University of Southampton

Faculty of Environmental and Life Sciences

Geography and Environmental Science

"Untangling" the effects of urban greenspace on mental health

by

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Thesis for the degree of Doctor of Philosophy (PhD)

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Abstract

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This thesis aimed to "untangle" the effects of urban greenspace on mental health and develop an understanding of how these effects may change according to the type and characteristics of greenspace. To identify and understand the methodological approaches that have thus far been used to explore the effect of greenspace on mental health, a systematic map of the literature was undertaken. The systematic map highlighted two research priorities: (1) the need to improve causal inference from secondary data, and (2) the need to evaluate the importance of different types and characteristics of urban greenspace that affect mental health. This thesis addressed both of these priorities.

To improve causality, this thesis used the counterfactual framework to develop two novel and statistically robust approaches to analyse the effect of urban greenspace on mental health. The first approach was a cross-sectional assessment that used statistical matching in addition to regression modelling to establish the effect of local public greenspace on a person's mental health for those with and without a private garden. The second approach used longitudinal data in a Before-After Control Intervention study design to establish the effect of the change in different greenspace characteristics on mental health when a person moved between urban areas. Both these approaches were applied to the British Household Panel Survey – a nationally representative survey of Great Britain containing individual-level information on mental health and the socio-economic confounders of mental health.

Findings from the first approach suggested that the effect of access to private greenspace on mental health outweighs the beneficial effects of access to public greenspace. Specifically, having a private domestic garden substantially reduced the maximum probability of poor mental health for men and women, regardless of their access to local public greenspace. The second approach highlighted the importance of greenspace quality and proximity for mental health. Bird species richness and distance to nearest greenspace, proxy measures for greenspace quality and proximity respectively, provided the most inference when modelling the effect of change in greenspace characteristics on mental health. Comparatively, measures of greenspace quantity and recognised standards and guidelines of greenspace access provided less inference than a model that did not include a measure of greenspace. Given these results, greenspace quality, proximity and access to private gardens should be a priority for future policies to improve the status of both urban greenspace and mental health in Great Britain.

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Research Thesis: Declaration of Authorship

Print name: Rebecca May Collins

Title of thesis: “Untangling” the effects of urban greenspace on mental health

I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
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6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
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Collins, R. M., Spake, R., Brown, K. A., Ogutu, B. O., Smith, D., and Eigenbrod, F., 2020. A systematic map of research exploring the effect of greenspace on mental health. Landscape and Urban Planning, 201, 103823.

Signature: .... Date: ....

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Definitions and Abbreviations

AIC .... Akaike Information Criterion

ANGSts .... Accessible Natural Greenspace Standards

AONBs .... Areas of Outstanding Natural Beauty

ART .... Attention Restoration theory

ATE .... Average Treatment Effect

BA .... Before-After

BACI .... Before-After Control Intervention

BAME .... Black, Asian and Minority Ethnic

BHPS .... British Household Panel Survey

CA .... Correspondence Analysis

CDDA .... Common Database on Designated Areas

CLC .... CORINE Land Cover

COMEAP .... Committee on the Medical Effects of Air Pollutants

Defra .... Department for Environment, Food and Rural Affairs

EEA .... European Environment Agency

EU .... European Union

GB .... Great Britain

GHQ-12 .... 12-item General Health Questionnaire

GI .... Green Infrastructure

GLM .... Generalised Linear Model

GLMM .... Generalised Linear Mixed Model

GLUD .... Generalised Land Use Database

GVIF .... Generalised Variance Inflation Factor

HM Government .... Her Majesty's Government

IMD .... Index of Multiple Deprivation

LAs .... Local Authorities

Definitions and Abbreviations

LCM .... Land Cover Map

LDPs .... Local Development Plans

LGS .... Local Green Space

LPAs .... Local Planning Authorities

LRT .... Likelihood Ratio Test

LSOA..................................... Lower Layer Super Output Area

MAUP..................................... Modifiable Areal Unit Problem

NDG..................................... National Design Guide

NDVI..................................... Normalised Difference Vegetation Index

NGOs..................................... Non-governmental Organisations

NHS .... National Health Service

NO .... Nitric Oxide

NO_2..................................... Nitrogen Dioxide

NO_x..................................... Oxides of Nitrogen

NPPF..................................... National Planning Policy Framework

OECD..................................... Organisation for Economic Co-operation and Development

OSMM..................................... Ordnance Survey MasterMap

PM..................................... Particulate Matter

PM_{10} .... Particulate Matter 10 microns in diameter

$PM_{2.5}$ .... Particulate Matter 2.5 microns in diameter

RCT .... Randomised Control Trial

sd .... standard deviation

SDGs..................................... Sustainable Development Goals

SF-12 .... 12-Item Short Form Health Survey

SF-36 .... 36-Item Short Form Health Survey

SIMD .... Scottish Index of Multiple Deprivation

SRT .... Stress Reduction Theory

UK .... United Kingdom

US .... United States

WEMWBS .... Warwick-Edinburgh Mental Well-Being Scale

WHO .... World Health Organization

Chapter 1 Introduction

1.0 The global mental health crisis

Globally depression is the leading cause of ill health and disability (World Health Organization 2017). The associated economic and social costs of mental health conditions such as depression and anxiety disorders are significant (McDaid et al. 2019). For example, in 2016, across the 28 European Union (EU) countries approximately 84 million people had a mental health problem, the annual cost of which is estimated to be more than €600 billion, approximately 4% of gross domestic product (OECD/EU 2018). As the view that nature improves mental health is becoming commonplace (e.g., Hartig et al. 2014, Gascon et al. 2015, Houlden et al. 2018, Callaghan et al. 2020), the provision and enhancement of greenspace is being discussed as a means to proactively reduce the burden of poor mental health through prevention (e.g., Public Health England 2020, World Health Organization 2021).

1.1 Defining mental health

Often 'mental health' is used to indicate common mental health disorders including depressive or anxiety disorders (Stansfeld et al. 2016). However, mental health is defined by the World Health Organization (WHO) as a state of wellbeing where an individual is able to realise their abilities, is able to cope with the normal stresses of life, is able to work productively and can make a contribution to their community (World Health Organization 2018). From this definition, it is clear that mental health is more than the absence of mental disorders or disabilities. The WHO considers mental health as an integral component of general health, which is why their adopted definition for health is: "a state of complete physical, mental and social wellbeing and not merely the absence of disease or infirmity" (World Health Organization 1948). Wellbeing is a state of positive feelings and functioning, and directly relates to an individual's experience of life and the comparison of their circumstances to social norms and values (Department of Health and Social Care 2014, Simons and Baldwin 2021).

1.2 Why study the effects of urban greenspace on mental health?

The use of greenspace such as parks for wellbeing can be traced back to the earliest large cities, for example, the villa gardens of ancient Egypt and the gardens of Mesopotamia (Ulrich and Parsons 1992). Despite this longstanding recognition, it has only been in the past 35 years that there has been an accumulation of theoretical and empirical evidence that links greenspace to positive mental health.

Poor mental health is by no means an urban issue and the evidence of the positive effects of greenspace (and more generally nature) on mental and physical health exists for both urban (e.g., (Alcock et al. 2014, Astell-Burt and Feng 2019) and rural environments (e.g., Alcock et al. 2015). In the context of unprecedented rates of urbanisation (United Nations 2018) further restricting the availability and accessibility of urban greenspace (Fuller and Gaston 2009, Wang et al. 2020) it is essential that the effects of urban greenspace on mental health is explored. Such research is vital to develop clearer and targeted greenspace planning that has the potential to maximise mental health benefits. Furthermore, the beneficial effect of urban greenspace on mental health presents an additional argument for biodiversity conservation in cities and supports the improvement, integration, and expansion of greenspace in urban environments.

1.3 Studying the effects of urban greenspace on mental health in Great Britain

England, Scotland and Wales, collectively known as Great Britain (GB), have a predominantly urban population and declining greenspace coverage (see Section 1.3.2). For these reasons, in addition to the data availability (see Chapter 4, the data landscape), there is a clear case to explore the mental health related benefits of urban greenspace in GB.

1.3.1 The mental health crisis in Great Britain

Recent estimates for GB predict that mental health problems cost approximately £114.5 billion annually (McDaid et al. 2022), the majority of which can be attributed to lost productivity with 1 in 6 people in any given week experiencing a common mental health problem (McManus et al. 2009). However, it is not an equal burden across society, there are many demographic inequalities among those experiencing mental health problems. For example, in the United Kingdom (UK) which includes Northern Ireland in addition to the three countries in GB, 26% of women aged 16-24 experience a common mental health disorder compared to only 9% of males of the same age (Mental Health Foundation 2016). Current treatments are not addressing the issues with these inequalities; people with lower incomes are likely to have requested but not received mental health treatment and people from Black, Asian and Minority Ethnic (BAME) groups have comparatively lower treatment rates in addition to higher rates for some mental health problems (Mental Health Foundation 2016). Specifically, black men are more likely to have experienced a psychotic disorder in the last year than white men (Memon et al. 2016, McDaid et al. 2022).

1.3.2 The status of urban greenspace in Great Britain

Approximately 65.2 million people live in GB (Office for National Statistics 2020a). The proportion of individuals living in urban areas varies by country with approximately 83%, 71%, and 67% of the population living in urban areas in England, Scotland and Wales respectively (Government Office for Science 2021, National Records of Scotland 2021). Within its urban areas, GB has approximately 0.55 million hectares of “natural” landcover which is approximately 31% of all urban space (Office for National Statistics 2019). The proportion of urban greenspace is declining (Public Health England 2020) and varies within the countries that make up GB; excluding private gardens, Scotland has the most greenspace cover at approximately 37%, compared to approximately 30% in both England and Wales (Office for National Statistics 2019). Private greenspaces account for a large, but declining, proportion of GB’s urban land cover. In 2019, private gardens were estimated to account for 29.5% of the urban area in GB, which is a slight decline from 2017 estimates of 29.9% of urban land (Office for National Statistics 2019). As with natural landcover, there is variation in the area of private gardens in urban areas within the countries that make up GB. England has the highest proportion of private gardens in urban areas with 31% of landcover, followed by Wales with approximately 28%. Despite having the highest proportion of natural landcover, Scotland has the lowest proportion of urban area allocated to private gardens at approximately 25% (Office for National Statistics 2019).

1.3.3 The mental health policy context in Great Britain

Mental health forms a key part of the Sustainable Development Goals (SDGs), specifically target 3.4. commits to reducing premature mortality from non-communicable diseases, by one-third by 2020, through prevention and treatment and promoting mental health and wellbeing (United Nations 2016). The target highlights the importance for all countries to implement mental health policies and practices to support those already affected by poor mental health, as well as protective/preventative actions that may be traditionally outside the health sector.

The UK is committed to achieving the SDGs. In the UK, the National Health Service (NHS) has a preventative duty to both secure improvement of mental health and prevent mental illness (National Health Service Act 2006). The importance of this preventative duty is emphasised by other supporting health legislation. For example, the Care Act 2014, specifically refers to “preventing and delaying” the need for care and places this duty on the responsible authority (i.e., the NHS) to promote mental and emotional wellbeing (Care Act 2014). However, despite legislation promoting a proactive and preventative approach to health and mental health, the growing burden of poor mental health in GB suggests that policies implemented are largely reactive and not preventative (McDaid et al. 2022). Preventative care as a whole (i.e., not just in mental health) is underfunded, in 2019 (pre-COVID pandemic) approximately 5% of public funding was directed towards prevention; subsequently, only £8 billion is spent on prevention compared to £117 billion on treating ill health (Office for National Statistics 2022). The reactive approach to mental health care is embedded in the Mental Health Act 1983. However, there are recent calls by the Department of Health and Social Care to reform this act to encourage a shift from reactive to preventative care to tackle poor mental health prevalence in GB and the UK (Secretary of State for Health and Social Care 2021).

The NHS's constitution (Department of Health and Social Care 2021) echoes this shift from reactive to preventative care and calls for an overall uplift in the delivery of mental health care so that it can be delivered in parity with physical health. This shift aligns with the SDGs and the WHO's definition of health (as defined in Section 1.1). However, the UK's action plan to achieve the SDGs relies on the *provision* of health care and fails to acknowledge wider preventative action (Cabinet Office et al. 2021) which has been called for since the first Marmot review on social determinants of health (Marmot 2010). Similarly, in England the "No health without mental health" report focuses on the delivery of health care provision and not preventative approaches (HM Government 2011). In cases where preventative approaches to improve health are discussed, for example in Chapter 2 of the NHS's Long term Plan, the focus is on preventative approaches for obesity, alcohol abuse and smoking – largely determinants of physical health (NHS 2019). However, the recent COVID-19 mental health and wellbeing action recovery plan has taken a better approach to encourage the delivery of protective solutions for mental health to be implemented at a community level (HM Government 2021).

1.3.4 The greenspace policy context in Great Britain

The UK's 25 Year Environment Plan (HM Government 2018), sets out the government's commitment to "green" towns and cities through the protection and expansion of a high-value habitat network and implementation of Green Infrastructure (GI). Since the publication of the plan, there has been a considerable increase in funding to support parks across the country. For example, the Secretary of State for Housing, Communities and Local Government has announced £9.7 million to Local Authorities (LAs) for park maintenance (Sunak 2019) and an additional £3.75 million for the Pocket Parks Plus Programme (Ministry of Housing, Communities and Local Government and Sunak 2019). This increase in funding supports the government's statutory target to halt the decline in species abundance by the end of 2030 (Environment Act 2021).

1.3.5 Links between greenspace and urban planning in Great Britain

One of the biggest threats to urban greenspace is development (Haaland and van den Bosch 2015). In GB, the Town and Country Planning Act (1990), places the responsibility on Local Planning Authorities (LPAs) for developing their own Local Development Plans (LDPs). LPAs are informed by the National Planning Policy Framework (NPPF) and subsequent guidance (Department for Levelling Up, Housing and Communities and Ministry of Housing, Communities and Local Government 2016, Ministry of Housing, Communities and Local Government 2021a). The NPPF does encourage the provision and enhancement of greenspaces through the implementation of GI. The NPPF defines GI as a network of multi-function greenspace that can deliver a range of benefits to people and communities (Ministry of Housing, Communities and Local Government 2021a). A GI network can consist of parks, woodlands, trees (including street trees), playing fields, allotments and as well as green roofs and walls (Ministry of Housing, Communities and Local Government 2021b, 2021a). National Design Guide (NDG) provides details on how GI can be used to enhance the natural environment, and that the purpose of GI is to contribute to sustainable development (Ministry of Housing, Communities and Local Government 2021b). The inclusion of GI within the NPPF and NDG is indicative of the provision of GI within developments by law (Jerome et al. 2019). However, in practice is not the case. Through the implementation of the NPPF, greenspace and other GI are not seen as a priority in the creation of LDPs and instead are seen as “nice to have” rather than essential to support sustainable development (Fisher et al. 2021). In addition, as it is the responsibility of the LPA to develop their LDA, there is regional variation in the delivery of greenspace and other GI.

Terminology within the NPPF creates further issues for LPAs when developing their LDAs. The NPPF calls for an “effective use of land” and deems the delivery of new housing as effective use. Through this terminology, LPAs have the power to justify the use of greenspace for housing to reach nation housing targets set out in the Housing and Planning Act 2016 which cements the national priority to build new homes. Consequently, the provision of new housing can be prioritised over the protection and delivery of greenspace (and other GI).

However, the NPPF does support the protection of local greenspaces through the designation of Local Green Space (LGS). A LGS designation protects greenspaces valued by communities who feel confident that these areas are at risk of development without the protection (Ministry of Housing, Communities and Local Government 2021a). Since its introduction in 2012, 6,515 locally valued greenspaces have been protected using LGS designations (The countryside charity 2022). Uptake of LGS designations has been successful in areas without other protective designations (e.g., National Parks and Green Belt), with approximately 64% of local councils (without any other designations) implementing a LGS (The countryside charity 2022). However, LGS designations have not been successfully implemented to ensure equitable access to greenspace; of the 100 local councils with the most greenspace deprived neighbourhoods, only 38% have an LGS designation (The countryside charity 2022). This indicates that not all LPAs are utilising the available tools to provide and protect urban greenspace.

Beyond urban planning policy, the cost of greenspace maintenance is another limiting factor in the delivery of greenspaces. LAs operate within financial limitations and maintenance funds from the central government are generally directed toward the maintenance of highways and buildings (Wilebore and Wentworth 2013), which results in greenspaces often being neglected.

1.3.6 Links between mental health and urban planning in Great Britain

Health and wellbeing are integrated into the planning system in two ways. First, the Health and Social Care Act 2012 places a requirement on LAs to have a Joint Strategic Needs Assessment and a Joint Health and Wellbeing Strategies. These are designed to inform local plans and improve the health and wellbeing of local communities. Second, the NPPF, from which England's planning policy is predominantly based, does place responsibility on delivering health and wellbeing. The NPPF that is used to inform LDPs, requires planning to support healthy communities by considering designs that promote wellbeing needs and requires planners to consult and cooperate with local health commissioners. This demonstrates an attempt within the UK's governance to promote an inter-disciplinary approach to develop and integrate health within planning. However, mental health is not explicitly captured in the NPPF. Within the NPPF, mental health is implied within the broader category of disability – as disability includes mental impairment (Equality Act 2010). However, mental health constitutes more than disability, there are positive dimensions to mental health such as happiness that are not captured within the category of mental impairment and disability. The framing of mental impairment has stronger links to a reactive approach to mental health policy, rather than the preventative approach that is encouraged by the SDGs.

In principle, via the above mechanisms, LAs have the ability to capture the wider determinants of health and wellbeing within their plans. Therefore, there is a means to enforce a preventative approach to supporting mental health and wellbeing via development. But these mechanisms have been criticised for not being proactive enough. Often, the collaboration required by the NPPF between health practitioners and planners is limited by conflicting systems; planners are restricted by statutory guidelines (which do not explicitly promote mental health) and health practitioners operate more broadly to deliver their aims and objectives, all within limited budgets (Carmichael et al. 2016).

1.3.7 A summary of policy affecting greenspace, mental health and urban planning in Great Britain

There is recognition in GB's legislation that a preventative approach to protect and promote mental health is needed. However, in practice, reactive care such as the delivery of health care provision remains the core response by the responsible authorities and wider preventative actions are not discussed. Until recently, with the publication of the COVID-19 recovery action plan (HM Government 2021), proactive health care has largely focussed on widely recognised determinants of physical health.

In addition, despite overarching targets to halt biodiversity loss (Environment Act 2021) and the importance of urban greenspace to achieve this, the wider policy context (i.e., urban planning policies) offers limited protection to or enhancement of urban greenspace. It is the decision of the LPA to prioritise greenspaces but is made difficult by competing land uses and requirements/local needs. Thus, in the context of housing targets and urbanisation, greenspace in cities is at risk of further decline.

This policy context makes GB an interesting study region for this thesis. Given the benefits of greenspace to mental health, there is an opportunity to deliver on policy targets for both greenspace and take a preventative approach to improve mental health.

1.4 Thesis aim and research questions

This thesis aims to "untangle" the effects of greenspace on mental health and develop an understanding of how these effects may change according to the type of greenspace (i.e., public, private, or specific characteristics), in the context of urban areas of GB. Based on knowledge gaps identified in Chapters 2 and 3 (the literature review and systematic map respectively) four research questions were developed:

1. What methodological approaches are used to explore the effects of greenspace on mental health?
2. How can research methods be modified to improve causal inference when exploring the greenspace and mental health relationship?
3. What are the relative effects of public and private greenspace on mental health?

4. What characteristics of greenspace provide the most evidence of a relationship between greenspace and mental health?

1.5 Thesis overview

1.5.1 General overview

This thesis takes the form of three papers and is structured in chapters, each contributing to answering the research questions outlined above. Here in the introduction, Chapter 1, presents the overall motivation behind the research into the effect of urban greenspace on mental health. Chapter 2, the literature review, provides a summary of the literature used to develop the hypotheses that inform the empirical chapters and discusses the possible study designs that can improve causal inference (research question 2). Chapters 3, 5 and 6 are empirical chapters, each one of these chapters presents one of the papers in this thesis. Chapter 3 is published in the Journal of Landscape and Urban Planning as Collins, R. M., Spake, R., Brown, K. A., Ogutu, B. O., Smith, D., and Eigenbrod, F., 2020. A systematic map of research exploring the effect of greenspace on mental health. Landscape and Urban Planning, 201, 103823. Since its publication in September 2020, Chapter 3 has had over 30 citations from other journal articles. Chapter 4, the data landscape, presents the process in which data were considered for use in this thesis and then presents the data selected for the empirical Chapters 5 and 6. Finally, Chapter 7 presents the general discussion of the three papers and summarises their findings (in reference to the research questions) and limitations. Chapter 7 continues to discuss the overall implications for policy and wider contributions.

1.5.2 Overview of empirical chapters

As a three paper thesis, the empirical chapters of this thesis (outlined below) are presented as papers. For all papers (Chapters 3, 5 and 6), all data management and analyses were performed by myself (Rebecca Collins), and the supervisory team (Felix Eigenbrod, Kerry Brown, Booker Ogutu, Dianna Smith, Rebecca Spake) provided feedback on the study designs, analyses and the structure of the papers.

1.5.2.1 Chapter 3: A systematic map of research exploring the effect of greenspace on mental health (paper 1)

Chapter 3, the first empirical chapter, is a systematic map of research exploring the effects of greenspace on mental health and thus addresses research question 1: “what methodological approaches are used to explore the effect of greenspace on mental health”. A sizable literature exists examining the effect of greenspace on mental health and Chapter 3 used systematic mapping methodologies to search, collate, and extract methodological details from studies, to establish what data and study designs were commonly used in research exploring the greenspace and mental health relationship. The systematic map highlighted two research priorities; (1) the need to improve causal inference from secondary data, and (2) the need to evaluate the importance of different types and characteristics of greenspace that affect mental health. These findings contributed to the development of research questions 2, 3 and 4, which are addressed in Chapters 5 and 6 of this thesis.

1.5.2.2 Chapter 5: The effects of private gardens exceed those of public greenspaces on mental health (paper 2)

Chapter 5 addresses research question 3 “what are the relative effects of public and private greenspace on mental health?” by defining exposure to greenspace as public parks and public gardens only and removing all other greenspace types which may not be publicly accessible. Using data from the British Household Panel Survey (BHPS; University of Essex 2018), the relationship between public greenspace and mental health was established using statistical matching. Individual-level mental health was measured using the 12-item General Health Questionnaire (GHQ-12) which is collected in each year of the BHPS. Special licence access to the BHPS was granted in May 2018. The presence of public greenspace was established using the Ordnance Survey MasterMap (OSMM) Greenspace Layer (version April 2020), and a licence for access to the Greenspace Layer for all urban areas of GB was granted in July 2020. *A priori* hypotheses were used to inform the inclusion of all individual and area-level variables for the statistical matching, the regression analyses and any interactions tested. Model averaging was used to predict and plot the relationship between all public greenspace and mental health. To explore the relative effects of private greenspace, individuals with and without private gardens are analysed separately and their predicted probability of poor mental health was compared.

1.5.2.3 Chapter 6: The effects of moving to areas with higher greenspace quality on mental health (paper 3)

The final empirical chapter, Chapter 6, addresses research question 4 “what characteristics of greenspace provide the most evidence of a relationship between greenspace and mental health?” by testing different characteristics of greenspace to establish which characteristics better explain variation in poor mental health. Characteristics were identified using a hypothesis-driven approach and were categorised into measures of quantity, proximity, access, and quality (as defined in the systematic map - Chapter 3).

Like Chapter 5, Chapter 6 also used the BHPS. However, unlike Chapter 5, Chapter 6 utilises the longitudinal structure of the data to look at individuals who had moved between urban areas and experienced a change in greenspace characteristics. In doing so, an individual's mental health pre -and- post-move were compared and the effect of the change in greenspace characteristics on mental health was estimated. Like Chapter 5, Chapter 6 used GHQ-12 as the measure of mental health but instead used multiple data sources to quantify different greenspace characteristics, as identified in the data landscape (Chapter 4). Characteristics were tested separately, and the models were compared according to their model fit. Characteristics that improved the model fit compared to the base model with no greenspace characteristics were selected as a priority for future greenspace policy.

1.5.2.4 Overview of empirical chapter's contribution to improving causal inference

Chapter 3 (the systematic map) highlighted the need to improve causal inference which led to the development of research question 2. Although Chapters 5, and 6 answer research questions 3, and 4 respectively both adopt novel methods that improve causal inference and therefore contribute to research question 2. The study designs for Chapters 5 and 6 were informed by a review of methods and study designs that improve causal inference (see Chapter 2, Section 2.4). Both designs are statistically robust and novel and therefore provide methodological contributions to the greenspace and mental health literature.

Chapter 2 Literature review

2.0 Introduction

The purpose of this chapter is to review the existing body of work that explores the effect of greenspace on mental health. This review has been organised into five sections. The first section of this review (Section 2.1) focuses on the mental health literature. Section 2.1.1 of this discusses the social determinants of mental health (outside of greenspace) and Section 2.1.2 the different measures of mental health. The second section of this review (Section 2.2) discusses the theoretical basis for the positive effects of greenspace on mental health. Specifically, the hypothesis that links greenspace (and more generally the natural environment) to mental health (Section 2.2.1) and the proposed pathways through which the benefits from greenspace to mental health are obtained (Section 2.2.2). The third section of this review (Section 2.3) focuses on the greenspace literature. A review of literature relating to defining greenspace, measuring exposure and access to greenspace is presented in Sections 2.3.1 to 2.3.3. The fourth section of this review (Section 2.4) discusses the analytical methods that could be used to explore the greenspace and mental health relationship. The focus of this section is to evaluate and discuss methods, not to establish what methods are used in the literature. An in-depth review of methods used in the greenspace and mental health literature is presented in Chapter 3 – a systematic map of research exploring the effect of greenspace on mental health. The review concludes with a summary (Section 2.5) and outlines how the findings of this review inform the empirical chapters of this thesis.

2.1 Mental health

2.1.1 Social determinants of health

Although genetic and biological factors are important influences on mental health (Eaton and Daniele 2019), social determinants can be viewed separately from these. The WHO defines social determinants of health as the conditions in which people are born, grow, live, work and age, and these are influenced by money, and the distribution of power and resources at multiple scales, including global, national and local levels (Allen et al. 2014, World Health Organization and Calouste Gulbenkian Foundation 2014). The social determinants of mental health are already shaped by these factors which operate at different stages of life and have the potential to persist and accumulate throughout life (Friedli 2009, World Health Organization and Calouste Gulbenkian Foundation 2014). Social determinants of health are collectively made up of compositional and contextual factors (Macintyre et al. 1993). Compositional factors are individual-level socio-demographic characteristics such as age, sex, ethnicity, health status and income, and contextual factors are the conditions in which individuals live and work and their access to essential services (Macintyre et al. 1993, 2002). Collectively, these factors exert layers of influence on health – as illustrated by Dahlgren and Whitehead's model of the social determinants of health (Figure 1). Their model places personal factors at the core, whilst emphasising the importance of contextual factors (Dahlgren and Whitehead 1991), and if contextual and compositional factors are not considered together inequalities in health and mental health can be widened (Bambra et al. 2010, Marmot 2010).

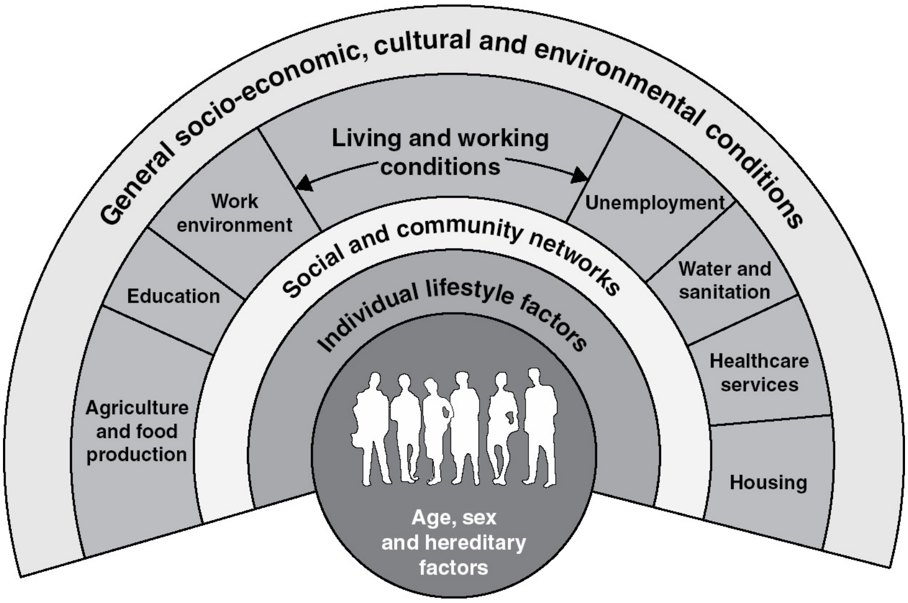

Figure 1: Dahlgren and Whitehead's model (1991) of the social determinants of health

The social determinants of mental health are well studied in high-income countries, and there is growing evidence in low- and middle-income countries (World Health Organization and Calouste Gulbenkian Foundation 2014). The consensus, across all countries, is that low socioeconomic position is systematically associated with increased rates of common mental disorders such as depression and anxiety (Allen et al. 2014). As a result, the poor and disadvantaged are disproportionately suffering from the consequences of living with poor mental health (Allen et al. 2014, World Health Organization and Calouste Gulbenkian Foundation 2014). Specifically, a study in GB found that after adjustment for income and other socio-demographic variables, people with more debt were more likely to suffer from a mental disorder, suicide, attempted suicide, obsessive compulsive disorder, panic disorder, generalised anxiety disorder and psychotic disorders (Jenkins et al. 2008). Those who are most disadvantaged, are most likely to be funding essential living costs with debt, and therefore most likely to be impacted by negative health (Royal Society for Public Health 2018) and thus widening inequalities. Connected to the issues of income and debt, unemployment and poor quality work (e.g., work-related stress) are major drivers of observed mental health inequalities (Durcan 2015). Staff absences attributed to poor mental health is the fourth leading cause of absence in 2020 and accounted for 11.6% of all absences (Office for National Statistics 2021). There are observed differences in ethnic background and work-related stress, despite controlling for other demographic and work characteristics (Durcan 2015). The relationship between mental health and socio-economic status is two-way, as a person's poor mental health can result in loss of income and unemployment which in turn negatively affect their socioeconomic status and can subsequently embed poor mental health. In England, the 2020 Marmot Review of inequality and health concluded that being in poverty has a marked effect on physical and mental health (Marmot 2020), and these inequalities have widened since the 2010 review (Marmot 2010).

It is important to recognise that compared to men, women frequently experience social, economic and environmental factors in different ways, and in England, the distribution of common mental disorders along a social class gradient is stronger in women compared to men (McManus et al. 2009). This gender disparity is apparent across European countries (Lehtinen et al. 2005). European countries, also experience similar patterns of common mental disorders and socio-economic status as those discussed for GB (Fryers et al. 2005). Although lesser researched, similar findings are also established for low and middle-income countries; in a systematic review of 115 studies (Lund et al. 2010), the prevalence of common mental disorders was found to be positively associated with multiple poverty measures.

Access to resources is one substantial social determinant of health, as described by Macintyre et al. (1993). The importance of context (i.e., where someone lives) as a driver for population-level inequalities in health is central to the research questions in this thesis. The structural inequalities (Macintyre 1997, Marmot 2010) which may limit easy access to greenspace act alongside other determinants of mental health to add layers of disadvantage for people who are less able to spend time in greenspace, which would benefit mental health.

To summarise, social determinants of mental health are intertwined and complex, and there are population subgroups that are at higher risk of poor mental health because of greater exposure to unfavourable social-economic conditions which are interrelated with gender and ethnicity (World Health Organization and Calouste Gulbenkian Foundation 2014, Marmot 2020). Access to greenspace is only one contextual factor that can affect mental health, and action on health inequalities requires action across all social determinants of health (Marmot 2010).

2.1.2 Measuring mental health

As the definition implies (see Section 1.1), mental health is multi-dimensional (World Health Organization 2018). Subsequently, there are many different measures of mental health adopted across the literature. Negative dimensions of mental health such as the prevalence of mental illness or mental health conditions are commonly used to measure the burden of mental health. For example, the GHQ-12, is a validated screening tool used to assess a person's risk of common mental disorders such as anxiety and depression (Goldberg and Hillier 1979, Goldberg et al. 1997, Jackson 2006). The GHQ-12 has six positively and six negatively phrased items. Whether these items measure one distress dimension or two correlated dimensions (positive and negative) is a topic of debate (Andrich and Schoubroeck 1989, Hankins 2008, Wang and Lin 2011). A second common measure of mental health that represents the negative dimensions of mental health is the Malaise Inventory. The Malaise Inventory is designed to measure psychological distress and consists of 24 self-completion items that include emotional and somatic symptoms (Rutter et al. 1970, Rodgers et al. 1999).

However, in adopting the WHO's definition of mental health (Section 1.1), mental health is not just the absence of illness. Many researchers and practitioners are now recognising the benefit of the quality of life measures over measures of ill health to capture hedonic and eudaimonic dimensions of mental health. Hedonic mental wellbeing is achieved through experiences of happiness, pleasure, and the avoidance of pain. Eudaimonic mental wellbeing is achieved through experiences of meaning, purpose and an individual's ability to fully function (Ryan and Deci 2003). The Warwick-Edinburgh Mental Well-Being Scale (WEMWBS) was developed to better measure the hedonic aspects of mental wellbeing (Tennant et al. 2007, Stewart-Brown et al. 2009). Unlike the GHQ-12 and Malaise Inventory, WEMWBS consists of entirely positively framed questions such as, "optimistic about the future" and "dealing with problems well". More general measures of quality of life are the 36-Item Short Form Health Survey (SF-36) and the 12-Item Short Form Health Survey (SF-12). Both were developed as part of the Medical Outcomes Study and cover eight domains of health. These domains cover elements of physical and mental health and were designed as a general measure of health. However, both have been validated as useful measures of mental health. Specifically, the SF-36 is reliable for people with schizophrenia (Su et al. 2014) and the SF-12 scores are comparable to the SF-36 (Ware et al. 1996), particularly in large populations (Gandek et al. 1998).

There is substantial debate over which measures, and subsequently domains, of mental health should be used in quantitative research. By using a measure of mental distress such as the GHQ-12, the hedonic and eudaimonic dimensions of health may not be captured. But the reverse is also true if the prevalence of mental disorders and mental distress are not considered. As people living with a mental disorder, as captured by the GHQ-12 and Malaise Inventory, can also achieve good levels of mental wellbeing by having meaningful experiences whilst living with distressing, or debilitating symptoms (World Health Organization and Calouste Gulbenkian Foundation 2014). However, there is evidence the WEMWBS and GHQ-12 assess mainly the same construct and therefore share a common dimension (Böhnke and Croudace 2016).

2.2 The theory underpinning the beneficial effect of greenspace on mental health

2.2.1 The Biophilia hypothesis

The literature exploring the effect of greenspace on mental health has grown over the past 35 years, since the publication of Edward O. Wilson's biophilia hypothesis (Wilson 1984). Originally, the term biophilia was first defined as "love of life or living systems" by psychoanalyst Erich Fromm (1964). Twenty years later, the term was redefined by Wilson to mean "an innate love of nature" (Wilson 1984). The critical distinction between the two definitions is the use of the word "innate", which Wilson used to mean genetically inherited via natural selection. The biophilia hypothesis is the idea that because people possess an innate love of nature, they (people) seek to form connections with nature and other life forms (Wilson 1984, Kellert and Wilson 1993). Wilson argues that the natural environment is as important to human evolutionary history as social behaviour, and therefore the origin of biophilia is unlikely to be recent in human evolutionary history.

The hypothesis can be supported by historical evidence and evolutionary logic. There is historical evidence of humanity's tendency and efforts to maintain contact with nature, for example, the villa gardens of ancient Egypt, and the elaborate gardens of early Persian and Chinese settlements (Ulrich 1993). In the present day, biophilic instinct emerges unconsciously when people travel long distances to visit natural environments, and this is a repetitive pattern across most cultures and societies (Wilson 1984, Kellert and Wilson 1993). For evolutionary logic, adaptive behavioural response for the approach and avoidance of specific elements of the natural environment would have been favoured during evolution to meet particular needs (Kellert and Wilson 1993). The avoidance of specific natural stimuli (e.g., fear or phobias) is also known as biophobia. As noted by Ulrich (1993), the strongest empirical data in support of Wilson's biophilia hypothesis are predominantly related to biophobia. Darwin (1877) first suggested that fears are innate and certain species are "pre-programmed" to fear certain stimuli. Logically biophobic behaviours have clear benefits for survival as fear of venomous snakes and spiders, and large carnivores would drive their avoidance (Gullone 2000). The contrast between biophilic and biophobic behaviour represents the spectrum and complexity of emotional responses people can have towards nature; i.e., people can demonstrate both positive and negative affiliations with life and life-like processes (Wilson 1984). However, in a review by Simaika and Samways (2010), it is argued that it is erroneous to use evidence of innate biophobia in support of innate biophilia as biophilia had not been demonstrated. Similarly, in a review by Kahn (1997), the use of biophobia as evidence of biophilia is further criticised by comparing people's aversion to snakes and spiders to aversions to human or man-made artefacts such as moving cars and guns. By using historical and anecdotal evidence as circumstantial support, it can be argued that there is equal support for an "affinity" towards unnatural or man-made spaces such as cityscapes, which have not formed a prolonged part of human evolutionary history (Kahn 1997, Simaika and Samways 2010). This raises the following questions: (1) is there a genetic basis for biophilia, or (2) if there is a genetic basis is it smaller than suggested by Wilson, and (3) should Fromm's original definition be adopted in favour of Wilson's hypothesis.

Biophilia being experiential (and not innate) links more strongly with the "extinction of experience" phenomena (Pyle 1978, Soga and Gaston 2016). First proposed by Pyle (1978) the term extinction of experience was used to describe the increasing disconnect, or alienation, between people and nature. The process attributes this disconnect to continued urbanisation which is decreasing the availability and access to natural spaces. As a result, people lose the opportunity to interact with, benefit from, or develop an appreciation of nature (Pyle 1978, Soga and Gaston 2016). The process is a cycle, with the disconnect leading to apathy towards environmental issues and as a result further degradation of nature; thus creating a shifting baseline or a cycle of continued disaffection (Soga and Gaston 2016). A similar phenomenon called "environmental generational amnesia" was developed by ecopsychologist Peter Kahn (1995, 2002). Kahn proposes that as each generation's experience of nature is diminished (due to lack of experience, memory, or knowledge of the past condition) humanity's "baseline" for nature shifts. This gradual change in people's accepted level of the natural environment is also known as "shifting baseline syndrome" and was first presented by Daniel Pauly, in a fisheries context (1995), independent from Kahn's environmental generational amnesia phenomena. In a more recent review by Soga and Gaston (2018), shifting baseline syndrome is identified as potentially one of the fundamental reasons societies tolerate the continued destruction and decline in the quality of the natural environment. Comparing these three concepts to Wilson's biophilia hypothesis, if biophilia were innate and rooted deep in humanity's evolutionary history, then would the generational effect (as proposed by the extinction of experience, environmental generational amnesia and shifting baseline syndrome) be so pronounced? This links with the initial critique of the hypothesis by Fischer (1994), who argued that the extent to which Wilson's hypothesis is embodied in genetic determinism should be reconsidered. As discussed by Kahn (1997), Kellert countered Fischer's critique in an unpublished response to the editor and argued that Fischer had oversimplified the biological determinism first presented by Wilson. Biophilia, like other patterns of behaviour, is complex and mediated by rules of learning. Biophilia can be viewed within the broader context of biocultural evolution, whereby a culture was developed under the influence of hereditary learning characteristics, and the genes for these characteristics were passed via natural selection in a cultural context (Kellert and Wilson 1993, Kahn 1997, Gullone 2000). As argued by Nabhan and St. Antoine (1993) a genetic predisposition for biophilia exists; however, the expression of biophilia in an individual needs to be triggered by both culture and the environment.

Whether biophilia is innate or experiential remains unknown. But given empirical evidence that nature does contribute to improvements in human health and wellbeing, there is the argument that establishing the origin of biophilia is not a research priority (Gullone 2000, Kellert 2009). By either definition (Fromm or Wilson), biophilia can be used as an interdisciplinary framework to investigate the beneficial effects of nature, or specifically greenspace.

2.2.2 Pathways to mental health benefits

Multiple pathways have been proposed to explain the overall health benefits of urban greenspace. In an attempt to organise empirical evidence from different disciplines, previous reviews predominantly have focused on four general pathways; (1) air quality, (2) physical activity, (3) stress and (4) social contact (De Vries et al. 2013, Hartig et al. 2014). Yet, in a comprehensive review of pathways Kuo (2015) identified up to 21 plausible pathways from nature to health (both physical and mental). Subsequently, the use of the four pathways may not be suitable for the topic of urban greenspace and health. An alternative approach proposed by Markevych et al. (2017) is to categorise pathways into three domains; (1) reducing harm, (2) building capacity, and (3) restoring capacity. These domains are complementary and are not mutually exclusive. As a result, organising pathways into these domains creates the opportunity for interdisciplinary exchange and the study of lesser-explored pathways in the context of other potential influencers of overall health. This theoretical summary adopts the domains from Markevych et al. (2017) to organise and present the pathways relevant to how urban greenspace affects mental health.

2.2.2.1 Domain 1: Reducing harm

It is hypothesised that the presence of urban greenspace mitigates the effect of an environmental hazard (Markevych et al. 2017). This review reflects on four environmental hazards that negatively impact mental health: (1) air pollution, (2) noise pollution, (3) exposure to sunlight, and (4) heat island mitigation. Under this domain, the presence of greenspace is enough to reduce the impact of the environmental hazards and obtain the benefit to mental health and it does not rely on individuals interacting with the greenspace (Markevych et al. 2017).

2.2.2.1.1 Air pollution

Worldwide, ambient (outdoor) air pollution is attributed to approximately 4.2 million deaths per year (World Health Organization 2021). Air pollution is a mix of particles and gasses of either natural or human origin. The link between air pollution and physical health (such as cardiovascular and respiratory diseases) is well established. But air pollution can have harmful impacts on all organs, including the brain. Several pathways have been identified to explain how air pollution can affect mental health including damage to the central nervous system and inflammation of the brain, both of which can result in stress and other mental health conditions such as depression (Calderón-Garcidueñas et al. 2016, Gładka et al. 2018, Heo et al. 2021).

A range of pollutants have been used to establish a link between air pollution and mental health. Most commonly studied are measures of Particulate Matter (PM), and oxides of nitrogen (NO_x), both of which are major components of air pollution in urban areas. PM is a generic term applied to a mixture of particles of varying sizes, shapes, and compositions. There are multiple classifications of PMs which relate to the aerodynamic size of the particle, such as PM_{10} for coarse particles of less than 10 microns in diameter, and $PM_{2.5}$ for fine particles that are less than 2.5 microns in diameter. NO_x is a mixture of nitrogen dioxide (NO_2) and nitric oxide (NO), both of which are primarily produced from diesel light-duty vehicles (cars and vans). Many studies (e.g., Oudin et al. 2016, Vert et al. 2017, Roberts et al. 2019, Bakolis et al. 2020, Heo et al. 2021), use both measures of PM and NO_x to establish if the effect on mental health varies according to the pollutant. Other pollutants studied include black carbon (Power et al. 2015) and Ozone (Bakolis et al. 2020). In addition to objective measures of air pollution, some studies have explored the effect of perceived air pollution on mental health (e.g., Dzhambov et al. 2018, Signoretta et al. 2019).

The effect of air pollution on mental health differs according to the period of exposure. Power et al. (2015) found a stronger association between short-term exposure to $PM_{2.5}$ and symptoms of anxiety compared to long-term exposure to $PM_{2.5}$. However, Liu et al. (2020) found no evidence that stress was directly influenced by real-time $PM_{2.5}$ exposure in young adults (15-25) in Plovdiv, Bulgaria. This finding is supported by Roberts et al. (2019) in a study of children living in London. Results showed that air pollution exposure at age 12 was not associated with age 12 mental health problems. However, in the same study, age 12 exposure to air pollution was significantly associated with depression at age 18. For adults, Vert et al. (2017) found a positive link between anti-depressant prescriptions and exposure to long-term air pollution.

Overall, there is less evidence of short-term effects of air pollution compared to long term exposure to pollution on mental health. But this may be a result of different studies using different measures of pollutants, and mental health at different points in the life course, which makes it difficult to draw generalisations from the literature (Misiak 2020). Vert et al. (2017) demonstrated that the mental health measure was important in establishing the relationship between air pollution and mental health. Although a link was found between pollution and the prescription of anti-depressants, no link was found for the diagnosis of anxiety disorders (Vert et al. 2017). To counter this, in a study of older adults, Pun et al. (2017) found significant associations between concentrations of $PM_{2.5}$ and both depressive and anxiety symptoms but found this association to only exist for anxiety during smaller exposure periods. This conflicting evidence for similar measures of mental health and different duration of exposure supports the argument that contextual factors are important when considering the relationship between air pollution and mental health (Macintyre et al. 1993). In addition, there are layers of contextual factors to consider (Dahlgren and Whitehead 1991). For example, the study by Pun et al. (2017) found that the association between anxiety and $PM_{2.5}$ was strongest for individuals with lower social-economic status. This raises the possibility that air pollution is associated with socioeconomic factors (i.e., poorer areas have worse air pollution and poorer mental health). However, in a meta-analysis by Heo et al. (2021) the association between suicide risk and air pollution did not significantly differ by income – a proxy for socioeconomic status. Due to conflicting evidence, it is difficult to draw a consensus and in a narrative review by Ventriglio et al. (2021) it was determined that most evidence is non-conclusive. Despite inconclusive evidence, as with many of the other factors under consideration in this pathway review, exposure to air pollution due to unequal socioeconomic circumstances is a social determinant of health.

The beneficial effect of urban vegetation on reducing the level of damaging pollutants is long-established (Zupancic et al. 2015, Hirabayashi and Nowak 2016, McDonald et al. 2016). This benefit is underpinned by two assumptions. First, pollutant sources are not present in greenspace (Markevych et al. 2017). Second, the vegetation within greenspaces directly removes air pollutants (such as $PM_{2.5}$, PM_{10}, and Ozone) via deposition (Kroeger et al. 2014, Hirabayashi and Nowak 2016). Therefore, in the context of the effect of urban greenspace on mental health; urban greenspace reduces the level of air pollution and therefore reduces exposure to air pollution and its negative effects on mental health.

