Greenspace quality and proximity are stronger predictors of mental health than quantity or access

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Abstract

As evidence grows for the mental health benefits of urban greenspaces, understanding which specific characteristics matter most is critical for guiding effective urban design and policy. This study compares multiple measures of greenspace exposure–focusing on proximity, quantity, access and quality–to determine which best predict changes in mental health. Individual-level mental health data were obtained from a nationally representative longitudinal survey in Great Britain (British Household Panel Survey, 1991-2008). The sample was restricted to individuals who moved neighbourhoods (n = 492), and a Before-After-Control-Intervention (BACI) study design was applied. Individual repeated measures from before and after the move were used to quantify the effects of changes in greenspace exposure on the probability of poor mental health, here defined using GHQ-12 with a score ≥3. Generalised linear mixed models were developed and their relative performance compared to identify the best-performing models. Among seven models tested, models incorporating local bird species richness (proxy for greenspace quality) and proximity to local public greenspace provided the best fit, outperforming models based on quantity and access. To our knowledge, this is the first study to compare the effect of multiple greenspace measures on mental health using a

BACI design specifically within an urban context. Our findings suggest the potential importance of urban greenspace quality and proximity in shaping mental health outcomes compared to measures of quantity and access. However, these findings are caveated by a temporal disconnect between exposure and outcome data; we therefore recommend future studies validate these findings using temporally-aligned data. Based on this study's findings, we recommend that future environmental planning and public health strategies prioritise these characteristics to maximise the mental health benefits of urban greenspaces.

1 Introduction

It is widely accepted that urban greenspace is beneficial for mental health and wellbeing (Keniger et al. 2013; Hartig et al. 2014; Shanahan et al. 2015; Houlden et al. 2017). Urban greenspaces are being created or enhanced in cities to provide residents with multiple benefits, including improved mental health (World Health Organization 2016; Public Health England 2020). Multiple pathways help explain how greenspace may influence mental health, and these can be organised into the complementary domains of reducing harm, building capacity, and restoring capacity (Markevych et al. 2017). Greenspaces can reduce exposure to environmental hazards such as air pollution, noise and excess heat, thereby potentially reducing harm to mental health (e.g., Thompson et al. 2018; Nobile et al., 2023; Hahad et al. 2025). They can also build capacity by providing an attractive setting that encourages physical activity and supports social cohesion, both of which have been associated with improved psychological wellbeing (e.g., Fone et al. 2014). Greenspaces can restore capacity through psychological restoration and stress reduction, as described in Attention Restoration Theory (Kaplan & Kaplan 1989) and Stress Reduction Theory (Ulrich 1983; Ulrich et al. 1991), where natural environments help alleviate mental fatigue and promote emotional recovery. Different characteristics of urban greenspace may engage these pathways in different ways. However, critical knowledge gaps exist in our understanding of how exposure to different characteristics of urban greenspaces affects mental health (Collins et al. 2020; Beute et al. 2023), which must be addressed to inform future urban planning effectively. To date, most studies have used a measure of the "quantity" of urban greenspace (such as area of greenspace) within a defined radius of an individual's home or local area to quantify the effect of exposure to greenspace on mental health (Collins et al. 2020). Measuring greenspace quantity may be an over-simplification of an individual's exposure to greenspace (Wheeler et al. 2015; Collins et al. 2020), and a more comprehensive consideration of different greenspace characteristics is required, since different characteristics of urban greenspace may result in different psychological responses (Pope et al. 2015; Markevych et al. 2017; Wyles et al. 2019).

A recent scoping review (Beute et al. 2023) that set out to compare different greenspace types or characteristics and their impact on mental health found that across studies, different greenspace characteristics have diverse effects on mental health, particularly for vegetation characteristics (e.g., higher vegetation density can be negative for mental health (Beute et al. 2023)). Such findings have important implications for greenspace design and policies. For example, if the quality of greenspace was determined to have a more favourable association with mental health than quantity, then improving the quality of existing greenspaces should take precedence over expansion of the network. There is a lack of studies which compare the different characteristics of greenspace within the same study design (Beute et al. 2023). Addressing this gap is essential for informing greenspace design because it remains unclear which characteristics are most beneficial to mental health.

This study aims to improve understanding of how different characteristics of urban greenspace may be associated with poor mental health using longitudinal data in which the same individuals were surveyed repeatedly over time. Poor mental health is defined as being at risk of common mental disorders such as anxiety or depression, which are prevalent in the general population, affecting an estimated 17% of adults in the previous week (Baker and Kirk-Wade, 2024). Seven measures of greenspace are included in the analysis, these are categorised into four different greenspace characteristics – proximity, quantity, quality, and access – as defined by Collins et al. (2020). These characteristics capture distinct but complementary dimensions of how people may experience urban greenspace. Proximity reflects how easily greenspaces can be reached and is often interpreted as a proxy for opportunities for routine exposure. Quantity represents the overall amount of greenspace available within a neighbourhood, which may influence visual contact with nature, and opportunities for recreation. In this study, quality captures ecological aspects of greenspace such as biodiversity, greenness, and the presence of protected or culturally significant natural features, which have previously been linked to restorative experiences and improved wellbeing (Annerstedt et al. 2012). Access reflects whether residents have a greenspace within a recommended walking distance, a measure widely used in planning policy, for example, England's Accessible Greenspace Standards (Natural England, 2023). Comparing these four characteristics enables evaluation of which characteristics of greenspace are most strongly associated with poor mental health and provides policy-relevant evidence for where investment in urban greenspace may be most beneficial. To compare these characteristics, we focus on individuals who changed neighbourhoods during the study period (hereafter "movers") to examine how a change in exposure to each greenspace measure influences mental health outcomes. Our overarching objective is to identify which greenspace characteristics (proximity, quantity, quality, or access) best explain the observed variation in the likelihood of poor mental health following a change in neighbourhood.

2 Methods

2.1 Greenspace characteristics and measures

We took a structured approach to selecting the greenspace characteristics and measures used in this study. First, we drew on the systematic map of greenspace and mental health research by Collins et al. (2020), which identified four greenspace characteristics previously examined in relation to mental health: proximity, quantity, quality, and access. For each characteristic, *a priori* predictions were developed by assuming their potential salutogenic (i.e., health-promoting) effects. These health-promoting effects are often explained by the 'biophilia' hypothesis which proposes that humans have an innate affinity for the natural environment which evolved through natural selection (Wilson 1984). Subsequently, four different but complementary predictions were formed (Table 1).

Table 1: *a priori* predictions about associations between greenspace characteristics and mental health, and examples of evidence to support these predictions. Greenspace characteristics were categorised using a recent systematic map of studies exploring the effect of greenspace on mental health (Collins et al. 2020).

Greenspace characteristic	**Predictions**	**Evidence to support the prediction**
Proximity	Living in an area that is in closer proximity to greenspace is expected to be associated with a lower probability of poor mental health..	Edwards et al. (2023) found that shorter walking distances to the nearest greenspace were associated with reduced risk of perceived stress.
Quantity	Living in an area with more greenspace (i.e., a greater quantity of greenspace) is expected to be associated with a lower probability of poor mental health	Astell-Burt et al. (2022) found that living in an area with more greenspace was associated with lower cumulative incident loneliness. This association was stronger for people living alone.
Quality	Living in an area with higher quality greenspace is expected to be associated with a lower probability of poor mental health	(Methorst et al. 2021) found that plant and bird species richness was associated with better mental health (measured using the mental health component scale).
Access	Living in an area with access to greenspace is expected to be associated with a lower probability of poor mental health	Gascon et al. (2018) found that access to green spaces was associated with a reduction in the odds of self-reported history of depression.

From the systematic map (Collins et al. 2020), we compiled a list of the characteristics associated measures. We then reviewed these characteristics to determine whether they were (1) relevant to urban areas in Great Britain (GB; comprising England, Scotland and Wales), and (2) supported by objective datasets available for GB. A total of eight measures of greenspace that were available for urban areas within GB were identified. These measures were classified into one of the four greenspace characteristics resulting in: one measure of proximity; two measures of quantity; one measure of access; and three measures of quality. For the greenspace characteristics of proximity, quantity and access, a distinction was made between public greenspace and all greenspace which included areas such as golf courses. Greenspace measures were calculated for the population-weighted centroids of the 2001 Lower Super Output Area (LSOA) or, for Scotland, a Data Zone. LSOAs and Data Zones are standard geographic units in the UK that are commonly used to report small-area statistics and have been previously used in research exploring the effect of greenspace on mental health (e.g., Mitchell and Popham 2008; Wheeler et al. 2015; Brindley et al. 2018). The average population size within LSOAs is 1500. The population-weighted centroids were used instead of geographic centroids to better represent the likely distribution of people within LSOAs, ensuring a better reflection of where populations are located within these proxy neighbourhoods. Greenspace measures are discussed in Sections 2.1.1–2.1.4 and summarised in Table 2.

Table 2: Summary of greenspace measures and associated data sources

Greenspace characteristic	Greenspace measure	Description of measure	Temporal coverage	Greenspace data source
Proximity	Distance to nearest public greenspace	Euclidean distance from the population-weighted centroid to nearest greenspace edge	2020	OSMM Greenspace Layer (2020), greenspace type “public parks and gardens”.
Quantity	Public greenspace area	Total area of public greenspace within 800m of the population-weighted centroid	2020	OSMM Greenspace Layer (2020), greenspace type “public parks and gardens”
	Total greenspace area	Total area of all greenspace types within 800 m of the population-weighted centroid	2020	OSMM Greenspace Layer (2020), all greenspace types
Quality	Regional bird species richness	Species richness value at the population-weighted centroid (10 km × 10 km resolution).	Records from 2007-2011	Gillings et al. (2019)
	Greenness	Mean maximum NDVI within 800m of the	Maximum values between 2011–2018	Landsat 8 surface reflectance products (United

		population-weighted centroid		States Geological Survey 2017)
	Protected area (PA)	presence (or absence) of designated trees or protected area within the population-weighted centroid’s 800m buffer	2019-2020	Combined datasets: the location of ancient, veteran or notable trees (Woodland Trust 2020) and the location of protected areas within the Common Database of designated areas (CDDA; European Environment Agency 2019).
Access	Public greenspace access within 800m	Presence or absence of public greenspace within 800 m of the population-weighted centroid	2020	OSMM Greenspace Layer, data for 2020. Greenspace type “public parks and gardens”

2.1.1 Greenspace proximity

Greenspace proximity was calculated as the straight-line (Euclidean) distance from the population-weighted LSOA/Data Zone centroid to the nearest public greenspace edge using the ‘sf’ package (Pebesma 2018) in R statistical software (R Core Team 2021). Locations and extents of public greenspace were determined using The Ordnance Survey’s Mastermap (OSMM) Greenspace Layer (version April 2020). The OSMM Greenspace Layer was a fine-scale vector dataset of urban greenspaces for 18 different greenspace types, including “public parks and gardens” (Ordnance Survey 2017), which was used to define public greenspace for this analysis. Data from 2020 was used because it represented the most up-to-date spatial dataset of UK public greenspaces available at the time of modelling. This resulted in a temporal disconnect between these greenspace data and the survey observations (1991-2008, see Section 2.2 for description).

2.1.2 Greenspace quantity

Greenspace quantity was defined as the total area greenspace within 800m of the LSOA’s population-weighted centroid. An 800m Euclidean distance buffer was chosen as it represented an approximate 10-minute walk (Murtagh et al. 2021) and aligned with the increasingly popular ‘20-minute neighbourhoods’ concept, which proposes that people should be able to meet most of their everyday needs within a 20-minute return walk (Emery and Thrift 2021). The concept has been implemented by local authorities and city planners in Melbourne (Victoria State Government Department of Environment 2021), Perth (Hooper et al. 2020) and has more recently been adopted as planning policy for the Scottish Government (Scottish Government 2024), and some London Boroughs (e.g., Ealing Council 2022). Two measures of greenspace quantity were calculated using the R ‘landscapemetrics’ package (Hesselbarth et al. 2019): (1) the total area of public greenspace and (2) the total area of all greenspace within an 800m buffer. Both measures were derived from the OSMM Greenspace Layer (version April 2020). For the total greenspace measure, all 18 categories of the OSMM Greenspace Layer were used including school grounds, playing fields and golf courses.

2.1.3 Greenspace access

The 20-minute neighbourhood concept was applied to estimate greenspace access within 800m of a person’s neighbourhood (Emery and Thrift 2021). The ‘landscapemetrics’ package (Hesselbarth et al. 2019) was used to determine the presence or absence of public greenspace (derived from the OSMM Greenspace Layer) within the population-weighted centroid’s 800m buffer (i.e., Euclidean distance). Euclidean distance was used instead of network distance for greenspace access, quantity, and proximity, and whilst it is a commonly adopted proxy for these characteristics, it does not represent real-world travel distances, which are shaped by the street network and additional barriers such as access restrictions and topography.

2.1.4 Greenspace quality

Three different measures were used to represent greenspace quality: (1) regional bird species richness, (2) the presence of protected areas within walking distance and (3) greenness (mean

NDVI within walking distance). We used regional bird species richness as a proxy for biodiversity (Hillebrand et al. 2018) and extrapolated that biodiversity can be used to quantify an ecological perspective of greenspace quality (Lovell et al. 2014; Sandifer et al. 2015; Wood et al. 2018). Bird species presence from a national bird monitoring survey recorded at a 10km x 10km resolution (Gillings et al. 2019) was used to calculate regional bird species richness (i.e., the count of the number of different species) at the same resolution. Records from between 2007 and 2011 were used. Rare and sensitive species that were recorded at coarser resolutions (20km x 20km and 50km x 50km, Gillings et al. 2019) were not included in this study, as these species would have generally not been seen by or interacted with most people (Gaston et al. 2018; Gaston 2020). Regional bird species richness value at each population-weighted centroid was extracted using the 'extract' function in the R 'raster' package (Hijmans 2021).

