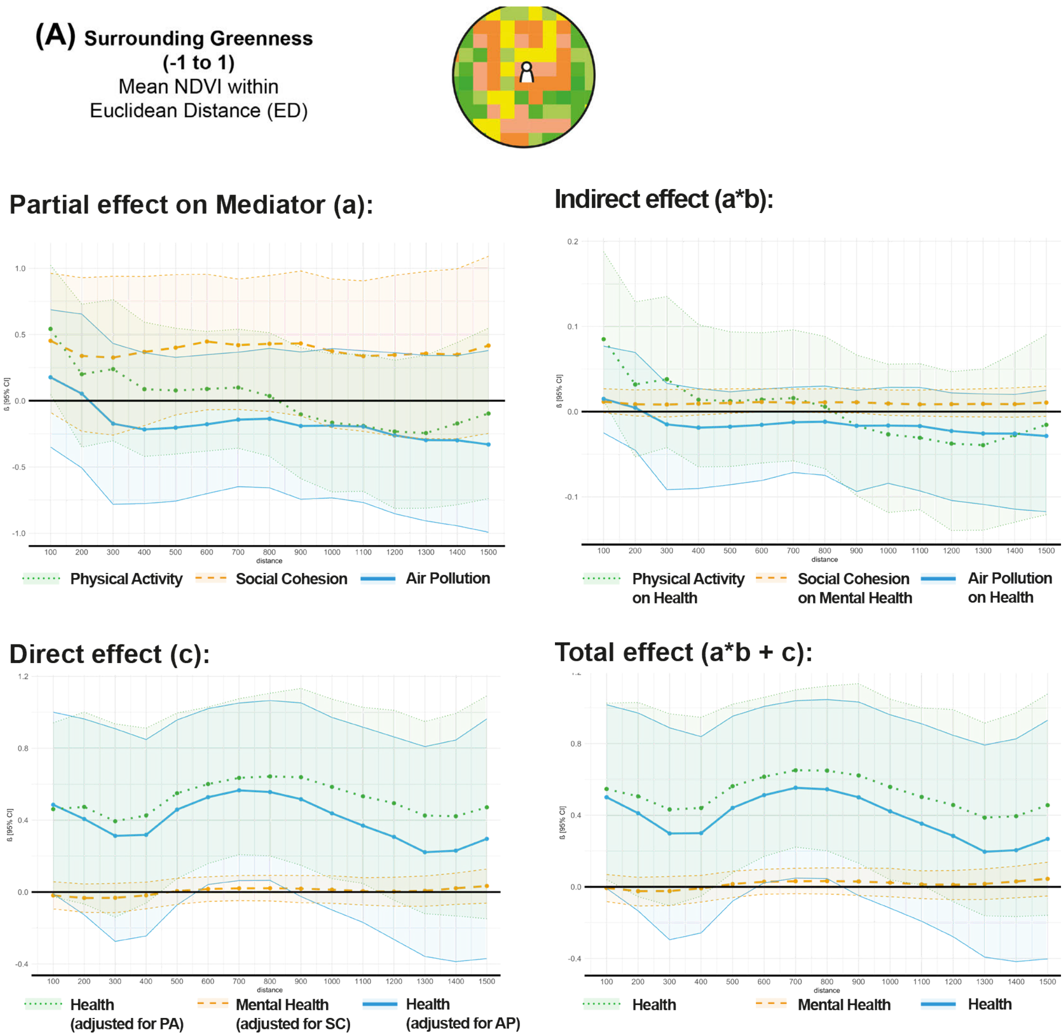


FIG. 7.1 Overlay of Sensitivity Analysis of Surrounding Greenness. Standardized Estimated ß (95% CI) of the 45 structural equation models (15 distances for 3 mediators); all models have been adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, satisfaction with shops, leisure facilities, public transport, population density and city. The air pollution model has additionally been adjusted for the area of the main roads within a 500m buffer. The physical activity model has additionally been adjusted for perceived neighbourhood safety; 5000 Bootstrap Samples; shaded area shows the 95% confidence interval. **Abbreviations**: PA = Physical Activity, SC = Social Cohesion, AP = Air Pollution

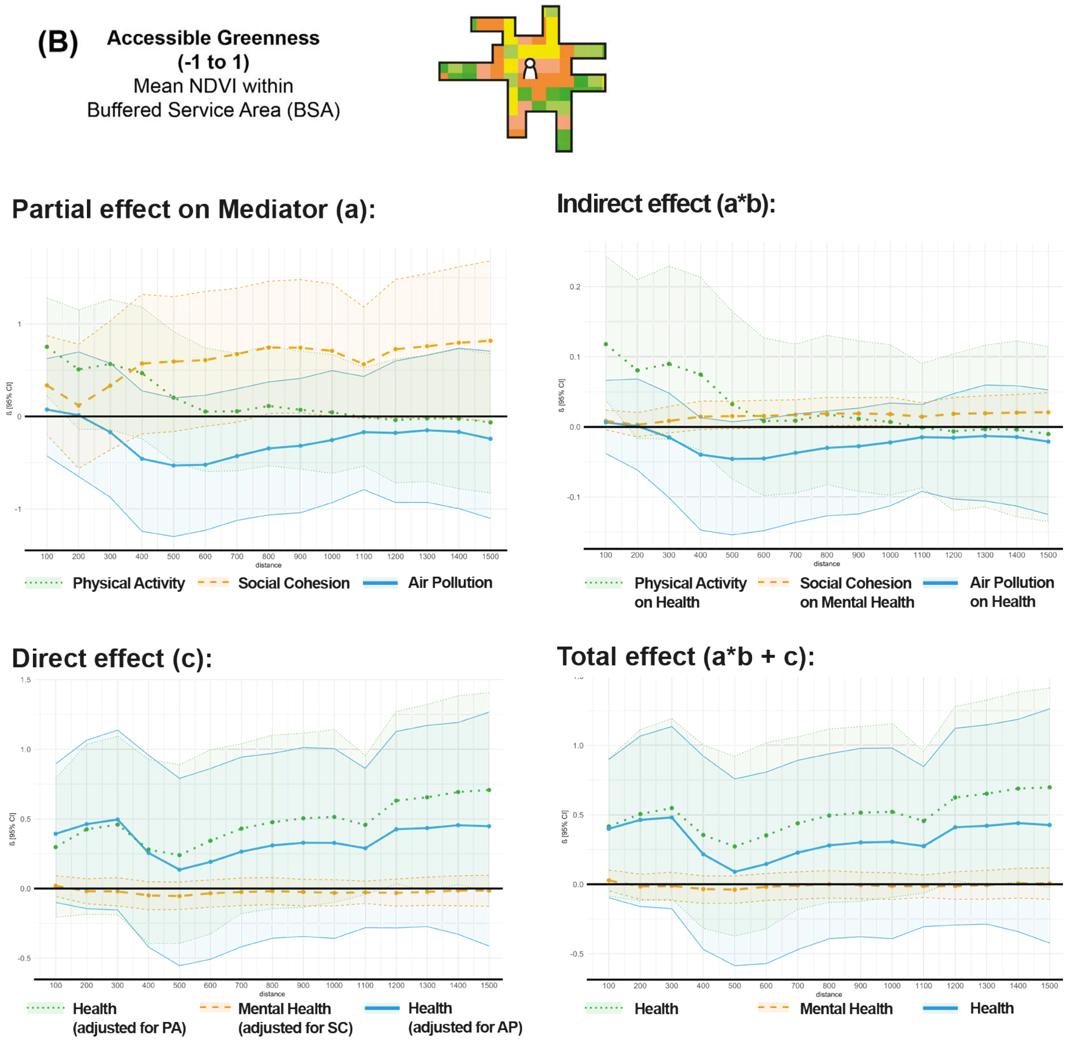


FIG. 7.2 Overlay of Sensitivity Analysis of Accessible Greenness. Standardized Estimated ß (95% CI) of the 45 structural equation models (15 distances for 3 mediators); all models have been adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, satisfaction with shops, leisure facilities, public transport, population density and city. The air pollution model has additionally been adjusted for the area of the main roads within a 500m buffer. The physical activity model has additionally been adjusted for perceived neighbourhood safety; 5000 Bootstrap Samples; shaded area shows the 95% confidence interval. **Abbreviations:** PA = Physical Activity, SC = Social Cohesion, AP = Air Pollution

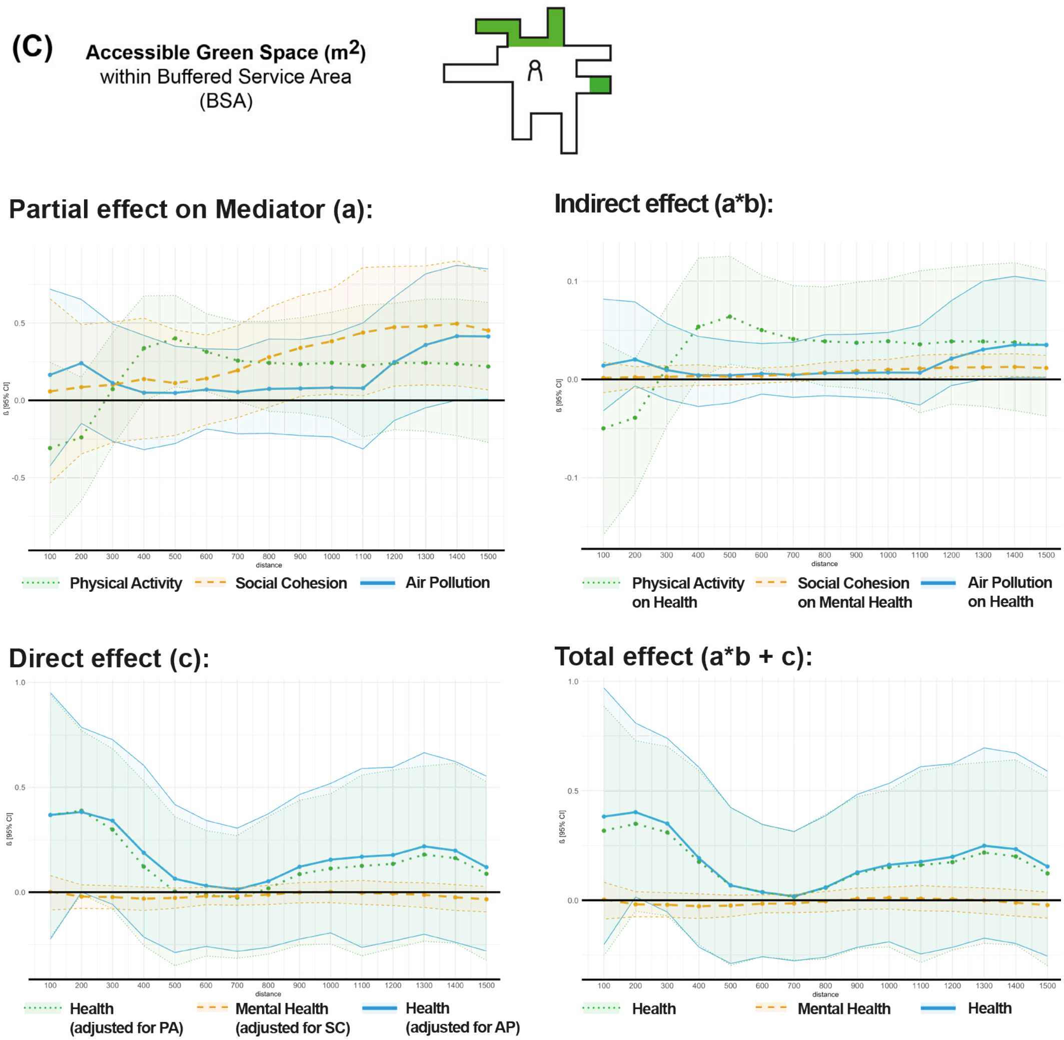


FIG. 7.3 Overlay of Sensitivity Analysis of Accessible Green Space. Standardized Estimated ß (95% CI) of the 45 structural equation models (15 distances for 3 mediators); all models have been adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, satisfaction with shops, leisure facilities, public transport, population density and city. The air pollution model has additionally been adjusted for the area of the main roads within a 500m buffer. The physical activity model has additionally been adjusted for perceived neighbourhood safety; 5000 Bootstrap Samples; shaded area shows the 95% confidence interval. **Abbreviations**: PA = Physical Activity, SC = Social Cohesion, AP = Air Pollution

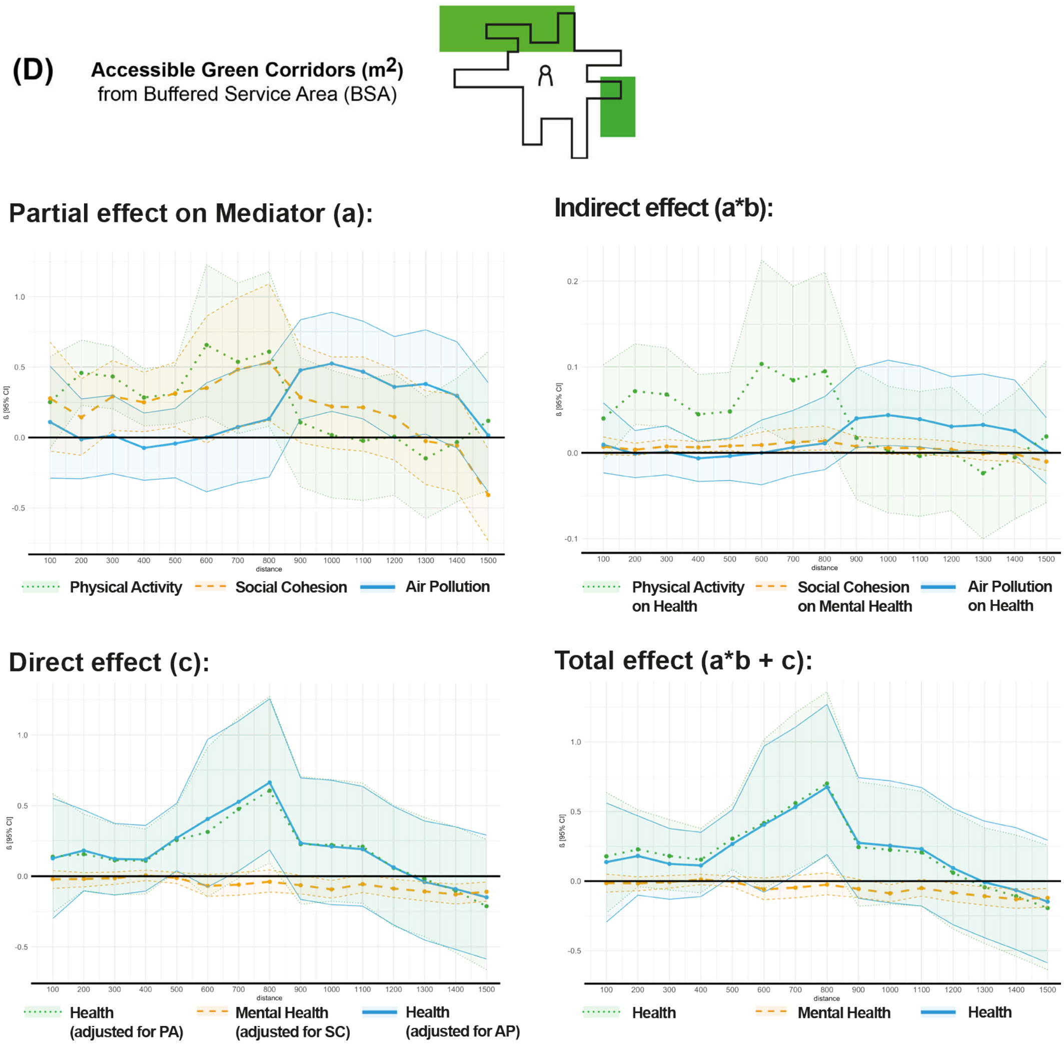


FIG. 7.4 Overlay of Sensitivity Analysis of Accessible Green Corridors (connectivity). Standardized Estimated ß (95% CI) of the 45 structural equation models (15 distances for 3 mediators); all models have been adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, satisfaction with shops, leisure facilities, public transport, population density and city. The air pollution model has additionally been adjusted for the area of the main roads within a 500m buffer. The physical activity model has additionally been adjusted for perceived neighbourhood safety; 5000 Bootstrap Samples; shaded area shows the 95% confidence interval. **Abbreviations:** PA = Physical Activity, SC = Social Cohesion, AP = Air Pollution

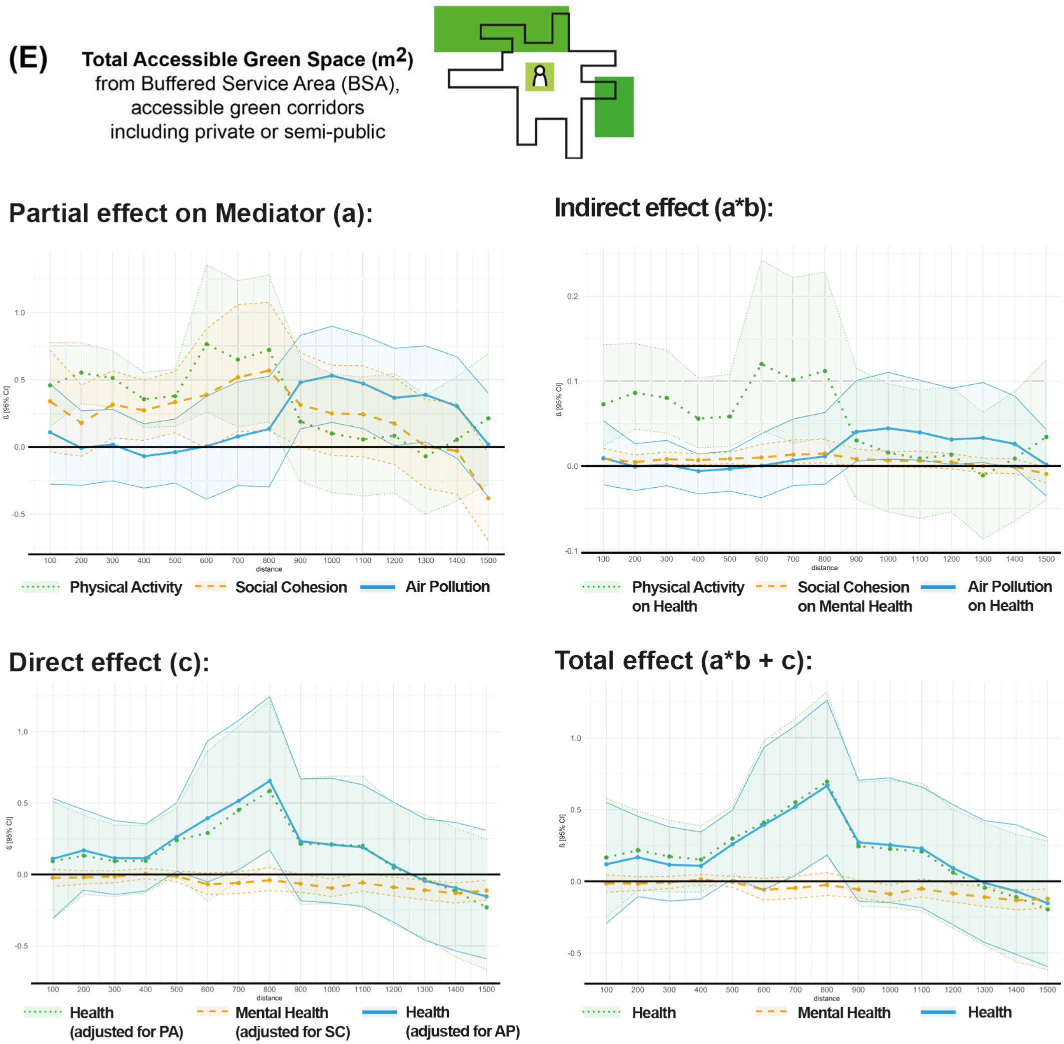


FIG. 7.5 Overlay of Sensitivity Analysis of Accessible Total Green Spaces. Standardized Estimated ß (95% CI) of the 45 structural equation models (15 distances for 3 mediators); all models have been adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, satisfaction with shops, leisure facilities, public transport, population density and city. The air pollution model has additionally been adjusted for the area of the main roads within a 500m buffer. The physical activity model has additionally been adjusted for perceived neighbourhood safety; 5000 Bootstrap Samples; shaded area shows the 95% confidence interval. **Abbreviations:** PA = Physical Activity, SC = Social Cohesion, AP = Air Pollution

