The associations between exposure to green and blue spaces with multimorbidity: observational analyses of UK Biobank cohort

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Abstract

Green and blue spaces can protect and promote mental and physical health by mitigating harm, restoring capacities, and promoting physical activity. However, little is still known about the ways different types of green and blue spaces affect the risk of having complex health states, such as multimorbidity.

To fill this gap, this thesis examined the relationships between exposure to several types of green and blue spaces with multimorbidity. First, a systematic literature review of longitudinal, observational studies on the relationships between green and blue spaces with long-term mental health conditions and non-communicable diseases (NCDs) was conducted. Results from the systematic review showed there is currently a lack of high-quality, comparative research on different types of green and blue spaces and how they affect the risk of developing long-term mental health conditions and NCDs. A data integration study with European Urban Atlas and UK Biobank was conducted to compute individual-level exposure data on availability of total green space, street trees, inland water bodies, and accessibility to parks. Finally, the cross-sectional associations between these green and blue space exposures with simple, complex, cardio-metabolic, respiratory, and mental multimorbidity were assessed. Results showed that only inland blue spaces moderately reduced the odds of having mental and complex multimorbidity, and that income and physical activity were not strong moderators in these relationships.

Although less commonly studied, inland blue spaces, such as rivers, canals and lakes, could offer opportunities for relaxation and mental restoration in all individuals, irrespective of income. Future research should aim to analyse these causal relationships by seeking to understand the underlying biological, social, and behavioural mechanisms. This can inform policy and public health practice. Incorporating blue natural environments into preventative care for multimorbidity can reduce the burden of multimorbidity on health systems and allow individuals to have higher quality of life.

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List of Abbreviations

AMS	Access Management System
CDC	Center for Disease Control and Prevention
CI	Confidence Interval
COPD	Chronic obstructive pulmonary disease
CVD	Cardio-vascular disease
DEFRA	Department for Environment and Rural Affairs
FUA	Functional Urban Areas
GAD	Generalised Anxiety Disorder
GIS	Geographic Information System
GLUD	Generalised Land Use Database
H-L	Hosmer–Lemeshow Test
HIC	High-income country
HQoL	Health-related quality of life
IQR	Inter-quartile Range
LAI	Leaf Area Index
LR	Likelihood ratio
LSOA	Lower Layer Super Output Areas
LTC	Long-term Condition
MET	Metabolic Equivalent of Task
MVPA	Moderate to Vigorous Physical Activity
NCD	Non-communicable disease
NDVI	Normalized Difference Vegetation Index
NHS	National health Service
NICE	National Institute for Health and Care Excellence
NOS	Newcastle-Ottawa Scale
OCD	Obsessive Compulsive Disorder
OR	Odds ratio
OS	Ordnance Survey
PCOS	Polycystic ovary syndrome
PECOS	Population, Exposure, Comparison, Outcomes, Study

PM	Particulate Matter
PRISMA-P	Preferred Reporting Items for Systematic reviews and Meta-Analyses for Protocols
PTSD	Post-traumatic Stress Disorder
QOF	Quality and Outcomes Framework
RR	Relative Risk
SD	Standard Deviation
SES	Socio-economic status
SMI	Severe Mental Illness
UA	Urban Atlas
UK	United Kingdom
UKBUMP	UK Biobank Urban Morphometric Platform
USA	United States of America
VCF	Vegetation Cover Fraction
WHO	World Health Organisation

Authors Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for a degree or other qualification at this University or elsewhere. All sources are acknowledged as references.

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Chapter 1: Introduction

Chapter summary

This chapter outlines the aim and objectives of thesis by providing an overview of definitions and current evidence for the relationship between exposure to green and blue spaces with health. An outline of the structure of the thesis is presented at the end of the chapter.

1.1 Green and blue spaces and their health-promoting roles throughout history

Over the last century, the world has experienced drastic social and economic changes. Urbanisation, increase in consumerism, and growing demands for housing have caused changes in the physical environment. Currently, over half of the world population live in cities, a number that is expected to increase to 72% by 2050 (Zhang, 2016). While cities undoubtably provide opportunities for employment and economic growth, they have led to scarcity and detachment from natural spaces and their healing properties (White et al., 2017).

Green and blue spaces can be broadly defined as areas of natural green vegetation (green space) and water (blue space). They can be naturally occurring, such as forests, rivers, and seas, or exist as a result of human intervention, such as urban parks, ponds and canals (Gascon et al., 2015). According to the biophilia hypothesis, humans have an innate connection with nature and often seek it for its therapeutic properties (Kellert and Wilson, 1993). Green vegetation and water are thought to elicit calmness, filter pollutants, and encourage social interaction and connectedness (Hartig et al., 2014). Nature has been an integral part of human life for many civilisations (Gerlach-Spriggs, Kaufman and Warner, 1998). The Ancient Egyptians and Romans bred and cultivated plants in domestic gardens for medicinal and aesthetic purposes. Hot springs and baths were also used by the Romans, Georgian and Victorians for recreation and socialisation. Often, they were key places to meet, relax and conduct business (Gerlach-Spriggs, Kaufman and Warner, 1998). The healing properties of greenness were also used in medieval English infirmaries, where outdoor gardens were considered vital for strengthening the body and mind (McLean, 2014).

Since humans began living in urban settlements, access to natural spaces has been declining and restricted (White et al., 2017). Until the 18th century, outdoor green spaces across the United Kingdom (UK) were mostly used by aristocrats for entertainment and sports, like horseback riding and hunting (Lambert, 2014). Private ownership of natural space has historically been observed in other cultures. In 6th century Japan, for example, Buddhist influences led to the creation of gardens in Japanese imperial palaces, which were used by the elite for entertainment and healing rituals. It wasn't until the industrialisation period of the mid-1800s that urban parks across Europe, Japan and USA became accessible to the public (Ward Thompson, 2011). Economic shifts towards manufacturing and urban expansion in Europe and North America led to a detachment of the working classes from nature. In the UK, initiatives were developed across large cities to provide public natural spaces for inner city factory workers in order to prevent contempt and social disorder. British politicians like Robert Peel campaigned for the right of access to public urban green spaces for all members of society (Ward Thompson, 2011), and as a result, parks in the mid-1800s became common grounds for recreation, sports, military activity, and socialisation for every urban dweller.

The latest and most prominent impact of green and blue spaces on health was observed during the 2020 COVID-19 pandemic, when the unprecedented disruption to daily lives left home-bound urban dwellers to seek parks, greenery and private gardens for recreation and socialisation (Foley and Garrido-Cumbrera, 2021). Having a green-blue space view from the window, a private outdoor space or higher tree canopy cover in the residential neighbourhood were all linked to better mental health (Lanza-León, Pascual-Sáez and Cantarero-Prieto, 2023; Garrido-Cumbrera et al., 2022) and lower psychological distress during the pandemic (Zhang et al., 2022a). However, access to such spaces was greatly determined by socio-economic position, as research showed that those from socio-economically disadvantaged communities spent less time visiting green and blue spaces and felt less socially connected compared to wealthier individuals during the COVID-19 lockdowns (Astell-Burt and Feng, 2021).

1.2 Pathways leading green and blue spaces to health

1.2.1 Overview

Green and blue spaces continuously play a role in tackling the health challenges posed by the modern world (Markevych et al., 2017; Hartig et al., 2014). Figures 1a and 1b show the conceptual models for the mechanisms driving the relationships between exposure to green and blue spaces with health, which were developed Markevych et al. (2017) (for green space) and White et al. (2020) (for blue space). Broadly, green and blue spaces promote and protect health through pathways of harm reduction, instoration (building capacities), and restoration (Markevych et al., 2017; White et al., 2020). Individual socio-demographic and environmental factors play important moderating roles in these relationships (Dahlgren and Whitehead, 1991). The amount, quality and presence of green and blue spaces in the neighbourhood, and the ways different groups of people use and benefit from these spaces is shaped by certain individual characteristics, such as age, sex, and income, as well as neighbourhood factors, such as safety and deprivation (Dahlgren and Whitehead, 1991). Next, I explain how each of the proposed conceptual pathways contributes to health.

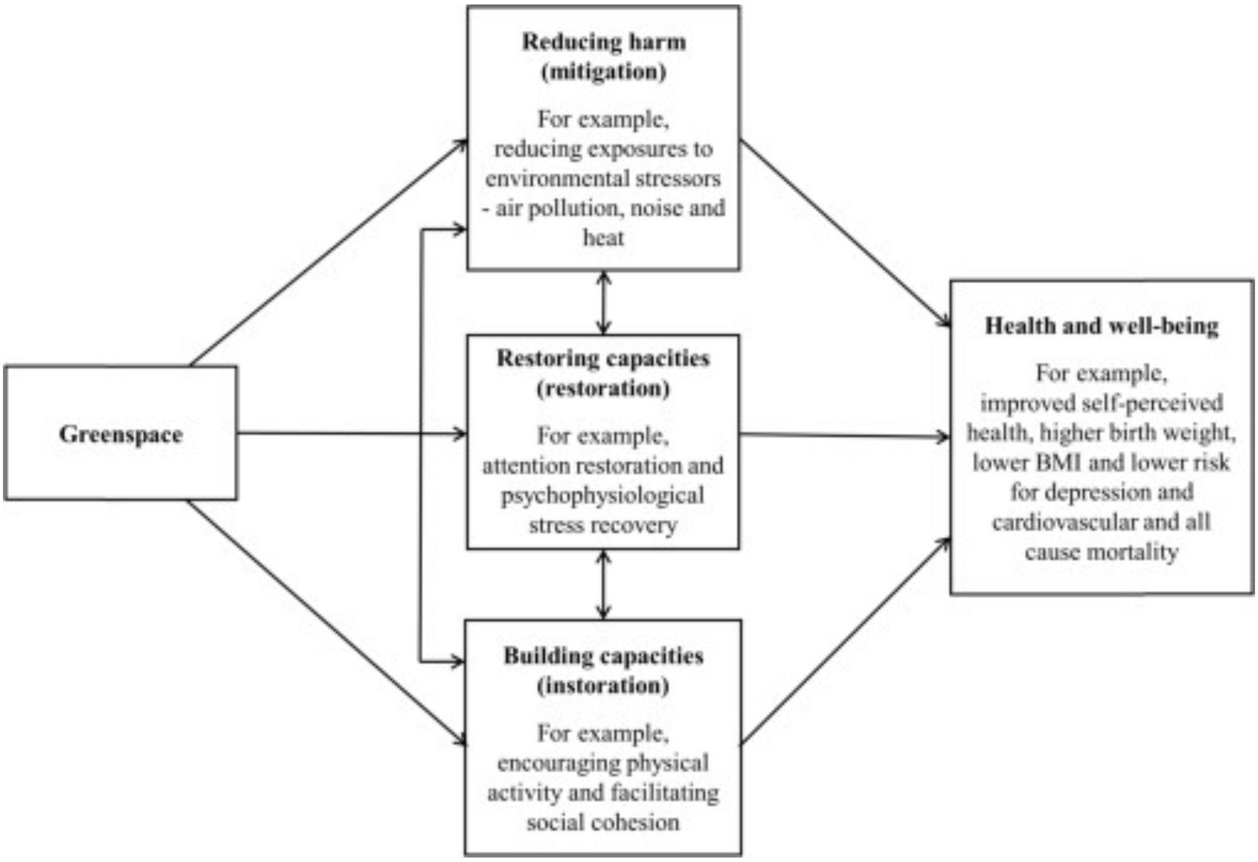

Figure 2a: Pathways linking green spaces to health (Image Source: Markevych et al., 2017)

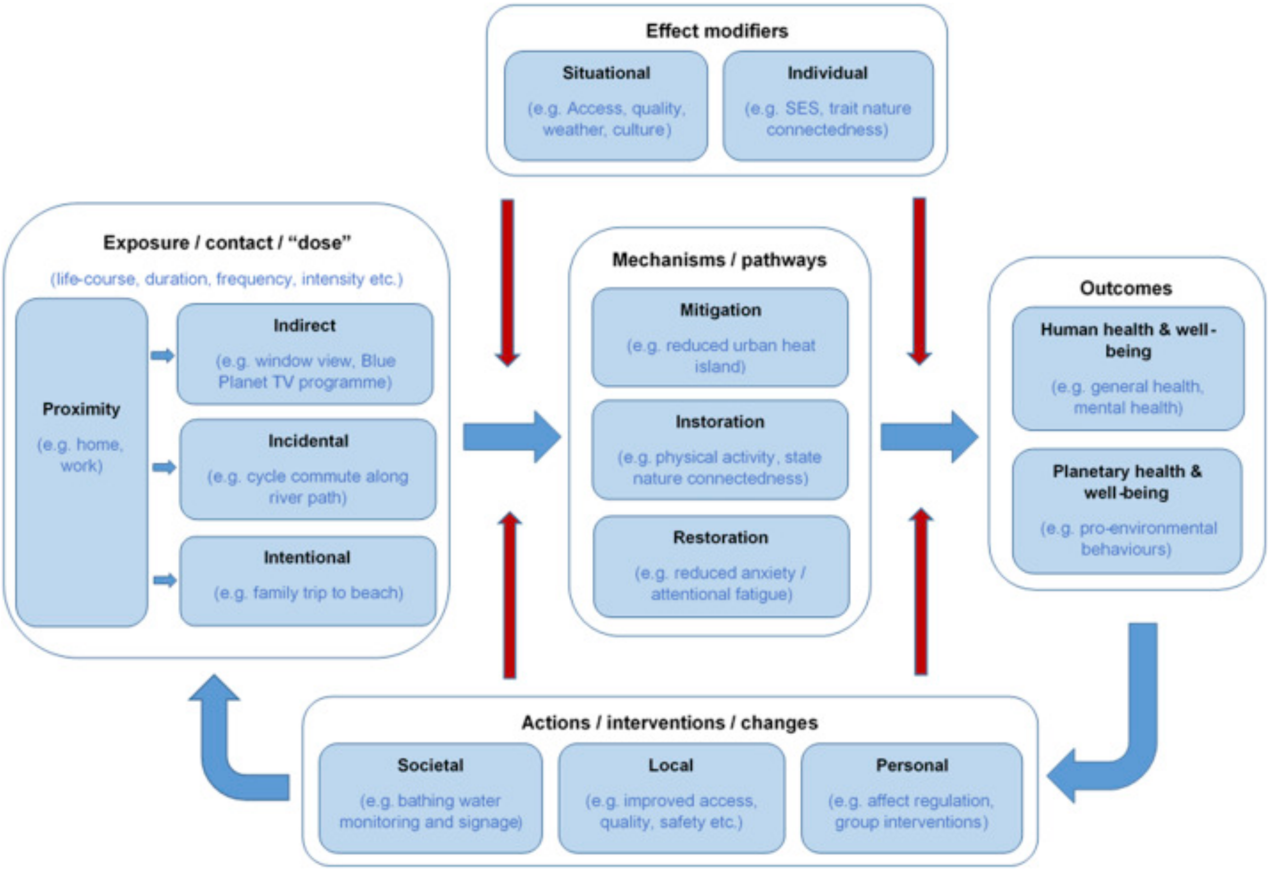

Figure 1b: Pathways linking blue spaces to health (Image Source: White et al., 2020)

1.2.2 Restoration

Some of the earliest working theories for the integration of nature in public health research focused on the restorative properties of natural spaces in improving attention and reducing stress. The Attention Restoration Theory (ART) (Kaplan, 1995) proposes that cognitive benefits of nature are gained by replenishing depleted mental capacity. Stress Reduction Theory (SRT) (Ulrich et al., 1991), on the other hand, focuses on using aspects of nature that elicit calming responses, such as species diversity, cleanness, and birdsong to reduce symptoms of stress. Replenishing mental capacity and reducing stress in return can lower the risk of developing chronic mental health conditions, such as depression and anxiety (Hartig, 2008).

1.2.3 Harm reduction

Another pathway linking green and blue spaces to health is harm reduction. Cities are hubs for air pollution and noise. Traffic, industry, high population density, and grey infrastructures trap and release heat, particulate matter (PM) and nitrous oxides, creating a potentially harmful environment for human health (Piracha and Chaudhary, 2022). Furthermore, climate change has increased the incidence of extreme weather events, such as heat waves and flooding, the effects of which are more pronounced in urban areas (Almaaitah et al., 2021). Presence of vegetation and water, however, can mitigate some this harm by trapping and filtering pollutants, lowering temperatures, and reducing surface run off (Almaaitah et al., 2021). Parks, canals, street trees and urban green infrastructure, for example, have often been used to block noise and cool surroundings (Markevych et al., 2017; van Renterghem et al., 2015; Koprowska et al., 2018; Li et al., 2010; Dzhambov and Dimitrova et al., 2015). The spatial configuration of urban green and blue spaces also creates urban zones of low traffic and air pollution that can be used for recreation and physical activity (Markevych et al., 2017). Large green spaces, on the other hand, can filter air pollutants by trapping and absorbing particles (Diener and Mudu, 2021). This has economic and environmental benefits, as it is estimated that larger green spaces in high-income countries (HICs), such as trees and forests, can lead to a $6.8 billion reduction cost of human health and in a 1% improvement in air quality (Nowak et al., 2014).

1.2.3 Instoration (building capacities)

Finally, green and blue spaces promote health by mechanisms of building capacities (also known as instoration). Building physical and mental capacity to deal with stressors increases resilience to poor mental and physical health, and prevents the development of non-communicable diseases (NCDs) (Van Dick et al., 2017; Osório et al., 2017). With their aesthetic properties and facilities for walking, childcare, and organised sport, green and blue spaces can encourage physical activity, socialisation, and community engagement. Studies have shown that adults living in greener areas tend to be more physically active (Klompmaker et al., 2018; Mytton et al., 2012; Sugiyama et al., 2008; Bancroft et al., 2015). Having more greenery around the residential address also improves physical activity levels over time (Astell-Burt et al., 2014). Moreover, visiting urban parks that have features like paved trails was associated with a 26-fold increase in physical activity levels in Canadian adults (Kaczynski et al., 2008). Observational studies have also found that green and blue spaces promote social cohesion (a term used to describe connectedness among social groups), which improves mental and general health (Peters et al., 2010; de Bell et al., 2017; Liu et al., 2020; Sugiyama et al., 2008; Maas et al., 2009), and reduces loneliness over time, especially in individuals living alone (Astell-Burt et al., 2022).

1.3 How can green and blue spaces help tackle emerging health challenges

1.3.1 Integration of green and blue space research in observational epidemiology

Although nature's healing properties have been greatly endorsed throughout history, evidence-based epidemiology didn't start quantifying the effects of green and blue spaces on health until the 1990s. Earliest epidemiological studies were mostly trials assessing the impact of short-term nature exposure on mood, cortisol levels, anxiety, and blood pressure (Bowler et al., 2010). However, advances in aerial photography and the development of remote sensing during the late 20th century have driven the production of high resolution, large-scale mapping of the Earth, which has allowed wide-scale green and blue space exposure assessment in observational epidemiological research. In the past 15 years, health cohort data linkages with environmental datasets like the Normalized Difference Vegetation Index (NDVI), land use maps, and LiDAR have increased the availability of objective information on residential, individual-level green and blue space, which has facilitated observational research into chronic health, NCDs and mental health disorders (de Keijzer et al., 2018; Bloemsma et al., 2019; Sarkar, Webster and Gallacher, 2015; Roscoe et al., 2022a; Fore et al., 2020).

Appropriate exposure assessment is imperative to studying the relationship between nature and health. To increase the accuracy of green space exposure measures and reduce the risk of introducing ecological fallacy bias, observational studies have increasingly adopted the buffer approach, which captures the availability or proximity of natural space around each individual's residential address (Browning and Lee, 2017). Remote-sensing data have been used to construct these objective measures of green and blue spaces (Labib et al., 2020). However, the integrity of such approaches vary greatly by data source, spatial resolution, and spatial scales (Labib et al., 2020). Remote-sensing datasets, such as land use maps and the NDVI are often open-access and easily accessible, however, they sometimes lack appropriate spatial and temporal resolution to capture green spaces in urban areas, which may be small, fragmented and subject to change (Le Texier et al., 2018; Klompmaker et al., 2018). Moreover, epidemiological studies adopting a buffer approach vary greatly by buffer type and size because of lack of consensus on appropriate spatial scales (Labib et al., 2020). Although the World Health Organisation (WHO) (2016b) recommends that everyone should have an accessible green space within 300m of their residential address, lack of data availability on accurate residential information and variation in buffer choice may produce incomparable results between studies (Labib et al., 2020). This suggests that epidemiological studies using large-scale, objective green and blue space exposure assessment are still susceptible to inaccuracies in exposure measures and potential bias, which can be overcome by using higher resolution data and measuring exposure change over time (Labib et al., 2020).

1.3.2 Ageing populations, the burden of non-communicable diseases (NCDs), and mental health

Currently, the world's population is ageing. Biological ageing is characterised by progressive degeneration of body tissues that leads to reduced functional ability (McNee, et al., 2014). In epidemiology, ageing is seen as a process of living longer and dying later (World Health Organisation, 2015). Since the 1950s, countries worldwide have seen an increase in the proportion of people aged 60 years and older (Tinker, 2002). By 2050, the number of people aged 60 year or over is expected to double, while the number of people aged 80 and over is expected to triple (World Health Organisation, 2015). The UK currently ranks 11th for highest ageing population, with about 18% of the total population being above the age of 65 years (Population Reference Bureau, 2022). Shifts in population distributions towards ageing in countries like the UK are directly caused by declining infant and adult mortality, improved sanitation and healthcare, and lower fertility rates. Although older individuals can live healthy and productive lives, ageing populations can put strain on healthcare systems and society. As the body loses ability to respond to different environmental stimuli (Bloom et al., 2015), the risk of developing and accumulating multiple long-term chronic health conditions and disability increases (Bloom et al., 2015).

Multimorbidity is the term given to describe the presence of two or more co-occurring long-term conditions (LTCs) (Prados-Torres et al., 2014). LTCs encompass both NCDs (like CVD, cancer and respiratory disease) and mental health disorders (like depression, anxiety, and severe mental illnesses (SMI) (such as schizophrenia and bipolar disorder). Multimorbidity is directly linked to aging and the increasing burden of NCDs and mental health conditions. NCDs are chronic, physical, non-infectious medical conditions characterised by long duration and slow progress (Budreviciute et al., 2020). They are non-transmittable, have long-term health consequences and often require prolonged treatment (Budreviciute et al., 2020; PAHO, 2021). Although mental health conditions, such as depression and anxiety, are sometimes included in the definition of NCDs (NICE, 2011), this thesis distinguishes NCDs from mental health disorders in order to establish clearer relationships between the bidirectional associations between mental and physical health conditions. Therefore, NCDs in this thesis are defined as chronic, physical health conditions only.

Currently, 71% of all deaths are attributable to NCDs, making them the leading cause of death globally (Bigna and Noubiap, 2019). Cardio-vascular disease (CVD), cancers, respiratory diseases, and diabetes are the four biggest killers, accounting for 32.4 out of the 41 million total NCDs deaths a year worldwide (World Health Organisation, 2019). NCDs are an outcome of multiple processes, including ageing populations, global economic shifts, higher urbanisation, increase in noise and air pollution, and shifts towards sedentary lifestyles, poor diets, and higher alcohol consumption (World Health Organisation, 2019). Although older individuals are more likely to develop multiple co-occurring NCDs and experience adverse health outcomes such as mortality, the prevalence of NCDs is increasingly growing in young and middle-aged adults due to poor diets, sedentary lifestyles, air pollution and poor mental health (Habib and Saha, 2010).

Experiencing NCDs can lead to compromised ability to deal with stressors (Prince et al., 2007). Treatment side effects, disability and loss of functioning can also result in poor mental health. Alongside the increasing burden of NCDs, the burden of mental health disorders has also increased. In 2005, neuropsychiatric conditions, including depressive, substance and alcohol use disorders, bipolar disorder, schizophrenia, and dementia accounted for over a quarter of Disability Adjusted Life Years (DALYs) globally (Prince et al., 2007). By 2030, unipolar depressive disorders are predicted to become the second biggest contributors of DALYs globally, after back pain (Lopez et al., 2006). The relationship between mental health conditions and NCDs is complex and bidirectional (Prince et al., 2007). Depression and other common and severe mental health disorders can result in poor diet, reduced physical activity, and increased alcohol consumption, which can increase the risk of developing NCDs like hypertension, obesity, and myocardial infraction (Celano and Huffman, 2011; Goldston and Baillie, 2008). Having multiple, co-occurring NCDs, on the other hand, can exasperate the risk of developing mental health conditions. A systematic review found that the risk of depression in individuals with two or more co-existing NCDs was twice that of individuals with only one NCD, and three times that of individuals without any existing NCD (Read et al., 2017). Depression and anxiety scores were also consistently higher in adults with multiple NCDs compared to adults with only one NCD (Lai et al., 2019; Zhao et al., 2021; Gould et al., 2016; Smith et al., 2014; Vancampfort et al., 2017).

1.3.3 How exposure to green and blue spaces can reduce the risk of mental health conditions and NCDs

Epidemiological evidence has found that greater amount of green space can improve well-being, general health, stress, and quality of life (Stigsdotter et al., 2010; de Vries et al., 2003; Maas et al., 2006). Recent observational studies have also attempted to quantify the effects of exposure to nature on the risk of developing chronic mental health conditions and NCDs like depression, CVD, and cancer. While some studies found no associations between exposure to green spaces and CVD, others deduced that higher amount of green space and better access to a park were associated with lower odds of hypertension in high-income country (HIC) adult populations (Yang et al., 2019; Liu et al., 2022; Bauwelink et al., 2020; Braziene et al., 2018). In a longitudinal study of Korean adults, moreover, the risk of developing CVD, myocardial infraction, and stroke was 15%, 23% and 13% lower, respectively, in those who had more green spaces in their neighbourhood (Seo et al., 2019). A recent UK Biobank study also found that higher amount of green and blue space were both associated with moderate reduction in the risk of developing irritable bowel disease (Zhang et al., 2022b). Meta-analyses have also found a 28% reduction in the risk of type 2 diabetes and a 23% reduction in the risk of stroke mortality with exposure to higher amount of green space (Twohig-Bennet and Jones, 2018; Yuan et al., 2021). However, such associations may be dependent on disease types and settings. In a study of older American adults, for example, Klompmaker et al. (2022) found that higher amount of blue space, higher amount of green space, and presence of park all reduced the risk of respiratory disease hospitalisation but has no effect on the risk of CVD hospitalisation.

Greater exposure to green space also affects common and severe mental health disorders. Evidence from longitudinal studies suggests that greater exposure to green space reduces the risk of developing schizophrenia (Engemann et al., 2018; Chang et al., 2020; Rotenberg et al., 2020). Individuals who lived in residential areas with lowest amount of residential greenery had 24% to 52% higher risk of developing schizophrenia compared with those who lived in greenest areas (Engemann et al., 2018; Rotenberg et al., 2020). A review of the epidemiological evidence also showed that there is a negative dose-response relationship between increasing density of green space in childhood and decreasing risk of schizophrenia in adulthood (Freitas and Valadas, 2021). In the UK, closer proximity to urban green space with a lake was also associated with lower prevalence of serious mental illnesses (Cruz et al., 2022).

Evidence also shows that green spaces can reduce the odds of having depression. In cross-sectional studies, individuals living in residential areas with lowest amount of park space had 16% to 27% higher odds of depression (Min et al., 2017), while middle-aged and older adults living in areas with higher proportion of green space had 31% lower odds of depression (Zhou et al., 2022). Living near a small park (vs living near a big park) also increased the odds of having depression threefold in Indian adults with pre-existing physical health conditions (Mukherjee et al., 2017). In comparative analyses between green and blue spaces, moreover, the odds of depression in Spanish adults decreased by 82% with better access to green spaces but not with better access to blue spaces (Gascon et al., 2018). A systematic review suggests that a significant relationship between greenness and depression only exists at a cross-sectional level (Rautio et al., 2017). However, a recent systematic review concluded that it is not necessarily amount of greenery but immersion in nature (going on walks) that reduces anxiety (Kotera et al., 2021), suggesting that the relationship between green space and health may be driven by specific interactions with green spaces. Little is still known about the ways blue spaces affect mental health (Hermanski et al., 2022), but studies of HIC adult populations show that certain types of blue space interactions, such as views from the window and visits to blue spaces can improve general mental health (Nutsford et al., 2016; Garrett et al., 2019).

Interactions with green and blue spaces in urban areas may be limited due to lack of space and sedentary lifestyles (Nutsford et al., 2016). To improve physical activity levels and mitigate the harmful effects of urbanisation, policy bodies and governments in UK, USA and Europe have used large-scale environmental regeneration interventions and community-based behavioural programs to increase the availability and usage of green and blue spaces (Bianconi et al., 2018). A systematic review found that urban green space renovations (such as building of green pathways, improving outdoor gym facilities and building more pedestrian routes) generally improve physical activity levels at a population level (Hernández et al., 2023). However, another systematic review comparing the effects of park renovation interventions with park-based physical activity programs found that park renovation interventions currently have greater effect on physical activity compared to park-based physical activity interventions (Derose et al., 2021). Green social prescribing, a term used to describe connecting patients to community-based programs that promote interactions with natural spaces, has been increasingly used as a cost-effective method to reduce loneliness and improve physical activity and mental health (Frost et al., 2023). Several studies have found positive effects of green social prescribing and nature-based interventions on mental health and loneliness (Coventry et al., 2021; Thomas et al., 2022). However, the efficacy of such interventions is contingent on reaching the right groups in the population. Individuals of low-income and those with multimorbidity are less likely to be involved in green social prescribing or use public green spaces due to social, physical and psychological barriers, including fear of discrimination, lack of accessible facilities and lack of organised activities that accommodate disabilities (Leavell et al., 2019; Wood et al., 2022). Increasing funding, education and curating activities suitable for such groups are, therefore, key to increasing park use and community involvement (McHale et al., 2020).

1.4 Exposure to green and blue spaces and multimorbidity

This thesis examines the relationships between exposure to different types of green and blue spaces with the risk of multimorbidity. Multimorbidity is a growing public health challenge driven by socio-demographic and behavioural changes in HIC populations (Lee et al., 2015; Makovski et al., 2019; Singer et al., 2019a). In the UK, multimorbidity prevalence has steadily grown over the past two decades and is especially pronounced in women and young and middle-aged individuals of low income (Barnett et al., 2012). Multimorbidity can have profound negative impacts on healthcare systems, individual disability, and quality of life (Lee et al., 2015; Makovski et al., 2019; Singer et al., 2019b). However, the natural environment can mitigate some of this burden by reducing the severity and rate of accumulation of LTCs in mid-life through pathways of harm reduction, physical activity, and restoration. Policy bodies and researchers have long proposed the need to study how green and blue spaces affect complex health states in order to inform and design interventions that minimise the incidence of multimorbidity and help individuals maintain high functioning and good mental health into old age (World Health Organization, 2015; Coventry et al., 2020). As I discussed above, observational epidemiologic research has broadly examined the relationships between exposure to green spaces with single chronic health conditions, such as CVD, diabetes, cancer and depression (Gascon et al., 2015, 2017), but little is still known about different types of urban green and blue spaces and how they affect the risk of having multiple long-term mental and physical health conditions.

1.5 Thesis aims and objectives

The aim of this doctoral research is to determine the extent to which green and blue spaces can explain the risk of multimorbidity.

To achieve this, the objectives of the thesis are as follows:

1. Conduct a systematic literature review to synthesise the available observational, longitudinal evidence about the relationship between exposure to green and blue spaces with mental health conditions and NCDs.

2. Using the systematically reviewed evidence on types of green and blue spaces and their relationships with mental health and NCDs, to compute and integrate multiple relevant measures of green and blue spaces into a large health cohort, the UK Biobank.

3. Using UK Biobank data, to comparatively analyse the associations between exposure to different types of green and blue spaces with simple and complex multimorbidity, and with associative multimorbidity clusters.

4. Assess how physical activity and income moderate the relationship between exposure to green and blue spaces with multimorbidity.

1.6 Structure of the thesis

This thesis is structured in three analytical parts and accompanied by an introduction, background, and discussion chapters.

In Chapter 2, I provide a conceptual and epidemiological background to multimorbidity to characterise its burden on healthcare systems and the individual. I summarise the available empirical and theoretical evidence on multimorbidity prevention and propose a framework for assessing the relationship between green and blue spaces with multimorbidity.

Chapter 3 is the first analytical chapter, which comprises of a systematic review of longitudinal, observational studies about the relationship between exposure to green and blue spaces with mental and physical health. Results from the systematic review are used to guide a data integration study using UK Biobank and European Urban Atlas.

Chapter 4 details the methodology and results of the data integration study conducted to compute and integrate European Urban Atlas data on total green space, street trees, parks, and inland blue space into 300,000 UK Biobank participants.

In Chapter 5, I describe the methods used to assess the cross-sectional associations between exposure to different types of green and blue spaces with several multimorbidity outcomes.

In Chapter 6, I present the results of the cross-sectional analyses, as well as results from interaction analyses between green/blue spaces with physical activity and stratified regression analyses by income.

Chapter 7 is a discussion that draws on the results of the cross-sectional analyses, as well as the systematic review and data integration study, to provide an explanation and insight on the roles of green and blue spaces in reducing the risk of multimorbidity. In Chapter 7, I also discuss the strengths and limitations of the thesis and outline the pathways to future research and implications for healthcare policy about mitigating the risk of multimorbidity.

Chapter 2: Background on Multimorbidity - Burden and Risk Factors

Chapter summary

This chapter provides an overview on multimorbidity, the magnitude of the multimorbidity burden on healthcare systems and individuals, and the modifiable and non-modifiable risk factors associated with multimorbidity prevalence and incidence in high-income countries. This chapter highlights the importance of multimorbidity prevention and how the natural environment can be used to reduce the risk and severity of multimorbidity. Drawing on previous literature on the roles of natural environments in health promotion, I propose a framework for studying the associations between green and blue spaces with multimorbidity.

2.1 Multimorbidity: definition and burden

2.1.1 Definition of multimorbidity

Multimorbidity is defined as the co-existence two or more LTCs within one individual (Mercer, Salisbury and Fortin, 2014; Mercer et al., 2016). The components of multimorbidity can be either mental or physical conditions, or a combination of both. Multimorbidity impacts function, quality of life, healthcare utilisation, costs, and mortality (Mercer, Salisbury and Fortin, 2014; Mercer et al., 2016; Singer et al., 2019a). The term 'multimorbidity' was first coined by van den Akker et al. in 1996, who proposed the need to distinguish between the clinically relevant term, comorbidity, and the broader, socio-demographic phenomenon that is the accumulation of diseases without the overt presence of an index condition (Singer et al., 2019b). While comorbidity and multimorbidity have been previously used interchangeably, multimorbidity generally carries broader implications to public health and policy (Singer et al., 2019b). It can be viewed as the product of shifts towards high prevalence of chronic mental health conditions and NCDs caused by a combination of socio-environmental factors such as ageing, low infant and maternal mortality, industrialisation, low physical activity, and poor diets (Singer et al., 2019c). Comorbidity, on the other hand, is the accumulation of diseases during the clinical course of an index disease in an individual and is more relevant to clinicians and treatment providers (Feinstein, 1970).

2.1.2 Prevalence of multimorbidity

Multimorbidity is a growing public health concern (World Health Organization, 2016a). Recent demographic shifts towards low birth rates, low infant and maternal mortality and improved sanitation have led to ageing populations (Uijen and van de Lisdonk, 2008). Old age is the biggest risk factor for multimorbidity (Sakib et al., 2019), with the oldest old (85 years or older) having the highest prevalence between 80% and 95% (Barnett et al., 2012; Singer et al., 2019a). At age 75, the prevalence of multimorbidity in the general population of HICs ranges between 13.1% to 71.8% (Fortin et al., 2012; Nguyen et al., 2019; Ho et al., 2022). Although ageing is an inevitable demographic phenomenon, rate of accumulation of LTCs in middle and early adulthood is largely shaped by socio-economic, behavioural, and environmental risk factors (Barnett et al., 2012; Singer et al., 2019b). Research from UK and other HICs consistently shows that women, individuals of low socio-economic status (SES) and ethnic minorities have higher prevalence of multimorbidity than their counterparts (Rizza et al., 2012; Harrison et al., 2014; Fortin et al., 2010; Rocca et al., 2014; Puth et al., 2017; Barnett et al., 2012; Low et al., 2019).

2.2 Socio-demographic drivers of multimorbidity

2.2.1 Socio-economic status (SES)

Socio-economic status (SES), commonly captured as level of education, income or deprivation, is an indicator of an individual's or family's social and economic position, and access to economic and social resources relative to others (Macintyre et al., 2003). SES is a strong determinant of both physical and mental health (Wang and Geng, 2019; Kivimäki et al., 2020), and those of lower incomes are at greater risk of poor mental and physical health compared to those with higher incomes (Lynch et al., 2000; Patel et al., 2018). There is a clear relationship between low SES and multimorbidity. A systematic review found the odds of having multimorbidity were 4.4 times higher for those of low income compared to those of high income (Ingram et al., 2021). Living in more deprived areas in the UK also increased the odds of multimorbidity 1.42-fold (Agborsangaya et al., 2012, 2013; Singer et al., 2019a). SES also shapes trajectories of multimorbidity in women and middle-aged and younger adults. Several cross-sectional studies of British and European adults have found that the association between low SES and higher risk of multimorbidity is stronger for women than men (Barnett et al., 2012; Marmot, 2020). Furthermore, the prevalence of mental-physical multimorbidity is especially high among young and middle-aged individuals of low SES, which suggests that multimorbidity is not necessarily a condition of old age but a health state that is shaped by multiple socio-demographic factors (Barnett et al., 2012; Marmot, 2020; Kessler et al., 2005; Bond et al., 2012).

In a UK context, low-income, high deprivation, and low education status all independently increase the risk of multimorbidity in middle-aged and older adults (Agborsangaya et al., 2012, 2013; Singer et al., 2019b). Individuals of low education also have a 1.64-fold increase in the risk of multimorbidity compared to individuals of high education (Pathirana and Jackson, 2018). Studies have also found that living in areas of higher deprivation is positively associated with multimorbidity prevalence

(Bisquera et al., 2022; Knies and Kumari, 2022; Ashworth et al., 2019), which suggests that multimorbidity risk is shaped not only by individual income but also by neighbourhood quality, which is a well-known risk factor for health (Bond et al., 2012).

2.2.2 Ethnicity

Individuals of ethnic minorities may be more likely to suffer from poor mental and physical health because of systemic discrimination and cultural differences in health practices (Kessler, Mickelson and Williams, 1999; Berkman and Mullen, 1997). In the UK, individuals of Black and South Asian ethnic minority are, respectively, 1.20 to 1.30 and 1.29 to 1.61 times as likely as white individuals to be multimorbid (Bisquera et al., 2022; Mathur et al., 2011). Similar relationships were observed for individuals of Turkish ethnic minority groups in the Netherlands (Verest et al., 2019), and for South Asian and Māori ethnicity in New Zealand (Aminisani et al., 2020; Ashworth et al., 2019).

The relationship between ethnicity and multimorbidity, however, is not unequivocal across all populations. In the United States (US), Asian and non-Hispanic black ethnic minorities have lower incidence of multimorbidity compared to white people (St Sauver et al., 2015; Quiñones et al., 2019). Accumulation of diseases and multimorbidity presentation can also vary between ethnic minority groups. In an 11-year longitudinal study, relative to white participants, Mexican Americans had slower accumulation of disease, but Black individuals had higher accumulation of disease (Quiñones et al., 2019). The burden of multimorbidity, measured as disease severity and healthcare utilisation, also tends to be higher in Black individuals then White individuals (Botoseneanu et al., 2022). Genetic, cultural, and societal factors can all partially explain these differences. Due to institutional racism, marginalised communities may be less likely to seek help on first presentation of symptoms, which can result in delayed diagnosis and treatment. Ethnic minority groups are also more likely to develop different types of multimorbidity to White individuals. A study from the US found that older Black individuals are more likely to have multimorbid conditions with diabetes, while White younger groups tend to have multimorbidity characterised by depressive disorders (Ashworth et al., 2019). Although multimorbidity patterns are highly heterogeneous between populations and study designs, individuals of ethnic minorities are also more likely to have a multimorbidity type that is distinct to their ethnic group (Alshakhs et al., 2022).

2.3 Burden of multimorbidity on individuals and the healthcare system

2.3.1 Resilience to multimorbidity through utilisation of individual, social and environmental resources

According to Wister et al's (2016) model of resilience to multimorbidity, individuals utilise different social, environmental, and personal resources over the course of their lifetime to strengthen their body's ability to deal with adverse health effects and prevent further health degeneration (figure 2). Building resillience to ill health can help retain better quality of life, lower healthcare utilisation and reduce premature mortality. Although multimorbidity risk is partially shaped by individual, non-modifiable characteristics such as age, sex and ethnicity; acquisition of certain behaviours, strengthening of support networks, and the availability of health-promoting environments over the lifecourse can further help build resillience to mutlimorbidity and its adverse side effects (Wister et al., 2016). In the following sections, I outline how multimorbidity can affect quality of life, mortality risk and healthcare utilisation, then move on to explain the ways different environments can help reduce the risk of multimorbidity.

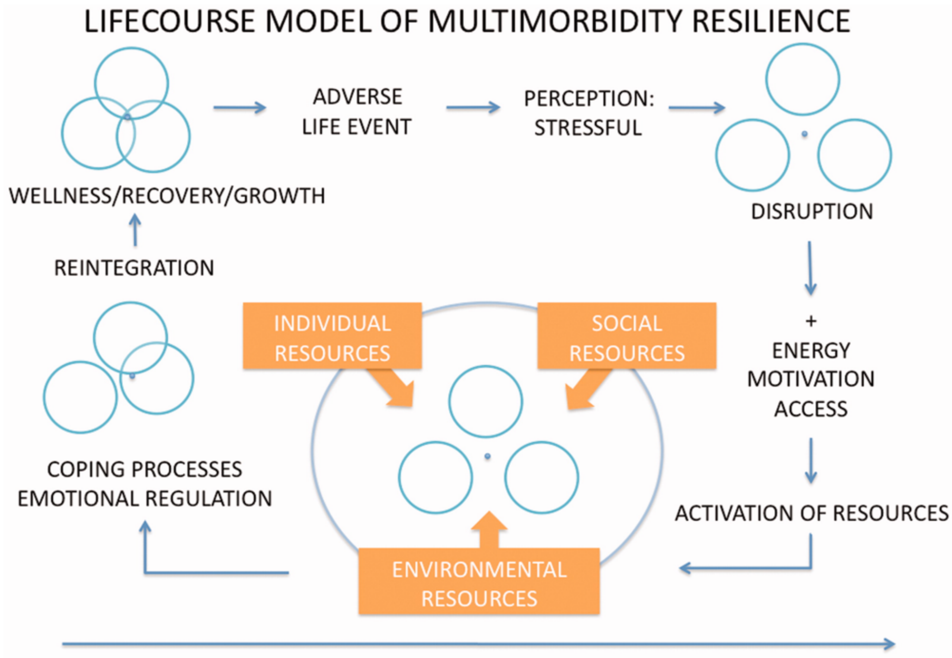

Figure 2: Lifecourse model of multimorbidity resilience by Wister et al. (2016) (Image Source: Wister et al., 2016)

2.3.2 Quality of life, disability and functional status

Preventing multimorbidity is important in maintaining good quality of life (QOL), physical and mental functioning. Systematic reviews, meta-analyses and observational studies have consistently shown that higher number of co-occurring conditions are associated with poorer physical functioning and quality of life (Makovski et al., 2019; Fortin et al., 2006, 2007, 2004; Marengoni et al., 2009). Less is known about the social and psychological impact of multimorbidity (Fortin et al., 2004), but studies have shown that young age is a strong moderator. A systematic review found that quality of life (QoL) was poorer among multimorbid individuals in their early mid-life than in multimorbid individuals in later mid-life (Kanesarajah et al., 2018). Different multimorbidity types may also have stronger impact on QOL than others due to specific symptom presentation and treatment side effects. In a cross-sectional study, individuals with mental multimorbidity, for example, had poorer QOL than individuals with cardio-vascular multimorbidity (Kanesarajah et al., 2018). Conditions such as depression, anxiety, stroke, bronchitis, and chronic pain also have stronger impact on QOL than other LTCs (Garin et al., 2014; Agborsangaya et al., 2013; Hunger et al., 2011).

2.3.3 Polypharmacy and frailty

Accumulation of chronic conditions can lead to compromised body system functions due to adverse medication side effects. Polypharmacy, the concomitant use of five or more medications, is highly prevalent in individuals with multimorbidity (Masnoon et al., 2017). Interactions between medicines can lead to adverse side effects, such as organ failure, reduced physical functioning, falls, disability, frailty, and poor mental health (Maher, Hanlon and Hajjar, 2014). Although polypharmacy is common in non-multimorbid individuals, individuals with two or more co-occurring LTCs may have compromised physiological and mental ability to deal with specific drug reactions. Having multimorbidity can also cause a recursive loop, where higher number of LTCs, CVD, and poor mental and physical functioning further increase the risk of being prescribed more medications (Khezrian et al., 2020; Rieckert et al., 2018).

Another adverse impact of multimorbidity is frailty, which is an age-related clinical syndrome characterised by increased vulnerability to stressors and decreased physiological reserves that lead to poor health outcomes (Fried et al., 2001). Frailty is measured either as a series of phenotypical symptoms and states, such as low energy, weight loss, slow walking speed, low physical activity, and low grip-strength (also known as the Phenotype model) (Fried et al., 2001; Searle et al., 2008), or as clinical conditions and diseases (known as the Frailty Index) (Cesari et al., 2013). The cost of treating and managing frailty in HICs can account for up to 76% of total care costs (Alkhodary et al., 2020), posing large economic challenges to healthcare systems. Like other complex relationships between ageing, accumulation of diseases and health-related outcomes, the relationship between multimorbidity and frailty is bidirectional (Villacampa-Fernández et al., 2017). Having multimorbidity can lead to compromised health states that eventually result in frailty, while being frail can increase the accumulation of LTCs within an individual, causing multimorbidity (Villacampa-Fernandez et al., 2017). Systematically reviewed evidence also shows that about 70% of individuals with frailty have multimorbidity, but only 16% of all multimorbid individuals are frail (Vetrano et al., 2019). Generally, the odds of having frailty in individuals with multimorbidity are 2.27 times as those of individuals without multimorbidity (Vetrano et al., 2019), but this can vary by multimorbidity type. Cardiac, respiratory, and psychiatric multimorbidity tend to have stronger associations with frailty and mortality from frailty than other disease combinations (Tazzeo et al., 2021; Oude Voshaar et al., 2021).

2.3.4 Mortality

Individuals with multiple chronic health conditions have higher risk of mortality than individuals without any chronic health conditions (Dugravot et al., 2020), however, this relationship varies by multimorbidity type and SES (Marengoni et al., 2009). The risk of mortality in multimorbid individuals tends to be greater for those with combinations of CVD, cardio-metabolic and/or respiratory diseases than individuals with CVD-mental, endocrine–kidney and cancer–mental multimorbidity (Singer et al., 2019a). A UK Biobank study also found that disease combinations of alcohol abuse, depression, epilepsy, cancer, and cardio-metabolic conditions showed stronger associations with mortality than other disease combinations (Jani et al., 2019). On the other hand, another observational study of German adults found that psychiatric, psychosomatic and pain disorders tend to have a protective effect on 5-year mortality (Schäfer et al., 2018).

In addition to disease-specific multimorbidity combinations, higher number of accumulated LTCs is also associated with higher mortality risk. The term complex multimorbidity is commonly used to describe the presence of three or more LTCs in an individual (Singer et al., 2019b). Higher number of co-occurring LTCs can significantly limit body functions due to interactions between body systems and medications. Studies show a positive linear trend between number of LCTs and risk of mortality (He et al., 2022; Jani et al., 2019). In the UK middle-aged adults, the risk of all-cause mortality in those with 4+ LTCs was almost three times as high as those with no LTCs (Jani et al., 2019). Although having any kind of multimorbidity increased the risk of mortality, having 4+ cardio-metabolic conditions (compared to having no cardio-metabolic conditions) increased the risk of mortality 8.20 times (Jani et al., 2019). These relationships, however, do not always stand, and other studies of Japanese and European adults have found that complex multimorbidity showed similar strengths of association with mortality as simple multimorbidity or having only one LTC (Marengoni et al., 2009; Kato et al., 2021). This suggests that the risk of mortality may also be shaped by presence of lethal disease combinations and not just number of accumulated conditions.

Socio-demographic characteristics such as sex and SES moderate the relationship between multimorbidity and mortality. A study of Norwegian adults found the relationship between multimorbidity, and mortality was stronger among those of low income (Vinjerui et al., 2020). The relationship was also more pronounced in men than women, as men of low SES with 0-2 LTCs and men of low SES with 3+ LTCs had 1.44- and 2.43-times higher hazard risk of death, respectively, as men of high SES with no multimorbidity (Vinjerui et al., 2020). Similar findings were observed in a Danish population-based study, where individuals of low education with simple and complex multimorbidity had 60% and 52% higher hazard risk of death, respectively, compared to individuals of high education and no multimorbidity (Lund Jensen et al., 2017). Contrary to this, the relationship between multimorbidity and mortality did not vary by income group in a UK Biobank study (Jani et al., 2019), and this could be explained by differences in cohort sample sizes and demographic structure of the population. In Brazilian adults, the risk of mortality in individuals with multimorbidity was also not attenuated by education, suggesting there may be other, socio-demographic or environmental drivers in middle-income country populations (Bernardes et al., 2021).

2.3.5 Impact on healthcare utilisation and costs

Multimorbidity of chronic conditions often requires complex management in primary or specialist care facilities, which increases costs and healthcare utilisation.

Measuring the true burden of multimorbidity on healthcare systems is difficult, but observational studies suggest that the odds of hospital admissions and the mean number of primary care consultations generally increase with increasing number of co-occurring LTCs (Glynn et al., 2011; van Oostrom et al., 2014). In a community-dwelling population, multimorbid individuals (2+ LCTs) had almost four times as higher healthcare utilisation costs as non-multimorbid individuals (Bähler et al., 2015). In HIC populations, total healthcare utilisation costs increased by 33% with each additional long-term health condition (Bähler et al., 2015). A positive linear relationship was also observed between number of conditions and hospitalisations in a Danish population (Frølich et al., 2019).

Complex multimorbidity has stronger impact on healthcare utilisation than any other multimorbidity types. In a longitudinal study, individuals with dementia and four or more chronic conditions had 88% higher risk of hospitalisation compared to individuals with dementia alone (Mondor et al., 2017). In a study comparing healthcare utilisation among different associative multimorbidity patterns in women, complex multimorbidity had highest odds of GP visits, hospitalisations, and outpatient visits compared to simple multimorbidity (Juul-Larsen et al., 2020). In men, however, degenerative and pulmonary disorders showed the strongest positive associations with higher number of GP visits, hospitalisations, and specialist visits (Juul-Larsen et al., 2020). Another study showed a positive association between higher number of health conditions and higher odds of prolonged hospital length of stay and avoidable admissions (Aubert et al., 2019). Out of those health conditions, individuals with renal failure-cancer multimorbidity had highest odds of avoidable readmission (out of 20 disease pairs), while individuals with mental multimorbidity had highest odds of prolonged length of stay (Aubert et al., 2019). Finally, an ecological study found the number of hospitalisations and number of doctor visits increased with increasing number of co-existing conditions (Palladino et al., 2016). Overall, the pooled number of annual doctor visits was almost double (mean 9.9 visits) for people with multimorbidity compared people with no multimorbidity (Palladino et al., 2016).

Type of multimorbidity and sex are potential moderators in the relationship between multimorbidity and healthcare utilisation. Some of these relationships, however, are also moderated by SES. Individuals with lower education had higher hospitalisation episodes, while those with no education had highest healthcare utilisation regardless of number of conditions (Frølich et al., 2019). However, a Taiwanese insurance-based healthcare provision study found that those with low income and multimorbidity had lower healthcare utilisation costs than those with high income and multimorbidity (Kuo and Lai, 2013), which could be explained by lower insurance premiums and higher deductibles.

2.4 Multimorbidity and the role of synergism

Rising prevalence of chronic health conditions poses challenges for individuals and healthcare systems. Higher number of co-occurring LTCs is associated with higher risk of mortality (Nunes et al., 2016), disability (Hunger et al., 2011), and lower quality of life (Fortin et al., 2004; Makovski et al., 2019). However, when two or more LTCs are present, their joined interactions can also produce effects on body systems that are greater than if they occurred independently of each other. This is called synergism (Fortin et al., 2007) and the negative synergistic effects of certain NCDs on individuals' physical functioning, quality of life and disability have been previously studied across many populations (Rijken et al., 2005; Marventano et al., 2014).

Certain multimorbidity combinations can have greater effect on individuals' quality of life, health expenditure and mortality than other combinations. In a large observational study, Rijken et al. (2005) found that paired combinations of diabetes, CVD and respiratory diseases had stronger negative synergistic effects on physical functioning than other chronic physical and mental pairs. Cardiac and respiratory disease combinations also showed greater negative synergistic effect on QOL in Canadian primary care patients (Fortin et al., 2007). In a population of older German adults, however, combinations of only cardio-metabolic conditions like coronary heart disease-stroke, and coronary heart disease-diabetes had higher synergistic effects on QOL than other types of multimorbidity (Hunger et al., 2011). Multimorbidity is highly heterogeneous, but evidence suggests that it is cardio-metabolic and respiratory pairs of diseases that tend to have the greater synergistic effects on QOL and functional status (Marventano et al., 2014). The diabetes-coronary heart disease pair, particularly, has shown negative synergistic effects on QOL, disability and functional status across many different populations (Oldridge et al., 2001; Maddigan, Feeny and Johnson, 2005), but these patterns may only be applicable for simple multimorbidity pairs. When disease triads were assessed in a Flemish general population, dorsopathy (musculoskeletal system condition), urinary problems, depression, allergy, and cardiac disease combinations had highest synergistic effects (Van Wilder et al., 2022). More research is needed to investigate how complex multimorbidity combinations impact QOL, functional impairment and disability.

Synergism between multimorbidity, frailty, and polypharmacy can also affect health expenditure, poor quality of life, disability and mortality. Having multimorbidity and frailty in Parkinson's disease primary care patients and community older adults increased healthcare expenditure more than just having multimorbidity (Tenison et al., 2020). In older community-dwelling older adults, moreover, the odds of being disabled in those who have both frailty and multimorbidity were also two times higher as those who were frail but not multimorbid (Lee et al., 2018). Similar effects were observed for multimorbidity, disability and geriatric syndrome on hospital admissions and specialist clinic attendance in older adults (Cheung et al., 2018). While synergistic effects of multimorbidity can lead to more negative health outcomes, such as higher health expenditure and greater risk of mortality, synergistic combinations of LTCs (like hypertension-diabetes) might be easier to manage through clinical and public health interventions than non-synergistic multimorbidity combinations like mental-physical multimorbidity, which usually require interdisciplinary and multifaceted interventions (Mercer et al., 2012).

2.5 Challenges measuring the true burden of multimorbidity

Multimorbidity is a largely heterogeneous health state of combinations of mental and physical conditions that operate over multiple body systems. The broad operational definition of multimorbidity creates variability in the way this health state is specified in research, making it difficult to compare the results from studies. Disease lists are frequently used as guidance for including certain health conditions (Barnett et al., 2012). They are constructed through a series of expert panel studies and evidence syntheses and can vary by population and study objectives. Systematic reviews have found that the prevalence of multimorbidity varies by the number of LTCs included in the operational definition of multimorbidity (Nguen et al., 2019; Fortin et al., 2012). However, heterogeneity also arises from the methods used to measure multimorbidity. When van den Akker et al. (1996) first coined the term multimorbidity, they proposed three methodological classifications: simple disease counts, where diseases co-occur but their association is unclear or random; associative clusters, where there is a statistical association between diseases; and causal patterns, where a causal relationship between diseases exists. Over the past 10 years, research has gradually shifted from conceptualising multimorbidity as simple disease counts and towards observing multimorbidity as a complex dimension of associative clusters which change and evolve over time (Hu et al., 2022; Bisquera et al., 2021; Launders et al., 2022).

2.6 Prevention of multimorbidity through behavioural and environmental risk factors

2.6.1 Why focus on preventing the inevitable?

The complexity of physiological processes operating in multimorbid individuals creates difficulty in treating conditions and managing side effects. In many instances, the relationship between multimorbidity and its side effects are bidirectional and synergistic. As accumulation of diseases within an individual increase, the body loses capacity and resilience to deal with stressors. Individuals may engage in less health-promoting behaviours, lose social networks, and experience isolation and income loss, which can lead to further deterioration of health. Multimorbidity is often difficult to manage in clinical settings, especially as healthcare systems are traditionally designed to treat single body system conditions (Whitty et al., 2020).

Treatment for multimorbidity is medication-centred and prevention of disease accumulation has often been overlooked because old age is considered inevitable (Singer et al., 2019a; Skou et al., 2022; Salive, 2013). However, the idea that multimorbidity is an inevitable outcome of aging has been challenged by policy bodies and researchers (Whitty et al., 2020; Head et al., 2021), and in recent years, emerging research has shown that multimorbidity progression can be prevented through health-promoting behaviours and environmental changes (Singer et al., 2019b; Skou et al., 2022; Salive, 2013).

The following section offers an overview of the main behavioural and environmental factors for prevention of multimorbidity to provide context for studying the associations between exposure to green and blue spaces with multimorbidity risk. In Chapter 1, I discussed how the surrounding natural environment promotes health through physical activity, relaxation, socialisation, and harm reduction. The rest of this chapter outlines the epidemiological evidence for the relationships between common health-promoting behaviours (like physical activity, diet and smoking), and environmental risk factors (like air pollution) with multimorbidity risk. This contextualises the rationale for studying multimorbidity in the context of green and blue spaces, which can be operationalised as environmental resources that prevent the development of multimorbidity and help build resilience to the adverse side effects of multimorbidity.

2.6.2 Physical activity

Physical activity is a health-promoting behaviour that involves active movement of the skeletal body muscles to expend energy (Piggin, 2020). This can include walking, cycling, gardening and active sports and household cleaning and has multiple benefits for mental and physical health. Physical activity can strengthen muscles and bone density, resulting in lower risk of musculoskeletal conditions. Physical activity is a strong determinant of health that can reduce inflammation, lower BMI and prevent the development of common chronic conditions like cancer, CVD, depression and anxiety (Reiner et al., 2013; Saxena et al., 2005; Warburton, Nicol and Bredin, 2006). To achieve health benefits from physical activity, the World Health Organisation (WHO) recommends that all adults undertake 150-300 mins of moderate-intensity, or 75-150 mins of vigorous-intensity physical activity per week, or a combination of both (Bull et al., 2020).

There is strong evidence that physical activity can slow the development and progression of multimorbidity. Cross-sectional studies have found that the odds of multimorbidity are lower in those who are physically active (Geda et al., 2021; He et al., 2021; Loprinzi, 2017). A negative dose-response relationship was also found between the odds of having multimorbidity and mild, moderate, and vigorous physical activity (Dhalwani et al., 2016). Specifically, middle-aged and older adults who participated in mild, moderate, and vigorous physical activity were 16%, 39%, and 55%, respectively, less likely to be multimorbid than those who did not participate in any physical activity (Dhalwani et al., 2016). However, the relationship between physical activity and multimorbidity risk may not be linear. In a 10-year longitudinal study, Balogun et al. (2021) found that Tasmanian adults who undertook less than 10,000 steps a day were less likely to develop multimorbidity, while those who undertook more than 10,000 steps had a higher likelihood of multimorbidity (Balogun et al., 2021).

There is still limited research into the ways different types of physical activity affect the risk of multimorbidity, but some studies have found that in participating in moderate-to-vigorous physical activity (MVPA) (compared to participating in no physical activity) reduced the 10-year risk of multimorbidity by 16% in middle-aged and older adults (Aminisani et al., 2020). A systematic review also found a small protective relationship between higher levels of physical activity and multimorbidity (Delpino et al., 2022) but some research suggests that physical activity is more important in protecting the development of multimorbidity in individuals with no pre-existing health conditions than in individuals with one health condition (Mounce et al., 2018). In a 10-year study of middle-aged and older adults, Mounce et al. (2018) found that low levels of physical activity among middle-aged and older UK adults were associated with 43% increase in the risk of developing two or more chronic conditions in those with no pre-existing health conditions at baseline. On the other hand, low physical activity levels in individuals with one pre-existing health condition increased the risk of developing additional chronic diseases at follow up by 19% (Mounce et al., 2018). Similarly, in a population of Australian women, not being physically active was associated with a 38% increase in the 20-year risk of developing two or more cardio-metabolic condition, and with a 22% increase in the risk of developing just one (Xu et al., 2018).

The relationship between physical activity and multimorbidity is complex and multifactorial. In addition to being most protective in individuals with no pre-existing health conditions, physical activity may have the strongest impact when performed at certain critical points throughout the life course. One study of Brazilian adults, for example, found that a reduction in the risk of multimorbidity at old age (>65 years) was observed for those who participated in physical activity at adolescence and at mid-life (around 55 years) but not at any other points during the life course, suggesting that the presence of critical time intervals for certain behavioural exposures can be a key determining factor (Feter et al., 2021).

The effect of physical activity on multimorbidity is also moderated by demographic characteristics, like sex. In a cross-sectional study of German adults, the odds of total multimorbidity and cardiometabolic multimorbidity were 27% and 31% lower, respectively, only in physically active German men, but not in physically active women (Autenrieth et al., 2013). Similarly, in a population of Brazilian adults, the relationship between physical activity and mental-physical multimorbidity was more pronounced in men than in women (Andrade-Lima et al., 2020). This study also found that men who were physically inactive and had two or more chronic conditions were 5.5 times as likely to have depression as men who had no chronic conditions and were physically active. Physically active women with two or more chronic conditions, on the other hand, were only 3.42 times as likely to be depressed as physically active women with no chronic conditions (Andrade-Lima et al., 2020).

In addition to lowering the risk of developing multimorbidity, physical activity also reduces the risk of adverse events in individuals who already have multimorbidity. Two out of three studies on European multimorbid populations found that the risk of mortality was around 70% lower in those who were regularly physically active compared to those who were not (Chudasama et al., 2019; Loprinzi, 2017; Martinez-

Gomez et al., 2017). Another study of British adults also found that an inverse dose-response relationship between higher physical activity levels and mortality among multimorbid individuals only stands for leisure-time, total self-reported and objective physical activity (Chudasama et al., 2019). Moreover, physical activity was associated with 16% decrease in the 10-year risk of hospital admissions in a population of multimorbid English middle-aged and older adults (Luben et al., 2020). Being physically active can also bring greater life satisfaction and improve quality of life in people with multimorbidity, which was especially pronounced in those who had multimorbidity with diabetes, mental health illness and cardiovascular disease (Alonzo et al., 2022; Subramaniam et al., 2019).

2.6.3 Alcohol consumption

Alcohol consumption is often considered a risk factor for poor mental and physical health due to its effects on the central and peripheral nervous system (Rehm et al., 2003). Consuming frequent and large volumes of alcohol can lead to dependence, intoxication, and harm to several organic body systems, resulting in higher risk of physical injury, violence, poor mental health and accumulation of chronic disease (Rehm et al., 2003). Around 4% of the global burden of disease is attributable to alcohol, but the relationship between higher alcohol consumption and multimorbidity does not entirely support the notion that alcohol consumption increases the risk of accumulating multiple LTCs (Rehm et al., 2003).

One cross-sectional study of middle-aged Canadian adults found that the odds of having multimorbidity were lower in both men and women who were daily drinkers compared to non-drinkers (Sakib et al., 2019). However, a similar study deduced that never drinking was associated with a small decrease (17%) in the odds of having multimorbidity compared to regular drinking (Geda et al., 2021). Although extensive research into the role of alcohol consumption on multimorbidity risk has not been conducted, longitudinal studies generally show protective relationships between regular alcohol consumption and multimorbidity. Compared to non-drinkers, regular alcohol drinkers were 20% less likely to develop multimorbidity in a longitudinal study of New Zealand adults (Aminisani et al., 2020). Similarly, the odds of developing complex multimorbidity and functional limitations were 35% and 53% lower, respectively, for daily drinkers compared to never drinkers (Singer et al., 2019a). Higher weekly alcohol consumption was also not associated with an increased 5 and 10-year risk of hospitalisation with adverse side effects in individuals with multimorbidity in a large English cohort of middle-aged adults (Luben et al., 2020).

Although there is a clear positive dose-response relationship between amount of alcohol and risk of chronic health conditions, emerging research suggests that other dimensions of alcohol consumption, such as frequency and type, might be protective of developing certain LTCs (Room, Babor and Rehm, 2005). Regular, low to moderate drinking is associated with lower risk of certain CVD outcomes like coronary heart disease (Rehm, Sempos and Trevisan, 2003). A range of physiological and genetic factors could explain this, including the protective effect of certain alcohol types on lipid accumulation and blood pressure (Matsumoto et al., 2014). As CVD is a major component of multimorbidity in most populations (Barnett et al., 2012), the protective relationships between alcohol and multimorbidity could be largely driven by CVD outcomes. In a cross-sectional study, for example, Nguyen et al. (2019) found that the odds of cardio-respiratory-cataracts-arthritis multimorbidity was 77% lower in regular drinkers compared to never-drinkers, but no significant relationship was observed between regular alcohol consumption and metabolic multimorbidity. More research is needed to study the effects of different type and frequency of alcohol consumption in the risk of multimorbidity.

2.6.4 Smoking and diet

The behavioural risk factors of multimorbidity still remain largely unexplored, but emerging research suggests that both diet and smoking can affect the risk of accumulating disease. In cross-sectional studies, smoking had no effect on the odds of multimorbidity in British, Canadian, and New Zealand adults (Aminisani et al., 2020; Mounce et al., 2018; Sakib et al., 2019; Singer et al., 2019a). One study found that never smoking and occasionally smoking were associated with 18% and 21%

lower odds of multimorbidity, respectively, compared to regularly smoking (Geda et al., 2021). Studies of Indian populations found that the population attributable risk for smoking was 1.2 % and that women smokers had a 91% higher relative risk of multimorbidity then women non-smokers (Hossain, Govil and Sk, 2021; Mishra et al., 2021). In longitudinal relationships, the negative effects of smoking are more pronounced. Australian women were 78% more likely to develop multimorbidity if they were current smokers than if they were never smokers (Xu et al., 2018). Middle-aged British current smokers also had a 74% increase in the risk of hospitalisation with multimorbidity compared to non-smokers (Luben et al., 2020). On the other hand, a longitudinal study showed British ex-smokers were 27% and 29% more likely to develop simple and complex multimorbidity, respectively, compared to never smokers (Singer et al., 2019a).

The impact of diet on multimorbidity has been modestly assessed through observational studies, all of which point towards protective relationships with good diet. Eating whole grains once to six times a week, for example, was associated with 64% greater odds of having multimorbidity in older men (Pereira et al., 2020). Consuming vegetables, fish and fruit also showed a small reduction (14%) in the odds of multimorbidity, while high meat, alcohol and potato consumption was associated with increased odds (83%) of multimorbidity in adults (Dekker et al., 2019). Furthermore, high adherence to a Mediterranean diet was associated with 32% decrease in odds of multimorbidity in a Cypriot population (Kyprianidou et al., 2021). In a longitudinal study of Chinese adults, moreover, higher intake of fruits and vegetables and higher intake of rice and wheat were both associated with healthier stages of multimorbidity (Ruel et al., 2014).

2.6.5 Combined effects of socio-demographic and behavioural factors

Physical activity, diet, alcohol consumption and smoking are well-known risk factors of chronic health and multimorbidity and their combined effects synergistically influence the development of multimorbidity (Dhalwani et al., 2017). In a population of older English adults, physical activity increased the risk of multimorbidity by 33%, however, being physically inactive and a smoker (compared to having no unhealthy behaviours) increased the hazard risk of multimorbidity by 135% (Dhalwani et al., 2017). Similar strengths and directions of associations were observed for those who were physically inactive and obese, obese and smokers, obese and with poor diet, smokers and with poor diet (Dhalwani et al., 2017). Health-promoting behaviours, like higher physical activity, can also partially mediate the relationship between certain non-modifiable risk factors and multimorbidity (Newsom et al., 2022). Newsom et al. (2022), for example, found that higher physical activity levels strongly mediate the relationship between ethnicity and changes in multimorbidity severity.

2.6.6 Social support

It is widely known that social networks can have strong impacts on mental and physical health (Ganster and Victor, 1988). Having strong support networks elicits feelings of belonging, strengthens social cohesion, and encourages participation in a community. This can lead to healthier lifestyles and in turn prevent the development of chronic health conditions (Ganster and Victor, 1988). Although the psychosocial risk factors of multimorbidity have been studied less frequently than other types of risk factors, current evidence generally suggests high social support increases the survival rate in individuals with one or two chronic conditions (Olaya et al., 2017). Cross-sectional studies have examined the relationship between living alone, with children and with a partner, and the prevalence of multimorbidity. While one study found that living with children was strongly protective of having multimorbidity, (Agborsangaya et al., 2012), another study found that living alone was associated with a very small (6%) reduction in the odds of having multimorbidity compared to those who lived with partner or children (Geda et al., 2021).

In a longitudinal study of older British adults, having supportive children or a partner had no effect on the risk multimorbidity (Singer et al., 2020). However, having no current partner and no friends was associated with 13%-15% and 14% higher odds of developing multimorbidity, respectively (Singer et al., 2020; Aminisani et al., 2020). Moreover, women who were divorced were 62% more likely to develop general and cardio-metabolic multimorbidity compared to women who were married (Xu et al., 2018). Less is known about the effect of loneliness on multimorbidity, but a study of older English adults found that feelings of loneliness increased the odds of developing multimorbidity by 20% (Singer et al., 2019a).

The relationship between social support and multimorbidity, however, may not be unidirectional. While social support and loneliness can affect health, having chronic health conditions and multimorbidity can exacerbate social isolation and illicit feelings of loneliness due to low quality of life, treatment side effects and disability (Hajek et al., 2020; Wister et al., 2021). This may create negative feedback loops where feelings of loneliness and low social support may lead to poor treatment adherence and unhealthy behaviours, resulting in further accumulation of diseases and degeneration of current health states. More research, however, is needed to explore these relationships in-depth.

2.7 Multimorbidity patterns, their burden and relationships with socio-demographic and behavioural risk factors

Although capturing the true burden of multimorbidity in HIC populations is difficult due to the heterogeneous definitions and measurement approaches used in different studies, emerging research has sought to better understand the prevalence and risk factors of different multimorbidity patterns and the ways they affect healthcare utilisations, quality of life and disability. Systematic reviews have found that distinct clusters of cardio-metabolic, mental, musculoskeletal conditions generally have the highest prevalence across most populations (Sinnige et al., 2013; Prados-Torres et al., 2014; Violan et al., 2014). However, type of multimorbidity can vary by age, sex and ethnicity. Mental and mental-physical multimorbidity, for example, tends to be most prevalent among younger age groups (below 45 years), men and white people (Violan et al., 2014), while cardio-metabolic and musculoskeletal multimorbidity are more common in older adults (Sinnige et al., 2013). Understanding multimorbidity clusters is also important in measuring the impacts of multimorbidity on individuals and healthcare systems. As discussed previously, co-occurring conditions can have negative synergistic effects that can lead to reduced physical functioning, disability and poor quality of life. Cardio-metabolic and respiratory multimorbidity, and sometimes combinations of both, have greater synergistic effects on physical functioning and quality of life than mental or musculoskeletal multimorbidity (Fortin et al., 2007; Rijken et al., 2005; Hunger et al., 2011).

When assessing risk factors of multimorbidity, however, Nguyen et al. (2019) warn that the effects of certain exposures would differ by multimorbidity type due to physiological differences between disease combinations. Although most studies have found physical activity to be protective of developing any kind of multimorbidity, Nguyen et al. (2019) demonstrated that higher physical activity and regular alcohol consumption both moderately decreased the odds of having cardio-respiratory-cataracts-arthritis multimorbidity, but had no effect on metabolic multimorbidity. Moreover, Singer et al. (2019a) found that smoking, alcohol consumption, and physical activity showed slightly stronger longitudinal relationships with complex multimorbidity (defined as presence of 3+ conditions) than simple multimorbidity (2 conditions). The reasons behind these relationships are not entirely understood, but Nguyen et al. (2019) propose that behavioural risk factors mainly strongly affect discordant multimorbidity, where co-occurring diseases have different pathology and symptoms. The development of concordant multimorbidity (like co-occurring diseases of a single body system class, such as metabolic multimorbidity), on the other hand, is mainly driven by shared biologic pathways that are not affected by behavioural risk factors (Nguyen et al., 2019). This, however, is not supported by further research and more observational studies are needed.

In summary, this section showed that multimorbidity risk is influenced by a range of social, demographic, and behavioural factors. Women, individuals of ethnic minorities, and individuals of low SES are more likely to develop multimorbidity earlier in life (Barnett et al., 2012; Singer et al., 2019a). Although traditionally considered an inevitable outcome of ageing, multimorbidity can be prevented by participating in physical activity, having a good diet, and having good social support networks (Olaya et al., 2017; Feter et al., 2021). Prevention of multimorbidity is important in reducing the burden on healthcare systems in the UK and other HICs, and in improving quality of life in old age (Skou et al., 2022; Whitty et al., 2020).

According to Dahlgren and Whitehead's (1991) model of social determinants of health, individual health-promoting behaviours like physical activity are largely shaped by the local communities within which individuals live. Local communities provide resources for relaxation, socialisation, and physical activity, but little is currently known about how certain features of the local community, like the presence of green and blue spaces, affect multimorbidity. In the next sections, I discuss how the surrounding environment and exposure to green and blue spaces in the residential neighbourhood can affect the risk of multimorbidity in adults and propose a framework for studying the relationships between types of green and blue spaces with different types of multimorbidity.

2.8 Social and environmental determinants of health and how they might affect multimorbidity

Individual behaviours, like smoking, diet, alcohol consumption and physical activity, all independently affect the risk of having multimorbidity (Singer et al., 2019a). According to Dahlgren and Whitehead's (1991) model of the social determinants of health, individual health behaviours are shaped by the local environments individuals live and socialise in. Local environmental factors, such as the density of food outlets, density of alcohol outlets, and tobacco advertisement can all affect diet, drinking and smoking behaviours (Caryl et al., 2022; Fone et al., 2016; Shortt et al., 2015). In a population-based record-linked study in Wales, for example, changes in alcohol outlet density were associated with changes in alcohol consumption and alcohol-related harm (measured by violence incidences and hospital admissions) (Fone et al., 2016). In particular, higher density of alcohol outlets was associated with increased alcohol consumption (Fone et al., 2016). Similar associations have been observed for density of fast-food outlets (Fraser et al., 2010). A UK Biobank study deduced that higher density of fast-food outlets in the neighbourhood was associated with 51% higher odds of obesity (Burgoine et al., 2018). Deprivation and income may have active roles in these relationships. A study of children in Scotland found that those living in most deprived areas were 2.8 to 4.8 times as likely to be exposed to alcohol outlets in their residential environment as those living in least deprived areas (Caryl et al., 2022). Alcohol and tobacco outlets are generally correlated with deprivation in UK, and their density increases in more deprived areas (Shortt et al., 2015). Food, alcohol and tobacco environments form part of an individual's exposome, a term used to describe every exposure an individual is subjected to from conception to death (Wild, 2012). The exposome shapes chronic health throughout the life course. Therefore, studying the risk factor of multimorbidity in middle and old age is determined by a combination of social, economic and environmental influences individuals experience throughout their life.

2.9 Research gap: natural environment and multimorbidity

The surrounding environment in which individuals live can have an impact on their health (Carp, 1977). Rising urbanisation and economic shifts have caused an increase in sedentary lifestyles and poor diets. Industrialisation and consumerism have also led to increases in air pollutants like particulate matter and nitrous oxides. Air pollution is now the largest environmental contributor to the burden of disease, causing over a quarter of all cases of stroke, ischaemic heart disease, lung cancer and COPD (Prüss-Ustün et al., 2019). Higher levels of particulate matter (PM2.5 and PM10) and nitrogen oxides (NOx) are linked to higher rates of respiratory mortality (Dong et al., 2012), higher incidence of cardio-vascular disease (CVD), higher incidence of heart failure (Wang et al., 2021; Pranata et al., 2020), higher risk of brain cancer (Raaschou-Nielsen et al., 2011), and higher prevalence of poor mental health (Bakolis et al., 2021; Yang et al., 2021; Fan et al., 2020). Latest findings from UK Biobank also showed a positive linear relationship between higher exposure to particulate matter and the risk of transitioning to cardio-metabolic multimorbidity in individuals with one pre-existing cardio-metabolic condition (Luo et al., 2022). These associations were also stronger for men and individuals of low income (Luo et al., 2022).

Green and blue spaces can mitigate the harmful effects of air pollution and noise, and promote healthy lifestyles through activity, social cohesion, relaxation and restoration (Markevych et al., 2017). Their therapeutic properties have been studied in relation to both well-being and chronic health outcomes (Gascon et al., 2015). As I outlined in Chapter 1, green and blue spaces can also reduce the risk of developing NCDs like cancer and CVD. However, the effects of green and blue spaces on the risk of developing certain multimorbidity patterns still remain underresearched. This could be due to several reasons, including lack of high-resolution environmental data linkages in health cohorts and lack of observational data that captures other social, economic and environmental determinants of health. Nevertheless, research into green space-multimorbidity relationships is increasing. In a recent longitudinal study of middle-aged Australian adults, for example, neither exposure to tree canopy nor grass cover was associated with fatal, non-fatal CVD events and myocardial infraction in individuals with pre-existing type II diabetes (Astell-Burt et al., 2021). However, two studies of Asian adults found that greater amount of green space is associated with low to moderate improvement (29%) in frailty status over time (Yu et al., 2018; Zhu et al., 2020).

The mechanisms driving the relationships between exposure to green and blue spaces with multimorbidity, however, are likely similar to the mechanisms in relationships between green spaces and CVD, respiratory disease, cancer and mental health (Hartig et al., 2014; Markevych et al., 2017). In figure 3, I propose a socio-ecological framework for the relationship between neighbourhood green and blue spaces and multimorbidity. I draw on Dahlgren and Whitehead’s (1991) model of social determinants of health, which shows that health is driven by a series of individual and socio-economic factors. According to their model, chronic health is largely shaped by individual behaviours, such a physical activity, diet, and smoking (Dahlgren and Whitehead’s, 1991). Whether individuals perform these behaviours is determined by their closer community networks, which themselves are a product of the wider socio-cultural and economic processes operating globally. The model in Figure 3 shows that green and blue spaces form part of the individuals’ closer community. Their presence in the residential neighbourhood mitigates noise and air pollution (which are products of global economic processes) and encourages behaviours like socialisation, relaxation, and physical activity. These pathways can initially slow the development of clinical symptoms of chronic illness or prevent the development of a single or multiple co-occurring LTCs, also called the initial health state. Over time, this initial health state can deteriorate or improve due to interactions between body systems, behaviours, and treatment side effects. As individuals age, subsequent chronic conditions may also develop, which can hinder engagement in health-promoting behaviours or lead to loss of income and social support. Exposure to green and blue spaces, however, can further mitigate some of these adverse effects by strengthening body functions through physical activity, supporting community engagement, and encouraging mental restoration. Individual socio-demographic characteristics moderate the relationships at every stage of this process. Income, age, sex and ethnicity independently shape health, the types of communities individuals live in, and the ways individuals interact with their surrounding natural environments.

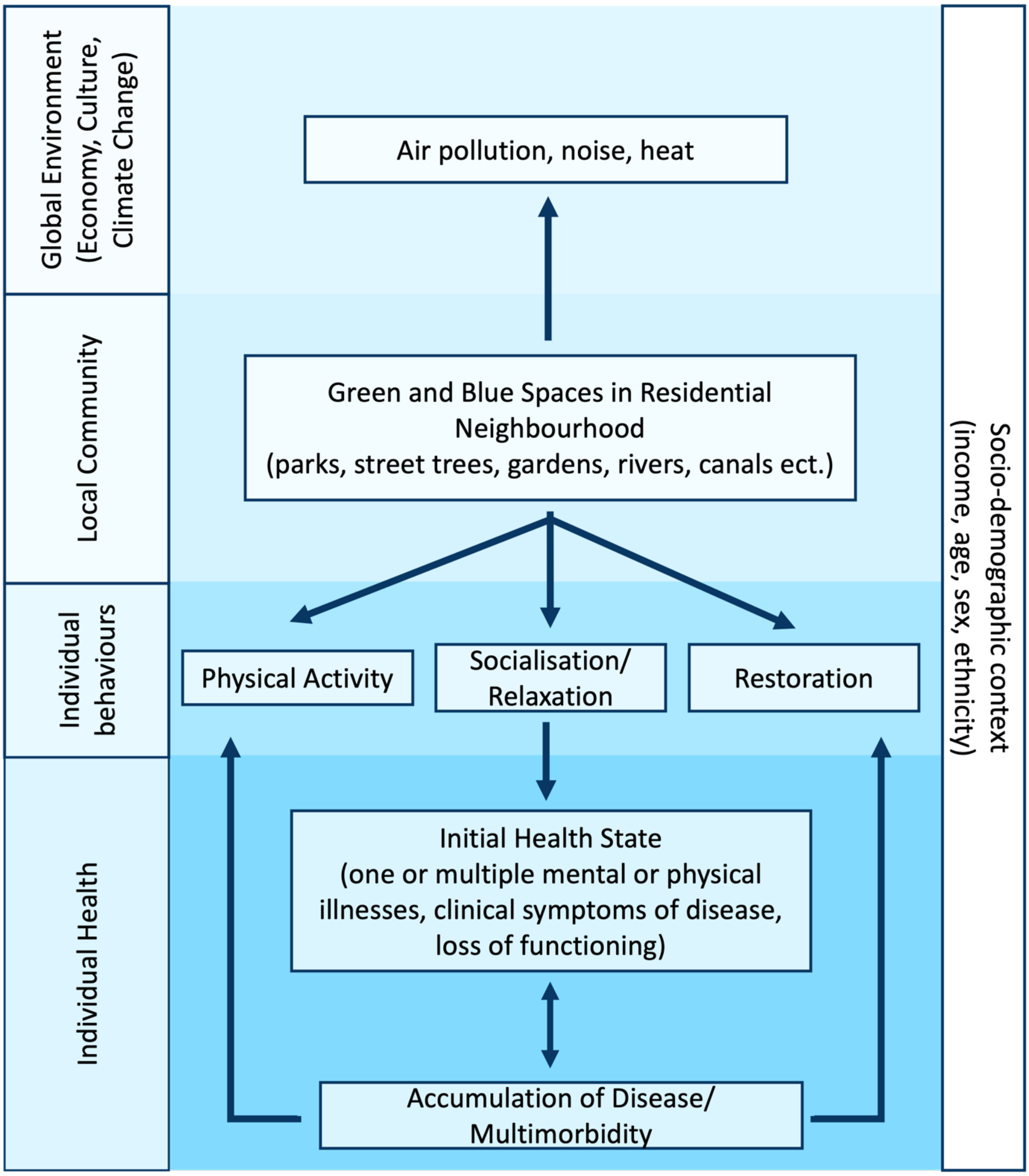

Figure 3: Socio-ecological framework for the relationship between exposure to residential green and blue spaces with multimorbidity (Model is adapted from Dahlgren and Whitehead's (1991) model of social determinants of health and conceptual models for studying the relationships between green and blue spaces with chronic health by Markevych et al. (2017)).

Next Steps

To assess the relationship between exposure to green and blue spaces and multimorbidity, I first conducted a systematic literature review of longitudinal observational studies (Chapter 3). This improved the understanding of the causal relationships between green and blue space exposures with specific mental and physical health outcomes. The results of the systematic review were then used to guide a data integration study, which was conducted with the aim to integrate different types of neighbourhood green and blue spaces into a large health cohort (UK Biobank). Using cross-sectional data from the UK Biobank, I then analysed the associations between different types of green and blue space exposures with the following multimorbidity outcomes: simple and complex multimorbidity (measured as disease counts), and clusters of cardio-metabolic, mental, and respiratory diseases. The next chapter presents the methods and results of the systematic review.