2.2.2.1.2 Noise pollution

Noise pollution is defined as harmful or annoying levels of sound. Several mechanistic links have been made to explain how noise pollution negatively impacts mental health. Generally, noise pollution is considered an “indirect” pollutant because its consequences on mental health are facilitated by generating stress as opposed to a biological mechanism (Ventriglio et al. 2021).

Night-time noise pollution resulting in poor sleep quality is a commonly cited mechanism as to how noise pollution results in poor mental health. Lack of (or poor quality) sleep can result in a low mood, fatigue, increased stress, and tiredness, all of which can have secondary effects to further exacerbate mental health by reducing willingness to participate in physical activity (Roswall et al. 2017, Dzhambov, Hartig et al. 2018), or reduced social contact (Dzhambov, Markevych et al. 2018). However, Frei et al. (2014) found that this mechanism is dependent on perceived noise annoyance on self-reported quality and the same link was not found for objective measures of annoyance and sleep quality. These findings are supported by Sygna et al. (2014), where a positive association was found between symptoms of psychological distress among participants with poor sleep quality. No association was found between traffic noise and mental health among individuals with good or medium self-reported sleep quality (Sygna et al. 2014). Whether an individual experiences annoyance from noise pollution may depend on many other individual-level factors, including their prior history of poor mental health or their coping strategies to mitigate the noise pollution (Clark and Paunovic 2018).

The general focus in the literature is on the impact of noise pollution from transport infrastructure on mental health. In a systematic review of 29 papers, Clark and Paunovic (2018) found that the majority of studies exploring the effect of noise on wellbeing examined road traffic noise exposure (83%), followed by aircraft noise exposure (41%). Due to the limited scope of articles, reviews of the literature have concluded that links between noise pollution and mental health are inconclusive and more studies are required to improve causality (Tzivian et al. 2015, Clark and Paunovic 2018).

There is grounded evidence that greenspace and GI can buffer the effects of noise pollution. Several mechanisms have been proposed to explain this relationship. First, greenspace can result in a physical noise reduction; for a review see Van Renterghem et al. (2015). Second, greenspace can psychologically buffer the stress response to noise. For example, visual shielding of the source of the pollution can reduce the perceived noise (Aylor and Marks 1976), or the combination of natural sounds with artificial noise (e.g., from cars) improves the perceived quality of the noise (Li et al. 2012, Annerstedt et al. 2013, Kang et al. 2016). Third, as with air pollution, the greater proportion of greenspace in an area means that there is less space available for infrastructure that can produce noise pollution (Markevych et al. 2017).

2.2.2.1.3 Exposure to sunlight

It is widely accepted that both climate and season can affect mental health (Sinclair et al. 1994, Keller et al. 2005). In temperate latitudes, more depressive symptoms are reported in the winter months than summer months (Friborg et al. 2012, Kerr et al. 2013, Cobb et al. 2014, Basnet et al. 2016, Patten et al. 2017). In 1984 this seasonal subtype of major depressive disorder, commonly referred to as seasonal affective disorder, was formally recognised (Rosenthal et al. 1984). Seasonal affective disorder is thought to be driven by changes in day length and disruption of circadian rhythms (Walton et al. 2011, Legates et al. 2014, Meyer et al. 2016) and can be more common in women than men (Harmatz et al. 2016, Lyall et al. 2018). However, both seasonal and non-seasonal depression have a relationship with light (Kent et al. 2009). Sunlight has been shown to affect the regulation of serotonin and melatonin, which in turn affects cognitive function (McColl and Veitch 2001, Srinivasan et al. 2009, Winkler et al. 2014). As serotonin in the brain regulates anxiety, happiness and mood, individuals who lack sufficient exposure to sunlight may result in low levels of serotonin and as a result increase their likelihood of feeling anxious and depressed (Benedetti et al. 2001, Kent et al. 2009). There is experimental evidence that increasing sunlight exposure in older people results in improved self-reported mental health (Samefors et al. 2020). Observational data linking daylight to the burden of schizophrenia in Ningbo, China has shown that female, middle-aged, and elderly individuals were most susceptible to the effects of sunlight (Gu et al. 2019). In contrast, other observational research indicates that sunlight, in addition to physical activity and social cohesion, moderates the link between air pollution and depression (Wang et al. 2019).

The presence of greenspace can increase people's exposure to sunlight by encouraging outdoor recreational activities (the benefit of recreational activities is discussed below in Section 2.2.2.2.2), and therefore can improve mental health outcomes.

2.2.2.1.4 Heat Island Mitigation

The link between high ambient temperature and physical health is well established (e.g., Armstrong 2006, Hajat et al. 2007, Sung et al. 2011, Intergovernmental Panel on Climate Change 2014, Xu et al. 2016). Although the effect of high temperatures on mental health has received less attention, a review by Thompson et al. (2018) showed that the evidence base is increasing, with the largest number of studies (17 studies) existing for the effect of heat on suicide rates. From the 17 studies, the overall consensus was that increased temperatures were positively correlated with suicide rates and only two studies did not find a significant effect of temperature on suicide rates (Page et al. 2007, Fernández-Arteaga et al. 2016). There is additional evidence for the effect of increased ambient temperatures on the prevalence of schizophrenia (Gupta and Murray 1992, Hermesh et al. 2000, Shiloh et al. 2005). However, in Thompson et al. (2018), there was no mention of the potential effect of heat on measures of mental wellbeing (i.e., to capture the hedonic and eudaimonic aspects of mental health). Therefore, there are gaps in the overall understanding of the impact of heat on mental health. Yet, the evidence of the effect of heat stress on measures of negative mental health such as mental disorders is sufficient to warrant its inclusion as a pathway.

In cities and other urban areas, higher temperatures caused by the urban heat island effect are well established (Voogt and Oke 2003), as is the mitigating effect of greenspace against the rise in temperatures (e.g., Spronken-Smith and Oke 1999, Bowler et al. 2010b, Morais et al. 2016). The presence of vegetation means that the overall albedo of the urban area is lowered, and more solar radiation is absorbed, in addition to a cooling effect through evapotranspiration. Therefore, the presence of greenspace can reduce the ambient temperature in a city, and subsequently improve mental health outcomes. Several studies have found heat-related stress to be lower in areas with more greenspace (e.g., Gronlund et al. 2015, Burkart et al. 2016, Son et al. 2016).

2.2.2.2 Domain 2: Building capacity

Greenspaces can provide a setting for activities beneficial for mental health, which in turn "builds", or supports, an individual's positive mental health. Two pathways are considered to build capacity: (1) Social cohesion and (2) physical activity and recreation.

2.2.2.2.1 Social value

There is a well-established protective effect between social support and mental health and wellbeing (e.g., Berkman 1995, Holt-Lunstad et al. 2010, World Health Organization et al. 2014, Mental Health Foundation 2016). The primary hypothesis is that the intensity and frequency of stressful experiences can be buffered by social support via emotional, informational, or instrumental resources provided by and shared with others (Allen et al. 2014). Social support can be provided at many levels, e.g., family, couple relationships, and community. Being (happily) married or in a stable relationship has a positive effect on mental health – specifically lower levels of stress and lower prevalence of depression (Holt-Lunstad et al. 2008). At a community level, social cohesion (i.e., how close-knit a community is) has been shown to counteract the adverse effects of material/social deprivation. For example, longitudinal data from a Welsh cohort study found that the negative effects of deprivation on mental health were significantly reduced in areas with high social cohesion, even after adjustment of other socio-economic factors (Fone et al. 2014). In England, similar protective effects of social cohesion against depression were observed in older people (Stafford et al. 2011). Social support, social capital, social cohesion, and sense of community are all terms that have been developed to reflect the potential value of social relationships and the support from these relationships and are often used synonymously.

It is hypothesised that greenspace can provide a setting for social interaction and the formation of a sense of community. Evidence indicates that social cohesion is a moderator between perceived neighbourhood greenness and mental health (Sugiyama et al. 2008). In a study by Maas et al. (2009), it was found that those with less greenspace in their living environment (1km from their home) were also more likely to experience feelings of loneliness and self-reported shortage of social support. At a smaller scale of exposure, De Vries et al. (2013) presented evidence that this relationship exists between the quality and quantity of streetscape greenery (as measured using a streetscape audit tool), perceived social cohesion and stress. This supports similar findings from a quasi-experiment in 1998, whereby individuals were assigned homes in architecturally similar high-rise buildings with varying amounts of vegetation outside (Kuo et al. 1998). The presence of trees and grass was positively associated with the use of common spaces and informal social contact (Kuo et al. 1998). These studies (Kuo et al. 1998, De Vries et al. 2013), suggest that the qualities or characteristics of greenspace are important when considering social cohesion as a pathway to mental health. Arguably, to promote social ties, local parks must be well maintained and provide attractive recreational facilities (Kaźmierczak 2013). However, when looking at larger public greenspaces, Francis et al. (2012) found neither measures of sense of community nor social support to be an important moderator between the quality of public open space and mental health.

Research on streetscape greenery revealed that social contact was positively related to one's sense of safety (Kuo et al. 1998). Additional studies have shown that buildings in areas with more trees and grass are associated with fewer crimes (Kuo et al. 1998, Kuo and Sullivan 2001). Overall, in a review of 45 papers on the effect of greenspace on violent crime in urban environments, it was concluded that the presence of greenspace reduces urban crime (Shepley et al. 2019). This is in agreement with an earlier review by Bogar and Beyer (2016). However, there is mixed evidence; specifically in dense urban areas, enclosed greenspaces may result in perceived safety concerns (Maas, Spreeuwenberg et al. 2009). Han et al. found that gun crimes are associated with long-term negative impacts on health due in part to the reduced use of parks, in addition to the short-term impacts on public safety (Han et al. 2018). Often this is context-dependent, i.e., whether it is a private or public space or time of day. For example, Donovan and Prestemon (2012) found that trees in public spaces were associated with lower crime rates. However, in private spaces (homes) view obstructing trees were associated with increased crime rates because in this context it is more difficult to observe criminal activity compared to trees within the public realm (Donovan and Prestemon 2012).

Overall, there is sufficient evidence to consider two pathways in which greenspace facilitates this social value: (1) promotes social contact and a sense of community, and (2) effects of greenspace on crime rates.

2.2.2.2.2 Physical activity and recreation

Physical activity and recreation are considered two vital components of good physical and mental health. Literature reviews have found that exercise has beneficial effects on a wide range of mental health issues including; depression (Stanton and Reaburn 2014), schizophrenia (Stanton and Happell 2014) and dementia (Forbes et al. 2015). In theory, greenspace can provide a safe and accessible setting for physical and recreational activities (Almanza et al. 2012, Mytton et al. 2012, Astell-Burt et al. 2013). This is supported by a large (although sometimes inconsistent) experimental evidence that suggests that performing physical activity in greenspace produces greater mental health benefits compared to physical activity not in a green setting (e.g., Pretty et al. 2005, Mitchell 2013, Duncan et al. 2014). Performing exercise outside in greenspace or nature is commonly referred to as "green exercise". In a systematic review of 11 controlled trials, Thompson Coon et al. (2011) concluded that generalisations are hampered by the poor methodological quality of the available evidence. More recently, in a meta-analysis of 19 controlled trials, Li et al. (2022) concluded that green exercise results in higher positive moods and emotions. However, the overall positive effect compared to a non-green setting was not statistically significant (Li et al. 2022). The meta-analysis (Li et al. 2022) revealed that wild environments compared to urban greenspaces may be more effective in improving vigour and comfort during green exercise. This suggests that the quality/characteristics of greenspace may be important when considering the effect of greenspace on mental health via physical activity.

However, experiments are short-term and by definition control the behaviour of the participant. As such observational studies can provide further insight into free-living populations. In observational studies, analysis has been used to establish whether greenspace promotes better mental health via physical activity (e.g., De Vries et al. 2013, Richardson et al. 2013, James et al. 2016b, McEachan et al. 2016). However, not all studies found a link (e.g., Astell-Burt et al. 2013, Triguero-Mas et al. 2015, Dadvand et al. 2016). This mixed evidence base could be partially explained by the “use” of greenspace, as the presence of greenspace does not imply its use. Specifically, when considering the use of greenspace for physical activity, the size of the greenspace or the facilities provided within the greenspace may be a better indicator than just the mere presence of the space (Giles-Corti et al. 2005, Kaczynski et al. 2009). Typologies of greenspace use and interaction are discussed further in Section 2.3.2.

In their review of pathways, Markevych et al. (2017) concluded that physical activity needs to be considered in combination with other confounding factors. In a meta-analysis by Hanson and Jones (2015), a total of 42 studies were found to examine the effect of walking group interventions on physiological and psychological wellbeing. Overall, the studies showed that participation in a walking group resulted in a reduction in depression (Hanson and Jones 2015). However, it should also be considered that there are social dynamics related to participation in a walking group. Evidence indicates that being a member of a walking group has supportive effects that encourage individuals to continue to participate and have a positive attitude towards physical activity (Kwak et al. 2006), in addition to companionship and a shared experience of wellness (Doughty 2013). Therefore, highlighting the importance of both physical activity and social cohesion within greenspace can affect mental health.

2.2.2.3 Domain 3: Restoring capacity

The restorative benefit of greenspace is guided by two commonly cited theories developed in environmental psychology: (1) the attention restoration theory (ART), and (2) stress reduction theory (SRT).

2.2.2.3.1 Attention restoration theory

ART proposes that vegetation and other natural features attract and hold a person's attention without effort, this enables the neurocognitive mechanism on which effortful attention depends to rest (Kaplan and Talbot 1983, Kaplan and Kaplan 1989, Kaplan 1995). Within cities, and the modern working environment, many tasks require a degree of directed attention (Mantler and Logan 2015). Prolonged periods of directed attention results in fatigue (Kaplan 1995), and mental fatigue results in a person's ability to direct attention decreasing and their susceptibility to stress increase (Hartig et al. 2014). Linking the ART with Wilson's biophilia hypothesis (Wilson 1984), Kaplan and Kaplan (1989) propose that people find nature inherently fascinating and this facilitates rest and rejuvenation; i.e., instead of directed attention, their attention is automatic or involuntary.

2.2.2.3.2 Stress reduction theory

Unlike ART which focuses on attention, SRT focuses on emotion; SRT proposes that contact or viewing vegetation and other natural features can very rapidly result in a positive effect on a person experiencing acute stress, this can block negative thoughts and feelings (Ulrich 1983, Ulrich et al. 1991). Similarly to ART, SRT is linked to Wilson's biophilia hypothesis (1984) in evolutionary terms. Positive moods can be evolutionarily advantageous in the same way that stress response to dangers is beneficial and hereditary, a mechanism for rapid stress recovery would also be beneficial to help humans prepare for the next survival task (Hartig et al. 2014). ART and SRT are complementary and often co-cited because mental fatigue caused by directed attention can result in stress and, without stress reduction, stress can promote further mental fatigue (Mantler and Logan 2015).

2.2.2.4 Pathway summary

The pathways through which greenspace exposure results in mental health benefits are not fully understood (de Keijzer et al. 2016). There is an imbalance in the evidence available for each pathway, yet the consensus from reviews of the literature is that multiple pathways are likely to operate simultaneously (Hartig et al. 2014, Mental Health Foundation 2016, World Health

Organization 2016, Markevych et al. 2017). However, for simplicity, many empirical studies have explored the pathways in isolation. This fails to consider the overall context (Macintyre et al. 1993) in which greenspace can influence mental health. To avoid oversimplifying or misestimating the contribution of greenspace to mental health benefits there is a need to consider all pathways, in parallel with other social determinants of health. In this thesis, suitable data for each pathway is discussed in Chapter 4– the data landscape.

2.3 Greenspace

The term greenspace has no universally accepted definition, particularly regarding its use in health and wellbeing research (World Health Organization 2016). Depending on the context, the term greenspace may be applied to describe a natural setting (e.g., parks and forests), or specific natural elements (e.g., street trees) or may extend to include "blue space" (e.g., lakes, ponds, and coastal zones). This can lead to ambiguity, particularly when the majority of studies fail to define what they mean when referring to greenspace, nature and blue space (Taylor and Hochuli 2017). Subsequently, it is difficult to compare studies and establish what types or characteristics of greenspace may be influencing the relationship between greenspace and mental health.

In this thesis, the term greenspace refers to an area (of any size) of grass, trees or other vegetation and greenspace and blue space are referred to as two separate entities. The benefit of using a broad definition is that it does not distinguish between the characteristics of the spaces. Therefore, the qualities of the spaces can be discussed separately from the presence of greenspace. Nevertheless, this thesis separates greenspace into two general categories; (1) all greenspace which takes the above definition and (2) public greenspace. The second refers to public parks and public gardens only, which are defined on the basis of accessibility and recognises that although a greenspace may exist it may not be publicly accessible (e.g., sports pitches and institutional grounds). As recognised by this distinction, greenspace access is another key theme within this thesis and is discussed further in Section 2.3.2.

2.3.1 Measuring exposure to greenspace

Reviews of the literature acknowledge that measuring exposure to greenspace can be challenging (Hartig et al. 2014, Gascon et al. 2015, Houlden et al. 2018) as, in accordance with Pretty (2004) and Keniger et al. (2013), exposure to greenspace infers at least one of the following interactions:

(1) Indirect – experiencing greenspace whilst not being physically present in it, e.g., viewing the greenspace through a window.
(2) Incidental – physically present within the greenspace as a result of engagement with another activity, e.g., experiencing greenspace whilst walking or driving.
(3) Intentional – physically engaging and interacting with greenspace through direct attention, e.g., recreational activities such as hiking, wildlife watching or gardening.

These typologies of interaction reflect the personal intent behind an interaction that can be more broadly classified as either active or passive (Keniger et al. 2013). One of the challenges in measuring exposure to greenspace is capturing these different forms of interaction within the chosen measure. For example, studies typically measure exposure in one of three ways: (1) the number of visits to, or activities in, greenspace, (2) proximity to greenspace, and (3) quantity of greenspace. Studies that quantify the number of visits a person makes to greenspace are capturing the effect of an intentional interaction with greenspace. Whereas, studies that quantify either the proximity a person lives to greenspace or the amount of greenspace in their local area instead capture all three typologies of interaction. Cox, Hudson et al. (2017) speculate that as urbanisation continues and greenspace in cities declines, interaction with greenspace will become the exception as opposed to the norm and intentional interactions are likely to become the most common form of interaction. In this case, measures of visits and activities would be a suitable way to quantify exposure to urban greenspace. Furthermore, in adopting measures of proximity to and quantity of greenspace it is not possible to distinguish which form of interaction (or combinations of interaction) is contributing to mental health. However, one of the benefits of using a measure of proximity or quantity instead of the number of visits to greenspace is that the focus isn't on one form of interaction; therefore, it is more likely that the overall benefits of greenspace to mental health will not be underestimated.

Measures of quantity are generally a percentage of greenspace within a defined area (Collins et al. 2020). However, this defined area varies within the literature; for example, Houlden et al. (2017) used statistical boundaries, Astell-Burt et al. (2013) used a 1km circular buffer, and Astell-Burt and Feng (2019) used a 1.6km road network distance buffer. As a result of this variation in defined areas within the literature, it is not known what scale or scales greenspace affects mental health and whether these are appropriate boundaries to aggregate area-level confounding factors (Markevych et al. 2017). Similarly, it is not known what distances to greenspace (i.e., proximity) best predict mental health (World Health Organization 2016). Proximity is an important factor when considering exposure to greenspace because it is seen as a physical barrier to use and therefore interaction (Browning and Lee 2017, Ekkel and de Vries 2017). Evidence shows that the use of greenspace declines with increasing distance from home. After 100-300m use of greenspace rapidly declines (Coombes et al. 2010, Ekkel and de Vries 2017). Although there is evidence that the use of greenspace declines at 300m, this does not necessarily mean that it is a suitable threshold to explore the mental health benefits of greenspace – this threshold is currently unknown (World Health Organization 2016).

The measures of exposure to greenspace discussed above (i.e., visit, proximity, and quantity) do not detail the characteristics or types of greenspace that may be beneficial for mental health. Existing reviews of the literature have identified that the mental health benefits of greenspace are likely to vary according to characteristics such as vegetation type (Gascon et al. 2017, Markevych et al. 2017, White et al. 2017). These characteristics of greenspace can be classified as measures of greenspace quality. Measures of greenspace quality can be quantified from two perspectives: (1) human and, (2) ecological (Gaston et al. 2018, Wood et al. 2018). A measure of greenspace quality from a human perspective quantifies characteristics such as cleanliness, lighting, and availability of amenities, which combined contribute to greenspace feeling safe and accessible (Parra et al. 2010, de Gelder et al. 2017, Pope et al. 2018). Whereas an ecological perspective of quality quantifies characteristics such as greenness, habitat diversity, species diversity, or ecological functions (Dallimer et al. 2012, Cox, Shanahan, Hudson, Plummer et al. 2017, Taylor et al. 2018). Both perspectives are important and offer insight into the greenspace and mental health relationship. In GB, there are standards that exist to indicate good quality greenspace, including: (1) the green flag award (Green Flag Award 2022), and (2) the place standards tool (Place Standard 2022). However, these standards are dependent on on-site surveys which are costly and difficult to scale up. When measuring exposure to greenspace quality it is important to consider the comparability and repeatability of the chosen measure (see Chapter 3 for further discussion). It is plausible the alternative greenspace measures (i.e., visits, proximity, quantity and quality) could give different results. However, results from Mitchell et al. (2011) suggest this is not necessarily the case. In a comparison between three green space indicators across 268 small areas within four UK cities, results showed an overall agreement between the health indicators (morbidity and self-reported mortality). However, the agreement was found to vary according to the area-level of socio-economic deprivation. This further highlights the need to consider the social determinants of mental health (as discussed in Section 2.1.1) in any assessment of the beneficial effects of greenspace on mental health.

2.3.2 Greenspace access

Greenspace access is a key factor to consider when assessing the relationship between greenspace and mental health (Public Health England 2020), as it is recognised that the likelihood of using a greenspace increases with good access to public open space (Giles-Corti et al. 2005). Considering the possible interactions with greenspace (indirect, incidental, and intentional) together with access to greenspace, there is variation in the interactions available for different people. For example, in a public greenspace, all types of interaction are possible for all people. Whereas, in private greenspaces such as sports grounds where access is restricted to a subset of individuals, only indirect and incidental interactions are possible for all people.

Availability measures that quantify neighbourhood greenspace generally do not distinguish between greenspace that is publicly accessible and that which is not (World Health Organization 2016). This review of the literature revealed inconsistencies in how private gardens were identified. Some studies aggregated gardens in with other “green” landcover to give an overall measure of greenspace (e.g., Alcock et al. 2014). Studies recognised that not all have access to gardens, and chose to exclude it from their analysis (e.g., Astell-Burt et al. 2014). This aggregation is misleading and ignoring it would be underestimating the effect of greenspace on mental health. Many studies explore the effect of gardens and gardening on mental health (for reviews see Clatworthy et al. 2013, and Soga et al. 2017). But these do not consider a person’s access to other forms of greenspace. The opportunity to access private greenspaces is shaped by socio-economic factors, such as age, gender, income, ethnicity and disability (Office for National Statistics 2020b, Public Health England 2020), which are also confounded with a person’s mental health (Allen et al. 2014). Therefore, it is essential that access to public and private spaces are considered and separated when exploring the effect of greenspace on mental health.

2.3.3 Measuring greenspace access in Great Britain

In GB, adequate greenspace access can be assessed using the Accessible Natural Greenspace Standards (ANGSt; Natural England 2010). The original standards were developed in the early 1990s and reviewed in 2008 by Natural England (Natural England 2010). They are currently undergoing a review by Natural England (2022), and the draft guidelines are presented in Table 1. The guidelines are presented as a useful tool for LAs to assess whether their current provision of publicly accessible greenspace is adequate, and where action needs to be taken to deliver appropriate levels of greenspace.

Table 1: A summary of Natural England's draft Accessible Natural Greenspace Standards (ANGSt)

Criterion	**Size and distance criterion**
Doorstep greenspace	0.5ha within 200m
Local natural greenspace	2ha within 300m
Neighbourhood natural greenspace	10ha within 1km
Wider neighbourhood	20ha within 2km
District	100ha within 5km
Sub-regional	500ha within 10km
Local nature reserves	1ha per 1,000 people

Within the ANGSt, emphasis is placed on the potential benefits greenspaces can provide to the people nearby. However, despite the focus of ANGSt being accessibility, there is no clarity within the standards as to what types of greenspace should be included within their threshold areas, and if these are partially or fully accessible to the public.

Alternative access guidelines are available within GB, including the Fields in Trust's Guidance for Outdoor Sport and Play access guidance. Unlike the ANGSts, the Fields in Trust does not specify a threshold size within their requirement of greenspace within 800m of a person's home which represents the average distance travelled in a ten-minute walk (Fields in Trust 2020). From a planning perspective, the 10-minute walk links with the concept of the 20-minute neighbourhood, where people should be able to meet most of their everyday needs within a 20-minute return walk; i.e., 10-minutes there and 10-minutes back (Emery and Thrift 2021). The concept is increasingly popular and has been implemented by local authorities and city planners in Melbourne (Grodach et al. 2019, Victoria State Government Department of Environment 2021), Perth (Hooper et al. 2020) and has more recently been identified as a potential strategy for the Scottish government (O'Gorman and Dillon-Robinson 2021). Similar to the ANGSt, the Fields in Trust's guidance is not clear on what types of greenspace (public or all) should be considered when assessing against their standards. Consequently, although there is guidance on greenspace accessibility within GB, there is ambiguity about which types of greenspace should be used to assess whether an individual or household meets the required threshold for access.

2.4 Analytical approaches used to explore the effect of greenspace on mental health

The relationship between greenspace and mental health is complex, there are multiple pathways (Section 2.2.2) and different measures of exposure to consider (Section 2.3.1). In addition to these factors, the relationship is further complicated to many social determinants of health, that can be confounded with exposure to greenspace (Allen et al. 2014). These complexities make it challenging to “untangle” the effects of greenspace on mental health. Chapter 3 of this thesis presents a review of the methods used to explore the effects of greenspace on mental health. One of the research priorities established in Chapter 3 is the need to improve causal inference in studies exploring the effect of greenspace on mental health. The remainder of this literature review will discuss the different analytical approaches that can be used to improve causal inference.

The term causal inference is used in reference to an intellectual discipline that considers the study design, assumptions, and methods that enable causal conclusions to be made based on the available data (Hill and Stuart 2015). There are multiple perspectives on causal inference such as non-parametric structural equations, and graphical models (see Pearl 2009 for details). The dominant perspective is the counterfactual framework (also referred to as the potential outcome framework), which is the standard approach for demonstrating causal inference in epidemiological and medical studies (Höfler 2005), and therefore will be the focus of this review.

2.4.1.1 Causal inference by counterfactuals

The counterfactual framework can be conceptualised as a missing data or prediction problem, with the effect of a specified treatment on a specified item being the difference between the predicted outcome conditional on the treatment (Huntington-Klein 2021). In statistical notation, for item i there is a treatment z (where the z can equal 0 or 1), a set of pre-treatment predictors x_i and potential outcomes y_{i0} and y_{i1} correspond to what would be observed under one treatment or the other. Therefore, the causal effect of the treatment $z_i = 1$ compared to $z_i = 0$ is then defined as $y_{i1} - y_{io}$ (Rubin 1974). It is assumed that the treatment z is stable and randomly assigned, which are the conditions under which Randomised Control Trials (RCTs) are performed.

2.4.1.2 Causal inference in randomised control trials

RCTs are considered the gold standard for obtaining causal inference as not only can they investigate the counterfactual, but because the randomisation balanced the observed and unobserved characteristics of the individuals between the “treatment” groups thus eliminating much of the bias associated with other study designs (Hariton and Locascio 2018). As such, RCTs have minimised the risk of confounding factors influencing the results, and it can be assumed that the difference in an observed mean outcome is an unbiased estimate of the study population’s Average Treatment Effect (ATE). Figure 2a shows the simplified structure of a randomised control trial.

The fundamental benefit of randomisation is making all systematic sources of bias into random sources of bias (Rubin 1974). However, RCTs are not attainable in all situations as it is not always possible to eliminate all systematic sources of bias through design (e.g., it is not always possible to control for all post-treatment effects). Secondly, even if the design is possible, RCTs can be prohibited by cost, ethical reasons, and/or timeframes (i.e., some results would take many years to obtain). There are also many criticisms over the generalisability of RCTs (for discussion see: Rothwell 2005). However, the issue of generalisability (although important) is separate from that of estimating causal inference. In situations where a RCT is not practical, it is reasonable to estimate the effects of treatment in a non-randomised study and utilise observational data (Rubin 1974). Indeed, it would be unreasonable to dismiss the use of observational data in the unrealistic pursuit of an ideal experiment, or for policy and decision-makers to make decisions without any data analysis.

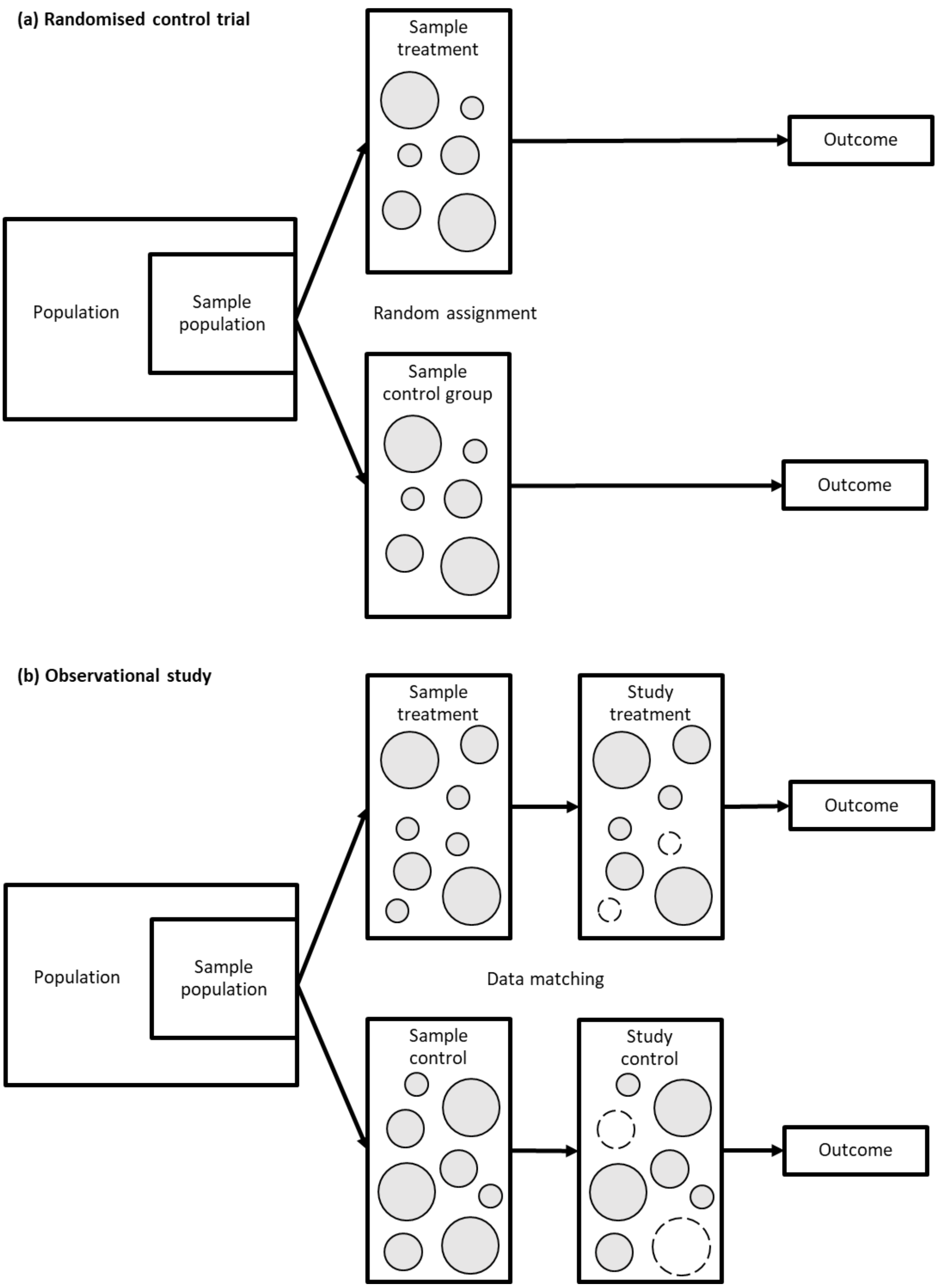

Figure 2: (a) the simplified structure of a Randomised Control Trial (RCT) showing the balance between sample characteristics between the randomly assigned control and treatment groups; (b) the simplified structure of an observational study where data-matching has been applied to balance observed characteristics between the control and treatment groups. Circles of different sizes represent individuals with different characteristics. Dotted circles represent individuals removed as a result of data matching. Figure adapted from Akobeng (2005) and Thompson (2015).

2.4.2 Applying the counterfactual framework to observational data

When using the counterfactual framework, a causal effect requires the comparison of at least two treatment levels (i.e., the control and treatment). The different control conditions represent different counterfactual states and therefore result in different causal effects (Gelman and Hill 2006). It has to be possible that the experimental unit (individuals) can experience each state (control or treatment). However, in observational studies, treatments are observed rather than randomly assigned. Observational data generally come in one of two forms: (1) cross-sectional data, consisting of only one set of observations for each unit of the observation (e.g., one set of observations at a given time point for each individual in a survey), and (2) longitudinal surveys, whereby repeated observations are made for individuals across successive interviews referred to as “waves”, “sweeps”, or “rounds” (Longhi and Nandi 2014, Elsevier 2022). Cross-sectional data provide a “snapshot” of the population at a particular point in time and is less expensive to collect. Alternatively, longitudinal data (also referred to as panel data) contain multiple sets of observations for each unit of observation (e.g., multiple observations over time for each individual in the survey). In longitudinal studies, it can be difficult to retain participants in the study (loss to follow up) and is relatively costly to maintain. Regardless of whether the data are longitudinal or cross-sectional, there is the challenge of controlling for systematic differences between the control and treatment groups that can affect the outcome y. Additional steps and stronger assumptions are required to account for variables other than the treatment that may causally affect the outcome y. To improve causal inference, the study design must control for these variables either by adjustment, statistical matching, or both.

2.4.2.1 Adjustment for pre-treatment covariates

Adjustment or controlling pre-treatment covariates are recommended for both experimental and observational studies. With observational data where the random assignment of the treatment is not possible, adjustment with pre-treatment variables helps us achieve the ignorability assumption. As it cannot be assumed that the treatment is randomised, it has to be assumed that by controlling for the confounding variables the distribution of individuals between the treatment groups can be ignored (i.e., the ignorability assumption). The ignorability assumption (also known as the ignorability of the treatment assignment) can be formalised by the conditional independence statement:

$$y^0, y^1 \perp \mathrm{T} \mid \mathrm{X}.$$

The distribution of the potential outcomes (y^0, y^1) are the same at the varying levels of the treatment (T) once the confounding factors (X) have been controlled for. In this context, the confounding factors are pre-treatment variables that are associated with both the treatment and the outcome (Gelman and Hill 2006). Therefore, if the predictors are conditioned to satisfy the ignorability assumption, causal inference can be made without randomisation of the treatment assignment. But it is key not to control for post-treatment variables (variables measured after the treatment) as this can result in bias and this bias can be of any size and in any direction for more information regarding the effects of conditioning on post-treatment variables (Gelman and Hill 2006, Huntington-Klein 2021).

2.4.2.2 Statistical matching

In RCTs, comparable control and treatment groups (i.e., sample matching) are created during sample recruitment and random assignment of treatment (see Figure 2a for conceptualisation). However, in observational studies, the control and treatment groups are often not comparable. To create comparable groups and improve causal inference, the characteristics of the control and treatment groups need to be balanced before analysis. Statistical matching is also known as data matching and refers to a suite of methods that prepare the data for statistical analysis through restricting and reorganising the original sample (Gelman and Hill 2006).

One-to-one matching is statistical matching in its simplest form. When adopting this method, the data are divided into “matching” pairs based on the pre-treatment variables and only differ according to their treatment assignment (see Figure2b). The “matching” pairs are similar as possible so that the matched sample are representing the region of data space where the treatment and control groups overlap (Gelman and Hill 2006). With one-to-one matching, there will be unmatched individuals when the control and treatment groups are not equally sized or when control and treatment groups have poor overlap (see Figureb). The matched data can then be analysed by estimating the difference in average outcomes across the two treatment groups, or regression-based approaches can then be used on the matched data to adjust for any further systematic differences between the control and treatment groups (Imbens and Rubin 2015). It is important to note that both methods are estimating the effect of the treatment within the samples' area of overlap (Gelman and Hill 2006). Statistical matching is primarily performed on cross-sectional data, although it should be noted that more complex alternatives are available to perform matching on longitudinal data, for details see Barban et al. (2017).

2.4.3 The use of longitudinal data to improve causal inference

Statistical matching still asks whether the treatment outcome average is different from the control outcome average. When using statistical matching to improve causal inference, similar assumptions to RCTs are made because the sample is balanced individual-level heterogeneity will not influence the outcome. With longitudinal data, the repeat observations are utilised within fixed-effect and mixed models to control for these individual-specific time-invariant unobserved factors.

2.4.3.1 Fixed effect models

In many fields, the term fixed effects refers to the factors within a mixed model (discussed in Section 2.4.3.2) to distinguish them from factors with random effects. However, in the context of longitudinal data analysis, fixed effect models are a method by which to estimate the effect of intrinsic characteristics of individuals such as genetics or a person's upbringing. In fixed effect methods, the repeat measures for each individual are used to control for the individual. In doing so, all factors (observed and unobserved) about the individual that do not change over time are controlled for. For example, a person's upbringing and arguably their personality does not change over time (Huntington-Klein 2021). By controlling for the individual, the variation between individuals is removed (also referred to as absorbing the fixed effect) and isolating the within-individual variation. To isolate the within-individual variation, the model allows the intercepts of the individuals to vary. Statistically, this can be summarised as:

$$Y_{it} = \beta_i + \beta_1 X_{it} + \varepsilon_{it}$$

And β_i can be defined as:

$$\beta_i = \beta_0 + \beta_2 Z_i$$

Where Z_i is a set of individual-level variables (that determine the individual effect). Comparing this to a classical regression:

$$Y = \beta_0 + \beta_1 X + \varepsilon$$

The intercept term in the fixed effect is now β_i not β_0 meaning all individuals in the data have their own intercept, but the slope (β_1) are the same for all individuals. Statistically, this is a weak method of allowing the intercepts to vary as only the within variation of the individual is accounted for. As a result, the estimated ATE is skewed towards individuals with more within variation. For example, to estimate the effect of physical health and household income, the coefficient for a household income is more accurate for estimating the effect of household income on physical health for individuals who have experienced a lot of change in household income over time. If an individual in the sample had a consistent household income throughout the survey, that individual contributes less towards the estimate of the household income coefficient (Huntington-Klein 2021). In addition, person-level characteristics that do not change over time (e.g., whether or not they have a private garden) are not accounted for using fixed-effect methods.

2.4.3.2 Mixed models

Mixed models (also referred to as random-effect, multi-level models and hierarchal models) incorporate both fixed and random effects. Unlike a fixed-effect model where the value of β_i is estimated from the individual's observations (and with only a few observations this can result in “noise”), in a mixed model β_i come from a pre-specified random distribution such as a normal distribution (Huntington-Klein 2021). As it is assumed that all observations come from the same distribution and that all observations are used to estimate that distribution, a more precise estimate with smaller standard errors can be obtained. In addition, weighted averages of both within and between variation can be used - not just within variation as is the case with fixed effects (Huntington-Klein 2021). Mixed models have the added benefit of being able to accommodate stratified data collection which is commonly adopted in longitudinal surveys (Feller and Gelman 2015). A simple hierarchal structure for longitudinal data is year t (lower-level) nested within individual i (higher-level), and a simple mixed model with random intercepts is structured as:

$$Y_{ti} = \beta_{0i} + \beta_1 X_{ti} + \varepsilon_{ti}$$

Where ε_{ti} is the residual for year t of the individual i, X_{ti} are a series of covariates that are measured at year t (lower-level) with the coefficient β_1, and β_{0i} represents the “macro” part of the model is defined as:

$$\beta_{0i} = \beta_0 + \beta_2 Z_i + \mu_i$$

Where β_0 is the intercept, Z_i is a set of variables measured at the individual (or higher) level with the coefficient β_2, and μ_i is the residual for the higher-level. The term μ_i allows for the differential intercept of the individual. By defining β_{0i} the effect of variables that do not change over time (e.g., gender or place of birth) on the outcome can be explored, such questions are beyond the scope of fixed-effect models. The second benefit of this mixed model is that individual between and within effects can be studied separately. Whereas fixed effect models can only explore within effects only.

In a traditional regression, it is assumed that regression slopes are the same across all contexts. In more complex mixed models, random slopes are used for situations that might violate this assumption. A mixed model with random slopes is defined as:

$$Y_{ti} = \beta_{0i} + \beta_{1i}X_{ti} + \varepsilon_{ti}$$

Where β_{1i} is defined as:

$$\beta_{1i} = \beta_1 + \beta_3 Z_i + \gamma_i$$

The above model has both random slopes and random intercepts, it is unusual to see random slopes without random intercepts because the variation in slopes (i.e., the relationship) would normally result in the overall variation in the overall level (or intercept) of the outcome variable. For both the random slopes and intercepts it is assumed that their coefficients (β_2 and β_3) are normally distributed around the overall model.

2.4.3.3 Applying the counterfactual framework to longitudinal data

As previously discussed, the analysis of observational data requires a treatment group to be defined, and in doing so the counterfactual can be identified. But unlike cross-sectional observational data, with longitudinal data, the temporal data about a person's address can be used to identify whether they have moved during their participation in the survey. In doing so, the treatment group and individual belongs to before a move can be identified, and whether this treatment changes post-move. Conceptually, this is comparable to a Before-After (BA) study design, and if the data permit a separate control group a Before-After Control Intervention (BACI) design can be adopted. BA and BACI both adopt the counterfactual framework: (1) in a BA study design, it is assumed that if the treatment had not been given then the trajectory would not change, and (2) for BACI design it is assumed that any observed differences between the control and treatment groups are a result of the treatment (Wauchope et al. 2021). Therefore, if the data allow for a BA or BACI study design, this would be the optimal method to help isolate the effect of a change from a variable outcome.

Combining a BACI design with a mixed model that allows for random intercepts and slopes will account for individual-level heterogeneity and will further contribute to causal inference. Without information on before and after the move, only the trajectory of the relationship between the focal variable and the individual would be explored. Whereas with a BACI design the focus is instead on the change in the focal variable. Although both are informative, the latter seems a more suitable design when attempting to answer targeted research questions. For example, when estimating the effect of distance to public greenspace on mental health, the focal variable has three possible treatments when the individual moves: (1) moving closer, (2) moving further, and (3) no change in distance. Conceptually the following three questions are asked when adopting a BACI design:

(1) If people move closer to a public greenspace, how much would their mental wellbeing have changed?
(2) If people move further from a public greenspace, how much would their mental wellbeing have changed?
(3) If people do not change the distance from a public greenspace when they move, how much would their mental wellbeing have changed?

Without information on the change, the following question is asked: "what is the effect of distance to greenspace on mental wellbeing?" This question lacks a counterfactual and therefore inference is limited.

Although longitudinal analysis accounts for much more heterogeneity, one important issue that remains when looking at individuals nested within neighbourhoods is how to control for the non-random selection of residents into these neighbourhoods. In an ideal (controlled) scenario, the neighbourhoods in which an individual lives would be random. This would provide a true causal effect of moving from a bad neighbourhood to a new one (Oakes 2004). However, this is not the case, and neighbourhood selection cannot be accounted for.

2.5 Literature review summary and considerations for future research

Research into the effect of greenspace on mental health is complex, and many factors discussed in this review need to be considered when exploring the effect of greenspace on mental health. First, there are multiple pathways hypothesising how greenspace influences mental health. Each pathway discussed has sufficient supporting evidence to warrant its consideration when attempting to quantify the effect of greenspace on mental health. This review has highlighted that when exploring the effect of greenspace on mental health, researchers should recognise that mental health has multi-dimensions (World Health Organization 2018). Different dimensions are captured in different measures of mental health, and it is important for researchers to consider and recognise which dimensions are represented when designing their study. Similarly, there are multiple measures of greenspace that can be used when quantifying a person's exposure to greenspace, and these measures capture different typologies of exposure passive (Pretty 2004, Keniger et al. 2013). Access is an important consideration when assessing greenspace exposure as not all individuals have access to all forms of greenspace. Hence, access is intertwined with different typologies of exposure to greenspace. For example, for public greenspaces such as (public) parks, intentional interactions are plausible for all groups of people. Whereas, for private greenspaces such as private domestic gardens and sports grounds intentional interactions are limited to those that have access to them. Like competing measures of mental health, researchers need to consider what dimensions of greenspace access and exposure are captured within the selected measure of greenspace. However, unlike measures of mental health which have been developed to be robust for different population subgroups (Goldberg and Hillier 1979, Goldberg et al. 1997, Jackson 2006), access and exposure to greenspace are confounded with socio-economic factors (Office for National Statistics 2020b, Public Health England 2020) – which themselves are determinants of poor mental health (Allen et al. 2014). Types of greenspace (i.e., public and private) and access are not the only features of greenspace that needs to be considered. The consensus in the literature is that the benefits of greenspace to mental health are likely to vary with different characteristics of greenspace such as greenness, species diversity and crime. It is important that these different qualities are explored in future studies so that these characteristics can be used to help improve and design future greenspaces that have the potential to maximise mental health benefits.

Combined, these complexities present a challenge for researchers to "untangle" the effect of greenspace on mental health. As discussed further in Chapter 3 (Collins et al. 2020), there is a call for studies to advance analytical approaches to contribute to improved causal inference. As the standard approach to demonstrating causal inference in epidemiological and medical studies (Höfler 2005), the counterfactual framework offers an opportunity to achieve this. Application of the counterfactual framework to establish a causal effect requires the comparison of at least two treatment levels: (1) the control (e.g., no access to greenspace), and (2) the treatment (e.g., access to greenspace). However, as discussed in this review, access to greenspace is confounded with socio-demographic factors that also affect mental health. Therefore, when using observational data, additional steps and stronger assumptions are required to account for the potential systematic differences between the control and treatment groups and study designs must control for the potentially confounding variables either by adjustment, statistical matching, or both.