The presence of protected areas was used as an indicator of greenspace quality. Previous studies have applied this measure in different ways. For example, Annerstedt et al. (2012) used the presence of protected areas to represent culture and to do so identified areas of national interests of cultural preservation and nature reservation areas. Alternatively, Wheeler et al. (2015) used protected areas to capture the ecological and biological importance of greenspaces. Wyles et al. (2019) used protected areas to represent biological and aesthetic qualities of the different sites. Like Wyles et al. (2019) in this study, we attempted to represent biological/ecological and aesthetic/cultural qualities using the presence of protected areas. Therefore, the presence of protected areas were identified by combining two datasets: the location of protected areas within the Common Database of designated areas (CDDA; European Environment Agency 2019), and the location of ancient, veteran or notable trees (Woodland Trust 2020). The Common Database on Designated Areas (CDDA) was used as the official source of protected area information. For GB the protected areas included; Sites of Special Scientific Interest, National Nature Reserves, Local Nature Reserves, National Parks, AONBs and a variety of Marine Protected Areas (Joint Nature Conservation Committee 2019 The Woodland Trust's Ancient Tree Inventory was used as an alternative data source to capture the cultural and ecological qualities of urban greenspaces (Woodland Trust 2020, 2021). The Woodland Trust (2020) define an ancient tree as a tree that has passed beyond maturity and is old in comparison to other trees of the same species and a veteran tree as a tree that displays some of the characteristics of an ancient tree (e.g., particularly large trunk compared to same species or the hollowing of the trunk) but can be of any age. Notable trees are defined as any tree that has local significance and stands out in its local environment (Woodland Trust 2020). A binary variable was created to indicate the presence (or absence) of designated trees or protected area within the population-weighted centroid's 800m buffer.

The Normalised Difference Vegetation Index (NDVI) was used to represent local area greenness. NDVI was calculated using Landsat 8 surface reflectance products (United States Geological Survey 2017) at a resolution of 30 m × 30 m. Images were processed in Google Earth Engine and the maximum NDVI values over eight years were obtained. Here, NDVI values for LSOAs/Data Zones were the mean value within the population-weighted centroid's 800m buffer was calculated using the R 'raster' package (Hijmans 2021).

2.2 Mental health

This study used longitudinal data from the British Household Panel Survey (BHPS; University of Essex 2018), a multi-purpose longitudinal survey conducted in English that started in 1991 and finished in 2008. To date, the majority of studies that used secondary data to estimate the effect of greenspace on mental health relied on cross-sectional mental health data, where data were from a single point in time (Collins et al. 2020). In cross-sectional data, various environmental and social drivers of mental health are typically correlated (e.g., area deprivation and access to quality greenspace; Mears et al. 2019). The use of longitudinal data provided an opportunity to control for individual-level, time-invariant, unobserved factors and strengthened causal inference since the individual-level effect of a change in greenspace exposure could be quantified.

The BHPS consisted of a nationally-representative sample of more than 10,300 individuals from 5,500 households (University of Essex 2018). Within the survey, each year is referred to as a "wave" such that the first wave (Wave 1) was in 1991 and the last wave (Wave 18) was in 2008. The BHPS' household geographic identifier was used to link individuals to 2001 LSOAs or Data Zones. In the BHPS, individuals self-assess their mental health using the 12-item General Health Questionnaire (GHQ-12; Goldberg & Hillier, 1979). The GHQ-12 is a screening tool that is used to assess a person's risk of common mental disorders such as anxiety and depression (Goldberg and Hillier 1979; Goldberg et al. 1997; Jackson 2006), and is robust to differences in gender, age and education (Goldberg et al. 1997). The 12 items of the GHQ-12 responses consisted of two lower categories and two higher categories (i.e., a four-point scale) where higher scores relate to poorer mental health. For this analysis, 'GHQ method' (Hankins 2008) was adopted and the responses to each item were coded as 0 and 1, for the lower and upper categories respectively. The newly coded responses were then summed to create a scale from 1 to 12. Using a commonly applied threshold, this scale was then used to create a binary measure of poor mental health, where all individuals with scores ≥3 were classified as having poor mental health (Shelton and Herrick 2009). GHQ-12 has been used previously in the identification of poor mental health and access to greenspace (e.g., Alcock et al. 2013).

Records from the BHPS span 1991–2008, which resulted in a temporal disconnect between the survey observations and the greenspace measures used (Table 2). We proceeded with the BHPS, rather than the more recent Understanding Society survey (2009–2020; University of Essex, 2025), which would have minimised this temporal disconnect, because Understanding Society lacked consistent data on private garden ownership; an important factor identified in the literature as influencing the relationship between greenspace and mental health (Gaston et al. 2005; Brindley et al. 2018; de Bell et al. 2020; Collins et al. 2023).

2.3 Individual and household-level characteristics

To establish which waves occurred "before" an individual moved, and which waves were after their move, the BHPS' geographic identifiers were used to create the binary variable "before-after move". From the BHPS, additional information on income, age, gender, marital status, and highest educational attainment were identified as potential individual-level confounding factors. Monthly household income was adjusted by household size to create the variable: "income per person per household". Unlike previous studies (e.g., White et al. 2013; Alcock et al. 2014; Houlden et al. 2017), individual-level variables such as hours of physical activity, commute time, and physical health conditions were not adjusted because they were considered post-treatment variables (Montgomery et al. 2018). Ethnicity was not included as a confounding variable in this analysis because the BHPS's small and imbalanced sample of Black, Asian and Minority Ethnic (BAME) made ethnicity an unsuitable variable to include in a mixed-effect model.

2.4 Area-level variables

Area-level deprivation and air pollution were identified as potential confounders of greenspace effects on mental health. The Townsend deprivation score from the 2011 Census was used to determine deprivation for LSOAs in England and Wales and Data Zones in Scotland (UK Data Service 2017). Higher scores indicate the most deprived areas, while lower (or negative) scores indicate the least deprived areas, scores in this sample ranged from -5 to 10. Air pollution was measured using modelled PM2.5 concentrations at a 100m resolution (Phillips et al. 2021). The mean exposure to PM2.5 within an 800m buffer around the population-weighted centroid was calculated. As area-level variables could vary with an individual's move, all area-level variables were tested for their potential correlation with the variable "before-after move". The area-level variables both before and after moving were only weakly correlated (Appendix A). A sensitivity analysis, in which air pollution was excluded from the model, was undertaken to explore potential bias introduced by air pollution as a potential mediator of the relationship between greenspace and mental health.

2.5 Analysis

The movers were used to emulate a Before-After (BA) study design where repeated measures of mental health pre -and- post-move were used to estimate the association of moving on an individual's mental health, and whether this association varied in relation to the change in greenspace exposure (Alcock et al. 2013; Van den Bosch et al. 2015). If the data permitted a control group (i.e., individuals who did not experience an objective change in greenspace exposure), a Before-After Control Intervention (BACI) design was applied. BACI study design was adopted as they were considered optimal to help isolate the association of a change from a variable outcome (Wauchope et al. 2021). In other applications of BACI, non-movers might be used as a control group; however, these individuals would not experience the same confounding conditions associated with moving. Therefore, where possible, internal control groups (i.e., individuals experiencing "no change" in greenspace exposure) were used.

2.5.1 Sample stratification

To establish a BACI design, the data were filtered to individuals who had moved neighbourhood (i.e., LSOA) between urban areas during the survey period (n = 4,635). Movers were identified using a question from the BHPS. For individuals who moved multiple times during the survey (n = 1,833), the consecutive locations where they lived the longest were used. The wave before the move and the wave after the individual's move were excluded to reduce immediate relocation influences on mental health (i.e., to avoid anticipation and adaptation effects; White et al. 2013). The remaining movers (n = 3,463) were then filtered to those with a minimum of three waves both before and after the move (n

= 579), to enable the estimation of random slopes representing the changes in mental health over time (see section 2.5.3 for details). To minimise the potential effect of private garden access on mental health (Collins et al. 2023), the sample was restricted to individuals whose private garden ownership status did not change during the move. This means that only those who consistently had or did not have a private garden both before and after the move were included. The final sample for analysis consisted of 4,552 observations from before and after the move from 492 individuals, of which 479 had a private garden and 13 had no private garden both before and after the move. The median number of observations per person was 10 waves. A summary of the sample characteristics according to years before and after moving is presented in Appendix C.

2.5.2 Observed change in greenspace exposure

To apply the BA or BACI design, individuals were grouped according to their observed change in greenspace exposure pre -and- post move (summarised in Table 3). The possible changes in greenspace exposure were binary or ternary (Table 3). The categorical and coarse resolution of some measures meant that some movers experienced "no change" in their greenspace exposure. For these variables, exposure change was represented by three groups. For example, an individual who lived within 800 m of a public greenspace before their move and still lived within 800 m after the move would be classified as having experienced no change in exposure. This third "no change" group was the internal control group for the movers to create the BACI study design. Greenspace measures without this "no change" group had a BA study design applied (Table 3). The number of individuals experiencing each change in greenspace was assessed (Appendix D), and a minimum threshold of 50 individuals for each observed change in greenspace was chosen. This was a conservative threshold based on recommendations from previous mixed-model simulation studies (Maas and Hox 2005; Paccagnella 2011; Schoeneberger 2016; Sommet and Morselli 2017).

Due to the temporal disconnect between the survey data (BHPS; 1991–2008) and the greenspace data (Table 2), we assumed that changes in greenspace over time were minimal, or that the rate of change in greenspace was temporally consistent across all LSOAs/Data Zones. However, the mixed evidence supporting this assumption (e.g., Dallimer et al. 2011 and The Committee on Climate Change, 2019) suggests that it may have led to the misclassification of individuals into groups (Table 3) that do not accurately reflect their true greenspace exposure. The potential implications of this assumption are discussed in Section 4.4.

Table 3: Greenspace characteristics and measures, their respective change in greenspace exposure experienced by "movers", and the corresponding Before-After (BA) or BACI (Before-After Control Intervention) study design

Greenspace characteristic	Greenspace measure	Change in exposure to greenspace	*n*	Study design
Proximity	Distance to public greenspace	Moved closer	246	BA
		Moved further	246	
Quantity	Public greenspace area	Increase in quantity	217	BA
		Decrease in quantity	275	
	Total greenspace area	Increase in quantity	246	BA
		Decrease in quantity	246	
Quality	Regional bird species richness	Moved more diverse	114	BACI
		No change	89	
		Moved less diverse	289	
	Greenness	Increase in greenness	209	BA
		Decrease in greenness	283	
	Protected area (PA)	Gained access to PA	91	BACI
		No change in access to PA	291	
		Lost access to PA	110	
Access	Public greenspace access within 800m	Lost access	89	BACI
		No change in access	324	

Gained access	79

2.5.3 Model selection and comparison

We developed a base model from which the models including greenspace characteristics were compared to assess the improvement of model fit from the different greenspace characteristics. We fitted generalised linear mixed models (GLMMs), with a logistic link function, to account for the hierarchical structure of the dataset where each individual has repeat observations (waves) before and after their move. The base model included the following individual-level confounders: income (£/person/household), gender (male/female), age (years), married (yes/no), and higher education (yes/no). Area-level confounders (Townsend deprivation scores and air pollution) were tested in a step-wise manner and were only included in the base model if they improved model fit, assessed using Akaike Information Criterion (AIC) and Likelihood Ratio Tests (LRTs). The 'pbkrtest' package (Halekoh and Højsgaard 2014) was used to perform restricted LRTs. Random intercepts were specified to identify repeated observations for each individual. To allow variation in individuals' mental health responses to moving , a random slope for the binary variable "before-after move" was fitted. Crossed random intercepts were tested for households and LSOAs/Data Zones to accommodate the structure of the data, as individuals can appear in multiple households and all individuals will appear in multiple LSOAs/Data Zones (one before the move and one after). The final base model consisted of both area-level variables (deprivation and air pollution), as they were found to improve the model fit (LRT p-value <0.01 and 0.01, respectively). Adding random intercepts for both household and LSOA/Data Zones resulted in a singular model (i.e., there was not enough clustering at these levels), therefore these were not included in the hierarchal structure of the base model.

Separate models for each greenspace measure were created by adding the binary or ternary variables representing the change in greenspace exposure for each measure (Table 3) to the base model (i.e., the model with no measure of greenspace). To test the average effect of the change in greenspace exposure, an interaction term between the change in exposure to the greenspace variable (Table 3) and the move variable was specified (Figure 1). All greenspace models were compared to the base model using AIC. Models with a lower AIC than the base model were deemed to have superior fit. The goodness of fit of each model was calculated using the theoretical marginal (R^2_m) and theoretical conditional (R^2_c) coefficients of determination (Bartoń 2016). Generalised Variance Inflation Factor (GVIF) scores were used to assess multicollinearity among the variables included in the models to ensure that collinearity does not inflate variance (Appendix E). Pearson's R correlation coefficients were calculated for all combinations of greenspace characteristics to ensure data independence (Appendix A, Figure A.1).

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

3 Results

We compared models that varied in their inclusion of a range of greenspace characteristics related to proximity, quantity, access and quality. Only two models were found to explain more variation in poor mental health compared to the base model with no greenspace and therefore were deemed to provide added inference to the base model (Table 4). The measures that improved model fit were regional bird species richness and distance to public greenspace; these were classified as greenspace quality and greenspace proximity characteristics, respectively (Table 3). For all other greenspace measures, the AIC and LRT values indicated that the base model provided a better fit to the data (Table 4 and Appendix E).

Table 4: Results from the model comparison of the seven measures of greenspace characteristics and the base model with no greenspace. Models are ranked according to AIC weight, the "best" performing models are those that have a lower AIC value compared to the base model. The goodness of fit was calculated using theoretical marginal (R^2_m) and conditional (R^2_c) values following (Nakagawa et al. 2019).