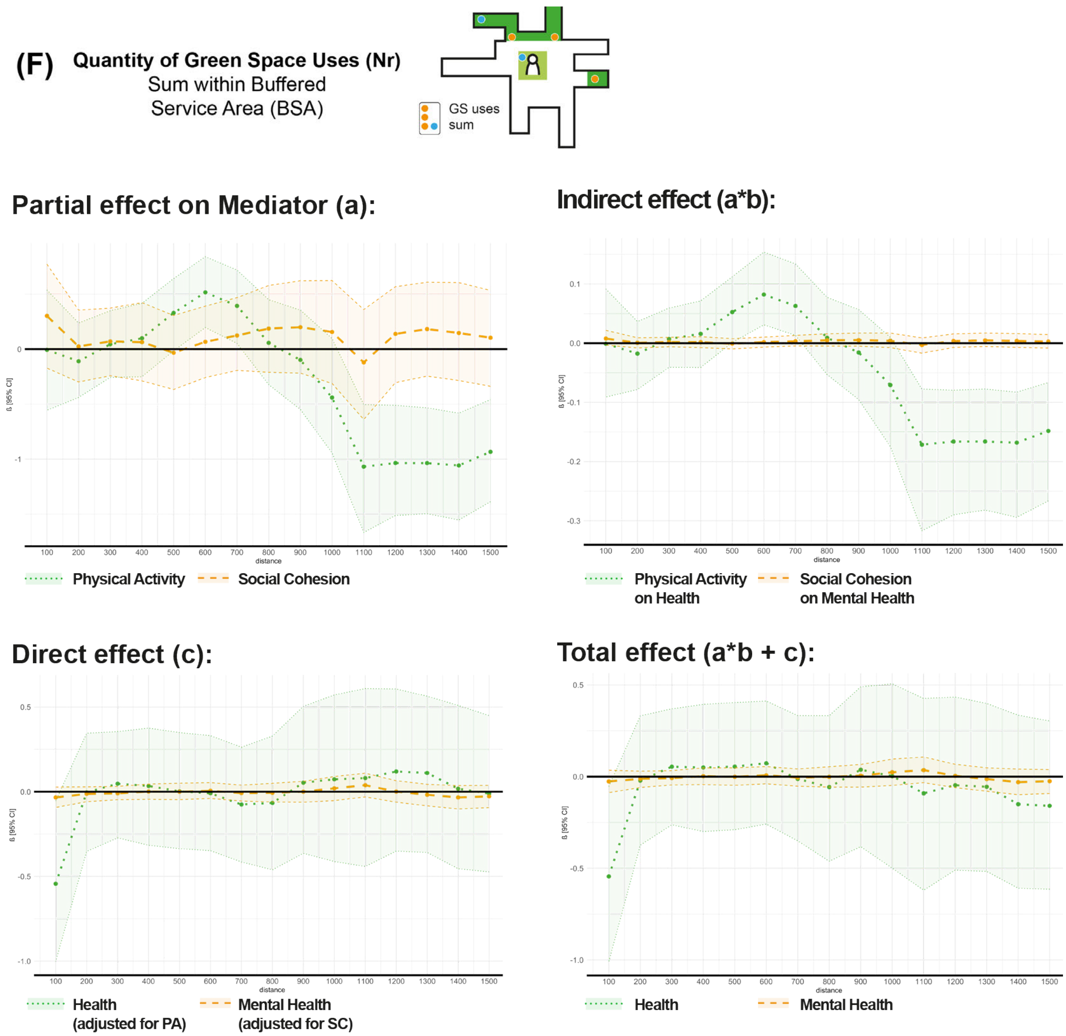


FIG. 7.6 Overlay of Sensitivity Analysis of Quantity of Green Space Uses. Standardized Estimated ß (95% CI) of the 30 structural equation models (15 distances for 2 mediators); all models have been adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, satisfaction with shops, leisure facilities, public transport, population density and city. The physical activity model has additionally been adjusted for perceived neighbourhood safety; 5000 Bootstrap Samples; shaded area shows the 95% confidence interval. **Abbreviations:** PA = Physical Activity, SC = Social Cohesion

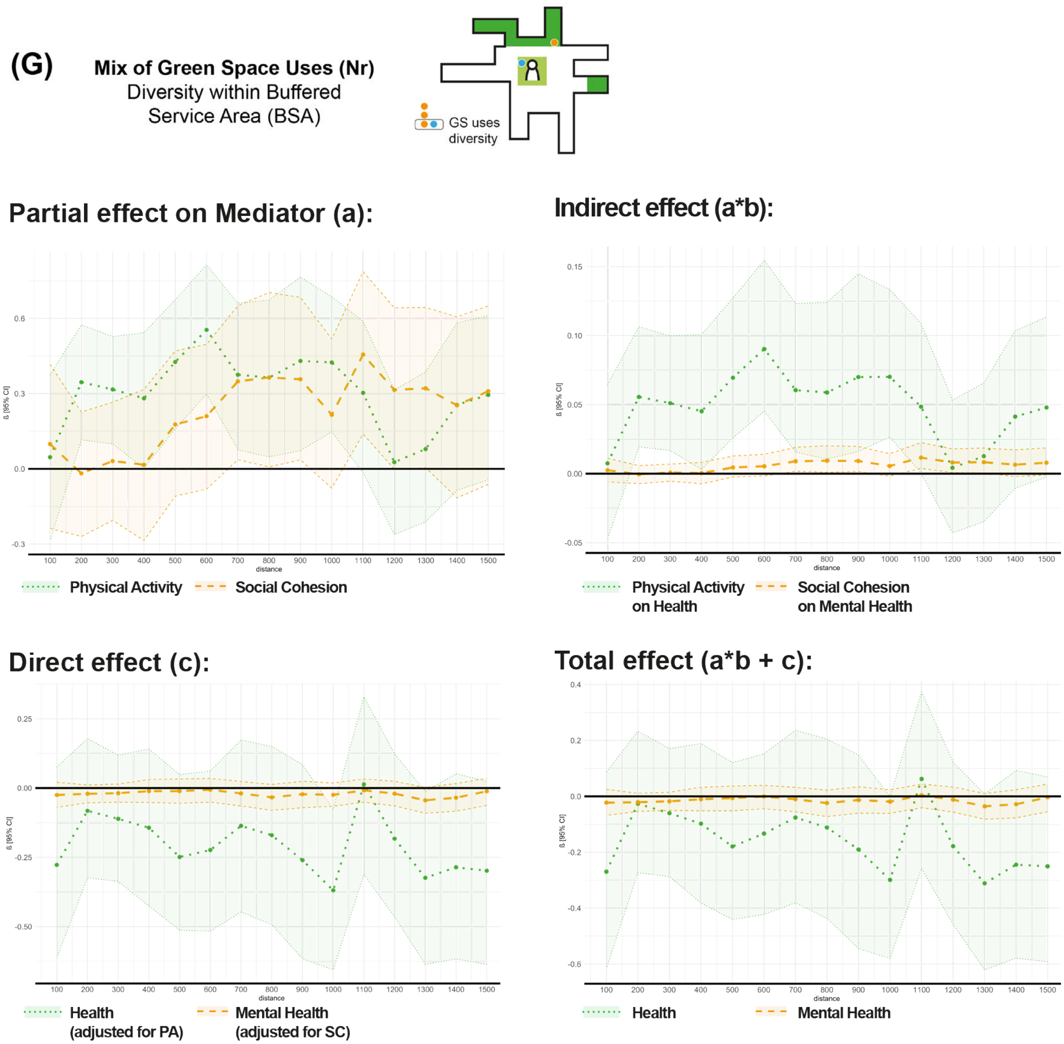
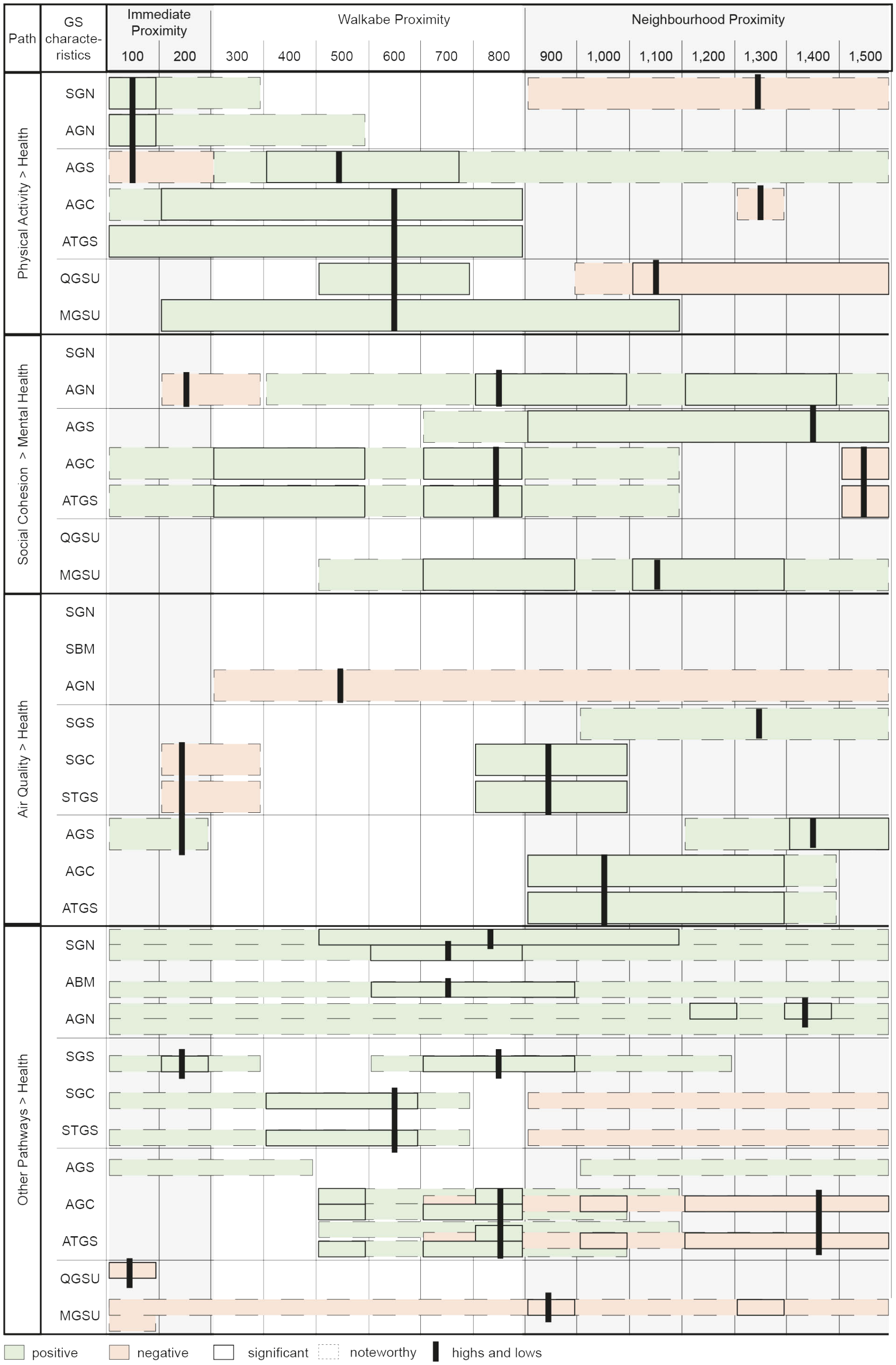


FIG. 7.7 Overlay of Sensitivity Analysis of Mix of Green Space Uses. Standardized Estimated ß (95% CI) of the 30 structural equation models (15 distances for 2 mediators); all models have been adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, satisfaction with shops, leisure facilities, public transport, population density and city. The physical activity model has additionally been adjusted for perceived neighbourhood safety; 5000 Bootstrap Samples; shaded area shows the 95% confidence interval. **Abbreviations:** PA = Physical Activity, SC = Social Cohesion

7.3.2 The role of proximity to green spaces

Immediate proximity (100-200 m) to green space showed positive and negative associations between health and mental health, depending on the pathway and green space characteristics (Figure 7.8). The results suggest that immediate proximity to greenness and green corridors can invite residents to be more physically active. In contrast, the results of this doctoral research suggest that there might also be negative associations between green corridors with air quality, which could be partially explained by the street canyon phenomenon, the potential increase of secondary air pollutants in fragmented green spaces and the harmful influence of pollen. These phenomena could also potentially explain the negative association of immediate street greenery (accessible greenness) on mental health via social cohesion since experienced air pollution is also negatively associated with mental health. Synthesising the results of chapters 5-7 on direct health effects, e.g. pathways that were not explicitly the target of this research, suggests that there might be other positive associations with health, especially for surrounding greenness and green space, although most of them showed no significant relationship. In summary, the results of this doctoral research suggest that the main characteristic of importance in immediate proximity is greenness with positive effects on physical activity. Attention needs to be paid to potential negative effects on air quality depending on the surrounding urban morphology.

Green Space characteristics in **walkable proximity (300-800 m)** showed strong positive associations for Instoration pathways, but also some noteworthy negative findings regarding air quality for street greenery (Figure 7.8). The synthesis of chapters 5-7 suggests that accessibility, connectivity and mix of use are all green space characteristics that might be able to invite residents to be more physically active and lead to more social cohesion. The relationship with physical activity was the strongest when green space characteristics were measured in 600m network distance, while the strongest association with social cohesion were measurable at slightly higher network distances of 800m and beyond. On the contrary, air pollution showed a constant negative association with street greenery (accessible greenness), although not significant. In this walkable proximity, other green space health mechanisms seem to function as well, as individual studies regularly found positive direct associations between green space indicators and health, especially for green corridors. It is likely that these effects are associated with other mitigation mechanisms like heat or noise mitigation. In summary, the results of this doctoral research suggest that in walkable proximity the main green space characteristics to trigger beneficial (mental) health effects are accessibility, connectivity and multifunctionality.


Path
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Walkabe Proximity
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Physical Activity > Health
SGN
AGN
AGS
AGC
ATGS
QGSU
MGSU
Social Cohesion > Mental Health
SGN
AGN
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ATGS
QGSU
MGSU
Air Quality > Health
SGN
SBM
AGN
SGS
SGC
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AGC
ATGS
Other Pathways > Health
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MGSU
positive
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significant
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FIG. 7.8 Synthesis of the empirical results. All models have been adjusted for sex, age, disabilities, years of education, income, occupation, years lived in the neighbourhood, satisfaction with shops, leisure facilities, public transport, population density and city. The physical activity model has additionally been adjusted for perceived neighbourhood safety; 5000 Bootstrap Samples; **Abbreviations**: SGN: Surrounding Greenness, SBM: Surrounding Biomass, AGN: Accessible Greenness, SGS: Surrounding Green Space; SGC: Surrounding Green Corridors; STGS: Surrounding Total Green Space, AGS: Accessible Green Space; AGC: Accessible Green Corridors; ATGS: Accessible Total Green Space, QGSU: Quantity of Green Space Uses, MGSU: Mix of Green Space Uses

Regarding the **neighbourhood proximity (900-1500 m)**, this doctoral research makes an important contribution in identifying that from the neighbourhood perspective, most of the pathways change direction (Figure 7.8). Physical activity is now negatively associated with higher surrounding greenness and with the quantity of green space uses, potentially due to a more car-dependent urban fabric or peer behaviour in very green neighbourhoods. In contrast, social cohesion seems to benefit from green space accessibility in this neighbourhood proximity, but also turns the positive relationship to green corridors to negative in this larger environment. The opposite behaviour can be seen in the results for the mitigation of air pollution, now showing a significant positive association with green corridors. Furthermore, the comparison of the direct effects of chapters 5-7 suggests that other positive mechanisms on health are working in this neighbourhood proximity, but also potentially further negative associations to mental health may exist. This requires more research since it might be equally likely that spurious relations are shown due to changes in the signal-to-noise ratio. It is plausible that the inviting character of green spaces approaches zero the further away they are from the resident's home. This makes associations in these distances vulnerable to reacting to noise in the data. A similar explanation might hold for mitigation mechanisms although the thresholds here are less established. More research is warranted. In summary, while the results indicate that greenness and connectivity are the most important characteristics at the neighbourhood level with a positive association with mitigation mechanisms and social cohesion, but potentially also a negative association with physical activity, these turning points need to be treated with caution and might show spurious relations.

7.4 Strengths and limitations

7.4.1 Composition of study participants

The underlying dataset provides a European perspective on satellite districts and their populations obtained in different climate zones and seasons. It addressed several contextual variables like age, gender, disabilities, income, level of education and even the years lived in the neighbourhood. Although the main confounders are addressed and bias is likely low, the diversity of potentially influential health determinants is broad, and a level of uncertainty about residual confounding and spatial autocorrelation due to the concentration of specific populations groups in these neighbourhoods cannot be ruled out. The study setting also means that the results cannot be generalized to other parts of the world or even more central or suburban districts. A level of uncertainty thus remains.

