

Green spaces and health

exploring potential effect modifiers

PHD THESIS

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Abstract

Noncommunicable diseases place the largest burden on mental and physical health in Europe and can be mitigated by green spaces near people's residences. However, there are many potentially important, yet understudied, effect modifiers that impact residential green space and health associations. These may change these associations' magnitude, shape and (mostly positive) direction.

In this thesis, I identify and assess four understudied potential effect modifiers of residential green space and health in three epidemiological analyses. I assess effect modification on green space associations with: general health from traffic in analysis 1, mental health from changes in local area socioeconomic deprivation in analysis 2 and mental health from green space naturalness and water in analysis 3. Analyses 1 and 3 are cross sectional, and analysis 3 is longitudinal.

I found that deprivation and water positively affected green spaces' association with better health. However, the effect of traffic and naturalness depended on the vegetation type and amount of green space present, respectively. A limited evidence base leads me to recommend further study of the impact of wetland, traffic and naturalness as effect modifiers. The latter's impact on green space and health was inconsistent with the established literature further justifying this recommendation. I suggest a policy of providing green space in socioeconomically deprived areas to benefit public health, supported by my research and a large body of literature.

Given the green spaces physical health benefits alone are approximately a third of the value of the United Kingdom's Natural Capital, a change in green spaces' impact on health attributable to effect modifiers, such as I have found, can influence how green spaces are designed and planned. Identifying and quantifying the value of effect modifiers should be a priority for all concerned with maximising the societal benefits we get from existing and new green space.

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Nomenclature

ART	Attention Restoration Theory
BIBD	Balanced Incomplete Block Design
BVOC	Biological Volatile Organic Compounds
CASE	Collaborative Awards in Science and Engineering
COA	Census Output Area
Copernicus TCD	Copernicus Land Monitoring service Tree Cover Density product
ESA	European Space Agency
GB	Great Britain
GDP	Gross Domestic Product
GIF	Green Infrastructure Framework
GLM	Generalised Linear Model
GPS	Global Positioning System
GVIF	Generalised Variance Inflation Factor
IMD	Index of Multiple Deprivation
IQR	Inter Quartile Range
LAD	Local Authority District
LCM	Land Cover Map
LSOA	Lower Layer Super Output Area
MICE	Multiple Imputation with Chained Equations
MNL	Multinomial Logit
MSOA	Middle Layer Super Output Area
NDVI	Normalized Difference Vegetation Index
NHS	National Health Service
NO ₂	Nitrous Oxide
O ₃	Ozone
OECD	Organisation for Economic Co-operation and Development
ONS	Office for National Statistics
OS	Ordnance Survey
PAW	Plantation on Ancient Woodland Site
PM	Particulate Matter
PWC	Population Weighted Centroid
SDG	Sustainable Development Goals
SE	Standard Error
sf-12	Short form 12 health survey

SO ₂	Sulphur Dioxide
SRT	Stress Reduction Theory
UK	United Kingdom
UKCEH	UK Centre for Ecology and Hydrology
UN	United Nations
VIF	Variance Inflation Factor
WHO	World Health Organisation
WWT	Wildfowl and Wetlands Trust

Statement of originality

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1 Introduction

There is a global rise in non-communicable diseases, which as of 2016 accounted for ~88% of European deaths ([WHO Regional Office for Europe, 2016](#)). In addition to physical health, recognised historically, mental health is now an integral health component ([Prince et al., 2007](#)) and a major contributor to this global disease burden ([Vigo et al., 2016](#)). The annual costs of mental ill health alone is estimated at €600bn in the European Union (4% GDP) ([OECD and Union, 2018](#)). Understanding what protects or improves physical and mental health is vital to reducing the non-communicable disease burden ([Collins et al., 2011](#)).

Green spaces near to where people live (hereafter residential green space), such as parks, gardens, woodlands, street trees and open fields, have been found to support the health and wellbeing of nearby residents, attributable to non-communicable diseases ([WHO Regional Office for Europe, 2017](#)). Recent systematic reviews have established that more residential green space, especially in developed countries, is better for health across the majority of health indicators studied, for example, all-cause mortality ([Rojas-Rueda et al., 2019](#)), an increased likelihood to engage in physical activity, and improved mood ([Kondo et al., 2018](#)). These benefits may also be economically substantial. In the United Kingdom of Great Britain and Northern Ireland (UK), for example, the avoided cost to the National Health Service (NHS) from green spaces was estimated at £2.4 billion annually ([Eftec, 2017](#)). More recent natural capital accounts have attributed a third of the UK's natural capital stock (~£600 billion out of ~£1.6 trillion) to green space's impact on physical health through recreation alone ([Office for National Statistics, 2022a](#)).

The role of green spaces in improving public health is increasingly being recognised by health care providers, policymakers, urban planners, designers and architects ([Millennium Ecosystem Assessment, 2005](#)). The World Health Organization (WHO) has identified protecting and creating green spaces in urban areas as part of the solution to tackle the global rise in non-communicable diseases ([WHO Regional Office for Europe, 2017](#)). However, there may be unaccounted effect modifiers that have the potential to change green space and health associations, many of which have not been investigated and identified ([Shanahan et al., 2015](#)). For example, not all studies demonstrate a beneficial impact of green spaces on health, and these inconclusive results may be due to unaccounted for effect modifiers ([Lee and Maheswaran, 2011](#)).

To what degree factors modify green space and health associations is important to understand when making planning and policy decisions about green space. In areas near to where people live, competition for land is high, and the sources of effect modifiers (e.g. traffic) may be planned or already exist around or inside green spaces to maximise space use. Should these factors be identified as effect modifiers, their negative or positive impact on green space and health associations may alter decisions on where to place or keep green space or sources of effect modifiers. For example, whether to include water within green spaces, provide green space equally within areas across a socioeconomic deprivation gradient, or adjacent to roads with and without traffic equally. There remains insufficient evidence on many potentially important understudied effect modifiers in terms of the robustness of their assessment or whether they have been assessed ([Marselle et al., 2021](#)).

1.1 PhD aim and objectives

The overall aim of this PhD thesis is to explore understudied potential effect modifiers of associations between residential green space and their physical and or mental health. My findings are intended to be generalisable to the population of the UK whilst also providing some lessons for countries with similar cultures, ecozones and development contexts.

1.1.1 Objectives

1. To conduct a literature review to identify pathways from residential green space to health and to identify understudied potential effect modifiers of residential green space and health associations.
2. To identify appropriate methodologies and datasets to determine if and to what degree green space impacts health and whether identified factors modify the effect of green spaces on health.
3. To conduct detailed epidemiological analyses to determine whether green space impacts health and how selected factors modify the association between green space and health.

1.2 Thesis structure

In Chapter 2 I first present background information on the theoretical basis for how residential green space impacts health (in the UK) and what factors may modify this relationship. This review includes a definition of green space and residential green space exposure and a review of health pathways that may explain associations between residential exposure to green space and health. I then identify potential effect modifiers of green space and health, which are understudied in terms of the robustness of evidence to support them or the number of analyses that have assessed them.

After reviewing several effect modifiers, I select four to study in epidemiological analyses which are the focus of this thesis. These are (1) traffic (analysis 1, Chapter 4), (2) socioeconomic deprivation (analysis 2, Chapter 5), (3) green space perceived naturalness and (4) green space wetness (both in analysis 3, Chapter 6). My outcome and study population for analysis 1 is the proportion of census output area residents with positive self-rated health in England and Wales as calculated from data recorded in the 2011 census. For analyses 2 and 3 I use Understanding Society – The UK Household Longitudinal Study 2009–2019, waves 1–9 (hereafter Understanding Society), as the source of health outcome and non-spatial covariates in analysis 2 and 3, which I describe in detail in Section 3.3.

I describe concepts, data, and variables common to each of my epidemiological analyses, in Chapter 3 and those that are unique to each analysis in the relevant chapter. In addition to describing the Understanding Society dataset I also outline the datasets I use to identify green space (Section 3.1), what spatial identifier I use to generate population/individual level residential green space exposure (Section 3.2) and the common covariates I identify as potential confounders to include in epidemiological analyses (Section 3.4).

In Chapter 7, I discuss cross-analysis findings, the implications of these findings, the shared strengths and weaknesses of my analyses and conclude with my key findings and take-home messages.

2 Background

2.1 Residential green space exposure and health

2.1.1 Defining green spaces

In this thesis, I define green space as vegetated land. While the definitions of green space can vary ([Taylor and Hochuli, 2017](#)), most often, it is defined as being vegetated and/or providing a “public” land use. The UK Ordnance Survey (OS) Greenspace map, for example, has been used to assess green space exposure ([Robinson et al., 2022](#)) and includes land uses such as parks, playgrounds, cemeteries and play areas. However, not all areas of these green spaces are vegetated, and therefore, under some definitions, a land-use defined as green space may not be vegetated.

When considered as vegetated land (as I do in this thesis), green space benefits are often generalised by its green cover vegetation types. This is due to different vegetation types providing different costs, benefits and management requirements, for example, the different cooling potential of green cover types ([Richards et al., 2020](#)) or the variety of ecosystem service quantities provided by woodland ([Burton et al., 2018](#)).

2.1.2 Mapping green spaces

Many national-scale maps of the UK's green spaces have been created at different spatial resolutions using varying classification schemes and approaches. The OS has manually mapped green spaces for 100's of years and now updates historical maps using manual checking of remotely sensed images. The OS master map topographic layer divides green space into vegetation types (e.g. trees, heath, marsh and grass) or as mixed natural (which may contain one or many vegetation types) ([Ordnance Survey, 2017a](#)). Historical inventories of habitat types, such as Ancient Woodland, have been created based on historical data from OS and other sources ([Natural England, 2020](#)).

Some studies classify land as green space if it has a Normalised Differential Vegetation Index (NDVI) value higher than a certain threshold ([Rugel et al., 2017](#)). An NDVI value is assigned to pixels remotely sensed from satellite data based on the amount of infrared light that it reflects and visible light it absorbs. This value directly correlates with the sum of their chlorophyll content in the vegetation on the said pixel, as plant chlorophyll uses (and therefore prevents the reflection of) visible light to grow and reflects near-infrared light ([Knipling, 1970](#)). The sum chlorophyll content within a vegetation type can vary either due to the vegetation density (e.g., described by the leaf area index), for example with layered canopies found in woodland; the physiological characteristics of plants within the vegetation type, e.g., heathland has less chlorophyll per unit leaf area; whether it is wet (this prevents near-infrared light reflectance) or due to leaf senescence caused by seasonal change, age or pest/diseases ([Knipling, 1970](#)). Many more recent green space maps use sets of complex machine and deep learning algorithms to classify layered satellite remotely sensed hyperspectral and ancillary survey/other remotely sensed datasets into green spaces of different vegetation types (e.g., trees, shrubs, and grass) as well as of different ecological types. For example, the UK Centre for Ecology and Hydrology (UKCEH) Land Cover Map (LCM) product series ([Morton, 2020](#); [Morton et al., 2021](#)) and the Copernicus Land Monitoring service Tree Cover Density product (Copernicus TCD) ([European Environment Agency, 2018](#)).

2.1.3 Approximating residential green space exposure

In many secondary datasets containing health outcomes there is limited or no data on how long people are close to green space to obtain its benefits. Therefore, indirect estimation through scenario evaluation must be conducted (U.S. EPA, 2019). One scenario often assumed is that an increased quantity of green space near a person's residence increases the frequency and duration of them being close enough to obtain its health benefits (see an extensive review of health benefits and pathways in Section 2.1.4). This is due to individuals being more likely to visit or be close to green spaces nearer home intentionally (Schindler et al., 2022) or incidentally when walking to the nearest facilities (e.g. school, work, shops, public transport). Furthermore, some mediators to green space health benefits impact a persons health at their residence more directly, for example, flood risk reduction, or decreased air temperatures, see Section 2.1.4.2. Residential green space, therefore, acts as a source of and proxy for potentially multiple true exposure events, which could impact health along different pathways (see Section 2.1).

Residential green space is often approximated using the metrics: *geographical area cover* (Alcock et al., 2014; Bu et al., 2022; Cummins and Fagg, 2012; Dennis et al., 2020; Dennis and James, 2017; Mytton et al., 2012; Schindler et al., 2022; White et al., 2019) or *accessibility*, or *availability* (Labib et al., 2020). Residential green space *accessibility* is often defined as the distance or travel time from a person's residence to the nearest green space of a predefined size, e.g., 1 ha as per WHO guidelines (WHO Regional Office for Europe, 2017). The assumption is that people are more likely to have a residential green space exposure (either incidentally or intentionally) if they are located closer to a meaningfully sized green space. Green space *geographical area cover* is the proportion/percentage green space within the geographical area that a person or a population resides in.

2.1.3.1 Green space availability

Residential green space *availability* is often defined as the proportion of green space within a set distance, for example, 400, 800 or 1,600 m from a person's dwelling or neighbourhood centre. Green space availability represents the probability of exposure to green space, which can be incidental or intentional. When walking to the nearest facilities (e.g. public transport or shops), individuals may intentionally (perhaps other options would be quicker) or

incidentally (it may be the fastest route) walk through a tree-lined street instead of a grey one. The distance at which a green space is considered available also provides a threshold past which a planned visit to a green space area is less likely, as the probability of visiting a green space decreases with its distance away from where a person lives (Schindler et al., 2022). Lastly, it can provide an approximation for green spaces provision of more disperse environmental improvements that lead to health impacts such as urban cooling (Richards et al., 2020).

The proportion of *available* green space within a fixed radius buffer from a person's residence administrative or census area centroid can be calculated (Labib et al., 2020). Other approaches include isochrones, polygons with boundary vertices at a set travel time (e.g., 5, 10 or 20 minutes) from a person's residence at different trajectories. There is little evidence on the performance of different *availability* vs *accessibility* metrics at predicted health or representing the types of green space exposure I outline in Section 2.1.4.1. However, research suggests a weak correlation between *accessibility* and *availability* using fixed-radius buffers (Jarvis et al., 2020).

In this thesis, I base all green space exposure assessments in epidemiological analysis on the *available* green space (or points of green space potential sensory exposure in Analysis 1 Chapter 4) near a person's neighbourhood population centroid. I used green space *availability* (from a person's local area population centroid) as it better approximated the *availability* of green space from postcodes than *geographical area cover*, which I also considered using; see Section 3.2.3 for the analysis I completed to determine this.

2.1.4 Residential green space exposure pathways

There are a several hypothesised pathways via which residential green space exposure impacts physical and mental health (Markevych et al., 2017; Marselle et al., 2021), yet the relative importance of these pathways is largely unknown. Here, I discuss the most often studied pathways between residential green space and health. I particularly focus on those most likely to be relevant in countries with similar cultural, climate and economic development contexts as the UK and those that impact mental health outcomes, as this will help contextualise findings in my later epidemiological analyses. I exclude, for example,

household-level food production as is only relevant to a small fraction of people within my study population.

Conceptually, I categorise these pathways into two groups as shown in the conceptual diagram in [Figure 1](#). Pathways in the first group assume that residential green space increase the likelihood of direct, short-range sensory exposure to nature (sights, smells, sounds, touch). Pathways in the second group assume that neighbourhood green space change nearby environmental conditions. Often, different green space-health pathways interact and influence each other. For example, shade provision (a local environmental condition) can impact health directly by reducing heat stress but also make walking in a green space more appealing, improving physical health and activating the stress reduction pathway. At the simplest level mental and physical health also influence each other ([Barnett et al., 2012](#)). These complex relationships are described in the sub-sections below, and the role of effect modifiers are outlined in [Section 2.2](#).

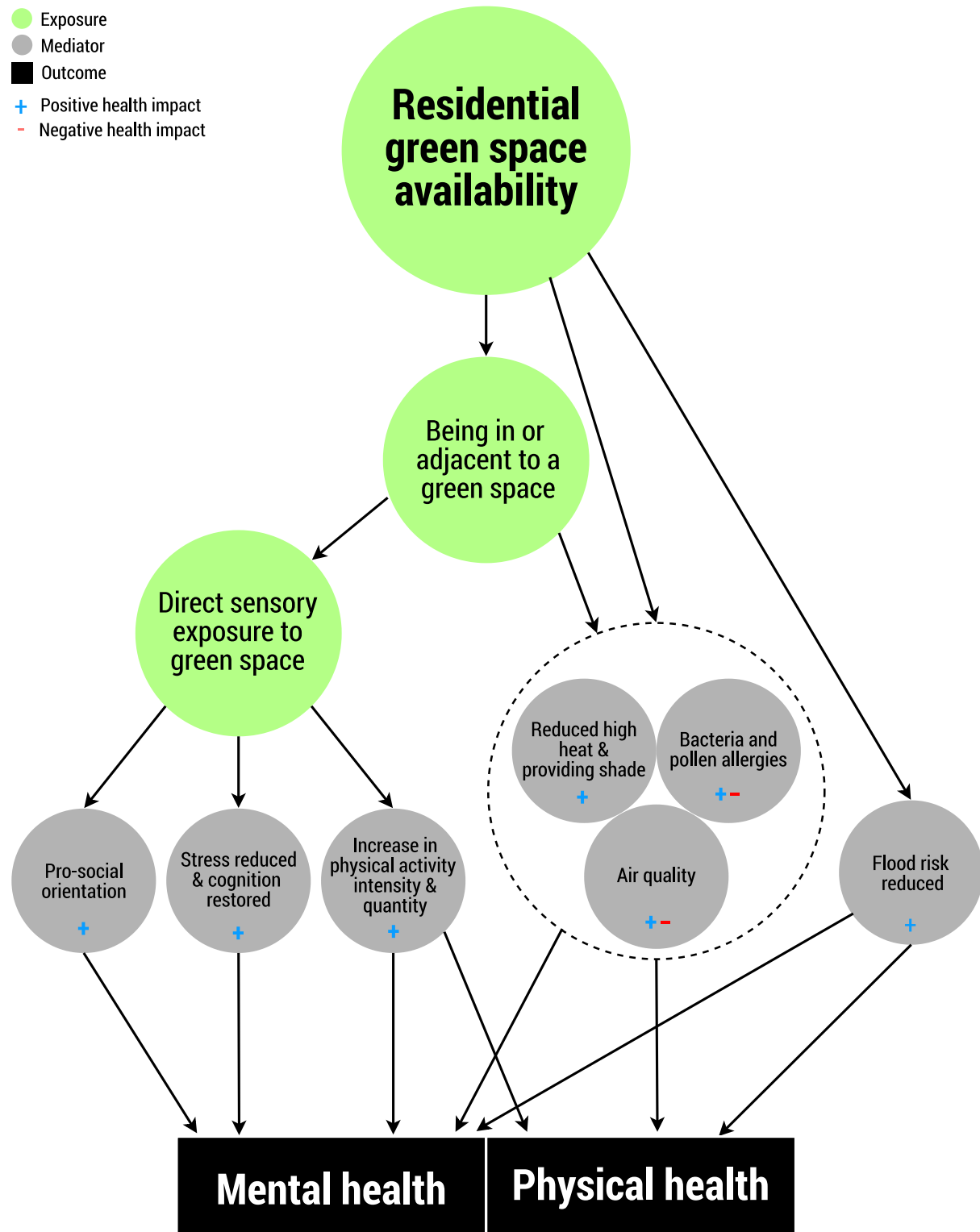


Figure 1. Pathways from residential green space availability to health through different sub-exposures and mediators. Details on these pathways and their positive or negative impacts on health are found in Sections 2.1.4.1 and 2.1.4.2. Feedback between exposures mediators and outcomes have been excluded from the diagram for clarity.

2.1.4.1 Direct sensory exposure pathway

Green space impacts mental health is mostly through sensory exposure (Figure 1). For example, it can directly reduce stress and improve cognition, as identified in the Stress Reduction Theory (SRT) (Ulrich, 1983) and Attention Restoration Theory (ART) (Kaplan and Berman, 2010). Indirectly, sensory exposure to green spaces can also encourage pro-social behaviour (Liu et al., 2018), which is again important for mental health (Miles et al., 2021) and makes physical activity more appealing (Hunter et al., 2015). The latter positively impacts both mental and physical health (Ohrnberger et al., 2017).

2.1.4.1.1 Sensory contact as part of nature experiences

During an experience of nature, individuals combine sensory information with an understanding of the ecosystems they are sensing and other aspects of the nearby environment, for example, the presence/absence of nearby traffic. Some senses work at a distance and can extend across different ranges. These include vision, hearing and, at shorter distances, smell. The important theoretical role of sensory perception has led to studies assessing sensory exposure to green spaces as a mediator of green space and health associations. Most studies have focused on sensing through vision and found views of green spaces to have a positive effect on health (Grinde and Patil, 2009). There is also empirical evidence that other senses (e.g. sounds, smells and touch), are important to our perception of natural environments (Franco et al., 2017). Furthermore, our senses work together to help us perceive our surroundings, including natural environments, as one total experience, which means that exposing multiple senses to natural environments may have non-additive and potentially multiplicative effects (Bundy et al., 2002; Grahn and Stigsdotter, 2010).

It is important to note that processes outside of a person's sensory range can influence their experience within their sensory range and, therefore, health. For example, take the case of a large forest behind a row of buildings. Although not directly within sensory range, the forest might contain many mobile species (for example, birds) that may cross a person's visual exposure range and give an increased perception of biodiversity and restoration (Dallimer et al., 2012). Another example is a park surrounded by a vast forest or grassland. Visiting this park may give someone a sense of 'being away' (an important component of ART) due to

their being a lack of urban developments nearby, even though they cannot see all of the forest/grassland.

2.1.4.1.2 *Environmental psychology theories*

Direct experiences of nature resulting from increased residential green space have been linked with improved cognition and reduced stress in different experiments and epidemiological studies, in line with the SRT (Ulrich, 1983) and ART (Kaplan, 1989). Both low perceived stress and low cognitive fatigue are important aspects of good mental health (Fusar-Poli et al., 2020). Therefore, these pathways are often cited as the reason for general improvements in mental health caused by nature in studies assessing residential green space and mental health associations.

2.1.4.1.2.1 *Biophilia and evolutionary theory*

Both SRT and ART argue that there is fundamental human appreciation of certain natural environments. This is broadly due to certain natural environments providing resources for drinking water, food and shelter from the elements, increasing the likelihood of pre-agricultural revolution survivability (Ulrich, 1993). Therefore, under natural selection, the share of individuals with traits that felt relaxed, restored, and positive feelings towards these environments would become a larger proportion of the population. This would have been the case for most of human evolutionary history. With the introduction of farming ~10,000 years ago, humans would find feelings in these environments less likely to increase their survivability.

What environments would increase the survivability of pre-agricultural revolution humans and our ancestors? More generally, it has been suggested that environments with “...*water, trees and foliage are all indicators of the habitats in which human survival is more likely*” (Kaplan, 1987). It has been argued that environments that seem easy to move through (allowing wildlife escape opportunities), provide shelter, and have resources for food and drinking water would be the most restorative (Ulrich, 1993). Due to natural selection pressures from other plants and animals, it is unlikely that ecosystems that enhanced survivability only had identifying features directly related to survivability. Therefore, there may have been natural selection for more obvious features of ecosystems that indicated it was a place that interacting with would enhance survival chances. One example is biodiversity,

more obvious from a distance as being a good indicator for the abundance of food and shelter resources within, and therefore may have been natural selection for humans that felt restored and de-stressed in biodiverse environments—it is well-established theory that ecosystem productivity increase with biodiversity per unit area (Ruijven and Berendse, 2005). Another possibility is that environments with abundant unthreatening wildlife suggest a low density of predators. Despite the argument that environments with characteristics that improve pre-agricultural revolution human survivability are better for restoration, there has been little in-depth research to identify ecosystems that meet these criteria (Joye and Dewitte, 2018). Much empirical research on ART and SRT has been driven by understanding the restorative qualities of environments commonly found in the study's geographic context or relevant to stakeholder decisions in planning and policymaking. Recent evidence in the UK shows that more natural landscapes may be more psychologically restorative (although other elements can be more subjectively aesthetically pleasing) (Hoyle et al., 2017). This may be because more natural landscapes are less of an abstraction of the environment humans would have evolved into.

2.1.4.1.2.2 *Stress reduction theory*

The developed SRT states that individuals will have an unconscious reaction when exposed to natural environments, followed by a cognitive and emotional appraisal, which leads to a physiological response (stress or relaxation) (Ulrich, 1983).

A systematic review of experiments (random controlled trials, controlled clinical trials, and before and after studies) on green space mental health benefits highlighted empirical support for different emotional and subsequent physiological and psychological indicators of stress reduction (Corazon et al., 2019). This review also found that only two studies out of 36 reported effect sizes, which makes the general understanding of the effect magnitude of nature experience stress relief difficult. Another finding is that psychological rather than physiological measures were more commonly used (Figure 2). While most psychological indicators were of the emotional affect, some also represented stress, and general mental wellbeing, which would be impacted “downstream”, a causal pathway after the emotional and cognitive appraisal.

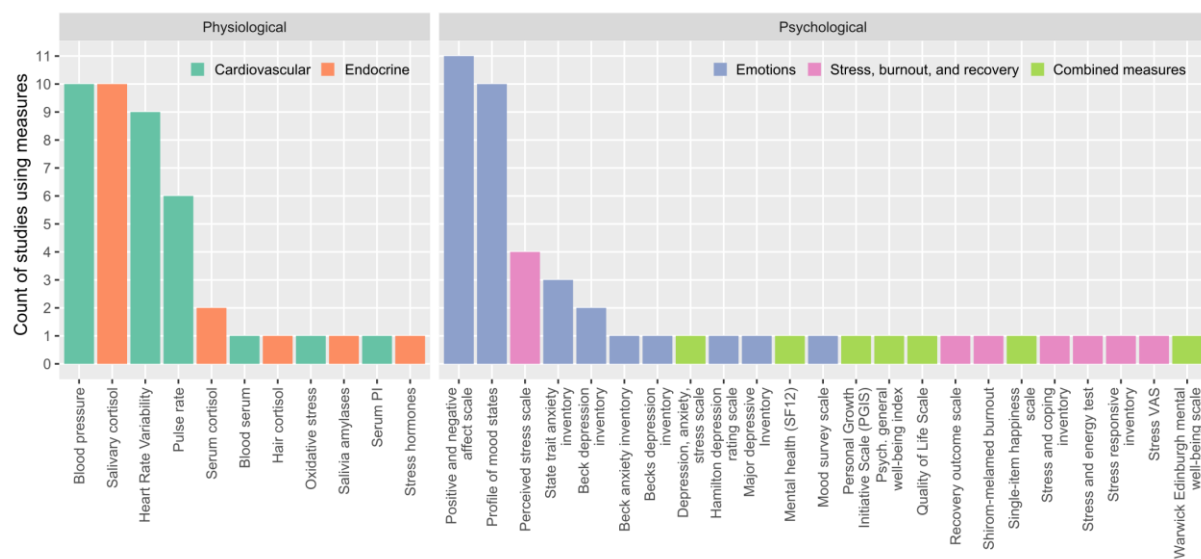


Figure 2. Physiological and psychological measured as response variables to green space exposure within experiment studies testing stress reduction theory. Data from (Corazon et al., 2019).

The review found a homogenous and statistically significant impact of natural environment exposure on unconscious emotional reactions (the focus of most studies). The few studies looking at impacts on self-perceived stress, well-being, and quality of life were also found to have positive impacts. Despite the widespread use of cardiovascular and endocrine measures, the evidence for a physiological response to natural environment exposure was less clear with many studies not including control groups. When they did, there was often no or little difference between natural environment exposure and the control group. More research in this area that includes controls, measurement instruments sensitive enough to pick up “meaningful” effects, and appropriate measurement intervals is needed.

2.1.4.1.2.3 Attention restoration theory

In the ART, experiencing natural environments (including those with water and vegetation) can reduce directed attention fatigue. Directed attention is the ability to focus on one stimulus while suppressing others (Kaplan and Berman, 2010). All humans have a finite capacity for direct attention to tasks, and once this is expended, cognitive function reduces. ART identifies four qualities as impacting the restorativeness of natural environments: soft fascination, being away, extent and compatibility (Kaplan, 1995). Fascination is defined as ease of attention. In natural environments, this attention is theorised to be effortless, allowing reflection and attention to occur simultaneously and is called soft fascination (Basu et al., 2019). Hard fascination (such as watching a television programme) is less restorative as it

forces all attention on it, not allowing for moments of reflection. Being away is defined as the absence of everyday concerns (for example, personal social or economic situations) and from sources of mental fatigue that can be induced by modern technology and the built environment. Extent is the scope of experiences that can be felt in a natural environment and the coherence of experiences. Having many things (for example, higher amounts of biodiversity) to see or do in a fixed area increases that area's scope of experience. Subsequently, having a larger area may also increase the opportunity for more of these experiences. Compatibility is achieved when an individual's expected experience in a natural environment is met. If a natural environment has the above characteristics but is not a desired experience, this can increase the amount of attention required from a user, reducing its ability to restore attention ([Kaplan, 2001](#)). Cognition is also impaired due to increased stress ([Sandi, 2013](#)), therefore, it may be that a reduction in stress caused by the mechanisms outlined in SRT (Section 2.1.4.1.2.2) is also partially responsible for observed improvements in cognition when exposed to natural environments.

A recent meta-analysis and review of experimental studies that test ART found compelling evidence that exposure to natural environments had positively impacted three domains of cognitive functioning (counteracting attention fatigue): working memory, increased attentional control (ignoring distractions when focusing on one task) and cognitive flexibility ([Stevenson et al., 2018](#)). Measures used to test the functioning of these three cognitive domains in the studies reviewed by Stevenson et al. (2019) are shown in [Figure 3](#) below.

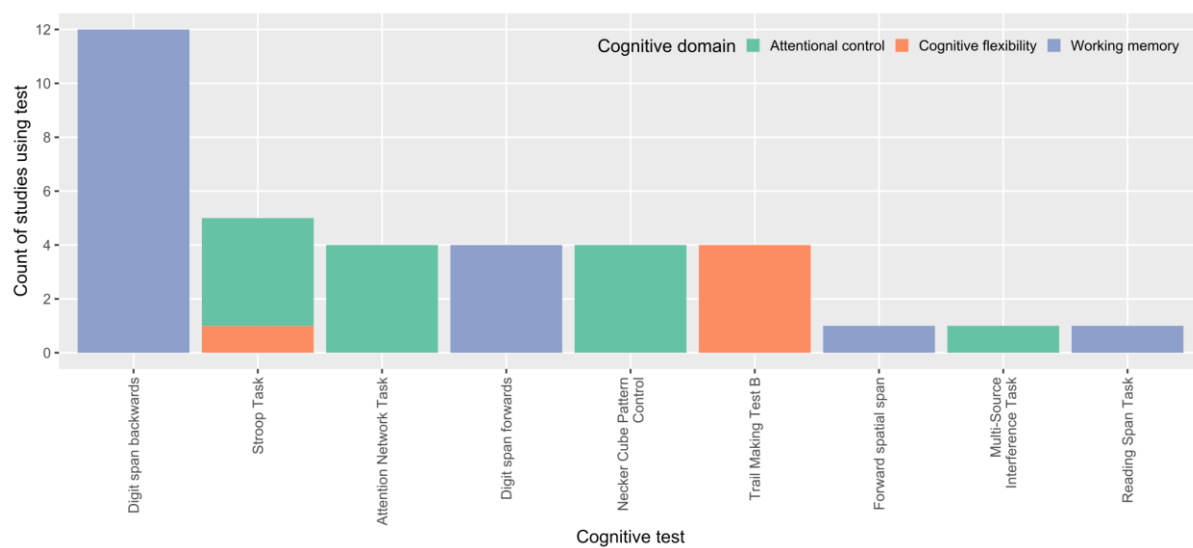


Figure 3. Count of studies that used cognitive tests to test restoration of cognitive fatigue after experiencing natural environments. Tests which were used on the same domain more than once in the same study were counted as one test. Data from (Stevenson et al., 2018).

The review by Stevenson et. al. (2018) found that experiencing natural environments had mixed or little effect on the three cognitive domains of: impulse control, processing speed, vigilance, and visual attention. The lack of consistent evidence that natural environment experiences impacted these three domains was due to either deficiencies in study design, a lack of studies or structurally within how the theory of ART is specified—the authors suggested more research in all these areas and further development of ART.

Determining cognitive functioning across multiple domains (including those with less compelling evidence) is possible by deriving different measures from the same cognitive test. For example, the Stroop Task can be used to assess both attentional control and cognitive flexibility. The functioning of one cognitive domain can be a mediator towards another. For example, attentional control is core to working memory (Shipstead et al., 2014).

Without controlling attention, sustaining the focus that manipulating working memory requires is difficult. A larger capacity for working memory also mediates increased control of emotional regulation—something important to a person’s general psychological wellbeing (Schmeichel et al., 2008). Furthermore, if a person is experiencing attention fatigue repeatedly, this may result in continuous poor working memory, which may lead to periods of poor emotional control, and subsequent periods of anxiety or anxiety disorders, which are detrimental to mental health (Kashdan et al., 2008). Recent studies have also found

improvements in working memory linked with reduced anxiety and depression vulnerability in adolescents (Beloe and Derakshan, 2019).