Chapter 3: Systematic Review: Relationship between green and blue spaces with mental and physical health: evidence from longitudinal, observational studies

Chapter summary

This chapter outlines the methods, results, and discussion of a systematic review of longitudinal observational studies which was conducted to better understand the associations between exposures to green and blue spaces with chronic mental and physical health. The chapter is an expanded version of a first authored paper that was published in 2021 (see Appendix I). This is the first analytical chapter, and it operationalises the focus of the thesis by systematically reviewing the evidence for the relationships between green and blue spaces with chronic health. Results from this systematic review are used to build a foundational case for further empirical work on exposure assessment and modelling of associative relationships between green and blue spaces with multimorbidity, which are presented in Chapters 4-6.

3.1 Introduction

3.1.1 Relationship between green and blue spaces with health

Interest in the health-promoting properties of green and blue spaces has grown due to the need for alternative solutions to tackle the health challenges posed by rapid urbanisation, shifts in sedentary lifestyles, and ageing populations (Wolch et al., 2014; Lee and Maheswaran, 2011). There is now growing evidence about the relationship between exposure to green and blue spaces and health. Cross-sectional study of Dutch adults, for example, showed positive associations between higher amount of green space and better self-perceived general health (de Vries et al., 2003). Higher amount of greenness was also associated with small reductions in CVD events, all-cause and respiratory mortality in a meta-analysis and observational studies of European and Japanese adults (Villeneuve et al., 2012; Rojas-Rueda et al., 2019; Seo et al., 2019). Greater exposure to green space can also be protective of different mental health conditions. In a cross-sectional study of Spanish adults, for example, higher accessibility to green space, but not higher accessibility blue space, was associated with an 82% reduction in the odds of self-reported depression (Gascon et al., 2018). On the other hand, a recent cross-sectional study of older adults deduced that it was not amount of blue space but a blue space aesthetic (i.e. view from the residential address) that increased the odds of good self-perceived health by 70% (Garrett et al., 2019), suggesting that the relationship between blue spaces and health could be driven by specific types and interactions with blue spaces. The spatial scale at which exposures are captured can also affect the strengths of associations with health. A study on morbidity in English primary care adults, for example, found that having 10% more green space than average is associated with lower risk of mental and physical morbidity, and that those relationships were stronger when green spaces captured at a small spatial scale (1km circular buffer) than at a large spatial scale (3km circular buffer) (Maas et al., 2009).

3.1.2 Moderating and mediating factors

Urban green and blue spaces are considered important for reducing noise, filtering certain air pollutants, and lowering temperatures (Escobedo et al., 2011; Grellier et al., 2017). Through direct contact, urban and rural green spaces can also promote socialisation and physical activity. Presence of high-quality, aesthetic green spaces with built features like benches may also encourage higher frequency and longer duration of visits (Nieuwenhuijsen et al., 2017). Overall, the effects of green spaces can be summarised by three major biopsychosocial pathways: reduction in harm (from air pollution, noise and heat); restoring capabilities (restoring attention and reducing stress); and building capacities (improving physical activity and social cohesion) (Markevych et al., 2017). Little is still known about the pathways driving the relationships between blue spaces and health, but it is considered that direct and indirect contact with blue spaces have similar health-promoting effects on health as green spaces (Grellier et al., 2017). Amenities like riverside paved paths and benches, cultural significance, and immersion in certain blue spaces can increase physical activity, reduce stress, and increase social cohesion (Grellier et al., 2017). Evidence for the mediating effects of physical activity, socialisation, and restoration on the relationships between green and blue spaces with health, however, is still limited (Nieuwenhuijsen et al., 2017). The associations between exposure to green and blue spaces and health may be multidimensional and driven by a series of socio-behavioural pathways (Kabisch et al., 2017).

Socio-demographic characteristics can play a moderating role in the relationship between green spaces and health. Mass et al. (2006), for example, found the relationship between higher amount of green space and general self-perceived health in the UK adults was stronger for those with lower-level education (Maas et al., 2006). Education also partially moderated the relationship between amount of green space and depression in British women living in Bradford (McEachan et al., 2015). This cross-sectional study found that women of low education living in greener neighbourhoods had a 26% reduction in the odds of depression compared to women of low education living in non-green neighbourhoods (McEachan et al., 2015). No significant relationships were observed for women of high education (McEachan et al., 2015). In a longitudinal study of Australian adults, on the other hand, higher amount of green space was associated with better general health in men but not in women (Astell-Burt et al., 2014). Mitchell and Popham (2007) also deduced that greater exposure to green space was associated with poorer general health in adults living in low-income areas in the UK. Type of occupation was also a moderator in the relationship between higher amount of green space and CVD in another longitudinal study of middle-aged English adults, which found a protective relationship between higher amount of green space and incident CVD only in non-manual occupation individuals (Dalton and Jones, 2020). Moreover, good quality and access to urban green spaces were predictors of good health among individuals of Black and other ethnic minority groups in the UK, but not for individuals of white ethnicity (Roe et al., 2016).

3.1.3 Rationale for systematic review of longitudinal, observational studies

Longitudinal, observational studies are important in deducing causality and informing public health interventions (Public Health England , 2020). Government bodies, such as Public Health England (PHE, 2020) have called for a need to improve quality, engagement, and access to green spaces, however, published systematic reviews warn that synthesising epidemiologic evidence about the relationships between green spaces and health is difficult due to high variation in the ways environmental exposures and health outcomes are measured (Gascon et al., 2015; de Keijzer et al., 2016). A large proportion of published systematic reviews report weak or no evidence of a relationship between exposure to green and blue spaces with chronic health outcomes (Gascon et al., 2015; de Keijzer et al., 2016; Kabisch et al., 2017). However, systematic reviews that have comparatively assessed type of epidemiological studies also state that the literature is largely saturated with cross-sectional studies that cannot prove temporal relationships (van den Berg et al., 2015; Gascon et al., 2015; Gascon et al., 2017; de Keijzer et al., 2016).

Current systematically reviewed literature on the relationship between green and blue spaces also highlights high heterogeneity in exposure and outcome measures. van den Berg et al. (2015), for example, found that there was strong evidence of a protective relationship between higher amount of green space, perceived mental health and all-cause mortality. Positive relationships between greater exposure to outdoor blue space with general mental health, wellbeing and physical activity levels were also observed by another systematic review (Gascon et al., 2017). However, there was little evidence of a protective relationship between exposure to green and blue spaces with chronic mental health conditions like depression and anxiety in adults (Gascon et al., 2015). Heterogeneity in exposure and outcome measures were considered plausible explanations for this (Gascon et al., 2015). A systematic review of the effects of exposure to green spaces on cognitive functioning also found inadequate evidence of significant relationships due to poor study quality, number of studies and study type (de Keijzer et al., 2016). Moreover, a systematic review evaluating the effect of green and blue spaces on health risks related urbanisation in children and older adults found weak evidence of a protective association between green and blue spaces with disease-specific mortality in older adults (Kabisch et al., 2017).

Due to the perceived restorative properties of natural spaces, systematically reviewed evidence has often focused on examining mental-ill health and multidimensional health outcomes, such as general health and well-being (Gascon et al., 2017; Gascon et al., 2015). However, less is known about the influences of green and blue spaces on specific NCDs and mental health outcomes. An early systematic review by Di Naro et al. (2010) found limited evidence of a relationship between green space, physical activity, and specific mental health conditions and NCDs, with majority of the studies having a cross-sectional design. A more recent systematic review, on the other hand, found that higher exposure to green space only reduced the risk of specific cardio-metabolic outcomes, such as diabetes risk and CVD mortality (Twohig-Bennett and Jones, 2018).

To address of these research gaps, this systematic review aimed to capture data from longitudinal, observational studies to examine the associations between exposure to green and blue spaces with mental health conditions, NCDs, health-related behaviours and multimorbidity-related health states. Little is also known about the roles of specific green and blue spaces on the risk of mental health conditions, NCDs and multimorbidity. Understanding the causal pathways between different types of green and blue spaces and health can also better inform urban planning and policy in designing and maintaining natural spaces suitable for health promotion. Finally, the inclusion of broad range of health conditions has the potential to identify differences in direction and strength of associations between green and blue spaces and specific chronic health conditions.

The Preferred Reporting Items for Systematic reviews and Meta-Analyses for Protocols (PRISMA-P) was used as guidance in protocol preparation and reporting of the review (Moher et al., 2015). Protocol was registered on PROSPERO (Appendix II)

The objectives for this review are as follows:

1. Assess whether significant relationships exist between exposure to green and blue spaces with chronic mental health conditions and NCDs, and summarise evidence of any confounding and mediating variables.

2. Identify which types of green and blue spaces are most frequently studied in longitudinal relationships with health, assess their measurement approaches, and assess whether relationships with health are stronger for specific types/ characteristics of green and blue spaces.

3. Determine whether multimorbidity as a concept is studied in relation to different green/ blue space exposures.

3.2 Methods

3.2.1 Inclusion/ exclusion criteria

Inclusion criteria for this study are based on the Population, Exposure, Comparison, Outcomes, Study (PECOS) framework for systematic reviews (Higgins et al., 2019). Table 1 summarises the inclusion/exclusion criteria for this review.

Table 1. Summary of systematic review inclusion/ exclusion criteria by PECOS framework domains

	Population	Exposure	Comparison	Outcome	Study
Inclusion	Adults (18 years or older); male and female; with pre-existing and/ or without pre-existing health conditions at baseline	Neighbourhood green space and blue space	Adults (mean age 18 years or over); male and female; with pre-existing and/ or without pre-existing health conditions at baseline, who are not exposed to neighbourhood green and/ blue spaces	Chronic non-communicable diseases (NCDs); common and serious mental health conditions; frailty; physical functioning; Quality of Life	Longitudinal, observational (cohort) epidemiological studies
Exclusion	Children (mean age below 18 years), adult prisoners	Indoor green and blue space; outdoor green and blue spaces without open access to the population; simulations of green and blue spaces	-	Infectious acute diseases; cognitive functioning; developmental and dissociative mental health disorders	All other type of studies: cross-sectional, case-control, case reports, experimental

3.2.2 Population

Studies of adults, male or female, with a mean age 18 years or older were included. Populations with both pre-existing health conditions and those without pre-existing health conditions at baseline were included. Populations were not limited to community-dwelling adults but also included individuals in primary, secondary or tertiary care settings. No restrictions on country of residence or occupation were applied. Child populations, with an average population age of >18 years and adult prisoners were excluded. While the prevalence of multimorbidity generally increases with age, research has shown that mental-physical multimorbidity and multimorbidity among low-income individuals is prevalent in young and middle- aged adults (McLean et al., 2017). As different cohorts have varying age inclusion criteria, including studies with mean population age of 18 years or older was used to avoid missing out relevant records. Including populations with pre-existing and without pre-existing health conditions was considered appropriate for determining the development of multimorbidity in both healthy populations and those with pre-existing health conditions at baseline.

3.2.3 Exposures: green and blue spaces

Exposures included any green and/ or blue spaces in the neighbourhood. The neighbourhood was defined as the area/s within which individuals reside, work, or socialise. Urban sociologists have argued that many individuals are now part of multiple neighbourhoods, as their places of work, recreation and socialisation often differ from the places of residence (Duncan et al., 2018). This systematic review included exposures to green and blue space at the place of residence, work and/ or recreation (if different from the place of residence). Both objective measures (e.g., distance buffers, Census dissemination statistics), and subjective measures (individual reports and perceptions of the neighbourhood) were included. Both types of measures are considered important as prior research has shown that individuals have varying perceptions of what their neighbourhood encompasses, and this influences health and health related behaviours (Wilson et al., 2004). Furthermore, research has shown that differences in health outcomes exist between objectively measured and self-perceived exposures (Orstad et al., 2016).

Green and blue spaces encompass a wide-range of environments, both naturally occurring or existing because of nature-based solutions to urbanisation or climate change (Lovell et al., 2018). The definition of green space in this review was taken from prior theoretical research and systematic reviews, and is defined as: any open, outdoor space with natural vegetation that can be either undeveloped or managed, such as fields, nature reserves, urban parks, public open spaces, and street greenery (Twohig-Bennett and Jones, 2018; Lachowycz and Jones, 2011). According to WHO (2016), exposure to green spaces can broadly fit into three categories: accessibility, availability, and usage. Within those categories, different green space indicators can be incorporated, which can be objective, such as validated indexes, tools, or professional assessments (e.g., using Geographic Information System (GIS)); or subjective, such as individual perceptions of safety and quality of green spaces (WHO, 2016). This review aimed to include all indicators associated with availability, accessibility, and usage of green spaces.

Blue space in this review was defined as fresh or saltwater bodies that are either naturally occurring (e.g., lakes, rivers, seas) or exist due to human intervention (e.g., canals, ponds). Epidemiologic research suggests that the health benefits of blue spaces are drawn from bio-physiological mechanisms (harm reduction, restoration and instoration) (Grellier et al., 2017), so any indicators of visibility, coverage and access were included. Both objective (e.g., using GIS or professional assessments); or subjective (e.g., based on individual reports or perceptions) measures of blue spaces were included in this systematic review.

3.2.2 Outcomes

3.2.2.1 Primary outcomes

Mental and physical health were the primary outcomes of this review, which included common and serious mental health disorders, and NCDs. Studies that measured the development (incidence or risk), number of events, or progression of these outcomes were included. Studies measuring mortality outcomes were excluded.

3.2.2.1.1 Mental health disorders

Common and serious mental health conditions were included as primary outcomes. The definition and classification of common and serious mental conditions was taken from NICE (2011). Common mental health disorders are those defined by NICE (2011) as, when combined, they affect more people than other mental disorders. These include depression, generalised anxiety disorder (GAD), panic disorder, phobias, social anxiety disorder, obsessive-compulsive disorder (OCD) and post-traumatic stress disorder (PTSD). Severe mental disorders (SMI) are bipolar disorder, psychosis, and schizophrenia (NICE, 2011). SMIs were included because they are frequently associated with poor general health, making them outcomes of interest for multimorbidity (Woodhead et al., 2014). Only outcomes measured through validated, self-reported instruments, clinician assessments, or clinical samples (e.g., MRI scrans) were included. All other mental conditions, such as neurodevelopmental, neurocognitive disorders, substance abuse, eating and impulse control disorders were excluded because they do not fit the scope of the thesis and the objectives of this review.

3.2.2.1.2 Non-communicable diseases (NCDs)

Non-communicable diseases (NCDs) are conditions which cannot be transferred from person to person and usually have slow progression (WHO, 2015). They are primary outcomes of this review because they are responsible for 60% of the global mortality burden (Daar et al., 2007). They also constitute a large proportion of the multimorbidity burden, as their high prevalence has implications on health systems and services (Daar et al., 2007). Only chronic NCDs were included, which are broadly defined by the Center for Disease Control and Prevention (CDC) (2021) as those that "*last 1 year or more and require ongoing medical attention or limit activities of daily living or both*". Any NCD that meets these criteria and is measured through either validated, self-reported instruments, clinician assessments, or clinical samples was included. Acute and infectious diseases were excluded because they have quick progression and short duration, meaning they don't fit the scope of this review and thesis.

3.2.2.2 Secondary outcomes

3.2.2.2.1 Overview

Health-related behaviours, physical functioning, frailty, and health-related quality of life (HQoL) were included as secondary outcomes because they relate to both mental and physical health and multimorbidity (Fortin et al., 2004).

3.2.2.2.2 Health-related behaviours

Health-related behaviours are important modifiable risk factors for many chronic health conditions, including mental health conditions and NCDs (Birch et al., 2018). This review's inclusion was limited to the four most widely studied behaviours in epidemiological literature: smoking, alcohol consumption, diet, and physical activity (Conner and Norman, 2017) because they are the most prominent risk factors of multimorbidity (as discussed in Chapter 2). Including these behaviours as secondary health outcomes aids the understanding of causal pathways between environmental exposures and chronic health. Studies that measure these behaviours through validated, self-reported instruments, or objective assessments (e.g., accelerometer) were included. All other types of health-related behaviours were excluded.

3.2.2.2.3 Physical functioning

Physical functioning is a health state defined through various laboratory-based measures of physiologic impairment, objectively measured, or self-reported instruments of physical activity; or through self-reported instruments or field tests of mobility and performance capacity (Painter and Marcus, 2013). Physical functioning was included as a secondary outcome because of its bidirectional relationship with multimorbidity, where it can be both an outcome or a risk factor to multimorbidity (Wei et al., 2019, Calderón-Larrañaga et al., 2019). This review included studies that measured physical functioning through any validated, self-reported instrument or objective measures.

3.2.2.2.4 Frailty

Frailty is broadly defined as a clinical state of increased vulnerability resulting from a decline in reserve and function across multiple physiologic systems (Xue, 2011). Frailty is a separate but related concept to multimorbidity. In a systematic review, over 70% of individuals with frailty also had multimorbidity, while having multimorbidity was associated with a two-fold risk of becoming frail (Vetrano et al., 2019). Currently, two models define frailty. The phenotype model categorises frailty into three states based on number of symptoms, while the frailty index quantifies the condition on a continuous scale based on several relevant health outcomes (Schoufour et al., 2017). This review included frailty measured through either model frailty.

3.2.2.2.5 Health-related quality of life

Health-related Quality of Life (HQoL) was included as a secondary outcome in this review because of its bidirectional relationship with multimorbidity (Makovski et al., 2019). HQoL is a measure of the level of satisfaction of people’s lives in relation to their health status (Karimi and Brazier, 2016). It is usually assessed through validated, self-reported instruments of peoples’ perception of health, and the extent to which poor health status influences daily activities, such as work, recreation and socialisation. HQoL measured through any validated instrument was included.

3.2.3 Search strategy

3.2.3.1 Electronic searches

This review included studies only published in peer-reviewed journals. Other grey literature, such as degree theses, government reports and conference proceedings were excluded. There was no date restriction on the search, however, only sources in English language were considered. To minimise additional bias in the systematic review, I aimed to search as many relevant electronic databases as possible. Due to the interdisciplinary nature of the review, MEDLINE, Embase as well as interdisciplinary and social science databases were searched.

The following databases were searched:

Embase
GreenFILE
MEDLINE
PsycINFO
Scopus
Science Citation Index

3.2.3.2 Search strategy

Systematic reviews of natural environment-health relationships are relatively new to the field of epidemiology, and currently there is no consensus on a best search strategy. Relevant key terms for this study were selected based in on knowledge of the topic and prior systematic reviews with similar aims and objectives (deKeijer et al., 2020; Rojas-Rueda et al. 2019). The terms for green and blue spaces aimed to capture a wide range of natural vegetation and water bodies in both rural and urban spaces worldwide. Some examples of the terms used are: "*natural environment", "green space", "blue space", "neighbourhood green", "urban green", "public park", "natural space", "nature reserve", "forest", "trees, "coasts", "lake", "rivers".* The full search strategy and terms can be found in Appendix III.

With the help of an information specialist from the University of York's Centre for Reviews and Dissemination, Kath Wright, search strategies striving for high sensitivity were designed and tested. Currently, there is little evidence of a highly sensitive, optimal search filter for identifying cohort studies and natural environmental exposures in online databases (Waffenschmidt et al., 2017). Therefore, I conducted two searches in all six bibliographic databases using two structurally different search strategies. The first search strategy included two sets of terms: one describing the exposures and one describing the longitudinal observational study design. The two sets of terms were combined with and '*AND*' Boolean operator. A set of search terms for health conditions was originally not included because the systematic review examined a wide range of health outcomes. The second search strategy, on the other hand, included search terms for exposures, study type, and a third set of search terms for health outcomes. The strategies can be found in Appendix III.

The first search strategy was revised because it yielded high returns, making screening infeasible due to time constraints. Limiting the search with a third set of terms for health outcomes reduced the return rate by almost half. I further conducted an examination of the records retrieved during the first search strategy but missed by the second search strategy. This was achieved by simultaneously running the two search strategies in MEDLINE with a '*NOT*' Boolean operator (see Appendix III). Titles and abstracts retrieved through this process were screened for potentially relevant studies. As very few potentially relevant studies were identified, the second, more-restricted search strategy was adopted and used in this review.

3.2.4 Data collection and analysis

3.2.4.1 Study selection

Study selection was conducted in two phases. First, titles and abstracts of studies were screened against the inclusion and exclusion criteria by one reviewer (MG). The second phase included full-text screening by one reviewer (MG). Reference lists were also screened for potentially eligible studies. Uncertainty about the inclusion of a study at all stages of the screening process was resolved through consensus meetings with a second reviewer (PC). If the problem could not be resolved through a meeting, the study was categorised into '*awaiting assessment*' group, where an attempt to contact the authors for clarification was made. If reaching the authors wasn't successful, further consensus meetings were held between the reviewers (Higgins et al., 2019).

A bibliographic reference software (EndNote, X9 Version) was used to organise records and remove duplicates. The duplicate with most extensive information was included to maximise the yield of information (Higgins et al., 2019). Retrieved studies were imported into Rayyan, a web-based application, which was used as a screening aid. Rayyan's usability has been previously tested in pilot studies. It is currently established as a valid tool for systematic review screening (Ouzzani et al., 2016). Rayyan supports imports from EndNote and allows flexibility in screening standards (Kellermeyer et al., 2018).

3.2.4.2 Data extraction

Data extraction was conducted by the reviewer (MG) and accompanied by consensus meetings with another reviewer (PC). The type of data extracted was guided by a pre-specified data extraction form, which was adapted from Cochrane by me to suit longitudinal observational studies (See Appendix IV for template). The data collection fields on the form were translated onto a Microsoft EXCEL spreadsheet where individual study data were recorded. The table below (table 2) outlines the type of data extracted.

Table 2. Summary of data collection points for narrative synthesis

Type	Details
Identification features of study	author/s; publication type/date; place of publication; country of origin; funding
Participant Characteristics	age; sex; ethnicity; socio-economic status; health status
Study Characteristics	aims and objectives; inclusion/ exclusion criteria; population source
Exposure Characteristics	type; definition; method of assessment; methods of assignment; additional exposures
Outcome Characteristics	effect estimates (and variability estimates); definition; tools of assessment; time points of assessment; additional outcomes recorded
Study Methods	method of participant recruitment; duration of follow-up; loss to follow-up; appropriateness of statistical methods used; subgroup and mediator analyses

3.2.4.3 Risk of bias assessment

The Newcastle-Ottawa Scale (NOS) was used as a risk of bias assessment tool in this review. It was developed using a Delphi method and is endorsed by the Cochrane as a suitable tool for observational cohort and case-control studies (Downes et al., 2016). NOS has previously yielded good content validity and interrater reliability (Lo et al., 2014). The tool consists of three domains that assess the quality of the cohort study. These include: selection of the study based on representativeness of cohort and exposure measures; comparability on the basis of design or analysis; and outcome assessment, including loss and adequacy of follow-up (see Appendix V for Manual). Selection and information bias were assessed using NOS. Particularly, I assessed for sampling bias, differential loss to follow-up, confounding and missing data. Reverse causality was assessed by demonstrating that the outcome was not present at the start of study. One reviewer (MG) assessed the risk of bias using NOS questionnaire and held consensus meetings with a second reviewer (PC) to resolve any uncertainty in the assessment. The NOS questionnaire awards points based on multiple choice questions. The maximum points are 9, with a score between 5 to 9 giving the study good methodological quality, and score of 0 to 4 giving the study poor quality (Gong et al., 2015).

3.2.4.4 Measures of effect estimate

Dichotomous and continuous effect estimates for relevant association were included. Dichotomous outcome effect measures include odds ratio, relative risk, incidence rate ratio, risk difference and beta coefficients. For continuous outcomes, I measured: beta coefficients, mean, mean difference and standardised mean difference. Measures of variability, such as 95% confidence intervals (CI) and standard deviation (SD), were also included alongside the effect measures.

3.2.4.5 Data synthesis

3.2.4.5.1 Narrative synthesis

Study characteristics, such as study type, publication date, participant characteristics, duration of follow-up, loss to follow- up, outcome and exposure type were narratively summarised in tables. This also included a summary of exposure types, their data sources, and spatial scales. Outcome type and definition were also summarised in the same table. Additionally, bar graphs were used to summarise the frequency of exposures and outcomes. Effect estimate/s and direction of association (including confidence intervals and other variability analyses) of each study were also reported.

3.2.4.5.2 Quantitative synthesis

It was not possible to conduct a quantitative synthesis of review studies due to high heterogeneity in exposure measurements. However, if studies were sufficiently homogeneous in population, intervention, and outcome, one or multiple meta-analyses would've been conducted. The results would've been presented in forest plots, depicting the individual effect estimates of each study (with 95% CIs and p-values at 0.05 significance level), study weight, and the pooled effect estimate (Haidich, 2010). A funnel plot to assess risk of bias would also have been produced.

3.2.4.6 Heterogeneity

In narrative synthesis, heterogeneity was assessed by qualitatively examining differences in populations, settings and exposure measurements. Heterogeneity of studies was not examined through statistical analyses, such as the Q-Test and I^2 due to lack of suitable data (Higgins et al., 2019).

3.2.4.7 Sensitivity analyses

A sensitivity analysis is a method of determining the robustness of the observed outcomes to the assumptions made during performing the analysis (Higgins et al., 2019). In a meta-analysis, sensitivity analyses are conducted by altering a factor, dataset, or including/ excluding studies to observe changes in effect estimates (Bown and Sutton, 2010). Sensitivity analyses were dependent on obtaining data suitable for meta-analysis, which was not possible in this systematic review. However, if such data were available, the influence of the following factors on the pooled estimate would have been examined:

- Restricting the analysis to studies that are rated with low risk of bias by the NOS scale
- Restricting the analysis to participants with pre-existing health conditions

- Restricting the analysis to publication features: country, source of funding, journal type
- Restricting the analysis to studies with long follow-up time

3.3 Results

3.3.1 Study selection

The final search was conducted on 17th July 2020. After removal of duplicates, 24,176 records were identified (See PRISMA flowchart in fig.4). Of these, 23,941 records were excluded during the title and abstract screening stage, leaving 233 records for full-text assessment. A further 189 records were excluded during the full-text screening, leaving a total of 44 records (equating to 44 studies) for the narrative synthesis. Three potentially relevant studies were identified from the bibliographic reference lists of the included 44 studies, but they did not meet the screening criteria and were excluded.

Just under half of the studies excluded during full-text screening (47.6%, n=90) did not include a green or blue space exposure that fit the specified inclusion criteria. Thirty-eight (20.1%) studies did not have an observational longitudinal study design. Eighteen studies were experimental, 17 were cross-sectional, 1 was a literature review, 1 was a discussion paper, and 1 was a case-control study. Thirty-seven studies (19.6%) were excluded based on outcome, which either did not fit the definition of a chronic condition (n=22), measured mortality (n=3), did not use a validated instrument (n=4), examined acute and/ or infectious diseases (n=7), or did not include a health condition as an outcome (n=1). Six studies were excluded based on population (all children) and 13 studies were excluded because of publication type (1 dissertation and 12 conference papers). Two records were also excluded because they were duplicates (fig.4).

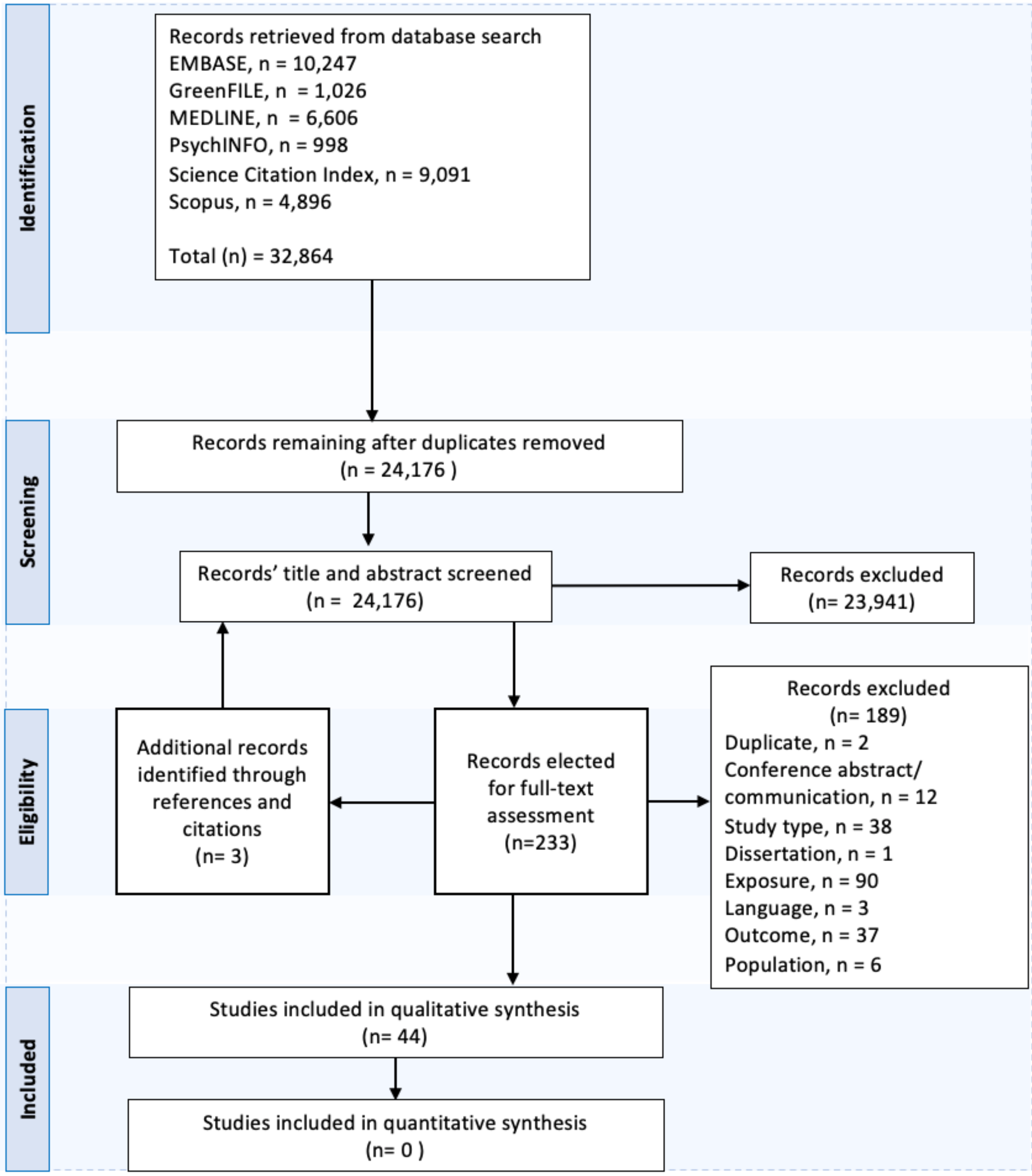

Figure 4: PRISMA flowchart of records included in the systematic review

3.3.2 Narrative synthesis

3.3.2.1 Overview

Forty-four studies were included in the narrative synthesis. The majority of studies were published between 2010 and 2020 (n=42) and based in high-income countries (n=35) (fig. 5; and table 4 for narrative descriptions). Only 9 studies were based in middle- and low-income countries (fig. 5; table 4). Duration of follow-up ranged from 9 months to 27 years, with the median duration being 7 years. Population sample sizes also varied between studies, from 513 to 4.25 million participants, with a median of 11,156 participants. Over 70% (n=31) of studies included populations of middle aged and older adults (35 years or older) (fig. 5; table 4). Seven studies included populations of all adult ages and another six examined young adults (18-35 years). Most studies (n=35) included both men and women participants. Six studies included only female participants and one study included only male participants (fig. 5; table 4). The majority of studies (95%) included predominantly healthy populations at baseline. Two studies included people with pre-existing health conditions, both of which were diabetes (Chong et al., 2019; Gariepy et al., 2015b). Five studies selected their populations based on occupation. Out of these, 3 studies included civil servants (de Keijzer et al., 2019a; de Keijzer et al., 2019b; Faerstein et al., 2018), 1 included public sector employees (Halonen et al., 2014) and one included women nurses (Banay et al., 2019). Most studies (n=40) used data from volunteer-based health cohorts (table 4), while 5 studies sourced information from health insurance databases (table 4).

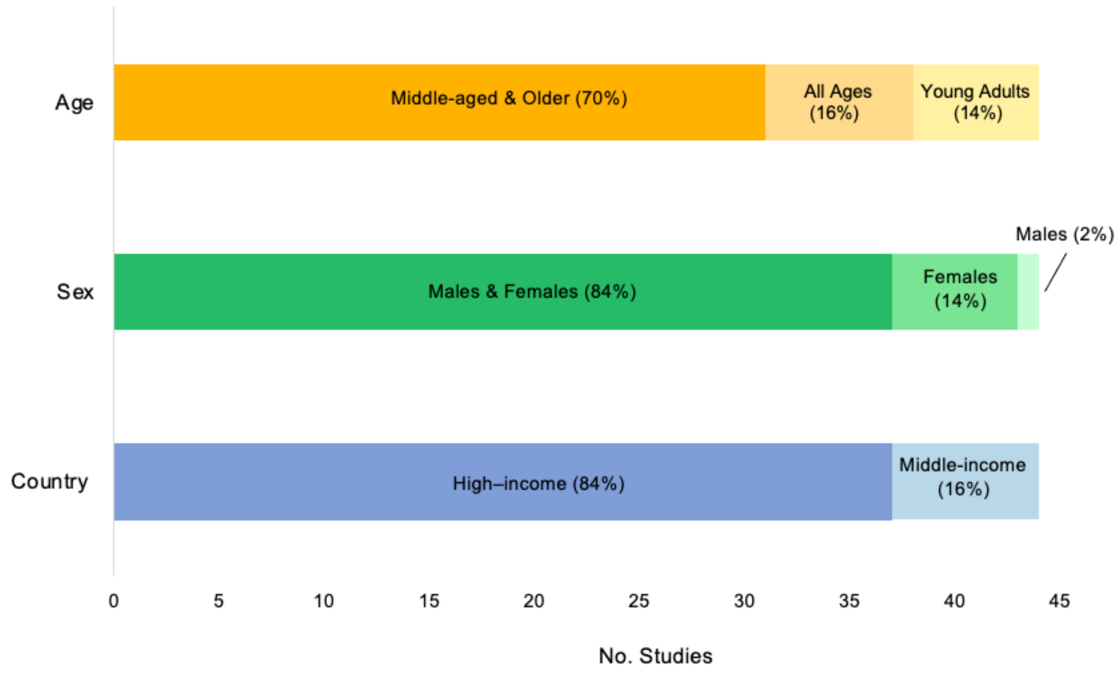

Figure 5: Summary of study populations of studies included in the systematic review

3.3.2.2 Exposures

3.3.2.2.1 Overview

The majority of studies included in this systematic review (n=40) assessed exposure to green spaces (fig. 6). Three studies comparatively assessed exposure to green and blue spaces (Halonen et al., 2014; de Keijzer et al., 2019b; Faerstein et al., 2018), and only 1 study assessed exposure to blue space (Haraldsdottir et al., 2017) (table 4). Altogether, only 4 studies assessed the relationships between blue space and health (fig. 6). Figure 6 shows the type and frequency of each exposure indicator used by studies included in this review. The majority of indicators (n=31) measured green space availability. Availability of green space can be defined as the quantity of greenness in the neighbourhood without distinction between publicly accessible and private green spaces (World Health Organisation, 2016b). The Normalized

Difference Vegetation Index (NDVI) was the most common indicator of green space availability (n=20), followed by proportion of green space (n=8). Green space accessibility indicators can capture both physical proximity to green spaces, access points of green spaces and whether spaces are accessible to the public (World Health Organisation, 2016b). Studies included in this systematic review measured green space accessibility as distance or presence of urban green spaces such as parks (n=13). Usage, on the other hand, can be broadly defined as a behaviour individuals exhibit when they visit and interact with green and blue spaces (World Health Organisation, 2016b). Only 1 study used a self-reported questionnaire to assess individual green space usage in this systematic review. All blue space indicators assessed accessibility to blue space (n=4), 2 of which measured distance to a blue area while 2 assessed residential proximity to the coast (fig. 6).

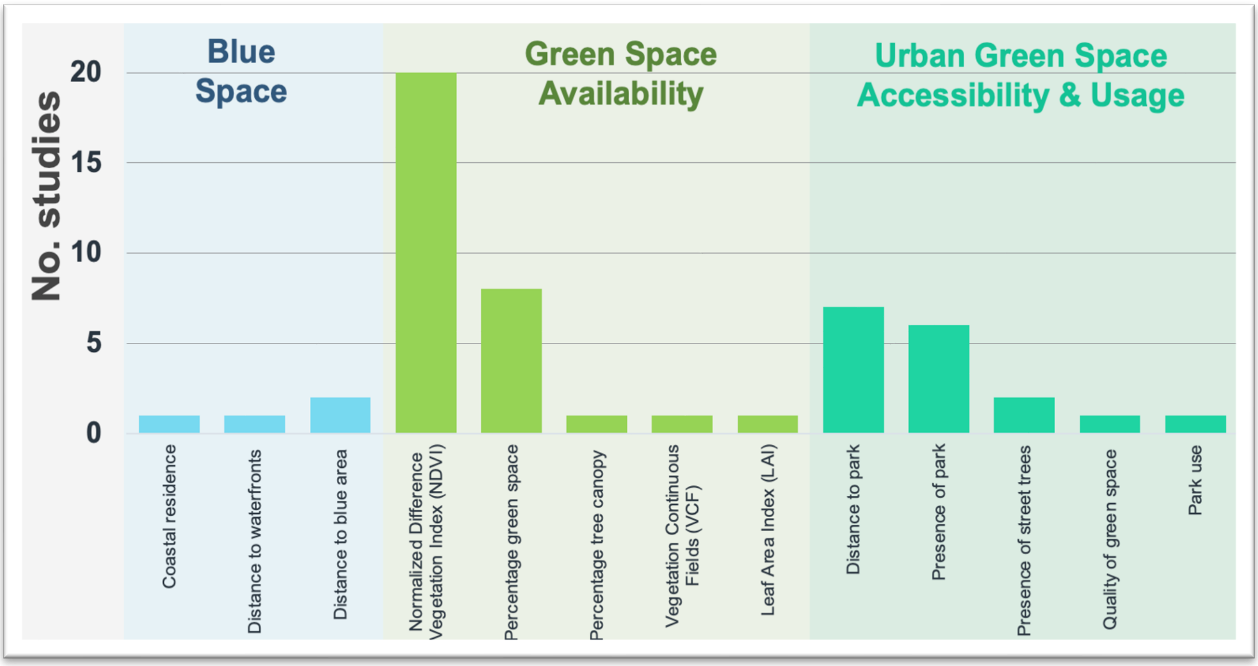

Figure 6: Bar graph of frequency and types of exposure indicators

3.3.2.2.2 Green space availability

The majority of studies (n=31) included in this systematic review measured availability of green spaces. The NDVI was the most frequently used indicator of availability (n=20). Sixteen studies exclusively used NDVI, while 4 studies used NDVI alongside other green/ blue space exposure indicators (table 4). Apart from NDVI, other indicators of availability included percent green space (n=8), percent tree canopy cover (n=1), and remote sensing vegetation indices (VCF, LAI) (n=2). All availability indicators were objectively measured through distance buffers around the residential address (n=27), census dissemination statistics areas (n=3) or both (n=1) (table 4).

3.3.2.2.3 Green space accessibility

Accessibility to green spaces was measured by proximity (n=7) or distance (n=7) to green spaces (fig. 6). Distance was measured either in a straight line (Euclidean distance) from individuals' residence, or along roads and paths only (table 4). Proximity was measured by the presence or absence of a specific green space in the residential neighbourhood. Six studies used a pre-specified distance buffer around the residential address to spatially define the residential neighbourhood (table 4). One study used the residential block group as a spatial scale (table 4). One study measured proximity public park with a self-reported questionnaire (Sugiyama et al., 2015).

3.3.2.2.4 Green space usage

Green space usage was assessed in one study (Tamosiunas et al., 2014) (fig. 6). A self- reported questionnaire was used to classify participants into park users and non-users. Stratified analyses by user status were then conducted to examine the association between distance to park and CVD risk.

3.3.2.2.5 Blue space indicators

This review identified four studies on the relationship between exposure to blue space and health (Halonen et al., 2014; de Keijzer et al., 2019b; Faerstein et al., 2018; Haraldsdottir et al., 2017). All studies used proximity indicators (fig. 6). Definitions of blue space were heterogeneous. Blue space was usually classified as a combination of different types of water bodies. Land cover or other national databases were used to objectively capture blue space proximity in the residential neighbourhood. One study used a self-report of residential address to capture availability of coasts (Haraldsdottir et al., 2017).

3.3.2.3 Health Outcomes

Just under half of all outcomes were non-communicable diseases (NCDs) (n=28) (fig. 7), of which diabetes (n=7), obesity (n=6), CVD (n=3), hypertension (n=3), cancer (n=3) and stroke (n=2) were most frequent. Over a quarter of outcomes were mental health conditions (n=11), of which depression was most frequent (n=9) (fig.7). One study assessed schizophrenia and another study assessed anxiety.

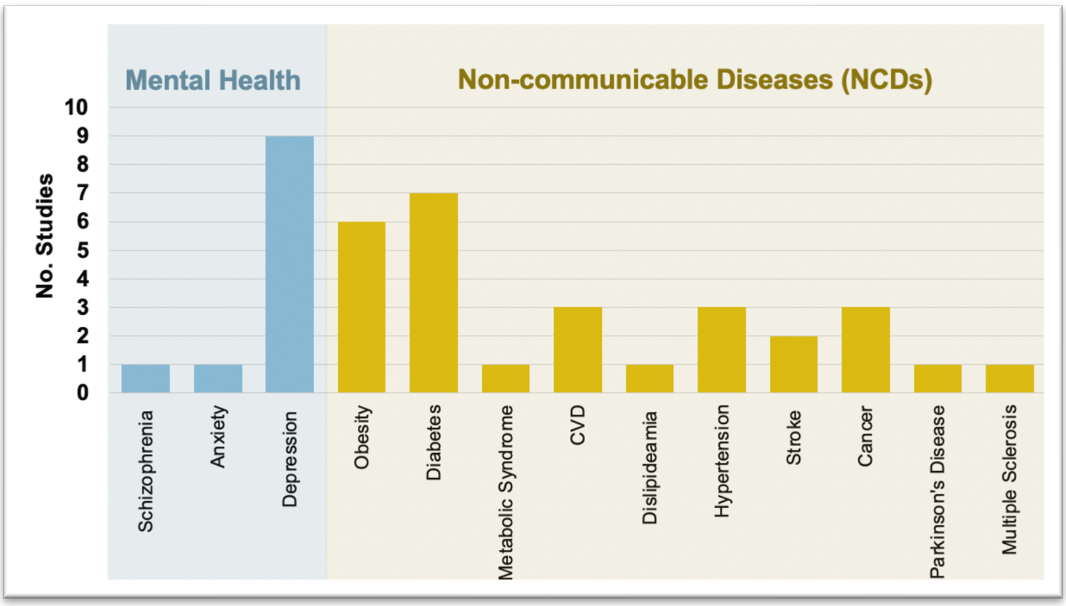

Figure 7: Bar graph of primary outcomes by study frequency

Figure 8 shows the frequency of all secondary outcomes. Physical activity was the most frequent outcome of this review (n=13). Overall, the definition and conceptualisation of physical activity in the review studies was heterogeneous. While all studies measured physical activity through validated, self-reported questionnaires, definition and unit of measurement differed. Over half of studies (n=7) measured types of physical activity related to green spaces, such as walking, jogging, cycling. The rest (n=6) measured total amount of physical activity. Seven studies measured weekly physical activity frequency (either in minutes or hours), while six measured the physical activity as a binary outcome based on guidelines cut-off points.

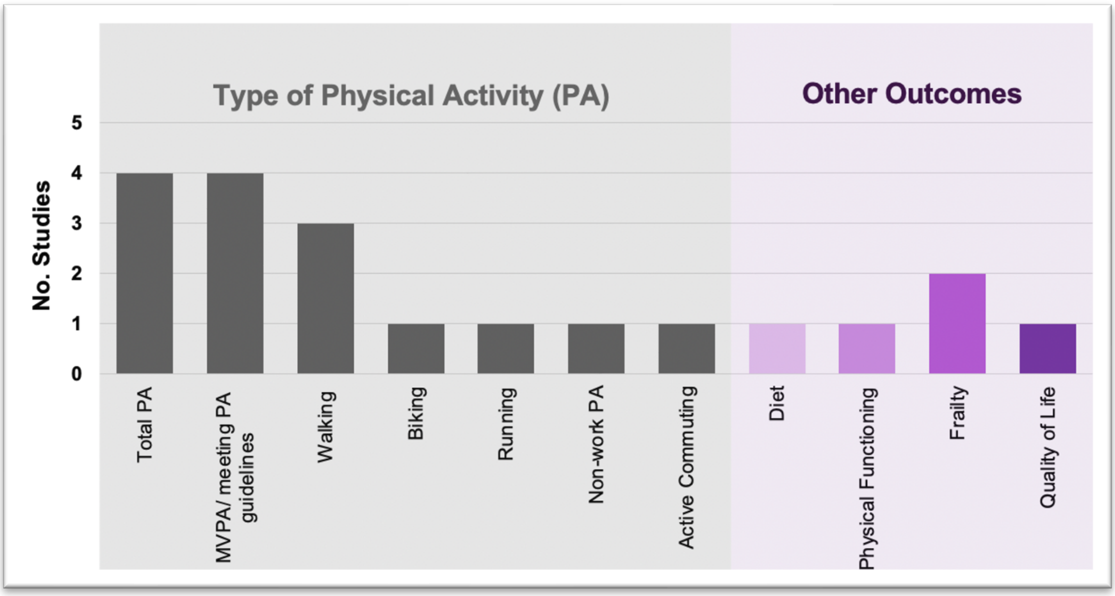

Figure 8: Bar graph of secondary outcomes by study frequency

3.3.2.4 Quality assessment

The Newcastle-Ottawa Scale (NOS) scale was used to assess risk of bias in each study (table 3). Overall, over half of studies (n=24; 54.5%) had good methodological quality. Fourteen (31.8%) studies had poor methodological quality and six (13.65%) studies had fair methodological quality. Scoring was calculated based on NOS's criteria. Most studies scored high on comparability, which assessed bias due to confounding. As a general trend, studies scored low on the *Selection* and *Outcome* domains. In particular, the representativeness of the cohort, outcome assessment and adequacy of follow-up components received low scores. Many study populations were not representative of the exposed in the community due to potential *healthy worker* effect and volunteer bias. Studies mainly scored low the outcome domain because they used self-reported outcomes, while adequacy of follow-up showed that over half of studies (n=24) did not account for participants lost to follow-up. Finally, less than half of studies (n=20) demonstrated that the outcome was not present at the beginning of the study.

Table 3. Quality appraisal ratings by Newcastle-Ottawa Scale domains

Study Reference	**Selection**				**Comparability (confounding)**		**Outcome**			
	Representativeness of the exposed	Selection of the non-exposed	Ascertainment of exposure	Demonstration outcome of interest not present at start	Main confounders†	Additional Confounders‡	Outcome assessment	Length of Follow-up	Adequacy of follow-up	Quality
Lee et al., 2017		*	*		*	*	*	*		Fair
de Keijzer et al., 2019b		*	*		*	*	*	*	*	Fair
Michael et al., 2010		*	*		*	*		*	*	Fair
Dalton et al., 2016 b		*	*		*	*		*	*	Fair
Hobbs et al., 2019		*	*		*	*		*	*	Fair
Lin et al., 2020		*	*		*	*		*	*	Fair
Chang et al., 2019	*	*	*	*	*	*	*	*		Good
Gariepy et al., 2015a	*	*	*		*	*		*	*	Good
Tomita et al., 2017	*	*	*	*	*	*		*	*	Good
Paquet et al., 2014	*	*	*		*	*	*	*		Good
de Keijzer et al., 2019a		*	*	*	*	*	*	*		Good
Dalton and Jones, 2020		*	*	*	*	*	*	*		Good
Paul et al., 2020		*	*	*	*	*	*	*		Good
Orioli et al., 2019	*	*	*	*	*	*	*	*		Good

Tamosiunas et al., 2014	*	*	*	*	*	*		*	*	Good
Pun et al., 2018	*	*	*		*	*		*	*	Good
Clark et al., 2017	*	*	*	*	*	*	*	*	*	Good
Datzman et al., 2018		*	*	*	*	*	*	*		Good
Conroy et al., 2017	*	*	*	*	*	*	*	*		Good
Yu et al., 2018	*	*	*		*	*	*	*	*	Good
Liao et al., 2019		*	*	*	*	*	*	*	*	Good
Persson et al., 2018	*	*	*		*	*	*	*	*	Good
Yuchi et al., 2020	*	*	*	*	*	*	*	*		Good
Zhu et al., 2020	*	*	*		*	*		*	*	Good
Fernandez-Nino et al., 2019		*	*	*	*	*		*	*	Good
Gariepy et al., 2015b		*	*	*	*	*		*	*	Good
Haraldsdottir et al., 2017	*	*		*	*	*	*	*	*	Good
Dalton et al., 2016a		*	*	*	*	*		*	*	Good
Melis et al.,2015	*	*	*	*	*	*	*	*	*	Good
Renzi et al., 2018	*	*	*	*	*	*	*	*	*	Good
Banay et al., 2019	*	*	*	*	*	*		*		Poor
Meyer et al., 2015		*	*		*	*		*		Poor
Chong et al., 2019	*	*	*		*	*		*		Poor
Josey and Moore., 2018		*	*		*	*		*		Poor
Yang et al., 2017		*	*		*			*		Poor
Cleland et al., 2009	*	*			*	*		*		Poor
Halonen et al., 2014	*	*	*		*	*		*		Poor
Picavet et al., 2016		*	*		*	*		*		Poor
Hogendorf et al., 2020		*	*		*	*		*		Poor
Coogan et al., 2009	*	*	*		*	*		*		Poor
Sugiyama et al., 2015	*	*			*	*		*		Poor
Astell-Burt and Feng, 2020	*	*	*		*	*		*		Poor
Astell-Burt and Feng, 2019	*	*	*	*	*	*		*		Poor
Faerstein et al., 2018		*	*		*	*		*		Poor

†age, sex

‡a measure of socio-economic position, such as education, income or deprivation

Table 4. Summary of extracted study characteristics, results and quality appraisal

Study Reference	Population Description	Sample Size	Cohort Name/ Data Source	Follow-up Duration	Exposure Indicator	Outcome	Outcome Measure	Main Results Effect Estimate (95% CI)	Confounders	Study Quality*
					Primary Outcomes					
					Mental Health					
Chang et al., 2019	men and women mean age: 43.36 (20.44) years (Taiwan)	869,484	Taiwan Longitudinal Health Insurance Database	10 years	NDVI at baseline; 2,000m circular buffer around hospital most frequently visited	Schizophrenia	Physician - diagnosed	HR: 0.37 (0.25, 0.55) Highest NDVI quintile	age, sex, health insurance rate, classification of the insured, temperature, relative humidity, precipitation	Good
Banay et al., 2019	women nurses; ≥ 30–55 years (USA)	121,701	Nurses' Health Study	10 years	NDVI averages for each year of follow-up; 250m and 1250m circular buffers	Depression	First self-report of physician / clinician diagnosis of depression or new regular use of antidepressants	250m Buffer HR: 0.87 (0.78, 0.98) Highest NDVI quintile 1,250m Buffer HR: 0.90 (0.80, 1.02) Highest NDVI quintile	age, race, mental health, marital status, educational attainment, husband's educational attainment, population density, income, median home value, PM2:5 level, BMI, smoking status and pack-years of smoking, alcohol consumption, physical activity, physical function,	Poor

									bodily pain (baseline), social network strength, care to ill family members (baseline), difficulty sleeping (baseline)	
Fernandez -Nino et al., 2019	men and women; ≥ 55 years (Mexico)	1,524	Study on Global Ageing and Adult Health (SAGE)	5 years	Street trees; total length of street covered in trees in a 950m road network buffer	Depression	Self-report of physician diagnosis	OR: 0.90 (0.29, 2.83) Highest quintile of street length covered in trees	sex, age, income index, functional limitations, margination index of the municipality	Good
Gariepy et al., 2015a	men and women; ≥ 18-80 years (Canada)	13,618	National Population Health Survey	10 years	Presence of a park within a 500m circular buffer	Depression	Self-reported instrument	β: -0.4 (-1.4, 0.6) For answering "yes" to presence of a park	age, sex, marital status, education, income adequacy, childhood life events, chronic condition, family history of depression	Good
Gariepy et al., 2015b	men and women; ≥ 18-80 years; with diabetes (any type) (Canada)	2,003	Diabetes Health Study (DHS)	5 years	NDVI	Depression	Self-reported instrument	HR: 0.94 (0.88, 1.01) Per decile increase in NDVI	sex, age, marital status, family income, educational level, employment	Good
Melis et al.,2015	men and women; ≥ 20-65 years (Italy)	547,263	Turin Longitudinal Study (TLS)	2 years	Availability of green space measured via index by area units	Depression	Antidepressant use	Men IRR: 0.98 (0.92, 1.04) Highest index value quintile green Women IRR: 1.00 (0.96, 1.08) Highest	sex, age, education level, activity status, citizenship, residential stability at same address	Good

							index value quintile of green		
Tomita et al., 2017	men and women; mean 20 years (South Africa)	11,156	South African National Income Dynamics Study (SA-NIDS	4 years	NDVI, 250m resolution square	Depression	Self-reported instrument	OR: 1.01 (1.01, 1.02) Each unit increase in NDVI value	age, sex, marital status, race, household income, employment, rurality	Good
Astell-Burt and Feng, 2019	men and women; ≥ 45 years (Australia)	46 786	45 and Up Study	6.2 (mean) years	Total percent green space; tree canopy in a 1600m road network buffer	Depression or anxiety	Self-report of doctor diagnosed	OR: 1.26 (0.89, 1.63) Highest percent quintile total green OR: 0.86 (0.80, 1.01) Highest percent quintile tree canopy	age, sex income, education, economic status, couple status	Poor
Pun et al., 2018	men and women; ≥ 57-85 years (USA)	3,005	National Social Life, Health, and Aging Project (NSHAP)	6 years	NDVI seasonal changes in 1000m circular buffer	Depression; anxiety	Self-reported instrument	Anxiety β: −0.104 (−0.322, 0.115) per unit increase in NDVI Depression β: − 0.274 (− 0.596, 0.048) per unit increase in NDVI	age, gender, questionnaire year, season, region, education attainment, 3-day moving average of temperature, 60-months moving average of PM2.5	Good
					NCDs					
Dalton and Jones, 2020	men and women; mean 59.2 years (United Kingdom)	25,639	European Prospective Investigation of Cancer (EPIC) Norfolk	14.5 (mean) years	Percent green space in 800m circular buffer	CVD	Health register	HR: 0.93 (0.88, 0.97) Highest percent quintile green	sex, age, BMI, diabetes, SES (individual and neighbourhood)	Good
Tamosiunas et al., 2014	men and women; ≥ 45-72 years (Lithuania)	5,112	Health, Alcohol, and Psychosocial Factors in Eastern	4.41 (mean) years	Distance to park and park use (self-reported)	CVD	Self-reported doctor diagnosed	User: HR: 1.58 (0.95, 2.63) Longest distance quintile	age, sex, education, smoking, arterial hypertension, physical activity,	Good

			Europe (HAPIEE)					Non-user: HR: 1.66 (1.01, 2.73) Longest distance quintile	total cholesterol level, fasting glucose level, BMI, diabetes mellitus, cognitive function, symptoms of depression, self-rated health, and quality of life	
Clark et al., 2017	men and women; ≥ 45-84 years; urban residents (Canada)	380,738	British Columbia mandatory health insurance database	4 years	NDVI yearly and seasonal; in 100m circular buffer	Diabetes	Health register	OR: 0.90 (0.87, 0.92) IQR increase in NDVI	sex, age, area-level household income, walkability, pollution	Good
Renzi et al., 2018	men and women; ≥ 35 years (Italy)	1,459,671	Rome Longitudinal Study	5.2 (mean) years	NDVI and LAI in a 300m circular buffer	Diabetes	Medical records	β: -1.87 (-7.40, 3.99) Per unit increase in NDVI	SES, marital status, educational level, occupation, place of birth, sex	Good
Dalton et al., 2016a	men and women; ≥ 40-80 years (United Kingdom)	25,633	European Prospective Investigation into Cancer (EPIC) Norfolk	11.3 (mean) years	Percent green space; in 800m	Diabetes (T2)	Self-report of physician diagnosis or medication	HR: 0.81 (0.65, 0.99) Highest percent quintile green	sex, age, BMI, parental diabetes, SES	Good
Liao et al., 2019	pregnant women; 25-29 years mean age group (China)	6,883	Visitors of Wuhan's Women and Children Medical and Healthcare Center	9 months or until development of gestational diabetes	NDVI for conception years; 300m circular buffer	Diabetes (genstational)	Clinical samples	RR: 0.66 (0.52, 0.84) Highest quintile NDVI	age, education years, BMI, passive smoking during pregnancy, parity, season	Good
Hobbs et al., 2019	men and women; ≥18-89 years (United Kingdom)	28,806	Yorkshire Health Study	3 years	Presence of park in a 2000m circular buffer	Obesity	BMI, self-report	OR: 0.99 (0.98, 1.02) for answering "*yes*" to presence of park	age, sex, education, deprivation, population density	Fair
Persson et al., 2018	men and women,	5,712	Stockholm Diabetes Prevention	8.9 (mean) years	NDVI; time-weighted in a 100m, 250m,	Obesity	Objective measures of BMI	IRR for IQR increase in NDVI 500m	age, alcohol consumption,	Good

	≥ 35-65 years (Sweden)		Program (SDPP)		500m circular buffer			Females: 1.05 (0.88, 1.26) Males: 1.06 (0.89, 1.26)	tobacco use, psychological distress, shift work, aircraft noise, railway noise, distance to water	
Halonen et al., 2014	men and women; public sector employees; mean: 47.7 years (non-movers) and among the movers 41.8 (Finland)	35,213	Finnish Public Sector study	8 years	Distance to green space; distance to blue space in meters, objectively measured	Obesity and overweight	Self-reported BMI	Green space OR: 1.50 (1.07, 2.11) Longest distance quintile Blue space OR: 1.15 (0.94, 1.39) Longest distance quintile	age, sex, education, chronic disease, neighbourhood socioeconomic disadvantage, BMI, smoking, heavy alcohol, physical inactivity	Poor
Lee et al., 2017	men and women; ≥ 19 years (48.6 years mean) (USA)	5,435	Offspring and Generation Three Cohorts of the Framingham Heart Study	6.4 years	Percent green space within a census block	Obesity; Diabetes	Blood samples; medication; objectively-measured BMI	Diabetes: OR: 0.70 (0.41, 1.19) Highest percent quintile green Obesity: no results	age, gender, smoking status, education, cohort status, fasting plasma glucose, BMI	Fair
Astell-Burt and Feng, 2020	men and women; ≥ 45 years (Australia)	53,196	45 and Up Study	6 years	Percent green space; tree canopy in a 1600m road network buffer	Diabetes, hypertension and CVD	Self-report of physician diagnosis	Diabetes OR: 1.10 (0.65, 1.95) Highest percent quintile total green OR: 0.71 (0.56, 0.91) Highest percent quintile tree canopy Hypertension OR: 0.72 (0.64, 1.12) Highest percent quintile total green	age, sex income, education, economic status, couple status	Poor

							OR: 0.82 (0.71, 0.95) Highest percent quintile tree canopy CVD OR: 0.89 (0.59, 1.13) Highest percent quintile total green OR: 0.79 (0.63, 0.92) Highest quintile tree canopy		
Paquet et al., 2014	men and women; ≥ 18 years (Australia)	4,056	North West Adelaide Health Study (NWAHS)	3.5 (mean) years	NDVI in 1000m road network buffer	Diabetes; hypertension; obesity; dyslipidaemia	Clinical samples	Per unit increase in NDVI Diabetes RR: 1.01 (0.90, 1.13) Hypertension RR: 0.97 (0.87, 1.07) Dyslipidaemia RR: 1.12 (1.00, 1.25) Obesity RR: 1.04 (0.92, 1.16)	age, gender, smoking status, education, cohort status, fasting plasma glucose, BMI	Good
de Keijzer et al., 2019a	men and women; ≥ 35-55 years civil servants (United Kingdom)	10,308	Whitehall II	14.1 (median) years	NDVI and VCF, 500m and 1000m circular buffers and LSOA	Metabolic Syndrome	Clinical samples	IQR increase in NDVI 500m HR: 0.87 (0.77, 0.99) 1,000m HR: 0.90 (0.79, 1.01) LSOA HR: 0.91 (0.79, 1.03)	age, sex, ethnicity, individual socioeconomic status (education and employment grade), neighbourhood socioeconomic status (income and employment deprivation)	Good

Datzman et al., 2018	men and women; mean 49.33 years; (Germany)	1,918,449	AOK Plus (health insurance database)	4 years	NDVI; 115 images for 4 years; statistical area units	Cancer: colorectal; mouth and throat, prostate, breast; non-melanoma skin	Health register	Per 10% increase in NDVI Colorectal: RR: 1.03 (0.98, 1.07) Mouth: RR: 0.89 (0.83, 0.96) Skin: RR: 0.84 (0.79, 0.90) Prostate: RR: 0.95 (0.90, 1.01) Breast: RR: 0.96 (0.92, 0.99)	age, sex, alcohol-related disorder, absolute number of physician contacts, proportion of short and long- term unemployment	Good
Conroy et al., 2017	women; ≥ 45-75 years; (African Americans, Japanese Americans, Latinos, Native Hawaiians, and White) (USA)	48,247	Multiethnic Cohort (MEC)	17 years	Presence of a park; based on number in a residential block group	Breast cancer (invasive)	Health register	HR: 1.03 (0.92, 1.15) No park in area	age, clustering effect of block group, ethnicity, risk factors, baseline BMI and adult weight change, neighbourhood SES, all neighbourhood obesogenic factors	Good
Haraldsdottir et al., 2017	women; mean: 53.9 years (Iceland)	10,049	Reykjavik Study	27.3 average	Coastal residence, self-reported	Breast cancer	Health registers	HR: 0.87 (0.72, 1.04) Coastal residence vs city	age, birth cohort, education, physical activity, parity, height, BMI in midlife, age at menarche, age at first child	Good
Orioli et al., 2019	men and women; ≥ 30 years	1,265,058	Rome Longitudinal Study	13 years	NDVI and LAI average for 2015 in 300m	Stroke	Health register	NDVI highest quintile	age, sex, educational level,	Good

	(Italy)				and 1000m circular buffer			300m HR: 0.95 (0.91, 0.98) 1,000m HR: 0.97 (0.93, 1.00)	marital status, occupational status, place of birth, area-level SES	
Paul et al., 2020	men and women; ≥ 35-100 years; urban residents Ontario (Canada)	4,251,146	Ontario Population Health and Environment Cohort (ONPHEC)	13 years	NDVI annual values, 250m circular buffer	Stroke	Health register	HR: 0.96 (95% CI: 0.95, 0.97) per IQR increase in NDVI	age, sex, SES, comorbidities, northern residence, population density, air pollution	Good
Yuchi et al., 2020	men and women; ≥ 45-84 years (Canada)	634,432 (parkinson disease); 7,232(multimple sclerosis)	Medical Services Plan (MSP) Vancouver, mandatory health insurance database	4 years	NDVI; yearly average in 100m circular buffer	Parkinson's disease Multiple sclerosis	Health records	Per IQR increase in NDVI Parkinson's Disease: OR: 0.97 (0.93, 1.01) Multiple Sclerosis: OR: 1.14 (1.00, 1.30)	Parkinson's disease: age, sex, comorbidities, household income, education, ethnicity Multiple sclerosis: age, sex, comorbidities, household income, education and ethnicity, comorbidities, household income, education, ethnicity	Good
Picavet et al., 2016	men and women; ≥ 18 to 55 years (Netherlands)	4,917	Doetinchem Cohort Study	15 years	Percent green space in 125m and 1000m circular buffer	Depression; Obesity; Hypertension	All self-reported instruments	Per unit increase in percent green space 125m Depression: OR: 0.97 (0.92, 1.04)	age, sex, SES	Poor

								Obesity: OR: 1.04 (1.01, 1.07) Hypertension: OR: 0.99 (0.97, 1.02) 1000m Depression OR: 0.86 (0.79; 0.93) Obesity: OR: 1.00 (0.96; 1.05) Hypertension: OR: 1.02 (0.98; 1.05)		
				Secondary Outcomes						
de Keijzer et al., 2019b	men and women; ≥ 35-55 civil servants (United Kingdom)	10,308	Whitehall II study	9 (median) years	NDVI and EVI; distance to blue space (any visible water); distance to green or blue space in 500m and 1000m circular buffer; distance in m	Physical Functioning	Clinical measures	**Walking speed** (difference baseline & follow-up): 500m NDVI β: 0.02 (0.01, 0.04) per IQR increase 1000m NDVI β: 0.03 (0.01, 0.04) per IQR increase Blue space β: −0.01 (−0.02, 0.01) per IQR increase **Grip strength** (difference baseline & follow-up): 500m NDVI	sex, ethnicity, marital status, height, alcohol use, intake of fruit and vegetables, smoking, rurality, education, employment grade, Index of Multiple Deprivation (IMD), income score and of the IMD, employment score	Fair

								β: −0.01 (−0.03, 0.01) per IQR increase 1000m NDVI β: −0.01 (−0.03, 0.01) per IQR increase Blue space β: −0.01 (−0.03, 0.01) per IQR increase		
Yu et al., 2018	men and women; ≥ 65 years (Hong Kong)	4,000	Mr and Ms Os Study	2 years	NDVI at baseline in a 300m circular buffer	Frailty	Self-reported instrume nt	OR: 1.29 (1.04, 1.60) Highest quintile NDVI	age, sex, marital status, SES, current smoking status, alcohol intake, diet quality, baseline frailty status, number of diseases, cognitive function, physical activity, depression	Good
Zhu et al., 2020	men and women; ≥ 65 years (China)	34,342	Chinese Longitudinal Healthy Longevity Survey (CLHLS)	9 years	NDVI; annual averages for each year in 500m buffer	Frailty	Self-reported instrume nt	OR: 1.02 (1.00, 1.04) Per unit increase in NDVI	age, sex, ethnicity, marital status, geographic region, urban or rural residence, education, occupation, financial support, social and leisure activity, smoking status, drinking status, physical activity	Good

Chong et al., 2019	men and women; ≥ 45 years with diabetes (T2) (Australia)	60,404	45 and Up Study and the follow-up Social, Economic and Environmental Factors (SEEF) Study	3.3 (mean) years	Percent green space in 500m, 1000m, and 2000m road network buffer	Physical Activity	Self-reported instrument (MVPA: min/week)	Per highest percent quintile green 500m Mean: 0.61 (-0.26, 1.49) 1,000m Mean: 0.94 (0.10, 1.79) 2,000m Mean: 0.75 (0.03, 1.48)	age, sex, country of birth, education, disadvantage, physical functioning, BMI, psychological distress	Poor
Cleland et al., 2009	women parents; mean: 42.4 years; (Australia)	698	Children Living in Active Neighbourhoods (CLAN)	2 years	Amount of greenery and quality of parks, self-reported satisfaction	Physical activity	Self-reported instrument (walking: for leisure and transport (min/ week))	Amount of greenery Persistently high vs persistently low PA: RR: 1.80 (1.04, 3.13) Increased vs persistently low PA: RR: 1.39 (0.90, 2.17) Quality of parks Persistently high vs persistently low PA: RR: 1.73 (1.17, 2.57) Increased vs persistently low PA: RR: 1.20 (0.89, 1.62)	age, marital status, number of children in the household, highest level of schooling	Poor
Coogan et al., 2009	black women; ≥ 21-69 years (USA)	21,820	Black Women's Health Study	2-6 years	Distance to park	Physical activity	Self-reported instrument (Walking	Recreation walking OR: 1.01 (0.89, 1.13) Shortest distance quintile	age, region, BMI, smoking, alcohol, marital status, parity, caregiver	Poor

				98,280 person-years of follow-up.			for recreation & total walking: y/n))	Exercise walking OR: 1.01 (0.91, 1.12) Shortest distance quintile	status, residential moves, chronic conditions, history of cancer, moving residence, vacant housing, SES, crime	
Dalton et al., 2016 b	men and women; mean age at baseline 62.2 (United Kingdom)	25,639	European Prospective Investigation into Cancer (EPIC) Norfolk	7.5 (mean) years	Percent green space at baseline for non-movers; 800m	Physical Activity	Self-reported instrument (Change in overall PA (hr/week))	β: 4.21 (1.60, 6.81) Highest percent quintile green	age, sex, marital status, waist to hip ratio, BMI, morbidity, urban/rural location	Fair
Faerstein et al., 2018	men and women; ≥ 18 years; civil servants (Brazil)	1,731	Pro-Saude study	13 years	NDVI (800m circular buffer); presence of trees (visual inspection); proximity to waterfronts;	Physical activity	Self-reported instrument (non-work PA: yes/no)	OR: 0.85 (0.44, 1.65) Highest quintile NDVI OR: 1.22 (0.62, 2.40) Highest percent quintile of trees OR: 2.46 (1.22, 4.93) Longest distance to waterfronts	sex, race, education, income, neighbourhood contextual variables	Poor
Hogendorf et al., 2020	men and women; mean: 53 years; (Netherlands)	4,758	Gezondheid en Levens Omstandigheden Bevolking Eindhoven en omstreken (GLOBE)	10 years	Area of green space within a 1000m circular buffer; Distance to green space	Physical activity	Self-reported instrument (total walking and cycling: min/week)	Total walking and cycling Per ha increase in area of green β: 0.82 (-178.84, 180.48) Distance per 100m increase in green β: -22.36 (-46.19, 1.48)	marital status, income, employment, smoking, self-rated health	Poor

Josey and Moore., 2018	men and women; ≥ 25years; urban residents (Canada)	2,707	Montreal Neighborhood Networks and Healthy Aging Panel (MoNNET-HA)	5 years	Distance to parks and green spaces	Physical Activity	Self-reported instrument (physical inactivity: y/n)	OR: 0.99 (0.99, 1.00) Per mile increase in distance	sex, age, self-reported health status, SES, household language, marriage status, residential duration, wave	Poor
Lin et al., 2020	men and women; ≥ 65-98 years (Hong Kong)	4,000	OS and Ms. OS Study	7.8 (mean) years	NDVI in 300m circular buffer	Physical activity	Self-reported instrument (Total PA score)	No relevant results	age, sex, marital status, education level, alcohol consumption, smoking, living alone, self-rated health, chronic conditions, functional impairment	Fair
Michael et al., 2010	men; ≥ 65 years (USA)	513	Neighborhoods and Physical Activity in Elderly Men	3.6 (mean) years	Distance to park	Physical activity	Self-reported instrument (walking: min/day)	RR for presence of park Low SES: 0.89 (0.70, 1.13) High SES: 1.34 (1.16, 1.55)	age, race education, occupation, marital status, self-reported health, BMI, smoking, drinking, chronic conditions	Fair
Sugiyama et al., 2015	men and women; mean: 54.4 years (Australia)	4,802	AusDiab study	7 years	Park or nature reserve in the neighbourhood, self-reported	Physical Activity	Self-reported instrument (meeting PA guidelines: y/n)	OR: 0.96 (0.80, 1.15) for having a park in neighbourhood	age, sex, education, work status change, child change, mobility, BMI	Poor
Yang et al., 2017	men and women; ≥ 40-79 years	25,633	European Prospective Investigation into Cancer (EPIC) Norfolk	7 years	Presence of park or green space in 800m circular buffer	Physical activity	Self-reported instrument (active	Park (yes): OR: 1.30 (0.96, 1.74)	No adjustment	Poor

	(United Kingdom)						commuting: y/n)	Green space (yes): OR: 1.12 (0.83, 1.53)		
Meyer et al., 2015	men and women; ≥ 18-30 years; black and white (USA)	5,115	Coronary Artery Risk Development in Young Adults (CARDIA)	13 years	Number of parks within a 3000m circular buffer	Physical activity; Diet Quality	Self-reported validated instruments (PA: frequency walking, biking, running/ week)	No relevant results	N/A	Poor
Picavet et al., 2016	men and women; ≥ 18 to 55 years (Netherlands)	4,917	Doetinchem Cohort Study	15 years	Percent green space in 125m and 1000m circular buffer	Physical activity; Quality of Life	All self-reported instruments (PA: meeting guidelines: y/n)	Per unit increase in NDVI 125m Physical activity: OR: 1.02 (0.99; 1.04) Quality of Life: Mixed 1000m Physical activity: OR: 1.01 (0.97; 1.05) Quality of Life: Mixed	age, sex, SES	Poor

Abbreviations
OR: Odds Ratio / HR: Hazard Ratio / RR: Relative Risk / CI: Confidence Intervals / PA: Physical activity / NDVI: Normalized Difference Vegetation Index / IQR: Inter-quartile Range
β: beta coefficient
*****Based on Newcastle-Ottawa Scale (NOS) for Cohort Studies

3.3.2.5 Relationship between green and blue space with health

3.3.2.5.1 Mental health conditions

Table 4 shows study characteristics, exposures, outcomes and effect estimates of the studies included in this systematic review. Nine studies assessed the longitudinal relationships between individual exposure to green spaces over time and the risk of developing depression (Banay et al., 2019; Fernandez-Nino et al., 2019; Gariepy et al., 2015a; Gariepy et al., 2015b; Melis et al.,2015; Tomita et al., 2017; Astell-Burt and Feng, 2019; Picavet et al., 2016; Pun et al., 2018). Depression was mostly assessed through validated instruments (Gariepy et al., 2015a; Gariepy et al., 2015b; Tomita et al., 2017; Picavet et al., 2016; Pun et al., 2018) or self-report of doctor diagnoses (Banay et al., 2019; Fernandez-Nino et al., 2019; Astell- Burt and Feng, 2019). One study assessed depression through medical records of antidepressant use to define depression (Melis et al., 2015). Majority of studies (n=6) did not find a significant association between green space and the risk of developing depression (table 4) (Fernandez-Nino et al., 2019; Gariepy et al., 2015a; Gariepy et al., 2015b; Melis et al.,2015; Astell-Burt and Feng, 2019; Pun et al., 2018). Out of those studies that found significant relationships, Tomita et al. (2017) deduced that the risk of developing depression increased by 1% with each unit increase in NDVI value, while Picavet et al. (2016) found that the risk of depression decreased by 14% with each IQR increase in percent total green space in a 1km buffer but not in a 125m buffer. By contrast, Banay et al. (2019) found that the risk of depression in nurses decreased with higher NDVI values in a small distance buffer (250m) but not in a large distance buffer (1250m). Nurses residing in neighbourhoods with highest availability of green space (NDVI) had a 13% lower risk of developing depression compared to nurses residing in neighbourhoods with lowest availability of green space (Banay et al., 2019).

Only one study assessed the relationship between green space and schizophrenia and found that those living in neighbourhoods with high availability of green space (quintile of NDVI) had 63% lower risk of developing schizophrenia compared to those living in neighbourhoods with lowest availability of green space (HR (95%CI): 0.37 (0.25, 0.55)) (Cheng et al., 2019). On the other hand, a study on anxiety did not find a significant relationship between availability of green space (NDVI) and risk of developing anxiety (Pun et al., 2018).

Large variation in populations, confounding and green space exposure metrics was observed across all studies on mental health. All studies adjusted for socio-demographic variables (age, sex, socio-economic position). Some adjusted additionally for air pollution and humidity (Pun et al., 2018; Chang et al, 2019), physical activity (Banay et al. 2019), chronic conditions (Banay et al., 2019) and family history of depression (Gariepy et al., 2015a). Sensitivity analyses of different distance buffer sizes (Pun et al., 2018; Gariepy et al., 2015b), missing data (Fernandez-Nino et al., 2019) and differences between movers and non-movers (Gariepy et al., 2015a) were conducted, but only Fernandez-Nino et al. (2019) found significant differences in missing data for education, SES, and urban residence. All other sensitivity analyses were consistent with their primary analyses.

3.3.2.5.2 Non-communicable diseases (NCDs)

3.3.2.5.2.1 Cardio-metabolic conditions

Four out of seven studies found the risk of developing diabetes was lower with exposure to higher amount of green space (Clark et al., 2017; Dalton et al., 2016a; Liao et al., 2019; Astell-Burt and Feng, 2020; Renzi et al., 2018; Hobbs et al., 2019; Lee et al., 2017). The highest reduction in risk of diabetes was observed by Clark et al. (2017) and Liao et al. (2019). Women who had the highest availability of greenery in their neighbourhood were 34% less likely to develop gestational diabetes during pregnancy compared to women who had the lowest availability of greenery in their neighbourhoods (NDVI) (Liao et al., 2019). Urban residents' risk of developing diabetes also decreased by 10% with each IQR increase in NDVI value (Clark et al., 2017), while the risk of developing Type 2 diabetes was 19% lower in those living in neighbourhoods with highest percent green space compared to those living in neighbourhoods with lowest percent green space (Dalton et al., 2016a).

Two out of six studies found a statistically significant relationship between green space and risk of becoming obese (Halonen et al., 2014; Picavet et al., 2016) (table

4). Obesity risk increased by 4% with increasing amount of greenness in a 125m circular buffer but not in a 1000m buffer (Picavet et al., 2016). On the other hand, Halonen et al. (2014) found green space to be protective of developing obesity, as those living furthest away from a green space had a 50% higher risk of obesity compared to those living closest to green spaces. A protective relationship was not found between distance to a blue space and obesity (Halonen et al., 2014).

Cardiovascular disease (CVD) was examined in three studies (Dalton and Jones, 2020; Tamosiunas et al., 2014; Astell-Burt and Feng, 2020). CVD was used as an umbrella term for events of ischaemic heart disease, cerebrovascular heart disease and/ or abnormal ECG findings. Each study had a different inclusion criterion. All studies showed consistent findings of a protective relationship between exposure to green space and CVD (Dalton and Jones, 2020; Tamosiunas et al., 2014; Astell-Burt and Feng, 2020). Living in a neighbourhood with high percent green space was associated with a 7% reduction in risk of CVD in middle-aged British adults (Dalton and Jones, 2020), while Lithuanian non-park users living furthest from a park had a 66% higher risk of developing CVD compared to non-users living closest to a park (Tamosiunas et al., 2014). Hypertension was another cardio-metabolic outcome (Astell-Burt and Feng, 2020; Paquet et al., 2014; Picavet et al., 2016) but higher availability of green space (measured through NDVI and land use classifications) was not associated with risk of developing hypertension (Astell-Burt and Feng, 2020; Paquet et al., 2014; Picavet et al., 2016).

Some studies found differences in relationships between types of green spaces and cardio-metabolic outcomes. Astell-Burt and Feng (2020), for example, found that significant protective relationships between risk of CVD, diabetes and hypertension existed only for greater availability of street trees but not for greater availability of total (grass and tree cover) proportion of green space (table 4). Similarly, a study assessing at the risk of Metabolic Syndrome (MS) found that higher availability of green space (NDVI) in a 500m buffer, but not higher availability of green space in a 1000m buffer or LSOA, was protective of developing Metabolic Syndrome (de Keijzer et al., 2019a).

Evidence across the retrieved studies suggests that there is only a partial significant relationship between green spaces and cardio-metabolic diseases. CVD and diabetes showed strongest protective relationship with green space. Some studies found that certain types of green spaces, like street trees (Astell-Burt and Feng, 2020) and exposures measured at smaller spatial scales (de Keijzer et al., 2019a; Picavet et al., 2016) show stronger protective relationships with cardio-metabolic outcomes. Confounding varied between all studies, but all adjusted for socio-demographic characteristics. Some studies additionally adjusted for environmental variables, such as season and noise and air pollution (Clark et al., 2017; Liao et al., 2019; Persson et al., 2018) and health behaviours (Halonen et al., 2014) but no differences in relationships were observed between studies that adjusted for different confounders. Out of the studies that conducted sensitivity analyses, Clark et al. (2017) found that the incidence of diabetes increased after adjustment for a census measure of neighbourhood with over 10% Chinese ethnicity. Small changes in effect estimate for diabetes were also observed when using a different type of distance buffer (road network instead of circular) (Dalton et al., 2016a). All other sensitivity analyses found results to be consistent with main analyses.

3.3.2.5.2.2 Cancer

Three studies assessed the effect of exposure to green and blue spaces on cancer risk (table 4). All cancer outcomes were ascertained through health registers (Datzman et al., 2018; Conroy et al., 2017; Haraldsdottir et al., 2017). Two studies focused only on breast cancer (Conroy et al., 2017; Haraldsdottir et al., 2017) and one studies focused on the risk of breast, skin, throat and mouth, colorectal and prostate cancer (Datzman et al., 2018). Haraldsdottir et al. (2017) found coastal residence proximity had no protective effect on breast cancer risk. Conroy et al. (2017) also found no association between presence of a park and breast cancer risk. The risk of developing breast, skin and mouth and throat cancer, however, was 4%, 16% and 11%, respectively, lower among adults living in neighbourhoods with higher availability of green space (NDVI) (Datzman et al., 2018). Overall, the studies were heterogeneous in exposure measurement. Sensitivity analyses found that repeating analyses using imputed missing values very slightly attenuated the effect estimate for the relationship between coastal proximity and risk of developing breast cancer (Haraldsdottir et al., 2017).

3.3.2.5.2.3 Stroke

This systematic review identified two studies on stroke (Orioli et al., 2019; Paul et al., 2020). Both studies examined stroke risk (hazard ratio) in relation to green space availability (NDVI used as indicator) and both found a small reduction in risk of incident stroke (5% and 4%, respectively) with increasing availability of greenness (Orioli et al., 2019; Paul et al., 2020). The studies were also homogeneous in confounding and population, as both included adults of 30 years or older in high income countries.

3.3.2.5.3 Physical activity

There was mixed evidence of a relationship between green and blue spaces and physical activity. Only five studies found a significant relationship (Chong et al., 2019; Cleland et al., 2008; Dalton et al., 2016b; Faerstein et al., 2018; Michael et al., 2010). Chong et al (2019) concluded that frequency of MVPA increased with increasing percent green space in 1000m and 2000m buffer, but not in a 500m buffer. Dalton et al (2016b) found a small increase in physical activity levels in those living in neighbourhoods with highest proportion of green space compared to those living in neighbourhoods with lowest proportion of green space. By comparison, Michael et al. (2010) found differences in physical activity levels between SES groups, as those of high SES who lived in neighbourhoods with a park were 34% more likely to walk daily compared to those of high SES who lived in neighbourhoods with no parks. No statistically significant relationship was found for those of low SES. Cleland et al. (2008) also showed that satisfaction with quality of parks and amount of greenery increased the risk of maintaining but not increasing physical activity levels at follow-up. Those with high satisfaction with park quality and higher surrounding greenery were more likely to maintain persistently high physical activity levels compared to those who were less satisfied with their park quality and high lower amount of greenery (Quality of park RR (95%): 1.73 (1.17, 2.57); amount of greenery RR (95%): 1.80 (1.04, 3.13)) (Cleland et al., 2008). Lastly, Faerstein et al. (2018) found proximity to blue space hindered non-work physical activity, as those who lived the furthest away from a waterfront were 146% more likely to participate in non-work physical activity compared to those who lived the shortest distance from waterfronts.

Adjustment for confounding varied between studies, but the majority adjusted for socio-demographic and neighbourhood contextual variables. Over half of studies (n=7) additionally adjusted for health conditions, such as BMI, physical functioning, and chronic diseases (Chong et al., 2019; Coogan et al., 2009; Dalton et al., 2016b; Hogendorf et al., 2020; Lin et al., 2020 Michael et al., 2010; Sugiyama et al., 2015), but no patterns between confounding and statistically significant relationships could be identified. In sensitivity analyses, two studies found the the effect estimates do not change when green space was measured at different spatial scales (using different buffer sizes) (Dalton et al., 2016b; Faerstein et al., 2018). All other sensitivity analysis results were similar to their main analysis.

3.3.2.5.4 Frailty

Two studies examining frailty status change in relation to green space availability were identified (Yu et al., 2018; Zhu et al., 2020). Both these studies included older Chinese adults and used the NDVI as an indicator of green space availability. Frailty status improved over time in those who were exposed to higher availability of greenness in both studies (Yu et al., 2018; Zhu et al., 2020). The odds of improved frailty status, measured according to the frailty index, increased by 2% for a unit increase in NDVI value (Zhu et al., 2020), while frailty status measured according to the Frailty Phenotype improved by 29% in those who resided in neighbourhoods with the highest quartile of availability of greenness compared to those who resided in neighbourhoods with the lowest quartile of availability of greenness (Yu et al., 2018).