7.4.2 Measurement of green space characteristics

This doctoral research contributed to the identification of unique green space characteristics and highlighted differences between greenness, accessibility, connectivity and multifunctionality in the researched pathways. However, these findings may be somewhat limited by the indicators chosen. For example, the green space data is based on OpenStreetMap and while it has been systematically assessed for bias with the developed PRIGSHARE reporting guidelines (Chapter 2), the manual assessment of such large maps may have not been fully accurate. Regarding greenness, it remains unknown if the NDVI is the most accurate proxy since different indices produce different results (Markevych et al., 2017). Furthermore, current research develops 3D measurements using LiDAR point clouds, which might lead to more accurate results, although it remains unknown if the higher effort needed to generate and work with LiDAR datasets actually leads to better results (Chapter 2). In addition, there are green space characteristics that were out of the scope of this doctoral research, like green space design quality and the maintenance of green spaces, which require further research.

7.4.3 Measurement of green space exposure

The chosen strategy to assess green space exposure through a series of Euclidean distances and network distances enabled the identification of turning points in the associations, where either the direction of the relationship changes or the true relationship approaches zero and the noise in the dataset dominates the relationship. The results of the doctoral research allowed for comparison across pathways and corroborated the theory that pathways work at different distances. However, the chosen approach likely also limits the ability to detect restorative mechanisms since they are theorized to work through actual contact with nature and not by simply living next to green space. Thus our findings may underestimate restorative mechanisms of green space and should be treated with caution. Other study designs like experimental studies or the recording of actual contact with nature through a GPS tracker seem to be promising approaches to further explore this pathway.

7.4.4 Measurement of mediators and health outcomes

The doctoral research heavily relied on self-reported data that allowed the development of a broad dataset suitable for examining multiple pathways. This made it possible to compare these mechanisms and uncover differences in associated green space characteristics and distances between these pathways. However, this approach also led to limitations due to the self-reported nature of the indicators. There is evidence that the self-reported physical activity, over- or underestimates the true activity levels (Lee et al., 2011). Similarly, self-rated air pollution data is associated with lower validity (Pelgrims et al., 2022), but it allowed fine granular spatial distribution of air pollution data. The same applies to the social cohesion indicator. Self-reported health is an accepted measure (Jylhä, 2009), but still subject to self-reported bias. The mental health indicator is based on a validated scale developed by Keyes and measures positive mental health (Keyes, 2018), in contrast to the often used GHQ-12 which measures mental illness. This limits the comparability to other studies but simultaneously provides new perspectives on positive mental health associations with green space.

7.4.5 Overall methodological approach

The applied detailed sensitivity analysis on up to 135 structural equation models for each pathway provided novel insights into where and how the researched pathways operate and which green space characteristics likely are the main contributors to these pathways. The comparison of green space characteristics and distances revealed important thresholds for measurable effects or even changes in the direction of the relationship. However, this strategy also introduced limitations to the possible complexity of the model. For example, in the pathway from green space to physical activity neither the theorized effect modification through age nor the hypothesized serial mediation from green space via environmental pollution indicators to physical activity and in turn to health could be modelled. This limits the generalizability and accuracy of our findings. Lastly, this doctoral research is based on a cross-sectional dataset, thus unable to establish causality. Although there is mounting evidence of a positive green space health relationship, most of it is based on cross-sectional studies. Thus, possible reverse causation is a limiting factor. For example, study participants with respiratory health conditions might have reported self-reported air pollution differently, than those without. Similarly, study participants with lower mental health might have rated social cohesion in the neighbourhood to be lower. A level of uncertainty thus remains, which requires more longitudinal studies to confirm the hypothesized causal direction.

7.5 Implications for research

7.5.1 Exploring the simultaneity of impact pathways

Impact pathways can remain undetected if the pathways are not considered in isolation. This doctoral research basically confirms the low signal-to-noise ratio in this research field (Hartig et al., 2014), which makes it necessary to better isolate individual effects of interest in order to arrive at interpretable results. This corroborates the recommendations of Dzhambov and colleagues, who recommend that impact pathways should mainly be investigated with mediators and structural equation models (A. M. Dzhambov et al., 2020). Future research is needed to explore these complex mechanisms. Research questions that could be asked include, how the pathways of *Mitigation, Instoration and Restoration* are connected, e.g. from green space to the mitigation of environmental stressors, which in turn invites more activity outdoors, which then manifests into restoration mechanism to actual contact with nature and ultimately health benefits. Another approach might be to go backwards from a specific health outcome to its potential influences that derive from green space in a complex path analysis. Another important area for research is the trade-offs within pathways through mechanisms that cause harm, like pollen and disease vectors. All three approaches benefit from the complex model structure that allows the identification of singular mechanisms more precisely, while also exploring the unanswered question of how these green space health mechanisms interact.

7.5.2 Explore thresholds and changes in the direction of green space health pathways

This doctoral research identified several thresholds where green space health mechanisms can be detected. It confirmed the hypothesis that pathways work at different distances and even types of distances. However, several questions remain unanswered at present. Further work is necessary to determine whether these thresholds are actual changes in direction, e.g. living in a very green rural environment might lead to a more inactive and car-dependent lifestyle, or if these changes are due to noise in the data and the actual relationship approaches zero, e.g. there is no connection to physical activity beyond walkable distances. Similar investigations are required for the other pathways. It is important to get a better understanding of these thresholds to give better guidance to urban planning practitioners about the right balance between urban density and natural environments.

7.5.3 A database for green spaces

The results of this doctoral research clearly indicate that different green space characteristics drive specific mechanisms. Specifically, the research suggests that a distinction between greenness and green space is necessary to robustly detect effects on physical activity and even air pollution. However, the availability of accurate green space data remains a challenge for this research field. As demonstrated in Chapter 2, several risks of bias and misconceptions are inherent in the common databases of Urban Atlas and OpenStreetMap. To advance the field, effort is needed to either generate more accurate databases or to automate the risk of bias assessment through geospatial tools and protocols.

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7.5.4 Establishing causality

Arguably the most pressing demand is to establish the causal link between green space and health, as this doctoral research, like the vast majority of studies, is cross-sectional. While this thesis provides an important foundation for longitudinal and quasi-experimental studies by calibrating the instruments, e.g. with what green space characteristics and in what proximity can each pathway be detected, it can only add to the mounting body of evidence that a true causal relationship likely exists. Future studies, which take these variables into account, will need to assess the causal and temporal link from green spaces to health, as it also remains unknown which timespan is needed for specific effects to occur.

7.5.5 Linking green space health research with research on Nature-based Solutions

This thesis provides evidence on green space health mechanisms. However, future research is required to confirm whether these mechanisms also exist for new forms of green space, like green walls and green roofs. These so-called nature-based solutions for urban areas currently have momentum and are recognized as an important strategy by the United Nations in their 27th Climate Summit (IUCN, 2022). Thus, they will likely play a key role in the urban green transformation of the 21st century. However, they lack specific evidence as an umbrella review on green walls has recently shown (Cardinali et al., 2023). Especially due to the massive funding dedicated to nature-based solutions, rare opportunities for quasi-experimental studies arise (European Commission. Directorate-General for Research and Innovation., 2021b) that provide promising frameworks to advance the green space health field in general, generate specific evidence for nature-based solutions, and link green space health research with the work on nature-based solutions and climate change.

7.6 Implications for urban design and planning practitioners

7.6.1 The green space design

The results of the research suggest that connectivity is a crucial factor in achieving positive effects of green spaces on health. For practitioners and aspiring urban designers, this means that connected green spaces should be pursued in urban design. Even more, the results partly corroborate the theory that fragmented green spaces may have negative effects on air quality. From the perspective of minimising the risks for NCDs, it seems that practitioners should focus on green mobility infrastructure wherever possible, to achieve the most beneficial effects for residents, instead of isolated green spaces like pocket parks or neighbourhood green (Figure 9). These corridors serve as meeting spaces, mobility corridors, air exchange facilitators, and air pollution barriers and seem to function as Ecosystems services that have other positive health effects as well. The thesis also suggests that for green corridors, many different types of green spaces, up to agricultural areas (if walkable) can be combined. This is especially true for the semi-public green spaces that should be embedded in or at least connected to these green corridors. In addition, the findings suggests that it is likely beneficial for health if green spaces are designed for multiple uses. To summarize, while singular green spaces might be beneficial, this thesis indicates that green corridors show stronger beneficial and less negative relationships, and thus strongly encourages practitioners to implement them in urban interventions.

7.6.2 Embedding in the urban fabric

The location of green spaces seems to be another important factor in achieving the desired health effects and avoiding negative impacts. The results suggest that, if possible, green space corridors should be accessible within a maximum of 10 minutes of walking distance, e.g. in around 800m (Figure 9). In addition, this doctoral research shows that the immediate proximity to green spaces might not always be positive. In particular, an ambivalent function is attributed to street greenery. It can lead to residents moving more, but possibly also to more air pollution due to the street canyon effect. For the neighbourhood environment, the doctoral research also shows ambivalent results. A very green environment can lead to lower air pollution and improved social cohesion. At the same time, it may promote physical inactivity. Although more research is warranted to confirm, the results suggest that there is a need for a sensitive balance between urbanity and green spaces. They indicate that green spaces should be large enough and sufficiently connected to trigger the positive effects, but should not lead to residents being dependent on cars for everyday destinations. Even though it was not explicitly the subject of this doctoral research, the results thus support the current planning strategies towards compact urban neighbourhoods, such as the 15-minute city.

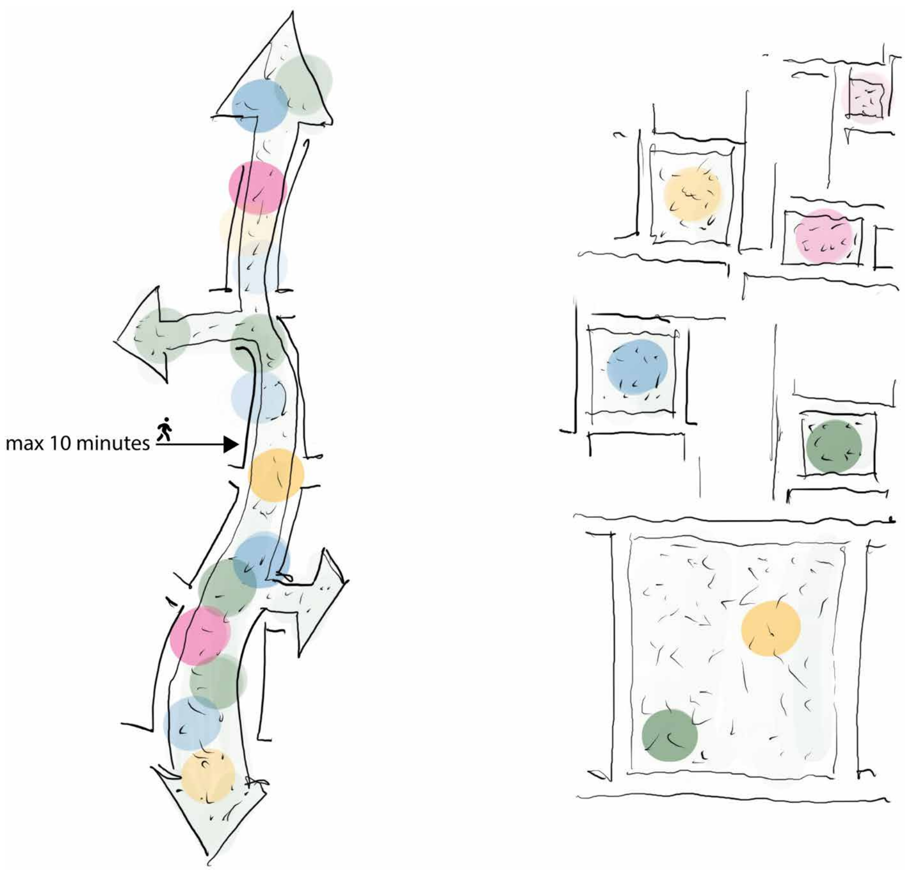

FIG. 7.9 Connected green spaces as a green mobility infrastructure vs fragmented green spaces (author)

7.7 Implications for decision-makers

7.7.1 Local and regional policy institutions

The results suggest that many of the current urban greening strategies may not be sufficient to exploit the full range of positive effects of green spaces on health. Many green space strategies are based on simple green space/resident or green space/hectare recommendations. For example, in major German cities ratios of 4 – 15 m^2/resident are used depending on the size and type of green space (Böhm et al., 2016). These kinds of ratios are not able to consider the connectivity and multifunctionality of those spaces. According to the results of this doctoral research, fragmented small green areas might even lead to negative associations with health, potentially through increased secondary air pollutants (Shen & Lung, 2017). It is therefore recommended to develop local green space strategies that focus more on multifunctional green space corridors, which at best simultaneously serve as mobility infrastructure to many destinations in the city. Examples of this type of green space strategy are the Feather Plan in Hamburg, the Finger Plan in Copenhagen and the *"groene scheggen"* (green hedges) in Amsterdam. Although their perspective was the urban and not the green space development, they resulted in protected radial green corridors from the city centre to the outskirts.

7.7.2 National and international policy institutions

This doctoral research confirms the assumption that investing in urban green space important for local authorities to sustainably improve the health and well-being of residents. The results offer important new insights into how an adequate green space strategy can reduce main risk factors for NCDs and contribute to the *Urban Health Research Agenda* published by the WHO (WHO - World Health Organization, 2022). The thesis may also complement the WHO Brief for Action published in 2017 (WHO Regional Office for Europe, 2017) with the significant factor of connectivity and recommendations to carefully consider the ambivalence of street greenery. In addition, it provides further support for the shared opportunities for action defined by the *NCD Alliance* and the *Global Climate & Health Alliance* (Beagley, Jess et al., 2016) by adding urban green spaces as another key element for co-benefits. Indirectly, the doctoral research thus also confirms the necessary intersection of local city government offices as well as environmental, urban planning and health institutions at national and international levels to address the global challenge of NCDs. More inter- and transdisciplinary collaboration is also required to better understand the causal relationships between green space and health. The necessary quasi-experimental and longitudinal studies require funding possibilities that can cover the period and resources to monitor urban green space interventions. To advance the urban green transformation of the 21st century, it is necessary that national and international policy institutions support the development of local green space strategies, as well as the monitoring and evaluation of these transformations through adequate funding channels, supporting integration science and transdisciplinary studies.

7.8 Concluding remarks

This dissertation started by recognizing the improvements in communicable disease risk reduction by 20th-century urbanism while also pointing at the new problems of NCDs and their risk factors. Arguably, car-friendly cities are one of the main root causes of air pollution and physical inactivity in today's European cities. While this doctoral research found potential to mitigate air pollution through green spaces, there is a need to remove the root causes, such as car dependency. Similarly, a root cause for physical inactivity is arguably not the absence of green spaces, but the built environment and the distance between everyday destinations in general. That is also why a pure electrification of cars is helpful but not sufficient. Thus, to be sustainable, the 21st century urban transformation would be best suited to focus on knowledge about human behaviour and habitats instead of treating singular symptoms. Professions like public health, epidemiology and behavioural science are important allies and resources to advance evidence-based urban design for a sustainable human habitat.

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Appendix

* These tables are identical and only repeated to illustrate the supplementary material for each publication

TABLE A1.1 URBiNAT Neighbourhood Survey Items

I. This survey targets only people that live in this neighbourhood. Please answer the following questions:		
How many years are you living in this neighbourhood?	___ years in the neighbourhood	
Please tell us where you live:	street ______________________________	house number ____

II. We will be interested in your satisfaction with the neighbourhood. For each of the elements mentioned, we suggest that you indicate if you are satisfied with the following on a scale from 5 (very satisfied) to 1 (not at all satisfied).					
	5. very satisfied	4. satisfied	3. moderately satisfied	2. not satisfied	1. not at all satisfied
Reputation of the neighborhood	☐	☐	☐	☐	☐
Appearance of buildings in your neighbourhood	☐	☐	☐	☐	☐
Upkeep of buildings and housing	☐	☐	☐	☐	☐
Level of safety in the neighbourhood (police, delinquency, theft, drugs,...)	☐	☐	☐	☐	☐
Distance between the buildings of your neighbourhood (luminosity in your buiding, intimacy regarding building opposite)	☐	☐	☐	☐	☐
Neighbourhood relations (conviviality, mutual aid, solidarity)	☐	☐	☐	☐	☐
The shops you have on site (Here we mean overall satisfaction: accessibility, number, quality...)	☐	☐	☐	☐	☐
Leisure facilities available on site (cafés, cultural sites, playgrounds...) (Here we mean overall satisfaction: accessibility, number, quality...)	☐	☐	☐	☐	☐
Public transport service to the district	☐	☐	☐	☐	☐
Upkeep of the streets	☐	☐	☐	☐	☐
Ability to walk on sidewalks in your neighbourhood	☐	☐	☐	☐	☐
Green areas and parks (Here we mean overall satisfaction: accessibility, number, quality...)	☐	☐	☐	☐	☐
Degree of naturality (soil, vegetation and natural waterlines, 'natural noise' (silence, birds, water)	☐	☐	☐	☐	☐

>>>

III. We will now ask you to give us your assessment of the level of discomfort caused by each of the following phenomena in your neighbourhood on a scale of: 5 (No invonvenience) to 1 (very high inconvenience).					
	5. No inconvenience	4. weak inconvenience	3. moderate inconvenience	2. high inconvenience	1. very high inconvenience
Air pollution (smoke, dust, exhaust fumes...)	☐	☐	☐	☐	☐
Household garbage and other waste	☐	☐	☐	☐	☐
Wastewater and rainwater disposal	☐	☐	☐	☐	☐
Noise due to the traffic	☐	☐	☐	☐	☐
Noise due to the neighbors	☐	☐	☐	☐	☐
Thermal discomfort outside (temperature, wind, humidity,..)	☐	☐	☐	☐	☐
Odors	☐	☐	☐	☐	☐

IV. We are interested in finding out about the kinds of physical and social activities that people do as part of their everyday lives. The questions will ask you about the time you spent being on specific activities in the last 7 days. Please think about the activities you do at work, as part of your house and yard work, to get from place to place, and in your spare time for recreation, exercise or sport.