Greenspace characteristics and measures	R^2_m	R^2_c	**ΔAIC**
Quality – Regional bird species richness	7.55%	46.18%	0
Proximity – Distance to public greenspace	7.41%	46.26%	4.95
Base model (no greenspace)	6.59%	46.13%	7.89
Access – public greenspace within 800m	7.42%	46.21%	8.49
Quality – Greenness	6.67%	46.24%	9.27
Quality – Protected area(s)	6.98%	46.15%	10.66
Quantity – Public greenspace area	6.69%	46.13%	11.03
Quantity – Total greenspace area	6.69%	46.11%	11.28

The regional bird species richness model, containing a variable that distinguished between individuals that moved to either a more or less diverse area, had the best fit according to the fixed effects (R^2_m, Table 4). This was followed by the distance to public greenspace model, containing a variable that distinguished between individuals that moved closer to or further from public greenspace. These two models explained 7.55% and 7.41% of the variation in mental health, respectively. For these top-performing models, all observed changes in greenspace exposure showed a decrease in the probability of poor mental health after the move, but the magnitude of the effect varied between the observed changes (Figure 1). The decrease in the probability of poor mental health for pre -and- post move was greatest for more "favourable" greenspace changes (i.e., moved to a more diverse location and moved closer to greenspace) compared to the less favourable changes (i.e., moved to less diverse location, experienced no change and moved further from greenspace). For the regional bird species richness model, the group that experienced no change had the smallest difference between pre -and- post-move probabilities of poor mental health (Figure 1a).

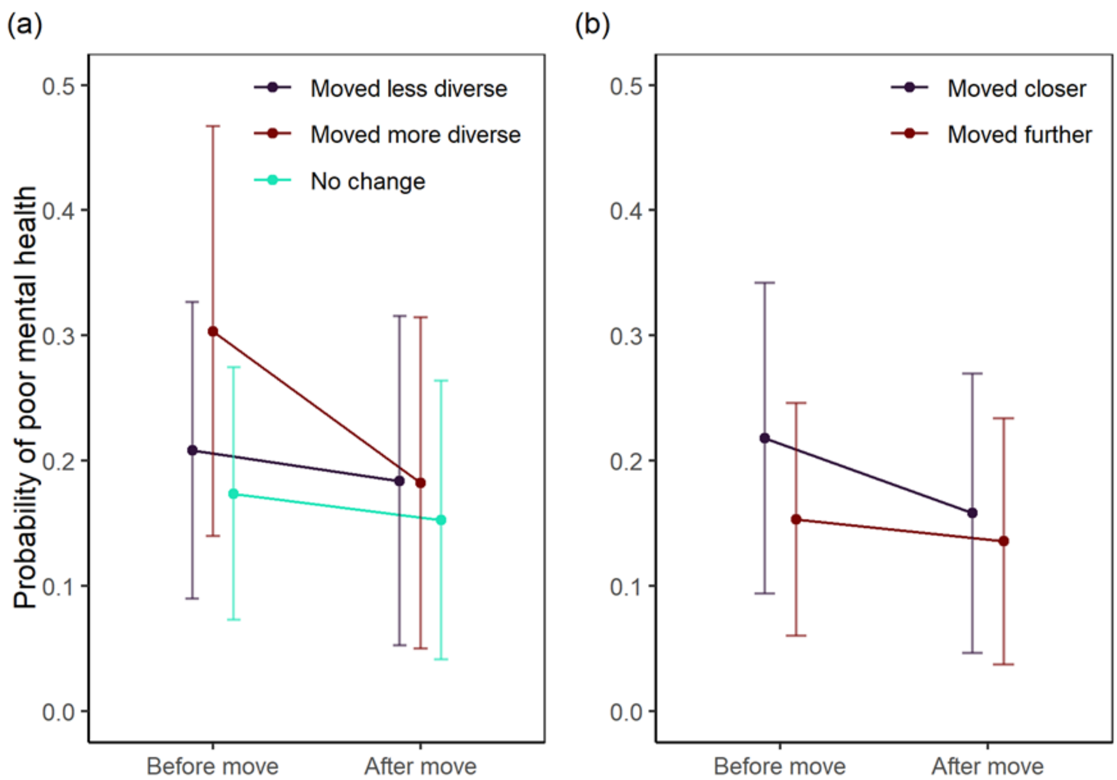

Figure 1: Predicted probability of poor mental health before and after relative to their respective changes in greenspace exposure of the two top-performing models (see text 2.5.3); (a) greenspace quality – regional bird species richness, and (b) greenspace proximity – distance to public greenspace. All other covariates were held at the median or mode of the sample. Error bars show the 95% confidence intervals for the predicted outcomes obtained through bootstrapping (1000 replications)

The other covariates (socio-economic and area-level variables) showed comparable mental health responses between the two best-fitting models (Figure 2). The regional bird species richness model predicted marginally higher probabilities of poor mental health across all covariates (Figure 2). For the categorical variables, the probability of poor mental health was higher for women compared to men and being married had a lower probability of poor mental health than not being married, and having achieved a higher education qualification marginally increased the predicted probability of poor mental health (Figure 2). For the continuous variables, the probability of poor mental health peaked at approximately 50 years old. Income and air pollution followed a negative linear relationship with poor mental health, whilst deprivation followed a positive linear relationship. The models predicted the probability of poor mental health to decline with an increase in income and the probability of poor mental health increased in more deprived areas (Figure 2). The observed relationships between the model covariates and the probability of poor mental health were expected, with the exception of the probability of poor mental health decreasing in areas with higher levels of air pollution.

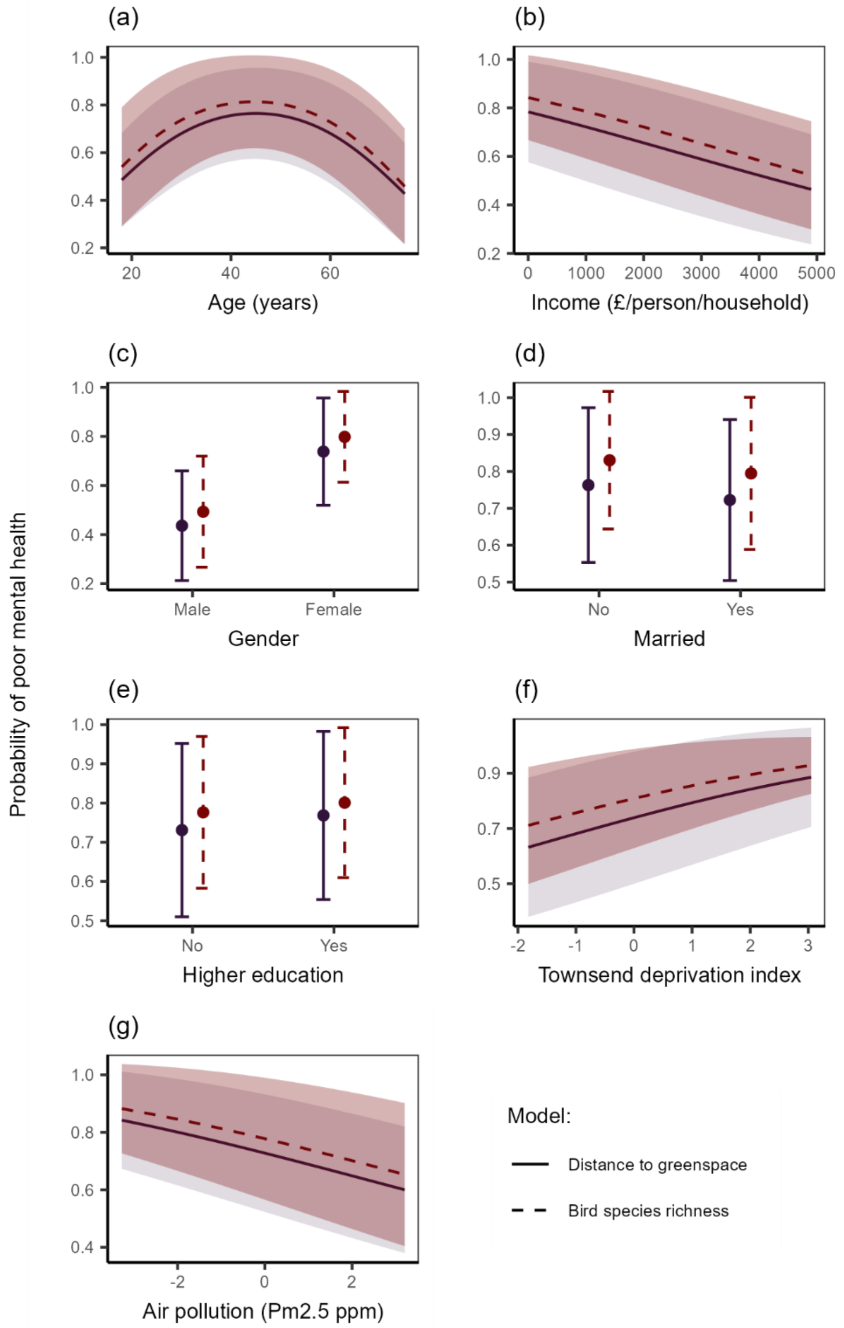

Figure 2: Predicted probability of poor mental health for individual and area-level variables from the two top-performing models in relation to: (a) age, (b) household income (£/person/household), (c) gender, (d) marital status (yes/no), (e) higher education attainment (yes/no), and (f) Area-level deprivation as measured by the Townsend deprivation score (-6 least deprived and 9 most deprived). For each graph, the greenspace variables were defined as "moved more diverse" and "moved closer". All other covariates were held at the median or mode of the sample. The shaded regions show the 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

4 Discussion

4.1 The comparative importance of greenspace quality and proximity

In our model comparison, we found that two of seven models containing measures of greenspace exposure explained more variation in poor mental health compared to the base model, which contained no measure of greenspace exposure. The top-performing model contained a variable that captured changes in exposure to regional bird species richness (i.e., distinguishing between individuals who moved to either a more or less diverse area). The second top-performing model included a variable that reflected changes in distance to public greenspace (i.e., distinguishing between individuals who moved closer to or further from public greenspace). The measures of regional bird species richness and distance to public greenspace relate to characteristics of quality and proximity, respectively. These results support previous findings that quality and proximity are important characteristics of greenspace when exploring the association between greenspace on mental health, highlighting that it is not simply the amount (i.e., area) of greenspace that is important when quantifying the effect of greenspace on mental health (Pope et al. 2015; Markevych et al. 2017; Wyles et al. 2019). The majority of past studies adopted measures of greenspace quantity as a way to evaluate an individual's exposure to greenspace (Collins et al. 2020; Beute et al. 2023). Measures of greenspace quantity treat all greenspaces as homogenous (James et al. 2015), which is insufficient to inform either conservation efforts or public health policies (Dean et al. 2011, Francis et al. 2012, Taylor and Hochuli 2017). The relative importance of closer proximity compared to measures of greenspace quantity and access (Table 4) suggests that urban greening policies that prioritise proximity may benefit urban residents' mental health. In cities where spatial constraints limit opportunities for large-scale greenspace development, a focus on delivering proximal small urban public greenspaces such as "pocket parks" may offer a practical solution for policy and decision-makers (Ministry of Housing, Communities and Local Government 2019; Dong at al. 2023). Combined with comparatively better performance of greenspace quality, the results suggest a potential "win-win" for investment in urban spaces that are protective of both mental health and nature. Given that proximity, quantity, access, and quality capture different dimensions of how people encounter greenspace, future research should examine whether these characteristics interact. Our BA/BACI design, which relied on within-person changes, did not provide enough overlap to estimate such interactions reliably. Nevertheless, understanding whether combinations of characteristics work together synergistically or provide overlapping benefits remains important for advancing theory and guiding greenspace policy. This perspective would help explore whether different characteristics operate independently or whether certain combinations of features amplify (or diminish) the mental-health benefits of urban greenspace provision.

4.2 Defining and measuring greenspace quality

The results indicated that not all measures of "quality" are of equal explanatory importance. In the models, change in NDVI and the presence of protected areas performed poorly as proxies for changes in greenspace quality, especially when compared to regional bird species richness (Table 4). Due to data availability for this national scale study, we were unable to include more measures of greenspace quality. We acknowledge that other features of greenspace quality – such as plant diversity (Methorst et al. 2021) or overall land cover diversity (Wheeler et al. 2015) – may also play important roles in shaping mental health outcomes and warrant further investigation. Importantly, our results do not distinguish whether it is regional bird species richness itself, or the underlying environmental conditions that promote regional species richness (e.g., plant diversity, habitat amount at broader extents; Methorst et al. 2021) that are driving the observed reduction in the probability of poor mental health.

Furthermore, the aggregation of species presence into a single measure of regional species richness implies that all species are of equal importance for benefits to mental health. A person's response to a species is dependent on the species and their opportunities and behaviour (Gaston et al. 2018). People are more likely to interact with common bird species that are accustomed to people (Gaston et al. 2018). We excluded rarer bird species from the regional species richness measure to better capture those species that people are more likely to see or interact with, which aligns more closely with potential human experiences of greenspaces. We recommend that future studies explore which bird species are most associated with improved mental health outcomes, whether these species share common traits, and whether traits such as bird song play a contributing role. Previous research has highlighted the restorative benefits of bird song (Ferraro et al. 2020, Riters et al. 2022) and other natural soundscapes (Uebel et al. 2021) on mental health. This understanding could inform urban greenspace management strategies aimed at encouraging the presence of beneficial bird species, thereby potentially enhancing the psychological benefits associated with greenspace exposure.