3.3.2.5.5 Other outcomes

This review identified one study on HRQoL (Picavet et al., 2016). The results were presented separately for each domain of the Short-Form 36 (SF-36) instrument and showed varying associations with green space. A study on physical functioning also found varying associations between exposure to green and blue space with grip strength and walking speed (de Keijzer et al., 2019b). No significant relationship was observed between green space exposure and multiple sclerosis or Parkinson's disease (Yuchi et al., 2020).

3.3.2.5.6 Multimorbidity

This review found negligible evidence of longitudinal relationships between multimorbidity and green and/ or blue space. Only one study examined the effects of green spaces on the development of depression in adults with pre-existing diabetes at baseline (Gariepy et al., 2015b), but found no significant associations between higher NDVI values and incident depression at 5-year follow-up. Other studies in this systematic review analysed relationships for predominantly healthy participants at baseline.

3.3.2.6 Mediation Analyses

Table 5 summarises evidence for mediation analyses conducted by studies included in this systematic review. Ten variables were examined as mediators in the relationship between green and blue spaces with health. Dog walking was found to partially mediate the relationship between amount of green space and physical activity (Dalton et al., 2016b). Mental health, gardening, air pollution and social engagement all partially mediated the relationship between green space and physical functioning (de Keijzer et al., 2019b), while physical activity and depression partially mediated the relationship between green space and frailty (Yu et al., 2018). Air pollution and physical activity were also partial mediators in the relationship between green space and Metabolic Syndrome (de Keijzer et al., 2019b) but not in the relationship between green space and diabetes or stroke (Liao et al., 2019; Orioli et al., 2019). Overall, the only evidence of mediation was present for physical functioning, Metabolic Syndrome, frailty and physical activity.

Table 5. Summary of mediation analyses

Mediator	Exposure	Outcome	Results	Study
Physical Activity	Percent green space	Diabetes	No mediation	Dalton et al., 2016a
Physical Activity	NDVI	Diabetes	No mediation	Liao et al., 2019
Physical Activity	NDVI; EVI distance to green and/ or blue space	Physical functioning	Partial mediation	de Keijzer et al., 2019b
Physical Activity	NDVI	Frailty	Partial mediation	Yu et al., 2018
Physical Activity	Percent green space	CVD	No mediation	Dalton and Jones, 2020
Physical Activity	NDVI; VCF	Metabolic Syndrome	Partial Mediation for VCF/ No medial for NDVI	de Keijzer et al., 2019a
Physical Activity	NDVI	Depression	No mediation	Banay ey al., 2019
Social Engagement	NDVI; EVI distance to green and/ or blue space	Physical functioning	Partial mediation	de Keijzer et al., 2019b
Social Engagement	NDVI	Depression	No mediation	Banay ey al., 2019
Air Pollution	NDVI; EVI distance to green and/ or blue space	Physical functioning	Partial mediation	de Keijzer et al., 2019b
Air Pollution	NDVI	Diabetes	No mediation	Liao et al., 2019
Air Pollution	NDVI; LAI	Stroke	No mediation	Orioli et al., 2019
Air Pollution	NDVI; VCF	Metabolic Syndrome	Partial mediation for both	de Keijzer et al., 2019a

Noise	NDVI; LAI	Stroke	No mediation	Orioli et al., 2019
Psychological Distress	Percent green space	Physical Activity	No mediation	Chong et al., 2019
Body Mass Index	Percent green space	Physical Activity	No mediation	Chong et al., 2019
Depression	NDVI	Frailty	Partial mediation	Yu et al., 2018
Gardening	NDVI; EVI distance to green and/ or blue space	Physical functioning	Partial mediation	de Keijzer et al., 2019b
Mental Health	NDVI; EVI distance to green and/ or blue space	Physical functioning	Partial mediation	de Keijzer et al., 2019b
Dog Walking	Percent green space	Physical activity	Partial mediation	Dalton et al., 2016b

3.3.3 Quantitative synthesis

It was not possible to conduct one or more meta-analyses due to the high heterogeneity of studies. Exposure type and outcome measurements were the two main sources of heterogeneity.

3.4 Discussion

3.4.1 Overview

This systematic review did not find strong evidence of significant longitudinal associations between exposure to green and blue spaces with mental and physical health outcomes. Where statistically significant associations existed, they were usually weak. There were some differences in confounding between studies, but most adjusted for socio-demographic variables, such as age, sex and SES. Only some studies additionally adjusted for relevant clinical and/ or behavioural confounders but no differences in strengths of associations could be observed between studies with minimal and extensive confounder adjustment. One reason for the lack of consistency in relationships could be due to exposure measures. The majority of studies used objective measures of amount or distance to green spaces but variation in spatial scales, follow-up measurements and data sources could have yielded different results. Other health-promoting aspects of green and blue spaces, such as type, usage, features, and safety were also not examined.

3.4.2 Green space and its relationship with mental and physical health

About two-third of studies found no significant relationship between depression and green space. Previous systematic reviews have shown that the odds of depression are lower with higher availability or accessibility of green space but only in cross-sectional studies (Clark et al., 2007; Rautio et al., 2018; Clark et al., 2007). Likewise, this systematic review found negligible evidence of a significant relationship between green and blue spaces with specific NCDs. Green space was weakly protective of diabetes in about half of the included studies (Clark et al., 2017; Dalton et al., 2016a; Liao et al., 2019; Astell-Burt and Feng, 2020). The rest showed no significant associations, which could be due to differences in both confounding and exposure measurements. Only two out of six studies found that greater exposure to green space reduces the risk of becoming obese at follow-up (Halonen et al., 2014; Picavet et al., 2016). Mixed results were also observed for other outcomes, such as CVD and cancer. This systematic review identified one study on the relationship between exposure to green spaces and schizophrenia (Chang et al., 2019). Chang et al. (2019) found that higher exposure to green space moderately reduced the risk of developing schizophrenia, and this is consistent with prior literature (Engemann et al., 2018). The mechanisms behind this relationship are not entirely understood, but it's hypothesised that several factors, such as reduction in urban air pollution and noise, are responsible (DeVerteuil et al., 2007). More research is needed to fully identify these causal mechanisms. An umbrella review showed that perinatal, early life health conditions and socio-demographic factors can simultaneously influence the development of schizophrenia (Radua et al., 2018) but little is known about the effect of early life exposure to green space on schizophrenia. Future research should seek to examine early life and life course exposure to green space in order to better understand the causal mechanism behind this relationship.

Due to high heterogeneity in exposure measures, length of follow-up and populations, it is not possible to fully explain differences in strengths and directions of associations. Prior systematic reviews have suggested that significant relationships between green space and NCDs only exist at a cross-sectional level (Lachowycz and Jones, 2010) but a recent systematic review found that it is exposure to green spaces throughout the life course that affects health (Li et al., 2021). Some epidemiological research suggests that the benefits of green spaces on late-life mental health and cognitive decline could be due to exposure during critical time periods in childhood (Cherrie et al., 2018; Pearce et al., 2018; Astell-Burt, Mitchell and Hartig, 2014). Studies conducting life course research were not identified in this systematic review, and this could be a potential reason for lack of significant, longitudinal relationships observed here.

In addition to length of follow-up, the lack of significant associations could be explained by inadequate adjustment for confounding. Although some studies in this systematic review adjusted for air quality, noise, and socio-demographic variables, other factors like built environment and clinical characteristics can also have an impact on the relationship. For example, research has shown that neighbourhoods with high crime, deprivation and social disorganisation can increase the risk of depression (Galea et al., 2005). Moreover, aspects of the built-environment, such as higher land-use mix and retail density are associated with greater odds of depression, especially in older populations (Saarloos et al., 2011). It is suggested that further adjustment for confounders such as childcare duties and green space use might play important roles in the relationships between green space and mental and physical health (Prince et al., 2011), but these variables were not accounted for in the studies included in this review, possibly due to lack of data availability. Lastly, there is longitudinal, bidirectional association between physical and mental health (Ronaldson et al., 2021), which suggests certain clinical variables, like chronic health and hereditary factors, might further attenuate the relationship between green space and mental health (Steinmo et al., 2014). On the other hand, some systematic review research suggests that socio-demographic confounders play little to no role in moderating the effect of green space on health (Kabisch, 2019). Despite most conceptual epidemiologic frameworks framing income as a moderator in the relationships between the surrounding and natural environment and health, Kabisch (2019) propose that it is socio-demographic factors like SES, age and sex that drive health and green space is simply a mediator in these relationships.

It was hypothesised that higher exposure to green and blue spaces would reduce the risk of developing depression and NDCs at follow-up due to their health-promoting effects. Green and blue spaces can be aesthetically pleasing spaces that provide opportunities for physical activity, restoration, and socialisation (Hartig, 2008; Beyer et al., 2014). Cross-sectional analyses have shown that physical and loneliness partially mediate the relationship between green space and poor mental health (van den Berg et al., 2017). However, this systematic review found physical activity and social engagement were not mediators in longitudinal relationships between green space and depression (Banay et al., 2019). Physical activity and air pollution were also not mediators in the relationship between green space and gestational diabetes (Liao et al., 2019) but they partially mediated the relationship with Metabolic Syndrome (de Keijzer et al., 2019a). Although physical activity, noise and air pollution are considered shared mediators in the relationships between green spaces and cardio-metabolic NCDs, cancer and mental health (Chandrabose et al., 2018), methodological differences in data analyses could explain why some studies found evidence of mediation and others did not. Further understanding into the underlying mechanisms in these relationships is needed. Social factors such as cultural significance of places, usage of green spaces, satisfaction with the surrounding neighbourhood and view from the window might also be mediating variables (Barton and Rogerson, 2017; Herzele and de Vries, 2011). Some of these social factors may even drive behaviours like physical activity and social engagement, which signifies the possibility of multiple mediating variables on the causal pathways between exposure to nature and health.

3.4.3 Multimorbidity

As previously mentioned, this review did not identify evidence of a longitudinal relationship between exposure to green or blue spaces with multimorbidity. Gariepy et al. (2015b) examined the effects of green spaces on the risk of developing depression in people with diabetes at baseline but found no significant associations. However, two studies measuring frailty were included in this systematic review, both of which showed that living in areas with higher NDVI was associated with low to moderate improvements in frailty status (Zhu et al., 2020; Yu et al., 2019). Green spaces can have a protective effect on frailty because they facilitate social engagement and physical activity, which leads to slower physical and cognitive decline (Martins et al., 2020). A scoping review also found that living in neighbourhoods of high deprivation and high socio-economic disadvantage increases the odds of having poorer frailty status (Fritz et al., 2020). Green spaces could mitigate some of the harmful effects caused by socio-economic advantage by promoting healthy behaviours and filtering noise and air pollutants (Markevych et al., 2017).

Although green spaces may be protective of frailty in Asian populations, little is still known about the role of exposures to green and blue spaces in multimorbidity risk. Multimorbidity is highly prevalent (70%) in frail individuals (Vetrano et al., 2018), but multimorbid individuals' interactions with natural environments may vary from those of non-multimorbid individuals. Multimorbid individuals are more likely to have higher physical impairment, reduced mobility, disabilities, and chronic pain (Peng et al., 2020), making their ability to use and access certain green spaces, like parks more difficult. There was no mention of multimorbidity in the two studies on frailty (Zhu et al., 2020; Yu et al., 2018) and further research should focus on examining how natural environments affect both multimorbidity and frailty and the complex interactions between both.

3.4.4 Physical activity

Physical activity was included as a secondary outcome in this systematic review because it is strongly linked to the incidence of multiple NCDs and is considered a common mediator in the relationship between greenness and health (Markevych et al., 2017). Over half of studies included in this systematic review did not find a statistically significant relationship between green or blue spaces with physical activity. However, a general improvement in physical activity levels was observed with closer residential proximity to urban park (Dalton et al., 2016b; Faerstein et al., 2018; Michael et al., 2010; Cleland et al., 2009). Although not all studies found significant associations between accessibility to park and physical activity (Sugiyama et al., 2015; Yang et al., 2017), these patterns indicate that accessible public parks likely promote physical activity due to availability of amenities and facilities such as paved trails, outdoor gyms, and spaces for communal recreation (Bedimo-Rung et al., 2005; Swierad and Huang, 2018).

3.4.5 Green space exposure: measures and associations with health

A broad range of green space exposure indicators were used to objectively capture greenery in the surrounding residential neighbourhood in studies included in this systematic review. The NDVI, percent green space and distance to park were most frequently used by studies included in this systematic review. There was high heterogeneity on choice of spatial scales. Buffer sizes, time-of-year NDVI measurements and other green space exposure data sources varied, making meaningful comparisons between studies difficult and the potential reason for differences in significance of associations. Heterogeneity of green space exposure metrics has been previously flagged by prior systematic reviews (de Keijzer et al., 2020; Vanaken and Dankaerts, 2018). This could be in part due to data governance laws in volunteer-based cohorts, which often anonymise data by restricting residential information. While this prevents identification of participants, inaccurate residential address data can lead to inaccurate data linkages with environmental variables. Nevertheless, this systematic review reiterates the need to establish empirically informed guidelines for measuring green spaces in epidemiological research. Currently, there is no agreement on optimal exposure to residential green space. Natural England (2010) recommends that everyone should have an accessible green space of at least 2ha no more than 300m from their residential address. The European Environment Agency (2013), on the other hand, recommends that everyone should have an accessible green space within a 15-minute walk (approx. 1500m) of their residential address. Studies in this systematic review loosely justified their exposure measures, usually by quoting prior literature or one of the above policy recommendations. Although NDVI was the most frequently used indicator of green space availability in this systematic review, it has some functional limitations. While it is an accessible, open-access source of green space data, NDVI was originally established for agriculture and ecological research. It has low resolution and poor capacity to differentiate between publicly accessible and private green spaces. The NVDI also cannot capture quality and features of greenery, which makes it unsuitable for capturing green spaces in urban areas, which are usually small, fragmented and promote health through built environment features such as paved trails, benches, and fountains (Le Texier et al., 2018; Klompmaker et al., 2018).

Distance and presence of urban park were the most frequently used indicators of green space accessibility. Euclidean (straight line) distance or presence of park within a circular buffer were used as objective measures of park accessibility. Only one study used a self-reported measure of accessibility to park (Sugiyama et al., 2015). While objective measures of exposures are usually considered optimal for minimising bias, distance and presence of park metrics may fail to capture specific characteristics and features urban green spaces that might be contributing factors to health. Some research, for example, indicates that physical activity levels are likely to be higher in parks with paved trails compared to parks with no paved trails (Kaczynski et al., 2008). Cross-sectional studies have also shown that the odds of park visitations are higher if parks have certain attributes, like trees, toilets, gym facilities, presence of lakes, ponds, and trees (Grilli et al., 2020; Costigan et al., 2017). The self-perceived safety, maintenance and aesthetic of green spaces are also considered determining factors for park-based visitations and physical activity (Groshong et al., 2018), but this review did not identify any studies that accounted for these factors.

Finally, this review found lack of comparative research between types of green spaces. Only one study conducted a comparative analysis between percent total green space and percent tree canopy cover (Astell-Burt and Feng, 2020). Astell-Burt and Feng (2020) found the risk of CVD, diabetes and hypertension were lower with greater exposure to tree canopy cover but not significant with greater percent total green space. This pattern was previously observed in cross-sectional studies, which found a protective relationship between tree canopy cover with hypertension and mental health (Moreira et al., 2020; Zhang and Tan, 2019). Street trees might be protective of health because their spatial configuration enables them to directly filter air pollution, block out noise and lower temperatures around residential surroundings. They may also contribute to walkability by providing aesthetic spaces for active commute (Roscoe et al., 2022b). Comparative research on types of green spaces in the urban environment is currently lacking in the epidemiological literature. This systematic review did not identify any studies that compared NDVI with accessibility to park or percent street tree canopy. Distinctions between types of green spaces and their differential function in driving health have also not been operationalised in current conceptual epidemiological models (Markevych et al., 2017). Pathways leading green spaces to health may be driven by specific features of green spaces, their size, accessibility, and position in the urban environment. Research has found that larger green spaces, such as forests and trees, filter larger volumes of air pollution than grassy spaces (Bernatzky, 1982; Lin et al., 2022). Public parks, on the other hand, may be more often used for childcare, recreation, and physical activity (Cohen et al., 2007; Cronan et al., 2008). The ability to study how specific bio-physiological pathways are driven by specific types of green spaces can better inform public health practice and aid the design of health interventions.

3.4.6 Review implications

Although meta-analyses could not be conducted due to high heterogeneity in study exposures and population, narrative synthesis of this systematic review identified key research gaps in the epidemiological literature on green and blue spaces. First, there was lack of comparative longitudinal research between types of green spaces in the urban environment and their differential impacts on chronic health. While the majority of studies used an average estimation of green space availability, research into different features, dosage and type is lacking (Bratman et al., 2019). A robust framework is needed to guide longitudinal research into incorporating measures of green space type, characteristics, quality, and usage. Understanding what characteristics, dosage of exposure, spatial scale and specific interactions with green spaces affect health can improve implementation of public health interventions and guide urban planning.

Second, there is need for more research into the health-promoting roles of blue spaces. Only four studies assessed the relationships between blue space and health (de Keijzer et al., 2019b; Haraldsdottir et al., 2017; Halonen et al., 2014; Faerstein et al., 2018) and most showed no significant relationships (de Keijzer et al., 2019b; Haraldsdottir et al., 2017; Halonen et al., 2014). Blue spaces have the potential to promote and protect health through similar bio-physiological pathways as green spaces (Grellier et al., 2017), but currently there are no health policy recommendations for optimum exposure to blue spaces (Elliot et al., 2018). Research bodies and environmental agencies, therefore, should seek to develop more robust guidelines based on emerging empirical research.

This systematic review also has methodological implications for further research into confounding and mediating analyses. Longitudinal research should seek to analyse appropriateness of socio-demographic, lifestyle and clinical confounders using theoretical background and statistical methods. More mediation analyses are also required to better understand the pathways between green and blue spaces and health. Majority of health cohorts identified in this review were volunteer-based and established for purposes of assessing behavioural exposures-health relationships. Natural environment data was often integrated through additional data linkages, which suggests that information on some relevant socio-behavioural factors, such as usage and perceptions of individual green spaces, might be lacking. These variables could be potential mediators or confounders in the relationships between green and blue spaces with health. More thorough data collection is needed in health cohort to increase the wealth of relevant information on individual perceptions, usage and interactions with the natural environment in order to identify policy-relevant associations between green and blue spaces and health.

Finally, the review identified lack of research into the ways green and blue spaces affect the development of multiple co-occurring, chronic conditions within an individual. It is known that multimorbidity management requires complex clinical interventions (Pati et al., 2019; Pearson-Stuttard et al., 2019). The natural environment could play an important role in reducing the burden of multimorbidity on individuals and healthcare systems by preventing the onset or slowing the progression of several chronic conditions. Prevention of multimorbidity has received little attention in the academic literature because it is considered an inevitable outcome of ageing (Head et al., 2020). Green and blue spaces, however, can influence behavioural change and promote good health through socio-ecological pathways (Hartig et al., 2014). Studying the causal effects of these environments on multimorbidity could inform nature-based interventions and partially draw multimorbidity care away from clinical settings.

3.4.7 Strengths and limitations

3.4.7.1 Strengths

This systematic review has several strengths. To the best of my knowledge, this was the first study to systematically review longitudinal observational studies about the relationships between green and blue space and chronic health. Summarising the published evidence from observational longitudinal studies allows for a better understanding of the temporal relationships between natural environmental exposures and health outcomes. This is important in guiding public health interventions and identifying gaps in literature. Although previous research has shown that green space has a protective effect on health (Gascon et al., 2015), this review found mixed evidence of causal relationships. Findings from this review, therefore, can be used to re-evaluate health guidelines and shift focus on improving methodologies in exposure assessment and causality. Including studies on both green and blue space also facilitated the identification of a research gap in the health-promoting role of water bodies. Having broad exposure and outcome inclusion criteria, moreover, allowed me to examine the overarching effects of these natural environments on mental conditions and NCDs in adults. This has several implications for further research and policy, including the need to conduct more comparative analyses using exposure measures that capture a broad range of natural spaces in the neighbourhood. This systematic review also informed the empirical work in this thesis, which assessed the relationship between multimorbidity and the natural environment.

Another strength of this study is the methodological, bibliographic search approach. Currently, there is no precise and optimized search filter for longitudinal observational studies in online bibliographic databases (Waffenschmidt et al., 2017). Similarly, there is little consensus on suitable search filters for green and blue space exposures, so a combination of information specialist expertise and prior reviews was used to optimise the search (de Keijzer et al., 2020; Lachowycz and Jones, 2011; Gascon et al., 2015), which reduced the chance of missing relevant publications. Two search strategies were conducted to reduce the number of records retrieved for abstract and title screening. As mentioned previously, the first search strategy was broader and used sets of terms for environmental exposures and study design. A restricted second search strategy was then conducted that limited the first search strategy to terms for health outcomes. The records captured by the broad search strategy but missed by the second search strategy were screened for potential relevance. While a sensitivity analysis was not conducted, the title and abstracts of each record was assessed. This additional step likely lowered the likelihood of missing out relevant records, which reduced uncertainty and improved accuracy of the search strategy, while at the same time showing that a search with greater restrictions has potential to have high sensitivity and low specificity.

3.4.7.2 Limitations

While this systematic review used robust, objective analyses to synthesise the published evidence on the relationships between exposures to green and blue space with health, it is not without its limitations. First, the NOS was used for risk of bias assessment, which was originally deemed suitable for single reviewer systematic reviews due its wide usability and minimal need for adjustment (Higgins et al., 2019). However, this review found that some NOS items, such as '*Demonstration outcome of interest was not present at start of study'* and '*Ascertainment of exposure'* rated studies incorrectly. A star for good quality was awarded if the outcome of the study was not present at baseline, which assesses the possibility of reverse causality. However, this approach only applies to disease outcomes like depression and NCDs. Studies examining health-related behaviours like physical activity may have potentially been labelled incorrectly as high risk of bias on the outcome domain because the majority assessed changes in physical activity levels from baseline to follow-up. Although risk of bias due to reverse causality was assessed for studies on NCDs and mental health outcomes, it is possible that NOS did not adequately assess reverse causality in studies on physical activity. This has been previously highlighted in other reviews (Lee and Maheswaran, 2011) and to date there are still limited methods of assessing reverse causality in green space-physical activity studies due to the bidirectional nature of these relationships.

Second, the NOS domain ascertaining exposure recall bias only awards points for good quality if the exposure is assessed through records or professional assessments. However, recall bias may not necessarily pose issues in green and blue space research, especially when self-reported perceptions of neighbourhood safety and accessibility are important factors in the ways individuals interact with their surrounding green spaces (McCormack et al., 2010). As analyses of environmental exposures were a major component of this review, NOS may not be the most appropriate tool for bias assessment. Prior systematic reviews assessing methodological quality of green space studies have developed and adapted a questionnaire specific to green space exposure assessment (de Keijzer et al., 2020; Lachowycz and Jones, 2011). This tool contains several items that separately assess and rate the exposure's data source, quality, use, type and possibility of misclassification (de Keijzer et al., 2020; Lachowycz and Jones, 2011; Gascon et al., 2015).

Another limitation of this review was that studies were singly screened and selected which might have exposed this process to potential bias. The Cochrane Collaboration recommends using at least two separate review authors in the screening, data extraction and analysis process to avoid bias (Higgins et al., 2019). While screening for this review was conducted with regular consultations with a second reviewer (PC), it is plausible that reviewer bias was introduced during the data extraction and NOS quality assessment. If the review were to be repeated with more resources, two or more reviewers are going to be involved in the screening and quality assessment process. The interrater reliability of different stages of the screening and data extraction process can then be calculated in order to analyse degree of reviewer agreement (McHugh, 2012).

3.4.8 Conclusion and next steps

This systematic review was conducted with the aim to better understand how exposure to different types of green and blue spaces affects the risk of developing mental health disorders and NCDs. Narrative synthesis results showed that there is inconsistent evidence of significant protective relationships between exposure to green spaces and health, which could be due to incomparable exposure measures, lack of adjustment of confounding variables, and inadequate length of follow-up. There was also very little evidence that multimorbidity has been studied in relation to exposure to green and blue spaces.

In order to assess the associations between exposure to green and blue spaces with multimorbidity, results from this systematic review will be used to guide the following research:

1. Assess residential exposure to green and blue spaces. This was done by computing and linking data on total green space, parks, street trees, and inland blue space from European Urban Atlas into the UK Biobank cohort (Chapter 4). This

systematic review showed there is currently lack of comparative research into types of green and blue spaces and the differential ways they affect health. Many studies used low resolution green space data that cannot differentiate between accessible and private green spaces. There was also some indication that street trees and parks may be more protective of health and physical activity than other types of greenery measures. To address this research gap and comparatively analyse the associations between each green and blue space type with multimorbidity, a data integration study with the UK Biobank was conducted (described in Chapter 4).

2. Assess the relationships between green and blue space exposures with simple, complex and associative multimorbidity clusters using cross-sectional data from UK Biobank. This systematic review yielded equivocal evidence about the longitudinal associations between exposure to green spaces with mental health conditions and NCDs. As this doctoral research is one of the first to quantify the relationships between green and blue spaces with multimorbidity, a cross-sectional research design was adopted to first build a robust exploratory model, which provided information on prevalence of different green and blue space exposures and multimorbidity outcomes (Chaters 5 and 6). This cross-sectional study has the potential to create empirical guidance for future longitudinal and life course research. Model building involved several steps. First, assessment for confounding was conducted by employing statistical methods of adjustment testing. This systematic review showed there is currently no optimum confounder adjustment but evidence from published literature indicates confounders in the relationships between green spaces and health can be socio-demographic, environmental and clinical. This thesis tests for confounder suitability in maximum likelihood models in Chapters 5 and 6. Second, the moderating effects of physical activity and income on the relationships between exposure to green and blue spaces with multimorbidity were assessed using interaction terms and stratification analyses. This systematic review showed there is little consistent evidence of mediation in the relationships between green and blue spaces and health, but evidence from the literature summary in Chapter 2 showed that income and physical activity are one of the key determinants of multimorbidity in middle-aged adults (Knies and Kumari, 2022; Singer et al., 2019a; Delpino et al., 2022). Finally, the associations between each green and blue space

type with simple, complex, and associative multimorbidity clusters were analysed to comparatively observe directions and strengths associations.

Chapter 4: Green and blue space data integration - joining green and blue space data from European Urban Atlas into UK Biobank

Chapter summary

This analytical chapter describes the methods and results of a data integration study I conducted to compute and integrate data on availability and accessibility of different types of urban green and blue spaces into the UK Biobank cohort. This chapter is guided by my systematic review in Chapter 3, which found negligible evidence of high-quality comparative epidemiological research on types of green and blue spaces and their effects on health. The methods of data integration, descriptive statistical parameters of the computed exposure metrics, and strengths and limitations of the study are described in separate sections. The green and blue space data integrated from this study are used in the third analytical part of this thesis (Chapters 5 and 6), which describes the cross-sectional associations between exposure to different types of urban green and blue spaces with multimorbidity patterns.

The aims and objectives of this study are as follows:

Aim: Integrate individual-level exposure data on total green space, parks, street trees, blue space, and green and blue space into a large health cohort.

Objectives:

- Source open access, validated environmental data to integrate into the UK Biobank cohort at baseline
- Compute exposure metrics of total green space provision, park proximity, street tree provision, blue space provision, and green and blue space

provision, and integrate them to the baseline residential location of UK Biobank participants

- Assess the intercorrelations and descriptive statistical parameters of the computed exposure metrics to test the agreement and accuracy for each variable

4.1 Introduction

4.1.1 Urbanisation and role of green spaces in promoting good health

Urbanisation is the process of mass migration of people to cities (United Nations, 2014). More than half of the world population currently live in cities (United Nations, 2014), which can have drastic impact on human health (Kuddus et al., 2020). Loss of biodiversity, higher traffic and air pollution levels, disparities in wealth between urban dwellers, changes towards sedentary lifestyles and poor diet have all been linked to increasing urbanisation (McMichael, 2020; Cyril et al., 2013). These factors concomitantly affect the risk of developing NCDs and mental health conditions, such as obesity, diabetes, and depression (McMichael, 2020; Cyril et al., 2013). As I discussed in Chapter 1, green and blue spaces have been considered key promoters of good health in urban areas due to their ability to reduce air pollution and noise, promote social cohesion and increase physical activity (Markevych et al., 2017). It is commonly thought that humans are drawn to nature due to the intrinsic beauty of greenness, and the cultural and interpersonal meanings certain green and blue spaces have to communities and individuals (De Kleyn et al., 2019). However, availability of greenness and connectedness with nature has been declining in urban areas due to lack of accessible natural space and increasing need for housing and industry development (Colding et al., 2020; Puplampu et al., 2021). In order to mitigate some of the harmful effects of urbanisation and promote good health in non-clinical settings, provision of accessible green spaces for urban dwellers has been a key policy recommendation of WHO for many high-income countries (World Health Organisation, 2016b).

4.1.2 Types of green spaces and their relationships with health

The systematic review in Chapter 3 deduced there was limited evidence of significant longitudinal associations between exposure to green and blue spaces with chronic mental and physical health outcomes. Although greater exposure to green space was observed as being protective of some cardio-metabolic and cancer outcomes, many studies were incomparable in exposure measures and population (Geneshka et al., 2021). Currently, there is lack of comparable epidemiological research on types of green and blue spaces and their differential impact on chronic health (Geneshka et al., 2021), despite growing evidence showing that, in addition to amount of green space, different types of green and blue space environments affect health differently (Lachowycz and Jones, 2011). In observational studies of British and USA adults, for example, grasslands, serene environments, higher number of forests, and higher number of urban green spaces were all associated with lower risk of poor mental health, but saltwater bodies, wetlands, rangeland, and agricultural land showed no significant associations with mental health (Alcock et al., 2015; Akpinar, Barbosa-Leiker and Brooks, 2016). In HIC urban settings, higher availability of street trees, but not higher availability of grass or total green space, was also associated with lower odds of diabetes and CVD (Astell-Burt and Feng, 2019, 2020). Furthermore, a comparative study on availability of public parks and total green space area showed that having more public park space in the residential neighbourhood reduced blood pressure, while larger areas of green space in the neighbourhood showed no significant relationships with blood pressure change (Jimenez et al., 2020).

Type, position, and duration of exposure to green and blue space could affect health at different rates and potentially through different causal pathways. In systematic reviews, higher amount of street trees, good accessibility to parks, and some types of land use classes showed stronger associations with health than higher availability of grass or total green space (Nguyen et al., 2021; Wolf et al., 2020; Rigolon et al., 2021). In 2016, the World Health Organisation (2016b) called for a need to include more objective and comparable measures of green space accessibility and usage in evidence-based research. However, due to lack of availability of objective environmental data in health cohorts and limited characterisation of different green spaces present in the surrounding environment, cohort studies still mainly use single measures of greenery, such as the NDVI, or proportion of green space (Gascon et al., 2015; Lachowycz and Jones, 2011; Geneshka et al., 2021). This data integration study demonstrates how the integration of open access environmental land use data from the European Urban Atlas (UA) into the UK Biobank can increase the availability of objective data on types of urban green and blue spaces, such as street trees, parks and inland water bodies. This data will then be used to examine the associations between exposure to different green and blue spaces with multimorbidity.

4.1.2 Urban Atlas

Green and blue space data on total green space provision, proximity to park, street trees provision, and inland blue space provision were acquired from the European Urban Atlas (UA) (European Environment Agency, 2012). UA is a land use dataset covering European Functional Urban Areas (FUA) for the years 2006, 2012 and 2018. FUAs are statistical unit areas defined by the European audit as urban zones with a population of at least 100,000 people. These areas usually include a metropolitan city and its surrounding commuting zone (Eurostat, 2021). The commuting zone is the area around the city where at least 15% of its employed residents commute into the city (European Environment Agency, 2012). The UA dataset contains 20 land use classes, 17 of which are built-environment urban classes with a minimum mapping unit (MMU) of 0.25 ha, and 3 are rural classes with a MMU of 1 ha (European Environment Agency, 2012). The overall minimum accuracy for the UA data is 80% and the minimum mapping width is 10m. The UA is collated from SPOT 5 satellite and other Very High Resolution (VHR) imagery for the years 2006, 2012 and 2018 (European Environment Agency, 2012).

The UA dataset has been widely used in health research to capture green space and other natural environmental data in the residential neighbourhood (Goldenberg et al., 2018; Dempsey et al., 2018; Zhou et al., 2021; Olsen et al., 2019; Barboza et al., 2021). The validity of UA in capturing amount and accessibility of green space has been previously tested with CORINE, UK Land Cover Map and NDVI datasets, all of which showed comparable results (Barboza et al., 2021; Zhou et al., 2021). The "*Urban green areas*" layer from the UA was also endorsed by WHO as a suitable indicator of urban green space accessibility and is now a preferred measure for capturing usable green spaces in European urban areas due to its high resolution and ability to capture green space change over time (van den Bosch et al., 2015). Therefore, the UA was chosen as a suitable source of objective green and blue space exposure assessment in this thesis due to its high resolution and data validity (European Environment Agency, 2012).

4.1.3 UK Biobank

The UK Biobank is a large, population-based prospective cohort of 502,650 men and women aged 40-69 years (Hewitt et al., 2015). Baseline information was collected between 2006 and 2010 in 22 assessment centres in the UK. Around 9.2 million invitations were sent for voluntary participation to members of the general public who are registered with a National Health Service (NHS) General Practitioner (GP) and lived within 25 miles of one of the assessment centres (Allen et al., 2012). Data about participants' socio-demographic characteristics, living arrangements, occupation, lifestyle factors, physical activity, alcohol consumption, diet, early life exposures, cognitive functions, medication history and medical conditions were collected through touchscreen questionnaires (Cassidy et al., 2016). Physical measures of height, weight and blood pressure and samples of blood, saliva, and urine were also collected at baseline assessment (Hewitt et al., 2015). Follow-up of the cohort is ongoing and disease status and mortality are tracked through electronic health records and cancer registries (Sudlow et al., 2015). Online questionnaires on current and lifetime mental health disorders, 24-hour diet recall, pain, digestive health and occupational history have been administered to around 300,000 participants since baseline (UK Biobank, 2021).

The UK Biobank was chosen for this data integration study due its availability of information on local environmental exposures (UK Biobank, 2021; Sarkar et al., 2015). Information on exposure to traffic intensity, residential noise, and air pollution (nitrogen oxides, nitrogen dioxide, PM10, PM2.5) were linked for every UK Biobank participant in 2010 (UK Biobank, 2021). In 2015, Sarkar et al. (2015) also created the UK Biobank Urban Morphometric Platform (UKBUMP), a high-resolution database of built-environment metrics such as residential density, density of health-promoting/ inhibiting destinations, accessibility to food outlets, and accessibility to health-specific destinations. Data for UKBUMP were processed and integrated from the UK Ordnance Survey and UKMap (Sarkar et al., 2015). The UKBUMP also contains a metric for greenness, measured through the NDVI in a 500m Euclidean distance (circular) buffer around every participant's residential address (Sarkar et al., 2015). Data on amount of domestic garden space, amount of green space, amount of blue space, distance to coast, and amount of natural environment space in 300m and 1000m circular buffers are also available for most UK Biobank participants from data linkages with Generalized land use database for England (GLUD) 2005 at Census Output Area level (UK Biobank, 2021). These will be used alongside data computed in this data integration study to measure the relationships between types of green and blue spaces with multimorbidity (Chapters 5 and 6).

The availability of environmental data in the UK Biobank has facilitated observational research into the roles of different green spaces on chronic health. Two cross-sectional studies, for example, found that higher NDVI was associated with lower risk of obesity and depression (Sarkar, 2017; Sarkar, Webster and Gallacher, 2018b). In longitudinal analyses, exposure to higher amount of green space reduced the risk of diabetes, prostate, and oral cavity cancer (Cao et al., 2023; Yang et al., 2023). In comparative analyses on types of green spaces, moreover, domestic garden space, total green space, and other urban greenery all showed protective associations with CVD and respiratory mortality (Roscoe et al., 2022a; Wan et al., 2022), but it was higher availability of private garden space that showed strongest protective relationships with mortality (Roscoe et al., 2022a). The availability of data on green space type, air quality, noise and built-environment characteristics makes the UK Biobank a valuable resource for examining associations between the natural environment and chronic health. This data integration study aimed to expand the scope of this comparative research by integrating data on provision of street trees, total green space, inland water bodies and proximity to parks from European Urban Atlas. These data, along with data already available for UK Biobank participants on domestic garden space, proximity to coast, and inland blue space in 1000m buffer were later used to assess the cross-sectional associations between types of green space and multimorbidity in the study described in Chapters 5 and 6.

4.2 Methods

4.2.1 Data Selection and processing

4.2.1.1 Urban Atlas nomenclature, exposure metrics

4.2.1.1.1 Overview

Urban Atlas (UA) data on green spaces, parks, street trees and inland blue space from 2006 and 2012 coinciding in location with UK Biobank participants' residential address at baseline was acquired from Copernicus Land Monitoring website (https://land.copernicus.eu). UK Biobank sample was limited to participants residing in urban areas for which UA data were available. UA data were available for about 300,000 UK Biobank participants in the following UK cities: London, Bristol, Cardiff, Stoke-on-Trent, Nottingham, Sheffield, Leeds, Manchester, Liverpool, Newcastle upon Tyne, Edinburgh, and Glasgow (see fig. 9).

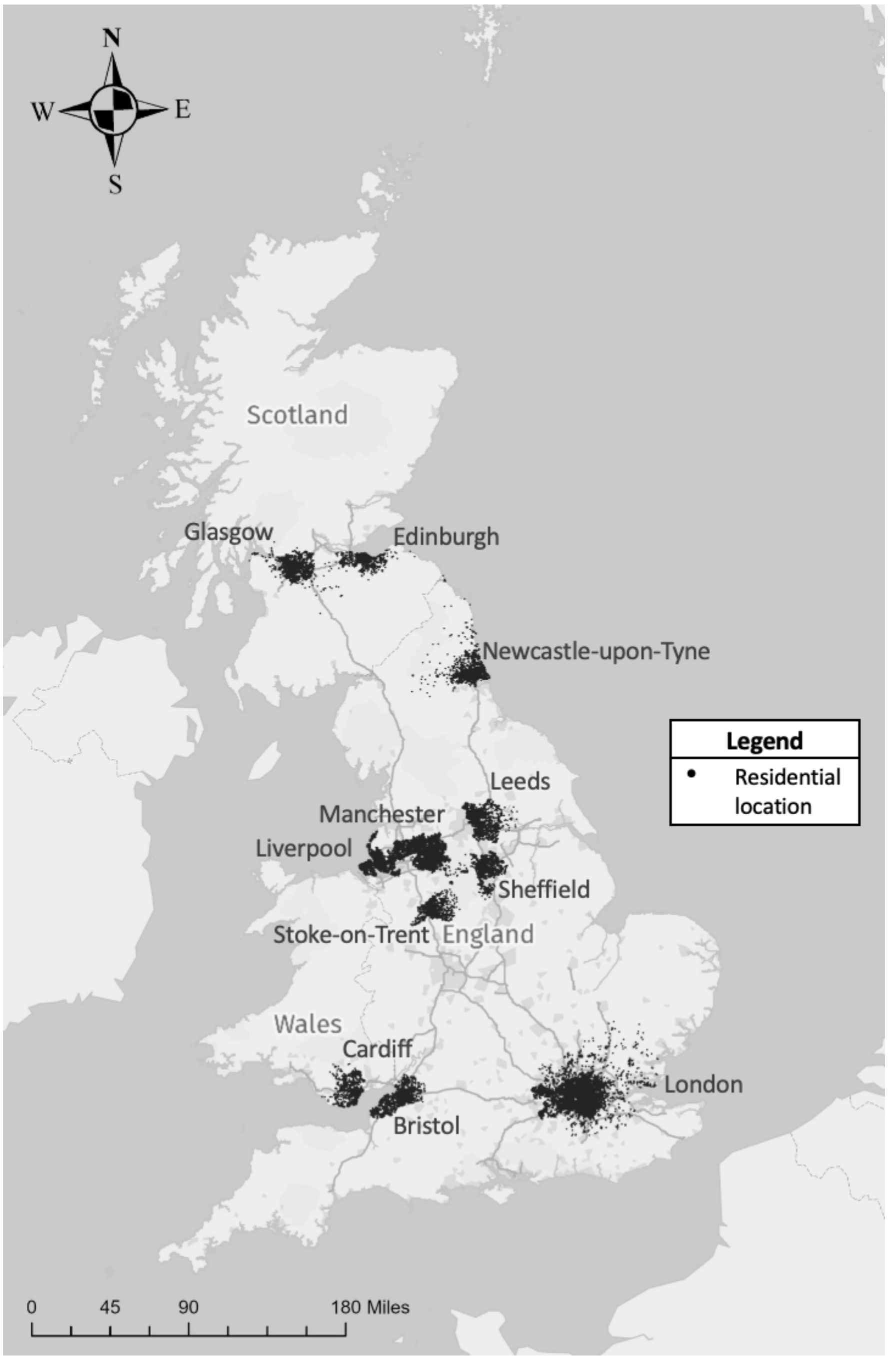

Figure 9: Map showing distribution of UK Biobank participants' residential address at baseline (2006-2010) for which UA data was available

Table 6 provides an overview off all the indicators that were constructed by me using UA data. In summary, these were: provision of total green space, proximity to park, availability of street trees, provision of inland blue space (also referred to as blue space), and provision of green and blue space. Data were integrated at an individual level using circular (Euclidean radial distance) buffers of different sizes around the residential address of UK Biobank participants at baseline (see table 6 for details). Provision indicators were measured as percent of buffer area occupied by each relevant land use class (table 6). Proximity to park was measured as presence or absence of a park within circular (Euclidean radial distance) buffers around the residential address, and as the straight-line (Euclidean) distance from the residential address to the edge of the nearest public park (table 6).

Table 6: Summary of exposure indicators and metrics computed by me using Urban Atlas data and linked into UK Biobank.

Exposure Indicator	**UA Land Use Class Nomenclature Used (year of data collection)**	**Exposure Metrics**
Provision of Total Green Space	Green urban areas (2006) Agricultural + seminatural + wetland areas (2006) Forests (2006)	Percent green space cover in 100m, 300m, 1500m, and 3000m circular (Euclidean radial distance) buffers around the residential address
Proximity to Park	Green urban areas (2006)	Presence in 300m and 1500m circular (Euclidean radial distance) buffers around the residential address Euclidean distance to nearest park
Provision of Street Trees	Street Tree Layer (2012)	Percent street canopy cover in 300m and 1500m circular (Euclidean radial distance) buffers around the residential address
Provision of Inland Blue Space	Water Bodies	Percent inland water surface area cover in 100m, 300m, 1500m, 3000m circular (Euclidean radial distance) buffers around the residential address
Provision of Green & Blue Space	Green urban areas (2006) Agricultural + seminatural + wetland areas (2006) Forests (2006) Water Bodies (2006)	Percent green and blue space cover in 100m, 300m, 1500m, 3000m circular (Euclidean radial distance) buffers around the residential address

4.2.1.1.2 Provision of total green space

Provision of total green space was measured as amount (percent) of green space cover in circular (Euclidean radial distance) buffers around the residential address (table 6). The following land use nomenclature layers from 2006 UA dataset were used to measure amount of total green space: "*Green urban areas*", "*Agricultural* + *seminatural* + *wetland areas*", and "*Forests*". I aimed to create a measure of provision of total green space that captures any type of greenery in the residential neighbourhood, therefore, any area covered by either of these three classes was included. "*Green urban areas*" layer captures public areas for predominantly recreational use, such as public parks, gardens, and zoos. "*Agricultural* + *seminatural* + *wetland areas*" layer captures natural open spaces such as arable land, pastures, grasslands, arable crops, moors, beaches, bare rocks, snow, ice and wetlands. The "*Forests*" layer captures natural areas with tree canopy cover of over 30% and tree height of over 5m (European Environment Agency, 2012). These lands use data have been previously used to measure amount of green space other epidemiologic studies (Kolcsár, Csikós and Szilassi, 2021; Coppel and Wüstemann, 2017; Dempsey, Lyons and Nolan, 2018). Although some studies additionally include the "*Sports and leisure facilities*" layer in green space measures (Dempsey, Lyons and Nolan, 2018), I decided to exclude this layer because it contains commercially and privately owned land, such as golf courses, water parks and camp sites, which are not publicly accessible and may not elicit the same health benefits as other natural spaces (European Environment Agency, 2012).

4.2.1.1.3 Proximity to park

Proximity to a park was captured in two ways: 1) as the presence or absence of a public urban green space within 300m and 1500m circular (Euclidean radial distance) buffers around participants' residential address; and 2) as the straight-line (Euclidean) distance from a participant's residential address to the edge of their nearest green urban area. The UA 2006 nomenclature layer "*Green urban areas*" was used to capture public parks, which were defined by UA as public areas for predominantly recreational use, such as public parks, gardens, and zoos (European Environment Agency, 2012).

4.2.1.1.4 Provision of street trees

Provision of street trees was measured as amount (percent) of street tree canopy cover in circular (Euclidean radial distance) buffers around the residential address using data from the 2012 UA nomenclature, "*Street Trees* layer". "*Street Trees layer*" captures contiguous patches of trees ($\geq$ 5m height) covering areas of at least 500m^2 over the Level 1 "*Artificial surfaces"* nomenclature layer (for more information on UA nomenclature see Appendix VI). The "*Street Trees layer*" only captures trees over built-up areas, like the discontinuous urban fabric (labelled as land use class nomenclature: *Artificial surfaces*). Any trees growing over natural land areas, such as forests and agricultural areas, are excluded (European Environment Agency, 2012).

4.2.1.1.5 Provision of inland blue space

Provision of inland blue space was measured as amount (percent) of surface inland water area cover in circular (Euclidean radial distance) buffers around the residential address. The 2006 UA "*Water bodies*" nomenclature layer data for UK was used to measure blue space, and it captures visible inland water surface area of any rivers, lakes, ponds and canals (European Environment Agency, 2012).

4.2.1.1.6 Provision of green and blue space

Provision of green and blue space was measured as amount (percent) of total green and blue space in circular (Euclidean radial distance) buffers around the residential address. The following UA nomenclature data were used to measure availability of green and blue space: "*Green urban areas*", "*Agricultural + seminatural + wetland areas*", and "*Forests*" for green space; and "*Water bodies*" for blue space. As the 2006 UA land use layers do not spatially overlap, amount of green and blue space was constructed by adding the percent values of the green space with the blue space variables. Participants were classed as having amount of green and blue space greater than 0% if they had at least 0.01% green space cover and at least 0.01% blue space cover within the same size buffer. Participants who had only one type of environment (e.g., only green or only blue space) within the same size buffer around the residential address were classed as having 0% green and blue space.

4.2.1.2 Spatial scales

The above exposures were captured in circular (Euclidean radial distance) buffers around the residential address of UK Biobank participants. Table 6 shows the size of distance buffers for each exposure metric. To date, there is little consensus about the most appropriate scale for measuring green space (Geneshka et al., 2021), however, I computed buffer sizes with radii of 100m, 300m, 1500m and 3000m to capture different types of neighbourhoods. Figure 10 shows a graphical visualisation of the circular distance buffers. A one-hundred-meter buffer was chosen to represent immediate exposure to green space. This is typically the distance participants can see from their doorstep or through the windows. Emerging research has shown that green and blue space view from the window can improve well-being and mental health (Elsadek, Liu and Xie, 2020; Pouso et al., 2021), but the UK Biobank currently has no proxy measure for green or blue space view from the window. Three-hundred-metre buffers were computed to capture the close neighbourhood. This is the recommended distance anyone should live from an accessible green space to gain health benefits (World Health Organisation, 2016b; Natural England, 2018). Buffers with radii of 1500m were computed to capture the 15-minute neighbourhood. This follows the principles of the ’15-minute’ city (Perry, 1929), a theory that focuses on the benefits of locality and pedestrian accessibility. The ability of urban dwellers to access all core functional amenities and health-promoting resources within a 15-minute walk from their residential address has been long considered promote sustainable, healthy urban living by reducing traffic and air pollution, and encouraging physical activity (Allam et al., 2022; Caselli et al., 2022). The concept of the ’15-minute’ city regained popularity during the COVID-19 pandemic, which shone light on the importance of meeting individuals’ demands for recreation within a walking distance from the home (Hanzl, 2021; Gaglione et al., 2022). Additionally, I included a 3000m buffer to capture green and blue spaces within the wider neighbourhood. Policy recommendations by Natural England for UK state that everyone should have access to green spaces of at least 20 ha in size within two kilometres of the residential address, and access to 100 ha accessible green spaces within five kilometres of the residential address (Natural England, 2010). Large-scale GIS analysis is computationally intensive and evidence for the protective effect of green spaces in larger buffers is mixed (Mazumdar et al., 2021; Klompmaker et al., 2018). I therefore pragmatically opted to use 3000m as a compromise measure of the wider known neighbourhood individuals way walk (approximately 30 mins.) or actively commute for jobs or services.

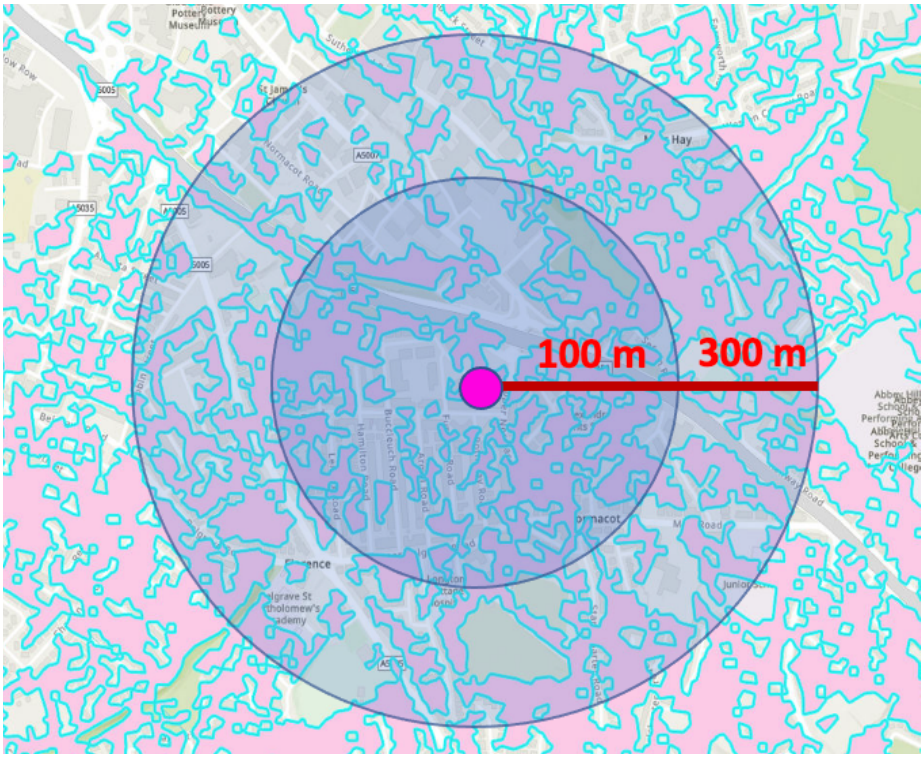

Figure 10: Illustrative example of circular buffer around a residential address (not to scale)

4.2.1.3 Data processing

All data were processed in ArcGIS Pro, a 64-bit Desktop application facilitated by Esri ArcGIS Platform, which provides tools for powerful geo-spatial data analysis and visualisation (Corbin, 2007). The six-digit residential location coordinates (northing and easting) of UK Biobank participants (rounded to 100m accuracy) were imported as points onto a base layer map. Using the *Buffer* tool, I computed circular (Euclidean radial distance) buffers around the residential locations of UK Biobank participants (see fig. 10 for reference). The selected UA land use nomenclature data were then imported into shapefiles and converted from vector to raster datasets (50m grid cell size for all 2006 UA layers and 10m grid cells for 2012 *Street Tree Layer*), using the analysis tool, *Feature to Raster*. The percent of the buffer area occupied by the relevant green/ blue space raster data was calculated using the tool, *Zonal Statistics as Table*. The *distance to urban park* exposure metric was computed using the *Near* tool, which measured the straight-line distance (in metres) from a participant's residential address to the edge of the nearest public green space that was captured by the "*Urban green space*" UA layer data. Participants whose residential address or buffer area fell outside of the boundaries of the UA data layers were excluded from the analyses.

To preserve anonymity of UK Biobank participants, this data integration study was conducted using a two-step process. First, the home location coordinates to 100m accuracy were granted to me with unique participant identifiers that were different to those of the main cohort. This prevented participant identification through linkages with other socio-demographic variables in the main dataset. Once the UA data computation was complete, the green and blue space variables were returned to the UK Biobank team, who removed the location coordinate data and sent back the green and blue space data variables with correct participant identifiers. I used these identifiers to link the green and blue space data to the main UK Biobank dataset. The data linkage of the green and blue space data into the UK Biobank cohort was conducted in RStudio using a full-join function in the *dyplr* package. The green and blue space data derived from this data integration study will become available to other researchers using UK Biobank data.

4.2.1.1.4 Data analysis

The computed green and blue space data were transferred from ArcGIS Pro to RStudio for analysis. Descriptive statistics, such as central tendency (e.g., means, medians), frequencies and dispersion measures (e.g., standard deviation and inter-quartile ranges) were calculated for each exposure metric in order to analyse the skewness of the data. Bivariate data analysis, chi-squared tests, Pearson tetrachoric, point biserial and product moment correlations were also applied to assess the interrelationships between each exposure metric.

4.2.2 Ethical approval

Researchers are not required to seek an ethics approval to use UK Biobank data. Approved users of UK Biobank data are covered under the UK Biobank ethics approval by the North West Multi-centre Research Ethics Committee (MREC) as a Research Tissue Bank. This project was approved by the UK Biobank's Access Management System (AMS), application no. 73700, and grants access to restricted UK Biobank Fields 22701 and 22703 (*home location – east coordinate* and *home location – north coordinate*).

4.3 Results

Table 7 describes the statistical parameters of the computed green and blue space exposure metrics. Just under two-thirds (62.94%) of UK Biobank participants had a park within 300m of their residential address and almost all participants (98%) had a park within 1500m of the residential address. The mean straight-line distance to a park from the residential address was 291.48m (table 7).

Table 7: Statistical parameters of computed green and blue space exposure metrics

Exposure Metrics	n (observed UK Biobank cases)	Mean (%)	Standard Deviation	Median (%)	Min (%)	Max (%)
Percent total green space in 100m	311,451	10.26	20.32	0.00	0.00	100.00
Percent total green space in 300m	308,979	15.40	18.32	8.84	0.00	99.03
Percent total green space in 1500m	239,747	27.78	20.57	21.19	0.04	99.74
Percent total green space in 3000m	192,094	32.31	21.10	25.94	1.47	98.85
Percent inland blue space in 100m	311,451	0.24	2.68	0.00	0.00	95.49
Percent inland blue space in 300m	308,979	0.46	2.66	0.00	0.00	87.54
Percent inland blue space in 1500m	271,118	1.12	2.55	0.21	0.00	50.51
Percent inland blue space in 3000m	219,462	1.20	1.70	0.56	0.00	47.92
Percent tree canopy in 300m	138,831	20.03	17.13	15.30	0.04	99.60

Percent tree canopy in 1500m	171,734	19.14	13.47	16.70	0.00	85.06
Percent total green and blue space in 100m	311,451	10.48	20.51	0.00	0.00	100.00
Percent total green and blue space in 300m	308,979	15.86	18.52	8.84	0.00	100.00
Percent total green and blue space in 1500m	239,719	28.93	20.50	22.85	0.29	99.74
Percent total green and blue space in 3000m	180,572	34.04	21.19	27.70	2.10	99.02
Distance to park (m)	312,284	291.48	378.90	201.15	0.00	15843.71
	Yes (%)			**No (%)**		
Presence of park in 300m	194,481 (62.94%)			114,498 (37.06%)		
Presence of park in 1500m	273,172 (98.14%)			5,190 (1.86%)		

Median and interquartile range values for the exposure metrics are shown in box and whisker plots in figure 11. Overall, the data were skewed towards the null. The median amount of green/blue space generally increased with buffer size. On average, UK Biobank participants had 0% total green space in a 100m buffer around the residential address, and around 26% total green space in a 3000m buffer around the residential address. On average, UK Biobank participants had 0% blue space in all buffer sizes around the residential address. Median amount of street tree canopy was 15% in 300m buffers and 17% in 1500m buffers.

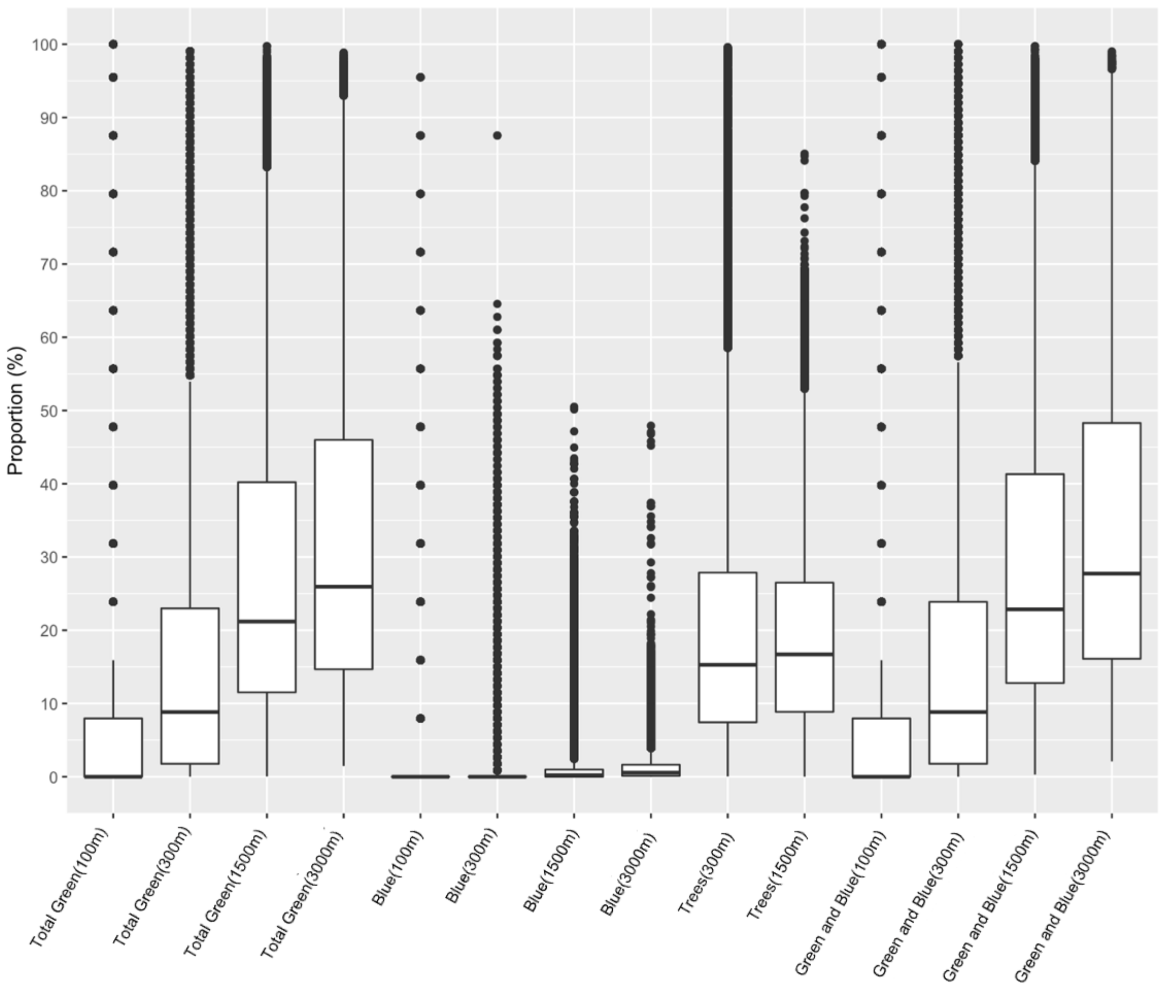

Figure 11: Box and whisker plots of exposure metrics

Figure 12 shows a Pearson correlation matrix of the computed exposure metrics. Overall, exposure metrics of the same indicator with different buffer sizes had strong positive correlations with each other. The correlation coefficients were weaker between metrics with larger buffer size differences. There was strong positive correlation between the street tree canopy cover metrics (r = 0.78).

The correlation matrix also showed negative correlations between the presence of park metrics, percent street tree canopy metrics and percent total green space metrics. Weak positive correlations were observed for presence of park in 300m buffer metric with percent total green space and percent green and blue space metrics. However, weak to moderate negative correlations were observed for presence of park in a 1500m buffer metric with percent total green space and percent green and blue space metrics (fig. 12). There were also weak negative correlations between percent street tree canopy in 1500m buffer metric and percent green and blue space metrics.

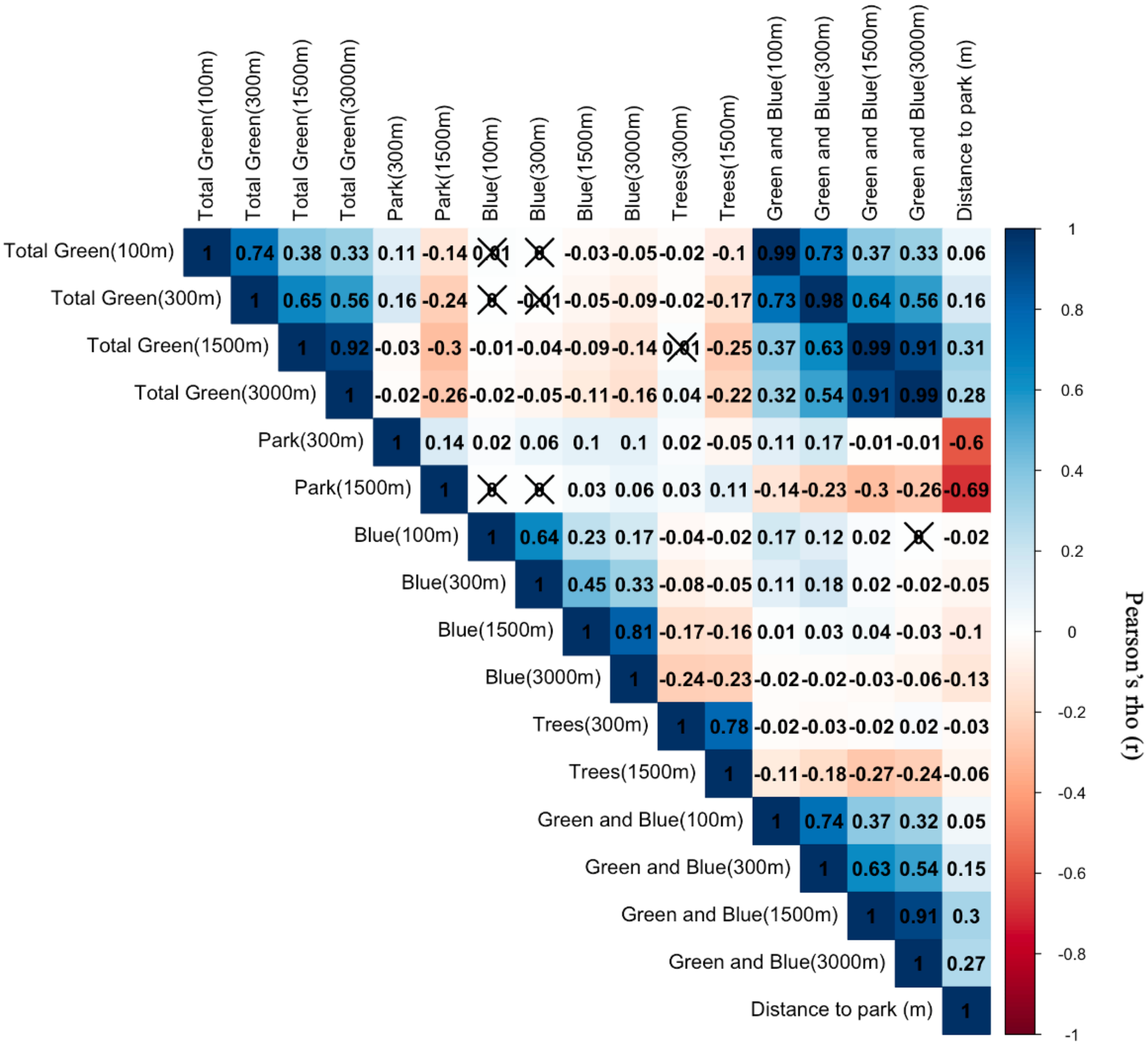

Figure 12: Pearson correlation matrix of exposure metrics

4.4 Discussion and Conclusion

4.4.1 Interpretation of results

The correlation heatmap was computed to assess the spatial configuration of each exposure metric. Exposure metrics of the same indicator with different buffer sizes showed strong positive correlations with each other, which suggests accurate computation of data. Percent street tree canopy metrics showed weak negative correlations with percent total green space and percent blue space exposure metrics, and very weak positive correlations with presence of park metrics. There was weak spatial overlap of data between percent street tree canopy metrics and presence of park due to the configuration of the UA "Street Tree layer", which spatially overlaps with the "*Urban green spaces*" layer (European Environment Agency, 2012). Presence of park metrics showed weak negative correlations with both percent total green space and percent blue space metrics, which suggests that there is no spatial overlap between these types of green spaces. Overall, correlation results confirm that my geospatial computation produced measures of spatially different types of green spaces in the urban environment.

4.4.2 Strengths and limitations

4.4.2.1 Strengths

This data integration study used high quality, open-access environmental data from UA to compute and integrate metrics of total green space provision, public park proximity, street tree provision, inland blue space provision, and green and blue space provision into 300,000 UK Biobank Participants. The UK Biobank was chosen for its availability of data on domestic garden space, proximity to coast, noise and air pollution, which were used alongside the integrated green and blue space data from UA to assess the relationships between exposure to different types of green and blue spaces with the prevalence of multimorbidity (Chapters 5 and 6).

This data integration study has several strengths. First, exposures were computed at an individual level, which improves accuracy in exposure measurement and reduces bias in exposure misclassification (Greenland and Morgenstern, 1989). Previously, green space exposure for England were measured at Lower Layer Super Output Areas (LSOAs) (Mitchell and Popham, 2007; Mears et al., 2020), which are population-density statistical dissemination units that provide aggregate values of green space availability. The application of aggregate values to individual analyses is not only prone to ecological fallacy but creates dispersion in data that requires additional statistical considerations. By conducting buffer-level individual analyses, I have partially prevented ecological bias, reduced inaccuracy in exposure measurement, and facilitated smoother statistical analyses.

Another strength of this data integration study is the development of exposure metrics on multiple spatial scales. WHO (2016b) has called for a need to include objective and comparable measures of green space amount, proximity and usage to better understand how different aspects of green and blue spaces affect health. Previously, epidemiologic research has lacked robust comparable analyses between different exposure indicators due to lack of available data in health cohorts (Geneshka et al., 2021). This is also the case for the UK Biobank, which has data on green and blue space provision for the year 2001 at 500m and 1000m circular buffers (UK Biobank, 2021). Circular buffer sizes were used as proxies for size of residential neighbourhood in this data integration study. It is highly likely that the spatial scale at which an exposure is measured predicts the strength of the relationship with health. Health policy recommendations state that everyone should have accessible green spaces within 300m of the residential address (WHO, 2016b; van den Bosch et al., 2017), but these policies are arbitrary and supported by little empirical research. Currently, there is no consensus about most appropriate spatial scales to measure greenness, although some studies suggest that larger buffer sizes (up to 2000m) are stronger predictors of health than smaller ones (Su et al., 2018; Browning and Lee, 2017). This data integration study, therefore, facilitates more comparative analyses on spatial scales to further aid the understanding of how green and blue spaces in different residential neighbourhoods affect health.

Another strength of this data integration study is the replicability of methods for exposure assessment across other European regions. The UA was chosen over other high-resolution green space datasets, such as the Ordnance Survey (OS) Greenspace Layer, because it measures land use change over time across other European urban settings. My methods of exposure assessment, therefore, are replicable to studying the effects of green and blue spaces on health across other European populations. Moreover, a strength of this data integration study is the integration of data on urban street tree canopy, which was previously unavailable for UK. Greater exposure to street tree canopy has previously shown strong protective relationships with CVD and other cardio-metabolic health conditions (Astell-Burt and Feng, 2019; Nguyen et al., 2021). It is considered that street trees can attenuate the micro-climate by capturing air pollution, limiting noise, and reducing temperatures (Salmond et al., 2016). Their position in the urban system (along roads, paths and front gardens) also provides an aesthetic domain which might further encourage active commuting, increase walkability, and improve individuals' perceptions of their local neighbourhood (Galenieks, 2017). However, research on their relationship with health has primarily focused on Australian populations (Astell-Burt and Feng, 2019), by using the 2012 "*Street Tree layer*" from the UA instead of the OS Greenspace Layer, I expanded the possibility of street tree research across UK.

4.4.2.2 Limitations

This data integration study has multiple strengths, but it is not without limitations. My analyses are primarily based on capturing amount of green and blue space within straight-line distance buffers. These buffers capture any exposure data that falls within the buffer's area, irrespective of its physical accessibility or ownership. One advance in GIS has been the ability to capture amount of green space only along roads and paths around the residential address (Madsen et al., 2014). The advantage of using road network buffers is the ability to capture green space that is physically accessible to the individual through paths and roads (Madsen et al., 2014; Oliver et al., 2007). A road-network buffer approach might be useful for assessing exposure to green spaces that are used for recreation and active commute, like street tree canopy and distance to park, however, the construction of the accessible road network around each participant's address is computationally intensive for large-scale data linkages. Moreover, circular and road-network buffers capture similar amount of green space (Bodicoat et al., 2014; Carthy et al., 2020), which suggests that the need for such computation is unnecessary.

Another limitation of this study is the geo-processing resolution of the data. The 2006 UA layers were converted into raster datasets with a resolution of 50m. Rasterising a vector feature in GIS may cause potential data loss in areas that are smaller than the size of the raster grid cell. Generally, smaller grid cell sizes provide more accurate raster data because they capture smaller areas of green and blue spaces. I chose 50m as the raster grid cell size because it facilitated smoother geoprocessing for the large sample size. Smaller grid cell sizes, while more accurate, could not enable large scale data analysis. I consider 50m to be a reasonable trade-off between accuracy and large sample size output. The 2012 "*Street Tree layer*" was rasterised at a 10m resolution because it contained fewer data points and was available for fewer areas.

The computation and integration of the UA data variables to UK Biobank was also limited by the temporal resolution of the UA dataset. First, UA green and blue space data was only available cross-sectionally for the years 2006 and 2012 . As baseline data collection for UK Biobank occurred over a 5-year period (2006 and 2010), it is likely that UK Biobank participants had some degree of inaccuracy in exposure measures due to unmeasured changes in amount of green and blue spaces in the surrounding environment between 2006 and 2012. Such inaccuracies, however, were not adjusted for in this data integration study because large physical changes in green and blue space availability over this time period are likely to be minimal.

This data integration study was also limited by the accuracy of the residential location coordinates provided by the UK Biobank. A 6-digit grid reference was used to locate the residential address of each UK Biobank participant, which is only accurate to 100m. This might have led to another inaccuracy in exposure measures, particularly in the measures for amount of green or blue space in 100m buffers, where 100m radial buffer analyses might have failed to capture the precise physical location of the residential address and produced exposure data for another participant or for a non-existent location. Although this is not likely to introduce bias, an 8-digit grid reference would produce residential location information accurate to 10m, which would reduce inaccuracy in exposure measurement. However, this is not possible for UK Biobank and many other volunteer-based cohorts due to data governance laws and preservation of anonymity (UK Biobank, 2021).

Finally, a limitation of this data integration study was the exclusion of participants whose buffers fell on or outside of the boundary of the UA data. This potentially limited the sample size to participants who live predominantly in inner city areas. To avoid excluding data, the UA data could have been overlaid with a larger land use dataset, such as CORINE, which would have allowed an ascertainment of land use types outside and on the edges of the UA boundaries. Due to the large sample size and time constraints, however, I chose to exclude missing and incomplete data.

4.4.3 Conclusion

In conclusion, this chapter described the methods and results of data integration study using high quality, open-access land use data from Urban Atlas to measure provision, amount, and type of green and blue spaces in the neighbourhood. Data on provision of total green space, proximity to park, provision of street trees, and provision of inland blue space was linked to 300,000 UK Biobank participants at an individual level using circular buffers.

Next Steps

Exposure metrics computed through this data integration study were used alongside data on domestic garden space and proximity to coast from UK Biobank to assess the cross-sectional relationships with multimorbidity. The next two chapters outline the methods and results of the cross-sectional analyses between green and blue space exposures with multimorbidity (Chapters 5 and 6).

Chapter 5: Relationship between exposure to green and blue spaces with multimorbidity: a cross-sectional UK Biobank study - Methods

Chapter 5 and Chapter 6 summary

Chapter 5 and Chapter 6 describe the methods and results for the cross-sectional associations between exposure to green and blue spaces with multimorbidity using data from the Urban-Atlas - UK Biobank data integration study, and other data available from UK Biobank. Chapter 5 outlines the methods, data sources and analytical approaches of the study. Results of these analyses are presented in Chapter 6.

The aims and objectives of this study are as follows:

Aim: Assess the cross-sectional relationships between exposure to different types of green and blue spaces with multimorbidity.

Objectives:

- Using baseline data from UK Biobank, construct a statistical model for analysing the associations between exposure to green and blue spaces with five relevant multimorbidity types: disease counts (measuring simple and complex multimorbidity), cardio-metabolic, respiratory and mental
- Assess suitability of confounders in the relationships using relevant statistical approaches
- Assess whether physical activity and income moderate the relationships between exposure to green and blue spaces with multimorbidity

5.1 Study design

This study used a cross-sectional design to conduct foundational exploratory analyses for the relationships between exposure to different green and blue spaces with the following four multimorbidity outcomes: disease counts (capturing simple and complex multimorbidity), and clusters of cardio-metabolic, respiratory and mental conditions. As I previously mentioned in Chapter 3, a cross-sectional design was employed in order to build a foundational, empirical model for studying the associations between green and blue spaces with multimorbidity. Cross-sectional analyses are usually preferred when epidemiological relationships between certain exposures and health outcomes have not been previously studied (Kesmodel, 2018). This cross-sectional study builds empirical foundations for future longitudinal research into the roles of the natural environment on multimorbidity risk by assessing the prevalence of multimorbidity, and testing for relevant confounding and moderating factors.

5.2 Cohort description

The UK Biobank was previously described in Chapter 4. In summary, the UK Biobank is a large, population-based prospective cohort of 502,000 men and women aged 40 to 75 years. Baseline data were collected between 2006 and 2010 in 22 assessment centres across England, Wales and Scotland (Littlejohns et al., 2019). Follow-up of the cohort is ongoing. To date, information on dietary habits, mental health, physical activity levels, and environmental exposures has been collected through various data linkages and resampling. Hospital inpatient episodes, ICD-specific mortality causes, and primary-care health diagnoses have also been linked to individual participants through NHS electronic health records and death registries (Hewitt et al., 2016). I used baseline self-reported clinician-diagnosed health data to measure multimorbidity, self-reported socio-demographic and physical activity data to measure confounding variables, and objective environmental data on air pollution, noise, crime, deprivation, green and blue space to study the associations between exposure to green and blue space with multimorbidity. This study did not require additional ethical approval. Research governance permissions are covered by the existing UK Biobank ethics approval from the North-West Multi-centre Research Ethics Committee (reference 16/NW/0274). Data for this study were obtained from the UK Biobank with an approved application (app. no. 70291), which can be found in Appendix VII.

5.3 Exposures: green and blue spaces

5.3.1 Overview

Green space exposure was assessed through the following indicators: provision of total green space (measured as amount (%)), proximity to park (measured as distance (m) and presence), provision of street tree canopy (measured as amount (%)), provision of domestic garden space (measured as amount (%)), provision of inland blue space (also referred to as blue space and measured as amount (%)), and proximity to coast (measured as distance in miles). Data on provision of domestic garden space, proximity to coast, and provision of inland blue space in 1000m buffer were previously available for UK Biobank (UKBiobank, 2021). Data on provision of total green space, proximity to parks, provision of street tree canopy, and provision of blue space in 100m, 300m, 1500m, and 3000m buffers were integrated into UK Biobank participants at baseline using the 2006 and 2012 European Urban Atlas data (European Environment Agency, 2012) (details of data integration study are described in Chapter 4). All exposures were measured objectively using remote-sensed data. Although this approach cannot fully determine the ownership and physical accessibility of all green spaces, this thesis excluded green spaces that are explicitly private or limited to the public, such as golf courses and sports facilities. Semi-private green spaces, such as domestic gardens were included because they provide non-direct benefits to the public, such as filtering of pollutants and cooling of the surrounding environment and increasing the aesthetic features of streets (for front gardens).

5.3.2 Exposures computed through data integration study with Urban Atlas

5.3.2.1 Amount of total green space

Amount (provision) of total green space in this study was measured as the percent of land covered in either green urban areas, agricultural, seminatural and wetland areas, or forests. Data on land classification was taken from the 2006 UA (European Environment Agency, 2012) and linked to UK Biobank participants. Chapter 4 describes the methods for data integration in full. To summarise, amount of total green space captures an overall percent of greenery in 100m, 300m, 1500m, and 3000m circular (Euclidean radial distance) buffers around the residential address of UK Biobank participants.

5.3.2.2 Proximity to park

This study defined parks as accessible green spaces that are open to the public (Le Texier, Schiel and Caruso, 2018). Proximity to park was measured as the presence or absence of a public urban green space in 300m and 1500m circular (Euclidean distance) buffers around the residential address of UK Biobank participants. The Euclidean (straight-line) distance (in meters) from each participant's residential address to the nearest park was also separately modelled. Data on parks was linked into UK Biobank using the 2006 UA layer, *public green areas"*, which captures public parks and any other green outdoor spaces generally used by the public for recreation and socialisations, such as church graveyards, zoos, memorial gardens, and castle parks (European Environment Agency, 2012).

5.3.2.3 Amount of street trees

Amount (provision) of street trees was measured as percent tree canopy cover in 300m and 1500m circular (Euclidean radial distance) buffers around the residential address. The 2012 UA data, "*Street Tree layer"*, was linked to UK Biobank participants at baseline (methods described in Chapter 4) and captures contiguous rows or patches of trees covering 500m² or more and with a minimum width (MinMW) of 10m over artificial, built-up surfaces. Artificial surfaces were defined as roads, paved paths, gardens (European Environment Agency, 2012).

5.3.2.4 Amount of inland blue space in 300m, 1000m, 1500m, and 3000m circular buffers

Amount (provision) of inland blue space (also referred to as blue space) was measured in percent water surface area in 300m, 1000m, 1500m, and 3000m circular (Euclidean radial distance) buffers around the residential address of UK Biobank participants. Amount of blue space for 300m, 1500m, and 3000m circular buffers was computed by integrating 2006 UA data on water into UK Biobank (European Environment Agency, 2012).

5.3.2.5 Amount of green and blue space

Amount (provision) of green and blue space was measured in percent green and blue space area in 300m, 1000m, 1500m, and 3000m circular (Euclidean radial distance) buffers around the residential address of UK Biobank participants. Details about the ways green and blue space were measured can be found in Chapter 4. In summary, green space was captured as percent of land covered in either green urban areas, agricultural, seminatural, wetland areas, or forests (data source: UA 2006). Blue space was captured as percent inland water surface area (data source: UA 2006). Only UK Biobank participants who had both green and blue space area greater than 0.01% in 300m, 1500m, and 3000m circular (Euclidean radial distance) buffers around the residential address were considered to have green and blue space amount greater than 0%. UK Biobank participants who had only green space or only blue space in each buffer size, but not both, were classed as having 0% green and blue space amount.

5.3.3 Exposures obtained from UK Biobank repository

5.3.3.1 Amount of domestic garden space

Amount (provision) of domestic garden space was measured as percent domestic garden space in 300m and 1000m circular (Euclidean radial distance) buffers around the residential address of UK Biobank participants. Data on domestic garden space was linked into the UK Biobank by Wheeler (2017) using data from the 2005 GLUD dataset as part of an initiative to increase the availability of environmental indicators in the UK Biobank cohort.

5.3.3.2 Proximity to coast

Data on proximity to coast were obtained from UK Biobank. Proximity to coast was measured as the straight-line (Euclidean) distance from a participant's residential address at baseline to their nearest coastline (Wheeler., 2017).

5.3.3.3 Amount of inland blue space in 1000m circular buffer

Data on amount (provision) of blue space in 1000m buffer were obtained from UK Biobank. These data were computed by integrating data on water from 2005 GLUD dataset to UK Biobank participant's residential address at baseline (Wheeler, 2017).

5.3.9 Spatial scales

Table 8 provides an overview of the spatial scales (buffers) used to capture each exposure. Currently, there is no optimum spatial scale for measuring exposure to green and blue spaces in epidemiological research, but an adequate measure of the surrounding neighbourhood is usually required for accurate exposure assessment (Singer et al., 2019b; Harrison et al., 2014). In Chapter 4, I discussed the reasons for computing green and blue space exposures at different spatial scales. In summary, circular (Euclidean radial distance) buffers of sizes 100m, 300m, 1500m, and 3000m were used to capture different types and sizes of residential neighbourhoods. One-hundred metres represents a view from the window and immediate surroundings.

Three-hundred metres was chosen to capture the immediate neighbourhood following recommendations proposed by WHO and Natural England, which state that every urban inhabitant should have an accessible green space of at least 2 ha within 300m (approx. 5 min walk) from their residential address. A buffer size of 1500m was chosen to capture the local neighbourhood, which follows the principles of the ’15-minute’ city (Perry, 1929), an urban theory of locality that proposes that all urban dwellers should have access to all core functional amenities and health-promoting resources within a 15 minute walk from their residential address in order to reduce air pollution, traffic and promote sustainable living (Singer et al., 2019a; Kabir et al., 2022). Additionally, I included a 3000m buffer to capture green and blue spaces within the wider neighbourhood (30-minute walk from the residential address). Due to high skewness of the data on blue space and green and blue space, exposure metrics on blue space in 100m buffers and green and blue space in 100m buffers were omitted from analyses based on data suitability. Although normal distribution of independent variables is usually not required as a data assumption in maximum likelihood analyses (Paciorek, 2007), histograms showed that there were not enough participants with sufficient exposure data greater than 0% (see Appendix VIII for more).

Table 8: Description of exposures included in regression analyses and their data sources

Exposure Type	**Description**	**Exposure Metrics**	**Data Source**
Amount of total green space	Green urban areas + Agricultural + seminatural + wetland areas + Forests	Percent green space in 100m, 300m, 1500m, 3000m circular buffers around residential address	Urban Atlas (2006)
Proximity to park	Green areas accessible to the public for predominantly recreational use, such as public parks, gardens, and zoos	Euclidean distance in metres from residential address to edge of green area	Urban Atlas (2006)
		Presence of park in 300m and 1500m circular buffers around residential address	
Amount of Street Trees	Contiguous patches of trees ($\geq$ 5 m height) covering an area of at least $500m^2$ over Level 1 *Artificial surfaces* nomenclature layers	Percent tree canopy cover in 300m and 1500m circular buffers around residential address	Urban Atlas (2006)

Amount of Domestic Garden Space	Domestic garden space land use layer from GLUD	Percent domestic garden space in 300m, 1000m circular buffers around residential address	GLUD (2005)
Amount of Blue Space	Surface area of inland water bodies including lakes, rivers, and ponds	Percent inland water surface cover in 100m, 300m, 1500m, 3000m circular buffers around residential address	Urban Atlas (2006)
		Percent inland water surface cover in 1000m circular buffer around residential address	GLUD (2005)
Amount of Green & Blue Space	Green urban areas + Agricultural + seminatural + wetland areas + Forests + Water Bodies	Percent green and blue space in 100m, 300m, 1500m, 3000m circular buffers around residential address	Urban Atlas (2006)
Proximity to coast	-	Euclidean distance in meters from residential address to edge of the coast	-

5.4 Outcomes: multimorbidity

5.4.1 Definition and data sources

Multimorbidity in this study was measured in disease counts and clusters of cardio-metabolic, mental, and respiratory diseases. Individuals were considered to have multimorbidity if they had two or more co-occurring LTCs at baseline (Singer et al., 2019c; Harrison et al., 2014). The type of LTCs included in this study was guided by a 45-item disease list previously adapted for measuring multimorbidity in the UK Biobank (Singer et al., 2019b; Kabir et al., 2022). The list was constructed using a panel study of medical experts, systematic reviews, and the quality and outcomes framework (QOF) of the UK GP contract (Barnett et al., 2012). The list only includes mental and physical conditions that are highly prevalent in the British population and have profound, chronic effect on quality of life and functional status. Any health condition not included on the list was discounted from the definition of multimorbidity and participants with such conditions were classed as having no multimorbidity. The list of conditions and their UK Biobank-specific coding can be found in the Appendix IX.