Think about all the **vigorous** activities that you did in the **last 7 days**. **Vigorous** physical activities refer to activities that take hard physical effort and make you breathe much harder than normal. Think only about those physical activities that you did for at least 10 minutes at a time.					
During the last 7 days, on how many days did you do vigorous physical activities like sports or hard manual work?	__ days per week		☐ no vigorous activities		
How much time did you usually spend on average doing vigorous physical activities on one of those days?	__ hours per day		☐ don't know / not sure		
How much of this kind of activity is spent outside in your neighborhood on a scale from 1 (all) to 5 (nothing)?	5. All of it	4. Most of it	3. About half of it	2. less than half of it	1. Nothing of it
	☐	☐	☐	☐	☐

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TABLE A1.1 URBiNAT Neighbourhood Survey Items

Think about all the **moderate** activities that you did in the **last 7 days**. **Moderate** activities refer to activities that take moderate physical effort and make you breathe somewhat harder than normal. Think only about those physical activities that you did for at least 10 minutes at a time.					
During the last 7 days, on how many days did you do moderate physical activities like carrying light loads, bicycling at a regular pace? Do not include walking.	___ days per week		☐ no moderate activities		
How much time did you usually spend on average doing moderate physical activities on one of those days?	___ hours per day		☐ don’t know / not sure		
How much of this kind of activity is spent outside in your neighbourhood on a scale from 5 (all) to 1 (nothing)?	5. All of it	4. Most of it	3. About half of it	2. less than half of it	1. Nothing of it
	☐	☐	☐	☐	☐

Think about the time you spent **walking** during the **last 7 days**. Think only about those walking that you did for at least 10 minutes at a time as recreation or to get from place to place.					
During the last 7 days, on how many days did you walk for at least 10 minutes at a time?	___ days per week		☐ no moderate activities		
How much time did you usually spend walking on average on one of those days?	___ hours per day		☐ don’t know / not sure		
How much of this kind of activity is spent outside in your neighbourhood on a scale from 5 (all) to 1 (nothing)?	5. All of it	4. Most of it	3. About half of it	2. less than half of it	1. Nothing of it
	☐	☐	☐	☐	☐

Think about the time you spent **relaxing or sitting** during the **last 7 days**. Include time spent at work, at home, while doing course work and during leisure time. This may include time spent sitting at a desk, visiting friends, reading, or sitting or lying down to watch television.					
During the last 7 days, how much time did you usually spend on average relaxing or sitting on a weekday?	___ hours per day		☐ don’t know / not sure		
How much of this kind of activity is spent outside in your neighborhood on a scale from 5 (all) to 1 (nothing)?	5. All of it	4. Most of it	3. About half of it	2. less than half of it	1. Nothing of it
	☐	☐	☐	☐	☐

>>>

TABLE A1.1 URBiNAT Neighbourhood Survey Items

Think about the time you spent **meeting your friends** during the **last 7 days**. **Include only people outside your own family**.						
During the last 7 days, on how many days did you meet your friends?		___ days per week		☐ no friends met (Skip to B16)		
During the last 7 days, how much time did you usually spend on average meeting your friends on one of those days?		___ hours per day		☐ don't know / not sure		
What activities did you spend your time together on? (multiple answers possible)	Sport (main intention to be active)	Entertainment (main intention to be entertained)	Recreational (main intention to relax)	Volunteering (main intention to help others)	Socializing (main intention to communicate)	Other
	☐	☐	☐	☐	☐	☐
How much of this kind of activity is spent outside in your neighbourhood on a scale from 5 (all) to 1 (nothing)?		5. All of it	4. Most of it	3. About half of it	2. less than half of it	1. Nothing of it
		☐	☐	☐	☐	☐

Think about the people in your **neighbourhood**. **Include only people outside your own family.**					
How many people do you approximately know the names of in the neighborhood?	>30	21-30	11-20	1-10	0
	☐	☐	☐	☐	☐
How many of these people do you consider friends (a person that you can trust and rely on) on a scale of 5 (all) to 1 (no one)?	5. All of it	4. Most of it	3. About half of it	2. less than half of it	1. Nothing of it
	☐	☐	☐	☐	☐

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TABLE A1.1 URBiNAT Neighbourhood Survey Items

V. We will be interested in your wellbeing and health during the past month. Please answer the following questions. Place a check mark in the box that best represents how often you have experienced or felt the following from a scale of 5 (high frequency) to 1 (low frequency).					
During the past month, how often did you feel ...	5. Almost every day	4. About 2 or 3 times a week	3. About once a week	2. once or twice a month	1. never
... happy	☐	☐	☐	☐	☐
... interested in life	☐	☐	☐	☐	☐
... satisfied with life	☐	☐	☐	☐	☐
... that you had something important to contribute to society	☐	☐	☐	☐	☐
... that you belonged to a community (like a social group, your school, or your neighborhood)	☐	☐	☐	☐	☐
... that our society is a good place, or is becoming a better place, for all people	☐	☐	☐	☐	☐
... that people are basically good	☐	☐	☐	☐	☐
... that the way our society works made sense to you	☐	☐	☐	☐	☐
... that you liked most parts of your personality	☐	☐	☐	☐	☐
... good at managing the responsibilities of your daily life	☐	☐	☐	☐	☐
... that you had warm and trusting relationships with others	☐	☐	☐	☐	☐
... that you had experiences that challenged you to grow and become a better person	☐	☐	☐	☐	☐
... confident to think or express your own ideas and opinions	☐	☐	☐	☐	☐
... that your life has a sense of direction or meaning to it	☐	☐	☐	☐	☐
How is your health in general?	5. very good	4. good	3. fair	2. bad	1. very bad
	☐	☐	☐	☐	☐

>>>

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VI. In order to better understand the answers you have given, we will be interested in your current personal situation Please answer the following questions.		
Gender	☐ Male	☐ Female
	☐ Other	
How old are you?	☐ years old	
Do you have any sensorial, motor, cognitive or organic specificity that requires personal assistance or particular equipment or care?	☐ Yes	☐ No
	☐ I don’t want to answer	
If you don’t mind, could you tell us what kind of specificity that is? (multiple answer possible)	☐ Physical (mobility/dexterity)	☐ Cognitive (understanding / language / learning)
	☐ Visual	☐ Organic (breathing or diet)
	☐ Hearing	☐ I don’t want to answer
Which is your level of formal education?	☐ Primary school	☐ Undergraduate
	☐ Sec. School	☐ Bachelor or Master
	☐ High School	☐ PhD
	☐ Vocational training	☐ I don’t want to answer
What is your main occupation?	☐ Self-employed	☐ Inactive
	☐ Employee	☐ Student
	☐ Unemyployed	☐ On maternity leave
	☐ Retired	☐ Other
In which main professional field are you working/studying?	☐ Administration	☐ IT
	☐ Research	☐ Architecture
	☐ Manufacturing	☐ Environmental work
	☐ Health care	☐ Arts and communication
	☐ Engineering	☐ Agriculture
	☐ Service-provider	☐ Other
Which is your monthly net income? (Please do not include welfare or other social benefits)	☐ <100 €	☐ 201-250 €
	☐ 101-150 €	☐ 251-300 €
	☐ 151-200 €	☐ >301 €
	☐ I don’t want to answer	
How many people are living with you?	_____ Number of People	☐ I don’t want to answer
In your life (childhood included), have you lived most of the time in such a city?(over 100.000 Inhabitants)	☐ Yes	☐ No
	☐ I don’t want to answer	
Which are the countries your grandparents were born?	Country 1 ___________	Country 3 ___________
	Country 2 ___________	Country 4 ___________
	☐ I don’t want to answer	

We appreciate your support! Thank you very much for your insights and your time!

TABLE A1.2 Sensitivity Analysis Automation Function in R

Sensitivity Analysis / Marcel Cardinali / 2024-02-24

```
sensitivity_analysis_c <- function (SEM, indicator_type, indicator_list, DF=df, mediator, File_Path,
bootstraps=1000, estim='DWLS') {
  library(lavaan)
  library(ggplot2)

  # SEM is a string containing the lavaan SEM model syntax. Example: SEM <- 'y ~ a + b'
  # indicator_type is a string used as part of the file name for unique identification.
  # indicator_list is a list of column names of the data frame that are used for the sensitivity analysis.
Example: NDVI_B_list <- c("NDVI_B100", "NDVI_B200", "NDVI_B300",..)
  # DF is the data frame to perform the sensitivity analysis on
  # mediator is the mediator in the structural equation model
  # File_Path is where the output will be stored
  # Bootstraps are prespecified to 1000 but can be changed to any value
  # estim is the estimator in lavaan, prespecified to DWLS, but can be changed to any estimator in lavaan.

  output <- data.frame()
  df <- DF

  for (i in indicator_list) {

      colnames(df)[colnames(df) %in% c(mediator) ]<- c('MED')
      colnames(df)[colnames(df) %in% c(i) ]<- c('GS')

      SEM001 <- SEM

      fit_SEM001 <- sem(data = df, model = SEM001, estimator=estim, se='bootstrap', bootstrap=bootstraps,
verbose=F, parallel='yes',
                        ordered = c('MED','WB_c2', 'h01', 'h01_c'))          # DVs

      parameters <- parameterEstimates(fit_SEM001, boot.ci.type='bca.simple')
      result <- parameters[parameters$label== 'GS_MED' | parameters$label== 'GS_MED_H' | parameters$label==
'direct_GS_H'| parameters$label== 'total_GS_H', c('label', 'est', 'ci.lower', 'ci.upper')]

      print(result)

      output <- rbind(output, result)

      cat('Dimensions of output:', dim(output), '\n')
      cat('Dimensions of result:', dim(result), '\n')

      colnames(df)[colnames(df) %in% c('MED')] <- c(mediator)
      colnames(df)[colnames(df) %in% c('GS')]  <- c(i)

    }
```

>>>

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Sensitivity Analysis / Marcel Cardinali / 2024-02-24

```
    distances <- c(100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200, 1300, 1400, 1500)

    GS_MED      <- cbind(distances, output[output$label== "GS_MED",])
    GS_MED_H    <- cbind(distances, output[output$label== "GS_MED_H",])
    GS_H_direct <- cbind(distances, output[output$label== "direct_GS_H",])
    GS_H_total  <- cbind(distances, output[output$label== "total_GS_H",])


  # Save dataframes
  file_path <- File_Path

  file_name1 <- paste0 (indicator_type, "_GS_MED.csv")
  write.csv(GS_MED, paste0(file_path, file_name1), row.names = TRUE)
  print(c("Saved as:", paste0(file_path, file_name1)))

  file_name2 <- paste0 (indicator_type, "_GS_MED_H.csv")
  write.csv(GS_MED_H, paste0(file_path, file_name2), row.names = TRUE)
  print(c("Saved as:", paste0(file_path, file_name2)))

  file_name3 <- paste0 (indicator_type, "_GS_H_direct.csv")
  write.csv(GS_H_direct, paste0(file_path, file_name3), row.names = TRUE)
  print(c("Saved as:", paste0(file_path, file_name3)))

  file_name4 <- paste0 (indicator_type, "_GS_H_total.csv")
  write.csv(GS_H_total, paste0(file_path, file_name4), row.names = TRUE)
  print(c("Saved as:", paste0(file_path, file_name4)))

  # Sensitivity plots
  df_list <- list(GS_MED, GS_MED_H, GS_H_direct, GS_H_total)

  for (df in df_list) {

    if (identical(df, GS_MED)) {
      df_name <- "GS_MED"

    } else if (identical(df, GS_MED_H)) {
      df_name <- "GS_MED_H"

    } else if (identical(df, GS_H_direct)) {
      df_name <- "GS_H_direct"

    } else {
      df_name <- "GS_H_total"
    }
```

>>>

TABLE A1.2 Sensitivity Analysis Automation Function in R

Sensitivity Analysis / Marcel Cardinali / 2024-02-24

```
    plot_df <- df #[order(df$distances),]
    plot_df$estimates <- paste0(sprintf("%.3f",round(plot_df$est, digits=3)), " [",
sprintf("%.3f",round(plot_df$ci.lower, digits=3)), ", ", sprintf("%.3f",round(plot_df$ci.upper, digits=3)),
"]")
    plot_df$row_names <- paste(plot_df$distances, " ", plot_df$city, " ", plot_df$estimates)
    plot_df$row_names

    ggplot(plot_df, aes(x = distances, y = est)) +
      ggtitle(df_name) +
      geom_line(size = 1.5) +
      geom_point(size = 2.5) +
      geom_ribbon(aes(ymin = ci.lower, ymax = ci.upper), alpha = 0.2) +
      labs(x = "distance", y = "ß [95% CI]") +
      theme_minimal() +
      geom_hline(yintercept = 0) +
      scale_x_continuous(breaks = distances) +
      theme(axis.line.x = element_line(size = 1.5), axis.text.x = element_text(size = 24), axis.line.y =
element_line(size = 0), axis.text.y = element_text(size = 24))

    # Save plot
    file_path <- File_Path
    file_name <- paste0 (indicator_type, "_", df_name, "_sensitivityplot.png")
    ggsave(paste0(file_path, file_name))
  }
}
```


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TABLE A2.1 PRIGSHARE Checklist Template

#	Section/Topic	Checklist Item	Reported	Page Nr.
OBJECTIVE				
1	Health Outcome(s)	Specify the health outcome(s) being researched		
2	Pathway(s)	Position the research within a theoretical pathway (Mitigation, Restoration, Instoration).		
3	Green Space Focus	Provide a clear definition of green space features being researched, distinguishing in particular between surrounding vegetation, contact with nature, and accessible green spaces.		
SCOPE				
4	Type of Distance	Specify the type of distance used with rationale (Euclidean Distance (ED), Network Distance (ND), Buffered Service Area (BSA), Administrative Units (AU)).		
5	Walkability Network	If accessibility to green spaces is part of the study design, indicate if the walkability network used to generate isochrones or buffered service areas has been checked for bias and how.		
6	Distance	Give a rationale for the chosen distance and indicate if different distances were tested (Sensitivity Analysis).		
SPATIAL ASSESSMENT				
7	Proxy for Exposure Variable	Define the spatial indicators used in research and indicate if different indicators were tested (Sensitivity Analysis).		
8	Data Source	Indicate which database was used and if there has been an adjustment for potential bias (expert assessment).		
9	Public Ownership Bias	Indicate if the dataset was controlled for the usability of green spaces from public-owned plots and how.		
10	Residential Ownership Bias	Indicate how semi-public residential green spaces have been handled.		
11	Classification Bias	Indicate how green spaces have been classified.		
12	Usability Bias	Indicate if the usability of green spaces was checked and report inclusion/exclusion criteria.		
13	Connectivity Bias	(Optional) Indicate if the database has been corrected for green space network connectivity and how.		

>>>

TABLE A2.1 PRIGSHARE Checklist Template

#	Section/Topic	Checklist Item	Reported	Page Nr.
VEGETATION ASSESSMENT				
14	Proxy for Exposure Variable	Specify the indicator(s) used to assess surrounding vegetation or nature and indicate if the sensitivity was tested.		
15	Data Source	Provide the data source of the satellite images and their resolution.		
16	Handling of Blue Spaces	Indicate how blue spaces have been handled.		
17	Handling of Seasons	Explain how variance in vegetation indices due to seasonality or changes in the built environment was handled.		
CONTEXT ASSESSMENT				
18	Personal Context	Give a rationale for the chosen personal context variables that have been tested or controlled for.		
19	Local Context	Give a rationale for the chosen local context variables that have been tested or controlled for.		
20	Urbanicity Context	Give a rationale for the chosen urbanicity context variables that have been tested or controlled for.		
21	Global Context	Indicate in which climate, and cultural setting the study was conducted. If several settings are part of the research explain how the results were controlled for potential confounding and tested for effect modification.		

TABLE A4.1 PRIGSHARE Checklist (Chapter 4)

#	Section/Topic	Checklist Item	Reported	Chapter
OBJECTIVE				
1	Health Outcome(s)	Specify the health outcome(s) being researched		4.2.3, 4.2.4
2	Pathway(s)	Position the research within a theoretical pathway (Mitigation, Restoration, Instoration).		4.1
3	Green Space Focus	Provide a clear definition of green space features being researched, distinguishing in particular between surrounding vegetation, contact with nature, and accessible green spaces.		4.2.2
SCOPE				
4	Type of Distance	Specify the type of distance used with rationale (Euclidean Distance (ED), Network Distance (ND), Buffered Service Area (BSA), Administrative Units (AU)).		4.2.2
5	Walkability Network	If accessibility to green spaces is part of the study design, indicate if the walkability network used to generate isochrones or buffered service areas has been checked for bias and how.		A4.2
6	Distance	Give a rationale for the chosen distance and indicate if different distances were tested (Sensitivity Analysis).		4.1, 4.2.2
SPATIAL ASSESSMENT				
7	Proxy for Exposure Variable	Define the spatial indicators used in research and indicate if different indicators were tested (Sensitivity Analysis).		4.2.2
8	Data Source	Indicate which database was used and if there has been an adjustment for potential bias (expert assessment).		4.2.2, A4.2
9	Public Ownership Bias	Indicate if the dataset was controlled for the usability of green spaces from public-owned plots and how.		4.2.2, A4.2
10	Residential Ownership Bias	Indicate how semi-public residential green spaces have been handled.		4.2.2, A4.2
11	Classification Bias	Indicate how green spaces have been classified.		4.2.2, A4.2
12	Usability Bias	Indicate if the usability of green spaces was checked and report inclusion/exclusion criteria.		4.2.2, A4.2
13	Connectivity Bias	(Optional) Indicate if the database has been corrected for green space network connectivity and how.		4.2.2, A4.2
VEGETATION ASSESSMENT				
14	Proxy for Exposure Variable	Specify the indicator(s) used to assess surrounding vegetation or nature and indicate if the sensitivity was tested.		4.2.2, A4.2
15	Data Source	Provide the data source of the satellite images and their resolution.		4.2.2
16	Handling of Blue Spaces	Indicate how blue spaces have been handled.		4.2.2
17	Handling of Seasons	Explain how variance in vegetation indices due to seasonality or changes in the built environment was handled.		4.2.5

>>>

TABLE A4.1 PRIGSHARE Checklist (Chapter 4)

#	Section/Topic	Checklist Item	Reported	Chapter
CONTEXT ASSESSMENT				
18	Personal Context	Give a rationale for the chosen personal context variables that have been tested or controlled for.		4.2.5
19	Local Context	Give a rationale for the chosen local context variables that have been tested or controlled for.		4.2.5
20	Urbanicity Context	Give a rationale for the chosen urbanicity context variables that have been tested or controlled for.		4.2.5
21	Global Context	Indicate in which climate, and cultural setting the study was conducted. If several settings are part of the research explain how the results were controlled for potential confounding and tested for effect modification.		4.2.5

TABLE A4.2 Inclusion/Exclusion Criteria for green spaces

ITEMS	DESCRIPTION	HOW HANDLED
ITEM 5	Walkability Network	Based on the available street network downloaded from OpenStreetMap Added: Informal pathways, missing sidewalks and pathways. Excluded: Highways, motorways, motorway links, trunks, trunk links, and construction sites.
ITEM 9	Public Ownership Bias	Considered as Public green space, when: • The green space is accessible and used by the public
ITEM 10	Residential Ownership Bias	Considered as Public green space, when: • The residential green space is part of a larger green infrastructure • Or the edge of the residential green space is only surrounded by buildings or garages on 1 or 2 sides. Considered as semi-public green space, when: • The residential green space is not part of a larger green infrastructure • And the edge of the residential green space is only surrounded by buildings or garages on 3 or 4 sides. Considered as private green space, when: • The plot belongs to a single-family home
ITEM 11	Classification Bias	Inclusion: • Public Parks, accessible sports fields, green cemeteries, agricultural land and forests with pathways, and smaller green spaces with benches. • Linear green spaces connecting parts of the green infrastructure or alongside a river Exclusion: • Inaccessible Forests, agricultural lands, bushes or grasslands • Green spaces in the roundabouts of a roadway, between street lanes or railroads • Cemeteries without grass and trees. • Sports Fields which belong to a sports club and are not public.
ITEM 12	Usability Bias	Inclusion: • Not fenced and no steep slopes • no entrance fee • Opening times at least 9 am to 5 pm Exclusion: • Fenced or unwalkable because of steep slope • With an entrance fee • Opening times shorter than 9 am to 5 pm
ITEM 13	Connectivity Bias	Manually connected or added: • connected green infrastructure that was interrupted by a road but has a crossing • merged green spaces directly next to each other • added linear green spaces that consist of walkable pathways with greenery

Notes: *Based on PRIGSHARE Reporting Guidelines (Cardinali, M., Beenackers, M. A., van Timmeren, A., & Pottgiesser, U. (2023). Preferred reporting items in green space health research. Guiding principles for an interdisciplinary field. Environmental Research, 228, 115893. https://doi.org/10.1016/j.envres.2023.115893)*

TABLE A4.3 Example for model summary statistics. Green space indicator: surrounding greenness in 100 m Euclidean distance tested with 5000 bootstrap sample.

lavaan 0.6.15 ended normally after 92 iterations	
Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	39
Number of observations	1365
Model Test User Model	
Test statistic	0.000
Degrees of freedom	0
Model Test Baseline Model	
Test statistic	27.639
Degrees of freedom	1
P-value	0.000
User Model versus Baseline Model	
Comparative Fit Index (CFI)	1
Tucker-Lewis Index (TLI)	1
Root Mean Square Error of Approximation	
RMSEA	0.000
90 Percent confidence interval - lower	0.000
90 Percent confidence interval - upper	0.000
P-value H_0: RMSEA <= 0.050	NA
P-value H_0: RMSEA >= 0.080	NA
Standardized Root Mean Square Residual	
SRMR	0.000
Parameter Estimates	
Standard errors	Bootstrap
Number of requested bootstrap draws	5000
Number of successful bootstrap draws	5000

>>>

TABLE A4.3 Example for model summary statistics. Green space indicator: surrounding greenness in 100 m Euclidean distance tested with 5000 bootstrap sample.