Chapter 3 A systematic map of research exploring the effect of greenspace on mental health

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3.0 Highlights

- We present a systematic map of research investigating greenspace and mental health.
- Experimental studies assess causality but had unrepresentative samples.
- Observational studies using longitudinal data were limited in number.
- Measures of greenspace “quantity” were more common than measures of “quality”.
- The possibility of scale-dependence in greenspace effects was rarely considered.

3.1 Abstract

The past 35 years have seen an accumulation of empirical evidence suggesting a positive association between greenspace and mental health. Existing reviews of the evidence are narrow in scope and do not adequately represent the broad range of disciplines working in this field. This study is the first systematic map of studies investigating greenspace effects on mental health. A total of 6,059 papers were screened for their relevance, 276 of which met inclusion criteria for the systematic map.

The map revealed several methodological limitations hindering the practical applications of research findings to public health. Critically, the majority of studies used cross-sectional mental health data which makes a causal inference about greenspace effects challenging. There are also few studies on the micro-features that make up greenspaces (i.e., their “quality”), with most focussing only on “quantity” effects on mental health. Moreover, few studies adopted a multi-scale approach, meaning there is little evidence about at which spatial scale(s) the relationship exists. A geographic gap in study location was also identified, with the majority of studies clustered in European countries and the United States.

Future research should account for both human and ecological perspectives of “quality” using objective and repeatable measures, and consider the potential of scale-dependent greenspace

effects to ensure that management of greenspace is compatible with wider scale biodiversity targets. To establish the greenspace and mental health relationship across a life course, studies should make better use of longitudinal data, as this enables stronger inferences to be made than more commonly used cross-sectional data.

3.2 Introduction

Unprecedented rates of urbanisation (United Nations 2018), have been identified as an important threat to biodiversity conservation on a global scale (Grimm et al. 2008, Seto et al. 2012, Güneralp and Seto 2013). But as the view that nature improves mental health becomes more commonplace (Keniger et al. 2013, Hartig et al. 2014, Hartig and Kahn 2016), the loss of natural ecosystems and biodiversity also represents a major challenge to human mental health and wellbeing (Dean et al. 2011, Sandifer et al. 2015, Wood et al. 2018). This is particularly the case in urban areas where nature is predominantly accessed through a fragmented network of multi-functional green and blue spaces, such as parks, public and private gardens, street trees, lakes, ponds, and community gardens. The role of greenspace in delivering mental health benefits in addition to other ecosystem services (ES) such as air quality regulation (Escobedo et al. 2011), biodiversity maintenance (Goddard et al. 2010, Beninde et al. 2015), and recreation (Kaczynski and Henderson 2007, O'Brien et al. 2017) has been widely studied. As increased rates of urbanisation further restrict the urban greenspace network (Fuller and Gaston 2009), billions of people may lose the opportunity to interact with, benefit from, or develop an appreciation of nature (Pyle 1978, Miller 2005, Turner et al. 2006, Fuller and Gaston 2009). This 'extinction of experience' (Pyle 1978, Soga and Gaston 2016) comes at a critical point: globally depression is the leading cause of ill health and disability (World Health Organization 2017). The associated economic and social costs of mental health are significant. For example, for the 28 European Union countries approximately 84 million people had a mental health problem in 2016, the annual cost of which is estimated to be in excess of 600 billion euros (approximately 4% of GDP) (OECD/EU 2018). What is needed is a sound understanding of how greenspace (broadly defined to be inclusive of blue space) can be effectively exploited or designed to enhance mental health. Such evidence not only helps mitigate the current mental health crisis but also presents one of the many arguments for biodiversity conservation (Sandifer et al. 2015, Wood et al. 2018) and supports the improvement, integration and expansion of greenspace in urban environments (Dean et al. 2011, Hartig and Kahn 2016).

The past three decades have seen an accumulation of theoretical and empirical evidence on the association between greenspace (and to a lesser extent, blue space) and mental health. This has coincided with the popularisation of Wilson's biophilia hypothesis that humanity has an innate affinity for the natural environment, evolved through natural selection (Wilson 1984). Theoretical research has largely been concentrated within the discipline of environmental psychology with the development of two prominent mechanistic pathways (Box 1). By contrast, empirical evidence for the relationship between greenspace and mental health from experimental and observational studies are published across multiple disciplines. In an attempt to offer generalisations concerning greenspace-mental health relationships, a growing number of systematic reviews have been published. However, systematic reviews are characterised by their specific scope, as they focus on either narrowly-defined questions or methodological approaches (Nakagawa et al. 2019). Therefore, systematic reviews may not adequately characterise the diverse methodological approaches that exist across multiple disciplines (Miake-Lye et al. 2016). For example, Tillmann et al. (2018) and Vanaken and Danckaerts (2018) synthesised studies measuring greenspace exposure effects on children and adolescents; with findings limited to these age groups. Gascon et al. (2015) reviewed studies that used objective greenspace measures (i.e., repeatable measures derived from remotely sensed data, NDVI that were assigned to a person's location of residence. Consequently, the included studies were predominantly from disciplines that typically adopt this methodological approach, such as in public health and epidemiology, and disciplines such as psychology and social sciences were comparatively underrepresented. The scope of included literature within existing systematic reviews is further limited by the adopted definitions of nature or greenspace. Many studies outside of ecology use the terms 'nature', 'biodiversity', or 'green' and 'blue' synonymously (Keniger et al. 2013, Botzat et al. 2016). For example, Gascon et al. (2015) used a broad definition of greenspace that included blue space, whereas Houlden et al. (2018) and Lee and Maheswaran (2011) defined it more narrowly to include only urban parks and open spaces. Variation in definitions of greenspace among disciplines (Taylor and Hochuli 2017) is problematic for reviews, as syntheses that adopt a narrow definition may omit entire disciplines and methodological approaches. The narrow scopes of previous reviews mean that a broad synthesis of the greenspace (inclusive of blue space) and mental health literature is lacking, and urgently required to direct future interdisciplinary research efforts.

Box 1: Mechanistic Pathways

Attention Restoration Theory (ART) proposes that vegetation and other natural features attract and hold a person's attention without effort, enabling the rest of the neurocognitive mechanism on which effortful attention depends (Kaplan and Kaplan 1989, Kaplan 1995; Kaplan and Talbot 1983).

Stress Reduction Theory (SRT) proposes that contact or viewing vegetation and other natural features can rapidly result in a positive effect within a person experiencing acute stress, which in turn can block negative thoughts and feelings (Ulrich 1983, Ulrich et al. 1991)

Achieving such a broad synthesis requires a systematic mapping methodology. Systematic mapping uses established searching protocols and a rigorous inclusion criteria to identify, categorise, and synthesise the available literature on a particular topic (James et al. 2016a). Systematic mapping is a recognised robust, repeatable, and transparent scientific method that is commonly used in social sciences (Haddaway et al., 2016, James et al. 2016a), and is now increasingly adopted in environmental management and conservation (e.g. Randall et al. 2015). Unlike a systematic review, systematic maps are not used to address a specific question but facilitate a broad synthesis of a research field (Nakagawa et al. 2019), by identifying and describing the nature, volume and characteristics of the evidence base (James et al. 2016a). Results can highlight knowledge gaps and direct future research priorities, including primary and secondary research, synopses of evidence, systematic reviews, and meta-analyses (Haddaway et al. 2016, James et al. 2016a).

In this study, we provide a broad synthesis of the literature evaluating the relationship between mental health and greenspace (inclusive of blue space) using a systematic mapping methodology. To our knowledge, this paper will be the first within the greenspace and mental health review literature to adopt a systematic mapping methodology to describe and catalogue studies of greenspace effects on mental health. Specifically, we characterise the range of methodological approaches adopted, identify trade-offs across disciplines and identify knowledge gaps that present opportunities for future research.

3.3 Methods

Standard systematic mapping methods (Collaboration for Environmental Evidence 2013, Jameset al. 2016a) were followed to collate empirical studies that aimed to identify the effects of greenspace in a person's environment on mental health. Definitions of greenspace are context-dependent and the term can be synonymous with 'nature' (Taylor and Hochuli 2017), may describe specific natural settings (e.g., parks, gardens or forests), or natural elements (e.g., street trees), or can extend to include 'blue space' (e.g., lakes, ponds and coastal zones). As such, we used multiple terms: (green* or blue* or "natural space" or "natural area" or "natural environment" or land* or ecosystem or "open-space" or "open space" or garden* or wilderness or outdoor or wood* or park or forest* or countryside or allotment or biod*) and mental health ((mental or psycholog* or emotion*) AND (health or wellbeing or "well-being" or "well being")).

The literature search was completed using the ISI Web of Science in August 2018. Retrieved articles were exported from Web of Science into R version 3.4.2 as a single library (R Core Team 2017). Using the R package 'metagear' (Lajeunesse 2016), articles identified through the search process were 'blinded' and their title and abstract screened for their potential relevance against the following criteria:

a) Studies that evaluated a quantitative measure of mental health outcome(s) in relation to a quantitative measure of the natural environment were included. Studies that evaluated the effects of natural or environmental hazards, such as air pollution, were excluded due to their potentially confounding effects of health hazards on the relationship between greenspace and mental health.
b) Mental health outcomes only included those associated with mood and anxiety disorders, due to stronger links with the theorised ART and SRT pathways (Box 1). Mental health outcomes relating to psychotic, eating disorders, dementias and other neurodevelopment disorders were excluded.
c) Only studies published in English within peer-reviewed journals were included. Purely descriptive or opinion pieces in addition to editorials, conference abstracts, methodological papers, book chapters and reviews were excluded.
d) Studies that solely assessed mental health outcomes relating to indoor "greening", or greening of the work or educational environments were excluded.
e) The study population were non-institutionalised people (i.e., those who are exposed or have the opportunity to be exposed to greenspace in their home/daily living). On this basis, studies in prisons, nursing homes or hospitals were excluded.
f) Studies on all age groups were included.
g) No date restrictions were applied, but the search was limited to the scope of the Web of Science database.

The inclusion criteria were applied by the lead author (RMC) at the title and abstract level to ensure a consistent understanding of the inclusion criteria.

3.3.1 Coding studies into a systematic map database

For the articles that met the review criteria, key variables were used to describe, categorise and code the studies, including; publication year, country, web of science research discipline, data source, study population, study population age, sample size, and study design. Study designs were defined as either ‘experimental’ or ‘observational’. Experimental studies were those carried out in a controlled or manipulated environment to determine the causal effect of a certain condition. Observational studies used data reported by, or about, the individual and the researcher made no change to the environment. For observational studies, measures of environmental exposure were classified into one of four categories; ‘proximity’ to greenspace, ‘quality’ of greenspace, ‘quantity’ of greenspace, or a ‘visit or activity’ to or in greenspace. Greenspace “quality” is arguably the most subjective measure, since definitions can relate to one or multiple greenspace characteristics such as aesthetics, safety, walkability, biodiversity, or the availability of social activities (Gascon et al. 2015). For this assessment, we have adopted a broad definition of quality (Table 2) to ensure that the multiple methods used to measure greenspace quality are represented within the systematic map’s findings. Additional variables and their definitions coded for experiments and observational studies are outlined in Table 2 and Table 3, respectively. The categorised variables were used to create a searchable map or database to identify key trends in the research, knowledge clusters and knowledge gaps. The database enables analysis by allowing simple numerical frequencies of each category, in addition to more complex cross-tabulations.

Table 2: Definition of coded variables for experimental studies

Coding Variable	**Categories**	**Definition**
Intervention	Activity	Experimental studies that evaluated the effect of a prescribed activity in greenspace, including walking, gardening and ‘green exercise’.
	Passive	Experimental studies that assessed the impact of the participant observing greenspace in person (with no other form of interaction).
	Pictorial	Experimental studies that assessed the impact of images and videos of the greenspace.
	Sensory	Experimental studies that assessed the impact of sound, audio clips, or smells of the greenspace.
	Mixed	Experiments that adopted more than two intervention methods.

Table 3: Definitions of coded variables for observational studies

Coding Variable	Categories	Definition
Environmental exposure	Proximity	A measure of distance to greenspace.
	Quality	A multi-dimensional measure of the greenspace's "micro" features or characteristics (e.g., biodiversity or self-reported quality).
	Quantity	A measure of the total amount of greenspace within a given area (e.g., percentage of land cover that is greenspace).
	Visit or activity	A measure of the number of visits to, or activities in, greenspace.
	Multiple	When two or more of the above exposures were adopted.
Blue space	Yes/No	Studies defined as 'Yes' included a measure of blue space within their exposure variable.
Measures of mental health	Single	Only one measure of mental health was used.
	Multiple	Two or more measures of mental health were used.
Data source	Primary	Data collected for the purpose of the study.
	Secondary	Data collected independently from the study but being utilised by the study for another purpose.
Analysis temporal scale	Cross-sectional	Data are from participants at a single point in time.
	Longitudinal	Data are obtained from the same sample at different points in time.
Analysis spatial scale	Single scale	The analysis used only one scale for the exposure variable (exposure to greenspace).
	Multiple scales	The analysis used two or more scales for the exposure variable (exposure to greenspace).

Coding Variable	Categories	Definition
Analysis of interactions	Yes/No	Studies defined as 'Yes' included interaction terms between independent variables i.e., an interaction between independent variables X and Y, which means the value of the dependent variable Z is determined jointly by X and Y. Interaction variables included the use of mediation analysis, where the interaction is dependent on the sequence of variables i.e., X to M to Y, whereby the independent variable (X) causes the mediator (M) and the mediator causes the dependent variable (Z).
Sensitivity analysis	Yes/No	Studies defined as 'Yes' explicitly stated that sensitivity analysis was performed. Sensitivity analysis included: (1) an evaluation of the influence of parameters; (2) the ranking of significant factors in accordance with their influence; and (3) quantifying the uncertainty of the model.

3.3.2 Visualising the systematic map with correspondence analysis

We use Correspondence Analysis (CA), an indirect gradient analysis ordination technique, to objectively visualise multiple study-wise variables within one figure (Hill 1974). The exploratory nature of indirect gradient analysis makes methods such as CA suitable for the application to systematic maps. The graphical outputs, such as correspondence plots, enable the visualisation of multiple study characterises simultaneously. Similar row (study) and column (characteristics) are distributed in two-dimensional space enabling category level comparison of their association. For this application, CA was used in favour of DCA as there was no observable “horseshoe effect” (Hill and Gauch 1980). The R package ‘FactoMineR’ (Lê et al. 2015) was used to perform all ordination analysis. Two additional visualisation packages ‘ggplot2’ (Wickham 2016) and ‘ggrepel’ (Slowikowski 2017) were used to develop the correspondence plots.

3.4 Results

The search terms returned a total of 6,059 articles, 543 of which met the inclusion criteria from their title and abstract, and were explored in full. A total of 271 papers met the inclusion criteria following a full-text review and were included in the final systematic map (Figure 3). Of the 271 papers, four papers had multiple studies which were included in the map as separate records. There were a total of five additional studies from these four papers, as a result, the total number of studies within the map was 276, of which 124 were experimental studies and 152 were observational studies (Figure 3).

The 276 studies came from 104 different journals from 36 different Web of Science defined disciplines. A total of 205 studies were distributed across 37 journals, with the greatest number of studies published in the International Journal of Environmental Research and Public Health (18%), followed by Landscape and Urban Planning (10%), Journal of Environmental Psychology (9%), Urban Forestry & Urban Greening (9%), and Health and Place (9%). The remaining 67 journals published a single paper each.

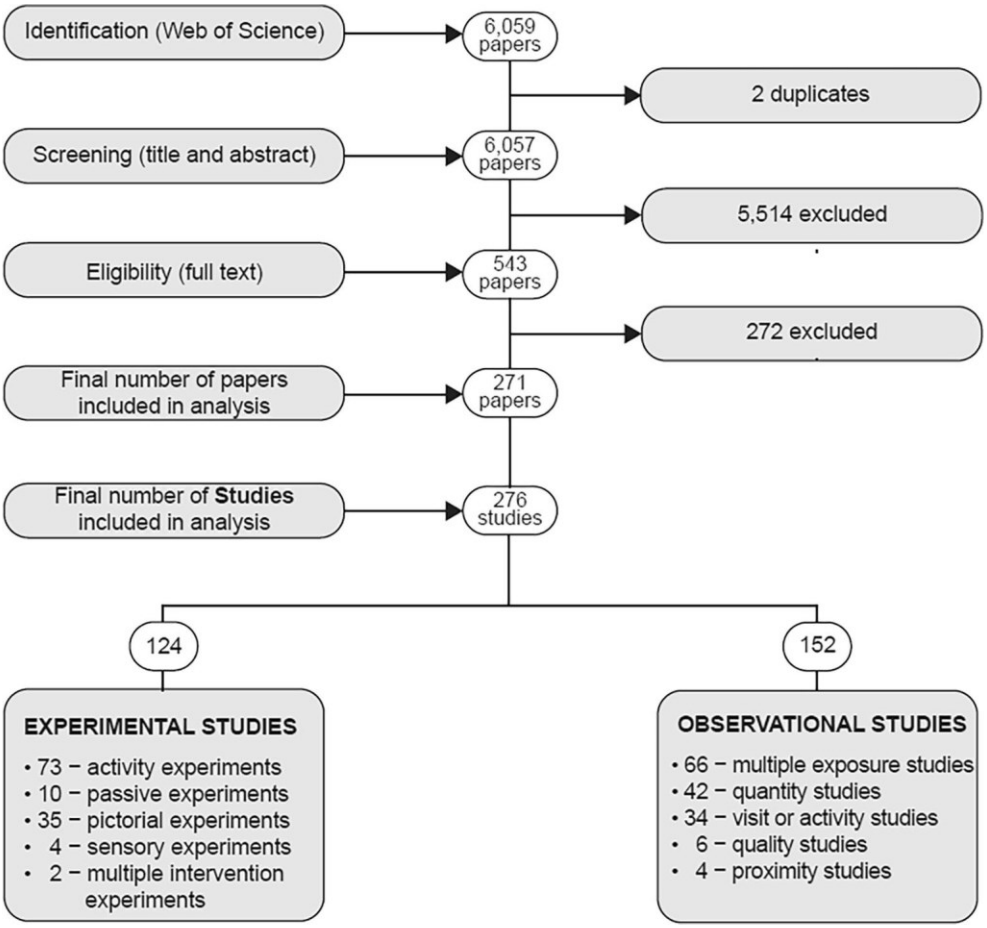

Figure 3: A conceptual diagram showing the selection process for the papers and the respective number of studies (within papers) included in the systematic map

If we do not consider 2018 (due to only 8 months' worth of data), the number of published articles assessing the association between greenspace and mental health increased exponentially between 1995 and 2017 (Figure 4), with a substantial increase occurring from 2013 onwards (Figure 4). Accounting for 24% of all studies, 2017 was the peak year for publications, of which 52% were observational (Figure 4).

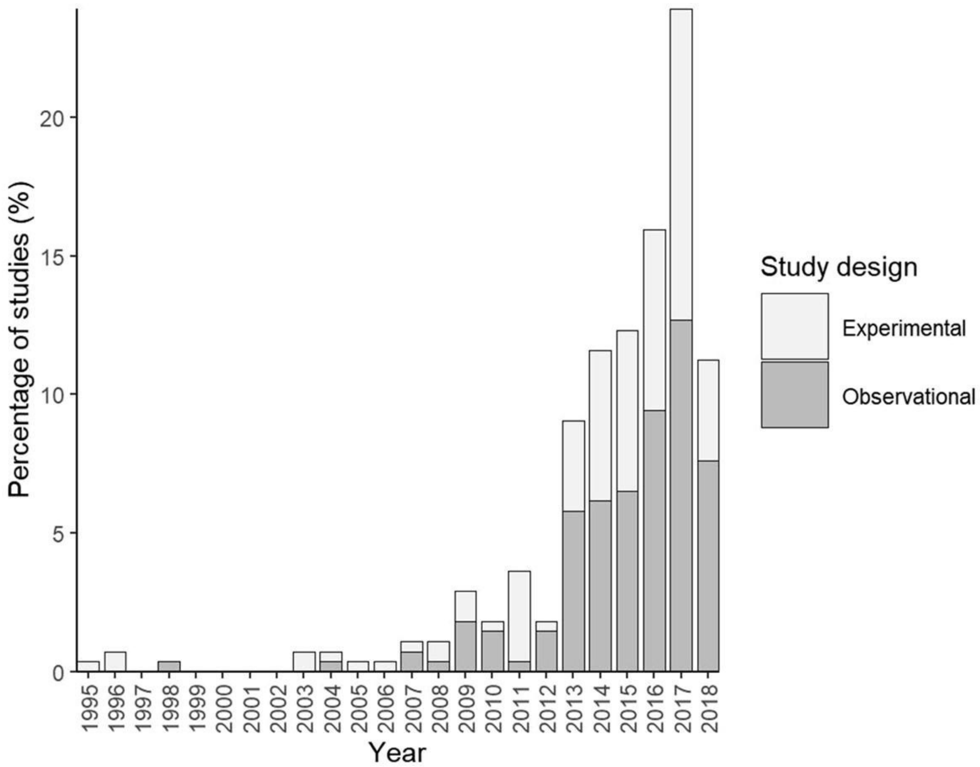

Figure 4: Percentage of published studies by year (to August 2018) and study design

3.4.1 Observational studies

Observational studies were published across 62 journals. The greatest number of which were published in the International Journal of Environmental Research and Public Health (12%), followed by Health and Place (10%), Landscape and Urban Planning (8%), and Urban Forestry and Greening (6%). A total of 41 journals published only one paper.

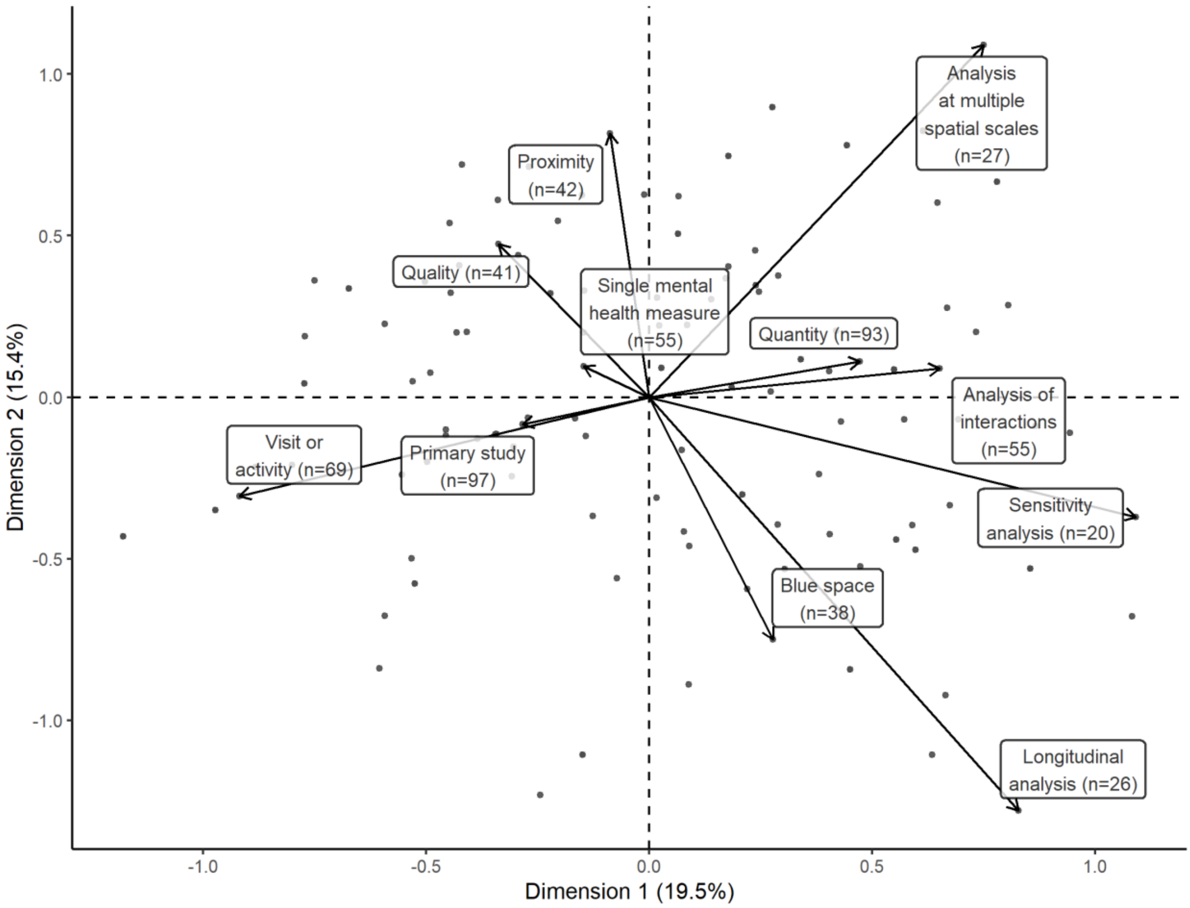

Figure 5: Biplot of the first two dimensions of a correspondence analysis of the study characteristics (vectors) of the 152 observational studies retrieved (dots).

The correspondence plot (Figure 5) shows the diversity of approaches employed in the observational studies (dots). The plot displays the first two dimensions, which together explained 35% of the total variability in study characteristics (Table 6). Dimension 1 explained 19.5% of the variation and represented studies that included interaction effects, sensitivity tests, and measures of greenspace “quantity” in the positive quadrant, and a tendency of studies to measure exposure to greenspace as a “visit or activity” in the negative quadrant. Dimension 2 explained 15.4% of the variation and was most closely related to studies that used longitudinal analysis, assessment made at multiple spatial scales, and exposure measures of “proximity” on the positive quadrant, and blue space assessment on the negative quadrant.

The global pattern and distribution of the greenspace exposure measures showed that greenspace “quantity” was negatively correlated with greenspace “quality” or “proximity” along Dimension 2 and a greenspace “visit or activity” along Dimension 1 (Figure 5). Greenspace “quantity” is the predominant measure of greenspace exposure (61% of observational studies). By year, from 2013 onwards, greenspace “quantity” has remained the most commonly adopted exposure measure followed by a measure of greenspace “visit or activity” (Figure 6). The frequency of studies using measures of greenspace “quality” peaked in 2017 (Figure 6). The number of observational studies peaked in 2017, which included those that assessed blue space (Figure 7). Investigations that focused on blue space accounted for 25% of all observational studies. However, unlike the general exponential increase in observational studies (Figure 6), the publication of blue space studies has varied over time (Figure 7). Studies that included a measure of blue space were negatively correlated with measures of “proximity” and “quality”, and positively associated with studies that assessed the “quantity” of greenspace (Figure 5).

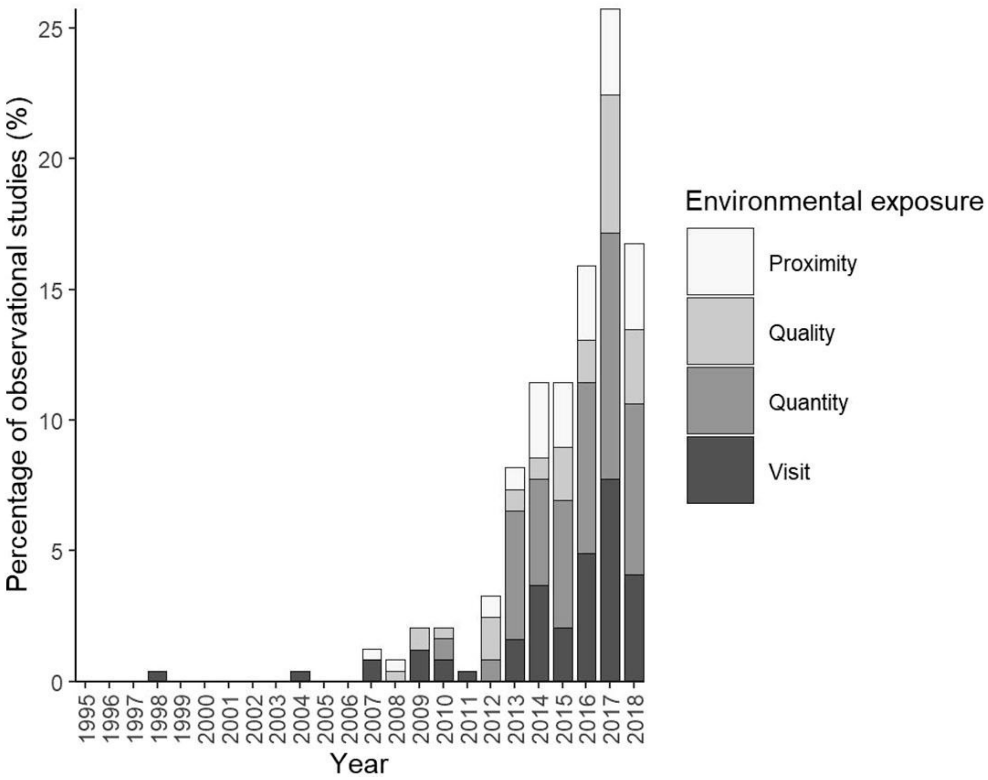

Figure 6: Percentage of observational studies by year (to August 2018) and measure of greenspace exposure

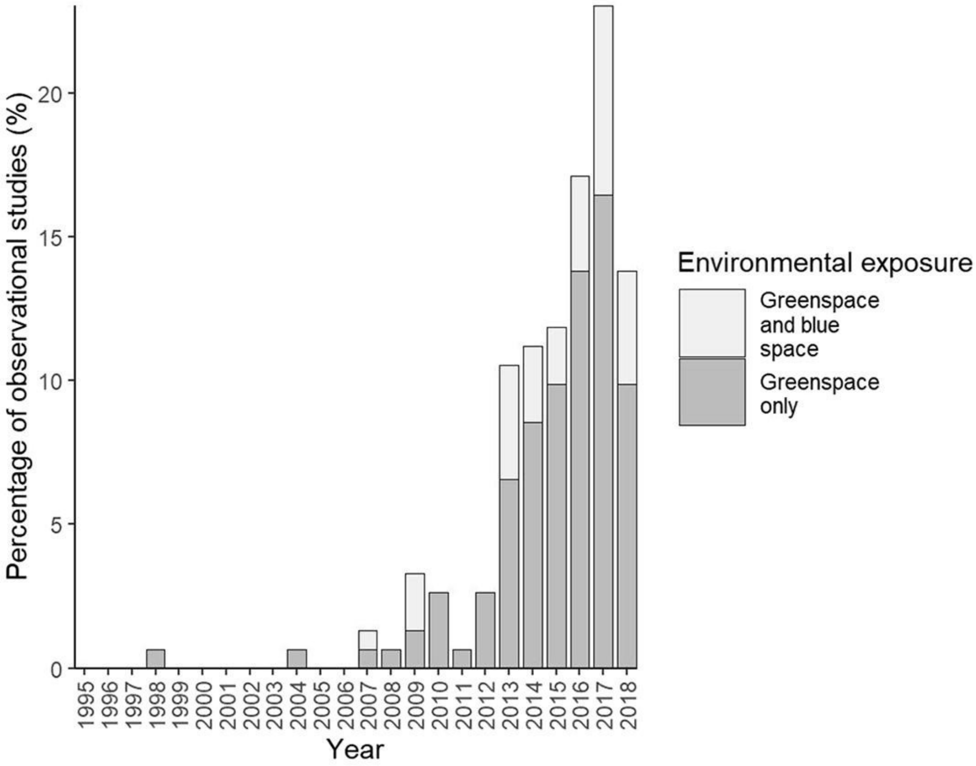

Figure 7: Number of observational studies measuring greenspace and blue space by year (to August 2018).

A total of 26 studies used longitudinal analysis to explore the effect of greenspace on mental health. The majority of longitudinal studies (n = 20) assessed exposure as “quantity” of greenspace (Appendix A - Table 16). As such, the variable “longitudinal analysis” was most closely related to the “quantity” exposure measure and negatively correlated the exposure variables “quality” and “proximity” (Figure 5), as well as studies that considered exposure to blue space.

All analytical variables (“analysis at multiple spatial scales”, “analysis of interactions”, “sensitivity analysis”, and longitudinal analysis”) were positively dispersed along Dimension 1 (Figure 5). Analysis conducted at multiple scales tended to use the greenspace variables “quantity” and “proximity”, a total of 23 and 12 studies, respectively (Appendix A - Table 17). The majority of observational studies included an interaction term within their analysis (n = 97) and did not carry out sensitivity analysis (n = 132). The variable “analysis of interactions” and the exposure measure “quantity” display a similar trajectory in the correspondence plot (Figure 5), suggesting a high level of similarity. Of the 55 studies that included an interaction term, 21 assessed exposure to greenspace as “quantity”, and 23 as “quantity” in addition to another exposure measure (Appendix A -Table 18). The variable “sensitivity analysis”, showed strong similarity to studies that included interaction terms; 15 of the 20 studies that included sensitivity analysis also included interaction terms. As such, the variable sensitivity analysis was most similar to the exposure measure “quantity” (Figure 5), 14 studies that performed sensitivity analysis used the exposure measure “quantity” of greenspace (Appendix A - Table 19).

A total of 55 studies used only one measure of mental health. The variable “single measure of mental health” is negatively correlated (along Dimension 1) with the variable blue space and greenspace measure of “quantity” (Figure 5). Greenspace measures of “quality”, “proximity” and “visit or activity” were more closely related to single measures of mental health (Figure 5).

3.4.2 Experimental studies

The coded variables for experimental studies differ from observational due to fundamental differences in their design. The variety of different experimental designs used for the studies included in this analysis made it difficult to create multiple and comparable categories without a high number of missing or not applicable cases. Therefore, fewer categories for experimental studies were used to ensure categories were common and therefore comparable across all studies. The 124 experimental studies were published across 58 different journals with 38 journals having published one study only. The greatest number of experimental studies were published in the International Journal of Environmental Research and Public Health (15%), followed by the Journal of Environmental Psychology (10%), the Journal of Environmental Psychology (10%), Urban Forestry and Greening (7%) and Landscape and Urban Planning (6%).

The number of experimental studies has increased over time (Figure 8). The majority of studies, approximately 80%, were published during or after 2013, with the greatest number published in 2017. The majority of experimental studies (59%) assessed the impact of a prescribed activity on the participants’ mental health. The average sample size of activity-based experiments was 75 participants, with maximum and minimum sample sizes of 498 and six participants, respectively. On average, pictorial experiments had the largest sample size with approximately 129 participants and a maximum and minimum sample size of 1,478 and 12 participants, respectively. On average, passive experiments where participants were exposed to greenspace, as opposed to imagery, had comparatively smaller sample sizes (e.g., approximately 50 participants).

Of the experimental intervention methods, pictorial experiments had the longest history, the first was published in 1995 (Figure 8). By 2017, greater volumes of experimental studies were employing a greater variety of interventions (Figure 8). The first sensory experiment was published in 2008 (Figure 8). The maximum, minimum and average sample size for a sensory experiment was 90, 30 and 57 participants, respectively. More recent still were experiments that adopted multiple intervention methods, all of which were published in 2017. A total of two studies used multiple intervention methods with sample sizes of 47 and 43 respectively. The majority of experimental studies recruited participants from specific sub-populations. For example, a total of 45 studies used convenience sampling to recruit from students or university staff to participate in their experiments, and a further 24 experiments sampled from only one gender (male = 14).

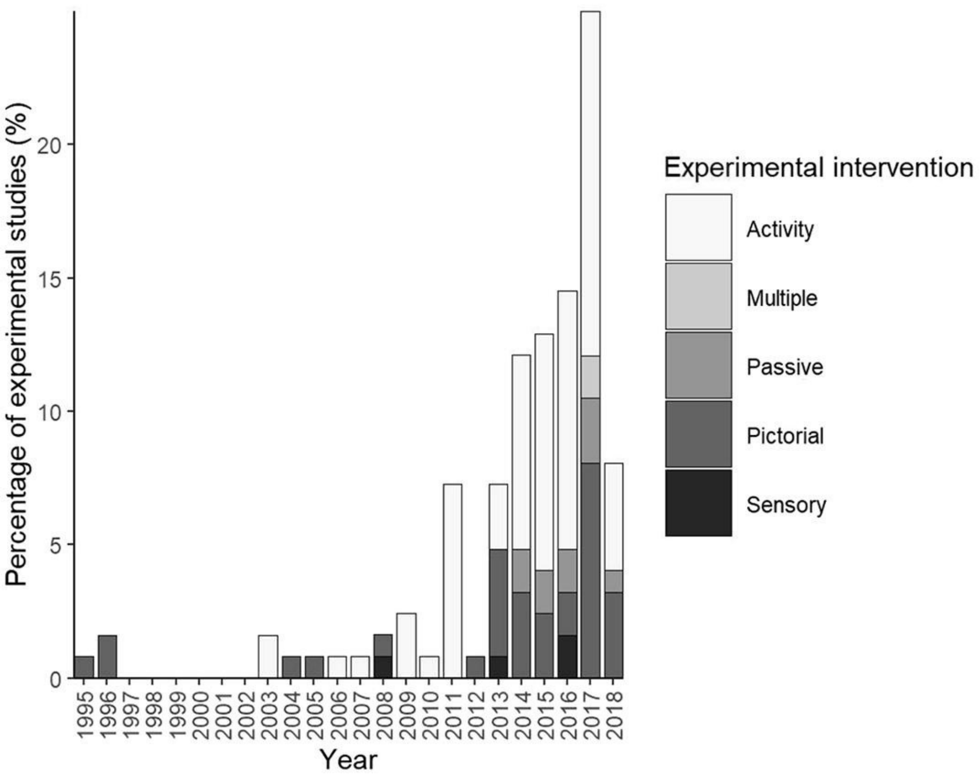

Figure 8: Percentage of published experiments studies by year (to August 2018) and experiment intervention.

3.4.3 Study location

Geographically, the majority of studies were from Europe (57%), North America (18%), Asia (15%), Australia and New Zealand (8%) and South America (1%). In terms of individual countries, the United Kingdom (UK) is overall the biggest contributor to this field accounting for 24% of all studies. Similar trends were observed for experimental and observational studies (Figure 9), though Japan was particularly well represented for experimental work (15% of experimental compared to 6% of total studies), the majority of which used activities as an intervention. Sweden was the only country that performed all four experiment types; activity (*n* = 11), passive (*n* = 1), pictorial (n = 3), sensory (n = 2). Sweden, therefore, accounted for half of all sensory studies; the remaining two sensory experiments were from Austria and Italy.

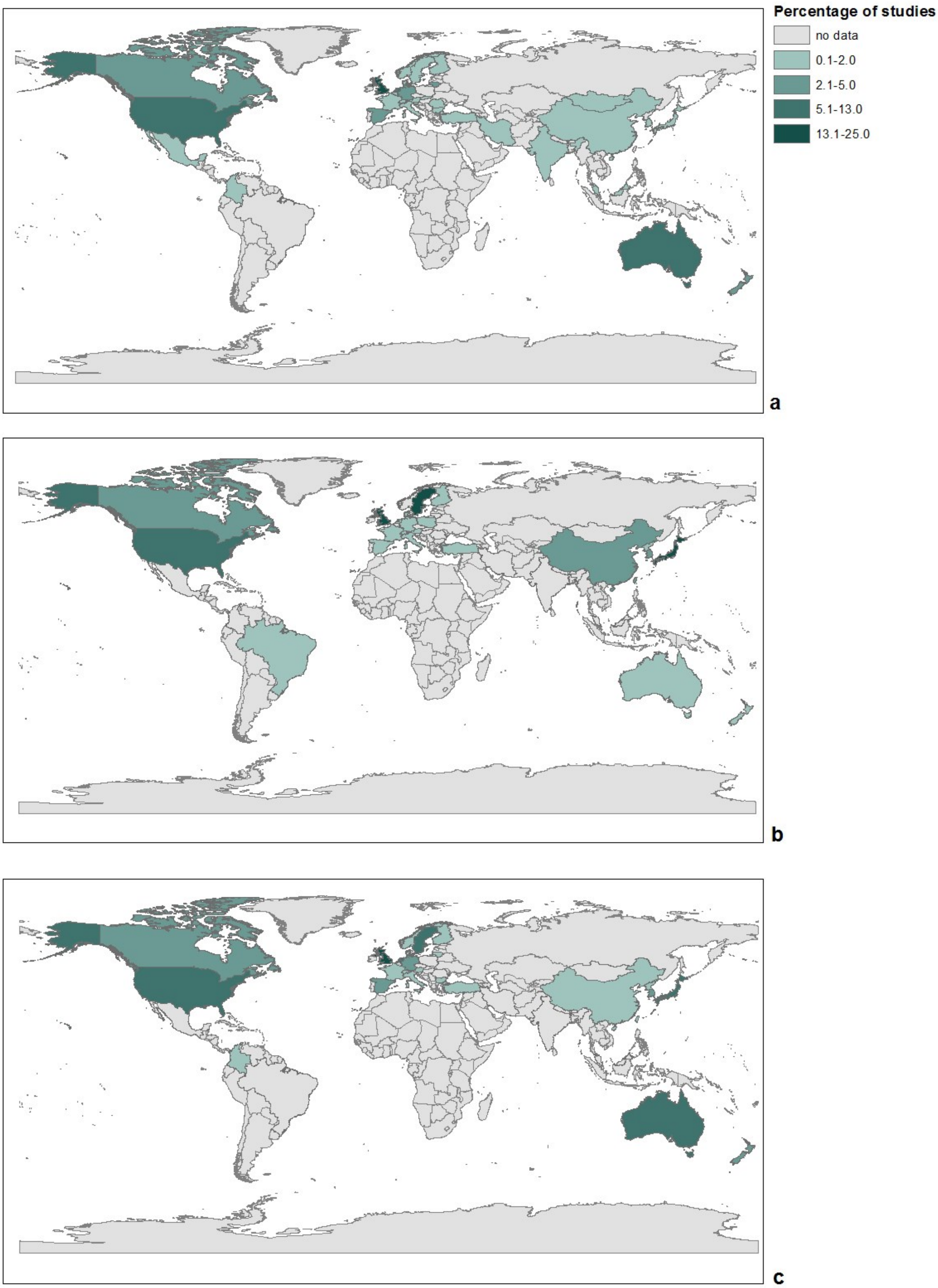

Figure 9: Global distribution of the retrieved studies. In this figure (a) is observational studies, (b) is experimental studies, and (c) is the total of all studies.

3.5 Discussion

Since 1984, there has been an exponential increase in the number of quantitative studies that describe the relationship between nature and mental health. While there have been numerous reviews of different aspects of this very broad question, this systematic map is the first to broadly collate studies across the breadth of disciplines this research covers. Results show that the majority of studies identified in this systematic map were observational studies, which assess exposure to the natural environment as a measure of greenspace “quantity” against standardised measures of mental health, followed by experimental studies that assess the effect of a prescribed activity on mental health. These both represent knowledge clusters (i.e., the majority of studies) and are areas of research that are suitable for further knowledge synthesis, such as a systematic review or meta-analysis (Nakagawa et al. 2019). Although insight has and could be gained through exploring knowledge clusters (for examples see existing systematic reviews and meta-analysis), our discussion focuses on knowledge gaps identified from a broad synthesis of this field.

Although most commonly adopted for observational studies, the exposure measure “quantity” reflects the total amount of greenspace within a given area. As such, greenspace is either present or absent. What is not known from measures of “quantity” are the micro-features or multi-dimensional characteristics (i.e., “quality”) or types of greenspace that are beneficial for mental health. Existing reviews have presented evidence that mental health benefits are likely to vary according to characteristics such as vegetation type (Markevych et al. 2017) and inclusion of blue space (Gascon et al. 2017). These ‘micro’ features of greenspace can be classified as measures of greenspace “quality”, and it is measures of greenspace “quality”, rather than “quantity”, that are recognised as a priority for future research (Hartig et al. 2014). Furthermore, measures of “quality” present the opportunity to assess whether attributes of greenspace are beneficial to both ecological and psychological wellbeing. Of the existing “quality” studies, the majority are cross-sectional and are limited in that they can only identify association and not causation. Experimental studies can identify causation, however, they are characterised by small sample sizes and a narrow geographic range that limits the conditions in which results can be applied. The use of secondary longitudinal data is recognised as a tool for identifying causal greenspace and mental health relationships for free-living populations (Hartig et al. 2014, Pearce 2018) as compared to cross-sectional designs (McIntosh et al. 2016). Despite the acknowledged benefits of longitudinal assessments, few have been undertaken for greenspace “quantity” (i.e., the majority of studies). Fewer still focus on greenspace “quality” (i.e., the priority for future studies), and none have assessed the "quality" of greenspace longitudinally at multiple spatial scales. This is an important consideration, as the critical scale at which people interact with nature is not known and any observed changes in effect size may be the true effect of the relationship or a statistical artefact. As there is no single scale to study and manage biodiversity and ES (Spake et al. 2019), the scale of effect should be considered alongside the scale of management interventions to ensure the management of urban greenspace is compatible with wider scale biodiversity targets.

3.5.1 Observational studies

Observational studies offer the opportunity to study 'realistic' environmental exposures in 'realistic' settings, and therefore better indicate the long-term impacts compared to experimental study findings (Frumkin et al. 2017). The correspondence plot revealed several clusters of observational studies adopting similar research methods. Trade-offs among research methods are apparent and represent future avenues of research.