All three measures of greenspace quality were based on ecological indicators, which may not fully capture aspects of quality from a human perspective, such as perceived safety and accessibility. Examples of greenspace qualities from a human perspective include measures of cleanliness, lighting and the availability of amenities (for examples see de Gelder et al. 2017, Parra et al. 2010, Pope et al. 2018). Incorporating these qualities into the design of greenspaces is needed to remove barriers to access and encourage people to visit, use and engage with these spaces to gain the potential benefits. Representational barriers – a subset of cultural barriers disproportionately affecting BAME populations (Ward et al. 2023) – must be considered in the design. However, managing greenspace purely from a human perspective might exclude species perceived as undesirable or threatening, negatively affecting species richness and the overall ecological integrity of urban greenspaces (Stanley et al. 2015, van Heezik and Brymer 2018). Similarly, species considered important for high ecological quality may not reflect the type needed for psychological benefits (Gaston et al. 2018). As few studies consider greenspace "quality", and fewer still both human and ecological perspectives of "quality", there is limited evidence of whether a trade-off between the two perspectives exists. Understanding which qualities from both a human and ecological perspective and the potential trade-off between these qualities is a priority for future research so that advice on practical greenspace management can be made.

4.3 Unexpected influences on mental health

All changes in exposure to greenspace showed a decrease in the probability of poor mental health post-move compared to pre-move despite removing the year before and the year of the move from the sample (Figure 1). It may be that the potential beneficial effects of moving to a new neighbourhood are buffering against the loss of beneficial greenspace characteristics. As the selection of a new neighbourhood is non-randomised we are unable to fully account for neighbourhood selection (Oakes 2004). Despite the overall beneficial effect of moving, the changes in exposure to greenspace relating to "favourable" changes (e.g., moving to an LSOA/Data Zone with higher regional species richness and moving closer to public greenspace) reduced the probability of poor mental health more than the no change and "less green" exposure. Although the benefits at an individual level are small, the aggregate gains at a population level could be important, as multiple people can benefit from one public greenspace (White et al. 2013). Therefore, significant aggregate gains may be achievable by increasing the provision of greenspace quality or decreasing the distance from people's homes to public greenspaces. Indeed, urban planners and policymakers should consider how to design a network of connected spaces – connected both in terms of people and biodiversity.

An unexpected result showed that higher levels of air pollution result in a reduced probability of poor mental health. This is contrary to previous epidemiological research (e.g., Power et al. 2015; Oudin et al. 2016; Vert et al. 2017; Roberts et al. 2019; Signoretta et al. 2019). While air pollution was not a focal driver of interest in our study, and may therefore correlate with other, unobserved confounders (e.g. urban density), one possible explanation could be that the measure of air pollution may be capturing aspects of unexplained social connectivity as the measure used was modelled from the road network (Phillips et al. 2021). Social connectivity can have protective effects on mental health (Maas et al. 2009; Sarkar et al. 2013; Ward Thompson et al. 2016) and is supported structurally by physical infrastructure, including road networks (Bettencourt 2021). Building on research from Stier et al. (2021), future research should investigate how the socio-economic networks and physical infrastructure of cities or urban areas may have protective effects on mental health.

4.4 Methodological limitations and data considerations

This study aimed to identify the characteristics of urban greenspace that best explain poor mental health among movers using a BACI study design. Such designs have been previously applied to explore the effect of "greenness" on mental health (e.g., Alcock et al. 2014), and to our knowledge, one previous study assessed the effect of multiple greenspace characteristics on mental health using a BA design (see Van den Bosch et al. 2015). However, Van den Bosch et al. (2015) limited their analysis to rural and sub-urban neighbourhoods and it is not known if similar patterns can be observed in urban areas. While the data and the methodological approach enabled us to compare the association between different greenspace characteristics and mental health, it does have limitations.

Due to limitations in the availability of data that distinguished between public and private greenspaces (used for measures of proximity, quantity and access), most of the greenspace data used in this study reflect the distribution of UK urban greenspace in 2020. This created a temporal disconnect between these greenspace measures and the BHPS survey data (1991–2009). Measures of bird species richness, greenness (NDVI) and protected areas were also not longitudinal (Table 2), resulting in a similar temporal mismatch for all greenspace characteristics used. To proceed with analysis, we assumed that changes in urban greenspace characteristics (proximity, quantity, quality and access) were minimal, or at least that rates of change were broadly consistent across LSOAs/Data Zones between 1991 and 2020. A consequence of this assumption is the potential misclassification of individuals into the "Change in exposure to greenspace" groups (e.g., *Moved closer*, *Moved further*; see Table 3). The degree of misclassification likely varied across greenspace characteristics and may have influenced model ranking (Table 4). Misclassification is more likely where a larger temporal gap exists, as greater changes in greenspace were more likely over longer periods. Thus, misclassification may have been more common for proximity, quantity and access (which rely on 2020 greenspace distribution) compared with bird species richness and greenness, which were temporally closer to the BHPS survey period. This may partly explain why bird species richness produced better-fitting models, as it was less temporally misaligned. Despite these limitations, the assumption of limited long-term change in urban greenspace was considered reasonable given constraints in greenspace data availability across the full BHPS timeframe (1991–2008). Evidence on long-term changes in greenspace in GB is mixed. For example, Dallimer et al. (2011) reported modest overall increases in greenness across English cities between 1991 and 2006, with most gains occurring before 2001 due to the conversion of abandoned industrial land to greenspace after 2001, several cities experienced greenspace loss, coinciding with UK planning policy changes that promoted urban densification and brownfield development (Dallimer et al. 2011). Statistics for England from 2001 to 2018 indicate an overall decline from 63% to 55% (The Committee on Climate Change, 2019). However, there was little overall change between 2011 and 2016; a further decline of 1% occurred between 2016 and 2018 (The Committee on Climate Change, 2019). Although changes in urban greenspace did occur, the overall magnitude of change was generally small, supporting our assumption that long-term shifts in greenspace characteristics were unlikely to substantially bias our analyses.

In this study's modelling approach, we treated all residential moves as equivalent, without accounting for the underlying reasons why individuals relocate within the model. This is an important study limitation because reasons and motivations to move can vary. For instance, some people move for job changes, relationship breakdown, housing affordability pressures, or retirement, all of which are known determinants of mental health. As a result, the observed reductions in poor mental health following a move (Figure 1) are likely to partly reflect these underlying life transitions rather than the effects of changes in greenspace exposure alone. If not controlled for, this could either amplify or mask the true influence of greenspace on mental health. To mitigate the immediate effects surrounding moves, we omitted the year before and after the move from our sample. Future research should seek to incorporate information on moving motivations, where available, to disentangle whether greenspace acts as a driver of relocation decisions, interacts with other life events, or correlates with broader constructs such as nature connectedness.

Due to data availability in this study, bird species richness was measured at a 10km resolution, which represents regional species richness. Results suggest that the relationship between greenspace quality and mental health could exist at a broader scale than previously tested – with previous studies using "site-level" measures of biodiversity (e.g., Fuller et al. 2007; Wood et al. 2018). We recognise that due to the coarse resolution of these data there could be false precision relating to this claim. As we are unable to assign species richness to greenspaces, we may not be capturing greenspace quality specifically, but instead the wider quality of a region. Given the resolution of available data, it is difficult to correct this. We recommend future research to explore whether the relationship between greenspace quality and mental health is scale-dependent, such exploration is beyond the scope of this paper.

Despite knowing the importance of private gardens for mental health (Gaston et al. 2005; Brindley et al. 2018; de Bell et al. 2020; Collins et al. 2023), we were unable to explore whether garden status influences the response to changes in greenspace exposure because of the small sample size within the BHPS movers. We attempted to minimise the effect of private garden ownership by only including people whose garden status did not change pre - and- post-move in this analysis. However, this does limit the generalizability of our findings. Furthermore, our desire to account for data on garden ownership limited our selection of longitudinal UK surveys to the BHPS (1991–2008). To align with this period, we used deprivation data from the 2011 census. Ideally, with improved data on private domestic garden access, the analysis could be updated to incorporate more recent measures of deprivation and greenspace.

A further limitation relates to the use of the self-reported GHQ-12 as the chosen measure of mental health. As a self-reported measure, respondents need to provide reliable and accurate responses to the survey to ensure the accuracy of the measure. Such measures are vulnerable to recall or introspection biases, as individuals may struggle to accurately assess or report their own symptoms, and to social desirability bias, where people provide responses they perceive as socially acceptable. These biases can lead to under- or over-reporting of poor mental health and introduce measurement error into the outcome. Brown et al. (2022) found that individuals in the BHPS, and its successor Understanding Society, tend to over-report psychological wellbeing, with reporting bias being greater among men. However, one advantage of using the BHPS is that it provides repeated observations for the same individuals over time, which helps to account for stable individual tendencies in self-reporting and reduces the influence of single-wave misclassification. While this does not eliminate bias, the longitudinal structure provides some protection against systematic differences in reporting across the respondents.

5 Conclusion

We applied BA and BACI approaches to improve causal inference using longitudinal data, demonstrating how these methods can help identify which greenspace characteristics influence the relationship between greenspace exposure and mental health. We found that changes in greenspace quality and proximity -specifically regional bird species richness and distance to the nearest public greenspace- best explained variation in poor mental health, outperforming other greenspace measures and a baseline model without any greenspace variable. The top-performing models showed a decrease in the probability of poor mental health following a move, regardless of the type of change in greenspace exposure. However, this beneficial association was strongest for individuals who experienced more “favourable” changes, such as moving to areas with higher regional bird species richness or closer proximity to public greenspace. Data availability for these characteristics resulted in a temporal disconnect between the survey data (BHPS 1991-2009) and these greenspace characteristics used. This assumption may have resulted in misclassification of individuals' greenspace exposure, which could have affected the model ranking (Table 4) and predicted outcomes (Figure 1). Future studies should apply the BA and BACI approaches using temporally aligned data to validate findings. Given the limitations associated with our data assumptions, and that the other tested characteristics are grounded in theory and have supporting evidence elsewhere in the literature (Table 1), the greenspace characteristics of access and quantity should not be dismissed. Furthermore, future research should examine whether greenspace characteristics interact to explore whether these different characteristics act independently or whether combinations of characteristics provide additional benefits beyond their individual contributions. Our results suggest that among the multiple characteristics tested in this study, regional bird species richness and distance to public greenspaces should be prioritised as proxies for greenspace quality and proximity. These characteristics may therefore offer important indicators for future policies aimed at designing urban greenspaces that are associated with better mental health and wellbeing.

Due to the coarse resolution of species richness (10km), it is possible that these findings primarily capture broader regional patterns in greenspace quality. We therefore recommend that future research explore whether the relationship between greenspace quality, in particular biodiversity, and mental health is scale-dependent; that is, whether the association or relative importance of species richness changes when measured at finer spatial resolutions. Furthermore, as bird species richness serves as a proxy for broader biodiversity in this study, future research should examine a wider range of biodiversity indicators to determine whether these associations reflect birds specifically or underlying ecological quality more generally.

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6 References

Alcock, I., White, M. P., Wheeler, B. W., Fleming, L. E. and Depledge, M. H., 2013. Longitudinal Effects on Mental Health of Moving to Greener and Less Green Urban Areas. *Environmental Science & Technology*, 48 (2), 1247–1255.

Astell-Burt, T., Hartig, T., Eckermann, S., Nieuwenhuijsen, M., McMunn, A., Frumkin, H. and Feng, X., 2022. More green, less lonely? A longitudinal cohort study. *International Journal of Epidemiology*, 51 (1), 99–110.

Baker, C. and Kirk-Wade, E., 2024. *Mental health statistics: prevalence, services and funding in England* [online]. Available from: https://commonslibrary.parliament.uk/research-briefings/sn06988/ [Accessed 28 Jan 2025].

Bartoń, K., 2016. *MuMIn: Multi-Model Inference* [online]. R package version 1.43.17. Available from: https://cran.r-project.org/package=MuMIn [Accessed 4 Sep 2024].

de Bell, S., White, M., Griffiths, A., Darlow, A., Taylor, T., Wheeler, B. and Lovell, R., 2020. Spending time in the garden is positively associated with health and wellbeing: Results from a national survey in England. *Landscape and Urban Planning*, 200, 103836.

Bettencourt, L. M. A., 2021. *Introduction to Urban Science: Evidence and Theory of Cities as Complex Systems*. Cambridge: Massachusetts Institute of Technology.

Beute, F., Marselle, M. R., Olszewska-Guizzo, A., Andreucci, M. B., Lammel, A., Davies, Z. G., Glanville, J., Keune, H., O'Brien, L., Remmen, R., Russo, A. and de Vries, S., 2023. How do different types and characteristics of green space impact mental health? A scoping review. *People and Nature*, 5 (6), 1839–1876.

Van den Bosch, M., Östergren, P.-O., Grahn, P., Skärbäck, E. and Währborg, P., 2015. Moving to Serene Nature May Prevent Poor Mental Health—Results from a Swedish Longitudinal Cohort Study. *International Journal of Environmental Research and Public Health*, 12 (7), 7974–7989.

Brindley, P., Jorgensen, A. and Maheswaran, R., 2018. Domestic gardens and self-reported health: a national population study. *International Journal of Health Geographics*, 17 (1), 31.

Brown, S., Harris, M.N., Srivastava, P. and Taylor, K., 2022. Mental health, reporting bias and economic transitions. *Oxford Economic Papers*, 74 (2), 541-564

Collins, R. M., Smith, D., Ogutu, B. O., Brown, K. A., Eigenbrod, F. and Spake, R., 2023. The relative effects of access to public greenspace and private gardens on mental health. *Landscape and Urban Planning*, 240, 104902.

Collins, R. M., Spake, R., Brown, K. A., Ogutu, B. O., Smith, D. and Eigenbrod, F., 2020. A systematic map of research exploring the effect of greenspace on mental health. *Landscape and Urban Planning*, 201, 103823.