2.1.4.1.3 Increased physical activity intensity and quantity

Several mechanisms are behind a green (vegetated) space's ability to encourage physical activity. It may be that these environments are more aesthetically pleasing (Shanahan et al., 2016). The attractiveness of physical activities in natural settings may also be increased by the mental health benefits from being in nature, including stress reduction and restoration of cognitive fatigue (Calogiuri and Chroni, 2014). Regulating ecosystem services that decrease in magnitude at further distances away from vegetation may also encourage physical activity when vegetation is present. For example, shade provision by trees over concrete with a high specific heat capacity may make walks more attractive in high temperatures (Cao et al., 2006). However, it would be expected that the direct impact of plants improving air quality would be much smaller than their ability to encourage physical activity through aesthetics and shade. This is due to the potential of plants to enhance air quality being relatively small (estimated at 1-2% of emissions in London) (Tallis et al., 2011) and consequently having a much smaller impact on health than encouraging physical activity under average pollutant concentrations (Tainio et al., 2016).

2.1.4.1.4 Prosocial orientation

Prosocial orientation is an individual's disposition to behave prosocially and be empathetic (Eisenberg et al., 2006). Green space sensory exposure is linked to a more positive emotional state due to lowered stress and cognitive fatigue (see Section 2.1.4.1.2.2 and 2.1.4.1.2.3) which is a mediator to increased prosocial orientation (Putra et al., 2020). Being more prosocially orientated supports a person having prosocial behaviours and is a mediator towards improved mental health (Nelson et al., 2016). Conversely, a handful of smaller experiments have found that larger group-size numbers can negatively impact perceived restoration from nature walks (Marselle et al., 2015), explained by increasing mental stimulation (from conversing with and looking after friends or family members). Understanding trade-offs or synergies between group sizes and restoration could lead to more social prescribing for restoration or the design of certain green and blue spaces, that allow for solitary psychological restoration. Green spaces may also provide a more attractive place to

individuals to gather more frequently, which may create a feedback-loop increasing an individual's pro-social orientation through time (Putra et al., 2020).

2.1.4.2 *Changing environmental conditions pathway*

Residential green space can impact a person's mental and physical health by changing local environment conditions. Changes in some environmental conditions caused by green space can occur farther away than typical "residential exposure" (Burkhard et al., 2014). For example, local green space may not only reduce flooding and subsequent health impacts in the place where people live but also downstream. However, residential green space would still impact the environmental conditions outlined below.

2.1.4.2.1 *Air quality*

Plants have a mixed impact on air quality and, therefore, the mental and physical health of those living nearby. In experimental settings, a higher plant leaf area has been correlated with reduced air pollutant concentrations by creating a larger deposition surface for Particulate Matter (PM) and O₃ and more stomata to uptake gaseous NO₂ and SO₂ (Diener and Mudu, 2021). However, the same surface area that retains deposited particulate matter also creates a barrier to trap pollution generated underneath it (for example, alongside roads), preventing it from dispersing, which reduces local air quality in these areas (L. Chen et al., 2016). In addition, plants in green spaces produce Biological Volatile Organic Compounds (BVOCs), which contribute to ground-level O₃ concentrations, which are responsible for respiratory diseases (Kim et al., 2020). For example, one study in Beijing found BVOCs to account for 30% of Ozone concentrations in the summer and are a significant contributor to respiratory disease (Ren et al., 2017).

A recent review has found a lack of health impact assessments of what may be a relatively small (estimated at 1-2% of emissions in London) (Tallis et al., 2011) total improvement in air quality caused by vegetation (rather than an absence of urban pollutant sources) (Diener and Mudu, 2021). A systematic review of (mostly cross-sectional) studies assessing green space as an effect modifier of air pollutants and health associations has found mostly inconsistent results (40% negative effect modification on poor health outcomes, 35% no or positive effect) (Son et al., 2021).

If plants were found to positively impact air quality overall (considering their potentially negative and positive effects), the evidence suggests this would lead to more positive mental and physical health outcomes. Systematic reviews have found poorer air quality associated with worse physical and mental health (Zundel et al., 2022). Robust longitudinal evidence also exists. For example, changes in mental health have been associated with changes in multiple air pollutants in prospective cohorts (Bakolis et al., 2021). A recent review argues that decreased air pollutant exposure during different pre and post-natal periods would ultimately lead to more pro-social behaviour in children due to improvements in cognitive development (Putra et al., 2020).

2.1.4.2.2 Reducing high heat and providing shade

Mental and physical health may be improved by living in a neighbourhood with more green space due to the ability of vegetation to reduce air and surface temperatures (Manoli et al., 2019). In the UK, for example, exposure to extreme heat has been found to increase poor physical health outcomes such as hospitalisations and mental health outcomes such as suicide (Page et al., 2007). Trees can reduce temperature by providing shade and through evapotranspiration, which removes latent heat (Taha, 1997). There is some evidence that municipality-level vegetation cover can modify temperature-mortality associations (Pascal et al., 2021).

2.1.4.2.3 Flood prevention

Mental health outcomes such as depression, anxiety and post-traumatic stress disorder in individuals who were victims of residential floods have been found to increase greatly in the following months (19–30% in the UK) (Cruz et al., 2020). The physical health impacts of flooding include mortality, skin infections and respiratory illnesses, although the incidence rates are lower compared to mental health outcomes (Alderman et al., 2012). One of the key benefits of urban green spaces is mitigating peak stormwater flows, which can lead to flash floods (Richards et al., 2022). Therefore, increasing green space may partially reduce the incidence of poor mental and physical outcomes due to flood events (Kingsley and Ontario, 2019). There is scarce evidence of the causal pathways from residential green space via flood impact mitigation to improved health outcomes.

2.1.4.2.4 Immunoregulation and allergies

There is a complex relationship between green space immunoregulation and pollen allergies. The biodiversity hypothesis suggests that early-life, pre and post-natal exposure to natural environments increases intestinal microbial diversity, improves immune balance and lowers allergenic response to pollen (Haahtela, 2019). However, urbanisation within cities and urban migration has decreased European populations' green space exposure (Fuller and Gaston, 2009). This has led to a decrease in early-life green space exposure, which has increased the number of people suffering from pollen allergies. Air pollutants also interact with pollen, creating more severe allergy symptoms (Lam et al., 2021). Therefore, theoretically, more residential green space may be associated with worse physical health outcomes in adults with pollen allergies. This may translate to mental health, as it could discourage socialising. However, epidemiological research has found positive associations between residential green space and mental health in individuals suffering from tree pollen allergies (Aerts et al., 2020). This indicates that the positive green space pathways may be more important for mental health than pollen allergies. Furthermore, likely due to the absence of air pollution, and without the presence of highly allergenic species in green spaces (such as *Betula pendula*) green space exposure has been found to reduce the risk of severe pollen allergy events (Stas et al., 2021). Gaps in understanding however, on what species of trees and grass that are more allergenic remain (Sousa-Silva et al., 2020).

2.2 Green space effect modifiers

Effect modification of green space and health associations is the process by which a factor causes a disruption in green space health impacts at one or many points along one or many of the green space exposure – health pathways (VanderWeele, 2009). This can translate to a change in one or many of the magnitude, direction, or shape of statistically modelled residential green space and health associations. It is assessed based on a counterfactual, specifically, the effect of green space on health with or without the presence of said factor (Bours, 2021). Effect modification is a theoretical rather than statistical concept and should not be misunderstood for regression interaction terms, which are one method used to assess effect modification (Bours, 2021).

Effect modifiers of associations between residential green space and health can be generalised into four broad categories: the physical characteristics of green space, environmental conditions within the green space itself and near to where people live, the socioeconomic conditions of the local area and personal characteristics. This is a modified framework from that proposed by [Marselle et al. \(2021\)](#).

2.2.1 Understudied effect modifiers

In the subsections below, rather than providing an exhaustive review of all potential effect modifiers, in each of these categories, I review a selection that are either understudied or require most robust evidence when it comes to assessing their modification of “residential green space exposure” (see definition in Section 2.1.3). For each effect modifier, I summarise why it may be important to study, the theoretical reasons why it may be an effect modifier, and the existing evidence base (or lack of it) to support it as an effect modifier.

I define an effect modifier of green space and health associations as being “understudied” if it meets one or many of the following criteria. (a) It has rarely (if ever) been studied as an effect modifier despite there being strong justification for why it may be. For example, it may be existing theory suggesting or previous experiment research finding it to modify the health benefits of one-time sensory exposure, which may translate to residential green space exposure. (b) If it is important to assess based on it impacting other priorities (e.g. environmental conservation). For example, it is assumed to have no effect despite impacting lots of green space). (c) If there is a lack of longitudinal evidence to support its modifying effect.

2.2.1.1 *Traffic*

Green cover alongside roadside verges has been promoted as a source of services that ultimately benefit health without understanding the role traffic has as an effect modifier ([Phillips et al., 2020](#)). Such evidence is essential to guide policy as there have been calls to define better how different types of public space infrastructure impact physical activity levels ([Koohsari et al., 2015](#)). Personalised transport networks are also one of the key components of urban design and planning, with footways often planned adjacent to roads. Therefore, if

simultaneous experiences of green space and traffic are found to change associations between green space and health, there are important implications for future urban planning and design.

Experiencing different types of green cover may have a different association with health when simultaneously experiencing traffic. Traffic generates noise pollution and visual distraction, which can reduce the sense of “being away” and otherworldliness that experiencing a natural environment experiences can provide, a factor hypothesised to impact natural environments stress reducing and cognitive restoration capacity (Kaplan, 1995).

Paths/trails in parks (with no traffic) are one of if not, the most important features of parks which impact their ability to encourage physical activity (Akpınar, 2019; Y. Chen et al., 2016; Schipperijn et al., 2013); which is a major health and perceived health determinant (Cavill et al., 2006). The presence of trees alongside a street (with traffic) has also been found to increase the likelihood of someone taking a walk (Barnett et al., 2017). However, previous work has found little difference between green cover adjacent to roads or total green cover within 1.6 km of a person’s residence associations with their body mass index in Ireland (Carthy et al., 2020). I could find no studies on the effect of road traffic green space and health associations (residential green space or otherwise). However, traffic is a considerable source of correlated air and noise pollution (Fecht et al., 2016). Irrespective of their source, these have been assessed as green space and health effect modifiers in a limited set of studies as discussed in Section 2.2.1.8. Furthermore, few studies consider how visible green space near where people live impacts their health and mostly assess the *availability* or *accessibility* of the nearest green space (see Section 2.1). Exceptions include one study in China, which found the average leaf area index from roadside images (calculated using Google Street View data) negatively correlated with incidences of geriatric depression, while the availability of natural environment land cover was not (Helbich et al., 2019).

2.2.1.2 Socioeconomic deprivation

Individuals living in neighbourhoods with higher socioeconomic deprivation have poorer health (Pathirana and Jackson, 2018), even after adjusting for individuals' socioeconomic position (Meijer et al., 2012). Should green space health associations be stronger in more socioeconomically deprived areas, providing or protecting green space in these areas could

reduce health inequalities, particularly in the UK, where health disparities amongst different socioeconomic groups are widening (Marmot, 2020).

There are some potential mechanisms to explain why deprivation may positively modify green space and health associations. Those living in less deprived areas could have the disposable income to substitute poor green space access (and its health benefits) with paid gyms, for example. Therefore, the health benefits of having additional green space for them would be lower than in more deprived populations (Rigolon et al., 2021). A second theory suggests that those in less socioeconomically deprived areas often have a health status that is more difficult to improve due to them having a higher socioeconomic position, which is linked to better health literacy (Svendsen et al., 2020) and health in general (Stringhini et al., 2010). Therefore, an increase in residential green space would not be linked to better health in those already healthy populations. Whereas, populations in more deprived areas that often have poorer health (Pathirana and Jackson, 2018) would conversely benefit from green space (Rigolon et al., 2021). A related theory is that individuals living in more deprived areas may have higher baseline stress levels compared to those in less deprived areas, and numerous studies have shown that a stressor is important for stress reduction from green space sensory exposure to occur according to SRT (see Section 2.1.4.1.2.2). Stressors are often introduced before experiments can detect green space health effects, e.g. the seminal study by Ulrich (1983).

The evidence for deprivation to modify green space-mental health associations is inconclusive, especially when compared to green space-physical health associations. Most analyses across 122 recently systematically reviewed studies on physical health association found deprivation to be a positive effect modifier, supporting the theory that green space has an equigenic effect (Mitchell and Popham, 2008; Rigolon et al., 2021). However, fewer studies have been on the modifying effect of socioeconomic deprivation on mental health and residential green space associations. Some found it to be a positive effect modifier (McEachan et al., 2016; Mitchell et al., 2015), while others have found no effect (Nichani et al., 2017; Sugiyama et al., 2016; Triguero-Mas et al., 2015). Systematic reviews on green space benefits to health have also repeatedly called for more longitudinal studies (Howard et al., 2017; Marselle et al., 2021; Nguyen et al., 2021). One recent longitudinal data analysis found that associations between mental health and cumulative exposure to green space over time were associated with better mental health (Geary et al., 2023). Furthermore, they found

that those in more deprived areas benefited more from cumulative exposure than those in less deprived areas. However, this was a between-person comparison, possibly leaving it vulnerable to within-person confounding.

2.2.1.3 *Perceived naturalness*

One green space characteristic that may be an important modifier of its benefits is its perceived naturalness. Most of the literature assessing this has recorded the health responses to individual visits to or views of green spaces perceived as more natural. However, the external validity of these studies could improve regarding the populations they represent and the impact of potentially cumulative exposure on their health over longer periods. As is the case with biodiversity (Section 2.2.1.6) and water (Section 2.2.1.4), it is important to identify the strength of effect modification of perceived naturalness of green space on mental health and green space associations to see if environmental conservation and public health promotion goals can be aligned in land-use decision making (Pett et al., 2016).

Different theories and hypotheses suggest the naturalness of a green space may modify different pathways from residential green space exposure to good health, and these suggest mostly positive effect modification to occur. According to SRT, the ecological complexity of green space supports stress reduction (Ulrich, 1993) (See Section 2.1.4.1.2.2). More natural environments in the UK tend to have a higher structural complexity and species richness, providing a wider extent of experiences and increasing their ability to generate soft fascination, a key mechanism in ART (Kaplan, 1989, 1995) (Section 2.1.4.1.2.3). The more natural a green space, the more it is like “being away” from typical human-created environments, another mechanism within ART that leads to increased environment restorativeness. Underlying ART and SRT, biophilia, and evolutionary theory propose that humans have evolved to be inherently drawn to more natural features of landscapes because they provide resources for survival (Kellert and Wilson, 1993) (see Section 2.1.4.1.2).

Furthermore, recent work has found that some individuals suffer from ecological grief after the ecological degradation of land from its most natural state, even over longer periods (Cunsolo and Ellis, 2018), which may negatively impact their mental health if they see this nearby. However, some theories suggest that more natural environments may be less beneficial to mental health due to poor visibility within them, making people less safe inside

them (Sonti et al., 2020). In a more natural deciduous forest with reduced visibility due to overlapping branches and an understory, visitors may feel prospective criminal refuge is increased, making it easier to commit crimes (Andrews and Gatersleben, 2010). This structural complexity may also hinder the development of footpaths, making said green space more inaccessible. Individuals may also have a biophobic reaction if they perceive more diverse landscapes to potentially harbour species they are frightened off, for example, spiders and snakes (Ulrich, 1993).

I found no residential exposure studies investigating the effect of residential green space perceived naturalness on health. However, there have been studies using other ecological quality indicators. A recent systematic found that the positive modifying effect on green space-mental health associations from another ecological quality indicator—biodiversity in these studies was inconclusive (Marselle et al., 2019). Furthermore, living further away from protected areas in London was associated with lower life satisfaction (Knight et al., 2022).

Some studies conducted in different parts of the world have investigated differences in the effect of green space on health across a gradient of perceived naturalness, from either true exposure events on the same day (Hoyle et al., 2017; Liu et al., 2018) or based on their memory of being in a green space (Liu et al., 2022). Additionally, many of these use convenience samples of university students as their study population. Most studies with university student populations find exposure to green space that is more natural is better at improving mental health. For example, in university students, this exposure gives them more self-rated psychological restoration (Liu et al., 2018) and vitality (a component of a psychological restorative state) (Van den Berg et al., 2014). University students have also identified more natural green spaces to be perceived as more psychologically restorative in complete crossover experiments based on pictures/audio/video (Carrus et al., 2013; Chen et al., 2023; Uebel et al., 2021). Conversely, one study did not find perceived naturalness as an important predictor of environment calmness (a potential mediator to mental health) by university students in outdoor exercise programs (Klaperski et al., 2019). Members of the general public have also declared green spaces that they have visited, which are more natural to be places of more positive affect (Fisher et al., 2021) and reduced stress (Schebella et al., 2019). Additionally, the perceived naturalness of environments to outdoor exercise program participants (again in the general public) has reduced their anxiety (Mackay and Neill, 2010) and, in those over 55, increased their emotional well-being (emotional affect and happiness)

through the mediator of perceived restorativeness (Marselle et al., 2016). Two analyses of the same participants ($n = 1411$) found that after walking in a more natural green spaces across multiple sites in the UK, was also perceived to be more restorative (Hoyle et al., 2019, 2017).

2.2.1.4 Water

Green spaces that are seasonally/permanently “wet” or seasonally water (wetlands) are some of the most biologically diverse ecosystems in the UK and are often priority habitats of concern for environmental conservation (Maltby et al., 2011). For example, in land management plans, riparian zones around rivers are protected (Lind et al., 2019), and a United Nations (UN) convention was created to protect wetlands (Ramsar Convention on Wetlands, 2007). In recent years there has also been a trend for encouraging “blue-green infrastructure” (i.e. wetlands), for both recreation and its ability to mitigate peak stormwater flows, particularly in urban areas by architects and planners (e.g. water-sensitive urban design) (Dolman et al., 2013; Pille and Säume, 2021). Determining if introducing wetland elements into green spaces modifies their health benefits will help determine if conservation, recreation, stormwater management and health benefits can align.

Theory suggests that introducing water into green spaces may make them more psychologically restorative. Specifically, having wet or seasonally wet areas overlapping green spaces may provide a larger extent of experiences and soft-fascination, which are drivers of an environment’s restorativeness under the ART (Basu et al., 2019). Photographs of green spaces that contain water have also been identified as the most restorative (White et al., 2010). Individuals would also be less likely to suffer heat stress in or near wet or wet green spaces on hot sunny days, which could translate to improved mental health (Thompson et al., 2018), owing to their higher levels of evaporative cooling (see Section 2.1.4.2). Wetlands are the coolest green spaces in temperate climates (Gohr et al., 2021).

The few studies in temperate climates have found wetlands to be associated with better visitor mental health (Maund et al., 2019; Reeves et al., 2019; Zhai and Lange, 2021). Another study also found them to provide an experience distinct from managed landscaped parks, providing a more natural experience and sense of refuge (Sonti et al., 2020). Researchers have suggested that between 3–7% of watersheds should be wetlands in temperate climates to provide benefits, e.g. flood control, which is also a potential mediator to health benefits (see

Section 2.1.4.2.3) (Mitsch and Gosselink, 2000). In the UK, wetlands may also be associated with negative health in the future. Vector-borne disease transmission (e.g. malaria) did occur in the UK before the turn of the 20th century (Gowland and Western, 2012; Kuhn et al., 2003). A reversal of wetland loss combined with global heating does have the potential to cause a re-emergence of malaria transmission in the UK, according to models (Baylis, 2017), and consideration of this has been advised when adopting broader green infrastructure policies in the UK, including introducing wetland elements (Medlock and Leach, 2015).

Despite evidence for a positive impact of wetland environments on mental health, there is a lack of studies on how water in green spaces' can impact mental health above and beyond what they ordinarily provide. Furthermore, whether inside a green space or not, freshwater environments are rarely investigated as an environment that may impact mental health (McDougall et al., 2020).

2.2.1.5 *Population pressure*

Studies have shown that while European cities are increasing in population density, the respective vegetated area per person has not proportionally expanded (Fuller and Gaston, 2009). This may generate population pressure on green spaces in high-density urban areas, making them feel crowded, which may harm the positive benefits of specific health pathways. A green space population pressure could be defined as the sum of time all nearby residents are likely to visit a green space, given equal (or distance-weighted) opportunity to visit a green space. There has been a recognition of the need to estimate how natural ecosystems' health benefits change with per capita population pressure on them increases (Ekkel and de Vries, 2017). However, few studies investigating associations between residential green space and health consider the population pressure on them (Engemann et al., 2019; Jarvis et al., 2020). While there are theoretical reasons to suggest that population pressure may be an important effect modifier, governments have only recently recognised this. As green spaces were one of the few places available for individuals to spend time during COVID-19 national lockdowns, there were reports of crowding in areas of low green space per capita (Slater et al., 2020), which has also verified in simulation studies in Italy (Geneletti et al., 2022). This has further highlighted the need to assess how green space crowding (a symptom of population pressure) impacts its health benefits.

Crowding from population pressure in a green space may reduce cognitive restoration, as previous experimental research has found experiencing crowds to be more cognitively fatiguing (Mavros et al., 2022). Furthermore, it may impact stress-reducing qualities, as they are perceived to be less natural, or the sounds and sights of biodiversity are masked by crowd noise. In addition, it may be less desirable for people to undertake physical activity in crowded green spaces (Arnberger, 2012; Neuts et al., 2012) and, more crowded green spaces may make infectious disease transmission easier, which was a concern in green spaces during the COVID-19 pandemic (Lopez et al., 2021).

As mentioned before, few studies investigate the impact of population pressure as a modifier of residential green space and health associations. However, some studies identify “urbanicity” as a potential effect modifier related to population pressure as, generally, there is a higher population pressure on green spaces in more urban areas. This is due to a lack of green space in higher population density areas (Fuller and Gaston, 2009), and population density being a key correlate of urbanicity. However, results have been mixed. In the UK the effect of vegetation metrics within a walkable distance from a persons residence was found to reduce adiposity more in the top two quantiles of urbanicity (Sarkar, 2017), but not to significantly vary amongst urban and rural areas in another study (Wheeler et al., 2015). One Dutch study found the effect of urbanicity to be inversely proportional to vegetation cover, and when both were included in models, its impact on modifying vegetation density's effect on health was small (Maas et al., 2006). Another Dutch study found larger reductions in morbidity associated with green space in moderately urban (rather than rural or urban) areas (J. Maas et al., 2009). In China, physical activity promotion from green space was found to be higher in the top quantile of urbanicity (Liu et al., 2019), and in the United States of America, the mental health benefits of natural environments were more significant in urban than rural areas (Bezold et al., 2018). However, few studies analyse how different levels of urbanicity within a city modify the relationship between natural environments and health. One study in Australia found that population density, often part of urbanicity definitions, did not modify the effect of natural environments on mental health in urban areas (Ambrey, 2016).

2.2.1.6 Biodiversity

The biodiversity of green space may be an important positive effect modifier along many green space-health pathways, both through sensory exposure and it changing environmental

conditions (Romanelli et al., 2015). However, a review found its impact on mental health inconsistent in experimental studies and rarely assessed in cross-sectional or longitudinal studies (Marselle et al., 2019). There has also been an interest in the alignment of experimental units for research in environmental conservation and the extinction of experience (both use biodiversity value as an important indicator) and other ecosystem services, such as mental health benefits from direct experiences of nature (Collins et al., 2020; Howard et al., 2017). This is to aid in the discovery of trade-offs and synergies between land-use decision-makers who want to maximise benefits to biodiversity and people (Washbourne et al., 2020).

Most of the research in assessing the mental health benefits of green space study used the SRT (Section 2.1.4.1.2.2) and ART (Section 2.1.4.1.2.3) frameworks to explain why biodiversity had a positive modifying effect (Marselle et al., 2019). Specifically, more biodiverse areas provide an experience closer to what we would have known in our evolutionary history and more opportunities for soft fasciation and a wider extent of experience. Variables to represent biodiversity in these studies ranged from species richness and abundance (of one taxon or multiple taxa), perceived species richness, composite measures of habitat diversity naturalness (combining vegetation structure composition and animal/plant diversity) and perceived naturalness (I explore this in more detail in Section 2.2.1.3). Other health pathways outside of ART and SRT may be modified by green space biodiversity. Given sufficient water availability, soil nutrition, sunlight and heat, areas that are allowed to develop to become more diverse have a higher overall ecosystem function and larger leaf area and living biomass (Brun et al., 2019; Ruijven and Berendse, 2005). Benefits that scale partially with leaf/living plant area, such as regulating services (stormwater regulation, air quality improvements), will therefore increase in more biodiverse green spaces (Harrison et al., 2014) along with the health benefits they support down pathway (see Section 2.1.4.2) in the right environmental conditions. Areas with a higher overall biodiversity often have a higher diversity of soil microbiota (e.g. bacteria) (Wagg et al., 2019). In the UK direct inhalation or ingestion of a higher diversity of soil microbes in more biodiverse environments in early-life increases immunoregulation throughout the life course (Gensollen et al., 2016; Rook et al., 2013) and ultimately physical (Valdes et al., 2018) and mental health (Lowry et al., 2016).

Only 14 of 24 studies in the Marselle et al. (2019) review found a statistically significant impact of green space biodiversity on its relationship with mental health (Marselle et al., 2019), although these effects were positive. The lack of statistically significant results may reflect the differences in how the sensory exposure to green spaces in these studies has been measured and modelled and the varying contexts of analyses. Most of this research has been experimental, with fewer large-scale studies conducted. The same Marselle et al. (2019) review found that fewer studies use secondary data on biodiversity and naturalness of green spaces near a person's residence (e.g. *availability, geographical area cover* or *accessibility*). Two cohort studies found no effect of neighbourhood species richness on health (Annerstedt et al., 2012; van den Bosch et al., 2015). Of cross-sectional studies with more than 1,000 people participating and using residential neighbourhood exposures, only four out of the eight in the review found a positive effect of these factors. For the rest, no effect was detected (Marselle et al., 2019). The impact of soil biodiversity on health is supported by empirical studies, which have found samples taken in the centre of a smaller town to have a higher diversity of airborne bacteria than in the centre of a nearby city (Bowers et al., 2013). Bacteria in rural homes were also found to be more diverse than in urban homes, with a negative association with the prevalence of atopy (Valkonen et al., 2015). However, few large-scale studies have investigated the role of exposure to residential soil biodiversity in modifying early-life residential green-space exposure and child or future adult health associations.

2.2.1.7 Sunlight, weather, and season

There is little evidence on how sunlight, weather, and season modify green space and health associations. One study found little effect of seasonality on mental health when exposing university students to a well-paved park (Brooks et al., 2017). Another found that landscape views in spring were more psychologically restorative according to physiological measures than the same views in autumn (Chen et al., 2023). If green space exposure is to be prescribed to improve mental health (Hart, 2016) it is important to determine if seasonality, weather and sunlight are limiting factors, as it could impact prescribing exposure to green space for mental health benefits during the majority of the year.

Why might sunlight, weather and or season be important effect modifiers? Temperate countries undergo large seasonal and inter-seasonal changes in weather conditions. Seasonal

changes have led to evolutionary adaptations from natural systems to go into periods of dormancy when nights become shorter and temperatures colder. During this time, many birds migrate or are less active, flowers are not visible, and leaves fall (making species harder to identify). This leads to lower actual and potentially perceived species richness in natural environments, which, when individuals are exposed to it, would impact psychological restoration (Dallimer et al., 2012). Effects may still be positive; for example, forest experiences in winter are psychologically restorative (Bielinis et al., 2018). More inclement weather (induced seasonally and non-seasonally) may provide mental stimulation, which will hamper restoration and reduce blue skies, which experiments using pictures show are better at psychological restoration than overcast ones (Beute and de Kort, 2013).

2.2.1.8 *Air and noise pollution*

In addition to environmental pollution being a mediator between residential green space exposure and health (see Section 2.1.4.2) it has also been identified as an effect modifier of green space and health associations in some studies. However, few studies investigate how environmental pollution modifies the relationship between actual (rather than subjective) health outcomes and different types of green space. This is despite denser vegetation overhanging roads potentially trapping air pollutants (L. Chen et al., 2016). No large cohort studies were found to be used to assess how environmental pollution may act as a modifier of green space and mental health associations. However, this has been done for physical health outcome data such as morbidity (Nieuwenhuijsen et al., 2018) and asthma hospitalisations in the UK (Alcock et al., 2017).

Green space with pollution may impact mental health by providing less psychological restoration due to it seeming less natural and making physical or pro-social activity (which green space encourages) less appealing. In experimental settings it was found that increased noise and a higher noise sensitivity were negative effect modifiers of associations between green space and self-reported or physiological proxies of psychological restoration (Dzhambov et al., 2018c; Gidlöf-Gunnarsson and Öhrström, 2007; Ojala et al., 2019; Wilson et al., 2016). Large scale survey-based research has also found that higher concentrations of particulate matter (PM₁₀, PM_{2.5}) can reduce the positive effect of neighbourhood vegetation (as measured by NDVI) and reported prescriptions of anxiolytics, hypnotics and sedatives (Klompaker et al., 2019a), self-reported incidents of depression and anxiety (Gascon et al.,

2018) and self-reported general health (Klompaker et al., 2019b). Structural equation modelling found lower noise levels and NO₂ concentrations linked with higher NDVI and better self-reported mental health in university students (Dzhambov et al., 2018b). Conversely, two other survey studies which included interactions with socio-demographic variables found no significant moderation of local perceived air quality and noise on the relationship between distance and amount of nearby natural outdoor environments (probability exposure metrics) and self-reported general cognitive abilities or general health (Dzhambov et al., 2018a; Zijlema et al., 2017).

2.2.2 Selected effect modifiers for analysis

I investigated four of the effect modifiers reviewed in Section 2.2.1 that were understudied in three epidemiological analyses. I only analysed four in order to conduct more focused analyses, and was unable to investigate all in a detailed way due to time constraints. I specifically analysed water and naturalness over other potential effect modifiers in Chapter 6 due to them being of particular interest to stakeholders in the conservation sector and there being a lack of studies conducted on them modifying residential green space and health associations. Conservationists, for example, my PhD Collaborative Awards in Science and Engineering (CASE) partner, the Wildfowl and Wetlands Trust (WWT) are interested in whether health improvements can be seen as a co-benefit to the positive conservation and recreational impacts of habitat restoration. A lack of studies on naturalness and wetness as residential green space and health effect modifiers made an exploratory cross-sectional analysis appropriate.

3 Common data and pre-processing steps

In this chapter, I summarise the common methods and datasets used to generate exposures, outcomes and effect modifier variables if included in more than one of three epidemiological analyses outlined in Chapters 4–6. Across my three epidemiological analyses, I use one or both of two datasets to identify “green space” as defined in Section 2.1.1: the UK Centre for Ecology and Hydrology Land Cover Map (UKCEH-LCM) ([Morton, 2020; Morton et al., 2021](#)) and the Copernicus tree cover density product ([European Environment Agency, 2018](#)).

I use two main data sources for health outcome data. The health outcome data also indicates individuals’ or population’s residential location which I used to estimate residential green space exposure and some confounders. The dataset I used in my first epidemiological analysis (Chapter 4) is the 2011 census in England and Wales. In Chapters 5 and 6, my health outcome data is from waves 1-9 of the Understanding Society panel/cohort survey. Both Understanding Society and 2011 England and Wales census link health outcomes to a small area of residence. The full details of the health outcomes recorded that I analysed from the 2011 census in the England and Wales dataset are explained in Section 4.2.2. Details of US, the variables I use across both analyses and why I selected them are outlined in Section 3.3.

3.1 Identifying green space

Broadly I define green space as vegetated land (see details in Section 2.1.1). For my analyses, I wanted to identify all potentially *available* green space (and visible from *available* footpaths in Analysis 1, Chapter 4).

For my epidemiological analyses, I use the UKCEH-LCM and the Copernicus TCD datasets. I chose the UKCEH-LCM data for analysis as green exposure health pathways discussed in Section 2.1.4 potentially occur at different quantities depending on the vegetation type. For example, woodland in the UK is a more ecologically natural vegetation type than many others (Chang Chien et al., 2020). Therefore, it is likely to have higher levels of biodiversity, which increases the stress reduction and attention-restoring qualities of green space (see Section 2.1.4.1.2). However, after visual inspection of the UKCEH-LCM product against satellite images and the Copernicus TCD product, I found that the UKCEH-LCM excluded many street trees in urban areas. Therefore, I supplemented the latter with the Copernicus TCD product in my first and second analyses (Chapters 4 and 5), as this can be an important green space exposure for many people. Reasons for excluding the Copernicus TCD product from analysis 3 are explained in Chapter 6.

3.1.1 Land cover map from the UK CEH

The UKCEH-LCM series has classified land into different cover types at different times from 1990 to 2021. I use the classified pixels of the UKCEH-LCM 2017 (20 x 20 m resolution) for analyses 1 and 2 in Chapters 4 and 5 and the newer UKCEH-LCM 2020 (10 x 10 m resolution) for analysis three in Chapter 6 as this newer version was available when I started that analysis. The UKCEH-LCM 2017 and 2020 products are created by classifying remotely sensed land cover hyperspectral imagery and ancillary data into 21 land cover classes (based on the United Kingdom Biodiversity Action Plan habitat descriptions), using a random forest classifier trained on the spectral signature of said classes as ground truth (Morton et al., 2011). Of the 21 UKCEH-LCM 2017 and 2020 classes, 12 are green space. A description of these can be found in Table 1.