Data on long-term health were obtained in a two-part assessment at baseline. First, UK Biobank participants were asked to indicate on a touchscreen questionnaire whether they had been told by a doctor that they have cancer, CVD or any other serious, long-term illnesses (UK Biobank, 2021). Each participant then attended a nurse-led interview to determine the exact type of diagnosis. If the participant was unsure of the name of their illness, they were asked to describe it to the nurse who coded it to the best of their ability based on provided descriptions and medications.

5.4.2 Multimorbidity as disease counts - simple and complex multimorbidity

Disease counts is the most common and replicable method of measuring multimorbidity in epidemiology (Fortin et al., 2005; Boyd and Fortin, 2010; Mokraoui et al., 2016). In this thesis, individuals were split into five mutually exclusive groups based the number of self-reported LTCs at baseline: No LTCs; 1 LTC; 2 LTCs; 3 LTCs; and 4 or more (4+) LTCs. Individuals with 2 LTCs were considered to have simple multimorbidity, while those with 3 and 4+ LTCs were considered to have complex multimorbidity (Singer et al., 2019b; Harrison et al., 2014). I chose to differentiate between simple and complex multimorbidity because of previously observed differences in functional status and care needs between the two groups (Singer et al., 2019a; Kabir et al., 2022), which may affect the ways individuals interact with their surrounding environments. Individuals with complex multimorbidity are more likely to be disabled and frail, and have reduced ability to perform instrumental activities of daily living (Storeng et al., 2020). In this sense, people with complex multimorbidity might use certain types of green and blue spaces differently to people with simple or no multimorbidity.

5.4.3 Associative multimorbidity clusters

In addition to disease counts, distinct clusters of cardio-metabolic, respiratory, and mental health conditions were also included in this study. Non-random associations between diseases exist because of shared aetiological, genetic, and environmental factors (Whitty et al., 2020; van den Akker, Buntinx and Knottnerus, 1996). The European Forum for Primary Care (2015) has long called for a need to move away from counting diseases and towards understanding the ways groups of co-occurring conditions form and operate in order to tailor interventions and design better care. Instead of conducting exploratory statistical analyses, such as confirmatory factor analysis, I used a previously published systematic review on replicable multimorbidity clusters and prior literature on the burden and prevalence of NCDs to derive multimorbidity clusters for the UK Biobank (Busija et al., 2019; Barnett et al., 2012). I included a cluster of cardio-metabolic conditions and a cluster of mental health disorders because they were found to be replicable across all settings in the systematic review (Busija et al., 2019). A multimorbidity cluster of respiratory diseases was additionally included because it was replicable in 75% of settings (Busija et al., 2019). Cardio-metabolic, mental health, and respiratory conditions are highly prevalent in middle-aged and older populations and known to be responsible for over 60% of the total burden of diseases (Barnett et al., 2012). Observational studies and systematic reviews have also shown that these types of multimorbidity clusters generally have the greatest effects on mortality, quality of life, and healthcare utilisation than any other types of multimorbidity (Kanesarajah et al., 2018; Rijken et al., 2005; Tran et al., 2022; Jani et al., 2019), making them key outcomes of interest.

The systematic review by Busija et al. (2019) further deduced that clusters of falls-fractures-hearing deficits, and clusters of Parkinson's disease-dementia are replicable in about 75% of settings. However, these were excluded in the current study because they do not fit the operational definition of multimorbidity as a chronic health state of multiple co-occurring LTCs. Fractures and falls are not classed as LTCs in the population level study 45-item list of commonly occurring long term conditions (Barnett et al., 2012). I also excluded neurodegenerative conditions like Parkinson's Disease and dementia because they are strongly correlated with frailty and have a low prevalence in age groups younger than 75 years (Berr, Wancata and Ritchie, 2005). Any occurrence of early-onset dementia is likely to linked to genetic factors, which can make study results incomparable to other multimorbidity disease clusters, which are likely driven by socio-demographic and behavioural factors (Miyoshi, 2009). Table 9 shows the types of conditions included in each multimorbidity cluster. Cardio-metabolic, respiratory, and mental multimorbidity were measured as binary variables. Individuals who had two or more conditions specific to the cluster were coded as having multimorbidity (yes), while individuals who had only one or no conditions specific to the cluster were coded as not having that type of multimorbidity (no).

Table 9: Summary of LTCs included in each type of multimorbidity outcome

Multimorbidity Type	LTC Included in Definition
Disease Counts	Coronary heart disease, Hypertension, Thyroid disorder, Diabetes, Stroke, Atrial Fibrillation, Peripheral vascular disease, Heart failure, PCOS, Depression, Anxiety, Alcohol dependency, Other substance use disorder, Dementia, Schizophrenia, Anorexia and other eating disorders, Pain, Asthma, Endometriosis, Osteoporosis, Chronic Fatigue Syndrome, Rheumatoid arthritis, COPD, Constipation, Kidney disease, Diverticulitis, Asthma, Prostate Disorder, Glaucoma, Epilepsy, Eczema, IBD, Migraine, Anaemia, Cancer, Multiple sclerosis, Hepatitis, Ménière's disease, Chronic sinusitis, Bronchiectasis, Parkinson’s disease
Cardio-metabolic	Coronary heart disease, Hypertension, Stroke, Atrial Fibrillation, Heart failure, Thyroid disorder, Diabetes, Peripheral vascular disease
Respiratory	Asthma, COPD
Mental	Depression, Anxiety, Alcohol dependency, Other substance use disorder, Anorexia and other eating disorders, Schizophrenia

5.6 Confounders

5.6.1 Overview

Age, sex, income, ethnicity, crime levels, area-level deprivation, physical activity, air pollution and noise were chosen as confounders for the regression analyses. Decisions about confounder adjustment were made on a theoretical and data-suitability basis. Currently, there is no consensus on most appropriate confounder adjustment, but systematic reviews and observational studies on the relationships of exposure to green and blue spaces with chronic mental and physical health all point towards the joint confounding effects of individual and area-level socio-demographic factors, physical activity, as well as air pollution and noise (Lachowycz and Jones, 2011; Twohig-Bennett and Jones, 2018; Bogar and Beyer, 2016; Geneshka et al., 2021). Multimorbidity prevalence and the ways individuals interact with their surrounding environment are all associated with age, sex, income, and ethnicity. Physical activity is considered one of the main health-promoting behaviours linking green and blue space to health and the strongest behavioural risk factor for multimorbidity (Delpino et al., 2022).

5.6.2 Age, sex, ethnicity

Information on sex, age, and ethnicity were acquired from baseline data collection (2006-2010). The UK Biobank data field, *Age at recruitment*, was used to measure age in this thesis. Age was measured as a continuous variable, and it represents the age of each participant when they attended the assessment centre for baseline data collection.

UK Biobank collected baseline information on sex from NHS records. In this thesis, sex is treated as binary biological entity based on health records, however, participants had an option to change that during self-assessment. Sex in this thesis was a binary variable indicating whether a participants was ‘male’ or ‘female’.

Ethnicity was self-reported at baseline. A multi-level stage questionnaire was used to assess ethnic background. First, participants had an option to choose one of the following categories: ‘white’, ‘mixed’, ‘Asian or Asian British’, ‘Black or Black British’. This was followed up by a multiple-choice questionnaire, where participants were asked to select the specific sub-category that best described their ethnic background. Descriptive analyses of the UK Biobank sample showed that over 90% of participants were white (see Chapter 6). Ethnicity in this thesis, therefore, was categorised as a binary variable of ‘white’ and ‘other’. Participants were considered white if they selected ‘white’ ethnic background during the first-stage questionnaire. Participants who selected anything other than ‘white’ were categorised as ‘other’. Participants who selected ‘Do not know’ and ‘Prefer not to answer’ were excluded from analyses.

5.6.3 Income

In this study, participants were divided in three groups based on their average household income before tax (expressed in British pounds [£]): low (income below £18,000); medium (income between £18,000 and £51,999); and high (income above £52,000). Data from 2008 official government statistics on low, medium and high income was used to categorise participants into these mutually exclusive categories (Cabinet Office, 2022). Raw income data from UK Biobank were self-reported at baseline. On a touchscreen questionnaire, participants were asked to select one of the following categories that best described their annual household income before tax: less than £18,000; £18,000 to £29,999; £30,000 to £51,999; £52,000 to £100,000; and greater than £100,000. Participants who selected ‘Do not know’ and ‘Prefer not to answer’ were excluded from analyses.

5.6.4 Physical activity

Physical activity (PA) was assessed at baseline using adapted questions from the International Physical Activity Questionnaire (IPAQ), which is a validated tool for measuring physical activity levels across different populations (Craig et al., 2003). Participants were asked in self-reported questionnaires to indicate how many days in a typical week they spent at least 10 minutes walking or engaging in moderate and vigorous physical activity. The number of days and minutes participants spent engaging in each type of activity were then weighted to calculate the metabolic equivalent of task (MET) minutes per week, which is a standardised metric for summarising physical activity levels (Cassidy et al., 2016). Participants who indicated that they spent less than 10 minutes a day engaging in a type of physical activity were coded as having 0 MET minutes for that activity (Murray, Coleman and Hunter, 2020). The MET min/week for walking, moderate and vigorous activity were summed by UK Biobank to produce the total MET min/week. The total MET min/week scores were used in this thesis to categorise participants into three mutually exclusive groups as per IPAQ guidelines and prior UK Biobank studies (Chudasama et al., 2019; Roscoe et al., 2022b): low PA (< 600 total MET min/week); moderate PA (≥ 600 to 2990 MET min/week); high PA (≥3000 MET min/week). Participants who selected ‘do not know’ and ‘prefer not to answer’, and those who indicated they spent the equivalent of 16 or more hours a day doing any type of physical activity were excluded from the analyses.

5.6.5 Deprivation

Deprivation was captured using the Townsend Index, which measures material deprivation based on four indicators: unemployment, overcrowding, non-car ownership, and non-home ownership (Jordan, Roderick and Martin, 2004). Individuals were assigned a Townsend score corresponding to the output area of their residential at baseline. In this thesis, deprivation was kept as a continuous confounder in regression analyses.

5.6.6 Safety

Safety was measured through the Crime domain of the Index of Multiple Deprivation (IMD) for England, which encompasses four major crime types: violence, theft, criminal damage, and burglary. Participants were assigned a score corresponding to the Lower Layer Super Output Area (LSOA) of their residential address at baseline. Participants recruited in 2006 were matched to the 2004 IMD values, those recruited in 2008 were matched to the 2007 IMD value, and those recruited in 2010 were matched to the 2010 IMD value. The IMD Crime domain was included as a continuous confounder in regression analyses.

5.6.7 Air Pollution and Noise

Air pollution in this thesis was measured in particulate matter with diameter less than or equal to 2.5 micrometres (PM 2.5). Data on air pollution for UK Biobank were obtained through annual average Land Use Regression estimates for 2010, which were linked to UK Biobank participants’ residential address at baseline by other researchers (UK Biobank, 2021). Noise was measured as the average 16-hour sound level of noise pollution in decibels (dB). Data for the year 2009 were linked to UK Biobank participants’ residential address at baseline through several data linkages (UK Biobank, 2021). Air pollution and noise were both included as continuous confounders in regression analyses.

5.6.8 Confounder assessment based on statistical suitability

In addition to basing confounder inclusion on theoretical and empirical evidence, a stepwise confounder adjustment method was applied to assess the suitability of each type of confounding variable to the regression models (Ranstam and Cook, 2016). This involved adding sets of confounders to the univariate models (green/ blue space exposure metric - multimorbidity outcome) in the following order: 1) age, sex, ethnicity and income; 2) deprivation and crime; 3) physical activity; 4) air pollution and noise. The percent change in effect estimate for the exposure metric was assessed at each adjustment stage. An arbitrary cut-off value of 10% change of exposure effect estimate is usually considered substantial for confounder inclusion (Lee, 2014), but I did not observe changes of this magnitude in most of my analyses (see table in Appendix X).

5.7 Data analyses

5.7.1 Hypothesis testing

Before conducting regression analyses, exploratory hypothesis testing analyses were applied to observe whether there are statistically significant differences in socio-demographic and environmental characteristics between participants who had multimorbidity and those who did not. This helped gain a better overview of sample characteristics and understand the relationships between each independent variable and multimorbidity outcome (Davis and Mukamal, 2006). Due to the non-normal distribution of some independent variables (air pollution, green and blue space), non-parametric tests such as the Mann-Whitney U test and the Kruskal-Wallis H test were applied to test differences in means between the continuous independent variables and each multimorbidity outcome (Nachar, 2008; MacFarland and Yates, 2016). The Chi-squared test was used to analyse differences between observed and expected values of the categorical independent variables (sex, ethnicity, physical activity, income) with each multimorbidity outcome (Franke, Ho and Christie, 2012).

5.7.2 Regression analyses

I fitted multivariable logistic regression models for each exposure metric and outcome. Logistic regression is a common statistical technique used to model the probability of a categorical outcome (dependent variable) occurring due to the presence of an exposure (independent variable) (Kahlert et al., 2017). In multivariable logistic regression, multiple independent variables can be added to adjust for confounding. The first dependent variable in this study, disease counts, was ordinal and comprised of five levels: 0 LTCs, 1 LTC, 2 LTCs, 3 LTCs, and 4+ LTCs. Multinomial logistic regression models, therefore, were fitted to assess the effect of each exposure metric on disease counts. The other three dependent outcomes of this study, cardio-metabolic, respiratory, and mental multimorbidity clusters, were binary (Yes: indicating presence of multimorbidity; and No: indicating absence of multimorbidity). The relationship between these multimorbidity clusters with green and blue space exposures was assessed by fitting binomial logistic regression models.

Regression can be expressed through the following equation:

$\hat{y} = b_0 + b_1X_i + b_2X_i + b_nX_i \ldots + \varepsilon_i$, where $\hat{y}$ is the multimorbidity outcome (dependent variable), and b_nX_i is each independent variable (green/ blue space exposure and all other relevant confounders).

5.7.3 Moderation analysis by physical activity and income

5.7.3.1 Physical activity

In addition to main analyses, I conducted moderation analyses by physical activity and income. Physical activity is conceptually considered one of the main drivers in the relationship between green and blue spaces with health (Markevych et al., 2017; Hartig et al., 2014). It is also a strong determinant of the risk and severity of multimorbidity, both in the UK Biobank and other middle-aged HIC populations (Chudasama et al., 2019; Martinez-Gomez et al., 2017). Green and blue spaces provide aesthetic and practical facilities for outdoor physical activity. Prior research has shown that levels of physical activity tend to be higher in those with greater exposure to neighbourhood greenness (Richardson et al., 2013; Mytton et al., 2012), but little is still known about which types of green space environments best promote physical activity (Feng, Toms and Astell-Burt, 2021). While it is commonly assumed that parks provide all the facilities necessary for recreational physical activity, emerging research points towards the roles of canals and street trees in active commuting and cycling (Feng, Toms and Astell-Burt, 2021; Lu, 2019; Gascon et al., 2017). I, therefore, assessed physical activity moderation for all exposure metrics to better understand how physical activity moderation might differ by type of green or blue space.

I chose to assess physical activity moderation through interaction terms with each green and blue space exposure metric. Interaction terms are a common statistical approach that assume an independent variable has a differential effect on the outcome depending on values of another independent variable. In other words, the effect of green and blue spaces on multimorbidity would vary by levels of physical activity. In logit models, the interaction terms between each green and blue space exposure metric with levels of physical activity were included in fully-adjusted models through the following equation: $\hat{y} = b_0 + b_1 \textit{Green/Blue Space} + b_2 \textit{Age} + b_3 \textit{Sex} + b_4 \textit{Ethnicity} + b_5 \textit{Physical Activity} \ldots + b_n \textit{Green/Blue Space x Physical Activity} + \varepsilon_i$

5.7.3.2 Income

To assess the moderating effect of income on the relationship between green and blue spaces with multimorbidity, I conducted stratification analyses by income group. Stratification is preferred to interaction terms for social moderators like income because analyses are easier to understand and apply to policy and practice (House et al., 1994). It is well-known that the odds of having and developing multimorbidity are greater for those of low-income (Ofori-Asenso et al., 2019; Pathirana and Jackson, 2018). The effects of green spaces on mental and physical health also tend to be greater for those of low incomes (Rigolon et al., 2021). Participants in this UK Biobank sample were divided into three categories based on their average household income before tax (expressed in in British pounds [£]): low (income below £18,000); medium (income between £18,000 and £51,999); and high (income above

£52,000) (Cabinet Office, 2022). The associations between the green and blue space exposures and outcomes were assessed separately for each income group through logistic regression models, which were adjusted for sex, age, deprivation, crime, physical activity, air pollution and noise. I did not adjust the models for ethnicity because of low cases of non-white participants in the mental and respiratory cluster groups (more discussed in section 5.11).

5.7.4 Goodness of fit and model assumptions

The Hosmer-Lemeshow (H-L) test, *Cg=∑1h=0∑gd=1{(Ohd−Ehd)2/Ehd}*, was used to assess goodness of fit of the data to the binary logistic models (Archer and Lemeshow, 2006). This test works by grouping observations into deciles (n=10) of equal groups that use the observed and expected probabilities to calculate the test statistic and p-value by following a distribution similar to the χ^2 (Fagerland and Hosmer, 2012) All fully-adjusted models in this study produced H-L p-values greater than 0.05, indicating good model fit.

The McFadden pseudo R^2 squared test was additionally applied to assess the predictive capacity of the regression models through the relative reduction in deviance due to added covariates (Veall and Zimmermann, 1992). This test uses the ratio of the log likelihood of the intercept model and the log likelihood of the full model to assess model fit ($R^2 = 1 – [\ln LL(\hat{M}_{full})]/[\ln LL(\hat{M}_{intercept})]$). Small ratio of log-likelihoods (values between 0.4 and 0.2) indicates good fit. The McFadden test values between the minimally adjusted and fully adjusted models were compared in this study. All models (both minimally and fully adjusted) showed R^2 values of decent model fits (Veall and Zimmermann, 1994).

Lastly, likelihood ratio tests (LR) $X_2^2 = 2\sum_{ij} n_{ij} \ln\left(\frac{n_{ij}}{E_{ij}}\right)$ were used for parameter estimation. Particularly, LR tests were applied to assess how well the minimally adjusted models (those adjusted only for age, sex, income and ethnicity) perform compared with the fully adjusted models (those adjusted for age, sex, income, ethnicity, deprivation, crime, physical activity, air pollution and noise) (Cohen, Kim and Wollack, 1996). LR tests in this study produced varying results but in general showed better fits (p-value below 0.05) for the fully adjusted models for all exposures and outcomes.

5.7.5 Data assumptions

Regression models in this study were fitted based on meeting the following assumptions: independence of errors in the data, linearity between the independent and dependent variable on the logit-transformed scale, no multicollinearity between independent variables, and lack of extreme outliers in the data (Stoltzfus, 2011). These assumptions have been tested through exploratory data analysis, such as correlation heatmaps and summary statistics. Histograms and correlation heatmaps were used to assess extreme outliers and correlation in the green and blue space exposure variables (see Appendix VIII).

5.7.6 Statistical Software

Data were processed with RStudio (version 4.2.2), which is a powerful tool for data analysis and visualisation (Van der Loo, 2012). Packages: *nnet*, *broom*, *tidy*, *stats* and *ggplot2* were used to fit the regression analyses and assess model fits.

5.7.7 Exclusions

Some green and blue space variables were excluded from analyses due to high skewness and low number of cases. First, amount of blue space and amount of green and blue space in 100m buffers contained too few values above 0.00% to be included in regression analyses (see Appendix VIII for table). Furthermore, some covariate and exposure data were excluded due to low number of cases. The minimum number of cases per parameter in logistic regression is arbitrary but most epidemiological studies require at least 10-15 cases (Stoltzfus, 2011). The presence of a park in 1500m buffer variable was excluded from fully-adjusted logistic regression analyses with respiratory and mental multimorbidity due to low number of cases per category (see table 11 in Chapter 6). There were only four participants with respiratory and mental multimorbidity who did not have park within 1500m of the residential address, a value that is too low to be fitted in maximum likelihood analyses. The presence of a park in 1500m buffer variable was also excluded from interaction analyses with physical activity and income-stratified analyses for all multimorbidity outcomes (disease counts, cardio-metabolic, respiratory, and mental multimorbidity) due to low number of cases per category (see Appendix XI for tables). Finally, ethnicity was omitted as a confounder from income-stratified analyses due to low number of non-white cases per income category (see Appendix XI).

5.7.8 Missing Data

Multiple imputations were not done for this study. However, sources of missing data and reasons for exclusion from the study were assessed through the flowchart in Figure 13. Green and blue space exposure data were missing from 190,982 participants because UA nomenclature data were not available for their residential location. A further 228,442 participants were excluded because part of their residential buffer area fell outside the boundary of the UA nomenclature data. This left 83,005 participants with complete exposure data, out of which 34,416 had missing covariate data.

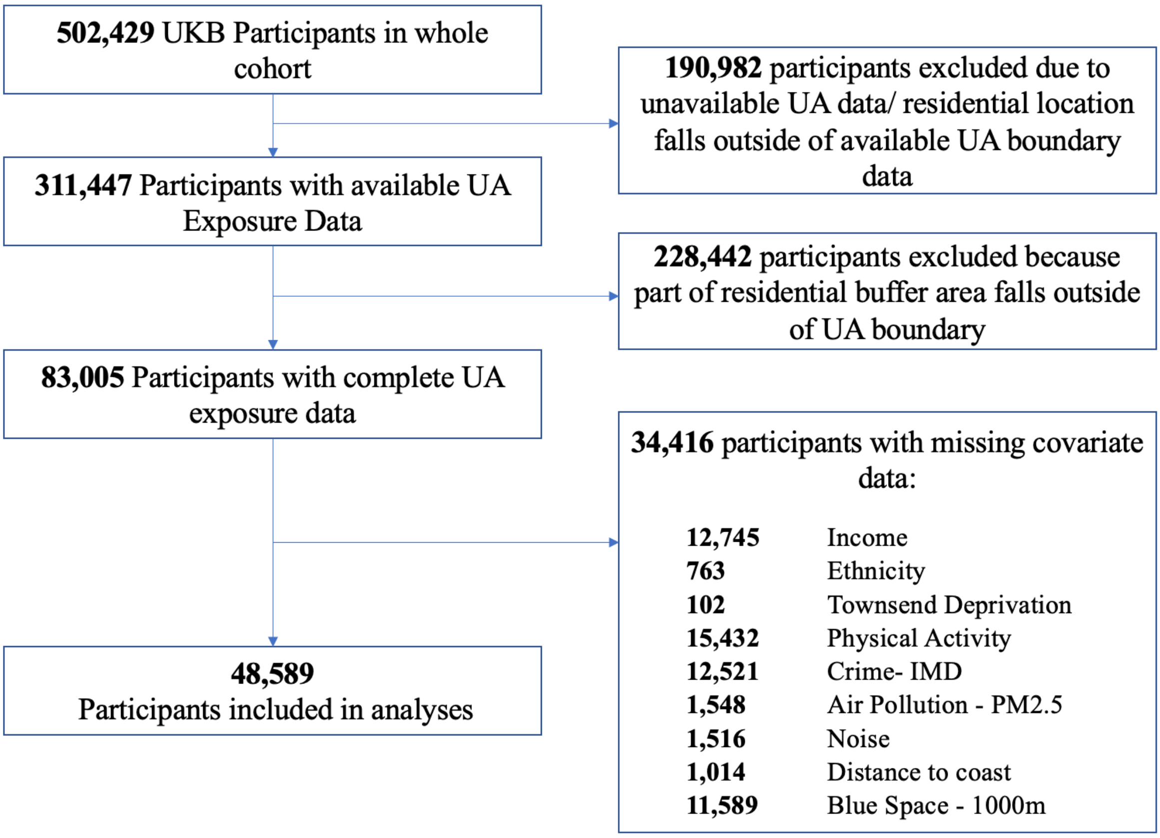

Figure 13: Flowchart of missing data sources

Chapter 6: Relationship between exposure to green and blue spaces with multimorbidity: a UK Biobank study - Results

6.1. Description of study sample

6.1.1 Study sample characteristics

After removal of missing data, 48,589 UK Biobank participants were included in the analytical sample. Table 10 shows the descriptive parameters of the sample. The mean age of the sample was 56 years. Fifty-two percent of participants were female and 88% were white. Just under half (47%) of all participants were of medium income (annual household income between £18,000 and £51,999) and just under one third (34%) were of high income (£52,000 or over). Less than 20% of participants were of low income (annual household income below £18,000). Over half of participants (53%) had moderate physical activity levels, 29% had high physical activity levels, and 18% had low physical activity levels.

Table 10: Descriptive parameters of UK Biobank analytical sample

Sample Characteristics	Mean / N	SD / %
Age (years)	56	(±)8.17
Sex		
Female	23,290	52%
Male	25,299	48%
Ethnicity		
White	42,812	88%
Other (non-white)	5,777	12%
Annual household income before tax (£)		
Low (Less than £18,000)	9,017	19%
Medium (£18,000 - £51,999)	23,075	47%
High (£52,000 and over)	16,497	34%
Physical Activity (MET min/week)		
Low (< 600 MET min/week)	8,764	18%
Moderate (≥ 600 to 2990 MET min/week)	25,819	53%
High (≥3000 MET min/week)	14,006	29%
Crime (IMD score), mean (SD)	0.15	(±) 0.63
Deprivation (Townsend Index), mean (SD)	-0.29	(±) 3.26

Annual average air quality for 2010 (PM2.5 µg/m3), mean (SD)	10.24	(±) 1.07
Noise (day & evening 2009 - LAeq,16hr in Db), mean (SD)	54.08	(±) 4.70
Cardio-metabolic Multimorbidity		
Yes	2,839	6%
No	45,750	94%
Respiratory Multimorbidity		
Yes	256	<1%
No	48,333	99%
Mental Multimorbidity		
Yes	284	<1%
No	48,305	99%
Disease Counts (no. LTCs)		
0	18,563	38%
1	16,156	33%
2	8,496	17%
3	3512	7%
4+	1862	4%

6.1.2 Prevalence of multimorbidity

The overall prevalence of multimorbidity (disease counts, measured as the presence of two or more LTCs) was 29% (fig.14). The prevalence of simple multimorbidity (2 LTCs) was 18%, while the prevalence of complex multimorbidity (3 or 4+ LTCs) was altogether 11% (fig.14). About 6% of sample participants had cardio-metabolic multimorbidity, 1% had mental multimorbidity, and less than 1% had respiratory multimorbidity.

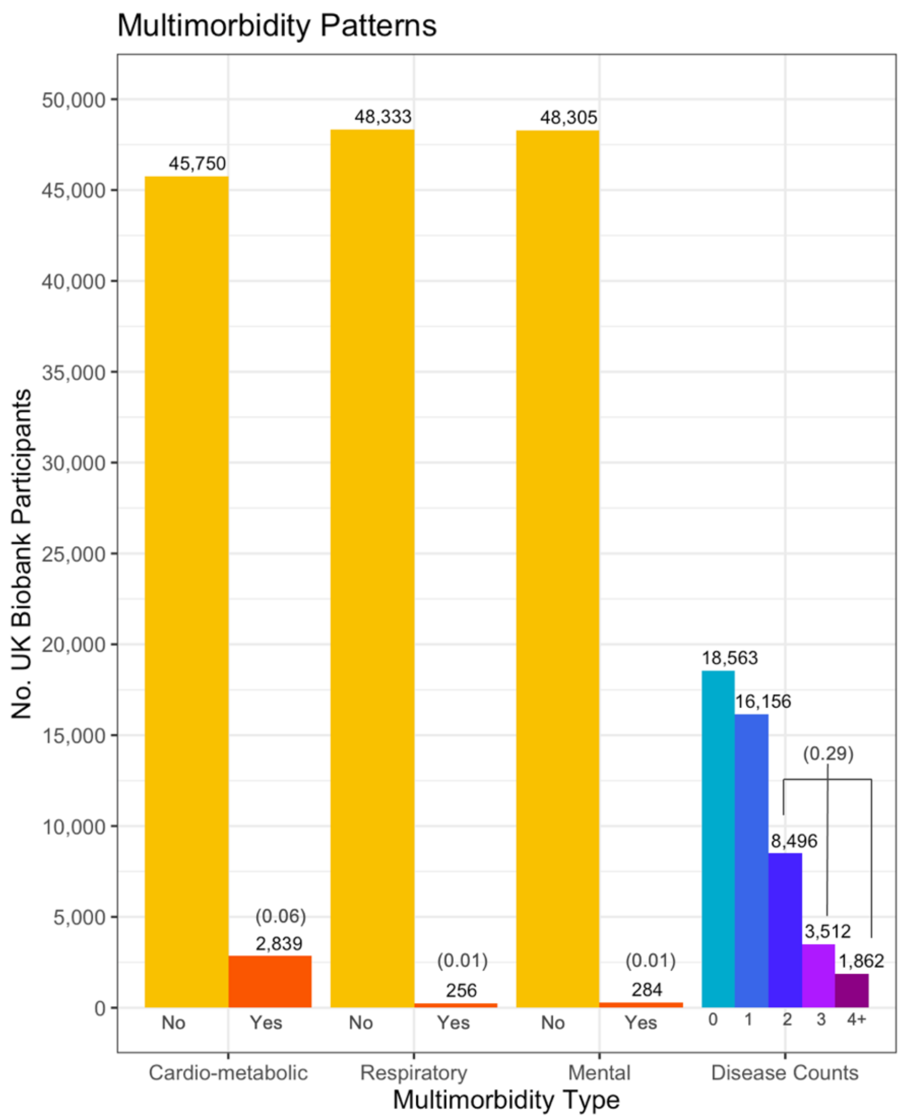

Figure 14: Patterns and prevalence of multimorbidity in the UK Biobank

6.1.3 Socio-demographic, economic, and spatial characteristics of UK Biobank population by multimorbidity type and hypothesis testing for comparison of means

Summary parameters for each exposure metric, socio-demographic variables, and environmental confounders by multimorbidity type are displayed in table 11. Measures of central tendency for hypothesis testing were applied to assess differences in multimorbidity prevalence by socio-demographic and environmental factors. Mann-Whitney U test, Chi-squared test, and Kruskal-Wallis H test were used depending on variable type, and their significance levels were measured using p-values (table 11). Generally, those who had simple (2 LTCs), complex (3 LTCs and 4+LTCs), cardio-metabolic and respiratory multimorbidity were older. Participants with mental multimorbidity were very slightly younger than those without mental multimorbidity. A larger proportion of men had cardio-metabolic multimorbidity (8.6% vs 3.3% for women), but a slightly higher proportion of women had mental multimorbidity (0.7% vs 0.5% for men). No significant differences between sexes were observed for respiratory multimorbidity and disease counts (simple and complex multimorbidity). A slightly higher proportion of non-white participants had respiratory (0.6% vs 0.3% for white) and mental multimorbidity (0.6% vs 0.3% for white), but no significant differences between ethnic backgrounds were observed for cardio-metabolic multimorbidity or disease counts.

Generally, higher proportion of low-income individuals had multimorbidity (table 11). The largest differences were observed for cardio-metabolic multimorbidity and disease counts, where 11.2% of those on low income had cardio-metabolic multimorbidity (compared to 3.2% of those on high income). About 22% of those on low income had 2 LTCs (compared to 14.3% of those on high income). Similar patterns were observed for individuals with low and high physical activity levels. Eight percent of individuals with low physical activity levels had cardio-metabolic multimorbidity (compared to 5.1% of individuals with high physical activity levels). Higher proportion of individuals with low physical activity levels also had complex multimorbidity compared to individuals with high physical activity levels (9.6% vs 6.6% for 3 LTCs, and 6.2% vs 3% for 4+ LTCs).

Individuals with any type of multimorbidity, on average, lived in areas with higher crime and deprivation levels. Significant differences between majority of green space exposure metrics and multimorbidity outcomes, however, were not observed except for amount of street trees and amount of domestic garden space in 300m buffers. On average, individuals with cardio-metabolic, respiratory, and complex multimorbidity (3 LTCs) had less street tree canopy cover and domestic garden space in 300m buffers compared to individuals without multimorbidity. However, these differences were small and almost negligible (table 11). Individuals with 2 LTCs and 3 LTCs also had slightly lower amount of blue space in 1000m, 1500m, and 3000m buffers around the residential address compared to individuals with 0 or 1 LTC.

Table 11: Socio-demographic and environmental characteristics of UK Biobank sample by multimorbidity type

	Multimorbidity Type										
	Cardio-metabolic		Respiratory		Mental		Disease Counts				
	No	Yes	No	Yes	No	Yes	0	1	2	3	4+
Age (years) in years, mean (SD)	55.5* (±8.16)	60.8* (±6.49)	55.8* (±8.17)	59.1* (±7.21)	55.8* (±8.17)	54.5* (±8.02)	53.3‡ (±8.02)	56.0 ‡ (±7.99)	58.2‡ (±7.65)	59.5‡ (±7.24)	60.3‡ (±6.92)
Sex											
Female	24,461† (96.7%)	838 † (3.3%)	25,167 (99.5%)	132 (0.5%)	25,133† (99.3%)	166† (0.7%)	9,720 (38.4%)	8,491 (33.6%)	4,329 (17.1%)	1,790 (7.1%)	969 (3.8%)
Male	21,289† (91.4%)	2,001† (8.6%)	23,166 (99.5%)	124 (0.5%)	23,172† (99.5%)	118† (0.5%)	8,843 (38.0%)	7,665 (32.9%)	4,167 (17.9%)	1,722 (7.4%)	893 (3.8%)
Ethnicity											
White	40,508 (94.6%)	2,304 (5.4%)	42,575† (99.4%)	237† (0.6%)	42,545† (99.4%)	267 † (0.6%)	16,341 (38.2%)	14,209 (33.2%)	7,481 (17.5%)	3,127 (7.3%)	1,654 (3.9%)
Other	52,42 (90.7%)	535 (9.3%)	5,758† (99.7%)	19† (0.3%)	5,760 † (99.7%)	17† (0.3%)	2,222 (38.5%)	1,947 (33.7%)	1,015 (17.6%)	385 (6.7%)	208 (3.6%)
Annual household income before tax (£)											
Low (< £18,000)	8,007† (88.8%)	1,010† (11.2%)	8,913† (98.8%)	104† (1.2%)	8,889† (98.6%)	128† (1.4%)	2,355† (26.1%)	2,828† (31.4%)	1,984 † (22.0%)	1,062† (11.8%)	788 † (8.7%)
Medium (£18,000 to £51,999)	21,776† (94.4%)	1,299† (5.6%)	22,969† (99.5%)	106† (0.5%)	22,966† (99.5%)	109† (0.5%)	8,628† (37.4%)	7,834† (34.0%)	4,146 † (18.0%)	1,659† (7.2%)	808† (3.5%)
High (Greater than £52,000)	15,967† (96.8%)	530† (3.2%)	16,451† (99.7%)	46† (0.3%)	16,450† (99.7%)	47† (0.3%)	7,580 † (45.9%)	5,494 † (33.3%)	2,366 † (14.3%)	791† (4.8%)	266† (1.6%)
Crime (IMD score), mean (SD)	0.14* (±0.625)	0.24* (±0.66)	0.148* (±0.627)	0.317* (±0.648)	0.149 (±0.627)	0.21 (±0.65)	0.14 ‡ (±0.63)	0.14 ‡ (±0.62)	0.16 ‡ (±0.63)	0.17‡ (±0.63)	0.22 ‡ (±0.64)
Deprivation (Townsend Index), mean (SD)	-0.32* (±3.24)	0.302* (±3.46)	-0.293* (±3.26)	0.717* (±3.48)	-0.29* (±3.25)	0.60* (±3.65)	-0.335‡ (±3.21)	-0.34‡ (±3.27)	-0.22‡ (±3.27)	-0.18 ‡ (±3.28)	0.14 ‡ (±3.49)

Physical Activity (MET min/week)											
Low (< 600 MET min/week)	8,035† (91.7%)	729† (8.3%)	8,681† (99.1%)	83† (0.9%)	8,686† (99.1%)	78† (0.9%)	2,851† (32.5%)	2,868 † (32.7%)	1,656† (18.9%)	843† (9.6%)	546† (6.2%)
Moderate (≥ 600 to 2990 MET min/week)	24,426† (94.6%)	1,393† (5.4%)	25,722† (99.6%)	97† (0.4%)	25,680† (99.5%)	139† (0.5%)	10,030† (38.8%)	8,690† (33.7%)	4,460 † (17.3%)	1,738 † (6.7%)	901† (3.5%)
High (≥3000 MET min/week)	13,289† (94.9%)	717† (5.1%)	13,930† (99.5%)	76† (0.5%)	13,939† (99.5%)	67† (0.5%)	5,682 (40.6%)	4,598 † (32.8%)	2,380 † (17.0%)	931† (6.6%)	415 † (3.0%)
Annual average air quality for 2010 (PM2.5 µg/m3), mean (SD)	10.2* (±1.07)	10.3* (±1.10)	10.2 (±1.07)	10.4 (±1.15)	10.2 (±1.07)	10.3 (±1.06)	10.2 (±1.09)	10.2 (±1.07)	10.2 (±1.05)	10.2 (±1.06)	10.2 (±1.08)
Noise (day & evening 2009 - LAeq,16hr in Db), mean (SD)	54.1 (±4.68)	54.2 (±4.97)	54.1 (±4.70)	54.3 (±4.78)	54.1* (±4.70)	53.8* (±4.88)	54.1 (±4.71)	54.1 (±4.66)	54.0 (±4.65)	54.1 (±4.76)	54.2 (±4.96)
Total Green Space (%) - 100m, mean (SD)	7.93 (±18.5)	7.70 (±17.8)	7.93 (±18.5)	6.78 (±17.1)	7.92 (±18.5)	7.20 (±16.3)	7.73‡ (±18.4)	7.93‡ (±18.5)	8.15‡ (±18.6)	7.84‡ (±18.1)	8.82 ‡ (±19.2)
Total Green Space (%) - 300m, mean (SD)	11.7* (±16.5)	11.8* (±15.8)	11.7 (±16.5)	11.1 (±15.9)	11.7 (±16.5)	11.6 (±16.1)	11.4‡ (±16.4)	11.7‡ (±16.4)	11.8‡ (±16.4)	12.0 ‡ (±16.6)	13.1‡ (±17.4)
Total Green Space (%) - 1500m, mean (SD)	22.6 (±19.1)	22.5 (±19.0)	22.6 (±19.1)	22.8 (±18.5)	22.6 (±19.1)	23.4 (±21.1)	22.2‡ (±19.0)	22.6‡ (±19.0)	22.7‡ (±19.0)	23.3‡ (±19.9)	24.5‡ (±19.8)
Total Green Space (%) - 3000m, mean (SD)	27.2 (±20.3)	27.1 (±20.3)	27.1 (±20.3)	27.4 (±21.0)	27.1 (±20.3)	27.4 (±21.6)	26.7‡ (±20.2)	27.2‡ (±20.2)	27.2‡ (±20.2)	28.0‡ (±21.0)	29.3‡ (±21.1)
Park (presence within 300m) - yes	23,941† (93.9%)	1,560† (6.1%)	25,366 (99.5%)	135 (0.5%)	25,347 (99.4%)	130 (0.6%)	9,712 (38.1%)	8,471 (33.2%)	4,431 (17.4%)	1,857 (7.3%)	1,030 (4.0%)
Park (presence within 300m) - no	21,810† (94.5%)	1,279† (5.5%)	22,967 (99.5%)	121 (0.5%)	22,958 (99.4%)	154 (0.6%)	8,851 (38.3%)	7,685 (33.3%)	4,065 (17.6%)	1,655 (7.2%)	832 (3.6%)
Park (presence within 1500m) - yes	44,978† (94.1%)	2,808† (5.9%)	47,534 (99.5%)	252 (0.5%)	47,506 (99.4%)	280 (0.6%)	18,270 (38.2%)	15,879 (33.2%)	8,354 (17.5%)	3,441 (7.2%)	1,842 (3.9%)
Park (presence within 1500m) - no	772† (96.1%)	31† (3.9%)	799 (99.5%)	4 (0.5%)	799 (99.5%)	4 (0.5%)	293 (36.5%)	277 (34.5%)	142 (17.7%)	71 (8.8%)	20 (2.5%)
Distance to park (meters), mean (SD)	332 (±360)	317 (±324)	331 (±358)	324 (±315)	331 (±358)	330 (±360)	329 (±353)	331 (±360)	335 (±360)	345 (±390)	313 (±305)

Domestic Garden Space (%) - 300m, mean (SD)	33.4* (±14.8)	32.5* (±14.7)	33.3* (±14.8)	30.7* (±13.6)	33.3 (±14.8)	32.0 (±14.1)	33.2‡ (±14.7)	33.5 ‡ (±14.9)	33.6‡ (±14.7)	33.0 ‡ (±14.8)	32.4 ‡ (±14.5)
Domestic Garden Space (%) - 1000m, mean (SD)	27.6 (±11.3)	27.0 (±11.3)	27.6 (±11.3)	25.9 (±11.3)	27.6 (±11.3)	26.3 (±11.0)	27.5 (±11.2)	27.7 (±11.4)	27.7 (±11.2)	27.4 (±11.4)	26.9 (±11.3)
Tree Canopy Cover (%) - 300m, mean (SD)	22.9* (±18.4)	21.8* (±17.8)	22.9* (±18.4)	19.5* (±16.3)	22.9 (±18.4)	22.1 (±19.0)	22.5‡ (±18.2)	23.2‡ (±18.6)	22.9‡ (±18.4)	22.5‡ (±18.3)	23.3‡ (±18.7)
Tree Canopy Cover (%) - 1500m, mean (SD)	21.2* (±13.7)	20.3* (±13.5)	21.1 (±13.7)	19.6 (±13.0)	21.1 (±13.7)	20.4 (±14.1)	20.9 (13.6)	21.3 (±13.8)	21.2 (±13.6)	20.7 (±13.6)	22.5±
Blue Space (%) - 100m, mean (SD)	0.23 (±3.03)	0.20 (±2.74)	0.230 (±3.02)	0.00 (±0.00)	0.229 (±3.02)	0.20 (±1.82)	0.26 (±3.31)	0.22 (±2.97)	0.221 (±2.88)	0.12 (±1.58)	0.21 (±2.93)
Blue Space (%) - 300m, mean (SD)	0.54 (±3.34)	0.53 (±3.13)	0.54 (±3.33)	0.58 (±3.09)	0.539 (±3.33)	0.27 (±2.09)	0.59 (±3.53)	0.52 (±3.31)	0.531 (±3.19)	0.45 (±2.80)	0.43 (±2.91)
Blue Space (%) - 1000m, mean (SD)	1.02 (±1.90)	0.90 (±1.54)	1.02 (±1.88)	0.81 (±1.41)	1.02 (±1.88)	0.78 (±1.34)	1.06‡ (±1.97)	1.02‡ (±1.87)	0.98‡ (±1.81)	0.92‡ (±1.63)	0.93‡ (±1.85)
Blue Space (%) - 1500m, mean (SD)	1.31 (±2.87)	1.20 (±2.90)	1.30 (±2.88)	0.99 (±2.27)	1.31 (±2.88)	0.89 (±2.02)	1.37 ‡ (±2.96)	1.31‡ (±2.86)	1.24‡ (±2.80)	1.17‡ (±2.73)	1.15‡ (±2.77)
Blue Space (%) - 3000m, mean (SD)	1.55 (±2.34)	1.46 (±2.47)	1.54 (±2.35)	1.39 (±1.92)	1.54 (±2.35)	1.39 (±1.92)	1.61‡ (±2.38)	1.54‡ (±2.35)	1.49‡ (±2.29)	1.41‡ (±2.35)	1.40‡ (±2.24)
Distance to coast (miles), mean (SD)	45.4 (±12.8)	45.8 (±13.1)	45.4 (±12.8)	45.4 (±12.4)	45.4 (±12.8)	45.6 (±13.4)	45.4 ‡ (±12.8)	45.4 ‡ (±12.8)	45.3 ‡ (±12.6)	45.3‡ (±12.8)	46.6‡ (±13.2)
Green & Blue Space (%) - 100m, mean (SD)	0.17 (±3.31)	0.20 (±3.81)	0.17 (±3.35)	0 (±0.00)	0.172 (±3.33)	0.39 (±5.38)	0.185 ± (3.45)	0.180 (±3.44)	0.172 (±3.33)	0.129 (±2.56)	0.0855 (±2.72)
Green & Blue Space (%) - 300m, mean (SD)	1.30 (±7.00)	1.25 (±6.78)	1.30* (±6.98)	1.84* (±7.96)	1.30 (±6.97)	1.58 (±9.37)	1.32 (±6.99)	1.26 (±6.86)	1.34 (±7.12)	1.28 (±7.09)	1.31 (±7.26)
Green & Blue Space (%) - 1500m, mean (SD)	12.6 (±18.9)	12.5 (±18.9)	12.6 (±18.9)	12.2 (±18.9)	12.6 (±18.9)	12.2 (±19.8)	12.7 (±18.7)	12.4 (±18.7)	12.5 (±18.9)	12.8 (±19.8)	13.7 (±20.2)
Green & Blue Space (%) - 3000m, mean (SD)	23.0 ± (±22.0)	23.3 (±22.0)	23.0 (±22.0)	23.2 (±22.2)	23.0 (±22.0)	22.7 (±22.9)	23.0‡ (±21.8)	22.8‡ (±21.9)	22.8‡ (±22.0)	23.3 ‡ (±22.9)	25.0‡ (±23.2)

* Mann-Whitney U test p-value < 0.05
† Chi-squared test p-value < 0.05
‡ Kruskal-Wallis H test p-value < 0.05

6.2. Main analytical finings

6.2.1 Overview of strengths and directions of associations of covariates in fully adjusted models

Figures 15a-d show forest plots of regression effect estimates for the fully adjusted models between each green and blue space exposure metric with each multimorbidity outcome (cardio-metabolic, respiratory, mental and disease counts). The effect estimates and 95% Confidence Intervals (CI) for each covariate in the models can also be found in tables in Appendix XII. Overall, most green space exposure metrics (amount of total green space, amount of street tree canopy, amount of domestic garden space, and accessibility to park) showed no significant associations with any of the multimorbidity outcomes. Protective associations were observed for exposure to blue space with mental multimorbidity and complex multimorbidity (3 LTCs and 4+LTCs), more of which is discussed in detail in the following sections. Age, sex, income, ethnicity, physical activity, deprivation, and crime were all significant predictors of all multimorbidity outcomes. Irrespective of adjustment for green or blue spaces, the strongest associations with multimorbidity were observed for income, ethnicity, and physical activity. Particularly, low income and low physical activity were consistently associated with high odds of having respiratory, mental, and complex multimorbidity (3 LTCs and 4+ LTCs) (exact effect estimates can be found in Appendix XII). Participants of white ethnicity were consistently more likely than non-white participants to have respiratory and mental multimorbidity, but less likely to have cardio-metabolic multimorbidity. Higher crime and higher deprivation were consistently associated with higher odds of cardio-metabolic, respiratory, and complex multimorbidity (4+ LTCs), but were non-significant for mental and simple multimorbidity (2 LTCs). Higher air pollution concentrations were associated with slightly lower odds of cardio-metabolic multimorbidity across most regression models but were non-significant for respiratory multimorbidity and disease counts.

Figure 15a: Forest plots showing estimates for fully-adjusted regression models between exposure to amount of total green space with multimorbidity

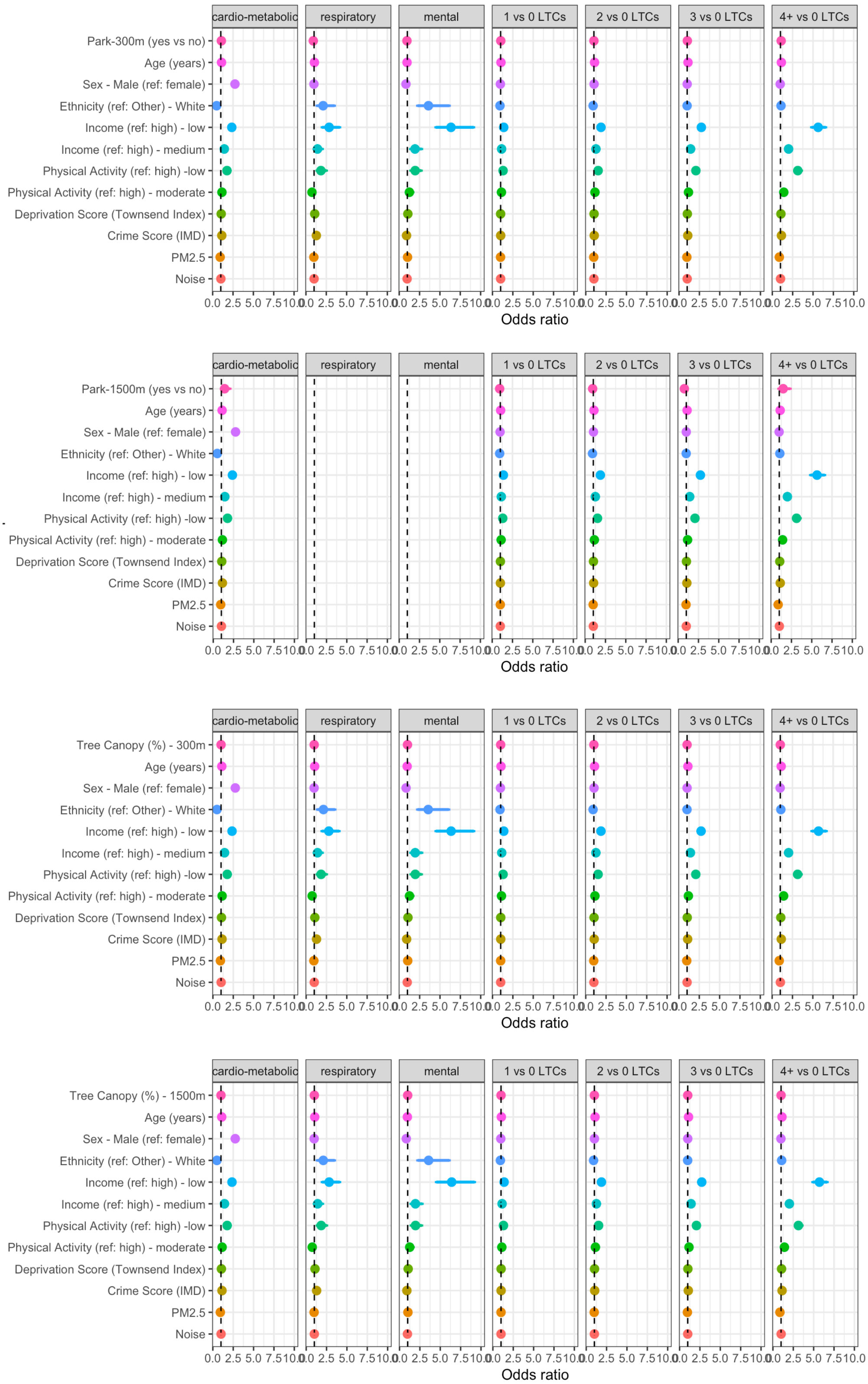

Figure 15b: Forest plots showing estimates for fully-adjusted regression models between exposure to presence of park and amount of street trees with multimorbidity

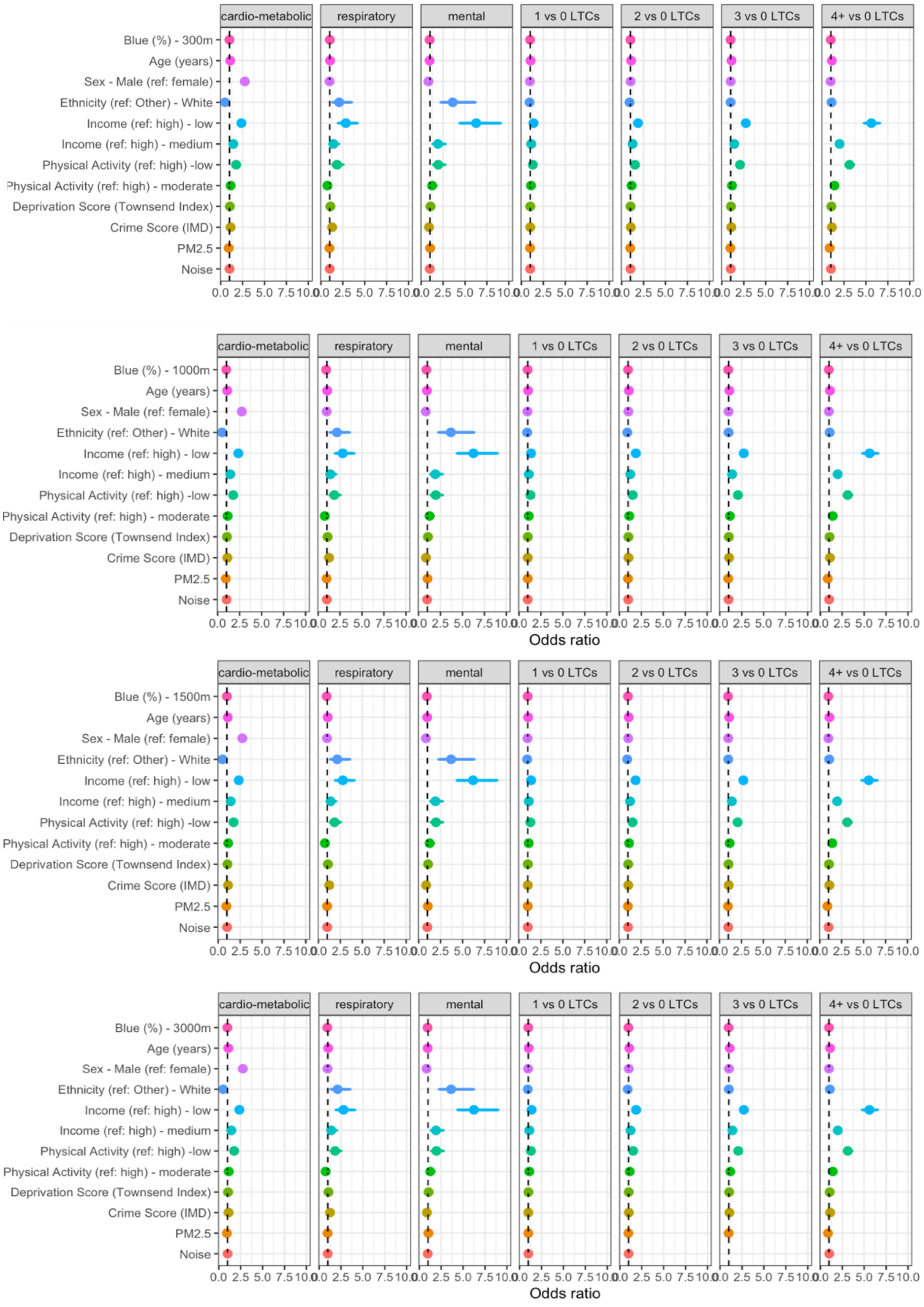

Figure 15c: Forest plots showing estimates for fully-adjusted regression models between exposure to amount of inland blue space with multimorbidity

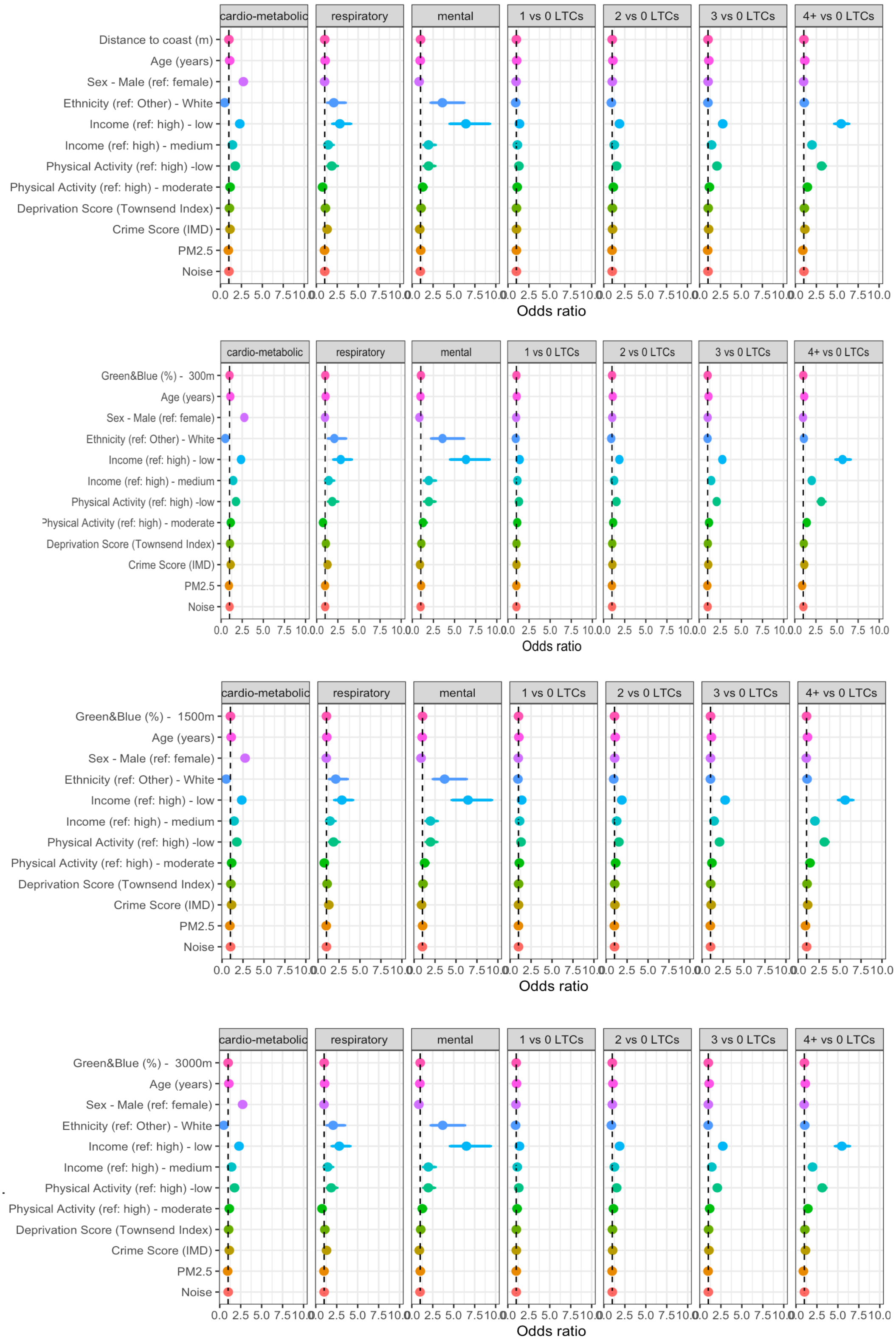

Figure 15d: Forest plots showing estimates for fully-adjusted regression models between exposure to amount of green and blue space and distance to coast with multimorbidity

6.2.2 Relationship between green and blue spaces with disease counts - simple and complex multimorbidity

Regression results for the associations between each green and blue space exposure metric with disease counts are displayed in table 12. Altogether, 19 separate multinomial regression analyses were analysed, each adjusted for age, sex, ethnicity, income, crime, deprivation, physical activity, air pollution, and noise. Significance level was assessed using a p-value with a cut-off point of 0.05 and 95% confidence intervals. Confounder effect estimates for each model can be found in Appendix XII.

No significant associations were observed for amount of total green space, accessibility to park, amount of street trees, amount of domestic garden space, distance to coast, and amount of green and blue space. However, exposure to amount of blue space in 3000m buffer around the residential address was associated with a slight reduction in the odds of having both simple and complex multimorbidity. Results showed that, for a 1% increase in the amount of blue space in 3000m buffer around the residential address (Blue Space (%) -3000m), the odds of having 2 LTCs, 3 LTCs and 4+ LTCs (relative to the odds of having 0 LTCs) decreased by 2% ($OR^{2\ LTCs\ vs\ 0\ LTCs}$: 0.98; CI: 0.97-0.99), 3% ($OR^{3\ LTCs\ vs\ 0\ LTCs}$: 0.97; CI: 0.95-0.98), and 3% ($OR^{4\ LTCs\ vs\ 0\ LTCs}$: 0.97; CI: 0.95-0.99), respectively (table 12). No significant associations were observed for amount of blue space in 300m buffer (Blue Space (%) -300m) and disease counts but having higher amount of blue space in 1000m (Blue Space (%) -1000m), and 1500m (Blue Space (%) -1000m) buffer around the residential address was associated with a decrease in the odds of having 3 LTCs (table 12). Specifically, for every 1 % increase in the amount of inland blue space in 1000m and 1500m buffer around the residential address, the odds of having 3 LTCs (relative to the odds of having 0 LTCs) decreased by 4% ($OR^{Blue1000}$: 0.96; CI: 0.94-0.99) and 2% ($OR^{Blue1500}$: 0.98; CI: 0.96-0.99), respectively (table 12). No significant associations were observed for amount of blue space in 1000m and 1500m buffers around the residential address and the odds of having 2 LTCs or 4+ LTCs (table 12)

Table 12: Results from regression analyses for the relationship between exposure to green and blue spaces with disease counts - simple and complex multimorbidity

Exposure Metrics	1 LTC (vs 0 LTCs)		2 LTCs (vs 0 LTCs)		3 LTCs (vs 0 LTCs)		4+ LTCs (vs 0 LTCs)	
	Fully Adjusted Model‖		Fully Adjusted Model‖		Fully Adjusted Model‖		Fully Adjusted Model‖	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Total Green Space (%) - 100m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Total Green Space (%) - 300m	**1.00§**	**(1.00 - 1.00)**	**1.00§**	**(1.00 - 1.00)**	**1.00§**	**(1.00 - 1.00)**	1.01	(1.00 - 1.01)
Total Green Space (%) - 1500m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	**1.00§**	**(1.00 - 1.01)**	1.01	(1.00 - 1.01)
Total Green Space (%) - 3000m	1.00	(1.00 - 1.00)	**1.00§**	**(1.00 - 1.00)**	**1.00§**	**(1.00 - 1.01)**	**1.01§**	**(1.00 - 1.01)**
Park (presence within 300m) - yes	1.02	(0.97 - 1.06)	1.00	(0.95 - 1.06)	1.02	(0.95 - 1.10)	1.09	(0.99 - 1.21)
Park (presence within 1500m) - yes	0.92	(0.77 - 1.09)	0.92	(0.75 - 1.14)	**0.76§**	**(0.58 - 1.00)**	1.46	(0.91 - 2.33)
Distance to park (m)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Domestic Garden Space (%) - 300m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)
Domestic Garden Space (%) - 1000m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Tree Canopy Cover (%) - 300m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)
Tree Canopy Cover (%) - 1500m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)
Blue Space (%) - 300m	1.00	(0.99 - 1.00)	1.00	(0.99 - 1.00)	0.99	(0.98 - 1.00)	0.99	(0.97 - 1.01)
Blue Space (%) - 1000m	0.99	(0.98 - 1.00)	**0.98§**	**(0.97 - 1.00)**	**0.96§**	**(0.94 - 0.99)**	**0.97§**	**(0.94 - 1.00)**
Blue Space (%) - 1500m	0.99	(0.99 - 1.00)	**0.99§**	**(0.98 - 1.00)**	**0.98§**	**(0.96 - 0.99)**	**0.98§**	**(0.96 - 1.00)**
Blue Space (%) - 3000m	0.99	(0.98 - 1.00)	**0.98§**	**(0.97 - 0.99)**	**0.97§**	**(0.95 - 0.98)**	**0.97§**	**(0.95 - 0.99)**
Distance to coast (m)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)
Green & Blue Space (%) - 300m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)
Green & Blue Space (%) - 1500m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)
Green & Blue Space (%) - 3000m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)

§ p-value < 0.05

‖ Models adjusted for: age, sex, ethnicity, income, crime, deprivation, physical activity, air quality and noise

6.2.3 Relationship between green and blue space with cardio-metabolic, respiratory, and mental multimorbidity

Regression results for the associations between each green and blue space exposure metric with cardio-metabolic, respiratory, and mental multimorbidity are displayed in table 13. Separate binomial regression analyses were run for each exposure metric and multimorbidity type. Each model was adjusted for age, sex, ethnicity, income, crime, deprivation, physical activity, air pollution and noise (table 13). Significance level was assessed using a p-value with a cut of point of 0.05 and 95% CI.

No significant associations were observed for amount of total green space, accessibility to park, amount of street trees, amount of domestic garden space, distance to coast, and amount of green and blue space with cardio-metabolic, respiratory, or mental multimorbidity. However, higher amount of blue space in 1000m, 1500m, and 3000m buffers around the residential address was associated with a decrease in the odds of having mental multimorbidity. Specifically, for a 1% increase in the amount of blue space in 1000m (Blue Space (%) - 1000m), 1500m (Blue Space (%) - 1500m), and 3000m (Blue Space (%) - 3000m) buffer around the residential address, the odds of having mental multimorbidity, relative to the odds having no mental multimorbidity, decreased by 10% ($OR^{Blue1000}$: 0.90; CI: 0.81-0.98), 8% ($OR^{Blue1500}$: 0.92; CI: 0.86-0.97), and 6% ($OR^{Blue3000}$: 0.94; CI: 0.88-0.99), respectively. Amount of blue space in 300m, 1000m, 1500m, or 3000m buffer did not affect the odds of having respiratory multimorbidity (table 13). However, for a 1% increase in the amount of blue space in a 1000m buffer around the residential address, the odds of having cardio-metabolic multimorbidity (relative to the odds of having no cardio-metabolic multimorbidity) decreased by 3% (OR: 0.97; CI: 0.95-0.99) (table 13).

Table 13: Results from regression analyses for the relationship between exposure to green and blue spaces with cardio-metabolic, respiratory and mental multimorbidity.

Exposure Metrics	Multimorbidity Type					
	Cardio-metabolic (yes vs no)		Respiratory (yes vs no)		Mental (yes vs no)	
	Fully Adjusted Models‖		Fully Adjusted Models‖		Fully Adjusted Models‖	
	OR	95% CI	OR	95% CI	OR	95% CI
Total Green Space (%) - 100m	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)	1.00	(0.99 - 1.00)
Total Green Space (%) - 300m	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)
Total Green Space (%) - 1500m	**1.00§**	**(1.00 - 1.00)**	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)
Total Green Space (%) - 3000m	**1.00§**	**(1.00 - 1.00)**	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)
Park (presence within 300m) - yes	1.07	(0.99 - 1.16)	0.95	(0.75 - 1.21)	0.90	(0.70 - 1.15)
Park (presence within 1500m) - yes	1.40	(0.98 - 2.08)				
Distance to park (m)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Domestic Garden Space (%) - 300m	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)
Domestic Garden Space (%) - 1000m	1.00	(0.99 - 1.00)	1.00	(0.98 - 1.01)	1.00	(0.99 - 1.01)
Tree Canopy Cover (%) - 300m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	0.99	(0.98 - 1.00)
Tree Canopy Cover (%) - 1500m	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)
Blue Space (%) - 300m	1.00	(0.99 - 1.01)	1.01	(0.96 - 1.04)	0.96	(0.89 - 1.01)
Blue Space (%) - 1000m	**0.97§**	**(0.95 - 0.99)**	0.92	(0.84 - 1.00)	**0.90§**	**(0.81 - 0.98)**
Blue Space (%) - 1500m	0.99	(0.97 - 1.00)	0.94	(0.89 - 1.00)	**0.92§**	**(0.86 - 0.97)**
Blue Space (%) - 3000m	0.98	(0.97 - 1.00)	0.95	(0.89 - 1.01)	**0.94§**	**(0.88 - 0.99)**
Distance to coast (m)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)
Green&Blue Space (%) - 300m	1.00	(0.99 - 1.01)	1.01	(0.99 - 1.02)	1.01	(0.99 - 1.02)
Green&Blue Space (%) - 1500m	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.00)
Green&Blue Space (%) - 3000m	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.00)

§ **p-value < 0.05**

‖ Models adjusted for: age, sex, ethnicity, income, crime, deprivation, physical activity, air quality and noise

6.3. Modification by physical activity

6.3.1 Disease counts - simple and complex multimorbidity

To assess the moderating effect of physical activity on the relationship between exposure to green and blue spaces with disease counts, interaction terms for each green and blue space exposure metric with physical activity were added to the fully adjusted models (table 14). If the interaction terms were significant, full model results were displayed in tables 15a-b.

Table 14 shows the effect estimates for each green and blue space exposure metric before and after adjustment for an interaction term between the green/blue space exposure metrics with physical activity. Adding an interaction term to the fully adjusted models did not alter the magnitude or significance of the exposure effect estimates for most models (table 14). Adding a physical activity interaction term to amount of blue space in 1500m and 3000m buffer slightly reduced the odds of having 3 LTCs for a 1% increase in amount of blue space in 1500m and 3000m buffers ($OR^{Blue15000}$: 0.95; 95% CI: 0.92-0.98; $OR^{Blue3000}$: 0.93; 95% CI: 0.90-0.97), respectively (table 14).

Significant interaction terms with physical activity were only observed for amount of blue space in 300m buffer and amount of blue space in a 3000m buffer (tables 15a and 15b). For every 1% increase in the amount of blue space in a 300m buffer, the odds of having complex multimorbidity (4+ LTCs) for individuals with moderate physical activity levels (relative to individuals with high physical activity levels) increased by 36% *($OR^{(Physical\ Activity\ -\ moderate)}$ 1.45 x $OR^{(Blue\ Space\ (\%)\ -\ 300m*Physical\ Activity\ -\ moderate)}$ 0.94 = 1.36)* (table 15a). Furthermore, for every 1% increase in the amount of blue space in a 3000m buffer, the odds of having 3 LTCs for individuals with moderate physical activity levels (relative to individuals with high physical activity levels) increased by 14% *($OR^{(Physical\ Activity\ -\ moderate)}$ 1.09 x $OR^{(Blue\ Space\ (\%)\ -\ 3000m*Physical\ Activity\ -\ moderate)}$ 1.05= 1.14)* (table 15b). However, the effect of physical activity on 3 LTCs ($OR^{3\ LTCs\ vs\ 0\ LTCs}$: 1.09) was not significant (p-value > 0.05) (table 15b).

Table 14: Results from regression analyses for the relationship between exposure to green and blue spaces with disease counts (simple and complex multimorbidity) with presence and absence of interaction terms with physical activity

Exposure Metrics	1 LTC (vs 0 LTCs)				2 LTCs (vs 0 LTCs)				3 LTCs (vs 0 LTCs)				4+ LTCs (vs 0 LTCs)			
	Fully Adjusted Model[ǁ]		Fully Adjusted Model + interaction[¶]		Fully Adjusted Model[ǁ]		Fully Adjusted Model + interaction[¶]		Fully Adjusted Model[ǁ]		Fully Adjusted Model + interaction[¶]		Fully Adjusted Model[ǁ]		Fully Adjusted Model + interaction	
	OR	95% CI	OR	95% CI	OR	95% CI		95% CI	OR	95% CI		95% CI	OR	95% CI	OR	95% CI
Total Green Space (%) - 100m	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(0.99-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.01)
Total Green Space (%) - 300m	**1.00[§]**	**(1.00-1.00)**	1.00	(1.00-1.00)	**1.00[§]**	**(1.00-1.00)**	1.00	(1.00-1.00)	**1.00[§]**	**(1.00-1.00)**	1.00	(1.00-1.01)	1.01	(1.00-1.01)	**1.01[**]**	**(1.00-1.01)**
Total Green Space (%) - 1500m	1.00	(1.00-1.00)	1.00	(1.00-1.00)	**1.00[§]**	**(1.00-1.00)**	1.00	(1.00-1.00)	**1.00[§]**	**(1.00-1.01)**	1.00	(1.00-1.01)	1.01	(1.00-1.01)	**1.01[**]**	**(1.00-1.01)**
Total Green Space (%) - 3000m	1.00	(1.00-1.00)	1.00	(1.00-1.00)	**1.00[§]**	**(1.00-1.00)**	1.00	(1.00-1.00)	**1.00[§]**	**(1.00-1.01)**	1.00	(1.00-1.01)	**1.01[§]**	**(1.00-1.01)**	**1.01[**]**	**(1.00-1.01)**
Park (presence within 300m) - yes	1.02	(0.97-1.06)	1.01	(0.93-1.09)	1.00	(0.95-1.06)	0.98	(0.89-1.08)	1.02	(0.95-1.10)	1.01	(0.88-1.17)	1.09	(0.99-1.21)	1.10	(0.89-1.35)
Distance to park (m)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)
Domestic Garden Space (%) - 300m	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.01)	1.00	(0.99-1.01)
Domestic Garden Space (%) - 1000m	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.00)	0.99	(0.98-1.00)

Tree Canopy Cover (%) - 300m	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.01)
Tree Canopy Cover (%) - 1500m	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.01)	1.00	(1.00-1.01)
Blue Space (%) - 300m	1.00	(0.99-1.00)	0.99	(0.98-1.01)	1.00	(0.99-1.00)	0.99	(0.98-1.01)	0.99	(0.98-1.00)	0.99	(0.97-1.01)	0.99	(0.97-1.01)	**1.00****	**(0.97-1.03)**
Blue Space (%) - 1000m	0.99	(0.98-1.00)	1.00	(0.97-1.02)	**0.98§**	**(0.97-1.00)**	0.99	(0.96-1.02)	**0.96§**	**(0.94-0.99)**	0.95	(0.91-1.00)	**0.97§**	**(0.94-1.00)**	0.96	(0.89-1.02)
Blue Space (%) - 1500m	0.99	(0.99-1.00)	0.99	(0.98-1.01)	**0.99§**	**(0.98-1.00)**	1.00	(0.98-1.02)	**0.98§**	**(0.96-0.99)**	0.95§	(0.92-0.98)	**0.98§**	**(0.96-1.00)**	0.97	(0.93-1.01)
Blue Space (%) - 3000m	0.99	(0.98-1.00)	0.99	(0.97-1.01)	**0.98§**	**(0.97-0.99)**	0.99	(0.97-1.02)	**0.97§**	**(0.95-0.98)**	0.93§	(0.90-0.97)	**0.97§**	**(0.95-0.99)**	**0.96****	**(0.92-1.01)**
Distance to coast (m)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(0.99-1.00)	1.00	(1.00-1.01)	1.01	(1.00-1.01)
Green&Blue Space (%) - 300m	1.00	(1.00-1.00)	1.00	(0.99-1.00)	1.00	(1.00-1.00)	1.00	(0.99-1.01)	1.00	(1.00-1.01)	1.00	(0.99-1.01)	1.00	(0.99-1.01)	1.00	(0.99-1.01)
Green&Blue Space (%) - 1500m	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	**1.00§**	**(1.00-1.01)**	1.00	(1.00-1.01)
Green&Blue Space (%) - 3000m	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.00)	1.00	(1.00-1.01)	1.00	(1.00-1.01)

‖ Models adjusted for: age, sex, ethnicity, income, crime, deprivation, physical activity, air quality and noise
¶Model adjusted for: age, sex, ethnicity, income, crime, deprivation, physical activity, air quality and noise + green/blue space exposure metric*physical activity interaction term
§ p-value < 0.05
**** interaction term p-value < 0.05 (see tables 15 (a-b))**

Table 15a: Results from regression analyses for the relationship between exposure to blue space in 300m buffer with disease counts (simple and complex multimorbidity) with presence of an interaction term with physical activity

	1 LTC (vs 0 LTCs)			2 LTCs (vs 0 LTCs)			3 LTCs (vs 0 LTCs)			4+ LTCs (vs 0 LTCs)		
	Odds Ratio	95% CI		Odds Ratio	95% CI		Odds Ratio	95% CI		Odds Ratio	95% CI	
Blue Space (%) - 300m	0.99	(0.98 -	1.01)	0.99	(0.98 -	1.01)	0.99	(0.97 -	1.01)	1.00	(0.97 -	1.03)
Age (years)	**1.04§**	**(1.04 -**	**1.04)**	**1.08§**	**(1.07 -**	**1.08)**	**1.10§**	**(1.09 -**	**1.11)**	**1.11§**	**(1.10 -**	**1.12)**
Sex												
Female	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref
Male	0.97	(0.93 -	1.01)	1.02	(0.96 -	1.07)	1.00	(0.93 -	1.08)	0.97	(0.88 -	1.08)
Income												
High (£52,000 and over)	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref
Medium (£18,000- £51,999)	**1.12§**	**(1.07 -**	**1.18)**	**1.25§**	**(1.17 -**	**1.33)**	**1.41§**	**(1.29 -**	**1.55)**	**1.99§**	**(1.72 -**	**2.31)**
Low (Less than £18,000)	**1.38§**	**(1.28 -**	**1.47)**	**1.87§**	**(1.72 -**	**2.03)**	**2.73§**	**(2.44 -**	**3.05)**	**5.61§**	**(4.80 -**	**6.55)**
Ethnicity												
Other	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref
White	**0.93§**	**(0.86 -**	**0.99)**	**0.90§**	**(0.82 -**	**0.98)**	0.99	(0.88 -	1.12)	1.08	(0.92 -	1.26)
Physical Activity (MET min/week)												
High (≥3000 MET min/week)	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref
Moderate (≥ 600 to 2990 MET min/week)	**1.10§**	**(1.05 -**	**1.16)**	**1.13§**	**(1.06 -**	**1.20)**	**1.16§**	**(1.06 -**	**1.26)**	**1.45§**	**(1.28 -**	**1.64)**
Low (< 600 MET min/week)	**1.30§**	**(1.22 -**	**1.39)**	**1.52§**	**(1.40 -**	**1.64)**	**2.08§**	**(1.86 -**	**2.31)**	**3.11§**	**(2.70 -**	**3.58)**

Crime Score (IMD)	**1.01**	**(0.97 -**	**1.04)**	**1.04**	**(0.99 -**	**1.09)**	**1.07**	**(1.00 -**	**1.14)**	**1.12**	**(1.02 -**	**1.22)**
Deprivation Score (Townsend Index)	**1.01§**	**(1.00 -**	**1.01)**	**1.02§**	**(1.01 -**	**1.03)**	**1.03§**	**(1.01 -**	**1.04)**	**1.06§**	**(1.04 -**	**1.08)**
PM2.5 (µg/m3)	0.99	(0.97 -	1.02)	0.98	(0.95 -	1.01)	0.96	(0.92 -	1.01)	0.86	(0.81 -	0.91)
Noise (LAeq,16hr in Db)	1.00	(0.99 -	1.00)	1.00	(0.99 -	1.00)	1.00	(0.99 -	1.01)	**1.01§**	**(1.00 -**	**1.02)**
Interaction term												
Blue Space (%) - 300m*Physical Activity - High (≥3000 MET min/week)	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref
Blue Space (%) - 300m* Physical Activity - Moderate (≥ 600 to 2990 MET min/week)	1.00	(0.99 -	1.02)	1.00	(0.99 -	1.02)	1.00	(0.97 -	1.03)	**0.94§**	**(0.89 -**	**0.98)**
Blue Space (%) - 300m*Physical Activity - Low (< 600 MET min/week)	1.00	(0.98 -	1.02)	1.01	(0.98 -	1.03)	0.98	(0.94 -	1.03)	1.01	(0.97 -	1.06)

§ p-value < 0.05

Table 15b: Results from regression analyses for the relationship between exposure to blue space in 3000m buffer with disease counts (simple and complex multimorbidity) with presence of an interaction term with physical activity

	1 LTC (vs 0 LTCs)			2 LTCs (vs 0 LTCs)			3 LTCs (vs 0 LTCs)			4+ LTCs (vs 0 LTCs)		
	Odds Ratio	95% CI		Odds Ratio	95% CI		Odds Ratio	95% CI		Odds Ratio	95% CI	
Blue Space (%) - 3000m	0.99	(0.97 -	1.01)	0.99	(0.97 -	1.01)	**0.93§**	**(0.90 -**	**0.97)**	0.96	(0.92 -	1.01)
Age (years)	**1.04§**	**(1.04 -**	**1.04)**	**1.08§**	**(1.07 -**	**1.08)**	**1.10§**	**(1.09 -**	**1.11)**	**1.11§**	**(1.10 -**	**1.12)**
Sex												
Female	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref
Male	0.97	(0.93 -	1.01)	1.02	(0.96 -	1.07)	1.00	(0.93 -	1.08)	0.98	(0.88 -	1.08)
Income												
High (£52,000 and over)	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref
Medium (£18,000- £51,999)	**1.12§**	**(1.07 -**	**1.18)**	**1.24§**	**(1.17 -**	**1.32)**	**1.41§**	**(1.28 -**	**1.54)**	**5.58§**	**(4.78 -**	**6.52)**
Low (Less than £18,000)	**1.38§**	**(1.28 -**	**1.47)**	**1.86§**	**(1.72 -**	**2.02)**	**2.71§**	**(2.43 -**	**3.03)**	**1.99§**	**(1.72 -**	**2.30)**
Ethnicity												
Other	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref
White	**0.93§**	**(0.87 -**	**0.99)**	**0.90§**	**(0.83 -**	**0.98)**	1.00	(0.88 -	1.13)	1.08	(0.92 -	1.27)
Physical Activity (MET min/week)												
High (≥3000 MET min/week)	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref	ref
Moderate (≥ 600 to 2990 MET min/week)	**1.10§**	**(1.04 -**	**1.17)**	**1.50§**	**(1.37 -**	**1.65)**	1.09	(0.98 -	1.21)	**1.45§**	**(1.25 -**	**1.67)**
Low (< 600 MET min/week)	**1.31§**	**(1.21 -**	**1.41)**	**1.17§**	**(1.09 -**	**1.26)**	**1.92§**	**(1.70 -**	**2.18)**	**2.92§**	**(2.48 -**	**3.45)**

Crime Score (IMD)	1.00	(0.97 -	1.04)	1.03	(0.98 -	1.08)	1.06	(0.99 -	1.13)	**1.11§**	**(1.01 -**	**1.21)**
Deprivation Score (Townsend Index)	**1.01§**	**(1.00 -**	**1.02)**	**1.02§**	**(1.01 -**	**1.04)**	**1.03§**	**(1.01 -**	**1.04)**	**1.06§**	**(1.04 -**	**1.08)**
PM2.5 (µg/m3)	1.00	(0.97 -	1.03)	0.98	(0.95 -	1.02)	0.98	(0.93 -	1.02)	0.87	(0.82 -	0.93)
Noise (LAeq,16hr in Db)	1.00	(0.99 -	1.00)	1.00	(0.99 -	1.00)	1.00	(0.99 -	1.01)	1.01§	(1.00 -	1.02)
Interaction term												
Blue Space (%) - 3000m*Physical Activity - High (≥3000 MET min/week)	ref	ref	ref	ref	ref	Ref	ref	ref	ref	ref	ref	ref
Blue Space (%) - 3000m* Physical Activity - Moderate (≥ 600 to 2990 MET min/week)	1.00	(0.98 -	1.02)	0.98	(0.95 -	1.00)	**1.05§**	**(1.01 -**	**1.09)**	0.99	(0.93 -	1.05)
Blue Space (%) - 3000m*Physical Activity - Low (< 600 MET min/week)	1.00	(0.97 -	1.03)	1.01	(0.98 -	1.04)	**1.06§**	**(1.00 -**	**1.11)**	1.05	(0.99 -	1.12)

§ p-value < 0.05

6.3.2 Cardio-metabolic, respiratory and mental multimorbidity

To assess the moderating effect of physical activity on the relationships between exposure to green and blue spaces with cardio-metabolic, respiratory, and mental multimorbidity, interaction terms for each exposure metric with physical activity were added to the fully adjusted models (table 16). Confounder effect estimates for each model can be found in Appendix XII. Only the interaction term between amount of blue space in 3000m buffer around the residential address and physical activity for mental multimorbidity was significant (table 16 and table 17).