Committee on Climate Change, 2019. *UK housing: Fit for the future?* Available from: https://www.theccc.org.uk/wp-content/uploads/2019/02/UK-housing-Fit-for-the-future-CCC-2019.pdf [Accessed: 26 Feb 2026].

Dallimer, M., Tang, Z., Bibby, P.R., Brindley, P., Gaston, K.J. and Davies, Z.G., 2011. Temporal changes in greenspace in a highly urbanized region. *Biology letters*, 7 (5), 763-766.

Dong, J., Guo, R., Guo, F., Guo, X. and Zhang, Z., 2023. Pocket parks- a systematic literature review. *Environmental Research Letters*, 18 (8), 083003.

Ealing Council, 2022. *Acton 20-minute neighbourhood framework* [online]. Available from: https://www.ealing.gov.uk/downloads/download/7020/acton_20-minute_framework [Accessed 4 Sep 2024].

Edwards, J. R., Gotschall, J. W., Clougherty, J. E. and Schinasi, L. H., 2023. Associations of greenspace use and proximity with self-reported physical and mental health outcomes during the COVID-19 pandemic. *PLOS ONE*, 18 (3), e0280837.

Emery, T. and Thrift, J., 2021. *20-Minute Neighbourhoods: Creating Healthier, Active, Prosperous Communities An Introduction for Council Planners in England* [online]. Available from: https://tcpa.org.uk/wp-content/uploads/2021/11/final_20mnguide-compressed.pdf [Accessed 4 Sep 2024].

European Environment Agency, 2019. *CDDA dataset* [online]. Available from: https://www.eea.europa.eu/data-and-maps/data/nationally-designated-areas-national-cdda-15/cdda [Accessed 4 Sep 2024].

Ferraro, D.M., Miller, Z.D., Ferguson, L.A., Taff, B.D., Barber, J.R., Newman, P. and Francis, C.D., 2020. The phantom chorus: Birdsong boosts human well-being in protected areas. *Proceedings of the Royal Society B*, 287(1941), 20201811.

Fone, D., White, J., Farewell, D., Kelly, M., John, G., Lloyd, K., Williams, G. and Dunstan, F., 2014. Effect of neighbourhood deprivation and social cohesion on mental health inequality: a multilevel population-based longitudinal study. *Psychological medicine*, 44(11), 2449-2460.

Francis, J., Wood, L. J., Knuiman, M., and Giles-Corti, B., 2012. Quality or quantity? Exploring the relationship between Public Open Space attributes and mental health in Perth, Western Australia. *Social Science & Medicine*, 74 (10), 1570–1577.

Fuller, R. A., Irvine, K. N., Devine-Wright, P., Warren, P. H. and Gaston, K. J., 2007. Psychological benefits of greenspace increase with biodiversity. *Biology Letters*, 3 (4), 390–394.

Gascon, M., Sánchez-Benavides, G., Dadvand, P., Martínez, D., Gramunt, N., Gotsens, X., Cirach, M., Vert, C., Molinuevo, J. L., Crous-Bou, M. and Nieuwenhuijsen, M., 2018. Long-term exposure to residential green and blue spaces and anxiety and depression in adults: A cross-sectional study. *Environmental Research*, 162, 231–239.

Gaston, K. J., 2020. Personalised ecology and detection functions. *People and Nature*, 2 (4), 995–1005.

Gaston, K. J., Soga, M., Duffy, J. P., Garrett, J. K., Gaston, S. and Cox, D. T. C., 2018. Personalised Ecology. *Trends in Ecology & Evolution*, 33 (12), 916–925.

Gaston, K. J., Warren, P. H., Thompson, K. and Smith, R. M., 2005. Urban Domestic Gardens (IV): The Extent of the Resource and its Associated Features. *Biodiversity and Conservation*, 14 (14), 3327–3349.

de Gelder, R., Koster, E. M., van Buren, L. P., van Ameijden, E. J. C., Harrison, A., Birt, C. A., and Verma, A., 2017. Differences in adults' health and health behaviour between 16 European urban areas and the associations with socio-economic status and physical and social environment. *European journal of public health*, 27 (2), 93–99.

Gillings, S., Balmer, D. E., Caffrey, B. J., Downie, I. S., Gibbons, D. W., Lack, P. C., Reid, J. B., Sharrock, J. T. R., Swann, R. L. and Fuller, R. J., 2019. Breeding and wintering bird distributions in Britain and Ireland from citizen science bird atlases. *Global Ecology and Biogeography*, 28 (7), 866–874.

Goldberg, D. P., Gater, R., Sartorius, N., Ustun, T. B., Piccinelli, M., Gureje, O. and Rutter, C., 1997. The validity of two versions of the GHQ in the WHO study of mental illness in general health care. *Psychological Medicine*, 27 (1), 191–197.

Goldberg, D. P. and Hillier, V. F., 1979. A scaled version of the General Health Questionnaire. *Psychological Medicine*, 9 (1), 139–145.

Hahad, O., Kuntic, M., Al-Kindi, S., Kuntic, I., Gilan, D., Petrowski, K., Daiber, A. and Münzel, T., 2025. Noise and mental health: evidence, mechanisms, and consequences. *Journal of Exposure Science & Environmental Epidemiology*, 35 (1), 16-23.

Halekoh, U. and Højsgaard, S., 2014. *A Kenward-Roger Approximation and Parametric Bootstrap Methods for Tests in Linear Mixed Models - The R Package pbkrtest*. Journal of Statistical Software, 59 (9).

Hankins, M., 2008. The factor structure of the twelve item General Health Questionnaire (GHQ-12): the result of negative phrasing? *Clinical Practice and Epidemiology in Mental Health*, 4 (1), 10.

Hartig, F., 2018. *DHARMa: Residual Diagnostics for Hierarchical (Multi-Level / Mixed) Regression Models* [online]. R package version 0.4.1. Available from: https://cran.r-project.org/package=DHARMa [Accessed 4 Sep 2024].

Hartig, T., Mitchell, R., de Vries, S. and Frumkin, H., 2014. Nature and Health. *Annual Review of Public Health*, 35 (1), 207–228.

van Heezik, Y. and Brymer, E., 2018. Nature as a commodity: What's good for human health might not be good for ecosystem health. *Frontiers in Psychology*, 9 (1673), 1–5.

Hesselbarth, M. H. K., Sciaini, M., With, K. A., Wiegand, K. and Nowosad, J., 2019. landscapemetrics : an open-source R tool to calculate landscape metrics. *Ecography*, 42 (10), 1648–1657.

Hijmans, R. J., 2021. *raster: Geographic Data Analysis and Modeling* [online]. R package version 0.4.1. Available from: https://cran.r-project.org/package=raster [Accessed 4 Sep 2024].

Hillebrand, H., Blasius, B., Borer, E. T., Chase, J. M., Downing, J. A., Eriksson, B. K., Filstrup, C. T., Harpole, W. S., Hodapp, D., Larsen, S., Lewandowska, A. M., Seabloom, E. W., Van de Waal, D. B. and Ryabov, A. B., 2018. Biodiversity change is uncoupled from species richness trends: Consequences for conservation and monitoring. *Journal of Applied Ecology*, 55 (1), 169–184.

Houlden, V., Weich, S. and Jarvis, S., 2017. A cross-sectional analysis of green space prevalence and mental wellbeing in England. *BMC Public Health*, 17 (1), 460.

Jackson, C., 2006. The General Health Questionnaire. *Occupational Medicine*, 57 (1), 79–79.

James, P., Banay, R. F., Hart, J. E., and Laden, F., 2015. A review of the health benefits of greenness. *Current Epidemiology Reports*, 2 (2), 131–142.

Dean, J., van Dooren, K., and Weinstein, P., 2011. Does biodiversity improve mental health in urban settings? *Medical Hypotheses*, 76 (6), 877–880.

Keniger, L., Gaston, K., Irvine, K. and Fuller, R., 2013. What are the Benefits of Interacting with Nature? *International Journal of Environmental Research and Public Healt*h, 10 (3), 913–935.

Lovell, R., Wheeler, B. W., Higgins, S. L., Irvine, K. N. and Depledge, M. H., 2014. A Systematic Review of the Health and Well-Being Benefits of Biodiverse Environments. *Journal of Toxicology and Environmental Health*, Part B, 17 (1), 1–20.

Maas, C. J. M. and Hox, J. J., 2005. Sufficient Sample Sizes for Multilevel Modeling. *Methodology*, 1 (3), 86–92.

Maas, J., van Dillen, S. M. E., Verheij, R. A. and Groenewegen, P. P., 2009. Social contacts as a possible mechanism behind the relation between green space and health. *Health & Place*, 15 (2), 586–595.

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., de Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M. J., Lupp, G., Richardson, E. A., Astell-Burt, T., Dimitrova, D., Feng, X., Sadeh, M., Standl, M., Heinrich, J. and Fuertes, E., 2017. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research*, 158, 301–317.

Mears, M., Brindley, P., Maheswaran, R. and Jorgensen, A., 2019. Understanding the socioeconomic equity of publicly accessible greenspace distribution: The example of Sheffield, UK. *Geoforum*, 103, 126–137.

Methorst, J., Bonn, A., Marselle, M., Böhning-Gaese, K. and Rehdanz, K., 2021. Species richness is positively related to mental health – A study for Germany. *Landscape and Urban Planning*, 211, 104084.

Mitchell, R. and Popham, F., 2008. Effect of exposure to natural environment on health inequalities: an observational population study. *The Lancet*, 372 (9650), 1655–1660.

Ministry of Housing, Communities and Local Government, 2019. *Pocket Parks: helping communities transform unloved, neglected or derelict areas into new green spaces* [online]. Available from:

https://assets.publishing.service.gov.uk/media/5df3ad17ed915d09343c1851/191025_PP_Prospectus.pdf [Accessed 26 Jun 2025].

Montgomery, J.M., Nyhan, B. and Torres, M., 2018. How conditioning on posttreatment variables can ruin your experiment and what to do about it. *American Journal of Political Science*, 62 (3), 760-775.

Murtagh, E.M., Mair, J.L., Aguiar, E., Tudor-Locke, C. and Murphy, M.H., 2021. Outdoor walking speeds of apparently healthy adults: A systematic review and meta-analysis. *Sports Medicine*, 51 (1), 125-141.

Natural England, 2023. *Green Infrastructure Standards for England: Summary.* Version 1.1. Available from: https://designatedsites.naturalengland.org.uk/GreenInfrastructure/downloads/Green%20Infrastructure%20Standards%20for%20England%20Summary%20v1.1.pdf [Accessed: 26 Feb 2026].

Nakagawa, S., Samarasinghe, G., Haddaway, N. R., Westgate, M. J., O'Dea, R. E., Noble, D. W. A. and Lagisz, M., 2019. Research Weaving: Visualizing the Future of Research Synthesis. *Trends in Ecology & Evolution*, 34(3), 224–238.

Nobile, F., Forastiere, A., Michelozzi, P., Forastiere, F. and Stafoggia, M., 2023. Long-term exposure to air pollution and incidence of mental disorders. A large longitudinal cohort study of adults within an urban area. *Environment international*, 181, 108302.

Oakes, J. M., 2004. The (mis)estimation of neighborhood effects: causal inference for a practicable social epidemiology. *Social Science & Medicine*, 58 (10), 1929–1952.

Office for National Statistics, 2020. *One in eight British households has no garden* [online]. Available from: https://www.ons.gov.uk/economy/environmentalaccounts/articles/oneineightbritishhouseholdshasnogarden/2020-05-14 [Accessed 4 Sep 2024].

Ordnance Survey, 2017. *OS MasterMap Greenspace Layer Technical Specification* [online]. Available from: https://www.ordnancesurvey.co.uk/documents/product-support/tech-spec/osmm-greenspace-layer-technical-specification.pdf [Accessed 4 Sep 2024].

Oudin, A., Bråbäck, L., Åström, D. O., Strömgren, M. and Forsberg, B., 2016. Association between neighbourhood air pollution concentrations and dispensed medication for psychiatric disorders in a large longitudinal cohort of Swedish children and adolescents. *BMJ Open*, 6 (6), e010004.

Paccagnella, O., 2011. Sample Size and Accuracy of Estimates in Multilevel Models. *Methodology*, 7 (3), 111–120.

Parra, D. C., Gomez, L. F., Sarmiento, O. L., Buchner, D., Brownson, R., Schimd, T., Gomez, V., and Lobelo, F., 2010. Perceived and objective neighborhood environment attributes and health related quality of life among the elderly in Bogotá, Colombia. *Social Science and Medicine,* 70 (7), 1070–1076.

Pebesma, E., 2018. Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal*, 10 (1), 439.

Phillips, B. B., Bullock, J. M., Osborne, J. L. and Gaston, K. J., 2021. Spatial extent of road pollution: A national analysis. *Science of The Total Environment*, 773, 145589.

Pope, D., Tisdall, R., Middleton, J., Verma, A., van Ameijden, E., Birt, C., Macherianakis, A. and Bruce, N. G., 2015. Quality of and access to green space in relation to psychological distress: results from a population-based cross-sectional study as part of the EURO-URHIS 2 project. *The European Journal of Public Health*, ckv094.

Power, M. C., Kioumourtzoglou, M.-A., Hart, J. E., Okereke, O. I., Laden, F. and Weisskopf, M. G., 2015. The relation between past exposure to fine particulate air pollution and prevalent anxiety: observational cohort study. *BMJ*, h1111.

Public Health England, 2020. *Improving access to greenspace A new review for 2020* [online]. London. Available from: https://assets.publishing.service.gov.uk/media/5f202e0de90e071a5a924316/Improving_access_to_greenspace_2020_review.pdf [Accessed 16 Aug 2024].

R Core Team, 2021. *R: A language and environment for statistical computing* [online]. R Foundation for Statistical Computing. Available from: https://www.R-project.org/. [Accessed 4 Sep 2024].