Table 1. Definitions of green space land-covers in the UKCEH-LCM 2017 and 2020. Definitions are paraphrased from the UKCEH Land Cover Class technical notes on the UK Biodiversity Action Plan Broad Habitat Descriptions, which the UKCEH-LCM land cover classes were based on ([Jackson, 2000](#)).

Land cover class	Description
Arable and horticulture	Annual crops, perennial crops such as berries, orchards, and freshly ploughed land.
Improved grassland	Grassland dominated by a small number of species, e.g., <i>Lolium spp.</i> , regularly mown for amenity purposes/silage production or grazing by livestock.
Calcareous grassland	Grassland on well-drained shallow soils with principally calcium carbonate basis such as chalk.
Neutral grassland	Semi-improved grassland. Examples include hay meadows and pastures like improved grassland but less intensively managed. Often found near water bodies.
Coniferous woodland	Woodland stands with 50% + cover of coniferous trees.
Saltmarsh	Wetlands are found exclusively in coastal areas mostly covered in grasses, <i>Suaeda spp.</i> and <i>Salicornia spp.</i>
Acid grassland	Grasses on soils deficient in lime, including areas dominated by Bracken and <i>Molinea caerulea</i>
Fen, marsh, and swamp	Inland wetland areas with mostly low-height vegetation. Larger patches are rare.
Heather	Land with more than 25% cover of heather or dwarf gorse.
Heather grassland	Grassland with heather cover less than 25%
Deciduous woodland	Woodland stands with 50% + cover of deciduous trees. Training data was based on non-evergreen trees, as large stands of deciduous evergreen trees are rare.
Bog	Areas of peat greater than 0.5 m in depth covered in mossy, herbaceous and ericaceous swards.

3.1.2 Copernicus tree cover density

The 20 x 20 m resolution Copernicus TCD product map for 2015 (± 1 year) indicates the percentage of tree cover within a pixel ([European Environment Agency, 2018](#)). The primary product input data were 20 x 20 m pixel resolution images from the Sentinel-2A and Landsat 8 satellites in 2014-2016. The product was created by classifying images using a support vector machine classifier trained on manually indicated tree cover proportions per pixel from higher resolution (e.g., SPOT-5 2.5 m x 2.5 m) data. Obvious errors in the data were corrected manually after classification by the Copernicus team.

3.2 Identifying areas of potential green space residential exposure

Health outcomes in the Understanding Society and 2011 England and Wales census are linked spatially to different UK census geographical areas. I use this information to generate residential green space exposures in later epidemiological analyses.

3.2.1 Census geographies

Although the most recent UK census was in 2021, all analyses in this thesis were calculated using 2011 census data and census geographies. This was because, at the time of writing this thesis, not all information at finer census geographies was available as it is released in stages. Furthermore, the Chapter 4 epidemiological analysis in this thesis was initiated in 2019 when no 2021 census data was available.

The UK is split into different census geographical areas for reporting health, environmental and socioeconomic data from the census and other data sources. Geographical areas are created based on them containing similar numbers of people. Census geographies at every level, therefore, vary in size, which greatly depends on their population density. Given the same location, the precision with which it is possible to know the location of a person or a population's residence depends on what census geography “level” this information is reported. Census output areas in Great Britain (GB) or the equivalent small areas in Northern Ireland (hereafter COAs) provide the most accuracy in knowing where a population/person resides as they are the lowest “level” geography. COAs are used to build and are fully spatially nested within all higher-level geographies, for example, the next level up – Lower Layer Super Output Areas (LSOAs). Each COA belongs to one LSOA, and each LSOA belongs to one Middle Layer Output Area (MSOA) or Local Authority District (LAD). This allows for census geographies to be fully spatially nested. COAs in 2011 were designed to be broadly aligned with previous census COA boundaries and the more recent enumeration district boundaries (e.g., 1971-1991, depending on the country) used before them ([Dibben, 2016](#)). Grouping of census geographies is based on them being spatially contiguous to ensure they have similar numbers of people residing within them and also the similarity of their populations to aid in administration (e.g. for local authority districts) or due to historical convention, e.g. they were socially similar neighbourhoods in the first censuses ([Dibben, 2016](#)).

Along with the physical boundary of the census geography, the Population Weighted Centroid (PWC) is reported for COAs and LSOAs. The definitions of the 2011 census geographies of England and Wales, Northern Ireland, and Scotland are broadly aligned and made accessible together through the InFuse service ([Office for National Statistics et al., 2017](#)).

3.2.2 Residential green space exposure from census geographies

A person or population census geography boundary can be used to calculate the green space *geographical area cover*, and their PWC can be used to calculate green space *availability* (see Section 2.1.3). The proportion of an LSOA, as defined by its administrative boundary covered in green space, would be an example of a *geographical area cover* metric (Houlden et al., 2017; Wheeler et al., 2015). In the UK, LSOA exposures are often used in studies on the health benefits of green spaces as these align with many different products, such as the Indices of Multiple Deprivation (IMD) (Houlden et al., 2017; Wheeler et al., 2015).

Boundaries and *availability* buffers from PWCs are used due to the precise location of residence (x, y coordinates) for participants in large health surveys (e.g., Understanding Society and the UK Census) not always being available to researchers due to concerns that it may be possible to identify individuals. COA is the lowest level geography to get health outcome data from the 2011 census in England and Wales. Within Understanding Society respondent level, health is recorded, and under a special license (the one obtained for my thesis), their LSOA is made available.

Despite the use of green space *geographical area cover* and *availability* metrics calculated from different levels of census geographies in the literature, it is unknown which best agrees with residential exposure and to what degree. Furthermore, the dependence of agreement on what geographical level both metrics are calculated from and the green space type exposure is being assessed is also unknown. It is important to select which of these two metrics best reflects residential exposure to reduce exposure misclassification, which can bias associations when green space variables are used in later statistical modelling (Flegal et al., 1986).

3.2.3 Exposure misclassification from defining residential green space exposure using UK census data

Here, I identify the degree to which the proportion of green space *available* from COA and LSOA PWCs and within different census geographies (from COA to LAD) agree with the proportion of green space *available* from places of residence, as indicated by all valid postcode locations across all England and Wales. This was to aid in deciding what census

geography to use for later epidemiological analysis and whether to use *geographical area* or *availability* metrics for these geographies.

3.2.3.1 Materials and methods

3.2.3.1.1 Defining green spaces

Green space data was taken from the UKCEH-LCM 2017 ([Morton, 2020](#)), see Section 3.1.1 for product details. I differentiated green space into three types based on their physical vegetation characteristics: i) *woodland*, ii), *ground cover* and iii) and both aggregated together: *all green cover*. I defined deciduous woodland and coniferous woodland as *woodland*, and I defined the remaining ten vegetation classes, including different types of arable land and grassland as *ground cover*.

3.2.3.1.2 True and approximated residential green space exposure

I defined true residential green space exposure as the proportion of land 1 km from all the 1,549,735 valid postcodes in England and Wales classified as each of the three green space types. I gathered all postcode locations in England and Wales from the OS Code-Point Open database version 2, which contains all postcode locations in GB ([Ordnance Survey, 2019](#)). At this stage, I removed 448 postcodes in England and Wales as no locational data was associated with them due to inconsistencies in data handling outlined in the OS Code-Point open database documentation ([Ordnance Survey, 2019](#)). The 1 km area around postcodes was calculated using the *sf* package in R ([Pebesma et al., 2019](#)).

I calculated six approximate metrics of postcode residential green space exposure to compare against their actual residential green space postcode exposure. The first four were the proportional coverage of each green space type within the postcode: COA, LSOA, MSOA and LAD full extent boundaries taken from the ONS ([Office for National Statistics, 2020](#)). These census geographies are spatially nested in the given order, where multiple lower-level geographies (for example, COAs) are contained within the higher-level geographies (for example, LSOAs). Further details on the census geographies and their hierarchies are outlined in Section 3.2.1. The remaining two metrics were the proportion of land classified as each green space type within 1 km from the PWC ([Office for National Statistics, 2017](#)) of each postcode's respective COA and LSOAs. To link postcodes to census geographies, I first

identified the COA that each postcode intersected using the “sf” package in R (Pebesma et al., 2019). I then identified the corresponding LSOA, MSOA and LAD to each output area using ONS lookup tables (Office for National Statistics, 2019).

3.2.3.1.3 Assessing the accuracy of approximate residential exposure metrics

Agreement methods are used to assess the accuracy of “gold-standard” measurement (in this case – residential green space exposure from postcodes) and other environmental exposures (Batty et al., 2016; Lupo and Symanski, 2009; Morley et al., 2015). The Concordance Correlation Coefficient (CCC) (Lin, 1989) is one agreement method (Morgan and Aban, 2016), where 1 and 0 indicate perfect agreement and disagreement, respectively. I calculated the CCC, 95% confidence intervals, location shift (i.e., the offset or constant bias) and scale shift (systematic bias) for each postcode and corresponding census geography exposures for the three green space types. In addition, I produced difference plots to assess the accuracy of residential exposure metrics (Figure 4). These showed the approximated exposure across all metrics from true residential green space exposure for all postcodes. They also present the mean accuracy across quintiles of postcode residential green space proportions and their 95% confidence intervals.

3.2.3.2 Results

There was greater concordance between postcode residential green space exposures and PWC exposure *availability* within 1 km than their corresponding and higher-level *geographical area cover* metrics (Table 2) across all green space types. Similarly, postcode level exposures at each quintile were least different from residential green space *availability* rather than geographical area cover metrics for COAs and LSOAs (Figure 4). COA was less accurate than MSOA and LSOA boundaries at approximating all postcode-level residential green space exposures. The latter most accurately replicated true residential green space exposures. Across all approximate metrics of residential green space exposures, concordance with postcode-level woodland exposures was lower than concordance with postcode-level ground cover exposures.

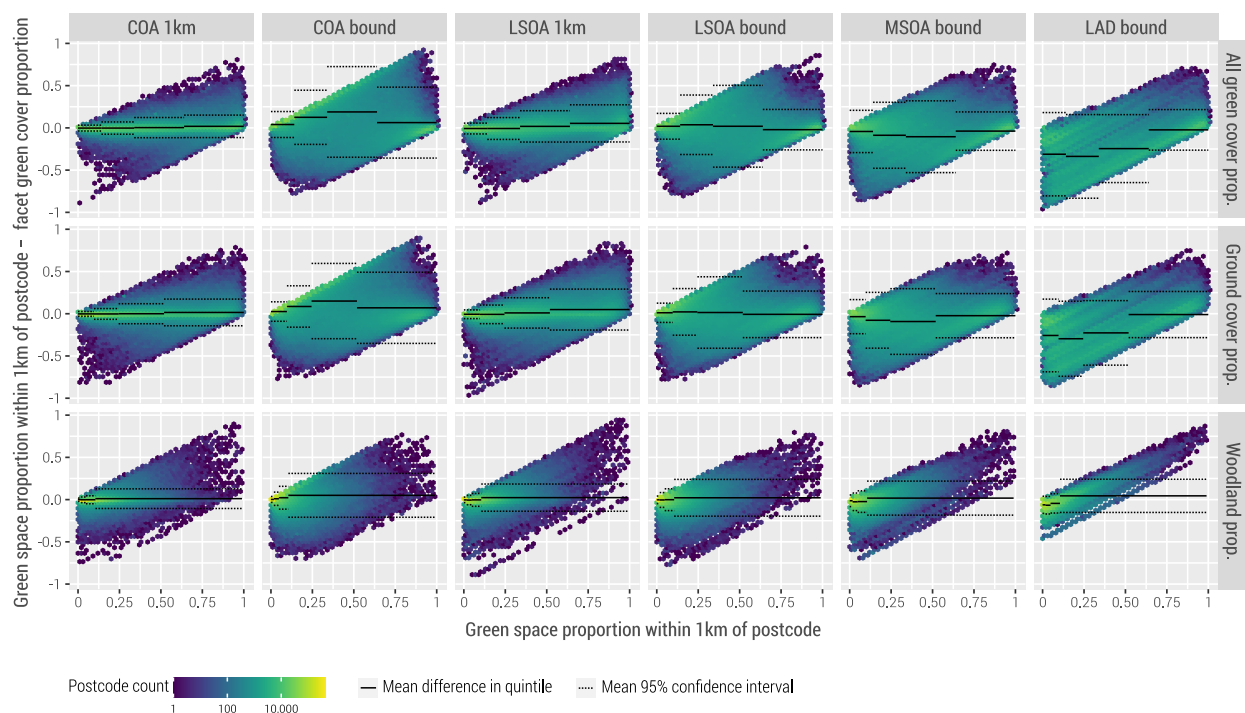


Figure 4. Accuracy of six approximate metrics of postcode residential green space exposure (top facets) when compared against three postcode-level green space type exposures (right facet). The x-axis indicates the postcode level exposures, which vary by the green space type. The y-axis indicates the difference between postcode level exposures and the approximated residential green space exposure metrics in the top facet column. The colour of a hexagon indicates the number of postcodes with coordinate values under it. In the top facet plots, “1km” = proportional cover within 1 km of the respective census geography PWC, and “bound” = proportional cover within the census geography boundary.

Table 2. The Concordance Correlation Coefficient (CCC), 95% confidence intervals, location shift (constant bias) and scale shift (systematic bias) between different green space type postcode level residential exposures and approximate exposure metrics for different green space types. Approximate exposure metrics suffix: “1km” = proportional cover within 1 km of the respective census geography PWC, and “bound.” = proportional cover within the census geography boundary.

Green cover type	Approximate exposure metric	CCC	95% CI	Location shift	Scale shift
All green cover proportion.	COA 1km	0.985	0.985 - 0.985	0.0144	1.02
	COA bound.	0.769	0.769 - 0.768	0.319	0.827
	LSOA 1km	0.955	0.955 - 0.955	0.0487	1.05
	LSOA bound.	0.864	0.864 - 0.864	0.0415	0.833
	MSOA bound.	0.832	0.832 - 0.832	-0.216	0.88
	LAD bound.	0.478	0.478 - 0.477	-0.798	1.06
Ground cover proportion	COA 1km	0.98	0.98 - 0.98	0.0106	1.01
	COA bound.	0.785	0.785 - 0.785	0.286	0.857
	LSOA 1km	0.946	0.946 - 0.945	0.0434	1.04
	LSOA bound.	0.867	0.867 - 0.867	0.0348	0.859
	MSOA bound.	0.83	0.83 - 0.829	-0.2	0.899
	LAD bound.	0.484	0.484 - 0.483	-0.756	1.06
Woodland proportion	COA 1km	0.924	0.924 - 0.924	0.016	1.03
	COA bound.	0.638	0.638 - 0.637	0.22	0.863

LSOA 1km	0.834	0.834 - 0.833	0.0311	1.06
LSOA bound.	0.723	0.723 - 0.722	0.0359	0.892
MSOA bound.	0.686	0.686 - 0.686	-0.127	0.968
LAD bound	0.422	0.422 - 0.42	-0.415	1.31

3.2.3.3 Discussion

There was better accuracy of first COA PWC and second LSOA PWC exposures in approximating postcode residential green space *availability* exposures. This that suggests lower level-census geography PWC *availability* exposures should be preferred against any *geographical area cover* metrics when approximating true residential green space exposure. LSOA was the *geographical area cover* census geography level that most accurately aligned with residential green space exposure as assessed from postcodes in the UK. This supports its continued use as one of if not the most popular census geography level to assess residential green space exposure using geographical area cover (Alcock et al., 2014; Bu et al., 2022; Dennis et al., 2020; Dennis and James, 2017; Schindler et al., 2022; White et al., 2019).

Theoretically, it would be expected that PWC *availability* would more accurately represent post-code residential green space exposures than the *geographical area cover* metrics. PWCs are at a point within a census geography that minimises the sum distance between its population. Therefore, the proportion of green cover within an *available* distance from a census geography PWC represents the “average” exposure people in the PWC would have. *Geographical area cover* metrics, however, can potentially exclude land that is within or include land far away from postcode 1 km *availability* buffers. Postcodes may be less than 1 km from the edge of their census geography boundary; therefore, outside the boundary will be correctly classified as an area where green space cover is *available*. In an extreme case, a postcode may be at the edge of an LSOA, which has no green space cover, and the LSOA adjacent to this LSOA edge may be fully covered in green space. Theoretically, the neighbouring LSOA's green space would be as *available* to them (as defined by the *availability* scenario evaluation, see limitations against this scenario), yet the LSOA geographical area cover metric would return a much lower green space exposure than that assessed from postcodes. When a postcode *availability* buffer is greater than a census geographies total area, there is greater potential to misestimate the residential green space exposure as defined by postcode *availability*. For example, for a COA that covers a small area, its proportional coverage of green space may be small because it contains only built-up

houses adjacent to each other. However, surrounding it within 1 km, there may be lots of green space, underestimating residential green space exposure. This issue is more likely for COAs being the lowest level census geography, with a min, mean, max, and interquartile range of COA areas in England and Wales being 0.00016km², 0.85 km², 202 km² and 0.0422–0.167 km² respectively, while 1 km *availability* buffers are much larger than the third quintile at 3.14 km². In another scenario, a postcode may be in the centre of an LSOA that is much larger than and completely encases a 1 km area around it. This can be the case as LSOAs in England and Wales, have a min, mean, max and interquartile range of 0.0184km², 4.44 km², 684 km² and 0.278–1.46 km² respectively (Office for National Statistics et al., 2017). Green space that is potentially very far (e.g., 10 km) away would be included in its residential green space exposure, but would not be within a 1 km distance from a person's postcode.

3.2.3.4 *Strengths weaknesses and future research*

In this study, I identify green space within 1 km of postcodes as true residential green space exposure. However, postcodes do not align with the exact location of residences. Postcode locations were selected as a proxy for actual residential addresses as I could find no available database for every household GPS location. While this may misestimate true residential green space exposure, postcodes still more accurately represent residence locations than census geographies at a spatially coarser scale. If a sample of household GPS data is available, the 1 km exposure generated from these could be compared with census geography approximate exposure metrics to determine if the above findings still hold.

I defined residential green space exposure as the *availability* of land within 1 km of a residence (using a postcode proxy). I chose an *availability* scenario as it reflects previous studies finding that green space closer to home is more likely to be interacted with. However, actual time spent experiencing nature may be better correlated with exposure generated from *geographical area cover* metrics, which could be investigated in future research. This might be due to systemic bias caused by, for example, those living in rural areas may have been willing to travel further to explore nature due to the extinction of experience hypothesis (those that grow up around nature are more likely to enjoy it and care for it and therefore potentially seek it out) (Soga and Gaston, 2016).

3.2.3.5 Conclusions

The accuracy of the proportion of green cover within geographical areas or *availability* from the PWC of said geographical areas at representing true residential green space exposure is unknown. My analysis found that PWC metrics more accurately reflect residential *availability* exposures. Further research should consider whether PWC metrics better reflect the combined duration and frequency of actual natural environment experiences, which are important mediators of health benefits from green spaces. However, I recommend using availability buffers from the highest census geography able use in future studies that use the evaluated scenario of residential green space exposure as their exposure of interest. Therefore for my PhD thesis rather than the proportional cover of small areas I identify green space available from small area PWCs (COAs in analysis 1 in Chapter 4 and LSOAs in analyses 2 and 3 in Chapters 5 and 6 respectively).

3.3 Understanding Society longitudinal panel survey

For epidemiological analyses 2 and 3 (Sections 5 and 6), I use mental health outcome, confounder, and spatial identifier variables from Understanding Society waves 1-9. Understanding Society participants are interviewed approximately once a year (within a 24-month window) and give one response per wave ([Institute for Social and Economic Research, 2021](#)). Survey participants respond to questions ranging from health and well-being to politics and social attitudes. Their geographical location is recorded and made available to researchers on a Special or Secure License. The former identifies the respondent's LSOA of residence and is made available remotely. The latter is available through a “secure lab” only accessible in a secure room at the University of Essex.

3.3.1 Sample size and exposure – effect modifier contrast

I selected Understanding Society for both analyses as it gave me a stronger likelihood of identifying individuals with rarer effect modifier and green space variable combinations. This is due to two factors. In GB, households were selected to participate in Understanding Society partially to ensure that different parts of the country and different population densities were represented ([Lynn, 2009](#)). Secondly, it is the largest panel survey in the UK, and one of the largest in the world ([Turek et al., 2021](#)), recording the health status of over 85,000 individuals distributed across households across the country, making it more likely that a unique combination is found by chance. Furthermore, this large sample size means that the likelihood of rarer exposure-effect modifier combinations being replicated also increases.

3.3.2 Longitudinal analysis

In addition to the reasons outlined in Section [3.3.1](#), I specifically selected Understanding Society for analysis 2 (Section [5](#)) as it records individuals moving their residence address through time, allowing within-person change in exposures to residential green space and levels of local area deprivation. The latter was my analysis 2 effect modifier, as within-person variation in exposure and effect modifier was crucial for this analysis approach; see Section [5.2.6](#) for details.

3.3.3 A nationally representative survey

I selected it for analysis three (Section [5](#)) as the survey can be used to generate a nationally representative sample in terms of ethnicity and socioeconomic status, which was a key feature of my analysis. Additionally, the Understanding Society support team produces weights that ensure the survey's representativeness even after attrition from the main survey. This is a complex process as these weights not only consider simple demographic but also spatial representativeness ([Lynn, 2009](#)).

3.3.4 The short-form 12 mental component summary score

I use the short-form 12 (sf-12) mental component summary score (which I define as *mental health score*) as my outcome variable in analyses 2 and 3 (Chapters 5 and 6). The *mental health score* is used as an indicator of mental health within the past month (rather than momentary mental health) on a scale of 0-100, with higher scores representing better mental health. It is calculated from answers to six questions (some Likert, some binary) on participants' feelings in the past four weeks (vitality, social functioning, role-emotional and mental health) (Ware et al., 1996, 2002). It is widely used to measure mental health in epidemiological research and has a high specificity and sensitivity when detecting the prevalence of medically diagnosed mental illness in the general population (Vilagut et al., 2013).

3.4 Covariate confounders

3.4.1 Understanding society

For my second and third analyses (Chapters 5 and 6, which both use Understanding Society data), I use the same covariate confounders aside from sex, which is only included in my third analysis due to this being time-invariant and my second analysis being completely within person (see Section 5.2.6). These covariate confounders were disposable income, age, employment status, people per bedroom, and commute time/status. The justification for these and how they were calculated are outlined below. All these variables were taken directly from or based on Understanding Society wave-specific responses and may change over time.

Older age, less disposable income, and unemployment are associated with major negative changes in health and may also plausibly correlate with within-person change and between-person differences in green space exposure (Nagasu and Yamamoto, 2020).

I followed the US-recommended approach to calculating individual disposable income (Institute for Social and Economic Research, 2021), specifically, household income minus outgoings for rent or mortgage, divided by an Organisation for Economic Co-operation and Development (OECD) equivalence factor based on the number of children and adults per

household, deflated to a 2015 base year using the UK consumer price index. Additionally, some participants may trade off the economic cost of moving to or living in a greener neighbourhood (Belcher et al., 2019) against other home characteristics, which may worsen their mental health. These factors may potentially confound (underestimate) positive residential green space and mental health associations. I, therefore, include the following as covariate confounders in adjusted models: having more household crowding (fewer bedrooms per person) (Pierse et al., 2016) and accepting a longer commute to their jobs (Feng and Boyle, 2014).

3.4.2 Spatial confounders

I included population density as a potential covariate confounder in all three epidemiological analyses and socioeconomic deprivation (as measured by the Carstairs index) as a potential confounder for my first and third epidemiological analysis (Sections 4 and 6). My second analysis used the Carstairs index to represent the socioeconomic deprivation effect modifier (Section 5). The reasons why I selected this as an effect modifier are outlined in Section 2.2.1.2. The value for each variable was linked to a respondent LSOA recorded at a specific wave and, therefore, may change if a person moves their residence to a different LSOA.

Socioeconomic deprivation is correlated with green space exposure and is a main health determinant (Garrett et al., 2019; Marmot and Bell, 2012). I used the Carstairs Index 2011 (Carstairs and Morris, 1990), an area-level composite measure. Higher local area deprivation scores represent greater socioeconomic deprivation. The Carstairs index was developed for epidemiological applications and is calculable for all COAs and LSOAs in the United Kingdom using information from the 2011 Census on unemployment, car ownership, overcrowding and low social class. I calculated Carstairs raw scores at the COA level (for all England and Wales COAs) for my first analysis, as this was my unit of analysis. The highest resolution of geographic identifiers for respondents in Understanding Society for my second and third analysis was LSOA. Therefore, I calculated the Carstairs index at the LSOA level (again for all LSOAs but in GB for analysis 2 and the UK for analysis 3, because my respective analysis populations are within each of those two areas). When I used it as a confounder in cross-sectional analysis, I categorised the Carstairs index into quintiles.

Population density is inversely correlated with green space (Fuller and Gaston, 2009) and correlated with many aspects of the urban environment that impact health (Beenackers et al., 2018). Areas of high population density, for example, often have better access to active transport facilities, encouraging physical activity and positively impacting health (Stevenson et al., 2016). I calculated the area-weighted mean population density near to home by intersecting the 100 m x 100 m resolution 2011 WorldPop product (Lloyd et al., 2017) with a 1 km buffer from each COA PWC for analysis 1, and a 1.6 km buffer from each LSOA PWC for analysis 2 and 3 (to align with the green space availability buffer used in those analysis, see their subsections for justification). I then extracted the total number of people within said buffer using the “exactextractr” and “sf” packages in R (Dowle et al., 2019; Hijmans et al., 2019; Pebesma, 2018; R Core Team, 2019).

4 Road traffic modifies green space and self-rated health associations across urban England and Wales

4.1 Introduction

Despite its potential importance as a green space and health effect modifier, empirical evidence on the effect of road traffic and how this impacts the ability of green space or different types of green cover to support health is lacking (see Section [2.2.1.1](#)). If quantified it may tip the balance on whether to (for example) conserve a green space that is away from traffic or encourage the creation of more green spaces closer to roads.

I present a cross-sectional small-area ecological study across urban Census Output COAs in England and Wales. I investigate (i) the direction, shape, magnitude and uncertainty of associations of green space visible from footpaths with self-rated positive health and; (ii) whether this association is consistent across different types of green space, including ground cover, woodland and tree outside woodland; and (iii) whether this association differs when

green space was experienced from a footpath with adjacent traffic (e.g. a sidewalk or footway) compared to a footpath without adjacent traffic (e.g. a woodland path).

4.2 Methods

4.2.1 Study area and analysis unit

I included all COAs in England and Wales classified as built-up (urban) by the Office for National Statistics (ONS) built-up area classification in my analysis ([Office for National Statistics, 2013](#)). The ONS defines built-up areas as contiguous 200,000 m² areas containing 50 m² grid cells defined as built-up land which are not more than 200 m apart ([Office for National Statistics, 2013](#)). A grid cell was defined by ONS as built up if it met one of two criteria. First, having a minimum proportion (unspecified by ONS) of “buildings and glasshouses, areas of tarmac, concrete, etc. and primarily gardens” according to the OS MasterMap Topography Layer (priority A areas) ([Office for National Statistics, 2013](#)) and second, meeting the minimum proportional land-cover threshold for priority A areas when “metalled surface of roads”, was also included as land use and is adjacent to priority A areas ([Office for National Statistics, 2013](#)). There are 146,970 built up (urban) COAs, which is 81% of all COAs ([Figure 5](#)). In 2011 these COAs contained 45.7 million people, or 81% of the population of England and Wales. They have an average population of 311 residents. I used COAs as the geographical unit of analysis as their high spatial resolution allows for a more precise prediction of the *availability* of green spaces from a person’s dwelling than coarser geographies (see [Section 3.2.3](#)), consequently increasing exposure contrast across geographic units.

4.2.2 Health outcome

My outcome variable was the proportion of COA residents with self-rated very good or good (positive) health, according to the 2011 census. I used positive self-rated health as it represents multiple aspects of an individual’s physical and mental health ([Simon et al., 2005](#)) and individuals’ perceptions of their health. Furthermore, self-rated health has been

previously used in studies measuring health benefits from natural environments, making results comparable to other studies (Brindley et al., 2018; Maas et al., 2006; Wheeler et al., 2015).

I used the age and sex-adjusted ratio of COA residents with positive self-rated health as a proportion of all COA residents as the dependent variable in all my models. This adjustment was done by directly standardising the proportion of residents in each COA with self-rated positive health to the average age and sex structure of all COAs in England and Wales using the “dsr” package (Kumar, 2019) in R (R Core Team, 2019).

4.2.3 Defining green spaces

I differentiated green spaces into four types based on their physical vegetation characteristics: i) *woodland*, ii) *tree outside woodland*, iii) *ground cover* and iv) all three types of green space aggregated together, herein referred to as *all green cover* (Table 3).

4.2.3.1 Green cover data

I fused two remote sensing products to capture a high diversity of green spaces in urban areas. These were the UKCEH-LCM 2017 (Morton, 2020) and the Copernicus TCD (European Environment Agency, 2018), both of which have a 20 m x 20 m resolution. See Section 3.1 for details on these products as I use them across all three of my epidemiological analyses.

4.2.3.2 Differentiating types of green cover

I combined the UKCEH-LCM 2017 classes *deciduous woodland* and *coniferous woodland* to *woodland* and the remaining ten vegetation classes, including different types of arable land and grassland to *ground cover* (Table 1). I defined grid cells not classified as woodland but with more than 50% tree cover based on Copernicus TCD as *tree outside woodland* (Table 3). This analysis was completed using the “raster” package (Hijmans et al., 2019) in R.

Woodland represents closed or near-closed tree canopies rather than individual trees. *Tree outside woodland* is tree cover outside the above definition and includes individual trees over *ground cover*. *Ground cover* is low-laying vegetation, including grassland (Table 3).

Table 3. Categorisation of green spaces into green cover types.

Green cover		Description	Data source and definition
All green cover	Woodland	Trees in clusters not mixed with non-vegetated surfaces. This includes stands of trees in parks and large woodland areas	Land in the Centre for Ecology and Hydrology Land Cover Map 2017 classed as deciduous woodland or coniferous woodland
	Tree outside woodland	Smaller patches of trees that may be interwoven with non-vegetated areas.	Land not <i>woodland</i> (see above) with a tree cover density of more than 50% in the Copernicus Tree Cover Density Product
	Ground cover	Low laying patches of vegetation including agricultural land and managed grassland	Areas that are not <i>tree outside woodland</i> (see above) and classed in the Land Cover Map 2017 as either: arable, improved grassland, neutral grassland, calcareous grassland, acid grassland, fen, heather, heather grassland, bog, or saltmarsh
	Ground cover	Low laying patches of vegetation including agricultural land and managed grassland	Areas that are not <i>tree outside woodland</i> (see above) and classed in the Land Cover Map 2017 as either: arable, improved grassland, neutral grassland, calcareous grassland, acid grassland, fen, heather, heather grassland, bog, or saltmarsh

4.2.4 Exposure assessment

I followed a three-step process to identify green cover experienceable from footpaths for each COA (see Figure 5). First, I identified footpaths that were *available* from each COA Population Density-Weighted Centroid (PWC). Second, I differentiated between those adjacent to traffic and those with no adjacent traffic. Third, I extracted the areal coverage of the experienceable green cover from each type of my three footpath types.



Figure 5. *Panel A:* Study area extent, including all built-up (urban) Census Output Areas (COAs) in England and Wales. *Panel B:* Distribution of Population Density-Weighted Centroids (PWC) for all COAs in Worthing Borough Council. *Panel C:* 1 km circular buffer from PWC of Findon Valley COA used to identify available footpaths. *Panel D:* Experienceable natural environments from every footpath within 1km of PWC, restricted to ~100 m from footpaths, overlaid with green cover type. *Panel E:* visible area from footpaths with adjacent traffic. *Panel F:* visible area from footpaths with no adjacent traffic.

4.2.4.1 Defining available footpaths

I identified footpaths using the Ordnance Survey (OS) Mastermap Highways Network: Road and Path products (Ordnance Survey, 2017b), which is the most accurate path network information across GB (Ordnance Survey, 2020a, 2020b). I defined *available* footpaths as *all footpaths* within a 1,000 m radius from a COA PWC (see Figure 5c). I used COA PWCs because they better approximate residential location than coarser census geographies where self-rated health data was also available (see Section 3.2.3).

A 1,000 m radius (representing approximately a 15-minute walk) was chosen as it is comparable to the range (300 m to 1.6 km) used in previous research linking the natural environment and health (Kondo et al., 2018; van den Berg et al., 2015) and it is the same radius used in many previous studies (Astell-Burt et al., 2013; Bell et al., 2008; de Vries et al., 2003; Jolanda Maas et al., 2009; Wolch et al., 2011).