Adding an interaction term to the fully adjusted models did not alter the magnitude or significance of the exposure effect estimates for most multimorbidity outcomes (table 16). After adding an interaction term with physical activity, the odds of having mental multimorbidity also decreased by 28% for a 1% increase in amount of blue space in 300m and 1000m buffer, respectively ($OR^{Blue300:}$ 0.72; 95% CI: 0.24-0.99) and 18% ($OR^{Blue1000:}$: 0.82; 95% CI: 0.63-0.99) (table 16).

A significant interaction term with physical activity was only observed with blue space in a 3000m buffer for mental multimorbidity (table 17). For a 1% increase in the amount of blue space in a 3000m buffer, the odds of having mental multimorbidity for individuals with moderate physical activity levels (compared to individuals with high physical activity levels) increased by 20% *(OR $^{(Physical\ Activity\ -\ moderate)}$ 1.39 x OR $^{(Blue\ Space\ (\%)\ -\ 3000m*Physical\ Activity\ -\ moderate)}$ 0.86= 1.20)* (table 17). No significant interaction terms were found for low physical activity.

Table 16: Results from regression analyses for the relationship between exposure to green and blue spaces with cardio-metabolic, respiratory, and mental multimorbidity with presence of an interaction term with physical activity

Exposure Metrics	Cardio-metabolic (yes vs no)				Respiratory (yes vs no)				Mental (yes vs no)			
	Fully Adjusted Model[‖]		Fully Adjusted Model + interaction[¶]		Fully Adjusted Model[‖]		Fully Adjusted Model + interaction[¶]		Fully Adjusted Model[‖]		Fully Adjusted Model + interaction[¶]	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Total Green Space (%) - 100m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)	0.99	(0.80 - 1.01)	1.00	(0.99 - 1.00)	0.99	(0.98 - 1.01)
Total Green Space (%) - 300m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.01)	1.00	(0.99 - 1.01)	0.99	(0.97 - 1.01)
Total Green Space (%) - 1500m	**1.00[§]**	**(1.01 - 1.00)**	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)
Total Green Space (%) - 3000m	**1.00[§]**	**(1.01 - 1.00)**	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.01)
Park (presence within 300m) - yes	1.07	(0.99 - 1.16)	1.16	(0.99 - 1.35)	0.95	(0.75 - 1.21)	0.88	(0.56 - 1.39)	0.9	(0.70 - 1.15)	1.24	(0.76 - 2.05)
Distance to park (m)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Domestic Garden Space (%) - 300m	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)	1.00	(0.99 - 1.01)	0.99	(0.98 - 1.01)	1.00	(0.99 - 1.01)	1.01	(0.99 - 1.03)
Domestic Garden Space (%) - 1000m	1.00	(0.99 - 1.00)	1.00	(0.99 - 1.00)	1.00	(0.98 - 1.01)	0.99	(0.97 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.02)
Tree Canopy Cover (%) - 300m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	0.99	(0.98 - 1.00)	0.99	(0.98 - 1.00)	1.00	(0.98 - 1.01)
Tree Canopy Cover (%) - 1500m	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.01)	1.00	(0.99 - 1.01)	0.99	(0.97 - 1.01)
Blue Space (%) - 300m	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.03)	1.01	(0.96 - 1.04)	1.02	(0.95 - 1.06)	0.96	(0.89 - 1.01)	**0.72[§]**	**(0.24 - 0.99)**
Blue Space (%) - 1000m	**0.97[§]**	**(0.95 - 0.99)**	0.96	(0.90 - 1.01)	0.92	(0.84 - 1.00)	0.96	(0.80 - 1.01)	**0.90[§]**	**(0.81 - 0.98)**	**0.82[§]**	**(0.63 - 0.99)**
Blue Space (%) - 1500m	0.99	(0.97 - 1.00)	0.98	(0.95 - 1.01)	0.94	(0.89 - 1.00)	0.96	(0.86 - 1.04)	**0.92[§]**	**(0.86 - 0.97)**	0.93	(0.82 - 1.03)
Blue Space (%) - 3000m	0.98	(0.97 - 1.00)	0.97	(0.93 - 1.00)	0.95	(0.89 - 1.01)	0.96	(0.85 - 1.06)	**0.94[§]**	**(0.88 - 0.99)**	**1.00**[**]	**(0.89 - 1.09)**

Distance to coast (m)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)	0.96	(0.85 - 1.06)	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.02)
Green&Blue Space (%) - 300m	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)	1.01	(0.99 - 1.02)	1.01	(0.99 - 1.03)	1.01	(0.99 - 1.02)	1.00	(0.99 - 1.03)
Green&Blue Space (%) - 1500m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.01)	1.00	(0.99 - 1.00)	1.00	(0.99- 1.01)
Green&Blue Space (%) - 3000m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.00)	1.00	(0.99 - 1.01)

[ll] Models adjusted for: age, sex, ethnicity, income, crime, deprivation, physical activity, air quality and noise

[¶]Models adjusted for: age, sex, ethnicity, income, crime, deprivation, physical activity, air quality and noise + green/blue space exposure metric*physical activity interaction term

[§] p-value < 0.05

**** interaction term p-value < 0.05 (see table 17)**

Table 17: Results from regression analyses for the relationship between exposure to blue space in 3000m buffer with mental multimorbidity with presence of an interaction term with physical activity

	Mental Multimorbidity (yes vs no)		
	Odds Ratio	95% CI	
Blue Space (%) - 3000m	1.00	(0.89 -	1.09)
Age (years)	0.96	(0.95 -	0.97)
Sex			
Female	ref	ref	ref
Male	0.84	(0.66 -	1.06)
Income			
High (£52,000 and over)	ref	ref	
Medium (£18,000- £51,999)	**1.91§**	**(1.36 -**	**2.72)**
Low (Less than £18,000)	**6.18§**	**(4.36 -**	**8.90)**
Ethnicity			
Other	ref		ref
White	**3.64§**	**(2.27 -**	**6.24)**
Physical Activity (MET min/week)			
High (≥3000 MET min/week)	ref	ref	ref
Moderate (≥ 600 to 2990 MET min/week)	**1.39§**	**(1.08 -**	**2.19)**
Low (< 600 MET min/week)	**2.00§**	**(1.34 -**	**2.97)**
Crime Score (IMD)	0.87	(0.71 -	1.07)
Deprivation Score (Townsend Index)	**1.07§**	**(1.02 -**	**1.12)**
PM2.5 (µg/m3)	1.05	(0.91 -	1.21)
Noise (LAeq,16hr in Db)	0.97	(0.95 -	1.00)
Interaction term			
Blue Space (%) - 3000m*Physical Activity - High (≥3000 MET min/week)	ref	ref	ref
Blue Space (%) - 3000m* Physical Activity - Moderate (≥ 600 to 2990 MET min/week)	**0.86§**	**(0.75 -**	**0.99)**
Blue Space (%) - 3000m*Physical Activity - Low (< 600 MET min/week)	0.99	(0.86 -	1.14)

§ p-value < 0.05

6.4. Stratification by income

6.4.1 Disease counts - simple and complex multimorbidity

Tables 18a-b show the effect estimates for each exposure metric with disease counts (simple and complex multimorbidity) stratified by income group. Models were adjusted for age, sex, physical activity, crime, deprivation, air quality and noise (table 18a-b). No significant associations were observed across income strata for exposure to amount of total green space, accessibility to park, amount of street trees, amount of domestic garden space, distance to coast, and amount of green and blue space with simple multimorbidity (2 LTCs) (table 18a). Significant associations were observed for exposure to higher amount of blue space with the odds of 2 LTCs in individuals of medium income. Specifically, the odds of having 2 LTCs in individuals with medium income (£18,000- £51,999) (relative to the odds of having 0 LTCs in individuals with medium income) decreased by 6% ($OR^{Blue1000}$: 0.94; 95% CI: 0.92-0.97), 3% ($OR^{Blue1500}$: 0.97; 95% CI: 0.95-0.98), and 4% ($OR^{Blue3000}$: 0.96; 95% CI: 0.94-0.98), respectively, for a 1% increase in the amount of blue space in a 1000m, 1500m, and 3000m buffer around the residential address (table 18a). No evidence of significant associations were observed between exposure to blue space and 2 LTCs for individuals of low or high incomes (table 18a).

No significant associations were observed across income strata for exposure to amount of total green space, amount of street trees, amount of private garden space, distance to coast, and amount of green and blue space with complex multimorbidity (3 or 4+ LTCs) (table 18b). The odds of having 4+ LTCs in individuals of low income increased by 25% (OR: $1.25^{4+ \text{ vs } 0 \text{ LTCs}}$; 95% CI: 1.05-1.48) with presence of a park in 300m of the residential address (table 18b).

Protective associations with amount of blue space and complex multimorbidity (3 or 4+ LTCs) were only observed for individuals of medium and high income but not for individuals of low income (table 18b). The odds having 3 LTCs in individuals of medium income decreased by 4% (OR: $0.96^{Blue3000}$; 95% CI: 0.93-0.98) for a 1 % increase in the amount of blue space in a 3000m buffer around the residential address. The odds of having 3 LTCs in individuals of high income also decreased by 5% (OR: $0.95^{Blue1000}$; 95% CI: 0.91-0.99) for every 1% increase in the amount of blue space in a 1000m buffer around the residential address (table 18b).

The odds of having 4+ LTCs in individuals of medium income decreased by 7% ($OR^{Blue1000}$: 0.93; 95% CI: 0.89-0.98) and 4% ($OR^{Blue3000}$: 0.96; 95% CI: 0.93-0.99), respectively, for a 1% increase in the amount of blue space in 1000m, and 3000m buffer around the residential address. On the other hand, the odds of having 4+ LTCs in individuals of high income decreased by 11% (OR: $0.89^{Blue1000}$; 95% CI: 0.82-0.97), 6% (OR: $0.94^{Blue15000}$; 95% CI: 0.89-0.99), and 8% (OR: $0.92^{Blue3000}$; 95% CI: 0.87-0.99), respectively, for every 1% increase in the amount of blue space in 1000m, 1500m, and 3000m buffer around the residential address (table 18b).

Proximity to coast was associated with an increase in the odds of having complex multimorbidity in individuals of low income but not individuals of medium or high income (table 18b). For a 1-mile increase in the distance between the coastal area and the residential address, the odds of having 4+ LTCs individuals of low income increased by 1% ($OR^{4+ \text{ vs } 0 \text{ LTCs}}$: 1.01; 95% CI: 1.01-1.02). No significant associations were observed between distance to coast and disease count in individuals of medium or high income.

Table 18a: Income stratified regression results for the relationship between exposure to green and blue spaces with simple multimorbidity (2 LTCs)

Exposure Metrics	1 LTC (vs 0 LTCs)						2 LTCs (vs 0 LTCs)					
	Income Level						Income Level					
	Low (Less than £18,000) [‖]		Medium (£18,000-£51,999) [‖]		High (£52,000 and over) [‖]		Low (Less than £18,000) [‖]		Medium (£18,000-£51,999) [‖]		High (£52,000 and over) [‖]	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Total Green Space (%) - 100m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Total Green Space (%) - 300m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Total Green Space (%) - 1500m	1.00	(1.00 - 1.00)	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)
Total Green Space (%) - 3000m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Park (presence within 300m) - yes	1.05	(0.94 - 1.18)	0.99	(0.93 - 1.06)	1.04	(0.97 - 1.11)	1.10	(0.97 - 1.24)	0.96	(0.89 - 1.04)	1.01	(0.92 - 1.11)
Distance to park (m)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Domestic Garden Space (%) - 300m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Domestic Garden Space (%) - 1000m	0.99	(0.98 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	0.99	(0.99 - 1.00)	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.00)
Tree Canopy Cover (%) - 300m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Tree Canopy Cover (%) - 1500m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Blue Space (%) - 300m	0.99	(0.97 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.00)	1.01	(0.99 - 1.03)	0.99	(0.98 - 1.00)	1.00	(0.99 - 1.01)

Blue Space (%) - 1000m	1.00	(0.97 - 1.04)	0.98	(0.97 - 1.00)	1.00	(0.98 - 1.02)	**1.04**[§]	**(1.00 - 1.07)**	**0.94**[§]	**(0.92 - 0.97)**	1.00	(0.98 - 1.02)
Blue Space (%) - 1500m	1.00	(0.98 - 1.02)	0.99	(0.98 - 1.00)	0.99	(0.98 - 1.01)	1.01	(0.99 - 1.03)	**0.97**[§]	**(0.95 - 0.98)**	0.99	(0.98 - 1.01)
Blue Space (%) - 3000m	1.00	(0.98 - 1.03)	0.98	(0.97 - 1.00)	1.00	(0.98 - 1.01)	1.10	(0.99 - 1.04)	**0.96**[§]	**(0.94 - 0.98)**	1.00	(0.98 - 1.02)
Distance to coast (m)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)
Green&Blue Space (%) - 300m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)	**1.01**[§]	**(1.00 - 1.02)**	1.00	(0.99 - 1.00)	1.00	(1.00 - 1.01)
Green&Blue Space (%) - 1500m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Green&Blue Space (%) - 3000m	1.00	(0.99 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)

[§] **p-value < 0.05**

[‖] Models adjusted for: age, sex, ethnicity, income, crime, deprivation, physical activity, air quality and noise

Table 18b: Income stratified regression results for the relationship between exposure to green and blue spaces with complex multimorbidity (3 and 4+ LTCs)

Exposure Metrics	3 LTCs (vs 0 LTCs)						4+ LTCs (vs 0 LTCs)					
	Income Level						Income Level					
	Low (Less than £18,000) ǁ		Medium (£18,000-£51,999) ǁ		High (£52,000 and over)) ǁ		Low (Less than £18,000) ǁ		Medium (£18,000-£51,999) ǁ		High (£52,000 and over) ǁ	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Total Green Space (%) - 100m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)
Total Green Space (%) - 300m	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)	1.01	(1.00 - 1.01)	1.01	(1.00 - 1.01)	1.01	(1.00 - 1.02)
Total Green Space (%) - 1500m	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)	1.01	(1.00 - 1.01)	1.01	(1.00 - 1.01)	1.01	(1.00 - 1.02)
Total Green Space (%) - 3000m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)	1.01	(1.00 - 1.01)	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.01)
Park (presence within 300m) - yes	1.01	(0.87 - 1.18)	1.03	(0.92 - 1.14)	1.05	(0.90 - 1.22)	**1.25§**	**(1.05 - 1.48)**	1.07	(0.92 - 1.24)	0.89	(0.69 - 1.14)
Distance to park (m)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Domestic Garden Space (%) - 300m	**0.99§**	**(0.99 - 1.00)**	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)	0.99	(0.99 - 1.00)	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.01)
Domestic Garden Space (%) - 1000m	0.99	(0.98 - 1.00)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)	0.99	(0.98 - 1.00)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.02)
Tree Canopy Cover (%) - 300m	1.00	(0.99 - 1.00)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)
Tree Canopy Cover (%) - 1500m	**0.99§**	**(0.99 - 1.00)**	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.00)	1.00	(0.99 - 1.01)
Blue Space (%) - 300m	1.01	(0.98 - 1.04)	0.98	(0.96 - 1.00)	0.99	(0.97 - 1.01)	1.01	(0.98 - 1.04)	0.97	(0.94 - 1.00)	0.99	(0.96 - 1.02)
Blue Space (%) - 1000m	0.98	(0.94 - 1.03)	0.97	(0.94 - 1.00)	**0.95§**	**(0.91 - 0.99)**	1.05	(1.00 - 1.10)	**0.93§**	**(0.89 - 0.98)**	**0.89§**	**(0.82 - 0.97)**

Blue Space (%) - 1500m	0.99	(0.96 - 1.02)	**0.98§**	**(0.96 - 1.00)**	0.98	(0.95 - 1.00)	1.00	(0.97 - 1.03)	**0.97§**	**(0.94 - 1.00)**	**0.94§**	**(0.89 - 0.99)**
Blue Space (%) - 3000m	0.99	(0.95 - 1.02)	**0.96§**	**(0.93 - 0.98)**	0.97	(0.94 - 1.01)	1.00	(0.96 - 1.03)	**0.96§**	**(0.93 - 0.99)**	**0.92§**	**(0.87 - 0.99)**
Distance to coast (m)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.00)	1.00	(0.99 - 1.00)	**1.01§**	**(1.01 - 1.02)**	1.00	(1.00 - 1.01)	0.99	(0.98 - 1.00)
Green&Blue Space (%) - 300m	**1.02§**	**(1.01 - 1.03)**	0.99	(0.98 - 1.00)	1.00	(0.99 - 1.01)	1.01	(1.00 - 1.02)	1.00	(0.99 - 1.01)	0.97	(0.94 - 1.00)
Green&Blue Space (%) - 1500m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.01)
Green&Blue Space (%) - 3000m	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)

§ p-value < 0.05

‖ Models adjusted for: age, sex, ethnicity, crime, deprivation, physical activity, air quality and nois

6.4.2 Cardio-metabolic, respiratory and mental multimorbidity

6.4.2.1 Cardio-metabolic multimorbidity

Income stratified analyses showed that significant associations between exposure to green and blue spaces with cardio-metabolic multimorbidity only exist for presence of park within 300m of the residential address and amount of blue space in a 1000m buffer around the residential address (table 19). Particularly, individuals of low income who had a park within 300m of the residential address were 20% more likely to have cardio-metabolic multimorbidity ($OR^{park\ (yesvs\ no):}$ 1.20; 95% CI: 1.04-1.38) (table 19). Blue space, however, showed protective association with cardio-metabolic multimorbidity among individuals of medium income. For a 1% increase in the amount of blue space in 1000m buffers around the residential address, the odds of having cardio-metabolic multimorbidity in individuals of medium income decreased by 4% ($OR^{Blue1000}$: 0.96; 95% CI: 0.92-0.99) (table 19).

Table 19: Income stratified regression results for the relationship between exposure to green and blue spaces with cardio-metabolic multimorbidity

Exposure Metrics	Cardio-metabolic Multimorbidity (yes vs no)					
	Income Level					
	Low (Less than £18,000) ‖		Medium (£18,000-£51,999) ‖		High (£52,000 and over) ‖	
	OR	95% CI	OR	95% CI	OR	95% CI
Total Green Space (%) - 100m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)
Total Green Space (%) - 300m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)
Total Green Space (%) - 1500m	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)
Total Green Space (%) - 3000m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)
Park (presence within 300m) - yes	**1.20§**	**(1.04 - 1.38)**	1.02	(0.91 - 1.14)	1.00	(0.84 - 1.20)
Distance to park (m)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Domestic Garden Space (%) - 300m	1.00	(0.99 - 1.00)	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)
Domestic Garden Space (%) - 1000m	0.99	(0.98 - 1.00)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)
Tree Canopy Cover (%) - 300m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.00)
Tree Canopy Cover (%) - 1500m	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(0.99 - 1.00)
Blue Space (%) - 300m	1.00	(0.97 - 1.02)	0.99	(0.96 - 1.01)	1.01	(0.99 - 1.03)
Blue Space (%) - 1000m	1.00	(0.96 - 1.04)	**0.96§**	**(0.92 - 0.99)**	0.95	(0.90 - 1.00)
Blue Space (%) - 1500m	0.98	(0.96 - 1.01)	0.99	(0.97 - 1.02)	0.98	(0.95 - 1.01)
Blue Space (%) - 3000m	0.99	(0.96 - 1.02)	0.99	(0.96 - 1.01)	0.97	(0.93 - 1.01)
Distance to coast (m)	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)
Green&Blue Space (%) - 300m	1.01	(1.00 - 1.01)	0.99	(0.98 - 1.00)	1.00	(0.99 - 1.01)
Green&Blue Space (%) - 1500m	1.00	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)
Green&Blue Space (%) - 3000m	1.01	(1.00 - 1.01)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.01)

§ p-value < 0.05

‖ Models adjusted for: age, sex, income, crime, deprivation, physical activity, air quality and noise

6.4.2.2 Respiratory multimorbidity

Income stratified analyses showed that significant associations between exposure to green and blue spaces with respiratory multimorbidity only exist for blue space in 1000m buffers around the residential address among individuals of high income (table 20). For a 1% increase in the amount of blue space in a 1000m buffer around the residential address, the odds of having respiratory multimorbidity decreased by 36% in individuals of high income ($OR^{Blue1000}$: 0.64; 95% CI: 0.42-0.87) (table 20).

Table 20: Income stratified regression results for the relationship between exposure to green and blue spaces with respiratory multimorbidity

Exposure Metrics	Respiratory Multimorbidity (yes vs no)					
	Income Level					
	Low (Less than £18,000) [ll]		Medium (£18,000-£51,999) [ll]		High (£52,000 and over) [ll]	
	OR	95% CI	OR	95% CI	OR	95% CI
Total Green Space (%) - 100m	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.00)	1.00	(0.98 - 1.01)
Total Green Space (%) - 300m	1.00	(0.99 - 1.02)	0.99	(0.98 - 1.00)	1.00	(0.98 - 1.02)
Total Green Space (%) - 1500m	1.00	(0.99 - 1.02)	1.01	(0.99 - 1.02)	1.00	(0.98 - 1.02)
Total Green Space (%) - 3000m	1.01	(1.00 - 1.02)	1.01	(0.99 - 1.02)	0.99	(0.97 - 1.01)
Park (presence within 300m) - yes	1.11	(0.74 - 1.67)	0.71	(0.48 - 1.04)	0.94	(0.52 - 1.69)
Distance to park (m)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Domestic Garden Space (%) - 300m	0.99	(0.97 -1.00)	1.00	(0.98 - 1.02)	1.00	(0.98 - 1.02)
Domestic Garden Space (%) - 1000m	0.99	(0.97 - 1.00)	1.00	(0.98 - 1.02)	1.00	(0.97 - 1.03)
Tree Canopy Cover (%) - 300m	0.99	(0.98 - 1.00)	1.00	(0.83 - 1.01)	0.99	(0.97 - 1.01)
Tree Canopy Cover (%) - 1500m	1.00	(0.98 - 1.01)	1.00	(0.99 - 1.02)	0.99	(0.96 - 1.01)

Blue Space (%) - 300m	1.04	(0.99 - 1.08)	0.99	(0.88 - 1.05)	0.88	(0.73 - 1.00)
Blue Space (%) - 1000m	1.04	(0.92 - 1.13)	0.88	(0.73 - 1.02)	**0.64** §	**(0.42 - 0.87)**
Blue Space (%) - 1500m	0.97	(0.89 - 1.04)	0.95	(0.85 - 1.03)	0.88	(0.73 - 1.00)
Blue Space (%) - 3000m	0.93	(0.83 - 1.02)	0.97	(0.88 - 1.06)	0.98	(0.88 - 1.06)
Distance to coast (m)	1.00	(0.99 - 1.02)	1.01	(0.99 - 1.02)	0.99	(0.96 - 1.02)
Green&Blue Space (%) - 300m	1.02	(1.00 - 1.04)	1.00	(0.97 - 1.02)	1.00	(0.97 - 1.02)
Green&Blue Space (%) - 1500m	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)	0.99	(0.67 - 1.01)
Green&Blue Space (%) - 3000m	1.01	(1.00 - 1.02)	1.00	(0.99 - 1.01)	0.99	(0.97 - 1.00)

§ **p-value < 0.05**

ll Models adjusted for: age, sex , income, crime, deprivation, physical activity, air quality and noise

6.4.2.3 Mental multimorbidity

Income stratified analyses showed that higher amount of blue space in 300m and 1500m buffers around the residential address reduce the odds of having mental multimorbidity in individuals of low income (table 21). For a 1% in the amount of blue space in a 300m and 1500m buffer around the residential address, the odds of having mental multimorbidity in individuals of low income decreased by 16% ($OR^{Blue300}$: 84; 95% CI: 0.59-0.99) and 8% ($OR^{Blue3000}$:92; 95% CI: 0.84-0.99), respectively (table 21). No significant associations were observed between exposure to green or blue space with mental multimorbidity in individuals of medium or high income.

Table 21: Income stratified regression results for the relationship between exposure to green and blue spaces with mental multimorbidity

Exposure Metrics	Mental Multimorbidity (yes vs no)					
	Low (Less than £18,000) ‖		Medium (£18,000-£51,999) ‖		High (£52,000 and over) ‖	
	OR	95% CI	OR	95% CI	OR	95% CI
Total Green Space (%) - 100m	1.00	(1.00 - 1.01)	1.00	(0.99 - 1.01)	0.99	(0.95 - 1.00)
Total Green Space (%) - 300m	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)	0.99	(0.97 - 1.01)
Total Green Space (%) - 1500m	1.00	(0.99 - 1.02)	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.02)
Total Green Space (%) - 3000m	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.02)
Park (presence within 300m) - yes	0.97	(0.68 - 1.39)	1.02	(0.69 - 1.49)	0.91	(0.50 - 1.61)
Distance to park (m)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)	1.00	(1.00 - 1.00)
Domestic Garden Space (%) - 300m	1.00	(0.99 - 1.02)	1.00	(0.98 - 1.01)	1.01	(0.99 - 1.03)
Domestic Garden Space (%) - 1000m	0.99	(0.98 - 1.01)	1.00	(0.98 - 1.02)	1.00	(0.97 - 1.02)
Tree Canopy Cover (%) - 300m	1.01	(1.00 - 1.02)	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.01)
Tree Canopy Cover (%) - 1500m	1.01	(0.99 - 1.02)	1.00	(0.99 - 1.01)	1.01	(0.98 - 1.03)
Blue Space (%) - 300m	**0.84 §**	**(0.59 - 0.99)**	1.02	(0.94 - 1.06)	0.91	(0.63 - 1.03)
Blue Space (%) - 1000m	0.90	(0.78 - 1.02)	0.93	(0.80 - 1.05)	0.83	(0.62 - 1.02)

Blue Space (%) - 1500m	**0.92 §**	**(0.84 - 0.99)**	0.96	(0.86 - 1.03)	0.88	(0.73 - 1.01)
Blue Space (%) - 3000m	0.92	(0.83 - 1.00)	0.96	(0.86 - 1.05)	0.96	(0.82 - 1.09)
Distance to coast (m)	1.00	(0.99 - 1.02)	1.00	(0.98 - 1.01)	1.00	(0.97 - 1.02)
Green&Blue Space (%) - 300m	0.98	(0.93 - 1.01)	1.02	(1.00 - 1.04)	1.01	(0.97 - 1.04)
Green&Blue Space (%) - 1500m	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)
Green&Blue Space (%) - 3000m	1.00	(0.99 - 1.01)	1.00	(0.99 - 1.01)	1.00	(0.98 - 1.01)

§ p-value < 0.05
‖ Models adjusted for: age, sex, income, crime, deprivation, physical activity, air quality and noise

6.5 Conclusion

Overall, no significant associations were found between exposure to amount of total green space, amount of street trees, amount of domestic garden space, and amount of green and blue space with disease counts (simple and complex multimorbidity), cardio-metabolic, respiratory, and mental multimorbidity. Higher amount of blue space in larger buffer sizes (above 1000m) around the residential address showed consistent protective associations with disease counts (2, 3 and 4+ LTCs) and mental multimorbidity. There was little evidence of significant moderation by physical activity, but some analyses showed that the relationships between blue space with complex multimorbidity (3 LTCs, 4+ LTCs) and mental multimorbidity vary by level of physical activity. Particularly, individuals with moderate physical activity levels who lived in areas with higher amount of blue space were more likely to have complex and mental multimorbidity, compared to individuals with high physical activity levels who lived in areas with higher amount of blue space. Stratification by income group showed that greater exposure to blue space was associated with lower odds of having complex multimorbidity (3 LTCs, 4+ LTCs), as well as respiratory multimorbidity among individuals of medium and high income. Individuals of low income who had higher amount of blue space had lower odds of having mental multimorbidity.

Next Steps

This chapter presented descriptive and regression model results for the associations between exposures to green and blue spaces with multimorbidity. The next chapter discusses the implications of this doctoral research by drawing on results from the systematic review, data integration study, and these cross-sectional analyses. The findings from this thesis are conceptualised with current literature on green and blue space exposure and health. Following this, the implications of this doctoral research on research and policy are discussed. The next chapter finishes by discussing the overall strengths and limitations of this thesis and setting out directions for future research.

Chapter 7: Discussion and Conclusion

Chapter summary

This chapter provides a critical interpretation of the cross-sectional regression results presented in Chapters 5 and 6. Drawing on prior literature on the roles of green and blue spaces on chronic health, findings are conceptualised with emerging theory and practice. The chapter also reflects on the total contribution of the thesis and considers recommendations for further research and policy. Additionally, the strength and limitations of this doctoral research are discussed.

7.1 Overview of the findings of this thesis

This thesis aimed to examine the associations between exposure to green and blue spaces with multimorbidity. First, a systematic literature review of longitudinal observational studies was conducted to assess the ways different types of green and blue spaces affect mental health and NCDs. Narrative synthesis showed there was little evidence of significant associations between greater exposure to green and blue spaces with mental health and NCDs, and that strengths of relationships were dependent on exposure and outcome measures. The review also concluded there was currently lack of comparative research on types of green and blue spaces and their differential impact on the risk of mental health and NCDs. To address this research gap, I used Urban Atlas data to construct multiple measures of provision of total green space, provision of street trees, provision of inland blue space, provision of green and blue space, and proximity to park. These were then linked to 300,000 UK Biobank participants. Using this environment data, as well as data available from UK Biobank on multimorbidity, socio-demographic characteristics, physical activity, domestic garden space, and distance to coast, I examined the cross-sectional associations between different green and blue spaces with disease counts, and multimorbidity clusters of cardio-metabolic, respiratory, and mental conditions. The results and critical discussion of the systematic review and data integration study are presented in Chapters 3 and 4. The following sections of this chapter discuss the results from the cross-sectional analyses.

7.2 Relationships between green and blue spaces with multimorbidity

7.2.1 Relationship between exposure to blue space with multimorbidity

The final analytical part of this thesis explored the relationship between exposure to types of green and blue spaces with multimorbidity using cross-sectional data from UK Biobank. The results from logistic regression analyses showed that it was not exposure to total green space, street trees, domestic garden space, accessibility to park, or proximity to coast but exposure to greater amount of inland blue space that reduced the odds of multimorbidity. The strongest associations were observed for mental multimorbidity. For a 1% increase in the amount of inland blue space in 1000m, 1500m, and 3000m buffers, the odds of having mental multimorbidity decreased by 10% (OR: 0.90, 95% CI: 0.81 - 0.98), 8% (OR: 0.92, 95% CI: 0.86 - 0.97), and 6% (OR: 0.94, 95% CI: 0.88 - 0.99), respectively. A higher amount of inland blue space also reduced the odds of complex and cardio-metabolic multimorbidity. For a 1% increase in the amount of inland blue space in 1000m, 1500m, and 3000m buffers, the odds of having 3 LTCs decreased by 4% (OR: 0.96, 95% CI: 0.94 - 0.99), 2% (OR: 0.98, 95% CI: 0.96 - 0.99), and 3% (OR: 0.97, 95% CI: 0.95 - 0.98), respectively. Similar strengths of associations were observed between exposure to inland blue space in a 3000m buffer with 2 LTCs (OR: 0.98, 95% CI: 0.97 - 0.99) and 4+ LTCs (OR: 0.97, 95% CI: 0.95 - 0.99). Inland blue space in a 1000m buffer was also weakly associated with lower odds of cardio-metabolic multimorbidity (OR: 0.97, 95% CI: 0.95 - 0.99).

Although few studies have assessed the association between the natural environment and multimorbidity, these findings are consistent with prior research on the influence of blue spaces on long-term mental and physical health conditions. Two systematic reviews found that exposure to blue space was associated with small but statistically significant improvement in both mental health and well-being (Gascon et al., 2017; Smith et al., 2021). Similar results were observed in cross-sectional studies, which showed that the odds of anxiety and mood disorders were lower among those with higher amount of blue space around the residential address (de Vries et al., 2016), and that frequently visiting blue spaces and participating in physical activity around blue spaces was associated with increased self-reported wellbeing (Garrett et al., 2019) In meta-analyses, moreover, Smith et al. (2021) deduced that availability of urban blue spaces (such as rivers, canals, and ponds) are very weakly associated with lower risk of obesity (β = -0.34, 95% CI -0.19; -0.09), but not with all-cause mortality (HR = 0.99, 95% CI 0.97; 1.00, p = 0.038). In a recent cohort study of UK adults, however, Tieges et al. (2020) argue that it is not simply the availability of river canals but the surrounding canal urban regeneration over a 17-year period that reduced the risk of all-cause mortality.

This thesis found that the relationships between exposure to blue spaces and multimorbidity were strongest for mental multimorbidity. This finding supports new emerging research into the health-promoting roles of freshwater bodies on mental health in adult British populations (McDougall et al., 2021, 2022). In a comparative panel study of Scottish adults, McDougall et al. (2022) showed that frequent visits to rivers and canals, but not lakes, was associated with better self-reported mental wellbeing. Moreover, exposure to higher amount of freshwater, and exposure to large freshwater lakes were both associated with lower antidepressant use in a population of older British adults (McDougall et al., 2021). Large cohort studies assessing the mediating pathways between blue spaces and mental health are still limited (McDougall et al., 2020; Geneshka et al., 2021), but qualitative research has strongly suggested that a preference for freshwater bodies as spaces for mental restoration could be a key driver of health (Völker and Kistemann, 2015; Völker, Matros and Claßen, 2016; Ampatzidis and Kershaw, 2020). Relaxation in clean spaces, pleasant features, and availability of amenities like paths are thought to be some of the most important determinants of blue space use among urban dwellers in UK and Europe (Smith et al., 2022; Matros and Claßen, 2016). Furthermore, interviews with urban dwellers have shown that rivers and water bodies, even within public parks, are more favourable places for recreation, socialisation and mental restoration (Völker and Kistemann, 2013) than urban green spaces (Völker and Kistemann, 2015). Although use and individual perceptions of green and blue spaces have not been previously assessed for UK Biobank participants, current research suggests that it is the appeal of blue spaces for restoration that could explain why protective relationships were observed only for blue space and mental multimorbidity, but not for blue space and cardio-metabolic or respiratory multimorbidity.

Results from cross-sectional analyses also showed that higher amount of inland blue space was associated with lower odds of complex multimorbidity (measured as disease counts of: 3 LTCs and 4+ LTCs). There is currently less research into the roles of blue spaces on NCDs (Geneshka et al., 2021), but a trial of office workers showed that walking near blue spaces lowered blood pressure and improved heart-rate variability (Vert et al., 2020). Blue spaces could be protective of NCDs, such as CVD and diabetes because they improve physical activity (Grellier et al., 2017). Alternatively, the significant protective relationships between exposure to blue space with both mental and complex multimorbidity in this thesis could be driven solely by mental disorders. Complex multimorbidity was measured in disease counts, which included mental and chronic physical health conditions from a pre-defined list of 43 LTCs (Barnett et al., 2012; Jani et al., 2019). Individuals with 3 or 4+ co-occurring LTCs, therefore, could have only mental or only physical health conditions, or a combination of both. Considering blue space had no effect on respiratory or cardio-metabolic multimorbidity, it is plausible that the statistical significance of relationships between blue space and complex multimorbidity are driven purely by individuals who only have co-occurring mental conditions.

In the main analyses, this thesis found protective relationships only existed between multimorbidity and inland blue spaces, but not with proximity to coast. Inland blue spaces, such as rivers, canals and lakes, might have a greater impact on health because they are located in or around large urban centres (McDougall et al., 2020). Rivers and canals are an integral part to everyday living in Britain and other European countries. On average, people in the UK live within 2.4 km of a freshwater body, which is a shorter distance than the global average of 3 km, and the Western European average of 2.6 (Kummu et al., 2011). UK Biobank participants also predominantly live in urban areas built on rivers. Rivers and canals were vital for transporting goods during the Industrial Revolution, but their current health-promoting properties likely began during the late 1990s when regeneration of urban waterside areas led to improvements in pedestrian infrastructure, greening of riverside areas, access to cycle paths, and commercialisation (Brownill, 2010; Cameron, 2003; Couch and Dennemann, 2000; Jones, 1998). While coastal environments have previously been shown to protect and promote health (Wheeler et al., 2012), UK Biobank individuals likely get their health-promoting benefits from inland water bodies because of every day interactions with rivers and canals, which enable cycling to work, lunchtime walks, or provide pleasant views from the window.

Although consistent, statistically significant relationships were observed between exposure to inland blue space and multimorbidity, the effect sizes were quite small. This indicates that greater amount of inland blue spaces is associated with very small reductions in the odds of multimorbidity. This is in line with other epidemiological research on the health-promoting roles of green and blue spaces, which has often found that, where significant relationships exist, they are generally weak (Astell-Burt et al., 2014; de Keijzer et al., 2016). Most epidemiological research now focuses on the effects of the natural environment on individual health, which could explain why mostly weak relationships are observed (de Keijzer et al., 2016). However, green and blue spaces can produce cumulative health benefits across populations, which has benefits for planetary health, including promotion of healthy lifestyles, and mitigation of harmful effects of human-induced climate change and urbanisation (Loureiro et al., 2021).

7.2.2 Relationship between exposure to street trees and domestic gardens with multimorbidity

No significant associations were observed between any of the multimorbidity outcomes and exposure to amount of street tree canopy and domestic garden space in this thesis. Although the relationship between natural environment and multimorbidity has not been previously examined in the published literature, prior longitudinal studies have generally found a protective relationships between exposure to higher amount of tree canopy cover, higher amount of private garden pace and psychological distress, CVD, respiratory mortality, and all-cause mortality (Roscoe et al., 2022a, 2021; Astell-Burt, Navakatikyan and Feng, 2020; Astell-Burt, Mitchell and Hartig, 2014; Astell-Burt and Feng, 2019). In two UK Biobank studies, having a private garden space reduced the risk of developing CVD and respiratory disease, non-injury, and all-cause mortality (Roscoe et al., 2022a; Wan et al., 2022). In comparison, public parks, sports facilities, and total amount of green space had weak or no associations with mortality in the UK Biobank participants (Roscoe et al., 2022a).

Despite the cross-sectional nature of this thesis, it was hypothesised that the presence of street trees and private gardens would reduce the odds of having multimorbidity because of the way these types of green spaces potentially support physical and mental health (Wolf et al., 2020; Moreira et al., 2020). Street trees can reduce air pollution, lower temperatures, and provide shade (Wolf et al., 2020), which can prevent the development of CVD and respiratory disease, and reduce the incidence of adverse events like stroke and mortality. Domestic garden space, on the other hand, can provide private outdoor areas for relaxation, gardening, and physical activity, which could lower BMI, improve attention, and reduce stress. Over the life course, these mechanisms can reduce the risk of developing long-term mental and physical health conditions. However, it is possible that these types of green spaces do not affect the risk of multimorbidity because they cannot influence the complex biological and social processes operating within multimorbid individuals (Barnett et al., 2012). Multimorbidity is a heterogenous health state of multiple co-occurring health conditions that can be driven by life course behavioural and physiological exposures (Singer et al., 2019a). Given that the strengths of relationships between individual NCDs and green spaces are generally very weak (Gascon et al., 2015; Geneshka et al., 2021; Yuan et al., 2021), it is likely that private gardens and street trees do not influence complex outcomes like multimorbidity.

7.2.3 Relationship between exposure to total green space with multimorbidity

This thesis also did not find any statistically significant relationships between exposure to amount of total green space with any of the multimorbidity outcomes. This is an unexpected finding, although the evidence for the relationships between greenness and health is somewhat equivocal (Geneshka et al., 2021; Yuan et al., 2021). In the UK Biobank, exposure to higher availability of green space (measured though the NDVI) showed weak protective associations with depression (Sarkar, Webster and Gallacher, 2018b). For every interquartile increase in NDVI, the odds of depression and obesity decreased by 4%, respectively (Sarkar, Webster and Gallacher, 2018b, Sarkar, 2017). Higher NDVI values were also associated with a reduction in odds of depression and cognitive decline in Canadian older adults (Hystatd al., 2019), but significant longitudinal relationships between mental health and green space are generally non-existent. While Banay et al. (2019) found that higher NDVI generally reduced the odds of developing depression in women, other studies found no associations between incidence of depression or anxiety and green space in adults (Tomita et al., 2017; Picavet et al., 2016; Gariepy et al., 2015; Melis et al., 2015).

The evidence for whether higher exposure to green space affects physical health is also equivocal. A meta-analysis, for example, found the odds of CVD mortality and stroke incidence were only 3% and 2% lower, respectively, for a one unit increase in NDVI (Liu et al., 2022). Higher greenness in the surrounding neighbourhood also showed weak protective relationships with respiratory and CVD mortality in older adults (Vienneau et al., 2017), but not with all-cause mortality (Klompmaker et al., 2020). In a cross-sectional study of older adults, living in the greenest areas was associated with a 52% reduction in odds of having CVD compared with living in least green areas (Massa et al., 2016). However, a meta-analysis of cohort studies found that higher NDVI values generally had no significant effect on the incidence of CVD in older adult populations (Yuan et al., 2021).

As discussed previously, higher availability of green space may not affect the odds of multimorbidity because multimorbidity is a complex health state strongly shaped by life course behavioural and socio-economic factors (Feter et al., 2021; Violan et al., 2014). Longitudinal studies assessing the impact of different types of green spaces on the development of multimorbidity in adults with pre-existing diabetes found that neither higher NDVI values, higher availability of grass cover, or higher availability of street tree canopy were associated with depression and CVD at follow-up (Gariepy et al., 2015b; Astell-Burt et al., 2021). On the other hand, studies of Asian populations have shown that green space is protective of frailty (Zhu et al., 2020; Yu et al., 2018), which is a separate but related concept to multimorbidity (Vetrano et al., 2019) and is measured either through a relevant clinical signs and symptoms (Frailty Phenotype), or through a list of conditions and disabilities (Frailty Index) (Cesari et al., 2013). Apart from differences in study design, one reason why green spaces might be protective of frailty but not multimorbidity could be due to population differences. Asian older adults may have more positive perceptions of the surrounding green areas and potentially engage in community activities in green space more frequently than British adults (Lau, Yung and Tan, 2021; Chow, 2013). Another reason may also be the role of physical activity in reducing the severity of frailty (Yu et al., 2018). Although physical activity also has the potential to prevent the development of multimorbidity, this generally occurs over long periods of time and only during critical time points during a person's life (Feter et al., 2021). Physical functioning and impairment related to frailty, on the other hand, can be reduced with regular bouts of physical activity even after individuals develop early signs of frailty (Angulo et al., 2020).

7.2.4 Why inland blue space but not green and blue space was protective of multimorbidity?

While having only inland blue space in the neighbourhood was associated with lower odds of mental and complex multimorbidity, having both green and blue space in the neighbourhood showed no significant associations with any of the multimorbidity outcomes. It is not entirely clear why having a higher availability of both green and inland blue space was not protective of multimorbidity, but potential reasons could be lack of accessible routes, obstruction of blue space view and access, and higher crime levels brough on by the availability of large greenery. Although green spaces are commonly considered promoters of good health (Hartig et al., 2014; Markevych et al., 2017), tall and unmanaged greenery, such as shrubs, forests and tall grass can encourage crime and reduce safety (Bogar and Beyer, 2016; Sreetheran and van den Bosch, 2014). Furthermore, having more tall greenery can hinder access and block views of blue spaces, which are considered two of the main health-promoting mechanisms of water bodies (Grellier et al., 2017; Garrett et al., 2019).

7.3 The moderating effect of income

7.3.1 Blue space and multimorbidity

Results from income-stratified regression analyses showed that higher amount of inland blue space was associated with a reduction in the odds of mental multimorbidity only in individuals of low-income (Blue 300 - OR: 0.84; 95% CI: 0.59-0.99, and Blue 1500 - OR: 0.92; 95% CI: 0.84-0.99). No significant relationships were found between exposure to blue space and mental multimorbidity in individuals of medium or high-income. However, higher amounts of blue space were also associated with a slight reduction in the odds of having 4+ LTCs in individuals of both medium and high income, but not in individuals of low-income (*Medium income*: Blue 1000 - OR: 0.93; 95% CI: 0.89-0.98; Blue 3000 - OR: 0.96; 95% CI: 0.93-0.99 | *High income*: Blue 1000 - OR: 0.89; 95% CI: 0.82-0.97; Blue 1500 - OR: 0.94; 95% CI: 0.89-0.99; Blue 3000 - OR: 0.92; 95% CI: 0.87-0.99).

Higher amounts of blue space might be more protective of complex multimorbidity (4+ LTCs) in medium and high-income groups because of higher availability of blue space in high-income areas and differences in perceptions of the natural environment. Although several studies have found that the benefits of green spaces are stronger for those of low SES (Maas et al., 2009; de Vries et al., 2003; Dadvand et al., 2012a, 2012b), this might not be the case for blue spaces. Blue space availability is generally higher in areas of low deprivation in the UK (Thornhill et al., 2022). Studies also indicate that individuals of high SES are also more likely to find nature important (de Bell et al., 2017), and to access and spend more time in urban waterways than those of low SES, even if they live further away (Haeffner et al., 2017; Schüle et al., 2019). Individuals of high SES might also have more free time and flexible working hours than those of low SES (Burchardt, 2010), which means they can spend more leisure time outdoors and as a result gain more benefits from blue spaces.

On the other hand, blue space might be protective of mental multimorbidity only in individuals of low income because they spend more time closer to their main residential address and have fewer resources to manage their mental health (Markevych et al., 2017). Individuals of low SES tend to be at higher risk of developing mental health disorders (Murali and Oyebode, 2004) and generally tend to have lower access to mental health services during childhood and adulthood (Amaddeo and Jones, 2007; McDaid, 2007). Therefore, it is possible that individuals of low income might experience greater benefits from the natural environment than individuals of high income who typically have greater access to other health-promoting resources (Murali and Oyebode, 2004).

7.3.2 Proximity to coast and multimorbidity

Although no relationships were found between proximity to coast and multimorbidity in the main analyses, results from stratified analyses showed that further distance from the coast was associated with a very weak increase in the odds of mental multimorbidity among individuals of low-income (OR: 1.01 for every mile increase in distance to coast from residential address). This is consistent with previous research that has shown that mental and general health improves with closer proximity to coast (White et al., 2013; Wheeler et al., 2012). Wheeler et al. (2012) found that general health was better for those living in closer proximity to British coastal areas, and these relationships were especially pronounced for those of low SES. It is suggested that the salutogenic effects of the coastal natural environment, such as cleaner air, may mitigate the effects of socio-economic disadvantage on health. However, the strength of association for the protective effect of coastal proximity on multimorbidity was very weak in this thesis (OR: 1.01 for every 1-mile increase in distance from coastal area to residential address) and could have occurred due to unobserved confounding.

7.3.3 The relationships between accessibility to park and multimorbidity

In stratified analyses, individuals of low income who had a park within 300m of the residential address were more likely to have both cardio-metabolic multimorbidity and 4+ LTCs ($OR^{\text{cardio-metabolic (yes vs no)}}$: 1.20, 95% CI: 1.04-1.38 and $OR^{\text{4+ LTCs vs 0 LTCs}}$: 1.25, 95% CI: 1.05-1.48), compared to individuals of low income who did not have a park within 300m of their residential address. Significant relationships between presence of a park and multimorbidity were not observed for individuals of medium or high income. Previous research has shown that higher availability of park and greenness around the residential address is generally protective of developing CVD (Kim et al., 2016; Dalton and Jones, 2020; Pereira et al., 2012; Tamosiunas et al., 2014; Seo et al., 2019), and these relationships are moderated by sex (Tamosiunas et al., 2014; Seo et al., 2019) and physical activity (Pereira et al., 2012). Fewer studies have investigated the moderating role of SES on the relationship between green spaces and health, but a recent UK Biobank study found that higher availability of green space near the residential address showed the strongest protective relationships with cancer-related hospital admissions in individuals of low-income (Mason, Pearce and Cummins, 2022). On the other hand, Seo et al. (2019) found that the odds of developing CVD decreased with higher amounts of green space in the surrounding neighbourhood in both low and high-income Korean individuals.

Individuals of low income may experience more adverse health events with greater residential proximity to park due to several reasons. First, parks in low-income and ethnically diverse areas tend to be less well-maintained, have fewer green wooded areas, and fewer places for rest/sitting (Bruton and Floyd, 2014). Qualitative studies have found that park features and amenities are important determinants of park use (Vaughan et al., 2018), but lack of facilities for recreation and physical activity, like benches, toilets and water fountains, may lead to low park use (Kamel, Ford and Kaczynski, 2014). Second, poorly maintained parks may also attract crime and anti-social behaviour (Boessen and Hipp, 2018). It is known that higher neighbourhood crime levels can increase the risk of mental health disorders, psychological distress and CVD (Baranyi et al., 2021; Sundquist et al., 2006; Sprung et al., 2019). Although my analyses were adjusted for objectively-measured crime levels (IMD Crime score) and deprivation (Townsend Index), I did not account for individual perceptions of neighbourhood safety. The ways individuals perceive the safety of their surroundings could have an impact on how they choose to use and interact with them. Ample evidence points towards a positive relationship between perceptions of park safety and park use (Lapham et al., 2016; Pérez-Tejera et al., 2022; Groshong et al., 2020;

Marquet et al., 2019), and low-income individuals may have lower positive perceptions of safety of their local parks.

Another reason individuals of low-income may experience an increased risk of multimorbidity with closer proximity to a park could be due to poor street connectivity and low road-network park accessibility (Guo et al., 2019). Park use tends to be lower among individuals who have to cross high-speed roads to access their local park (Kaczynski et al., 2014), but a natural experiment in low-income neighbourhoods in Columbia (USA) found that total park use increased and remained constant after installation of a pedestrian crosswalk (Schultz et al., 2017). This suggests that increasing accessibility to parks through improvements in road-network pedestrian connectivity in deprived and low-income areas could improve park use.

7.4 The moderating effect of physical activity on the relationship between green and blue spaces with multimorbidity

The benefits of green and blue spaces on human health may be linked to physical activity (Bouchard, Blair and Haskell, 2012). Through interaction term analyses, this thesis found that physical activity moderated the relationships between exposure to inland blue space with complex (3 LTCs) and mental multimorbidity. Specifically, for every 1% increase in the amount of blue space in 3000m buffers, individuals with moderate physical activity levels had 14% and 20% higher odds of 3 LTCs and mental multimorbidity, respectively, compared to individuals of high physical activity levels. Recent systematic review evidence found that, in addition to restoration, greater exposure of blue space also promotes physical activity (Georgiou et al., 2021). Although, no consistent evidence of moderation by physical activity was found for green space, my interaction term findings are consistent with the main analyses of this thesis, which found that inland blue spaces are protective of mental multimorbidity. Physical activity is beneficial for lowering stress and improving mental well-being (Fox, 1999), and blue spaces in urban areas may promote good mental health by encouraging on-land physical activity, like walking and active commuting (Pasanen et al., 2019). More research, however, is needed to understand the pathways through which inland blue spaces encourage physical activity (White et al., 2014).

7.5 Implications for research and policy

7.5.1 Research

7.5.1.1 Life course approach to multimorbidity research

This thesis examined the cross-sectional associations between exposure to different green and blue space environments with multimorbidity and found consistent evidence of a protective relationship between blue space and mental and complex multimorbidity. These findings offer foundational learning to support future longitudinal research. Multimorbidity is a complex health state that generally progresses with age. In epidemiological terms, aging is defined as the process of living longer and dying later, a demographic shift that affects an ever-growing proportion of the human population (World Health Organisation, 2022). Prevention of multimorbidity has received little attention in the academic literature because, until recently, it was considered an inevitable outcome of ageing (Whitty et al., 2020). However, emerging epidemiological evidence shows that the accumulation of disease is not just a static process driven by biological depletion of body reserves but rather a multifaceted state that is shaped by different social, psychological, and behavioural factors throughout the life course (Suls, Green and Davidson, 2016; Head et al., 2021; Skou et al., 2022).

Suls et al. (2016) propose that the aetiology of multimorbidity and particularly common multimorbid patterns of diabetes-CVD, mental illness, and musculoskeletal conditions, is driven by an intertwined network of socio-economic and behavioural factors that operate throughout the life course. Epidemiological studies have found that physical activity, diet, smoking, and socio-economic status independently affect the risk of multimorbidity (Agborsangaya et al., 2013; Aminisani et al., 2020; Mounce et al., 2018; Geda et al., 2021; Luben et al., 2020; Nguyen et al., 2019; Xu et al., 2018). The relationship between these factors and subsequent accumulation of disease is complex and bidirectional (Suls, Green and Davidson, 2016). In their life course framework, Wister et al. (2016) suggest that, while developing multimorbidity is inevitable with old age, individual, behavioural, and social exposures throughout the life course help build resilience to the adverse side effects of diseases, which explains why some individuals can maintain better quality of life and physical functioning than others.

Evidence for the role of life course exposures in prevention of multimorbidity is slowly growing. Some research shows that resilience to multimorbidity may be built when an individual experiences certain socio-environmental stimuli during critical time periods in their life (Ben-Shlomo and Kuh, 2002). For example, low physical activity levels and financial hardship during childhood and adolescence, but not at other time points in the life course, can independently increase the risk of developing multimorbidity later in life (Feter et al., 2021; Tucker-Seeley et al., 2011). Green and blue space research adopting this critical time period model is still very limited (Wood and Smyth, 2020), but a systematic review found that exposure to natural space at any given life stage is not necessarily stronger at predicting mental health than other life stages (Li et al., 2021).

7.5.1.2 Implementing life course research in green and blue space epidemiology

Advances in GIS has facilitated large-scale green and blue space exposure assessment in cohort studies (Higgs, Fry and Langford, 2012). Open-access datasets such as the NDVI, land use maps, and LiDAR have been used to ascertain accurate and objective green and blue space exposure data over large areas (Li, Saphores and Gillespie, 2015; Irwin and Bockstael, 2004; Caynes et al., 2016), which has driven innovation in longitudinal green space-health research (Gascon et al., 2015). However, this approach has limited applications to life course exposure assessment due to lack of readily-available historic, computerised environment data (Pearce et al., 2018). Vast urban regeneration during the late 20th century means the availability and quality of urban green spaces have changed drastically through time (Meliker et al., 2005). To assess exposure to greenness at every stage during the life course, Pearce et al. (2016) suggest using archival record linkages and historical land surveys. Qualitative, interview-based, research can also be adopted to better understand how individual perceptions of safety and quality during childhood and early adulthood affected interactions with green and blue spaces (Wood and Smyth, 2020). These approaches have proven effective in assessing relationships between life course exposure to green spaces and mental health but have some drawbacks (Pearce et al., 2016), including being time-consuming and incomplete in data, meaning study samples might be limited in size and geographic area (Pearce et al., 2016).

Assessing the availability of blue space throughout the life course of individuals is perhaps easier due to the unbated location of rivers and lakes. Unlike urban green spaces, which are often subject to change due to land regeneration (Kim and Kim, 2019), the locations of urban blue spaces are often more static in time. This can facilitate objective blue space exposure assessment from conception and throughout childhood, however, it does not take into account health-promoting features and facilities around urban blue spaces (White et al., 2020). Factors like cleanliness, pedestrian accessibility, and safety likely play important roles in whether urban dwellers interact and benefit from their blue spaces. Future blue space research incorporating a life course approach should, therefore, focus on using a combination of historic land surveys, deprivation indices, property values and land use change over time to construct measures of blue space availability that assess the historical accessibility and attractiveness of urban blue spaces. Where possible, qualitative methods, like interviews, can also be incorporated to better understand the individuals’ perceptions of their surrounding blue spaces during childhood and adolescence.

7.5.1.3 Understanding use and individual perceptions of green and blue spaces

Often, objective assessment is the preferred method for exposure ascertainment (National Research Council (US) Committee on Environmental Epidemiology and National Research Council (US) Commission on Life Sciences, 1997). Cohort studies have largely used GIS-modelled green space data linkages to study relationships with health, which is useful for large sample sizes and cohorts that were not originally constructed for natural environment- health research. However, future initiatives should focus on assessing use and perceptions of green and blue spaces in addition to incorporating objective measures of availability and accessibility to nature. Perceptions, change of perception, and use of green and blue spaces have shown consistent relationships with health (Cleary et al., 2019; McDougall et al., 2021; Jakstis et al., 2022). New research from the first COVID-19 lockdown era has also highlighted the importance of positive perceptions of surrounding green spaces in preventing ill-mental health (Lopez, Kennedy and McPhearson, 2020; Ugolini et al., 2020; Poortinga et al., 2021; Reid, Rieves and Carlson, 2022). Individual perceptions of green and blue spaces are important to study because they determine use and immersion (Markevych et al., 2017; Grellier et al., 2017). Whether individuals use their surrounding natural spaces is largely driven by how they perceive their cleanliness, safety, and quality (Lopez, Kennedy and McPhearson, 2020). Incorporating self-reported information on participants' use and perceptions of their surrounding green and blue spaces in large health cohorts can help broaden the scope of epidemiological research and confounding. Follow-up of the UK Biobank cohort is ongoing, which opens opportunities to collect this type of self-reported data. The Likert scale is an example of an adaptable and inexpensive instrument to measure the perceived quality of surrounding green spaces (Feng and Astell-Burt, 2018; Joshi et al., 2015).

7.5.1.4 Implications for research in middle- and low-income countries

A strength of this doctoral research is the replicability of the exposure assessment methods to other countries and settings. The UA dataset was especially chosen for its high-resolution green space data, which is available for large cities across western and eastern Europe (European Environment Agency, 2021). It is possible, therefore, to capture green and blue space exposures for populations in both high-income countries and middle-income European countries, such as those in Eastern Europe. This broadens the scope of environmental research to studying the impacts of green and blue spaces on health in middle-income European populations that have previously been understudied but likely interact with green and blue spaces in a similar way to high-income populations. Remote sensing imagery can also be used to measure objective change in green and blue spaces in low-income countries. However, caution should be taken when assessing the impact of the natural surrounding environment on health in low-income country urban populations because of differences in cultural norms, climatic changes and accessibility and usage of natural spaces (Shuvo et al., 2020). Low-income countries in Africa and South America are experiencing rapid urbanisation with minimal infrastructure, which commonly leads to the development of slums and shanty towns (van der Molen, 2014). Public green spaces, therefore, may not be accessible for the majority of the public. Second, most green and blue space frameworks on health promotion are designed for temperate climatic regions and high-income country populations. Individuals living in tropical climatic zones might benefit from different types of natural environments that are not necessarily green or vegetated but have a critical role in community engagement, such as outdoor sites of worship (Nawrath et al., 2021). Finally, differences in cultural norms can play a role in the ways individuals in low- and middle-income countries use, interact and benefit from green spaces. In Turkey, for example, parks are mainly used for passive recreation, such as resting and socialisation (Nawrath et al., 2021). This differs to park usage in UK, which is largely used for physical activity. Designing frameworks that account for social, climatic and cultural differences between different populations, therefore, is key to studying the effects of the natural environment on health.

7.5.2 Policy

7.5.2.1 Environmental interventions for improving access to urban blue spaces for individuals with mental and complex multimorbidity

This thesis found that exposure to inland blue space was protective of both complex and mental multimorbidity, which has implications for urban health policy. Combating NCDs, increasing climate resilience, and improving access to equitable, safe natural spaces are three of the main goals of WHO’s Sustainable Cities initiative, which was designed to help national policy planners meet the United Nations’ Sustainable

Development Goal (UN SDG) on building sustainable, healthy cities that can tackle the challenges posed by ageing populations and climate change (Giles-Corti, Lowe and Arundel, 2020). In response to UN SDGs, the UK's Department for Environment and Rural Affairs (DEFRA) (2023) created a 25-year environment plan, which specifically aims to provide clean plentiful water with the aim to increase biodiversity and reduce the risk of environmental hazards like flooding. UK residents have higher than average accessibility to water spaces, and rivers form an integral part of UK cityscapes. In addition to providing habitats for biodiversity and mitigating the impact of climate change, urban water bodies can be used to promote good health and reduce the risk developing co-occurring NCDs and mental health disorders.

Blue spaces are considered to promote health mainly through restorative pathways (McDougall et al., 2022; Georgiou et al., 2021; Völker and Kistemann, 2013), which means urban regeneration of waterways should first aim to understand how individuals use blue spaces for restoration and recreation. As I mentioned in section 7.5.1.3, qualitative research from Europe indicates that individuals may visit water bodies in order to relax and socialise in aesthetically pleasing spaces (Völker, Matros and Claßen, 2016). However, future urban regeneration projects should be designed to serve the right groups in the population. Participants with mental multimorbidity in the UK Biobank population, for example, were on average younger compared to those without mental multimorbidity. Policies incorporating blue space in mental health promotion should therefore aim to first understand how middle-aged and younger adults engage with blue spaces differently to older individuals. Loneliness and isolation are strong drivers of ill-health and multimorbidity, but new research shows that it is lonely younger adults who are more likely to experience mental health problems (Matthews et al., 2019; Groarke et al., 2020). Young and middle-aged adults are more likely to be employed or have childcare duties (Cohen et al., 2016), so they might benefit from higher availability of child-friendly playgrounds or cycle and pedestrian routes along city centre river areas. Older adults, on the other hand, might be more likely seek blue spaces with better accessibility routes and places for rest, like benches and shade.

In this thesis, blue spaces reduced the odds of mental multimorbidity in low-income individuals, and the odds of complex multimorbidity in medium and high-income individuals. As those of higher SES have better access and availability of nature closer to their residential address, polices should aim to improve availability, accessibility, and quality of blue spaces for those of lower SES. This can have both social and economic challenges. Low-income individuals and individuals from ethnically diverse communities may be less willing to engage as community stakeholders (Withall, Jago and Fox, 2011) and are least likely to benefit from large-scale environmental urban regeneration (Cameron, 1992).

7.5.2.2 Environmental regeneration, the ‘green’ space paradox and gentrification

While urban inland blue spaces were shown to be protective of multimorbidity, land regeneration, greening of derelict riverside areas and building more pedestrian paths around blue spaces in low-income and deprived areas can lead to gentrification (Lim et al., 2013; Wallace, 2015). Gentrification from large-scale environmental regeneration occurs when places become more attractive to live and property values increase, which leads to a displacement of the marginalised communities the interventions were originally meant to serve (Pearsall and Eller, 2020). Gentrification after increasing availability and access of neighbourhood green space has been observed across most HICs, a phenomenon called the “green space paradox” (Wolch, Byrne and Newell, 2014). Although specifically applied for green spaces, the green space paradox is largely visible for urban blue spaces around the UK too. Inner-city canal and river regeneration has occurred in most major UK cities with a focus to improve pedestrian accessibility, increase availability of housing, and attract investment back to the city centres (Brownill, 2010; Cameron, 2003; Couch and Dennemann, 2000; Jones, 1998). However, these large-scale, top-down interventions have inevitably led to large increases in property values, influx of private investments and displacement of lower-income and ethnically diverse communities away from inner-city riverside and dockland areas (Butler, 2007; Cameron, 2003).

Adopting a systems-based approach, Kindermann et al. (2021) propose that it is socio-economic position that drives the relationships between the natural environment and health. Green and blue spaces may shape health and well-being through bio-physiological pathways like social cohesion and physical activity, but it is SES that determines the availability, accessibility, and use of these spaces. The framework reinforces the notion that income and social inequalities are the strongest facilitators of nature-health relationships and future policy makers should ensure that provision of green and blue spaces is equitable and aims to serve the right communities (Kindermann et al., 2021).

Research into the health-promoting role of water bodies is relatively new compared with green spaces but a recent review by Brückner et al. (2021) highlights three main objectives that drive urban blue space regeneration in HICs: 1) environmental sustainability and biodiversity; 2) attracting global investment to promote economic growth; 3) improving population health and social interactions. Given that environmental regeneration is expensive, most blue space regeneration projects should target all three objectives, however, it is generally public sector and community-led projects that focus on health and social reform. Drawing from literature on green spaces, one way to reduce the rate of gentrification is to design projects led by the local communities themselves (Wolch, Byrne and Newell, 2014). Although large, top-down environmental regeneration projects can deliver the highest quality of urban green and blue spaces, Wolch, Byrne, and Newell (2014) argue that projects need to be 'just green enough' to satisfy locals' needs. Often, this might mean adopting smaller-scale projects like building community gardens or cleaning riverside paths (Wolch, Byrne and Newell, 2014). Engaging community stakeholders, therefore, is the first step towards understanding specific community needs.

7.5.2.3 Public health interventions

This doctoral research has implications for public health practice. Blue spaces reduce the odds of mental and complex multimorbidity in middle-aged urban dwellers in UK. As I previously discussed, rivers are integral parts of urban living in UK but interventions aimed at using blue spaces in promoting health should be targeted at the right groups in the population. The UK government and NHS have long proposed policies for promoting good mental and physical health through community networks (Alderwick and Dixon, 2019). A place-based systems approach, where integrated care and social prescribing are used to improve population health through engagement with the natural environment are some of the key priorities of the NHS's long-term plan (Drinkwater et al., 2019). Engaging community health workers, local authorities and primary care services in building communities and places that are walkable, safe and green can improve health and in turn reduce strain on health services. Blue spaces can also be an integral part in this plan. With the help of funding from the UK government's Levelling-Up policy, which aims to reduce geographical inequalities (Connolly et al., 2021), blue and green spaces can aid community engagement and improve physical activity in deprived and marginalised communities. For example, in 2019, the London Borough of Camden organised weekly, peer-led women's walking groups in Regent's park with the aim to strengthen community cohesion and provide safe spaces for outdoor physical activity. However, such initiatives across northern England are minimal due to lack of appropriate funding and inability to reach the individuals who would benefit most from them, which include individuals of ethnic minorities and individuals from deprived communities (Rigby et al., 2020). Removing barriers to participation, which commonly include lack of awareness and fear of discrimination, therefore, is the first step to delivering such interventions (Rigby et al., 2020).

7.6 Strengths and Limitations

7.6.1 Strengths

7.6.1.1 Environmental approach to multimorbidity

This thesis has some powerful strengths. First, this is one of the first projects to investigate the relationship between the natural environment and multimorbidity. The burden of multimorbidity is increasingly growing in both HICS and LMICs (Galea, 2021). Researchers and policy bodies are increasingly calling for preventative strategies to minimise the severity of multimorbidity and reduce the rate of accumulation of diseases (Skou et al., 2022; Dankel, Loenneke and Loprinzi, 2015; Head et al., 2021; Salive, 2013). Cross-sectional and longitudinal studies have already investigated the effect of physical activity on multimorbidity and many have found moderate to strong protective relationships (Loprinzi, 2016; Vancampfort et al., 2017; Ryan et al., 2018; Dhalwani et al., 2016; Feter et al., 2021). This thesis expands the scope of prevention in multimorbidity to the natural environment. In a world where health resources are limited, natural spaces can be used to promote healthy behaviours and aid the reduction in the incidence of accumulation of chronic mental and physical diseases. By conducting in-depth cross-sectional analyses, this thesis has been able to lay the foundational groundwork for better understanding about how different types of green and blue spaces reduce the odds of different types of multimorbidity.

7.6.1.2 Assessment of different types of green and blue spaces

Another strength of this thesis is the integration of different types of green and blue spaces into a large health cohort. Often, health cohorts lack appropriate data on the natural environment and as a result epidemiological studies have failed to conduct exposure comparative research (Astell-Burt, Mitchell and Hartig, 2014; Astell-Burt and Feng, 2019; Astell-Burt, Navakatikyan and Feng, 2020; Nguyen et al., 2021). Using Urban Atlas data to model individual-level exposures to street tree canopy, public green spaces, inland water bodies and total amount of green space, this thesis was able to broaden the scope of natural environment research. By integrating natural environment exposures into the data rich UK Biobank this project was able to control for confounding and broadly analyse the roles of different natural spaces on multimorbidity.

7.6.1.3 Large sample size of UK Biobank and measures of different types of multimorbidity

The cross-sectional analyses of this thesis benefited from the large sample size of the UK Biobank (~ 49,000 participants), which can strengthen the internal and external validity of the study (Faber and Fonseca, 2014). Larger sample sizes can also give analyses more power and are preferable when variation in an outcome is high (Hajian-Tilaki, 2011), which frequently occurs with multimorbidity (Violan et al., 2014). This project also improved the understanding of the prevalence of different types of multimorbidity clusters. In addition to examining complex and simple multimorbidity through disease counts, this project also looked at several empirically replicable associative multimorbidity patterns. This approach of conceptualising multimorbidity has implications for how health services and health interventions are delivered. Understanding which multimorbidity patterns have the highest prevalence and how they are influenced by exposure to green and blue spaces can help plan and target interventions and efficiently engage different stakeholders in decision-making.

7.6.2 Limitations

7.6.2.1 Exposure assessment

While this thesis thoroughly investigated the relationships between different types of green and blue spaces, it did not measure use, visitations, or quality of surrounding neighbourhood natural spaces. Results showed that having higher amounts of blue space in the neighbourhood decreased the odds of several types of multimorbidity, but no information was obtained on whether individuals use their surrounding blue spaces. Grellier et al. (2017) propose that the pathways leading blue space to health involve indirect, intentional, and incidental exposure to blue spaces. Coastal and inland blue space view from the window was previously associated with better self-reported and mental health (Garrett et al., 2019; Nutsford et al., 2016), while spending time near blue spaces was associated with improved psychological well-being (de Bell et al., 2017; MacKerron and Mourato, 2013). In a recent comparative study of Scottish adults, McDougall et al. (2022) found that simply assessing residential proximity to inland water bodies showed no significant relationships with mental health, but, when frequent visitations to blue spaces were assessed as indicators of blue space, a positive association was found with mental health (McDougall et al., 2022). How individuals perceive and interact with their environments is likely to influence the benefits they gain from them (Reid, Rieves and Carlson, 2022; Sefcik et al., 2019), which is why it is important to incorporate self-reports of cleanliness, use and perceived quality of the natural environment into epidemiological research. Many large health cohorts currently lack data on use and individual perceptions of the surrounding environment, which limits exposure assessments to objective measures of availability and accessibility.

Second, this thesis did not assess the quality of green and blue spaces. Previously, I discussed the importance of perceptions of the local environment, which can determine health and individual interactions with these spaces. Mishra et al. (2020) recently developed the BlueHealth Environmental Assessment Tool (BEAT), which specifically assesses the quality of blue spaces based on aesthetic, social and physical domains of surrounding blue spaces. The tool accounts for biodiversity, physical characteristics, and objective and subjective measures of accessibility and attractiveness of inland and blue spaces (Mishra et al., 2020). Unlike measures of availability and distance, this tool can provide a broader and more objective assessment of surrounding blue space quality by taking into consideration a multitude of health-promoting factors, like facilities for recreation and physical activity, safety, and attractiveness. Another way to measure quality of green and blue spaces is through biodiversity. Certain ecological characteristics, such as higher diversity of specific plant and animal species, can increase the attractiveness of green and blue spaces, reduce more air pollution, and prevent flooding (Marselle et al., 2021). Ecological quality, particularly, in accessible public green spaces can be important for mental health and well-being. A study of adults in Greater London, for example, found that life satisfaction was higher for individuals who lived closer to Sites of Importance for Nature Conservation (Knight, McClean and White, 2022). The UK Habitat Classification database and the National biodiversity Network can be used to provide information on plant and animal species distribution, which can be used as a proxy for biodiversity (UK Habitat Classification, 2023; Harding, 2003), however, such data is usually limited to certain areas and cannot be used for nation-wide exposure assessment.

Another limitation of this thesis was that I did not assess exposure to different types of inland blue spaces and non-urban green spaces. Research from the UK has shown that visitations to rivers and canals, but not lakes, reduces the odds of poor mental health (McDougall et al., 2022). Water features, and flowers in urban parks have also shown to be linked to greater likelihood of park use for rest and recovery (Nordh and Østby, 2013). While Urban Atlas is a high-resolution dataset for assessing amount of inland blue space, it cannot distinguish between rivers, canals, lakes and ponds. Using data with specific blue space attributes like the UK Lakes database and the OS Open Rivers data, in addition to land use datasets, can help model the availability of different types of inland blue spaces for future epidemiological research. Additionally, this thesis did not separately model exposure to non-urban green spaces such as forests and agricultural areas. Total green space exposure metrics captured percent of land covered in forests, agricultural areas, or parks but the variables didn't differentiate between these types of spaces. Although most UK Biobank participants live in urban areas, exposure to amount of forestland had previously shown to reduce mental health complaints in British populations (Akpinar, Barbosa-Leiker and Brooks, 2016).

Lastly, the impact of the built environment on the relationship between green and blue spaces and multimorbidity was not assessed. Although regression analyses were adjusted for air quality and noise, network accessibility and walkability were not integrated into green and blue space exposure metrics. Given that the majority of the UK Biobank population sample reside in urban areas, built-environment features like road-networks, density of housing and amenities, shops, and transport stops, likely play a role in the ways in which individuals are able to interact with their surrounding green and blue spaces (Frank et al., 2006). Walkability is an index constructed to measure the extent to which urban environments are walkable by incorporating factors like population density, road network connectivity and density of certain destinations such as shops, bus stops, amenities and places of worship (Dovey and Pafka, 2020). Walkability has been previously associated with better physical activity, lower BMI, and CVD outcomes in HIC populations (Coffee et al., 2013; Van

Cauwenberg et al., 2016; Zhao and Chung, 2017), and the UK Biobank (Sarkar, Webster and Gallacher, 2018a). A recent UK Biobank study additionally found that incorporating green space into a walkability index further increased physical activity levels (Roscoe et al., 2022b). A green walkability index, therefore, could be constructed that incorporates amount of green space with population density, street connectivity and points of interest to better assess how a combination of natural and built environment features jointly affect multimorbidity.

7.6.1.2 UK Biobank cohort

This thesis used the UK Biobank cohort to assess the relationships between green and blue spaces with multimorbidity. Although the UK Biobank was chosen for its large sample size and abundance of environmental data, the cohort and subsequent results of this thesis may not be representative of the entire British population because UK Biobank participants are more likely to be female, live in urban areas, and have higher socio-economic status (Fry et al., 2017), which could imply that the results from this thesis are biased due to the ‘healthy volunteer’ effect. As many volunteer-based cohorts are susceptible to selection bias (Pizzi et al., 2012; Andreeva et al., 2015), the best approach towards gathering population-representative data is through administrative datasets like the NHS GP records. Working with such data, however, is computationally intensive, fragmented and often unnecessary. Fry et al. (2015) argue that the (un)representativeness of the cohort is not necessarily a limitation in exposure-disease studies if other sources of bias, like confounding and reverse causation, are accounted for.

7.6.1.3 Moderating impact of sex

Another limitation of this thesis is that it did not assess the moderating effect of sex on the relationships between the natural environment and multimorbidity. Perceptions of the surrounding green spaces may differ by sex (Bennett et al., 2007). Women, especially of low-income, may use green spaces predominantly for childcare and socialisation, while men may use them more for recreational physical activity (Cohen et al., 2010; Braçe, Garrido-Cumbrera and Correa-Fernández, 2021).

A systematic review found that green spaces have a stronger impact on CVD and obesity in women than men (Sillman et al., 2022). A UK Biobank study also found that higher amount of greenness showed stronger protective relationships with the odds of depression in women than in men (Sarkar, Webster and Gallacher, 2018b). The pathways leading green and blue spaces to health should be assessed separately for men and women in order to identify and design suitable public health interventions. Multimorbidity is also more prevalent in women than men (Violan et al., 2014). Middle aged and older British women in particular are more likely to suffer from mental-physical multimorbidity than men, and often present with a combination of conditions like depression, CVD and pain (Agur et al., 2016), the burden of which could potentially be reduced through the interaction of green and blue spaces.

7.6.1.4 Statistical analyses, missing data and adjustment for multiple testing

The results from this thesis could also be limited by lack of additional statistical analyses to account for missing data and adjustment for multiple testing. First, UK Biobank participants with missing environment, confounder and outcome data were excluded from the analyses. Multiple imputation is a statistical approach used to handle missing data by deriving missing values from distributions and relationships in the observed data (Pedersen et al., 2017). This can increase sample size and reduce selection bias, however, multiple imputation in observational epidemiological research is highly contingent on specific assumptions, which could not be tested in this thesis. Most multiple imputation analyses assume that the data are missing at random (Pedersen et al., 2017), which was not tested for this UK Biobank sample because it was not possible to obtain and model all variables that predict the missing values and influence the causes of the missing data. These included variables of social determinants of health that influence missing health and socio-demographic data, which were the most common sources of missing data in this sample. Furthermore, the sample size in my analyses was limited due to missing green and blue space data, which were not missing at random and generally have a non-normal distribution, making them unsuitable for multiple imputation analyses.

Second, the analyses for the relationships between exposure to green and blue spaces with multimorbidity may be limited due to lack of adjustment for multiple testing. This thesis tested multiple hypotheses for the relationships between different types of green and blue spaces with multimorbidity, which could have increased the probability of incorrectly rejecting the null hypothesis and deducing there is a statistically significant relationship where there is not (also known as Type I error) (Rothman, 2010). This could have been minimised by applying a Bonferroni correction to the analyses, which would adjust the p-values to account for the probability of Type I errors (Streiner et al., 2011). Although some the relationships between green and blue spaces with multimorbidity might have occurred due to a Type I error, this thesis observed consistent patterns of significant reductions in the odds of complex and mental multimorbidity with greater amount of blue space (but not other exposures), which implies that true cross-sectional relationships might be present in the UK Biobank population. Nevertheless, future causal analyses of such nature should be conducted with the Bonferroni correction.

7.7 Conclusion

This thesis examined the associations between exposure to green and blue spaces with multimorbidity by adopting a population-based approach. A systematic review of longitudinal studies was first conducted to better understand how exposure to different types of green and blue spaces affects mental health and NCDs. As the systematic review showed there is currently lack of high-quality comparative health research on types of green and blue spaces, a data integration study using Urban Atlas land use data was conducted to construct exposure measures of total green space provision, park proximity, street tree provision, inland blue space provision, and green and blue space provision. This data were linked at an individual-level to 300,000 UK Biobank participants. Data on LTCs from UK Biobank was then used to construct a cross-sectional model on the relationships between each green and blue space exposure with four multimorbidity outcomes. The results from these analyses showed that only higher amount of inland blue space was associated with moderate reductions in the odds of complex and mental multimorbidity. Research on the health-promoting roles of blue spaces is still expanding, but results from this thesis indicate that blue spaces can be important in reducing the risk of complex health states. This has implications for future research and policy. Particularly, epidemiological research should aim to analyse the relationships between life course exposure to blue spaces with the incidence of multimorbidity to better understand the biological, social, and environmental factors driving these relationships. On the other hand, urban regeneration interventions should involve local and community stakeholders in decision-making in order to provide equitable improvements in the access to blue spaces that serve low-income and marginalised groups.

Appendix I: Systematic Review Publication

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Systematic Review

Relationship between Green and Blue Spaces with Mental and Physical Health: A Systematic Review of Longitudinal Observational Studies

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Abstract: There is growing interest in the ways natural environments influence the development and progression of long-term health conditions. Vegetation and water bodies, also known as green and blue spaces, have the potential to affect health and behaviour through the provision of aesthetic spaces for relaxation, socialisation and physical activity. While research has previously assessed how green and blue spaces affect mental and physical wellbeing, little is known about the relationship between these exposures and health outcomes over time. This systematic review summarised the published evidence from longitudinal observational studies on the relationship between exposure to green and blue space with mental and physical health in adults. Included health outcomes were common mental health conditions, severe mental health conditions and noncommunicable diseases (NCDs). An online bibliographic search of six databases was completed in July 2020. After title, abstract and full-text screening, 44 eligible studies were included in the analysis. Depression, diabetes and obesity were the health conditions most frequently studied in longitudinal relationships. The majority of exposures included indicators of green space availability and urban green space accessibility. Few studies addressed the relationship between blue space and health. The narrative synthesis pointed towards mixed evidence of a protective relationship between exposure to green space and health. There was high heterogeneity in exposure measures and adjustment for confounding between studies. Future policy and research should seek a standardised approach towards measuring green and blue space exposures and employ theoretical grounds for confounder adjustment.

Keywords: environment; green space; blue space; mental health; long-term health; systematic review; cohort studies

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1. Introduction

It is well established that noncommunicable diseases (NCDs) are the largest contributors to the global burden of disease [1]. NCDs are medical conditions that are non-infectious and non-transmittable from person to person, and in 2017 they accounted for 73% of all global deaths [2]. Cardiovascular disease (CVD), diabetes, cancer and chronic lung disease are the most prevalent NCDs [3] but they often tend to co-occur with common and severe mental health conditions such as depression, schizophrenia and bipolar disorder [4]. The relationship between physical and mental health is bidirectional and characterised by complex interactions [5,6]. Poor mental health increases the risk of developing NCDs due to engagement in unhealthy behaviours and low help seeking [7,8]. Having a long-term physical health condition, on the other hand, puts people at greater risk of depression and anxiety due to reduced quality of life, treatment side effects and disability [5,9]. Physical activity, diet, alcohol consumption and smoking play an important role in moderating this relationship but also independently affect the risk of developing both mental and physical health conditions [10]. While these modifiable risk factors are key drivers of NCDs, environmental exposures have also emerged as important determinants of health [11]. Noise and air pollution are now proven contributors to the global burden of disease and there is currently growing interest in studying the pathways between the natural environment and the development and progression of long-term health conditions. [11,12]. Green and blue spaces are areas of varying size that have been colonised by plants and/or fresh or saltwater. They make up a large proportion of the natural environment and can be both naturally occurring or existing as a result of human intervention [13,14]. Overall, the effects of green and blue spaces on health can be summarised by three major biopsychosocial pathways: reduction in harm (capturing and limiting air pollution, noise and heat); restoring capabilities (restoring attention and reducing stress); and building capacities (improving physical activity and social cohesion) [15–20].

There is now ample evidence about the relationship between exposure to different types of green and blue spaces and health. Cross-sectional research found greater exposure to an amount of green space and a blue space aesthetic (view from the window) to increase the odds of having good self-perceived general health [21,22]. A study on morbidity in primary care also deduced that, in general, having 10% more green space than average in the surrounding environment is associated with a lower risk of having mental and physical morbidity [23]. This relationship was stronger when green space was captured in a 1 km circular buffer than in a 3 km buffer [23]. Small reductions in CVD events, and the risk of all-cause and respiratory mortality were also observed with an increasing amount of greenness by cohort studies and meta-analysis [24–26]. Moreover, the size of urban green spaces affects the odds of having multimorbidity, as those with CVD and/or diabetes living near a park with a relatively small area had 3.1 times higher odds of having depression compared to those who lived near a park with a big area [27]. These relationships also vary by sociodemographic characteristics. Some studies have shown that the health benefits of green spaces are greater for those of low socioeconomic status (SES), nonwhite ethnicity and male sex [23,28,29].

Several systematic reviews of epidemiological studies have summarised the relationships between green and blue spaces and health [30–36]. While greater exposure to green space was associated with better mental and physical wellbeing [31], better general self-perceived health [32], reduced risk of all-cause mortality [32], reduced risk of CVD mortality, diabetes and preterm birth [33]; no relationship was observed for mental ill-health [30], cognitive functioning [34], urbanisation-related health conditions [35] and long-term physical health conditions [36]. Plausible explanations for this included poor study quality, study type or heterogeneity in exposure measurements [34–36]. Earlier systematic reviews studying the relationship between exposure to green space and physical long-term health conditions also found the literature to be saturated with cross-sectional studies that cannot prove causality [32,33,36].

It is apparent that a broad range of health and wellbeing outcomes have been studied in systematic reviews on green and blue space. However, the effect of the natural environment on the development of highly prevalent long-term mental and physical health conditions over time is still uncertain. This systematic review addresses several gaps in the literature. First, it captures only longitudinal observational data to study the relationship between exposures to green and blue spaces with long-term mental and physical health conditions. Longitudinal, observational studies are important in deducing causality and informing public health interventions [37]. Government bodies, such as Public Health England [38], have called for a need to improve quality, engagement and access to green spaces to promote good health, acknowledging there is high variation in the ways environmental exposures and types of health outcomes are used in research. Including both green and blue space exposure further addresses the methodological approaches in exposure measurements and aids the understanding of underlying mechanisms in the relationship. Thirdly, our systematic review aims to examine the relationship between exposure to green and blue spaces with the development and progression of multimorbidity. While prior systematic reviews have attempted to ascertain the relationship between the natural environment and single long-term conditions [33,36], little is known about the natural environment's role in the development of multiple chronic conditions within an individual. Multimorbidity is a growing concern among aging populations because it reduces individuals' quality of life, increases the risk of disability and puts financial strain on health systems [39]. Fourthly, the inclusion of both mental and physical health outcomes offers opportunities to identify differences in the direction and strength of associations between different outcomes.