Regressions	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
physical_activity ~						
srrn_GN100 (a)	0.565	0.252	2.243	0.025	0.565	0.094
Porto	-0.378	0.121	-3.110	0.002	-0.378	-0.161
Sofia	0.188	0.124	1.512	0.130	0.188	0.080
Hoje	0.393	0.119	3.310	0.001	0.393	0.127
yers_n_NBH	0.595	0.237	2.516	0.012	0.595	0.102
sex	-0.377	0.134	-2.816	0.005	-0.377	-0.086
age	-1.232	0.219	-5.613	0.000	-1.232	-0.259
disabilits	0.124	0.088	1.414	0.158	0.124	0.047
yrs_f_dctn	-0.294	0.167	-1.759	0.079	-0.294	-0.070
employed	0.189	0.090	2.103	0.035	0.189	0.086
income	-0.019	0.149	-0.128	0.898	-0.019	-0.005
ppltn_dnst	-0.692	0.147	-4.713	0.000	-0.692	-0.159
NBH_safety	-0.083	0.122	-0.680	0.497	-0.083	-0.023
NBH_shops	-0.107	0.144	-0.741	0.459	-0.107	-0.028
NBH_leisur	-0.023	0.143	-0.160	0.873	-0.023	-0.006
NBH_pblc_t	0.371	0.136	2.736	0.006	0.371	0.090
health ~						
srrn_GN100 (c)	0.454	0.244	1.860	0.063	0.454	0.065
physcl_ctv (b)	0.164	0.034	4.749	0.000	0.164	0.142
Porto	-0.156	0.113	-1.382	0.167	-0.156	-0.058
Sofia	0.247	0.117	2.118	0.034	0.247	0.091
Hoje	-0.396	0.121	-3.269	0.001	-0.396	-0.111
yers_n_NBH	-0.265	0.204	-1.299	0.194	-0.265	-0.039
sex	-0.167	0.128	-1.309	0.191	-0.167	-0.033
age	-1.634	0.219	-7.460	0.000	-1.634	-0.298
disabilits	-0.839	0.084	-9.989	0.000	-0.839	-0.276
yrs_f_dctn	0.016	0.170	0.096	0.923	0.016	0.003
employed	0.069	0.084	0.814	0.415	0.069	0.027
income	0.187	0.146	1.282	0.200	0.187	0.043
ppltn_dnst	0.044	0.129	0.343	0.732	0.044	0.009
NBH_safety	0.114	0.112	1.013	0.311	0.114	0.027
NBH_shops	0.113	0.134	0.840	0.401	0.113	0.026
NBH_leisur	-0.051	0.135	-0.378	0.705	-0.051	-0.012
NBH_pblc_t	0.251	0.132	1.895	0.058	0.251	0.053

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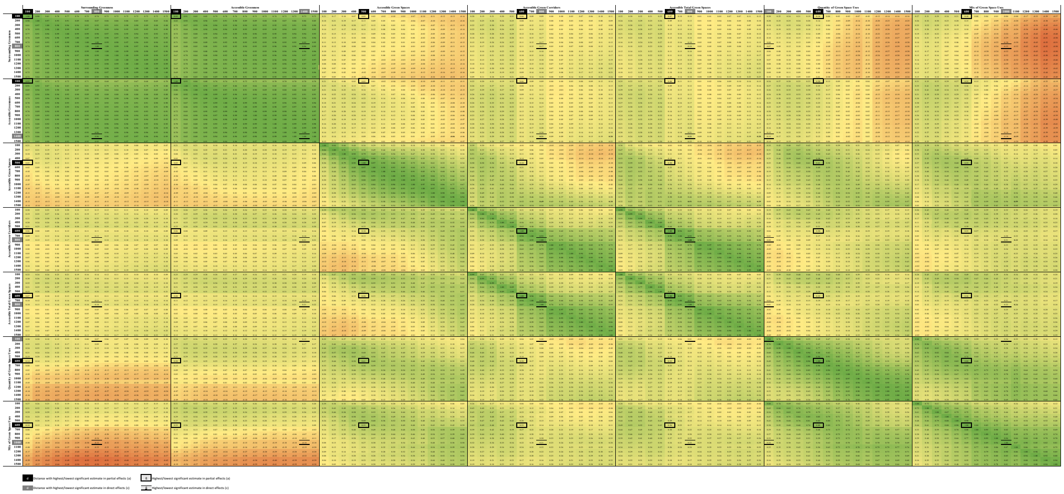
TABLE A4.3 Example for model summary statistics. Green space indicator: surrounding greenness in 100 m Euclidean distance tested with 5000 bootstrap sample.

Intercepts	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.physical_ctvty	0.000				0.000	0.000
.health	0.000				0.000	0.000
Thresholds	**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**	**Std.lv**	**Std.all**
physcl_ctvty|1	-0.878	0.242	-3.635	0.000	-0.878	-0.801
physcl_ctvty|2	0.335	0.240	1.399	0.162	0.335	0.305
health|t1	-2.974	0.270	-11.035	0.000	-2.974	-2.346
health|t2	-2.044	0.256	-7.969	0.000	-2.044	-1.612
health|t3	-0.971	0.251	-3.867	0.000	-0.971	-0.766
health|t4	0.399	0.250	1.597	0.110	0.399	0.315
Variances	**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**	**Std.lv**	**Std.all**
.physical_ctvty	1.000				1.000	0.831
.health	0.973				0.973	0.605
Scales y*	**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**	**Std.lv**	**Std.all**
physical_ctvty	1.000				1.000	1.000
health	1.000				1.000	1.000
R-Square	**Estimate**					
physical_ctvty	0.169					
health	0.395					

TABLE A4.4 Correlation Matrix of green space characteristics.



Notes: *Downloadable version available at the 4TU Repository:*
https://doi.org/10.4121/5e3539a0-d632-4095-876b-dc8768e8e2f3

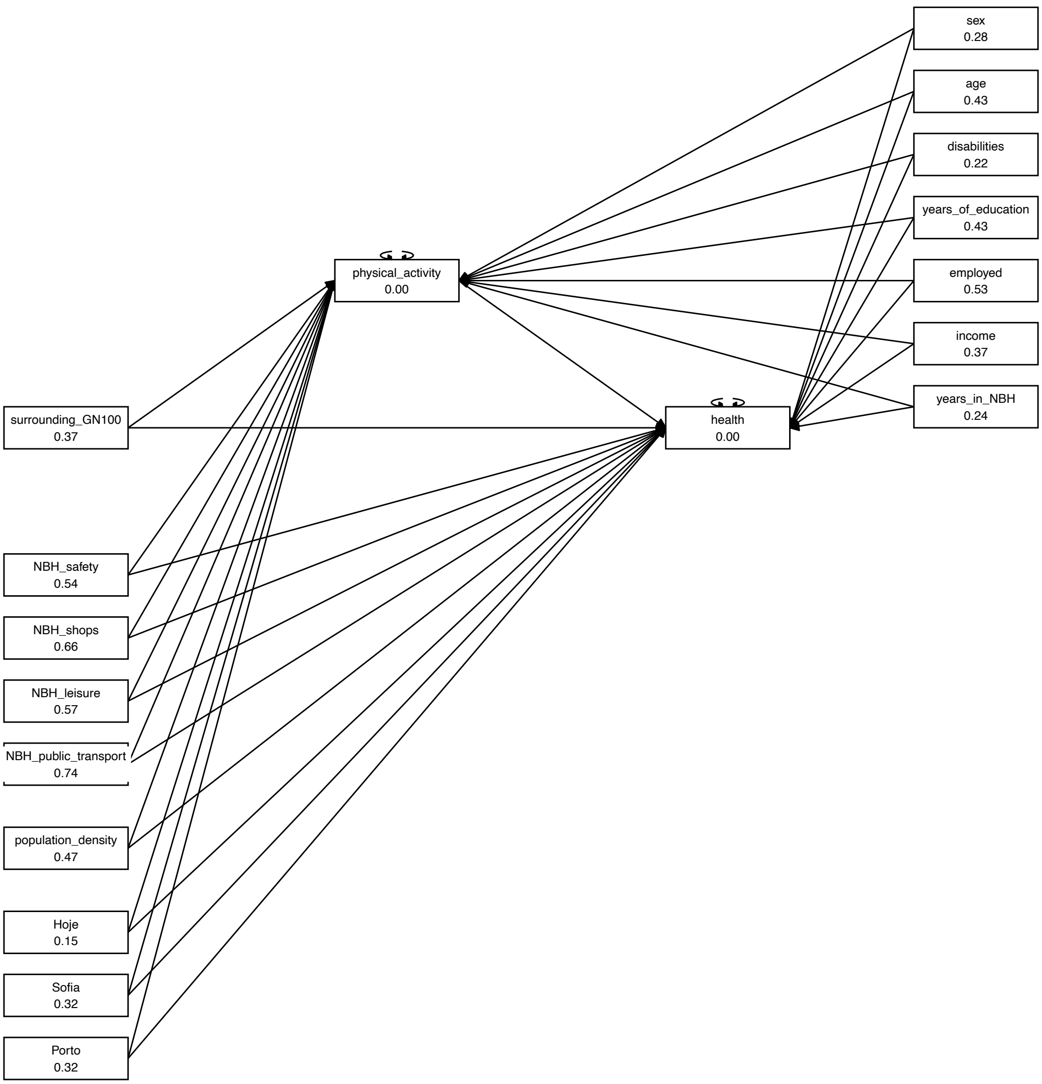


FIG. A4.1 Full Structural Equation Model used for the statistical analysis. The green space indicator (here surrounding greenness in 100 m Euclidean distance) was exchanged 105 times.

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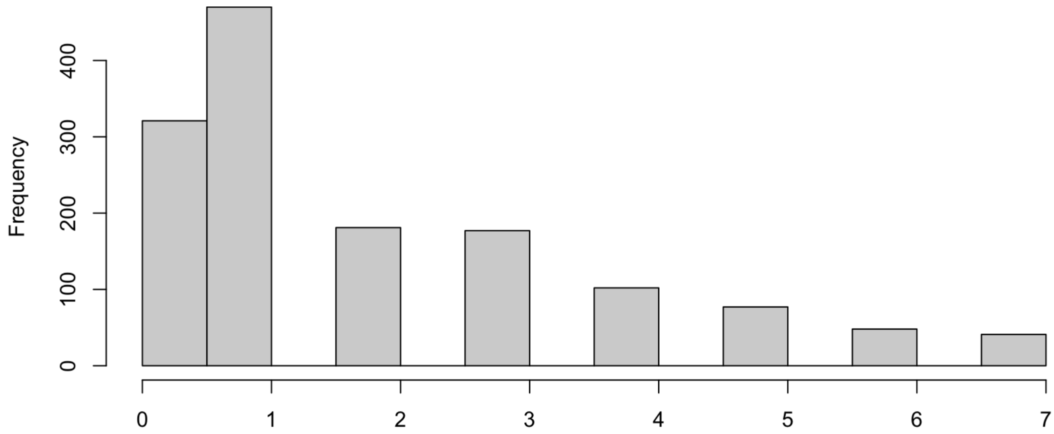

FIG. A4.2 Histogram of ordinal physical variable. Notes: physical activity levels (very high: > 12,000, high: 7,500-12,000, high-moderate 5,000-7,500, moderate: 3,600-5,000, low moderate: 2,400-3,600, low: 1,600-2,400, very low: 400-1,600, no: 0-400).

TABLE A5.1 PRIGSHARE Checklist (Chapter 5)

#	Section/Topic	Checklist Item	Reported	Chapter
OBJECTIVE				
1	Health Outcome(s)	Specify the health outcome(s) being researched		5.2.3, 5.2.4
2	Pathway(s)	Position the research within a theoretical pathway (Mitigation, Restoration, Instoration).		5.1
3	Green Space Focus	Provide a clear definition of green space features being researched, distinguishing in particular between surrounding vegetation, contact with nature, and accessible green spaces.		5.2.2
SCOPE				
4	Type of Distance	Specify the type of distance used with rationale (Euclidean Distance (ED), Network Distance (ND), Buffered Service Area (BSA), Administrative Units (AU)).		5.2.2
5	Walkability Network	If accessibility to green spaces is part of the study design, indicate if the walkability network used to generate isochrones or buffered service areas has been checked for bias and how.		A5.2
6	Distance	Give a rationale for the chosen distance and indicate if different distances were tested (Sensitivity Analysis).		5.1, 5.2.2
SPATIAL ASSESSMENT				
7	Proxy for Exposure Variable	Define the spatial indicators used in research and indicate if different indicators were tested (Sensitivity Analysis).		5.2.2
8	Data Source	Indicate which database was used and if there has been an adjustment for potential bias (expert assessment).		5.2.2, A5.2
9	Public Ownership Bias	Indicate if the dataset was controlled for the usability of green spaces from public-owned plots and how.		5.2.2, A5.2
10	Residential Ownership Bias	Indicate how semi-public residential green spaces have been handled.		5.2.2, A5.2
11	Classification Bias	Indicate how green spaces have been classified.		5.2.2, A5.2
12	Usability Bias	Indicate if the usability of green spaces was checked and report inclusion/exclusion criteria.		5.2.2, A5.2
13	Connectivity Bias	(Optional) Indicate if the database has been corrected for green space network connectivity and how.		5.2.2, A5.2
VEGETATION ASSESSMENT				
14	Proxy for Exposure Variable	Specify the indicator(s) used to assess surrounding vegetation or nature and indicate if the sensitivity was tested.		5.2.2, A5.2
15	Data Source	Provide the data source of the satellite images and their resolution.		5.2.2
16	Handling of Blue Spaces	Indicate how blue spaces have been handled.		5.2.2
17	Handling of Seasons	Explain how variance in vegetation indices due to seasonality or changes in the built environment was handled.		5.2.5

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TABLE A5.1 PRIGSHARE Checklist (Chapter 5)

#	Section/Topic	Checklist Item	Reported	Chapter
CONTEXT ASSESSMENT				
18	Personal Context	Give a rationale for the chosen personal context variables that have been tested or controlled for.		5.2.5
19	Local Context	Give a rationale for the chosen local context variables that have been tested or controlled for.		5.2.5
20	Urbanicity Context	Give a rationale for the chosen urbanicity context variables that have been tested or controlled for.		5.2.5
21	Global Context	Indicate in which climate, and cultural setting the study was conducted. If several settings are part of the research explain how the results were controlled for potential confounding and tested for effect modification.		5.2.5

TABLE A5.2 Spatial Assessment. Inclusion/Exclusion Criteria for green spaces

ITEMS	DESCRIPTION	HOW HANDLED
ITEM 5	Walkability Network	Based on the available street network downloaded from OpenStreetMap Added: Informal pathways, missing sidewalks and pathways. Excluded: Highways, motorways, motorway links, trunks, trunk links, and construction sites.
ITEM 9	Public Ownership Bias	Considered as Public green space, when: • The green space is accessible and used by the public
ITEM 10	Residential Ownership Bias	Considered as Public green space, when: • The residential green space is part of a larger green infrastructure • Or the edge of the residential green space is only surrounded by buildings or garages on 1 or 2 sides. Considered as semi-public green space, when: • The residential green space is not part of a larger green infrastructure • And the edge of the residential green space is only surrounded by buildings or garages on 3 or 4 sides. Considered as private green space, when: • The plot belongs to a single-family home
ITEM 11	Classification Bias	Inclusion: • Public Parks, accessible sports fields, green cemeteries, agricultural land and forests with pathways, and smaller green spaces with benches. • Linear green spaces connecting parts of the green infrastructure or alongside a river Exclusion: • Inaccessible Forests, agricultural lands, bushes or grasslands • Green spaces in the roundabouts of a roadway, between street lanes or railroads • Cemeteries without grass and trees. • Sports Fields which belong to a sports club and are not public.
ITEM 12	Usability Bias	Inclusion: • Not fenced and no steep slopes • no entrance fee • Opening times at least 9 am to 5 pm Exclusion: • Fenced or unwalkable because of steep slope • With an entrance fee • Opening times shorter than 9 am to 5 pm
ITEM 13	Connectivity Bias	Manually connected or added: • connected green infrastructure that was interrupted by a road but has a crossing • merged green spaces directly next to each other • added linear green spaces that consist of walkable pathways with greenery