4.2.4.2 Identifying footpaths with and without traffic

I defined footpaths adjacent to traffic (*footpaths-with-traffic*) as any road or path, except those that are illegal to walk on (i.e. motorways and slip roads), shared-use carriageways (as these are principally for use by pedestrians, as defined by OS) and those with little or no traffic (i.e. tracks, closed roads, roads under construction, roads that had access restrictions for motor vehicles, or a ‘no entry’ sign) (Ordinance Survey, 2017b). I defined footpaths which are not adjacent to traffic (*footpaths-no-traffic*) as any path in the product or any road that was either a shared-use carriageway, or a track or road that had access restrictions for motor vehicles (Ordinance Survey, 2017b). I processed this data using R packages “data.table” and “dplyr” (Dowle et al., 2019; Wickham et al., 2019).

4.2.4.2.1 Identifying experienceable green cover from available footpaths

I defined experienceable green cover as green cover that is visible from a footpath. As such, I first identified the visible area from *available* footpaths for each COA and then overlaid these with the green cover types (see Figure 5d). I use the same definition for footpath *availability* as I do for green space *availability*. The basis for identifying the visible area around footpaths *available* from COAs was an using a uniform ray casting Isovist function that I created in R. Isovists extract two-dimensional field of view, unobstructed by buildings (Weitkamp et al., 2014).

4.2.4.2.2 Creating Isovists around all urban footpaths in England and Wales

I started by generating viewpoints, regularly spaced points (every 50 m or at the centre of paths/roads < 50 m long) along each *available* footpath (Figure 6a). At each viewpoint 41 equiangular rays were generated (Figure 6b). Each ray length corresponded to a view distance from the footpath viewpoint. To reduce bias view distances must be restricted in simple outdoor isovists. Landscape features not buildings impede ground level views (e.g., terrain elevation, fences), and these are likely to accumulate within a view after certain distances, especially in an urban environment and unrestricted isovists could cover vast distances. I restricted the view distance to a maximum of 100 m for *footpaths-no-traffic* and 100 m plus half the road width for *footpaths-with-traffic*. I added half the road width, as footpaths-with traffic are beside not in the centre of roads. Road width information was taken from the OS Mastermap highways product (Ordinance Survey, 2017b). Width was known for 99.7% of all

A and B roads, but only for 47% of local, minor, and secondary roads. As local, minor or secondary access roads are typically no more than two lanes (whilst A and B roads are of single lanes or dual carriageways), I assumed half a standard road and footway width of 4.75 meters for all roads with no information on their width (Standards for Highways, 2020). Each ray was intersected with OS Vectormap local buildings (which have a minimum areal coverage of 50 m²) within its cast (view) distance (Ordnance Survey, 2018), creating one or more ray line segments. The ray line segment closest to the viewpoint was then extracted, and the furthest away vertex of this line segment was taken as a boundary vertex. The boundary vertices were joined in a clockwise direction to create each viewpoint Isovist (Figure 6b).

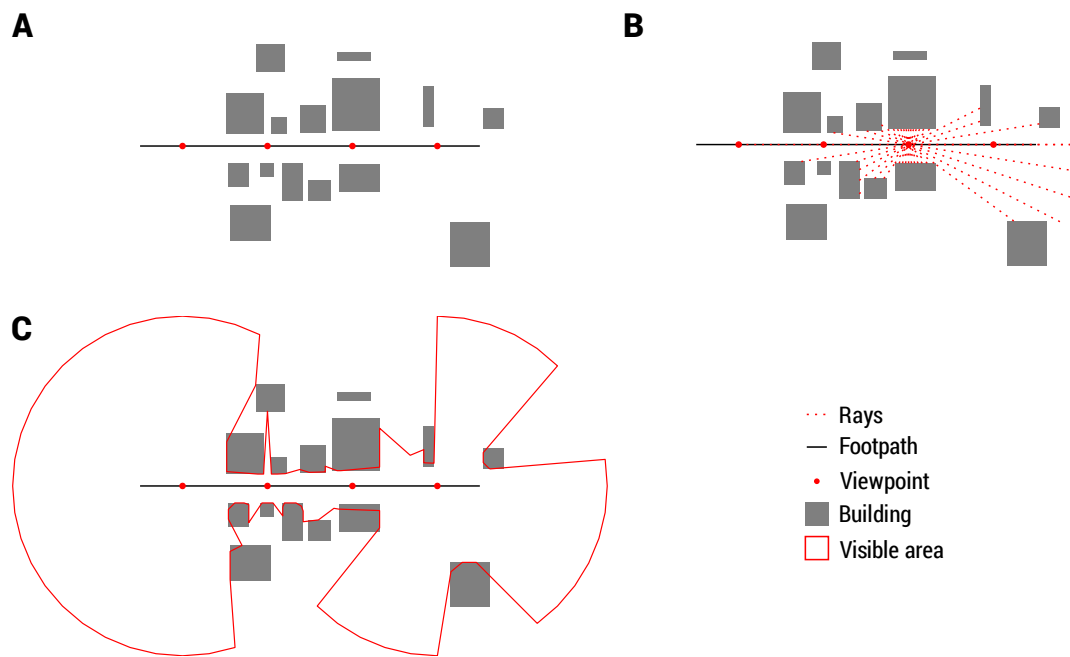


Figure 6. Diagrams showing process of generating visibility polygons. A = illustration of a hypothetical urban area with buildings a footpath with viewpoints from which visibility is assessed. B shows rays case to identify areas where line of site is blocked. C shows visibility polygon merged from isovists.

4.2.4.2.3 Visible area available from COA centres

I combined the visible areas across all viewpoints for *all footpaths*, *footpaths-with-traffic*, and *footpaths-no-traffic*, within each COA. Figure 5D, Figure 5E and Figure 5F show the example of one COA's visible green cover from *available all footpaths*, *footpaths-with-traffic* and *footpaths-no-traffic*, respectively (Figure 6c). All operations were performed in R using

the packages “sf”, “lwgeom”, “data.table” and “dplyr” (Dowle et al., 2019; Pebesma et al., 2019; Wickham et al., 2019).

I then computed the total area (in km²) covered by each of the four green cover types (*all green cover*, *woodland*, *tree outside woodland* and *ground cover*) within each of the three visible areas from *all footpaths*, *footpaths-with-traffic* and *footpaths-no-traffic*, therefore, creating 12 green space-footpath combinations (Table 4). For this purpose, all grid cells whose geometric centroid intersected the visible area were extracted using R package “velox” (Hunziker, 2019; R Core Team, 2019).

Table 4. Green space-footpath variables of interest that were created for statistical analysis.

Green space type	Footpath type	Variable name
All green cover	All footpaths	All green-all foot
	Footpaths with traffic	All green-with traffic
	Footpaths with no traffic	All green-no traffic
Woodland	All footpaths	Woods-all foot
	Footpaths with traffic	Woods-with traffic
	Footpaths with no traffic	Woods-no traffic
Tree outside woodland	All footpaths	Trees-all foot
	Footpaths with traffic	Trees-with traffic
	Footpaths with no traffic	Trees-no traffic
Ground cover	All footpaths	Ground-all foot
	Footpaths with traffic	Ground-with traffic
	Footpaths with no traffic	Ground-no traffic

4.2.5 Confounders

I included socioeconomic deprivation as indicated by the Carstairs index and population density as potential areal level confounders, see Section 3.4.2 for justification as to why. My indicator of socioeconomic deprivation was the Carstairs index 201 (Carstairs and Morris, 1990), for England and Wales, an area-level composite measure of categorised into quintiles. The Carstairs index was developed for epidemiological applications and is calculable for all COAs in England and Wales using information from the 2011 Census on unemployment, car ownership, overcrowding and low social class.

I derived population density by intersecting the 100 m x 100 m resolution 2011 WorldPop product (Lloyd et al., 2017) with a 1 km buffer from each COA PWC and extracted the total

number of people within said buffer using the “`exactextractr`” (Baston et al., 2022) and “`sf`” packages in R. The 1 km buffer was used to estimate the population density in the area around a COA.

4.2.6 Statistical methods

I produced outcome and exposure variables descriptive statistics and frequency polygons to explore their skewness and heteroskedasticity.

I used binomial Generalised Linear Models (GLMs) to assess the association between positive self-rated health and my exposure variables and the 12 green space-footpath combinations. To account for overdispersion due to my dependent variable (the age and sex adjusted ratio of COA residents with positive self-rated health) being a proportion rather than a binary variable, I fitted a quasi-binomial error structure (Dunn and Smyth, 2018). To identify any non-linear associations, I applied natural cubic splines with internal knots at the 25th, 50th and 75th percentile and boundary knots at the minimum and maximum of each exposure variable using the “`splines`” package in R (Perperoglou et al., 2019).

Models 1–12 (Figure 7) are only adjusted for age and sex (using direct standardisation), regressing each of my 12 green space-footpath variables against age and sex adjusted proportion of people with positive self-rated health. I built four additional models that adjust for potential confounders using covariates (Models 13–16 in Figure 7). All these models include area level confounders socioeconomic deprivation and population density as covariates as potential confounders. In addition, I adjust for other green space-footpath variables within the same level of green space disaggregation, either by green cover type, or by whether there is roadside traffic nearby. This adjusts for potential confounding between green cover types within the same level of green space disaggregation. For example, the area of one green cover type (e.g., *woodland*) may be positively correlated with another green cover type (e.g. *ground cover*) and *ground cover* might, therefore, confound any association of *woodland* with self-rated health. I include disaggregated forms of green cover types (*woodland*, *ground cover* and *tree outside woodland*) in the same model (Models 15 and 16 in Figure 7). I also include the *no traffic* and *with traffic* measures of the same green cover type in the same model to (Models 14 and 16 in Figure 7).

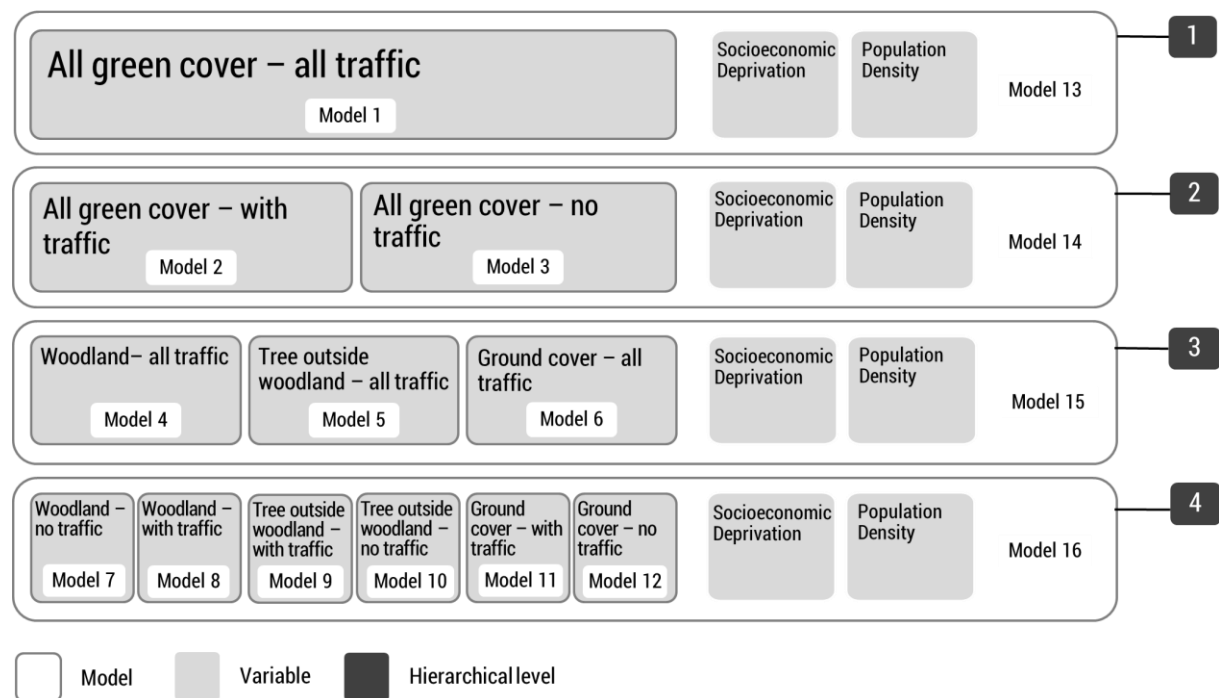


Figure 7. Variables included in models. Each hierarchical level of covariate adjusted models disaggregates green space by type (all disaggregated green cover types or not), footpath type (disaggregated by whether they have traffic) or both to adjust for other green space covariates within the same hierarchical level.

To assess collinearity between variables in the same covariate adjusted model (Models 13-16) I calculated covariate Generalised Variance Inflation Factors (GVIF) (Fox and Monette, 1992) using the “semEff” package (Murphy, 2020). GVIF represents the level of uncertainty around parameter estimates due to collinearity with other variables in the model (Fox, 2005). GVIF is used instead of Variance Inflation Factors (VIF) when a variable has one or more level, for example if it has spline terms or multiple factor levels. To assess collinearity using the more commonly used VIF thresholds I squared variable GVIF scores (Fox, 2002). A covariate GVIF between 1 and 2.5 was taken as acceptably colinear, following guidance for epidemiological studies (Johnston et al., 2018), which was the case for all models (Table 5).

Table 5. Variance inflation factors for each variable included in the four covariate adjustment models in [Figure 7](#)

Model ref.	Model explanatory variable	$(GVIF^{(1/(2 \times Df))})^2$
13	All green-all foot	1.18
	Carstairs index	1.05
	Population density	1.19
14	All green-no traffic	1.18
	All green-with traffic	1.37
	Carstairs index	1.05
	Population density	1.23
15	Ground-all foot	1.25
	Woods-all foot	1.17
	Trees-all foot	1.10
	Carstairs index	1.05
	Population density	1.28
16	Ground-no traffic	1.51
	Ground-with traffic	1.67
	Woods-no traffic	2.11
	Woods-with traffic	2.09
	Trees-no traffic	2.28
	Trees-with traffic	2.11
	Carstairs index	1.05
	Population density	1.32

4.3 Results

The mean proportion of individuals reporting self-rated positive health after age-sex standardisation was 0.8 [IQR 0.75–0.85] and followed a slightly negatively skewed distribution ([Figure 8](#) and [Table 6](#)). Every green-traffic exposure was highly positively (right) skewed with fewer recorded exposures at larger quantities ([Figure 9](#) and [Table 6](#)).

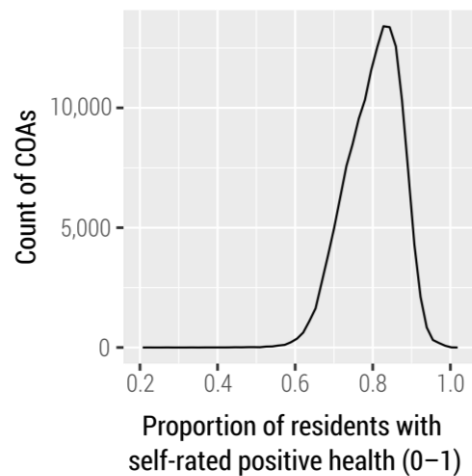


Figure 8. Frequency polygon showing distribution of the directly age and sex standardised proportion of individuals with positive self-rated health in all urban COAs in England and Wales.

Table 6. Summary statistics of the directly age and sex standardised proportion of individuals with positive self-rated health and green space-traffic measures per all urban census output areas in England and Wales. Positive health / ordinary residents were adjusted directly using age and sex-specific very good or good health rates. $n = 146,970$

Group	Variable	min	mean	max	SD	Q0.25	median	Q0.75
Dependent variable	Age and sex std. positive health / ordinary residents	0.22	0.80	1.00	0.07	0.75	0.81	0.85
Green experienceable from all footpaths	All green-all foot	0.00	0.82	2.78	0.36	0.55	0.80	1.06
	Woods-all foot	0.00	0.16	2.02	0.18	0.04	0.11	0.23
	Trees-all foot	0.00	0.28	1.44	0.16	0.16	0.25	0.36
	Ground-all foot	0.00	0.38	2.21	0.26	0.18	0.33	0.53
Green experienceable from footpaths with adjacent traffic	All green-with traffic	0.00	0.65	2.36	0.30	0.43	0.63	0.85
	Woods-with traffic	0.00	0.12	1.87	0.13	0.03	0.08	0.16
	Trees-with traffic	0.00	0.24	1.39	0.15	0.14	0.21	0.31
	Ground-with traffic	0.00	0.29	1.68	0.21	0.13	0.24	0.40
Green experienceable from footpaths with no adjacent traffic	All green-no traffic	0.00	0.48	2.65	0.27	0.28	0.44	0.64
	Woods-no traffic	0.00	0.11	1.79	0.13	0.02	0.06	0.14
	Trees-no traffic	0.00	0.17	0.85	0.11	0.09	0.15	0.23
	Ground-no traffic	0.00	0.20	1.47	0.15	0.09	0.16	0.27

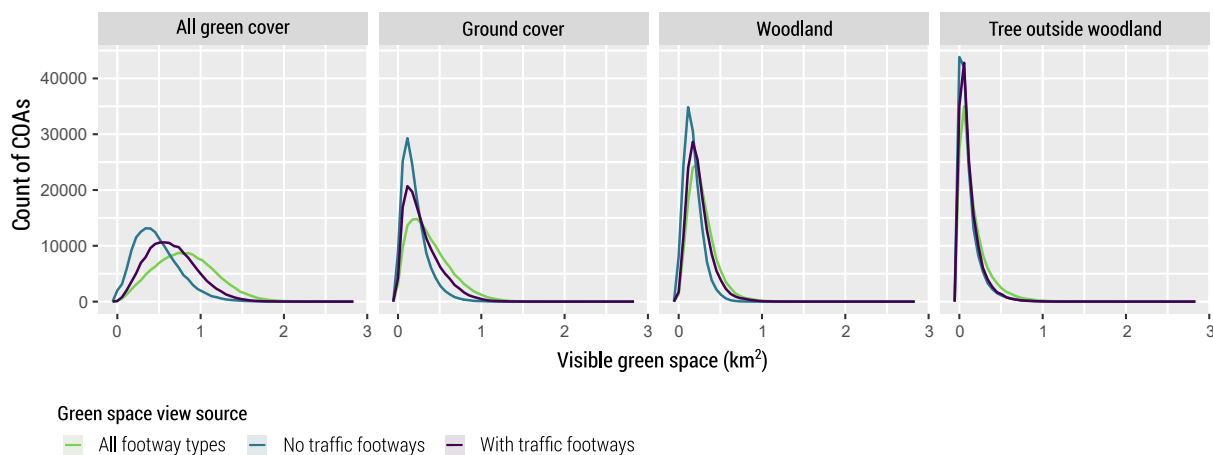


Figure 9. Frequency polygons showing distribution of green space-footpath variables.

Increasing all types of green space visible from any foot path type had positive associations with self-rated health before adjustment (Figure 10). Covariate confounder adjustment in models 13-16 attenuated the effect sizes for all green space variables (Figure 10e,f,g,h). After adjustment *ground cover-all traffic* and *all green cover-all traffic* had mostly positive J-shaped associations with self-rated health (Figure 10e,f) and *tree outside woodland-all traffic* had a mostly positive S-shape association. Associations were inconsistent for *woodland-all traffic* which had a U-shaped association (Figure 10g).

I saw little evidence of effect modification by traffic adjacent to footpaths for *all green cover* and *ground cover* (Figure 10e, f). For *woodland* and *tree outside woodland* associations diverged markedly with the absence and presence of traffic, albeit in opposite directions (negative and positive respectively, Figure 10g, h). The negative effect modification by traffic was more pronounced if the visible area of *woodland* was larger than 1 km² with no effect modification for values below 0.5 km². At the highest level of COA exposure to *woodland-with traffic* (1.72 km²), 83.7% (95% CI 82.63–84.72) of the population rated their health as positive if experienced from footpaths without traffic, compared to 78.59% (95% CI 77.3–79.82) if experienced from footpaths with adjacent traffic (holding deprivation and population density at their third quintile) a difference of 5.11%. Effect modification by traffic was consistent across the range of *tree outside woodland*, but less pronounced than *woodland* (Figure 10,h).

Increasing all green-traffic variables aside from *tree outside woodland - with traffic* and *all traffic* from 0 km² by a relatively small amount (~ 0.2 km²), had a sharp negative association with self-rated health in adjusted models (Figure 10e,f,g,h).

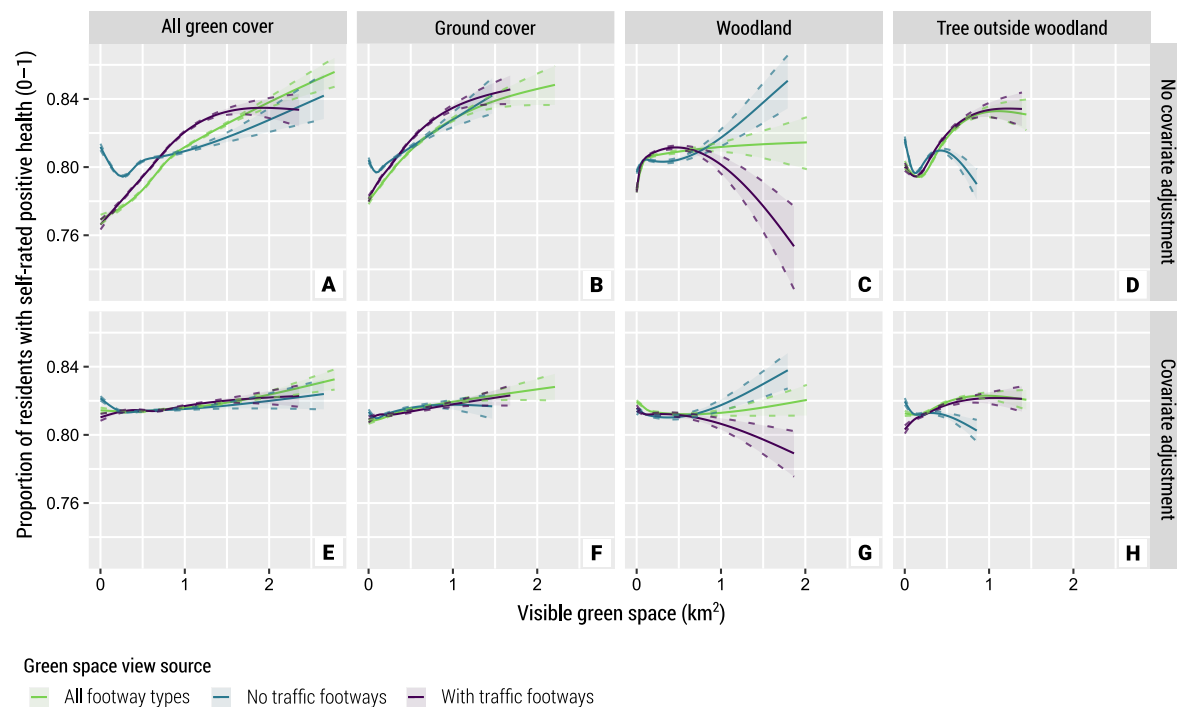


Figure 10. Predicted effects of green cover visible from footpaths on the directly age-sex standardised proportion of census output area resident with self-rated positive health from binomial generalised linear models. Dotted lines with shaded areas show 95% confidence intervals. The top row shows predicted effects of each green cover–traffic combination from models 1–12 (no covariate adjustment). The bottom row shows predicted effects after covariate adjustment (models 13–16). All predictions and confidence intervals were backtransformed from logit scale to proportions. Continuous covariates were held constant at their mean levels and socio economics deprivation was held constant at its third quintile in covariate adjusted models.

4.3.1 Confounder–health associations

In the four covariate adjusted models (Models 13–16) the self-rated positive health of people in the least deprived areas was 15.87–16.01% higher than those living in the most deprived areas (Appendix 1 - Figure 20). There was a positive association between the proportion of residents with self-rated positive health and population density (Figure 21).

4.4 Discussion

Across all urban COAs in England and Wales I found mostly positive self-rated health associations for three of the four types of green space cover types I investigated (all green cover, ground cover and tree outside woodland). This positive effect is consistent with what most studies investigating associations between green space and a variety of health indicators have found, according to a recent systematic review (Yang et al., 2021). It adds extra support to these studies as I only include green space visible from points of possible exposure (see Section 2.1 for literature and Section 4.2.4.2.2 for how I did this). Furthermore, in this analysis I include an important but often neglected green space exposure in my composite residential green space measure type—*trees outside woodland* with traffic i.e. street trees, which has been assessed at city but rarely (if ever) at national scales (de Vries et al., 2013; Lovasi et al., 2008; Marselle et al., 2020; Taylor et al., 2015).

Associations with *all green space* were not modified by traffic (Figure 10e), however, traffic did modify associations for some green space subtypes. Effect modification was most prominent for *woodland* visible from *available* footpaths, with negative associations observed for footpaths with adjacent traffic and positive associations for footpaths without traffic, after covariate adjustment (Figure 10g). Positive self-rated health associations with *tree outside woodland* were in the opposite direction, with positive associations for footpaths with adjacent traffic and negative association for footpaths with no traffic (Figure 10h). No effect modification for associations with *ground cover* was detected (Figure 10f).

The positive association of visible *woodland* from footpaths without adjacent traffic with self-rated health may be due no traffic environments seeming the most natural and being able to support more biodiversity. There is evidence that perceived biodiversity positively impacts mental health associations (Marselle et al., 2019). Biodiversity in woodland away from roads is generally higher (Polak et al., 2013). A lack of traffic may also make *woodland* seem more natural (Knez et al., 2018) and add a sense of “being away” from urban experiences, which is a mechanism of cognitive restoration in Attention Restoration Theory (Kaplan, 1995). Reduced stress and enhanced cognition may lead to COA residents to self-rate their health as positive (Levinson and Kaplan, 2014; Liu et al., 2018). The negative association of *woodland* visible from footpaths with adjacent traffic may be plausibly explained by these footpaths being less

appealing for walking (Tainio et al., 2021), resulting in resident undertaking less physical activity, worsening their health and perceived health (which is correlated with health).

The positive associations observed for visible *tree outside woodland* from all footpaths and footpath with adjacent traffic support previous findings that sparse trees alongside roads with traffic, for example, street trees are associated with better self-rated health (Reid et al., 2017).

I found associations of similar magnitude and shape for associations of ground cover visible from footpaths with and without adjacent traffic. Parks in urban spaces are often classified as *improved grassland* (a type of ground cover) in the UKCEH-LCM2017 (Morton et al., 2011). A higher availability of parks has been linked to increases in physical activity (Kaczynski and Henderson, 2007). *Ground cover* visible from footpaths with adjacent traffic, for example, road verges, may positively impact health through similar mechanisms such as improving aesthetics, increasing exertion, reducing stress and cognitive fatigue (O’Sullivan et al., 2017). There has been little empirical research or theory development, however, on the benefits of *ground cover* adjacent to roads (O’Sullivan et al., 2017; Säumel et al., 2016). However, recent work has found that amongst many other benefits, more biodiverse, free-growing roadside verges are more attractive to residents (Southon et al., 2017), which is a mediator towards increased physical activity.

I found little evidence of effect modification by traffic for *all green cover* visible from footpaths (Figure 10e). This is likely due to the opposite association for *woodland* without traffic and *tree outside woodland* with traffic adjacent to footpaths, which was of similar magnitude and, therefore, potentially counteracting when aggregated to *all green cover*. This highlights the importance of disaggregating green space green cover into separate types as health pathways and effect modification might differ by said types.

4.4.1 Strengths and limitations

My exposure assessment only included green space that was *visible* from footpaths near to where people live. This moves beyond studies which use buffers from footpaths which don’t remove views blocked by buildings (Carthy et al., 2020), or most studies that do not integrate the visibility of green space from points where it can be viewed at all (Labib et al., 2020).

Most equate residential green space exposure as the distance to nearest green space, green space in their local area or within a 0.4km²–2km² radius around their home (Labib et al., 2020). To identify visible areas along a footpath I implemented an isovist model in R. I invite future researchers to use this mode, particularly when assessing the visibility of areas from footpaths in urban environments for large scale exposure assessments, where a three dimensional viewshed analysis is too computationally intensive. This was the case for us as I had >7 million viewpoints. However, I assumed that any green space visible from footpaths *available* from approximate locations of residence would have sensory exposure to or feel the environmental benefits of. This is a feature of the residential green space availability exposure I used across all my epidemiological analyses (see Section 2.1) and is therefore a limitation I discuss in the context of my thesis more broadly in Section 7.1.3.1.

My analysis took a simplified view of roadside traffic, as I did not differentiate between low trafficked and high trafficked roads next to footpaths. Effect modification may have varied by a more specific amount of traffic and should be investigated in further research.

My analysis outcome was the proportion of COA residence with self-rated positive general health. As a self-rated health status measure, this has inherent biases. It is also on a Likert scale which has other biases. This is discussed in detail in Section 7.1.3.3 as both these aspects are a feature of the outcome variables in all my epidemiological analyses.

My analysis is cross-sectional and based on observational rather than experiment data. This limits its internal validity at the sacrifice of a large sample size and external validity. I explore this in more detail in my overall thesis limitations, as they are issues related to all my analyses.

4.4.2 Recommendations

My finding that some green space green cover types were modified by traffic supports investigation of potential green space – health effect modifiers more generally, which are relatively understudied (Marselle et al., 2021), see Section 7.1.2. Furthermore, the fact I only found effect modification for some green cover types, highlights that it may also be important

to disaggregate green space by green cover type when investigating other effect modifiers where possible.

As one of the first studies to investigate how simultaneous exposure to traffic may impact green cover and health associations, my findings should be replicated across different types of analysis of different datasets (see Section 7.1.4 for details). This could be similar analysis using different outcomes or study areas. Longitudinal analyses or experiments on traffic modifying effect on green space health associations would allow for an exploration of whether my associations are causal. For example, comparing the change in health of individuals which are randomly assigned to either experiences of green space near a road or away from a road.

My results support the presence of trees outside woodland in urban areas by roads and conversely, woodland away from roads for human health benefits to those living nearby. The finding that woodland is beneficial to health when away from roads also aligns with biodiversity conservation objectives, as wildlife is often deterred by roadside noise (Polak et al., 2013). Architects, urban planners, and policy makers should consider the important role that traffic may play in impacting the benefits green space can have to human health in decision making, particularly in UK but perhaps also in places with a similar cultural and climatic context (see Section 7.1.4).

4.5 Conclusion

My study provided an exploratory systematic comparison of the effect that traffic adjacent to footpaths had on natural environments association with self-rated health of all 45.7 million urban residents of England and Wales in my study. I linked the self-rated health responses of these individuals from the 2011 census with measures of natural environment experiences adjacent to and away from roads with traffic. Residential green space (*all green cover*) had mostly positive associations with health, when experienceable from any footpath. Traffic had little impact on self-rated health and neighbourhood *ground cover* and neighbourhood *all green cover* associations. However, the proportion of residents self-rating their health as positive in a neighbourhood increased when there was more *woodland* with no traffic nearby

and decreased when they had more *woodland-with traffic*. Conversely, *tree outside woodland* had the strongest positive association with self-rated health when experienceable from footpaths adjacent to roads with traffic. My findings highlight the importance of considering how exposures concurrent to natural environments can modify whether and to what degree green spaces benefit health.

5 Socioeconomic deprivation modifies green space and mental health associations: a quasi-experimental analysis

5.1 Introduction

We need to strengthen the internal validity for the previously observed modifying effect of deprivation on residential green space and mental health associations (see Section 2.2.1.2). This can be achieved, for example, using longitudinal analysis that control for within person confounding (Howard et al., 2017; Marselle et al., 2021; Nguyen et al., 2021). One quasi-experimental study type (Bärnighausen et al., 2017) that only uses within-person variation is fixed-effect models (Gunasekara et al., 2014). Conceptually fixed-effect models treat a person's mean health and exposures through multiple responses in time as a control for their outcome, exposures, and effect modifiers as recorded in each response (Quintana, 2021).

Some studies have used fixed-effects models to associate mental health and residential green space exposure, where the exposure variation comes from moving their home address. Most of these found positive associations (Cleary et al., 2019; Gubbels et al., 2016, 2016; Krekel et

al., 2016; White et al., 2013), while one did not (Noordzij et al., 2020). The latter studies' authors consider that there may not have been enough within-person variation to detect significant effects of the same size as previous studies.

I am unaware of studies investigating whether local area socioeconomic deprivation change modifies associations between green space change and mental health, completely within persons. Here I present multiple fixed-effects analyses of participants in the Understanding Society cohort (Institute for Social and Economic Research, 2021) resident in GB to address this knowledge gap. I hypothesise that: (i) higher levels of exposure to residential green space improves mental health. (ii) Increased local area deprivation positively modifies this green space-mental health association.

5.2 Methods

5.2.1 Study population and data source

My study population for this analysis was all participants in Understanding Society – The UK Household Longitudinal Study (US) 2009–2019 (waves 1-9). Details on this dataset and its usefulness to this analysis (and additionally analysis 3) are outlined in Section 3.3. I managed this data using the R packages "data.table" and "dplyr" (Dowle et al., 2019; Wickham et al., 2022).

5.2.2 Health outcome

The outcome of interest was the participant's score on the Mental Component Summary of the Short-Form 12 Health Survey (hereafter, *mental health score*). Details of this can be found in Section 3.3.4 as I also use it as my outcome variable in analysis 3.