This review, therefore, aims to:

1. Assess whether a significant relationship between exposures and outcomes exists.
2. Identify the type of environmental exposures, type of health conditions and behaviours studied together in longitudinal relationships.
3. Determine whether multimorbidity as a concept is studied in relation to different green/blue space exposures.

2. Materials and Methods

The Preferred Reporting Items for Systematic reviews and Meta-Analyses for Protocols (PRISMA-P) statement was used as guidance in protocol preparation and review reporting [40]. A protocol was registered via the International Prospective Register of Systematic Reviews (PROSPERO), identification number: CRD42020175965.

2.1. Selection Criteria

Studies published in academic journals in English were included. No date restrictions were applied. Only studies of a longitudinal, observational design with a population of male and/or female adults (mean population age: 18 years or older) were included. Populations with pre-existing health conditions and populations without pre-existing health conditions at baseline were included. Any study measuring green and/or blue space exposure that fits the broadly accepted definition of an area of naturally growing outdoor vegetation and/or water body was included. Studies that used objective (e.g., remote sensing) and/or subjective (self-reports) measures of green and blue spaces were eligible for inclusion. The primary outcome was mental and/or physical health. Mental health conditions included those which are classified by the National Institute for Health and Care Excellence NICE [41,42] as common (depression, generalised anxiety disorder (GAD), panic disorder, phobias, social anxiety disorder, obsessive-compulsive disorder (OCD) and post-traumatic stress disorder (PTSD)) and severe mental health disorders (bipolar disorder, psychosis and schizophrenia). As defined by the Centre for Diseases Control, physical health included NCDs with a duration of one year or more that "require ongoing medical attention or limit activities of daily living or both" [43]. Secondary outcomes related to health were also included: health-related behaviours (physical activity, diet, smoking, alcohol consumption), physical functioning, frailty and health-related quality of life (QoL). Eligible outcomes were included if they were reported via structured clinical interviews or by validated self-reported instruments.

The search strategy was compiled in consultation with an information specialist from the University of York Centre for Reviews and Dissemination. A search strategy striving for high sensitivity was run on 17 July 2020 in six online databases: Embase, GreenFILE, MEDLINE, PsycINFO, Scopus, Science Citation Index (see Supplementary Material S1). Search terms for longitudinal study design, green and blue space exposures, and mental and physical health were included and combined with appropriate Boolean operators.

2.2. Data Extraction

Retrieved records were imported into Rayyan, a web-based application commonly used as a screening aid. Rayyan is a validated tool for systematic review screening that allows for flexibility in setting screening standards [44,45]. After duplicates were identified and removed, study titles and abstracts were screened against the inclusion and exclusion criteria by one reviewer (MG). Following this, the full text of each potentially eligible study was screened by one reviewer (MG). Reference lists of studies were also screened for potentially eligible records. Uncertainty about the inclusion of a study at all stages of the screening process was resolved through consensus meetings with a second reviewer or an attempt to contact the authors for clarification. Relevant data from selected studies were extracted into Microsoft Excel using a prespecified data extraction form adapted from Cochrane [46,47] by the reviewers to suit longitudinal observational studies (see Supplementary Material S2). Data extraction was executed by one reviewer (MG) and accompanied by consensus meetings with a second reviewer to resolve uncertainties.

2.3. Quality Appraisal

The Newcastle–Ottawa Scale (NOS) was used for risk of bias assessment. It is endorsed by the Cochrane as a suitable tool for observational cohort and case-control studies [47,48] with established validity and interrater reliability [49]. NOS consists of three domains that assess the quality of the cohort study. These include *selection* of the study based on the representativeness of cohort and exposure measures; *comparability* based on the design or analysis; and *outcome assessment*, including loss and adequacy of follow-up. A star was awarded if a study met the criteria specified by NOS' developers (See Supplementary Material S3) [48,49]. The overall rating of the study was based on the sum of the stars across all domains. Good quality was awarded if a study scored 3 or 4 stars on the selection domain and 1 or 2 stars on the comparability domain and 2 or 3 stars on the outcome domain. Fair quality was awarded if a study scored 2 stars on the selection domain and 1 or 2 stars on the comparability domain and 2 or 3 stars on the outcome domain. Poor quality was awarded to those studies that scored 0 or 1 star on the selection domain or 0 stars on the comparability domain or 0 or 1 star on the outcome domain (See Supplementary Material S3 for more information) [48]. This tool allowed for selection and information bias to be assessed, particularly, sampling bias, differential loss to follow-up and confounding. One reviewer (MG) conducted the quality appraisal.

3. Results

3.1. Overview

The PRISMA-P flowchart in Figure 1 shows the process of identification, screening and inclusion of studies. The search yielded 24,176 studies after removal of duplicates (Figure 1). Of these, 23,941 were excluded during the title and abstract screening stage, leaving 233 studies for full-text assessment. One hundred and eighty-nine full-text records were excluded during that stage, leaving 44 studies for the qualitative narrative synthesis. Just under half (n = 90, 47.6%) of the excluded studies in the full-text screening stage did not include a green or blue space exposure, while another 38 (20.1%) studies did not have an observational longitudinal study design. A further 37 (19.6%) studies were excluded based on outcome, which either did not fit the definition of an NCD (n = 22), measured mortality (n = 3), did not use a validated instrument (n = 4), examined acute and/or infectious diseases (n = 7), or did not include a health condition (n = 1). Six studies were excluded because of the population type (all children) and 13 because of the publication type (one dissertation and twelve conference papers). Two records were also excluded because they were duplicates (See Supplementary Material S4).

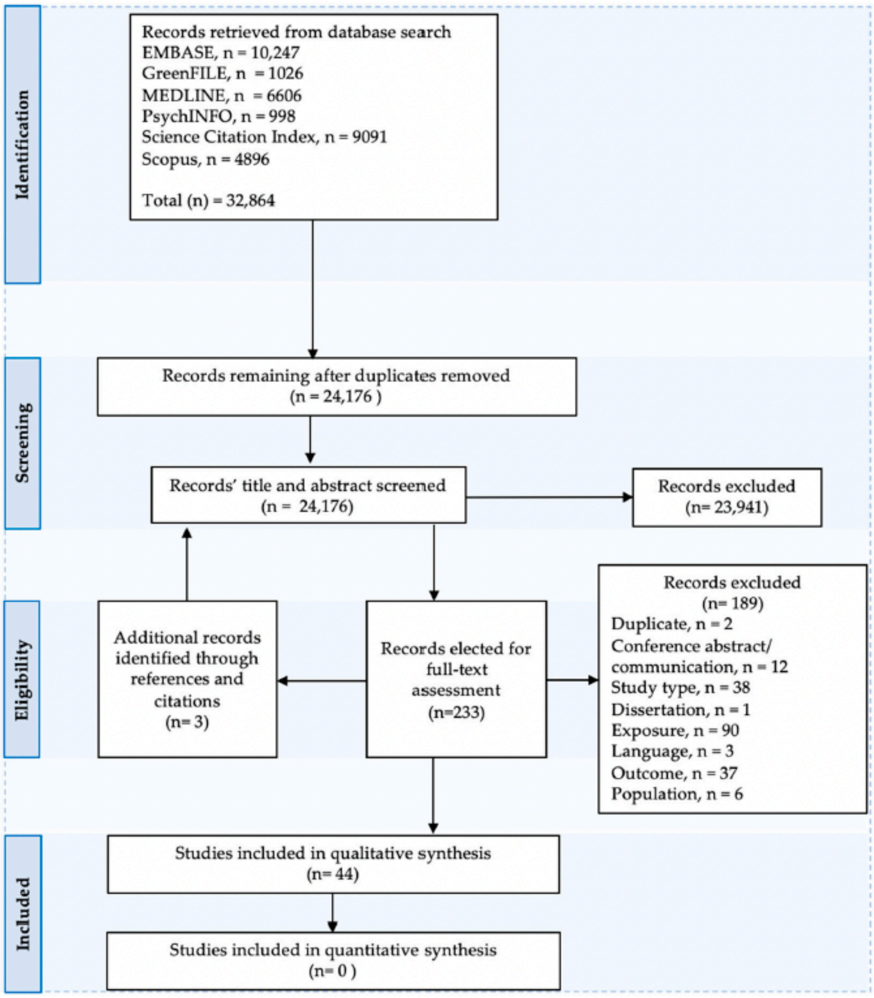


Figure 1. PRISMA-P Flowchart.

Forty-four independent studies were included in the narrative synthesis [50–93]. The majority (n = 42) were published between 2010 and 2020 and based in high-income countries (n = 35) (Table 1). Nine studies were based in middle- and low-income countries. Study populations mainly comprised of adults aged 35 years or older (n = 31) (Table 1). Seven studies included populations of all age groups and another six included young adults (18–35 years). Most studies included both men and women participants (n = 35). Six studies included only female participants [50,65,74,75,83,84] and one study included only male participants [90] (Table 1). Almost all studies (n = 42, 95%) included predominantly healthy populations at baseline. Two studies included people with pre-existing health conditions, of which both were diabetes [53,82].

Table 1. Summary of study characteristics, results and quality appraisal.

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Primary Outcomes											
Mental Health											
Banay et al. [50]	women nurses; ≥30–55 years [USA]	121,701	Nurses' Health Study	10 years	NDVI [1] averages for each year of follow-up; 250 m and 1250 m circular buffers	Availability	Depression	First self-report of physician/clinician diagnosis of depression or new regular use of antidepressants	250 m Buffer HR [1]: 0.87 [0.78, 0.98] Highest NDVI quintile 1250 m Buffer HR: 0.90 [0.80, 1.02] Highest NDVI quintile	age, race, mental health, marital status, educational attainment, husband's educational attainment, population density, income, median home value, PM [1] 2.5 level, BMI [1], smoking status and pack-years of smoking, alcohol consumption, physical activity, physical function, bodily pain [baseline], social network strength, care to ill family members [baseline], difficulty sleeping [baseline]	Poor
Fernandez-Nino et al. [51]	men and women; ≥55 years [Mexico]	1524	Study on Global Ageing and Adult Health [SAGE]	5 years	Street trees; total length of street covered in trees in a 950 m road network buffer	Accessibility	Depression	Self-report of physician diagnosis	OR [1]: 0.90 [0.29, 2.83] Highest quintile of street length covered in trees	sex, age, income index, functional limitations, margination index of the municipality	Good
Gariepy et al. [52]	men and women; ≥18–80 years [Canada]	13,618	National Population Health Survey	10 years	Presence of a park within a 500 m circular buffer	Accessibility	Depression	Self-reported instrument	B [1]: −0.4 [−1.4, 0.6] For answering "yes" to presence of a park	age, sex, marital status, education, income adequacy, childhood life events, chronic condition, family history of depression	Good

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Gariepy et al. [53]	men and women; ≥18–80 years; with diabetes [any type] [Canada]	2003	Diabetes Health Study [DHS]	5 years	NDVI	Availability	Depression	Self-reported instrument	HR: 0.94 [0.88, 1.01] Per decile increase in NDVI	sex, age, marital status, family income, educational level, employment	Good
Melis et al. [54]	men and women; ≥20–65 years [Italy]	547,263	Turin Longitudinal Study [TLS]	2 years	Availability of green space measured via index by area units	Availability	Depression	Antidepressant use	Men IRR [1]: 0.98 [0.92, 1.04] Highest index value quintile green Women IRR: 1.00 [0.96, 1.08] Highest index value quintile of green	sex, age, education level, activity status, citizenship, residential stability at same address	Good
Picavet et al. [55]	men and women; ≥18 to 55 years [Netherlands]	4917	Doetinchem Cohort Study	15 years	Percent green space in 125 m and 1000 m circular buffer	Availability	Depression	Self-reported instruments	Per unit increase in percent green space 125 m OR: 0.97 [0.92, 1.04] 1000 m OR: 0.86 [0.79; 0.93]	age, sex, SES [1]	Poor
Tomita et al. [56]	men and women; mean 20 years [South Africa]	11,156	South African National Income Dynamics Study [SA-NIDS	4 years	NDVI, 250 m resolution square	Availability	Depression	Self-reported instrument	OR: 1.01 [1.01, 1.02] Each unit increase in NDVI value	age, sex, marital status, race, household income, employment, rurality	Good

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Gariepy et al. [53]	men and women; ≥18–80 years; with diabetes [any type] [Canada]	2003	Diabetes Health Study [DHS]	5 years	NDVI	Availability	Depression	Self-reported instrument	HR: 0.94 [0.88, 1.01] Per decile increase in NDVI	sex, age, marital status, family income, educational level, employment	Good
Melis et al. [54]	men and women; ≥20–65 years [Italy]	547,263	Turin Longitudinal Study [TLS]	2 years	Availability of green space measured via index by area units	Availability	Depression	Antidepressant use	Men IRR [1]: 0.98 [0.92, 1.04] Highest index value quintile green Women IRR: 1.00 [0.96, 1.08] Highest index value quintile of green	sex, age, education level, activity status, citizenship, residential stability at same address	Good
Picavet et al. [55]	men and women; ≥18 to 55 years [Netherlands]	4917	Doetinchem Cohort Study	15 years	Percent green space in 125 m and 1000 m circular buffer	Availability	Depression	Self-reported instruments	Per unit increase in percent green space 125 m OR: 0.97 [0.92, 1.04] 1000 m OR: 0.86 [0.79; 0.93]	age, sex, SES [1]	Poor
Tomita et al. [56]	men and women; mean 20 years [South Africa]	11,156	South African National Income Dynamics Study [SA-NIDS	4 years	NDVI, 250 m resolution square	Availability	Depression	Self-reported instrument	OR: 1.01 [1.01, 1.02] Each unit increase in NDVI value	age, sex, marital status, race, household income, employment, rurality	Good
Astell-Burt and Feng [57]	men and women; ≥45 years [Australia]	46,786	45 and Up Study	6.2 [mean] years	Total percent green space; tree canopy in a 1600 m road network buffer	Availability	Depression or anxiety	Self-report of doctor diagnosed	OR: 1.26 [0.89, 1.63] Highest percent quintile total green OR: 0.86 [0.80, 1.01] Highest percent quintile tree canopy	age, sex income, education, economic status, couple status	Poor

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Pun et al. [58]	men and women; ≥57–85 years [USA]	3005	National Social Life, Health, and Aging Project [NSHAP]	6 years	NDVI seasonal changes in 1000 m circular buffer	Availability	Depression; anxiety	Self-reported instrument	Anxiety β: −0.104 [−0.322, 0.115] per unit increase in NDVI Depression β: −0.274 [−0.596, 0.048] per unit increase in NDVI	age, gender, questionnaire year, season, region, education attainment, 3-day moving average of temperature, 60-months moving average of PM2.5	Good
Chang et al. [59]	men and women mean age: 43.36 [20.44] years [Taiwan]	869,484	Taiwan Longitudinal Health Insurance Database	10 years	NDVI at baseline; 2000 m circular buffer around hospital most frequently visited	Availability	Schizophrenia	Physician-diagnosed	HR: 0.37 [0.25, 0.55] Highest NDVI quintile	age, sex, health insurance rate, classification of the insured, temperature, relative humidity, precipitation	Good
						NCDs					
Dalton and Jones [60]	men and women; mean 59.2 years [United Kingdom]	25,639	European Prospective Investigation of Cancer [EPIC] Norfolk	14.5 [mean] years	Percent green space in 800 m circular buffer	Availability	CVD [1]	Health register	HR: 0.93 [0.88, 0.97] Highest percent quintile green	sex, age, BMI, diabetes, SES [individual and neighbourhood]	Good
Tamosiunas et al. [61]	men and women; ≥45–72 years [Lithuania]	5112	Health, Alcohol, and Psychosocial Factors in Eastern Europe [HAPIEE]	4.41 [mean] years	Distance to park and park use [self-reported]	Accessibility	CVD	Self-reported doctor diagnosed	User: HR: 1.58 [0.95, 2.63] Longest distance quintile Nonuser: HR: 1.66 [1.01, 2.73] Longest distance quintile	age, sex, education, smoking, arterial hypertension, physical activity, total cholesterol level, fasting glucose level, BMI, diabetes mellitus, cognitive function, symptoms of depression, self-rated health, and quality of life	Good

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Clark et al. [62]	men and women; ≥45–84 years; urban residents [Canada]	380,738	British Columbia mandatory health insurance database	4 years	NDVI yearly and seasonal; in 100 m circular buffer	Availability	Diabetes	Health register	OR: 0.90 [0.87, 0.92] IQR [1] increase in NDVI	sex, age, area-level household income, walkability, pollution	Good
Renzi et al. [63]	men and women; ≥35 years [Italy]	1,459,671	Rome Longitudinal Study	5.2 [mean] years	NDVI and LAI in a 300 m circular buffer	Availability	Diabetes	Medical records	β: −1.87 [−7.40, 3.99] Per unit increase in NDVI	SES, marital status, educational level, occupation, place of birth, sex	Good
Dalton et al. [64]	men and women; ≥40–80 years [United Kingdom]	25,633	European Prospective Investigation into Cancer [EPIC] Norfolk	11.3 [mean] years	Percent green space; in 800 m circular buffer	Availability	Diabetes[T2]	Self-report of physician diagnosis or medication	HR: 0.81 [0.65, 0.99] Highest percent quintile green	sex, age, BMI, parental diabetes, SES	Good
Liao et al. [65]	pregnant women; 25–29 years mean age group [China]	6,883	Visitors of Wuhan's Women and Children Medical and Healthcare Center	9 months or until devel-opment of gestational diabetes	NDVI for conception years; 300 m circular buffer	Availability	Diabetes [genstational]	Clinical samples	RR[1]: 0.66 [0.52, 0.84] Highest quintile NDVI	age, education years, BMI, passive smoking during pregnancy, parity, season	Good
Hobbs et al. [66]	men and women; ≥18–89 years [United Kingdom]	28,806	Yorkshire Health Study	3 years	Presence of park in a 2000 m circular buffer	Accessibility	Obesity	BMI, self-report	OR: 0.99 [0.98, 1.02] for answering "*yes*" to presence of park	age, sex, education, deprivation, population density	Fair
Persson et al. [67]	men and women, ≥35–65 years [Sweden]	5712	Stockholm Diabetes Prevention Program [SDPP]	8.9 [mean] years	NDVI; time-weighted in a 100 m, 250 m, 500 m circular buffer	Availability	Obesity	Objective measures of BMI	IRR for IQR increase in NDVI 500 m Females: 1.05 [0.88, 1.26] Males: 1.06 [0.89, 1.26]	age, alcohol consumption, tobacco use, psychological distress, shift work, aircraft noise, railway noise, distance to water	Good

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Halonen et al. [68]	men and women; public sector employees; mean: 47.7 years [nonmovers] and among the movers 41.8 [Finland]	35,213	Finnish Public Sector study	8 years	Distance to green space; distance to blue space in meters, objectively measured	Accessibility	Obesity and overweight	Self-reported BMI	Green space OR: 1.50 [1.07, 2.11] Longest distance quintile Blue space OR: 1.15 [0.94, 1.39] Longest distance quintile	age, sex, education, chronic disease, neighbourhood socioeconomic disadvantage, BMI, smoking, heavy alcohol, physical inactivity	Poor
Lee et al. [69]	men and women; ≥19 years [48.6 years mean] [USA]	5435	Offspring and Generation Three Cohorts of the Framingham Heart Study	6.4 years	Percent green space within a census block	Availability	Obesity; Diabetes	Blood samples; medication; objectively-measured BMI	Diabetes: OR: 0.70 [0.41, 1.19] Highest percent quintile green Obesity: no results	age, gender, smoking status, education, cohort status, fasting plasma glucose, BMI	Fair
Astell-Burt and Feng [70]	men and women; ≥45 years [Australia]	53,196	45 and Up Study	6 years	Percent green space; tree canopy in a 1600 m road network buffer	Availability	Diabetes, hypertension and CVD	Self-report of physician diagnosis	Diabetes OR: 1.10 [0.65, 1.95] Highest percent quintile total green OR: 0.71 [0.56, 0.91] Highest percent quintile tree canopy Hypertension OR: 0.72 [0.64, 1.12] Highest percent quintile total green OR: 0.82 [0.71, 0.95] Highest percent quintile tree canopy CVD OR: 0.89 [0.59, 1.13] Highest percent quintile total green OR: 0.79 [0.63, 0.92] Highest quintile tree canopy	age, sex income, education, economic status, couple status	Poor

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Paquet et al. [71]	men and women; ≥18 years [Australia]	4056	North West Adelaide Health Study [NWAHS]	3.5 [mean] years	NDVI in 1000 m road network buffer	Availability	Diabetes; hypertension; obesity; dyslipidaemia	Clinical samples	Per unit increase in NDVI Diabetes RR: 1.01 [0.90, 1.13] Hypertension RR: 0.97 [0.87, 1.07] Dyslipidaemia RR: 1.12 [1.00, 1.25] Obesity RR: 1.04 [0.92, 1.16]	age, gender, smoking status, education, cohort status, fasting plasma glucose, BMI	Good
de Keijzer et al. [72]	men and women; ≥35–55 years civil servants [United Kingdom]	10,308	Whitehall II	14.1 [median] years	NDVI and VCF, 500 m and 1000 m circular buffers and LSOA	Availability	Metabolic Syndrome	Clinical samples	IQR increase in NDVI 500 m HR: 0.87 [0.77, 0.99] 1000 m HR: 0.90 [0.79, 1.01] LSOA HR: 0.91 [0.79, 1.03]	age, sex, ethnicity, individual socioeconomic status [education and employment grade], neighbourhood socioeconomic status [income and employment deprivation]	Good
Datzman et al. [73]	men and women; mean 49.33 years; [Germany]	1,918,449	AOK Plus [health insurance database]	4 years	NDVI; 115 images for 4 years; statistical area units	Availability	Cancer: colorectal; mouth and throat, prostate, breast; non-melanoma skin	Health register	Per 10% increase in NDVI Colorectal: RR: 1.03 [0.98, 1.07] Mouth: RR: 0.89 [0.83, 0.96] Skin: RR: 0.84 [0.79, 0.90] Prostate: RR: 0.95 [0.90, 1.01] Breast: RR: 0.96 [0.92, 0.99]	age, sex, alcohol-related disorder, absolute number of physician contacts, proportion of short and long-term unemployment	Good

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Conroy et al. [74]	women; ≥45–75 years; [African Americans, Japanese Americans, Latinos, Native Hawaiians, and White] [USA]	48,247	Multiethnic Cohort [MEC]	17 years	Presence of a park; based on number in a residential block group	Accessibility	Breast cancer [invasive]	Health register	HR: 1.03 [0.92, 1.15] No park in area	age, clustering effect of block group, ethnicity, risk factors, baseline BMI and adult weight change, neighbourhood SES, all neighbourhood obesogenic factors	Good
Haraldsdottir et al. [75]	women; mean: 53.9 years [Iceland]	10,049	Reykjavik Study	27.3 average	Coastal residence, self-reported	Availability	Breast cancer	Health registers	HR: 0.87 [0.72, 1.04] Coastal residence vs. city	age, birth cohort, education, physical activity, parity, height, BMI in midlife, age at menarche, age at first child	Good
Orioli et al. [76]	men and women; ≥30 years [Italy]	1,265,058	Rome Longitudinal Study	13 years	NDVI average for 2015 in 300 m and 1000 m circular buffer	Availability	Stroke	Health register	NDVI highest quintile 300 m HR: 0.95 [0.91, 0.98] 1000 m HR: 0.97 [0.93, 1.00]	age, sex, educational level, marital status, occupational status, place of birth, area-level SES	Good
Paul et al. [77]	men and women; ≥35–100 years; urban residents Ontario [Canada]	4,251,146	Ontario Population Health and Environment Cohort [ONPHEC]	13 years	NDVI annual values, 250 m circular buffer	Availability	Stroke	Health register	HR: 0.96 [95% CI: 0.95, 0.97] per IQR increase in NDVI	age, sex, SES, comorbidities, northern residence, population density, air pollution	Good
Yuchi et al. [78]	men and women; ≥45–84 years [Canada]	634,432 [parkinson disease]; 7232 [multiple sclerosis]	Medical Services Plan [MSP] Vancouver, mandatory health insurance database	4 years	NDVI; yearly average in 100 m circular buffer	Availability	Parkinson's disease Multiple sclerosis	Health records	Per IQR increase in NDVI Parkinson's Disease: OR: 0.97 [0.93, 1.01] Multiple Sclerosis: OR: 1.14 [1.00, 1.30]	Parkinson's disease: age, sex, comorbidities, household income, education, ethnicity Multiple sclerosis: age, sex, comorbidities, household income, education and ethnicity, comorbidities, household income, education, ethnicity	Good

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Picavet et al. [55]	men and women; ≥18 to 55 years [Netherlands]	4,917	Doetinchem Cohort Study	15 years	Percent green space in 125 m and 1000 m circular buffer	Availability	Obesity; Hypertension	All self-reported instruments	Per unit increase in percent green space 125 m Obesity: OR: 1.04 [1.01, 1.07] Hypertension: OR: 0.99 [0.97, 1.02] 1000 m Obesity: OR: 1.00 [0.96; 1.05] Hypertension: OR: 1.02 [0.98; 1.05]	age, sex, SES	Poor
Secondary Outcomes											
de Keijzer et al. [79]	men and women; ≥35–55 civil servants [United Kingdom]	10,308	Whitehall II study	9 [median] years	NDVI and EVI; distance to blue space [any visible water]; distance to green or blue space in 500 m and 1000 m circular buffer; distance in m	Availability Accessibility	Physical Functioning	Clinical measures	Walking speed [difference baseline and follow-up]: 500 m NDVI β: 0.02 [0.01, 0.04] per IQR increase 1000 m NDVI β: 0.03 [0.01, 0.04] per IQR increase Blue space β: −0.01 [−0.02, 0.01] per IQR increase Grip strength [difference baseline and follow-up]: 500 m NDVI β: −0.01 [−0.03, 0.01] per IQR increase 1000 m NDVI β: −0.01 [−0.03, 0.01] per IQR increase Blue space β: −0.01 [−0.03, 0.01] per IQR increase	sex, ethnicity, marital status, height, alcohol use, intake of fruit and vegetables, smoking, rurality, education, employment grade, Index of Multiple Deprivation [IMD], income score and of the IMD, employment score	Fair

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Yu et al. [80]	men and women; ≥65 years [Hong Kong]	4000	Mr and Ms Os Study	2 years	NDVI at baseline in a 300 m circular buffer	Availability	Frailty	Self-reported instrument	OR: 1.29 [1.04, 1.60] Highest quintile NDVI	age, sex, marital status, SES, current smoking status, alcohol intake, diet quality, baseline frailty status, number of diseases, cognitive function, physical activity, depression	Good
Zhu et al. [81]	men and women; ≥65 years [China]	34,342	Chinese Longitudinal Healthy Longevity Survey [CLHLS]	9 years	NDVI; annual averages for each year in 500 m buffer	Availability	Frailty	Self-reported instrument	OR: 1.02 [1.00, 1.04] Per unit increase in NDVI	age, sex, ethnicity, marital status, geographic region, urban or rural residence, education, occupation, financial support, social and leisure activity, smoking status, drinking status, physical activity	Good
Chong et al. [82]	men and women; ≥45 years with diabetes [T2] [Australia]	60,404	45 and Up Study and the follow-up Social, Economic and Environmental Factors [SEEF] Study	3.3 [mean] years	Percent green space in 500 m, 1000 m, and 2000 m road network buffer	Availability	Physical Activity	Self-reported instrument [MVPA: min/week]	Per highest percent quintile green 500 mMean: 0.61 [−0.26, 1.49] 1000 mMean: 0.94 [0.10, 1.79] 2000 mMean: 0.75 [0.03, 1.48]	age, sex, country of birth, education, disadvantage, physical functioning, BMI, psychological distress	Poor

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Cleland et al. [83]	women parents; mean: 42.4 years;[Australia]	698	Children Living in Active Neighbourhoods [CLAN]	2 years	Amount of greenery and quality of parks, self-reported satisfaction	Availability Accessibility	Physical activity	Self-reported instrument [walking: for leisure and transport [min/week]]	Amount of greeneryPersistently high vs. persistently low PA: RR: 1.80 [1.04, 3.13] Increased vs. persistently low PA: RR: 1.39 [0.90, 2.17] Quality of parks Persistently high vs. persistently low PA: RR: 1.73 [1.17, 2.57] Increased vs. persistently low PA: RR: 1.20 [0.89, 1.62]	age, marital status, number of children in the household, highest level of schooling	Poor
Coogan et al. [84]	women; ≥21–69 years; Black ethnicity [USA]	21,820	Black Women's Health Study	2-6 years 98,280 person-years of follow-up.	Distance to park	Accessibility	Physical activity	Self-reported instrument [Walking for recreation and total walking: y/n]]	Recreation walking OR: 1.01 [0.89, 1.13] Shortest distance quintile Exercise walking OR: 1.01 [0.91, 1.12] Shortest distance quintile	age, region, BMI, smoking, alcohol, marital status, parity, caregiver status, residential moves, chronic conditions, history of cancer, moving residence, vacant housing, SES, crime	Poor
Dalton et al. [85]	men and women; mean age at baseline 62.2 [United Kingdom]	25,639	European Prospective Investigation into Cancer [EPIC] Norfolk	7.5 [mean] years	Percent green space at baseline for nonmovers; 800 m	Availability	Physical Activity	Self-reported instrument [Change in overall PA [hr/week]]	β: 4.21 [1.60, 6.81] Highest percent quintile green	age, sex, marital status, waist to hip ratio, BMI, morbidity, urban/rural location	Fair
Faerstein et al. [86]	men and women; ≥18 years; civil servants [Brazil]	1731	Pro-Saude study	13 years	NDVI [800 m circular buffer]; presence of trees [visual inspection]; proximity to waterfronts;	Availability Accessibility	Physical activity	Self-reported instrument [nonwork PA: yes/no]	OR: 0.85 [0.44, 1.65] Highest quintile NDVI OR: 1.22 [0.62, 2.40] Highest percent quintile of trees OR: 2.46 [1.22, 4.93] Longest distance to waterfronts	sex, race, education, income, neighbourhood contextual variables	Poor

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Hogendorf et al. [87]	men and women; mean: 53 years; [Netherlands]	4758	Gezondheid en Levens Omstandigheden Bevolking Eindhoven en omstreken [GLOBE]	10 years	Area of green space within a 1000 m circular buffer; Distance to green space	Availability Accessibility	Physical activity	Self-reported instrument [total walking and cycling: min/week]	Total walking and cycling Per ha increase in area of green β: 0.82 [−178.84, 180.48] Distance per 100 m increase in green β: −22.36 [−46.19, 1.48]	marital status, income, employment, smoking, self-rated health	Poor
Josey and Moore. [88]	men and women; ≥25years; urban residents [Canada]	2707	Montreal Neighborhood Networks and Healthy Aging Panel [MoNNET-HA]	5 years	Distance to parks and green spaces	Accessibility	Physical Activity	Self-reported instrument [physical inactivity: y/n]	OR: 0.99 [0.99, 1.00] Per mile increase in distance	sex, age, self-reported health status, SES, household language, marriage status, residential duration, wave	Poor
Lin et al. [89]	men and women; ≥65–98 years [Hong Kong]	4000	OS and Ms. OS Study	7.8 [mean] years	NDVI in 300 m circular buffer	Availability	Physical activity	Self-reported instrument [Total PA score]	No relevant results	age, sex, marital status, education level, alcohol consumption, smoking, living alone, self-rated health, chronic conditions, functional impairment	Fair
Michael et al. [90]	men; ≥65 years [USA]	513	Neighborhoods and Physical Activity in Elderly Men	3.6 [mean] years	Distance to park	Accessibility	Physical activity	Self-reported instrument [walking: min/day]	RR for presence of park Low SES: 0.89 [0.70, 1.13] High SES: 1.34 [1.16, 1.55]	age, race education, occupation, marital status, self-reported health, BMI, smoking, drinking, chronic conditions	Fair
Sugiyama et al. [91]	men and women; mean: 54.4 years [Australia]	4802	AusDiab study	7 years	Park or nature reserve in the neighbourhood, self-reported	Accessibility	Physical Activity	Self-reported instrument [meeting PA guidelines: y/n]	OR: 0.96 [0.80, 1.15] for having a park in neighbourhood	age, sex, education, work status change, child change, mobility, BMI	Poor

Table 1. *Cont.*

Study Reference	Population Description	Sample Size	Cohort Name/Data Source	Follow-Up Duration	Exposure Indicator Description	Exposure Indicator Type	Outcome	Outcome Measure	Main Results Effect Estimate [95% CI [1]]	Confounders	Study Quality *
Yang et al. [92]	men and women; ≥40–79 years [United Kingdom]	25,633	European Prospective Investigation into Cancer [EPIC] Norfolk	7 years	Presence of park or green space in 800 m circular buffer	Accessibility	Physical activity	Self-reported instrument [active commuting: y/n]	Park [yes]: OR: 1.30 [0.96, 1.74] Green space [yes]: OR: 1.12 [0.83, 1.53]	No adjustment	Poor
Meyer et al. [93]	men and women; ≥18–30 years; black and white [USA]	5115	Coronary Artery Risk Development in Young Adults [CARDIA]	13 years	Number of parks within a 3000 m circular buffer	Accessibility	Physical activity; Diet Quality	Self-reported validated instruments [PA: frequency walking, biking, running/ week]	No relevant results	N/A	Poor
Picavet et al. [55]	men and women; ≥18 to 55 years [Netherlands]	4917	Doetinchem Cohort Study	15 years	Percent green space in 125 m and 1000 m circular buffer	Availability	Physical activity; Quality of Life	All self-reported instruments [PA: meeting guidelines: y/n]	Per unit increase in NDVI 125 m Physical activity: OR: 1.02 [0.99; 1.04] Quality of Life: Mixed 1000 m Physical activity: OR: 1.01 [0.97; 1.05] Quality of Life: Mixed	age, sex, SES	Poor

[1] Abbreviations: BMI: Body Mass Index/CI: Confidence Intervals/HR: Hazard Ratio/IQR: Interquartile Range/MVPA: Moderate-to-vigorous physical activity/NDVI: Normalized Difference Vegetation Index/OR: Odds Ratio/PA: Physical activity/PM: Particulate matter/RR: Relative Risk/SES: Socioeconomic status/β: Beta coefficient; * Based on Newcastle–Ottawa Scale [NOS] for Cohort Studies.

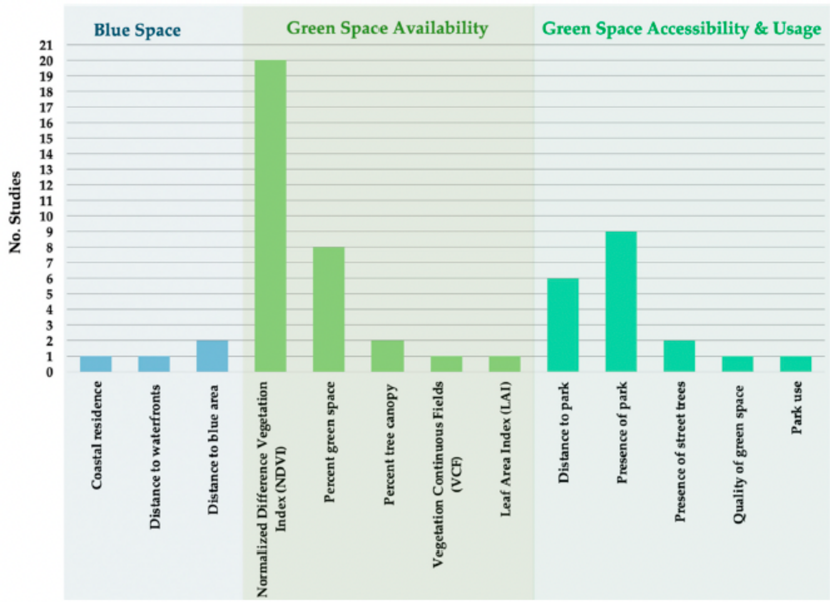
3.2. Quality Assessment

The methodological quality of more than half of all the included studies was rated as good (n = 24, 54.5%). Around one third (n = 14, 31.8%) of the studies scored poor and the rest (n = 6, 13.65%) scored fair on the overall NOS rating. Most studies scored high on the *comparability* domain of the scale, which assessed bias due to confounding. In general studies scored low on the *selection* and *outcome* domains (see Supplementary Material S5).

3.3. Exposures and Outcomes

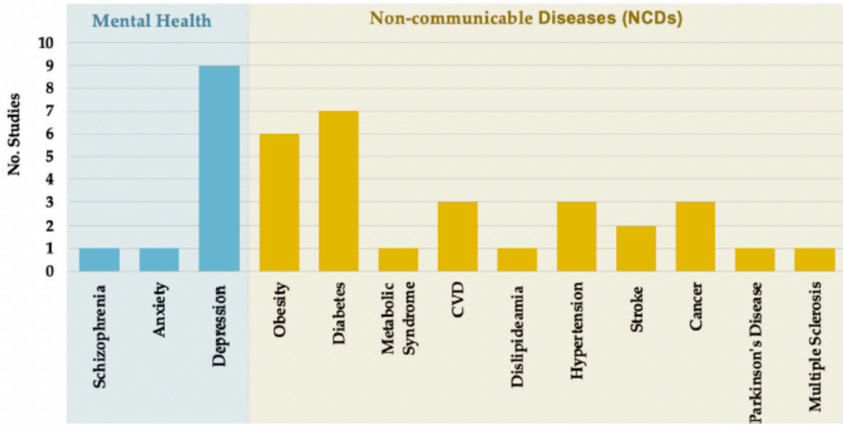
Figure 2a,b provides an overview of the type and frequency of exposures and primary outcomes of the studies. Some studies used multiple indicators of green and blue space exposures and assessed more than one relevant outcome (see Table 1 for more information). There was high variation in exposure indicators, but a large proportion measured green space availability. The Normalised Difference Vegetation Index (NDVI) was the most frequently used indicator of green space availability, followed by percent green space. Almost all accessibility indicators measured either distance or presence of an urban park. One study measured green space usage [61], while only four studies measured exposure to blue space [68,75,79,86].

Studies examined a wide range of mental and physical health outcomes. Depression was the most frequently studied (n = 9) mental health outcome. One study examined anxiety and another schizophrenia. Ten different types of NCDs were identified, of which diabetes (n = 7), obesity (n = 6), CVD (n = 3), hypertension (n = 3), cancer (n = 3) and stroke (n = 2) were most frequently studied (Figure 2b).



(a)

Figure 2. *Cont.*



(b)

Figure 2. Frequency and type of selected studies by: (**a**) exposure; (**b**) primary outcome.

3.4. Relationship between Exposure to Green and Blue Space and Mental and Physical Health

Table 1 presents a summary of the effect estimates for the relationship between green and blue spaces with all relevant outcomes of this review. Overall, there was mixed evidence of a relationship between exposures and outcomes. Nine studies examined whether green space affects the risk of developing depression [50–58] but six of those did not find a statistically significant association (n = 6) (Table 1) [51–54,57,58]. Out of those with a significant relationship, two studies found a small reduction [50,55], while one study found a small increase in the risk of depression with a greater availability of green space [56]. One study [59] found a high reduction in the risk of developing schizophrenia in those exposed to the highest quintile of NDVI compared with those exposed to the lowest quintile (HR (95% CI): 0.37 (0.25, 0.55)).

There was also mixed evidence of a relationship between exposure to green and blue space and the development of NCDs. Four studies found the risk of developing diabetes was reduced with greater exposure to an amount of green space [62,64,65,70]. The rest (n = 3) found no statistically significant relationship [63,66,69]. All studies about CVD showed a significant reduction in the risk of having CVD events with a greater exposure to green space [60,61,70]. On the other hand, only two out of six studies on the development of obesity found a statistically significant relationship [55,68]. A small reduction in the risk of developing cancer was also observed with a greater exposure to green space in one out of three studies [73].

Evidence across the retrieved studies suggests there is only a partial temporal relationship between exposure to green spaces and mental and physical health. CVD and diabetes were the conditions with strongest evidence of a protective relationship with green space. There was some evidence that the type of green space influences the relationship with health [70]. Astell-Burt and Feng [70] found exposure to a greater percent of tree canopy, but not a greater percent of total green space (tree canopy and grass cover), moderately decreased the risk of developing CVD, diabetes and hypertension. While some studies found exposure spatial scales (e.g., size of distance buffers) attenuated the relationship [55,72], in sensitivity analyses most studies found no change in effect estimates when analyses were repeated using different buffer sizes (see Supplementary Material S6). Confounding variables also varied among studies, but all adjusted for sociodemographic characteristics. Some studies additionally adjusted for environmental variables, such as season, noise, air pollution and humidity [50,58,59,62,65,67] and health behaviours, like physical activity [50,61,65,67–69,71,75]. No differences in relationships were observed between studies that adjusted only for sociodemographic variables and those that additionally adjusted for environmental and behavioural factors.

3.5. Relationship between Green Space and Physical Activity

Physical activity was the most frequently studied outcome in this review (n = 13). Over half of the studies (n = 7) measured physical activity by type, such as walking, jogging, cycling. The rest measured total physical activity over the course of a prespecified time period (Table 1). Only five studies found a significant association between green space exposure and physical activity [82,83,85,86,90]. There was some variation in adjustment for confounding variables between studies, but most adjusted for sociodemographic and neighbourhood contextual variables. Over half of the studies (n = 7) additionally adjusted for health status, including BMI, physical functioning and chronic diseases [82,84,85,87,89–91]. However, no patterns between confounding and statistically significant findings could be identified. While one study found differences in results between exposure buffer sizes [82], in sensitivity analyses, two studies found that the effect estimates did not change when green space was measured at different spatial scales (using different buffer sizes) [85,86].

3.6. Multimorbidity

This review found negligible evidence in the published literature of a longitudinal relationship between multimorbidity and green and/or blue space. One study examined how green space exposure affects the development of depression in adults with diabetes at baseline [53] and found no significant association between higher NDVI values and incident depression at the 5-year follow-up. Two studies additionally observed a general trend of improvement in frailty status with increasing greenness [80,81]. Despite being a concept closely related to multimorbidity, the studies on frailty did not conceptualise or measure multimorbidity.

4. Discussion

4.1. Relationship between the Natural Environment and Health

This systematic review showed there is currently minimal evidence of a consistent, significant longitudinal relationship between exposure to green and blue space and mental and physical health. Where statistically significant relationships existed, the associations were quite weak. Highest reductions in the risk of developing long-term health conditions with greater exposure to green space was observed for diabetes, CVD, stroke and schizophrenia. While prior systematic reviews and observational studies have shown there to be some significant cross-sectional associations between depression, diabetes and obesity [33,36,94–96], this systematic review concludes the relationship does not generally hold longitudinally. Due to the recent nature of the research, the reasons behind this are not entirely clear. One potential explanation could be the methodological design of longitudinal studies and the measurement of environmental exposures. First, the heterogeneity of green space exposure measures is well documented in the academic literature [34,97,98]. This is also supported by studies in our systematic review. A range of data sources, including remote sensed imagery from land use maps, regional government databases and self-reported information, is commonly used to ascertain green space exposure in the neighbourhood [99]. Such data sources are often incomplete and provide a varying degree of accuracy, which increases the difficulty of sourcing enough data to measure green space both at baseline and follow-up. Very often, green space exposures in longitudinal studies are measured only at one point in time with the assumption that the presence of vegetation doesn't change drastically over time [51,53,54,58,59,61,63,65,66,70,71,74,76,80,83–89,91]. However, urban areas undergoing regeneration or expansion may experience drastic changes in the amount and availability of greenery [100]. While cross-sectional studies only measure green space at a single point in time, longitudinal studies require multiple and complex exposure measurements. The unavailability of data to assess these changes in exposure over time could be a reason for the lack of longitudinal relationships.

Another potential explanation for the differences in results between cross-sectional and longitudinal studies could be the duration of follow-up of longitudinal studies. The dosage and duration of green space exposures required to influence health is still not entirely understood. However, there is some evidence that environmental factors in childhood and even from preconception and birth can shape the health of a person decades later [101]. Sensitive periods during human development are discrete time points at which certain environmental stimuli must be encountered for mental and physical development to occur [102]. The need to incorporate a life-course approach when studying the effects of green spaces on health has been previously highlighted, but its feasibility requires extensive utilisation and interpolation of historical data from varying sources [103]. While positive associations between green space and health observed in cross-sectional studies may be caused by sample size or sampling bias, the lack of relationship at a longitudinal level may be due to the low duration of follow-up. More research, therefore, is required to understand whether exposure to green space during sensitive periods of human development affects health later in life. This would better inform the duration of follow-up and study design of future longitudinal research.

It should be noted that our systematic review examined a broad range of mental and physical health outcomes, which yielded different strengths of associations. A finding that stood out was the relationship between exposure to green space and schizophrenia [59]. Chang et al. [59] found the risk of developing schizophrenia to be reduced by 63% (HR (95% CI): 0.37 (0.25, 0.55)) in those exposed to the highest quintile NVDI compared to those exposed to the lowest. This is consistent with prior research on the relationship between green space and schizophrenia [104]. The reasoning behind these findings is not entirely clear but it is known that the risk of schizophrenia is often influenced by environmental exposures such as air pollution and urbanicity [105]. Biological mechanisms that affect brain development is a potential explanation for the increased risk of developing schizophrenia with greater exposure to air pollution [105]. As green spaces have the ability to reduce and capture air pollution, it is plausible that they counteract the negative effects of hazardous environmental factors.

Confounding could be a potential contributor to differences in results between studies included in this systematic review. Variation in confounding between studies was observed, but most adjusted for sociodemographic variables, such as age, sex and socioeconomic position. Although some studies additionally adjusted for physical activity, air quality and noise, no differences in relationships could be observed between minimally adjusted studies and those adjusting for additional environmental and behavioural variables. The review deduced there is currently no consensus on appropriate confounder adjustment, but it should be acknowledged that additional contextual factors like the built environment and clinical characteristics can also have an impact on the relationship. For example, studies have shown that neighbourhoods with high crime, deprivation, social disorganisation, a high retail density and land-use mix, can increase the risk of depression [106,107]. It is also hypothesised that further consideration of childcare duties and types of work might play an important role in the ways people utilise and interact with their environment [108]. We found that studies in this systematic review generally lacked adjustment for such variables, possibly due to a lack of such data in health cohorts.

Apart from confounding, differences in results could be due to exposure measurements. This review found a broad range of exposure indicators were used to conceptualise green space. The NDVI, percent green space and distance to park were the most frequently used, however, there was high heterogeneity between studies on the choice of spatial scale and exposure classes. Buffer sizes, time-of-year NDVI measurements and other green space exposure data sources varied, making meaningful comparisons between studies difficult and a potential reason for the differences in results. These findings have been previously flagged in prior systematic reviews [34,109,110]. Where studies examined the type of green space, they mainly included urban parks. For most, this was measured as either the distance from the residential address or presence within a distance buffer. These are common measures of green space accessibility [111] but have some limitations. First, such spatial measures fail to capture specific characteristics and features of urban parks. Some research, for example, indicates that physical activity is higher in parks with paved trails [112], and visits to green spaces are more likely to occur if they have certain attributes, like trees, toilets, gym facilities, and the presence of lakes, ponds and trees [113,114]. Only one study included in this systematic review conducted a comparative analysis between exposure to trees and the total amount of vegetation in the neighbourhood [70]. They found the risk of CVD, diabetes and hypertension were all reduced with greater exposure to percent tree canopy cover, but not with greater exposure to percent total green space [70]. Greater exposure to street trees has been previously shown to reduce the odds of having hypertension [115] and poor mental health [116]. While other studies of this review compared effect estimates using different buffer sizes (and found negligible differences), this finding suggests that it is the type and location of green spaces rather than the spatial scale that affects health. However, further comparative research is needed to establish this.

4.2. Strengths and Limitations

To the best of our knowledge, this is the first systematic review to summarise the published longitudinal literature on the relationship between green and blue spaces and chronic health. This is important for informing intervention design and policy decision making. According to the Medical Research Council's framework for evaluating complex interventions [117], appropriate methods need to be employed to first identify existing evidence and use it to guide theory development that is critical to intervention design. This systematic review contributed to the identification and synthesis of existing evidence and could help bridge the gap between empirical research and the development of programme theory about the role of green space in the maintenance of mental and physical health. Including both mental and physical health outcomes as well as related health states and behaviours additionally allowed for a comprehensive analysis and summary of the effects of the natural environment on highly prevalent NCDs and mental health problems. It also enabled comparisons of the strength and direction of associations. The choice to include both green and blue spaces as exposures, on the other hand, better informed of current research gaps in the published literature on the relationships between water bodies and health. Lastly, we summarised the limited evidence of longitudinal relationships between green and blue spaces and multimorbidity. While prior systematic reviews have assessed the effects of green spaces on health, they have not considered how these exposures may influence the development of multiple chronic conditions within an individual [30–36]. This systematic review, therefore, flags additional research gaps in the study of multimorbidity development in relation to the natural environment.

There are a number of limitations. First, heterogeneity in study exposures and populations prevented us from conducting a quantitative synthesis analysis. While a narrative synthesis enabled a summary of results and associations, a meta-analysis may improve generalisability of the results by producing a pooled effect estimate and identifying sources of heterogeneity and bias [118]. Second, the Newcastle–Ottawa Scale is not as robust and as comprehensive a measure as ROBINS-I which is widely regarded as offering gold standard assessments of risk of bias of nonrandomised intervention studies [119]. The exposure domain on the Newcastle–Ottawa Scale might not be optimal for assessing information bias because it only classifies the quality of a study as good if the exposure is measured through objective measures. In the context of our review, objective measurements of green space are typically made by professional assessments or satellite imagery. However, self-reported exposures of natural environments are important in assessing the ways people interact with these spaces and may not necessarily introduce recall bias like clinical exposures [120]. Additionally, the Newcastle–Ottawa Scale includes domains that are critical to assessing key parameters of methodological quality of longitudinal cohort studies and in this sense functioned as a pragmatic solution for this review.

4.3. Review Implications

Despite the qualitative analysis of this review showing little relationship of exposure to green and blue space with health, this systematic review aided the identification of some key research gaps. First, there is a lack of framework to study the type and components of green and blue spaces on health. Longitudinal research has typically used an average estimation of green space availability or accessibility, and this is loosely based on European Environment Agency [121] and Natural England's [122] recommendations of having an accessible green area of at least 2 ha no more than 300 m or within a 15-min walk from the residential address. Future research, however, should adopt a more holistic approach whereby different characteristics, dosage of exposure and specific person–environment interactions are studied in relation to health. This could improve the understanding of the different pathways between green space exposure and health, and lead to the design and implementation of evidence-based public health interventions.

Second, there is a need for more research into the relationship between blue space and health, as only four longitudinal studies were identified [68,75,79,86]. Prior academic literature has conceptualised the relationship between blue space and health to be driven by socio-environmental factors similar to those for green space [123]. Unlike green space, health policy recommendations for accessibility or availability of blue space are limited and primarily focused on coastal zones [124]. Government bodies and environmental agencies, therefore, should seek to develop more robust guidelines based on empirical research.

Finally, this review identified a lack of research into the ways green and blue spaces affect the development of multiple chronic conditions within an individual, also known as multimorbidity. The management of multimorbidity usually requires complex clinical interventions that have a negative impact on quality of life and put strain on healthcare systems [125–127]. Green and blue spaces can influence behavioural change and promote good health through socio-ecological pathways and so the natural environment could play an important role in reducing the multimorbidity burden by preventing the onset or slowing the progression of several chronic conditions.

5. Conclusions

This systematic review showed there to be mixed evidence of a longitudinal relationship between green and blue spaces and mental and physical health, with just over half of all analyses indicating a nonsignificant relationship between exposures and health outcomes. The majority of published longitudinal observational studies assess exposure to green space through indicators of availability or urban green space accessibility. Few studies assess the effects of blue spaces on health. There was high heterogeneity between studies in exposure measures and confounding. This could be explained by a lack of existing framework and uniform guidelines on studying the effects of the natural environment on health. Future longitudinal research should incorporate a more holistic approach towards conceptualising green and blue space that moves beyond the amount or distance and towards capturing types and characteristics. This could greatly aid the understanding of causal pathways and improve intervention design.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/ijerph18179010/s1, Supplementary Material S1: Search Strategy, Supplementary Material S2: Data extraction form adapted from Cochrane, Supplemental Material S3: NOS scale manual for cohort studies, Supplemental Material S4: Summary of excluded studies during full-text screening, Supplementary Material S5: Table of studies' NOS rating, Supplementary Material S6: Summary of studies' sensitivity analyses.

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Appendix II: Systematic Review Protocol

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Centre for Reviews and Dissemination

Systematic review

A list of fields that can be edited in an update can be found here

* Review title.

Give the title of the review in English

Do natural environments impact mental and physical health in adults? A systematic review of longitudinal observational studies

Original language title.

For reviews in languages other than English, give the title in the original language. This will be displayed with the English language title.

* Anticipated or actual start date.

Give the date the systematic review started or is expected to start. 11/03/2020

* Anticipated completion date.

Give the date by which the review is expected to be completed. 01/12/2020

This field uses answers to initial screening questions. It cannot be edited until after registration.

Tick the boxes to show which review tasks have been started and which have been completed.

Update this field each time any amendments are made to a published record.

The review has not yet started: No

Review stage	Started	Completed
Preliminary searches	Yes	No
Piloting of the study selection process	Yes	No
Formal screening of search results against eligibility criteria	Yes	No
Data extraction	No	No
Risk of bias (quality) assessment	No	No
Data analysis	No	No

Provide any other relevant information about the stage of the review here.

6. * Named contact.

The named contact is the guarantor for the accuracy of the information in the register record. This may be any member of the review team.

Mariya Geneshka

Email salutation (e.g. "Dr Smith" or "Joanne") for correspondence:

Ms Geneshka

7. * Named contact email.

Give the electronic email address of the named contact.

mmg529@york.ac.uk

8. Named contact address

Give the full institutional/organisational postal address for the named contact.

Research Centre for Social Sciences, University of York, Heslington, York YO10 5ZF

9. Named contact phone number.

Give the telephone number for the named contact, including international dialling code.

07999984958

10. * Organisational affiliation of the review.

Full title of the organisational affiliations for this review and website address if available. This field may be completed as 'None' if the review is not affiliated to any organisation.

University of York

Organisation web address:

https://www.york.ac.uk/

11. * Review team members and their organisational affiliations.

Give the personal details and the organisational affiliations of each member of the review team. Affiliation refers to groups or organisations to which review team members belong. **NOTE: email and country now MUST be entered for each person, unless you are amending a published record.**

Ms Mariya Geneshka. University of York Dr Peter Coventry. University of York

Professor Simon Gilbody. University of York Dr Joana Cruz. University of York

12. * Funding sources/sponsors.

Details of the individuals, organizations, groups, companies or other legal entities who have funded or sponsored the review.

Research funded by National Institute for Health Research (NIHR) Applied Research Collaboration Yorkshire

and Humber https://www.arc-yh.nihr.ac.uk/.

Grant number(s)

State the funder, grant or award number and the date of award

13. * Conflicts of interest.

List actual or perceived conflicts of interest (financial or academic). None

Give the name and affiliation of any individuals or organisations who are working on the review but who are not listed as review team members. **NOTE: email and country must be completed for each person, unless you are amending a published record.**

Kath Wright. University of York

15. * Review question.

1. Is there a temporal relationship between natural environments and mental and physical health among adults?

2. If there is a relationship, what is the direction of association?

3. Which natural environments most strongly influence different health outcomes?

4. Does the relationship differ by age, socio-economic status and pre-existing health conditions?

State the sources that will be searched (e.g. Medline). Give the search dates, and any restrictions (e.g. language or publication date). Do NOT enter the full search strategy (it may be provided as a link or attachment below.)

MEDLINE, Embase, Scopus, Web of Knowledge, PsycINFO, GreenFILE will be searched for

relevant journal articles and grey literature, such as conference findings. Bibliographies of eligible articles will also be searched for relevant studies.

Searches will be limited to: English language, human

participants. There are no date restrictions on publications.

Attempts will also be made to source unpublished studies through professional connections.

Additional search strategy information can be found in the attached PDF document (link provided below).

Upload a file with your search strategy, or an example of a search strategy for a specific database, (including the keywords) in pdf or word format. In doing so you are consenting to the file being made publicly accessible. Or provide a URL or link to the strategy. Do NOT provide links to your search **results**.

https://www.crd.york.ac.uk/PROSPEROFILES/175965_STRATEGY_20201003.pdf

Alternatively, upload your search strategy to CRD in pdf format. Please note that by doing so you are consenting to the file being made publicly accessible.

Do not make this file publicly available until the review is complete

18. * Condition or domain being studied.

Give a short description of the disease, condition or healthcare domain being studied in your systematic review.

Mental and physical health.

Specify the participants or populations being studied in the review. The preferred format includes details of both inclusion and exclusion criteria.

Inclusion: Adults, men and women, aged 18 years and older (study included if average age of population is equal or over 18 years).

Health status: adults with pre-existing chronic mental and/or physical health conditions, as well as adults with no pre-existing mental and/or physical health conditions. This includes people in care homes and other health institutions.

Exclusion:

Children under 18 years of age; adult prisoners; adults with pre-existing acute, infectious diseases.

20. * Intervention(s), exposure(s). [1 change]

Give full and clear descriptions or definitions of the interventions or the exposures to be reviewed. The preferred format includes details of both inclusion and exclusion criteria.

Natural environments: neighbourhood green space and blue space.

Neighbourhood is defined as: the area/s, within which an individuals' permanent residence; place of work, recreation and socialisation are based. This is measured objectively (eg. Lower/ Middle Layer Super Output Areas, buffers around residential address); or subjectively, based on individual perception.

Green space: any open, outdoor space with natural vegetation, including urban green spaces, such as public parks and street greenery. This includes both naturally occurring and human-made spaces.

Blue space: fresh and salt water bodies that are either naturally occurring (e.g lakes, rivers) or human-made

Green and blue spaces are captured through: access, distance, amount, type, number, size, visibility, quality and natural and man-made features. These are measured: objectively, through the use of validated tools or professional assessments (e.g. using Geographic Information System (GIS)); or subjectively, based on individual perception.

Exclusions:

Indoor green and blue spaces; spaces that do not permit open access to the public.

21. * Comparator(s)/control.

Where relevant, give details of the alternatives against which the intervention/exposure will be compared (e.g. another intervention or a non-exposed control group). The preferred format includes details of both inclusion and exclusion criteria.

Adults, men and women, aged 18 years or over, part of a longitudinal study who are not exposed to long- term natural environments.

Give details of the study designs (e.g. RCT) that are eligible for inclusion in the review. The preferred format includes both inclusion and exclusion criteria. If there are no restrictions on the types of study, this should be stated.

Longitudinal, quantitative, observational studies only.

23. Context.

Give summary details of the setting or other relevant characteristics, which help define the inclusion or exclusion criteria.

Give the pre-specified main (most important) outcomes of the review, including details of how the outcome is defined and measured and when these measurement are made, if these are part of the review inclusion criteria.

Mental health: common and severe mental health disorders measured through validated, self-reported instruments; clinician assessments; or clinical samples. Common mental health disorders are those defined by National Institute of Clinical Excellence (NICE) as: when combined, they affect more people than other mental health problems (2018). These include: depression, generalised anxiety disorder (GAD), panic disorder, phobias, social anxiety disorder, obsessive-compulsive disorder (OCD) and post-traumatic stress disorder (PTSD). Severe mental health disorders are: bipolar disorder, psychosis and schizophrenia, as outlined by NICE (2018).

Physical health: any non-communicable chronic condition coded in the International Classification of Diseases (11th Revision) (ICD-11), measured through validated, self-reported instruments; clinician assessments; or clinical samples.

Health-related behaviours: behaviours that modify the risk of developing a chronic mental or physical health condition. This review will include only the four most widely studied behaviours in public health: smoking, alcohol consumption, physical activity and diet, measured through validated, self-reported instruments; or objectively (where applicable, e.g. accelerometers for physical activity).

Frailty: defined by the various definitions used in clinical practice and measured through validated instruments and tools as described in NICE's multimorbidity guidelines (2018).

Measures of effect

Please specify the effect measure(s) for you main outcome(s) e.g. relative risks, odds ratios, risk difference, and/or 'number needed to treat.

Descriptive effect estimates, such as mean difference and mean change from baseline will also be considered.

List the pre-specified additional outcomes of the review, with a similar level of detail to that required for main outcomes. Where there are no additional outcomes please state 'None' or 'Not applicable' as appropriate

to the review

Physical, non-communicable diseases and conditions: defined by International Classification of Diseases (ICD)-11 and diagnosed through clinical assessment/s.

Physical Functioning: defined through: laboratory-based measures of physiologic impairment; or through self- reported instruments or field tests of mobility and performance capacity.

Health-related Quality of Life (HQoL): an indicator of the impact of mental and physical health status on

individuals' quality of life. This is measured through validated, self-reported instruments (e.g. 36-item Short Form (SF-36)).

Measures of effect

Please specify the effect measure(s) for you additional outcome(s) e.g. relative risks, odds ratios, risk difference, and/or 'number needed to treat.

Descriptive effect estimates, such as mean difference and mean change from baseline will also be considered.

26. * Data extraction (selection and coding).

Describe how studies will be selected for inclusion. State what data will be extracted or obtained. State how this will be done and recorded.

Sources' titles and abstracts will be first screened against the inclusion criteria by one review author. Then, sources' full-text will be analysed by one review author.

Consensus meetings will be held at all stages of the screening process with a second review author to resolve any uncertainty in the inclusion. If uncertainties cannot be resolved by the meetings, attempts will be made to contact the study authors for clarification. A meeting with be held with a third review author if necessary to further resolve the problem.

A bibliographic reference software (EndNote, Version X9) will be used throughout the screening process to manage the references, detect and delete duplicates.

Searches will also be exported from EndNote to Rayyan, a web-based tool, which will aid the screening and selection process (https://rayyan.qcri.org/welcome).

Data extraction will be conducted by one reviewer. Type of data we will extract will be

guided by a pre-specified data extraction form, which will be an adapted version for longitudinal studies from the Cochrane Collaboration.

Examples of type of data include:

- Identification features of the study: author/s, publication date, place of publication, country of origin and

funding.

- Participant characteristics (both at baseline and follow-up): socio-demographic characteristics, such as age, sex, socio-economic status, and health status

- Exposure characteristics: primary exposure/s type, definition, and method of assignment.

- Outcome characteristics: effect estimates and variances, outcome definition/s, methods/ tools of outcome assessment, time points of outcome assessment. We will also extract information on whether the studied outcome is the primary outcome in the study and whether other outcomes are also measured.

- Study Characteristics and Methods: study inclusion/ exclusion criteria, aims and objectives, population source, method of participant recruitment, duration and loss to follow-up, appropriateness of statistical methods used, subgroup and mediator analyses.

27. * Risk of bias (quality) assessment.

State which characteristics of the studies will be assessed and/or any formal risk of bias/quality assessment tools that will be used.

The Newcastle-Ottawa Quality Assessment Scale (NOS) for Observational Cohort Studies will be used

We will assess for selection bias by examining participant selection methods (e.g were exposed and non- exposed participants selected from the same sample), and how representative the cohort is to the population.

We will also assess for information bias, including procedures of exposure ascertainment and assignment, outcome assessment (e.g were assessors blinded, were there health record linkages), as well as adequacy of follow-up and whether bias would be likely to occur due to loss to follow-up.

We will also use a funnel plot to assess for publication bias.

28. * Strategy for data synthesis.

Data will be synthesised in a narrative and numeric format.

Study characteristics, study type, publication type, participant characteristics, duration of follow-up, loss to follow- up, outcome and exposure type will be narratively summarised.

We will summarise whether exposures are measured objectively or subjectively. Exposure characteristics, metrics used, and methods of assigning the exposures will be additionally summarised.

Outcome type (e.g mental health disorders, type of physical health disorders and health behaviours), definition and assessment tools used will be summarised in a table.

Studies will be additionally grouped by exposure and outcome type in order to graphically visualise the most common exposures and outcomes studied in the literature.

Effect estimate/s (including confidence intervals and other variance analyses) of each study will also be reported in graphic form. Summary statistics, mediators, subgroup analyses and missing data will be additionally assessed.

Lastly, studies will be rated on risk of bias using Newcastle-Ottawa Quality Assessment Scale for Observational Studies results. This will also be graphically presented.

If sufficient data is available and studies are homogeneous enough, we will perform one or multiple meta- analyses to produce a forest plot and pooled effect estimates of the association between natural environments and health. The risk of bias assessment from the NOS scale will also be presented in a table next to the plot, as each study will be rated with a “low” and “high” risk of bias.

Heterogeneity of studies will also be examined statistically through the Q-test and I^2 test. If heterogeneity is identified, we will further analyse the reasons behind it.

29. * Analysis of subgroups or subsets.

State any planned investigation of 'subgroups'. Be clear and specific about which type of study or participant will be included in each group or covariate investigated. State the planned analytic approach.

If sufficient data is available, we will conduct subgroup analyses based on: age, socio-economic status and pre-existing health condition/s.

30. * Type and method of review.

Select the type of review, review method and health area from the lists below.

Type of review

Cost effectiveness
No

Diagnostic
No

Epidemiologi
c No

Individual patient data (IPD) meta-
analysis No

Interventio
n No

Living systematic
review No

Meta-analysis
Yes

Methodology
No

Narrative
synthesis Yes

Network meta-analysis
No

Pre-clinical
No

Prevention
No

Prognostic
No

(PMA) No

Review of
reviews No

Service delivery
No

Synthesis of qualitative
studies No

Systematic
review Yes

Othe
r No

Health area of the review

Alcohol/substance misuse/abuse No

Blood and immune
system No

Cancer
No

Cardiovascula
r No

Care of the
elderly No

Child
health No

Complementary therapies
No

COVID-19
No

Crime and justice
No

31. Language.

Select each language individually to add it to the list below, use the bin icon to remove any added in error. English

There is not an English language summary

32. * Country.

Select the country in which the review is being carried out. For multi-national collaborations select all the countries involved.

England

33. Other registration details.

Name any other organisation where the systematic review title or protocol is registered (e.g. Campbell, or The Joanna Briggs Institute) together with any unique identification number assigned by them. If extracted data will be stored and made available through a repository such as the Systematic Review Data Repository (SRDR), details and a link should be included here. If none, leave blank.

34. Reference and/or URL for published protocol.

If the protocol for this review is published provide details (authors, title and journal details, preferably in Vancouver format)

Add web link to the published protocol.

Or, upload your published protocol here in pdf format. Note that the upload will be publicly accessible. Yes I give permission for this file to be made publicly available

Please note that the information required in the PROSPERO registration form must be completed in full even if access to a protocol is given.

35. Dissemination plans.

Do you intend to publish the review on completion?

Yes

Give brief details of plans for communicating review findings.?

The review will be written-up both as a chapter in a Postgraduate Research thesis and as an article published in a peer-reviewed journal.

36. Keywords.

Give words or phrases that best describe the review. Separate keywords with a semicolon or new line. Keywords help PROSPERO users find your review (keywords do not appear in the public record but are included in searches). Be as specific and precise as possible. Avoid acronyms and abbreviations unless these are in wide use.

37. Details of any existing review of the same topic by the same authors.

If you are registering an update of an existing review give details of the earlier versions and include a full bibliographic reference, if available.

38. * Current review status.

Update review status when the review is completed and when it is published.New registrations must be ongoing so this field is not editable for initial submission.

Please provide anticipated
publication date

39. Any additional information.

Provide any other information relevant to the registration of this review.

40. Details of final report/publication(s) or preprints if available.

Leave empty until publication details are available OR you have a link to a preprint (NOTE: this field is not editable for initial submission). List authors, title and journal details preferably in Vancouver format.

Give the link to the published review or preprint.

Appendix III: Systematic Review Search Strategy

MEDLINE via Ovid

1 exp Depression/ 118775

2 exp Anxiety Disorders/ 79201

3 exp Obsessive-Compulsive Disorder/ 14545

4 exp Stress Disorders, Post-Traumatic/ 32558

5 exp Psychotic Disorders/ 52066

6 exp Bipolar Disorder/ 40222

7 exp Schizophrenia/ 104398

8 (depression or depressive or dysthymi* or anxiety or (anxiety adj disorder*) or (panic adj disorder*) or (generali?ed adj anxiety adj disorder*) or ocd or (obsessive adj compulsive) or obsessive-compulsive or ptsd or posttrauma* or (post adj trauma* adj disorder*) or bipolar or (bipolar and (affective or disorder*)) or schizophreni* or psychosis).ti,ab,kw.
692588

9 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 / 792883

10 physical health.ti,ab,kw.
20946

11 (cardio-vascular or cardiovascular or (cardio adj vascular) or myocardial).ti,ab,kw.
723463

12. cancer.ti,ab,kw.
1697426

13	(obesity or BMI or (body adj mass) or diabetes).ti,ab,kw.
872407

14	(respiratory or cardio-respiratory or cardiorespiratory or (cardio adj respiratory)).ti,ab,kw.
444098

15	Endocrine ti,ab,kw.
121939

16	Musculoskeletal Diseases/
12705

17	(musculoskeletal or musculo-skeletal).ti,ab,kw.
51498

18	exp Cardiovascular Diseases/
2380012

19	neoplasms/ or musculoskeletal diseases/ or digestive system diseases/ or respiratory tract diseases/ or nervous system diseases/ or eye diseases/ or "skin and connective tissue diseases"/ or "nutritional and metabolic diseases"/ or endocrine system diseases/ or immune system diseases/ or "disorders of environmental origin"/ or occupational diseases/
632776

20	(physical adj function*).ti,ab,kw.
24092

21	"Quality of Life"/
194476

22	((quality adj of adj life) or insomnia or sleep or (sleep adj disrupt*)).ti,ab,kw.
439635

23	Frailty/
2627

24
(frail or frailty).ti,ab,kw.
21871

25 10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24
6104617

26 (health adj promot* adj behavio?r*).ti,ab,kw.
1454

27 health promot* behavio?r*.ti,ab,kw.
1417

28 Diet/
159149

29 exp Exercise/
194919

30
exp Smoking/
147018

31 exp Alcohol Drinking/
68918

32 ((physical* adj activ*) or (physical adj activity) or walking or running).ti,ab,kw.
233038

33 ((alcohol adj drinking) or (alcohol adj consumption) or smoking or diet).ti,ab,kw.
568833

34 26 or 27 or 28 or 29 or 30 or 31 or 32 or 33
1041527

35 9 or 25 or 34
7332636

36 *Environment/ or *Environment Design/
29764

37 (green adj2 (area$ or cover or environment$ or gym$ or neighbourhood$ or neighborhood$ or roadside$ or space$)).ti,ab,kw.
2444

38 ((city or cities or environment$ or neighbourhood or neighborhood or urban) adj2 greening).ti,ab,kw.
104

39 ((ambient or city or cities or environment$ or neighbourhood or neighborhood or residential or surrounding or urban) adj2 greenness).ti,ab,kw.
186

40 (greenery or greenspace* or greenness).ti,ab,kw.
1246

41 (garden$ or park or parks).ti,ab,kw.
31889

42 sports field$.ti,ab,kw.
99

43 wilderness area$.ti,ab,kw.
179

44 public open space$.ti,ab,kw.
99

45 neighbourhood open space$.ti,ab,kw.
2

46 neighborhood open space$.ti,ab,kw.
4

47 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46
63889

48 *Residence Characteristics/
13633

49 47 or 48
76049

50 *Water/
61472

51 *Rivers/
12620

52 *"Oceans and Seas"/
1126

53 (bluespace$ or blue space$).ti,ab,kw.
114

54 bluehealth.ti,ab,kw.
1

55 blue water$.ti,ab,kw.
190

56 blue gym$.ti,ab,kw.
3

57 50 or 51 or 52 or 53 or 54 or 55 or 56
75208

58 *air pollution/
22636

59 *air quality/
22636

60 (air adj2 (quality or pollution)).ti,ab,kw.
32154

61 ((ambient or neighbourhood or neighborhood or outdoor) adj2 air).ti,ab,kw.
12961

62 58 or 59 or 60 or 61
51241

63 exp noise/
23996

64 *noise pollution/
12458

65 ((traffic or aircraft or industr$ or neighbourhood or neighborhood or outdoor) adj2 noise).ti,ab,kw.
2190

66 (noise adj2 pollution).ti,ab,kw.
832

67 63 or 64 or 65 or 66
24736

68 *Nature/
546

69 ((natural or outdoor$ or salutogenic) adj2 environment$).ti,ab,kw.
14691

70 ((nature or natural) adj2 space$).ti,ab,kw.
396

71 68 or 69 or 70
15550

72 49 or 57 or 62 or 67 or 71
237726

73 35 and 72
43562

74 exp animals/ not humans.sh.
4718023

75 73 not 74
38821

76 exp cohort studies/
2010640

77 ((cohort or longitudinal or follow-up or prospective or retrospective) adj2 stud*).ti,ab.
782804

78 (cohort or follow-up or longitudinal).ti,ab.
1565994

79 longitudinal study/
135701

80 76 or 77 or 78 or 79
2909197

81 (health adj promot$ adj2 environment$).ti,ab,kw.
247

82 75 or 81
39051

83	80 and 82
6606

EMBASE via Ovid

1	exp depression/
472047

2	exp anxiety/
208150

3	exp anxiety disorder/
240819

4	exp obsessive compulsive disorder/
39417

5	exp posttraumatic stress disorder/
59929

6	exp psychosis/
277139

7	exp bipolar disorder/ or bipolar depression/ or bipolar II disorder/ or bipolar I disorder/
62961

8	exp schizophrenia/
177844

9	(depression or depressive or dysthymi* or anxiety or (anxiety adj disorder*) or (panic adj disorder*) or (generali?ed adj anxiety adj disorder*) or ocd or (obsessive adj compulsive) or obsessive-compulsive or ptsd or posttrauma* or (post adj trauma* adj disorder*) or bipolar or (bipolar and (affective or disorder*)) or schizophreni* or psychosis).ti,ab,kw.
938420

10 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9
1218837

11 physical health.ti,ab,kw.
27892

12 (cardio-vascular or cardiovascular or (cardio adj vascular) or myocardial).ti,ab,kw.
1054449

13 cancer.ti,ab,kw.
2447213

14 (obesity or BMI or (body adj mass) or diabetes).ti,ab,kw.
1357330

15 (respiratory or cardio-respiratory or cardiorespiratory or (cardio adj respiratory)).ti,ab,kw.
613602

16 endocrine.ti,ab,kw.
175359

17 exp musculoskeletal disease/
2218427

18 (musculoskeletal or musculo-skeletal).ti,ab,kw.
74352

19 cardiovascular risk/ or exp cardiovascular disease/
4070078

20 exp malignant neoplasm/
3427572

21 exp digestive system disease/
3092666

22 exp respiratory tract disease/
2411729

23 exp neurologic disease/
3451283

24 exp eye disease/
906215

25 skin disease/
66380

26 metabolic disorder/
64409

27 exp diabetes mellitus/
952361

28 exp obesity/
516495

29 exp endocrine disease/
2002252

30 immunopathology/
26115

31 exp occupational disease/
128603

32 exp environmental disease/
1414

33 (neoplasm* or musculoskeletal disease* or digestive system or respiratory tract diseases* or nervous system or eye disease* or "skin and connective tissue diseases" or "nutritional and metabolic diseases" or endocrine system disease* or immune system disease* or environmental disease* or HIV or human immunodeficiency or occupational disease or diabetes or diabetic or myocardial).ti,ab,kw.
2376383

34 exp rare disease/
37860

35 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26 or 27 or 28 or 29 or 30 or 31 or 32 or 33 or 34
15877053

36 (physical adj function*).ti,ab,kw.
38340

37 "quality of life"/
469182

38 (quality of life or insomnia or sleep or sleep disrupt*).ti,ab,kw.
694792

39 insomnia/
66505

40 exp frailty/
11054

41 (frail or frailty).ti,ab,kw.
34138

42 (health adj promot* adj behavio?r*).ti,ab,kw.
1559

43	health promot* behavio?r*.ti,ab,kw.
1559

44	diet/
216331

45	exercise/ or "physical activity, capacity and performance"/
275876

46	exp physical activity/
418363

47	exp smoking/
385634

48	exp alcohol consumption/
127555

49	((physical* adj activ*) or (physical adj activity) or walking or running).ti,ab,kw.
316971

50	((alcohol adj drinking) or (alcohol adj consumption) or smoking or diet).ti,ab,kw.
780403

51	36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50
2489556

52	10 or 35 or 51
17346597

53	(green adj2 (area$ or cover or environment$ or gym$ or neighbourhood$ or neighborhood$ or roadside$ or space$)).ti,ab,kw.
2828

54 ((city or cities or environment$ or neighbourhood or neighborhood or urban) adj2 greening).ti,ab,kw.
132

55 ((ambient or city or cities or environment$ or neighbourhood or neighborhood or residential or surrounding or urban) adj2 greenness).ti,ab,kw.
213

56 (greenery or greenspace* or greenness).ti,ab,kw.
1314

57 (garden$ or park or parks).ti,ab,kw.
38736

58 sports field$.ti,ab,kw.
140

59 wilderness area$.ti,ab,kw.
220

60 public open space$.ti,ab,kw.
116

61 neighbourhood open space$.ti,ab,kw.
2

62 neighborhood open space$.ti,ab,kw.
3

63 (bluespace$ or blue space$).ti,ab,kw.
117

64 bluehealth.ti,ab,kw.
1

65 blue water$.ti,ab,kw.
225

66 blue gym$.ti,ab,kw.
3

67 air pollution/
60231

68 air quality/
16896

69 (air adj2 (quality or pollution)).ti,ab,kw.
50338

70 ((ambient or neighbourhood or neighborhood or outdoor) adj2 air).ti,ab,kw.
17790

71 exp noise/
108517

72 exp noise pollution/
8939

73 ((traffic or aircraft or industr$ or neighbourhood or neighborhood or outdoor) adj2 noise).ti,ab,kw.
2870

74 (noise adj2 pollution).ti,ab,kw.
1165

75 ((natural or outdoor$) adj2 environment$).ti,ab,kw.
16533

76 ((nature or natural) adj2 space$).ti,ab,kw.
417

77 exp cohort analysis/
594604

78 longitudinal study/
141374

79 ((cohort or longitudinal or follow-up or prospective or retrospective) adj2 stud*).ti,ab.
1156722

80 (cohort or follow-up or longitudinal).ti,ab.
2450549

81 77 or 78 or 79 or 80
3045207

82 (health adj promot$ adj2 environment$).ti,ab,kw.
290

83 53 or 54 or 55 or 56 or 57 or 58 or 59 or 60 or 61 or 62 or 63 or 64 or 65 or 66 or 67 or 68 or 69 or 70 or 71 or 72 or 73 or 74 or 75 or 76
262719

84 52 and 83
85760

85 82 or 84
86038

86 81 and 85
10247

PsychInfo ia Ovid

1 exp "Long-term Depression (Neuronal)"/ or exp Spreading Depression/ or exp "Depression (Emotion)"/ or exp Major Depression/ or exp Reactive Depression/ or exp Beck Depression Inventory/ or exp Treatment Resistant Depression/ or exp Postpartum Depression/ or exp Atypical Depression/ or exp Endogenous Depression/ or exp Anaclitic Depression/ or exp Recurrent Depression/ or exp Late Life Depression/
157037

2 exp Anxiety Disorders/
53997

3 exp Anxiety/
71596

4 exp Panic/ or exp Panic Disorder/
9213

5 exp Obsessive Compulsive Disorder/
15127

6 exp Posttraumatic Stress Disorder/
33049

7 exp Schizophrenia/ or exp Diagnosis/ or exp Psychosis/
315653

8 exp Bipolar Disorder/
30512

9 (depression or depressive or dysthymi* or anxiety or (anxiety adj disorder*) or (panic adj disorder*) or (generali?ed adj anxiety adj disorder*) or ocd or (obsessive adj compulsive) or obsessive-compulsive or ptsd or posttrauma* or (post adj trauma* adj disorder*) or bipolar or (bipolar and (affective or disorder*)) or schizophreni* or psychosis).ti,ab.
570777

10 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9
773959

11 physical health.ti,ab.
19009

12 (cardio-vascular or cardiovascular or (cardio adj vascular) or myocardial).ti,ab.
32556

13 cancer.ti,ab.
59494

14 (obesity or BMI or (body adj mass) or diabetes or diabetic).ti,ab.
77289

15 (respiratory or cardio-respiratory or cardiorespiratory or (cardio adj respiratory)).ti,ab.
17587

16 endocrine.ti,ab.
8450

17 exp Musculoskeletal Disorders/
18258

18 (musculoskeletal or musculo-skeletal).ti,ab.
5586

19 exp Cardiovascular Disorders/
62101

20 exp Neoplasms/
51916

21 exp Digestive System Disorders/
13924

22 exp Respiratory Tract Disorders/
14722

23 exp Nervous System/
366236

24 exp Eye Disorders/
4837

25 exp Metabolic Rates/
1141

26 exp Endocrine Disorders/
22096

27 exp Immune System/
4795

28 exp HIV/ or exp Immune System/
47620

29 exp Occupational Health/
3974

30 (neoplasm* or musculoskeletal disease* or digestive system or respiratory tract diseases* or nervous system or eye disease* or "skin and connective tissue diseases" or "nutritional and metabolic diseases" or endocrine system disease* or immune system disease* or environmental disease* or HIV or human immunodeficiency or occupational disease or diabetes or diabetic or myocardial).ti,ab.
132516

31 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26 or 27 or 28 or 29 or 30
708983

32 (physical adj function*).ti,ab.
6250

33 exp "Quality of Life"/
43074

34 ((quality adj of adj life) or insomnia or sleep or (sleep adj disrupt*)).ti,ab.
135559

35 (frail or frailty).ti,ab.
4367

36 (health adj promot* adj behavio?r*).ti,ab.
1036

37 health promot* behavio?r*.ti,ab.
1036

38 exp Diets/
17057

39 exp Exercise/
26402

40 exp Physical Activity/
41965

41 exp Tobacco Smoking/
32604

42 exp alcoholism/
30678

43 ((physical* adj activ*) or (physical adj activity) or walking or running).ti,ab.
62325

44 ((alcohol adj drinking) or (alcohol adj consumption) or smoking or diet).ti,ab.
87131

45 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44
337589

46 10 or 31 or 45
1489329

47 environment/
17774

48 (green adj2 (area$ or cover or environment$ or gym$ or neighbourhood$ or neighborhood$ or roadside$ or space$)).ti,ab.
555

49 ((city or cities or environment$ or neighbourhood or neighborhood or urban) adj2 greening).ti,ab.
16

50 ((ambient or city or cities or environment$ or neighbourhood or neighborhood or residential or surrounding or urban) adj2 greenness).ti,ab.
16

51 (greenery or greenspace* or greenness).ti,ab.
205

52 (garden$ or park or parks).ti,ab.
8630

53 sports field$.ti,ab.
49

54 wilderness area$.ti,ab.
40

55 public open space$.ti,ab.
41

56 neighbourhood open space$.ti,ab.
0

57 neighborhood open space$.ti,ab.
3

58 (bluespace$ or blue space$).ti,ab.
29

59 bluehealth.ti,ab.
0

60 blue water$.ti,ab.
10

61 blue gym$.ti,ab.
1

62 47 or 48 or 49 or 50 or 51 or 52 or 53 or 54 or 55 or 56 or 57 or 58 or 59 or 60 or 61
26918

63 (air adj2 (quality or pollution)).ti,ab.
1272

64 ((ambient or neighbourhood or neighborhood or outdoor) adj2 air).ti,ab.
280

65	((traffic or aircraft or industr$ or neighbourhood or neighborhood or outdoor) adj2 noise).ti,ab.
402

66	(noise or (noise adj2 pollution)).ti,ab.
26936

67	63 or 64 or 65 or 66
28225

68	62 or 67
54795

69	46 and 68
15761

70	(health adj promot$ adj2 environment$).ti,ab.
102

71	69 or 70
15856

72	exp Cohort Analysis/
1440

73	((cohort or longitudinal or follow-up or prospective or retrospective) adj2 stud*).ti,ab.
114282

74	(cohort or follow-up or longitudinal).ti,ab.
262889

75	exp Longitudinal Studies/
16477

76 72 or 73 or 74 or 75
288811

77 71 and 76
998

Science Citation Index via Web of Knowledge

# 30	9,094	#29 AND #26 *Indexes=SCI-EXPANDED Timespan=All years*
# 29	2,655,212	#28 OR #27 *Indexes=SCI-EXPANDED Timespan=All years*
# 28	364,325	(TS = ((cohort NEAR/2 stud*) OR (longitudin* NEAR/2 stud*) OR (follow-up NEAR/2 stud*))) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 27	2,655,212	((TS= (cohort or longitudin* or follow-up or prospective or retrospective or incidence))) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 26	71,677	(#25 not #23) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 25	74,209	#24 OR #22 *Indexes=SCI-EXPANDED Timespan=All years*

# 24	15,983	(TS = ((health NEAR/1 promot* NEAR/1 environment*) or (health promot* environment*))) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 23	2,253,183	(TI=(rat or rats or mouse or mice or bird or birds or cow o r cattle or bovine or sheep or goat* or ovine or horse or equine or pig or pigs or porcine or fish or fishes)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 22	59,082	#21 AND #5 *Indexes=SCI-EXPANDED Timespan=All years*
# 21	339,119	#20 OR #15 OR #11 *Indexes=SCI-EXPANDED Timespan=All years*
# 20	162,848	#19 OR #18 OR #17 OR #16 *Indexes=SCI-EXPANDED Timespan=All years*
# 19	11,526	(TS = ((traffic or aircraft or industr* or neighbourhood or neighborhood or outdoor or environment*) NEAR/2 noise)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 18	3,747	(TS = (noise pollution)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 17	32,621	(TS = ((ambient OR neighbourhood or neighborhood OR outdoor) NEAR/2 air)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 16	131,233	(TS = (air pollution OR air quality)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*

# 15	153,909	#14 OR #13 OR #12 *Indexes=SCI-EXPANDED Timespan=All years*
# 14	104,846	(TS = (water cover* or blue cover*)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 13	42,025	(TS = (bluehealth or blue water or blue gym)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 12	10,091	(TS = (blue space or bluespace)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 11	27,086	#10 OR #9 OR #8 OR #7 OR #6 *Indexes=SCI-EXPANDED Timespan=All years*
# 10	14,251	(TS = (public park OR public parks OR public space OR public open space OR neighbourhood open space OR neighborhood open space)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 9	324	(TS = ((ambient OR city OR cities OR environment* OR neighbourhood OR neighborhood OR residential OR surrounding OR urban) NEAR/2 greenness)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 8	6,354	(TS = ((city or cities or environment* or neighbourhood or neighborhood or urban or residential) NEAR/2 greening)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 7	8,844	(TS = (green NEAR/2 (cover* or environment* or gym* or neighbourhood* or neighborhood* or roadside* or space*))) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*

# 6	4,344	(TS = (greenness OR greenspace OR greenery)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 5	8,430,658	#4 OR #3 OR #2 OR #1 *Indexes=SCI-EXPANDED Timespan=All years*
# 4	1,697,764	(TS= ((health promot* behavio?r*) or diet or (physical activity) or (physical* activ*) or walking or running or exercise or smoking or (alcohol drinking) or (alcohol NEAR/2 consum*))) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 3	798,489	(TS = ((physical function*) or (physical functioning) or (quality of life) or ("Quality of Life") or insomnia or sleep or (sleep disrupt*) or frail or frailty)) *AND* **LANGUAGE:** (English) *Indexes=SCI-EXPANDED Timespan=All years*
# 2	6,220,283	TS= ((physical health) or cardio-vascular or cardiovascular or (cardio vascular) or myocardial or cancer or respiratory or cardio-respiratory or cardiorespiratory or (cardio respiratory) or diabetes or diabetic or BMI or (Body Mass Index) OR endocrine or musculoskeletal or musculo-skeletal or neoplasms or (digestive system) or digestive or (respiratory tract) or (nervous system) or neurological or eye disease*or (skin and connective tissue) or dermatologic* or (nutritional dis*) or metabolic or endocrine system or immune or HIV or (hum an immunodeficiency)) *Indexes=SCI-EXPANDED Timespan=All years*

# 1	831,083	TS= (depression or depressive or dysthymi* or anxiety or anxiety disorder* or panic disorder* or panic or generali?ed anxiety or obsessive-compulsive disorder* or obsessive-compulsive or obsessive compulsive or ocd or ptsd or posttrauma* or post-traumatic or post traumatic or bipolar or bipolar disorder* or psychotic or (bipolar and (affective or disorder*)) or schizophreni* or psychosis) *Indexes=SCI-EXPANDED Timespan=All years*

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((((TITLE-ABS-KEY (*depression* OR *depressive* OR *dysthymi** OR *anxiety* OR (*anxiety* AND *disorder**) OR (*panic* AND *disorder**) OR (*panic*) OR (*generali?ed* AND *anxiety*) OR (*obsessive-compulsive* AND *disorder**) OR (*obsessive-compulsive*) OR (*obsessive* AND *compulsive*) OR *ocd* OR *ptsd* OR (*posttrauma**) OR *post-traumatic* OR (*post* AND *traumatic*) OR (*bipolar*) OR (*bipolar* AND *disorder**) OR *psychotic* OR (*bipolar* AND (*affective* OR *disorder**)) OR *schizophreni** OR *psychosis*)) OR (TITLE-ABS-KEY ((*physical* AND *health*) OR (*cardio-vascular*) OR (*cardiovascular*) OR (*cardio* AND *vascular*) OR *myocardial* OR *diabetes* OR *diabetic* OR *cancer* OR *respiratory* OR (*cardio-respiratory*) OR *cardiorespiratory* OR (*cardio* AND *respiratory*) OR *endocrine* OR *musculoskeletal* OR (*musculo-skeletal*) OR (*neoplasms*) OR (*digestive* AND *system*) OR *digestive* OR (*respiratory* AND *tract*) OR (*nervous* AND *system*) OR *neurological* OR (*eye* AND *disease**) OR (*skin* AND *connective* AND *tissue*) OR *dermatologic** OR (*nutrition** AND *dis**) OR *metabolic* OR *endocrine* OR *immune* OR *hiv* OR (*human* AND *immunodeficiency*) OR *obesity* OR *bmi* OR *obese* OR (*body* AND *mass* AND *index*))) OR (TITLE-ABS-KEY ((*physical* AND *function**) OR (*physical* AND *functioning*) OR (*quality* AND *of* AND *life*) OR (*"Quality of Life"*) OR *insomnia* OR *sleep* OR (*sleep* AND *disrupt**) OR *frail* OR *frailty*)) OR (TITLE-ABS-KEY ((*health* AND *promot** AND *behavio?r**) OR *diet* OR (*physical* AND *activity*) OR (*physical** AND *activ**) OR *walking* OR *running* OR *exercise* OR *smoking* OR (*alcohol* AND *drinking*) OR (*alcohol* AND *near/2* AND *consum**)))) AND ((TITLE-ABS-KEY ((*recreational* AND *park*) OR (*recreational* AND *parks*))) OR (TITLE-ABS-KEY (*garden* OR *park* OR *parks* OR (*public* AND *park*) OR (*public* AND *parks*))) OR (TITLE-ABS-KEY (((*neighbourhood* OR *neighborhood* OR *public*) W/2 *open* AND *space*))) OR (TITLE-ABS-KEY ((*green* AND *space*) OR *greenspace*)) OR (TITLE-ABS-KEY ((*green** W/2 (*area* OR *cover** OR *environment* OR *gym* OR *neighbourhood* OR *neighborhood* OR *roadside* OR *city* OR *cities*)))) OR (TITLE-ABS-KEY (((*area* OR *neighbourhood* OR *neighborhood* OR *roadside* OR *city* OR *cities* OR *urban* OR *ambient* OR *residential* OR *surrounding*) W/2 (*greening* OR *greenness*)))) OR (TITLE-ABS-KEY (*bluespace* OR (*blue* AND *space*) OR (*bluehealth*) OR (*blue* W/2 *cover**) OR (*blue* AND *gym*) OR (*air* AND *pollution*) OR (*air* AND *quality*) OR (*noise* AND *pollution*) OR ((*traffic* OR *aircraft* OR *industr** OR *neighbourhood* OR *neighborhood* OR *outdoor*) W/2 *noise*) OR (*n* *oise* W/2 *pollution*))))) OR (TITLE-ABS-KEY ((*salutogenic* W/2 *environment**) OR (*health* AND *promot** W/2 *environment**)))) AND (TITLE-ABS-KEY (*cohort* OR *longitudinal* OR *follow-* AND *up* OR *epidemiol** OR *prospective* OR *retrospective* OR *incidence*)) AND (LIMIT-TO (LANGUAGE , *"English"*))

21

((((TITLE-ABS-KEY (depression OR depressive OR dysthymi* OR anxiety OR (anxiety AND disorder*) OR (panic AND disorder*) OR (panic) OR (generali?ed AND anxiety) OR (obsessive-compulsive AND disorder*) OR (obsessive-compulsive) OR (obsessive AND compulsive) OR ocd OR ptsd OR (posttrauma*) OR post-traumatic OR (post AND traumatic) OR (bipolar) OR (bipolar AND disorder*) OR psychotic OR (bipolar AND (affective OR disorder*)) OR schizophreni* OR psychosis)) OR (TITLE-ABS-KEY ((physical AND health) OR (cardio-vascular) OR (cardiovascular) OR (cardio AND vascular) OR myocardial OR diabetes OR cancer OR respiratory OR (cardio-respiratory) OR cardiorespiratory OR (cardio AND respiratory) OR endocrine OR musculoskeletal OR (musculo-skeletal) OR (neoplasms) OR (digestive AND system) OR digestive OR (respiratory AND tract) OR (nervous AND system) OR neurological OR (eye AND disease*) OR (skin AND connective AND tissue) OR dermatologic* OR (nutrition* AND dis*) OR metabolic OR endocrine OR immune OR hiv OR (human AND immunodeficiency) OR obesity OR bmi OR obese)) OR (TITLE-ABS-KEY ((physical AND function*) OR (physical AND functioning) OR (quality AND of AND life) OR ("Quality of Life") OR insomnia OR sleep OR (sleep AND disrupt*) OR frail OR frailty)) OR (TITLE-ABS-KEY ((health AND promot* AND behavio?r*) OR diet OR (physical AND activity) OR (physical* AND activ*) OR walking OR running OR exercise OR smoking OR (alcohol AND drinking) OR (alcohol AND near/2 AND consum*)))) AND ((TITLE-ABS-KEY ((recreational AND park) OR (recreational AND parks))) OR (TITLE-ABS-KEY (garden OR park OR parks OR (public AND park) OR (public AND parks))) OR (TITLE-ABS-KEY (((neighbourhood OR neighborhood OR public) W/2 open AND space))) OR (TITLE-ABS-KEY ((green AND space) OR greenspace)) OR (TITLE-ABS-KEY ((green* W/2 (area OR cover* OR environment OR gym OR neighbourhood OR neighborhood OR roadside OR city OR cities)))) OR (TITLE-ABS-KEY (((area OR neighbourhood OR neighborhood OR roadside OR city OR cities OR urban OR ambient OR residential OR surrounding) W/2 (greening OR greenness)))) OR (TITLE-ABS-KEY (bluespace OR (blue AND space) OR (bluehealth) OR (blue W/2 cover*) OR (blue AND gym) OR (air AND pollution) OR (air AND quality) OR (noise AND pollution) OR ((traffic OR aircraft OR industr* OR neighbourhood OR neighborhood OR outdoor) W/2 noise) OR (noise W/2 pollution))))) OR (TITLE-ABS-KEY ((salutogenic W/2 environment*) OR (health AND promot* W/2 environment*))))) AND (TITLE-ABS-KEY (cohort OR longitudinal OR follow- AND up OR epidemiol* OR prospective OR retrospective OR incidence)) ...