3.5.1.1 Environment exposure assessment

The majority of studies use a measure of greenspace "quantity" as a way to evaluate an individual's exposure to greenspace. Measures of "quantity" treat all greenspaces as homogenous and are too coarse to account for detailed, small-scale environmental changes that could influence mental health (James et al. 2015). Also, using "quantity" as the sole exposure measure does not explicitly describe the biodiversity being considered with terms such as urban greenspace, forest or parks being adopted without a detailed explanation of ecological features they contain (Bratman et al. 2012, Clark et al. 2014). Consequently, research using only measures of "quantity" is not sufficient to inform either conservation efforts or public health policies (Dean et al. 2011, Francis et al. 2012, Taylor and Hochuli 2017). As previously mentioned, it is the consideration of the micro-features (or "quality") of greenspace that is important for future studies (Jorgensen and Gobster 2010, Francis et al. 2012, Hartig et al. 2014), as benefits are likely to vary according to vegetation types, as well as spatial and temporal characteristics (Markevych et al. 2017). Greenspace "quality" can be quantified from two perspectives: human and ecological (Gaston et al. 2018, Wood et al. 2018). From a human perspective, the micro-features considered are factors that make greenspace feel safe and accessible, such as greenspace cleanliness, lighting, and availability of amenities (for examples see de Gelder et al. 2017, Parra et al. 2010, Pope et al. 2018). Alternatively, an ecological perspective would result in the quantification of factors such as habitat diversity, species diversity, or ecological functions (for examples see Dallimer et al. 2012, Cox, et al. 2017, Taylor and Hochuli 2017). Although a human perspective of "quality" is needed to ensure that people will interact with greenspaces (and therefore nature), designing and managing greenspace purely from a human perspective might exclude species perceived as undesirable or threaten the ecological integrity of urban greenspaces (Stanley et al. 2015, van Heezik and Brymer 2018). The reverse is true from an ecological perspective whereby species considered important for conservation may not reflect the type needed for psychological benefits (Gaston et al. 2018). Critically, without an ecological perspective, urban greenspaces will become increasingly biodiversity-poor and lead to compromised ES (van Heezik and Brymer 2018). As few studies consider greenspace "quality", and fewer still both human and ecological perspectives of "quality", there is limited evidence of whether a trade-off between the two perspectives exists. Therefore, future studies need to consider both perspectives to ensure both psychological and ecosystem wellbeing.

It is important to consider the comparability and repeatability of future studies and use approaches that obtain measures of "quality" without resorting to costly and difficult to scale methods such as site surveys. The use of remotely sensed data is one solution for future measures of greenspace "quality". Presently, remotely sensed data are more commonly used in the greenspace and mental health studies as a measure of greenspace "quantity" rather than "quality" because specialist technical skills and training are required for further processing (Shoshany 2012, Markevych et al. 2017). Furthermore, studies may be restricted in their use of remotely sensed data by the spatial and temporal availability of satellite images (Markevych et al. 2017). However, eight studies use secondary data sources to create quantitative and repeatable measures of "quality". Tsai et al. (2018) used the US' 2011 National Land Cover Database to generate seven landscape metrics, such as patch density and edge density to characterise landscape patterns. Results showed that these characteristics had a stronger association with mental health than a presence-absence (or "quantity") approach. Similarly, Annerstedt et al. (2012) used the National Land Survey of Sweden to map five predefined green qualities ("serene", "wild", "lush", "spacious", and "culture"). Interestingly, the results of this study showed that mental health was not affected by access to, or the amount of, the chosen green qualities. These studies demonstrate that objective and repeatable measures of greenspace "quality" are possible, and an increase in the number of studies measuring greenspace "quality" in this way will enable the comparison between studies, and the identification of greenspace qualities that promote better mental health.

The approach for measuring mental health is as important a consideration as the exposure measure. This systematic mapping approach showed that studies measuring "quality" are closely related to studies measuring only one measure of mental health, which supports findings from existing reviews whereby “sophisticated” measures of greenspace has focused on a relatively narrow range of human health and wellbeing measures (Jorgensen and Gobster 2010). Mental health and wellbeing are comprised of both happiness and life satisfaction, and not just the absence of mental distress (World Health Organization 2016). As identified by previous reviews (e.g., Houlden et al. 2017), multidimensional measures of mental health are required (Tennant et al. 2007). Therefore, there is a requirement for future research to explore in more detail the effect of different outcome measures used when looking at the effect of greenspace “quality” has on mental health.

Relative to greenspace, blue space research is in its infancy, and the blue space concept is not common (Gascon et al. 2017). Understanding of whether greenspace includes blue space differs in the literature (Taylor and Hochuli 2017). We recognise that the relative absence of blue space studies in this map may be a result of not using multiple blue space search terms such as lakes, ponds and ocean. However, the results agree with the existing literature and reviews increasingly acknowledge the relative absence of blue space research. One review has called for the increase in the number of longitudinal assessments and natural experiments to better understand the causal associations between blue spaces, health and wellbeing as well as the influence of change in circumstances and exposure over a life course (Gascon et al. 2017). However, the correspondence plot indicates that there is a level of similarity between studies adopting longitudinal assessments and measures of blue space. Nine of the 26 longitudinal studies assess blue space. The priority areas for future research would be the variables negatively correlated with blue space, such as using exposure measures of “quality” and “proximity”. Only two studies identified within the map assess greenspace “quality” whilst considering blue space (i.e., Bakolis et al. 2018, Beute and de Kort 2018). In both studies, participants used smartphone applications (apps) to report the presence or absence of water, in combination with other natural features, to indicate exposure to the “quality” of greenspace. Although the presence of blue space has been considered as a component of environmental “quality”, the “quality” of blue space has itself not been taken into account. Subsequently, these two studies do not consider a life course perspective as they only follow participants for one week taking multiple measures of mood and natural environment exposure per day. Therefore, “quality” assessments of exposure to blue space (in addition to greenspace) remains a gap in the literature.

3.5.1.2 Analysis methods

Existing reviews, both systematic and narrative, have identified longitudinal assessment of the relationship between greenspace and mental health as a research priority (e.g., Hartig et al. 2014, Houlden et al. 2018). Generally, longitudinal studies benefit from large sample sizes across a wider geographic space, for example, the UK's British Household Panel Survey (BHPS) (University of Essex 2018b), Understanding Society (University of Essex 2018a), and Berlin Aging Study (Baltes et al. 1993). Unlike cross-sectional studies, longitudinal studies track habits over time (often a life-course), and can provide stronger evidence of causality, at a broad geographic extent (Pearce, 2018). Although there is considerable debate about the circumstances under which causal inference can be tested and assumed (Lawlor et al. 2016, Munafò and Davey Smith 2018, Pearce and Lawlor 2016), the temporal perspective of longitudinal studies might enable researchers to identify points in time when exposure to the greenspace can generate the greatest benefit (Astell-Burt et al. 2014, Pearce 2018). The map identifies a total of 26 longitudinal studies, and this low representation suggests that studies on greenspace and health have primarily relied on cross-sectional designs to establish an association (Hartig et al. 2014, Craig and Prescott 2017, Markevych et al. 2017). Results from both cross-sectional and longitudinal studies are complementary to understanding greenspace-mental health relationships. The integration of these different approaches, each with different types of biases, will allow for an improved understanding of greenspace-mental health relationships (i.e., 'triangulation', Lawlor et al. 2016).

The majority of longitudinal studies use "quantity" of the greenspace as the exposure variable, hence the comparatively closer proximity of these variables within the correspondence plot. However, cross-sectional studies have identified that "quality" of the greenspace such as amenities or species composition, have the potential to change interaction and therefore influence mental health benefits (e.g., Francis et al. 2012). Despite cross-sectional evidence, the correspondence plot illustrates that "quality" of greenspace in combination with longitudinal assessment remains underrepresented with only seven studies addressing this gap. This being said, the number of assessments of "quality" are increasing over time, as are the number of assessments considering "quality" alongside other exposure measures. Assessment of multiple exposure measures are an important consideration, as evidence shows that different types of exposure are associated with different aspects of wellbeing (White et al. 2017). To establish what types and characteristics of greenspace affect mental health at different points of a life-course, future research should increase their use of "quality" measurements combined with longer-term longitudinal health data (Hartig et al. 2014).

Studies within the systematic map adopt different exposure measures, at differing spatial scales and few studies have identified what the most appropriate geographical scale is for defining exposure to the greenspace. As a result, not enough is known about the critical scales at which people interact and experience the greenspace (Jorgensen and Gobster 2010, Astell-Burt et al. 2014), or whether the scale at which the interaction occurs aligns with suitable scales for biodiversity conservation. Existing studies have highlighted the possibility that different effect sizes may occur as a result of neighbourhood level exposures being measured at different scales (e.g., Astell-Burt et al. 2014). This may be the 'real' effect of scale and the effect of greenspace may affect people's mental health at different scales (Openshaw 1984), or alternatively, it may be an artefact of the Modifiable Areal Unit Problem (MAUP), whereby analytical results for the same data in the same study area differ depending on the scale adopted (Openshaw 1984). Attention should be paid to the MAUP, and as there is no available information on how to optimally define exposure for different health outcomes, pathways and population groups, several scales, buffer sizes and shapes should be tested. Adopting methods commonly used in landscape ecology presents an opportunity to do so. For example by using a 'scale of effect' approach that examines explanatory variables characterised within the same focal areas but at varying grain sizes (Jackson and Fahrig 2012). This allows identification of the scale at which a relationship exists; i.e., the scale at which a given variable has the strongest statistical relationship (Holland et al. 2004). Tools developed within landscape ecology have been developed to automate and simplify multi-scale analysis. For example, the R function 'multifit' (Huais 2018) has been developed to simultaneously run multiple statistical models for a response variable at multiple spatial scales, and visualise model outputs in a simple way, allowing users to select to compare and select the most appropriate scale.

In many cases, the scale at which the analysis is performed is dependent on the grain at which health data can be obtained (Pearce 2018). Thus, analysis is often limited to administrative geographic units. Administrative geographic units have been determined for purposes other than the study's aims and maybe awkwardly shaped, create edge effects, or impose an inappropriate neighbourhood scale (Branas et al. 2011). There is limited evidence that administrative boundaries are an appropriate scale to assess exposure to greenspace, nor is there evidence that management at these boundary levels is suitable for biodiversity conservation. There is no single natural scale at which biodiversity should be studied (Levin 1992). Ecological systems demonstrate variability at a range of spatial scales, and as management boundaries are not based on these ecological considerations, but instead based on socio-economic factors such as administrative boundaries and ownership, spatial mismatches occur (Borgström et al. 2006, Cumming et al. 2006, 2013). Spatial mismatches are an important cause of failure in natural resource management and are often more pronounced in urban landscapes, where nature is scattered in small and dissimilar patches (Borgström et al. 2006). This makes it difficult to target and coordinate appropriate management (Cumming et al. 2006). Until an understanding of scale-dependent management effects is achieved (Spake et al. 2019), biodiversity within urban greenspace must be managed at multiple scales whilst also considering the scale at which the nature and mental health relationship exists. Without the coordination of management resources at multiple scales, management practices used at smaller scales can be incompatible with wider scale biodiversity targets (Aronson et al. 2017).

Moreover, administrative boundaries may not be the appropriate unit of measurement to aggregate area-level confounding factors (Markevych et al. 2017). All assumptions about individuals based on aggregate data are vulnerable to ecological fallacy, as the relationship may be a result of data aggregation effects rather than any real association (Openshaw 1984). This can become more pronounced when a series of confounding factors are unaccounted for, as confounding factors can result in bias and a change in effect size. Sensitivity analysis offers one solution to assess the impact of unmeasured confounding factors (Markevych et al. 2017). However, very few studies within the map have conducted sensitivity analysis and the correspondence plot shows that these two characteristics ("sensitivity analysis" and "analysis at multiple spatial scales") are negatively correlated along Dimension 2. As previously mentioned, one of the benefits of longitudinal analysis is addressing confounding factors. However, the correspondence plot shows that the variables of analysis at multiple scales and longitudinal analysis are also negatively correlated on Dimension 2. Of the 27 studies assessing multiple scales, only two longitudinal perform analysis at multiple scales and both assessed "quantity" using repeatable exposure measures such as NDVI and land use cover. The first, Gariepy et al. (2014) was used in a sensitivity model to determine which area was most relevant for analysis, a buffer of 500m was determined to have the best fit in the model. The second, Picavet et al. (2016), found a significant association between greenspace and depressive complaints within a 1 km radius and not 125m. It is plausible that no single scale is relevant across all stages of the life-course (Astell-Burt et al. 2014) and there is a need for more longitudinal assessments measuring exposure at multiple scales to consider establishing this. In addition, further consideration needs to be given as to whether the scale at which the greenspace mental health relationship exists aligns with the scale at which greenspace should be managed to ensure the longevity of benefits, and by using methods and tools commonly adopted in landscape ecology; e.g., the scale of effect

(Jackson and Fahrig 2012) and R function ‘multifit’ (Huais 2018) it is easier to link these to the ecological benefits of greenspace.

3.5.2 Experimental studies

Experiments are typically carried out in the earlier stages of research to establish associations that then inform the wider-scale survey and observational studies (Hartig et al. 2014). However, the proportion of experimental studies and the dominance of activity based experiments have remained consistent through time. Activity based experiments assume that participants interact intentionally (or actively) with greenspace. Intentional interaction means a physical engagement with greenspace as a primary activity (Keniger et al. 2013). However, the interactions with greenspace can also be passive (i.e., visual engagement with greenspace). With the ‘extinction of experience’ paradigm, active interaction with nature is becoming the exception as opposed to the norm (Cox et al. 2017). As a result, a person’s connection to nature is now more positively associated with passive and incidental experiences (Cox and Gaston 2016, Cox et al. 2017a). More recent experimental studies have adopted alternative interventions to activities, including sensory and passive experiments that assess these incidental interactions. However, the overall number of these types of intervention are low (*n* = 4 and *n* = 10, respectively) and there is a need for future studies to expand the evidence base for experiments assessing the incidental experiences of nature.

One of the notable features of the experimental studies retrieved by this map are the small sample sizes and narrow study sites or extent. This limits the conditions in which associations can be applied (Magliocca et al. 2018). Many experiments identified in the systematic map failed to obtain a representative sample, with a large number of experiments focusing on sub-populations, such as males only (*n* = 11), and university or college students (*n* = 25). This dominance of experimental studies using university students of the same gender has been noted by an existing review (Kondo et al. 2018). Other reviews have established that contact with nature is strongly patterned by socio-economic characteristics, which are themselves, linked to a person’s health (Bowler et al. 2010a, Hartig et al. 2014). Therefore, caution should be taken when generalising these results, as they may be biased by experiences specific to these sub-populations. Despite potential limitations with generalisation, ‘true’ experiments are still considered to be the ‘gold’ standard in science, as their controlled nature enables the identification of causal effect mechanisms (Magliocca et al. 2018). This is particularly beneficial when considering the use of new and innovative measures of mental health such as stress indicators cortisol, amylase, skin conductance (Roe and Aspinall 2011, Beil and Hanes 2013, Jiang et al. 2014), and measures of brain activity including novel electroencephalogram (EEG) methods (Bratman et al. 2015). Therefore, in order to account for the small samples sizes and to infer broader patterns, it is necessary for future studies to repeat these small-scale experiments in different places and with different sub-populations.

3.5.3 Study location

The scope of countries carrying out research is limited, with the majority of studies concentrated within the UK and other North-West European countries. Many countries, particularly African and South American, are completely absent from the systematic map. This international bias may be a result of included publications only being written in English. However, it is a finding that is supported by results from previous reviews of the literature (e.g., van den Berg et al. 2015). The concentration of studies within cool temperate climates in countries with high income means there is low social and spatial variation in current findings (Frumkin et al. 2017). Cultural and environmental differences between countries may modify the greenspace and mental health relationship (Frumkin et al. 2017, Markevych et al. 2017). Therefore, the extent to which current knowledge can be generalised to countries absent from the systematic map is unknown. Future studies in under-represented low and middle-income countries are required. International collaborations, that enable inter-country comparisons, are also needed to improve understanding of how greenspace and culture influence reporting of mental health.

3.6 Conclusions and future research opportunities

To our knowledge, this is the first systematic map to explore research on the effect of greenspace on mental health. As a systematic map, this study presents evidence of knowledge clusters and gaps from trade-offs between research methods within the broader literature. Knowledge clusters (e.g., observational studies that used measures of greenspace “quantity” and experimental studies that assessed the impact of an activity in greenspace on mental health) present the opportunity for a more detailed data synthesis method (e.g., a systematic review or meta-analysis). Such approaches make a logical follow-on from this study, but require a narrower inclusion criteria to enable the comparison of results, and given the existing numbers of such reviews, we believe that greater attention and research investment should be directed towards the map’s identified knowledge gaps.

This map identified knowledge gaps within the methodological approaches adopted. The majority of observational studies used cross-sectional data to evaluate the relationship between greenspace and mental health. From these studies, it is not known whether there is a causal relationship between greenspace and mental health, nor the strength of such a relationship. Future research needs to assess the causality of the greenspace and mental health relationship and to do so experimental or longitudinal observational studies are preferred. As a result of small and unrepresentative samples, the experimental studies identified in this map are limited in their ability to make knowledge generalisations. Rather than prioritising research efforts to obtain representative samples for experimental studies we believe that longitudinal assessments, which also provide information across a life-course in addition to providing stronger causal inferences than standard observational approaches, should be the priority for future research and ultimately should become the methodological standard for evaluating greenspace and mental health relationships. Longitudinal assessments have been used to establish life course relationships for measures of greenspace “quantity” (e.g., Astell-Burt et al. 2014), but what is not known are what types and characteristics of greenspace, or greenspace “quality”, affect mental health and whether this relationship extends to blue space “quality”, or the critical scale at which this relationship occurs. For future studies, greenspace “quality” needs to be considered from both a human and ecological perspectives. The former to ensure that people will continue to interact with urban greenspaces, and the latter to maintain the ecological integrity of urban greenspaces and the provision of ES. Little is also known about whether management of greenspace for mental health has wider biodiversity or ES impacts. As there is no single scale to manage biodiversity and ES, the scale of the “quality” effect should be considered alongside the scale of management interventions to ensure that the management of urban greenspace is compatible with wider scale biodiversity targets.

Taking the above recommendations, a future study looking into the greenspace and mental health relationship might use a countrywide longitudinal survey that consistently collects data on mental health, and create a composite measure of greenspace “quality” through identifying existing spatial data that have theoretical links with human and ecological perspectives of quality. One starting point for measuring “quality” would be identifying a high-resolution baseline level of “greenness” such as NDVI data at 30m resolution from LandSat 8 (United States Geological Survey 2017). This enables the identification of small areas of greenspace that may be missed by lower resolution land cover metrics commonly used in greenspace “quantity” measures. This being said, as discussed, it is not just the spatial resolution of data that indicates ecological “quality”, this measure of greenness should be combined with additional sources of data to create a composite measure of “quality”. For example, when using the UK as a case study, a baseline measure of NDVI could be combined with additional sources such as the Land Cover Map 2015 (Rowlands et al. 2015) that classifies land cover based on the UK Biodiversity Action Plan Broad Habitats classes, and the Ordnance Survey's Open Greenspace (Ordnance Survey 2020) can be used to indicate more human aspects of "quality" within the UK such as allotments, sports facilities and play spaces. Such measures of quality could then be linked to longitudinal studies with consistent measures of mental health available to researchers. In the UK these include, the BHPS (University of Essex 2018b) and Understanding Society (University of Essex 2018a). Both of which provide annual data on participants' mental health. The statistical analysis of these data should include not only the multi-scale approach outlined earlier but also careful consideration of the covariance structure and range of variance of the key predictors of both greenspace and mental health. The latter is important to ensure robust statistical inference is possible from the study (Eigenbrod et al. 2011); subsampling approaches can aid in achieving this (Fahrig et al. 2011). Although this example is UK centric, it shows how spatial data can be identified and their links between human and ecological perspectives of quality can be made. Adopting such an approach is beneficial for creating reproducible and objective measures of greenspace "quality".

Finally, knowledge gaps exist in the global distribution of research efforts, with the majority of studies concentrated within European countries and the United States. Future research is needed across a broader range of countries, particularly in those where it is currently absent, to better understand any cultural differences in the mental health benefits provided by nature.

Chapter 4 Data landscape

This chapter presents the process in which data were identified and considered for use in the empirical analysis of this thesis (specifically Chapters 5 and 6) and discusses the benefits and limitations of these data. Two separate data landscapes were undertaken: (1) to identify suitable greenspace and area-level data that relate to the pathways set out in Chapter 2 and, (2) to identify the suitable mental health data that are suitable for the analytical approaches discussed in Chapter 2.

4.0 Greenspace and area-level characteristics

The aim of this first landscape was to reflect on the greenspace and associated area-level data that have been previously used to explore the effect of greenspace on mental health and assess whether these data were; (1) relevant and available for urban areas of GB, and (2) if not suitable, or available, identify a suitable alternative.

A systematic approach was taken to identify characteristics that may moderate the effect of greenspace exposure on mental health. Collins et al.'s (2020) systematic map of studies quantifying greenspace-mental health relationships (Chapter 3) was used to draw up a comprehensive list of characteristics that have been previously included as confounding or modifying factors when exploring the effect of greenspace on mental health. To organise characteristics, this landscape used the model proposed by Markevych et al. (2017) and grouped characteristics into three broad domains: (1) reducing harm, (2) restoring capacity, and (3) building capacity. The list of characteristics was then supplemented with an additional review of the literature Chapter 2 – the literature review. The final characteristics (presented in Table 4 to Table 6) were then assessed for their relevance and suitability for urban GB (i.e., the data landscape presented in Sections 0 to 4.0.3).

Table 4: List of characteristics identified for Domain 1 – reducing harm – grouped by the associated pathway and hypothesis.

Pathway	Hypothesis	Characteristics
A. Air pollution	Higher levels of air pollution are associated with poor mental health, and the presence of greenspace improves air pollution and therefore improves mental health.	1. Perceived air pollution (Dzhambov et al. 2018) 2. Air Pollution Index (Zhang et al. 2017) 3. Modelled $PM_{2.5}$ (Oudin et al. 2016, Pun et al. 2017, Vert et al. 2017, Ha and Shao 2019, Wang et al. 2019) 4. Modelled PM_{10} (Bixby et al. 2015, Oudin et al. 2016) 5. Modelled NO_2 (Oudin et al. 2016, Vert et al. 2017) 6. Modelled NO_x (Vert et al. 2017) 7. Modelled black carbon (Power et al. 2015)
B. Noise Pollution	Higher levels of anthropogenic noise pollution are associated with poor mental health, and the presence of greenspace improves noise pollution and therefore improves mental health.	1. Distance to the artillery range (Annerstedt et al. 2012) 2. Distance to wind power (Annerstedt et al. 2012) 3. Traffic noise (Sygna et al. 2014, Seidler et al. 2017, Dzhambov, Markevych, et al. 2018) 4. Railway noise (Seidler et al. 2017) 5. Aircraft noise (Chowns et al. 1970, Schreckenberg et al. 2010, Wright et al. 2018) 6. A regional noise inventory (Annerstedt et al. 2012)
C. Exposure to sunlight	Indirect sunlight and lower levels of exposure to sunlight (i.e., shorter days) are associated with poor mental health, and the presence of greenspace can increase people's exposure to sunlight and therefore improves mental health.	1. Daily sunshine duration daily (Gu et al. 2019, Ha and Shao 2019) 2. Self-reported sunlight exposure (An et al. 2016) 3. Solar radiation (Kent et al. 2009)

Pathway	Hypothesis	Characteristics
D. Heat island mitigation	Extreme heat exposure is associated with poor mental health and increased incidents of mental health disorders, and the presence of greenspace can have a cooling effect and therefore improves mental health.	1. Daily temperature (Sung et al. 2011, Noelke et al. 2016, Peng et al. 2017, Schneider et al. 2020) 2. Monthly temperature increase (Tsai and Cho 2012, Yarza et al. 2020)

Table 5: List of characteristics identified for Domain 2 – building capacity – grouped by the associated pathway and hypothesis.

Pathway	Hypothesis	Characteristics
A. Social Value i. Social contact and sense of community	The use of greenspace can increase social ties and/or a sense of community and therefore improves mental health.	1. Social interaction/connectivity (Sarkar et al. 2013): • Street connectivity • Walkability • Public transport density 2. Self-reported social support, wellbeing and/or cohesion (Maas et al. 2009, Ward Thompson et al. 2016)
ii. Crime and sense of safety	Presence of greenspace reduces crime which improved sense of community and therefore improves mental health.	1. Crime rates (Kuo and Sullivan 2001, Branas et al. 2011, Donovan and Prestemon 2012) 2. Experimental control plot (Branas et al. 2011)
	Greenspace can result in perceived safety issues and reduce the use of greenspace and therefore negatively impact mental health.	1. Crime rates (Branas et al. 2011, Donovan and Prestemon 2012)

Pathway	Hypothesis	Characteristics
B. Physical activity i. Recreation	The use of greenspace for outdoor physical activity and recreation improves mental health.	1. Short Questionnaire to Assess Health enhancing physical activity (Dzambov et al. 2016) 2. General practice physical activity questionnaire (McEachan et al. 2018) 3. Walking groups (Marselle et al. 2019)
ii. Gardening/horticultural therapy	Exposure to greenspace through gardening (personal gardens, community gardens and allotments improves mental health.	1. Gardening participation (Van Den Berg and Custers 2011, Vujcic et al. 2017)

Table 6: List of characteristics identified for Domain 1 – restoring capacity – grouped by the associated pathway and hypothesis.

Pathway	Hypothesis	Characteristics
A. Stress reduction	Exposure to greenspace or greenspace qualities reduces stress and therefore improves mental health.	1. Greenness (Taylor et al. 2015, 2018, Triguero-Mas et al. 2015, McEachan et al. 2016, Cox, Shanahan, Hudson, Fuller, et al. 2017): • NDVI • Street trees • Street greenery • Vegetation cover 2. Land cover (Annerstedt et al. 2012, White et al. 2013, Alcock et al. 2014, Flouri et al. 2014, Wu et al. 2015, Bixby et al. 2015, Triguero-Mas et al. 2015, Gidlowet al. 2016a, Gidlowet al. 2016b, McEachan et al. 2016, Houlden et al. 2017): • CLC • LCM

Pathway	Hypothesis	Characteristics
		• Urban Atlas • GLUD 3. Protected areas (Annerstedt et al. 2012) 4. Biodiversity (Carrus et al. 2015) 5. Species richness (Fuller et al. 2007, Wheeler et al. 2015, Cox, Shanahan, Hudson, Fuller, et al. 2017, Southon et al. 2018, Taylor et al. 2018): • Perceived species richness • Bird species richness 6. Private gardens (White et al. 2013, Alcock et al. 2014, Flouri et al. 2014, Wu et al. 2015) 7. Blue space (White et al. 2013, Triguero-Mas et al. 2015, Wheeler et al. 2015, Gidlow et al. 2016a) 8. Urbanity (White et al. 2013, Triguero-Mas et al. 2015, McEachan et al. 2016, Houlden et al. 2017)
B. Attention restoration	Exposure to greenspace or greenspace qualities reduces mental fatigue and therefore improves mental health.	1. Greenness (Triguero-Mas et al. 2015, McEachan et al. 2016, Cox et al. 2018, Dzhambov, Hartig, et al. 2018, Taylor et al. 2018): • NDVI • Street trees • Street greenery • Vegetation cover 2. Land cover (Annerstedt et al. 2012, White et al. 2013, MacKerron and Mourato 2013, Alcock et al. 2014, Flouri et al. 2014, Taylor et al. 2015, Triguero-Mas et al. 2015, Wheeler et al. 2015, Wu et al. 2015, Bixby et al. 2015, Gidlow et al. 2016b, Cox, Shanahan, Hudson, Plummer, et al. 2017, Houlden

Pathway	Hypothesis	Characteristics
		et al. 2017, Dzhambov, Hartig, et al. 2018, Meyer-Grandbastien et al. 2020): • CLC • LCM • Urban Atlas • GLUD 3. Protected areas (Annerstedt et al. 2012, Wheeler et al. 2015, Wyles et al. 2019) 4. Biodiversity (Carrus et al. 2015, Southon et al. 2018, Wood et al. 2018) 5. Species richness (Fuller et al. 2007, Luck et al. 2011, Dallimer et al. 2012, Wheeler et al. 2015, Cox, Shanahan, Hudson, Fuller, et al. 2017, Taylor et al. 2018): • Perceived species richness • Bird species richness • Plant species richness • Butterfly species richness 6. Blue space (White et al. 2013, Wheeler et al. 2015) 7. Private gardens (White et al. 2013, Flouri et al. 2014, Wu et al. 2015) 8. Urbanity (White et al. 2013, Triguero-Mas et al. 2015, Cox et al. 2018)

Domain 1 – Reducing harm

4.0.1.1 Air Pollution

As identified in the pathway review (Table 4), multiple modelled air pollution data were linked to adverse mental health. Modelled air quality data for GB were readily available between 2001 and 2018 as part of the UK's fulfilment of the European Union's directives on ambient air quality. Annual air pollution data modelled at 1km resolution were available to download from the Department for Environment, Food and Rural Affairs (Defra) for the following major pollutants PM_{10}, $PM_{2.5}$, NO_x and NO_2, carbon monoxide, sulphur dioxide, Ozone, and Benzene. For these pollutants, the modelled data were calibrated using measurements within the national network of background measurements (Department for Environment, Food and Rural Affairs 2018). GB's monitoring of black carbon had fewer monitoring sites (UK Air Information Resource n.d., Butterfield et al. 2014), and therefore full coverage of GB was not possible.

For Chapters 5 and 6, $PM_{2.5}$ was favoured as a measure of air pollution compared to NO_2 and NO_x because $PM_{2.5}$ sources were predominantly regional (Air Quality Expert Group 2012). For NO_2 and NO_x pollutants, local sources were more important (Air Quality Expert Group 2012). Therefore, considering the resolution of the available data (1km) it was more appropriate to select $PM_{2.5}$ as a measure of exposure to air pollution. This aligned with the Committee on the Medical Effects of Air Pollutants' (COMEAP) recommendation to use $PM_{2.5}$ as a measure for long-term air pollution for quantitative assessments of the mortality risks (COMEAP 2009, COMEAP and Public Health England 2015). Modelled data from Phillips et al. (2021) were identified as a finer resolution (100m) source of $PM_{2.5}$ air pollution in GB. The data from Phillips et al. (2021) used the Defra data for air pollution source strength to model the spatial extent of road pollution. Data exploration showed that the $PM_{2.5}$ concentrations across the urban Lower Layer Super Output Areas (LSOAs) were more normally distributed in the Phillips data compared to the Defra data. As a result, the Phillips data were considered an improvement compared to the coarser resolution Defra data.

4.0.1.2 Noise Pollution

Several sources of noise pollution were relevant to mental health, including: being within audible range of an artillery range or onshore wind turbine, traffic noise, railway noise and aircraft noise. The contribution of artillery ranges and wind turbines to noise pollution were considered negligible for urban areas. Traffic, railway and aircraft were deemed the main contributors to noise pollution in an urban setting.

For England, Scotland and Wales, 2017 noise maps were readily available to download (Department for Environment, Food and Rural Affairs 2017, Scotland's Environment 2017, Welsh Government 2017). These maps represented the main contributors of environmental noise, including noise from large urban areas and transport such as road, rail, and aviation. In generating these maps, no actual noise measurements were made; all pollution assumptions were based on proximity and information such as traffic flow and vehicle type data. However, the main benefit of using these data is the fine resolution. The data were available to download as a shapefile, therefore fine scale heterogeneity was captured within the local area buffers. Again, modelled data from Phillips et al. (2021) were identified as an alternative but in this case at a coarser resolution (100m). As the finer resolution data from the 2017 noise maps showed no collinearity with the other data sources, it was chosen for the analysis in Chapters 5 and 6.

4.0.1.3 Heat island mitigation

Measures of daily temperatures were most commonly used in the literature to represent the cooling effect of greenspace to mitigate the urban heat island effect. For GB, temperature grids for daily, monthly, seasonal and annual timescales, in addition to long term averages for a set of climatological reference periods were available from the HadUK-Grid provided by the Met Office (Met Office 2020). For data exploration, average monthly temperature at a 5km resolution was chosen (Met Office 2020). Data exploration revealed a high correlation between average monthly temperature and average monthly sunlight hours ($R^2 = 0.97$). Monthly temperature was excluded from the analysis in Chapters 5 and 6 in favour of including average monthly daylight hours. The primary reason for this decision was because the resolution of temperature data (5km) were considered to be too coarse to pick up the hypothesised mediating effect of local greenspaces on the urban heat island effect. Whereas the scale (5km) was more appropriate to capture the seasonal and spatial variation of daylight hours (see Section 4.0.1.4 below).

4.0.1.4 Exposure to Sunlight

Self-reported sunlight exposure, daily sunshine duration, and measures of solar radiation were identified as possible measures of exposure to sunlight. Self-reported exposure to sunlight was not available within the BHPS. As individual-level exposure to sunlight could not be accounted for, sunshine data from the Met Office's HadUK-Grid at a 5km resolution were identified as a reliable and consistent data source to capture objective regional variation of bright sunlight hours across GB (Met Office 2020). The data provided average daylight hours per month. This temporal consideration was important due to the overall skew in the months in which participants took part in the BHPS. By applying the monthly average to the corresponding month the person took the survey the temporal variation in daylight hours across GB was better accounted for.

4.0.2 Domain 2 – Restoring capacity

4.0.2.1 Social value

As discussed in Section 2.2.2.2.1, social value is made up of two parts: (1) social contact and a sense of community, and (2) crime. The literature examples in Table 5 adopted both objective and subjective measures to represent the social contact and sense of community pathway. Subjective measures included individual self-reported social wellbeing (Ward Thompson et al. 2016) and social cohesion, and objective measures focused on aspects of the local environment such as walkability, transport, and deprivation. The quantification of the psychological components of a sense of community through objective environmental measures was challenging. Arguably, these should be left for the individual to disclose as different people can have different affiliations to places and experience places differently. At an individual-level, depending on the survey's wave, the BHPS has variables that could be used as a proxy for social contact and a sense of community. For the former, alternate years of the survey asked if the individual had a close friend, and from Wave 4 onwards how many close friends an individual had. For a sense of community, from Wave 7 (1997) onwards individuals were asked about the frequency in which they spoke to their neighbours. However, the difficulty with using these self-reported variables from the BHPS, as with all subjective measures, was their limited application to a broader spatial extent. Secondly, in the analysis of Chapters 5 and 6, a cautious approach regarding the selection of individual-level covariates to limit the effect of post-treatment bias was taken. Post-treatment bias occurs when a regression includes a consequence of the treatment as a control variable. Therefore, using these subjective variables was not best practice to avoid post-treatment bias (Montgomery et al. 2018).

Instead of an individual-level variable, an objective area-level proxy for social contact and a sense of community was preferred to reduce the possibility of bias. The benefit of using an area-level measure instead of a measure of individual perception was that it could be assumed that the measure is a fixed characteristic of the treatment variable (i.e., public greenspace), rather than a possible effect of the treatment. In a study by Sarkar et al. (2013) street connectivity, walkability and public transport were used as proxies for social connectivity, and social connectivity was one element of the urban built environment configuration, with the Normalised Difference Vegetation Index (NDVI) being included as another element. Sarkar's study was for a much smaller area than this thesis; Caerphilly, Wales. Therefore, walkability measures suitable for a broader study scope were considered. The walkability index used by Wilding et al. (2020) and developed by Frank et al. (2010) was identified as a possible scalable index for GB. However, one of the main components of this index is the landuse mix. There were several obstacles to obtaining landuse data for use in this thesis. Although landcover data is readily available for GB, this is not the case for land use.

The only landuse data identified for GB was the 2010 Generalised Land Use Database (GLUD; Office for National Statistics 2010). These data categorised the land-cover features of Ordnance Survey MasterMap (OSMM) into nine landuse categories. As the OSMM is used to define the treatment variable (public greenspace) in Chapter 5, it was deemed as not suitable to be used to create one of the control variables when attempting to keep the modelled variables independent. Secondly, the walkability index required the number of road intersections to be included. As the chosen noise pollution layer related to pollution from roads, data independence was also considered to also be an issue here. As an independent walkability index could not be created, it was omitted from the analysis in Chapters 5 and 6. Consequently, due to data limitations, the pathways social contact and sense of community could not be represented in this thesis' analysis. Instead, the second pathway – crime – had to be explored as means to represent "social value".

For crime, objective measures are readily available for England and Wales from: https://data.police.uk/. However, crime data for Scotland were not reported or available in the same way. For Scotland, Police recorded crime data were used to construct the crime domain of the Scottish Index of Multiple Deprivation (SIMD), which was available to download. However, recorded crime statistics for England and Wales were not directly comparable with those in Scotland. The recorded crime statistics for England and Wales used the National Crime Recording Standard and the Home Office Counting Rules (Home Office 2013), whereas Scotland used the Scottish Crime Recording Standard (Justice Analytics Services 2019). Although both ensured the consistency of crime recording and their principles were similar, there were differences between the two. One key difference was their approach to counting the number of crimes that were considered as a result of a single incident. For England and Wales, crime counting more generally reflected the number of incidents whereas in Scotland it was the number of crimes within an incident. Therefore, for the scope of this thesis' analysis (GB) crime rates were not suitable data for the empirical analysis.

In the absence of suitable crime data, the feasibility of using measures of deprivation as a proxy for crime rates was explored. As previously mentioned, crime was a component of the Index of Multiple Deprivation (IMD), it is through this reasoning that using deprivation as a proxy indicator was considered. There is an established relationship between socioeconomic deprivation and health (Marmot 2010, 2020). The IMD is commonly included as a moderator of the greenspace and mental health relationship (e.g., McEachan et al. 2016, Houlden et al. 2017, White et al. 2017). However, the IMD scores for England, Scotland, and Wales were not directly comparable and each score reflected the rank of deprivation within each nation. An adjusted IMD score for 2008 was identified as a solution to address this issue (Abel et al. 2016). The adjusted IMD score was included in the data exploration stage of Chapter 5's analysis, in addition to a "universal" measure of deprivation (the Townsend deprivation score for 2011) that did not require adjusting. After data exploration, the Townsend deprivation score was chosen instead of the adjusted IMD primarily due to year. The Townsend deprivation score was based on more recent data, and all three nations are from the same years. Whereas the adjusted score used data from 2008 and 2010, depending on the nation. In addition, by using the Townsend deprivation score, the assumptions that were made in the creation of the adjusted IMD were avoided.

The difficulty in finding data that adequately captured social value emphasised the complexity of the relationship between social wellbeing, greenspace and mental health. A compromise to use the Townsend deprivation score was made to ensure data independence and to reduce the possibility of post-treatment effects in this research. The benefit of using a measure of deprivation as a proxy for crime was that it captured elements of social contact and a sense of community and therefore was an appropriate measure to represent the overall pathway.

4.0.2.2 Physical activity

At an individual-level, physical activity was a variable available in the BHPS. However, physical activity was considered a post-treatment effect; i.e., someone with access to local greenspace (the treatment) was more likely to partake in physical activity than someone without local greenspace. Therefore an individual measure of physical activity was not used in Chapters 5 and 6 to avoid post-treatment bias.

The use of the OSMM Greenspace Layer as an objective area-level proxy for physical activity and recreation was considered. The OSMM Greenspace Layer contained spatial information on sporting layers, golf courses, and playing fields. However, the public access to these layers could not be determined and therefore public and private greenspaces could not be separated.

4.0.3 Domain 3 – Building capacity

When identifying variables, the two aspects of building capacity (ART, and SRT) were rarely considered in isolation. Many studies did not discuss the pathways in detail and simply attribute the mental health benefits to one of these two mechanisms. Those that explored only one pathway often negated to justify why the alternative pathway was not appropriate (i.e., they failed to acknowledge the competing/complementary theory). As discussed in the literature review (Chapter 2) stress, restoration, and human evolutionary history are fundamentally linked, making the pathways difficult to separate. Unlike the previous sections of this data landscape, measures from studies were assigned to multiple pathways. Therefore, for simplicity, in this part of the data landscape, the suitability of each of the measures is discussed independently of the pathway (instead of each pathway in isolation). This is the benefit of categorising via Markevych's domains and not the pathways. As the domains are not mutually exclusive, organising pathways into these domains creates opportunities for interdisciplinary exchange and the study of lesser-explored pathways in the context of other potential influencers of health (Markevych et al. 2017). In total there were 16 different measures of greenspace or greenspace qualities identified in the literature, which were placed into seven categories: (1) greenness, (2) landcover, (3) protected areas, (4) biodiversity, (5) private gardens, (6) blue space, and (7) urbanity.

4.0.3.1 Greenness

The most common measure of greenness used was the NDVI (McEachan et al. 2016, Cox et al. 2018, Dzhambov, Hartig et al. 2018, Taylor et al. 2018). All studies calculated NDVI from Landsat 8 imagery at a resolution of 30m. Although NDVI was widely used to measure "greenness", the processing of satellite imagery and definitions of exposure differed between the studies using NDVI. For example, Dzhambov et al. (2018) used satellite images taken from a single day and extracted the mean NDVI for the areas of interest. Taylor et al. (2018) used a broader range of satellite images to increase the number of scenes without cloud cover. But like Dzhambov et al. (2018), Taylor et al. (2018) used the absolute values to calculate the mean NDVI in the area of interest. Instead of absolute values, McEachan et al. (2016) used the relative differences between values (using quintiles), and Cox et al. (2018) used a threshold of 0.2 to create a dichotomous layer of vegetated (>0.2) from non-vegetated pixels (<0.2), which was used to calculate the percentage cover vegetation.

Tree cover or density was an alternative measure of greenness used by fewer studies than NDVI (Luck et al. 2011, Taylor et al. 2015, Dzhambov, Hartig et al. 2018). Again, different approaches were taken to calculate the measure. For example, Dzhambov et al. (2018) used the 2012 tree cover density map developed by the European Environment Agency (EEA; Copernicus Land Monitoring Service 2018). Whereas, Taylor et al. (2015) extracted the number of street trees in each London borough by using the Greater London Authorities per tree maintenance allowance. The tree maintenance allowance was not available across GB and the data only concerns street trees and not those in parks. Therefore, it did not adequately capture the overall greenness of the area. Unlike the street tree maintenance allowance, the EEA tree cover data were available for GB. However, limiting the measure of greenness to just trees was considered to be restrictive. Cox et al. (2017b) had a broader inclusion and used LiDAR data to create vegetation cover maps. However, they restricted it to vegetation greater than 0.7m, which also excluded important vegetation that contributes to the overall greenness of the area. Luck et al. (2011) included the proportion of woody and non-woody vegetation in the measure of vegetation cover/density, but also required measures of vegetation density taken in the field which made it an unsuitable measure for GB. The OSMM Greenspace Layer (Ordnance Survey 2022) was identified as an alternative source for street greenness that was not just limited to trees or vegetation above 0.7m. However, NDVI was considered to be the best approach to capture the overall greenness of an area as it encompasses multiple "green" components such as trees, grassy playing fields, private gardens, and street greenery.

4.0.3.2 Landcover and landuse

The most commonly used landuse data were the GLUD (Office for National Statistics 2010), used by; White et al. 2013, 2017, Alcock et al. 2014, Flouri et al. 2014, Wu et al. 2015, Gidlow et al. 2016a, Gidlow et al. 2016b, and Houlden et al. 2017. GLUD was last updated in 2010 and consisted of 10 different landuses mapped at a 1km^2 resolution (Office for National Statistics 2010). For this research, the landuse of domestic gardens and greenspace were of interest, both of which were available for LSOAs.

As an alternative to landuse, landcover has been used by other studies to identify the area, or presence or absence, of greenspace (e.g., Annerstedt et al. 2012, MacKerron and Mourato 2013, Bixby et al. 2015, Triguero-Mas et al. 2015, Wheeler et al. 2015). Annerstedt et al. (2012) and Triguero-Mas et al. (2015) both used the CORINE Land Cover (CLC) inventory (Copernicus Land Monitoring Service 2021). The CLC has been produced for 2000, 2006, 2012, and 2018 and consisted of 44 classes with a minimum mapping unit of 25ha. Although Annerstedt et al. (2012) obtained and used finer resolution data (25m x 25m) for Sweden. The Land Cover Map (LCM) was identified as a finer resolution alternative for landcover within GB. Used by MacKerron and Mourato (2013), Bixby et al. (2015), and Wheeler et al. (2015) the LCM was available for multiple years at a 20m raster grid (https://www.ceh.ac.uk/ukceh-land-cover-maps).

The aim of using either these land cover or landuse data sets was to identify either the area of greenspace in an individual's local area or the presence or absence of greenspace within the individual's local area. Consequently, a finer resolution data set was preferred to more accurately estimate an individual's exposure to greenspace. The OSMM Greenspace Layer was identified as an even finer resolution alternative to identifying local greenspaces. In addition to the high-quality resolution, the OSMM Greenspace Layer included "public parks and gardens" as a type of greenspace, which meant that public and private spaces were distinguished from the overall greenspace within the local area. The disadvantage of the OSMM Greenspace Layer was its coverage, the data were only available for urban places, whereas the LCM had full GB coverage. As the research questions regarded only urban greenspace, and given the quality of the OSMM Greenspace Layer, it was the most appropriate source to identify local urban greenspaces in GB.

4.0.3.3 Protected areas

The presence of protected areas was used to represent different qualities of greenspaces. For example, Annerstedt et al. (2012) used the presence of protected areas to represent culture and to do so identified areas of national interests of cultural preservation and nature reservation areas. Alternatively, Wheeler et al. (2015) used protected areas to capture the ecological and biological importance of greenspaces, and subsequently, excluded National Parks and Areas of Outstanding Natural Beauty (AONBs) as they were designated based on cultural heritage and aesthetics. Whereas, Wyles et al. (2019) kept all designated areas to capture both biological and aesthetic qualities of the different sites. Like Wyles et al. (2019) it was decided that for this thesis both biological/ecological and aesthetic/cultural qualities should be captured using the presence of protected areas. The Common Database on Designated Areas (CDDA) was used as the official source of protected area information. For GB the protected areas included; Sites of Special Scientific Interest, National Nature Reserves, Local Nature Reserves, National Parks, AONBs and a variety of Marine Protected Areas (Joint Nature Conservation Committee 2019). The Woodland Trust's Ancient Tree Inventory was used as an alternative data source to capture the cultural and ecological qualities of urban greenspaces. The inventory included ancient, veteran and notable trees that have high ecological and cultural value (Woodland Trust 2020, 2021). Given their cultural and ecological value, the measure of protected areas was extended to include the presence or absence of ancient and veteran trees.

4.0.3.4 Biodiversity

There were occurrences where biodiversity was measured using site surveys/assessments. For example, Carrus et al. (2015) identified four sites with varying levels of biodiversity, and Wood et al. (2018) took a similar approach in comparing different sites but instead used four "biodiversity-related" variables; plant, bird, and bee/butterfly species richness, and habitat number. As it is not practical to measure biodiversity at all levels (i.e., genetic, species, and habitat), to a broad spatial extent, the majority of studies used a single component to represent overall biodiversity. Measures of species richness were most commonly used to represent biodiversity (Hillebrand et al. 2018).