5.2.3 Residential green space exposure

I defined residential green space exposure as the percentage of land within 1,600 metres (m) of each participant's wave-specific household LSOA PWC covered in vegetation (hereafter, in this analysis *residential green space*). A participant's household wave specific LSOA was given to us from Understanding Society under a "special license" and is identified through postcodes that Understanding Society interviewers record during each wave. A 1,600 m distance buffer is at the upper end of commonly used buffers in studies of residential green space and health associations (generally between 300 m and 1,600 m) (Kondo et al., 2018; van den Berg et al., 2015). I chose a distance buffer at the larger end of this spectrum as previous research found them to be more sensitive to the modifying effect of deprivation on green space and physical health associations in a previous systematic review (Rigolon et al., 2021). I chose 1,600 m specifically as it approximates a maximum 20-minute walk. I used buffers from the PWC as it better approximates residential green space exposure than proportional coverage of LSOAs (see Section 3.2.3).

I defined green space as vegetated land as outlined in Section 2.1.1. This equated to all classes of woodland, arable, grassland, fen, heather, and bog according to the UKCEH-LCM 2017 (Morton, 2020) (20 x 20 m resolution) or land with over 50% tree cover according to 2015 Copernicus TCD product (European Environment Agency, 2018) (20 x 20 m resolution). I used both products as tree cover outside woodland is a typical green space exposure in cities (for example, street trees) (Salmond et al., 2016) and is not represented in the UKCEH-LCM 2017, which is more comprehensive across grassland cover than Copernicus products. Finally, to obtain *residential green space* I extracted the percentage coverage of the summed pixel fractions for each buffer, which is my final exposure of interest. As with earlier studies, I assumed green space to be static over time and that exposure change only occurs when a respondent moves to a different LSOA (White et al., 2013). I completed my exposure assessment using R's packages "raster", "exactextractr", and "sf" (Dowle et al., 2019; Hijmans et al., 2019; Pebesma, 2018; R Core Team, 2019).

5.2.4 Socioeconomic deprivation as an effect modifier

The effect modifier was the continuous Carstairs index of socioeconomic deprivation of each participant's wave-specific LSOA (hereafter in this analysis, *local area deprivation*) (Carstairs and Morris, 1990). The Carstairs index is frequently used in epidemiological analyses to represent socioeconomic deprivation across GB. The Carstairs index is a composite measure of deprivation based on 2011 census variables related to the proportion of male unemployment, lack of car ownership, overcrowding, and low social class. Higher *local area deprivation* scores (as measured by Carstairs) represent greater socioeconomic deprivation. Like *residential green space*, I assumed that an area's *local area deprivation* score stayed the same over time (based on my 2011 census variables) and that any change in local area socioeconomic deprivation was due to individuals moving residence.

5.2.5 Confounders

I include potential confounders that are plausibly correlated with changes in *mental health score* and *residential green space*. A detailed explanation of these confounders is outlined in Section 3.4. I used the same area level confounders as analysis 1 and 3 (aside from socioeconomic deprivation which I used as an effect modifier) and the same Understanding Society dataset confounders as analysis 3.

5.2.6 Statistical methods

After calculating exploratory statistics (see Section 5.3), I ran fixed-effects models to investigate whether a change in a person's *residential green space* exposure (from moving residence) is associated with changes in their mental health and whether changes in their *local area deprivation* (again from moving residence) modified this. By design, fixed-effects models do not model differences between persons (or groups) but differences (changes) within persons, which impacts the interpretation of coefficients (Quintana, 2021).

5.2.6.1 Determining change using within-person differences

Change in respondents' *mental health score*, *residential green space*, *local area deprivation*, and confounders, as defined in fixed effects (and therefore my analyses), is relative to their multi-wave mean score. For example, a person's *residential green space* exposure in wave 5 is subtracted from their mean exposure in waves 1-9 to obtain their change in *residential green space* exposure score for wave 5. This process is called "demeaning" and is the standard approach in fixed-effects models (Quintana, 2021). Therefore, readers should interpret my model associations as changes within people rather than differences between people (Mummolo and Peterson, 2018). Demeaning also happens for dummy-coded categorical variables. This represents their wave-specific category presence/absence relative to their mean presence in a category across waves, leading to dummy coded scores outside 0 and 1. For example, if a respondent participating in 6 waves was "employed" in 5 waves (waves 1-5) and "unemployed" in 1 (wave 6), their dummy coded "employed" score in wave 6 would be -0.833. That is their membership of the "employed" category in wave 6 is -0.833 relative to their mean membership. This person's deviation from their average "employed" status would be higher in wave 6 than for example, a person who was only "employed" for 2 waves, and not for the remaining four waves (score would be -0.33).

5.2.6.2 Summary statistics

I produced several summary statistics to better understand potential collinearity between variables, the distribution of outcome data (for developing statistical models), and to incorporate into interpretation of results. Specifically, I produced Pearson's correlation plots between demeaned outcome, effect modifier, exposures, and potential confounders, histograms between effect modifier and outcome, and summary tables showing the number of times individuals participated in a Understanding Society wave and moved LSOA.

5.2.6.3 Modelling approach

I regressed change in nearby green space exposure against change in *mental health score* before (Model 1) and after (Model 2) adjustment for potential confounders. I explored effect modification by a change in *local area deprivation* in Model 3 by introducing a multiplicative term between *residential green space* and *local area deprivation* (Table 7).

Table 7. Fixed variables used in models.

Model	Fixed variables
Model 1 – Green only	Mental health score ~ residential green space
Model 2 – Green adjusted for potential confounders	Mental health score ~ residential green space + local area deprivation + age + income + employment status + residents per bedroom + commuting time + nearby population density
Model 3 – Green adjusted for potential confounders under effect modification	Mental health score ~ residential green space + local area deprivation + residential green space*local area deprivation + age + income + employment status + residents per bedroom + commuting time + nearby population density

I excluded cases where a person's *mental health score*, *residential green space* exposure, or *local area deprivation* or confounder information was unavailable (incomplete cases).

Unavailability was either because of question non-response or mistakes in survey administration or participants residing in Northern Ireland (outside my exposure and effect modifier data domain).

I used the "panelR" package function "wbm" to calculate my fixed-effects models (Long, 2021). This package uses a multilevel modelling framework to calculate standard errors (and subsequent confidence intervals and *p*-values) that account for within-participant correlation of errors by fitting a random intercept for each participant (Abadie et al., 2017). The interaction of changes from mean *residential green space* and mean *local area deprivation* in Model 2 was double-demeaned (Giesselmann and Schmidt-Catran, 2020), something essential to obtain a purely within-person estimator of interaction variables in fixed-effects models (Quintana, 2021).

After running models, I used the Johnson-Neyman technique to identify at what range modification from a change in *local area deprivation* led to a significant slope (*p*-value < 0.05) of a change in *residential green space* from zero (Bauer and Curran, 2005). I calculated Johnson-Neyman intervals using the R package "interactions" (Long, 2019). I produced effect modification and association plots using a combination of the R packages: "dplyr", "effects", "ggplot2", "interactions", and "patchwork" (Fox and Weisberg, 2019, 2018; Long, 2019; Pedersen, 2020; Wickham, 2016; Wickham et al., 2022).

5.3 Results

The final sample included 300,710 responses from 54,666 individuals, out of a possible 409,863 responses from 86,094 individuals. Individuals participated for an average of 4.84 waves across a potential 9 waves (Table 8). Less than one-quarter of respondents (12,385 or 23%) moved LSOA at least once and therefore had variation in their *residential green space* exposure or *local area deprivation* (Table 9). At a population level there was a balance of people's *mental health score*, *residential green space* and *local area deprivation* increasing or decreasing (Figure 11). The distribution of change in mental health, *residential green space*, and *local area deprivation* was approximately normal (Figure 11), which remained true for movers only. The standard deviation of change in *mental health score*, *residential green space*, and *local area deprivation* were 6.40, 5.98, and 0.75, respectively. Within-person increases in *residential green space* were moderately negatively correlated with within-person decreases in *local area deprivation* and nearby population density ($r = -0.41$ and -0.72 , respectively, see supplementary materials I).

The range of *local area deprivation* and *residential green space* before demeaning was -5.13 – 14.3 and 0.832 – 99.9 , respectively. Prior to demeaning, local area deprivation (Carstairs score) and *residential green space* (percent cover) had a mean of 0.0181 and 49.8 , respectively.

Table 8. The number of responses per participant in my final dataset. We removed individuals with less than two responses and missing information on explanatory variables and confounders (see study population and data source above).

Number of responses	Number of individuals
2	10,017
3	6,997
4	5,019
5	4,840
6	4,668
7	5,865
8	8,994
9	8,266

Table 9. The number of times respondents moved their LSOA during the nine Understanding Society waves studied.

Number of times moved LSOA	Number of individuals	Percentage of individuals
0	42,281	77.34
1	9,271	16.96

2	2,246	4.11
3	630	1.15
4	194	0.35
5	36	0.07
6	8	0.01

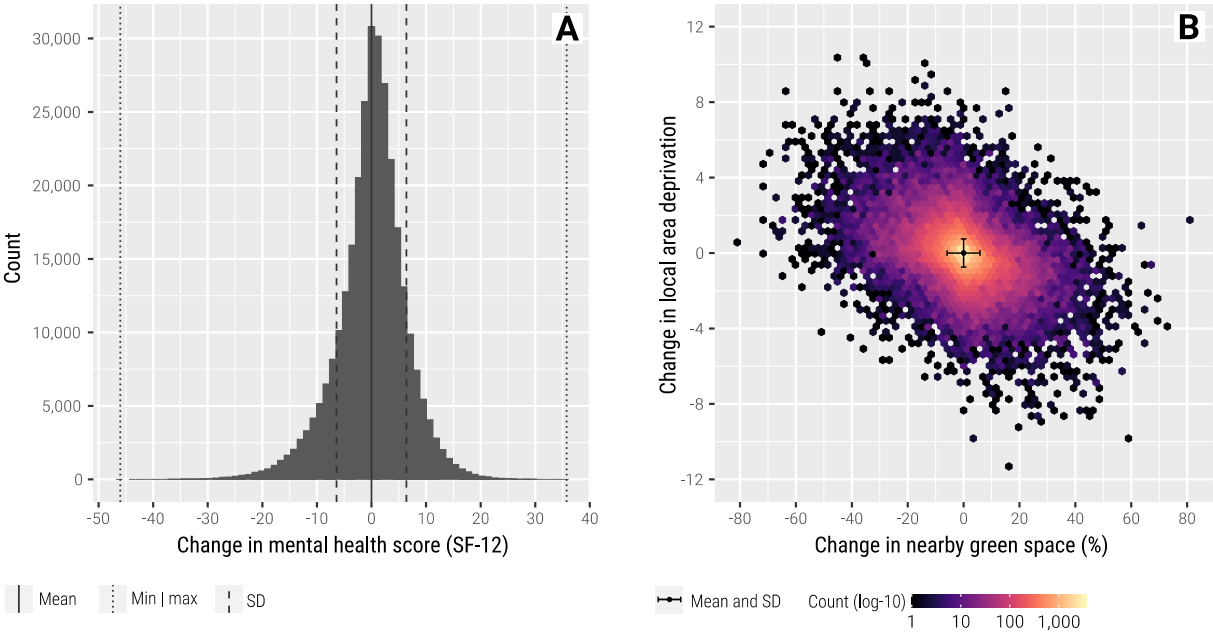


Figure 11. Distribution of change in outcome (A) and exposure and effect modifier (B). Each n is one score (from one wave). (A) Histogram of change from within-person mean mental health score (the mental score component of the SF-12 survey) n = 300,710. (B) density plot of change in local area deprivation scores (Carstairs index) and residential green space from their respective within-person mean, n = 78,065. I removed 222,645 points (74% of all responses) in (B) from individuals who did not change LSOA for display purposes only. The minimum and maximum deprivation score change was -11.2 and 10.3, respectively. The minimum and maximum green space change was -80.9 and 81.2, respectively. Density counts in plot B are on a log-10 scale.

In the univariate analysis, I found no significant association between *residential green space* change and *mental health score* change (Model 1 in Table 10). However, after adjusting for potential confounders, the association between *residential green space* change and *mental health score* change was significant (Model 2 in Table 10). *Local area deprivation* change had a significant ($p < 0.05$) positive modifying effect on the *mental health score* change – *residential green space* change association (Model 3 in Table 10). Johnson-Neyman intervals revealed that the slope of *residential green space* change significantly differed from zero when *local area deprivation* increased by more than -0.09 in Model 3. Potential socioeconomic confounders had the expected direction of association when statistically significant (Figure 13).

Table 10. Results from fixed-effects models in Table 7, where the dependent variable is change in mental health score relative to the within-person mean. More positive estimates indicate better mental health. Model 1 is the univariate association between residential green space and mental health score, model 2 additionally adjusts for potential confounders, and model 3 additionally includes socioeconomic deprivation as a potential effect modifier. Coefficients are predicted for each model explanatory variable's one-unit increase relative to each respective variable within-person mean. Numbers (aside from *p*-values) are shown to three significant digits. CI = 95% confidence intervals. Est. = estimated effect on mental health score.

Explanatory variable	Model 1			Model 2			Model 3		
	Est.	CI	<i>p</i> -value	Est.	CI	<i>p</i> -value	Est.	CI	<i>p</i> -value
Residential green space (%)	0.00418	-0.000119 – 0.00848	0.057	0.0069	0.000589 – 0.0132	0.032	0.0069	0.000209 – 0.0128	0.32
Local area deprivation (Carstairs score)				-0.0482	-0.0871 – -0.0117	0.01	-0.0481	-0.0857 – -0.0103	0.013
Residential green space*local area deprivation							0.00273	0.0000939 – 0.00537	0.04
Population density (residents per ha)				0.00695	-0.00523 – 0.0191	0.292	0.00735	-0.00483 – 0.0195	0.237
Residents per bedroom				-0.31	-0.393 – -0.231	<0.001	-0.309	-0.258 – -0.0886	<0.001
Disposable household income (£1,000's)				0.0134	-0.00287 – 0.0297	0.138	0.0134	-0.00295 – 0.0297	0.108
Age									
15–30 years (reference)				—	—	—	—	—	—
30–42 years				-1.72	-1.91 – -1.52	<0.001	-1.72	-1.91 – -1.52	<0.001
42–52 years				-2.67	-2.93 – -2.42	<0.001	-2.67	-2.93 – -2.42	<0.001
52–65 years				-3.06	-3.36 – -2.75	<0.001	-3.06	-3.36 – -2.76	<0.001
65–102 years				-3.16	-3.51 – -2.81	<0.001	-3.17	-3.52 – -2.81	<0.001
Employment status									
Unemployed (reference)				—	—	—	—	—	—
Employed				1.40	1.21 – 1.6	<0.001	1.4	1.21 – 1.60	<0.001
Outside workforce				1.29	1.11 – 1.46	<0.001	1.29	1.11 – 1.46	<0.001
Commute time									
0–15 minutes (reference)				—	—	—	—	—	—
15–30 minutes				-0.333	-0.456 – -0.209	<0.001	-0.333	-0.457 – -0.210	<0.001
30–60 minutes				-0.451	-0.602 – -0.299	<0.001	-0.451	-0.602 – -0.299	<0.001
>60 minutes				-0.475	-0.728 – -0.223	<0.001	-0.475	-0.728 – -0.223	<0.001
No commute information				-0.211	-0.354 – -0.0678	0.004	-0.211	-0.354 – -0.0676	0.004

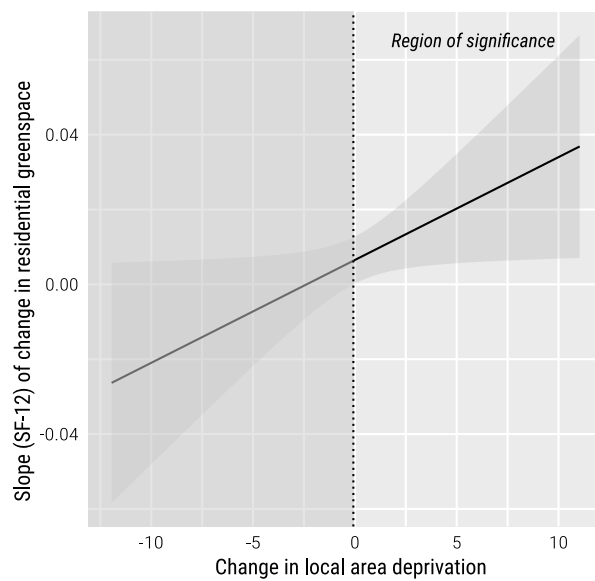


Figure 12. Johnson-Neyman plot showing the effect modification of change in local area deprivation on change in residential green space and change in mental health associations with adjustment for potential covariate confounders (Model 3). All values have been demeaned within persons, showing the effect of change of each wave response from the multi-wave within-person means. The region of significance indicates the levels of change in local area deprivation where the slope of residential green space is significantly different from zero.

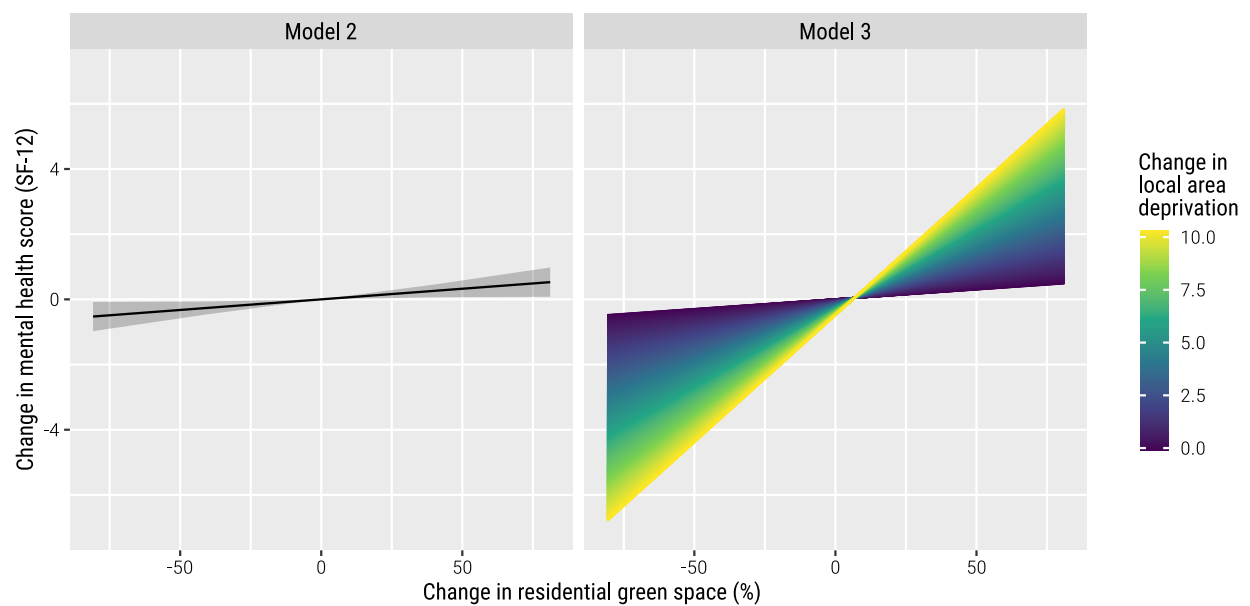


Figure 13. Predicted associations between residential green space change and mental health score change under effect modification from a change in local area deprivation (see definitions in Methods). All values have been demeaned within persons, showing the effect of a change from the within-person means. The predicted model 3 surface is clipped to values where the slope of change in residential green space significantly differs from zero according to Johnson-Neyman intervals (see [Figure 12](#)).

5.3.1 Confounder–health associations

Confounders had the expected effect direction, specifically respondent health worsened when moving into older age categories, having more residents per bedroom, and having a longer commute; but was most positive when population density increased, when they were no longer unemployed, and they had a higher income (Table 10)

5.4 Discussion

I found a significant positive association between changes in residential green space and changes in mental health (Table 10 and Figure 13). This finding aligns with the majority of previous research investigating residential green space and mental health associations cross-sectionally (Kondo et al., 2018; Twohig-Bennett and Jones, 2018) and longitudinally using fixed effects (Cleary et al., 2019; Gubbels et al., 2016, 2016; Krekel et al., 2016; White et al., 2013). It also supports creating and protecting green spaces for public health in the UK.

I also found a significant positive modifying effect of local area deprivation change on the green space change and mental health score change association (Table 10). This finding aligns with the few previous cross-sectional studies (Rigolon et al., 2021). However, the slope of residential green space was only significant when deprivation stayed constant or increased, as revealed by Johnson-Neyman intervals (Figure 12). This indicates that for residential green space to have an increased effect the area where a person moved to needed to be more deprived relative to their average amount of local area deprivation exposure. Furthermore, decreasing a person's residential green space exposure (through moving) had a minor impact on their mental health unless local area deprivation also increased (effect size near zero, Figure 13).

My results, contingent on the direction of deprivation change and the amount of deprivation change, have a few possible explanations. Firstly, if an individual's mental health is impacted from moving to a more deprived area, they may be more amenable to the restorative benefits of residential green space. This is something supported by experimental evidence grounded in ART and SRT whereby individuals are first given a stressor before the restorative benefits of

green space can be detected (Kaplan and Berman, 2010; Ulrich, 1983). This is related to previous work that has also suggested the health of individuals in less socioeconomically deprived areas is close the best it can be without green space, and therefore adding more green space is less likely to improve their health (Rigolon et al., 2021). Secondly, an individual's mental health may be damaged if an individual feels forced to live in a particular geographic location that is both less green and more socioeconomically deprived to have access to work and/or family. These may be the only places where these individuals can buy/rent a property of the required size and within a travelling distance needed to be near work and family. Thirdly, the probability of encountering the effects of local area deprivation (for example, crime and violence, lack of resources) may also be lower in a greener area due to there being fewer built-up surfaces that can show apparent signs of deprivations effects (Bellis et al., 2008; Rees-Punia et al., 2018).

5.4.1 Strengths and limitations

Variation in green space and neighbourhood socioeconomic deprivation exposure was within respondents and came from individuals moving home. Only modelling within-person variation was the primary strength of this analysis, as it allowed us to control for bias from between-person confounding (see overall thesis strengths and limitations Section 7.1.3.2). However, the act of moving itself could have an impact on health. Future research should investigate the impact of changing levels of deprivation and residential green space on health within the same location.

Conducting a fixed-effects analysis by demeaning my variables with a simple linear regression allowed us a greater number of degrees of freedom with which to estimate associations than would be possible using, for example trends over time using a first difference estimator (Wooldridge, 2010). However, this assumed that each yearly exposure to residential green space and local area deprivation was an individual exposure-response event. However, there may be cumulative or adaptive effects from living in an environment for more than one year (Alcock et al., 2014). For example, a respondent's first year of exposure to more residential green space after moving may be associated with only temporary mental health improvements, but their mental health may return to pre-move levels in subsequent

years. In this case, my model predicted associations might underestimate green space benefits in the first year after moving and overestimate them later.

I also may not have identified all time-variant confounders, which could potentially bias associations (see Section 7.1.3.2). My exposure assessment assumed exposure to residential green space within walking distance from home and did not quantify whether respondents had actual sensory exposure to or were close to green space (important mediators, see Section 7.1.3.1). Many people do not use residential green spaces, so the expected mental health impact on those who do will likely be underestimated.

I used a combination of recently produced 20 m land cover maps for my green space exposure assessment to produce one exposure surface representing one time point, the UKCEH-LCM 2017 and the Copernicus TCD map ([European Environment Agency, 2018](#); [Morton, 2020](#)). This allowed us to quantify exposure to smaller green space patches, which can be important residential exposures (e.g., street trees). However, only having one land cover map (as opposed to many of different time points) was a limitation as it makes the false assumption that a local area's green space (and deprivation) did not change over time. This may introduce further misclassifications of local area deprivation score and residential green space, for example, if there was a dynamic land cover or socioeconomic change throughout the 9 Understanding Society waves. However, change in green space cover of GB cities (where most people live) is relatively stable, with a median change of 5% between 2000 and 2015 ([Richards and Belcher, 2020](#)).

5.4.2 Recommendations

My findings support conserving and providing green space in more deprived areas to address health disparities across a deprivation gradient—a global population health issue ([UN General Assembly, 2015](#)), evident in the UK ([Marmot, 2020](#)) and also a key to the United Nations Sustainable Development Goal (SDG) 11.7 to provide “universal access to green and public spaces” ([UN General Assembly, 2015](#)). The moderate negative correlation between change in residential green space and change in local area deprivation shows that individuals moving to a more deprived area are less likely to have green space nearby. It also adds to cross-sectional evidence that green space provision is lower in more deprived areas ([Ridgley](#)

[et al., 2020](#)). I recommend caution on extrapolating these results to outside of the UK, due to the impact of how green space is used across different cultures and climates (see [Section 7.1.4](#))

5.5 Conclusion

I have completed one of the first studies to investigate how a change in local area deprivation modifies the benefits to mental health from changing residential green space, which varied due to individuals moving to a different local area. By using a fixed-effects approach, my findings add robustness to the limited cross-sectional evidence that green space is more beneficial to the mental health of those living in (or moving to) more deprived areas. I also add to the broader evidence that adding green space to socioeconomically deprived areas can reduce inequalities in health ([Rigolon et al., 2021](#)). These findings support calls from international bodies such as the World Health Organization ([WHO Regional Office for Europe, 2017](#)) and the United Nations SDG 11.7 to provide universal access to urban green space by 2030 ([UN General Assembly, 2015](#)).

6 Water and perceived naturalness modify green space associations with mental health: a nationally representative study

6.1 Introduction

Two potential effect modifiers of green space and mental health associations that have shared implications for green space design, protection and environmental conservation, are its perceived naturalness and whether it is a wetland (contains seasonal water or is permanently/seasonally wet). See Sections [2.2.1.3](#) and [2.2.1.4](#) for why each of these factors may be potentially important effect modifiers and understudied. However, despite their respective importance there have been few, if any, large-scale cross-sectional analysis on how residential exposure to green space to these effect modifiers impacts mental health (Section [2.2.1.3](#) and [2.2.1.4](#)). Using a larger sample of respondents that are stratified by the same social, demographic and even locational composition of the UK would provide more external validity and generalisability to the UK population. There are many nationally representative,

large sample size long-term panel data such as the UK-based Understanding Society (Lynn, 2009) that have these characteristics (Silva et al., 2018). Understanding Society also records longer-term self-reported mental health data than just those experienced while in a green space (e.g. mental health in the past month), another limitation of the existing evidence base (Turek et al., 2021).

Here, I present a cross-sectional repeated measures random effects model, using the Understanding Society survey, as my sample of respondents (Institute for Social and Economic Research, 2021). This design complements the existing experimental literature, increasing external validity by having over 245,000 responses across more than 71,000 participants weighted to be nationally representative of the UK population. My outcome is a person's mental health in the past month, with green space exposure and effect modifiers around where people live being assessed. This compliments experimental research investigating immediate benefits after being in or seeing green spaces of varying levels of naturalness (Section 2.2.1.3) or the proportion of wetland (Section 2.2.1.4) that may be far away from these study participants' homes. I hypothesise that (1) higher levels of exposure to residential green space improve mental health; (2) residential green space naturalness positively modifies association 1; and (3) the proportion of green space wetland positively modifies association 1.

I also advance assessments of exposure to green space with varying levels of naturalness by creating the first UK “perceived naturalness” map (see Section 6.2). This is through completing a nationally representative choice experiment with 2,001 respondents on the perceived naturalness of said landcover/use descriptions and then transfer these scores onto national maps for use by other researchers.

6.1.1 Mapping the perceived naturalness of large areas

One potential reason for there being no large cross-sectional studies spanning cities, regions or nations on the effect modification from perceived naturalness on residential and green space associations is a lack of available maps on perceived naturalness from which to extract residential exposure.

Larger scale maps that place the qualities of landscapes (including their naturalness) that are not directly measured are most often made using a type of spatial value transfer method (Brown et al., 2020, 2016; Troy and Wilson, 2006), as collecting primary data on different indicators at this scale is resource intensive. Using this approach, qualities of either types of landscape, or locations in space are assessed for both their objective (e.g., ecological naturalness) (Pizzolotto and Brandmayr, 1996) and subjective (e.g., perceived naturalness) qualities.

Experts often use their scientific knowledge of land covers to create national/regional naturalness maps based on land-cover types (Pizzolotto and Brandmayr, 1996). This is because land-cover map classes are often defined in ways that map onto naturalness criteria. For example, a UK based study classified green space (according to Ordnance Survey maps) that had less management intensity and more freedom of succession as being more natural on a scale of 1–3 (Kazmierczak et al., 2010). Natural England later modified this scale in their 2010 ‘Nature Nearby’ Accessible Natural Greenspace Guidance (scale 1–3) (Natural England, 2010), who modified it again for their 2022 Green Infrastructure Framework (GIF) (scale 1–4) (Natural England, 2022). Since the original Kazmierczak et al. (2010) scale, Carver et al. (2012) defined the naturalness of the full ecological diversity of green space types contained within the UKCEH-LCM 2020 (Morton et al., 2011). The UKCEH-LCM 2020 defines green space partially by its naturalness, which helps facilitate this. The authors only mapped the naturalness of parts of Scotland. This scale has also more recently been adapted to map the naturalness of green space across GB, but at over 5 km hexagonal grid cells (Chang Chien et al., 2020). None of the nationwide green space naturalness maps in the UK (and few outside the UK) identify green space's perceived rather than expert-assessed naturalness. Although Carver et al. (2012) and the Natural England GIF scales use expert-assessed ecological naturalness of green space types based on their vegetation composition and other features as a proxy for this, ecological naturalness does not always equate to its perceived naturalness by the public (Tveit et al., 2006), and therefore, exposure to more ecologically natural environments may not modify pathways that rely on perception e.g. ART and SRT (Sections 2.1.4.1.2, 2.2.1.3 and 2.2.1.4). Most individuals have little ecological training, and while they may be able to identify ecosystems that are most divergent in their naturalness, e.g., agricultural monocultures compared to deciduous woodland, subtler

differences in naturalness, e.g., semi-natural grassland and improved grassland may be less detectable by them.

Where the perceptual qualities of green spaces are assessed, for example, perceived naturalness, a form of public participation is required. This is most often in the context of cultural ecosystem service quantification ([Millennium Ecosystem Assessment, 2005](#)). Using a spatial value transfer approach, one study in the Ebro Delta, north-eastern Spain ([Palacio Buendía et al., 2021](#)) mapped landscapes such as green space's subjective qualities, including their perceived naturalness. This was done through a smooth interpolation of naturalness ratings at different points selected by participants. Interpolation methods are limited where point data is scarce, as landscape characteristics between points may have a huge impact on their desirability. For example, an open pit mine would be modelled as high desirability for recreation, if surrounded by nice looking areas when it is unlikely to be desirable for this purpose. An alternative approach to interpolation is “generic feature mapping” ([Scholte et al., 2015](#)). This approach assesses the perceptual qualities, landscape photographs taken at specific locations, and consists of the following basic steps using naturalness as an example quality. Spatial data over a large study area is first compiled, for example, land cover ([Liepa et al., 2023](#)), and additionally other factors such as their objective naturalness, slope and geology ([Zoderer et al., 2019](#)). The values of these spatial datasets at the point where each photograph was taken is extracted. The naturalness of each photograph is then be modelled as a function of the spatial dataset values assigned to each photograph, using regression or choice models, depending on the original survey instrument ([van Zanten et al., 2016](#)). The results of this model are then predicted over the spatial data covering the large study area. Generic feature mapping approaches of landscape perceptual qualities, such as perceived naturalness, rely on photographs that provide a representative and realistic stand-in for actual experiences in said landscapes.

6.1.1.1 Choosing photographs for generic feature mapping of green space naturalness

Photos of environments have been used as a reasonable stand-in for experiences in them in previous health and landscape preference studies ([Silvennoinen et al., 2022](#)). However, they are limited because they only provide a visual representation, and for example, in the case of

naturalness, sounds and movement of wildlife, for example, may influence how natural a green space is perceived. The goal of selecting photos for naturalness map creation using generic feature mapping is to ensure that the naturalness ratings given by viewers (respondents) of said photos match the ratings they would give if they were present in the green space where the photo was taken (representational validity). Most guidance on this comes from landscape preference and tourism studies ([Silvennoinen et al., 2022](#); [Steen Jacobsen, 2007](#)).

6.1.1.2 Previous work quantifying the relative perceived naturalness of green spaces

Studies have assessed the perceived naturalness of green spaces separated by their structural characteristics, land-cover types or expertly assessed ecological naturalness and other characteristics not the focus of this research (biodiversity, presence of facilities, for example). These studies have asked respondents to use Likert/semantic differential scales to rate the perceived naturalness of a randomly assigned green space type /all green spaces in a study. One set of these studies has assessed photograph/video/audio, which I refer to as the photograph based studies ([Braun Kohlová et al., 2021](#); [Carrus et al., 2013](#); [Chen et al., 2023](#); [Ode et al., 2009](#); [Sevenant and Antrop, 2010](#); [Suppakittpaisarn et al., 2020](#); [Uebel et al., 2021](#); [Van den Berg et al., 2014](#)). Another set has assessed green space(s) that they have freely chosen to visit in person, either on the day of the survey or in the past which I refer to as visit based studies ([Fisher et al., 2021](#); [Hoyle et al., 2019, 2017](#); [Klaperski et al., 2019](#); [Krapez et al., 2021](#); [Liu et al., 2018, 2022](#); [Mackay and Neill, 2010](#); [Marselle et al., 2016](#); [Schebella et al., 2019](#)).