Riters, L.V., Polzin, B.J., Maksimoski, A.N., Stevenson, S.A. and Alger, S.J., 2022. Birdsong and the neural regulation of positive emotion. *Frontiers in Psychology, 13,* p.903857.

Roberts, S., Arseneault, L., Barratt, B., Beevers, S., Danese, A., Odgers, C. L., Moffitt, T. E., Reuben, A., Kelly, F. J. and Fisher, H. L., 2019. Exploration of NO2 and PM2.5 air pollution and mental health problems using high-resolution data in London-based children from a UK longitudinal cohort study. *Psychiatry Research*, 272, 8–17.

Sandifer, P. A., Sutton-Grier, A. E. and Ward, B. P., 2015. Exploring connections among nature, biodiversity, ecosystem services, and human health and well-being: Opportunities to enhance health and biodiversity conservation. *Ecosystem Services*, 12, 1–15.

Sarkar, C., Gallacher, J. and Webster, C., 2013. Urban built environment configuration and psychological distress in older men: Results from the Caerphilly study. *BMC Public Health*, 13 (1), 695.

Schoeneberger, J. A., 2016. The Impact of Sample Size and Other Factors When Estimating Multilevel Logistic Models. *The Journal of Experimental Education*, 84 (2), 373–397.

Scottish Government, 2024. L*ocal living and 20 minute neighbourhoods: planning guidance* [online]. Available from: https://www.gov.scot/publications/scottish-government-planning-guidance-local-living-20-minute-neighbourhoods/ [Accessed 4 Sep 2024].

Shanahan, D. F., Fuller, R. A., Bush, R., Lin, B. B. and Gaston, K. J., 2015. The Health Benefits of Urban Nature: How Much Do We Need? *BioScience*, 65 (5), 476–485.

Shelton, N. J. and Herrick, K. G., 2009. Comparison of scoring methods and thresholds of the General Health Questionnaire-12 with the Edinburgh Postnatal Depression Scale in English women. *Public Health*, 123 (12), 789–793.

Signoretta, P. E., Buffel, V. and Bracke, P., 2019. Mental wellbeing, air pollution and the ecological state. *Health & Place*, 57, 82–91.

Sommet, N. and Morselli, D., 2017. Keep Calm and Learn Multilevel Logistic Modeling: A Simplified Three-Step Procedure Using Stata, R, Mplus, and SPSS. *International Review of Social Psychology*, 30 (1), 203–218.

Stanley, M. C., Beggs, J. R., Bassett, I. E., Burns, B. R., Dirks, K. N., Jones, D. N., Linklater, W. L., Macinnis-Ng, C., Simcock, R., Souter-Brown, G., Trowsdale, S. A., and Gaston, K. J.,

2015. Emerging threats in urban ecosystems: A horizon scanning exercise. *Frontiers in Ecology and the Environment*, 13 (10), 553–560.

Stier, A. J., Schertz, K. E., Rim, N. W., Cardenas-Iniguez, C., Lahey, B. B., Bettencourt, L. M. A. and Berman, M. G., 2021. Evidence and theory for lower rates of depression in larger US urban areas. *Proceedings of the National Academy of Sciences*, 118 (31).

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

Thompson, R., Hornigold, R., Page, L., and Waite, T., 2018. Associations between high ambient temperatures and heat waves with mental health outcomes: a systematic review. *Public Health*, 161, 171–191.

Uebel, K., Marselle, M., Dean, A.J., Rhodes, J.R. and Bonn, A., 2021. Urban green space soundscapes and their perceived restorativeness. *People and Nature,* 3(3), pp.756-769.UK Data Service, 2017. *2011 UK Townsend Deprivation Scores* [online]. Available from: https://statistics.ukdataservice.ac.uk/dataset/2011-uk-townsend-deprivation-scores [Accessed 4 Sep 2024].

United States Geological Survey, 2017. *Landsat 8* [online]. Available from: https://www.usgs.gov/landsat-missions/landsat-8?qt-science_support_page_related_con=0#qt-science_support_page_related_con [Accessed 4 Sep 2024].

University of Essex, Institute for Social and Economic Research. (2018). *British Household Panel Survey: Waves 1-18, 1991-2009: Special Licence Access.* [data collection]. UK Data Service. SN: 8380, DOI: http://doi.org/10.5255/UKDA-SN-8380-1

University of Essex, Institute for Social and Economic Research. (2025). *Understanding Society: Waves 1-15, 2009-2024 and Harmonised BHPS: Waves 1-18, 1991-2009.* [data collection]. 20th Edition. UK Data Service. SN: 6614, DOI: http://doi.org/10.5255/UKDA-SN-6614-21

Vert, C., Sánchez-Benavides, G., Martínez, D., Gotsens, X., Gramunt, N., Cirach, M., Molinuevo, J. L., Sunyer, J., Nieuwenhuijsen, M. J., Crous-Bou, M. and Gascon, M., 2017. Effect of long-term exposure to air pollution on anxiety and depression in adults: A cross-sectional study. *International Journal of Hygiene and Environmental Health*, 220 (6), 1074–1080.

Ward, C., Palmer, A.K., Brockett, B.F.T., Costanza, R., Hatfield, J., Kubiszewski, I., Langford, P., Pickett, K., & Willis, C. (2023). Perceptions, preferences, and barriers: A qualitative study on greenspace and underrepresentation in Leeds, UK. *People and Nature, 5*(4), 1284–1298.

Ward Thompson, C., Aspinall, P., Roe, J., Robertson, L. and Miller, D., 2016. Mitigating Stress and Supporting Health in Deprived Urban Communities: The Importance of Green Space and the Social Environment. *International Journal of Environmental Research and Public Health*, 13 (4), 440.

Wauchope, H. S., Amano, T., Geldmann, J., Johnston, A., Simmons, B. I., Sutherland, W. J. and Jones, J. P. G., 2021. Evaluating Impact Using Time-Series Data. *Trends in Ecology & Evolution*, 36 (3), 196–205.

Wheeler, B. W., Lovell, R., Higgins, S. L., White, M. P., Alcock, I., Osborne, N. J., Husk, K., Sabel, C. E. and Depledge, M. H., 2015. Beyond greenspace: an ecological study of population general health and indicators of natural environment type and quality. *International Journal of Health Geographics*, 14 (1), 17.

White, M. P., Alcock, I., Wheeler, B. W. and Depledge, M. H., 2013. Would You Be Happier Living in a Greener Urban Area? A Fixed-Effects Analysis of Panel Data. *Psychological Science*, 24 (6), 920–928.

Wilson, E. O., 1984. *Biophilia*. Massachusetts: Harvard University press.

Wood, E., Harsant, A., Dallimer, M., Cronin de Chavez, A., McEachan, R. R. C. and Hassall, C., 2018. Not All Green Space Is Created Equal: Biodiversity Predicts Psychological Restorative Benefits From Urban Green Space. *Frontiers in Psychology*, 9.

Woodland Trust, 2020. *Ancient Tree Inventory GB and NI* [online]. Available from: https://ati.woodlandtrust.org.uk/ [Accessed 4 Sep 2024].

World Health Organization, 2016. *Urban green spaces and health*. Copenhagen.

Wyles, K. J., White, M. P., Hattam, C., Pahl, S., King, H. and Austen, M., 2019. Are Some Natural Environments More Psychologically Beneficial Than Others? The Importance of

Type and Quality on Connectedness to Nature and Psychological Restoration. *Environment and Behavior*, 51 (2), 111–143.

Appendix A Area-level variables and their correlations

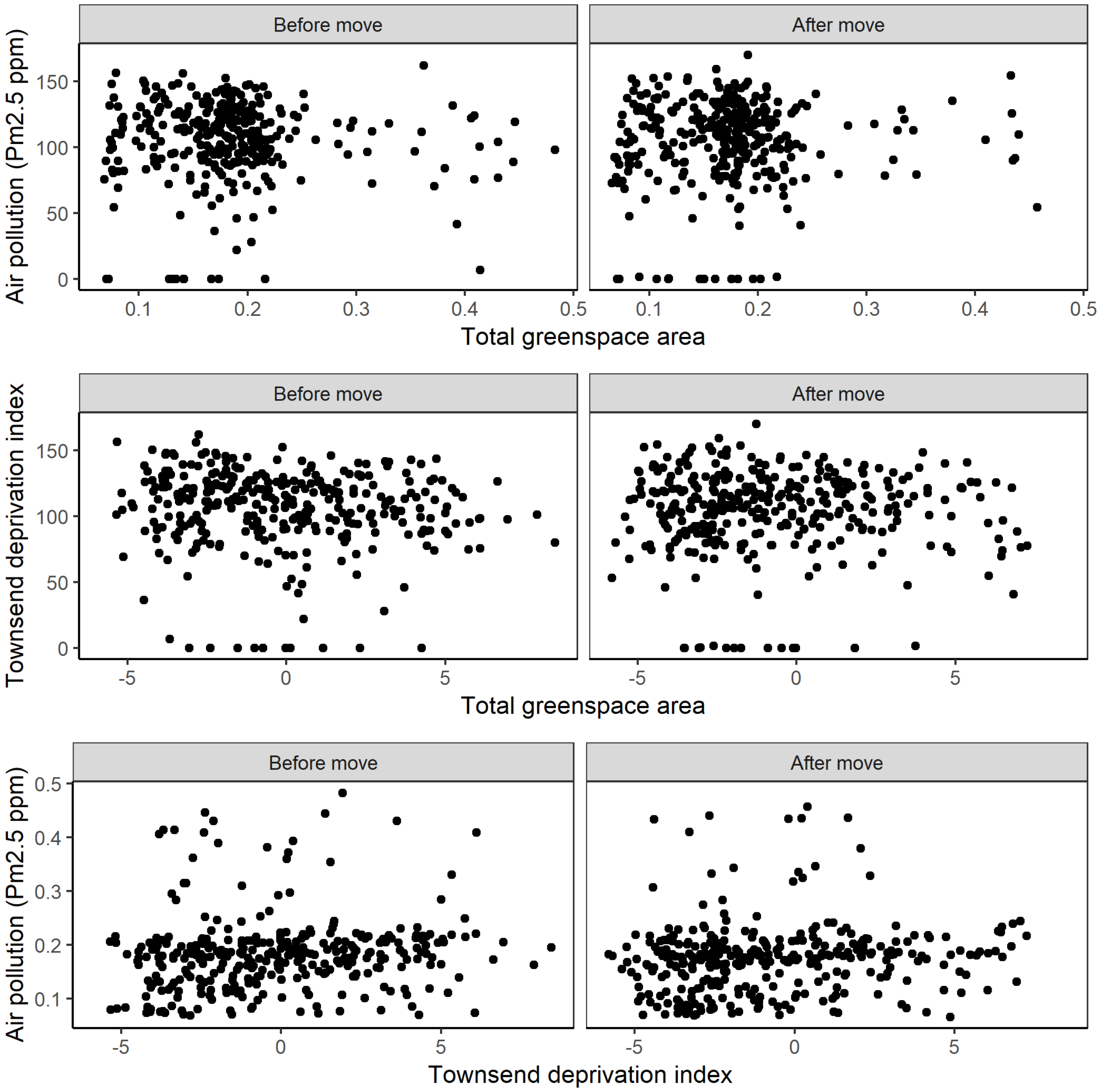

Figure A.1: Correlations between area-level variables before and after moving

Appendix B Air pollution sensitivity analysis

A sensitivity analysis in which air pollution was excluded from the model was undertaken to explore potential bias introduced by air pollution as a potential mediator of the relationship between greenspace and mental health. The results of this sensitivity analysis are presented in Table B.1 and Figures B.1–B.2. All results are consistent with those presented in Section 3 and Appendix E; model ranking is consistent but with two additional models (Access – public greenspace within 800m and Quality – greenness) performing marginally better than the base model. Predicted effects are comparable, with the exception of the predicted effects of protected areas (Figure B.1f), which show the opposite effect for the decrease-in-quality group compared with the models including air pollution (Figure E.1d).

Table B.1: Results from the model comparison of the seven measures of greenspace characteristics and the base model with no greenspace. Models are ranked according to AIC weight, the "best" performing models are those that have a lower AIC value compared to the base model. The goodness of fit was calculated using theoretical marginal (R^2_m) and conditional (R^2_c) values following (Nakagawa et al. 2019).