However, even single measures of biodiversity can be difficult to measure at a broad extent, and studies often used species richness as a proxy for biodiversity. Commonly used measures of species richness were for: (1) birds (Fuller et al. 2007, Luck et al. 2011, Dallimer et al. 2012, Taylor et al. 2015, Wheeler et al. 2015, Cox, Shanahan, Hudson, Fuller et al. 2017), (2) plants (Fuller et al. 2007, Dallimer et al. 2012, Southon et al. 2018), and (3) butterflies (Fuller et al. 2007, Dallimer et al. 2012). These studies used mixed sources to obtain species richness data, some undertook field surveys (Fuller et al. 2007, Luck et al. 2011, Dallimer et al. 2012, Cox, Shanahan, Hudson, Fuller et al. 2017, Southon et al. 2018, Wood et al. 2018), which for the analysis of GB is not feasible. Secondary data sources for bird species richness were used by Taylor and Hochuli (2017) and Wheeler et al. (2015). Taylor et al. (2018) obtained bird species richness from BirdLife International (https://www.birdlife.org/) and Wheeler et al. (2015) from the British Trust for Ornithology Bird Atlas 2007-11 (Gillings et al. 2019). The spatial extent of the Bird Atlas made it the most suitable data source for the analysis in this thesis.

4.0.3.5 Private gardens

Very few studies separated the effects of public and private greenspaces. As previously mentioned, the GLUD included landuse for both gardens and greenspaces and several studies combined these two land covers to provide the overall area of greenspace in a person's household's local area (e.g., White et al. 2013, and Wu et al. 2015). Only one study, Flouri et al. (2014), separated public and private greenspace at a household level (rather than an area-level). Flouri et al. (2014) used data from the Millennium Cohort Study (https://cls.ucl.ac.uk/cls-studies/millennium-cohort-study/) and controlled for the effect of having a private garden on emotional and behavioural problems from early to middle childhood. Like the Millennium Cohort Study, the BHPS provided information on whether an individual (or household) had access to a private or shared garden (Understanding Society 2021). This individual-level information on access to a private garden was deemed more informative for the analysis in Chapters 5 and 6 compared to aggregate alternatives.

4.0.3.6 Blue space

Blue space is often included within the definition of greenspace (Taylor and Hochuli 2017), which made it difficult to distinguish all studies that included blue space. Yet there were different measures of blue space adopted within the literature. The majority of studies used landuse to identify the area, or the presence or absence, of blue space. For example, White et al. (2013, 2017), Gidlow et al. (2016a), and Gidlow et al. (2016b) used the GLUD classes. As previously discussed, the resolution of the landuse and land cover data were coarse, making them ill-suited to capture the presence of blue spaces within an individual's local area. One study used blue space data as a proxy for landscape quality; Wheeler et al. (2015) used data surface water quality data from the Environmental Agency for England and Wales. Data were available for 2011 and reported quality using a 5-point scale (High, Good, Moderate, Poor, and Bad) and the average quality (as weighted by LSOA size) was obtained. Although these data provided quality information at a fine resolution, Scotland was not included. The data for Scotland were reported differently. Therefore, were not suitable data for this thesis exploring the effect of urban greenspace on mental health in GB. Furthermore, the pathways from blue space to mental health benefits were conceptually different from greenspace and were not included within the scope of this thesis.

4.0.3.7 Urbanity

Urbanity is a term used to describe the level of urbanisation as a characteristic of an area. Houlden et al. (2017), Triguero-Mas et al. (2015), and White et al. (2013) did this by categorising urban and rural spaces. Continuous measures of urbanity were used by Cox et al. (2018) and Luck et al. (2011). Cox et al. (2018) used the number of building polygons from OSMM to calculate the percentage of building cover around respondents' homes. Similarly, Luck et al. (2011) used the proportional cover of impervious surfaces in each neighbourhood as measured by ALOS. However, as this thesis aimed to “untangle” the effect of urban greenspace on mental health, it was not suitable to establish the area of “grey” space as this confounds the available space for greenspace.

4.1 Mental health

As discussed in Section 2.1.2 there were many different measures of mental health. The purpose of this landscape was to identify surveys that had a representative sample of people living in GB and also collected objective measures of mental health.

4.1.1 Cross-sectional vs longitudinal

In this landscape, survey data were categorised as either cross-sectional or longitudinal. Cross-sectional data were from participants at a single point in time, whereas longitudinal data were from the same sample at different points in time. In longitudinal data, each point was referred to as a “wave”. Therefore, for the annual longitudinal survey (with repeat surveys each year) each year was one wave. As discussed in the literature review Section 2.4.3, longitudinal data can be used to improve causal inference, and therefore this data landscape was limited to longitudinal surveys only.

4.1.2 Selecting longitudinal data

A systematic approach was taken to identify representative longitudinal surveys for adults in GB. The UK Data Service and the Medical Research Council websites were used to conduct the search. A total of 11 data sets were identified and provisionally reviewed for their overall objective and inclusion of a mental health indicator. Four of the ten datasets were excluded because their scope was limited to one country in GB, the excluded studies were: (1) English Longitudinal Study of Aging, (2) Growing Up in Scotland, (3) Next Steps (or Longitudinal Study of Young People in England) and (4) Our Future (or Longitudinal Study of Young People in England 2). The Millennium Cohort study was next excluded because the only included children as the cohort started in 2000.

The remaining five surveys were explored in more detail to establish which objective measures of mental health were collected within the surveys. Four objective measures of mental health were identified: (1) the GHQ-12, (2) WEMWBS, (3) Malaise inventory, and (4) the SF-36 or the SF-12. For these measures of mental health, the number and consistency of waves within each of the surveys were identified and recorded (Figure 10).

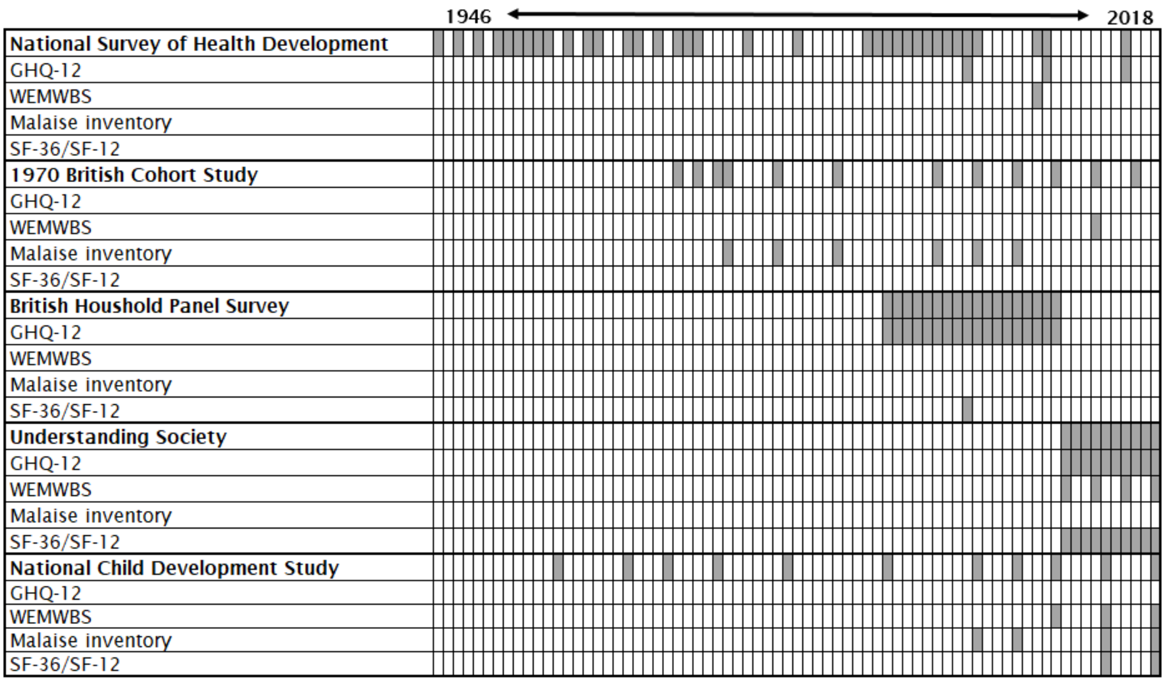

Figure 10: The years in which the longitudinal surveys were conducted and the years in which respondent mental health information was collected. Each tile represents one year, and grey tiles represent the years in which information was collected.

The BHPS and Understanding Society were most consistent with collecting mental health variables, specifically the GHQ-12. The BHPS collected only one wave of the SF-36, whereas all waves of Understanding Society collected the SF-36. Understanding Society also collected information on the positively framed measure of mental health, WEMWBS, every 4-years. Both surveys were household-based with a UK wide representative sample. From Wave 19, the BHPS became part of Understanding Society, therefore there were up to 25 years' worth of data available for some households. The consistency of data collected, and the spatial and temporal span of these two data sets made them most suitable for the research presented in this thesis.

4.2 Summary of available data

The data selected for this thesis is summarised in Figure 11. These data were deemed most suitable given the scope of the data required (GB), the pathways being represented and the limitations discussed in this landscape. For mental health, the BHPS was deemed more appropriate compared to Understanding Society because the BHPS contained information on whether individuals have private gardens which were discussed under the domain qualities that restore (Figure 11).

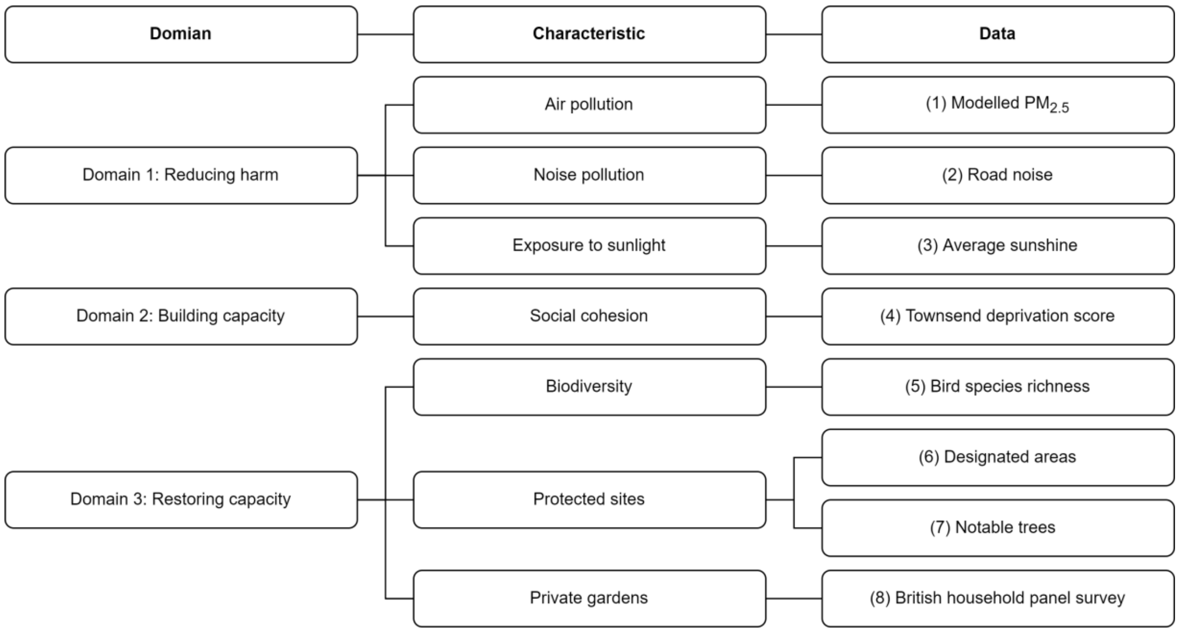

Figure 11: Summary of the most suitable characteristics and their respective data identified from the greenspace and area-level characteristics data landscape. Organised according to domain to the mental health benefits. Data sources are as follows; (1) Modelled $PM_{2.5}$ – Phillips et al. (2021), (2) Road noise – Department for Environment, Food and Rural Affairs (2017), Scotland's Environment (2017), Welsh Government (2017), (3) Average sunshine – Met Office (2020), (4) Townsend deprivation score – UK Data Service (2017), (5) Bird species richness – Gillings et al. (2019), (6) Designated sites – European Environment Agency (2019), (7) Notable trees – Woodland Trust (2020), and (8) British household panel survey – University of Essex (2018b).

Chapter 5 The effects of private gardens exceed those of public greenspaces on mental health

5.0 Abstract

Although the beneficial effects of urban greenspace on mental health are widely accepted, the comparative effects of public and private greenspace on mental health are poorly understood. Here, we provide an assessment of the effect of local public greenspace on a person's mental health for those with and without a private garden in Britain. Individual-level data on private garden ownership and mental health status were obtained from a nationally representative survey (the British Household Panel Survey). A combination of statistical matching and regression models were used to account for individual and area-level confounders and to test for interactions. We show that the positive effects of private greenspace exceed those of public greenspace on mental health. Specifically, having a private garden substantially reduces the maximum probability of poor mental health for men and women, regardless of their access to local public greenspace. However, the beneficial effects differ depending on age and gender. Given our results, we recommend that the provision of private gardens is considered within greenspace guidance and policy, which is currently dominated by the provision of, or access to, public greenspaces.

5.1 Significance

Urban greenspace can provide benefits to mental health. This study provides strong evidence that the effect of private garden ownership on mental health is greater than the influence of access to public greenspace. Therefore, having a private garden substantially reduced the peak in poor mental health for both men and women, regardless of their access to a public greenspace. Importantly, the beneficial effect of private gardens is dependent on gender and access to public greenspace. Our findings highlight that the provision of private greenspaces in urban areas is an important strategy to help improve the mental health of urban populations.

5.2 Introduction

A consensus has emerged that greenspace in cities has beneficial effects on the mental health and wellbeing of residents (for reviews see; Houlden et al. 2018, Collins et al. 2020). Time spent in nature can promote psychological restoration (Kaplan and Talbot 1983) and reduce stress (Ulrich

1983). These beneficial effects are usually explained by our 'biophilia' – humans' innate affinity for the natural environment, which evolved through natural selection (Wilson 1984). With 68% of the world's population projected to live in cities by 2050 (United Nations 2018), populations are becoming increasingly dependent on a small and restricted network of public and private greenspaces for mental health benefits. However, critical knowledge gaps still exist in our understanding of the greenspace and mental health relationship in cities, which must be addressed to effectively inform future urban planning. Specifically, research that quantifies the relationship between greenspace and mental health rarely defines or differentiates between public and private greenspaces (Taylor and Hochuli 2017, Collins et al. 2020), despite their differences in accessibility. The aggregation of public and private greenspaces into measures of total greenspace amount (e.g., total greenness of an area) may lead to incorrect inferences about the importance of public greenspace to mental health, and consequently poor urban planning decisions that could widen social and health inequalities; indeed, those who are at greatest risk of poor mental health may already have little access to greenspace (Allen et al. 2014).

To our knowledge, there are no studies that compare the effects of access to private and public greenspaces on mental health. Studies have demonstrated positive associations between mental health and area-level coverage of public and private greenspaces collectively (e.g., Alcock et al. 2014). Alternatively, they have used only one type of greenspace in their analysis. Urban public greenspaces such as parks are associated with the improved mental wellbeing of local residents (e.g., Houlden et al. 2019). Similarly, access to private (domestic) gardens, which present an immediate opportunity to observe or engage with nature (Gaston, Warren et al. 2005), can improve mental health (de Bell et al. 2020). Importantly, private gardens may influence how individuals engage or interact with other forms of greenspace, therefore it is essential that private garden access is explicitly considered in greenspace research to understand the comparative effects of private and public greenspace on health outcomes in different contexts. A challenge to disentangling the effects of private and public greenspace is that access to greenspace is often confounded with individual, household and area-level characteristics that can also influence mental health (Allen et al. 2014). For example, a person with greater access to greenspace – either through a private garden or by being able to afford housing in 'greener' areas - may be less likely to experience poor mental health through having a higher income, stable housing, employment, or access to private healthcare. It is therefore critical to separate the confounding effects of greenspace access from individual and area-level drivers.

In this paper, we present an assessment of the relative effects of urban public and private greenspace on the probability of poor mental health in Britain (England, Scotland and Wales). We adopt counterfactual approaches (Rosenbaum and Rubin 1983) and explicitly distinguish between the effects of public greenspace and private gardens from individual and area-level confounding factors. We use individual-level (n = 5,248) mental health outcomes from survey data in Britain, the British Household Panel Survey (BHPS; University of Essex 2018b), together with the Ordnance Survey MasterMap (OSMM) Greenspace Layer (Ordnance Survey 2022), to separate public parks and public gardens (i.e., accessible greenspaces) from the overall greenspace provision in a person's local area. We separately test the effects of public and private greenspaces on the probability of poor mental health by distinguishing individuals by their access to a private garden. For those with and without a garden, we account for individual-level and area-level factors that confound the greenspace and mental health relationship by applying statistical matching and regression models, which strengthens causal inference from observational datasets (Stuart 2010). In accordance with the biophilia hypothesis (Wilson 1984), we hypothesised that access to greenspace (whether it be public or private) will reduce the probability of poor mental health. As such, we expected to find a stronger effect of public greenspace on the probability of poor mental health for those without private gardens. Similarly, we expected the effect of having a private garden on the probability of poor mental health to be stronger for those without access to public greenspace. However, we had no prior expectation for the comparative effect of public and private greenspace on the probability of poor mental health for individuals with or without access to both, due to the gap in comparative studies of public and private greenspace.

5.3 Results

Overall, for individuals aged 18-75 years old living in urban areas of Britain, those without a private garden were more likely to exhibit poor mental health outcomes compared to those with a private garden (Figure 12). At the peak of poor mental health risk (approximately age 40 for both men and women Figure 12), the effects of a private garden exceeded those of public greenspace on mental health (Table 7). The effect of private garden ownership on mental health changed with age: for older women (aged over 64 and 70 with and without public greenspace, respectively) having a private garden slightly increased the probability of poor mental health. For men, this trend is dependent on whether they have access to public greenspace. Similar to women, older men (aged 72 and over) with access to public greenspace and a private garden exhibit a small increase in the probability of poor mental health compared to men with access to public greenspace and no private garden. For men without access to public greenspace, the benefit of garden ownership for their mental health continues in older age (aged 64-75).

The predicted probability of poor mental health averaged across the top-performing models (Table 7) showed that the overall effect of public greenspace on poor mental health was small, regardless of garden ownership. Garden ownership did not alter the magnitude of the predicted effect of public greenspace access on the probability of poor mental health. For instance, the maximum difference in the peak probability of poor mental health for men without access to a private garden was 0.09 (Table 7).

The effect of area deprivation (as measured by the Townsend deprivation score (UK Data Service 2017) on mental health, depended on private garden ownership (Figure 13). For individuals without a private garden, those living in the least deprived areas were more at risk of poor mental health than those living in highly deprived areas. In contrast, individuals who owned a private garden showed the opposite relationship; those living in the least deprived areas were less likely to report poor mental health than those living in more deprived areas.

For other individual-level socio-economic covariates, mental health was not contingent on garden ownership. Generally, individuals with a private garden have an overall lower risk of poor mental health compared to individuals without a private garden (Figure 13).

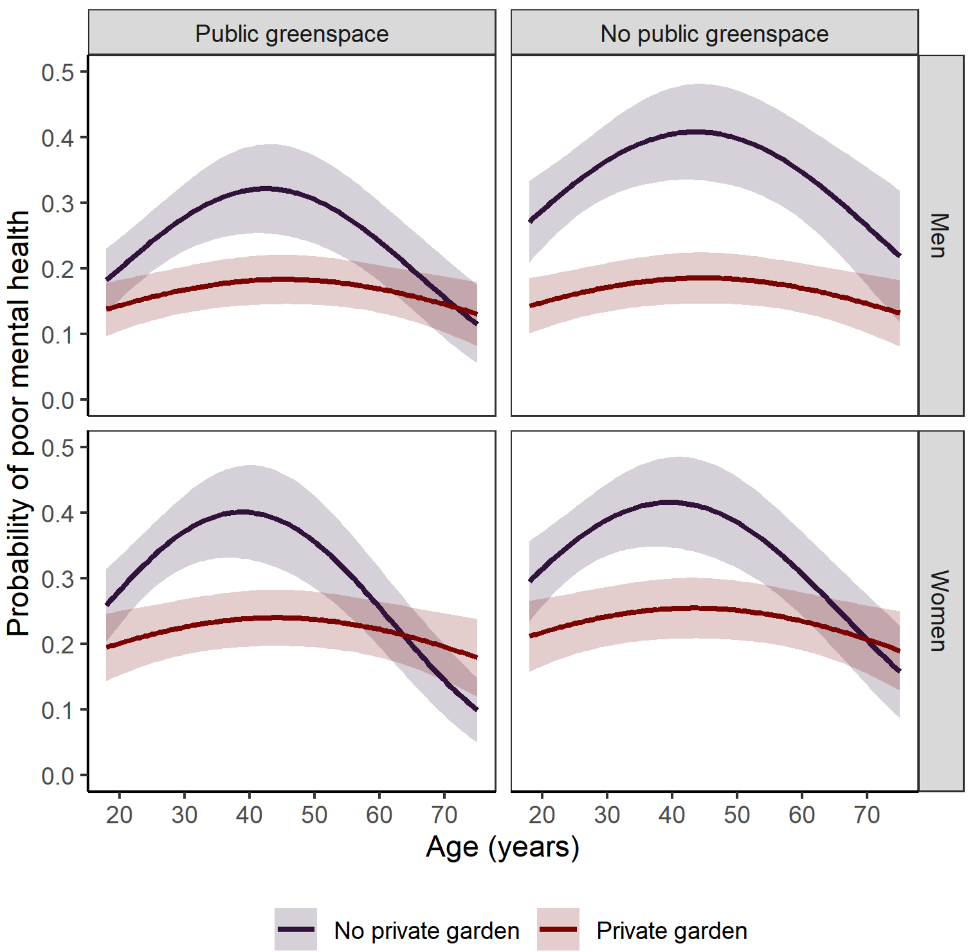

Figure 12: The predicted probability of poor mental health averaged across the top-performing models (ΔAIC<6, see text) for individuals without (purple line) and with (red line) a private garden in relation to access to public greenspace (within 800m of the

population-weighted centroid of their LSOA or Data Zone), gender, and having a private garden. All other covariates were held at their median or mode (See Materials and methods). Shaded region shows 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

Table 7: The predicted probability of poor mental health averaged across the top-performing models (ΔAIC<6, see text) for individuals with and without a private garden in relation to access to public greenspace (within 800m of the population-weighted centroid of their LSOA) and gender. Predictions were made for individuals that were aged forty, corresponding to an age where the risk of poor mental health peaked for garden and non-garden owners. All other covariates were held at their median or mode (See Materials and methods).

Access to public greenspace	**No private garden**		**Private garden**		**Difference**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
No public greenspace	0.41	0.42	0.18	0.25	0.22	0.16
Public greenspace	0.32	0.40	0.18	0.24	0.14	0.16
Difference	0.09	0.02	<0.01	0.01	NA	NA

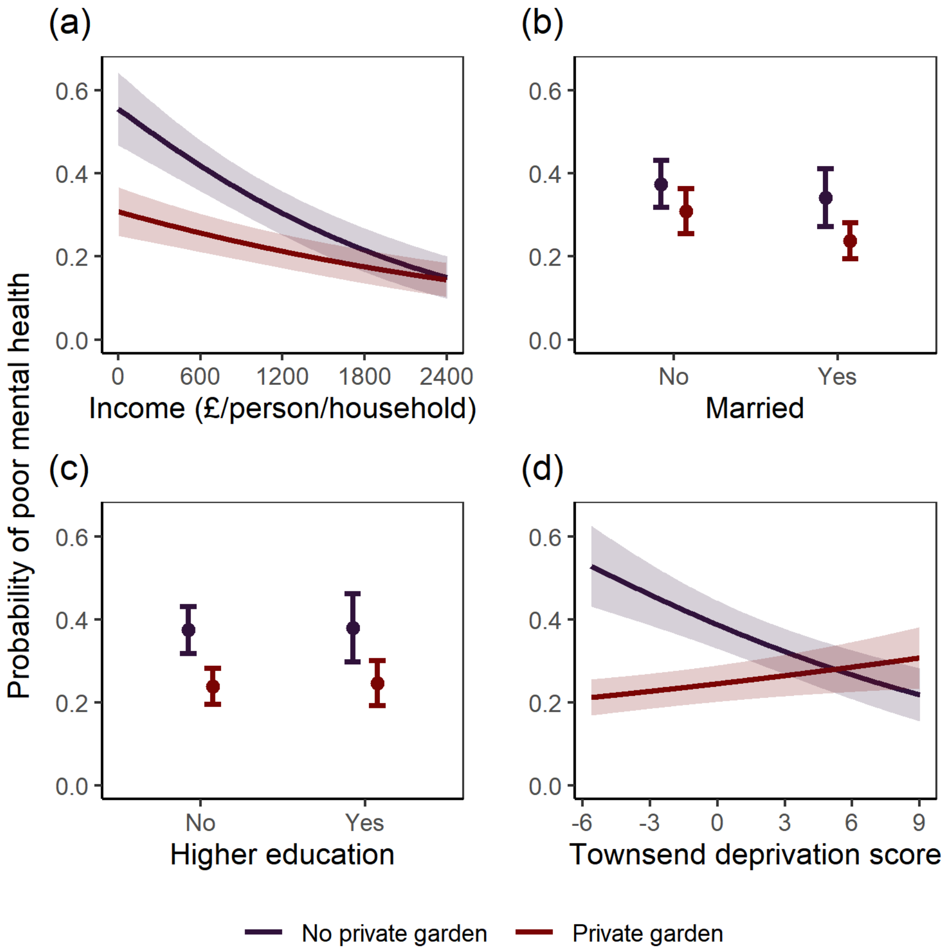

Figure 13: The predicted probability of poor mental health averaged across the top-performing models (ΔAIC<6, see text) for individuals without (purple line) and with (red line) a private garden in relation to; (a) income per person per household (£), (b) marital status (Yes/No), (c) higher education attainment (Yes/No), and (d) Townsend deprivation score (-5 least deprived and 10 most deprived). For each graph, all other covariates were held at their median or mode (See Materials and methods for details). Shaded region shows 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

5.4 Discussion

We expected public greenspaces to more strongly influence mental health for individuals without gardens. We found no support for this hypothesis; public greenspace effects on poor mental health did not detectably vary between individuals with or without a private garden. Moreover, public greenspace effects were relatively small to those of private gardens. Indeed, having a private garden substantially reduced in poor mental health for both men and women. However, the magnitude of this beneficial effect is dependent on age, gender and access to public greenspace.

We expected the probability of poor mental health to be highest in the most deprived areas for all individuals (Allen et al. 2014). However, we detected an opposite trend for individuals without a private garden (Figure 13). This intriguing and policy relevant finding demonstrates the importance of context for understanding the effect of deprivation on mental health. This observation may be indicative of “garden envy”, experienced by individuals without gardens in wealthier, less deprived, neighbourhoods towards their neighbours with private gardens. There is evidence for this hypothesis from previous findings investigating the effect of relative deprivation on an individual’s risk of poor mental health (Mishra and Carleton 2015, Beshai et al. 2017). However, this is one possible explanation for this observed trend, and future research is needed to better understand the effect of deprivation and private garden access on mental health.

The stronger effect of private gardens on mental health outcomes has clear policy implications. Urban greenspace is typically planned using a recreational standards approach (Boulton et al. 2018), which ignores private gardens in their assessments and focuses on public spaces. For example, the focus in the United States (US) remains on the delivery of public greenspaces as opposed to private greenspaces, as evidenced by $150 million that will be distributed to local communities through the Outdoor Recreation Legacy Partnership grant program to create close to home outdoor recreation experiences (U.S. Department of the Interior 2021). Similarly, in England, LAs, are guided by the National Planning Policy Framework and the National Design Guide (Ministry of Housing, Communities and Local Government 2021b, 2021a) both of which focus on the provision of public and shared open spaces. The lack of policy around private gardens is particularly important as the average garden size is decreasing in many countries. In England, 12% of residential gardens were converted for residential use between 2017 and 2018 (Ministry of Housing, Communities and Local Government 2019), and in Germany, the average garden size has decreased from 450 m^2 in 1991 to 311 m^2 in 2015 (Petzke et al. 2021). Without changes to applicable guidance, the proportion and/or size of private gardens in urban areas is likely to decline with negative consequences on mental health. However, little is known about how strategies to promote private gardens will affect disadvantaged urban residents; such strategies could lead to the widening of socio-inequalities which have been observed in the past. For example, an increase in greenspace has been associated with an increase in house prices in Los Angeles, US (Conway et al. 2010), and Beijing, China (Wu and G. Rowe 2022). It is possible that shared gardens may offer a way to mitigate the trade-offs between the negative equity and space implications of increasing private gardens and their mental health benefits. However, currently, there is little research into the effect of shared gardens on mental health. A small sample meant we were unable to explore the effect of a shared garden on the probability of poor mental health in this study. Given projected levels of urbanisation and space constraints, shared gardens may become more common and therefore research into the effect of shared gardens on mental health is a priority for the future.

More generally, while the data and the methodological approach enabled us to compare the effect of public greenspace access and garden ownership on mental health, it does have important limitations. First, statistical matching reduces sample sizes and subsequently subgroups that were already small become even smaller post-matching. The relatively small sample sizes of Black, Asian and Minority Ethnic (BAME) in the BHPS meant we were unable to account for an individual's ethnicity which, in Britain, is correlated with garden ownership (Office for National Statistics 2020b). Future research that adopts targeted sampling rather than representative sampling (Rothman et al. 2013), is required to untangle the potential confounding effects of ethnicity and access to a private garden. Secondly, access to greenspace has been measured at 800m – the distance typically travelled in a ten-minute walk (Fields in Trust 2020). From a planning perspective, this links to the increasingly popular 20-minute neighbourhoods concept (Emery and Thrift 2021). However, there is limited research into the scale of this interaction and in this analysis we were unable to test alternative scales for interaction due to limitations in creating a balanced sample with statistical matching. Finally, we chose to use the GHQ-12 as a measure of poor mental health. The GHQ-12 was developed as a screening tool to identify mental disorders, which are only one aspect of mental health. Mental health is multi-faceted and by using a measure of mental distress we may not be adequately capturing happiness and life satisfaction (World Health Organization 2016). As a result, we may be underestimating the effect of public and private greenspace on mental health.

In summary, our study has highlighted the importance of considering private garden ownership in assessments of urban greenspace-mental health relationships. We found that access to a private garden has a greater effect on a person’s mental health compared to access to a public greenspace. Currently, there is little guidance or policy that encourages the creation of private gardens in new developments and the focus largely remains on the delivery of public greenspaces. We recommend that guidance be amended to encourage the delivery of more private spaces whilst ensuring equitable access. To do so, future research is needed to inform what garden characteristics influence mental health (e.g., quality or size) and develop strategies that deliver urban private gardens without exacerbating socio-demographic inequalities. However, such research requires targeted sampling of different subgroups instead of representative study populations. Similarly, a targeted sampling strategy selecting individuals with shared gardens will enable future research to establish the effect of shared garden ownership on mental health compared to private and public greenspaces. Addressing these gaps is essential for further developing policy recommendations that can contribute to improved mental health outcomes.

5.5 Materials and methods

5.5.1 Description of data

5.5.1.1 Public green space

A map of public greenspace was derived from the OSMM Greenspace Layer (version April 2020), a fine-scale vector dataset of urban greenspaces in Britain which included both publicly accessible and private greenspaces (Ordnance Survey 2022). We selected polygons corresponding to public parks or public gardens (i.e., spaces that are accessible to the public). To create a binary variable for the presence or absence of public greenspace within an individual's local area, an 800m buffer was applied to the 2011 Lower Layer Super Output Area (LSOA) or, for Scotland, Data Zone population-weighted centroids. Data Zones and LSOAs are commonly used standard geographic units (proxy neighbourhoods) to report small-area statistics and have previously been used to establish the greenspace and mental health relationship; e.g., Alcock et al. (2014). An 800m buffer was selected to represent the average distance travelled in a ten-minute walk which aligns with the Fields in Trust’s Guidance for Outdoor Sport and Play access guidance (Fields in Trust 2020). From a planning perspective, the chosen 10-minute walk aligns with the ‘20-minute neighbourhoods’ concept which stipulates that people should be able to meet most of their everyday needs within a 20-minute return walk from their residence (Emery and Thrift 2021). The concept has been implemented by local authorities and city planners in Melbourne (Victoria State Government Department of Environment 2021) and Scotland (O’Gorman and Dillon-Robinson 2021).

5.5.1.2 Mental health

This study used data from the BHPS, a nationally representative longitudinal survey of more than 5,000 households in the United Kingdom (UK) that ran annually for 18 years from 1991 to 2008 (University of Essex 2018b) as a measure of individual-level mental health. Each year of the survey is referred to as a “wave”. A household geographic identifier was used to link BHPS respondents to a LSOA (England and Wales) or Data Zone (Scotland). Although the BHPS has a representative sample for the UK, we restricted our analysis to individuals in Britain due to the availability of spatial datasets (namely public greenspace and deprivation).

Mental health in the BHPS was measured using the 12-item General Health Questionnaire (GHQ-12). The GHQ-12 is a validated screening tool used to assess a person’s risk of common mental disorders such as anxiety and depression (Goldberg and Hillier 1979) and is considered robust across genders, ages and education (Goldberg et al. 1997). The responses to the 12-items of the GHQ-12 consist of two lower categories and two higher categories which were coded as 0 and 1 and then summed to create a scale from 1 to 12 (Hankins 2008). Following Shelton and Herrick (Shelton and Herrick 2009), scores were converted to a binary (0/1) variable “poor mental health” with ≥ 3 indicating poor mental health.

5.5.1.3 Individual and household-level characteristics

The BHPS retrieved information on a range of variables including individuals’ private garden access, income, age, gender, marital status, and level of education, which are potential confounders of poor mental health (Allen et al. 2014). Monthly total household income was adjusted for household size to create the variable “income per person per household”. Unlike previous studies using the BHPS (e.g., White et al. 2013), individual-level variables such as hours of physical activity, commute time, and presence of physical health conditions were disregarded because they were considered post-treatment variables (i.e. not independent of access to public greenspace), which can bias estimates of treatment effects in causal models (Montgomery et al. 2018). We did not include ethnicity as a confounding variable in this analysis due to the low sample sizes of BAME groups.

5.5.1.4 Area-level characteristics

We took a systematic approach to identify potential area-level variables that moderate the effect of greenspace exposure on mental health. Variables were identified by reviewing studies included in a systematic map that collated studies quantifying greenspace-mental health relationships (Collins et al. 2020). From these, we first collated a comprehensive list of area-level characteristics that have been previously included as confounders or modifiers of greenspace effects on mental health. Second, this full list was then reviewed to determine whether the variables were relevant to and supported by appropriate data for urban areas in Britain. The data assessment identified a total of seven area-level characteristics which were used in this analysis and are summarised in Table 8.

Table 8: Area-level characteristics that were hypothesised to influence mental health directly or indirectly by modifying the influence of greenspace

Area-level characteristic	**Proxy variable**	**Data source and processing**
Greenness	Normalised Difference Vegetation Index (NDVI)	NDVI was calculated using Landsat 8 surface reflectance products (United States Geological Survey 2017) at a resolution of 30m × 30m. Images were processed in Google Earth Engine and the maximum NDVI values over eight years were obtained. NDVI values for LSOAs were abstracted as the mean value within the population-weighted centroid 800m circular buffer.
Diversity	Bird species richness	Bird species recorded at a 10km resolution (Gillings et al. 2019) were used to calculate species richness. The species richness at each LSOA population-weighted centroid was extracted. Rarer species recorded at coarser resolutions (>10km) were not used as these species would have generally not been seen by the majority of people and therefore the majority of people do not interact with them (Gaston et al. 2018).

Area-level characteristic	Proxy variable	Data source and processing
Protected sites	Ancient, veteran or notable trees Common Database of designated areas (CDDA)	Point data noting the location of the ancient, veteran or notable trees (Woodland Trust 2020) were combined with location data for protected areas from the CDDA (European Environment Agency 2019). A binary variable was then created to represent whether either feature was present within an 800m buffer around the population-weighted centroid.
Social cohesion	Townsend deprivation index	Townsend deprivation index from the 2011 Census was used to determine deprivation for LSOAs in England and Wales and Data Zones in Scotland (UK Data Service 2017). Higher scores indicate the most deprived areas, while lower (or negative) scores indicate the least deprived areas.
Air pollution	$PM_{2.5}$	Modelled $PM_{2.5}$ concentrations at a 100m resolution from (Phillips et al. 2021) were used to extract the mean exposure to $PM_{2.5}$ within an 800m buffer around the population-weighted centroid.

Area-level characteristic	Proxy variable	Data source and processing
Noise pollution	Road noise pollution (Yes/No)	24-hour annual average noise levels from roads were extracted from the England, Wales and Scotland strategic noise maps (Department for Environment, Food and Rural Affairs 2017, Scotland's Environment 2017, Welsh Government 2017) and were converted into 25m resolution. As the noise maps were derived along major traffic routes only a large number of LSOAs contained no noise pollution. To accommodate the large number of zero cases, noise pollution was converted into a binary variable. This variable groups together LSOAs that contain noise pollution from major roads (within an 800m buffer of the population-weighted centroid) and those with no noise pollution from major roads.
Spatial and temporal sunshine	Hours of sunshine	The sunshine hours for the individual's LSOA population-weighted centroid for the month in which the individual was interviewed was extracted from 1km resolution data (Met Office 2020)

5.5.2 Analysis

5.5.2.1 Sample stratification

In order to limit inference to urban areas in Britain, the sample was restricted to urban LSOAs, identified using the 2011 Urban Rural Classification (Office for National Statistics 2017). All outliers and individuals with missing data were excluded (details provided in Appendix B). To maximise the sample size available for analysis, all waves of the BHPS were used. To remove any potential non-independence among members of the same household and waves, one person from each household was selected at random. A random wave was selected for individuals that participated in multiple survey waves.

Data exploration showed that the majority of individuals (94%) that responded to the BHPS were surveyed in the autumn and winter months. Low sample sizes in the summer and spring precluded the modelling of seasonal variation effects on mental health and were, therefore, removed from the sample, leaving respondents interviewed between September 1st and March 1st. The sample was then separated into two samples for subsequent analysis: individuals with and individuals without a private garden. These samples were analysed separately because private garden access is strongly correlated with other socio-demographic factors that confound mental health (Office for National Statistics 2020b).

5.5.2.2 Statistical matching

We used statistical matching to control for confounding variables that influence mental health. We classified public greenspace access as a binary variable denoting whether public greenspace was present within 800-m of the population-weighted centroid. Greenspace access was designated as the focal treatment variable to which the following individual-level and area-level confounders were matched: age, income per person per household, marital status (married not married), higher education attainment (yes/no), gender, Townsend deprivation index, presence of designated areas (yes/no), bird species richness, Normalised Difference Vegetation Index (NDVI), air pollution, presence of noise pollution (binary) and daylight hours.

Three widely-used matching methods were implemented using the R package ‘MatchIt’ (Ho et al. 2011): nearest neighbour matching, optimal full matching, and Mahalanobis distance matching. The matching method that yielded the “best” matched samples was selected for regression analysis, which corresponded to the method that minimised the standardised mean differences in variables between the control and treatment groups. (Stuart 2010, Schleicher et al. 2020). While matched samples were similar across all methods, the nearest neighbour matching method achieved marginally better matching (Appendix C). Statistical matching reduced the BHPS sample from 7,206 to 4,768 individuals with a private garden and from 1,515 to 480 individuals without a private garden. Descriptive statistics for the two matched samples are shown in Table 9.

Table 9: Descriptive statistics for the matched BHPS data, private garden, and no private garden samples. For continuous variables, the mean is reported with the standard deviation (sd) in parentheses.

		Private garden		No private garden	
Categorical variables		*n*	%	*n*	%
Individuals		4,768	100.00	480	100.00
No public greenspace		2,384	50.00	240	50.00
Poor mental health		1,237	25.94	139	28.96
Gender:	Male	2,234	46.85	220	45.83
	Female	2,534	53.15	260	54.17
Married		2,503	52.50	112	23.15
Not married		2,265	47.50	368	76.67
Higher education		806	16.90	88	18.33
No higher education		3,962	83.10	392	81.67
Presence of protected areas		2,282	47.86	274	57.08
No protected areas		2,486	52.14	206	42.92
Presence of noise pollution		3,334	69.92	359	74.79
No noise pollution		1,434	30.08	121	25.21
Continuous variables		*n*	**Mean (sd)**	*n*	**Mean (sd)**
Age		4,768	41.31(16.07)	480	37.81(17.81)
Income/person/household (£)		4,768	924.24(501.39)	480	904.49(531.76)
Townsend index of deprivation		4,768	-0.79(2.91)	480	2.91(2.83)
NDVI		4,768	0.69(0.08)	480	0.66(0.08)
Bird species richness		4,768	199.51(30.18)	480	198.76(29.61)
Air pollution (PM2.5)		4,768	0.17(0.05)	480	0.18(0.05)
Hours of sunshine		4,768	3.55(1.08)	480	3.49(1.10)

5.5.2.3 Multimodel inference

To quantify the effect of greenspace presence on the risk of poor mental health, Generalised Linear Models (GLMs) with a logistic link function were fitted to two matched datasets, corresponding to samples of individuals with and individuals without a private garden. We constructed a ‘base model’ for each sample that included the following confounders of mental health: income per person per household, marital status, age, gender, and highest educational attainment. The samples included multiple individuals per LSOA. The degree of non-independence was greater for the sample of garden owners (1 to 23 individuals, median = 1), than for the no garden sample (1 to 6 individuals, median = 1). Using the base models, we explored whether the inclusion of a random intercept term, identifying individuals from a common LSOA, improved model fit for each sample. Base models with and without the random intercept were compared using a log-likelihood ratio test. The inclusion of a random intercept term improved model fit for the sample of private garden owners only. The base model for the garden owning sample, therefore, included this intercept term (i.e. was a Generalised Linear Mixed Model, GLMM). These base models were compared with models that varied in their inclusion of the following variables: public greenspace, Townsend deprivation index, a quadratic function of age, and interactions between public greenspace, gender, and age. These interactions were examined because of their support in the literature (e.g., Astell-Burt et al. 2014). This yielded a total of 56 models for comparison.

The ‘dredge’ function from the R package ‘MuMIn’ (Bartoń 2016) was used to run and compare model fits using the Akaike information criterion (AIC). The top-performing models were identified using a ΔAIC threshold of <6 (Burnham et al. 2011, Harrison et al. 2018). The goodness of fit of each top-performing model was estimated using the theoretical marginal (Rm^2) and theoretical conditional (Rc^2) coefficients of determination (Bartoń 2016). Multicollinearity tests (including variance inflation factors) were used to ensure models were robust to collinearity (Fox 2015). Model assumptions were checked by plotting residuals versus fitted values against each covariate in the global model (including all variables) and again for the reduced model (variables in the averaged model) using the R package ‘DHARMa’ (Hartig 2018).

The top-performing models (ΔAIC<6) explained 9.1-9.4% and 4.9-8.8% of the variation in mental health for the private garden and no private garden samples, respectively. These models were used to predict the risk of poor mental in response to public greenspace presence (details of model selection and prediction averaging in Appendix D). To visualise the relationship between covariates and the predicted values of poor mental health, we plotted the average predicted probabilities from the top-performing models (Cade 2015), whilst holding all other covariates at their median or mode value for numerical and categorical variables, respectively. Public greenspace was “access” was used to generate Figure 13, see Appendix E for the corresponding figure for “no access”. Confidence intervals for the predicted values were obtained through bootstrapping with 1000 replications. As a key decision with statistical matching concerns the variables used to match on, additional models were fitted using data that matched only socio-demographic variables and data with no matching to see how the matched variables influenced model results (Appendix F). Indeed, the difference in predicted poor mental health between individuals with and without a garden is observably less without statistical matching (Appendix, Figure 23). Therefore, without using statistical matching, erroneous conclusions could have been made.

Chapter 6 The effects of moving to areas with higher greenspace quality on mental health

6.0 Abstract

As the research into the effect of urban greenspace on mental health continues to grow, there is increasing interest in identifying which characteristics of urban greenspace are contributing to the mental health benefits obtained. In this study, a hypothesis driven approach is taken to identify which greenspace characteristics have the greatest effect on mental health. A total of 16 different measures of greenspace were identified and categorised into the following characteristics: proximity, quantity, quality, and accessibility. Individual-level data on mental health status were obtained from a nationally representative longitudinal survey from Great Britain (the British Household Panel Survey). The sample consisted of individuals who moved between urban areas and had a minimum of 3 years of participation in the survey before and after their move, excluding the year before the move and the year of the move (n = 492). Using the repeat measures from the individuals before and after their move, a Before-After Control Intervention study design was used and the effect of the change in greenspace characteristic on mental health was calculated. To account for the effect of individual-level heterogeneity on mental health, mixed models were used. A total of 11 models were compared, each one with a different measure of greenspace and an additional baseline model with no measure of greenspace. The models were ranked according to their fit and compared their performance compared to the baseline model. Two of the models with greenspace measures resulted in an improved fit compared to the baseline model. Bird species richness, a proxy for greenspace quality, resulted in the best performing model to explain mental health, closely followed by greenspace proximity (as measured by distance to public greenspace). All other measures tested (proxies for quantity and access) did not provide an improved model explanation for mental health compared to the baseline model without greenspace. The results of this study highlight the importance of greenspace quality and proximity to mental health. Therefore, we recommend that these characteristics are prioritised in future environmental policies to promote public mental health benefits.

6.1 Introduction

Globally depression is the leading cause of ill health and disability (World Health Organization 2017). Numerous studies have demonstrated the positive association between urban greenspace and mental health and wellbeing (for reviews see: Keniger et al. 2013, Hartig et al. 2014, Shanahan et al. 2015). Subsequently, the provision and enhancement of greenspace is being discussed as a means to reduce the burden of poor mental health (e.g., Public Health England 2020, World Health Organization 2021). Despite rapid growth in this field, very few studies (e.g., van den Bosch et al. 2015, Wheeler et al. 2015, Akpinar et al. 2016, Astell-Burt and Feng 2019) have asked whether different greenspace characteristics result in the same mental health benefit. Instead, the majority of studies in this field adopt a restricted characterisation of exposure to urban greenspace, such as overall "quantity" (Collins et al. 2020). The use of simplistic characterisation may be over-simplifying an individual's exposure to urban greenspace (Wheeler et al. 2015, Collins et al. 2020). With 68% of the world's population projected to live in cities by 2050 (United Nations 2018) it is important to identify which greenspace characteristics affect mental health, to more practicably inform urban planning and policy. This study aimed to address this gap by identifying the characteristics of urban greenspace in best explain mental health using a hypothesis-driven approach and a quasi-experimental study design to improve causal inference.