Many visit-based studies have used university students as their study population, which has limitations (e.g. Section 2.2.1.3). Using convenience samples (e.g. of university students) impacts the generalisability of findings to other populations (e.g. the general public), as they may have a different perception of green space naturalness than other groups ([Jager et al., 2017](#)). It should be noted, however, that convenience samples based on actual experiences may be more reliable. This is because if a respondent has never been to said green space, they are relying purely on how they imagine them to be based on photos/videos/recordings. If even if they have, they may experience recall bias ([Althubaiti, 2016](#)).

There are limitations to using Likert/semantic differential scales more generally, specific to previous visit-based studies, and some trade-offs between using either the photograph or visit-based approaches listed above (see Section 7.1.3.3 for more discussion on the limitations of self-ratings as they are also a limitation of the outcomes that I use to assess the health benefits of green spaces).

Individuals may use Likert scales differentially depending on their cultural or economic background. For example, a perceived naturalness score of 7 may mean the same as 5 to another group (Jw et al., 2002). This scale-use bias may generalise to populations whose residential green space exposure has a consistent level of low naturalness in urban centres. In the case of visit-based studies, should, for example, an urban resident (participant A) frequently visit one type of low ecological naturalness green space, they may feel this is the typical naturalness of any green space and rate it highly. In contrast, an individual (participant B) who visits more ecologically natural green spaces may give again the same average score. When shown pictures sequentially (or taken into multiple green space types), respondents may feel a cognitive burden to remain constantly calibrated to ensure they rate naturalness fairly (Burton et al., 2019). However, this calibration (Tong and Dubé, 2022) and their central tendency (Allred et al., 2016) may drift as the other revealed pictures inform respondents about the spectrum of naturalness they are assessing, causing order bias. Within a Likert questionnaire, order bias and precision can be reduced if a) respondents are presented with all green spaces, for example in photograph-based studies simultaneously or b) if they are allowed to change their scores retrospectively. However, showing all photos and changing answers also increases respondent cognitive burden. Randomly ordering pictures can also reduce order bias, but precision would still be reduced. Regardless, respondents may use the extremes of the scales in different ways.

6.1.1.2.1 *Maximum difference experiments for relative perceived naturalness ratings*

One alternative approach to Likert scales when identifying the perceived naturalness of green spaces is Maximum Difference (MaxDiff) choice experiments (Cohen, 2003). MaxDiff experiments have been used to rate the relative performance of different characteristics across a variety of studies, ranging from those rating public preference for green space characteristics (Madureira et al., 2018) to ranking of food safety interventions (Finn and Louviere, 1992) to health studies more broadly (Hollin et al., 2022).

In a MaxDiff experiment, participants are shown a subset of items (for example, land covers/uses) several times (a choice exercise) and each time are asked to select which item best and worst represents the latent attribute in question (for example naturalness). A person's cognitive burden in a MaxDiff is eased compared to Likert ratings as respondents do not need to remember previous choices and relative scorings, and there is no possibility of scale-use bias due to their being no scale (Burton et al., 2019; Cohen, 2003). In the most basic analysis of MaxDiff data, the number of times an item is voted the best is subtracted by the number of times it is voted the worst in a counts analysis, giving a relative score (e.g., perceived naturalness), which can then be scaled. To avoid bias in this score, each item must have an equal chance of being selected best or worst. Balanced Incomplete Block Designs (BIBDs) avoid this bias by completely equalising the number of times each item is shown, the number of times it is shown with every other item and the order in which it appears with every other item (they are perfectly balanced). This helps reduce order bias and, importantly, occurrence bias, as the outcome modelled is the proportion of times an item is ranked best/worst.

However, BIBDs only exist for pre-defined experimental design parameters. These parameters are the number of “items” in an experiment (e.g., the number of land covers), items shown per choice (e.g., four land covers) and the total number of choice exercises undertaken (e.g. 15). Researchers may want or require a design with specific levels of these design parameters. Specifically, the number of items may be pre-determined, and having many items per choice or choice exercises per respondent may increase the study time or cognitive burden. In light of BIBD design restrictions, Sawtooth designs have become more popular in recent years (Hollin et al., 2022) and are the second most common MaxDiff design in health studies (behind BIBDs) (Hollin et al., 2022). They achieve near balance but allow the research to vary design parameters (Sawtooth Software, 2020). To find the most balanced Sawtooth design, an algorithm maximises three criteria in order of priority, proceeding to the next criteria if multiple designs converge at the same level of balance. In order of importance, these are one-way item frequencies (each item appearing an equal number of times), two-way item frequencies (the number of times an item appears with another item) and balance in item position within choice sets (Cohen, 2003). Items within designs must also be connected so that they cannot be split into two groups where no item in one group is present in the other.

Multinomial logit (MNL) regression models are most often used to model MaxDiff responses and yield the relative importance of factors, specifically their “preference share” (probability

of being selected as the most/least important) (Hollin et al., 2022). More generally, MNLs are used when a dependent variable indicates a choice for one item over alternative items that are mutually exclusive (Cramer, 2003). They are a linked set of binary logit models. For example, in the case of a MaxDiff experiment with three items, there would be two sub-model models, which predict the probability of selecting items three over one (the reference category) (Aizaki and Fogarty, 2023).

6.2 Methods

6.2.1 Study area, data, and health outcome

My study area was the United Kingdom (UK). My initial population sample was Understanding Society (waves 1-9) participants (Institute for Social and Economic Research, 2021). Details of Understanding Society are in Section 3.3. I collated and managed the multi-wave Understanding Society data using the R packages "data.table" and "dplyr" (Dowle et al., 2019; Wickham et al., 2022).

I used the Short Form-12 Health survey, Mental Component Summary (hereafter *mental health score*), as my outcome. Details of why I selected this as an outcome for analysis are in Section 3.3.4.

6.2.2 Green space perceived naturalness and wetland

To identify residential *availability* of green space under different levels of effect modification from naturalness and wetland (see Section 2.1.3.1 for *availability* definition) I first created a map of green space perceived naturalness and of areas of green space that were wetland.

6.2.2.1 Perceived green space naturalness from a Maximum Difference experiment

I created a UK nationwide perceived green space naturalness map using a generic feature mapping approach, which relies on rating the naturalness of pictures tagged with landscape

features (Scholte et al., 2015). To do so, I followed the following process. First, I created a land-cover feature surface over the UK (6.2.2.1.1). Second, I obtained a set of green space photographs, which were taken within and representative of each land-cover type mapped nationally (Section 6.2.2.1.2). I then predicted the perceived naturalness of each land-cover type using a Maximum Difference (MaxDiff) experiment with 2,001 respondents, with associated choice modelling (Mühlbacher et al., 2016).

6.2.2.1.1 Land cover feature surface

I used the UKCEH-LCM 2020 (Morton et al., 2021) as my national land cover/landscape feature surface base. This was the latest version of the UKCEH-LCM during this analysis. See section 3.1.1 for features of the UKCEH-LCM. I used vegetated UKCEH-LCM 2020 classes as my landscape feature surface. I selected the UKCEH-LCM product as its classes can be differentiated by their ecological naturalness (Chang Chien et al., 2020), and therefore, individuals may perceive differences in naturalness. I only included contiguous green space patches greater than 1 ha in my landscape feature surface. This was to ensure that a naturalness score given to a land-cover type is based on the green cover rather than on other nearby urban features or land cover types, which can blend when multiple landscapes are considered. I added *Ancient Woodland* (continuously wooded since at least 1800) as an additional land-cover class (not available in the UKCEH-LCM 2020 classification scheme), as they are some of the most natural areas in the UK (Razzaque and Lester, 2021) and maps of *Ancient Woodland* extent are available for each nation within the UK,

To create my final land cover/land feature surface, I first polygonised the 10 m x 10 m resolution UKCEH-LCM classified pixels raster using the “terra” package in the R programming language (Hijmans et al., 2023). I then intersected *Ancient Woodland* from the non-overlapping *Ancient Woodland Inventory* products from England (Natural England, 2020), Scotland (Scottish Natural Heritage, 2010), Wales (Natural Resources Wales, 2011) and Northern Ireland (Woodland Trust, 2007) with the polygonised UKCEH-LCM using the package “sf” in R (Pebesma et al., 2019). I excluded *Ancient Replanted Woodland* and *Plantations on Ancient Woodland Sites*, as some native trees are replaced with exotic (not natural native) species at these locations. I also removed woodland identified as lost (data available for Northern Ireland inventory only). I categorised all *Ancient Woodland* intersecting the UKCEH-LCM 2020 cover as Ancient Woodland. There was no classification

conflict when I intersected Ancient Woodland with UKCEH-LCM 2020 woodland, as *Ancient Woodland* is a sub-category of woodland. This slightly changed the meaning of other woodland classes, which are now woodland without ancient woodland. Where it intersected other classes, I took the Ancient Woodland inventories as authoritative because they were created by manually georeferencing historical maps and checking persistence in 2007 through archive research and field surveys, while the UKCEH-LCM 2020 was based on an unsupervised classification with some prediction error. Finally, I then created the geometric union of pixels that were contiguous with each other within the same land cover type to create contiguous green space patches. I then removed any feature less than 1 ha as if experienced, they are more likely to be part of a blend of multiple land cover types. My MaxDiff experiment revealed ratings of pictures that represented discrete experiences in each land-cover type. The land-cover classes used, and a summary of their definitions and sources as listed in [Table 11](#).

Table 11. Definitions of green space land covers used as landscape features for generic feature mapping of perceived green space naturalness. Definitions are paraphrased from the Ancient Woodland inventory descriptions and the UKCEH Land Cover Class technical notes on the UK Biodiversity Action Plan Broad Habitat Descriptions, which the UKCEH-LCM 2020 land cover classes were based on ([Jackson, 2000](#)).

Land cover class	Description	Source
Arable and horticulture	Annual crops, perennial crops such as berries, orchards, and freshly ploughed land.	(Morton et al., 2021)
Improved grassland	Grassland dominated by a small number of species, e.g., <i>Lolium spp.</i> , regularly mown for amenity purposes/silage production or grazing by livestock.	
Calcareous grassland	Grassland on well-drained shallow soils with principally calcium carbonate basis such as chalk.	
Neutral grassland	Semi-improved grassland. Examples include hay meadows and pastures like improved grassland but less intensively managed. Often found near water bodies.	
Coniferous woodland	Woodland stands with 50% + cover of coniferous trees.	
Saltmarsh	Wetlands are found exclusively in coastal areas mostly covered in grasses, <i>Suaeda spp.</i> and <i>Salicornia spp.</i>	
Acid grassland	Grasses on soils deficient in lime, including areas dominated by Bracken and <i>Molinia caerulea</i>	
Fen, marsh, and swamp	Inland wetland areas with mostly low-height vegetation. Larger patches are rare.	
Heather	Land with more than 25% cover of heather or dwarf gorse.	
Heather grassland	Grassland with heather cover less than 25%	
Deciduous woodland	Woodland stands with 50% + cover of deciduous trees. Training data was based on non-evergreen trees, as large stands of deciduous evergreen trees are rare.	
Bog	Areas of peat greater than 0.5 m in depth covered in mossy, herbaceous and ericaceous swards.	<i>Ancient Woodland Inventory</i> products from England (Natural England, 2020), Scotland (Scottish Natural Heritage, 2010), Wales (Natural Resources Wales, 2011) and Northern Ireland (Woodland Trust, 2007)
Ancient woodland	Areas continuously wooded since at least 1800 (in many cases much longer). Excludes plantations on Ancient Woodland Sites (PAWs) and replanted ancient woodland.	

6.2.2.1.2 Land cover pictures

I generated a total sample of 420 pictures that were taken and representative of each land category in Table 11 for use in my MaxDiff experiment on the perceived naturalness of land-cover types. All pictures can be found in Appendix 2 (Section 9). My first step to identify land cover pictures was to extract all photographs that were license-free or had a Creative Commons license geotagged by users of Flickr (the image-sharing social-media platform) taken within a patch >1 ha (justification for this size is in Section 6.2.2.1.1) of every land class in Table 11, using the Flickr Application Programming Interface (API) in the “photosearcher” package in R (Fox et al., 2020). I then selected a smaller subset of pictures for each land cover type that were representationally valid (see Section 6.1.1.1). The location of these photos and their respective land cover type can be seen in Figure 14. I screened out pictures that did not represent the overall land cover they were taken in (e.g. if there was a

picture of grassland in a location defined as woodland). I was only concerned with the perceived differences between the ecological characteristics of vegetated green spaces, and therefore, I removed any photos that contained people or an artificial element. Including these elements may cause respondents to rate a land-cover type as less natural if there were systematically more of them in a picture of said land-cover type. I removed large continuous patches of the sky from pictures, as this can be interpreted as representing the patch size, which I did not represent in my item set. Lastly, I adjusted pictures to ensure they had similar exposure levels using the photo editing software Dark Table (Hanika, 2022).

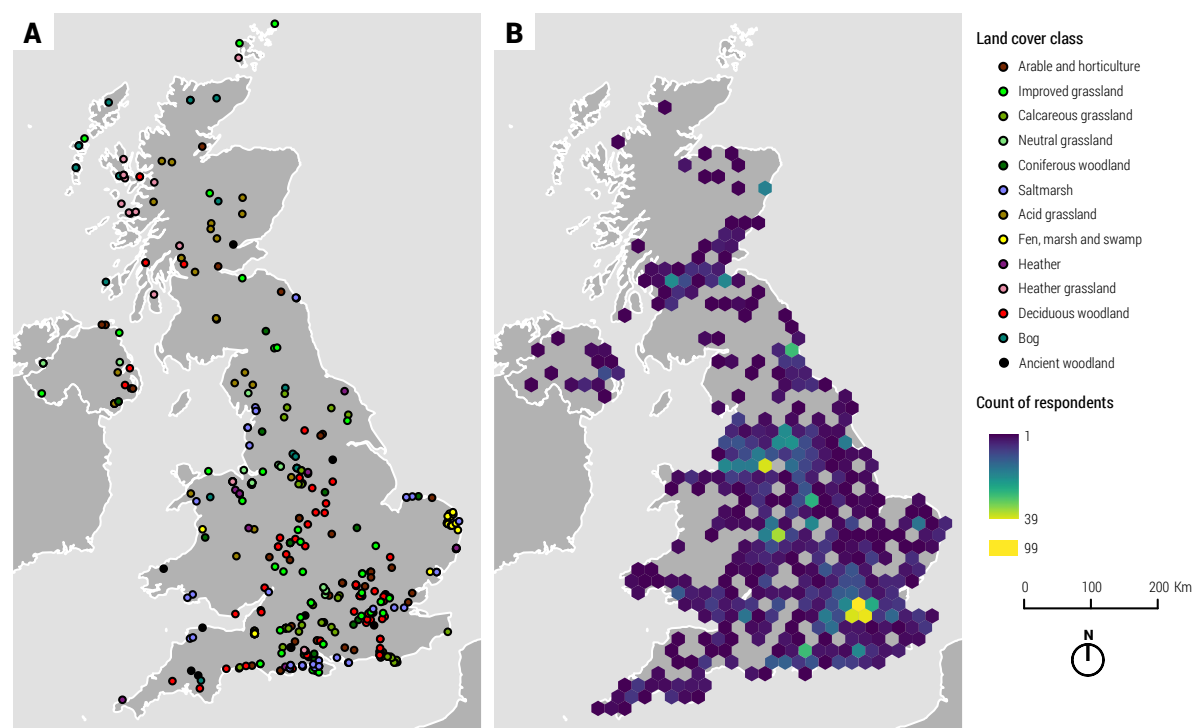


Figure 14. Location and land-cover type of pictures used in the MaxDiff experiment (panel A) and location of respondents in the MaxDiff survey (panel B).

6.2.2.1.3 Respondent recruitment

I recruited 2,001 survey respondents from Prolific Academic for my MaxDiff experiment. Prolific Academic is an online platform that has been used to recruit participants in studies ranging from behavioural research (Peer et al., 2022) to perceptions on vaccines, pain relief and climate change (Bacon and Taylor, 2022; Berger and Wyss, 2021; Rosa et al., 2020). My recruited sample was representative of the UK population. Specifically, I recruited the same proportion of individuals within subgroups defined by age, sex, and ethnicity as there are

proportion of individuals within that subgroup in the UK. For example, my recruited sample contained the same proportion of 28–37 year-old Asian men as the UK population in 2011 (2021 census data was unavailable at the time of data collection). This was achieved using the Prolific quota system, where each demographic subgroup is allocated a quota proportional to its UK population representation.

6.2.2.1.4 Survey question design and process

Before undertaking the MaxDiff experiment, I held discussions with the Public Community Oversight Group of the Medical Research Council Centre for Environment and Health on the 1st of December 2022, to determine whether the public would easily understand the survey. Feedback given was generally positive, with only changes made to the description of the purpose of the survey to make it easier to understand. Upon entering the survey, respondents are presented with the purpose and content of the survey and how respondents' data would be used. I then asked respondents to give informed consent to participate. Participants were compensated £1.50 (in 2023), the default amount recommended by Prolific, and the median survey completion time was 6 minutes 37 seconds.

In my MaxDiff survey, respondents were asked to pick the least and most natural picture (representing a land cover, see section) out of a set of four (a choice exercise) 15 times, which were my first two fixed experimental design parameters. These parameters were set to balance information gathering and respondent cognitive load (Brosnan et al., 2021). My third fixed design parameter was the total number of items in the MaxDiff experiment—which was the 13 land uses/covers I wanted to obtain the perceived naturalness of (Table 11). No BIBD existed for these fixed design parameters. Therefore, I adopted a Sawtooth experimental design (see Section 6.1.1.2.1 for details on this design type). I underwent ethical approval for this survey as required by Imperial College London, Imperial College Research Ethics Committee reference number: 6492322.

6.2.2.1.5 Analysis and results of survey responses

I received a total of 30,015 perceived naturalness ratings across 2,001 respondents. I ran a multinomial logit model (see Section 6.1.1.2.1 for details of this model) using the “mlogit” function in the R “mlogit” package (Croissant, 2020). To identify the relative *perceived naturalness score* of land covers, I calculated their preference shares using the “bws.sp”

function in the R “support.BWS” package (Aizaki, 2023). The perceived naturalness score of each land cover class can be seen in Figure 15. Incidentally, this aligns broadly with the ecological ranking of natural environments based on their land cover (Chang Chien et al., 2020).

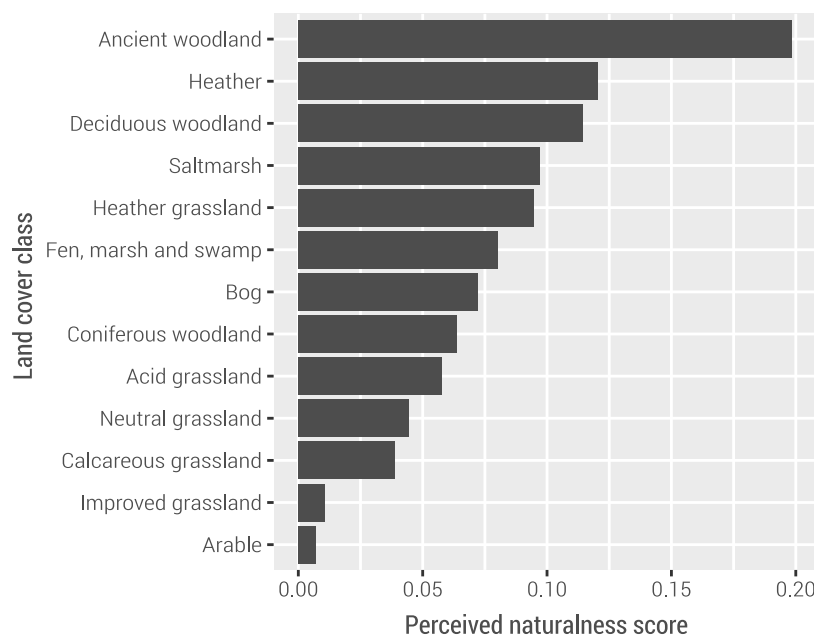


Figure 15. Perceived naturalness score of each land-cover class as identified from a multinomial logit model of responses to the perceived naturalness of land-covers MaxDiff experiment.

6.2.2.2 Identifying green space wetland

Various products exist that define areas as wetland ecosystems. Within the UKCEH-LCM, there are two categories, *Saltmarsh* and *Fen*, described as wetland. However, there are wetland subtypes within, for example, deciduous woodland (e.g., wet woodland) and improved grassland (e.g., around reservoirs that are seasonally inundated). The Copernicus Water & Wetness product does identify land that is *Permanently wet*, *Seasonally wet* or *Seasonally water* at a 10 x 10 m resolution (European Environment Agency, 2020).

Therefore, in addition to its perceived naturalness class, I classify *Wetland* as land that was either *Permanently wet*, *Seasonally wet*, or *Seasonally water* according to the Copernicus Water & Wetness product or *Saltmarsh* or *Fen* (regardless of its Water & Wetness status) according to the UKCEH-LCM 2020.

6.2.2.3 Creating the final perceived naturalness and wetness map

To create my final perceived naturalness and wetness map, I first merged the perceived naturalness class of each land cover type (see [Figure 15](#)) with the polygon features of the land-cover surface created in [Section 6.2.2.1.1](#), creating a national map of vegetated land perceived naturalness. I then intersected this map with the polygonised Copernicus Water & Wetness product. In addition to their naturalness class, *Permanently wet*, *Seasonally wet*, or *Seasonally water* features Water & Wetness features or *Saltmarsh* or *Fen* (regardless of its Water & Wetness status) according to the UKCEH-LCM 2020 also had the tag “Wetland”.

6.2.3 Exposure and effect modifiers

My residential green space exposure was tertiles of the proportion of vegetated land (excluding areas with no vegetated land) within 1,600 metres (m) of each participant's wave-specific household LSOA PWC (hereafter *residential green space* in this analysis), according to the perceived naturalness and wetness map created in [Section 6.2.2.3](#). I selected the respondent LSOA as a proxy for the household location, as this was the highest resolution locational data made available to me by Understanding Society under “special license” (see [Section 3.3](#) for details). I took any green space within 1.6 km from a respondent's household LSOA-PWC as *available*. This *availability* distance has been commonly used in studies of green space-health associations but is at the upper end of what has been used (most between 300 m and 1,600 m) ([Kondo et al., 2018](#); [van den Berg et al., 2015](#)). I selected a larger distance buffer as recent research suggests this more realistically represents the median distance individuals will travel to visit green spaces in European areas (1.4–1.9 km) ([Schindler et al., 2022](#)), than shorter WHO targets, such as 300 m, for example ([WHO Regional Office for Europe, 2017](#)). It is also approximately a maximum 20-minute walk. I used buffers from the PWC to better approximate residential green space exposure than proportional coverage of LSOAs (see [Section 3.2.3](#)).

Key to the analysis was to explore whether associations between green space and health depended on the green space's naturalness and whether it had water (the effect modifiers). Therefore, I identified tertiles of the proportion of residential green-space *available* to every respondent household LSOA that was wetland (hereafter *percentage green space wetland* and

tertiles of the area-weighted average perceived naturalness of said green space according to the perceived naturalness and wetness map I created in Section 6.2.2.3 (hereafter *perceived naturalness*).

I excluded unvegetated land from *residential green space* tertiles as it is impossible to calculate the naturalness of or calculate a proportion of wetland green space in areas that do not have it. The remaining cases were then an additional category for *residential green space*, and both effect modifiers indicated an area with no *available* green space (hereafter *no green*). However, once the *residential green space* and two categorical effect modifier variables were automatically “dummy-coded” (recoded into a set of separate binary variables that indicate membership of a tertile) for inclusion in regression models (see Section 6.2.6), there were two or three (depending on whether one or both effect modifiers were assessed) identical *no green* columns. I removed the one or two identical *no green* columns to avoid rank deficiency in later statistical models.

6.2.4 Confounders

The confounders used in this analysis were the same as my second epidemiological analysis of Understanding Society data, a justification for these is outlined in Section 3.4.2. In addition, I used quintiles of Carstairs index as an additional confounder (this was used as an effect modifier in analysis 2). These were constructed in the same way as epidemiological analysis 1 and again, justification for its use can be seen in Section 3.4.2.

6.2.5 Creating a nationally representative sample

The Understanding Society survey has been designed so that analysis of it can be nationally representative (see Section 3.3.3). To ensure the generalizability of my study findings to the UK population, I weighted each response by US-created nationally representative cross-sectional weights for each wave (see details in Section 6.2.5.1). To maintain survey representativeness, I ensured every response with a weight was a complete case (contained all model variables) (Kaminska and Lynn, 2019). First, I excluded waves 2 and 6, which had many missing responses to the sf-12 *mental health score*. This left 246,350 cases, of which 7,091 (2.96%) were incomplete from the remaining waves due to missing information on

outcomes, exposure, confounders, and effect modifiers. Missing data in these Understanding Society waves was present due to non-response to questions or mistakes in survey administration. I used Multiple Imputation using Chained Equations (MICE) (Javadi et al., 2021) to “fill in” (impute) missing variables in each case. Multiple imputation is more robust than other imputation techniques (see Section 6.2.5.2). The classical recommendation for the number of imputations per variable using MICE is 3–5, and therefore, I imputed each variable five times using a fully conditional specification, leading to five datasets (Rubin, 2018).

I imputed continuous variables (*mental health score*, *people per bedroom*, *population density* and *disposable household income*) using a linear mixed effects-based imputation model, with a random intercept for *respondent id*. A different record of the same variable within-person (e.g., their income) is likely to be similar and therefore, a *respondent id* random intercept would provide a more accurate prediction of the missing responses in said variable. I used the most popular R imputation package, “mice”, with additional mixed-effect model imputation functions from “miceadds” to impute continuous variables (Buuren et al., 2023; Robitzsch et al., 2023). There was no difference in the recorded *sex* of individuals between waves (either *not available*, *male*, or *female*), and therefore, it was not possible to use within-person values of *sex* to predict *not available* values of *sex* with a random intercept model. To impute *sex*, I used the “mice” package default – a standard logistic regression imputation (Enders, 2023). There was no difference in individual recorded *sex* between waves because if a respondent had a *not available* code, it was for all waves. A respondent received a *not available* code for their *sex* in every wave if it was inconsistently recorded, and a consistent response in one or many waves was assumed to apply to all waves by Understanding Society. Imputation of categorical variables in larger datasets (100,000’s responses) using models which take into account their multi-level structure is currently computationally demanding (and, for me, infeasible), even with the latest software packages (Enders, 2023). Therefore, I used the “mice” package defaults for imputing categorical variables (*green space - naturalness - wetland interaction*, *socioeconomic deprivation quintiles*, *age-category*, and *employment status*) (Enders, 2023).

6.2.5.1 *Weights and missing data in Understanding Society*

Understanding Society has several weights that can be used in statistical models depending on the population intended to be represented. Understanding Society cross-sectional weights were created to represent the UK population spatially regarding where people live and demographically (see Section 3.3) (Lynn, 2009). Since the original study design, there has been unequal recruitment and attrition amongst different sub-demographic and spatial groups in different waves (again see Section 3.3) (Kaminska and Lynn, 2019), creating a need for wave-specific weights. Following Understanding Society guidance, I used main interview weights for wave 1 and self-completion interview weights for waves 2-9 (Kaminska and Lynn, 2019). Questions used to calculate the participant sf-12 *mental health score* were only asked in the wave 1 in-person interview but were asked in both the main and self-completion interviews for waves 2-9.

In waves 2 and 6, an unusually large number of responses to questions were used to calculate their sf-12 *mental health score* from respondents with non-zero case weights. In wave 2 this was due to administration errors, and in wave 6, questions used to derive the sf-12 *mental health score* were not asked of the ethnic minority boost sample. I therefore excluded all responses from waves 2 and 6 from later analysis.

6.2.5.2 *Multiple Imputation using Chained Equations*

Before multiple imputation techniques such as MICE were popularized, missing variables were “filled in” using a single imputation by predicting said variable as a function of other informative explanatory variables using a regression model or similar (Rubin, 2018).

However, when this value is only predicted once, it artificially deflates the variation in said variable. Multiple imputation addresses this by creating multiple versions of the variable that reflect the uncertainty in what a single imputation predicts them to be (Javadi et al., 2021). In the case of missing values in one variable, MICE creates multiple versions of a said variable with filled-in values that reflect the uncertainty of what a single imputation predicts them to be (Javadi et al., 2021).

6.2.6 Statistical methods

I produced exposure and outcome descriptive statistics, histograms, and categorical variable frequency tables for my final imputed data to explore their skewness and heteroskedasticity and later model interpretation. Rather than calculating these statistics for every one of the five imputed datasets, I calculated them on one dataset for ease of presentation and interpretation, which I call the *average imputed dataset*. Where a variable value differed across cases (due to imputation, see Section 6.2.4), I selected their mean across imputations for continuous variables and randomly selected the mode for the 146 cases of categorical/binary variables with more than one.

I ran two sets of five Linear Mixed Effect Regressions (LMER), which were adjusted for potential covariate confounders listed in Section 6.2.4 and had *respondent id* as a random effect. Model set 1 identified associations between *mental health score* and each of the *residential green space* tertiles. Model set 2 assessed within *residential green space* tertiles the associations between mental health score and *percentage green space wetland* tertiles *green space perceived naturalness* tertiles, and both effect modifier tertiles. The five models within each set were run on one of the five imputed datasets containing the variables they calculated (see Section 6.2.5). Models were run using R's "lme4" package (Bates et al., 2020).

I created pooled predicted values and confidence intervals of exposures and effect modifiers in each model using Rubins rules (Rubin, 2018) as implemented in "mice" and plotted the "ggeffects" packages in R (Buuren et al., 2023; Lüdtke et al., 2023), to aid in interpretation. The *mental health score* associations of the medium and high *residential green space* tertiles in the pooled results of model set 1 without covariate confounders identified in Section 6.2.4 were substantially larger in magnitude in models unadjusted for potential covariate confounders although showed similar trends (see Appendix 5 Section 12). This suggests there was some covariate confounding. Therefore I limit my interpretation of residential green space tertiles to adjusted models as they are more valid when interpreting associations (Etminan et al., 2021)

I compared the difference between the *mental health score* association of different tertiles of *residential green space* before and after modification from different tertiles of *green space*

perceived naturalness and the *percentage of green space wetland*, using a multiple comparison procedure with contrasts (Hothorn et al., 2008).

My first set of contrasts compared whether *mental health scores* in higher *residential green space* tertiles were significantly (as indicated by *p*-values) higher than lower ones (including the no *residential green space* category), based on results from model set 1.

I ran a second set of contrasts to see if whether any differences identified in my first set of contrasts persisted after adjusting for potential confounders and effect modifiers. To adjust for effect modifiers in model set 2, I calculated the mean of each *green space naturalness* and the *percentage of green space wetland* combination factor within each tertile using custom contrast coding, weighted for the number of responses within each of these combination factors (Grotenhuis et al., 2017) in “emmeans” (Lenth et al., 2022). Although the frequency of responses within each class was approximately equal, this weighting considered, for example, that residential green space tertile 1 was slightly skewed towards the *percentage of green space wetland* 0–1.2% with *low perceived naturalness* (Figure 18).

I ran two additional sets of contrasts to see if whether my two proposed effect modifiers created any additional differences. To do so I tested for the difference between each tertile of each effect modifier, holding each green space tertile constant and averaging over the values of the other effect modifier not assessed (Grotenhuis et al., 2017). For example, I averaged the mean of all *perceived green space naturalness* tertiles within each *percentage of green space wetland* tertile when comparing differences in the mental health score of different percentage green space wetland tertiles for residential green space tertile 1. Again, this averaging was weighted to account for the proportion of responses within each wetland tertile. Due to the exploratory nature of the analysis, with very few (if any) pre-planned hypotheses (see Section 2.2.1.3 and 2.2.1.4) I did not adjust for multiple comparisons (Greenland and Hofman, 2019; Patel and Ioannidis, 2014; Rothman, 1990). The planned contrasts within each model set were pooled using Rubin’s rules with “emmeans” (Lenth et al., 2022).

I assessed model variable collinearity using squared Generalised Variance Inflation Factors (GVIF) (Fox and Monette, 1992) calculated in the “semEff” package (Murphy, 2020). I used squared scores to interpret GVIF in the more commonly used VIF scale (Fox, 2002). As no

pooling approach exists for GVIF, I took the highest GVIF scores from each variable across every model set it was in as the model GVIF. Following rules formulated for epidemiological studies (Johnston et al., 2018), no variables were unacceptably colinear (greater than 2.5), as seen in Table 12.