Notes: *Based on PRIGSHARE Reporting Guidelines (Cardinali, M., Beenackers, M. A., van Timmeren, A., & Pottgiesser, U. (2023). Preferred reporting items in green space health research. Guiding principles for an interdisciplinary field. Environmental Research, 228, 115893. https://doi.org/10.1016/j.envres.2023.115893)*

TABLE A5.3 Dimension of Mental Health Continuum and associated items (Keyes, 2018)

Theoretical dimension		Mental Health Continuum item (numbers show item order):
Emotional Well-being		
		We will be interested in your wellbeing and health during the past month. Please answer the following questions. Place a check mark in the box that best represents how often you have experienced or felt the following from a scale of 1 (high frequency) to 5 (low frequency). During the past month, how often did you feel ...
Happyness	(1)	... happy
Interest in life	(2)	... interested in life
Satisfaction with life	(3)	... satisfied with life
Social Well-being		
Contribution to society	(4)	... that you had something important to contribute to society
Belonging to a community	(5)	... that you belonged to a community (like a social group, your school, or your neighbourhood)
Society is a good place	(6)	... that our society is a good place, or is becoming a better place, for all people
People are basically good	(7)	... that people are basically good
Society makes sense	(8)	... that the way our society works made sense to you
Psychological Well-being		
Like your personality	(9)	... that you liked most parts of your personality
Managing responsibilities	(10)	... good at managing the responsibilities of your daily life
Trusting Relationships	(11)	... that you had warm and trusting relationships with others
Experience in becoming a better person	(12)	... that you had experiences that challenged you to grow and become a better person
Express own ideas and opinions	(13)	... confident to think or express your own ideas and opinions
Life as a sense of direction or meaning	(14)	... that your life has a sense of direction or meaning to it

Reference: *Keyes, C. L. M. (2018). Overview of The Mental Health Continuum Short Form (MHC-SF). https://doi.org/10.13140/RG.2.2.24204.62088*

TABLE A5.4 Example for model summary statistics. Green space indicator: surrounding greenness in 100m Euclidean distance with 5000 bootstrap samples.

lavaan 0.6.15 ended normally after 79 iterations	
Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	37
Number of observations	1365
Model Test User Model	
Test statistic	0.000
Degrees of freedom	0
Model Test Baseline Model	
Test statistic	33.292
Degrees of freedom	1.000
P-value	0.000
User Model versus Baseline Model	
Comparative Fit Index (CFI)	1.000
Tucker-Lewis Index (TLI)	1.000
Root Mean Square Error of Approximation	
RMSEA	0.000
90 Percent confidence interval - lower	0.000
90 Percent confidence interval - upper	0.000
P-value H_0: RMSEA <= 0.050	NA
P-value H_0: RMSEA >= 0.080	NA
Standardized Root Mean Square Residual	
SRMR	0.000
Parameter Estimates	
Standard errors	Bootstrap
Number of requested bootstrap draws	5000
Number of successful bootstrap draws	5000

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TABLE A5.4 Example for model summary statistics. Green space indicator: surrounding greenness in 100m Euclidean distance with 5000 bootstrap samples.

Regressions	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
social_cohesion ~						
srrn_GN100 (a)	0.453	0.267	1.699	0.089	0.453	0.075
Porto	0.821	0.124	6.599	0.000	0.821	0.348
Sofia	-0.124	0.117	-1.053	0.292	-0.124	-0.052
Hoje	0.016	0.117	0.134	0.893	0.016	0.005
yers_n_NBH	0.434	0.212	2.050	0.040	0.434	0.074
sex	-0.021	0.123	-0.170	0.865	-0.021	-0.005
age	-0.152	0.196	-0.778	0.437	-0.152	-0.032
disabilits	-0.126	0.090	-1.406	0.160	-0.126	-0.048
yrs_f_dctn	-0.284	0.168	-1.686	0.092	-0.284	-0.067
employed	0.025	0.086	0.290	0.771	0.025	0.011
income	0.142	0.151	0.941	0.347	0.142	0.037
ppltn_dnst	0.376	0.121	3.104	0.002	0.376	0.086
NBH_shops	0.455	0.145	3.133	0.002	0.455	0.119
NBH_leisur	0.369	0.139	2.653	0.008	0.369	0.099
NBH_pblc_t	0.108	0.155	0.695	0.487	0.108	0.026
mental_health ~						
srrn_GN100 (c)	-0.019	0.038	-0.494	0.621	-0.019	-0.020
socil_chsn (b)	0.026	0.005	5.515	0.000	0.026	0.162
Porto	0.092	0.020	4.720	0.000	0.092	0.247
Sofia	0.044	0.019	2.346	0.019	0.044	0.116
Hoje	0.062	0.018	3.441	0.001	0.062	0.127
yers_n_NBH	0.013	0.032	0.416	0.678	0.013	0.014
sex	0.000	0.018	-0.005	0.996	0.000	0.000
age	-0.060	0.032	-1.871	0.061	-0.060	-0.080
disabilits	-0.038	0.013	-2.965	0.003	-0.038	-0.091
yrs_f_dctn	-0.010	0.025	-0.401	0.689	-0.010	-0.015
employed	0.047	0.014	3.349	0.001	0.047	0.134
income	0.014	0.021	0.651	0.515	0.014	0.023
ppltn_dnst	-0.047	0.019	-2.418	0.016	-0.047	-0.068
NBH_shops	-0.016	0.022	-0.724	0.469	-0.016	-0.026
NBH_leisur	0.087	0.021	4.124	0.000	0.087	0.147
NBH_pblc_t	0.033	0.021	1.581	0.114	0.033	0.051

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TABLE A5.4 Example for model summary statistics. Green space indicator: surrounding greenness in 100m Euclidean distance with 5000 bootstrap samples.

Intercepts	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.social_cohesin	0.000				0.000	0.000
.mental_health	0.591	0.039	15.221	0.000	0.591	3.395
Thresholds	**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**	**Std.lv**	**Std.all**
social_chsn|t1	-0.820	0.249	-3.292	-0.001	0.820	-0.744
social_chsn|t2	-0.294	0.246	-1.193	-0.233	0.294	-0.267
social_chsn|t3	0.653	0.246	2.655	0.008	0.653	0.593
social_chsn|t4	1.810	0.249	7.276	0.000	1.810	1.643
Variances	**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**	**Std.lv**	**Std.all**
.social_cohesin	1.000				1.000	0.823
.mental_health	0.026	0.001	19.196	0.000	0.026	0.852
Scales y*	**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**	**Std.lv**	**Std.all**
social_cohesin	1.000				1.000	1.000
R-Square	**Estimate**					
social_cohesin	0.177					
mental_health	0.148					

TABLE A5.5 Sensitivity Analysis without Porto sample (n=926): Partial Effects (a). Green Space – Social cohesion.

Standardized Estimated ß (95% CI) for partial effects (a) of green space indicators on social cohesion in the 105 structural equation models each with 5000 bootstrap samples.

Greenness				
Distance	(A) Surrounding GN		(B) Accessible GN	
100	0.648 (0.085, 1.416)	*	0.516 (-0.384, 1.075)	
200	0.637 (-0.268, 1.433)		0.333 (-0.461, 0.958)	
300	0.510 (-0.190, 1.259)		0.483 (-0.198, 1.478)	
400	0.662 (-0.244, 1.507)		0.682 (-0.052, 1.597)	
500	0.837 (0.054, 1.623)	*	0.853 (0.135, 1.677)	*
600	1.069 (0.419, 1.862)	*	1.048 (0.343, 1.659)	*
700	1.171 (0.465, 2.281)	*	1.396 (0.617, 2.296)	*
800	1.301 (0.505, 2.249)	*	1.640 (0.862, 2.479)	*
900	1.264 (0.375, 2.133)	*	1.753 (1.121, 2.636)	*
1000	1.202 (0.372, 1.979)	*	1.802 (0.801, 2.537)	*
1100	1.207 (0.342, 2.251)	*	1.877 (1.056, 2.618)	*
1200	1.265 (0.332, 2.456)	*	1.916 (1.236, 2.733)	*
1300	**1.282 (0.062, 2.068)**	*	1.990 (1.082, 2.795)	*
1400	1.160 (-0.086, 1.861)		2.167 (1.040, 2.869)	*
1500	1.200 (0.282, 2.275)	*	**2.338 (1.379, 3.433)**	*

Green Space Accessibility						
Distance	(C) Accessible GS		(D) Accessible GC		(E) Accessible TGS	
100	0.181 (-0.618, 0.793)		0.350 (-0.070, 0.876)		0.416 (0.073, 0.875)	*
200	0.247 (-0.174, 0.669)		0.175 (-0.083, 0.423)		0.214 (-0.109, 0.526)	
300	0.303 (-0.127, 0.827)		0.336 (0.024, 0.558)	*	0.361 (0.103, 0.742)	*
400	0.366 (-0.008, 1.051)		0.303 (0.011, 0.522)	*	0.328 (0.081, 0.570)	*
500	0.323 (-0.063, 0.642)		0.390 (0.114, 0.633)	*	0.411 (0.190, 0.656)	*
600	0.344 (-0.015, 0.722)		0.433 (-0.098, 0.776)		0.472 (-0.040, 1.078)	
700	0.424 (-0.057, 0.857)		0.560 (0.100, 1.109)	*	0.599 (0.184, 1.357)	*
800	0.514 (0.238, 0.973)	*	**0.641 (0.126, 1.186)**	*	**0.681 (0.225, 1.189)**	*
900	0.571 (0.238, 1.163)	*	0.378 (0.098, 0.894)	*	0.408 (0.127, 0.729)	*
1000	0.613 (0.161, 1.083)	*	0.305 (-0.059, 0.570)		0.338 (-0.004, 0.670)	
1100	0.705 (0.270, 1.163)	*	0.310 (-0.031, 0.801)		0.343 (0.001, 0.621)	*
1200	0.715 (0.287, 1.362)	*	0.243 (-0.094, 0.638)		0.274 (-0.149, 0.648)	
1300	0.699 (0.188, 0.994)	*	0.055 (-0.330, 0.368)		0.086 (-0.233, 0.486)	
1400	**0.672 (0.295, 1.092)**	*	0.004 (-0.392, 0.521)		0.037 (-0.319, 0.437)	
1500	0.586 (0.255, 0.873)	*	-0.373 (-0.800, -0.048)	*	-0.340 (-0.651, 0.088)	

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TABLE A5.5 Sensitivity Analysis without Porto sample (n=926): Partial Effects (a). Green Space – Social cohesion.

Standardized Estimated ß (95% CI) for partial effects (a) of green space indicators on social cohesion in the 105 structural equation models each with 5000 bootstrap samples.

Green Space Usability				
Distance	(F) Quantity of GSU		(G) Mix Of GSU	
100	0.234 (-0.498, 0.706)		0.040 (-0.435, 0.422)	
200	0.049 (-0.474, 0.357)		-0.002 (-0.412, 0.271)	
300	0.177 (-0.159, 0.554)		0.231 (-0.193, 0.509)	
400	0.220 (-0.441, 0.592)		0.291 (-0.032, 0.623)	
500	0.097 (-0.385, 0.439)		0.385 (-0.023, 0.694)	
600	0.229 (-0.047, 0.821)		0.382 (0.039, 0.652)	*
700	0.362 (-0.006, 0.779)		0.583 (0.301, 0.855)	*
800	0.582 (0.243, 1.169)	*	0.598 (0.068, 0.870)	*
900	0.574 (-0.009, 0.937)		0.470 (0.316, 0.798)	*
1000	0.494 (0.010, 1.013)	*	0.453 (0.232, 0.714)	*
1100	0.111 (-0.453, 0.745)		0.705 (0.454, 1.057)	*
1200	0.341 (0.025, 0.804)	*	0.628 (0.283, 0.926)	*
1300	0.330 (-0.007, 0.808)		0.767 (0.291, 1.006)	*
1400	0.241 (-0.140, 0.639)		**0.993 (0.597, 1.364)**	*
1500	0.180 (-0.206, 0.521)		0.950 (0.473, 1.455)	*

Notes: *Adjusted for sex, age, disabilities, education, income, occupation, years lived in the neighbourhood, perceived neighbourhood safety, satisfaction with shops, leisure facilities, public transport, change in elevation within 500m buffer, and population density.*

Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with individual accessible private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);* ***** *Coefficient is statistically significant; bold estimates indicate the distance with the highest significant estimate.*

TABLE A5.6 Sensitivity Analysis without Porto sample (n=926): Indirect Effects (a*b). Green Space – Social cohesion – Health.

Standardized estimated ß (95% CI) for the indirect effect (a*b) of green space indicators, mediated by social cohesion on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Greenness				
Distance	(A) Surrounding GN		(B) Accessible GN	
100	0.013 (0.001, 0.030)	*	0.010 (-0.003, 0.027)	
200	0.013 (-0.002, 0.036)		0.007 (-0.008, 0.028)	
300	0.010 (-0.003, 0.029)		0.009 (-0.001, 0.030)	
400	0.013 (-0.003, 0.032)		0.013 (0.001, 0.033)	*
500	0.016 (0.002, 0.034)	*	0.016 (0.002, 0.045)	*
600	0.020 (0.003, 0.041)	*	0.020 (0.007, 0.045)	*
700	0.022 (0.004, 0.048)	*	0.026 (0.014, 0.048)	*
800	0.024 (0.009, 0.055)	*	0.030 (0.014, 0.079)	*
900	0.024 (0.005, 0.055)	*	0.032 (0.015, 0.074)	*
1000	0.022 (0.009, 0.054)	*	0.033 (0.010, 0.061)	*
1100	0.023 (0.005, 0.056)	*	0.034 (0.015, 0.058)	*
1200	0.024 (0.007, 0.068)	*	0.035 (0.018, 0.062)	*
1300	**0.024 (0.006, 0.059)**	*	0.036 (0.016, 0.066)	*
1400	0.022 (-0.003, 0.041)		0.040 (0.011, 0.074)	*
1500	0.023 (0.005, 0.055)	*	**0.044 (0.010, 0.071)**	*

Green Space Accessibility						
Distance	(C) Accessible GS		(D) Accessible GC		(E) Accessible TGS	
100	0.004 (-0.015, 0.017)		0.007 (0.000, 0.024)		0.008 (0.003, 0.028)	*
200	0.005 (-0.002, 0.017)		0.003 (-0.001, 0.010)		0.004 (-0.001, 0.011)	
300	0.006 (-0.001, 0.022)		0.007 (0.002, 0.014)	*	0.007 (0.002, 0.015)	*
400	0.007 (0.000, 0.017)		0.006 (0.001, 0.012)	*	0.006 (0.003, 0.014)	*
500	0.006 (-0.001, 0.021)		0.008 (0.003, 0.018)	*	0.008 (0.004, 0.018)	*
600	0.007 (0.002, 0.020)	*	0.009 (0.001, 0.019)	*	0.009 (0.000, 0.025)	*
700	0.008 (0.002, 0.021)	*	0.011 (0.001, 0.027)	*	0.012 (0.002, 0.028)	*
800	0.010 (0.005, 0.024)	*	**0.013 (0.004, 0.031)**	*	**0.014 (0.005, 0.032)**	*
900	0.011 (0.004, 0.020)	*	0.008 (0.003, 0.020)	*	0.008 (0.001, 0.018)	*
1000	0.012 (0.000, 0.025)	*	0.006 (0.001, 0.019)	*	0.007 (0.000, 0.015)	
1100	0.013 (0.004, 0.028)	*	0.006 (0.000, 0.016)		0.007 (0.000, 0.016)	
1200	0.014 (0.004, 0.031)	*	0.005 (-0.001, 0.013)		0.006 (-0.001, 0.020)	
1300	0.014 (0.004, 0.023)	*	0.001 (-0.006, 0.008)		0.002 (-0.004, 0.013)	
1400	**0.013 (0.004, 0.027)**	*	0.000 (-0.008, 0.011)		0.001 (-0.007, 0.008)	
1500	0.012 (0.004, 0.020)	*	-0.007 (-0.021, -0.002)	*	-0.006 (-0.017, -0.001)	*

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TABLE A5.6 Sensitivity Analysis without Porto sample (n=926): Indirect Effects (a*b). Green Space – Social cohesion – Health.

Standardized estimated ß (95% CI) for the indirect effect (a*b) of green space indicators, mediated by social cohesion on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Green Space Usability				
Distance	(F) Quantity of GSU		(G) Mix Of GSU	
100	0.005 (-0.006, 0.017)		0.001 (-0.009, 0.007)	
200	0.001 (-0.007, 0.009)		0.000 (-0.011, 0.006)	
300	0.003 (-0.002, 0.015)		0.005 (-0.002, 0.012)	
400	0.004 (-0.006, 0.015)		0.006 (0.000, 0.021)	
500	0.002 (-0.007, 0.009)		0.007 (0.000, 0.019)	
600	0.004 (-0.001, 0.015)		0.007 (0.002, 0.015)	*
700	0.007 (0.000, 0.018)		0.012 (0.004, 0.021)	*
800	0.011 (0.003, 0.025)	*	0.012 (0.004, 0.021)	*
900	**0.011 (0.002, 0.023)**	*****	0.009 (0.005, 0.019)	*
1000	0.009 (0.001, 0.024)	*	0.009 (0.005, 0.018)	*
1100	0.002 (-0.005, 0.017)		0.014 (0.007, 0.026)	*
1200	0.007 (0.000, 0.019)		0.012 (0.004, 0.022)	*
1300	0.006 (0.000, 0.021)		0.015 (0.004, 0.028)	*
1400	0.005 (-0.002, 0.015)		**0.020 (0.010, 0.031)**	*****
1500	0.004 (-0.004, 0.012)		0.019 (0.005, 0.033)	*

Notes: *Adjusted for sex, age, disabilities, years of education, income, employment status, years lived in the neighbourhood, well-being, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with individual accessible private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);* ***** *Coefficient is statistically significant; bold estimates indicate the distance with the highest significant estimate.*

TABLE A5.7 Sensitivity Analysis without Porto sample (n=926): Direct Effects (c). Green Space – Mental Health.