Greenspace characteristics and measures	**R^2_m**	**R^2_c**	**ΔAIC**
Quality – Regional bird species richness	0.056	0.462	0
Proximity – Distance to public greenspace	0.052	0.460	9.57
Access – public greenspace within 800m	0.054	0.461	12.63
Quality – Greenness	0.045	0.462	13.89
Base model (no greenspace)	0.043	0.460	14
Quality – Protected area(s)	0.044	0.460	16.88
Quantity – Public greenspace area	0.044	0.460	17.27
Quantity – Total greenspace area	0.044	0.461	20.32

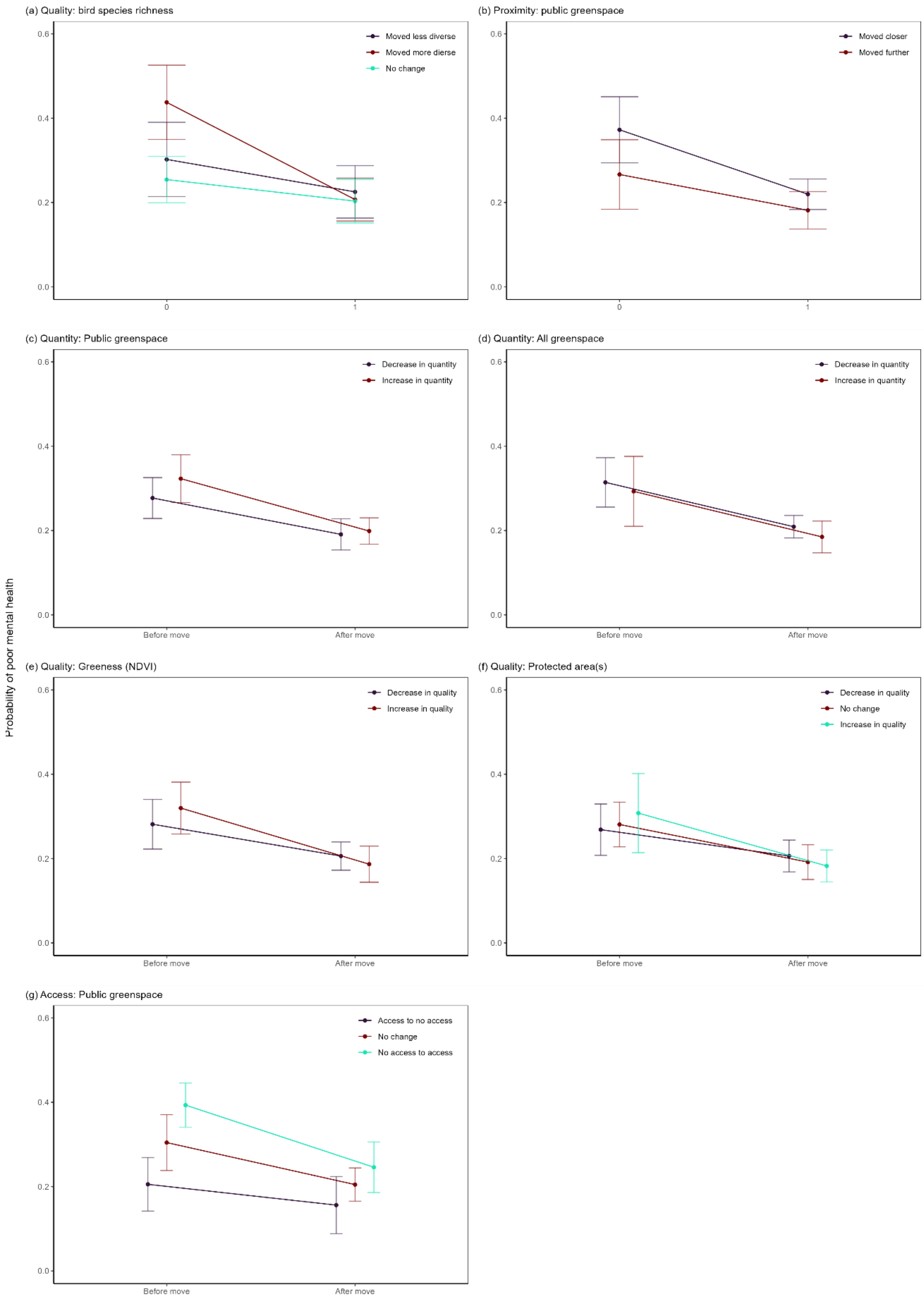

Figure B.1: Predicted probability of poor mental health before and after moving in relation to their respective changes in exposure to greenspace for all models (except the bae model). Error bars show the 95% confidence intervals for the predicted intervals obtained through bootstrapping (100 replications).

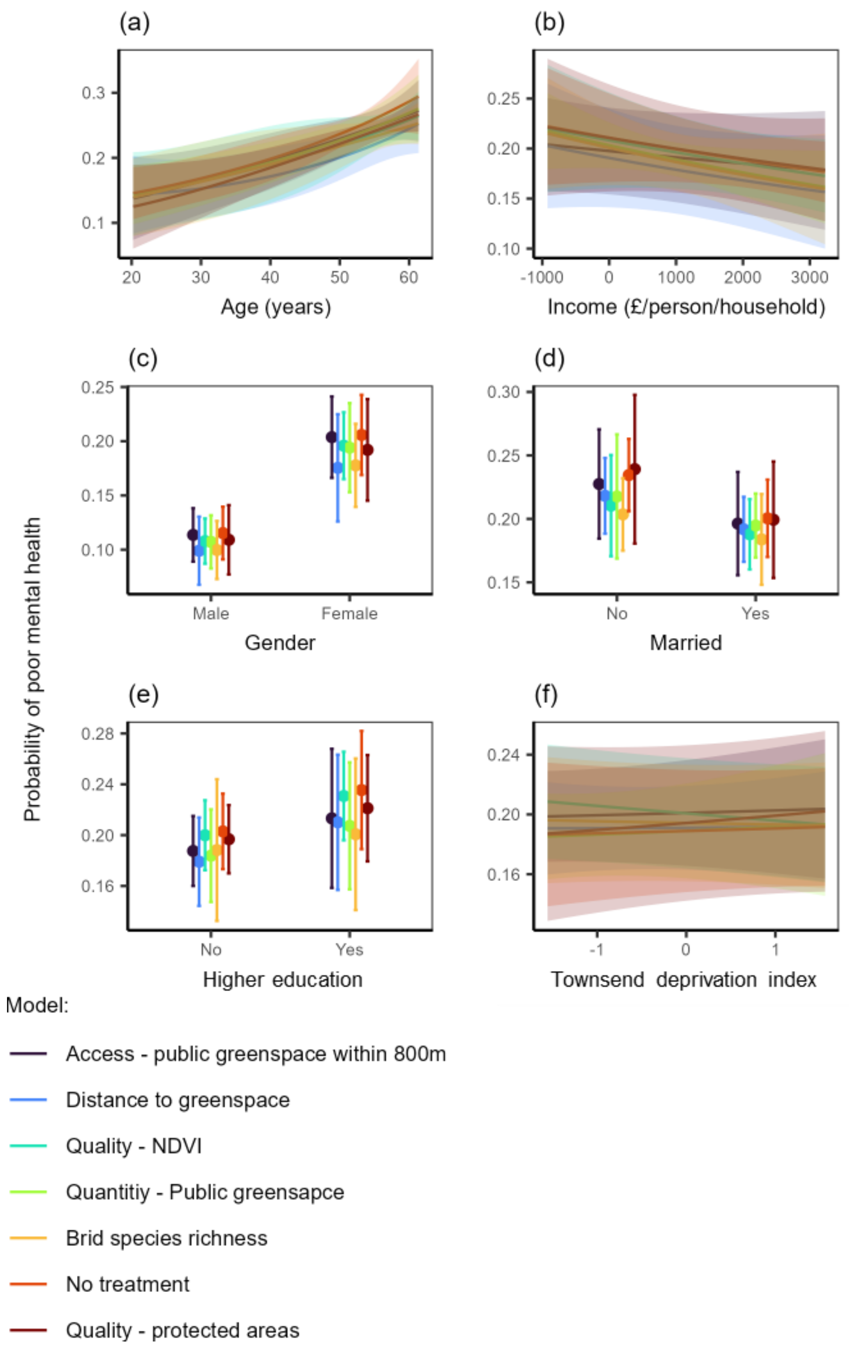

Figure B.2: Predicted probability of poor mental health for individual and area-level variables for the base model and all models. Shaded regions show the 95% confidence intervals for the predicted intervals obtained through bootstrapping (100 replications).

Appendix C Filtered BHPS sample descriptive statistics

Descriptive statistics for the filtered BHPS sample pre -and- post-move are presented in Tables C.1 and C.2 respectively.

Table C.1: Descriptive statistics in the years before an individual moves, including: the number of individuals (*n*), the mean and standard deviation (sd) for continuous variables, or for categorical variables the percentage (%).

	Years before move															
	9		**8**		**7**		**6**		**5**		**4**		**3**		**2**	
	n	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**
Individual-level variables:																
Individuals	17	100.00%	46	100.00%	102	100.00%	189	100.00%	312	100.00%	486	100.00%	486	100.00%	479	100.00%
Good mental health	14	82.35%	35	76.09%	72	70.59%	133	70.37%	242	77.56%	366	75.31%	370	76.13%	345	72.03%
Poor mental health	3	17.65%	11	23.91%	30	29.41%	56	29.63%	70	22.44%	120	24.69%	116	23.87%	134	27.97%
Male	6	35.29%	18	39.13%	42	41.18%	78	41.27%	130	41.67%	205	42.18%	205	42.18%	201	41.96%
Female	11	64.71%	28	60.87%	60	58.82%	111	58.73%	182	58.33%	281	57.82%	281	57.82%	278	58.04%
Not married	10	58.82%	18	39.13%	34	33.33%	79	41.80%	128	41.03%	198	40.74%	184	37.86%	167	34.86%
Married	7	41.18%	28	60.87%	68	66.67%	110	58.20%	184	58.97%	288	59.26%	302	62.14%	312	65.14%
No higher education	14	82.35%	41	89.13%	86	84.31%	159	84.13%	249	79.81%	377	77.57%	374	76.95%	365	76.20%
Higher education	3	17.65%	5	10.87%	16	15.69%	30	15.87%	63	20.19%	109	22.43%	112	23.05%	114	23.80%
Age (years)	17	30.29 (8.03)	46	37 (13.13)	102	36.47 (11.55)	189	36.22 (11.8)	312	36.08 (11.18)	486	36.49 (11.8)	486	37.49 (11.81)	479	38.59 (11.84)

	Years before move															
	9		**8**		**7**		**6**		**5**		**4**		**3**		**2**	
	n	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**
Income (£/person/household)	17	812.14 (467.02)	46	920.73 (498.25)	102	970.96 (612.18)	189	955.51 (646.52)	312	917.29 (549.2)	486	962.51 (618.15)	486	1032.86 (664.01)	479	1064.75 (718.25)
Area-level variables:																
Townsend index of deprivation	17	0.62 (2.91)	46	0.03 (2.75)	102	-0.82 (2.79)	189	-0.23 (2.94)	312	-0.16 (2.99)	486	-0.26 (2.86)	486	-0.26 (2.86)	479	-0.25 (2.88)
Air pollution (PM2.5)	17	0.17 (0.04)	46	0.18 (0.05)	102	0.18 (0.07)	189	0.18 (0.07)	312	0.19 (0.07)	486	0.18 (0.07)	486	0.18 (0.07)	479	0.18 (0.07)
No protected area(s)	8	47.06%	24	52.17%	49	48.04%	86	45.50%	161	51.60%	244	50.21%	243	50.00%	240	50.10%
Protected area(s)	9	52.94%	22	47.83%	53	51.96%	103	54.50%	151	48.40%	242	49.79%	243	50.00%	239	49.90%

Table C.2: Descriptive statistics in the years after an individual moves, including: the number of individuals (*n*), the mean and standard deviation (sd) for continuous variables, or for categorical variables the percentage (%).

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

	Years after move															
	1		**2**		**3**		**4**		**5**		**6**		**7**		**8**	
	n	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**	**n**	**Mean (sd)/%**
Townsend index of deprivation	476	-1.04 (2.82)	478	-1.02 (2.88)	482	-0.94 (2.92)	390	-1.02 (2.79)	281	-0.94 (2.92)	180	-1.21 (2.85)	109	-1.17 (3.02)	39	-1.68 (2.96)
Air pollution (PM2.5)	476	0.17 (0.07)	478	0.17 (0.07)	482	0.17 (0.07)	390	0.17 (0.07)	281	0.17 (0.07)	180	0.16 (0.07)	109	0.16 (0.06)	39	0.15 (0.07)
No protected area(s)	223	46.85%	225	47.07%	225	46.68%	178	45.64%	121	43.06%	71	39.44%	43	39.45%	14	35.90%
Protected area(s)	253	53.15%	253	52.93%	257	53.32%	212	54.36%	160	56.94%	109	60.56%	66	60.55%	25	64.10%

Appendix D Observed change in greenspace exposure

Table D.1: The number of individuals (*n*) experiencing each change in exposure to greenspace

Characteristic		Greenspace tested	Change in exposure to greenspace	*n*
Proximity	Distance to public greenspace	Public greenspace	1. Moved closer	246
			2. Moved further	246
Quantity	Public greenspace area	Public greenspace	1. Increase in quantity	217
			2. Decrease in quantity	275
	Total greenspace area	All greenspace	1. Increase in quantity	246
			2. Decrease in quantity	246
Quality	Bird species richness	NA	1. Moved less diverse	114
			2. No change	89
			3. Moved more diverse	289
	Greenness	NA	1. Increase in quality	209
			3. Decrease in quality	283
	Protected area(s)	NA	1. Increase in quality	91
			2. No change in quality	291
			3. Decrease in quality	110
Access	greenspace within 800m	Public greenspace	1. Access to no access	89
			2. No change	324
			3. No access to access	79

Appendix E Model results

E.1 Model parameter estimates

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

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

E.2 Model predicted probabilities

To visualise the relationship between covariates and the predicted values of poor mental health, we plotted the predicted probabilities from all characteristic models with sufficient sample sizes for the observed changes in exposure to greenspace (Table E.1), whilst holding all other covariates at their median or mode value for numerical and categorical variables respectively. Confidence intervals for the predicted intervals were obtained through bootstrapping with 1000 replications.

Table E.1: Characteristics of greenspace in models with less inference than the base model (no greenspace model).