6.1.1 The hypothesised link between greenspace characteristics and mental health

The biophilia hypothesis proposes that humanity has an innate affinity for the natural environment that has evolved by natural selection (Wilson 1984). Therefore, exposure to nature can promote stress reduction (Ulrich 1983, Ulrich et al. 1991) or psychological restoration (Kaplan and Talbot 1983, Kaplan and Kaplan 1989, Kaplan 1995). However a more comprehensive consideration of this hypothesis is required because it is plausible that different characteristics of urban greenspace may result in different psychological responses (Markevych et al. 2017, Pope et al. 2018, Wyles et al. 2019). For example, four different but complementary hypotheses are presented in Table 10. Each hypothesis relates to a different greenspace characteristic (as defined in Collins et al. 2020). Although all characteristics are hypothesised to have a beneficial effect on mental health (see Table 10), the policy implications of each hypothesis would be substantially different.

Table 10: *a priori* hypotheses linking greenspace characteristics to mental health. Hypotheses and greenspace characteristics were developed based on the findings of a recent systematic map of studies exploring the effect of greenspace on mental health (Collins et al. 2020).

Greenspace characteristic	Hypothesis
Proximity	Living in an area that is in closer proximity to greenspace will reduce the probability of poor mental health.
Quantity	Living in an area with more greenspace (i.e., a greater quantity of greenspace) will reduce the probability of poor mental health.
Quality	Living in an area with higher quality greenspace will reduce the probability of poor mental health.
Accessibility	Living in an area with access to greenspace will reduce the probability of poor mental health.

6.1.2 Improving causal inference when exploring the effect of greenspace on mental health

The majority of studies using secondary data set out to quantify the effect of greenspace on mental health using cross-sectional mental health data, where data are from a single point in time (Collins et al. 2020). In such datasets, various environmental and social drivers of mental health are typically correlated; e.g., deprivation and access to quality greenspace (Mears et al. 2019). As a result, establishing causal inference about greenspace effects is challenging. Longitudinal datasets, wherein the same individuals are surveyed repeatedly over time, provide an opportunity to control for individual-level, time-invariant, unobserved factors and provide stronger evidence of causality. Studies that have used longitudinal data to measure greenspace effects on mental health have tended to adopt a "life-course perspective", that aims to establish how the relationship between greenspace and mental health varies as a person ages (Astell-Burtet al. 2014). A life-course perspective can identify critical periods in life when greenspace is particularly pertinent for understanding mental health (Pearce 2018). However, although informative, studies that adopted a life-course perspective have not quantified the individual-level effect of a change in greenspace exposure.

To improve causal inference, quasi-experimental designs can be applied to longitudinal datasets. Specifically, individuals who experience changes in their exposure to residential greenspace parameters by moving residence ("movers" from hereon) can be used to emulate a Before-After

(BA) design. In this approach, mental health pre -and- post-move can be used to quantify the effect of moving on an individual's mental health, and whether this effect varies in relation to the change in greenspace exposure. Conceptually, this is comparable to a BA study design, or a Before-After Control Intervention (BACI) design if the data permits a non-mover control for each mover. BACI study designs are considered optimal to help isolate the effect of a change, or "treatment", from a variable outcome (Wauchope et al. 2021). One previous study that assessed the effect of multiple greenspace characteristics on mental health using a BA design was identified: van den Bosch et al. (2015). However, in this study, the scope was limited to rural and sub-urban neighbourhoods and it is not known if similar patterns can be observed for an urban context. In the context of rapid urbanisation (United Nations 2018), this is a vital gap in the knowledge that needs to be addressed to help inform urban policy and planning. To address this gap, this study adopted a quasi-experimental design to improve causal inference.

6.2 Methods

This study used longitudinal data from the British Household Panel Survey (BHPS; University of Essex 2018), a multi-purpose longitudinal survey that started in 1991 and finished in 2008. The survey consisted of a nationally representative sample of more than 10,300 individuals from 5,500 households in England, Scotland, Wales and Northern Ireland (University of Essex 2018b). Within the survey, each year is referred to as a "wave" such that the first wave (Wave 1) was in 1991, and the last wave (Wave 18) was in 2008. The survey gathered information on socio-demographic variables including household income, gender and highest education attainment, in addition to the individual's health and mental health. The BHPS' household geographic identifier was used to link individuals to a 2011 Lower Layer Super Output Area (LSOA) or, for those living in Scotland, a Data Zone. On average, LSOAs contained 1,500 residents and Data Zones had between 500 to 1,000 residents. LSOAs and Data Zones are standard geographic units that are commonly used to report small-area statistics. Both have been previously used in research exploring the effect of greenspace on mental health (e.g., Mitchell and Popham 2008, Wheeler et al. 2015, Brindley et al. 2018).

6.2.1 Measures of greenspace characteristics

A systematic approach was taken to select measures of greenspace to include in this analysis. The systematic map of the greenspace and mental health literature (Collins et al. 2020) was used to compile a list of greenspace measures and their respective data sources that have previously been used to explore the effect of greenspace on mental health. The measures and data were then reviewed to determine the data used and whether the data were: (1) available for urban areas within England, Scotland and Wales, collectively known as Great Britain (GB), and (2) if not available, were suitable alternatives available for urban areas within GB. A total of 16 measures of greenspace were identified and were categorised into one of the four hypothesised greenspace characteristics (Table 10). Following this approach one measure of proximity, two measures of quantity, three measures of quality, and 10 measures of accessibility were identified (Table 12).

6.2.1.1 Greenspace proximity

The Ordnance Survey's Mastermap (OSMM) Greenspace Layer (version April 2020), which maps public parks and gardens, was used to determine the presence of public parks and gardens. Greenspace proximity was calculated as the distance from the population-weighted LSOA centroid to the nearest public greenspace using the R 'sf' package (Pebesma 2018).

6.2.1.2 Greenspace quantity

Greenspace quantity was defined as the total area of greenspace within 800m of the LSOA's population-weighted centroid. An 800m buffer was chosen to align with the Fields in Trust's accessibility standards (Fields in Trust 2020), and the increasingly popular 20-minute neighbourhoods concept where people should be able to meet most of their everyday needs within a 20-minute return walk (Emery and Thrift 2021). The concept has been implemented by local authorities and city planners in Melbourne (Victoria State Government Department of Environment 2021), Perth (Hooper et al. 2020) and more recently identified as a potential strategy for the Scottish government (O'Gorman and Dillon-Robinson 2021). Two measures of greenspace quantity were calculated: (1) the total area of public parks and gardens, and (2) the total area of all greenspace. Both measures of availability were derived from the OSMM Greenspace Layer (version April 2020). For the former, only greenspace categorised as "public parks and gardens" was used to calculate the area of greenspace within an 800m buffer of the individual's population-weighted centroid. The latter used all 18 categories of greenspace types within an 800m buffer, such as school grounds, playing fields and golf courses. The two measures of greenspace quantity were calculated using the R 'landscapemetrics' package (Hesselbarth et al. 2019).

6.2.1.3 Greenspace quality

Three different measures were used to represent greenspace quality: (1) bird species richness, (2) presence of protected areas, and (3) greenness. First, bird species recorded at a 10km resolution (Gillings et al. 2019) were used to calculate bird species richness, with richness at each LSOA population-weighted centroid extracted using the R 'raster' package (Hijmans 2021). Rarer species recorded at coarser resolutions (>10km) were not used, as these species would have generally not been seen by or interacted with most people (Gaston et al. 2018, Gaston 2020). Second, the presence of protected areas was identified by combining two datasets: (1) location of ancient, veteran or notable trees (Woodland Trust 2020) and (2) location of protected areas (from the Common Database of designated areas, CDDA; European Environment Agency, 2019). A binary variable was then created to represent whether either feature was present within an 800m buffer around the population-weighted centroid. Third, Normalised Difference Vegetation Index (NDVI) was used to represent local area greenness. NDVI was calculated using Landsat 8 surface reflectance products (United States Geological Survey 2017) at a resolution of 30 m × 30 m. Images were processed in Google Earth Engine and the maximum NDVI values over eight years were obtained. NDVI values for LSOAs were the mean value within the population-weighted centroid 800m circular buffer calculated using the R 'raster' package (Hijmans 2021). Similar to measures of greenspace quality, an 800m circular buffer was selected for all measures of greenspace quality to align with the Fields in Trust's accessibility standards (Fields in Trust 2020) and the concept of the 20-minute neighbourhood (Emery and Thrift 2021).

6.2.1.4 Greenspace accessibility

Recognised standards and guidelines were used to measure the accessibility of greenspace, specifically: (1) the Accessible Natural Greenspace Standards (ANGSt; Natural England 2010), and (2) the Fields in Trust's access requirement (Fields in Trust 2020). The ANGSt are seen as a useful tool for local authorities to assess whether their current provision of publicly accessible greenspace is adequate. These standards emphasise the potential benefits nature and greenspaces can provide to the people nearby. The original standards were developed in the early 1990s and reviewed in 2008 by Natural England (Natural England 2010). They are currently undergoing a review by Natural England (2022). Here we have adopted the more rigorous draft guidelines (Table 11) in favour of the 2008 guidelines. To test the sensitivity of the analysis to the ANGSt threshold areas, the presence of any sized greenspace within a 200m and 300m buffer of the LSOA population-weighted centroids was also tested. Unlike the ANGSt, the Fields in Trust does not specify a threshold size within their requirement of greenspace within 800m of a person's home which represents the average distance travelled in a ten-minute walk (Fields in Trust 2020).

The presence of greenspace, as derived from the OSMM Greenspace Layer, was used to determine if an LSOA had accessible greenspace as defined by the ANGSt and Fields in Trust access requirements. The OSMM Greenspace Layer was a fine-scale vector dataset of urban greenspaces in GB and therefore enabled an accurate assessment of whether greenspaces reached the threshold size required by ANGSt. The OSMM Greenspace Layer provided information on 18 different greenspace types (Ordnance Survey 2022). The assessment of greenspace access used two categorisations of these greenspace types: (1) public parks and gardens only, and (2) all greenspaces.

Table 11: A summary of Natural England's draft Accessible Natural Greenspace Standards (ANGSt)

Criterion	**Size and distance criterion**
Doorstep greenspace	0.5ha within 200m
Local natural greenspace	2ha within 300m
Neighbourhood natural greenspace	10ha within 1km
Wider neighbourhood	20ha within 2km
District	100ha within 5km
Sub-regional	500ha within 10km
Local nature reserves	1ha per 1,000 people

6.2.2 Treatment group assignment

We identified categorical "treatment groups" for each greenspace characteristic that distinguish individuals by their change in greenspace exposure experienced when moving. That is, each individual was assigned to one treatment group per characteristic (Table 12). Depending on the greenspace characteristic and whether there were any individuals in the sample that experienced "no change" in the character when they moved, the treatment groups were either binary (e.g., the person moved closer or further from public greenspace) or ternary to include the "no change" treatment group.

Table 12: Greenspace characteristics and their respective treatment groups

Characteristic		Greenspace tested	Treatment groups
Proximity	Distance to public greenspace	Public greenspace	1. Closer proximity 2. Further proximity
Quantity	Public greenspace area	Public greenspace	1. Increase in quantity 2. Decrease in quantity
	Total greenspace area	All greenspace	1. Increase in quantity 2. Decrease in quantity
Quality	Bird species richness	NA	1. Increase in quality 2. No change 3. Decrease in quality
	Greenness	NA	1. Increase in quality 2. Decrease in quality
	Protected area	NA	1. Increase in quality 2. No change 3. Decrease in quality
Access	ANGSt doorstep greenspace	Public and all greenspace	1. Access to no access 2. No change 3. No access to access
	ANGSt local natural greenspace	Public and all greenspace	1. Access to no access 2. No change 3. No access to access
	ANGSt neighbourhood natural greenspace	Public and all greenspace	1. Access to no access 2. No change 3. No access to access
	ANGSt wider neighbourhood	Public and all greenspace	1. Access to no access 2. No change 3. No access to access
	ANGSt district	Public and all greenspace	1. Access to no access 2. No change 3. No access to access
	ANGSt sub-regional	Public and all greenspace	1. Access to no access 2. No change 3. No access to access
	ANGSt local nature reserves	Public and all greenspace	1. Access to no access 2. No change 3. No access to access
	Greenspace within 200m	Public and all greenspace	1. Access to no access 2. No change 3. No access to access
	Greenspace within 300m	Public and all greenspace	1. Access to no access 2. No change 3. No access to access
	Fields in Trust greenspace within 800m	Public and all greenspace	1. Access to no access 2. No change 3. No access to access

Note: ANGSt - Accessible Natural Greenspace Standards (Natural England 2010)

6.2.3 Individual-level variables

In the BHPS, individuals self-assess their mental health using the 12-item General Health Questionnaire (GHQ-12; Goldberg and Hillier 1979). The GHQ-12 is considered to be a robust screening tool that is used to assess a person's risk of common mental disorders such as anxiety and depression (Goldberg and Hillier 1979, Goldberg et al. 1997, Jackson 2006). The GHQ-12 is robust to differences in gender, age and education (Goldberg et al. 1997). The 12 items of the GHQ-12 responses consisted of two lower categories and two higher categories (i.e., a four-point scale). For this analysis, 'GHQ method' (Hankins 2008), was adopted and the responses to each item were coded as 0 and 1, for the lower and upper categories respectively. The newly coded responses were then summed to create a scale from 1 to 12. This scale was then used to create a dichotomous measure of poor mental, where all individuals with scores $\geq$3 being classified as having poor mental health (Shelton and Herrick 2009).

From the BHPS, additional information on income, age, gender, marital status, and highest educational attainment were identified as potential individual-level confounding factors. Monthly household income was adjusted by household size to create the variable: "income per person per household". Unlike previous studies (e.g., White et al. 2013, Alcock et al. 2014, Houlden et al. 2017), individual-level variables such as hours of physical activity, commute time, and physical health conditions were not adjusted for because they were considered post-treatment effects (i.e., not necessarily independent of access to public greenspace). Although not considered a post-treatment effect, ethnicity was not included as a confounding variable in this analysis because the BHPS's small and imbalanced sample of Black, Asian and Minority Ethnic (BAME) made ethnicity an unsuitable variable to include in a mixed-effect model, particularly given ethnicity's known collinearity with other variables such as private gardens (Office for National Statistics 2020b). To establish which waves occurred "before" an individual moved, and which waves were after their move, the BHPS' geographic identifiers were used to create the binary variable "before-after move".

6.2.4 Area-level variables

Two area-level characteristics that may confound the effect of greenspace exposure on mental health were identified: deprivation and air pollution. The Townsend deprivation score from the 2011 Census was used to determine deprivation for LSOAs in England and Wales and Data Zones in Scotland (UK Data Service 2017). Higher scores indicate the most deprived areas, while lower (or negative) scores indicate the least deprived areas. Air pollution was measured using modelled $PM_{2.5}$ concentrations at a 100m resolution (Phillips et al. 2021). The mean exposure to $PM_{2.5}$

within an 800m buffer around the population-weighted centroid was calculated. As area-level variables could vary with the move, all area-level variables were tested for their potential correlation with the variable “before-after move”. No correlations between the area-level variables both before and after moving were identified (Appendix G).

6.2.5 Sample stratification

Analysis was restricted to individuals living in urban areas of GB, to ensure full coverage of the greenspace characteristics data. From this subsample, individuals who had moved between urban areas during the survey period were selected (*n* = 4,635). For individuals who moved multiple times during the survey (*n* = 1,833), the location with the most repeated observations both before and after was selected for the analysis. Individuals who moved within urban LSOAs and therefore did not experience a change in greenspace were excluded (*n* = 849). Observations taken within the years immediately before and after the individual’s move were then excluded to reduce immediate relocation influences on mental health (i.e., to avoid capturing the stress of moving house within our estimate). The remaining movers (*n* = 3,463) were then filtered to those with a minimum of three waves both before and after the move (*n* = 579). As private garden ownership has been shown to positively influence mental health (Chapter 5), to minimise the influence of private gardens on this analysis the sample was restricted to those who did not change their private garden ownership between moving (i.e., only those who moved from a house with a private garden to another house with a garden and vice versa were included in the analysis). The final sample for analysis consisted of 4,552 observations from 492 individuals, of which 479 had a private garden and 13 had no private garden. The median number of observations per person is 10 waves. A summary of the sample characteristics are presented in Table 13, Appendix H presents a full summary according to years before and after moving.

Table 13: Individual and area-level descriptive statistics for the filtered BHPS data for continuous variables, the mean is reported with the standard deviation (sd) in parentheses.

Variable		***n***	**Mean (sd)/%**
Individuals		492	100.00%
Poor mental health		86	17.48%
Gender:	Male	207	42.07%
	Female	285	57.93%
Married		167	33.94%
Not married		325	66.06%
Age		492	40.33 (11.81)
Income (£/person/household)		492	1,139.88 (608.48)
Higher education		122	24.80%
No higher education		370	75.20%
Townsend index of deprivation		492	-0.63 (2.46)
Air pollution ($PM_{2.5}$)		492	0.18 (0.06)
Presence of noise pollution		169	34.35%
No noise pollution		323	65.65%
Presence of protected area(s)		233	47.36%
No protected area(s)		259	52.64%

6.2.6 Base model

We developed a base model from which the treatment models were compared to assess added inference of the different greenspace characteristics. We fitted generalised linear mixed models (GLMMs) with a logistic link function to the binary mental health scores, to account for the hierarchical structure of the dataset wherein repeat observations (waves) before and after the move are nested within the individual. The base model included the following individual-level confounders: income (£/person/household), gender (male/female), age (years), married (Yes/No), and higher education (yes/no).

Area-level confounders were tested in a step-wise manner and were only included in the base model if they improved model fit, assessed using Akaike Information Criterion (AIC) and Likelihood Ratio Tests (LRTs). The 'pbkrtest' package (Halekoh and Højsgaard 2014) was used to perform restricted LRTs. Random intercepts were specified to identify repeated observations for each individual. To allow an individual's probability of poor mental health to change after they moved, a random slope for the binary variable "before-after move" was fitted. Crossed random intercepts were tested for households and LSOAs to accommodate the structure of the data, as individuals can appear in multiple households and all individuals will appear in multiple LSOAs (one before the move and one after).

The final base model consisted of both area-level variables (deprivation and air pollution), as they were found to add inference (LRT p-value <0.01 and 0.01 respectively). We found that adding random intercepts for both household and LSOA resulted in a singular model, i.e., there was not enough clustering at these levels, therefore these were not included in the hierarchal structure of the base model.

6.2.7 Model comparison

Each greenspace characteristic, and its respective treatment groups, were added to the base model in turn. To test the average effect of a treatment on the individual, an interaction was fitted between the treatment variable and the move variable. Treatment models were compared to the base model using AIC. Treatment models with a lower AIC than the base model were deemed to have the "best" fit, and as such, the characteristic the treatment represented provided the most inference in the greenspace and mental health relationship.

Greenspace characteristics were tested individually to avoid multicollinearity. Generalised Variance Inflation Factor (GVIF) scores were used to check the independence of all variables. The goodness of fit of each model was calculated using the theoretical marginal (R^2c) and theoretical conditional (R^2c) coefficients of determination (Bartoń 2016). A total of 24 greenspace characteristics were tested. The sample sizes of each treatment group were assessed and a minimum threshold of 50 individuals for each treatment group was chosen. This threshold was considered cautious based on recommendations made from mixed-model simulation studies (Maas and Hox 2006, Paccagnella 2011, Schoeneberger 2015, Sommet and Morselli 2017). All models with treatment groups that did not meet the threshold were dismissed.

To visualise the relationship between independent variables and the probability of poor mental health, we plotted the predicted probabilities from selected models, whilst holding all other covariates at their median or mode value for numerical and categorical variables, respectively. The 95% confidence intervals for the predicted intervals were obtained through bootstrapping with 1000 replications. Model assumptions were checked by plotting residuals versus fitted values against each covariate using the R 'DHARMa' package (Hartig 2018). In addition to the variables in the model, the residuals were assessed for temporal and spatial dependency using the survey year and location of the population-weighted centroid (Appendix I).

6.3 Results

We compared models that varied in their inclusion of a range of greenspace characteristics related to accessibility, proximity, quantity, and quality. In total, 24 treatments were linked to *a priori* hypotheses and tested, but only ten had sufficient samples across treatment groups to perform the GLMMs (see Appendix J for summary of treatment group sizes). Of the ten characteristics, four are related to greenspace access and five other greenspace characteristics.

Although all treatments were supported by a set of *a priori* candidate models, only two models (bird species richness and distance to public greenspace) were found to explain more variation in poor mental health compared to the base model with no treatment and therefore are deemed to provide added inference to the base model (Table 14). We consider these two measures of bird species richness and distance to public greenspace to relate to greenspace quality and greenspace access, respectively. For all other treatments, the AIC and LRT values indicate that the base model provides a better explanation of the data than with the treatments. The results for the model comparison process for the ten treatments are presented in Table 14, full details for the models included in the step-wise process are presented in Appendix I along with their respective predicted outcomes.

Table 14: Results from the model comparison of the ten different greenspace characteristics and the baseline no treatment model. Models are ranked according to AIC weight, the “best” performing models are those that have a lower AIC value compared to the base (or no treatment) model. Goodness of fit was calculated using theoretical marginal (R^2m) and conditional (R^2c) values following (Nakagawa et al. 2017).

Greenspace characteristic and treatment	**R2m**	**R2c**	**ΔAIC**
Quality – Bird species richness	7.55%	46.18%	0
Proximity – Distance to public greenspace	7.41%	46.26%	4.95
Base model (No treatment)	6.59%	46.13%	7.89
Access – Fields in Trust public greenspace within 800m	7.42%	46.21%	8.49
Quality – Greenness	6.67%	46.24%	9.27
Quality – Protected area(s)	6.98%	46.15%	10.66
Quantity – Public greenspace area	6.69%	46.13%	11.03
Quantity – Total greenspace area	6.69%	46.11%	11.28
Access – ANGSt doorstep total greenspace	6.86%	46.06%	11.59
Access – Public greenspace within 300m	6.81%	46.19%	13.38
Access – Public greenspace within 200m	6.67%	46.19%	14.81

The model with the treatment “bird species richness” had the best fit, followed by “distance to greenspace”; these models explained 46.18% and 46.26% of the variation in mental health, respectively. For these top two models, all treatment groups showed a decrease in the probability of poor mental health after the move, but the magnitude of the effect varied between treatment groups (Figure 14). For the bird species richness model, the treatment group “moved more diverse” reduced the probability of poor mental health post-move the most compared to pre-move levels; the “no change” treatment group had the smallest difference between pre and post-move probabilities of poor mental health (Figure 14a). For the distance to greenspace model the treatment group “moved closer” to the greenspace has the greatest effect on the probability of poor mental health between pre -and- post-move compared to the treatment group “moved further” (Figure 14b).

The other covariates showed comparable trends between the two best-fitting models. The bird species richness model predicted marginally higher probabilities of poor mental health across all covariates (Figure 15). For the categorical variables, the probability of poor mental health was higher for women compared to men and being married had a lower probability of poor mental health than not being married, and having achieved a higher education qualification marginally increased the predicted probability of poor mental health (Figure 15). For the continuous variables, the probability of poor mental health peaked at approximately 50 years old. Income and air pollution all followed a negative linear relationship with poor mental health, whilst deprivation followed a positive linear relationship. The models predicted the probability of poor mental health to decline with an increase in income. The probability of poor mental health increased in more deprived areas and decreased in more polluted areas (Figure 15).

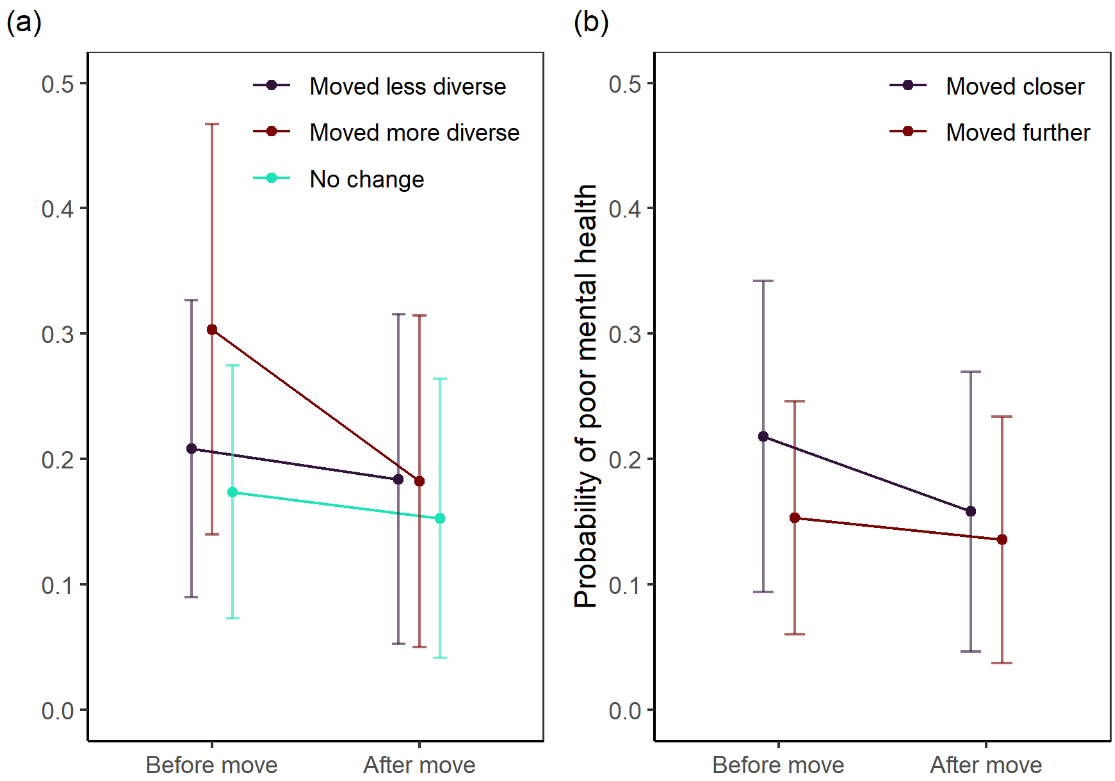

Figure 14: Predicted probability of poor mental health before and after in relation to their respective treatment groups from the 'best' performing models (see text); (a) greenspace quality – Bird species richness. Error bars show the 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications), and (b) greenspace proximity – distance to public greenspace.

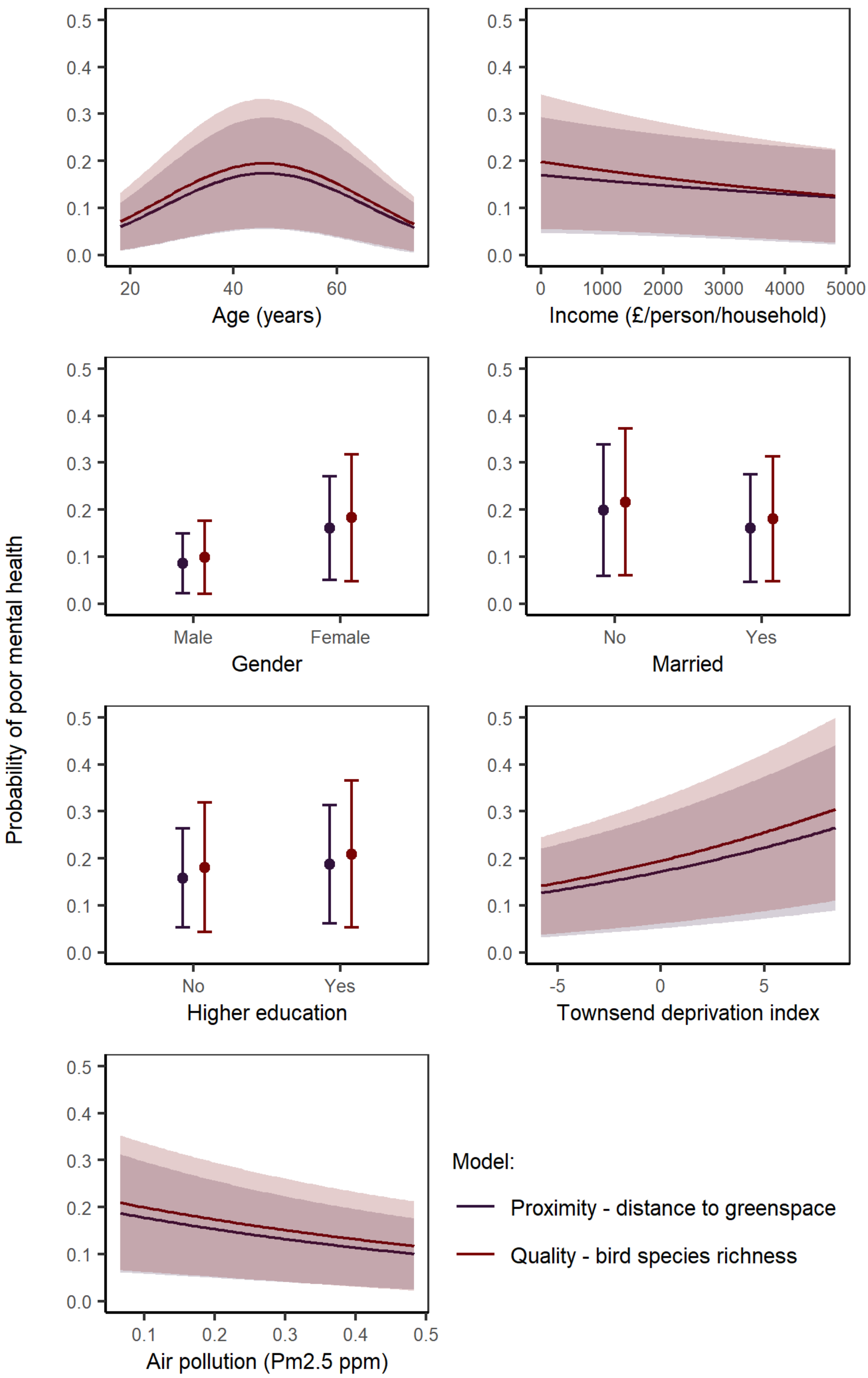

Figure 15: Predicted probability of poor mental health for individual and area-level variables from the best performing models. Shaded regions show the 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

6.4 Discussion

We found that only two models were able to explain more variation in poor mental health compared to the base model with no treatment. These two models, bird species richness and distance to public greenspace, relate to characteristics of quality and access, respectively. Assuming that bird species richness is a proxy for biodiversity (Hillebrand et al. 2018) and that biodiversity can be used to quantify an ecological perspective of greenspace quality (Lovell et al. 2014, Sandifer et al. 2015, Wood et al. 2018). From this perspective, the results support previous findings that greenspace quality is important when exploring whether greenspace affects mental health, highlighting that it is not simply the amount of greenspace that is important when quantifying the effect of greenspace on mental health (Markevych et al. 2017, Pope et al. 2018, Wyles et al. 2019). This is further supported by the relatively poor performance of models with quantity characteristics compared to all quality characteristics (Table 14). Previous studies using biodiversity as a proxy for greenspace quality on mental health have used "site-level" measures of biodiversity (e.g., Fuller et al. 2007, Wood et al. 2018b). Due to data availability, in this study bird species richness was measured at a 10km resolution, which indicates that the relationship between greenspace quality and mental health could exist at a broader scale than previously tested. However, we do recognise that due to the coarse resolution of the data there could be false precision relating to this claim. As we are unable to assign species richness to greenspaces, we may not be capturing greenspace quality specifically, but instead the wider quality of an area. Given the resolution of available data, it is difficult to correct this. We recommend future research to explore whether the relationship between greenspace quality and mental health is scale-dependent. However such exploration is beyond the scope of this paper.

For the best fitting models, all treatment groups showed a decrease in the probability of poor mental health post-move compared to pre-move despite removing the year before and year of the move from the sample. It may be that the beneficial effects of moving to a new neighbourhood are buffering against the loss of beneficial greenspace characteristics. As the selection of a new neighbourhood is non-randomised we are unable to fully account for neighbourhood selection (Oakes 2004). However, despite the overall beneficial effect of moving, the effect sizes of the treatment groups were as hypothesised. Treatment groups relating to "greener" characteristics (e.g., moving to an LSOA with higher species richness and moving closer to public greenspace) reduced the probability of poor mental health more than the no change and "less green" treatment groups. Although the benefits at an individual-level are small, the aggregate gains at an area-level could be important, as multiple people can benefit from one greenspace (White et al. 2013). Therefore, significant aggregate gains could be made by increasing the provision of greenspace quality or decreasing the distance from people's homes to public greenspaces.

For greenspace access, distance to public greenspace provided the best fit compared to all other treatments that represented a greenspace accessibility standard (i.e., ANGSt and distance thresholds). Although these are UK standards, the systematic approach adopted in this paper can be applied to other guidelines to assess whether they are applicable standards for explaining the greenspace and mental health relationship. Unfortunately, given the restricted sample size of movers, we were unable to test the majority of the treatments derived from the ANGSt and therefore we are unable to comment on the suitability of these guidelines for mental health. However, for public greenspace access, three thresholds had sufficient sample sizes for testing, greenspace within 200m, 300m and 800m of the person's home. These treatments did not improve the model fit compared to the no treatment model. This highlights the importance of an individual's closest greenspace (the selected distance to greenspace model) compared to the overall provision and access within a given area.

Restrictions on the sample size also prevented the separation of individuals with and without a private garden and those who changed whether they owned a private garden. This means, despite knowing the importance of private gardens for mental health (Gaston et al. 2005, Brindley et al. 2018, de Bell et al. 2020, and Chapter 5), we were unable to explore whether garden status influences the response to the treatments tested. However, we have minimised the effect of private garden ownership by only including people whose garden status did not change pre -and-post-move in this analysis. The relatively small sample size means we are limited in the power of our results.

An unexpected result showed that higher levels of air pollution result in a reduced probability of poor mental health. This is contrary to previous epidemiological research (e.g., Power et al. 2015, Oudin et al. 2016, Vert et al. 2017, Roberts et al. 2019, Signoretta et al. 2019). One possible explanation could be that the selected air pollution variable may be capturing aspects of unexplained social connectivity. There is evidence that increased social connectivity has a protective effect on mental health (Maas, van Dillen et al. 2009, Sarkar et al. 2013, Ward Thompson et al. 2016), and people living in cities generally have more social connections because a person is statistically more likely to interact with more people in a given space and time (Bettencourt 2021). Social connections are supported structurally by physical infrastructure, including road networks (Bettencourt 2021). As the measure of air pollution used in this study is modelled from the road network (Phillips et al. 2021), we can reasonably assume that air pollution is higher in areas with more roads. These road networks would not only result in higher levels of pollution but also increased social networks and the protective effects of social networks may outweigh the hypothesised negative effects of air pollution on mental health. Building on research from Stier et al. (2021), future research should investigate how the socio-economic networks and or physical infrastructure of cities or urban areas may have protective effects on mental health.

6.5 Conclusion

We have presented a hypothesis-driven approach to improving causal inference with longitudinal data and demonstrated how this approach can be applied to identify characteristics of greenspace that affect the greenspace and mental health relationship. We found that characteristics relating to greenspace quality and proximity (specifically bird species richness and distance to nearest public greenspace) provided the most explanation. Given the other tested models are grounded in theory (i.e., the *a priori* hypothesis approach), the characteristics of greenspace assessed in these models should not be dismissed, particularly since our effective sample size for testing some models was relatively small. However, given limited resources, our results indicate that of the multiple characteristics tested in this study, we recommend that bird species richness and distance to public greenspace should be the focus of future policies for designing greenspaces to promote better mental health and wellbeing.

Chapter 7 General discussion and conclusion

The overall aim of this thesis was to “untangle” the effects of urban greenspace on mental health, and the component chapters of this thesis were guided by aim. To summarise, Chapter 1 presented four research questions developed to achieve this aim and address the gaps in the literature. The gaps in the literature were informed by two reviews: (1) a narrative review, and (2) a systematic map. Chapter 2, the narrative review, summarised the theoretical background linking greenspace to mental health and identified potential pathways from which greenspace could benefit mental health. These pathways were used as a framework for the data landscape, presented in Chapter 4. In addition, Chapter 2, provided an overview of analytical approaches and methods to improve causal inference, which informed the study designs of Chapters 5 and 6. Chapter 3, the empirical review chapter systematically identified studies that explored the effect of greenspace on mental health to objectively detect research gaps. The studies identified in Chapter 3 were used as a starting point for the data landscape (Chapter 4). The data identified in that data landscape (Chapter 4) were used in Chapters 5 and 6. Chapters 5 and 6 use novel study designs to improve causal inference and contribute to answering the research questions outlined in Chapter 1.

This chapter first presents a summary of how the key findings from the empirical chapters (Chapters 4, 5 and 6) address the research questions presented in Chapter 1. Second, this chapter discusses how the thesis contributes to the wider literature, followed by a summary of the limitations that are shared by the empirical chapters. The policy implications of the research findings are then discussed, in addition to the areas for future research. Finally, the overall concluding remarks of this thesis are presented.

7.0 Assessment of research questions

A total of four research questions were presented in Chapter 1. These questions targeted gaps in the literature and guided the analysis presented in this thesis. In this section, the research questions are reflected upon separately and this thesis’ novel contribution to addressing these questions are summarised.

7.0.1 Research question 1: What methodological approaches are used to explore the effect of greenspace on mental health?

Previous reviews of the literature were too specific to identify knowledge clusters and gaps within the methods adopted to explore the effects of greenspace on mental health. In this context, the term “method” refers to the overall approach of the study design and not the specific statistical methods; i.e., what data were used and how was exposure to greenspace measured? Chapter 3 addresses this gap and answers research question 1 by providing a synthesis of the methods and evidence of knowledge clusters and gaps from trade-offs between research methods. Chapter 3 used CA as a novel approach to objectively visualise the characteristics of multiple observational study designs simultaneously. From the CA plot, clusters and gaps in the methods were identified. The key finding was confirmation that the majority of observational studies used measures of greenspace “quantity” with cross-sectional mental health data and less is known about how greenspace “proximity” and “quality” can affect mental health. In the map, quality was defined as a measure of the greenspace’s characteristics and therefore includes greenspace types (e.g., playing field or public park) in addition to measures of other features such as biodiversity and species richness. As such, the evaluation of greenspace types and characteristics was identified as a key knowledge gap for future studies to address. Specifically, the map highlighted the need for exploration of the effect of greenspace characteristics with longitudinal data, instead of the more commonly utilised cross-sectional data to improve causal inference.

7.0.2 Research question 2: How can research methods be modified to improve causal inference when exploring the greenspace and mental health relationship?

The literature review, Chapter 2, discusses appropriate study designs to improve causal inference via the counterfactual framework when using secondary observational data. Statistical matching for cross-sectional data and the analysis of “movers” in longitudinal data to create a BACI study were identified as two suitable study designs to improve causal inference, Chapters 5 and 6 implement these study designs, respectively. Both designs have not previously been used to establish the effect of urban greenspace types or characteristics on mental health in GB. Both Chapters 5 and 6 used a hypothesis-driven to ensure potential confounding factors and pathways to the mental health benefits were considered.

Chapter 5 aimed to improve causal inference through statistical matching. By using one-to-one statistical matching, the study sample was restricted to comparable groups of those with access to public greenspace within 800m (the treatment group) and those without (the control group).

To account for any further systematic differences between the control and treatment groups a logistic regression was performed on the matched data. Statistical matching has been previously applied to the BHPS by Green et al. (2015). Green et al. (2015) used matching to control for confounding factors and reduce bias when examining the association between migration and self-reported health status. Chapter 5 is a novel methodological contribution to the greenspace and mental health literature, as to our knowledge it is the first paper to use statistical matching to demonstrate the effects of urban public greenspace on mental health using secondary data.

Chapter 6 used the longitudinal information provided in the BHPS to create a BACI. Repeat measures from the individuals before and after their move to a new LSOA or Data Zone were used to define treatment groups. As with statistical matching, by defining treatment groups counterfactual questions can be accommodated within the study design; therefore, improving causal inference. The hierarchal structure of the BHPS and individual-level heterogeneity were accounted for using a mixed model with a logistic link function. An interaction was fitted between the “move” event and the greenspace characteristic to obtain the ATE. To our knowledge, Chapter 6 is the first paper within the greenspace and mental health literature to consciously adopt a BACI study within a mixed modelling framework.

In Chapter 5, exploratory sensitivity analysis revealed that the beneficial effects of private gardens compared to greenspace was only established when data matching had taken place. Without matching there was no difference between the mental health outcome of those with or without a private garden. For Chapter 6, no such sensitivity analysis could be undertaken to demonstrate the effect of a BACI design on inference, because conceptually the strength of this analysis lies in its implementation of a counterfactual framework for causal inference. Without a change in greenspace (i.e., the BA or the “before and after” of the BACI) no counterfactual can be established. The study designs in Chapters 5 and 6 are statistically robust and novel and therefore provide methodological contributions to the greenspace and mental health literature in addition to improved causal inference.

7.0.3 Research question 3: What are the relative effects of public and private greenspace on mental health?

To date, the majority of studies have not distinguished between public and private greenspaces. This can result in an overestimate of an individual's exposure to greenspace, or an underestimate of the importance of public greenspace on mental health. This knowledge gap led to the development of research question 3, which is addressed in Chapter 5. In Chapter 5 exposure to greenspace is restricted to public parks and public gardens only, as opposed to an overall measure of greenspace amount (e.g., total greenness of an area or NDVI). To explore the relative effects of private greenspace, individual-level data from the BHPS regarding private garden ownership was used.

Results in Chapter 5 showed that compared to public greenspace, the effect of private garden ownership on mental health is much more pronounced. Private garden ownership affected the pattern of poor mental health between both men and women, specifically having a private garden substantially reduced the peak in poor mental health regardless of the availability of public greenspace in their area. The relative beneficial effects of having a private garden compared to public greenspace change with age and gender. Overall, the findings in Chapter 5 show that exposure to public greenspace within an individual's local area had a much smaller effect on their mental health compared to having a private garden.

7.0.4 Research question 4: What characteristics of greenspace provide the most evidence of a relationship between greenspace and mental health?

There is an overall consensus in the greenspace and mental health literature that characteristics of greenspace, or greenspace "quality", should be investigated to establish what characteristics best explain the greenspace and mental health relationship. Chapter 6 addresses this gap by testing different characteristics of greenspace. Characteristics were identified using a hypothesis-driven approach and characteristics were categorised into measures of quantity, proximity, access and quality (as defined in Chapter 3). Results from Chapter 6 found that characteristics relating to greenspace quality and proximity (specifically measures of bird species richness and distance to nearest public greenspace) provided the most explanation for the greenspace and mental health relationship. Given the other models tested in Chapter 6 were grounded in theory (i.e., the *a priori* hypothesis approach), the characteristics of greenspace assessed in these models should not be dismissed, particularly given the effective sample size for testing some of these models was relatively small.

7.1 Contributions to the literature

This thesis contributes to the literature in terms of the methodologies adopted. The three empirical chapters (Chapters 3, 5 and 6) each adopted a novel methodology. Chapter 3 used CA to visualise the characteristics of multiple observational study designs at once. This enabled the objective identification of knowledge gaps and clusters within the literature. This technique has since been used by Mutono et al. (2021) in their review of literature on the relationship between waterborne diseases and water sufficiency in Africa. Thus, demonstrating that the methods adopted in Chapter 3 are transferable to other research areas. As previously discussed, the study designs in Chapters 5 and 6 are robust and novel contributions to the literature. Although in this thesis, these methods were applied to the greenspace and mental health, these methods can be applied to different topics, provided care has been taken to identify suitable data sources (as in the data landscape in Chapter 4) that align with a set of *a priori* hypotheses that are relevant to their field.

In addition to the methodological contributions, the findings in this thesis addressed several gaps in the greenspace and mental health literature and have contributed to the knowledge of the urban greenspace and mental health relationship. Specifically, Chapter 5 established the importance of private gardens compared to public greenspace on mental health, and Chapter 6 identified a measure of greenspace quality as the most parsimonious model to represent the greenspace and mental health relationship. Both findings are novel in their contribution but also align with the wider literature. First, the importance of private gardens supports growing literature on the beneficial effects of private gardens and gardening on mental health (e.g., Clatworthy et al. 2013, Soga et al. 2017, de Bell et al. 2020). Second, the relative importance of bird species richness (compared to other greenspace characteristics) supports findings from studies that specifically used bird species richness as a proxy to establish the effect of biodiversity on mental health (e.g., Fuller et al. 2007, Luck et al. 2011, Dallimer et al. 2012, Taylor et al. 2015, Wheeler et al. 2015, Cox et al. 2017c, Cameron et al. 2020).

7.2 Limitations

The specific limitations of each empirical chapter are discussed within their respective chapters. However, there are common limitations across the empirical chapters that are discussed here. First, for both Chapters 5 and 6, the BHPS was selected as a suitable survey to obtain individual-level data. However, the BHPS had a small sample of BAME participants, this does restrict some of the transferability of some of the results. This was a particular issue in Chapter 5 which separated the effect of public and private greenspace on mental health because figures from the Office for National Statistics show that BAMEs more likely to not have a garden, but more likely to have access to local greenspace (Office for National Statistics 2020b, 2020c). Therefore, there could be a confounding effect of the individual's race which could not be accounted for due to the restrictions within the BHPS. As identified in Chapter 4, GB is rich in longitudinal data, but despite the small sample of BAME individuals in the BHPS, the survey was deemed the most suitable option for use in this thesis because it contained individual-level data on mental health in addition to private garden ownership. The latter of which was not available in other surveys.

There is a wider issue of sample sizes in the analysis presented in this thesis. In Chapters 5 and 6, the sample sizes were small and were restricted by the study designs to improve causal inference. Improved causal inference is an acceptable trade-off compared to the possibility of improved power, restricting the samples meant that certain questions could not be asked. For example, in Chapter 5 and Chapter 6, shared gardens could not be accounted for as there were too few cases. In Chapter 6, we were unable to account for private garden ownership separately as we did in Chapter 5, because the percentage of people without gardens is small, and smaller still is the percentage of movers without private gardens. Similarly, in Chapter 6, the restriction of the sample to movers meant that the sample sizes to explore the effect of the greenspace accessibility standards were too small.