Standardized Estimated ß (95% CI) for the direct effect (c) of green space indicators on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Greenness				
Distance	(A) Surrounding GN		(B) Accessible GN	
100	-0.061 (-0.140, 0.040)		-0.037 (-0.194, 0.031)	
200	-0.033 (-0.150, 0.052)		-0.044 (-0.142, 0.038)	
300	-0.009 (-0.112, 0.081)		-0.024 (-0.113, 0.068)	
400	0.002 (-0.102, 0.119)		-0.006 (-0.097, 0.100)	
500	0.023 (-0.067, 0.157)		0.019 (-0.095, 0.108)	
600	0.049 (-0.079, 0.146)		0.047 (-0.047, 0.194)	
700	0.065 (-0.116, 0.159)		0.049 (-0.044, 0.141)	
800	0.075 (-0.043, 0.207)		0.061 (-0.023, 0.166)	
900	0.084 (-0.046, 0.220)		0.057 (-0.050, 0.172)	
1000	0.090 (-0.050, 0.204)		0.062 (-0.042, 0.140)	
1100	0.087 (-0.043, 0.236)		0.080 (-0.030, 0.181)	
1200	0.089 (-0.034, 0.224)		0.080 (-0.024, 0.247)	
1300	0.088 (-0.046, 0.277)		0.078 (-0.066, 0.187)	
1400	0.090 (-0.082, 0.214)		0.073 (-0.035, 0.226)	
1500	0.089 (-0.066, 0.265)		0.061 (-0.067, 0.190)	

Green Space Accessibility						
Distance	(C) Accessible GS		(D) Accessible GC		(E) Accessible TGS	
100	0.050 (-0.060, 0.169)		-0.005 (-0.062, 0.051)		-0.009 (-0.106, 0.044)	
200	0.036 (-0.032, 0.093)		-0.011 (-0.051, 0.044)		-0.013 (-0.068, 0.027)	
300	0.034 (-0.015, 0.118)		-0.008 (-0.062, 0.039)		-0.009 (-0.040, 0.050)	
400	0.022 (-0.072, 0.074)		0.014 (-0.023, 0.052)		0.013 (-0.042, 0.043)	
500	0.015 (-0.034, 0.058)		-0.003 (-0.039, 0.038)		-0.004 (-0.037, 0.034)	
600	0.012 (-0.040, 0.039)		-0.067 (-0.178, -0.001)		-0.068 (-0.145, -0.002)	
700	0.010 (-0.028, 0.057)		-0.062 (-0.135, 0.017)		-0.063 (-0.171, -0.003)	
800	0.015 (-0.041, 0.057)		-0.044 (-0.130, 0.021)		-0.046 (-0.122, 0.036)	
900	0.021 (-0.030, 0.068)		-0.063 (-0.129, 0.031)		-0.064 (-0.110, 0.029)	
1000	0.025 (-0.023, 0.072)		-0.093 (-0.144, -0.034)	*	-0.095 (-0.165, -0.041)	*
1100	0.028 (-0.042, 0.070)		-0.056 (-0.096, 0.067)		-0.058 (-0.114, -0.003)	
1200	0.020 (-0.063, 0.071)		-0.088 (-0.161, -0.018)	*	-0.090 (-0.152, -0.017)	*
1300	0.007 (-0.071, 0.074)		-0.106 (-0.177, -0.034)	*	-0.108 (-0.203, -0.043)	*
1400	-0.011 (-0.059, 0.048)		**-0.131 (-0.190, -0.044)**	*****	**-0.134 (-0.192, -0.050)**	*****
1500	-0.024 (-0.090, 0.036)		-0.118 (-0.191, -0.079)	*	-0.121 (-0.171, -0.049)	*

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TABLE A5.7 Sensitivity Analysis without Porto sample (n=926): Direct Effects (c). Green Space – Mental Health.

Standardized Estimated ß (95% CI) for the direct effect (c) of green space indicators on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

	Green Space Usability			
Distance	(F) Quantity of GSU		(G) Mix Of GSU	
100	-0.008 (-0.074, 0.064)		0.010 (-0.029, 0.069)	
200	-0.003 (-0.048, 0.038)		-0.003 (-0.044, 0.050)	
300	0.005 (-0.032, 0.067)		-0.007 (-0.045, 0.031)	
400	0.031 (-0.017, 0.103)		0.026 (-0.023, 0.080)	
500	0.030 (-0.024, 0.074)		0.018 (-0.029, 0.069)	
600	0.031 (-0.037, 0.096)		0.012 (-0.020, 0.059)	
700	0.015 (-0.040, 0.081)		-0.014 (-0.052, 0.022)	
800	0.021 (-0.033, 0.081)		-0.035 (-0.077, 0.011)	
900	0.024 (-0.044, 0.088)		-0.017 (-0.057, 0.011)	
1000	0.051 (-0.016, 0.122)		-0.023 (-0.057, 0.019)	
1100	0.060 (0.001, 0.138)	*	0.001 (-0.035, 0.032)	
1200	0.014 (-0.072, 0.074)		-0.009 (-0.051, 0.043)	
1300	-0.007 (-0.069, 0.050)		-0.016 (-0.070, 0.035)	
1400	-0.020 (-0.072, 0.023)		-0.027 (-0.077, 0.053)	
1500	-0.016 (-0.080, 0.042)		-0.010 (-0.076, 0.065)	

Notes: *Adjusted for sex, age, disabilities, education, income, occupation, years lived in the neighbourhood, perceived neighbourhood safety, satisfaction with shops, leisure facilities, public transport, change in elevation within 500m buffer, and population density.*

Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with individual accessible private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);* ***** *Coefficient is statistically significant; bold estimates indicate the distance with the highest significant estimate.*

TABLE A5.8 Sensitivity Analysis without Porto sample (n=926): Total Effects (a*b+c). Green Space – Social cohesion – Mental Health.

Estimated ß (95% CI) for the total effect (a*b + c) of green space indicators, both indirectly via social cohesion, and directly on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Greenness				
Distance	**(A) Surrounding GN**		**(B) Accessible GN**	
100	-0.048 (-0.134, 0.044)		-0.027 (-0.167, 0.054)	
200	-0.021 (-0.147, 0.073)		-0.038 (-0.139, 0.047)	
300	0.001 (-0.099, 0.086)		-0.014 (-0.113, 0.078)	
400	0.014 (-0.080, 0.147)		0.007 (-0.075, 0.113)	
500	0.039 (-0.084, 0.161)		0.036 (-0.061, 0.127)	
600	0.069 (-0.063, 0.161)		0.067 (0.001, 0.234)	
700	0.087 (-0.092, 0.169)		0.075 (-0.019, 0.164)	
800	0.100 (-0.015, 0.226)		0.092 (0.000, 0.189)	
900	0.108 (-0.023, 0.263)		0.090 (-0.021, 0.200)	
1000	0.113 (0.002, 0.243)	*	0.095 (0.006, 0.181)	*
1100	0.109 (-0.019, 0.262)		0.114 (-0.002, 0.242)	
1200	0.113 (-0.012, 0.249)		0.115 (0.036, 0.288)	*
1300	0.112 (-0.030, 0.285)		0.114 (-0.036, 0.224)	
1400	0.112 (-0.052, 0.231)		0.113 (-0.002, 0.238)	
1500	0.112 (-0.056, 0.275)		0.105 (-0.026, 0.231)	

Green Space Accessibility						
Distance	**(C) Accessible GS**		**(D) Accessible GC**		**(E) Accessible TGS**	
100	0.053 (-0.078, 0.157)		0.002 (-0.057, 0.056)		-0.001 (-0.105, 0.052)	
200	0.041 (-0.024, 0.100)		-0.008 (-0.045, 0.049)		-0.008 (-0.066, 0.033)	
300	0.040 (-0.010, 0.124)		-0.001 (-0.057, 0.045)		-0.002 (-0.032, 0.054)	
400	0.029 (-0.031, 0.092)		0.020 (-0.027, 0.056)		0.019 (-0.038, 0.049)	
500	0.021 (-0.025, 0.070)		0.005 (-0.029, 0.051)		0.004 (-0.026, 0.046)	
600	0.018 (-0.032, 0.049)		-0.059 (-0.172, 0.008)		-0.059 (-0.143, 0.006)	
700	0.019 (-0.015, 0.078)		-0.051 (-0.129, 0.025)		-0.051 (-0.168, 0.004)	
800	0.025 (-0.028, 0.065)		-0.032 (-0.106, 0.046)		-0.032 (-0.105, 0.051)	
900	0.031 (-0.021, 0.086)		-0.056 (-0.125, 0.040)		-0.056 (-0.114, 0.028)	
1000	0.037 (-0.020, 0.079)		-0.087 (-0.147, -0.032)	*	-0.088 (-0.152, -0.033)	*
1100	0.042 (-0.028, 0.084)		-0.050 (-0.087, 0.079)		-0.051 (-0.108, 0.003)	
1200	0.034 (-0.044, 0.093)		-0.083 (-0.153, -0.011)	*	-0.085 (-0.151, -0.020)	*
1300	0.020 (-0.039, 0.089)		-0.104 (-0.178, -0.035)	*	-0.106 (-0.196, -0.035)	*
1400	0.002 (-0.051, 0.057)		**-0.131 (-0.184, -0.039)**	*****	**-0.133 (-0.190, -0.067)**	*****
1500	-0.013 (-0.081, 0.046)		-0.125 (-0.204, -0.084)	*	-0.127 (-0.189, -0.056)	*

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TABLE A5.8 Sensitivity Analysis without Porto sample (n=926): Total Effects (a*b+c). Green Space – Social cohesion – Mental Health.

Estimated ß (95% CI) for the total effect (a*b + c) of green space indicators, both indirectly via social cohesion, and directly on self-perceived general health in the 105 structural equation models each with 5000 bootstrap samples.

Green Space Usability				
Distance	(F) Quantity of GSU		(G) Mix Of GSU	
100	-0.003 (-0.069, 0.070)		0.010 (-0.030, 0.072)	
200	-0.002 (-0.048, 0.043)		-0.003 (-0.050, 0.047)	
300	0.008 (-0.028, 0.074)		-0.002 (-0.048, 0.033)	
400	0.035 (-0.020, 0.089)		0.032 (-0.019, 0.089)	
500	0.032 (-0.020, 0.077)		0.025 (-0.025, 0.081)	
600	0.035 (-0.036, 0.099)		0.019 (-0.013, 0.061)	
700	0.022 (-0.038, 0.078)		-0.002 (-0.036, 0.031)	
800	0.032 (-0.025, 0.096)		-0.023 (-0.065, 0.020)	
900	0.035 (-0.038, 0.094)		-0.008 (-0.046, 0.017)	
1000	0.061 (-0.007, 0.135)		-0.014 (-0.041, 0.032)	
1100	0.062 (0.006, 0.135)	*	0.015 (-0.023, 0.045)	
1200	0.021 (-0.060, 0.081)		0.003 (-0.045, 0.051)	
1300	0.000 (-0.061, 0.053)		-0.001 (-0.053, 0.045)	
1400	-0.016 (-0.069, 0.026)		-0.007 (-0.064, 0.074)	
1500	-0.013 (-0.077, 0.046)		0.008 (-0.066, 0.069)	

Notes: *Adjusted for sex, age, disabilities, years of education, income, employment status, years lived in the neighbourhood, well-being, satisfaction with shops, leisure facilities, public transport, population density and city.*
Abbreviations: *(A) Surrounding GN: Surrounding Greenness (measured as mean NDVI within Euclidean Distance), (B) Accessible GN: Accessible Greenness (measured as mean NDVI within network distance), (C) Accessible GS: Accessible Green spaces (measured as public green space within network distance), (D) Accessible GC: Accessible Green Corridors (measured as public green space accessible from network distance), (E) Accessible TGS: Accessible Total Green Space (measured like E, but with individual accessible private or semi-public green spaces included), (F) Quantity of GSU: Quantity of Green Space Uses (measured as sum of points within network distance), (G) Mix of GSU: Mix of Green Space Uses (measured as sum of different uses within network distance);* ***** *Coefficient is statistically significant; bold estimates indicate the distance with the highest significant estimate.*

TABLE A5.9 Correlation Matrix of Green Space Indicators

Table A13: Correlation Matrix of Green Space Indicators

Notes: d Distance with highest/lowest significant estimate in partial effects (path a) r Correlation between those green space variables with the highest/lowest significant estimates in partial effects (path a)

How to read this table:

*Does the variable **accessible greenness in 800m** represent a unique mechanism or is it highly correlated with another green space variable that showed a significant association to the mediator (indicated by the bold frame)?*

Accessible Greenness

*Does the variable **accessible green space in 1400m** represent a unique mechanism or is it highly correlated with another green space variable that showed a significant association to the mediator (indicated by the bold frame)?*

Accessible Green Space

*Does the variable **accessible green corridors in 800m or in 1500m** represent a unique mechanism or is it highly correlated with another green space variable that showed a significant association to the mediator (indicated by the bold frame)?*

Accessible Green Corridors

*Does the variable **accessible total green space in 800m or 1500m** represent a unique mechanism or is it highly correlated with another green space variable that showed a significant association to the mediator (indicated by the bold frame)?*

Accessible Total Green Spaces

*Does the variable **accessible mix of green space uses in 1100m** represent a unique mechanism or is it highly correlated with another green space variable that showed a significant association to the mediator (indicated by the bold frame)?*

Mix of Green Space Uses

Notes: *Downloadable version available at the 4TU Repository: https://doi.org/10.4121/9e6581a4-d5ce-4b94-8642-4774051a2fd8*

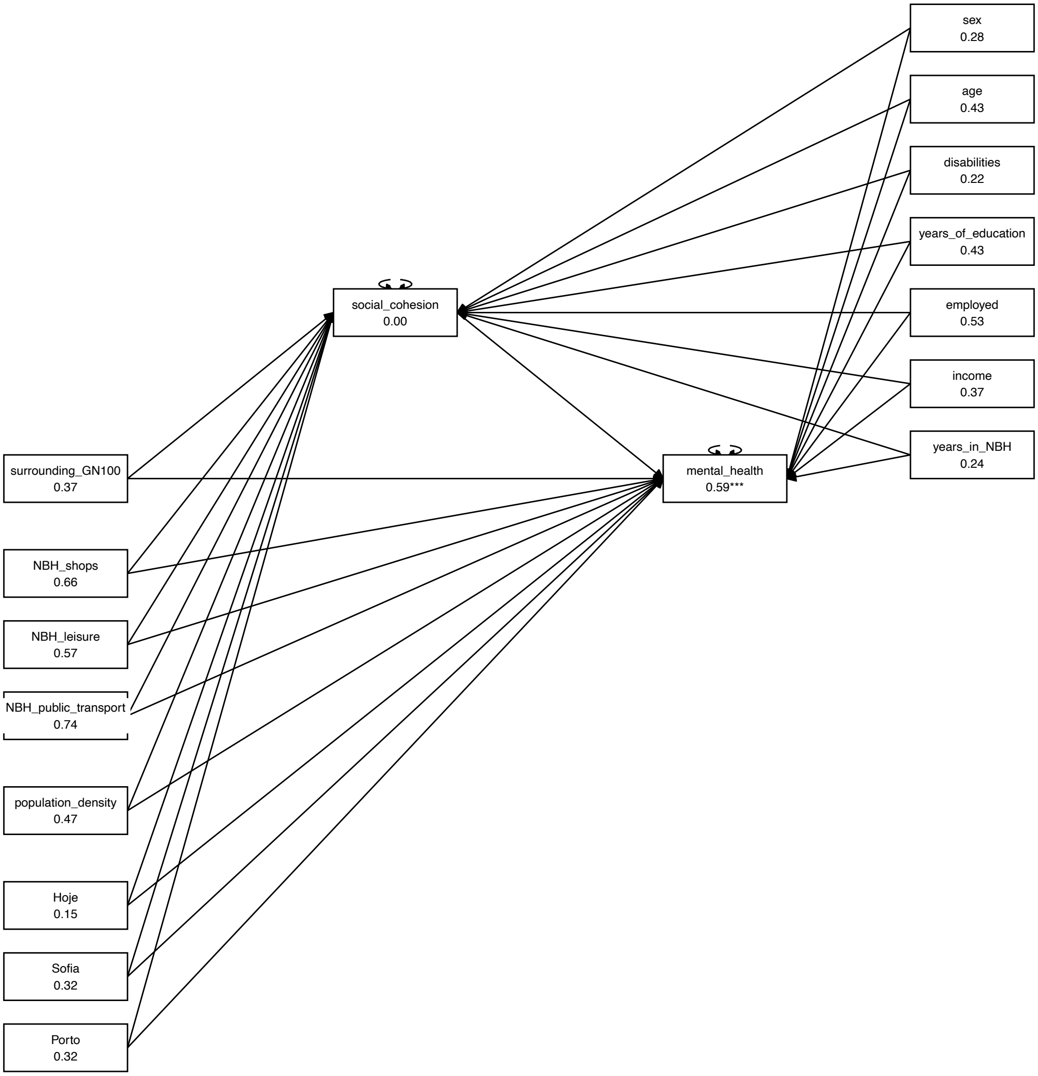

FIG. A5.1 Full Structural Equation Model used for the statistical analysis. The green space indicator (here surrounding greenness in 100m Euclidean distance) was exchanged 105 times.