Characteristic
Access – public greenspace within 800m
Quality – Greenness
Quality – Protected area(s)
Quantity – Public greenspace area
Quantity – Total greenspace area

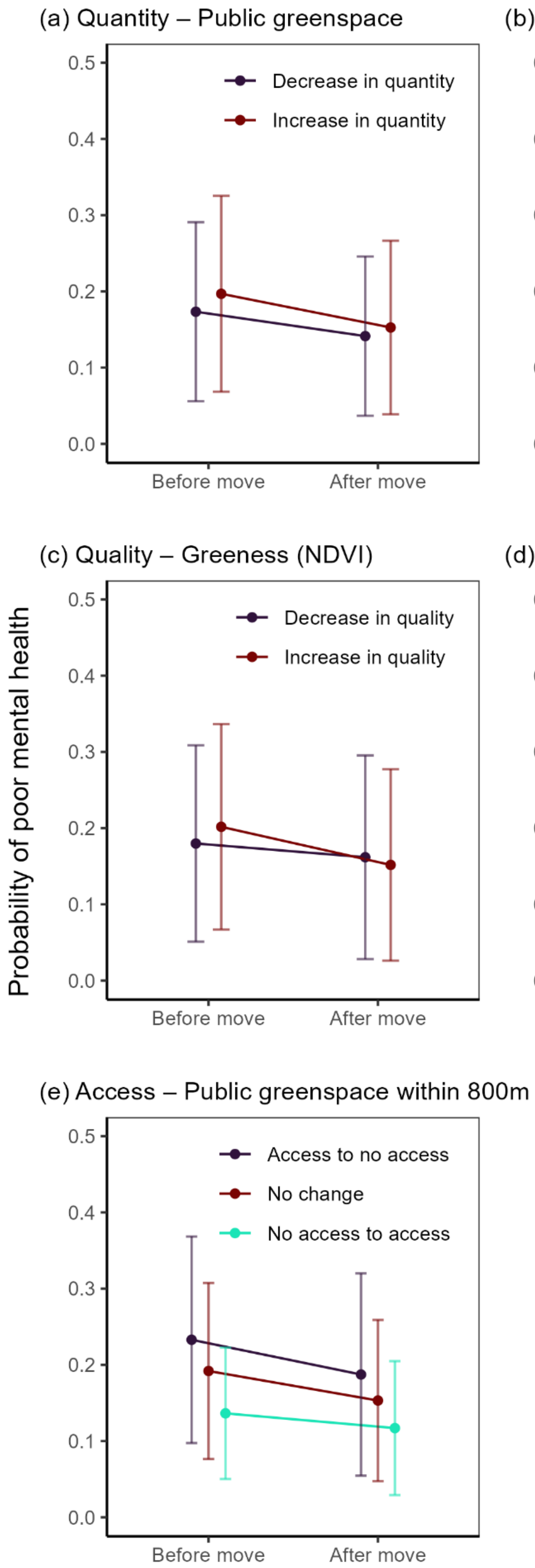

Figure E.1: Predicted probability of poor mental health before and after moving in relation to their respective changes in exposure to greenspace for the models that were a poorer fit compared to the base model. Error bars show the 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

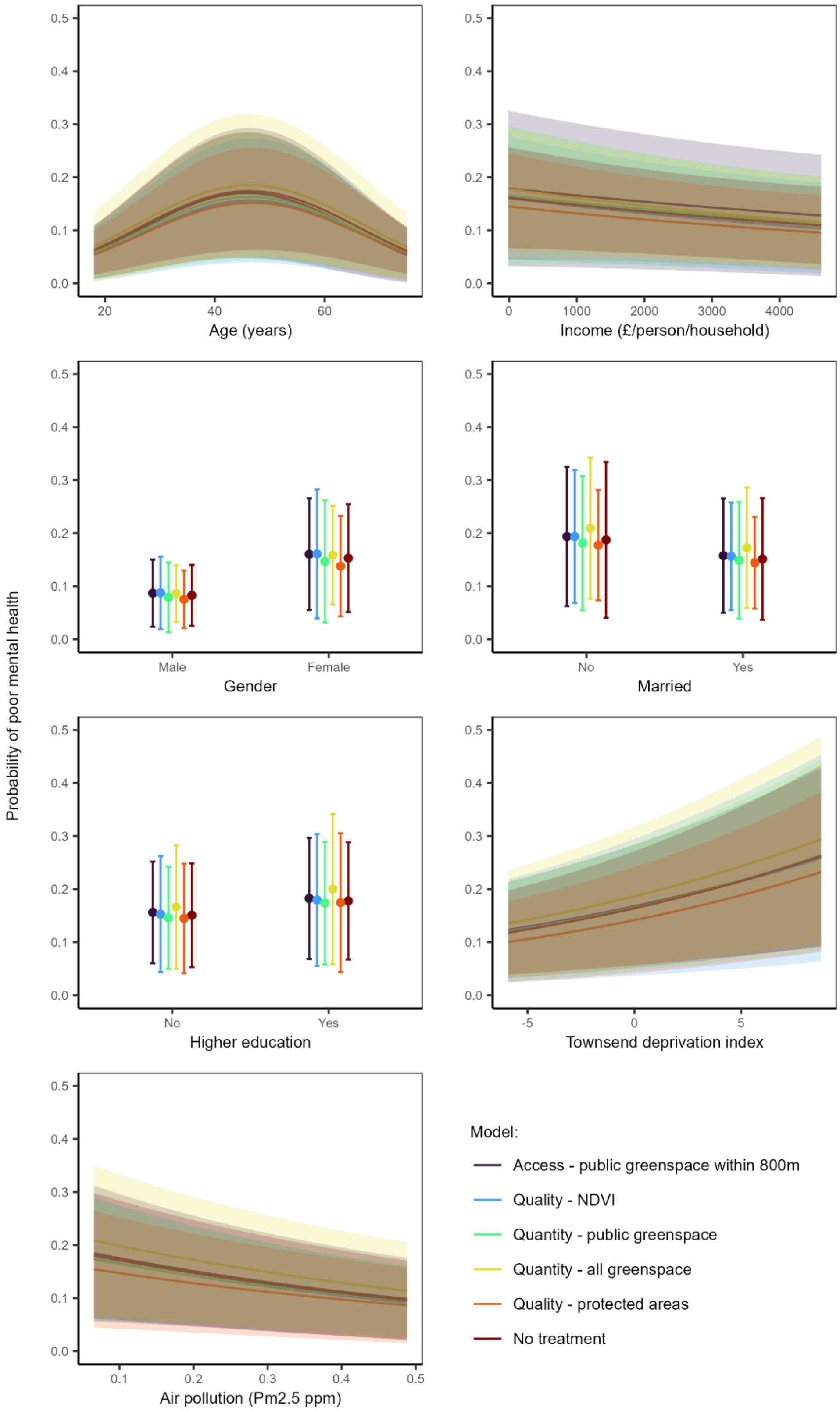

Figure E.2: Predicted probability of poor mental health for individual and area-level variables for the base model and all models that were a poorer fit compared to the base model. Shaded regions show the 95% confidence intervals for the predicted intervals obtained through bootstrapping (1000 replications).

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

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

E.3.1 Residuals

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

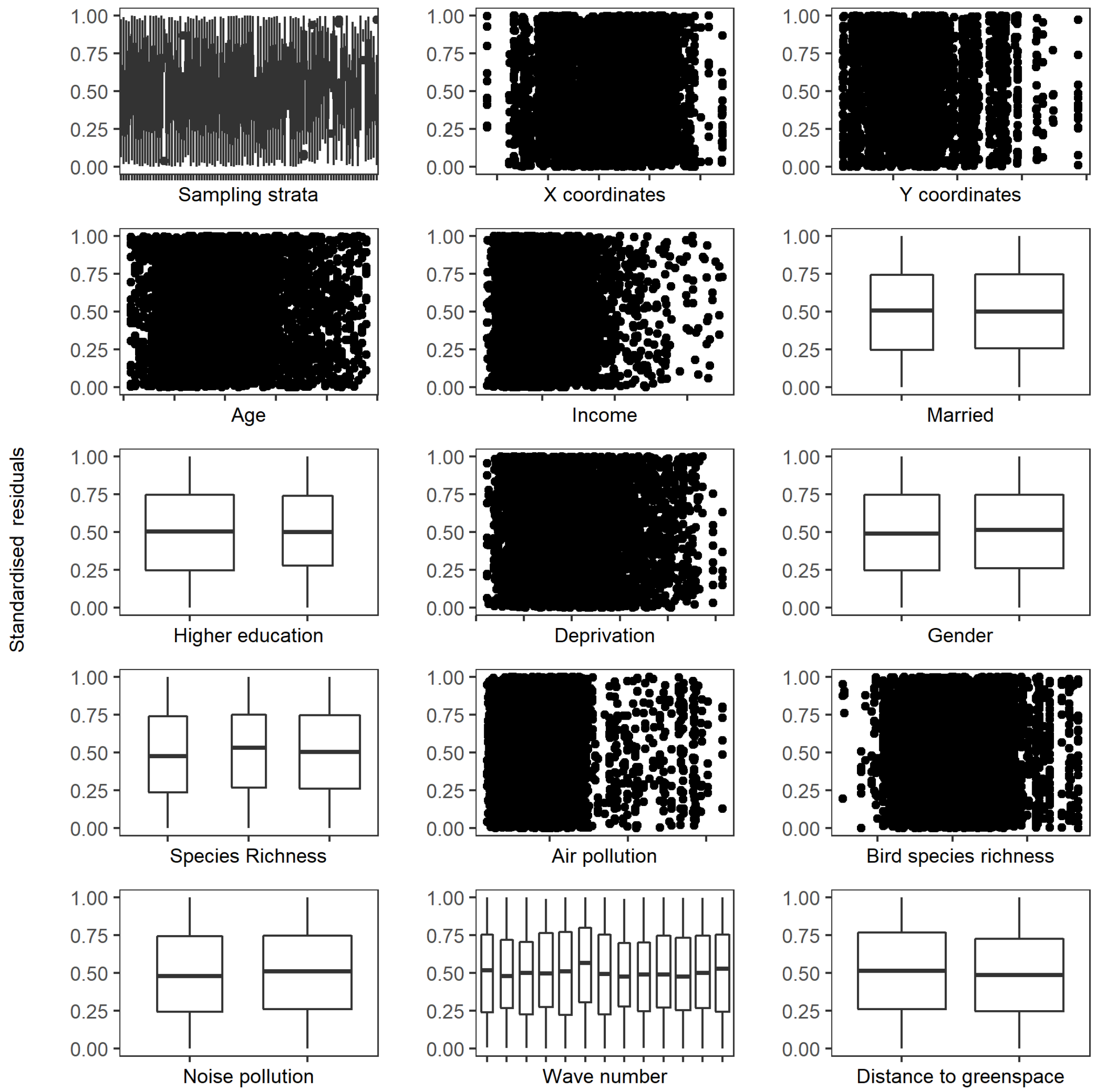

Figure E.3: Absence of residual patterns for the model: Quality – Bird species richness

E.3.2 Generalised variance inflation factors

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

Table E.2: Generalised variance inflation factors for terms contained within the model: Quality – Bird species richness.

Term	**GVIF$^{(1/(2\times df))}$**
Townsend deprivation index	1.042474
Income per person per household	1.065416

Gender	1.013217
Age	1.060504
Married	1.064881
Higher education	1.065133
Air pollution (Pm2.5 ppm)	1.017908
Before and after move	1.694468
Quality – Bird species richness	1.129940
Before and after move:Age:Public greenspace	1.398191

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

E.4.1 Residuals

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

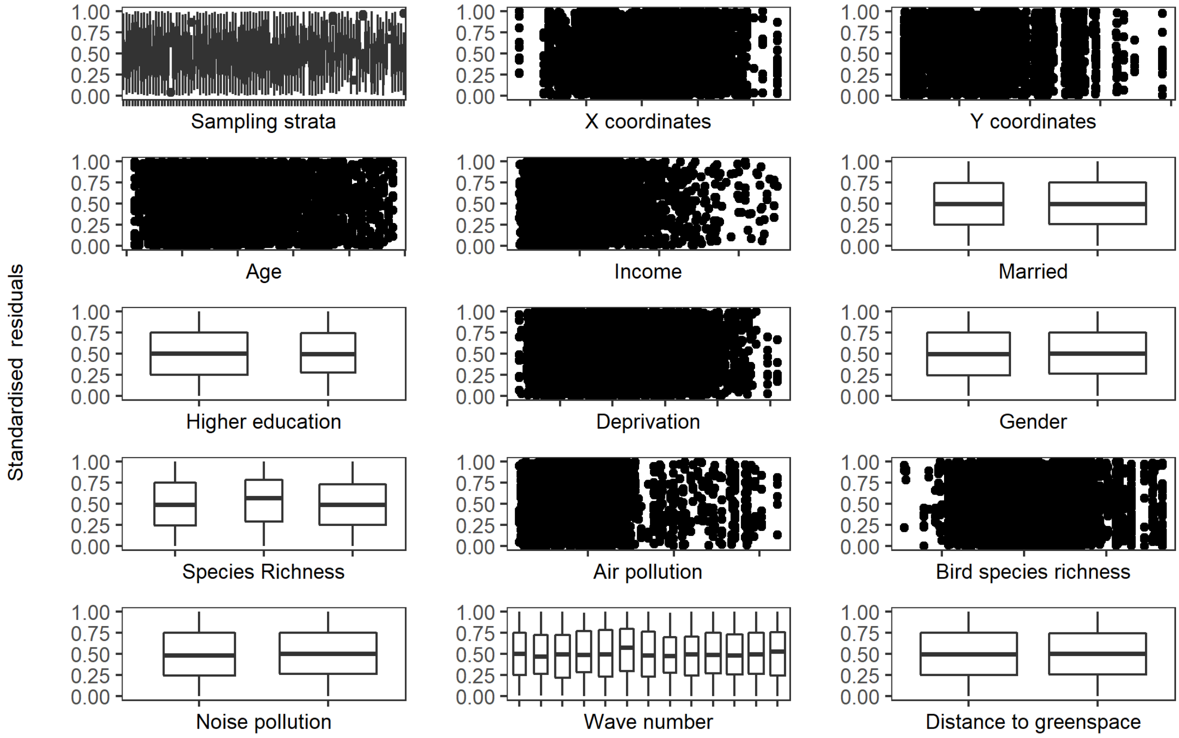

Figure E.4: Absence of residual patterns for the model: Proximity – Distance to public greenspace

E.4.2 Generalised variance inflation factors

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

Table E.3: Generalised variance inflation factors for terms contained within the model: Proximity – Distance to public greenspace.

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