Looking beyond the effect of sample sizes, data availability meant that despite a human assessment of quality being called for in the systematic map (Chapter 3), the data landscape (Chapter 4) did not identify a suitable objective measure to represent the social value of greenspace. As a compromise, the Townsend deprivation score was used to account for the hypothesised social value pathway to mental health benefits (Chapters 2). However, as deprivation has theoretical links with mental health independent of the presence or absence of greenspace (Allen et al. 2014, World Health Organization and Calouste Gulbenkian Foundation 2014), deprivation was not considered as a measure of greenspace quality.

Finally, due to the limited availability of temporal greenspace data in the UK, in particular during the period in which the BHPS was carried out (1991-2008), in Chapters 5 and 6, it is assumed that greenspace is fixed through time. This can be viewed as a crude assumption, but not unreasonable given the scope of the research (GB) and the general focus on public parks and gardens. If greenspace data were available over time, this thesis would have been able to use different approaches to untangle the effect of greenspace characteristics on mental health. For example, in Chapter 6, it was essential for the BACI design that individuals experienced a change in greenspace. If data were available through time, then the study sample for this chapter would not be limited to individuals who moved. Consequently, a larger sample would have been available for the analysis, which would have improved both power and generalisability.

Overall, the limitations discussed are common with secondary data analysis and primarily relate to data availability. Despite a conscious effort being made to identify the most suitable data for analysis (see Chapter 4 the data landscape), not all limitations could be avoided. However, this thesis demonstrates that despite the limitations of the data robust statistical assessments can be made.

7.3 Policy implications

As discussed in the introduction (Chapter 1), the beneficial effect of greenspace on mental health creates an opportunity to contribute towards achieving the UK's commitment to reverse the decline in species abundance by the end of 2030 (the Environment Act 2021) and the NHS's goal to delivery of protective solutions for mental health (National Health Service Act 2006, Department of Health and Social Care 2021). Chapters 5 and 6 provided evidence to help shape policy recommendations to achieve these complementary targets.

Chapter 6 established that higher species richness reduces the risk of poor mental health. Urban greenspaces are a critical component of the urban GI network that supports biodiversity and species richness (HM Government 2018). To avoid a decline in species richness, changes to planning policy are needed to protect greenspace against future development. The current planning guidance (i.e., the NPPF and NDG) offers limited protection for existing greenspace and the delivery of new GI (Fisher et al. 2021). Of the protection that is available (such as LGS designations), there has been limited uptake, particularly in deprived areas (The countryside charity 2022). To protect greenspaces from future development, it is recommended that the NPPF is amended to define greenspace as an "effective use of land", as is the case with new housing. Through this change in terminology, LPAs would have to view greenspace equal to new housing; thus, making it more difficult for LPAs to justify converting greenspace to housing. In situations where housing is deemed essential and is justified, the NPPF should be amended so that the implementation of GI in a development is not just seen as "nice to have" but as essential (Fisher et al. 2021).

Chapter 5 found that private domestic gardens have a larger beneficial effect on mental health compared to public greenspace. A starting point to increase access to private gardens is to increase their provision in new developments. In England, the responsibility for determining public and private greenspaces lies with the LA. But the LAs are guided by the NPPF and the

National Design Guide to support their decisions (Ministry of Housing, Communities and Local Government 2021b, 2021a). Neither of the guides nor the framework actively encourages the provision of private gardens and instead focuses on the provision of shared and public spaces. Based on the result of Chapter 5, a change to both the guide and framework to emphasise the provision of private gardens to local authorities is recommended. These changes will promote the inclusion of private gardens in future developments and will establish the delivery of private gardens as a priority for LAs.

However, this recommendation to policy falls sort of taking the socio-demographic inequalities associated with private garden access into account, and more needs to be done to make access to private gardens more affordable, which is difficult when evidence from both Los Angeles, United States and Beijing, China, have shown that including private greenspaces can make new developments more desirable and subsequently less affordable (see Conway et al. 2010, and Wu and G. Rowe 2022, respectively). In addition, the effect of increasing the provision of private gardens should be considered within the context of wider biodiversity targets and the importance of species richness on mental health (Chapter 6). As private domestic garden designs are driven by the owner’s personal preferences, to promote species richness, efforts need to be made to encourage wildlife gardening. Currently, Non-governmental Organisations (NGOs) are the main actors promoting wildlife gardening among households in GB. For example, the Wildlife Trust (The Wildlife Trusts 2022), the Royal Society for the Protection of Birds (RSPB 2022), and the Royal Horticultural Society (RHS 2022) have multiple campaigns that encourage garden owners to practice more wildlife-friendly gardening. Due to the scale-dependent pressures in garden management, whereby the individual garden is much smaller than the unit of management needed to retain viable populations (Gaston et al. 2005, Goddard et al. 2010), there is limited scope in which these NGOs can act. The government needs to play a more active role to ensure the benefits to mental health from private gardens and species richness (as identified in Chapters 5 and 6 respectively) are maintained.

7.4 Areas for future research

Within the scope of this thesis, not all the key knowledge gaps highlighted in the systematic map (Chapter 3) could be accounted for. For example, Chapter 3 highlighted a geographic gap in the literature exploring the effect of greenspace and mental health, with the majority of studies clustered within European countries. As GB is particularly well placed in terms of data available for research into greenspace and mental health, it made it a suitable study region for this thesis.

How GB's mental health status compares globally is largely unknown because comparable data on mental health is limited. However, it would be naïve to assume that the associations between greenspace types and characteristics and mental health in GB (established in Chapters 5 and 6) will be similar across different countries due to the differences in climate, vegetation and culture. Future studies, in different countries, should replicate the approaches taken in this thesis to establish whether the findings here (e.g., the relative importance of private gardens and greenspace quality) are common across different countries. In addition to increasing the knowledge base, more research in different countries will improve the geographic gap identified in Chapter 3 which this thesis was unable to address.

In addition, the findings from the systematic map (Chapter 3) emphasised the importance of using objective and repeatable measures of greenspace quality, from both a human and ecological perspective. As discussed in the previous section (Section 7.2 – Limitations) this thesis was unable to account for a human perspective of greenspace quality in its assessment of greenspace characteristics on mental health (Chapter 6), which was highlighted . Therefore, this remains a future avenue of research. As this thesis demonstrates the benefits of taking a hypothesis and stepwise process to identify which greenspace factors influence mental health, future studies with objective human-centric measures of greenspace quality should adopt a similar approach. In doing so, there is the opportunity to compare human and ecological measures of quality and identify which is providing a better explanation of the greenspace and mental health relationship.

Finally, Chapter 3 found that few studies adopted a multi-scale approach, meaning there is little evidence about at which spatial scale(s) the relationship exists. To address this gap, Chapter 3 urged the prioritisation of investigating the scale-dependent greenspace effects. This thesis was unable to fully address the effect of scale due to data limitations. In Chapter 6, different distances for greenspace access were adopted, but due to the BHPS sample size, only three distances (200m, 300m, and 800m) for public greenspace had sufficient sample sizes to perform the analysis. These three distances did show variation with their model fit and public park access within 800m was the best performing model out of the three distances. However, none of the three distances performed better than the base model (without a greenspace measure). As for the other measures of greenspace tested (proximity, quantity and quality), values were determined using an 800m buffer around the population-weighted centroid. Future studies should build upon the findings in Chapter 6 to establish the scale-dependent effects of greenspace on mental health in GB for measures of greenspace access, proximity, quantity and quality.

7.5 Concluding remarks

This thesis first systematically and objectively identified knowledge clusters and gaps (Chapter 3). Second, demonstrated the relative importance of private gardens over public greenspaces for mental health in GB (Chapter 5). Third, established that proxies for greenspace quality and proximity provide the most inference when modelling the effect of greenspace characteristics on mental health in GB (Chapter 6). Together, the findings of this thesis can improve the development of future study designs and inform policy to improve both greenspace and mental health in GB.

Appendix A Chapter 3 supporting information

Table 15: Number of observational studies per different measure of exposure to greenspace

Greenspace exposure measure	Number of greenspace exposure measures	
	One measure of greenspace	Multiple measures of greenspace
Proximity	4	38
Quality	6	35
Quantity	42	51
Visit or activity	34	35
Total	86	159

Note: The total for multiple measures of greenspace exceeds the total number of observational studies as greenspace exposure measures are not mutually exclusive.

Table 16: Number of observational studies for each category of temporal scale assessment per different measure of exposure to greenspace

Number of greenspace exposure measures	Cross-sectional analysis				Longitudinal analysis			
	Proximity	Quality	Quantity	Visit or activity	Proximity	Quality	Quantity	Visit or activity
One	4	5	29	30	0	1	13	4
Multiple	35	29	44	33	3	6	7	2
Total	39	34	73	63	3	7	20	6

Note: The total for multiple measures of greenspace exceeds the total number of observational studies as greenspace exposure measures are not mutually exclusive.

Table 17: Number of observational studies for each category of spatial scale assessment per different measures of exposure to greenspace

Number of greenspace exposure measures	Analysis at a single spatial scale				Analysis at multiple spatial scales			
	Proximity	Quality	Quantity	Visit or activity	Proximity	Quality	Quantity	Visit or activity
One	3	6	34	33	1	0	8	1
Multiple	27	29	36	28	11	6	15	7
Total	30	35	70	61	12	6	23	8

Note: The total for multiple measures of greenspace exceeds the total number of observational studies as greenspace exposure measures are not mutually exclusive.

Table 18: Number of observational studies that used interaction terms in their assessment per different measures of exposure to greenspace

Number of greenspace exposure measures	Analysis excluded interaction terms				Analysis included interaction terms			
	Proximity	Quality	Quantity	Visit or activity	Proximity	Quality	Quantity	Visit or activity
One	1	5	21	30	3	1	21	4
Multiple	24	26	28	22	14	9	23	13
Total	25	31	49	52	17	10	44	17

Note: The total for multiple measures of greenspace exceeds the total number of observational studies as greenspace exposure measures are not mutually exclusive.

Table 19: Number of observational studies that used sensitivity analysis per different measures of exposure to greenspace

Number of greenspace exposure measures	Did not perform sensitivity analysis				Performed sensitivity analysis			
	Proximity	Quality	Quantity	Visit or activity	Proximity	Quality	Quantity	Visit or activity
One	3	5	34	32	1	1	8	2
Multiple	31	32	45	32	7	3	6	3
Total	34	37	79	64	8	4	14	5

Note: The total for multiple measures of greenspace exceeds the total number of observational studies as greenspace exposure measures are not mutually exclusive.

Appendix B Chapter 5 data management details

This SI details how the data were filtered and outliers identified.

First, individuals with missing cases were excluded. Despite the GHQ-12 being administered in all 18 waves of the BHPS, other variables of interest such as garden access were limited to Waves 6 to 18 of the survey. Therefore, by removing missing cases, only Waves 6 to 18 of the BHPS were used in this analysis.

Second, we restricted the age range to 18-75 years old, because of limited cases beyond this range and further outliers were detected using the 'boxplot' function in R. Accordingly, a total of 6 variables were identified as having outliers, and were restricted to the following ranges:

i. Income: £0-£2403.41 per person per household
ii. NDVI: 0.41- 0.88
iii. Townsend deprivation index: -7.03- 10.44
iv. Bird species richness: 117-294 species
v. Air pollution: 0.05- 0.32 $PM_{2.5}$ ppm
vi. Hours of sunshine: 0.94- 7.07 hours

From filtering age and outliers a total of 1,865 individuals were removed from the sample before statistical matching. The total sample before statistical matching was 10,693 individuals for garden and no garden owners combined.

Appendix C Chapter 5 Quality of statistical matching

For each sample (individuals with and without private gardens), three matching approaches were tested: propensity score or nearest neighbour matching, optimal full matching and Mahalanobis distance matching. The quality of the match was assessed by comparing the similarity of control and treatment groups (post matching) and comparing the similarity of the pre-matched treatment group with the post-matched treatment group (Schleicher et al. 2020). Following Stuart (2010), we used a post-matching standardised mean difference of <0.25 as an indication of acceptable balance between control and treatment groups. In this context, the control group was defined as individuals with public greenspace within 800m of their population-weighted centroid and the treatment group are individuals without public greenspace within 800m of their population-weighted centroid.

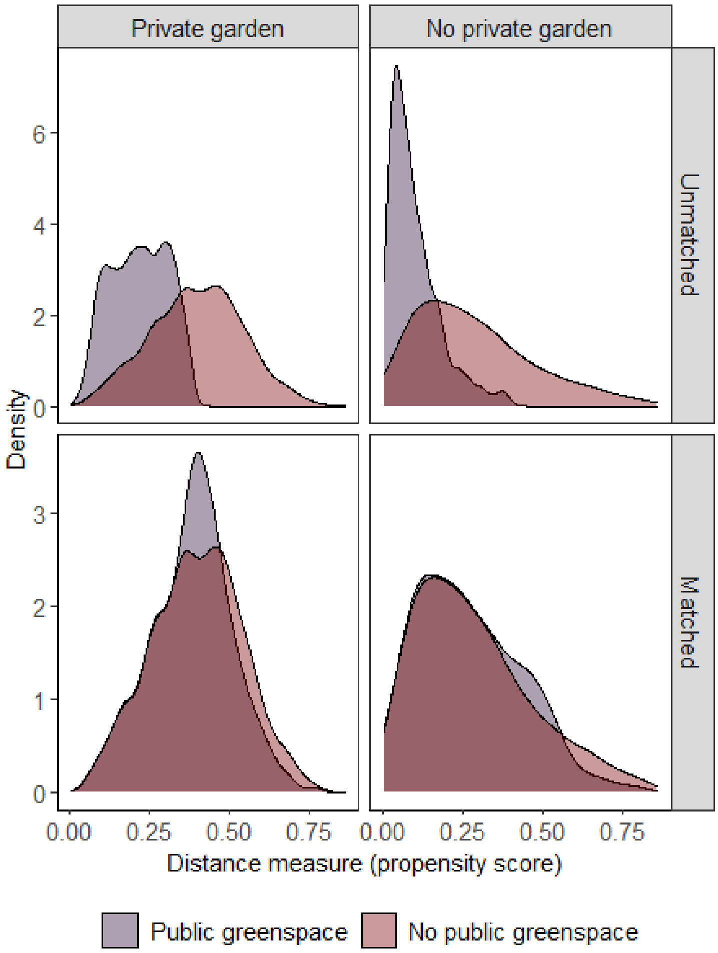

Figure 16: Distribution of covariate distance measures before and after the best matching method; propensity score (or nearest neighbour) statistical matching

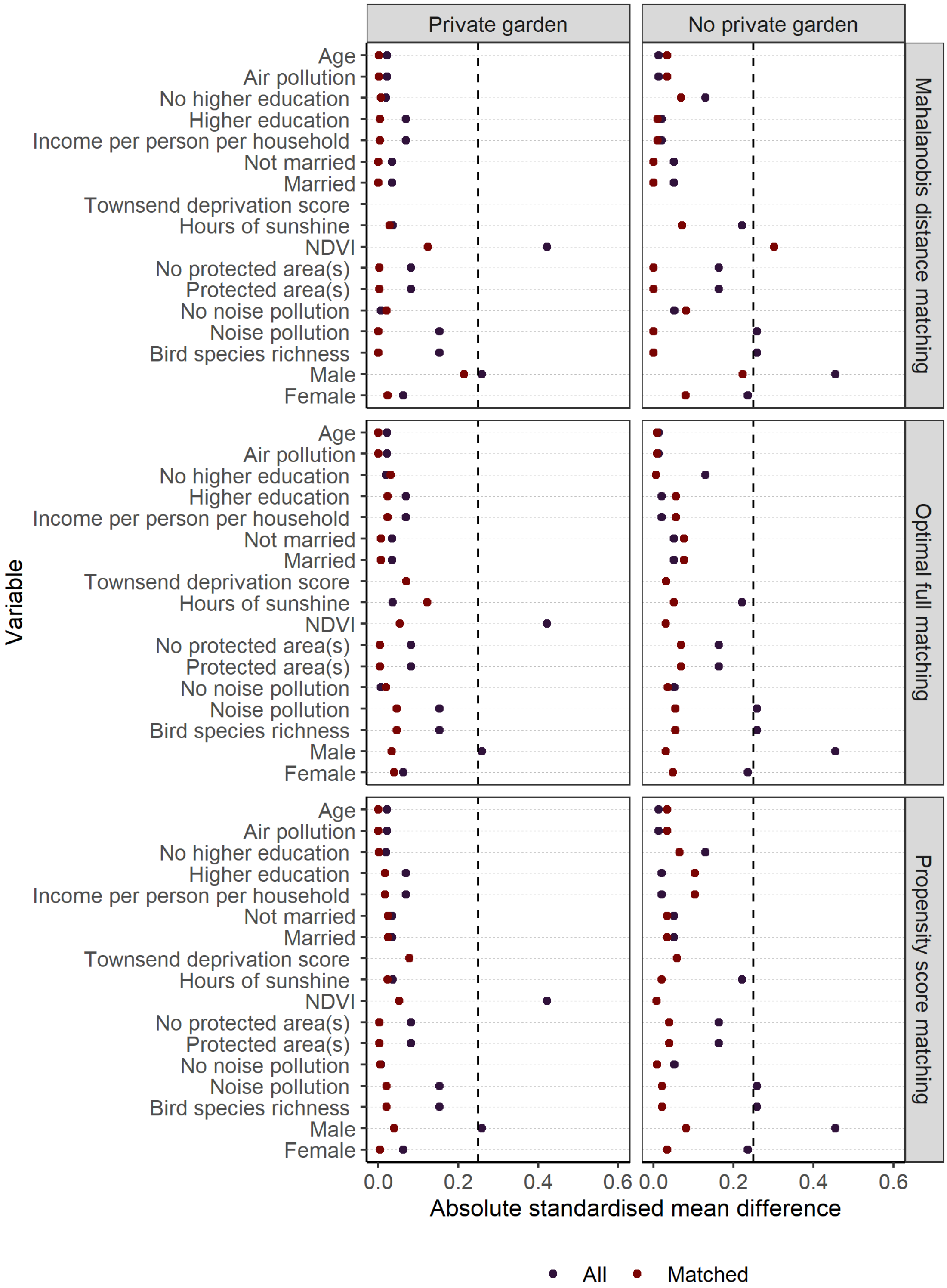

Figure 17: Covariate balance before and after statistical matching, for each statistical matching method selected; propensity score (nearest neighbour matching), optimal full matching and Mahalanobis distance matching

Appendix D Chapter 5 Results of multi-model inference

D.1 Individuals with a private garden

Table 20: Generalised linear mixed models (with random intercept) of individuals with a private garden contained within the top-performing models, identified by Akaike's information criterion (AIC) with ΔAIC<6 (Harrison et al. 2018). Shown are the standardised regression coefficients for each continuous term (column) in each model (rows). For the top-performing models goodness of fit was calculated using theoretical marginal (R^2m) and conditional (R^2c) values following (Nakagawa et al. 2017).

Model number	Intercept	Age	Age^2	Higher Education	Income per person per household	Married	Townsend deprivation index	Public greenspace	Gender	Age:Public greenspace	Age:Gender	Age^2:Public greenspace	Age^2:Gender	Public greenspace:Gender	Age:Public greenspace:Gender	Age^2:Public greenspace:Gender	K	R^2m	R^2c	ΔAIC
\	-1.194	0.034	-0.094	+	-0.180	+	0.085		+								9	0.056	0.091	0.000
4	-1.226	0.034	-0.094	+	-0.180	+	0.086	+	+								10	0.057	0.092	0.995
10	-1.190	0.061	-0.095	+	-0.180	+	0.085		+		+						10	0.056	0.091	1.535
34	-1.176	0.033	-0.115	+	-0.180	+	0.085		+				+				10	0.057	0.091	1.685
68	-1.184	0.035	-0.095	+	-0.181	+	0.085	+	+					+			11	0.057	0.093	1.823
12	-1.222	0.061	-0.094	+	-0.180	+	0.086	+	+		+						11	0.057	0.093	2.509

Model number	Intercept	Age	Age^2	Higher Education	Income per person per household	Married	Townsend deprivation index	Public greenspace	Gender	Age:Public greenspace	Age:Gender	Age^2:Public greenspace	Age^2:Gender	Public greenspace:Gender	Age:Public greenspace:Gender	Age^2:Public greenspace:Gender	K	R^2m	R^2c	ΔAIC
36	-1.208	0.033	-0.114	+	-0.180	+	0.086	+	+				+				11	0.057	0.092	2.708
8	-1.225	0.048	-0.094	+	-0.181	+	0.087	+	+	+							11	0.057	0.092	2.777
42	-1.161	0.070	-0.126	+	-0.180	+	0.085		+		+		+				11	0.057	0.091	2.860
20	-1.221	0.034	-0.098	+	-0.180	+	0.086	+	+			+					11	0.057	0.092	2.976
76	-1.180	0.062	-0.096	+	-0.181	+	0.085	+	+		+			+			12	0.057	0.093	3.331
100	-1.165	0.034	-0.115	+	-0.181	+	0.085	+	+				+	+			12	0.058	0.093	3.521
72	-1.183	0.049	-0.095	+	-0.181	+	0.086	+	+	+				+			12	0.057	0.093	3.580
84	-1.180	0.035	-0.099	+	-0.181	+	0.085	+	+			+		+			12	0.057	0.093	3.809
44	-1.193	0.070	-0.125	+	-0.180	+	0.086	+	+		+		+				12	0.057	0.093	3.871
16	-1.221	0.074	-0.094	+	-0.180	+	0.087	+	+	+	+						12	0.057	0.093	4.302
40	-1.207	0.047	-0.114	+	-0.181	+	0.087	+	+	+			+				12	0.057	0.092	4.481
28	-1.217	0.061	-0.099	+	-0.180	+	0.086	+	+		+	+					12	0.057	0.093	4.486
108	-1.149	0.071	-0.127	+	-0.181	+	0.085	+	+		+		+	+			13	0.058	0.094	4.665
24	-1.215	0.051	-0.104	+	-0.180	+	0.087	+	+	+		+					12	0.057	0.092	4.683
52	-1.204	0.033	-0.117	+	-0.180	+	0.086	+	+			+	+				12	0.057	0.092	4.693
80	-1.179	0.075	-0.095	+	-0.181	+	0.086	+	+	+	+			+			13	0.057	0.093	5.118
104	-1.163	0.049	-0.116	+	-0.181	+	0.086	+	+	+			+	+			13	0.058	0.093	5.262
92	-1.176	0.062	-0.100	+	-0.181	+	0.085	+	+		+	+		+			13	0.057	0.093	5.311

Model number	Intercept	Age	Age^2	Higher Education	Income per person per household	Married	Townsend deprivation index	Public greenspace	Gender	Age:Public greenspace	Age:Gender	Age^2:Public greenspace	Age^2:Gender	Public greenspace:Gender	Age:Public greenspace:Gender	Age^2:Public greenspace:Gender	K	R^2m	R^2c	ΔAIC
88	-1.173	0.053	-0.104	+	-0.181	+	0.086	+	+	+		+		+			13	0.057	0.093	5.491
116	-1.163	0.034	-0.118	+	-0.181	+	0.085	+	+			+	+	+			13	0.058	0.093	5.513
48	-1.192	0.084	-0.125	+	-0.180	+	0.087	+	+	+	+		+				13	0.057	0.093	5.654
60	-1.189	0.071	-0.129	+	-0.180	+	0.086	+	+		+	+	+				13	0.057	0.093	5.853

Appendix D

Table 21: Parameter estimates of the averaged model that explained poor mental health for individuals with gardens. Variables were centred and scaled prior to modelling.

Term	**Estimate**	**S.E**	**P**
Intercept	-1.195	0.086	<0.001
Age	0.046	0.046	0.319
Age^2	-0.102	0.042	0.014
Has higher education	0.039	0.083	0.637
Income per person per household	-0.180	0.033	<0.001
Married	-0.303	0.067	<0.001
Townsend deprivation score	0.086	0.030	0.005
Female	0.328	0.081	<0.001
Public greenspace	0.026	0.088	0.763
Public greenspace:Female	0.129	0.119	0.277
Age:Female	-0.047	0.063	0.449
Age^2:Female	0.039	0.062	0.528
Age:Public greenspace	-0.029	0.060	0.627
Age^2:Public greenspace	0.009	0.059	0.872

D.1.1 Model validation

7.5.1.1 Residuals

Standardised residuals were plotted against each covariate in the global and reduced models and against their respective time (wave number) and space variables (X, Y). Residuals were estimated using the 'DHARMa' package (Hartig 2018).

Appendix D

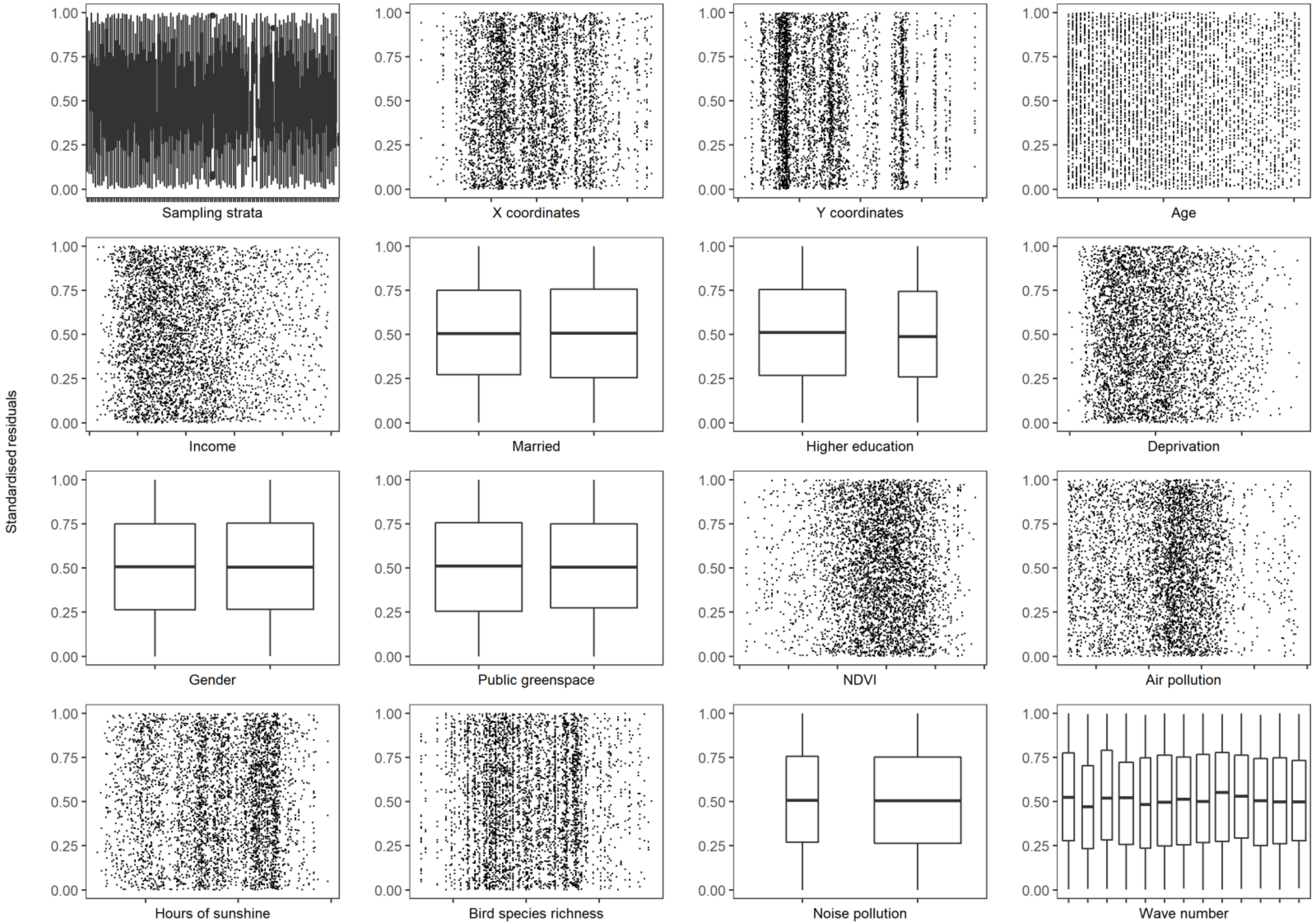

Figure 18: Absence of residual patterns for the global model

7.5.1.2 Generalised variance inflation factors

Generalised variance inflation factors GVIF$^{1/(2\times df))}$ were calculated. All values are <5 suggesting collinearity is not a problem (Fox 2015).

Table 22: Generalised variance inflation factors for terms contained within the global model

Term	**GVIF$^{(1/(2\times df))}$**
Townsend deprivation index	1.041
Income per person per household	1.033
Gender	1.426
Age	2.259
Married	1.163
Higher education	1.581
Public greenspace	2.240
Gender:Age	2.332
Gender:Public greenspace	1.883
Gender:Age:Public greenspace	2.357

D.2 Individuals without a private garden

Table 23: Generalised linear models (fixed effects only) of individuals with a private garden contained within the top-performing models, identified by Akaike's information criterion (AIC) with ΔAIC<6 (Harrison et al. 2018). Shown are the standardised regression coefficients for each continuous term (column) in each model (rows). For the top-performing models goodness of fit (pseudo-R^2) was calculated using (Nagelkerke 1991).

Model number	Intercept	Age	Age^2	Higher Education	Income per person per household	Married	Townsend deprivation index	Public greenspace	Gender	Age:Public greenspace	Age:Gender	Age2:Public greenspace	Age^2:Gender	Public greenspace:Gender	Age:Public greenspace:Gender	Age^2:Public greenspace:Gender	K	R^2	ΔAIC
4	-0.992	0.103	-0.326	+	-0.363	+	-0.222	+	+								9	0.071	0.000
68	-1.153	0.101	-0.326	+	-0.369	+	-0.215	+	+					+			10	0.076	0.106
2	-0.846	0.112	-0.334	+	-0.356	+	-0.217		+								8	0.064	0.296
12	-0.980	0.235	-0.329	+	-0.362	+	-0.224	+	+		+						10	0.075	0.618
76	-1.138	0.229	-0.327	+	-0.368	+	-0.216	+	+		+			+			11	0.080	0.813
10	-0.834	0.245	-0.338	+	-0.357	+	-0.220		+		+						9	0.068	0.898
20	-0.905	0.105	-0.426	+	-0.358	+	-0.219	+	+			+					10	0.074	1.015
84	-1.065	0.104	-0.432	+	-0.363	+	-0.211	+	+			+		+			11	0.079	1.017
36	-1.055	0.106	-0.245	+	-0.354	+	-0.220	+	+				+				10	0.072	1.436
100	-1.223	0.105	-0.240	+	-0.360	+	-0.212	+	+				+	+			11	0.078	1.483
28	-0.887	0.243	-0.434	+	-0.356	+	-0.221	+	+		+	+					11	0.078	1.529

Model number	Intercept	Age	Age^2	Higher Education	Income per person per household	Married	Townsend deprivation index	Public greenspace	Gender	Age:Public greenspace	Age:Gender	Age2:Public greenspace	Age^2:Gender	Public greenspace:Gender	Age:Public greenspace:Gender	Age^2:Public greenspace:Gender	K	R^2	ΔAIC
34	-0.909	0.115	-0.255	+	-0.348	+	-0.215		+				+				9	0.066	1.734
92	-1.045	0.229	-0.430	+	-0.361	+	-0.212	+	+		+	+		+			12	0.083	1.783
8	-0.998	0.063	-0.323	+	-0.361	+	-0.218	+	+	+							10	0.071	1.859
72	-1.159	0.061	-0.323	+	-0.368	+	-0.211	+	+	+				+			11	0.077	1.959
52	-0.969	0.109	-0.342	+	-0.347	+	-0.216	+	+			+	+				11	0.076	2.295
116	-1.125	0.107	-0.345	+	-0.353	+	-0.209	+	+			+	+	+			12	0.081	2.425
16	-0.986	0.194	-0.325	+	-0.360	+	-0.220	+	+	+	+						11	0.075	2.464
44	-0.985	0.231	-0.323	+	-0.362	+	-0.224	+	+		+		+				11	0.075	2.616
80	-1.140	0.197	-0.325	+	-0.367	+	-0.213	+	+	+	+			+			12	0.080	2.737
108	-1.153	0.219	-0.310	+	-0.366	+	-0.215	+	+		+		+	+			12	0.080	2.797
42	-0.838	0.243	-0.334	+	-0.356	+	-0.220		+		+		+				10	0.068	2.897
88	-1.040	0.146	-0.457	+	-0.363	+	-0.215	+	+	+		+		+			12	0.080	2.921
24	-0.882	0.144	-0.449	+	-0.358	+	-0.223	+	+	+		+					11	0.074	2.935
40	-1.064	0.062	-0.239	+	-0.352	+	-0.215	+	+	+			+				11	0.073	3.264
104	-1.226	0.066	-0.237	+	-0.358	+	-0.208	+	+	+			+	+			12	0.078	3.347
208	-1.138	0.349	-0.337	+	-0.376	+	-0.218	+	+	+	+			+	+		13	0.084	3.390

Appendix D

Model number	Intercept	Age	Age^2	Higher Education	Income per person per household	Married	Townsend deprivation index	Public greenspace	Gender	Age:Public greenspace	Age:Gender	Age2:Public greenspace	Age^2:Gender	Public greenspace:Gender	Age:Public greenspace:Gender	Age^2:Public greenspace:Gender	K	R^2	ΔAIC
32	-0.862	0.284	-0.458	+	-0.357	+	-0.225	+	+	+	+	+					12	0.078	3.440
60	-0.901	0.231	-0.417	+	-0.354	+	-0.220	+	+		+	+	+				12	0.078	3.509
96	-1.014	0.292	-0.464	+	-0.361	+	-0.216	+	+	+	+	+		+			13	0.083	3.605
124	-1.058	0.219	-0.413	+	-0.359	+	-0.211	+	+		+	+	+	+			13	0.083	3.767
224	-1.000	0.478	-0.492	+	-0.371	+	-0.224	+	+	+	+	+		+	+		14	0.088	4.069
56	-0.946	0.148	-0.365	+	-0.348	+	-0.219	+	+	+		+	+				12	0.076	4.212
120	-1.101	0.151	-0.370	+	-0.353	+	-0.212	+	+	+		+	+	+			13	0.081	4.326
372	-1.099	0.108	-0.377	+	-0.352	+	-0.208	+	+			+	+	+		+	13	0.081	4.366
48	-0.994	0.188	-0.316	+	-0.360	+	-0.220	+	+	+	+		+				12	0.075	4.459
112	-1.157	0.184	-0.306	+	-0.365	+	-0.212	+	+	+	+		+	+			13	0.080	4.716
240	-1.144	0.343	-0.331	+	-0.375	+	-0.218	+	+	+	+		+	+	+		14	0.084	5.387
64	-0.876	0.273	-0.441	+	-0.355	+	-0.224	+	+	+	+	+	+				13	0.078	5.420
128	-1.025	0.283	-0.450	+	-0.360	+	-0.216	+	+	+	+	+	+	+			14	0.083	5.596
380	-1.034	0.219	-0.441	+	-0.358	+	-0.211	+	+		+	+	+	+		+	14	0.083	5.713
3	-1.318	-0.124	NA	+	-0.296	+	-0.194	+	+								8	0.049	5.748
67	-1.477	-0.123	NA	+	-0.304	+	-0.188	+	+					+			9	0.054	5.852

Table 24: Parameter estimates of the averaged model that explained poor mental health for individuals without gardens. Variables were centred and scaled prior to modelling.

Term	**Estimate**	**S.E**	**P**
Intercept	-1.014	0.261	<0.001
Age	0.157	0.179	0.381
Age^2	-0.346	0.161	0.033
Has higher education	0.017	0.253	0.947
Income per person per household	-0.360	0.103	0.001
Married	-0.113	0.226	0.618
Townsend deprivation score	-0.217	0.090	0.016
Female	0.264	0.277	0.341
Public greenspace	0.331	0.296	0.263
Public greenspace:Female	-0.476	0.358	0.184
Age:Female	-0.233	0.220	0.292
Age^2:Female	-0.101	0.216	0.642
Age:Public greenspace	-0.012	0.246	0.962
Age^2:Public greenspace	0.206	0.206	0.319
Age:Public greenspace:Female	0.458	0.389	0.240
Age^2:Public greenspace:Female	-0.091	0.380	0.811

D.2.1 Model validation

7.5.1.3 Residuals

Standardised residuals were plotted against each covariate in the global and reduced models and against their respective time (wave number) and space variables (X, Y). Residuals were estimated using the ‘DHARMa’ package (Hartig 2018).

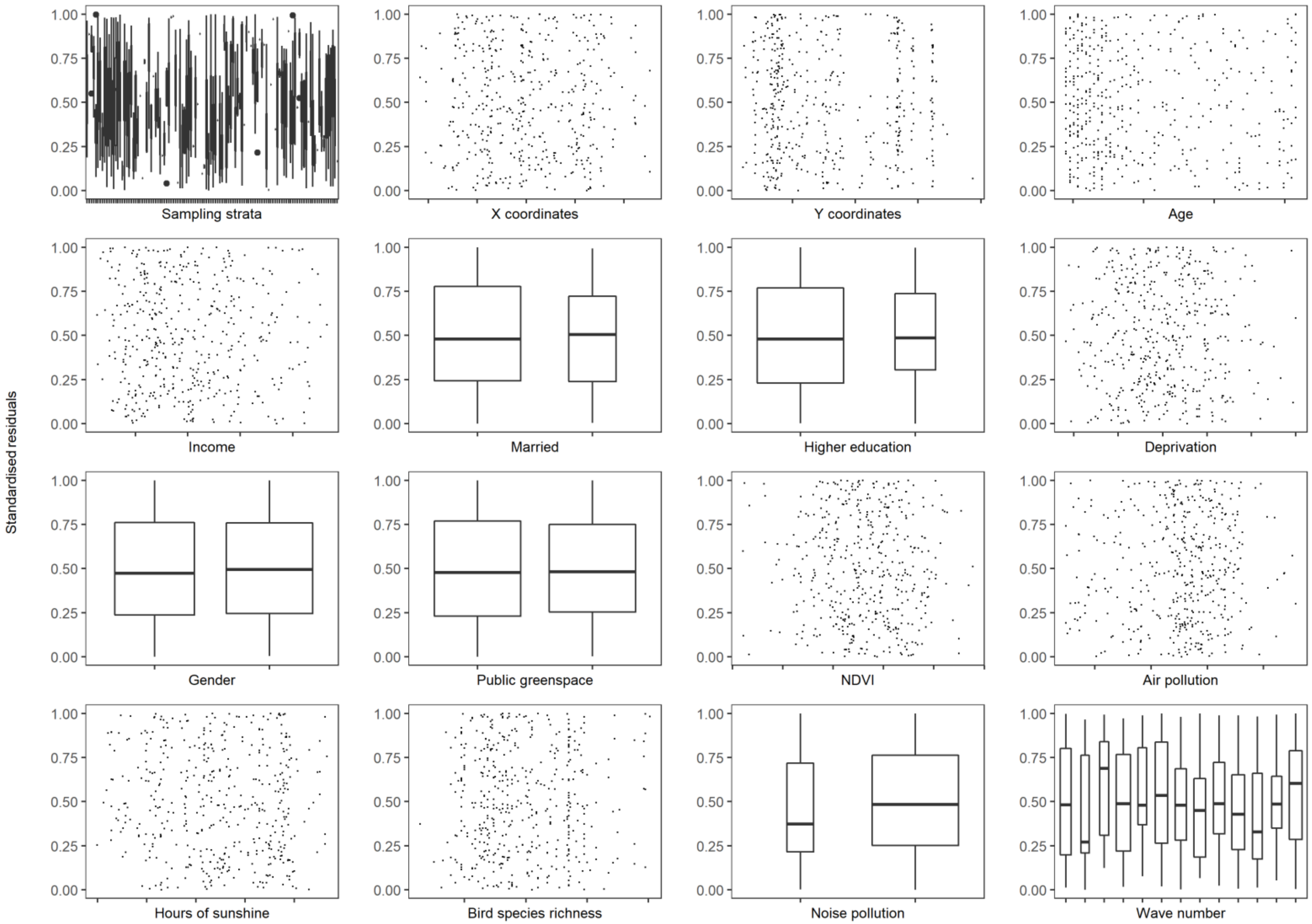

Figure 19: Absence of residual patterns for the global model

7.5.1.4 Generalised variance inflation factors

Generalised variance inflation factors $GVIF^{1/(2\times df))}$ were calculated. All values are <5 suggesting collinearity is not a problem (Fox 2015).

Table 25: Generalised variance inflation factors for terms contained within the global model

Term	$GVIF^{(1/(2\times df))}$
Townsend deprivation index	1.050
Income per person per household	1.065
Gender	1.642
Age	2.536
Married	1.107
Higher education	1.629
Public greenspace	2.409
Gender:Age	2.409
Gender:Public greenspace	1.949
Gender:Age:Public greenspace	2.297

Appendix E Chapter 5 Average predicted probabilities from the top-performing models with no access to public greenspace

Figure 13 in the Results section presented the average predicted probabilities from the top-performing models with "access" to public greenspace (i.e., the median value see Materials and methods for details). Figure 20 presents the corresponding plot with "no access" to public greenspace, whilst holding all other covariates at their median or mode value for numerical and categorical variables, respectively. There is no observable difference between Figure 13 and Figure 20, therefore for the covariates: income per person per household, marital status, higher education attainment and Townsend deprivation score their effect on mental health is not contingent on access to public greenspace.

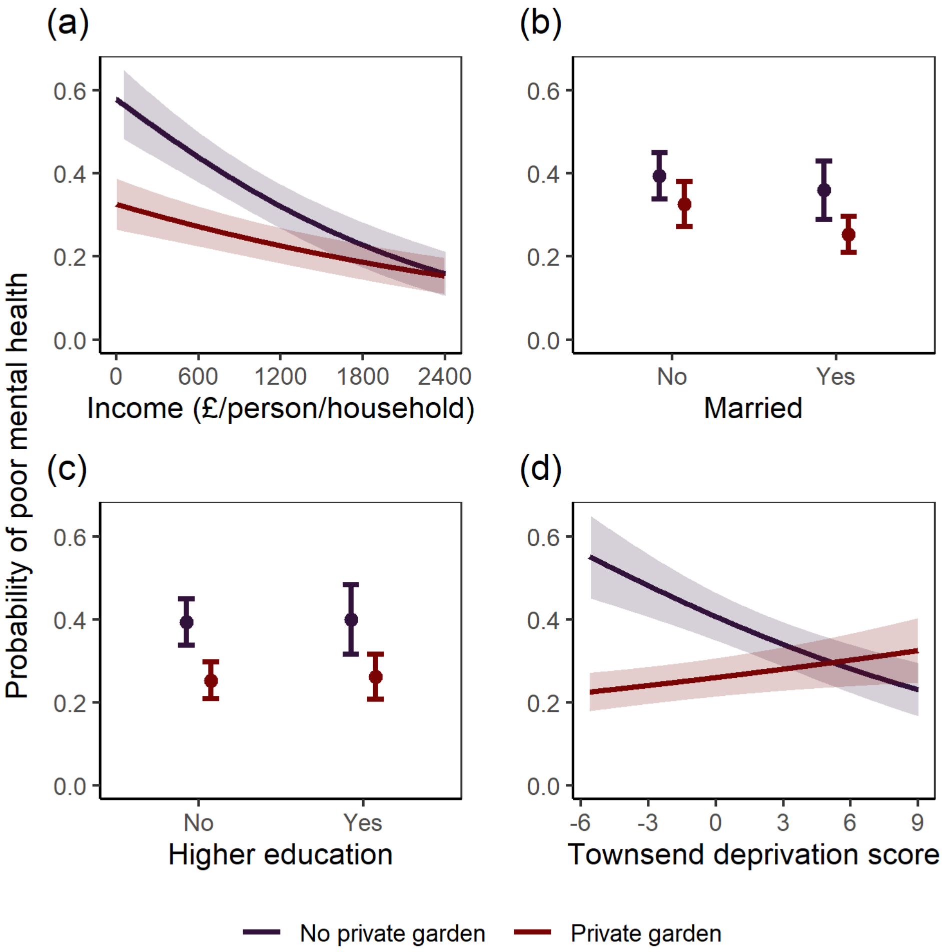

Figure 20: The predicted probability of poor mental health averaged across the top-performing models (ΔAIC<6, see text) for individuals without (purple line) and with (red line) a private garden in relation to; (a) income per person per household (£), (b) marital status (Yes/No), (c) higher education attainment (Yes/No), and (d) Townsend deprivation score (-5 least deprived and 10 most deprived). For each graph, there was no access to public greenspace, all other covariates were held at their median or mode (See Materials and methods for details). Shaded region shows 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

Appendix F Chapter 5 Additional models – sensitivity analysis of the effect of statistical matching on results

With the exception of completely orthogonal datasets, the outcomes of statistical matching are dependent on the variables that are matched on. Therefore additional models were fitted to data that matched on only socio-demographic variables and the full, unmatched data to see how matching decisions (choice of matching variables and unmatched data) influenced model results. We applied the same model selection procedure (described in Multimodel inference) to the following three datasets:

(1) Full matching where we matched using individual socio-demographic variables and greenspace qualities (the results of which are presented in the main text).
(2) Partial matching where we matched only using individual-level socio-demographic variables and not the green space qualities.
(3) No statistical matching.