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20
TITLE-ABS-KEY (cohort OR longitudinal OR follow- AND up OR epidemiol* OR prospective OR retrospective OR incidence)
2,218,663 document results
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19
(((TITLE-ABS-KEY (depression OR depressive OR dysthymi* OR anxiety OR (anxiety AND disorder*) OR (panic AND disorder*) OR (panic) OR (generali?ed AND anxiety) OR (obsessive-compulsive AND disorder) OR (obsessive-compulsive) OR (obsessive AND compulsive) OR ocd OR ptsd OR (posttrauma*) OR post-traumatic OR (post AND traumatic) OR (bipolar) OR (bipolar AND disorder*) OR psychotic OR (bipolar AND (affective OR disorder*)) OR schizophreni* OR psychosis)) OR (TITLE-ABS-KEY ((physical AND health) OR (cardio-vascular) OR (cardiovascular) OR (cardio AND vascular) OR myocardial OR diabetes OR cancer OR respiratory OR (cardio-respiratory) OR cardiorespiratory OR (cardio AND respiratory) OR endocrine OR musculoskeletal OR (musculo-skeletal) OR (neoplasms) OR (digestive AND system) OR digestive OR (respiratory AND tract) OR (nervous AND system) OR neurological OR (eye AND disease*) OR (skin AND connective AND tissue) OR dermatologic* OR (nutrition* AND dis*) OR metabolic OR endocrine OR immune OR hiv OR (human AND immunodeficiency) OR obesity OR bmi OR obese)) OR (TITLE-ABS-KEY ((physical AND function*) OR (physical AND functioning) OR (quality AND of AND life) OR ("Quality of Life") OR insomnia OR sleep OR (sleep AND disrupt*) OR frail OR frailty)) OR (TITLE-ABS-KEY ((health AND promot* AND behavio?r*) OR diet OR (physical AND activity) OR (physical* AND activ*) OR walking OR running OR exercise OR smoking OR (alcohol AND drinking) OR (alcohol AND near/2 AND consum*)))) AND ((TITLE-ABS-KEY ((recreational AND park) OR (recreational AND parks))) OR (TITLE-ABS-KEY (garden OR park OR parks OR (public AND park) OR (public AND parks))) OR (TITLE-ABS-KEY (((neighbourhood OR neighborhood OR public) W/2 open AND space))) OR (TITLE-ABS-KEY ((green AND space) OR greenspace)) OR (TITLE-ABS-KEY ((green* W/2 (area OR cover* OR environment OR gym OR neighbourhood OR neighborhood OR roadside OR city OR cities)))) OR (TITLE-ABS-KEY (((area OR neighbourhood OR neighborhood OR roadside OR city OR cities OR urban OR ambient OR residential OR surrounding) W/2 (greening OR greenness)))) OR (TITLE-ABS-KEY (bluespace OR (blue AND space) OR (bluehealth) OR (blue W/2 cover*) OR (blue AND gym) OR (air AND pollution) OR (air AND quality) OR (noise AND pollution) OR ((traffic OR aircraft OR industr* OR neighbourhood OR neighborhood OR outdoor) W/2 noise) OR (noise W/2 pollution))))) OR (TITLE-ABS-KEY ((salutogenic W/2 environment*) OR (health AND promot* W/2 environment*))) ...
95,186 document results
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18
TITLE-ABS-KEY ((salutogenic W/2 environment*) OR (health AND promot* W/2 environment*))
2,849 document results

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17
((TITLE-ABS-KEY (depression OR depressive OR dysthymi* OR anxiety OR (anxiety AND disorder*) OR (panic AND disorder*) OR (panic) OR (generali?ed AND anxiety) OR (obsessive-compulsive AND disorder) OR (obsessive-compulsive) OR (obsessive AND compulsive) OR ocd OR ptsd OR (posttrauma*) OR post-traumatic OR (post AND traumatic) OR (bipolar) OR (bipolar AND disorder*) OR psychotic OR (bipolar AND (affective OR disorder*)) OR schizophreni* OR psychosis)) OR (TITLE-ABS-KEY ((physical AND health) OR (cardio-vascular) OR (cardiovascular) OR (cardio AND vascular) OR myocardial OR diabetes OR cancer OR respiratory OR (cardio-respiratory) OR cardiorespiratory OR (cardio AND respiratory) OR endocrine OR musculoskeletal OR (musculo-skeletal) OR (neoplasms) OR (digestive AND system) OR digestive OR (respiratory AND tract) OR (nervous AND system) OR neurological OR (eye AND disease*) OR (skin AND connective AND tissue) OR dermatologic* OR (nutrition* AND dis*) OR metabolic OR endocrine OR immune OR hiv OR (human AND immunodeficiency) OR obesity OR bmi OR obese)) OR (TITLE-ABS-KEY ((physical AND function*) OR (physical AND functioning) OR (quality AND of AND life) OR ("Quality of Life") OR insomnia OR sleep OR (sleep AND disrupt*) OR frail OR frailty)) OR (TITLE-ABS-KEY ((health AND promot* AND behavio?r*) OR diet OR (physical AND activity) OR (physical* AND activ*) OR walking OR running OR exercise OR smoking OR (alcohol AND drinking) OR (alcohol AND near/2 AND consum*)))) AND ((TITLE-ABS-KEY ((recreational AND park) OR (recreational AND parks))) OR (TITLE-ABS-KEY (garden OR park OR parks OR (public AND park) OR (public AND parks))) OR (TITLE-ABS-KEY (((neighbourhood OR neighborhood OR public) W/2 open AND space))) OR (TITLE-ABS-KEY ((green AND space) OR greenspace)) OR (TITLE-ABS-KEY ((green* W/2 (area OR cover* OR environment OR gym OR neighbourhood OR neighborhood OR roadside OR city OR cities)))) OR (TITLE-ABS-KEY (((area OR neighbourhood OR neighborhood OR roadside OR city OR cities OR urban OR ambient OR residential OR surrounding) W/2 (greening OR greenness)))) OR (TITLE-ABS-KEY (bluespace OR (blue AND space) OR (bluehealth) OR (blue W/2 cover*) OR (blue AND gym) OR (air AND pollution) OR (air AND quality) OR (noise AND pollution) OR ((traffic OR aircraft OR industr* OR neighbourhood OR neighborhood OR outdoor) W/2 noise) OR (noise W/2 pollution)))) ...
92,463 document results
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16
(TITLE-ABS-KEY ((recreational AND park) OR (recreational AND parks))) OR (TITLE-ABS-KEY (garden OR park OR parks OR (public AND park) OR (public AND parks))) OR (TITLE-ABS-KEY (((neighbourhood OR neighborhood OR public) W/2 open AND space))) OR (TITLE-ABS-KEY ((green AND space) OR greenspace)) OR (TITLE-ABS-KEY ((green* W/2 (area OR cover* OR environment OR gym OR neighbourhood OR neighborhood OR roadside OR city OR cities)))) OR (TITLE-ABS-KEY (((area OR neighbourhood OR neighborhood OR roadside OR city OR cities OR urban OR ambient OR residential OR surrounding) W/2 (greening OR greenness)))) OR (TITLE-ABS-KEY (bluespace OR (blue AND space) OR (bluehealth) OR (blue W/2 cover*) OR (blue

AND gym) OR (air AND pollution) OR (air AND quality) OR (noise AND pollution) OR ((traffic OR aircraft OR industr* OR neighbourhood OR neighborhood OR outdoor) W/2 noise) OR (noise W/2 pollution)))
616,097 document results
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394,968 document results
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14
TITLE-ABS-KEY (((area OR neighbourhood OR neighborhood OR roadside OR city OR cities OR urban OR ambient OR residential OR surrounding) W/2 (greening OR greenness)))
1,629 document results
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TITLE-ABS-KEY ((green* W/2 (area OR cover* OR environment OR gym OR neighbourhood OR neighborhood OR roadside OR city OR cities)))
20,202 document results
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TITLE-ABS-KEY ((green AND space) OR greenspace)
36,352 document results
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1,645 document results
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TITLE-ABS-KEY (garden OR park OR parks OR (public AND park) OR (public AND parks))
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5,341 document results

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(TITLE-ABS-KEY (depression OR depressive OR dysthymi* OR anxiety OR (anxiety AND disorder*) OR (panic AND disorder*) OR (panic) OR (generali?ed AND anxiety) OR (obsessive-compulsive AND disorder) OR (obsessive-compulsive) OR (obsessive AND compulsive) OR ocd OR ptsd OR (posttrauma*) OR post-traumatic OR (post AND traumatic) OR (bipolar) OR (bipolar AND disorder*) OR psychotic OR (bipolar AND (affective OR disorder*)) OR schizophreni* OR psychosis)) OR (TITLE-ABS-KEY ((physical AND health) OR (cardio-vascular) OR (cardiovascular) OR (cardio AND vascular) OR myocardial OR diabetes OR cancer OR respiratory OR (cardio-respiratory) OR cardiorespiratory OR (cardio AND respiratory) OR endocrine OR musculoskeletal OR (musculo-skeletal) OR (neoplasms) OR (digestive AND system) OR digestive OR (respiratory AND tract) OR (nervous AND system) OR neurological OR (eye AND disease*) OR (skin AND connective AND tissue) OR dermatologic* OR (nutrition* AND dis*) OR metabolic OR endocrine OR immune OR hiv OR (human AND immunodeficiency) OR obesity OR bmi OR obese)) OR (TITLE-ABS-KEY ((physical AND function*) OR (physical AND functioning) OR (quality AND of AND life) OR ("Quality of Life") OR insomnia OR sleep OR (sleep AND disrupt*) OR frail OR frailty)) OR (TITLE-ABS-KEY ((health AND promot* AND behavio?r*) OR diet OR (physical AND activity) OR (physical* AND activ*) OR walking OR running OR exercise OR smoking OR (alcohol AND drinking) OR (alcohol AND near/2 AND consum*)))
14,274,792 document results
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4
TITLE-ABS-KEY ((health AND promot* AND behavio?r*) OR diet OR (physical AND activity) OR (physical* AND activ*) OR walking OR running OR exercise OR smoking OR (alcohol AND drinking) OR (alcohol AND near/2 AND consum*))
2,677,567 document results
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3
TITLE-ABS-KEY ((physical AND function*) OR (physical AND functioning) OR (quality AND of AND life) OR ("Quality of Life") OR insomnia OR sleep OR (sleep AND disrupt*) OR frail OR frailty)
1,553,071 document results
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(nutrition* AND dis*) OR metabolic OR endocrine OR immune OR hiv OR (human AND immunodeficiency) OR obesity OR bmi OR obese)
10,839,391 document results
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1
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S27
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S26
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Select item 23

S23
ab(health promot* OR salutogenic NEAR/2 environment*) OR su(health promot* OR salutogenic NEAR/2 environment*) OR ti(health promot* OR salutogenic NEAR/2 environment*)
Applied Social Sciences Index & Abstracts (ASSIA) 31,315 Actions
Select item 22
S22
S20 AND S21
Applied Social Sciences Index & Abstracts (ASSIA) 14,605 Actions
Select item 21
S21
S1 or S2 Or S3 or S4
Applied Social Sciences Index & Abstracts (ASSIA) 306,350 Actions
Select item 20
S20
S6 OR S7 OR S8 OR S9 OR S10 OR S11 OR S12 OR S13 Or S14 OR S15 OR S16 OR S17 OR S18 OR S19
Applied Social Sciences Index & Abstracts (ASSIA) 57,226 Actions
Select item 19
S19
ab(((traffic OR aircraft OR industr* OR neighbourhood OR neighborhood OR outdoor) NEAR/2 noise)) OR su(((traffic OR aircraft OR industr* OR neighbourhood OR neighborhood OR outdoor) NEAR/2 noise)) OR ti(((traffic OR aircraft OR industr* OR neighbourhood OR neighborhood OR outdoor) NEAR/2 noise))
Applied Social Sciences Index & Abstracts (ASSIA) 69 Actions
Select item 18
S18
ab((noise OR noise pollution)) OR su((noise OR noise pollution)) OR ti((noise OR noise pollution))
Applied Social Sciences Index & Abstracts (ASSIA) 2,073 Actions
Select item 17
S17
ab(((ambient OR neighbourhood OR neighborhood OR outdoor) NEAR/2 air)) OR su(((ambient OR neighbourhood OR neighborhood OR outdoor) NEAR/2 air)) OR ti(((ambient OR neighbourhood OR neighborhood OR outdoor) NEAR/2 air))
Applied Social Sciences Index & Abstracts (ASSIA) 196 Actions
Select item 16
S16
ab(air pollution OR air quality) OR su(air pollution OR air quality) OR ti(air pollution OR air quality)
Applied Social Sciences Index & Abstracts (ASSIA) 975 Actions
Select item 15
S15
ab(blue health OR blue water OR blue gym) OR su(blue health OR blue water OR blue gym) OR ti(blue health OR blue water OR blue gym)
Applied Social Sciences Index & Abstracts (ASSIA) 359 Actions
Select item 14

S14
ab(bluespace OR blue space) OR su(bluespace OR blue space) OR ti(bluespace OR blue space)
Applied Social Sciences Index & Abstracts (ASSIA) 32 Actions
Select item 13
S13
ab(public open space OR neighbourhood open space OR neighborhood open space) OR su(public open space OR neighbourhood open space OR neighborhood open space) OR ti(public open space OR neighbourhood open space OR neighborhood open space)
Applied Social Sciences Index & Abstracts (ASSIA) 155 Actions
Select item 12
S12
ab(garden OR park OR parks OR public park OR public parks) OR su(garden OR park OR parks OR public park OR public parks) OR ti(garden OR park OR parks OR public park OR public parks)
Applied Social Sciences Index & Abstracts (ASSIA) 2,696 Actions
Select item 11
S11
ab(greenery OR greenspace or greenness) OR su(greenery OR greenspace or greenness) OR ti(greenery OR greenspace or greenness)
Applied Social Sciences Index & Abstracts (ASSIA) 86 Actions
Select item 10
S10
ab(((ambient OR city OR cities OR environment OR neighbourhood OR neighborhood OR residential OR surrounding OR urban) NEAR/2 greenness)) OR su(((ambient OR city OR cities OR environment OR neighbourhood OR neighborhood OR residential OR surrounding OR urban) NEAR/2 greenness)) OR ti(((ambient OR city OR cities OR environment OR neighbourhood OR neighborhood OR residential OR surrounding OR urban) NEAR/2 greenness))
Applied Social Sciences Index & Abstracts (ASSIA) 10 Actions
Select item 9
S9
ab(((city OR cities OR environment* OR neighbourhood OR neighborhood OR urban OR residential OR surrounding) NEAR/2 greening)) OR su(((city OR cities OR environment* OR neighbourhood OR neighborhood OR urban OR residential OR surrounding) NEAR/2 greening)) OR ti(((city OR cities OR environment* OR neighbourhood OR neighborhood OR urban OR residential OR surrounding) NEAR/2 greening))
Applied Social Sciences Index & Abstracts (ASSIA) 9 Actions
Select item 8
S8
ab((green NEAR/2 (area* OR cover* OR environment* OR gym* OR neighbourhood* OR neighborhood* OR roadside OR space*))) OR su((green NEAR/2 (area* OR cover* OR environment* OR gym* OR neighbourhood* OR neighborhood* OR roadside OR space*))) OR ti((green NEAR/2 (area* OR cover* OR environment* OR gym* OR neighbourhood* OR neighborhood* OR roadside OR space*)))
Applied Social Sciences Index & Abstracts (ASSIA) 264 Actions
Select item 7

S7
ab(recreational park*) OR su(recreational park*) OR ti(recreational park*)
Applied Social Sciences Index & Abstracts (ASSIA) 86 Actions
Select item 6
S6
ab(environment) OR su(environment) OR ti(environment)
Applied Social Sciences Index & Abstracts (ASSIA) 51,970 Actions
Select item 4
S4
ab(((health promot* behavio?r*) or diet or (physical activity) or (physical* activ*) or walking or running or exercise or smoking or (alcohol drinking) or (alcohol NEAR/2 consum*))) OR ti(((health promot* behavio?r*) or diet or (physical activity) or (physical* activ*) or walking or running or exercise or smoking or (alcohol drinking) or (alcohol NEAR/2 consum*))) OR su(((health promot* behavio?r*) or diet or (physical activity) or (physical* activ*) or walking or running or exercise or smoking or (alcohol drinking) or (alcohol NEAR/2 consum*)))
Applied Social Sciences Index & Abstracts (ASSIA) 79,197 Actions
Select item 3
S3
ab(((physical function*) or (physical functioning) or (quality of life) or ("Quality of Life") or insomnia or sleep or (sleep disrupt*) or frail or frailty)) OR ti(((physical function*) or (physical functioning) or (quality of life) or ("Quality of Life") or insomnia or sleep or (sleep disrupt*) or frail or frailty)) OR su(((physical function*) or (physical functioning) or (quality of life) or ("Quality of Life") or insomnia or sleep or (sleep disrupt*) or frail or frailty))
Applied Social Sciences Index & Abstracts (ASSIA) 48,401 Actions
Select item 2
S2
ab(((physical health) or cardio-vascular or cardiovascular or (cardio vascular) or myocardial or cancer or respiratory or cardio-respiratory or cardiorespiratory or (cardio respiratory) or diabetes or diabetic or BMI or (Body Mass Index) OR endocrine or musculoskeletal or musculo-skeletal or neoplasms or (digestive system) or digestive or (respiratory tract) or (nervous system) or neurological or eye disease*or (skin and connective tissue) or dermatologic* or (nutritional dis*) or metabolic or endocrine system or immune or HIV or (human immunodeficiency))) OR ti(((physical health) or cardio-vascular or cardiovascular or (cardio vascular) or myocardial or cancer or respiratory or cardio-respiratory or cardiorespiratory or (cardio respiratory) or diabetes or diabetic or BMI or (Body Mass Index) OR endocrine or musculoskeletal or musculo-skeletal or neoplasms or (digestive system) or digestive or (respiratory tract) or (nervous system) or neurological or eye disease*or (skin and connective tissue) or dermatologic* or (nutritional dis*) or metabolic or endocrine system or immune or HIV or (human immunodeficiency))) OR su(((physical health) or cardio-vascular or cardiovascular or (cardio vascular) or myocardial or cancer or respiratory or cardio-respiratory or cardiorespiratory or (cardio respiratory) or diabetes or diabetic or BMI or (Body Mass Index) OR endocrine or musculoskeletal or musculo-skeletal or neoplasms or (digestive system) or digestive or (respiratory tract) or (nervous system) or neurological or eye disease*or (skin and connective tissue) or dermatologic* or (nutritional dis*) or metabolic or endocrine system or immune or HIV or (human immunodeficiency)))
Applied Social Sciences Index & Abstracts (ASSIA) 132,800 Actions
Select item 1

S1
ab((depression or depressive or dysthymi* or anxiety or anxiety disorder* or panic disorder* or panic or generali?ed anxiety or obsessive-compulsive disorder* or obsessive-compulsive or obsessive compulsive or ocd or ptsd or posttrauma* or post-traumatic or post traumatic or bipolar or bipolar disorder* or psychotic or (bipolar and (affective or disorder*)) or schizophreni* or psychosis)) OR ti((depression or depressive or dysthymi* or anxiety or anxiety disorder* or panic disorder* or panic or generali?ed anxiety or obsessive-compulsive disorder* or obsessive-compulsive or obsessive compulsive or ocd or ptsd or posttrauma* or post-traumatic or post traumatic or bipolar or bipolar disorder* or psychotic or (bipolar and (affective or disorder*)) or schizophreni* or psychosis)) OR su((depression or depressive or dysthymi* or anxiety or anxiety disorder* or panic disorder* or panic or generali?ed anxiety or obsessive-compulsive disorder* or obsessive-compulsive or obsessive compulsive or ocd or ptsd or posttrauma* or post-traumatic or post traumatic or bipolar or bipolar disorder* or psychotic or (bipolar and (affective or disorder*)) or schizophreni* or psychosis))

Greenfile

S27
S23 AND S26
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (1,026)View DetailsEdit
S26
S24 OR S25
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (13,758)View DetailsEdit
S25
TI (((cohort or follow-up or longitudinal or prospective or retrospective) N2 study)) OR KW (((cohort or follow-up or longitudinal or prospective or retrospective) N2 study)) OR AB (((cohort or follow-up or longitudinal or prospective or retrospective) N2 study))
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (3,453)View DetailsEdit
S24

TI (cohort or cohorts or follow-up or longitudinal or incidence) OR KW (cohort or cohorts or follow-up or longitudinal or incidence) OR AB (cohort or cohorts or follow-up or longitudinal or incidence)
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (13,323)View DetailsEdit
S23
S21 OR S22
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (7,014)View DetailsEdit
S22
TI (((health promot* or salutogenic) N2 environment*)) OR AB (((health promot* or salutogenic) N2 environment*)) OR KW (((health promot* or salutogenic) N2 environment*))
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (14)View DetailsEdit
S21
S15 AND S20
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (7,002)View DetailsEdit
S20
(S16 OR S17 OR S18 OR S19)
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (50,795)View DetailsEdit
S19
TI (((health promot* behavio?r*) or diet or (physical activity) or (physical* activ*) or walking or running or exercise or smoking or (alcohol drinking) or (alcohol NEAR/2 consum*))) OR AB (((health promot* behavio?r*) or diet or (physical activity) or (physical* activ*) or walking or running or exercise or smoking or (alcohol drinking) or (alcohol NEAR/2 consum*))) OR KW (((health promot* behavio?r*) or diet or (physical activity) or (physical* activ*) or walking or running or exercise o ...
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (17,451)View DetailsEdit
S18
TI (((physical function*) or (physical functioning) or (quality of life) or ("Quality of Life") or insomnia or sleep or (sleep disrupt*) or frail or frailty)) OR AB (((physical function*) or (physical functioning) or (quality of life) or ("Quality of Life") or insomnia or sleep or (sleep disrupt*) or frail or frailty)) OR KW (((physical function*) or (physical functioning) or (quality of life) or ("Quality of Life") or insomnia or sleep or (sleep disrupt*) or frail or frailty))
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (1,819)View DetailsEdit
S17
TI (((physical health) or cardio-vascular or cardiovascular or (cardio vascular) or myocardial or cancer or respiratory or cardio-respiratory or cardiorespiratory or (cardio respiratory) or diabetes or diabetic or BMI or (Body Mass Index) OR endocrine or musculoskeletal or musculo-skeletal or neoplasms or (digestive system) or digestive or (respiratory tract) or (nervous system) or neurological or eye disease* or (skin and connective tissue) or d ...
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (33,709)View DetailsEdit
S16
TI ((mental health or depression or depressive or dysthymi* or anxiety or anxiety disorder* or panic disorder* or panic or generali?ed anxiety or obsessive-compulsive disorder* or obsessive-compulsive or obsessive compulsive or ocd or ptsd or posttrauma* or post-traumatic or post traumatic or bipolar or bipolar disorder* or psychotic or (bipolar and (affective or disorder*)) or schizophreni* or psychosis)) OR AB ((mental health or depression or depressive or dysthymi* or anxiety or anxie ...
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (926)View DetailsEdit
S15
S1 OR S2 OR S3 OR S4 OR S5 OR S6 OR S7 OR S8 OR S9 OR S10 OR S11 OR S12 OR S13 OR S14

Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

View Results (88,879)View DetailsEdit
S14

TI (coast* or water cover* or blue cover*) OR AB (coast* or water cover* or blue cover*) OR KW (coast* or water cover* or blue cover*)
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S13
TI (((traffic or aircraft or industr* or neighbourhood or outdoor) N2 noise)) OR AB (((traffic or aircraft or industr* or neighbourhood or outdoor) N2 noise)) OR KW (((traffic or aircraft or industr* or neighbourhood or outdoor) N2 noise))
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S12
TI (noise or noise pollution) OR AB (noise or noise pollution) OR KW (noise or noise pollution)
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S11
TI (((ambient OR neighbourhood OR outdoor) N2 air)) OR AB (((ambient OR neighbourhood OR outdoor) N2 air)) OR KW (((ambient OR neighbourhood OR outdoor) N2 air))
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S10
TI (air pollution OR air quality) OR AB (air pollution OR air quality) OR KW (air pollution OR air quality)
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S9
TI (blue space or bluespace) OR AB (blue space or bluespace) OR KW (blue space or bluespace)
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S8
TI (bluehealth or blue water or blue gym) OR AB (bluehealth or blue water or blue gym) OR KW (bluehealth or blue water or blue gym)
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S7
TI ((neighbourhood or neighborhood) N2 open space) OR AB ((neighbourhood or neighborhood) N2 open space) OR KW ((neighbourhood or neighborhood) N2 open space)

Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S6
TI (public N2 (open space or park or parks or space)) OR AB (public N2 (open space or park or parks or space)) OR KW (public N2 (open space or park or parks or space))
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S5
TI (garden or park or parks or sports field) OR AB (garden or park or parks or sports field) OR KW (garden or park or parks or sports field)
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S4
TI (((ambient or city or cities or environment* or neighbourhood or neighborhood or residential or surrounding or urban) N2 greenness)) OR AB (((ambient or city or cities or environment* or neighbourhood or neighborhood or residential or surrounding or urban) N2 greenness)) OR KW (((ambient or city or cities or environment* or neighbourhood or neighborhood or residential or surrounding or urban) N2 greenness))
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S3

TI (((city or cities or environment* or neighbourhood or neighborhood or urban) N2 greening)) OR AB (((city or cities or environment* or neighbourhood or neighborhood or urban) N2 greening)) OR KW (((city or cities or environment* or neighbourhood or neighborhood or urban) N2 greening))
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S2
TI ((green N2 (area* or cover or environment* or gym* or neighbourhood* or neighborhood* or roadside* or space*)).) OR AB ((green N2 (area* or cover or environment* or gym* or neighbourhood* or neighborhood* or roadside* or space*)).) OR KW ((green N2 (area* or cover or environment* or gym* or neighbourhood* or neighborhood* or roadside* or space*)))
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

RerunView DetailsEdit
S1
TI (green space OR greenspace OR greenery) OR AB (green space OR greenspace OR greenery) OR KW (green space OR greenspace OR greenery)
Expanders - Apply equivalent subjects

Search modes - Boolean/Phrase

Appendix IV: Data Extraction Form for Systematic Review Template

Study No.

Date form completed (dd/mm/yyyy)
Name/ID of person extracting data
Report title
(title of paper/ abstract/ report that data are extracted from)
Report ID
Reference details
Reference details
Report author contact details
Publication type

Study funding source
(including role of funders)
Possible conflicts of interest

Notes:

Eligibility

Is the Study Longitudinal and Observational?
Population
Exposure
(type/ characteristics)
Health Outcome
Decision
Study Methods
Population Description
Setting/ Source
Cohort name/ data source description
Prospective or Retrospective Study
Methods of Participant Recruitment
Aims/ Objectives

Duration of Follow -up
Participants
Sample Size
Total Sample Size
Age Group
Sex
Ethnicity
Socio-economic Status

Other Characteristics
#NAME?
Exposures
Type
(e.g green, blue space)
Definition
Characteristics Description
(e.g access, distance, proportion)

Exposure Metrics Used

Method of Measuring Exposure
(e.g Satellite imaging, interviews)
Method of Exposure Assignment
(e.g GIS, census data)
Unit of Analysis
(e.g. individual, area)
Additional Exposures
(those not studied in the review)
Comparator Group
(e.g no exposure; exposure to different environmental variable)

Primary Outcomes

Outcome/s Type
(e.g. behaviour, mental/physical health condition)
Outcome Definition
Measurement Tools
(e.g. self-reported instrument; clinician assessment)
Outcome Variable Type
(e.g dichotomous, continuous variable)
Stats
Additional Outcomes
Outcome/s Type
(e.g. behaviour, mental/physical health condition)
Outcome Definition
Measurement Tools
(e.g. validated, self-reported instrument; clinician assessment)
Time Points Recorded

Effect Estimate of Outcome/s
Results

Outcome/s

Results
(effect estimate & variance)
Type of Effect Estimate (e.g Odds Ratio, Incidence ratio, Beta, mean)
Unit of Analysis
(e.g individual, group)
Confounders
Statistical Methods
Appropriateness of Statistical Methods Used
Subgroup Analyses
Mediators
(if any)
Loss to Follow-Up Number and Reasons
Handling of Missing Data
Discussion
Main Discussion Points

Other Notes

Conclusion and Limitations
Limitations
Strengths
Strategies to Overcome Limitations
Conclusions
Notes

Other Information
Does the study directly address review question?
References to other relevant studies
Correspondence required for further study information
(what and from whom)
Further study information requested (from whom, what and when)
Correspondence received (from whom, what and when)

Notes

Appendix V: Newcastle-Ottawa Scale Manual

CODING MANUAL FOR COHORT STUDIES

SELECTION

1) Representativeness of the Exposed Cohort

Item is assessing the representativeness of exposed individuals in the community, not the representativeness of the sample of women from some general population. For example, subjects derived from groups likely to contain middle class, better educated, health oriented women are likely to be representative of postmenopausal estrogen users while they are not representative of all women (e.g. members of a health maintenance organisation (HMO) will be a representative sample of estrogen users. While the HMO may have an under-representation of ethnic groups, the poor, and poorly educated, these excluded groups are not the predominant users users of estrogen).

Allocation of stars as per rating sheet

2) Selection of the Non-Exposed Cohort

Allocation of stars as per rating sheet

3) Ascertainment of Exposure

Allocation of stars as per rating sheet

4) Demonstration That Outcome of Interest Was Not Present at Start of Study

In the case of mortality studies, outcome of interest is still the presence of a disease/ incident, rather than death. That is to say that a statement of no history of disease or incident earns a star.

COMPARABILITY

1) Comparability of Cohorts on the Basis of the Design or Analysis

A maximum of 2 stars can be allotted in this category
Either exposed and non-exposed individuals must be matched in the design and/or confounders must be adjusted for in the analysis. Statements of no differences between groups or that differences were not statistically significant are not sufficient for establishing comparability. Note: If the relative risk for the exposure of interest is adjusted for the confounders listed, then the groups will be considered to be comparable on each variable used in the adjustment.
There may be multiple ratings for this item for different categories of exposure (e.g. ever vs. never, current vs. previous or never)

Age = ☆ , Other controlled factors =☆

OUTCOME

1) Assessment of Outcome

For some outcomes (e.g. fractured hip), reference to the medical record is sufficient to satisfy the requirement for confirmation of the fracture. This would not be adequate for vertebral fracture outcomes where reference to x-rays would be required.

a) Independent or blind assessment stated in the paper, or confirmation of the outcome by reference to secure records (x-rays, medical records, etc.) ☆
b) Record linkage (e.g. identified through ICD codes on database records) ☆
c) Self-report (i.e. no reference to original medical records or x-rays to confirm the outcome)
d) No description.

2) Was Follow-Up Long Enough for Outcomes to Occur

An acceptable length of time should be decided before quality assessment begins (e.g. 5 yrs. for exposure to breast implants)

3) Adequacy of Follow Up of Cohorts

This item assesses the follow-up of the exposed and non-exposed cohorts to ensure that losses are not related to either the exposure or the outcome.

Allocation of stars as per rating sheet

Appendix VI: Urban Atlas Nomenclature Description

Image source: (European Environment Agency, 2012)

Table 3: UA LULC nomenclature (in bold, classes without any further subdivision)

Urban Atlas Land Use/Land Cover			
UA No.	Code	Nomenclature	Additional Information
1		Artificial surfaces	
1.1		Urban Fabric	
1.1.1	**11100**	**Continuous urban fabric (S.L. > 80%)**	HRL IMD required
1.1.2		Discontinuous Urban Fabric (S.L. 10% - 80%)	
1.1.2.1	**11210**	**Discontinuous dense urban fabric (S.L. 50% - 80%)**	HRL IMD required
1.1.2.2	**11220**	**Discontinuous medium density urban fabric (S.L. 30% - 50%)**	HRL IMD required

Urban Atlas Land Use/Land Cover			
UA No.	**Code**	**Nomenclature**	**Additional Information**
1.1.2.3	**11230**	**Discontinuous low density urban fabric (S.L. 10% - 30%)**	HRL IMD required
1.1.2.4	**11240**	**Discontinuous very low density urban fabric (S.L. < 10%)**	HRL IMD required
1.1.3	**11300**	**Isolated structures**	
1.2		Industrial, commercial, public, military, private and transport units	
1.2.1	**12100**	**Industrial, commercial, public, military and private units**	zoning data / field check recommended
1.2.2		Road and rail network and associated land	COTS or OSM data required
1.2.2.1	**12210**	**Fast transit roads and associated land**	COTS or OSM data required
1.2.2.2	**12220**	**Other roads and associated land**	COTS or OSM data required
1.2.2.3	**12230**	**Railways and associated land**	COTS or OSM data required
1.2.3	**12300**	**Port areas**	zoning data / field check recommended
1.2.4	**12400**	**Airports**	zoning data / field check recommended
1.3		Mine, dump and construction sites	
1.3.1	**13100**	**Mineral extraction and dump sites**	
1.3.3	**13300**	**Construction sites**	
1.3.4	**13400**	**Land without current use**	
1.4		Artificial non-agricultural vegetated areas	
1.4.1	**14100**	**Green urban areas**	
1.4.2	**14200**	**Sports and leisure facilities**	
2		Agricultural areas	1 ha MMU

Urban Atlas Land Use/Land Cover			
UA No.	**Code**	**Nomenclature**	**Additional Information**
2.1	**21000**	**Arable land (annual crops)**	
2.2	**22000**	**Permanent crops**	
2.3	**23000**	**Pastures**	
2.4	**24000**	**Complex and mixed cultivation**	
3		Natural and (semi-)natural areas	1 ha MMU
3.1	**31000**	**Forests**	
3.2	**32000**	**Herbaceous vegetation associations**	
3.3	**33000**	**Open spaces with little or no vegetation**	
4	**40000**	**Wetlands**	**1 ha MMU**
5	**50000**	**Water**	**1 ha MMU**
9.1	**91000**	**No data (Clouds and shadows)**	
9.2	**92000**	**No data (Missing imagery)**	

Appendix VII: UK Biobank Data Access Application

The purpose of the application is for UK Biobank to determine whether the proposed research project is health-related, feasible and in the public interest. For this, we require a brief synopsis of the research plan (i.e. a description of the aims, methods and intended outputs) rather than a full scientific review. Please refer to the online help for guidance and examples.

A1. Project title (200 characters):

Assessing the impact of natural and other environmental exposures on multimorbidity.

A2. Research question(s) and aim(s) (up to 5000 characters or 200 words):

What is the relationship between exposure to green and blue space and mental-physical multimorbidity in adults?

Aims:

Model several measures of green and blue space exposures in the neighbourhood using suitable environmental data sources.

Explore the prevalence and identify types of multimorbidity in the UK Biobank population by employing and critically assessing established measurement approaches in the academic literature.

Assess the cross-sectional association of exposure to different green and blue spaces with mental-physical multimorbidity.

The majority of applications to UK Biobank are for data only. As such, the first two questions we ask are whether your application involves access to samples or re-contact as this will require some additional information and as is set out in the Access Procedures (our data are not depletable, but our samples and re-contact opportunities are depletable) recontact/sample applications are assessed to a different (more exacting) standard.

Does your project require biological samples?
Yes
<u>No</u>

Does your project require UK Biobank to re-contact participants:
Yes
<u>No</u>

Please provide information on each of the following:
A3. The background and scientific rationale of the proposed research project in general (up to 5000 characters or 300 words):

Multimorbidity is commonly defined as the presence of two or more health conditions in one individual. Multimorbidity of chronic mental and physical conditions has received attention in academic literature because of its impact on individuals' life and the healthcare system. Multimorbid individuals have poorer health-related quality of life, lower physical functioning and are at higher risk of disability and mortality than those without multimorbidity (Walker et al., 2016). Multimorbidity also puts strain on healthcare systems, as it is associated with higher health service utilisation, higher costs and resource allocation (McPhail, 2016). Currently, management of multimorbidity involves drug therapy adherence and other clinical interventions (Salisbury et al., 2018). However, it is known that multimorbidity can be prevented by managing the severity of chronic conditions or preventing their occurrence (AMS, 2018). According to World Health Organisation (2016), the surrounding environments in which people live in have an effect on their health. Exposures to green and blue spaces can have beneficial impacts on human health. The conceptualisation and measurement of these exposures are integral parts in understanding how they affect health through different socio-ecological and clinical pathways. Characteristics of green and blue spaces (such as type, quality and size) have been shown to impact health differently (WHO, 2016). Availability, accessibility and usage are the approaches most commonly used to conceptualise green space in the immediate surrounding environment (WHO, 2016). While there is emerging research in identifying what aspects of green and blue spaces impact single health conditions, research in relation to multimorbidity is sparse. This project aims to narrow this gap by employing a methodological approach of using environmental data sources to create several measures of green/ blue space availability and accessibility and examine their relationship with mental-physical multimorbidity.

A4. A brief description of the method(s) to be used (up to 5000 characters or 300 words):

First, environmental data will be identified and sourced. Geographical Information System (GIS) tools will be used to create different exposure metrics of indicators of availability and accessibility of green/ blue space. A candidate indicator of availability of green space is the Normalized Difference Vegetation Index (NDVI). This is sourced as an open access dataset with a resolution of 30m x 30m from Google Earth Engine. Several indicators of accessibility of green and blue space will also be used. The first is proportion of green and blue space in the immediate surroundings. This will include several types of green space (tree and ground cover) and it will be measured through radial and road network buffers from the residential address. Proximity to a green or blue space is going to be the second indicator of accessibility. Exposure metrics will include linear and/ or road network distances from the permanent residence. Academic literature will be used to inform decisions about sizes of buffers and distances. Currently, recommendations by Natural England (2010) state that everyone should live at least within 300m linear distance from a green space. Light Detection and Ranging (LiDAR) (Edina Digimap) is a suitable, high-resolution candidate dataset for computing these green and blue space exposures.

The environmental data will then be linked using R to each UK Biobank participant using the residential address as a proxy for permanent residence.

In order to better understand the prevalence and type of multimorbidity in the UK Biobank population, well-known theoretical and empirical approaches of measuring multimorbidity will be employed and critically assessed. Some of these include disease counts; severity indices and cluster analyses. This will facilitate an in-depth conceptualisation of multimorbidity and aid the identification of mental-physical multimorbidity.

The cross-sectional relationship between green and blue space exposures and mental-physical multimorbidity will then be examined.

A5. The type and size of dataset required (e.g. men only, imaging data only, whole cohort, etc.) (up to 5000 characters or 100 words):

Whole cohort.

A6. The expected value of the research (taking into account the public interest requirement) (up to 5000 characters or 100 words):

This research adds value to the understanding and transfer of knowledge of modifiable environmental risk factors of multimorbidity in several ways:

1. The methodological innovation of modelling and linking natural environment data for an in-depth conceptualisation of natural environmental exposures in the surrounding neighbourhood.

2. Increase the foundational knowledge about the pathways between exposures to natural environments and risk of mental-physical multimorbidity.

3. Inform the implementation of public health and environmental interventions to reduce the risk of mental-physical multimorbidity in the community.

A7. Please provide up to 6 keywords which best summarise your proposed research project:

Environment; Greenspace; Bluespace; Multimorbidity; Mental health; Physical health

A8. Please provide a lay summary of your research project in plain English, stating the aims, scientific rationale, project duration and public health impact (up to 5000 characters or 400 words):

People with multimorbidity have two or more long-term health conditions at the same time. These can either be physical conditions, mental conditions or a combination of both. Multimorbidity is an important topic to study because it has a negative impact on individuals' lives, healthcare systems and the economy. Those who have multimorbidity are more likely to have poorer quality of life and become disabled. They also tend to take multiple long-term medications to manage their conditions, which have unpleasant side effects. Multimorbid individuals also require complex healthcare management plans and in general tend to use health services more. This puts financial strain on government bodies. However, the natural environment in which people live, work or socialise can have an impact on their health. For example, having greenery (known as green space) or water bodies (known as blue space) in a neighbourhood could improve people's mental and physical health. This happens in several ways, including more socialisation, increased physical activity and reduction in city air pollution and noise. While, there is research into the ways these natural environments impact a single mental or physical health condition, such as having either depression or diabetes, little research has been done on the impact of having two or more co-existing conditions on a person. This project aims to examine the relationship between different green and blue spaces and multimorbidity in adults. This will involve linking data on the local environment to UK Biobank participants' residential addresses. Such an approach will allow us to measure different types of green and blue spaces, such as parks, street trees, lakes or canals. Being able to identify how accessible and available these types of spaces are in the surrounding neighbourhood will further increase our understanding of the ways they might impact multimorbidity differently.

In order to better understand how common multimorbidity is in the population; a range of statistical techniques will be employed. The relationship between different green and blue spaces and the probability of having multimorbidity will then be examined. This research is conducted as part of a PhD project and is expected to take 24 months. It will generate new knowledge and expand the field of environmental health.

A9. Will the research project result in the generation of any new data fields derived from existing complex datasets, such as imaging, accelerometry, electrocardiographic, linked healthcare data, etc, which might be of significant utility to other researchers:

This research will generate new data fields on neighbourhood green and blue space from existing, open source environmental datasets for the United Kingdom. Geospatial modelling will facilitate the creation and conceptualisation of different green and blue space exposure measures. Green and blue space exposures will be modelled at an individual-level to represent and capture amount, quality, proximity and type in the neighbourhood. The use of multi-purpose environmental datasets will also examine the possibility of using non-traditional methods of measuring natural environments.

A10. What is the estimated duration of your project, in months? If you consider (because for example the project is one involving the generation of hypotheses) that it would be difficult to set a fixed end point, we are prepared to consider a rolling 3-year period (during which annual updates are required):

The project is expected to take 24 months.

Please note that you are expected to publish (or to make publicly available) your results and return to UK Biobank:

- any important derived variables
- a description of the methods used to generate them
- the underlying syntax/code used to generate the main results of the paper, and
- a short layman's description that summarises your findings.

These should be provided within six months of each publication or within 12 months of the project end date (whichever comes first). We also ask that you send us a copy of your accepted manuscript at least two weeks prior to publication and alert us if there are any ethical or contentious issues surrounding the findings.

B. Selection of data-fields[Link to online help]

This part of the application form asks some general questions relating to required data for your research project. In addition, clicking the 'Create Application Basket' button below allows you to access Data Showcase, create a basket, and add the data-fields needed for your research. Please refer to the online help for guidance and examples. Owing to the large size of some data items, researchers may wish to link their data to existing bulk UK Biobank datasets held at their institute (and if so, UK Biobank is happy to facilitate this).

B1.Would you like to access an existing copy of the genotyping dataset held at your institute?
Yes
No

B2. Would you like to access an existing copy of bulk imaging files held at your institute?
Yes
No

B3. Would you like to re-use an existing dataset already held at your institute to conduct your research (i.e. that contains all the data you need for this new project)?:
Yes
No

Please use the button below to transfer to our Data Showcase where you can create/edit/view a Basket of data items you wish to receive from UK Biobank. Once you have finished, please click the "AMS" button there (at top right) to return here.
Create application basket.

I plan on requesting:

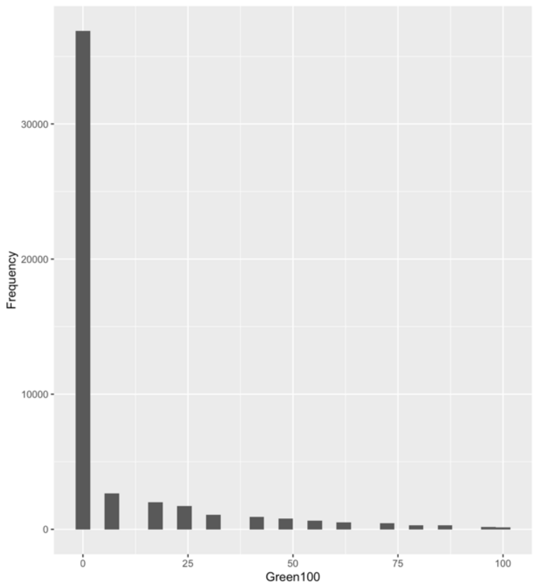
- All socio-demographic characteristics of the cohort at baseline and follow-up
- All environmental exposures from BUMP, air pollution and noise
- Information of health behaviours, like physical activity, diet, smoking
- Information on participants' mental and physical health assessed by NHS primary, secondary and tertiary sectors (GP and hospital records).
- UKB Assessment Centre information, like physical and cognitive function measures and mental health assessments.

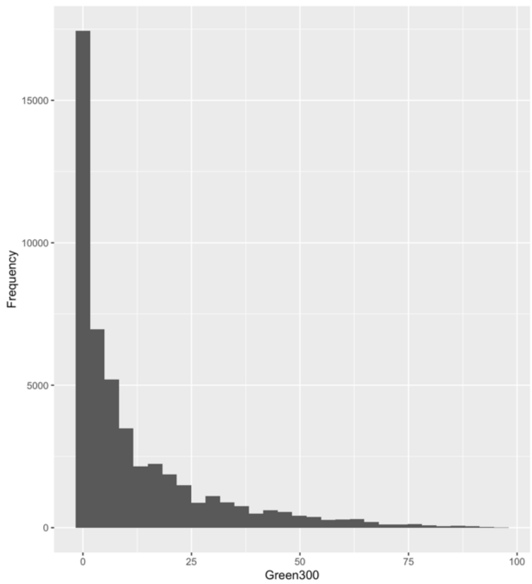
You may return to the Data Showcase to alter your selection any time before submitting this Application.

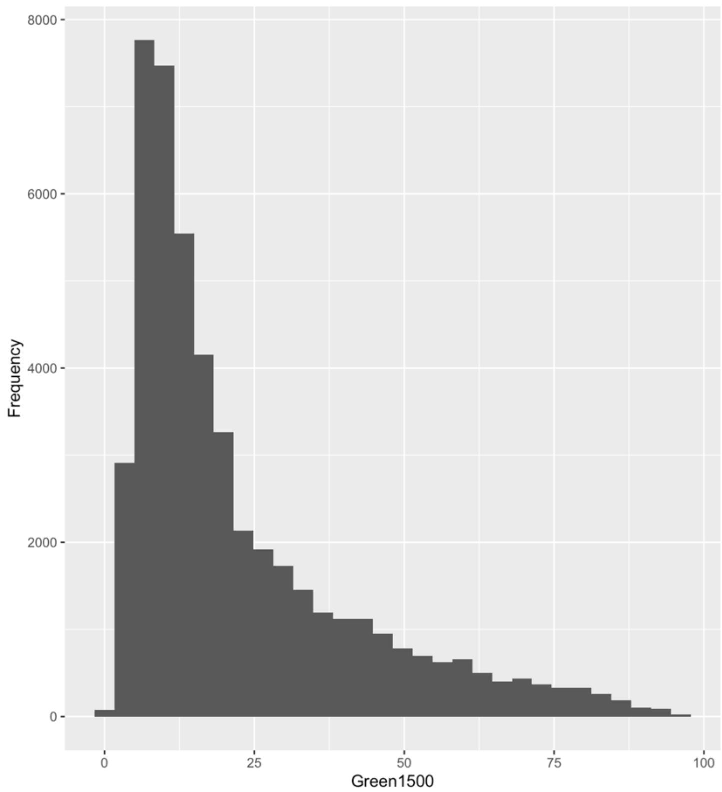
C. Selection of samples[Link to online help]
You have stated that your project does not require biological samples. You do not need to provide any further information in this section.

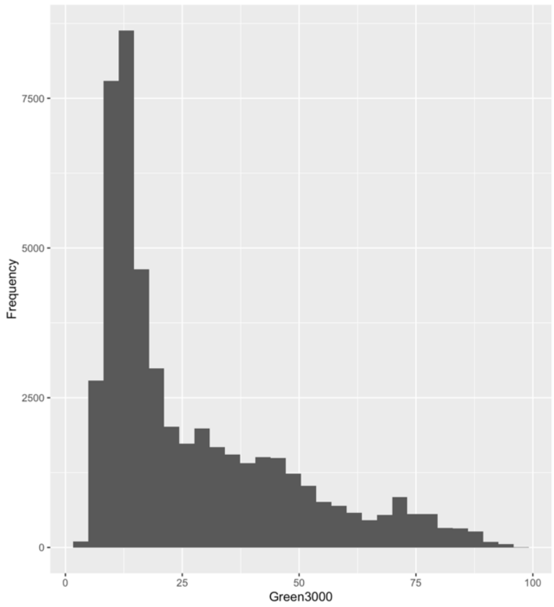
D. Re-contacting participants[Link to online help]
You have stated your project does not require UK Biobank to re-contact individuals. You do not need to provide any further information in this section.

Appendix VIII: Histograms and Correlation Heatmap of Green and Blue Space Exposure Variables








Frequency
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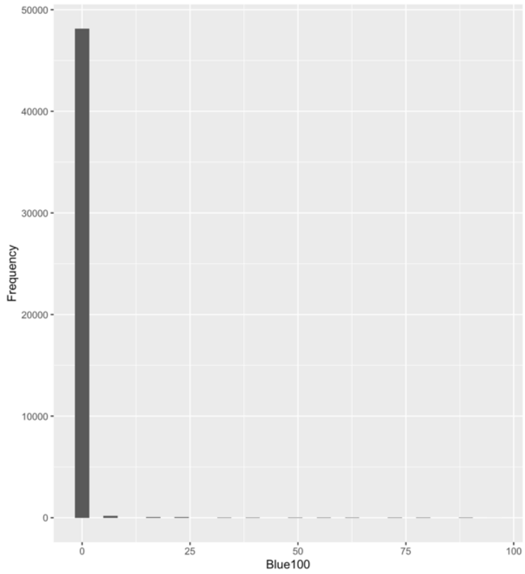
Frequency
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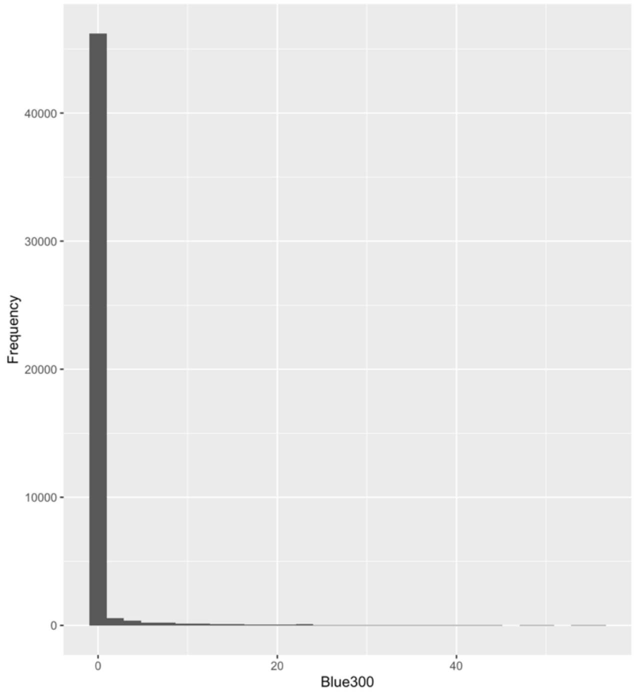
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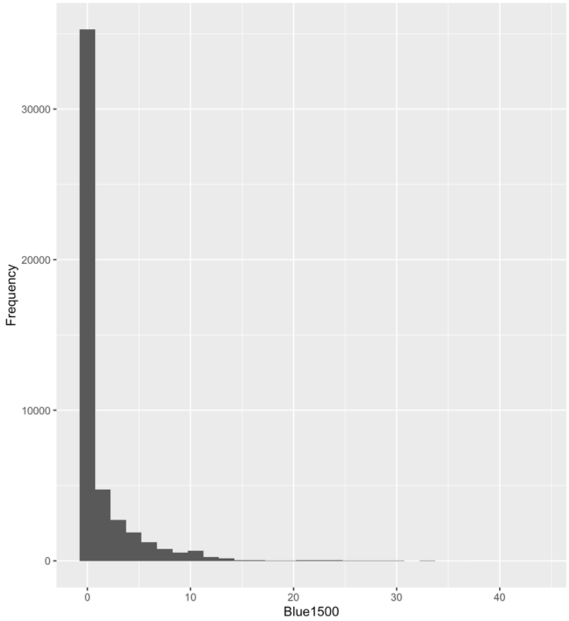
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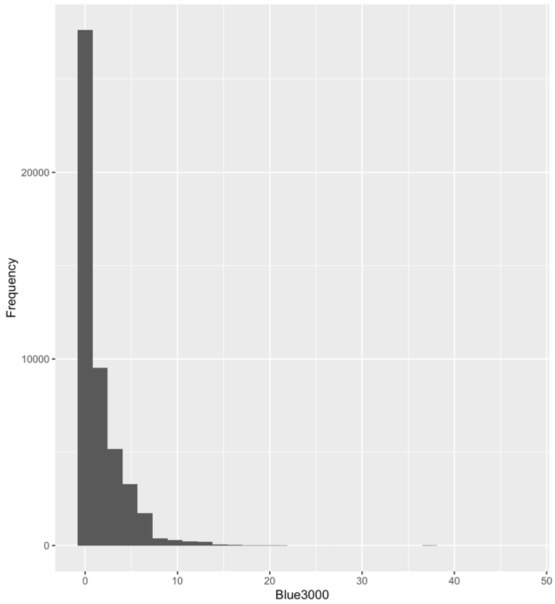
10000
20000
30000
0
10
20
30
40
Blue1500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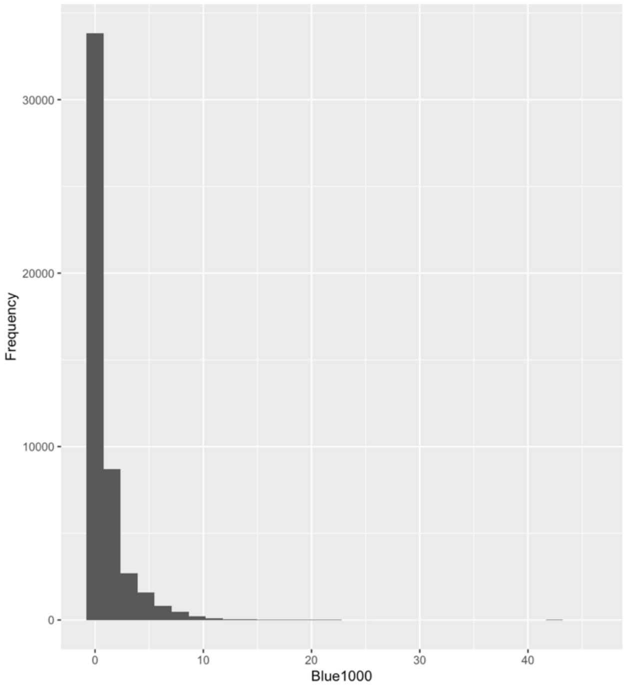
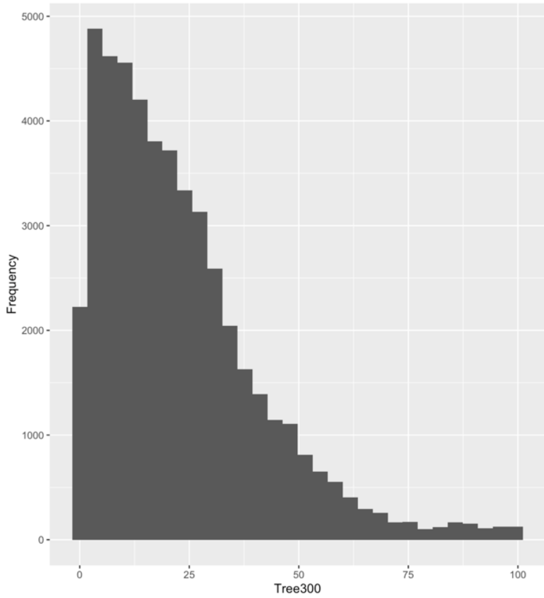
20000
0
10
20
30
40
50
Blue3000


Frequency
0
10000
20000
30000
0
10
20
30
40
Blue1000


Frequency
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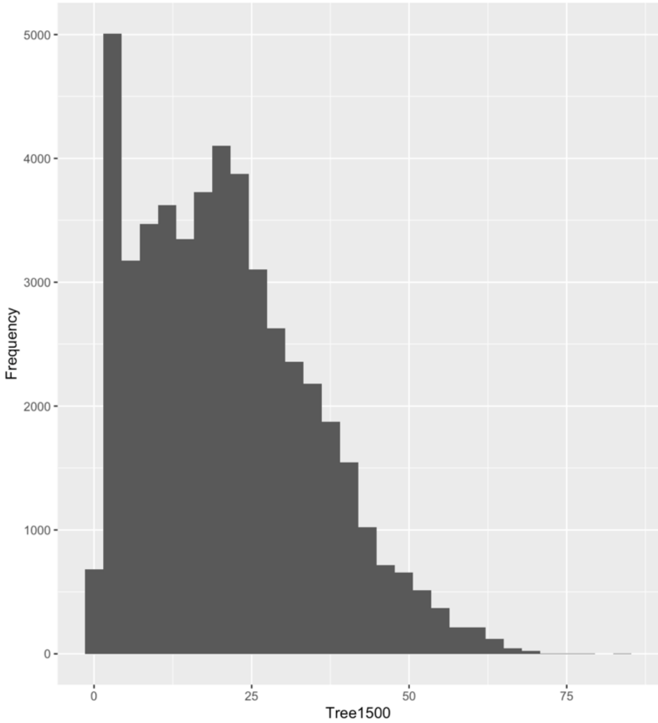
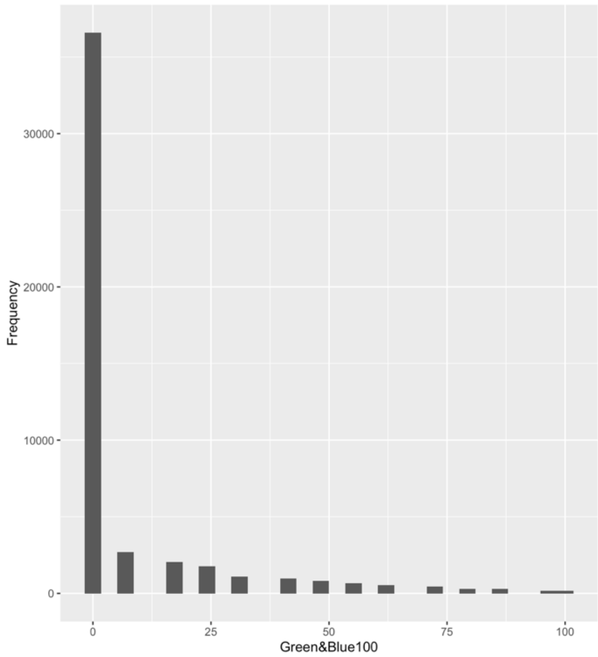
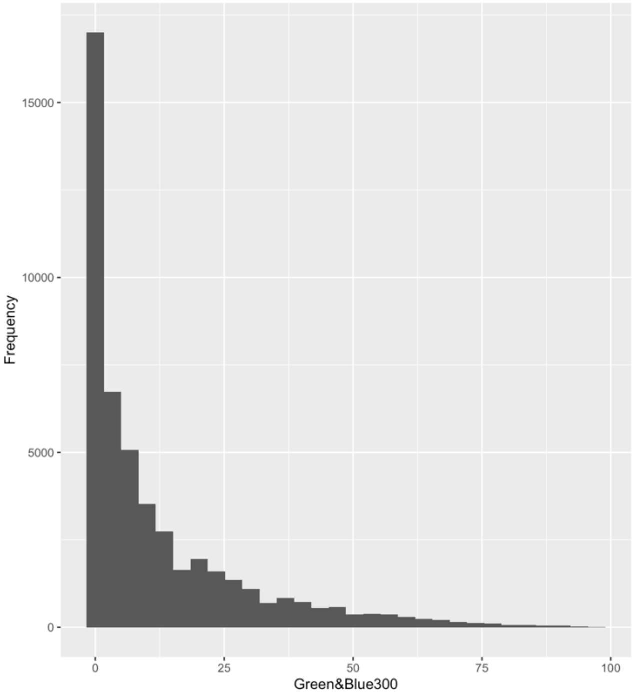
1000
2000
3000
4000
5000
0
25
50
75
100
Tree300

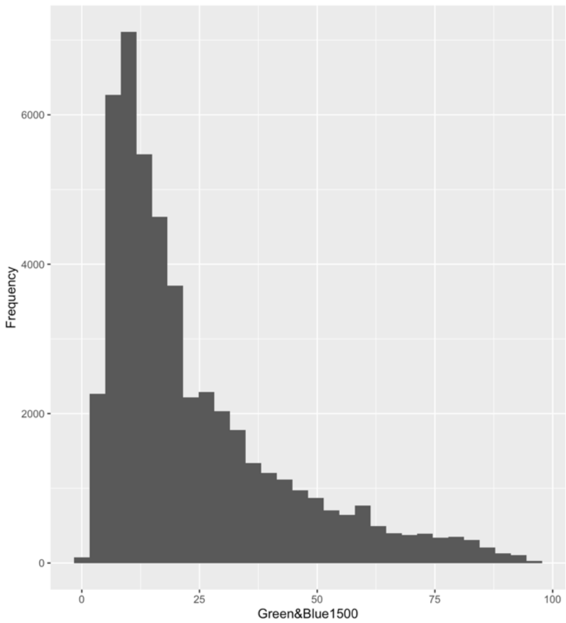


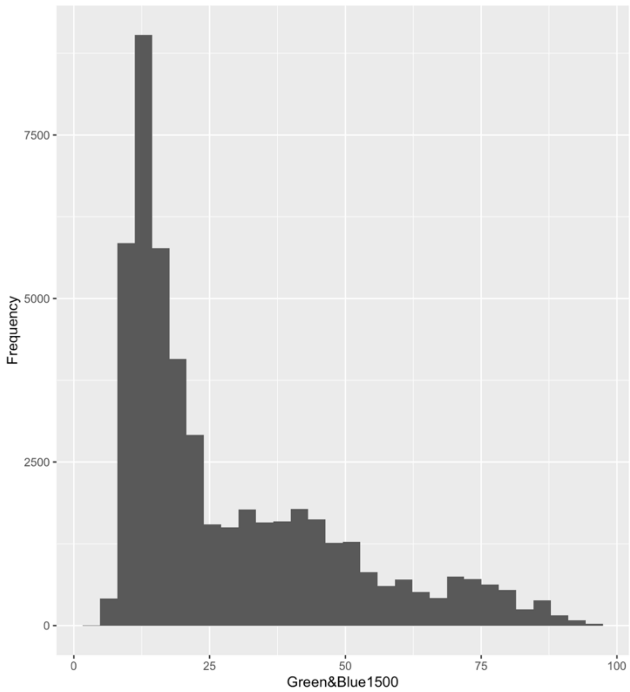
5000
4000
3000
2000
1000
0
Frequency
0
25
50
75
Tree1500



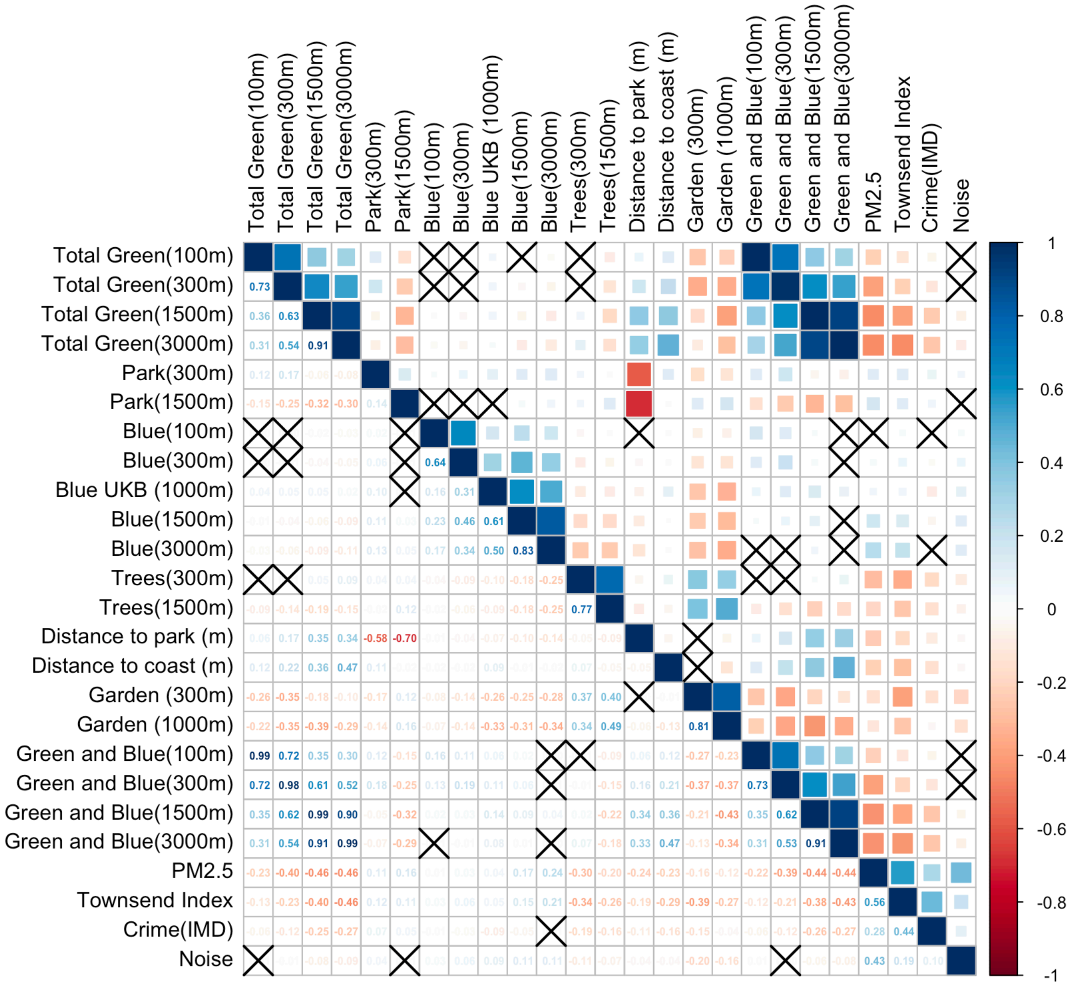
30000
20000
10000
0
Frequency
0
25
50
75
100
Green&Blue100


15000
10000
5000
0
Frequency
0
25
50
75
100
Green&Blue300


6000
4000
2000
0
Frequency
0
25
50
75
100
Green&Blue1500


7500
5000
2500
0
Frequency
0
25
50
75
100
Green&Blue1500

Correlation Heatmap (Pearson's) of Environment Variables



Appendix IX: List of Long-term Conditions Included in Operationalisation of Multimorbidity and their UK Biobank Coding

1111 Asthma
1471 Atrial fibrillation
1114 Bronchiectasis
1482 Chronic fatigue syndrome
1192 Renal/kidney failure
1193 Renal failure requiring dialysis
1194 Renal failure not requiring dialysis
1427 Polycystic kidney
1519 Kidney nephropathy
1520 IGA nephropathy
1607 Diabetic nephropathy
1112 Chronic obstructive airways disease/COPD
1113 Emphysema/chronic bronchitis
1472 Emphysema
1416 Chronic sinusitis
1322 Myositis/myopathy
1373 Connective tissue disorder
1377 Polymyalgia rheumatica
1381 Systemic lupus erythematosis/SLE
1382 Sjogren's syndrome/sicca syndrome
1383 Dermatopolymyositis
1384 Scleroderma/systemic sclerosis
1456 Malabsorption/coeliac disease
1464 Rheumatoid arthritis
1477 Psoriatic arthropathy
1480 Dermatomyositis
1481 Polymyositis
1074 Angina
1075 Heart attack/myocardial infarction
1263 Dementia/alzheimers/cognitive impairment
1220 Diabetes
1222 Type 1 diabetes
1223 Type 2 diabetes
1276 Diabetic eye disease
1468 Diabetic neuropathy/ulcers
1607 Diabetic nephropathy
1458 Diverticular disease/diverticulitis
1138 Gastro-oesophageal reflux/gastric reflux
1139 Oesophagitis/barretts oesophagus

1142 Gastric/stomach ulcers
1143 Gastritis/gastric erosions
1442 Helicobacter pylori
1457 Duodenal ulcer
1474 Hiatus hernia
1510 Dyspepsia/indigestion
1402 Endometriosis
1264 Epilepsy
1277 Glaucoma
1076 Heart failure/pulmonary oedema
1079 Cardiomyopathy
1588 Hypertrophic cardiomyopathy
1156 Infective/viral hepatitis
1578 hepatitis A
1579 hepatitis B
1580 Hepatitis C
1581 Hepatitis D
1582 Hepatitis E
1065 Hypertension
1072 Essential hypertension
1461 Inflammatory bowel disease
1462 Crohn's disease
1463 Ulcerative colitis
1154 Irritable bowel syndrome
1141 Oesophageal varicies
1157 Non-infective hepatitis
1158 Liver failure/cirrhosis
1506 Primary biliary cirrhosis
1421 Ménière disease
1265 Migraine
1261 Multiple sclerosis
1309 Osteoporosis
1257 Trapped nerve/compressed nerve
1294 Back problem
1311 Spine arthritis/spondylitis
1312 Prolapsed disc/slipped disc
1313 Ankylosing spondylitis
1436 Headaches (not migraine)
1465 Osteoarthritis
1466 Gout
1476 Sciatica
1478 Cervical spondylosis
1523 Trigeminal neuralgia
1532 Disc problem
1533 Disc degeneration
1534 Back pain
1537 Joint pain

1538 Arthritis
1540 Plantar fasciitis
1541 Carpal tunnel syndrome
1542 Fibromyalgia
1573 Shingles
1262 Parkinson’s disease
1067 Peripheral vascular disease
1087 Leg claudication/intermittent claudication
1331 Pernicious anaemia
1350 Polycystic ovarian syndrome
1207 Prostate problem (not cancer)
1396 Enlarged prostate
1516 Benign prostatic hypertrophy
1452 Eczema/dermatitis
1453 Psoriasis
1081 Stroke
1082 Transient ischaemic attack
1086 Subarachnoid haemorrhage
1491 Brain haemorrhage
1583 Ischaemic stroke
1224 Thyroid problem (not cancer)
1225 Hyperthyroidism/thyrotoxicosis
1226 Hypothyroidism/myxoedema
1428 Thyroiditis
1522 Grave’s disease
1610 Thyroid goitre
1287 Anxiety/panic attacks
1288 Nervous breakdown
1469 Post-traumatic stress disorder
1615 Obsessive compulsive disorder
1614 Stress
1616 Insomnia
1243 Psychological/psychiatric problem
1286 Depression
1531 Postnatal depression
1289 Schizophrenia
1291 Mania/bipolar disorder/manic depression
1408 Alcohol dependency
1604 alcoholic liver disease
1409 Opioid dependency
1410 Other substance abuse/dependency
1599 Constipation
1470 Anorexia, bulimia/other eating disorder

Appendix X: Tables of Effect Estimates for Stepwise Confounder Adjustment

	Cardio-metabolic Multimorbidity (yes vs no)																	
	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
Predictors																		
	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
Green (%) - 100m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Green (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Green (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.00	1.00
Green (%) - 3000m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.00	1.00	1.00	1.00
Park (presence within 300m) - yes	**1.11**	**1.03**	**1.20**	**1.11**	**1.02**	**1.20**	1.07	0.98	1.15	1.07	0.98	1.15	1.07	0.99	1.16	1.15	0.98	1.35
Park (presence within 1500m) - yes	**1.55**	**1.10**	**2.28**	**1.50**	**1.05**	**2.21**	1.32	0.93	1.95	1.30	0.91	1.92	1.39	0.97	2.06	**2.24**	**1.07**	**5.75**
Distance to park (m)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Garden (%) - 300m	1.00	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
Garden (%) - 1000m	1.00	0.99	1.00	0.99	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00
Trees (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00
Trees (%) - 1500m	1.00	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01
Blue (%) - 300m	1.00	0.98	1.01	1.00	0.99	1.02	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01
Blue (%) - 1500m	0.99	0.97	1.00	1.00	0.98	1.01	0.99	0.97	1.00	0.99	0.97	1.00	0.99	0.98	1.01	0.99	0.98	1.00
Blue (%) - 3000m	0.98	0.97	1.00	1.00	0.98	1.02	0.98	0.97	1.00	0.98	0.97	1.00	0.99	0.97	1.00	0.99	0.97	1.00
Distance to coast (m)	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01
Green&Blue (%) - 300m	1.00	0.99	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01
Green&Blue (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Green&Blue (%) - 3000m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00