Table 12. Variance inflation factors for each variable included in the four covariate adjustment models in Figure 7

Model ref.	Model explanatory variable	$(GVIF^{(1/(2 \times Df))})^2$
Model set 1	Age	1.09
	Sex	1.01
	Employment status	1.5
	Commute time	1.16
	Disposable household income	1.03
	People per bedroom	1.16
	Carstairs index	1.08
	Population density	2.08
	Green space tertiles	1.27
Model set 2	Age	1.09
	Sex	1.01
	Employment status	1.5
	Commute time	1.16
	Disposable household income	1.03
	People per bedroom	1.16
	Carstairs index	1.08
	Population density	2.14
	Green space tertiles & naturalness tertiles & wetness tertiles	1.09

6.3 Results

My final sample for analysis was 246,350 cases from 71,372 respondents across seven Understanding Society waves (1,3,4,5,7,8,9). 7,091 (2.96%) of my final sample cases had at least one variable with missing values and was therefore imputed using MICE. The percentage of missing values for each variable is in Figure 16. There was no wave-specific LSOA and, therefore, exposure, effect modifiers and spatial confounders across 0.0248% of cases. The mental health score distribution was broadly normal (Hair et al., 2009) with slight negative skew and slight excess positive kurtosis (Figure 17). There was an approximately equal distribution of wetland and naturalness quintiles within each green space quintile (Figure 18). However, the *no green* category in the green space tertiles variable had by far the

lowest frequency (467), 175 times lower than the next largest category (*residential green space* - 18.9–45.9%, 81,891 cases).

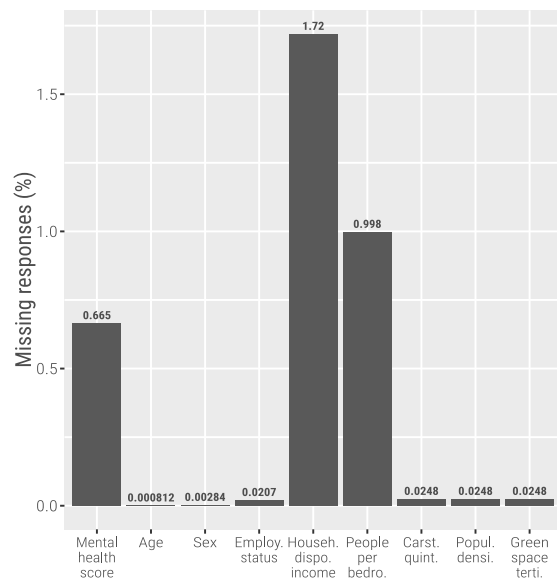


Figure 16. Percentage of missing values for each model variable. Wetland and naturalness are excluded (they are the same as green space). Commute category was excluded as it had no missing values.

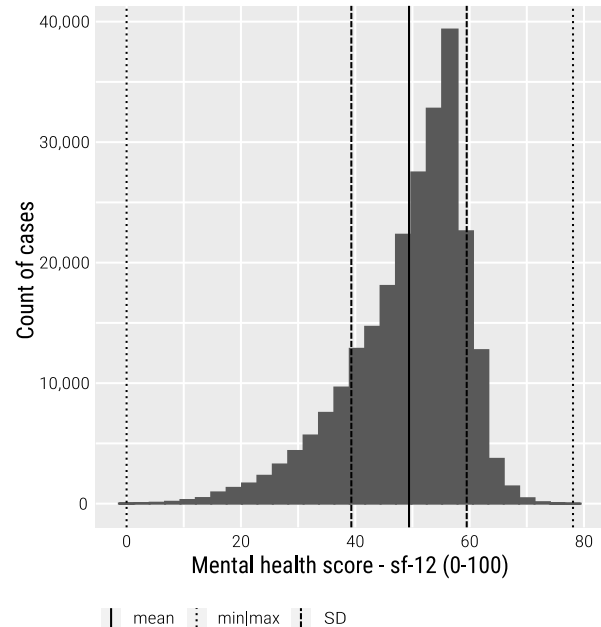


Figure 17. Distribution of mental health score (outcome). Each count is one score (from one wave). Includes the mean of imputed values.

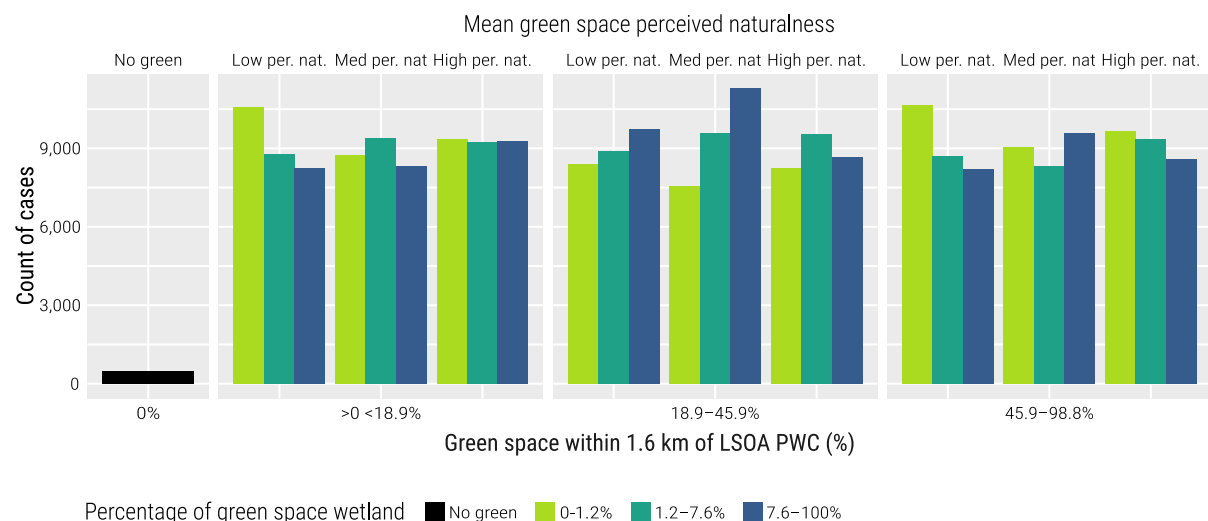


Figure 18. Frequency of each green space, naturalness, and wetland tertiles combinations. An additional factor was created to represent cases without green space. Each count is the tertile combination a respondent had for one wave. Per. nat. = perceived naturalness.

6.3.1 Green space and mental health score

Having any *residential green space*, at any level of *perceived naturalness of green space* and the *percentage of green space wetland* was significantly associated with having a better *mental health score* before (Table 13 and Figure 19a) and after effect modification (Figure 19b). A respondent *residential green space* cover of 45.9–98.8% had a statistically significant and better *mental health score* than a *residential green space* cover of >0 <18.9% and 18.9–45.9% in both model sets 1 and 2 (Table 13 and Figure 19a,b). Additionally, in model set 2, respondents with a *residential green space* cover of 18.9–45.9% had a better *mental health score* than those with >0 <18.9% *residential green space* cover.

The magnitude of differences between having any tertile of green space compared to no green space was greater than the differences between green space tertiles in models set 1 and 2 (Table 13 and Figure 19a,b). However, the predicted mean for no green space was much more uncertain than any green space tertile predicted mean.

Table 13. Results of contrasts used to assess whether more residential green space improved mental health score. Est. = the predicted mean value of the green space reference category subtracted from the green space contrast category, which in model set 2 was after averaging the predicted mean of each green space naturalness and percentage green space wetland combination. SE = Standard Error. Contrasts of the five mixed-effects models run on each multiple imputation within each set were averaged using Rubins rules (see methods). Parameter estimates of significant (p-value <0.05) contrasts are in bold.

Model set	Residential green space tertile		Est.	SE	p-value
	Contrast	Reference			
Model set 1	>0 <18.9%	0%	1.92	0.659	0.004
	18.9–45.9%		2.06	0.663	0.002
		>0 <18.9%	0.146	0.0818	0.075
	45.9–98.8%	0%	2.23	0.667	0.001
		>0 <18.9%	0.309	0.101	0.002
		18.9–45.9%	0.163	0.0746	0.028
Model set 2	>0 <18.9%	0%	1.94	0.659	0.003
	18.9–45.9%		2.1	0.664	0.002
		>0 <18.9%	0.167	0.0821	0.042
	45.9–98.8%	0%	2.28	0.667	0.001
		>0 <18.9%	0.342	0.101	0.001
		18.9–45.9%	0.175	0.0747	0.019

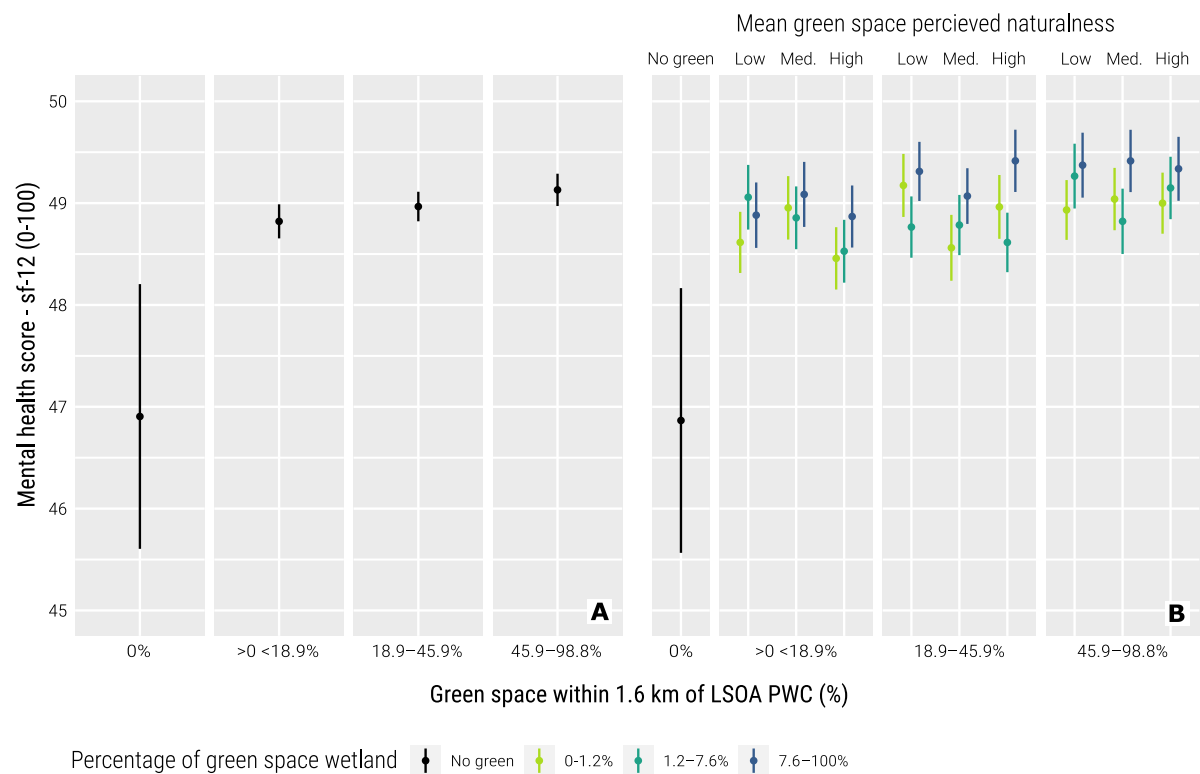


Figure 19. Predicted effects of model sets 1 and 2 in panels A and B, respectively. Bars indicate 95% intervals around the mean predicted mental health score within each green space–effect modifier category.

6.3.2 Effect modification from naturalness and wetland

In some cases, *perceived naturalness* had a positive and negative modifying effect on *residential green space* and *mental health score* associations in the higher and lower or medium residential green space tertiles, respectively (Table 14, Figure 19b). When green space was held constant at >0 <18.9%, areas with a high *perceived naturalness* had worse mental health than those with medium or low *perceived naturalness*. Where *residential green space* was 18.9–45.9% cover if it had medium *perceived naturalness* respondents had worse mental health than if it had low *perceived naturalness*. Holding residential green space constant at 45.9–98.8% if *green space perceived naturalness* was high, they had a better *mental health score* than when it was perceived as medium or low.

Table 14. Contrasts to assess effect modification of green space perceived naturalness on residential green space and mental health score associations. Est. = the predicted mean value of the naturalness reference category subtracted from the naturalness contrast category. See methods for details on how percentage green space wetland levels were averaged. SE = Standard Error. Contrasts of

the five mixed-effects models run on each multiple imputation within each set were averaged using Rubins rules (see methods). Parameter estimates of significant (p -value <0.05) contrasts are in bold.

Residential green space tertile	Perceived naturalness tertile		Est.	SE	p -value
	Contrast	Reference			
>0 <18.9%	Med per. nat	Low per. nat.	0.125	0.115	0.276
	High per. nat.		-0.218	0.112	0.053
		Med per. nat	-0.343	0.114	0.003
18.9–45.9%	Med per. nat	Low per. nat.	-0.25	0.114	0.028
	High per. nat.		-0.104	0.115	0.368
		Med per. nat	0.147	0.115	0.201
45.9–98.8%	Med per. nat	Low per. nat.	0.0963	0.12	0.421
	High per. nat.		0.389	0.12	0.001
		Med per. nat	0.292	0.122	0.016

The *percentage of green space wetland* significantly modified *residential green space* and *mental health score* associations in most cases (Table 15, Figure 19b). This significant effect modification was always positive. Specifically, those living in areas with 7.6–100% *percentage of green space wetland* had better mental health than those with (a) 1.2–7.6% or 0–1.2% when green space was held constant at 45.9–98.8% or 18.9–45.9% and (b) 0–1.2% when green space was held constant at >0 <18.9%. Respondents with the largest *percentage of green space wetland* tertile had the highest association with mental health within the same combination of *residential green space* and *perceived naturalness* tertile eight out of nine times (Figure 19d).

Table 15. Contrasts to assess effect modification of percentage of green space wetland on residential green space and mental health score associations. Est. = the predicted mean value of the wetland reference category subtracted from the wetland contrast category. See methods for details on how levels of green space perceived naturalness were averaged. SE = Standard Error. Contrasts of the five mixed-effects models run on each multiple imputation within each set were averaged using Rubins rules (see methods). Parameter estimates of significant (p -value <0.05) contrasts are in bold.

Residential green space tertile	Percentage green space wetland		Est.	SE	p -value
	Contrast	Reference			
>0 <18.9%	1.2–7.6%	0–1.2%	0.143	0.118	0.227
	7.6–100%	0–1.2%	0.276	0.121	0.023
		1.2–7.6%	0.133	0.12	0.269
18.9–45.9%	1.2–7.6%	0–1.2%	-0.19	0.123	0.122
	7.6–100%	0–1.2%	0.339	0.122	0.005
		1.2–7.6%	0.529	0.116	<0.001
45.9–98.8%	1.2–7.6%	0–1.2%	0.0963	0.12	0.421
	7.6–100%	0–1.2%	0.389	0.12	0.001
		1.2–7.6%	0.292	0.122	0.016

6.3.3 Confounder–health associations

Being in a more deprived area and having a longer commute was associated with worse mental health ([Appendix 6 - Table 18](#)). Age had a mixed association with mental health – those aged 30–52 had worse mental health than those 15–30; conversely, those over 52 had a better mental health than those 15–30. Being male, in a higher population density area, having more disposable income, being employed outside of the workforce (in comparison to being unemployed) and (surprisingly) having more residents per bedroom was associated with better *mental health scores*.

6.4 Discussion

6.4.1 Residential green space mental health association

Individuals living in areas with more residential green space cover had better mental health, adjusting for covariate confounders ([Table 13](#) and [Figure 19a](#)) and also effect modifiers ([Figure 19b](#)), aligning with the findings in epidemiological analyses 1 and 2 ([Section 4](#) and [5](#)) as well as previous cross-sectional studies ([Kondo et al., 2018](#); [Twohig-Bennett and Jones, 2018](#)). I provide a unique assessment of residential green space mental health benefits by completing a nationally representative analysis using Understanding Society weights. This provides more externally valid findings than have used non-nationally representative analysis on how green space impacts the subjective mental health of people ([Houlden et al., 2017](#)). This finding is, in brief, explained by the theoretical pathways starting with more residential green space, leading to an increased probability of sensory exposure and changes in environmental conditions, which have positive mental health impacts (see [Section 2.1.4](#)).

6.4.2 Perceived naturalness effect modification

The perceived naturalness of green space was both a negative and positive effect modifier depending on the amount of residential green space. When individuals had less residential green space, it being classed as having a higher mean perceived naturalness was associated

with poorer mental health. A few plausible explanations exist for why *residential green space cover* may have had opposite effect modification in these two contexts.

More natural areas may be associated with poorer mental health in less green areas as individuals may fear encountering a concealed person who may be undertaking criminal activity (see Section 2.2.1.3). This may be more likely in areas with less residential green space cover, as they typically have more people and are more urban (Fuller and Gaston, 2009). The opposite would be true in more rural locations, where the likelihood may be so low that negative and positive effects cancel each other out.

Green space naturalness may have had been a positive effect modifier in areas with more green space due to it being better able to provide a feeling of “being away” from urban life, activating one of the key mechanisms behind the benefits of perceived naturalness to mental health according to ART and SRT (see Section 2.1.4.1.2.1). People living in less urban areas (negatively correlated with green space cover) may be more able to recognize the diversity of the green spaces and therefore receive soft fascination from it (see Section 2.2.1.3 and Section 2.1.4.1.2.1) than the UK general population used to generate scores in the MaxDiff experiment results and perceived naturalness surface. This is recognized in related biodiversity research (Dallimer et al., 2012) and in the extinction of experience theory (Soga and Gaston, 2016).

Green spaces that have a lower perceived naturalness may be used for different purposes depending on whether there is little or abundant *residential green space cover*, which may contribute to why it had opposite effect modification in these two contexts. Firstly, it is important to note that the most common green space of lower perceived naturalness (Figure 15) found in the UK is improved grassland and agricultural land (Marston et al., 2023). Secondly, there is a correlation between “urban” cover (as measured by population density) and residential green space accessibility (Richards et al., 2022). Therefore, lower residential green space tertiles may have acted as a proxy for “urban” green spaces. It is possible that in urban areas, there was little agricultural land or grazed improved grassland > 1 ha in size, and instead, most low perceived naturalness land was improved grassland in the form of playing fields, with the opposite being true in more rural areas. The overall health impact of having more amenity grassland (even of low perceived naturalness areas) may have been greater

than that of more natural vegetation types, for example, by providing an *available* area for physical activity (see Section 2.1.4.1.3). Conversely, in rural areas, grazing fields and agricultural land are likely to be less accessible and be less of a “destination” for activities, for example, as is the case with UK Forestry Commission sites (Binner et al., 2017). Future research could try and develop a map and analyses which quantifies the degree to which amenity grassland and grazing differ in their mental health associations.

The finding that more natural areas are less beneficial to mental health conflicts with the existing evidence base I reviewed, which found neutral or positive effects of green space naturalness, often explicitly within urban contexts (see Section 2.2.1.3). This may be due to how these studies were designed. Experimental studies were based on populations of university students, which may perceive the naturalness levels more accurately than the general population (see Section 2.2.1.3). Additionally, respondents in observation studies were typically recruited on-site or responded to mailed surveys. There may be a bias for those with a greater affinity with nature, and therefore, they can better recognize its naturalness to self-select to participate in studies quantifying its benefits (see Section 2.2.1.3).

Furthermore, the health indicators in many of these studies were mediators to good health, such as “perceived restorativeness”. It may be that while naturalness is a positive effect modifier for this mediator, other mediators are negatively impacted by it (e.g., accessibility for physical activities, see Section 2.1.4). Additional research could assess whether the perceived naturalness has a different modifying effect in specific types of built environments (e.g., city centres, suburban areas) and amongst populations with different demographics.

6.4.3 Wetland effect modification

Respondents whose *residential green space* consisted of more than 7.6% wetland had better mental health than those whose residential green space had little to no water (Table 15). This effect was consistent across all green space tertiles. The potential reasons for wetland areas providing enhanced benefits to mental health are outlined in Section 2.2.1.4. In brief, they provide a wider extent and diversity of experiences, a mediator to mental health improvements according to ART and SRT (Section 2.1.4.1.2.1), and they may also provide several environmental improvements that can have down-path impacts on mental health. This

finding compliments the very limited literature assessing how combinations of green space and wet areas combined positively impact mental health (Section 2.2.1.4).

6.4.4 Strengths and limitations

My results had high external validity and generalisability to the UK, as the sample I used was nationally representative of the UK and included over 71,000 respondents. Furthermore, looking at differences between persons allowed me to have many individuals within each residential green space – naturalness and residential green space – wetland tertile combination, giving me a greater exposure-effect modifier contrast. However, this came at the cost of internal validity (see overall thesis limitations Section 7.1.3.2). I also missed potential covariate confounders for which green space acted as a proxy, and the associations I found were not causal.

The outcome variable that I used in my analysis was based on self-declared mental health. This has the potential to bias results and is explored in my overall thesis discussion and conclusions as it is relevant to all three epidemiological analyses, which have self-declared health status as outcome variables (see Section 7.1.3.3).

A limitation of this study was that it used an evaluated scenario of *residential green space* exposure rather than actual time spent in nature (see details of this in Section 2.1 and what limitations it placed on my epidemiological analyses in Section 7.1.3.1)

6.4.4.1 *Strengths and limitations of perceived naturalness mapping*

One of my effect modifiers of interest was the perceived naturalness of residential green space. A step in identifying this was creating a national perceived naturalness map based on a MaxDiff experiment. This experiment had some strengths and weaknesses, translating to the interpretation of the exposure and effect modifier assessment.

One strength of my MaxDiff experiment was how I selected and adjusted the pictures used for respondents to select the most and least natural green space types. Specifically, I standardised pictures to exclude other elements (e.g., people, artificial structures, sky, broader landscapes, pictures of blended land cover types etc.; see Section 6.1.1.1). This translated to

the perceived naturalness of green spaces effect modifier variable only representing “exclusive” patches of each green space type. Avoiding artificial elements may have prevented naturalness ratings from being systematically biased, e.g., if the probability of artificial elements in pictures of one land-cover class taken from Flickr, was different from the probability of them being inside said land-cover. Blended land-cover pictures may have been seen as more inherently natural and diverse (due to their visual variety), and these pictures may have been more likely in some 1 ha patches of land cover types, biasing up the naturalness of these land covers. Additionally, my survey was nationally representative across demographics, and respondents’ residences had a good spatial distribution across the UK.

However, these strengths also gave rise to a few weaknesses. Not including patches < 1 ha in my analysis removed green space exposures that can impact health, and I could not produce any recommendations for these green space types. For example, individual trees alongside roads and other areas are often less than 1 ha in size and were excluded. Although my research question solely concerned the vegetation, features I removed to avoid biasing vegetation naturalness ratings, such as roads, benches etc., may impact how “natural” green spaces feel.

6.4.5 Recommendations

My findings suggest protecting and creating more natural green spaces in areas dominated by green space and with more water elements to support the mental health of those living nearby in the UK. However, these are both rarely studied effect modifiers, being some of the first at the city to national scales, and additional studies should be conducted to support the associations I found here (see thesis recommendations in Section [7.1.4.3](#)). Despite the need for more studies, what I have found aligns with environmental conservation goals and could be considered complimentary benefits from, for example, rewilding initiatives (see Section [7.1.4.4](#)). Wetland areas are also a target for environment conservation due to their ability to support high biodiversity and their rarity. More broadly, it is important to consider my findings in the context of green space's benefits, as including more wetland or natural areas may create trade-offs (again, see Section [7.1.4.3](#)).

I found that green space, which is less natural, has a more positive association with good mental health than more natural areas. This should be considered when, for example, supporting woodland planting initiatives in urban areas, as the mental health benefits may not materialise. However, I advise caution as the results of this finding goes against the existing experimental literature, and the greater proportion of benefits associated with more natural environments more generally, e.g. from cooling the air (Richards et al., 2020) to sequestering carbon (Richards et al., 2022) and supporting biodiversity (Pett et al., 2016).

6.5 Conclusions

We know little about how the perceived naturalness and wetland areas within a green space can impact the mental health of those living nearby. I explored this across a demographically and spatially representative sample of UK respondents. When residential green space cover was high, naturalness's effect was negative, and low was positive. As a result, I recommend further investigating the impact of green space naturalness, given its contradictory effect in areas with less and more green spaces. Wetland had a positive impact when it made up larger proportions of the green space cover. Therefore, I recommend integrating wetland elements into green spaces for improved public health. This impact should be considered alongside the multiple benefits that green spaces can provide to people's wellbeing.

7 Discussion and conclusion

The importance of each chapter's results, their implications and the strengths and weaknesses are discussed in each analysis subsection. Here, I reflect more broadly on how I met my overall thesis objectives, the links between each analysis and their joint implications. I also discuss the strengths and weaknesses applicable to all my analyses. Lastly, I discuss future research considering my thesis and provide concluding remarks.

7.1 Discussion

7.1.1 Green spaces positive health association

I extend research on green space and health associations in different ways. I include an important but rarely assessed exposure in my “all green space” composite variable in Analysis 1, add more evidence to the conflicting findings that changes in green space exposure impact mental health (Analysis 2, Section 4) and conduct one of the few nationally representative assessments on residential green space and mental health associations in the UK (Analysis 3, Section 6). In these analyses, residential green space was positively associated with self-rated health (general and mental) after adjusting for potential covariates and without considering effect modification (Sections: 4.3 - Figure 10, 5.3 - Figure 13, and 6.3 - Figure 19). This further supports most studies, which have found a similar effect across

different health indicators populations and nuances in how green space is defined (Kondo et al., 2018; Rojas-Rueda et al., 2019).

7.1.2 Effect modification

My thesis aimed to identify and assess potential understudied effect modifiers of residential green space and health associations to assess if they should be considered in green space planning and design for health. I add additional evidence that demonstrates composite green space (or nature) to have differing effects depending on its surrounding and internal environment, something that has been considered a priority research agenda for studies on green spaces and health (Beute et al., 2023; Hunter et al., 2023; Marselle et al., 2021; Nguyen et al., 2021) as well as numerous other socioeconomic and broad ecosystem service indicators (Ali, 2023; Birkhofer et al., 2015; Dade et al., 2019). I also identify that there are potential understudied modifiers which can impact residential green space and health associations. This was demonstrated in three out of the four of the effect modifiers I studied (traffic, perceived naturalness and wetland). All three of these effect modifiers are rarely assessed in the literature (see Section 2.2.2) and also having a significant effect on them (Section 4 and 6). Additionally, the impact of changes in socioeconomic deprivation (my fourth effect modifier) on specifically associations between within-person changes in green space and mental health has previously rarely been assessed (see Section 2.2.1.2), and I found it to be a significant effect modifier (Section 5).

7.1.2.1 *Green space naturalness and woodland*

One key synergistic finding from two analyses was that woodland areas should be away from areas of human development to maximise their benefits to perceived general and mental health. Areas of less human development are more likely to have more woodland visible from footpaths with no traffic due to population density being correlated with roads (Glover and Simon, 1975) and more green space cover (Fuller and Gaston, 2009). The green space perceived to be most natural in my third analysis was woodland (Section 6.2.2.1.5, **Figure 15**). In analysis 1, woodland in areas of less human development (more footpaths with no traffic) had positive associations with health (Section 4.3, **Figure 10**), unlike woodland with traffic, which had a negative association. Similarly, in analysis 3, people living in areas that

were more natural (more likely to be woodland) that had less human development (were dominated by green cover) had better mental health than those in areas with little green cover, which had a high perceived naturalness (Section 6.4.2 and Table 14). These finding, alongside the positive effect modification of water on green space and mental health associations has important synergies and implications for environmental conservation planning and policy (see Section 7.1.4.4).

7.1.3 Strengths and limitations

7.1.3.1 Residential green space exposure assessment

The analyses I conducted, and much of the residential green space and health literature, have the limitation of assuming individuals are exposed to green space near where they live (Section 2.1). However, this may not be the case. Individuals may only walk in green space near to their place of work, for example. This impacts the validity of residential green space exposure as a scenario to represent true green space exposure. Furthermore, a person's residential location may not be known, and a proxy for it must be used, for example, their COA and LSOA, which are the geographical identifiers I use in my analyses. Both factors may create exposure misclassification, reducing the precision of and potentially biasing associations, reducing analyses' internal validity (Flegal et al., 1986). I explore below (Section 7.1.3.2) how a loss in internal validity is a trade-off in utilising the main strengths of the two large-scale surveys I selected (the England and Wales Census and Understanding Society).

In my second and third epidemiological analysis (Sections 5 and 6), residential green space exposure was the percentage of natural environments within a set distance from a person's dwelling (*availability* of green space). In my first analysis, I took a more nuanced view that residential green space exposure was the areas of natural environments *visible* from footpaths within a set distance (*available*) from where they live. Across all my analyses, the *availability* scenario assumes that the closer green space or points of green space exposure to home equate to an increased quantity of both sensory exposure (Section 2.1.4.1) and exposure to the environmental improvements (Section 2.1.4.2), which leads to better health (see Section 2.1 for justification). However, individuals may never intentionally go to a green space, for example, due to their preferences, priorities and lack of time, even when it is locally abundant

(Labib et al., 2020; Picascia and Mitchell, 2022). Incidental exposure to green space may also never happen due to a person's specific mobility patterns. The quickest route, e.g., to public transport or the local shops along footpaths, may be completely devoid of green space nearby, yet much of the neighbourhood may be covered in green space; alternatively, they may mostly travel by car. In my last two analyses, I assume that green space is visible, an important sensory exposure leading to health impacts (Section 2.1.4.1). However, green space may be hidden behind buildings, fences, and other structures, even in areas of high green space, again reducing their true exposure and inducing exposure misclassification.

COA is the most geographically accurate level and highest population resolution of the England and Wales 2011 census data. For Understanding Society the special license I used only had access to respondents LSOA. I mitigated this by generating exposures from the population weighted centres of this census geographies, as my analysis in Section 3.2.3 suggested generating exposures from that best represented residential green space exposure (as defined by green space availability) rather than the alternative geographical area cover approach (see Section 3.2.3).

7.1.3.2 *Large-scale survey data and target validity*

My epidemiological analyses' internal and external validity (target validity) depended on the selected populations I analysed, and my analysis approaches (Lesko et al., 2020). Broadly, I selected analysis approaches to complement the existing evidence base. Specifically, I conducted exploratory cross-sectional analyses on effect modification from traffic, perceived naturalness and the presence of water that was more externally but less internally valid than my quasi-experimental study on deprivation as a potential effect modifier. The more externally valid analyses I conducted may be very important, considering that many of the factors I studied may modify pathways that involve people's perceptions and opinions, which can be diverse and may not be captured in smaller experimental samples. Findings may, therefore, be biased to specific sub-populations. For example, ART relies on the compatibility of an environment which may not exist for some individuals or populations (Kaplan, 1995). Furthermore, existing knowledge of biodiversity may be needed for it to be recognised and provide a bigger extent of experience and more soft fascination, improving mental health (Basu et al., 2019).

My first and third analyses (Sections 4 and 6) had strong generalisability to their intended (UK) populations and transferability to similar populations, e.g. to those that have a similar green space use culture (Steckler and McLeroy, 2008). In my first analysis this was due to the study population in my first analysis being all residents of England and Wales (Section 4.2.1). In my third analysis this was due to me using a sample of over 71,000 Understanding Society respondents being representative of the UK population spatially and demographically (Section 6.2.5). In analysis two (Chapter 5), I took a more internally valid quasi-experimental approach, analysing the within-person change in local area socioeconomic deprivation exposures effect modification on associations between changes in residential green space and mental health. However, my population was only individuals who moved residence, potentially reducing its external validity. The strengths and weaknesses in terms of target validity of this approach are outlined in more detail in Section 5.4. The large sample sizes of my analyses also made it possible to find residential green space exposure-effect modifier combinations much rarer than only green space exposure levels.

Across all three of my epidemiological analyses individuals were not randomly allocated to green space exposures under different levels of effect modifiers. Random assignment is particularly problematic in green space and health studies, where the researcher intends to look at a difference in health status attributable to medium (e.g., a month or more) to long-term (years) green space exposures, as it is rare and costly for participants to move home for an experiment over such long periods. This made bias from systemic confounders generalisable to those living in greener areas (for example, socioeconomic status) more likely, which I did attempt to adjust for confounding using covariates in all my analyses (see Section 3.4). However, I may have missed covariates, which may be the true underlying causes of the associations I found. Alternatively, my exposures and effect modifiers of interest may sufficiently correlate unmeasured confounders to make it impossible to differentiate which was the true cause of the mental health score differences at different exposure and effect modifier combinations. Exploring the VIFs in cross-sectional analysis and correlation tables indicated that the latter was not true for variables included in the models I constructed. Despite including confounders, the lack of random assignment reduced the internal validity of my conclusions and my ability to make causal inferences (Campbell and Stanley, 2015).

7.1.3.3 *Self-declared health status*

Across all my analyses, my outcome variables were based on responses to one or more questions on respondent self-declared health. In my first analysis (Section 4), individuals were directly asked about their positive health on a Likert scale of 1-5, which I then used to calculate the proportion of individuals within a COA with self-rated positive health (see Sections 5 and 6). In my last two analyses, my outcome was the mental component summary score of the sf-12 (see details in Section 3.3.4), constructed from questions asked on a Likert scale. These scales have known biases that may translate to specific populations, leading to an under or over-estimation of the current or changing of individuals. This may bias green space and health associations if green space levels correlate with the location of populations that misestimate their health status.