F.1 Partial statistical matching

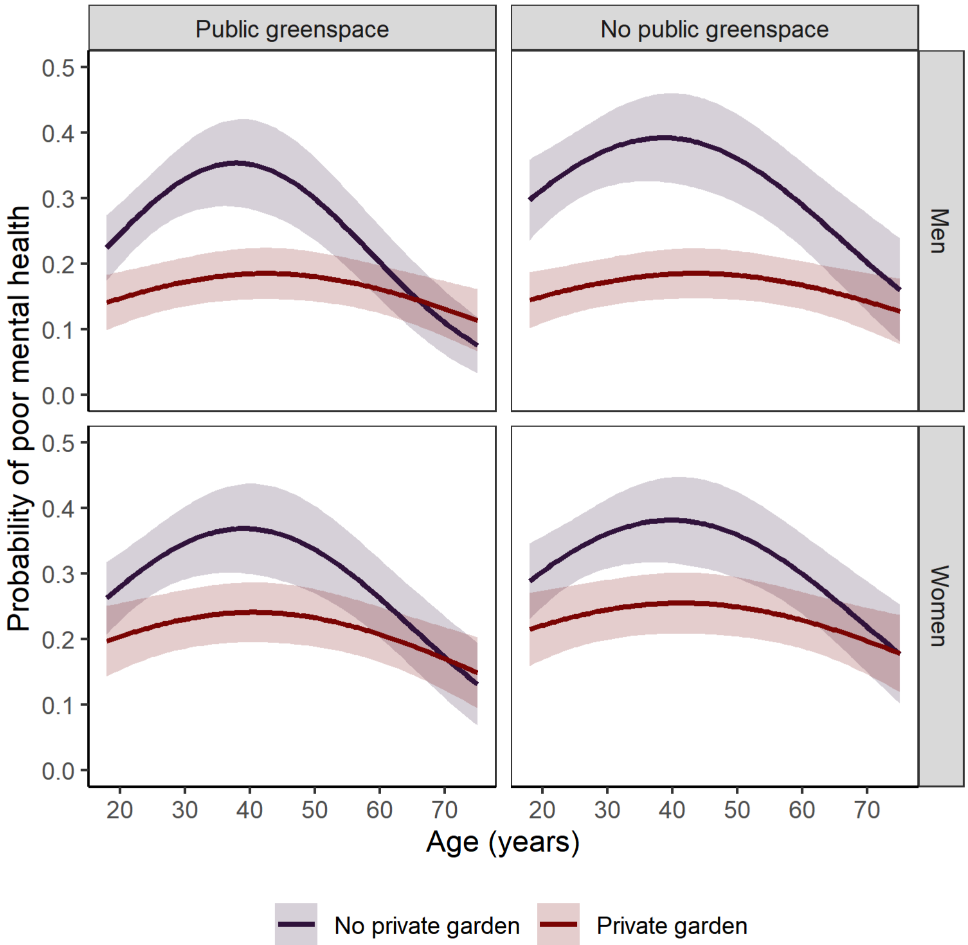

Figure 21: The predicted probability of poor mental health averaged across the top-performing models (ΔAIC<6) with partial statistical matching for individuals without (purple line) and with (red line) a private garden in relation to access to public greenspace (within 800m of the population-weighted centroid of their LSOA or Data Zone), gender, and having a private garden. All other covariates were held at their median or mode (See Materials and methods). Shaded region shows 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

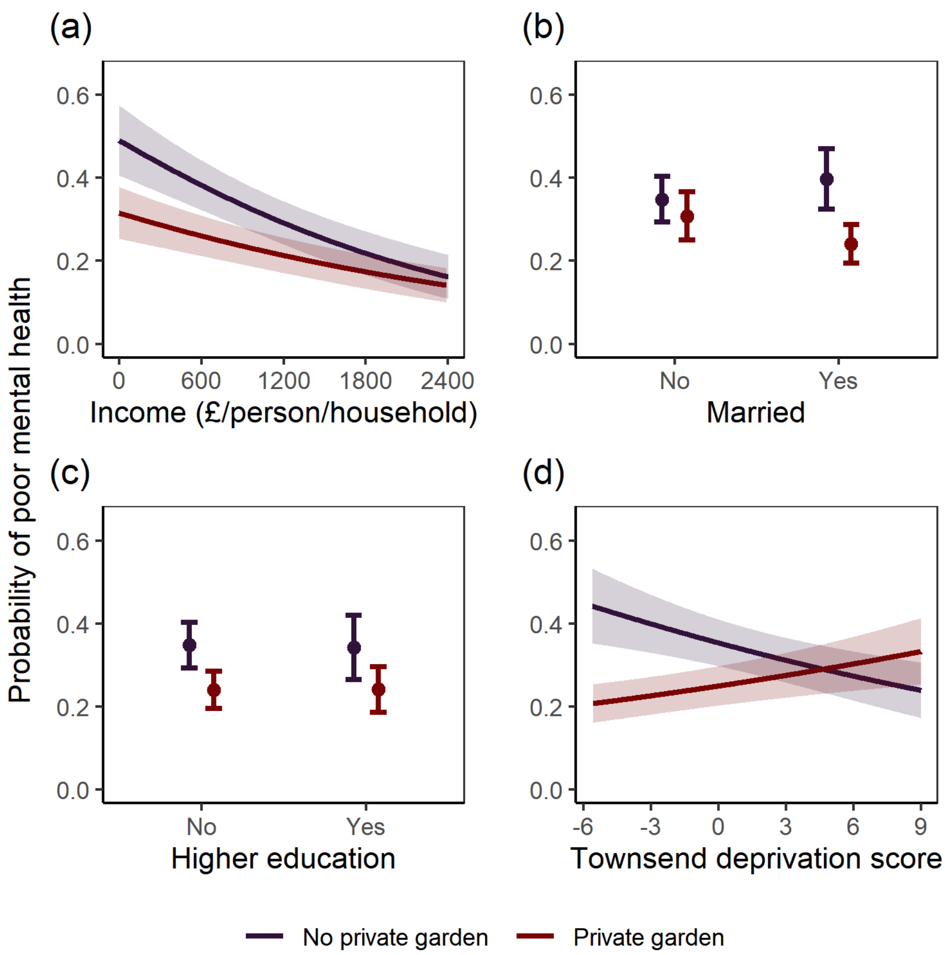

Figure 22: The predicted probability of poor mental health averaged across the top-performing models (ΔAIC<6) with partial statistical matching for individuals without (purple line) and with (red line) a private garden in relation to; (a) income per person per household (£), (b) marital status (Yes/No), (c) higher education attainment (Yes/No), and (d) Townsend deprivation score (-5 least deprived and 10 most deprived). For each graph, all other covariates were held at their median or mode (See Materials and methods for details). Shaded region shows 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

F.2 No statistical matching

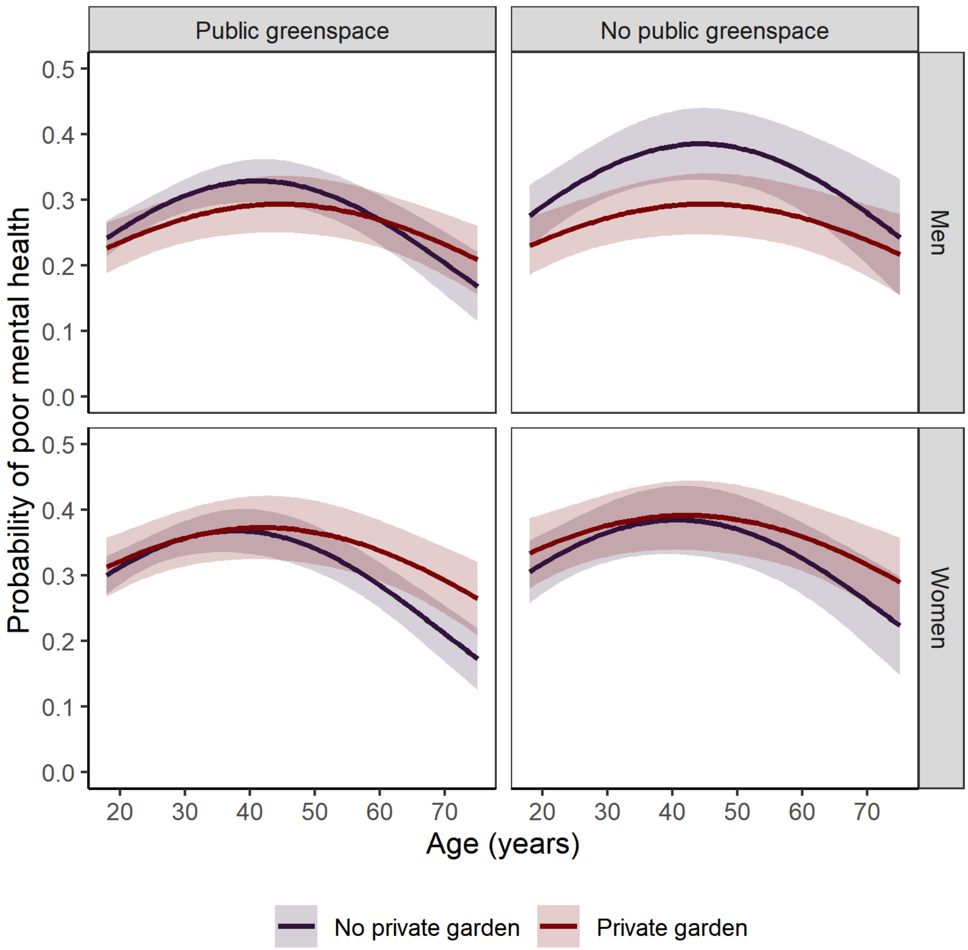

Figure 23: The predicted probability of poor mental health averaged across the top-performing models (ΔAIC<6) with no statistical matching for individuals without (purple line) and with (red line) a private garden in relation to access to public greenspace (within 800m of the population-weighted centroid of their LSOA or Data Zone), gender, and having a private garden. All other covariates were held at their median or mode (See Materials and methods). Shaded region shows 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

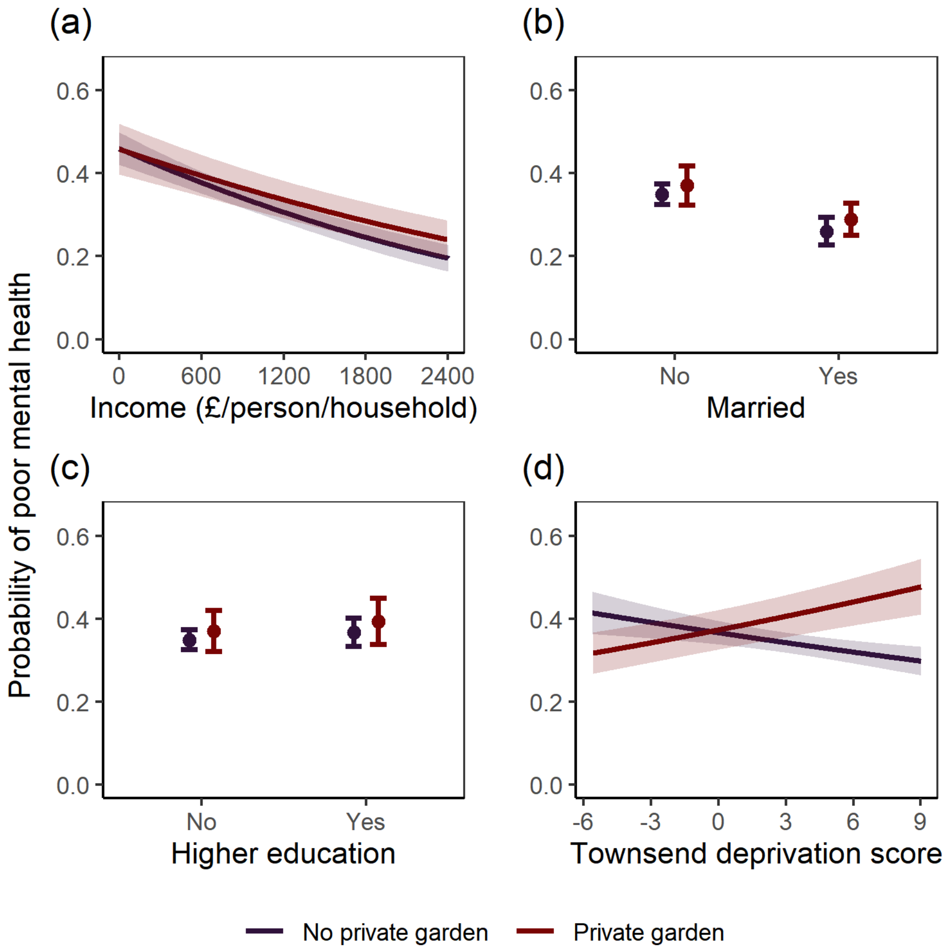

Figure 24: The predicted probability of poor mental health averaged across the top-performing models (ΔAIC<6) with no statistical matching for individuals without (purple line) and with (red line) a private garden in relation to; (a) income per person per household (£), (b) marital status (Yes/No), (c) higher education attainment (Yes/No), and (d) Townsend deprivation score (-5 least deprived and 10 most deprived). For each graph, all other covariates were held at their median or mode (See Materials and methods for details). Shaded region shows 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

Appendix G Chapter 6 area-level variables and their correlations before and after moving

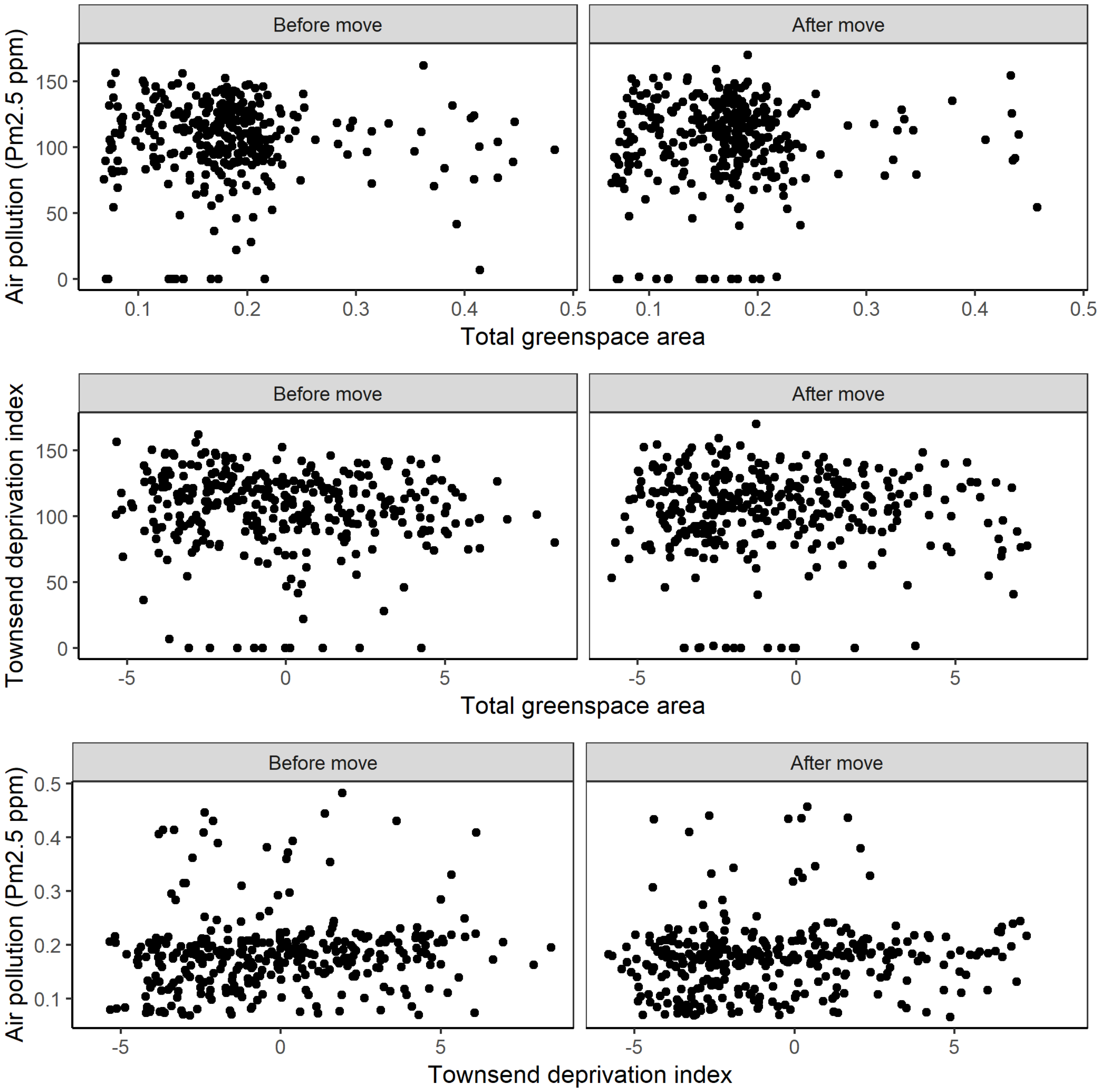

Figure 25: correlations between area-level variables before and after moving

Appendix H Chapter 6 filtered BHPS sample descriptive statistics

Descriptive statistics for the filtered BHPS sample pre -and- post-move are presented in Tables 26 and 27 respectively.

Table 26: Descriptive statistics in the years before an individual moves, including: the number of individuals (*n*), the mean and standard deviation (sd) for continuous variables, or for categorical variables the percentage (%).

	Years before move															
	9		**8**		**7**		**6**		**5**		**4**		**3**		**2**	
	n	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**
Individual-level variables:																
Individuals	17	100.00%	46	100.00%	102	100.00%	189	100.00%	312	100.00%	486	100.00%	486	100.00%	479	100.00%
Good mental health	14	82.35%	35	76.09%	72	70.59%	133	70.37%	242	77.56%	366	75.31%	370	76.13%	345	72.03%
Poor mental health	3	17.65%	11	23.91%	30	29.41%	56	29.63%	70	22.44%	120	24.69%	116	23.87%	134	27.97%
Male	6	35.29%	18	39.13%	42	41.18%	78	41.27%	130	41.67%	205	42.18%	205	42.18%	201	41.96%
Female	11	64.71%	28	60.87%	60	58.82%	111	58.73%	182	58.33%	281	57.82%	281	57.82%	278	58.04%
Not married	10	58.82%	18	39.13%	34	33.33%	79	41.80%	128	41.03%	198	40.74%	184	37.86%	167	34.86%
Married	7	41.18%	28	60.87%	68	66.67%	110	58.20%	184	58.97%	288	59.26%	302	62.14%	312	65.14%
No higher education	14	82.35%	41	89.13%	86	84.31%	159	84.13%	249	79.81%	377	77.57%	374	76.95%	365	76.20%
Higher education	3	17.65%	5	10.87%	16	15.69%	30	15.87%	63	20.19%	109	22.43%	112	23.05%	114	23.80%

	Years before move															
	9		8		7		6		5		4		3		2	
	n	Mean (sd)/%	n	Mean (sd)/%	n	Mean (sd)/%	n	Mean (sd)/%	n	Mean (sd)/%	n	Mean (sd)/%	n	Mean (sd)/%	n	Mean (sd)/%
Age (years)	17	30.29 (8.03)	46	37 (13.13)	102	36.47 (11.55)	189	36.22 (11.8)	312	36.08 (11.18)	486	36.49 (11.8)	486	37.49 (11.81)	479	38.59 (11.84)
Income (£/person/household)	17	812.14 (467.02)	46	920.73 (498.25)	102	970.96 (612.18)	189	955.51 (646.52)	312	917.29 (549.2)	486	962.51 (618.15)	486	1032.86 (664.01)	479	1064.75 (718.25)
Area-level variables:																
Townsend index of deprivation	17	0.62 (2.91)	46	0.03 (2.75)	102	-0.82 (2.79)	189	-0.23 (2.94)	312	-0.16 (2.99)	486	-0.26 (2.86)	486	-0.26 (2.86)	479	-0.25 (2.88)
Air pollution (PM2.5)	17	0.17 (0.04)	46	0.18 (0.05)	102	0.18 (0.07)	189	0.18 (0.07)	312	0.19 (0.07)	486	0.18 (0.07)	486	0.18 (0.07)	479	0.18 (0.07)
No noise pollution	4	23.53%	13	28.26%	34	33.33%	65	34.39%	112	35.90%	165	33.95%	166	34.16%	164	34.24%
Noise pollution	13	76.47%	33	71.74%	68	66.67%	124	65.61%	200	64.10%	321	66.05%	320	65.84%	315	65.76%
No protected area(s)	8	47.06%	24	52.17%	49	48.04%	86	45.50%	161	51.60%	244	50.21%	243	50.00%	240	50.10%
Protected area(s)	9	52.94%	22	47.83%	53	51.96%	103	54.50%	151	48.40%	242	49.79%	243	50.00%	239	49.90%

Table 27: Descriptive statistics in the years after an individual moves, including: the number of individuals (*n*), the mean and standard deviation (sd) for continuous variables, or for categorical variables the percentage (%).

	Years after move															
	1		**2**		**3**		**4**		**5**		**6**		**7**		**8**	
	n	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**
Individual-level variables:																
Individuals	476	100.00%	478	100.00%	482	100.00%	390	100.00%	281	100.00%	180	100.00%	109	100.00%	39	100.00%
Good mental health	366	76.89%	376	78.66%	362	75.10%	292	74.87%	209	74.38%	136	75.56%	83	76.15%	24	61.54%
Poor mental health	110	23.11%	102	21.34%	120	24.90%	98	25.13%	72	25.62%	44	24.44%	26	23.85%	15	38.46%
Male	203	42.65%	200	41.84%	207	42.95%	166	42.56%	118	41.99%	78	43.33%	45	41.28%	17	43.59%
Female	273	57.35%	278	58.16%	275	57.05%	224	57.44%	163	58.01%	102	56.67%	64	58.72%	22	56.41%
Not married	147	30.88%	155	32.43%	144	29.88%	113	28.97%	74	26.33%	49	27.22%	27	24.77%	7	17.95%
Married	329	69.12%	323	67.57%	338	70.12%	277	71.03%	207	73.67%	131	72.78%	82	75.23%	32	82.05%
No higher education	354	74.37%	358	74.90%	361	74.90%	290	74.36%	207	73.67%	131	72.78%	71	65.14%	22	56.41%
Higher education	122	25.63%	120	25.10%	121	25.10%	100	25.64%	74	26.33%	49	27.22%	38	34.86%	17	43.59%
Age (years)	476	41.47 (11.76)	478	42.51 (11.85)	482	43.44 (11.86)	390	45.23 (12.14)	281	46.28 (11.51)	180	47.09 (11.04)	109	47.22 (10.3)	39	47.62 (9.9)
Income (£/person/household)	476	1178.11 (771.2)	478	1229.46 (799.75)	482	1241.49 (768.57)	390	1269.19 (756.4)	281	1261.56 (893.31)	180	1294.22 (854.12)	109	1329.97 (857.07)	39	1382.58 (983.66)
Area-level variables:																

	Years after move															
	1		**2**		**3**		**4**		**5**		**6**		**7**		**8**	
	n	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**
Townsend index of deprivation	476	-1.04 (2.82)	478	-1.02 (2.88)	482	-0.94 (2.92)	390	-1.02 (2.79)	281	-0.94 (2.92)	180	-1.21 (2.85)	109	-1.17 (3.02)	39	-1.68 (2.96)
Air pollution (PM2.5)	476	0.17 (0.07)	478	0.17 (0.07)	482	0.17 (0.07)	390	0.17 (0.07)	281	0.17 (0.07)	180	0.16 (0.07)	109	0.16 (0.06)	39	0.15 (0.07)
No noise pollution	172	36.13%	174	36.40%	178	36.93%	144	36.92%	96	34.16%	61	33.89%	41	37.61%	18	46.15%
Noise pollution	304	63.87%	304	63.60%	304	63.07%	246	63.08%	185	65.84%	119	66.11%	68	62.39%	21	53.85%
No protected area(s)	223	46.85%	225	47.07%	225	46.68%	178	45.64%	121	43.06%	71	39.44%	43	39.45%	14	35.90%
Protected area(s)	253	53.15%	253	52.93%	257	53.32%	212	54.36%	160	56.94%	109	60.56%	66	60.55%	25	64.10%

Appendix I Chapter 6 model results

I.1 Model parameter estimates

Table 28: Parameter estimates of the models included in the model comparison of greenspace characteristics. . Variables were centred and scaled prior to modelling. For characteristics with three treatment groups; Treatment 1 represents “no change”, and Treatment 2 represents a “gain” in the greenspace characteristic (i.e., an individual moved from not having the characteristic to having the characteristic). For characteristics with two treatment groups; Treatment 1 represents an increase in a greenspace characteristic, with the exception of greenspace proximity whereby Treatment 1 is an increase in proximity (i.e., further away) from greenspace.

Characteristic	**Intercept**	**Age**	**Age^2**	**Income/person / household**	**Gender**	**Higher Education**	**Married**	**Townsend deprivation index**	**Air pollution**	**After move**	**Treatment 1**	**Treatment 2**	**After Move:treatment 0**	**After Move:treatment 1**	**AIC**	**LRT (p-value)**
Quality – Bird species richness	-1.56	0.17	-0.21	-0.06	0.67	0.21	-0.24	0.15	-0.10	-0.09	0.40	-0.24	-0.50	0.02	4559.95	0.00
Proximity – Distance to public greenspace	-1.41	0.19	-0.22	-0.04	0.68	0.23	-0.27	0.14	-0.10	-0.29	-0.42	NA	0.23	NA	4564.90	0.03
No treatment	-1.62	0.19	-0.21	-0.05	0.66	0.23	-0.27	0.15	-0.10	-0.17	NA	NA	NA	NA	4567.84	NA
Access – Fields in Trust public greenspace within 800m	-1.96	0.18	-0.22	-0.04	0.67	0.22	-0.27	0.15	-0.10	-0.06	0.39	0.59	-0.14	-0.11	4568.44	0.12
Quality – Greenness	-1.71	0.19	-0.21	-0.05	0.67	0.23	-0.27	0.14	-0.11	-0.04	0.15	NA	-0.24	NA	4569.22	0.27
Quality – Protected area(s)	-1.62	0.19	-0.21	-0.05	0.66	0.24	-0.28	0.16	-0.09	0.11	0.00	0.13	-0.33	-0.39	4570.61	0.27
Quantity – Public greenspace area	-1.66	0.19	-0.21	-0.05	0.67	0.23	-0.26	0.15	-0.10	-0.16	0.13	NA	-0.05	NA	4570.98	0.65
Quantity – Total greenspace area	-1.60	0.19	-0.21	-0.05	0.66	0.23	-0.26	0.15	-0.10	-0.14	-0.06	NA	-0.06	NA	4571.23	0.74

Characteristic	Intercept	Age	Age^2	Income/person / household	Gender	Higher Education	Married	Townsend deprivation index	Air pollution	After move	Treatment 1	Treatment 2	After Move:treatment 0	After Move:treatment 1	AIC	LRT (p-value)
Access – ANGSt doorstep total greenspace	-1.46	0.19	-0.21	-0.05	0.67	0.23	-0.27	0.15	-0.10	-0.21	-0.16	-0.34	-0.02	0.33	4571.54	0.37
Access – Public greenspace within 300m	-1.72	0.19	-0.21	-0.05	0.67	0.23	-0.27	0.14	-0.10	-0.18	0.08	0.33	0.05	-0.17	4573.33	0.64
Access – Public greenspace within 200m	-1.63	0.19	-0.21	-0.05	0.66	0.23	-0.27	0.15	-0.09	-0.27	0.01	0.11	0.14	0.05	4574.76	0.90

I.2 Model predicted probabilities

To visualise the relationship between covariates and the predicted values of poor mental health, we plotted the predicted probabilities from all characteristic models with sufficient treatment groups (Table 29), whilst holding all other covariates at their median or mode value for numerical and categorical variables respectively. Confidence intervals for the predicted intervals were obtained through bootstrapping with 1000 replications.

Table 29: Characteristics of greenspace in models with less inference than the base model: "no treatment"

Characteristic
Access – Fields in Trust public greenspace within 800m
Quality – Greenness
Quality – Protected area(s)
Quantity – Public greenspace area
Quantity – Total greenspace area
Access – ANGSt doorstep total greenspace
Access – Public greenspace within 300m
Access – Public greenspace within 200m

Appendix I

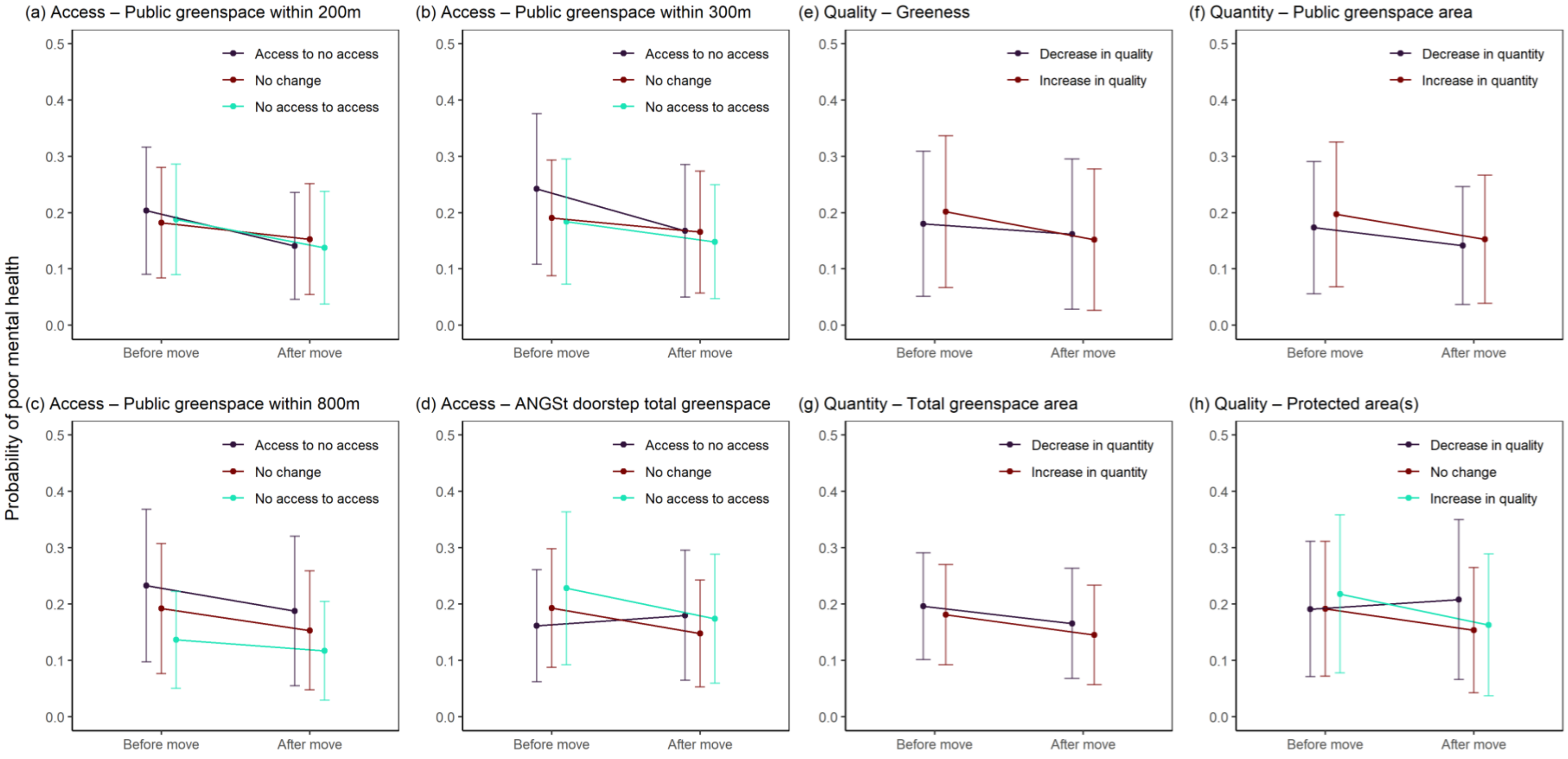

Figure 26: Predicted probability of poor mental health before and after moving in relation to their respective treatment groups for the models that provide less inference that the base model. Error bars show the 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

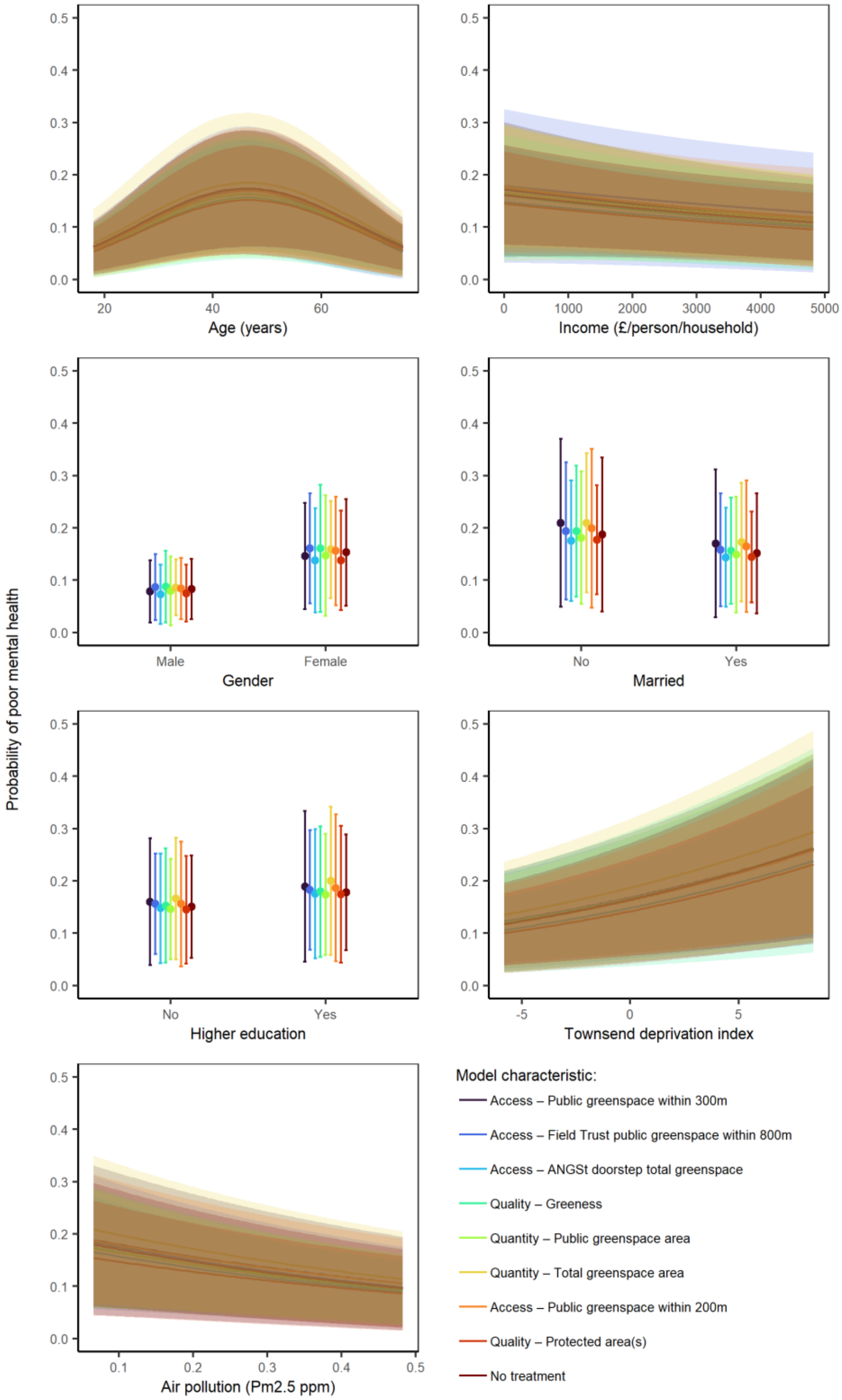

Figure 27: Predicted probability of poor mental health for individual and area-level variables for the base model and all models that provide less inference than the base model. Shaded regions show the 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

I.3 Model validation – Quality – Bird species richness.

For the best performing models (Quality – Brid species richness and Proximity – distance to public greenspace) we undertook the following model validation: checking standardised residuals, and GVIF$^{(1/(2\times df))}$.

I.3.1 Residuals

Standardised residuals were plotted against each covariate in the best performing model and against its respective time (wave number) and space variables (X, Y) (Zuur and Ieno 2016). Residuals were estimated using the 'DHARMa' package (Hartig 2018).

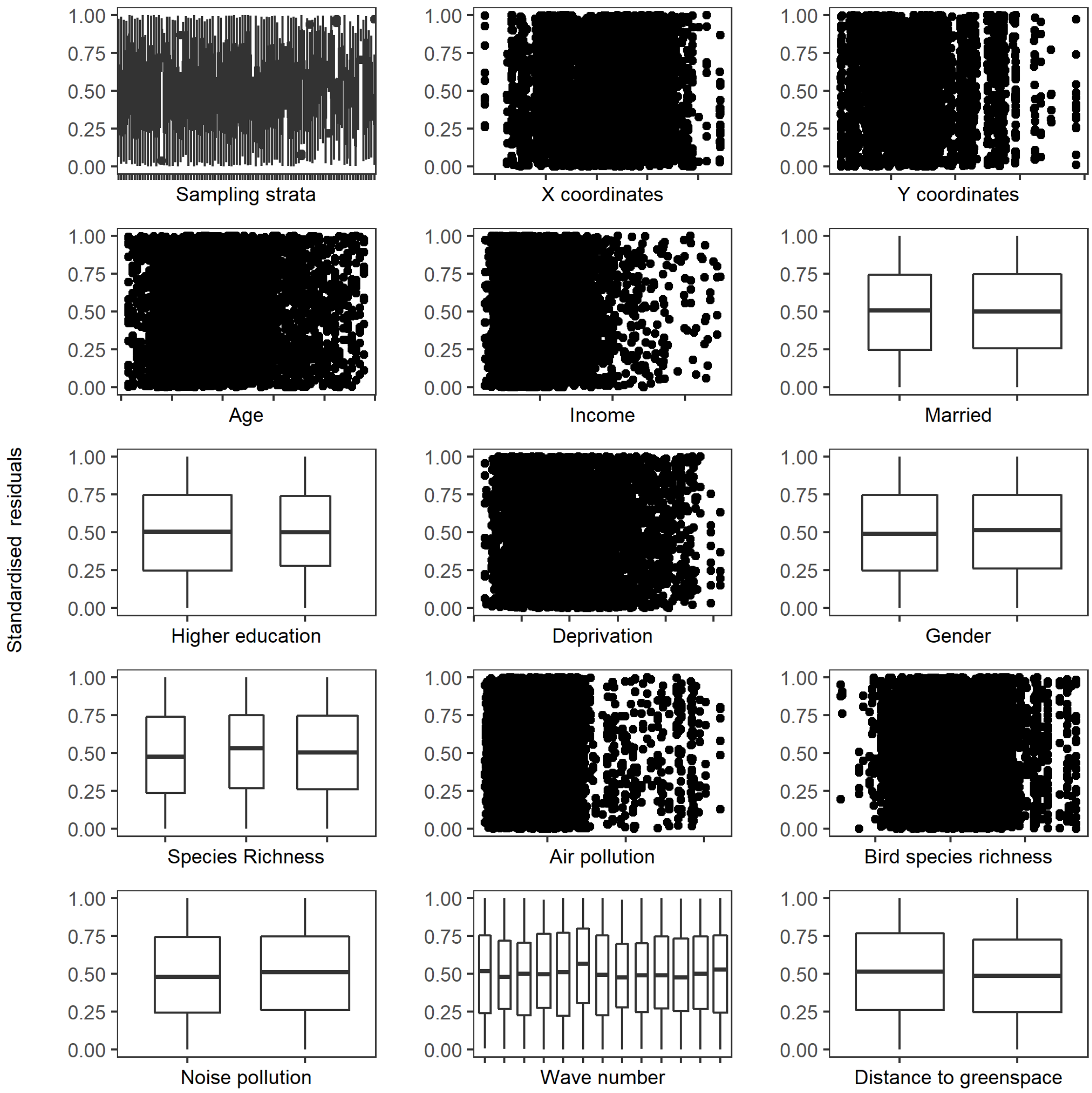

Figure 28: Absence of residual patterns for the model: Quality – Bird species richness

I.3.2 Generalised variance inflation factors

Generalised variance inflation factors GVIF$^{1/(2\times df))}$ were calculated following (Fox and Monette 1992). All values are <5 suggesting collinearity is not a problem (Fox 2015).

Table 30: Generalised variance inflation factors for terms contained within the model: Quality – Bird species richness.

Term	**$GVIF^{(1/(2\times df))}$**
Townsend deprivation index	1.042474
Income per person per household	1.065416
Gender	1.013217
Age	1.060504
Married	1.064881
Higher education	1.065133
Air pollution (Pm2.5 ppm)	1.017908
Before and after move	1.694468
Quality – Bird species richness	1.129940
Before and after move:Age:Public greenspace	1.398191

I.4 Model Validation – Proximity – Distance to public greenspace

I.4.1 Residuals

Standardised residuals were plotted against each covariate in the second-best performing models and against their respective time (wave number) and space variables (X, Y) (Zuur and Ieno 2016). Residuals were estimated using the 'DHARMa' package (Hartig 2018).

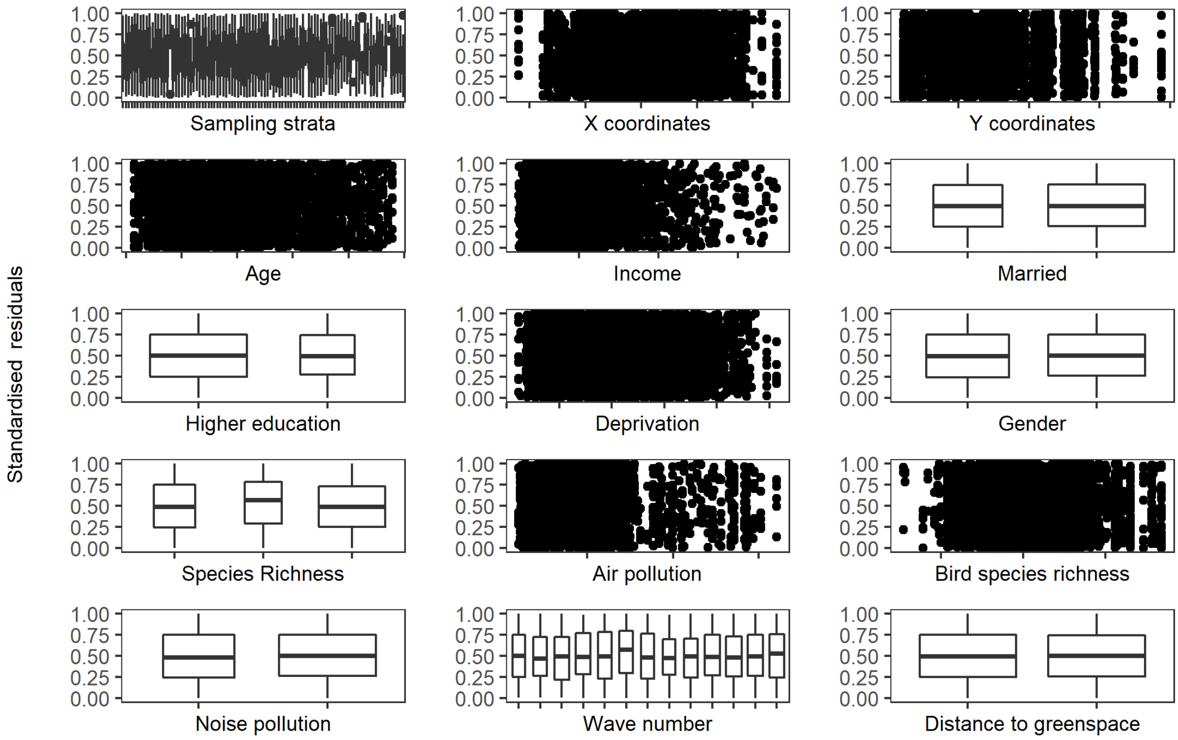

Figure 29: Absence of residual patterns for the model: Proximity – Distance to public greenspace

I.4.2 Generalised variance inflation factors

Generalised variance inflation factors GVIF$^{1/(2\times df))}$ were calculated following (Fox and Monette 1992). All values are <5 suggesting collinearity is not a problem (Fox 2015).

Table 31: Generalised variance inflation factors for terms contained within the model: Proximity – Distance to public greenspace.

Term	**GVIF$^{(1/(2\times df))}$**
Townsend deprivation index	1.045014
Income per person per household	1.068803
Gender	1.011677
Age	1.062252
Married	1.063503
Higher education	1.063348
Air pollution (Pm2.5 ppm)	1.017916
Before and after move	1.283723
Proximity – Distance to public greenspace	1.159435
Before and after move: Proximity – Distance to public greenspace	1.353597

Appendix J Chapter 6 treatment groups

Table 32: Treatment groups and their respective number of individuals (*n*)

Characteristic		**Greenspace tested**	**Treatment group**	***n***
Proximity	Distance to public greenspace	Public greenspace	1. Closer proximity	246
			2. Further proximity	246
Quantity	Public greenspace area	Public greenspace	1. Increase in quantity	217
			2. Decrease in quantity	275
	Total greenspace area	All greenspace	1. Increase in quantity	246
			2. Decrease in quantity	246
Quality	Bird species richness	NA	1. Increase in quality	114
			2. No change in quality	89
			3. Decrease in quality	289
	Greenness	NA	1. Increase in quality	209
			3. Decrease in quality	283
	Protected area(s)	NA	1. Increase in quality	91
			2. No change in quality	291
			3. Decrease in quality	110
Access	ANGSt doorstep greenspace	Public	1. Access to no access	53
			2. No change	404
			3. No access to access	35
		All greenspace	1. Access to no access	86
			2. No change	316
			3. No access to access	90
	ANGSt local natural greenspace	Public	1. Access to no access	28
			2. No change	443
			3. No access to access	21
		All greenspace	1. Access to no access	36
			2. No change	419
			3. No access to access	37
	ANGSt neighbourhood natural greenspace	Public	1. Access to no access	37
			2. No change	437
			3. No access to access	18
		All greenspace	1. Access to no access	5
			2. No change	483
			3. No access to access	4
	ANGSt wider neighbourhood	Public	1. Access to no access	22
			2. No change	454
			3. No access to access	16
		All greenspace	1. Access to no access	3
			2. No change	487
			3. No access to access	2
	ANGSt district	Public	1. Access to no access	0
			2. No change	492
			3. No access to access	0
		All greenspace	1. Access to no access	1
			2. No change	488
			3. No access to access	3

Characteristic		Greenspace tested	Treatment group	*n*
	ANGSt sub-regional	Public	1. Access to no access	0
			2. No change	492
			3. No access to access	0
		All greenspace	1. Access to no access	0
			2. No change	491
			3. No access to access	1
	Greenspace within 200m	Public	1. Access to no access	59
			2. No change	375
			3. No access to access	58
		All greenspace	1. Access to no access	12
			2. No change	474
			3. No access to access	6
	Greenspace within 300m	Public	1. Access to no access	81
			2. No change	342
			3. No access to access	69
		All greenspace	1. Access to no access	12
			2. No change	474
			3. No access to access	6
	Fields in Trust` greenspace within 800m	Public	1. Access to no access	89
			2. No change	324
			3. No access to access	79
		All greenspace	1. Access to no access	5
			2. No change	483
			3. No access to access	4

Note: ANGSt - Accessible Natural Greenspace Standards (Natural England 2010)

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