TABLE A6.1 STROBE Statement - Checklist of items that should be included in reports of cross-sectional studies

	Item No	Recommendation	Section
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	Abstract
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	Abstract
Introduction			
Background/ rationale	2	Explain the scientific background and rationale for the investigation being reported	6.1
Objectives	3	State specific objectives, including any prespecified hypotheses	6.1
Methods			
Study design	4	Present key elements of study design early in the paper	6.2.1
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	6.2.1
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants	6.2.1
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	6.2.2.-6.2.5
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	6.2.2-6.2.5
Bias	9	Describe any efforts to address potential sources of bias	6.2.2-6.2.6
Study size	10	Explain how the study size was arrived at	6.2.1, 6.2.6
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	6.2.2-6.2.6
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	6.2.6
		(*b*) Describe any methods used to examine subgroups and interactions	6.2.6
		(*c*) Explain how missing data were addressed	6.2.6
		(*d*) If applicable, describe analytical methods taking account of sampling strategy	6.2.6
		(*e*) Describe any sensitivity analyses	6.2.2, 6.2.6

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TABLE A6.1 STROBE Statement - Checklist of items that should be included in reports of cross-sectional studies

	Item No	Recommendation	Section
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	6.3.1
		(b) Give reasons for non-participation at each stage	NA
		(c) Consider use of a flow diagram	NA
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	6.3.1, Table 6.1
		(b) Indicate number of participants with missing data for each variable of interest	NA (6.2.6)
Outcome data	15*	Report numbers of outcome events or summary measures	6.3.1, Table 6.1
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	6.3.2 – 6.3.4
		(*b*) Report category boundaries when continuous variables were categorized	NA
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	NA
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	6.3.2-6.3.4
Discussion			
Key results	18	Summarise key results with reference to study objectives	6.4.1
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	6.4.6
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	6.4.7
Generalisability	21	Discuss the generalisability (external validity) of the study results	6.4.6
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	Funding

TABLE A6.2 PRIGSHARE Checklist (Chapter 6)

#	Section/Topic	Checklist Item	Reported	Chapter
OBJECTIVE				
1	Health Outcome(s)	Specify the health outcome(s) being researched		6.2.3, 6.2.4
2	Pathway(s)	Position the research within a theoretical pathway (Mitigation, Restoration, Instoration).		6.1
3	Green Space Focus	Provide a clear definition of green space features being researched, distinguishing in particular between surrounding vegetation, contact with nature, and accessible green spaces.		6.2.2
SCOPE				
4	Type of Distance	Specify the type of distance used with rationale (Euclidean Distance (ED), Network Distance (ND), Buffered Service Area (BSA), Administrative Units (AU)).		6.2.2
5	Walkability Network	If accessibility to green spaces is part of the study design, indicate if the walkability network used to generate isochrones or buffered service areas has been checked for bias and how.		A6.2
6	Distance	Give a rationale for the chosen distance and indicate if different distances were tested (Sensitivity Analysis).		6.1, 6.2.2
SPATIAL ASSESSMENT				
7	Proxy for Exposure Variable	Define the spatial indicators used in research and indicate if different indicators were tested (Sensitivity Analysis).		6.2.2
8	Data Source	Indicate which database was used and if there has been an adjustment for potential bias (expert assessment).		6.2.2, A6.2
9	Public Ownership Bias	Indicate if the dataset was controlled for the usability of green spaces from public-owned plots and how.		6.2.2, A6.2
10	Residential Ownership Bias	Indicate how semi-public residential green spaces have been handled.		6.2.2, A6.2
11	Classification Bias	Indicate how green spaces have been classified.		6.2.2, A6.2
12	Usability Bias	Indicate if the usability of green spaces was checked and report inclusion/exclusion criteria.		6.2.2, A6.2
13	Connectivity Bias	(Optional) Indicate if the database has been corrected for green space network connectivity and how.		6.2.2, A6.2
VEGETATION ASSESSMENT				
14	Proxy for Exposure Variable	Specify the indicator(s) used to assess surrounding vegetation or nature and indicate if the sensitivity was tested.		6.2.2, A6.2
15	Data Source	Provide the data source of the satellite images and their resolution.		6.2.2
16	Handling of Blue Spaces	Indicate how blue spaces have been handled.		6.2.2
17	Handling of Seasons	Explain how variance in vegetation indices due to seasonality or changes in the built environment was handled.		6.2.5

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TABLE A6.2 PRIGSHARE Checklist (Chapter 6)

#	Section/Topic	Checklist Item	Reported	Chapter
CONTEXT ASSESSMENT				
18	Personal Context	Give a rationale for the chosen personal context variables that have been tested or controlled for.		6.2.5
19	Local Context	Give a rationale for the chosen local context variables that have been tested or controlled for.		6.2.5
20	Urbanicity Context	Give a rationale for the chosen urbanicity context variables that have been tested or controlled for.		6.2.5
21	Global Context	Indicate in which climate, and cultural setting the study was conducted. If several settings are part of the research explain how the results were controlled for potential confounding and tested for effect modification.		6.2.5

TABLE A6.3 Inclusion/Exclusion Criteria for green spaces

ITEMS	DESCRIPTION	HOW HANDLED
ITEM 5	Walkability Network	Based on the available street network downloaded from OpenStreetMap Added: Informal pathways, missing sidewalks and pathways. Excluded: Highways, motorways, motorway links, trunks, trunk links, and construction sites.
ITEM 9	Public Ownership Bias	Considered as Public green space, when: • The green space is accessible and used by the public
ITEM 10	Residential Ownership Bias	Considered as Public green space, when: • The residential green space is part of a larger green infrastructure • Or the edge of the residential green space is only surrounded by buildings or garages on 1 or 2 sides. Considered as semi-public green space, when: • The residential green space is not part of a larger green infrastructure • And the edge of the residential green space is only surrounded by buildings or garages on 3 or 4 sides. Considered as private green space, when: • The plot belongs to a single-family home
ITEM 11	Classification Bias	Inclusion: • Public Parks, accessible sports fields, green cemeteries, agricultural land and forests with pathways, and smaller green spaces with benches. • Linear green spaces connecting parts of the green infrastructure or alongside a river Exclusion: • Inaccessible Forests, agricultural lands, bushes or grasslands • Green spaces in the roundabouts of a roadway, between street lanes or railroads • Cemeteries without grass and trees. • Sports Fields which belong to a sports club and are not public.
ITEM 12	Usability Bias	Inclusion: • Not fenced and no steep slopes • no entrance fee • Opening times at least 9 am to 5 pm Exclusion: • Fenced or unwalkable because of steep slope • With an entrance fee • Opening times shorter than 9 am to 5 pm
ITEM 13	Connectivity Bias	Manually connected or added: • connected green infrastructure that was interrupted by a road but has a crossing • merged green spaces directly next to each other • added linear green spaces that consist of walkable pathways with greenery

Notes: *Based on PRIGSHARE Reporting Guidelines (Cardinali, M., Beenackers, M. A., van Timmeren, A., & Pottgiesser, U. (2023). Preferred reporting items in green space health research. Guiding principles for an interdisciplinary field. Environmental Research, 228, 115893. https://doi.org/10.1016/j.envres.2023.115893)*

TABLE A6.4 Model summary statistics. Green space indicator Example: surrounding greenness in 100m Euclidean distance tested with 5000 bootstrap samples.

lavaan 0.6.15 ended normally after 83 iterations	
Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	41
Number of observations	1365
Model Test User Model	
Test statistic	0.000
Degrees of freedom	0
Model Test Baseline Model	
Test statistic	8.770
Degrees of freedom	1
P-value	0.003
User Model versus Baseline Model	
Comparative Fit Index (CFI)	1.000
Tucker-Lewis Index (TLI)	1.000
Root Mean Square Error of Approximation	
RMSEA	0.000
90 Percent confidence interval - lower	0.000
90 Percent confidence interval - upper	0.000
P-value H_0: RMSEA <= 0.050	NA
P-value H_0: RMSEA >= 0.080	NA
Standardized Root Mean Square Residual	
SRMR	0.000
Parameter Estimates	
Standard errors	Bootstrap
Number of requested bootstrap draws	5000
Number of successful bootstrap draws	5000

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TABLE A6.4 Model summary statistics. Green space indicator Example: surrounding greenness in 100m Euclidean distance tested with 5000 bootstrap samples.

Regressions	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
air_pollution ~						
srrn_GN100 (a)	0.177	0.265	0.669	0.504	0.177	0.029
Porto	-0.543	0.141	-3.859	0.000	-0.543	-0.229
Sofia	-1.033	0.136	-7.591	0.000	-1.033	-0.433
Hoje	0.123	0.122	1.005	0.315	0.123	0.039
yers_n_NBH	-0.155	0.232	-0.668	0.504	-0.155	-0.026
sex	-0.362	0.120	-3.006	0.003	-0.362	-0.081
age	0.084	0.215	0.388	0.698	0.084	0.017
disabilits	0.011	0.089	0.121	0.904	0.011	0.004
yrs_f_dctn	-0.003	0.174	-0.015	0.988	-0.003	-0.001
employed	-0.002	0.092	-0.018	0.985	-0.002	-0.001
income	-0.138	0.144	-0.964	0.335	-0.138	-0.036
ppltn_dnst	0.452	0.128	3.538	0.000	0.452	0.103
main_roads	-0.691	0.215	-3.214	0.001	-0.691	-0.148
NBH_shops	0.052	0.143	0.365	0.715	0.052	0.013
NBH_leisur	-0.129	0.134	-0.966	0.334	-0.129	-0.034
NBH_pblc_t	0.221	0.147	1.504	0.133	0.221	0.053
health ~						
srrn_GN100(c)	0.486	0.253	1.917	0.055	0.486	0.070
air_polltn (b)	0.085	0.035	2.418	0.016	0.085	0.074
Porto	-0.064	0.121	-0.529	0.597	-0.064	-0.024
Sofia	0.306	0.131	2.334	0.020	0.306	0.112
Hoje	-0.391	0.125	-3.137	0.002	-0.391	-0.109
yers_n_NBH	-0.166	0.207	-0.805	0.421	-0.166	-0.025
sex	-0.210	0.127	-1.658	0.097	-0.210	-0.041
age	-1.836	0.215	-8.537	0.000	-1.836	-0.334
disabilits	-0.825	0.086	-9.617	0.000	-0.825	-0.272
yrs_f_dctn	-0.027	0.171	-0.158	0.875	-0.027	-0.006
employed	0.099	0.085	1.165	0.244	0.099	0.039
income	0.190	0.145	1.307	0.191	0.190	0.043
ppltn_dnst	-0.159	0.131	-1.214	0.225	-0.159	-0.032
main_roads	-0.298	0.194	-1.534	0.125	-0.298	-0.056
NBH_shops	-0.116	0.136	0.851	0.395	0.116	0.026
NBH_leisur	0.042	0.139	-0.304	0.761	-0.042	-0.010
NBH_pblc_t	0.317	0.130	2.440	0.015	0.317	0.066

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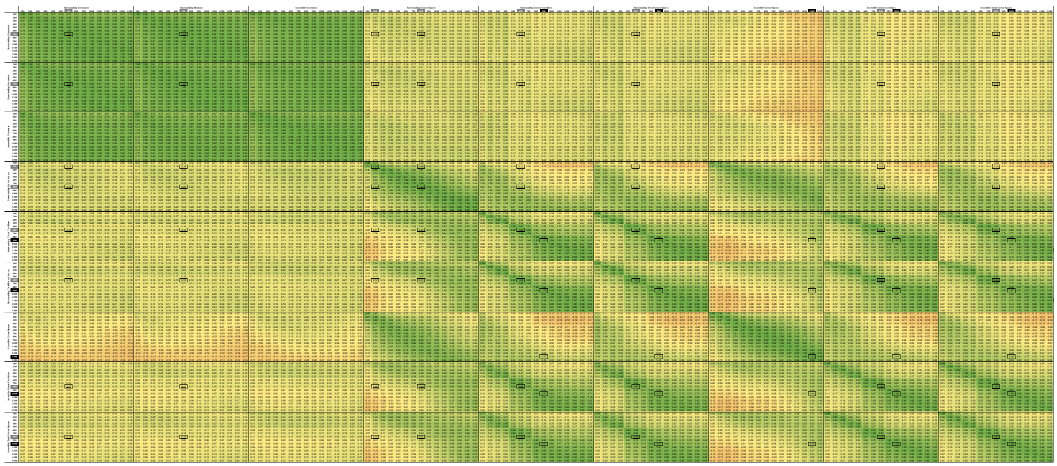
TABLE A6.4 Model summary statistics. Green space indicator Example: surrounding greenness in 100m Euclidean distance tested with 5000 bootstrap samples.

Intercepts	Estimate				Std.lv	Std.all
.air_pollution	0.000				0.000	0.000
.health	0.000				0.000	0.000
Thresholds	**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**	**Std.lv**	**Std.all**
air_pollutn|t1	-2.006	0.276	-7.276	0.000	-2.006	-1.806
air_pollutn|t2	-1.368	0.269	-5.075	0.000	-1.368	-1.231
air_pollutn|t3	-0.597	0.267	-2.237	0.025	-0.597	-0.537
air_pollutn|t4	0.018	0.265	0.070	0.945	0.018	0.017
health|t1	-3.174	0.296	-10.711	0.000	-3.174	-2.501
health|t2	-2.242	0.284	-7.882	0.000	-2.242	-1.767
health|t3	-1.170	0.277	-4.222	0.000	-1.170	-0.922
health|t4	0.202	0.274	0.737	0.461	0.202	0.159
Variances	**Estimate**				**Std.lv**	**Std.all**
.air_pollution	1.000				1.000	0.810
.health	0.993				0.993	0.617
Scales y*	**Estimate**				**Std.lv**	**Std.all**
air_pollution	1.000				1.000	1.000
health	1.000				1.000	1.000
R-Square	**Estimate**					
air_pollution	0.190					
health	0.383					

TABLE A6.5 Correlation Matrix of green space characteristics

Table A9: Correlation Matrix of green space characteristics



Notes: *Downloadable version available at the 4TU Repository: https://doi.org/10.4121/ea7ea070-8df9-49b2-b60e-8a25759af8dc*

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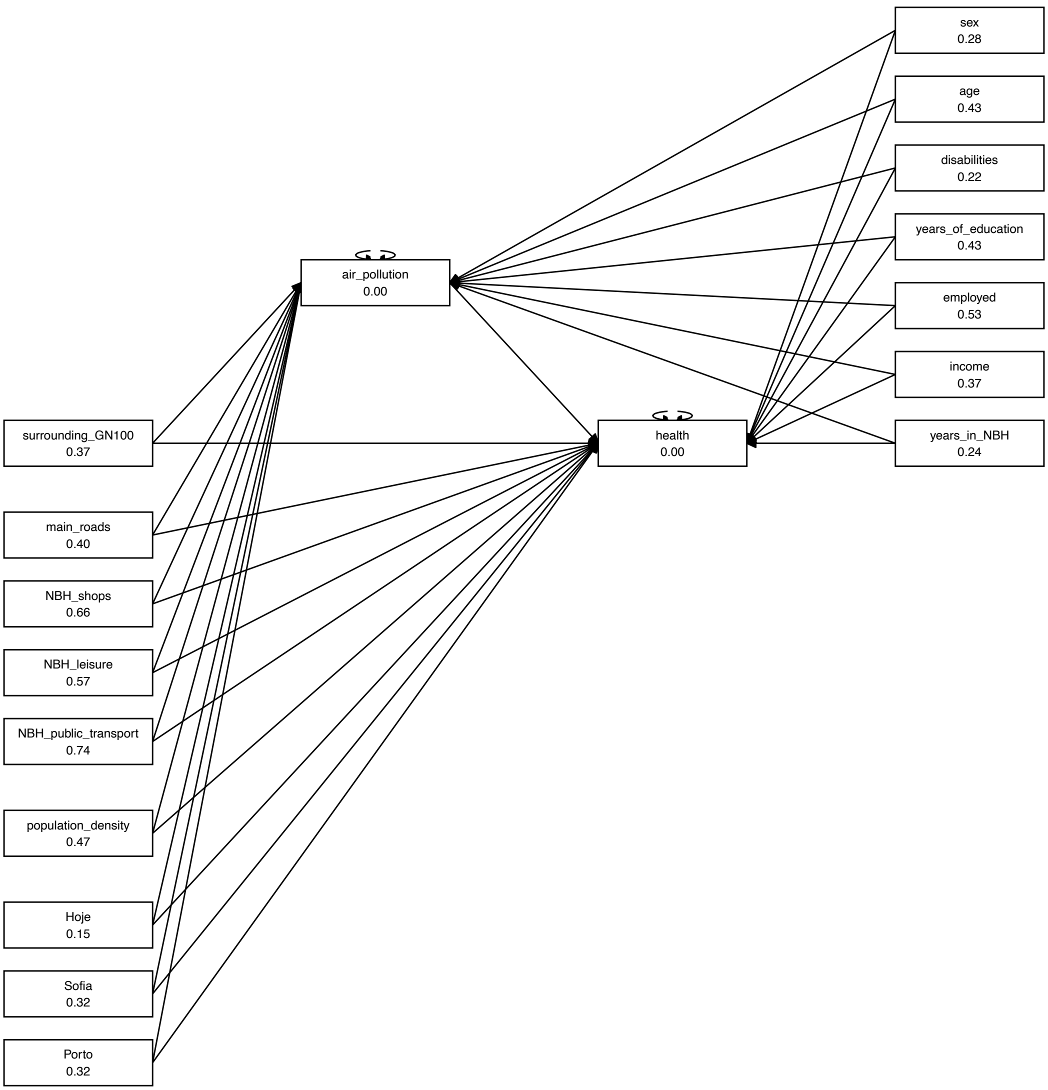

FIG. A6.1 Full Structural Equation Model used for the statistical analysis. The green space indicator (here surrounding greenness in 100m Euclidean distance) was exchanged 135 times.

Curriculum Vitae

Marcel Cardinali is an urban planner and researcher specializing in the fields of 15-Minute City, Nature-Based Solutions, and human built environment research. He is based at the Institute for Design Strategies (IDS) and TU Delft. In addition, he is working on the Horizon2020 research project URBiNAT (Urban Inclusive Innovative Nature, 2018-2024) where he is leading the team working on the impact of Nature-Based Solutions on health and well-being. He is a member of the European Commission Taskforce on Impact Evaluation of Nature-based Solutions and in the German Association for Urban, Regional and National Planning (SRL). He was the Co-editor in Chief of the urbanLab Magazine and author of several publications on how urban planning can help tackle societal challenges like climate change, non-communicable diseases, and social cohesion.

Education

2020 - **PhD Candidate |** TU Delft / TH OWL „*Green Health. Examining the role of green space characteristics and their proximity in green space health pathways.*“ Supervisors Prof. Dr. Uta Pottgiesser (TH OWL / TU Delft), Prof. Dr. Arjan van Timmeren (TU Delft), Dr. Mariëlle Beenackers (Erasmus MC Rotterdam)

2015 - 2017 **MASTER OF SCIENCE URBAN PLANNING |** TH Köln.

2012 - 2015 **BACHELOR OF ARTS URBAN PLANNING |** TH OWL.

2005 - 2008 **APPRENTICESHIP AS ARCHITECTURAL DRAFTSMAN |** Kuhre Betonwerk

Professional Experience

01.2021 -	**Institute for Design Strategies | TH OWL |** Research Associate
04.2021 - 07.2021	**Chair for energy-efficient and sustainable Planning and Building | TU Munich |** Teaching Assistant
01.2018 - 12.2020	**urbanLab | TH OWL |** Research Associate
03.2016 - 12.2017	**urbanLab | TH OWL |** Research Assistant

Publications

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24#09

Green Health

Examining the role of green space characteristics and their proximity in green space health pathways

Marcel Cardinali

This doctoral thesis critically examines green space characteristics and their proximity to residents in their ability to help reduce the global disease burden of non-communicable diseases. By dissecting three pivotal pathways of theorized green space health effects through increased physical activity, increased social cohesion, and reduced air pollution, the thesis aims to provide new insights into which green space characteristics drive these relationships and in which distance they occur. To achieve these aims, this thesis develops reporting guidelines for the research field, a QGIS script for automatization of green space indicator development and uses two complementary sources for data collection. It builds on the self-reported data on physical activity, social cohesion, air pollution, health and mental health from the URBiNAT project and its case studies in the four European satellite neighbourhoods Nantes-Nord (France), Porto-Campanhã (Portugal), Sofia-Nadezhda (Bulgaria), and Høje-Taastrup (Denmark) and complements it with a rigorous spatial analysis. This enabled a rigorous sensitivity analysis based on up to 135 structural equation models per pathway. The results of this doctoral research revealed distinct green space characteristics and proximities that drive each pathway, including thresholds where these associations disappear or even change direction. It concludes that interconnected, multi-use green corridors are more beneficial than isolated patches for all analysed health pathways, challenging current municipal green space strategies to shift focus from mere ratios to green mobility infrastructures. Although rooted primarily in European contexts and of a cross-sectional nature, the doctoral research provides new evidence for urban planning and public health. It emphasizes the practical implications of how to design green spaces to address health concerns. The results not only resonate with the WHO's Urban Health Research Agenda but also provide tangible recommendations for a healthier human habitat.

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