Model 1: unadjusted
Model 2: Model 1 + age, sex, ethnicity, income
Model 3: Model 2 + crime , Townsend Index
Model 4: Model 3 + physical activity
Model 5: Model 4 + air pollution (pm2.5) + noise
Model 6: Model 5 + interaction: green/ blue space * physical activity

p-value < 0.05

	Respiratory Multimorbidity (yes vs no)																	
Predictors	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
Green (%) - 100m	1.00	0.99	1.00	0.99	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	0.99	0.98	1.01
Green (%) - 300m	1.00	0.99	1.01	1.00	0.99	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.98	1.01
Green (%) - 1500m	1.00	0.99	1.01	1.00	0.99	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	0.99	1.01
Green (%) - 3000m	1.00	0.99	1.01	1.00	0.99	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	0.99	1.01
Park (presence within 300m) - yes	1.01	0.79	1.29	0.97	0.76	1.24	0.89	0.70	1.15	0.89	0.69	1.14	0.89	0.69	1.15	0.87	0.55	1.37
Distance to park (m)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Garden (%) - 300m	0.99	0.98	1.00	0.99	0.98	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	0.99	0.98	1.01
Garden (%) - 1000m																		
Trees (%) - 300m	1.01	0.79	1.29	0.97	0.76	1.24	0.89	0.70	1.15	0.89	0.69	1.14	0.89	0.69	1.15	0.87	0.55	1.37
Trees (%) - 1500m	0.99	0.98	1.00	0.99	0.98	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.98	1.01
Blue (%) - 300m	1.00	0.96	1.03	1.01	0.97	1.04	1.01	0.96	1.04	1.01	0.96	1.04	1.01	0.96	1.04	1.02	0.95	1.06
Blue (%) - 1000m	0.93	0.84	1.00	0.93	0.84	1.01	0.92	0.84	1.00	0.95	0.90	1.01	0.92	0.84	1.00	0.92	0.83	1.00
Blue (%) - 1500m	0.95	0.90	1.00	0.96	0.90	1.01	0.95	0.89	1.00	0.94	0.89	1.00	0.95	0.89	1.00	1.02	0.95	1.06
Blue (%) - 3000m	0.97	0.91	1.02	0.98	0.92	1.03	0.95	0.89	1.01	0.95	0.90	1.01	0.96	0.90	1.01	0.96	0.86	1.05
Distance to coast (m)	1.00	0.99	1.01	0.99	0.99	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	0.96	0.85	1.06
Green&Blue (%) - 300m	1.01	0.99	1.02	1.01	0.99	1.02	1.01	0.99	1.02	1.01	0.99	1.02	1.01	0.99	1.02	1.01	0.99	1.04
Green&Blue (%) - 1500m	1.00	0.99	1.01	1.00	0.99	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.98	1.01
Green&Blue (%) - 3000m	1.00	0.99	1.01	1.00	0.99	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	0.99	1.01	1.00	0.99	1.01

Model 1: unadjusted
Model 2: Model 1 + age, sex, ethnicity, income
Model 3: Model 2 + crime , Townsend Index
Model 4: Model 3 + physical activity
Model 5: Model 4 + air pollution (pm2.5) + noise
Model 6: Model 5 + interaction: green/ blue space * physical activity

p-value < 0.05

	Mental Multimorbidity (yes vs no)																	
Predictors	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
Green (%) - 100m	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00			
Green (%) - 300m	1.00	0.99	1.01	1.00	0.99	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	0.99	0.97	1.01
Green (%) - 1500m	1.00	1.00	1.01	1.00	0.99	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	0.44	0.06	3.19
Green (%) - 3000m	1.00	0.99	1.01	1.00	0.99	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.98	1.01
Park (presence within 300m) - yes	1.07	0.85	1.36	0.98	0.77	1.24	0.95	0.75	1.21	**0.16**	**0.06**	**0.38**	0.95	0.75	1.20	1.23	0.75	2.04
Distance to park (m)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Garden (%) - 300m	0.99	0.99	1.00	1.00	0.99	1.01	1.01	1.00	1.01	1.00	1.00	1.01	1.00	0.99	1.01	1.01	0.99	1.03
Garden (%) - 1000m	0.99	0.98	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.98	1.02
Trees (%) - 300m	1.00	0.99	1.00	1.00	0.99	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	0.98	1.01
Trees (%) - 1500m	1.00	0.99	1.00	1.00	0.99	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	0.99	0.97	1.01
Blue (%) - 300m	0.96	0.89	1.01	0.96	0.89	1.01	0.96	0.89	1.01	0.96	0.89	1.01	0.96	0.89	1.01	**0.72**	**0.24**	**0.99**
Blue (%) - 1000m	0.91	0.83	0.98	**0.91**	**0.83**	**0.98**	**0.89**	**0.81**	**0.97**	0.89	0.81	0.97	**0.90**	**0.81**	**0.98**	**0.82**	**0.63**	**0.99**
Blue (%) - 1500m	**0.93**	**0.88**	**0.98**	**0.94**	**0.88**	**0.99**	**0.92**	**0.86**	**0.97**	**0.92**	**0.86**	**0.97**	**0.92**	**0.86**	**0.97**	0.93	0.82	1.03
Blue (%) - 3000m	0.96	0.90	1.01	0.96	0.91	1.01	**0.94**	**0.88**	**0.99**	**0.94**	**0.88**	**0.99**	0.94	0.88	1.00	1.00	0.89	1.09
Distance to coast (m)	1.00	0.99	1.01	0.99	0.99	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.98	1.02
Green&Blue (%) - 300m	1.01	0.99	1.02	1.00	0.99	1.02	1.00	0.99	1.02	1.00	0.99	1.02	1.01	0.99	1.02	1.00	0.96	1.03
Green&Blue (%) - 1500m	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.01
Green&Blue (%) - 3000m	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.01

Model 1: unadjusted
Model 2: Model 1 + age, sex, ethnicity, income
Model 3: Model 2 + crime , Townsend Index
Model 4: Model 3 + physical activity
Model 5: Model 4 + air pollution (pm2.5) + noise
Model 6: Model 5 + interaction: green/ blue space * physical activity

p-value < 0.05

Disease Count (0 - ref)	Exposures	Total Multimorbidity (disease counts)																	
		Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
1	Green (%) - 100m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1	Green (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1	Green (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1	Green (%) - 3000m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1	Park (presence within 300m) - yes	1.00	0.96	1.05	1.02	0.97	1.06	1.02	0.97	1.06	1.02	0.97	1.06	1.02	0.97	1.06	1.01	0.93	1.09
1	Park (presence within 1500m) - yes	0.92	0.78	1.08	0.93	0.79	1.10	0.92	0.78	1.09	0.92	0.77	1.08	0.92	0.77	1.09	0.81	0.61	1.08
1	Distance to park (m)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1	Garden (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1	Garden (%) - 1000m																		
1	Trees (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01
1	Trees (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01
1	Blue (%) - 100m	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.02
1	Blue (%) - 300m	0.99	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	0.99	0.98	1.01
1	Blue (%) - 1000m	0.99	0.98	1.00	0.99	0.98	1.00	0.99	0.98	1.00	0.99	0.98	1.00	0.99	0.98	1.00	1.00	0.97	1.02
1	Blue (%) - 1500m	0.99	0.99	1.00	0.99	0.99	1.00	0.99	0.99	1.00	0.99	0.99	1.00	0.99	0.99	1.00	0.99	0.98	1.01
1	Blue (%) - 3000m	0.99	0.98	1.00	0.99	0.98	1.00	0.99	0.98	1.00	0.99	0.98	1.00	0.99	0.98	1.00	0.99	0.97	1.01
1	Distance to coast (m)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1	Green&Blue (%) - 100m	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.00	1.00	0.99	1.01	1.00	0.99	1.01	1.01	0.991	1.02
1	Green&Blue (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
1	Green&Blue (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1	Green&Blue (%) - 3000m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	Green (%) - 100m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	Green (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	Green (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	Green (%) - 3000m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	Park (presence within 300m) - yes	0.99	0.94	1.05	1.01	0.96	1.07	1.00	0.95	1.05	1.00	0.95	1.05	1.00	0.95	1.06	0.98	0.89	1.08
2	Park (presence within 1500m) - yes	0.94	0.77	1.15	0.96	0.78	1.18	0.92	0.75	1.13	0.91	0.74	1.12	0.92	0.75	1.14	0.94	0.65	1.36
2	Distance to park (m)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	Garden (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01
2	Garden (%) - 1000m																		
2	Trees (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	Trees (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01
2	Blue (%) - 100m	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	0.98	0.96	1.01
2	Blue (%) - 300m	1.00	0.99	1.00	1.00	0.99	1.01	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.01	0.99	0.98	1.01
2	Blue (%) - 1000m	**0.98**	**0.96**	**0.99**	0.98	0.97	1.00	0.98	0.97	1.00	0.98	0.97	1.00	0.98	0.97	1.00	0.99	0.96	1.02
2	Blue (%) - 1500m	**0.98**	**0.98**	**0.99**	0.99	0.98	1.00	0.99	0.98	1.00	**0.99**	**0.98**	**0.99**	0.99	0.98	1.00	1.00	0.98	1.02
2	Blue (%) - 3000m	**0.98**	**0.97**	**0.99**	0.99	0.98	1.00	**0.98**	**0.97**	**0.99**	**0.98**	**0.97**	**0.99**	0.98	0.97	1.00	0.99	0.97	1.02
2	Distance to coast (m)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	Green&Blue (%) - 100m	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	0.98	0.95	1.01
2	Green&Blue (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.01
2	Green&Blue (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	Green&Blue (%) - 3000m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

3	Green (%) - 100m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
3	Green (%) - 300m	0.09	0.09	0.10	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01
3	Green (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01
3	Green (%) - 3000m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01
3	Park (presence within 300m) - yes	1.02	0.95	1.10	1.04	0.96	1.12	1.02	0.95	1.10	1.02	0.95	1.10	1.02	0.95	1.10	1.09	0.89	1.34
3	Park (presence within 1500m) -	0.78	0.60	1.01	0.80	0.61	1.04	**0.75**	**0.57**	**0.99**	**0.74**	**0.56**	**0.97**	**0.75**	**0.57**	**0.99**	0.70	0.44	1.13
3	Distance to park (m)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	Garden (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01
3	Garden (%) - 1000m																		
3	Trees (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	Trees (%) - 1500m	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01
3	Blue (%) - 100m	0.99	0.98	1.01	0.98	0.96	1.00	0.98	0.96	1.00	0.98	0.96	1.00	0.98	0.96	1.00	0.97	0.92	1.02
3	Blue (%) - 300m	0.99	0.97	1.00	0.99	0.98	1.00	0.99	0.98	1.00	0.99	0.98	1.00	0.99	0.98	1.00	0.99	0.97	1.01
3	Blue (%) - 1000m	**0.96**	**0.94**	**0.98**	**0.97**	**0.95**	**0.99**	**0.97**	**0.94**	**0.99**	**0.97**	**0.94**	**0.99**	**0.97**	**0.94**	**0.99**	**0.95**	**0.91**	**1.00**
3	Blue (%) - 1500m	**0.97**	**0.96**	**0.99**	**0.98**	**0.97**	**0.99**	**0.98**	**0.96**	**0.99**	**0.98**	**0.96**	**0.99**	**0.98**	**0.96**	**0.99**	**0.95**	**0.92**	**0.98**
3	Blue (%) - 3000m	**0.96**	**0.95**	**0.98**	**0.98**	**0.96**	**0.99**	**0.97**	**0.95**	**0.99**	**0.97**	**0.95**	**0.99**	**0.97**	**0.95**	**0.99**	**0.93**	**0.90**	**0.97**
3	Distance to coast (m)	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
3	Green&Blue (%) - 100m	0.99	0.98	1.01	1.00	0.98	1.01	1.00	0.98	1.01	0.99	0.98	1.01	0.99	0.98	1.01	1.01	0.98	1.03
3	Green&Blue (%) - 300m	1.00	0.99	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	0.99	1.01
3	Green&Blue (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	Green&Blue (%) - 3000m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4+	Green (%) - 100m	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.00	1.01	1.00	1.00
4+	Green (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01
4+	Green (%) - 1500m	1.01	1.00	1.01	1.00	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01
4+	Green (%) - 3000m	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01
4+	Park (presence within 300m) - yes	**1.13**	**1.03**	**1.24**	**1.12**	**1.01**	**1.23**	1.08	0.98	1.19	1.08	0.98	1.19	1.09	0.99	1.21	1.01	0.87	1.16
4+	Park (presence within 1500m) - yes	1.48	0.94	2.33	1.48	0.93	2.36	1.33	0.84	2.12	1.29	0.81	2.05	1.46	0.91	2.33	**1.19**	**0.72**	**1.96**
4+	Distance to park (m)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4+	Garden (%) - 300m	1.00	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	0.99	1.01
4+	Garden (%) - 1000m																		
4+	Trees (%) - 300m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01
4+	Trees (%) - 1500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01
4+	Blue (%) - 100m	0.99	0.98	1.01	1.00	0.98	1.01	1.00	0.98	1.01	1.00	0.98	1.01	1.00	0.98	1.01	0.99	0.95	1.04
4+	Blue (%) - 300m	0.98	0.97	1.00	0.99	0.98	1.01	0.99	0.97	1.01	0.99	0.97	1.01	0.99	0.97	1.01	1.00	0.98	1.04
4+	Blue (%) - 1000m	**0.96**	**0.94**	**0.99**	0.98	0.95	1.01	0.98	0.95	1.00	0.98	0.95	1.00	0.97	0.95	1.00	0.96	0.89	1.02
4+	Blue (%) - 1500m	**0.97**	**0.95**	**0.99**	0.98	0.96	1.00	**0.98**	**0.96**	**0.99**	**0.98**	**0.96**	**0.99**	0.98	0.96	1.00	0.97	0.93	1.01
4+	Blue (%) - 3000m	**0.96**	**0.94**	**0.98**	0.98	0.96	1.00	**0.97**	**0.94**	**0.99**	**0.97**	**0.94**	**0.99**	**0.97**	**0.95**	**0.99**	0.96	0.92	1.01
4+	Distance to coast (m)	1.01	1.00	1.01	1.00	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.00	1.00	1.01	1.01	1.00	1.01
4+	Green&Blue (%) - 100m	0.99	0.97	1.01	0.99	0.97	1.01	0.99	0.97	1.01	0.99	0.97	1.01	0.99	0.97	1.01	**0.83**	**0.82**	**0.83**
4+	Green&Blue (%) - 300m	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01	1.00	0.99	1.01
4+	Green&Blue (%) - 1500m	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01
4+	Green&Blue (%) - 3000m	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.00	1.01

Model 1: unadjusted Model 2: Model 1 + age, sex, ethnicity, income Model 3: Model 2 + crime , Townsend Index Model 4: Model 3 + physical activity Model 5: Model 4 + air pollution (pm2.5) + noise Model 6: Model 5 + interaction: green/ blue space * physical activity
p-value < 0.05

Appendix XI: Tables of Sample Characteristics by Income and Physical Activity Levels

	Income: Low (< £18,000)										
	Multimorbidity Type										
	Cardio-metabolic		**Respiratory**		**Mental**		**Disease Counts**				
	No	**Yes**	**No**	**Yes**	**No**	**Yes**	**0**	**1**	**2**	**3**	**4+**
Sex											
Female	3366	662	4941	48	4916	73	1326	1593	1090	569	411
Male	4,641	348	10613	46	3973	55	1029	1235	894	493	377
Ethnicity											
White	6622	801	7326	97	7305	118	1865	2295	1671	913	679
Other	1385	209	1587	7	1584	10	490	533	313	149	109
Physical Activity (MET min/week)											
Low (< 600 MET min/week)	1492	298	1752	38	1749	41	336	493	424	274	263

Moderate (≥ 600 to 2990 MET min/week)	3854	470	4286	38	4270	54	1143	1403	941	493	344
High (≥3000 MET min/week)	2661	242	2875	28	2870	33	876	932	619	295	181
Park (presence within 300m) - yes	4459	616	5011	64	5001	74	1292	1581	1136	585	481
Park (presence within 300m) - no	3548	394	3902	40	3888	54	1063	1247	848	477	307
Park (presence within 1500m) - yes	7911	998	105	3	8782	127	19	35	28	19	7
Park (presence within 1500m) - no	96	12	8808	101	107	1	2336	2793	1956	1043	781

	Income: Medium (£18,000 to £51,999)										
	Multimorbidity Type										
	Cardio-metabolic		**Respiratory**		**Mental**		**Disease Counts**				
	No	**Yes**	**No**	**Yes**	**No**	**Yes**	**0**	**1**	**2**	**3**	**4+**
Sex											
Female	12031	385	12356	60	12354	62	4692	4250	2179	862	433
Male	9745	914	10613	46	10612	47	3936	3584	1967	797	375
Ethnicity											
White	19189	1054	20149	94	20139	104	7500	6883	3641	1492	727
Other	2587	245	2820	12	2827	5	1128	951	505	167	81
Physical Activity (MET min/week)											
Low (< 600 MET min/week)	3714	291	3972	33	3977	28	1314	1339	771	372	209

Moderate (≥ 600 to 2990 MET min/week)	11394	658	12011	41	11994	58	4482	4143	2182	828	417
High (≥3000 MET min/week)	6668	350	6986	32	6995	23	2832	2352	1193	459	182
Park (presence within 300m) - yes	11423	685	12060	48	12050	58	4592	4101	2113	874	428
Park (presence within 300m) - no	10353	614	10909	58	10916	51	4036	3733	2033	785	380
Park (presence within 1500m) - yes	21374	1287	22556	105	22554	107	153	144	75	32	10
Park (presence within 1500m) - no	402	12	413	1	412	2	8475	7690	4071	1627	798

	Income: High (Greater than £52,000)										
	Multimorbidity Type										
	Cardio-metabolic		**Respiratory**		**Mental**		**Disease Counts**				
	No	**Yes**	**No**	**Yes**	**No**	**Yes**	**0**	**1**	**2**	**3**	**4+**
Sex											
Female	7789	105	8581	22	7863	31	3702	2648	1060	359	125

Male	8178	425	7870	24	8587	16	3878	2846	1306	432	141
Ethnicity											
White	14697	449	15100	46	15101	45	6976	5031	2169	722	248
Other	1270	81	1351	0	1349	2	604	463	197	69	18
Physical Activity (MET min/week)											
Low (< 600 MET min/week)	2829	140	2957	12	2960	9	1201	1036	461	197	74
Moderate (≥ 600 to 2990 MET min/week)	9178	265	9425	18	9416	27	4405	3144	1337	417	140
High (≥3000 MET min/week)	3960	125	4069	16	4074	11	1974	1314	568	177	52
Park (presence within 300m) - yes	8059	259	8295	23	8296	22	3828	2789	1182	398	121
Park (presence within 300m) - no	7908	271	8156	23	8154	25	3752	2705	1184	393	145
Park (presence within 1500m) - yes	15693	523	16170	46	16170	46	7459	5396	2327	771	263
Park (presence within 1500m) - no	274	7	281	0	280	1	121	98	39	20	3

	Physical Activity - Low (< 600 MET min/week)										
	Multimorbidity Type										
	Cardio-metabolic		**Respiratory**		**Mental**		**Disease Counts**				
	No	**Yes**	**No**	**Yes**	**No**	**Yes**	**0**	**1**	**2**	**3**	**4+**
Sex											
Female	4128	202	4282	48	4289	41	1414	1421	806	431	258
Male	3907	527	4399	35	4397	37	1437	1447	850	412	288
Ethnicity											
White	6950	598	1206	10	7475	73	2421	2468	1450	727	482
Other	1085	131	7475	73	1211	5	430	400	206	116	64
Income (£)											
Low (< £18,000)	1492	298	1752	38	1749	41	336	493	424	274	263
Medium (£18,000 to £51,999)	3714	291	3972	33	3977	28	1314	1339	771	372	209
High (Greater than £52,000)	2829	140	2957	12	2960	9	1201	1036	461	197	74

Park (presence within 300m) - yes	4206	421	4581	46	4581	46	1485	1485	902	440	315
Park (presence within 300m) - no	3829	308	4100	37	4105	32	1366	1383	754	403	231
Park (presence within 1500m) - yes	7911	724	8553	82	13682	65	2808	2823	1628	833	543
Park (presence within 1500m) - no	124	5	128	1	257	2	43	45	28	10	3

	Physical Activity - Moderate (≥ 600 to 2990 MET min/week)										
	Multimorbidity Type										
	Cardio-metabolic		**Respiratory**		**Mental**		**Disease Counts**				
	No	**Yes**	**No**	**Yes**	**No**	**Yes**	**0**	**1**	**2**	**3**	**4+**
Sex											
Female	13432	410	13800	42	13755	87	5438	4711	2305	912	476
Male	10994	983	11922	55	11925	52	4592	3979	2155	826	425
Ethnicity											
White	21663	1103	3049	4	22637	129	8889	7631	3900	1552	794
Other	2763	290	22673	93	3043	10	1141	1059	560	186	107
Income (£)											

Low (< £18,000)	3854	470	4286	38	4270	54	1143	1403	941	493	344
Medium (£18,000 to £51,999)	11394	658	12011	41	11994	58	4482	4143	2182	828	417
High (Greater than £52,000)	9178	265	9425	18	9416	27	4405	3144	1337	417	140
Park (presence within 300m) - yes	12678	731	13360	49	13342	67	5190	4537	2279	920	483
Park (presence within 300m) - no	11748	662	12362	48	12338	72	4840	4153	2181	818	418
Park (presence within 1500m) - yes	395	20	25308	96	25267	137	9874	8553	4388	1699	890

Park (presence within 1500m) - no	24031	1373	414	1	413	2	156	137	72	39	11

	Physical Activity - High (≥3000 MET min/week)										
	Multimorbidity Type										
	Cardio-metabolic		**Respiratory**		**Mental**		**Disease Counts**				
	No	**Yes**	**No**	**Yes**	**No**	**Yes**	**0**	**1**	**2**	**3**	**4+**
Sex											
Female	6901	226	7085	42	7089	38	2868	2359	1218	447	235
Male	6388	491	6845	34	6850	29	2814	2239	1162	484	180
Ethnicity											
White	11895	603	1503	5	12433	65	5031	4110	2131	848	378
Other	1394	114	12427	71	1506	2	651	488	249	83	37
Income (£)											
Low (< £18,000)	2661	242	2875	28	2870	33	876	932	619	295	181
Medium (£18,000 to £51,999)	6668	350	6986	32	6995	23	2832	2352	1193	459	182

High (Greater than £52,000)	3960	125	4069	16	4074	11	1974	1314	568	177	52
Park (presence within 300m) - yes	7057	408	7425	40	7424	41	3037	2449	1250	497	232
Park (presence within 300m) - no	6232	309	6505	36	6515	26	2645	2149	1130	434	183
Park (presence within 1500m) - yes	253	6	13673	74	13682	65	5588	4503	2338	909	409
Park (presence within 1500m) - no	13036	711	257	2	257	2	94	95	42	22	6

Appendix XI: Tables of Fully-Adjusted Regression Models

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Green (%) - 100m	1.00	0.69	1.00	1.00	1.00	0.35	0.99	1.00	1.00	0.47	0.99	1.00
Age (years)	1.09	0.00	1.09	1.10	1.04	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.53	2.99	0.98	0.87	0.76	1.26	0.83	0.13	0.66	1.06
Income (ref: high) - low	2.36	0.00	2.10	2.66	2.85	0.00	1.98	4.16	6.38	0.00	4.50	9.18
Income (ref: high) - medium	1.43	0.00	1.29	1.60	1.42	0.05	1.00	2.04	1.95	0.00	1.38	2.78
Ethnicity (ref: Other) - White	0.50	0.00	0.45	0.55	2.11	0.00	1.34	3.51	3.60	0.00	2.24	6.17
Physical Activity (ref: high) -low	1.76	0.00	1.57	1.97	1.84	0.00	1.34	2.52	1.95	0.00	1.41	2.72
Physical Activity (ref: high) - moderate	1.13	0.01	1.03	1.25	0.74	0.05	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.13	0.00	1.05	1.21	1.28	0.03	1.03	1.59	0.90	0.31	0.73	1.10
Deprivation Score (Townsend Index)	1.05	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.01	1.01	1.11
PM2.5	0.92	0.00	0.88	0.97	0.96	0.57	0.82	1.11	1.01	0.90	0.87	1.17
Noise	1.01	0.12	1.00	1.02	1.00	0.83	0.97	1.03	0.98	0.09	0.95	1.00

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Green (%) - 300m	1.00	0.25	1.00	1.00	1.00	0.71	0.99	1.01	1.00	0.84	0.99	1.01
Age (years)	1.09	0.00	1.09	1.10	1.04	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.52	2.99	0.98	0.88	0.76	1.26	0.83	0.13	0.66	1.06
Income (ref: high) - low	2.35	0.00	2.09	2.64	2.85	0.00	1.97	4.16	6.37	0.00	4.49	9.17
Income (ref: high) - medium	1.43	0.00	1.29	1.59	1.42	0.05	1.00	2.03	1.94	0.00	1.38	2.77
Ethnicity (ref: Other) - White	0.49	0.00	0.44	0.55	2.10	0.00	1.34	3.51	3.59	0.00	2.24	6.17
Physical Activity (ref: high) -low	1.76	0.00	1.58	1.97	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.72
Physical Activity (ref: high) - moderate	1.14	0.01	1.03	1.25	0.74	0.05	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.13	0.00	1.05	1.21	1.28	0.03	1.03	1.59	0.90	0.31	0.73	1.10
Deprivation Score (Townsend Index)	1.05	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.01	1.01	1.11
PM2.5	0.93	0.01	0.89	0.98	0.96	0.62	0.82	1.12	1.01	0.85	0.87	1.18
Noise	1.01	0.21	1.00	1.02	1.00	0.86	0.97	1.03	0.97	0.09	0.95	1.00

Disease count (ref: 0 Ltcs)		Odds Ratio	p-value	CI - low	CI - high
1	Green (%) - 300m	1.00	0.05	1.00	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.18	0.93	1.01
1	Income (ref: high) - low	1.37	0.00	1.28	1.47
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.02	0.86	0.98
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.11	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.71	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	0.25	1.00	1.01
1	PM2.5	1.01	0.68	0.98	1.03
1	Noise	1.00	0.49	0.99	1.00
2	Green (%) - 300m	1.00	0.05	1.00	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.01	0.60	0.96	1.07
2	Income (ref: high) - low	1.86	0.00	1.72	2.02
2	Income (ref: high) - medium	1.24	0.00	1.17	1.32
2	Ethnicity (ref: Other) - White	0.89	0.01	0.82	0.97
2	Physical Activity (ref: high) -low	1.53	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.12	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.99	0.57	0.96	1.03
2	Noise	1.00	0.16	0.99	1.00
3	Green (%) - 300m	1.00	0.17	1.00	1.00
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.93	0.93	1.08
3	Income (ref: high) - low	2.72	0.00	2.44	3.04
3	Income (ref: high) - medium	1.41	0.00	1.29	1.55
3	Ethnicity (ref: Other) - White	0.98	0.77	0.87	1.11
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.07	0.04	1.00	1.14
3	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
3	PM2.5	0.98	0.37	0.93	1.03
3	Noise	1.00	0.89	0.99	1.01
4+	Green (%) - 300m	1.00	0.01	1.00	1.01
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.97	0.57	0.88	1.07
4+	Income (ref: high) - low	5.57	0.00	4.77	6.50
4+	Income (ref: high) - medium	1.99	0.00	1.72	2.30
4+	Ethnicity (ref: Other) - White	1.06	0.50	0.90	1.24
4+	Physical Activity (ref: high) -low	3.14	0.00	2.73	3.61
4+	Physical Activity (ref: high) - moderate	1.42	0.00	1.25	1.60
4+	Crime Score (IMD)	1.12	0.01	1.03	1.22
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.89	0.00	0.84	0.95
4+	Noise	1.01	0.27	0.99	1.02

Disease count (ref: 0 Ltcs)		Odds Ratio	p-value	CI - low	CI - high
1	Total Green Space (%) - 100m	1.00	0.42	1.00	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.19	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.29	1.48
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.02	0.86	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.73	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	0.25	1.00	1.01
1	PM2.5	1.00	0.88	0.97	1.03
1	Noise	1.00	0.67	0.99	1.00
2	Green (%) - 100m	1.00	0.11	1.00	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.01	0.59	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.72	2.03
2	Income (ref: high) - medium	1.25	0.00	1.17	1.33
2	Ethnicity (ref: Other) - White	0.89	0.01	0.82	0.97
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.12	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.31	0.95	1.02
2	Noise	1.00	0.22	0.99	1.00
3	Green (%) - 100m	1.00	0.91	1.00	1.00
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.91	0.93	1.08
3	Income (ref: high) - low	2.74	0.00	2.45	3.06
3	Income (ref: high) - medium	1.42	0.00	1.29	1.56
3	Ethnicity (ref: Other) - White	0.99	0.84	0.87	1.12
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.26
3	Crime Score (IMD)	1.07	0.04	1.00	1.14
3	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
3	PM2.5	0.96	0.13	0.92	1.01
3	Noise	1.00	0.89	0.99	1.01
4+	Green (%) - 100m	1.00	0.20	1.00	1.00
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.97	0.61	0.88	1.08
4+	Income (ref: high) - low	5.63	0.00	4.82	6.57
4+	Income (ref: high) - medium	2.00	0.00	1.73	2.31
4+	Ethnicity (ref: Other) - White	1.07	0.42	0.91	1.25
4+	Physical Activity (ref: high) -low	3.13	0.00	2.73	3.60
4+	Physical Activity (ref: high) - moderate	1.41	0.00	1.25	1.60
4+	Crime Score (IMD)	1.12	0.01	1.03	1.22
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.87	0.00	0.82	0.93
4+	Noise	1.01	0.14	1.00	1.02

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Green (%) - 1500m	1.00	0.01	1.00	1.01	1.00	0.24	1.00	1.01	1.00	0.41	1.00	1.01
Age (years)	1.09	0.00	1.09	1.10	1.05	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.74	0.00	2.52	2.98	0.97	0.84	0.76	1.25	0.83	0.13	0.65	1.05
Income (ref: high) - low	2.31	0.00	2.05	2.61	2.75	0.00	1.90	4.03	6.23	0.00	4.38	8.99
Income (ref: high) - medium	1.42	0.00	1.27	1.58	1.39	0.07	0.98	2.00	1.92	0.00	1.36	2.74
Ethnicity (ref: Other) - White	0.49	0.00	0.44	0.54	2.03	0.00	1.29	3.40	3.52	0.00	2.19	6.05
Physical Activity (ref: high) -low	1.76	0.00	1.58	1.97	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.72
Physical Activity (ref: high) - moderate	1.14	0.01	1.04	1.25	0.75	0.06	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.13	0.00	1.06	1.22	1.29	0.02	1.04	1.60	0.91	0.34	0.74	1.11
Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.01	1.02	1.11
PM2.5	0.94	0.02	0.90	0.99	1.00	0.97	0.86	1.17	1.04	0.58	0.90	1.21
Noise	1.01	0.25	1.00	1.01	1.00	0.97	0.97	1.03	0.97	0.06	0.94	1.00

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Green (%) - 3000m	1.00	0.00	1.00	1.01	1.00	0.23	1.00	1.01	1.00	0.99	0.99	1.01
Age (years)	1.09	0.00	1.09	1.10	1.05	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.74	0.00	2.51	2.98	0.97	0.83	0.76	1.25	0.83	0.13	0.65	1.06
Income (ref: high) - low	2.28	0.00	2.03	2.57	2.72	0.00	1.88	4.00	6.35	0.00	4.46	9.17
Income (ref: high) - medium	1.41	0.00	1.27	1.57	1.38	0.07	0.98	1.99	1.94	0.00	1.38	2.77
Ethnicity (ref: Other) - White	0.48	0.00	0.43	0.54	2.02	0.00	1.28	3.38	3.58	0.00	2.23	6.16
Physical Activity (ref: high) -low	1.76	0.00	1.58	1.97	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.72
Physical Activity (ref: high) - moderate	1.14	0.01	1.04	1.26	0.75	0.06	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.14	0.00	1.06	1.22	1.29	0.02	1.04	1.60	0.90	0.31	0.73	1.10
Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08	1.08	0.00	1.03	1.14	1.06	0.01	1.01	1.11
PM2.5	0.95	0.03	0.90	0.99	1.00	1.00	0.86	1.16	1.02	0.78	0.88	1.18
Noise	1.01	0.25	1.00	1.01	1.00	0.99	0.97	1.03	0.97	0.08	0.95	1.00

		Odds Ratio	p-value	CI - low	CI - high
Disease count (ref: 0 Ltcs)					
1	Green (%) - 1500m	1.00	0.15	1.00	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.18	0.93	1.01
1	Income (ref: high) - low	1.37	0.00	1.28	1.47
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.01	0.86	0.98
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.11	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.63	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	0.18	1.00	1.02
1	PM2.5	1.00	0.87	0.97	1.03
1	Noise	1.00	0.60	0.99	1.00
2	Green (%) - 1500m	1.00	0.07	1.00	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.01	0.61	0.96	1.07
2	Income (ref: high) - low	1.86	0.00	1.71	2.01
2	Income (ref: high) - medium	1.24	0.00	1.17	1.32
2	Ethnicity (ref: Other) - White	0.89	0.01	0.82	0.97
2	Physical Activity (ref: high) -low	1.53	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.09	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.99	0.47	0.95	1.02
2	Noise	1.00	0.20	0.99	1.00
3	Green (%) - 1500m	1.00	0.01	1.00	1.01
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.97	0.93	1.08
3	Income (ref: high) - low	2.69	0.00	2.41	3.01
3	Income (ref: high) - medium	1.40	0.00	1.28	1.54
3	Ethnicity (ref: Other) - White	0.97	0.62	0.86	1.10
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.08	0.02	1.01	1.15
3	Deprivation Score (Townsend Index)	1.03	0.00	1.01	1.04
3	PM2.5	0.99	0.56	0.94	1.03
3	Noise	1.00	0.82	0.99	1.01
4+	Green (%) - 1500m	1.01	0.00	1.00	1.01
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.97	0.53	0.88	1.07
4+	Income (ref: high) - low	5.42	0.00	4.64	6.34
4+	Income (ref: high) - medium	1.96	0.00	1.70	2.27
4+	Ethnicity (ref: Other) - White	1.03	0.72	0.88	1.21
4+	Physical Activity (ref: high) -low	3.14	0.00	2.73	3.61
4+	Physical Activity (ref: high) - moderate	1.42	0.00	1.26	1.61
4+	Crime Score (IMD)	1.14	0.00	1.04	1.24
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.09
4+	PM2.5	0.90	0.00	0.85	0.96
4+	Noise	1.01	0.29	0.99	1.02

		Odds Ratio	p-value	CI - low	CI - high
Disease count (ref: 0 Ltcs)					
1	Green (%) - 3000m	1.00	0.07	1.00	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.17	0.93	1.01
1	Income (ref: high) - low	1.37	0.00	1.27	1.46
1	Income (ref: high) - medium	1.12	0.00	1.07	1.17
1	Ethnicity (ref: Other) - White	0.92	0.01	0.85	0.98
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.11	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.60	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	0.13	1.00	1.02
1	PM2.5	1.00	0.84	0.98	1.03
1	Noise	1.00	0.59	0.99	1.00
2	Green (%) - 3000m	1.00	0.03	1.00	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.01	0.63	0.96	1.07
2	Income (ref: high) - low	1.85	0.00	1.70	2.00
2	Income (ref: high) - medium	1.24	0.00	1.16	1.32
2	Ethnicity (ref: Other) - White	0.88	0.00	0.81	0.96
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.08	1.00	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
2	PM2.5	0.99	0.49	0.95	1.02
2	Noise	1.00	0.20	0.99	1.00
3	Green (%) - 3000m	1.00	0.00	1.00	1.01
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	1.00	0.93	1.08
3	Income (ref: high) - low	2.66	0.00	2.38	2.98
3	Income (ref: high) - medium	1.40	0.00	1.27	1.53
3	Ethnicity (ref: Other) - White	0.96	0.54	0.85	1.09
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.08	0.02	1.01	1.16
3	Deprivation Score (Townsend Index)	1.03	0.00	1.01	1.05
3	PM2.5	0.99	0.56	0.94	1.03
3	Noise	1.00	0.83	0.99	1.01
4+	Green (%) - 3000m	1.01	0.00	1.00	1.01
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.97	0.51	0.88	1.07
4+	Income (ref: high) - low	5.34	0.00	4.56	6.25
4+	Income (ref: high) - medium	1.94	0.00	1.68	2.25
4+	Ethnicity (ref: Other) - White	1.02	0.85	0.86	1.20
4+	Physical Activity (ref: high) -low	3.14	0.00	2.73	3.61
4+	Physical Activity (ref: high) - moderate	1.42	0.00	1.26	1.61
4+	Crime Score (IMD)	1.14	0.00	1.05	1.24
4+	Deprivation Score (Townsend Index)	1.07	0.00	1.05	1.09
4+	PM2.5	0.90	0.00	0.85	0.96
4+	Noise	1.01	0.26	1.00	1.02

	cardio-metabolic				respiratory				mental			
term	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
(Intercept)												
Park (presence within 300m) - yes - yes	1.07	0.10	0.99	1.16	0.90	0.40	0.70	1.15	0.95	0.68	0.75	1.21
Age (years)	1.09	0.00	1.09	1.10	1.04	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.74	0.00	2.52	2.99	0.98	0.88	0.77	1.26	0.83	0.14	0.66	1.06
Income (ref: high) - low	2.35	0.00	2.09	2.65	2.85	0.00	1.98	4.16	6.36	0.00	4.49	9.16
Income (ref: high) - medium	1.43	0.00	1.29	1.59	1.42	0.05	1.00	2.03	1.94	0.00	1.38	2.77
Ethnicity (ref: Other) - White	0.49	0.00	0.44	0.55	2.11	0.00	1.34	3.52	3.59	0.00	2.24	6.17
Physical Activity (ref: high) -low	1.76	0.00	1.57	1.97	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.72
Physical Activity (ref: high) - moderate	1.14	0.01	1.03	1.25	0.74	0.05	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.12	0.00	1.05	1.21	1.28	0.02	1.03	1.60	0.90	0.31	0.74	1.10
Deprivation Score (Townsend Index)	1.05	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.01	1.01	1.11
PM2.5	0.92	0.00	0.88	0.97	0.97	0.73	0.84	1.13	1.02	0.76	0.89	1.18
Noise	1.01	0.13	1.00	1.02	1.00	0.92	0.97	1.03	0.97	0.08	0.95	1.00

	cardio-metabolic			
term	Odds Ratio	p-value	CI - low	CI - high
(Intercept)				
Park (presence within 1500m) - yes	1.40	0.07	0.98	2.08
Age (years)	1.09	0.00	1.09	1.10
Sex - Male	2.75	0.00	2.53	2.99
Income (ref: high) - low	2.36	0.00	2.10	2.66
Income (ref: high) - medium	1.43	0.00	1.29	1.60
Ethnicity (ref: Other) - White	0.50	0.00	0.45	0.55
Physical Activity (ref: high) -low	1.76	0.00	1.57	1.96
Physical Activity (ref: high) - moderate	1.13	0.01	1.03	1.25
Crime Score (IMD)	1.13	0.00	1.05	1.21
Deprivation Score (Townsend Index)	1.05	0.00	1.04	1.07
PM2.5	0.92	0.00	0.87	0.96
Noise	1.01	0.11	1.00	1.02

Disease count (ref: 0 Ltcs)	term	Odds Ratio	p-value	CI - low	CI - high
1	Park (presence within 300m) - yesyes	1.02	0.46	0.97	1.06
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.18	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.29	1.48
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.02	0.86	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.74	0.97	1.05
1	Deprivation Score (Townsend Index)	1.00	0.27	1.00	1.01
1	PM2.5	0.99	0.71	0.97	1.02
1	Noise	1.00	0.74	0.99	1.00
2	Park (presence within 300m) - yesyes	1.00	0.98	0.95	1.06
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.02	0.58	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.73	2.03
2	Income (ref: high) - medium	1.25	0.00	1.17	1.33
2	Ethnicity (ref: Other) - White	0.90	0.01	0.82	0.98
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.12	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.16	0.95	1.01
2	Noise	1.00	0.30	0.99	1.00
3	Park (presence within 300m) - yesyes	1.02	0.57	0.95	1.10
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.92	0.93	1.08
3	Income (ref: high) - low	2.74	0.00	2.45	3.06
3	Income (ref: high) - medium	1.42	0.00	1.29	1.56
3	Ethnicity (ref: Other) - White	0.99	0.82	0.87	1.11
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.07	0.04	1.00	1.14
3	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
3	PM2.5	0.96	0.12	0.92	1.01
3	Noise	1.00	0.90	0.99	1.01
4+	Park (presence within 300m) - yesyes	1.09	0.08	0.99	1.21
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.97	0.59	0.88	1.07
4+	Income (ref: high) - low	5.63	0.00	4.82	6.57
4+	Income (ref: high) - medium	2.00	0.00	1.73	2.31
4+	Ethnicity (ref: Other) - White	1.07	0.43	0.91	1.25
4+	Physical Activity (ref: high) -low	3.13	0.00	2.72	3.60
4+	Physical Activity (ref: high) - moderate	1.41	0.00	1.25	1.60
4+	Crime Score (IMD)	1.12	0.01	1.03	1.22
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.86	0.00	0.81	0.91
4+	Noise	1.01	0.10	1.00	1.02

Disease count (ref: 0 Ltcs)	term	Odds Ratio	p-value	CI - low	CI - high
1	Park (presence within 1500m) - yes	0.92	0.32	0.77	1.09
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.19	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.29	1.48
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.02	0.86	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.73	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	0.25	1.00	1.01
1	PM2.5	1.00	0.85	0.97	1.02
1	Noise	1.00	0.69	0.99	1.00
2	Park (presence within 1500m) - yes	0.92	0.47	0.75	1.14
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.02	0.58	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.73	2.03
2	Income (ref: high) - medium	1.25	0.00	1.17	1.33
2	Ethnicity (ref: Other) - White	0.90	0.01	0.82	0.98
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.12	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.20	0.95	1.01
2	Noise	1.00	0.28	0.99	1.00
3	Park (presence within 1500m) - yes	0.76	0.05	0.58	1.00
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.92	0.93	1.08
3	Income (ref: high) - low	2.74	0.00	2.45	3.06
3	Income (ref: high) - medium	1.42	0.00	1.29	1.56
3	Ethnicity (ref: Other) - White	0.99	0.81	0.87	1.11
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.07	0.04	1.00	1.14
3	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
3	PM2.5	0.97	0.21	0.93	1.02
3	Noise	1.00	0.99	0.99	1.01
4+	Park (presence within 1500m) - yes	1.48	0.10	0.93	2.36
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.98	0.62	0.88	1.08
4+	Income (ref: high) - low	5.65	0.00	4.84	6.60
4+	Income (ref: high) - medium	2.00	0.00	1.73	2.32
4+	Ethnicity (ref: Other) - White	1.07	0.38	0.92	1.26
4+	Physical Activity (ref: high) -low	3.13	0.00	2.72	3.60
4+	Physical Activity (ref: high) - moderate	1.41	0.00	1.25	1.60
4+	Crime Score (IMD)	1.12	0.01	1.03	1.22
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.86	0.00	0.81	0.91
4+	Noise	1.01	0.08	1.00	1.02

	cardio-metabolic				respiratory				mental			
term	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
(Intercept)												
Tree Canopy (%) - 300m	1.00	0.33	1.00	1.00	0.99	0.07	0.98	1.00	1.00	0.36	1.00	1.01
Age (years)	1.09	0.00	1.09	1.10	1.05	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.53	2.99	0.98	0.87	0.76	1.25	0.83	0.13	0.65	1.06
Income (ref: high) - low	2.35	0.00	2.09	2.65	2.79	0.00	1.93	4.07	6.37	0.00	4.49	9.17
Income (ref: high) - medium	1.43	0.00	1.28	1.59	1.40	0.06	0.99	2.00	1.95	0.00	1.39	2.78
Ethnicity (ref: Other) - White	0.50	0.00	0.45	0.55	2.13	0.00	1.36	3.56	3.55	0.00	2.22	6.10
Physical Activity (ref: high) -low	1.76	0.00	1.58	1.97	1.84	0.00	1.34	2.51	1.96	0.00	1.41	2.73
Physical Activity (ref: high) - moderate	1.13	0.01	1.03	1.25	0.74	0.05	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.12	0.00	1.05	1.21	1.28	0.03	1.03	1.59	0.90	0.31	0.74	1.10
Deprivation Score (Townsend Index)	1.05	0.00	1.04	1.07	1.07	0.01	1.02	1.12	1.06	0.01	1.02	1.11
PM2.5	0.92	0.00	0.88	0.97	0.95	0.49	0.82	1.10	1.03	0.67	0.89	1.19
Noise	1.01	0.13	1.00	1.02	1.00	0.88	0.97	1.03	0.97	0.08	0.95	1.00

	cardio-metabolic				respiratory				mental			
term	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
(Intercept)												
Tree Canopy (%) - 1500m	1.00	0.35	1.00	1.00	1.00	0.66	0.99	1.01	1.00	0.37	0.99	1.01
Age (years)	1.09	0.00	1.09	1.10	1.05	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.52	2.99	0.98	0.86	0.76	1.25	0.83	0.14	0.66	1.06
Income (ref: high) - low	2.35	0.00	2.09	2.64	2.82	0.00	1.95	4.12	6.40	0.00	4.51	9.22
Income (ref: high) - medium	1.43	0.00	1.28	1.59	1.41	0.06	1.00	2.02	1.95	0.00	1.39	2.79
Ethnicity (ref: Other) - White	0.50	0.00	0.45	0.55	2.10	0.00	1.33	3.50	3.57	0.00	2.22	6.12
Physical Activity (ref: high) -low	1.76	0.00	1.58	1.97	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.73
Physical Activity (ref: high) - moderate	1.14	0.01	1.03	1.25	0.74	0.05	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.12	0.00	1.05	1.21	1.28	0.03	1.03	1.59	0.90	0.31	0.73	1.10
Deprivation Score (Townsend Index)	1.05	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.01	1.02	1.11
PM2.5	0.92	0.00	0.88	0.97	0.97	0.67	0.84	1.12	1.03	0.72	0.89	1.18
Noise	1.01	0.13	1.00	1.02	1.00	0.91	0.97	1.03	0.97	0.08	0.95	1.00

Disease count (ref: 0 Ltcs)	term	Odds Ratio	p-value	CI - low	CI - high
1	Tree Canopy (%) - 300m	1.00	0.12	1.00	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.19	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.29	1.48
1	Income (ref: high) - medium	1.13	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.02	0.86	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.69	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	0.16	1.00	1.02
1	PM2.5	1.00	0.91	0.97	1.03
1	Noise	1.00	0.73	0.99	1.00
2	Tree Canopy (%) - 300m	1.00	0.69	1.00	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.02	0.58	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.72	2.03
2	Income (ref: high) - medium	1.25	0.00	1.17	1.33
2	Ethnicity (ref: Other) - White	0.90	0.01	0.82	0.98
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.12	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.15	0.94	1.01
2	Noise	1.00	0.30	0.99	1.00
3	Tree Canopy (%) - 300m	1.00	0.17	1.00	1.00
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.91	0.93	1.08
3	Income (ref: high) - low	2.72	0.00	2.44	3.04
3	Income (ref: high) - medium	1.41	0.00	1.29	1.55
3	Ethnicity (ref: Other) - White	0.99	0.88	0.88	1.12
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.26
3	Crime Score (IMD)	1.07	0.04	1.00	1.14
3	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
3	PM2.5	0.96	0.09	0.92	1.01
3	Noise	1.00	0.89	0.99	1.01
4+	Tree Canopy (%) - 300m	1.00	0.05	1.00	1.01
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.98	0.62	0.88	1.08
4+	Income (ref: high) - low	5.70	0.00	4.88	6.66
4+	Income (ref: high) - medium	2.02	0.00	1.74	2.33
4+	Ethnicity (ref: Other) - White	1.07	0.44	0.91	1.25
4+	Physical Activity (ref: high) -low	3.13	0.00	2.73	3.60
4+	Physical Activity (ref: high) - moderate	1.41	0.00	1.25	1.60
4+	Crime Score (IMD)	1.12	0.01	1.03	1.23
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.87	0.00	0.82	0.92
4+	Noise	1.01	0.10	1.00	1.02

Disease count (ref: 0 Ltcs)	term	Odds Ratio	p-value	CI - low	CI - high
1	Tree Canopy (%) - 1500m	1.00	0.31	1.00	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.20	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.29	1.48
1	Income (ref: high) - medium	1.13	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.02	0.86	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.70	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	0.20	1.00	1.01
1	PM2.5	1.00	0.79	0.97	1.02
1	Noise	1.00	0.73	0.99	1.00
2	Tree Canopy (%) - 1500m	1.00	0.79	1.00	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.01	0.58	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.72	2.03
2	Income (ref: high) - medium	1.25	0.00	1.17	1.33
2	Ethnicity (ref: Other) - White	0.90	0.01	0.82	0.98
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.12	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.16	0.95	1.01
2	Noise	1.00	0.30	0.99	1.00
3	Tree Canopy (%) - 1500m	1.00	0.11	0.99	1.00
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.94	0.93	1.08
3	Income (ref: high) - low	2.72	0.00	2.43	3.03
3	Income (ref: high) - medium	1.41	0.00	1.28	1.55
3	Ethnicity (ref: Other) - White	0.99	0.85	0.87	1.12
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.26
3	Crime Score (IMD)	1.07	0.05	1.00	1.14
3	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
3	PM2.5	0.96	0.10	0.92	1.01
3	Noise	1.00	0.89	0.99	1.01
4+	Tree Canopy (%) - 1500m	1.00	0.13	1.00	1.01
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.98	0.63	0.88	1.08
4+	Income (ref: high) - low	5.71	0.00	4.89	6.67
4+	Income (ref: high) - medium	2.02	0.00	1.74	2.33
4+	Ethnicity (ref: Other) - White	1.07	0.40	0.91	1.26
4+	Physical Activity (ref: high) -low	3.13	0.00	2.73	3.60
4+	Physical Activity (ref: high) - moderate	1.41	0.00	1.25	1.60
4+	Crime Score (IMD)	1.12	0.01	1.03	1.23
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.86	0.00	0.81	0.92
4+	Noise	1.01	0.10	1.00	1.02

	cardio-metabolic				respiratory				mental			
term	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
(Intercept)												
Distance to park (m)	1.00	0.25	1.00	1.00	1.00	0.52	1.00	1.00	1.00	0.32	1.00	1.00
Age (years)	1.09	0.00	1.09	1.10	1.04	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.52	2.99	0.98	0.87	0.76	1.25	0.83	0.14	0.66	1.06
Income (ref: high) - low	2.36	0.00	2.10	2.66	2.83	0.00	1.97	4.14	6.37	0.00	4.49	9.17
Income (ref: high) - medium	1.43	0.00	1.29	1.60	1.41	0.05	1.00	2.03	1.94	0.00	1.38	2.77
Ethnicity (ref: Other) - White	0.50	0.00	0.44	0.55	2.10	0.00	1.33	3.50	3.59	0.00	2.24	6.16
Physical Activity (ref: high) -low	1.76	0.00	1.57	1.96	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.73
Physical Activity (ref: high) - moderate	1.13	0.01	1.03	1.25	0.74	0.05	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.12	0.00	1.05	1.21	1.28	0.02	1.03	1.60	0.90	0.32	0.74	1.11
Deprivation Score (Townsend Index)	1.05	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.01	1.01	1.11
PM2.5	0.92	0.00	0.87	0.96	0.98	0.78	0.84	1.14	1.03	0.66	0.89	1.19
Noise	1.01	0.11	1.00	1.02	1.00	0.95	0.97	1.03	0.97	0.07	0.94	1.00

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Distance to coast (m)	1.00	0.00	1.00	1.01	1.00	0.79	0.99	1.01	1.00	0.67	0.99	1.01
Age (years)	1.09	0.00	1.09	1.10	1.05	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.73	0.00	2.51	2.98	0.98	0.85	0.76	1.25	0.83	0.14	0.66	1.06
Income (ref: high) - low	2.30	0.00	2.04	2.59	2.81	0.00	1.94	4.12	6.42	0.00	4.51	9.26
Income (ref: high) - medium	1.42	0.00	1.27	1.58	1.41	0.06	1.00	2.02	1.95	0.00	1.39	2.78
Ethnicity (ref: Other) - White	0.49	0.00	0.44	0.54	2.08	0.00	1.32	3.48	3.61	0.00	2.25	6.20
Physical Activity (ref: high) -low	1.76	0.00	1.57	1.96	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.73
Physical Activity (ref: high) - moderate	1.14	0.01	1.03	1.25	0.74	0.05	0.55	1.01	1.25	0.14	0.94	1.69
Crime Score (IMD)	1.13	0.00	1.05	1.21	1.28	0.03	1.03	1.59	0.90	0.31	0.74	1.10
Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.02	1.01	1.11
PM2.5	0.93	0.00	0.89	0.98	0.97	0.73	0.84	1.13	1.02	0.82	0.88	1.17
Noise	1.01	0.17	1.00	1.02	1.00	0.92	0.97	1.03	0.97	0.08	0.95	1.00

Disease count (ref: 0 Ltcs)	term	Odds Ratio	CI - low	CI - high
1	Distance to park (m)	1.00	1.00	1.00
1	Age (years)	1.04	1.04	1.04
1	Sex - Male	0.97	0.93	1.01
1	Income (ref: high) - low	1.38	1.29	1.48
1	Income (ref: high) - medium	1.12	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.86	0.99
1	Physical Activity (ref: high) -low	1.30	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	1.05	1.16
1	Crime Score (IMD)	1.01	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	1.00	1.01
1	PM2.5	1.00	0.97	1.02
1	Noise	1.00	0.99	1.00
2	Distance to park (m)	1.00	1.00	1.00
2	Age (years)	1.08	1.07	1.08
2	Sex - Male	1.02	0.96	1.07
2	Income (ref: high) - low	1.87	1.73	2.03
2	Income (ref: high) - medium	1.25	1.17	1.33
2	Ethnicity (ref: Other) - White	0.90	0.83	0.98
2	Physical Activity (ref: high) -low	1.52	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	1.06	1.20
2	Crime Score (IMD)	1.04	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	1.01	1.03
2	PM2.5	0.98	0.95	1.01
2	Noise	1.00	0.99	1.00
3	Distance to park (m)	1.00	1.00	1.00
3	Age (years)	1.10	1.09	1.10
3	Sex - Male	1.00	0.93	1.08
3	Income (ref: high) - low	2.74	2.46	3.06
3	Income (ref: high) - medium	1.42	1.29	1.56
3	Ethnicity (ref: Other) - White	0.99	0.88	1.11
3	Physical Activity (ref: high) -low	2.07	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	1.06	1.26
3	Crime Score (IMD)	1.07	1.01	1.15
3	Deprivation Score (Townsend Index)	1.03	1.01	1.04
3	PM2.5	0.97	0.94	1.02
3	Noise	1.00	0.99	1.01
4+	Distance to park (m)	1.00	1.00	1.00
4+	Age (years)	1.11	1.10	1.12
4+	Sex - Male	0.97	0.88	1.07
4+	Income (ref: high) - low	5.64	4.83	6.58
4+	Income (ref: high) - medium	2.00	1.73	2.31
4+	Ethnicity (ref: Other) - White	1.07	0.91	1.26
4+	Physical Activity (ref: high) -low	3.13	2.72	3.59
4+	Physical Activity (ref: high) - moderate	1.41	1.25	1.60
4+	Crime Score (IMD)	1.12	1.02	1.22
4+	Deprivation Score (Townsend Index)	1.06	1.04	1.08
4+	PM2.5	0.85	0.81	0.90
4+	Noise	1.01	1.00	1.02

		Odds Ratio	p-value	CI - low	CI - high
Disease count (ref: 0 Ltcs)					
1	Distance to coast (m)	1.00	0.52	1.00	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.18	0.93	1.01
1	Income (ref: high) - low	1.37	0.00	1.28	1.47
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.02	0.86	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.70	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	0.21	1.00	1.01
1	PM2.5	1.00	0.78	0.97	1.02
1	Noise	1.00	0.72	0.99	1.00
2	Distance to coast (m)	1.00	0.62	1.00	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.01	0.60	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.72	2.03
2	Income (ref: high) - medium	1.25	0.00	1.17	1.33
2	Ethnicity (ref: Other) - White	0.90	0.01	0.82	0.97
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.11	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.18	0.95	1.01
2	Noise	1.00	0.29	0.99	1.00
3	Distance to coast (m)	1.00	0.42	1.00	1.00
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.01	0.88	0.93	1.08
3	Income (ref: high) - low	2.76	0.00	2.47	3.09
3	Income (ref: high) - medium	1.42	0.00	1.29	1.56
3	Ethnicity (ref: Other) - White	0.99	0.89	0.88	1.12
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.26
3	Crime Score (IMD)	1.07	0.04	1.00	1.14
3	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
3	PM2.5	0.96	0.11	0.92	1.01
3	Noise	1.00	0.87	0.99	1.01
4+	Distance to coast (m)	1.01	0.00	1.00	1.01
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.97	0.51	0.88	1.07
4+	Income (ref: high) - low	5.46	0.00	4.67	6.39
4+	Income (ref: high) - medium	1.97	0.00	1.71	2.28
4+	Ethnicity (ref: Other) - White	1.05	0.54	0.89	1.23
4+	Physical Activity (ref: high) -low	3.12	0.00	2.71	3.59
4+	Physical Activity (ref: high) - moderate	1.42	0.00	1.25	1.60
4+	Crime Score (IMD)	1.12	0.01	1.03	1.22
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.09
4+	PM2.5	0.87	0.00	0.82	0.92
4+	Noise	1.01	0.13	1.00	1.02

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Blue (%) - 300m	1.00	0.98	0.99	1.01	1.01	0.76	0.96	1.04	0.96	0.20	0.89	1.01
Age (years)	1.09	0.00	1.09	1.10	1.04	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.53	2.99	0.98	0.87	0.76	1.25	0.83	0.13	0.65	1.05
Income (ref: high) - low	2.36	0.00	2.10	2.66	2.84	0.00	1.97	4.15	6.28	0.00	4.43	9.05
Income (ref: high) - medium	1.43	0.00	1.29	1.60	1.42	0.05	1.00	2.03	1.92	0.00	1.37	2.74
Ethnicity (ref: Other) - White	0.50	0.00	0.45	0.55	2.09	0.00	1.33	3.49	3.60	0.00	2.25	6.18
Physical Activity (ref: high) -low	1.76	0.00	1.57	1.97	1.84	0.00	1.34	2.52	1.95	0.00	1.41	2.72
Physical Activity (ref: high) - moderate	1.14	0.01	1.03	1.25	0.74	0.05	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.13	0.00	1.05	1.21	1.28	0.03	1.03	1.59	0.89	0.27	0.73	1.09
Deprivation Score (Townsend Index)	1.05	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.01	1.02	1.11
PM2.5	0.92	0.00	0.88	0.97	0.97	0.71	0.84	1.13	1.02	0.83	0.88	1.17
Noise	1.01	0.13	1.00	1.02	1.00	0.93	0.97	1.03	0.98	0.09	0.95	1.00

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Blue (%) - 1000m	0.97	0.02	0.95	0.99	0.92	0.09	0.84	1.00	0.90	0.02	0.81	0.98
Age (years)	1.09	0.00	1.09	1.10	1.04	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.53	3.00	0.98	0.88	0.77	1.26	0.83	0.14	0.66	1.06
Income (ref: high) - low	2.35	0.00	2.09	2.64	2.80	0.00	1.94	4.09	6.25	0.00	4.41	8.99
Income (ref: high) - medium	1.43	0.00	1.28	1.59	1.40	0.06	0.99	2.01	1.91	0.00	1.36	2.72
Ethnicity (ref: Other) - White	0.50	0.00	0.45	0.56	2.14	0.00	1.36	3.57	3.68	0.00	2.29	6.32
Physical Activity (ref: high) -low	1.76	0.00	1.58	1.97	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.72
Physical Activity (ref: high) - moderate	1.14	0.01	1.03	1.25	0.75	0.06	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.11	0.00	1.04	1.19	1.24	0.05	1.00	1.55	0.86	0.17	0.70	1.06
Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.07	0.00	1.02	1.12
PM2.5	0.92	0.00	0.88	0.97	0.97	0.69	0.84	1.13	1.02	0.79	0.88	1.18
Noise	1.01	0.09	1.00	1.02	1.00	0.80	0.98	1.03	0.98	0.12	0.95	1.01

		Odds Ratio	p-value	CI - low	CI - high
Disease count (ref: 0 Ltcs)					
1	Blue (%) - 300m	0.99	0.12	0.99	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.19	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.28	1.47
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.93	0.02	0.86	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.80	0.97	1.04
1	Deprivation Score (Townsend Index)	1.01	0.20	1.00	1.01
1	PM2.5	0.99	0.70	0.97	1.02
1	Noise	1.00	0.81	0.99	1.00
2	Blue (%) - 300m	1.00	0.43	0.99	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.02	0.58	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.72	2.03
2	Income (ref: high) - medium	1.25	0.00	1.17	1.33
2	Ethnicity (ref: Other) - White	0.90	0.01	0.83	0.98
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.13	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.15	0.95	1.01
2	Noise	1.00	0.32	0.99	1.00
3	Blue (%) - 300m	0.99	0.08	0.98	1.00
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.91	0.93	1.08
3	Income (ref: high) - low	2.73	0.00	2.44	3.05
3	Income (ref: high) - medium	1.41	0.00	1.29	1.55
3	Ethnicity (ref: Other) - White	0.99	0.87	0.88	1.12
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.07	0.05	1.00	1.14
3	Deprivation Score (Townsend Index)	1.03	0.00	1.01	1.04
3	PM2.5	0.96	0.11	0.92	1.01
3	Noise	1.00	0.81	0.99	1.01
4+	Blue (%) - 300m	0.99	0.18	0.97	1.01
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.97	0.61	0.88	1.08
4+	Income (ref: high) - low	5.62	0.00	4.81	6.56
4+	Income (ref: high) - medium	1.99	0.00	1.72	2.31
4+	Ethnicity (ref: Other) - White	1.08	0.37	0.92	1.26
4+	Physical Activity (ref: high) -low	3.13	0.00	2.72	3.60
4+	Physical Activity (ref: high) - moderate	1.41	0.00	1.25	1.60
4+	Crime Score (IMD)	1.12	0.01	1.02	1.22
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.86	0.00	0.81	0.91
4+	Noise	1.01	0.08	1.00	1.02

		Odds Ratio	p-value	CI - low	CI - high
Disease count (ref: 0 Ltcs)					
1	Blue (%) - 1000m	0.99	0.22	0.98	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.19	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.29	1.47
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.93	0.03	0.87	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.11	0.00	1.05	1.16
1	Crime Score (IMD)	1.00	0.84	0.97	1.04
1	Deprivation Score (Townsend Index)	1.01	0.21	1.00	1.01
1	PM2.5	1.00	0.71	0.97	1.02
1	Noise	1.00	0.83	0.99	1.00
2	Blue (%) - 1000m	0.98	0.02	0.97	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.02	0.57	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.72	2.02
2	Income (ref: high) - medium	1.24	0.00	1.17	1.32
2	Ethnicity (ref: Other) - White	0.90	0.02	0.83	0.98
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.03	0.21	0.98	1.08
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.14	0.94	1.01
2	Noise	1.00	0.41	0.99	1.00
3	Blue (%) - 1000m	0.96	0.00	0.94	0.99
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.90	0.93	1.08
3	Income (ref: high) - low	2.72	0.00	2.44	3.04
3	Income (ref: high) - medium	1.41	0.00	1.28	1.55
3	Ethnicity (ref: Other) - White	1.00	1.00	0.89	1.13
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.06	0.11	0.99	1.13
3	Deprivation Score (Townsend Index)	1.03	0.00	1.01	1.04
3	PM2.5	0.96	0.11	0.92	1.01
3	Noise	1.00	0.66	0.99	1.01
4+	Blue (%) - 1000m	0.97	0.05	0.94	1.00
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.98	0.62	0.88	1.08
4+	Income (ref: high) - low	5.62	0.00	4.81	6.56
4+	Income (ref: high) - medium	1.99	0.00	1.72	2.30
4+	Ethnicity (ref: Other) - White	1.08	0.33	0.92	1.27
4+	Physical Activity (ref: high) -low	3.13	0.00	2.73	3.60
4+	Physical Activity (ref: high) - moderate	1.42	0.00	1.25	1.60
4+	Crime Score (IMD)	1.11	0.02	1.02	1.21
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.86	0.00	0.81	0.91
4+	Noise	1.01	0.07	1.00	1.02

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Blue (%) - 1500m	0.99	0.13	0.97	1.00	0.94	0.05	0.89	1.00	0.92	0.01	0.86	0.97
Age (years)	1.09	0.00	1.09	1.10	1.05	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.53	2.99	0.98	0.87	0.76	1.26	0.83	0.14	0.66	1.06
Income (ref: high) - low	2.35	0.00	2.09	2.65	2.78	0.00	1.93	4.06	6.20	0.00	4.37	8.92
Income (ref: high) - medium	1.43	0.00	1.28	1.59	1.39	0.07	0.98	2.00	1.90	0.00	1.35	2.71
Ethnicity (ref: Other) - White	0.50	0.00	0.45	0.56	2.14	0.00	1.36	3.57	3.68	0.00	2.29	6.31
Physical Activity (ref: high) -low	1.76	0.00	1.58	1.97	1.84	0.00	1.35	2.52	1.96	0.00	1.41	2.73
Physical Activity (ref: high) - moderate	1.14	0.01	1.03	1.25	0.74	0.06	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.12	0.00	1.04	1.20	1.23	0.07	0.99	1.53	0.85	0.14	0.70	1.05
Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.07	1.08	0.00	1.03	1.14	1.07	0.00	1.02	1.12
PM2.5	0.93	0.00	0.88	0.97	0.99	0.88	0.85	1.15	1.04	0.55	0.91	1.20
Noise	1.01	0.12	1.00	1.02	1.00	0.85	0.97	1.03	0.98	0.10	0.95	1.00

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Blue (%) - 3000m	0.98	0.08	0.97	1.00	0.95	0.13	0.89	1.01	0.94	0.04	0.88	0.99
Age (years)	1.09	0.00	1.09	1.10	1.05	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.53	3.00	0.98	0.87	0.76	1.26	0.83	0.14	0.66	1.06
Income (ref: high) - low	2.35	0.00	2.09	2.65	2.79	0.00	1.94	4.08	6.23	0.00	4.39	8.97
Income (ref: high) - medium	1.43	0.00	1.28	1.59	1.40	0.06	0.99	2.01	1.91	0.00	1.36	2.73
Ethnicity (ref: Other) - White	0.50	0.00	0.45	0.56	2.12	0.00	1.35	3.53	3.62	0.00	2.26	6.21
Physical Activity (ref: high) -low	1.76	0.00	1.58	1.97	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.73
Physical Activity (ref: high) - moderate	1.14	0.01	1.03	1.25	0.75	0.06	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.12	0.00	1.04	1.20	1.25	0.05	1.00	1.56	0.87	0.19	0.71	1.07
Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.07	1.08	0.00	1.03	1.14	1.07	0.00	1.02	1.12
PM2.5	0.93	0.00	0.88	0.97	0.99	0.90	0.85	1.15	1.05	0.52	0.91	1.21
Noise	1.01	0.13	1.00	1.02	1.00	0.92	0.97	1.03	0.97	0.08	0.95	1.00

		Odds Ratio	p-value	CI - low	CI - high
Disease count (ref: 0 Ltcs)					
1	Blue (%) - 1500m	0.99	0.13	0.99	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.19	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.28	1.47
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.93	0.03	0.87	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.11	0.00	1.05	1.16
1	Crime Score (IMD)	1.00	0.88	0.97	1.04
1	Deprivation Score (Townsend Index)	1.01	0.18	1.00	1.01
1	PM2.5	1.00	0.83	0.97	1.02
1	Noise	1.00	0.80	0.99	1.00
2	Blue (%) - 1500m	0.99	0.00	0.98	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.02	0.57	0.96	1.07
2	Income (ref: high) - low	1.86	0.00	1.72	2.02
2	Income (ref: high) - medium	1.24	0.00	1.17	1.32
2	Ethnicity (ref: Other) - White	0.90	0.02	0.83	0.98
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.03	0.25	0.98	1.08
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
2	PM2.5	0.98	0.25	0.95	1.01
2	Noise	1.00	0.37	0.99	1.00
3	Blue (%) - 1500m	0.98	0.00	0.96	0.99
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.90	0.93	1.08
3	Income (ref: high) - low	2.72	0.00	2.43	3.03
3	Income (ref: high) - medium	1.41	0.00	1.28	1.54
3	Ethnicity (ref: Other) - White	1.00	0.98	0.88	1.13
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.06	0.11	0.99	1.13
3	Deprivation Score (Townsend Index)	1.03	0.00	1.01	1.04
3	PM2.5	0.97	0.21	0.93	1.02
3	Noise	1.00	0.77	0.99	1.01
4+	Blue (%) - 1500m	0.98	0.01	0.96	1.00
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.98	0.62	0.88	1.08
4+	Income (ref: high) - low	5.60	0.00	4.80	6.54
4+	Income (ref: high) - medium	1.99	0.00	1.72	2.30
4+	Ethnicity (ref: Other) - White	1.08	0.32	0.92	1.27
4+	Physical Activity (ref: high) -low	3.13	0.00	2.73	3.60
4+	Physical Activity (ref: high) - moderate	1.42	0.00	1.25	1.60
4+	Crime Score (IMD)	1.10	0.03	1.01	1.21
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.87	0.00	0.82	0.92
4+	Noise	1.01	0.08	1.00	1.02

		Odds Ratio	p-value	CI - low	CI - high
Disease count (ref: 0 Ltcs)					
1	Blue (%) - 3000m	0.99	0.07	0.98	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.19	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.28	1.47
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.93	0.03	0.87	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.11	0.00	1.05	1.16
1	Crime Score (IMD)	1.00	0.86	0.97	1.04
1	Deprivation Score (Townsend Index)	1.01	0.16	1.00	1.02
1	PM2.5	1.00	0.91	0.97	1.03
1	Noise	1.00	0.77	0.99	1.00
2	Blue (%) - 3000m	0.98	0.00	0.97	0.99
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.02	0.57	0.96	1.07
2	Income (ref: high) - low	1.86	0.00	1.72	2.02
2	Income (ref: high) - medium	1.24	0.00	1.17	1.32
2	Ethnicity (ref: Other) - White	0.90	0.02	0.83	0.98
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.03	0.21	0.98	1.08
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
2	PM2.5	0.98	0.31	0.95	1.02
2	Noise	1.00	0.32	0.99	1.00
3	Blue (%) - 3000m	0.97	0.00	0.95	0.98
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.01	0.89	0.93	1.08
3	Income (ref: high) - low	2.71	0.00	2.43	3.03
3	Income (ref: high) - medium	1.41	0.00	1.28	1.54
3	Ethnicity (ref: Other) - White	1.00	0.99	0.88	1.13
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.06	0.10	0.99	1.13
3	Deprivation Score (Townsend Index)	1.03	0.00	1.01	1.04
3	PM2.5	0.98	0.31	0.93	1.02
3	Noise	0.00	0.00	0.00	0.00
4+	Blue (%) - 3000m	0.97	0.01	0.95	0.99
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.98	0.63	0.88	1.08
4+	Income (ref: high) - low	5.60	0.00	4.79	6.54
4+	Income (ref: high) - medium	1.99	0.00	1.72	2.30
4+	Ethnicity (ref: Other) - White	1.08	0.33	0.92	1.27
4+	Physical Activity (ref: high) -low	3.13	0.00	2.73	3.60
4+	Physical Activity (ref: high) - moderate	1.42	0.00	1.25	1.60
4+	Crime Score (IMD)	1.11	0.02	1.01	1.21
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.87	0.00	0.82	0.93
4+	Noise	1.01	0.09	1.00	1.02

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Green&Blue (%) - 300m	1.00	0.91	0.99	1.01	1.01	0.21	0.99	1.02	1.01	0.50	0.99	1.02
Age (years)	1.09	0.00	1.09	1.10	1.05	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.53	2.99	0.98	0.87	0.76	1.25	0.83	0.13	0.65	1.06
Income (ref: high) - low	2.36	0.00	2.10	2.66	2.84	0.00	1.97	4.14	6.35	0.00	4.48	9.14
Income (ref: high) - medium	1.43	0.00	1.29	1.60	1.42	0.05	1.00	2.04	1.94	0.00	1.38	2.77
Ethnicity (ref: Other) - White	0.50	0.00	0.45	0.55	2.08	0.00	1.32	3.47	3.57	0.00	2.23	6.13
Physical Activity (ref: high) -low	1.76	0.00	1.57	1.97	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.72
Physical Activity (ref: high) - moderate	1.14	0.01	1.03	1.25	0.74	0.05	0.55	1.01	1.25	0.13	0.94	1.69
Crime Score (IMD)	1.13	0.00	1.05	1.21	1.28	0.02	1.03	1.59	0.90	0.32	0.74	1.11
Deprivation Score (Townsend Index)	1.05	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.01	1.01	1.11
PM2.5	0.92	0.00	0.88	0.97	0.98	0.81	0.85	1.14	1.03	0.72	0.89	1.18
Noise	1.01	0.13	1.00	1.02	1.00	0.99	0.97	1.03	0.97	0.07	0.94	1.00

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Green&Blue (%) - 1500m	1.00	0.23	1.00	1.00	1.00	0.83	0.99	1.01	1.00	0.33	0.99	1.00
Age (years)	1.09	0.00	1.09	1.10	1.04	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.75	0.00	2.52	2.99	0.98	0.87	0.76	1.26	0.83	0.14	0.66	1.06
Income (ref: high) - low	2.35	0.00	2.09	2.64	2.84	0.00	1.97	4.15	6.43	0.00	4.53	9.26
Income (ref: high) - medium	1.43	0.00	1.29	1.59	1.42	0.05	1.00	2.03	1.95	0.00	1.39	2.78
Ethnicity (ref: Other) - White	0.49	0.00	0.44	0.55	2.10	0.00	1.33	3.51	3.64	0.00	2.27	6.25
Physical Activity (ref: high) -low	1.76	0.00	1.58	1.97	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.73
Physical Activity (ref: high) - moderate	1.14	0.01	1.03	1.25	0.74	0.05	0.55	1.01	1.25	0.14	0.94	1.69
Crime Score (IMD)	1.13	0.00	1.05	1.21	1.28	0.03	1.03	1.59	0.89	0.26	0.73	1.09
Deprivation Score (Townsend Index)	1.05	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.01	1.01	1.11
PM2.5	0.93	0.00	0.88	0.97	0.97	0.69	0.84	1.12	1.01	0.89	0.88	1.16
Noise	1.01	0.17	1.00	1.02	1.00	0.90	0.97	1.03	0.98	0.09	0.95	1.00

		Odds Ratio	p-value	CI - low	CI - high
Disease count (ref: 0 Ltcs)					
1	Green&Blue (%) - 300m	1.00	0.60	1.00	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.19	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.29	1.48
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.02	0.86	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.74	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	0.24	1.00	1.01
1	PM2.5	0.99	0.70	0.97	1.02
1	Noise	1.00	0.78	0.99	1.00
2	Green&Blue (%) - 300m	1.00	0.59	1.00	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.02	0.58	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.73	2.03
2	Income (ref: high) - medium	1.25	0.00	1.17	1.33
2	Ethnicity (ref: Other) - White	0.90	0.01	0.82	0.98
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.12	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.18	0.95	1.01
2	Noise	1.00	0.27	0.99	1.00
3	Green&Blue (%) - 300m	1.00	0.91	0.99	1.01
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.91	0.93	1.08
3	Income (ref: high) - low	2.74	0.00	2.45	3.06
3	Income (ref: high) - medium	1.42	0.00	1.29	1.56
3	Ethnicity (ref: Other) - White	0.99	0.84	0.87	1.12
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.26
3	Crime Score (IMD)	1.07	0.04	1.00	1.14
3	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
3	PM2.5	0.96	0.12	0.92	1.01
3	Noise	1.00	0.89	0.99	1.01
4+	Green&Blue (%) - 300m	1.00	0.79	0.99	1.01
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.97	0.61	0.88	1.08
4+	Income (ref: high) - low	5.65	0.00	4.84	6.60
4+	Income (ref: high) - medium	2.00	0.00	1.73	2.32
4+	Ethnicity (ref: Other) - White	1.07	0.39	0.91	1.26
4+	Physical Activity (ref: high) -low	3.13	0.00	2.72	3.60
4+	Physical Activity (ref: high) - moderate	1.41	0.00	1.25	1.60
4+	Crime Score (IMD)	1.12	0.01	1.03	1.22
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.86	0.00	0.81	0.91
4+	Noise	1.01	0.09	1.00	1.02

		Odds Ratio	p-value	CI - low	CI - high
Disease count (ref: 0 Ltcs)					
1	Green&Blue (%) - 1500m	1.00	0.37	1.00	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.19	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.29	1.48
1	Income (ref: high) - medium	1.13	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.93	0.03	0.87	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	0.00	1.05	1.16
1	Crime Score (IMD)	1.00	0.81	0.97	1.04
1	Deprivation Score (Townsend Index)	1.01	0.25	1.00	1.01
1	PM2.5	0.99	0.66	0.97	1.02
1	Noise	1.00	0.81	0.99	1.00
2	Green&Blue (%) - 1500m	1.00	0.95	1.00	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.02	0.58	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.73	2.03
2	Income (ref: high) - medium	1.25	0.00	1.17	1.33
2	Ethnicity (ref: Other) - White	0.90	0.01	0.82	0.98
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.12	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.17	0.95	1.01
2	Noise	1.00	0.30	0.99	1.00
3	Green&Blue (%) - 1500m	1.00	0.74	1.00	1.00
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.92	0.93	1.08
3	Income (ref: high) - low	2.74	0.00	2.45	3.06
3	Income (ref: high) - medium	1.42	0.00	1.29	1.56
3	Ethnicity (ref: Other) - White	0.99	0.82	0.87	1.11
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.07	0.04	1.00	1.15
3	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.04
3	PM2.5	0.97	0.14	0.92	1.01
3	Noise	1.00	0.93	0.99	1.01
4+	Green&Blue (%) - 1500m	1.00	0.16	1.00	1.00
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.97	0.59	0.88	1.07
4+	Income (ref: high) - low	5.60	0.00	4.79	6.54
4+	Income (ref: high) - medium	2.00	0.00	1.73	2.31
4+	Ethnicity (ref: Other) - White	1.06	0.47	0.90	1.25
4+	Physical Activity (ref: high) -low	3.13	0.00	2.72	3.60
4+	Physical Activity (ref: high) - moderate	1.41	0.00	1.25	1.60
4+	Crime Score (IMD)	1.13	0.01	1.03	1.23
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.87	0.00	0.82	0.92
4+	Noise	1.01	0.14	1.00	1.02

	cardio-metabolic				respiratory				mental			
	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high	Odds Ratio	p-value	CI - low	CI - high
Green&Blue (%) - 3000m	1.00	0.00	1.00	1.01	1.00	0.63	1.00	1.01	1.00	0.27	0.99	1.00
Age (years)	1.09	0.00	1.09	1.10	1.05	0.00	1.03	1.06	0.96	0.00	0.95	0.97
Sex - Male	2.73	0.00	2.51	2.98	0.98	0.85	0.76	1.25	0.84	0.14	0.66	1.06
Income (ref: high) - low	2.30	0.00	2.04	2.59	2.80	0.00	1.93	4.10	6.51	0.00	4.58	9.39
Income (ref: high) - medium	1.41	0.00	1.27	1.57	1.41	0.06	0.99	2.02	1.97	0.00	1.40	2.81
Ethnicity (ref: Other) - White	0.48	0.00	0.43	0.54	2.07	0.00	1.31	3.46	3.68	0.00	2.29	6.32
Physical Activity (ref: high) -low	1.76	0.00	1.57	1.97	1.84	0.00	1.34	2.52	1.96	0.00	1.41	2.73
Physical Activity (ref: high) - moderate	1.14	0.01	1.04	1.25	0.74	0.05	0.55	1.01	1.25	0.14	0.94	1.68
Crime Score (IMD)	1.14	0.00	1.06	1.22	1.28	0.02	1.03	1.60	0.89	0.28	0.73	1.10
Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.07	1.08	0.00	1.03	1.13	1.06	0.02	1.01	1.10
PM2.5	0.94	0.01	0.89	0.98	0.98	0.78	0.84	1.13	1.01	0.94	0.87	1.16
Noise	1.01	0.23	1.00	1.01	1.00	0.95	0.97	1.03	0.98	0.09	0.95	1.00

		Odds Ratio	p-value	CI - low	CI - high
Disease count (ref: 0 Ltcs)					
1	Green&Blue (%) - 3000m	1.00	0.92	1.00	1.00
1	Age (years)	1.04	0.00	1.04	1.04
1	Sex - Male	0.97	0.19	0.93	1.01
1	Income (ref: high) - low	1.38	0.00	1.29	1.48
1	Income (ref: high) - medium	1.12	0.00	1.07	1.18
1	Ethnicity (ref: Other) - White	0.92	0.02	0.86	0.99
1	Physical Activity (ref: high) -low	1.30	0.00	1.22	1.39
1	Physical Activity (ref: high) - moderate	1.10	0.00	1.05	1.16
1	Crime Score (IMD)	1.01	0.74	0.97	1.05
1	Deprivation Score (Townsend Index)	1.01	0.26	1.00	1.01
1	PM2.5	1.00	0.73	0.97	1.02
1	Noise	1.00	0.75	0.99	1.00
2	Green&Blue (%) - 3000m	1.00	0.57	1.00	1.00
2	Age (years)	1.08	0.00	1.07	1.08
2	Sex - Male	1.01	0.59	0.96	1.07
2	Income (ref: high) - low	1.87	0.00	1.72	2.03
2	Income (ref: high) - medium	1.25	0.00	1.17	1.33
2	Ethnicity (ref: Other) - White	0.89	0.01	0.82	0.97
2	Physical Activity (ref: high) -low	1.52	0.00	1.41	1.65
2	Physical Activity (ref: high) - moderate	1.13	0.00	1.06	1.20
2	Crime Score (IMD)	1.04	0.11	0.99	1.09
2	Deprivation Score (Townsend Index)	1.02	0.00	1.01	1.03
2	PM2.5	0.98	0.20	0.95	1.01
2	Noise	1.00	0.27	0.99	1.00
3	Green&Blue (%) - 3000m	1.00	0.34	1.00	1.00
3	Age (years)	1.10	0.00	1.09	1.11
3	Sex - Male	1.00	0.94	0.93	1.08
3	Income (ref: high) - low	2.72	0.00	2.43	3.04
3	Income (ref: high) - medium	1.41	0.00	1.29	1.55
3	Ethnicity (ref: Other) - White	0.98	0.75	0.87	1.11
3	Physical Activity (ref: high) -low	2.07	0.00	1.86	2.30
3	Physical Activity (ref: high) - moderate	1.16	0.00	1.06	1.27
3	Crime Score (IMD)	1.07	0.03	1.01	1.15
3	Deprivation Score (Townsend Index)	1.03	0.00	1.01	1.04
3	PM2.5	0.97	0.18	0.92	1.01
3	Noise	1.00	0.97	0.99	1.01
4+	Green&Blue (%) - 3000m	1.00	0.00	1.00	1.01
4+	Age (years)	1.11	0.00	1.10	1.12
4+	Sex - Male	0.97	0.53	0.88	1.07
4+	Income (ref: high) - low	5.47	0.00	4.68	6.40
4+	Income (ref: high) - medium	1.97	0.00	1.71	2.28
4+	Ethnicity (ref: Other) - White	1.04	0.66	0.88	1.22
4+	Physical Activity (ref: high) -low	3.13	0.00	2.72	3.60
4+	Physical Activity (ref: high) - moderate	1.42	0.00	1.25	1.60
4+	Crime Score (IMD)	1.13	0.00	1.04	1.24
4+	Deprivation Score (Townsend Index)	1.06	0.00	1.04	1.08
4+	PM2.5	0.88	0.00	0.83	0.93
4+	Noise	1.01	0.18	1.00	1.02

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