Self-assessed health statuses are liable to biases where individuals may rate their health lower or higher to try and enact policy change, for example (strategic voting bias) (Vossler and Evans, 2009). Differences in what respondents perceive as positive health may lead to individuals with the same health status diagnosed by a medical professional (physical and mental) rating their health differently. This variance in scale use could generalise to sub-populations. For example, one sub-population could systematically undervalue their health or not understand their health), which may cause some confounding with green space and health associations (Mühlbacher et al., 2016). For example, deprived populations systematically overestimating their good health and being in an area with less green space would cause the magnitude of the true green space-health association to be underestimated.

7.1.3.4 *Differing study populations, outcomes, and exposures*

The study populations, types of green space exposure and analysis approaches differed across my three analyses, limiting empirical comparisons between them (Sections 4, 5 and 6). This prevented me from comparing the strength of associations between different effect modifiers, which was a weakness. However, tailoring effect modification to each study allowed me to use approaches which best represented the exposure and effect modifier context or limitations of the current evidence base. For example, in analysis 1 (Section 4), I hypothesised the effect modification to occur during experiences of traffic rather than due to the overall level of traffic around where a person lives. Therefore, I created separate with and no traffic variables of the

same green space type to effect modification. Conversely, in the case of socioeconomic deprivation, I hypothesised it was an effect defined by LSOA boundaries, which are created based on them having similar populations.

7.1.4 Recommendations

The findings of my thesis chapters have implications for stakeholders concerned with health and green space planning, policies, and management. In terms of those that create and manage green space, findings are most relevant to stakeholders in the UK. This includes local authorities responsible for the planning, design, and maintenance of most urban green spaces and local health practitioners interested in social prescribing, to national government policy setters and public bodies (e.g., the Environment Agency) that influence and make recommendations to them. My findings may also be able to guide policy and practice outside of the UK in countries with similar cultures and demographics. However, I do advise caution when doing so as populations' relationships with and benefits they receive from green space can vary greatly depending on the socioeconomic and climate context (Richards et al., 2019, 2022). I also provide further guidance on priority research areas, considering the potential societal impact of green space and health effect modifiers.

7.1.4.1 Policy context of PhD findings

Decision-making over green spaces near to where people live is partially made considering the benefits it provides to people. This has been true historically, where aside from it provisioning food and firewood, green spaces were promoted for health and well-being by Romans by bringing the “...the country in the city...” (Taylor et al., 2016) and the London Lincoln’s Inn fields in 1630 being planned for “pleasure and freshness for the health and recreation” (Macpherson, 1805). Today, ecosystem services or nature's benefits to people is core to how green spaces are planned and designed, including in the UK, where improved health is considered one of many benefits (Hansen and Pauleit, 2014). For example, see the London Environment Strategy, first created in 2017, which planned the creation of green infrastructure considering the “...full economic value that green infrastructure provides – from better physical and mental health and increased property values to reduced flood and heat risk.” (Greater London Authority, 2018). Policymakers and planners now use tools to

support which types of green space to encourage to provide the maximum relevant benefits to people. For example, i-Tree eco has been used (again in London) to assess to what degree trees can reduce environmental impacts present at different levels ([Mayor of London Office, 2022](#)).

Despite green spaces being historically designed to improve public health, integrating their value to health quantitatively into tools assessing a diverse range of green space benefits is rare. More recent natural capital accounting has done so, but only quantifying one health benefit from green space at a national scale. This was the physical health benefits from active recreation of more than 30 minutes and was quantified alongside agricultural production, water provision, timber production and other ecosystem services. This health benefit alone accounted for over a third of the total value of all green spaces in the UK at £600 billion (out of £1.8 trillion total benefits) ([Office for National Statistics, 2022a](#)). A likely underestimation of total health benefits as mental health benefits of these experiences and the variety of other types of nature exposures, such as incidental experiences that impact mental and physical health, were not quantified (see Section 2.1.4). Given the lack of comparative quantification (e.g., monetary value or other), it is difficult to determine how important the total health benefits of green spaces are relative to others more readily assessed (e.g. carbon sequestration, stormwater management).

Nonetheless, the health benefits have been greatly recognised by policymakers and frequently appear as an important part of city green space plans, e.g. in Cardiff, Glasgow, London, Manchester and Sheffield ([Glasgow City Council and Connecting Nature, 2020, 2020](#); [Greater London Authority, 2018](#); [Manchester City Council, 2017](#); [Sheffield City Council, 2010](#)). More effort is expected by the governments in the UK to improve the accuracy of quantifying nature benefits to people (health or otherwise) in the common years. This is because natural capital and ecosystem services are the central pillar of its 25-year environment plan launched in 2018 ([Curnow, 2019](#)).

7.1.4.2 Integrating green space mental health benefits into cost-benefit analysis

My confirmatory finding for green space to positively impact mental health has a few implications. It can further justify the burgeoning research on green social prescribing

(Fixsen and Barrett, 2022; McHale et al., 2020) and other active green care initiatives (Bragg, 2014). Importantly, it should be integrated into tools/methodologies for assessing green space benefit trade-offs and national accounts, especially as the total value of active trips to nature improving physical activity has already been assessed at a third of the UK ecosystems total capital value (see above) (Office for National Statistics, 2022a). This can help aid in decision making on where to protect old or create new green spaces.

7.1.4.3 Importance and further study of effect modifiers

Varying the quantity of green space effect modifiers I studied could make a potentially large difference to the net societal benefit from green space. A more than 2% change in the physical health benefits of active visits to green space (as assessed economically based on avoided NHS costs) is valued at more than £12 billion, which, according to the same government accounts in 2022, is the value of all standing timber in the UK timber stock (Office for National Statistics, 2022a). The existing evidence base provides consistent and strong support for positive effect modification of, for example, socioeconomic deprivation on green space and physical health outcomes. Given how people in more deprived areas disproportionality benefit from green space, the difference between the societal benefit (as measured by natural capital accounts) of green space in the most and least deprived areas could be greater than the total societal value of UK timber production. This is without considering mental health benefits. Therefore, localised estimates of the societal value of nature, when not considering socioeconomic deprivation, could be greatly misestimating the total quantitative benefits of green space these populations have, using existing tools and approaches. Assessing this should be a priority for natural capital accounts and green space assessment tools to make better decisions on which green spaces to create and protect. Because of historically inconsistent results (see Section 2.2.1.2), I argue for more studies on the modifying effect of socioeconomic deprivation on green space and mental health associations before these are considered quantitatively in decision-making. Nonetheless, as a quasi-experimental study, it strengthens the internal validity of this effect, and these can be considered potentially important co-benefits qualitatively.

Given the large value of health benefits from green spaces to society, further research should be conducted on the importance of naturalness, wetland, traffic and other effect modifiers to green space and physical or mental health associations, as my studies were some of the few in

these areas (see Section 2.2.2). This is particularly true for my findings relating to naturalness, as its negative impact at smaller scales conflicts with the existing literature, which is more internally but less externally valid (see Section 6.4.2 and 2.2.1.3). Unlike naturalness and water, longitudinal analyses or experiments on traffic's modifying effect on green space health associations are rare. These should be conducted to explore whether the effect modification caused by traffic is causal, for example, by comparing the change in the health of individuals randomly assigned to either an experience of green space near a road or away from a road.

7.1.4.4 More natural, wet, and wooded areas for conservation and mental health

Respondents with green spaces perceived to be more natural in areas dominated by green cover had better mental health than those with green spaces perceived to be less natural (but had the same green cover). In my MaxDiff experiment, ancient and deciduous woodland was perceived as the most natural green space type. This means individuals with more ancient and deciduous woodland nearby would be expected to have better mental health. These two green space types are also some of the UK's most ecologically natural green spaces (Chang Chien et al., 2020). Conserving more natural ecosystems is a priority for environmental conservationists in the UK and globally (Simmonds et al., 2023). Furthermore, wetland and woodland, especially ancient woodland ecosystems, are also some of the most biodiverse in the UK (Maltby et al., 2011; Rackham, 1980), and conserving ecosystems with high biodiversity is also a priority for environmental conservationists. The two goals of maximising green space that is more natural and wooded away from traffic, in areas dominated by green space, as well as the positive effect of it containing water, aligns with environmental conservation goals. Managers and planners of areas protected for their biodiversity and naturalness could consider these mental health co-benefits to generate more support and funding for their conservation, as is done for, e.g. carbon sequestration schemes (Salete Capellesso et al., 2021).

7.2 Conclusion

My PhD aimed to identify and assess modifiers of associations between residential green space and health. The context was to build on the existing evidence base around green spaces and their benefits to people, specifically their health. This was to help decide to what degree we should provide green spaces near where people live and what types of internal and external environments they should have or be within.

I identified four potentially important and understudied effect modifiers, which I assessed in three epidemiological analyses. These were: traffic, the socioeconomic deprivation of a local area, the proportion of green space that is wetland, and the perceived naturalness of green spaces. My epidemiological analyses also assessed the health impact of different residential green space types on different populations, using different methodological approaches. I found that green space positively impacted self-rated general and mental health using these new approaches and populations. Furthermore, the four effect modifiers were important to these associations; however, not always in the expected way. For good mental health and residential green space associations, area-level socioeconomic deprivation and the proportion of green space wetland had the expected positive effect modification. The naturalness of green spaces and the presence of traffic had some unexpected findings. Specifically, traffic was unexpectedly a positive effect modifier for fragmented trees outside woodland, but as expected, was a negative effect modifier for woodland. Similarly, more natural green spaces only positively impacted green space and mental health associations in areas where green space was high and unexpectedly had the opposite association when green space was low.

Broadly, my thesis has demonstrated that some important effect modifiers of green space and health association are understudied, which I have partially addressed. However, due to inconsistencies with the established literature and theory, naturalness should be further investigated as an effect modifier. Additionally, wetland and traffic should again be further investigated, due to them being rarely studied. Providing more green space in more socioeconomically deprived areas should be considered a priority due to the confirmatory findings of my second analysis, and existing evidence base supporting it to be a positive effect modifier. More generally the importance of the understudied effect modifiers in my

analyses, supports the exploration of other understudied potential effect modifiers, e.g. population pressure, sunlight, weather and season.

Given the considerable value of one green space health pathway (approximately 1/3rd of the UK total natural capital value), effect modifiers changing green space and health associations by as little as 2% have the potential to change the benefits we get from nature more than whole fields of ecosystem service assessment ([Office for National Statistics, 2022a, 2022b](#)). Identifying and quantifying the value of effect modifiers should be a priority for all concerned with maximising the societal benefits we get from existing and new green space.

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8 Appendix 1 – Confounder health associations from epidemiological analysis 1

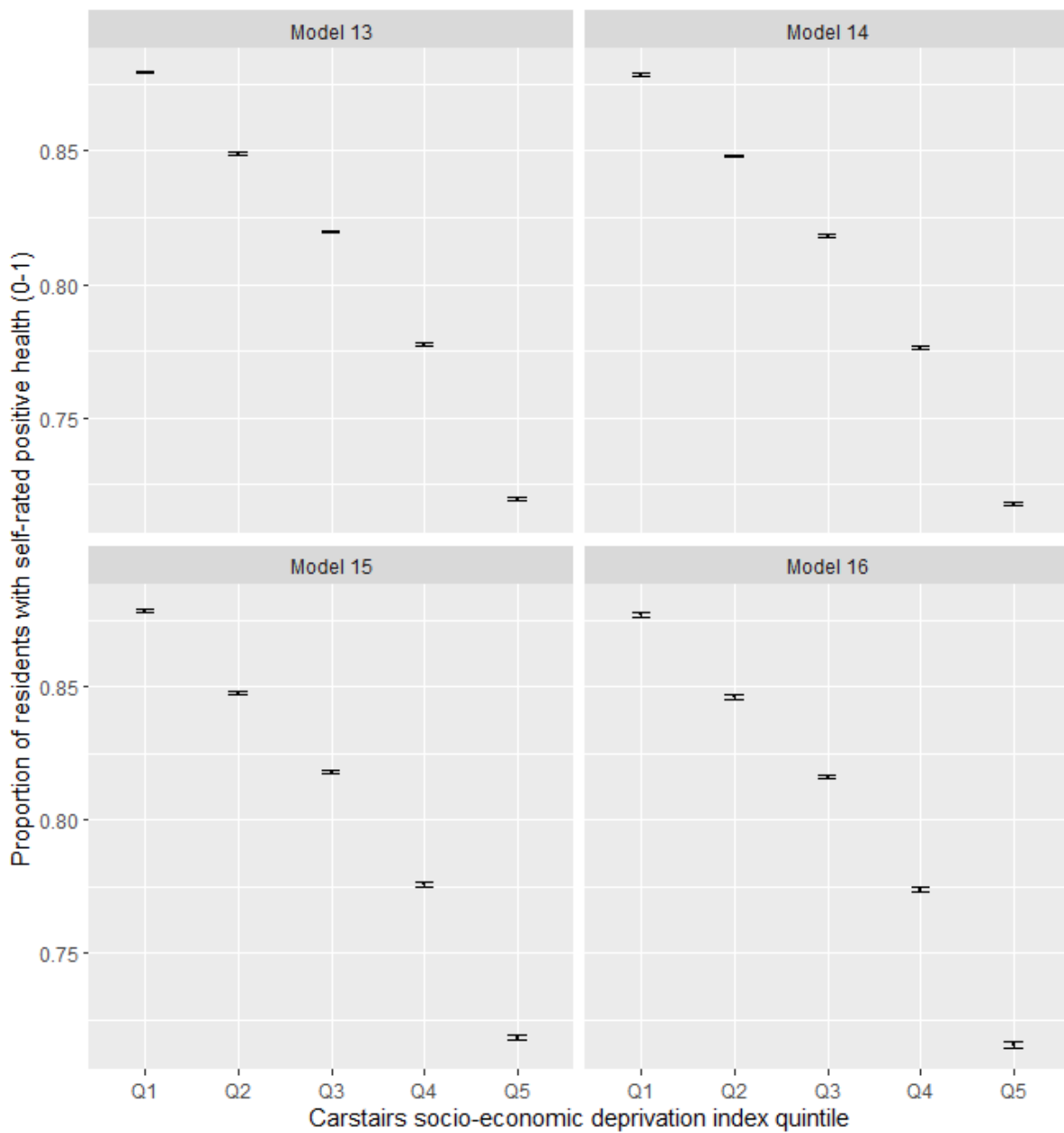


Figure 20. Predicted effects of COA socio-economic deprivation, as indicated by Carstairs index scores, on the directly age-sex standardised proportion of census output area resident with self-rated positive health from covariate adjusted models (models 13–16). Error bars show 95% confidence intervals. All predictions and confidence intervals were back transformed from logit scale to proportions. Continuous covariates were held constant at their mean level's.

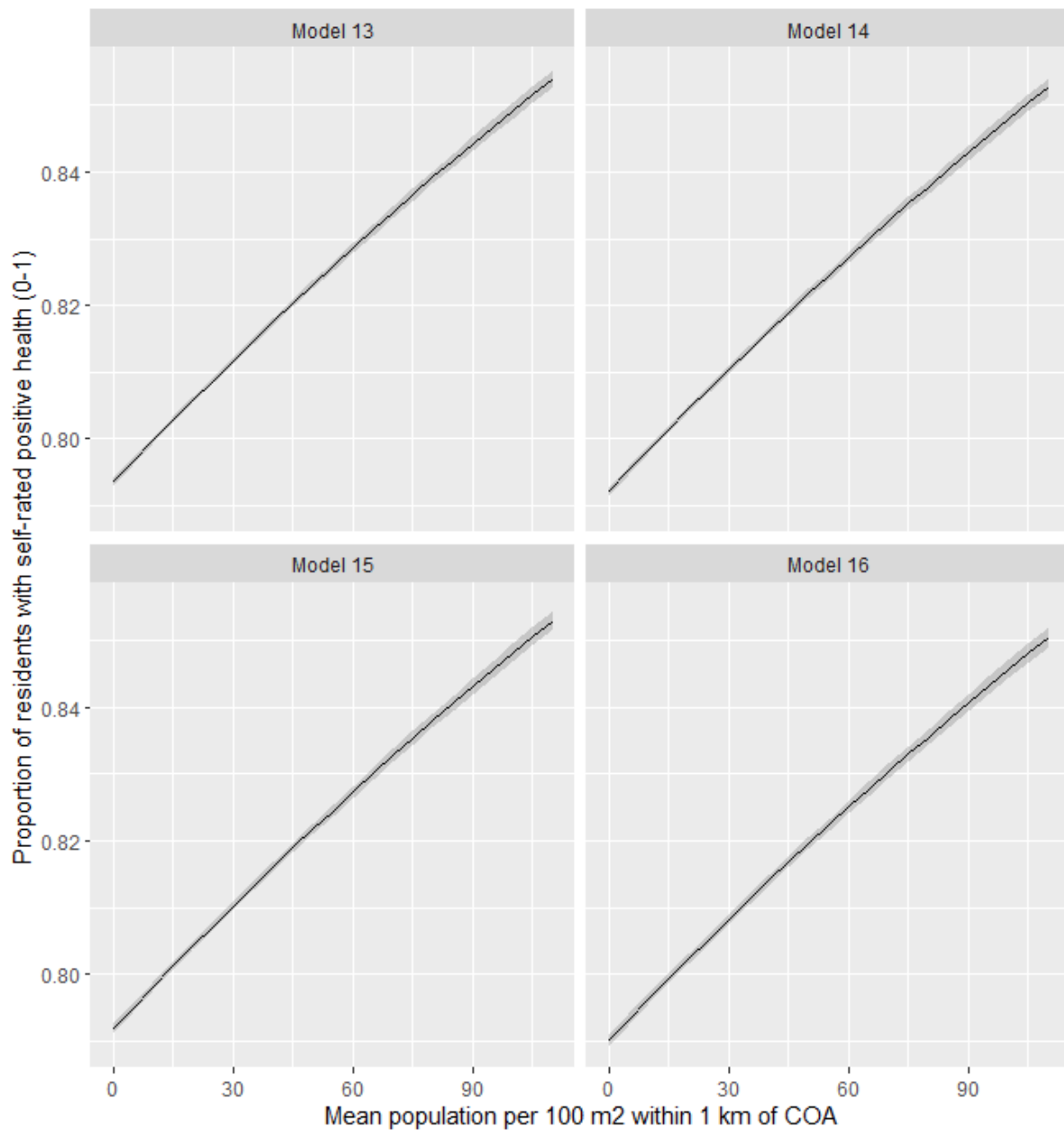
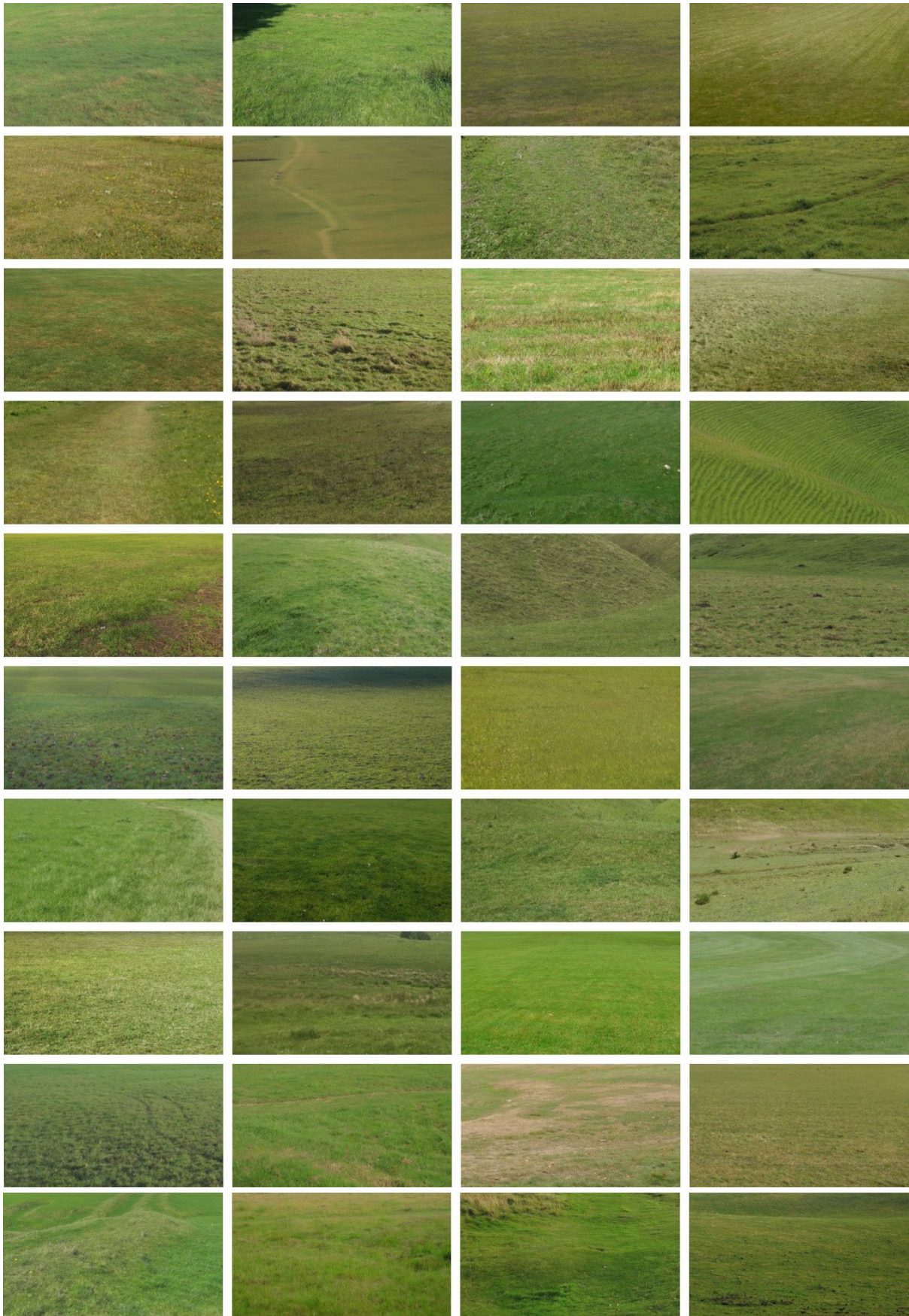


Figure 21. Predicted effects of population density around COA-PWC's on the directly age-sex standardised proportion of census output area resident with self-rated positive health from covariate adjusted models (models 13–16). Error bars show 95% confidence intervals. All predictions and confidence intervals were back transformed from logit scale to proportions. Continuous covariates were held constant at their mean level's. Deprivation was held constant at its third quintile.

9 Appendix 2 – Pictures used to represent land-covers in MaxDiff study



ssland



Calcareous grassland





Neutral grassland



Coniferous woodland



Saltmarsh





Acid grassland



Fen, marsh and swamp





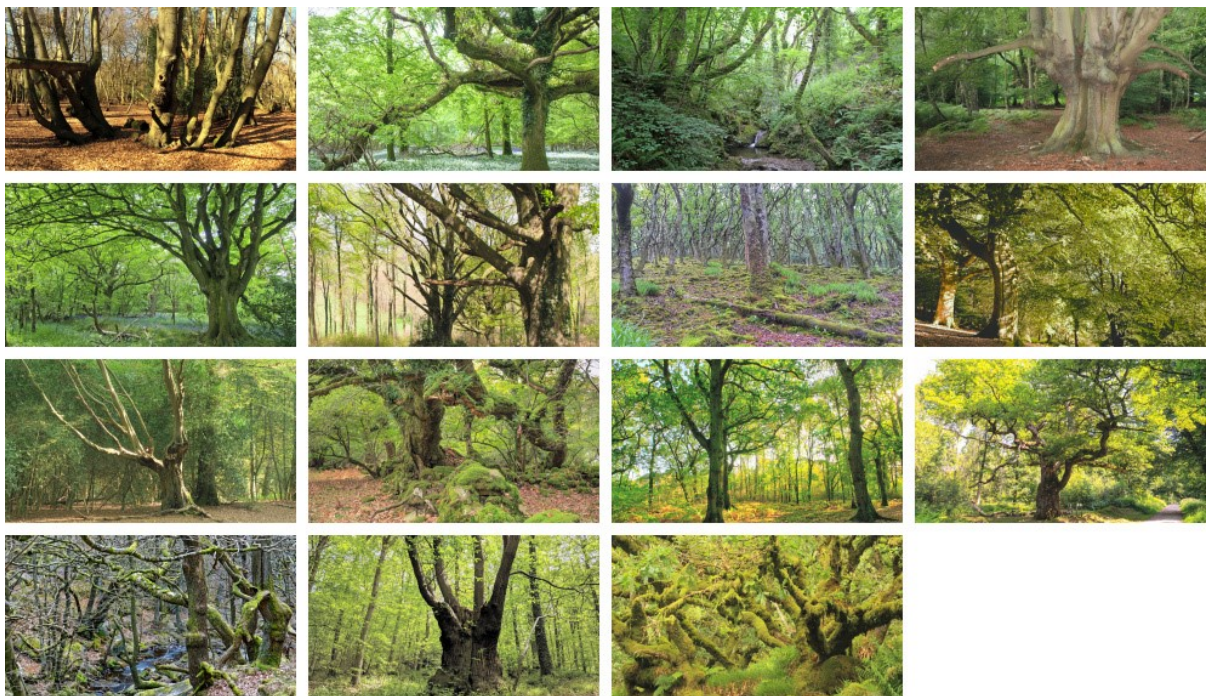
Heather



Heather grassland



Ancient woodland



Deciduous woodland





Bog



10 Appendix 3 – Results of mixed multinomial logit model used to model relative perceived naturalness from MaxDiff experiment

Table 16. Coefficients from multinomial logit model of land-cover perceived naturalness. Odds ratios are the odds of picking predictors as the most natural over *Arable* land cover (the reference category).

Predictors	Odds Ratios	CI	<i>p</i> -value
Ancient woodland	27.45	25.95 – 29.04	<0.001
Coniferous woodland	8.84	8.37 – 9.34	<0.001
Heather	16.67	15.77 – 17.62	<0.001
Heather grassland	13.10	12.40 – 13.85	<0.001
Bog	10.01	9.48 – 10.58	<0.001
Saltmarsh	13.42	12.69 – 14.18	<0.001
Fen	11.10	10.51 – 11.73	<0.001
Neutral grassland	6.16	5.83 – 6.50	<0.001
Calcareous grassland	5.35	5.06 – 5.64	<0.001
Deciduous woodland	15.84	14.99 – 16.75	<0.001
Acid grassland	7.96	7.53 – 8.40	<0.001
Improved grassland	1.47	1.40 – 1.55	<0.001

11 Appendix 4 – Correlations between covariates in epidemiological analysis 2 (Section 5)

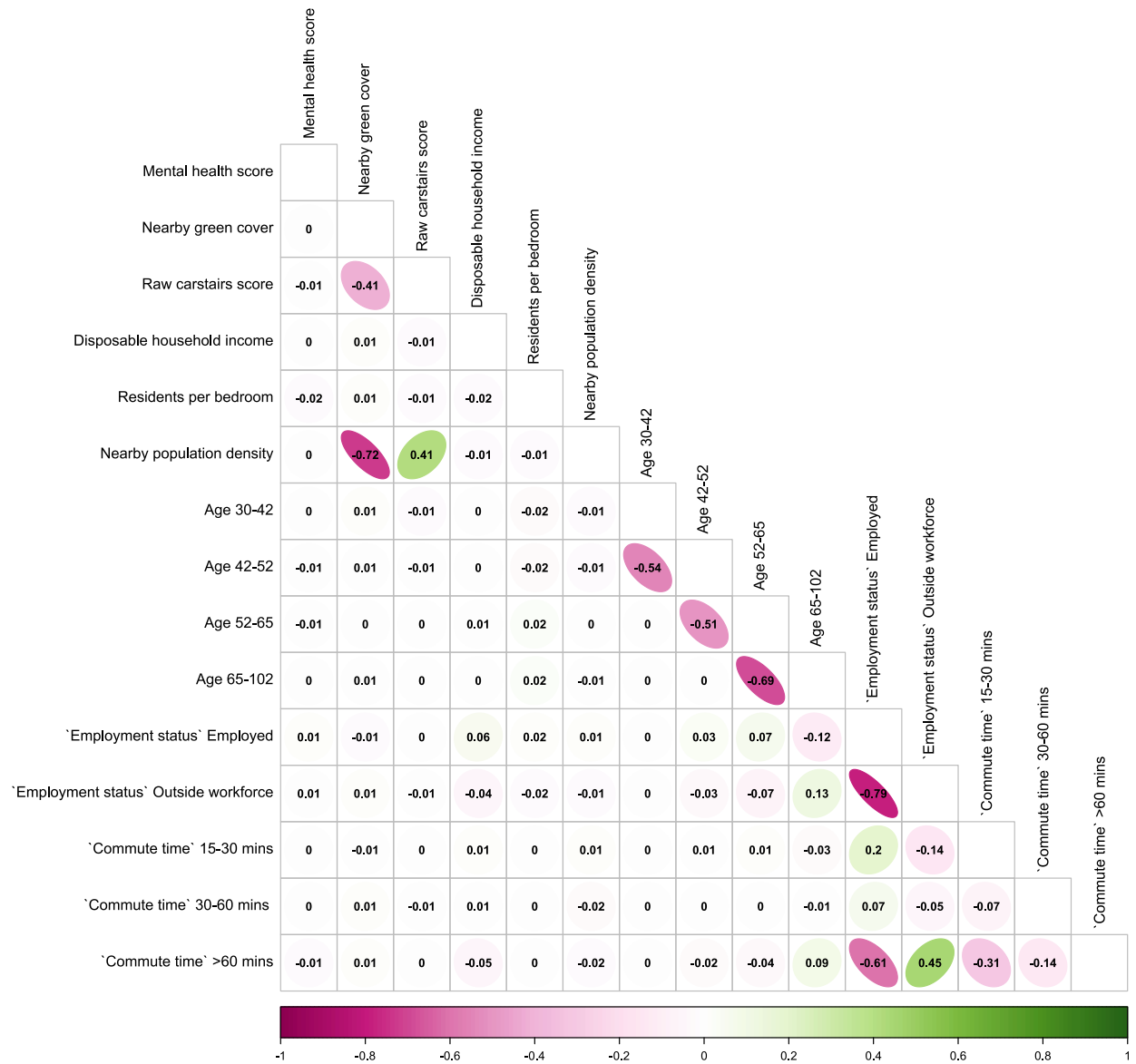


Figure 22. Correlations between covariates in epidemiological analysis 2 (Section 5)

12 Appendix 5 – Univariate associations between residential green space and health from Epidemiological analysis 3 (Chapter 6)

Table 17. Results of contrasts used to assess whether more residential green space improved mental health score in univariate model unadjusted for potential covariate confounders. Est. = the predicted mean value of the green space contrast category subtracted from the green space reference category (no green space cover). SE = Standard Error. Contrasts of the five mixed-effects models run on each multiple imputation within each set were averaged using Rubins rules (see methods). Parameter estimates of significant (p -value <0.05) contrasts are in bold.

Residential green space tertile	Est.	SE	p -value
>0 <18.9%	2.31	0.673	<0.001
18.9–45.9%	2.81	0.674	<0.001
45.9–98.8%	3.42	0.674	<0.001

13 Appendix 6 – Confounder health associations from epidemiological analysis 3 (Chapter 6)

Table 18. Associations between mental health score and potential covariate confounders from epidemiological analysis 3 (Section 6).

Explanatory variable	Est.	SE	p-value
Population density (residents per ha)	0.0103	0.00306	0.001
Residents per bedroom	0.212	0.0559	<0.001
Disposable household income (£1,000's)	0.096	0.0122	<0.001
Socioeconomic deprivation (Carstairs index)			
<i>Q1 (reference)</i>	—	—	—
<i>Q2</i>	-0.51	0.0879	<0.001
<i>Q3</i>	-1.07	0.09	<0.001
<i>Q4</i>	-1.46	0.096	<0.001
<i>Q5</i>	-2.17	0.105	<0.001
Sex			
<i>Female (reference)</i>	—	—	—
<i>Male</i>	2.1	0.065	<0.001
Age			
<i>15–30 years (reference)</i>	—	—	—
<i>30–42 years</i>	-0.735	0.0746	<0.001
<i>42–52 years</i>	-0.397	0.0814	<0.001
<i>52–65 years</i>	1.18	0.0859	<0.001
<i>65–102 years</i>	2.64	0.0964	<0.001
Employment status			
<i>Unemployed (reference)</i>	—	—	—
<i>Employed</i>	2.23	0.104	<0.001
<i>Outside workforce</i>	1.22	0.0927	<0.001
Commute time			
<i>0–15 minutes (reference)</i>	—	—	—
<i>15–30 minutes</i>	-0.427	0.0662	<0.001
<i>30–60 minutes</i>	-0.52	0.08	<0.001
<i>>60 minutes</i>	-0.651	0.135	<0.001
<i>No commute information</i>	-0.537	0.0752	<0.001